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Social Referral Programs for Freemium Platforms

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Abstract. We examine how freemium platforms can design social referral programs to encourage growth and engagement without sacrificing revenue. On the one hand, social referral programs generate new referrals from users who would not have paid for the premium features. On the other hand, they also attract new referrals from users who would have paid but prefer to invite others, resulting in more referrals but fewer paying users. We use data from a large-scale randomized field experiment in an online dating platform to assess the effects of adding referrals programs to freemium platforms and changing the referral requirements on users' behavior, namely, on their decisions to invite, pay, and engage with the platform. We find that introducing referral programs in freemium platforms can significantly contribute to increasing the number of referrals at the expense of revenue. Platforms can avoid the loss in revenue by reserving some premium features exclusively for paying users. We also find that increasing referral requirements in social referral programs can work as a double-edged sword. Increasing the referral threshold results in more referrals and higher total revenue. Yet these benefits appear to come at a cost. Users become less engaged, decreasing the value of the platform for all users. We explore two mechanisms that help to explain the differences in users' social engagement. Finally, and contrary to prior findings, we find that the quality of the referrals is not affected by the referral requirements. We discuss the theoretical and practical implications of our research.

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Keywords: field experiment • freemium business models • platform strategy • referral program

1. Introduction

Freemium business models can be an effective growth and monetization strategy for platforms. On the one hand, providing free access to a set of features in the platform can decrease entry barriers for new users and increase traffic (Niculescu and Wu 2014, Zhang et al. 2016, Shi et al. 2019). On the other hand, providing users with the option to pay for access to premium features can help monetize the platform and increase user engagement (e.g., Bapna et al. 2018). Social referrals, in contrast, are mainly used as a growth strategy as they focus on customer acquisition rather than revenue (e.g., Bialogorsky et al. 2001, Godes and Mayzlin 2009, Lee et al. 2019).¹ There are

some notable examples of well-known platforms that have successfully implemented social referrals,² and an increasing number of digital platforms have been integrating social referrals in their freemium business models. Whereas referral programs vary in multiple dimensions—such as in the type of reward (e.g., monetary, one-time voucher, access to premium features), who receives the reward (e.g., the referrer, the referral, or both), and the reward payment schedule (e.g., after each successful referral, after a predetermined number of successful referrals)—social referrals in freemium platforms frequently reward existing users with *free access* to premium features of the platform in exchange for a predetermined number of referrals

(users who were referred by existing users). These *threshold referral programs* are commonly used along with freemium business models with subscriptions because of their simplicity and ease of implementation (Lobel et al. 2016).³

Whereas the effectiveness of paying for premium features is studied in prior literature (e.g., Bapna et al. 2018), there is limited research on how freemium platforms can design social referrals to encourage growth and engagement without sacrificing revenue. Moreover, the implications of using social referrals together with freemium models are not trivial. Social referrals, on the one hand, generate referrals from users who would not have paid for the premium features—effectively increasing the number of users in the platform. On the other hand, they also attract referrals from users who would have paid but, given the option, prefer to invite others—effectively resulting in more referrals but fewer paying users. Moreover, for threshold referral programs, the number of successful referrals users are required to invite to access premium features—that is, the referral threshold—can have important implications on users' behavior, namely, on their decisions to invite, pay, and engage with the platform. In addition, imposing higher referral requirements on users may dilute the quality of the referrals as referrers may end up inviting lower quality users, which may harm the platform in the long run (Kumar 2014). Therefore, an important question for freemium platforms that want to use referral programs is how to design such programs so that they can balance growth with revenue while ensuring the quality of their user base. Specifically, our study aims to address the following questions: How do different threshold designs affect referrals, revenue, and platform engagement? How does changing the referral threshold affect different types of users (i.e., users that invite versus users that pay)? Does changing the referral threshold affect the quality of referrals? Finally, to what extent should freemium platforms use threshold referral programs?

To answer these questions, we first develop a stylized model in which users vary with respect to how much they value the platform and how much it costs them to invite referrals. The model shows that social referral programs with a higher threshold lead to (1) an increase in the number of *lurkers* (low-value users who do not pay or invite new referrals), (2) a decrease in the number of *recruiters* (users who invite referrals), and (3) an increase in the number of *payers* (users who pay for premium access). These effects occur because a fraction of the users who would self-select to be recruiters under a referral program with a lower referral threshold become payers under a higher referral threshold as they find it harder to get the required number of successful referrals and, therefore, prefer to pay for the premium access. Second, under a higher referral threshold, fewer users self-select to become

recruiters, leading to fewer users inviting referrals but each with a higher number of referrals. However, whether the total number of successful referrals increases and what the effects on revenue and user engagement are remain empirical questions.

We use data from a large-scale randomized field experiment spanning multiple years in an online dating platform in which social referral programs with *different* referral requirements were used to invite individuals to join the platform. We report three main sets of findings. First, we show that increasing referral requirements in social referral programs can work as a double-edged sword. On the one hand, asking users to invite more new users in order to access premium features provides benefits in terms of not only more successful referrals, but also higher total revenue. On the other hand, these benefits appear to come at the cost of a reduced level of user engagement. More specifically, referral programs that require existing users to recruit one additional referral to access premium features lead to an *increase* in the number of successful referrals and an increase in total revenue. Surprisingly, these programs lead to a *decrease* in user engagement as measured by the number of visits to the platform. These results are robust to different specifications and alternative measures. The effects we observe are also economically significant. In our platform, moving from a referral program that requires only one referral to a program that requires three referrals for accessing premium features results in an overall increase of 26% of the average payment per user for the first eight weeks after joining the platform. We further provide suggestive empirical evidence for two behavioral mechanisms that can explain the decline in user engagement under referral programs with a higher threshold. In such programs, users (1) take longer to access premium features, thus engaging less with the platform and providing lower value to other users as well, and (2) are likely to have fewer friends and acquaintances on the platform, which reduces their social utility, leading to lower platform engagement.

Second, we assess how changing referral requirements affects the quality of new referrals. In contrast with the existing empirical literature on the value of new referrals (e.g., Helm 2003; Kumar et al. 2007, 2010), we find that, despite observing homophily between existing users and referrals, the average quality of the referrals is not affected by the increased referral threshold imposed by the platform. In addition, recruiters increased their platform engagement more when compared with payers as a result of increasing the referral threshold.

Third, leveraging on data from specific experimental conditions, we further assess how adding referral programs to freemium platforms affects user behavior in terms of referrals, payment, and engagement. We find that introducing referral programs to freemium

platforms can significantly contribute to increasing the number of referrals at the expense of revenue. This corresponds to the traditional trade-off between growth and monetization. However, we find that platforms can still take advantage of referrals to grow their user base without hurting revenue by splitting premium features into different tiers and allowing users to access tier 1 premium features via referrals but requiring them to pay for access to tier 2 premium features. This allows the platforms to incentivize users to invite their friends to the platform without forgoing revenue.

Our work contributes to the literature in multiple ways. First, this study establishes the impact of threshold referral programs on freemium business models, particularly in how adding referral programs to freemium platforms and manipulating referral requirements affect user behavior on these platforms. Prior research on monetization strategy of freemium platforms primarily focuses on the effect of *paying* for premium access. For example, Bapna et al. (2018) focus on the effect of paying on social engagement and demonstrate that users that convert from free to premium are likely to become more socially engaged. Our paper, focusing on the effectiveness of different social referral program designs in freemium platforms (threshold design: varying in the number of required social referrals), is—to our knowledge—the first to study a dimension of the referral programs previously not studied and to conceptualize how users change their referral behavior when facing different requirements for accessing premium features.

Second, our research adds to the findings in the literature on social referral programs. We find that, contrary to prior findings in the literature (e.g., Schmitt et al. 2011, Van den Bulte et al. 2018), social referral programs with a higher threshold do not seem to be affected by the quality of the referrals: users pay as much and are as engaged as those invited by users in the referral programs with a lower threshold. We also contribute to a better understanding of the mechanisms that link premium adoption to social engagement. Whereas previous research finds that paying for premium leads to more social engagement (Bapna et al. 2018), we show that users who invite referrals become even more engaged than those who pay for access to premium features, extending prior findings in this area. We also find evidence that both access timing and social enrichment may be the mechanisms at play that explain the differences in users' social engagement.

Third, our paper is, to our knowledge, the first to make use of data from a large-scale randomized control trial to *causally* assess the impact of threshold referral programs on user behavior (referrals and social engagement) and on freemium platform

performance (new customer acquisition and revenue). Overall, we examine how social referral programs can be used as a complement to traditional pay-for-access freemium models, making substantive contributions to both the freemium model and social referral literatures. Our research also offers useful managerial implications and provides a better understanding of user behavior on platforms that combine referral programs with freemium business models.

2. Related Literature

We draw from two streams of research in information systems and marketing that are important for the development of our paper: freemium business models and social referral programs.

2.1. Freemium Business Models

Freemium business models are characterized by the simultaneous existence of free and premium versions of the same product (Anderson 2009). Whereas the former typically offers a limited set of features—providing a satisfying experience for the majority of users—the latter offers enhanced features at a price. According to the versioning literature on information goods, these distinctions create vertically differentiated versions of the same product (Bhargava and Choudhary 2001). In this paper, we focus on what Niculescu and Wu (2014) call the feature-limited freemium model, which allows users to use certain features for free and have the option to access premium features for a fee.

Freemium business models have proven to be an effective strategy to attract new users, generate traffic, and increase sales (Liu et al. 2014, Bapna et al. 2018, Gu et al. 2018). Whereas theoretical work in this area focuses on exploring the economics of freemium (Niculescu and Wu 2014, Zhang et al. 2016, Shi et al. 2019), empirical literature looks at the dynamics of user behavior for firms adopting freemium models (e.g., Oestreicher-Singer and Zalmanson 2013, Bapna and Umyarov 2015, Fang et al. 2019). For example, some studies focus on linking social engagement and peer influence to increase premium subscriptions (Oestreicher-Singer and Zalmanson 2013). Bapna et al. (2018) flip the question and examine how users' premium adoptions influence their engagement on an online music platform. They find that purchasing a premium membership leads users to increase their social engagement.

An important challenge that platforms using freemium models face is how to monetize their user base. The literature on platform pricing distinguishes between the money and subsidy sides of a platform (Parker and Van Alstyne 2005). In the context of freemium platforms, this means premium users who pay for access to premium

features subsidize free users. Whereas most of the prior studies focus on asking users to pay in exchange for access to premium features, limited attention has been paid to using social referrals as a monetization strategy. Our paper is one of the first studies to investigate the effectiveness of different referral program designs (threshold design: varying in the number of required social referrals) in freemium platforms. We study how these platforms can design social referral programs—specifically, how they can adjust the number of required referrals—to influence users' decisions with respect to continuing using the free version, inviting referrals, or paying for access to premium features.

2.2. Social Referral Programs

Social referral programs are traditionally used by firms in off-line settings in which customers were encouraged to recommend their friends and acquaintances to purchase a product or service. The emergence of online platforms and social media has facilitated the spread of word-of-mouth (WoM) and social sharing (e.g., Galbreth et al. 2012, Shi et al. 2014, Vilnai-Yavetz and Levina 2018, Sun et al. 2020a) and made it possible to refer across larger social distances (e.g., Hong et al. 2017).

On the theoretical side, a group of studies in this area provides guidance on the conditions in which rewards should be offered. These conditions include the customers' valuation of the product (e.g., Biyalogorsky et al. 2001, Lobel et al. 2016), what triggers them to make referrals (e.g., Biyalogorsky et al. 2001, Kornish and Li 2010, Lobel et al. 2016), their network of friends and acquaintances (e.g., Lobel et al. 2016), their costs of making referrals (e.g., Kamada and Öry 2020), and whether they value their friends' benefits (e.g., Kornish and Li 2010).

Another set of theoretical work centers on the optimality of referral incentives to maximize firms' revenue. For example, Kamada and Öry (2020) study the referral incentive scheme in a scenario in which existing customers benefit from inviting new customers through WoM either because they get a referral reward from the platform or benefit directly from having their referrals in the platform (referral externalities). Their model predicts that referral rewards should be used when externalities accrued from inviting new users to the platform are low and free products can substitute referral rewards only when the fraction of premium users is low. Lobel et al. (2016) propose a model that incorporates the network structure and models consumers as being able to strategically anticipate how many of their friends will adopt the product. They find that the optimal incentive scheme may be nonmonotonic in the number of successful referrals. This is because users with more

friends have a higher incentive in purchasing the product as they are more likely to recover their investment. Thus, users with more friends need lower incentives to refer their friends. Other related prior theoretical work studies when rewards should be offered (Biyalogorsky et al. 2001, Kornish and Li 2010) and has quantified the impact of rewards and tie strength on referral likelihood (Wirtz and Chew 2002, Ryu and Feick 2007) and the monetary value of making a referral (Helm 2003; Kumar et al. 2007, 2010).

Among empirical studies, prior work can be categorized into two main camps. One set of studies focuses on assessing the impact of referral programs and documents significant economic benefits, including a higher contribution margin, a higher retention rate, and a higher customer lifetime value (e.g., Schmitt et al. 2011, Garnefeld et al. 2013, Van den Bulte et al. 2018). Another group of studies focuses on how to effectively design social referral programs and answer questions, such as which consumers should be targeted for referrals (e.g., Hinz et al. 2011), which types of ties are most effective for referrals (e.g., Ryu and Feick 2007), how to design incentives (e.g., Hong et al. 2017, Sun et al. 2020b), which types of messages work the best (e.g., Jung et al. 2020), and how to design viral features to generate social contagion effects (e.g., Aral and Walker 2011, Belo and Ferreira 2022).

Our work adds to the latter stream of literature by studying referral threshold designs in freemium platforms. Specifically, we examine whether changes in social referral requirement would influence users' referrals, payment, and engagement. We focus on threshold referral programs in which the reward is fixed and users can access premium features once they successfully invite a predetermined number of referrals. In terms of rewards, whereas prior studies primarily focus on monetary-based social referral programs, including cash gifts, discounts, and coupons (Hong et al. 2017, Hanson and Yuan 2018, Sun et al. 2020b), our paper studies nonmonetary-based social referral programs. Such programs are particularly useful for freemium platforms that use subscription models. In these platforms, incentivizing free users to refer a friend with monetary rewards may not work as they are not currently paying for the service and are unlikely to be motivated by a discount. Instead, they are more likely to be motivated by a feature upgrade. Such rewards also allow platforms to promote a broader use of the platform through user engagement.

Our paper is different from prior work on social referral programs in the following ways. First, unlike some of the prior studies focusing on *linear referral programs* (Lobel et al. 2016, Lee et al. 2019), in which the reward varies and is proportional to the number of

referrals that users acquire, we focus on threshold referral programs, in which the reward is fixed and referrals are costly. The platform we study operates under a freemium model in which the rewards for a successful referral correspond to getting access to premium features in the platform. Second, unlike Kamada and Öry (2020), we study a setting in which a firm provides freemium plans for all its users and an option to upgrade to premium versions. Third, similar to Lobel et al. (2016) and Kamada and Öry (2020), we focus on users' reactions to different referral requirements in threshold referral programs. In our case, the platform determines how many successful referrals an existing user must bring to get the reward, but the rewards are constant (i.e., access to premium versions of the platform).

Moreover, our work also contributes to related research on the profitability of referral programs for freemium platforms. On the one hand, prior work challenges whether increasing referral requirements could be profitable for companies (Lee et al. 2019). This is because a customer-to-customer referral program is mainly used for customer acquisition, and a large number of free users, sometimes up to 90%, do not contribute to firm's revenue (Lee et al. 2019). On the other hand, one may argue that increasing referral requirements could result in lower referral quality that negatively affects platform's revenue. By building on and extending the literature in freemium business models and social referral programs, our paper is the first study to empirically examine the interplay between threshold referral programs and freemium platforms through the investigation of changes in user behavior (referral, payment, and social engagement) and the profitability of freemium platforms.

3. Context, Experiment, and Data

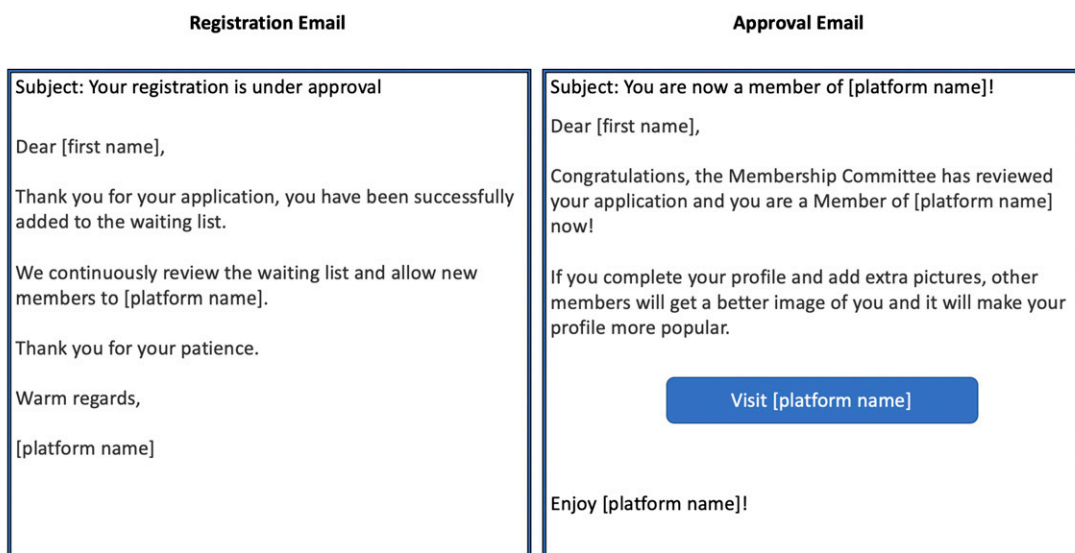
3.1. Research Context

We use data from a large-scale randomized field experiment in collaboration with an online dating platform. This platform is positioned in the “selective dating” segment, focusing on young professionals. In this platform, new members go through a manual screening process before getting approved to join. At the registration, individuals need to provide their personal information, including age, gender, an adequate profile picture, and personal preferences. They are also required to connect their profile on the platform to either Facebook or LinkedIn. The screening process ensures, to a large extent, that individuals provide truthful information about themselves and discourages false profiles. Individuals that register but do not get approved stay in a probation state until they provide adequate information.

Upon registration, users are informed—both through the registration page and by email—that their registration is under review (see left pane in Figure 1 for an example email). When approved, they get an email stating they were approved, and they can start using the platform (see right pane in Figure 1).

On the platform, approved users can freely perform four types of activities: visit other users' profiles, send messages to other users, send winks (click on a “wink” button to express their interest in other users), and like other users (click on a “like” button to express their interest in other users). These are considered free features in the platform. On the receiving end—to access information about views, messages, winks, and likes they have received, which are considered premium features—users are required either to recruit

Figure 1. (Color online) Mock Screenshots: Registration and Approval Emails



new users to the platform or to pay a monthly fee. The platform has defined two tiers for their premium features. Tier 1 premium features include accessing information on received profile views and messages, whereas tier 2 premium features include accessing information on winks and matches. A match occurs when two users like each other.

Typically, a focal user receives a notification when another user interacts with the focal user (i.e., visits the profile, sends a message, sends a wink, or matches with the focal user). When a user logs in, the user is able to see that others have interacted with the user via a badge that indicates the total number of activities that were not yet checked. The user can only access the respective information if the referral program allows it. Otherwise, the user is presented with a screen informing the user of the actions the user can take to gain access to premium features (see Figure 2). In our context, users only get to know exactly about their restrictions when they try to access premium features that are reserved for premium members.

In our setting, an existing user who makes a successful referral follows three steps: (1) an existing user sends invitations to friends or acquaintances to join the platform (*invitations*), (2) the referrals register on the platform (*registrations*), and (3) the referrals are approved by the platform (*approvals*).

3.2. Experimental Setup

For its new rollout in a major European city in 2015, our partner platform introduced social referral programs aiming to grow its user base. To do so, the platform employed a large-scale randomized field experiment to assess the effectiveness of different social referral

programs. A referral program is determined by how many new users (successful referrals) each existing user is required to get in order to gain access to the platform's premium features. An example of a referral program is a user is required to get two successful referrals in order to access tier 1 premium features and one additional successful referral to access tier 2 premium features. Note that paying a monthly subscription fee is always an option, irrespective of the referral program. During the experimental period, the platform charged the equivalent of roughly €20 (~US\$23) for a monthly subscription fee, which is in line with other dating platforms.

In this study, we use an experimental data set of two years between March 2015 and February 2017. In general, for each week of the experiment, the platform determined a set of referral programs with different thresholds to be active for that week and randomly assigned each new user to one of the active referral programs at the moment of user registration. The referral program to which a new user is assigned does not change over time. Appendix A provides more details on the experimental setup and the randomization procedure, together with descriptions on users' assignment to specific programs over time.

Table 1 shows how many new users were assigned to each referral program for accessing tier 1 and 2 premium features. For example, a total of 20,254 users were assigned to a referral program that requires an existing user to get one successful referral for accessing tier 1 premium features. Out of these, 7,463 users could also access tier 2 premium features without any additional referral, 8,265 users were requested to get one additional successful referral to access tier 2

Figure 2. (Color online) Mock Screenshot: User Gets Prompted to Invite Referrals or Pay for Premium Features When Trying to Access Information About Profile Views, Messages, Winks, and Matches

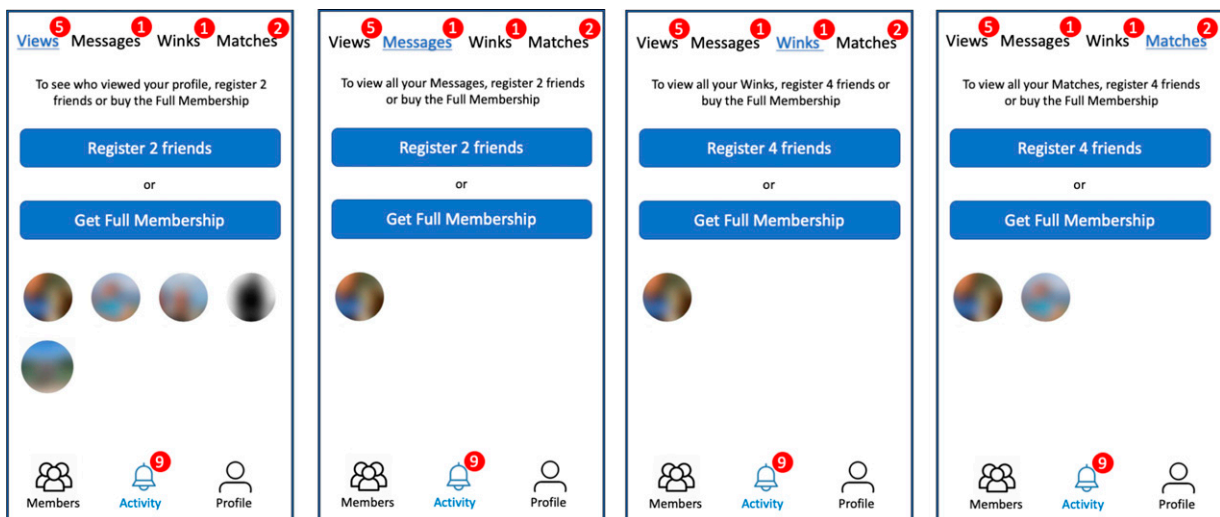


Table 1. Referral Program Experimental Conditions (Frequency)

	Number of referrals for tier 2 premium features				
	0	1	2	3	Total
Number of referrals for tier 1 premium features	0	0	13,143		13,143
	1	7,463	8,265	4,526	20,254
	2	5,966	7,140	4,198	17,304
	3	689	257	1,135	2,081
Total	14,118	15,662	23,002		52,782

Notes. Number of approvals for tier 1 premium features represents how many successful referrals are necessary for a user to have access to tier 1 premium features. Number of approvals for tier 2 premium features represents how many additional new successful referrals (on top of those required to access tier 1 premium features) are necessary for a user to have access to tier 2 premium features.

premium features, and 4,526 users were requested to get two additional successful referrals to access tier 2 premium features.

3.3. Data and Variables

Our data include all 52,782 new users who were approved in the focal city within the experimental period. These users invited a total of 25,792 users, out of which 18,171 registered on the platform, and 9,579 ended up approved by the platform. Note that all the 9,579 successful referrals are part of the 52,782 users we have in our data set. We present the descriptive statistics on user demographics in Table 2. We can see that about 62% of all users are women; the average user is 28 years old with the youngest being 18 and the oldest being 76 years old. About 62% of the users specified their education. Out of these, about 49% of the users reported having a bachelor’s degree and 33% reported having a master’s degree. Among the 45% of users who reported their height, the average is 174 cm; out of the 35% of users who provided information about whether they smoke, 5% responded affirmatively; and out of the 39% of users who provided information about having children, 2% said yes.

Dating platforms usually exhibit high turnover, in which users are initially very active because they suddenly have access to a new pool of potentially interesting people. In addition, new users get considerable attention from existing users as they are usually shown in a “new members” tab.⁴ After some time, the novelty wears off or, ideally, users stop using the platform because of a successful outcome. Figure 3 depicts user activities over the first eight weeks on the platform.

The figure shows that all types of activities decay after the first week except for messages sent, which peaks at the second week. Such decay in user activity level is expected based on the nature of the platform. Therefore, in this paper, we focus on the first eight weeks of each user’s tenure on the platform after approval as most user activity happens during the first eight weeks.⁵

We evaluate three outcome variables when assessing the impact of changing referral programs on user behavior: the total number of successful referrals a user gets (*successful referrals*), the total amount of payments performed by the user (*payment*), and how engaged the user is with the platform (*user engagement*), measured by the number of platform visits either on the website or through the mobile app. Table 3 shows the summary statistics of these three main dependent variables. We also include the number of invitations that an existing user sent and the number of registrations among these invitations. On average, existing users invite 0.49 referrals to the platform and are able to successfully get 0.18 referrals during their first eight weeks. An average user visits the platform 56 times and pays €4.3 during the first eight weeks.

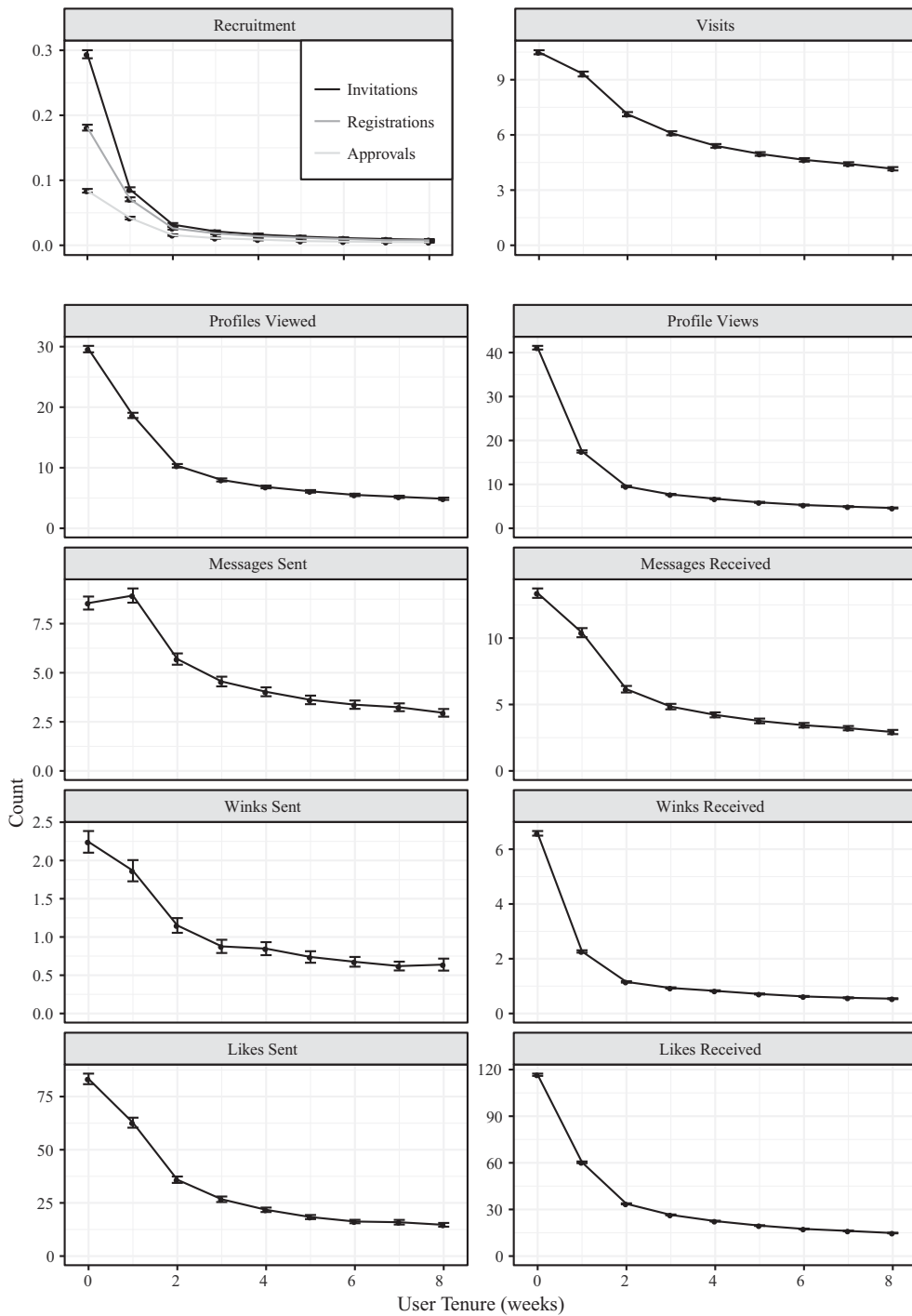
3.4. Randomization Checks

On this platform, new users are randomly allocated to one of the social referral programs active at the moment of registration. In order to evaluate whether the referral program allocation was indeed random, we regress demographics on referral program assignment using age and week fixed effects. We use age fixed

Table 2. Summary Statistics for User Demographics

Variable	N	Mean	Median	Standard deviation	Minimum	Maximum
Age	52,782	28.123	27	4.953	18	76
Female	52,782	0.621	1	0.485	0	1
Education, years	32,892	15.367	15	1.522	0	20
Height	23,765	174.320	174	9.684	150	206
Smoker	18,702	0.049	0	0.215	0	1
Children	20,908	0.023	0	0.149	0	1

Figure 3. User Behavior over Time



effects because, during a certain period of time, the platform had different social referral programs for users that are 27 years old or younger. We use week fixed effects because different sets of referral programs were available in different weeks. The results are shown in Table 4. We see no significant relationship between

referral program assignment and our demographic variables (i.e., education, gender, height, whether a user reported being a smoker or having children). In Appendix A, we perform additional robustness checks in light of the additional details we provide about the experimental setup and randomization procedure.

Table 3. Summary Statistics for Key Outcome Variables (First Eight Weeks)

Variable	<i>N</i>	Mean	Median	Standard deviation	Minimum	Maximum
<i>Invitations</i>	52,782	0.489	0	1.100	0	74
<i>Registrations</i>	52,782	0.344	0	0.895	0	70
<i>Approvals</i>	52,782	0.181	0	0.573	0	24
<i>Visits</i>	52,782	55.525	17	87.388	0	1,562

4. How Does Changing the Referral Threshold Impact User Behavior?

In this section, we look into how users make decisions when they face referral programs with different referral thresholds in the context of freemium business models. We first develop a stylized model that provides intuition on users’ decisions as a function of referral program threshold. The model then sets the stage for our empirical strategy.

4.1. A Stylized Model

We start by assuming that users are heterogeneous across two dimensions: (1) how much they value the platform, V , and (2) how much it costs them to get one successful referral to the platform, $c(\cdot)$. Some users derive more value from the platform and, therefore, may have a higher willingness to pay for it. Cost, c , represents how hard it is for users to reach others and get them as successful referrals to the platform. Whereas some users may be able to easily tap into their social network to get referrals, others may have limited social connections or may not want to reveal to their friends or acquaintances that they are using such a platform. Given the option of either getting referrals to the platform or paying a price p to upgrade, users choose the option that yields the highest utility. The utility of a user can be defined as

$$u_i = V_i - \min\{c_i(r), p\}, \quad (1)$$

where $V_i \equiv V + v_i$ in which v_i is an error term with mean zero and r represents the number of successful referrals an existing user needs to access premium features. We assume $c_i(\cdot)$ is an increasing function in its

argument. Users use the platform if their valuation is higher than the minimum between the cost of getting the required number of successful referrals and the price they need to pay to get access to the premium version. Otherwise, they either use the free but restricted version of the platform or stop using it. Thus, the utility of a user can be defined as

$$u_i = \begin{cases} V_i - c_i(r), & \text{for } V_i \geq c_i(r) \leq p \quad (\text{recruiter}) \\ V_i - p, & \text{for } V_i \geq p < c_i(r) \quad (\text{payer}) \\ 0, & \text{for } V_i < c_i(r) \text{ and } V_i < p \quad (\text{lurker}). \end{cases} \quad (2)$$

Figure 4 shows the decision regions as a function of an individual’s platform valuation and the individual’s cost of getting successful referrals. Figure 4(a) shows, for reference, the decision regions for a freemium-only model, that is, a model in which users are not rewarded by getting successful referrals. In this case, users pay for accessing the premium features if they value those features more than their price, and the cost of inviting does not play a role in a user’s decision. Figure 4(b) shows the decision regions for a referral program that requires existing users to either get one successful referral or pay a fee to get access to premium features. We distinguish between three types of user status: (1) users with relatively high valuation and low cost of recruiting decide to recruit new users (labeled as “recruiter”); (2) users with a relatively high valuation and high cost of recruiting decide to pay (labeled as “payer”); and (3) users with low valuation and high cost of recruiting decide to use the restricted version of the platform or leave the platform entirely (labeled as “lurker”).

Table 4. Randomization Check: Demographics as a Function of Referral Programs

	Dependent variable				
	<i>Educ_years</i> (1)	<i>Female</i> (2)	<i>Height</i> (3)	<i>Smoker</i> (4)	<i>Children</i> (5)
Number of referrals for tier 1	0.013 (0.018)	0.003 (0.005)	0.060 (0.148)	-0.004 (0.004)	-0.001 (0.002)
Number of additional referrals for tier 2	0.007 (0.019)	0.004 (0.005)	-0.040 (0.142)	-0.001 (0.004)	0.0004 (0.002)
Observations	32,892	52,782	23,765	18,702	20,908
R^2	0.013	0.022	0.020	0.008	0.022
Adjusted R^2	0.010	0.020	0.016	0.002	0.017

Notes. Fixed effects: age > 27, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure 4. (Color online) A Stylized Model (Depicting User Decision Regions as a Function of How Much They Value the Platform and Their Cost of Recruiting Other Users to the Platform)

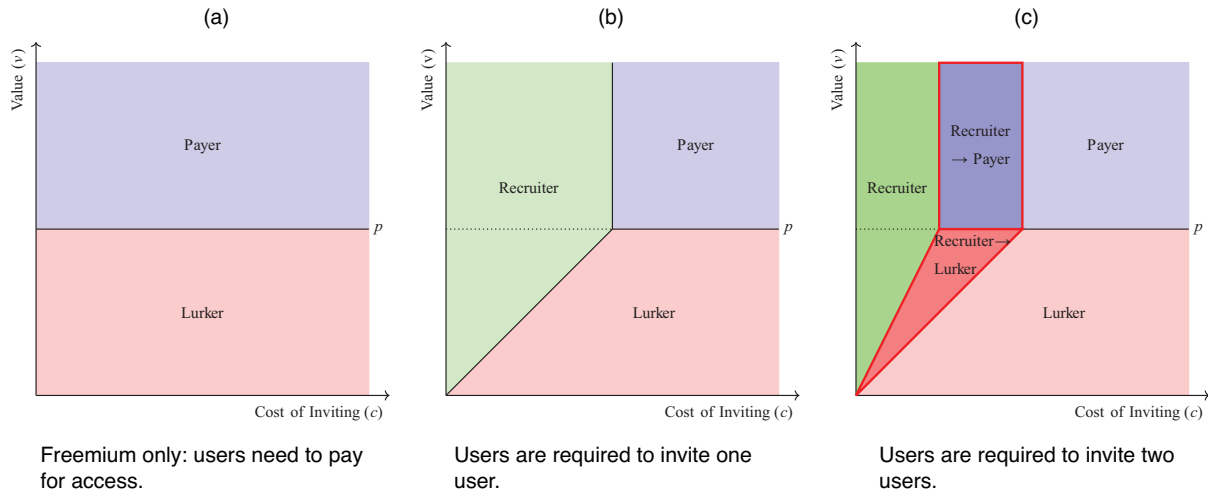


Figure 4(c) shows the decision regions for a referral program that requires existing users to get two successful referrals. Changing from a referral program with a lower threshold increases the cost of recruiting as free users now need to recruit more new users in order to upgrade to premium. As a result, some users previously labeled as recruiters become either payers or lurkers. The region marked with “recruiter → payer” includes users who decide to pay because they find it too costly to get one additional referral and prefer to pay the fee to access premium features. The region marked with “recruiter → lurker” includes users who decide to use only the restricted version of the platform or to leave because they do not value the platform enough to pay or to incur the cost of referring one additional user. This is consistent with our formulation in Equation (2): as r increases, the shares of individuals who are payers and lurkers increase as well, whereas the share of individuals who are recruiters decreases. Appendix B contains the derivations for these expressions using comparative statics.

In summary, social referral programs with a higher threshold always result in an increase in the number of payers and in total revenue. A fraction of the existing users that would self-select to be recruiters under programs with a lower threshold decide to become payers when the threshold is higher as they find it harder to get the required number of referrals and less costly to pay for access premium features. Also, in referral programs with a higher threshold, fewer existing users self-select to become recruiters, leading to fewer users recruiting referrals but each with a higher number of successful referrals. However, whether the total number of successful referrals increases is determined by the functional form of $c(\cdot)$, which is mostly

an empirical question. Finally, we are interested in assessing the effects of threshold design on user engagement and on the quality of the referrals. Our model is agnostic about these questions, so we explore them empirically, informed by the literature. We explain how we empirically examine the impact of threshold design on the number and quality of successful referrals, total revenue, and user engagement in the next section.

4.2. Empirical Strategy

We start by estimating the effects of changing the referral threshold on three types of user behavior, namely, the number of successful referrals, total revenue, and user engagement as measured by visits to the platform. We depart from the details of the stylized model and use linear specifications because we are mainly interested in obtaining marginal effects of increasing the referral threshold, which linear models readily provide (Angrist and Pischke 2008). To do so, we regress our dependent variables on the referral program, using education, age, gender, user tenure, and time as fixed effects. We use the equation

$$y_{it} = c_i(r_i) + x_i + w_t + v_{it} \quad (3)$$

in which y_{it} represents one of our dependent variables and vectors x_i and w_t represent individual characteristics and time covariates that we use as fixed effects. We are unable to use individual fixed effects in our setting because referral program assignment is performed at the individual level and does not change over time. Using individual-level fixed effects would, thus, preclude us from identifying the effects of interest.

We assume $c_i(\cdot)$ is linear in its argument with an idiosyncratic term (θ_i) representing the individual cost of

recruiting new users: $c_i(r) \equiv \gamma r + \theta_i$. We further decompose r into two terms to reflect our empirical setting

$$r = \delta_1 r_1 + \delta_2 r_2$$

in which r_1 represents how many successful referrals an existing user needs to get to access tier 1 premium features and r_2 represents how many additional successful referrals the user needs to get to access tier 2 premium features. Then,

$$y_{it} = \beta_1 r_{1i} + \beta_2 r_{2i} + x_i + w_t + \varepsilon_{it}, \quad (4)$$

where $\beta_1 \equiv \gamma \delta_1$ and $\beta_2 \equiv \gamma \delta_2$ are our main parameters of interest, representing how much requiring an existing user to get a successful referral to access different premium features, respectively, contributes to a change in the measured dependent variable. Finally, $\varepsilon_{it} \equiv v_{it} + \theta_i$ represents the error term composed of the unobserved components of V_i and c_i .

5. Results: Estimating the Effects of Changing the Referral Threshold on User Behavior

Following our empirical strategy, we first present the main results related to the effects of changing referral requirements on user behavior. Then, we present a set of robustness checks of our main results by using alternative measures of engagement and test for the existence of nonlinear effects of referral program requirements. Next, we explore the heterogeneous treatment effects for age, gender, and education. Finally, we examine the changes in the quality of the referrals as a result of increasing the referral threshold.

5.1. Main Results

We start by looking at the impact of different referral programs on user behavior: successful referrals, payment, and user engagement (as measured by visits). Our unit of analysis is a user in a week, and we estimate these effects with pooled linear models. Each of the dependent variables is modeled as a linear function of the required number of referrals for accessing tier 1 and 2 premium features in a referral program. We use fixed effects for education, age, gender, user tenure, and time (i.e., week)⁶ to account for potential variations across these factors. We cluster the standard errors at the user level. We present our main results in Table 5.

Social referral programs with different thresholds were randomly assigned at the user level for each week; thus, the coefficients in these regressions have a causal interpretation. Columns (1)–(3) show that referral programs with higher thresholds tend to increase the number of successful referrals. Requiring one additional successful referral in order to access tier 1

premium features leads to an increase of 2% of a standard deviation in the weekly number of invited new users ($p < 0.01$). On top of this, requiring one additional successful referral to access tier 2 premium features leads to a further increase of 2.5% of a standard deviation in the weekly number of invited users ($p < 0.01$). These values decrease slightly for registrations and approvals. This is as expected because new users register on the platform after they are invited, and their approval is conditional on their platform registration. Requiring one additional successful referral to access tier 1 (tier 2) premium features results in an increase of 1.4% (1.9%) of a standard deviation in new user registrations ($p < 0.01$) and in an increase of 0.9% (1.2%) of a standard deviation in their approvals ($p < 0.01$).

Our results also show that referral programs with higher thresholds lead to an increase in payment regarding access to both tier 1 and 2 premium features. Column (4) shows that requiring an additional referral to access tier 1 (tier 2) premium features leads to an increase of 2.6% (2.2%) of a standard deviation in the weekly amount paid ($p < 0.01$). This increase in payment as a result of increasing the threshold is consistent with our stylized model, that is, some users may find it hard to invite enough referrals and decide to pay to access premium features.

We also find that referral programs with higher thresholds lead users to decrease their platform engagement as measured by the number of visits. Column (5) shows that requiring users to get an additional successful referral to access tier 1 (tier 2) premium features leads to a decrease of 5.4% (2.9%) of a standard deviation ($p < 0.01$).

We also check the robustness of our main results using alternative measures of user engagement. We use other types of platform activities, including user interactions with other members on both directions: profile views, messages, winks, likes, and matches based on mutual likes and on the number of exchanged messages. Table 6 shows that users assigned to referral programs with higher thresholds have much lower levels of engagement as measured by profile views, messages, winks, and likes. Table 7 shows the same results for matches. We use four different definitions of match. Two users are considered to match with each other if they have sent a like to each other (mutual like) or if they have exchanged at least three, five, or seven messages with at least one, two, and three messages in each direction, respectively. All these results are consistent with our main results.

It is unlikely that the positive effect of referral programs on total user number and payment grows indefinitely regardless of the required number of successful referrals. At some point, requiring users to refer one more user has a smaller effect on their

Table 5. Main Results: Effect of Changing Referral Requirements on User Behavior

	Dependent variable				
	<i>Invitations</i> (1)	<i>Registrations</i> (2)	<i>Approvals</i> (3)	<i>Payment</i> (4)	<i>Visits</i> (5)
Number of referrals for tier 1	0.020*** (0.003)	0.014*** (0.003)	0.009*** (0.003)	0.026*** (0.003)	−0.054*** (0.005)
Number of additional referrals for tier 2	0.025*** (0.003)	0.019*** (0.003)	0.012*** (0.003)	0.022*** (0.003)	−0.029*** (0.005)
Observations	463,470	463,470	463,470	463,470	463,470
R ²	0.077	0.048	0.025	0.020	0.079
Adjusted R ²	0.076	0.048	0.025	0.020	0.078

Notes. Fixed effects: education, age, gender, tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

behavior. We test the existence of nonlinear effects of referral program requirements on user behavior. As expected, requiring an additional referral in order to gain tier 1 premium features leads to an increase in invitations, registrations, approvals, and payment but only up to a certain point. In our specifications, the maximum benefit is attained when requiring between two and three referrals to access tier 1 premium features. We do not observe a nonlinear effect of increasing referral requirements on user engagement. The results of this analysis are provided in Appendix C.

5.2. Heterogeneous Treatment Effects

Our main results are robust to potential heterogeneity across users as we use the same fixed effects. Nevertheless, we can take advantage of the referral programs' random assignment to assess potential heterogeneity in the effects of different referral thresholds on users' activities. To do so, we run three sets of regressions in which we explicitly control for age, gender, and education, removing the respective fixed effects and interacting referral programs with different threshold designs

with each of these controls. It is worth noting that the results show women are more likely to invite new users but less likely to pay and are, on average, less engaged with the platform. In addition, increasing the referral threshold with respect to tier 2 premium features has an effect on women's engagement, but not on men's. Users older than 27, on average, get fewer successful referrals, pay more, and are more engaged with the platform. In addition, for these users, increasing the referral threshold with respect to tier 2 premium features has a larger effect on invitations, registrations, approvals, and payments. The platform could consider using this information to adjust referral requirements for different user groups in order to increase user acquisition and payment without hurting engagement. All results for the heterogeneous treatment effects are shown in Appendix D.

5.3. Does Increasing the Referral Threshold Change Referral Quality?

Our main results show that increasing required referrals leads to an increased number of successful referrals

Table 6. Alternative Measures of User Engagement: Profile Views, Messages, Winks, and Likes

	Dependent variable								
	<i>Visits</i> (1)	<i>Profiles viewed</i> (2)	<i>Profile views</i> (3)	<i>Messages sent</i> (4)	<i>Messages received</i> (5)	<i>Winks sent</i> (6)	<i>Winks received</i> (7)	<i>Likes sent</i> (8)	<i>Likes received</i> (9)
Number of referrals for tier 1	−0.054*** (0.005)	−0.026*** (0.004)	−0.017*** (0.004)	−0.020*** (0.004)	−0.023*** (0.004)	−0.005 (0.004)	−0.018*** (0.004)	−0.015*** (0.004)	−0.035*** (0.004)
Number of additional referrals for tier 2	−0.029*** (0.005)	−0.018*** (0.004)	−0.012*** (0.004)	−0.004 (0.004)	−0.012*** (0.004)	−0.017*** (0.005)	−0.012*** (0.004)	−0.015*** (0.004)	−0.016*** (0.004)
Observations	463,470	463,470	463,470	463,470	463,470	463,470	463,470	463,470	463,470
R ²	0.079	0.081	0.219	0.020	0.031	0.013	0.210	0.032	0.381
Adjusted R ²	0.078	0.080	0.219	0.020	0.031	0.013	0.209	0.031	0.381

Notes. Fixed effects: education, age, gender, tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7. Alternative Measures of User Engagement: Matches

	Dependent variable			
	Mutual like (1)	Three messages (2)	Five messages (3)	Seven messages (4)
Number of referrals for tier 1	-0.029*** (0.005)	-0.035*** (0.004)	-0.033*** (0.004)	-0.031*** (0.004)
Number of additional referrals for tier 2	-0.023*** (0.005)	-0.019*** (0.005)	-0.018*** (0.005)	-0.017*** (0.005)
Observations	463,470	463,470	463,470	463,470
R ²	0.036	0.026	0.024	0.023
Adjusted R ²	0.036	0.025	0.024	0.022

Notes. Fixed effects: education, age, gender, tenure, time. Standard errors clustered at the user level.
 * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

and to higher average payments. Does increasing the referral threshold change the quality of the referrals? The referral program assigned to a referrer could affect the observed behavior for the referrals even though the assignment was random. This could happen if, for example, individuals assigned to referral programs with a higher threshold invite different users from those who were invited by the individuals who were assigned to referral programs with a lower threshold (as suggested in Van den Bulte et al. (2018) and Schmitt et al. (2011)) or if their behavior influences their referrals' behavior (e.g., Bapna and Umyarov 2015, Iyengar et al. 2015).

To answer this question, we look at the effect of changing the referral threshold on the total number of successful referrals, payment, and engagement from users who joined the platform as a result of an invitation from the referrer. The results, shown in Table 8, suggest that none of these mechanisms is likely to play in our case. Columns (1) and (2) show effects on referrals, columns (3) and (4) show effects on payments, and columns (5) and (6) show effects on engagement as measured by visits to the platform. Columns (1), (3), and (5) show the effects on the direct referrals of focal users and columns (2), (4), and (6) show the aggregate effects not only on direct referrals, but also on referrals of referrals and so on. Overall, this table shows that there is little or no effect of referral program assignment on referrals' behavior in terms of total number of referrals, total revenue, or engagement. If anything, column (3) shows that requiring an additional referral to access tier 2 premium features leads the users' referrals to increase their total payment by 0.8% of a standard deviation ($p < 0.05$), which corresponds to about one third of the magnitude of the effect on the focal user. However, this fades away when looking at the whole network of referrals. Column (6) also shows that requiring an additional referral to access tier 1 premium features leads to a small decrease in total engagement when considering the whole network of users (1.2% of a

standard deviation, $p < 0.05$). In sum, our findings suggest that increasing the referral threshold does not change the quality of referrals.

6. Explaining the Decline in User Engagement

Our stylized model helps us understand why increasing the referral threshold increases both the total number of successful referrals and total revenue but does not explain why these users become less engaged on average. We delve further into the data to better understand what might explain this decrease in user engagement.

6.1. User Engagement Heterogeneity Across User Status

Even though we observe an overall decrease in user engagement for referral programs with higher thresholds, such a decrease is likely not uniform across all users, and it may be partly determined by their status. For example, users who self-select into being recruiters may not react in the same way to an increase in referral requirements than users who self-select into being payers. Higher referral requirements likely affect only a subset of the recruiters by changing either their engagement (recruit more referrals) or their status (become lurkers or payers). However, they are unlikely to change the engagement of those who would self-select into being payers as the required number of successful approvals should not matter for those who would pay anyway. The same argument applies for users who would be lurkers under a referral program with a higher threshold.

In our setting, we consider users as payers from the moment they pay on the platform; otherwise, in case they get the required number of successful referrals, they are considered as recruiters, and all the remaining users are considered as lurkers.⁷ Figure 5 shows how the number of users within each user status changes with user tenure during the first eight weeks. We can see that user status is fairly constant; about

Table 8. Results of Examining Referral Quality

	Dependent variable					
	Referrals		Payment		Visits	
	Direct referrals (1)	Aggregate (2)	Direct referrals (3)	Aggregate (4)	Direct referrals (5)	Aggregate (6)
Number of referrals for tier 1	0.002 (0.003)	-0.002 (0.003)	0.004 (0.003)	-0.001 (0.003)	0.003 (0.005)	-0.012** (0.005)
Number of additional referrals for tier 2	0.004 (0.003)	-0.002 (0.003)	0.008** (0.004)	0.003 (0.003)	0.00000 (0.005)	-0.003 (0.005)
Observations	463,470	463,470	463,470	463,470	463,470	463,470
R ²	0.003	0.003	0.002	0.002	0.014	0.006
Adjusted R ²	0.003	0.002	0.001	0.002	0.014	0.006

Notes. Fixed effects: education, age, gender, tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

82% (41,135) of the users are lurkers, 3% (1,739) are recruiters, and 15% (7,342) are payers.

We regress user engagement on referral program assignment but interact with user status. This allows us to test whether increasing the referral requirement contributes differently to engagement depending on user status. Columns (1)–(3) in Table 9 show regressions of user engagement on referral program assignment and user status. As expected, payers and recruiters are more active than lurkers. In column (4), we add interactions of being a payer and a recruiter with referral program assignment. The main effects of different referral programs, which now correspond to the effect on lurkers, remain negative and mostly unchanged, meaning that, when faced with referral programs with higher thresholds, lurkers become less engaged with the platform. The interaction coefficients are negative but not statistically significant for payers and positive and statistically significant for

recruiters. This means that, similar to lurkers, payers also react negatively to increasing referral requirements. Recruiters, on the other hand, increase their engagement with the platform considerably. In sum, the results are in line with the idea that increasing referral requirements has a differential effect in different subsets of users. Whereas increasing referral requirements results in an overall decrease in engagement, these results show that the effects are considerably different: recruiters increase their engagement, whereas payers and lurkers reduce their engagement.⁸

Having established that (1) referral programs with higher thresholds lead to an overall lower user engagement and (2) this decrease is driven by payers and lurkers, whereas recruiters actually become more engaged, we now investigate the underlying mechanisms of the observed decline in user engagement. We explore two plausible explanations. First, referral programs with higher threshold may prevent some users

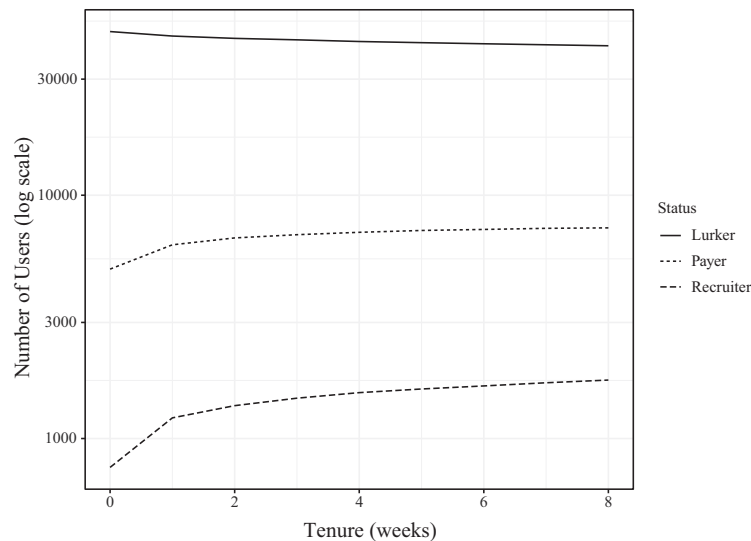
Figure 5. User Status over Time

Table 9. User Engagement as a Function of Referral Program Assignment Interacted with User Status

	Dependent variable			
	Visits			
	(1)	(2)	(3)	(4)
Number of referrals for tier 1	-0.054*** (0.005)		-0.057*** (0.005)	-0.055*** (0.004)
Number of additional referrals for tier 2	-0.029*** (0.005)		-0.021*** (0.005)	-0.024*** (0.005)
Payer		0.886*** (0.013)	0.877*** (0.014)	0.929*** (0.039)
Recruiter		0.709*** (0.025)	0.694*** (0.026)	0.444*** (0.072)
Payer × Number of referrals for tier 1				-0.027* (0.016)
Payer × Number of additional referrals for tier 2				-0.014 (0.018)
Recruiter × Number of referrals for tier 1				0.154*** (0.055)
Recruiter × Number of additional referrals for tier 2				0.189*** (0.038)
Observations	463,470	472,101	463,470	463,470
Adjusted R ²	0.078	0.172	0.163	0.164

Notes. Fixed effects: education, age, gender, tenure, time. Standard errors clustered at the user level.
 * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

from getting access to premium features, leading them to get access later, as they may need more time to either acquire the additional required referrals or decide to pay. This may lead to a lower overall engagement as engagement is likely determined in part by whether users have access to premium features of the platform. Second, we investigate whether the social enrichment hypothesis plays a role in our setting; that is, users derive more value from the platform when their referrals are also active in the platform (Van den Bulte et al. 2018).

6.2. Mechanism Number 1: Delayed Access to Premium Features

The first plausible mechanism underlying the observed decline in user engagement is that referral programs with higher thresholds restrict access to some premium features, which results in lower engagement. We start by testing whether users of referral programs with higher thresholds are less likely (or take longer) to get access to premium features. We regress access to tier 1 and 2 premium features on referral requirements. Table 10 shows the results. Referral programs with higher thresholds with respect to tier 1 premium features decrease users' likelihood of getting access to tier 1 premium features. Conversely, referral programs with higher thresholds concerning tier 2 premium features increase users' likelihood of getting access to tier 1 premium features and decrease their likelihood of getting access to tier 2 premium features. These results provide evidence that setting a higher threshold to access

certain premium features is likely to lead to fewer users reaching the required threshold. This justifies the negative coefficients for the requirements associated with the respective premium features. Also, being assigned to a referral program with a higher threshold may prompt some users to exert a greater effort to meet the referral requirements, leading to more referrals overall. This also justifies why we see an increase in the likelihood of getting access to tier 1 premium features as a function of the tier 2 premium features requirement (column (1) of Table 10): users exert more effort to get access to tier 2 premium features, and as a side effect, they end up getting access to tier 1 premium features.

Next, we assess whether getting access to premium features leads to more engagement. We start by

Table 10. Mechanism Number 1 Testing: Delayed Access to Premium Features

	Dependent variable	
	Tier 1 access (1)	Tier 2 access (2)
Number of referrals for tier 1	-0.267*** (0.002)	-0.003 (0.002)
Number of additional referrals for tier 2	0.175*** (0.002)	-0.016*** (0.002)
Observations	463,470	463,470
Adjusted R ²	0.493	0.055

Notes. Fixed effects: education, age, gender, tenure, time. Standard errors clustered at the user level.
 * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

plotting the number of visits for users who get access to premium features during their first eight weeks in the platform as a function of time relative to the moment each user gets access to the respective premium features. Figure 6 shows that the average number of visits to the platform remains fairly constant up to the moment when users get access to premium features. Once users get access to these features, their visits to the platform increase. This jump is more pronounced when users acquire access to tier 2 premium features with most of the increase in activity decaying over the following few weeks. This plot shows suggestive evidence that, indeed, users become more engaged with the platform once they get access to premium features.

As shown, referral programs with higher thresholds could, indeed, result in lower engagement because of users requiring more time to get access to premium features. This, by itself, could justify the negative coefficient for the main effect observed in column (4) of Table 9. In order to assess to what extent this mechanism explains the decrease in user engagement, we regress user engagement on whether a user has access to premium features or not. To do so, we use individual fixed effects to further control for user heterogeneity. In this case, we can use individual fixed effects because users get access to premium features over their tenure in the platform, and we can assess how they change their engagement, controlling for individual, user tenure, and time fixed effects. Table 11 shows the results. Consistent with the plots shown in Figure 6, column (1) shows that users become more engaged when they gain access to premium features. Engagement increases as much as 0.59 of a standard deviation for access to tier 1 premium features ($p < 0.01$)

and an extra 0.29 standard deviation for access to tier 2 premium features ($p < 0.01$). Column (2) shows that these results hold even when controlling for the number of successful referrals a user gets.

In summary, referral programs with higher thresholds do contribute to a decrease in the likelihood of getting access to premium features (or delay the access timing) and, consequently, to a decrease in user engagement. However, getting access to premium features does not fully explain the decrease in engagement: (1) recruiters become more engaged with the platform even after controlling for access to premium features (Table 9, column (4)), and (2) users become more engaged when their referrals get approved to the platform (Table 11, column (2)).

6.3. Mechanism Number 2: Social Enrichment Hypothesis

The second plausible mechanism that could explain the observed effect of changing the referral threshold on user engagement is the *social enrichment hypothesis* (Van den Bulte et al. 2018). One would expect that users with friends or acquaintances in a platform may end up interacting more with those they invite, either directly on the platform or via alternative channels, increasing their valuation and engagement. This is commonly observed on social networks, such as Facebook. However, online dating platforms, such as ours, are different. Users on these platforms derive more value from having access to a pool of participants outside of their close connections but not necessarily from having close friends or acquaintances on the platform. So it is not clear whether we can expect users to derive higher value from the platform when their friends are also on the platform.

Figure 6. User Engagement (Visits) Relative to Access to Premium Features

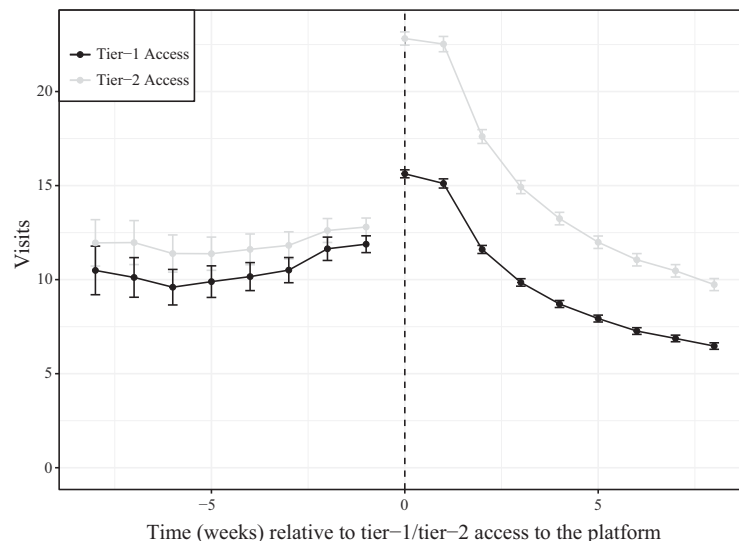


Table 11. Fixed Effects Results: Engagement as a Function of Getting Access to Premium Features and User Approvals

	Dependent variable	
	Visits	
	(1)	(2)
Tier 1 access	0.589*** (0.017)	0.574*** (0.017)
Tier 2 access	0.288*** (0.023)	0.276*** (0.023)
Number of successful referrals (standardized)		0.046*** (0.002)
Observations	470,753	470,753

Notes. Fixed effects: user, tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

We test the existence of the social enrichment hypothesis in our setting in three steps. First, we look at what happens to user engagement when a user’s referrer leaves the platform, that is, when the user significantly reduces the level of participation. We consider that a user leaves the platform if the user does not visit for at least four consecutive weeks. Table 12 shows that, when referrers leave the platform, the engagement of the referrals is reduced significantly. This table shows regressions over the users who were referred by other users and joined the platform. We regress weekly activity as a function of whether the referrer of a user dropped the platform. We also control for the referral requirement and include fixed effects for education, age, gender, tenure, and week. The results show that, when referrers leave the platform, the engagement (all types of activity) of the referrals is reduced significantly, consistent with the social enrichment hypothesis.

Second, we test whether users are more likely to exchange messages with those they invite as compared with exchanging messages with similar users—that is, users of the same age and gender—who joined the platform in the same period. We perform this analysis by creating two types of pairs of users. For each *actual* pair of referrer–referral users, we also create pairs of users that contain the actual referrer and users who are identical to the actual referral with respect to age, gender, and timing of approval in the platform. We name the latter as *fake* referrer–referral pairs of users. This results in a total of 4,974 actual referrer–referral pairs and more than 50,000 fake referrer–referral pairs. Table 13 shows statistics for exchanged messages between actual and fake referrer–referral pairs (i.e., pairs including the referrer and users similar to the respective referral) as baseline. We find that referrers are 145 times more likely to exchange messages with those they invite than with comparable users. The difference is significant for messages both sent and received by the referrer, but the biggest difference seems to be that referrals tend to message their referrers via the platform. This is clear evidence that referrals communicate with their referrers and a strong indication they may value their presence in the platform.

Third—and to complement the second strategy—we test the hypothesis that connected users (via a referral) talk about other users in the platform. Even in the absence of messages exchanged in the platform, two users may talk about a third user, which may increase the likelihood that both of them visit this third user’s profile or send the user a message (i.e., one user tells another about someone’s specific profile, and the second person ends up finding that profile in the platform). We test this by creating referrer–referral pairs and measuring how frequently referrers visit the same users’ profiles as referrals. Similar to the last

Table 12. Changes in Engagement When Referrer Drops the Platform

	Dependent variable								
	Visits				Messages				
	Visits (1)	Profiles viewed (2)	Profile views (3)	Messages sent (4)	Messages received (5)	Winks sent (6)	Winks received (7)	Likes sent (8)	Likes received (9)
Referrer dropped	−0.133*** (0.017)	−0.030** (0.012)	−0.075*** (0.012)	−0.038*** (0.009)	−0.055*** (0.010)	0.028 (0.025)	−0.071*** (0.013)	−0.013 (0.014)	−0.123*** (0.012)
Number of referrals for tier 1	−0.083*** (0.017)	−0.039*** (0.013)	−0.044*** (0.013)	−0.042*** (0.011)	−0.046*** (0.011)	−0.021 (0.016)	−0.028** (0.012)	−0.025* (0.013)	−0.060*** (0.012)
Number of additional referrals for tier 2	−0.064*** (0.018)	−0.038*** (0.013)	−0.026** (0.013)	−0.031*** (0.011)	−0.036*** (0.012)	−0.038* (0.021)	−0.008 (0.013)	−0.042*** (0.013)	−0.041*** (0.013)
Observations	53,565	53,565	53,565	53,565	53,565	53,565	53,565	53,565	53,565
R^2	0.093	0.089	0.254	0.028	0.040	0.042	0.235	0.045	0.426
Adjusted R^2	0.088	0.084	0.251	0.024	0.036	0.038	0.231	0.040	0.423

Notes. Fixed effects: education, age, gender, referrer tenure, referral tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 13. Who Do Referrals Communicate with?

Variable	Statistic	Fake referrer–referral pairs	Actual referrer–referral pairs	Difference	<i>t</i> value	<i>p</i> value
<i>Messages exchanged</i>	Average	0.004	0.58	−0.58	−10.38	<0.001
	Standard deviation	0.29	3.93			
	<i>N</i>	52,145	4,974			
<i>Messages sent</i>	Average	0.002	0.07	−0.07	−5.20	<0.001
	Standard deviation	0.18	0.93			
	<i>N</i>	52,145	4,974			
<i>Messages received</i>	Average	0.002	0.51	−0.51	−10.05	<0.001
	Standard deviation	0.18	3.58			
	<i>N</i>	52,145	4,974			

Note. Summary statistics and *t* test on the number of users' profiles viewed in common by actual referrer–referral pairs versus those viewed in common by fake referrer–referral pairs.

analysis, as a baseline for comparison—and for each referral—we construct fake referrer–referral pairs between the actual referrer and users of the same age and gender and that have been approved by the platform in the same period as the actual referral. This results in a total of 7,272 actual and almost 130,000 fake referrer–referral pairs. Table 14 shows summary statistics on the common third-party user profiles visited by both the actual and fake referrer–referral pairs. We see that, on average, actual referrer–referral pairs view about 1.31 users' profiles in common, whereas fake referral–referral pairs view only 0.27 profiles in common during the first four weeks of the referral tenure ($p < 0.001$). In addition, actual referrer–referral pairs are more likely to send messages to the common third-party users than fake referrer–referral pairs.

In summary, these results suggest that users communicate with their connections and talk about other users in the platform even though this may also happen outside of the platform's own messaging system. We provide evidence for the social enrichment hypothesis in our setting that users value having their friends in the platform. Therefore, being assigned to a referral program with a higher threshold prompts users to exert more effort to meet the higher referral requirements with some users deciding to invite referrals (recruiters) and others deciding to become paying members (payers). Payers are more likely to end up with fewer friends on the platform and, according to the social enrichment hypothesis, are less engaged

because of lower social utility they derive from using the platform.

7. Adding Social Referral Programs to Freemium Platforms

In this section, we explore yet another dimension of the interplay between social referral programs and freemium platforms. Even though our experiment was designed to assess the effects of different referral requirements on user behavior, our data allows us to go further and—under mild assumptions—assess the effects of adding social referral programs to freemium platforms. This analysis allows us to provide a more comprehensive assessment of how referral programs interact with freemium models and how they can be used to help digital platforms achieve a good balance between growth and revenue.

As mentioned in Section 3.2 and detailed in Appendix A, the platform made available different versions of referral programs with different requirements for accessing premium features. These versions were implemented through what we call *iterations*. Within an iteration, the platform randomly assigned users to referral programs with either a lower or higher threshold.

In one of the iterations in the experiment, users in the higher threshold condition were required to pay for access to both tier 1 and 2 premium features and did not have the option of accessing premium features via referrals.⁹ This means that these users experience a

Table 14. Summary Statistics and *t* Test on the Number of Users' Profiles Viewed and Messaged in Common by Actual Referrer–Referral Pairs vs. Those in Common by Fake Referrer–Referral Pairs

Variable	Statistic	Fake referrer–referral pairs	Actual referrer–referral pairs	Difference	<i>t</i> value	<i>p</i> value
<i>Common profile views</i>	Average	0.27	1.31	−1.04	−12.72	<0.001
	Standard deviation	5.42	6.85			
	<i>N</i>	129,343	7,272			
<i>Common message recipients</i>	Average	0.02	0.05	−0.03	−3.85	<0.001
	Standard deviation	0.78	0.49			
	<i>N</i>	48,914	4,568			

pure freemium plan: they could access the free features but were required to pay to access premium features. In the same iteration, users in the lower threshold condition experience a *hybrid plan*: they are required to pay for accessing tier 2 premium features but have the *option* of referring two new users to get access to tier 1 premium features. The only difference between users in the lower and higher thresholds of this iteration is that users in the lower threshold program have the extra option of inviting referrals to access tier 1 premium features. Thus, by comparing these two groups of users, we can measure the effect of moving from a pure freemium plan to a hybrid plan in which users have the option to invite referrals in exchange for accessing tier 1 premium features. Appendix E provides more detail on how the pure freemium and hybrid plans relate to plans that allow for referrals both for tier 1 and 2 features.

Given our context, we decompose the effects of adding referral programs to a freemium plan in two parts. First, we estimate the effect of adding a referral option to access tier 1 premium features without changing the requirement of paying to access tier 2 premium features. Second, we estimate the effect of dropping the payment requirement for accessing tier 2 premium features, that is, the effect of allowing users to access both tier 1 and 2 premium features in exchange for the same two referrals. We choose to estimate these two effects because (1) they correspond to changing requirements in only one of the dimensions at a time (i.e., tier 1 or 2 premium features), helping us understand the effects of adding referral programs as an option to freemium business model (i.e., studying the extensive margin) and (2) our data allows us to provide unbiased causal estimates for these effects under extremely mild assumptions.

We estimate the aforementioned effects by contrasting users in the pure freemium and hybrid plans and

users in a referral program that allows access to tier 1 and 2 premium features in exchange for two referrals. There are 1,688 users in the freemium plan, 1,708 users in the hybrid plan, and 5,966 users in the referral program of interest. Users in the freemium and hybrid plans belong to the same iteration, and were randomly assigned to their plans. Thus, we can interpret any differences in outcomes between these two groups as causal. The users in the referral program of interest are also comparable as they belong to the same age range and to the iteration immediately before the iteration containing the users in the freemium and hybrid plans. Table 15 shows *F*-tests on user demographics among the three groups, and these corroborate the idea that these users are comparable. Moreover, we continue using the same fixed effects in our estimates for consistency with our main analyses and to account for any potential imbalance among these groups.

Table 16 shows the results of adding the referral program option in order to access tier 1 premium features (*Freemium*→*Hybrid*) and the effects of allowing the same number of referrals to access tier 2 premium features (*Hybrid*→*Referral*). Adding the option of getting two successful referrals in exchange for access to tier 1 premium features contributes to a significant increase in invitations, registrations, and approvals, whereas payments and engagement do not seem to be significantly affected. This suggests that adding referral programs as an option in exchange for access to tier 1 premium features seems to be beneficial for platform growth without significantly affecting payments and engagement. Further, allowing users to access tier 2 premium features in exchange for the same two successful referrals (i.e., in effect, moving to a plan that allows users to access premium features in exchange for the same number of successful referrals) has little effect on the total number of referrals, reduces payment significantly, and increases engagement.

Table 15. ANOVA *F* Tests on User Demographics Among the Three Groups

Variable	Statistic	Freemium (pay, pay)	Hybrid (2, pay)	Referral (2, +0)	<i>F</i> value	Pr(> <i>F</i>)
<i>Educ_years</i>	Average	15.59	15.43	15.59	3.70	0.02
	Standard deviation	1.09	1.68	1.41		
	<i>n</i>	703	738	2,351		
<i>Female</i>	Average	0.63	0.65	0.63	1.83	0.16
	Standard deviation	0.48	0.48	0.48		
	<i>n</i>	1,668	1,708	5,966		
<i>Height</i>	Average	173.20	172.95	173.51	1.19	0.31
	Standard deviation	10.88	9.74	9.58		
	<i>n</i>	849	871	2,865		
<i>Smoker</i>	Average	0.03	0.04	0.04	1.06	0.35
	Standard deviation	0.18	0.18	0.20		
	<i>n</i>	631	656	2,322		
<i>Children</i>	Average	0.04	0.05	0.04	0.42	0.66
	Standard deviation	0.20	0.22	0.20		
	<i>n</i>	721	749	2,644		

Table 16. Results of Adding Referral Programs to Premium Platforms

	Dependent variable				
	Invitations (1)	Registrations (2)	Approvals (3)	Payment (4)	Visits (5)
Refer for tier 1: (<i>Pay, Pay</i>) → (<i>2, Pay</i>)	0.135*** (0.012)	0.109*** (0.012)	0.062*** (0.011)	-0.037 (0.034)	-0.021 (0.033)
Refer for tier 2: (<i>2, Pay</i>) → (<i>2, +0</i>)	-0.011 (0.020)	0.013 (0.020)	0.044** (0.018)	-0.338*** (0.038)	0.144*** (0.042)
Observations	80,006	80,006	80,006	80,006	80,006
Adjusted R ²	0.062	0.044	0.021	0.040	0.113

Notes. Fixed effects: education, age, gender, tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

These results are in line with the main results obtained when studying the effects of changing referral requirements on user behavior: increasing threshold requirement contributes to an increase in payments and a decrease in engagement. As highlighted by our stylized model (Figure 4), providing users with the option of getting successful referrals in exchange for access to premium features results in an increase in the number of successful referrals (users now have incentives to recruit). On the other hand, it leads to lower payments as some users end up getting access to premium features through inviting referrals instead of paying (Figure 4(b)). According to our stylized model and estimates, the loss in payments can be mitigated (up to a point) by an increase in the referral threshold, that is, requiring users to invite more referrals in exchange for access to premium features: more users opt to pay, and those who continue opting to refer are required to invite more (Figure 4(c)).

Finally, the decision on whether to add referral programs to freemium models hinges on how much a platform values growing its user base versus generating revenue. Our results suggest that it is best to request users to get referrals in exchange for *partial* access to premium features (i.e., tier 1 premium features). This is because it creates, at least in our context, incentives to invite (from both users who would otherwise pay and who would remain as lurkers) and does not seem to decrease revenue or engagement (as users are still incentivized in paying to access tier 2 premium features).

8. Discussion and Conclusion

Our paper contributes to the literature on freemium business models and social referral programs by investigating how threshold referral programs can complement pay-for-access freemium models. Prior work in this area focuses on paying for premium access as the monetization strategy for freemium platforms. Our paper is the first to examine the interplay between social referral programs and freemium platforms. Social referral programs are useful in contexts

in which a fraction of users value the premium features below their price but are willing to recruit referrals to access them. In our paper, users are heterogeneous in their referral costs, leading them to self-select into being a payer, recruiter, or lurker. As such, for the role of social referral programs in freemium platforms, our findings point to a more nuanced relationship between growth and monetization.

Our work is also the first to combine both theoretical and empirical perspectives with studying a type of referral programs previously not studied before, that is, threshold referral programs in freemium platforms. This paper is the first to provide causal evidence that increasing the referral threshold improves successful referrals and revenue but lowers overall user engagement. We also explore mechanisms that explain this reduction in user engagement. Our results show how behavioral mechanisms, such as access timing and social enrichment, can explain the user behavior patterns observed in our context, providing evidence for these explanations in our field experiment. Our finding suggests that users value having their friends on the platform, which contributes to an increase in their engagement. This finding also adds to the empirical evidence to the presence of social utility in a different context (Gilchrist and Sands 2016, Lee et al. 2019).

In addition, our study provides the first insight into the effects of adding referral programs to freemium platforms on user behavior. We find that allowing users to access some of the freemium features (i.e., tier 1 premium features) significantly boosts platform growth whereas not affecting revenue and user engagement. Platform revenue seems to be affected *only* when users are asked to invite referrals to access full premium features. A future avenue for research is to further explore which types of features should be placed in each access tier (i.e., tier 1 versus 2).

Furthermore, prior studies suggest that paid premium users become more socially engaged (Bapna et al. 2018). Our findings extend that line of work and demonstrate that, when facing referral programs, social engagement is higher for the users who invite

referrals compared with those that pay. In the social referral literature, previous research suggests that, over time, the user base is likely to be diluted with low-quality users (users who are more price-sensitive or who see less value in the service) (Kumar 2014). In contrast, our findings show that increasing referral requirements do not affect the quality of the referrals: they pay as much and are as engaged as those invited by users with a lower threshold. Finally, our paper is the first to make use of data from a large-scale randomized field experiment to causally assess how user behavior changes with changes in the referral program threshold in terms of new customer acquisition, payments, and engagement with the platform.

These findings have important managerial implications. First, we show that referral programs can allow users to self-select into the role that best suits them, allowing for a good balance between growth and revenue. Platforms that use freemium business models could amplify social contagion and accelerate product purchases by explicitly requesting users to invite their friends and acquaintances. This can have important implications to customer lifetime value (CLV) and the platform's bottom line (see Appendix F for a CLV analysis). Second, the increase in new user acquisitions and revenue comes at the expense of other metrics. Platforms need to carefully assess the effectiveness of these social referral programs, closely monitor how they affect user engagement, and pay attention to the potential negative consequences in implementing these programs. Third, our empirical findings also suggest that individuals value having their friends on the platform. In this case, social referral programs designed to enhance the shared experience of online dating (e.g., organizing off-line activities) could be particularly effective in increasing platform engagement. Finally, our findings on heterogeneous treatment effects suggest that certain groups do not seem to have their engagement affected by referral requirements with respect to premium features. Practically, the platform could consider using this information to adjust referral requirements for different user groups in order to increase user acquisition and payment without hurting engagement. This adjustment could be dynamic: the platform would start by assigning a freemium plan to all users, and after assessing users' behavior during the first weeks, decide to whom to give the option of getting referrals in exchange for access to premium functionality.

We also acknowledge some limitations that create exciting avenues for future research. First, in this paper, we explore heterogeneity in user behavior concerning referral requirements. Future research can dive more in-depth and explore how platforms can design personalized referral programs for each user to optimize their performance.

Second, it is unlikely that the positive effect of referral policies on user base and payment grows infinitely regardless of the required number of successful referrals. At some point, requiring users to refer one more user will have no or even a negative effect on their behavior. In this paper, we explore the existence of this nonlinear effect of the required number of referrals to get access to premium features. Future research can explore regions of this parameter that go beyond what we implement in our experiment.

Another limitation of this research is related to the identification of the behavioral mechanisms. Our findings suggest that delayed access to premium features and social enrichment may explain the decline in social engagement among paid users who were asked to invite more referrals. However, other mechanisms, such as peer effects or social learning may also be at play. Future research can implement field experiments specifically designed to tease out the differential effects of these conditions.

Finally, our research context also deserves some attention. Even though the main ideas and dynamics we uncover in this paper can be applied to a wide set of contexts—and especially to other matching platforms—the exact trade-offs can be very different, depending on the specificities of the platform. For example, we acknowledge that dating platforms usually exhibit high turnover, and users tend to decrease their activity over time. Decreasing activity in these contexts does not mean a lack of success. Users may stop using the platform because they found a match. Therefore, even though we consider this factor in our analyses and conclusions, one could benefit by testing our findings in a different context. Further, network effects in our platform can also be different from network effects in other platforms. Whereas, for some platforms, network effects are present at a local scale, that is, users derive value from interactions with their close connections (Sundararajan 2007), for other platforms, network effects are weak at a local scale but strong at a global scale, that is, users derive value mostly from interactions with users not directly connected in the network. This is the case for online dating platforms, in which users may have a lower incentive to invite referrals. Our findings show that social referral programs can be beneficial for such platforms without strong local network effects. Thus, one may expect even higher benefits for platforms with both strong local (and global) network effects because the users have a stronger incentive to invite connections to join. A future avenue for research is to look into how these platforms can effectively use social referral programs.

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Appendix A. Randomization Process

In this appendix, we provide a detailed description of how the randomization was implemented. The platform uses an A/B testing framework developed internally to continuously test different designs and to guide the development of new features. Over the period of our analysis—from March 2015 until February 2017—the platform experimented with multiple referral program configurations over time. In general, for each week, the platform determined a set of referral programs to be active for that week and randomly assigned each new user to one of the active referral programs at the moment of user registration. For each week, a total of two or four referral programs were active. During the weeks in which four different referral programs were active, two of them were targeted to young users (age 27 and younger) and two of them were targeted to regular users (older than 27). Therefore, each new user was randomly assigned to one of the two referral programs available to them, conditional on their registration date and age. Over time, the platform made available different versions of these referral programs with different requirements for accessing tier 1 and 2 features for each of the target populations (young/regular). These versions were implemented through what we call iterations. An iteration can be active for only a few weeks or for several months. Within an iteration and for each subpopulation (young/regular), users were assigned to either lower or higher threshold referral programs. The referral program with a higher threshold requires existing users to get more successful referrals in order to be granted full access to the platform.

There was a total of 11 iterations over the period of observation. Table A.1 provides summary statistics for each of these 11 iterations, including target population, start and end date, and requirements for tier 1 and 2 features together with the number of users who registered

and were assigned to each of the programs. As part of the randomization check, in Table 1, we see that the proportion of users assigned to referral programs with lower and higher thresholds in each iteration is very close to 50%, which gives us confidence in the platforms' randomization procedure. Moreover, Figure A.1 shows the referral program assignment (lower/higher threshold) to newly registered users over time by iteration (1 to 11) and target population (young/regular).

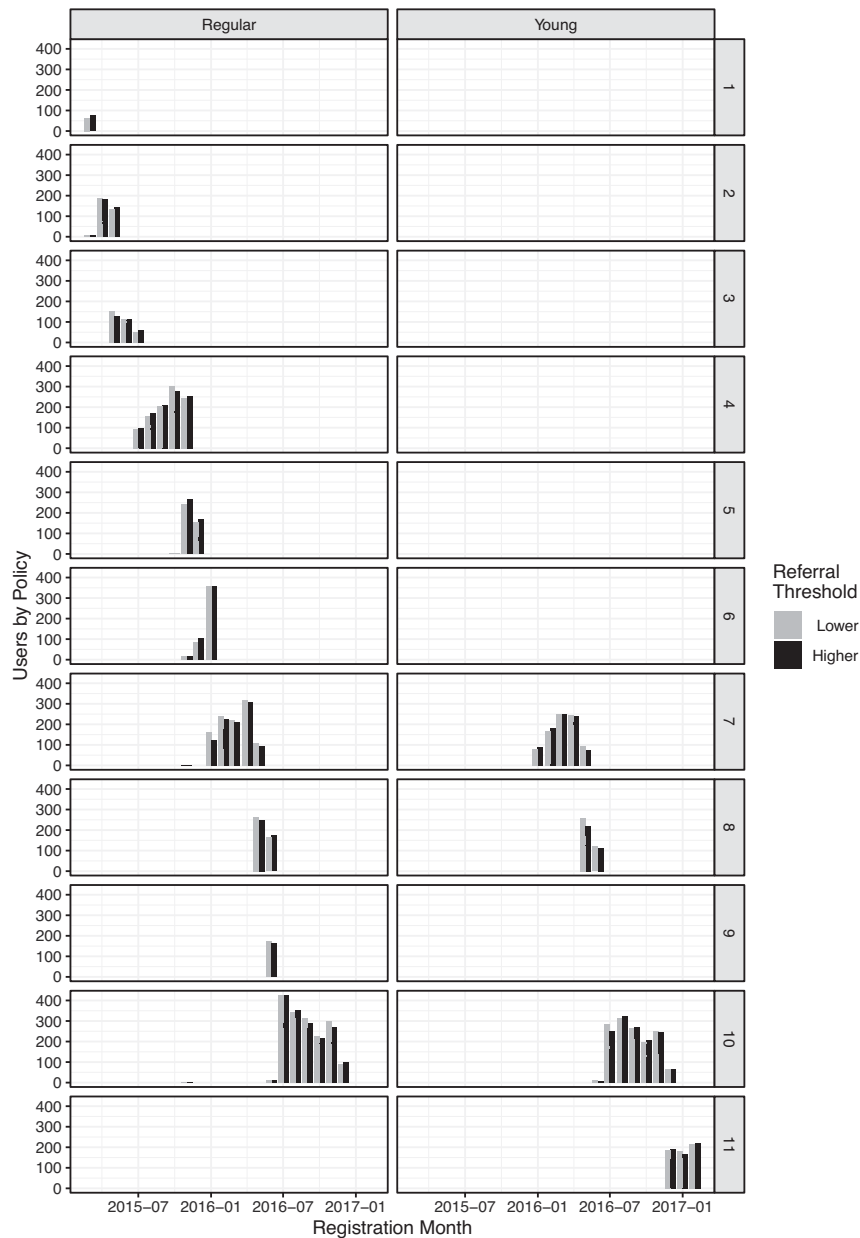
There are a few details we note here. First, in iterations 1–6, there was no age-based distinction, and all users were assigned to either lower or higher threshold referral programs irrespective of their age.¹⁰ Second, iteration 11 in our sample does not contain regular users. This is because the platform decided that, for this iteration, regular users can only access premium functionality by paying and not by inviting referrals. Therefore, we removed these users from our analysis because their referral programs do not include the option of inviting. Even though iteration 11 is composed only of “young” users, all the results are still valid as we use age fixed effects throughout the paper (along with fixed effects for education, week, gender, and user tenure). For completeness, we also ran our analyses removing users from iteration 11, and as expected, all the results are qualitatively the same. Third, out of the 52,782 users in our analysis, a total of 200 users registered before the platform officially launched in the city. They were, nevertheless, assigned to a referral program and, thus, were included in our analyses. These users represent less than 0.3% of our user base. For a robustness check, we removed them from our analysis and found our results remain virtually the same. Table A.2 shows our main result after removing these 200 users and the 3,909 young users in iteration 11.

Given the nature of the randomization process described, the best way to assert that randomization was performed adequately is to perform *t* tests across demographics between lower and higher threshold referral programs within each

Table A.1. Summary Statistics of Referral Programs (per Iteration)

Iteration	Target	Start	End	Lower threshold		Higher threshold		N	N soft	N hard	Prop. hard
				Tier 1	Tier 2	Tier 1	Tier 2				
1	Regular	2015-03-01	2015-03-22	0	2	2	2	246	104	142	0.577
2	Regular	2015-03-29	2015-05-17	1	1	1	1	1,764	884	880	0.499
3	Regular	2015-05-24	2015-07-05	1	1	3	0	1,424	735	689	0.484
4	Regular	2015-07-05	2015-11-15	1	0	1	1	5,979	2,994	2,985	0.499
5	Regular	2015-10-04	2015-12-13	1	1	1	2	1,745	891	854	0.489
6	Regular	2015-11-15	2016-01-24	2	1	2	2	2,546	1,278	1,268	0.498
7	Regular	2015-11-15	2016-05-01	0	2	1	2	4,775	2,436	2,339	0.490
7	Young	2016-01-24	2016-05-08	1	1	2	1	3,755	1,890	1,865	0.497
8	Regular	2016-05-01	2016-06-19	1	2	2	2	2,619	1,333	1,286	0.491
8	Young	2016-05-01	2016-06-26	2	2	3	2	2,364	1,229	1,135	0.480
9	Regular	2016-06-19	2016-06-26	2	2	3	1	530	273	257	0.485
10	Regular	2015-11-15	2016-12-04	0	2	2	0	11,965	5,999	5,966	0.499
10	Young	2016-06-26	2016-12-04	0	2	1	0	8,961	4,492	4,469	0.499
11	Regular	2016-12-04	2017-01-29	2				3,376	1,708	1,668	0.494
11	Young	2016-12-04	2017-02-26	2	1	2	1	3,909	1,921	1,988	0.509

Figure A.1. Registered Users by Month and Referral Program



iteration (1–11) and age group (young/regular). In the interest of space, we omit these results from this appendix, but as expected, all p -values are above 0.05, indicating that the randomization was properly done. These results are available upon request. Table A.3 presents a condensed version of these results by showing t tests of the same demographics per age group (young/regular) but aggregating all iterations. The results are, as expected, similar.

Appendix B. Model: Comparative Statics

From the firm’s perspective, both v_i and c_i are unobserved, and only their joint distribution is known. For simplicity, we assume users are distributed uniformly in the space ($V \in [0, 1]$, $c \in [0, 1]$) and that $p \in [0, 1]$. Under these assumptions, the

fraction of users in each condition is

$$\alpha_p(r) = (1 - p) \left(1 - \frac{p}{c(r)} \right)$$

$$\alpha_r(r) = (1 - p) \frac{p}{c(r)} + \frac{p^2}{2c(r)}$$

$$\alpha_l(r) = (1 - p) \left(1 - \frac{p}{c(r)} \right) + \frac{p^2}{2c(r)}$$

in which α_p , α_r , and α_l represent the fraction of payers, recruiters, and lurkers, respectively.

In this paper, we are interested in the effects of referral programs on user behavior. Thus, we use comparative statics to assess how users behave as a function of a change in the referral programs to which they are assigned. We start

Table A.2. Robustness Check: Effect of Referral Programs on User Behavior (Removing 200 Users Registered Before the Platform’s Official Launch in the City and 3,909 Young Users in Iteration 11)

	Dependent variable				
	Invitations (1)	Registrations (2)	Approvals (3)	Payment (4)	Visits (5)
Number of referrals for tier 1	0.019*** (0.003)	0.011*** (0.004)	0.007** (0.003)	0.022*** (0.003)	−0.052*** (0.005)
Number of additional referrals for tier 2	0.024*** (0.003)	0.017*** (0.003)	0.011*** (0.003)	0.019*** (0.003)	−0.027*** (0.005)
Observations	438,057	438,057	438,057	438,057	438,057
R ²	0.075	0.046	0.024	0.022	0.076
Adjusted R ²	0.074	0.045	0.023	0.021	0.075

Notes. Fixed effects: education, age, gender, tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

by checking how payments ($\alpha_p p$) change as a function of referral requirements, r :

$$\frac{\partial \alpha_p p}{\partial r} = p(1-p) \left(1 + p \frac{c'(r)}{c(r)^2} \right) > 0.$$

This means that referral programs with higher requirements always result in an increase in the number of payers and total payments. A fraction of the existing users who would self-select to be recruiters under a referral program with a lower requirement become payers under a higher threshold referral program as they find it harder

to get the required number of successful referrals and less costly to pay for the full membership.

Looking at the fraction of recruiters (α_r) and the total number of referrals ($\alpha_r r$), we have

$$\frac{\partial \alpha_r}{\partial r} = - \left((1-p)p \frac{c'(r)}{c(r)^2} + p^2 \frac{c'(r)}{2c(r)^2} \right) < 0$$

$$\frac{\partial \alpha_r r}{\partial r} = - \left((1-p)p \frac{c'(r)}{c(r)^2} + p^2 \frac{c'(r)}{2c(r)^2} \right) r + (1-p) \left(1 - \frac{p}{c(r)} \right) + \frac{p^2}{2c(r)}.$$

Table A.3. Randomization Check: Demographics as a Function of Lower and Higher Threshold Referral Programs

Variable	Target	Statistic	Soft	Hard	Difference	t value	p value
<i>Education</i>	Regular	Average	3.91	3.91	−0.001	−0.05	0.96
		Standard deviation	1.49	1.51			
		N	13,155	12,802			
	Young	Average	3.79	3.78	0.01	0.40	0.69
		Standard deviation	1.42	1.45			
		N	5,364	5,195			
<i>Female</i>	Regular	Average	0.62	0.62	0.004	0.69	0.49
		Standard deviation	0.49	0.49			
		N	16,927	16,666			
	Young	Average	0.63	0.62	0.005	0.65	0.52
		Standard deviation	0.48	0.49			
		N	9,532	9,457			
<i>Height</i>	Regular	Average	174.27	174.21	0.06	0.38	0.70
		Standard deviation	9.44	9.46			
		N	7,999	7,653			
	Young	Average	174.44	174.47	−0.03	−0.13	0.90
		Standard deviation	10.20	10.04			
		N	4,099	3,908			
<i>Smoker</i>	Regular	Average	0.04	0.04	0.005	1.34	0.18
		Standard deviation	0.21	0.20			
		N	6,613	6,297			
	Young	Average	0.07	0.06	0.01	1.18	0.24
		Standard deviation	0.25	0.24			
		N	2,915	2,782			
<i>Children</i>	Regular	Average	0.03	0.03	0.01	1.78	0.07
		Standard deviation	0.18	0.17			
		N	7,470	7,102			
	Young	Average	0.003	0.002	0.001	0.95	0.34
		Standard deviation	0.06	0.04			
		N	3,159	3,073			

Table C.1. (Nonlinear) Effects of Referral Programs on User Behavior

	Dependent variable				
	Invitations (1)	Registrations (2)	Approvals (3)	Payment (4)	Visits (5)
Number of referrals for tier 1	0.044*** (0.012)	0.038*** (0.012)	0.026** (0.011)	0.057*** (0.010)	-0.055*** (0.017)
Number of referrals for tier 1 squared	-0.009** (0.004)	-0.009** (0.004)	-0.007* (0.004)	-0.011*** (0.004)	0.0004 (0.005)
Number of additional referrals for tier 2	0.045*** (0.013)	0.031** (0.013)	0.027** (0.014)	0.044*** (0.012)	-0.038* (0.022)
Number of additional referrals for tier 2 squared	-0.007 (0.006)	-0.003 (0.006)	-0.005 (0.007)	-0.007 (0.006)	0.005 (0.010)
Observations	463,470	463,470	463,470	463,470	463,470
R ²	0.077	0.048	0.025	0.021	0.079
Adjusted R ²	0.076	0.048	0.025	0.020	0.078

Notes. Fixed effects: education, age, gender, tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Under programs with higher thresholds, fewer existing users self-select to become recruiters, leading to fewer users recruiting referrals but each with a higher number of referrals. However, whether the total number of successful referrals increases under programs with higher thresholds is determined by the functional form of $c(\cdot)$, which is mostly an empirical question. Thus, our model is inconclusive on the global effect of a referral program change on the changes in the total number of successful referrals.

For completeness, we also look at how the fraction of lurkers (α_l) changes as a function of referral threshold, r :

$$\begin{aligned} \frac{\partial \alpha_l}{\partial r} &= (1-p) \left(1 + p \frac{c'(r)}{c(r)^2} \right) - \frac{1}{2} p^2 \frac{c'(r)}{c(r)^2} \\ &= (1-p) + p \left(1 - \frac{3}{2} p \right) \frac{c'(r)}{c(r)^2} > 0. \end{aligned}$$

This shows that the fraction of lurkers always increases with referral threshold.

Appendix C. Nonlinear Effects of Social Referrals on User Behavior

It is unlikely that the positive effect of referral programs on the user base and payments grows infinitely regardless of the required number of successful referrals. At some point, requiring users to refer one more user will have no effect on their behavior. Table C.1 shows regressions that test for the existence of nonlinear effects of referral requirements on user behavior. In our setting, requiring an additional referral in order to gain access to tier 1 features leads to an increase in invitations (column (1)), registrations (column (2)), approvals (column (3)), and payment (column (4)) but only up to a certain point. In our specifications, the maximum benefit is attained when requiring between two and three referrals to access tier 1 features. However, we do not observe a nonlinear effect in the required number of referrals to get access to tier 2 features. This means that, at least in the studied region of this parameter, referral programs with higher thresholds for tier 2 features always lead to more invitations, registrations,

Table C.2. Effects of Referral Programs on User Behavior (Indicator Variables Specification)

	Dependent variable				
	Invitations (1)	Registrations (2)	Approvals (3)	Payment (4)	Visits (5)
One referral for tier 1	0.040*** (0.010)	0.029*** (0.010)	0.020** (0.009)	0.061*** (0.008)	-0.051*** (0.015)
Two referrals for tier 1	0.052*** (0.009)	0.040*** (0.010)	0.026*** (0.009)	0.068*** (0.008)	-0.108*** (0.014)
Three referrals for tier 1	0.059*** (0.013)	0.034** (0.014)	0.021 (0.013)	0.095*** (0.012)	-0.155*** (0.018)
One additional referral for tier 2	0.039*** (0.007)	0.028*** (0.008)	0.022*** (0.008)	0.041*** (0.007)	-0.032** (0.013)
Two additional referrals for tier 2	0.062*** (0.009)	0.049*** (0.009)	0.032*** (0.009)	0.062*** (0.008)	-0.057*** (0.013)
Observations	463,470	463,470	463,470	463,470	463,470
R ²	0.077	0.048	0.025	0.021	0.079
Adjusted R ²	0.076	0.048	0.025	0.020	0.078

Notes. Fixed effects: education, age, gender, tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table D.1. Heterogeneous Effects: Age

	Dependent variable				
	<i>Invitations</i> (1)	<i>Registrations</i> (2)	<i>Approvals</i> (3)	<i>Payment</i> (4)	<i>Visits</i> (5)
Number of referrals for tier 1	0.019*** (0.004)	0.015*** (0.004)	0.009** (0.004)	0.023*** (0.003)	−0.054*** (0.006)
Number of additional referrals for tier 2	0.020*** (0.003)	0.016*** (0.003)	0.008** (0.003)	0.015*** (0.003)	−0.023*** (0.006)
Age >27	−0.010 (0.011)	−0.012 (0.012)	−0.027** (0.011)	0.089*** (0.013)	0.190*** (0.021)
Number of referrals for tier 1 × (Age >27)	0.008 (0.006)	0.003 (0.006)	0.004 (0.005)	0.020*** (0.006)	−0.003 (0.010)
Number of additional referrals for tier 2 × (Age >27)	0.015*** (0.005)	0.010* (0.005)	0.011** (0.005)	0.026*** (0.006)	−0.008 (0.010)
Observations	463,470	463,470	463,470	463,470	463,470
R^2	0.076	0.048	0.025	0.017	0.076
Adjusted R^2	0.076	0.048	0.025	0.016	0.076

Notes. Fixed effects: education, gender, tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

approvals, and payments. Moreover, we do not see nonlinear effects of referral programs on user engagement as measured by the number of visits to the platform. Furthermore, we also use indicators for the number of successful referrals required to access tier 1 and 2 features. Table C.2 shows the results, which are consistent with those obtained when modeling a quadratic relationship.

Appendix D. Heterogeneous Treatment Effects

Our main results are robust to potential heterogeneity across users as we use fixed effects for age, gender, education, tenure, and time. Nevertheless, we can take advantage of the referral programs' random assignment to assess potential heterogeneity in the effects of referral threshold on users' activity. To do so, we run three sets of regressions in which we explicitly control for age, gender, and education, removing the respective fixed effects and interacting referral threshold with each of these controls.

Table D.1 shows the results of heterogeneous treatment effects across user age. We remove age fixed effects and control for whether a user is older than 27. This table shows that older users, on average, get fewer users approved, pay more, and are more engaged with the platform. In addition, requiring users to recruit referrals to the platform for access to tier 2 features has a larger effect on invitations, registrations, approvals, and payments for users older than 27.

Table D.2 shows the results of heterogeneous treatment effects across gender. We explicitly control for gender and interact the referral program with gender as well. This table shows women are more likely to invite new users, but less likely to pay and are, on average, less engaged with the platform. In addition, requiring users to get successful referrals to the platform for access to tier 2 features has an effect on women's engagement but not on men's.

Table D.2. Heterogeneous Effects: Gender

	Dependent variable				
	<i>Invitations</i> (1)	<i>Registrations</i> (2)	<i>Approvals</i> (3)	<i>Payment</i> (4)	<i>Visits</i> (5)
Number of referrals for tier 1	0.015*** (0.004)	0.011** (0.005)	0.010** (0.005)	0.020*** (0.005)	−0.060*** (0.008)
Number of additional referrals for tier 2	0.021*** (0.005)	0.018*** (0.005)	0.013*** (0.005)	0.017*** (0.005)	−0.011 (0.009)
Female	0.028*** (0.010)	0.011 (0.010)	0.018* (0.011)	−0.054*** (0.011)	−0.151*** (0.020)
Number of referrals for tier 1 × Female	0.007 (0.005)	0.004 (0.005)	−0.002 (0.005)	0.010* (0.005)	0.010 (0.009)
Number of additional referrals for tier 2 × Female	0.006 (0.005)	0.002 (0.005)	−0.002 (0.005)	0.007 (0.005)	−0.028*** (0.010)
Observations	463,470	463,470	463,470	463,470	463,470
R^2	0.077	0.048	0.025	0.020	0.079
Adjusted R^2	0.076	0.048	0.025	0.020	0.078

Notes. Fixed effects: education, age, tenure, time. Standard errors clustered at the user level.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table D.3. Heterogeneous Effects: Education

	Dependent variable				
	Invitations (1)	Registrations (2)	Approvals (3)	Payment (4)	Visits (5)
Number of referrals for tier 1	0.003 (0.005)	0.001 (0.005)	-0.001 (0.005)	0.038*** (0.005)	-0.056*** (0.007)
Number of additional referrals for tier 2	0.007 (0.005)	0.005 (0.005)	0.0001 (0.005)	0.010** (0.005)	-0.041*** (0.008)
Master's degree	0.008 (0.013)	0.007 (0.014)	0.002 (0.014)	0.001 (0.015)	0.104*** (0.028)
Number of referrals for tier 1 × Master's degree	0.015** (0.007)	0.012* (0.007)	0.006 (0.007)	-0.0002 (0.008)	-0.018 (0.013)
Number of additional referrals for tier 2 × Master's degree	0.017** (0.007)	0.012* (0.007)	0.014** (0.007)	0.031*** (0.008)	0.017 (0.013)
Observations	325,700	325,700	325,700	325,700	325,700
R ²	0.084	0.051	0.026	0.021	0.069
Adjusted R ²	0.084	0.050	0.025	0.020	0.068

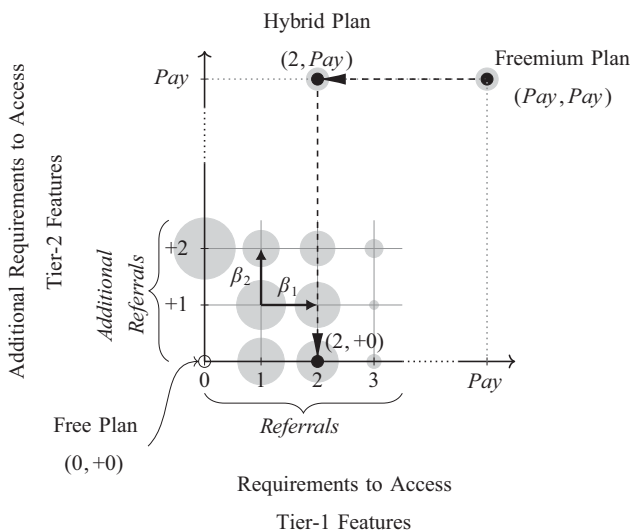
Notes. Fixed effects: gender, age, tenure, time. Standard errors clustered at the user level.
 * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table D.3 shows the results of heterogeneous treatment effects for different levels of education. We remove the respective fixed effects and control for whether a user has reported having a master's degree or higher. This table shows that users with a master's degree are, on average, more engaged with the platform. In addition, requiring users to recruit referrals to the platform to access tier 2 features has, in general, a stronger effect for users with a master's degree, especially in terms of invitations, approvals, and payments. Overall, even though these results show some degree of heterogeneity across users, all the directions remain the same as for the main results.

Appendix E. Referral Programs Space

Figure E.1 depicts the space of referral programs we analyze in our paper. In this figure, the x -axis represents the requirements to access tier 1 premium functionality, and the y -axis represents the additional requirements to access

Figure E.1. Referral Program Space



tier 2 premium functionality. In this representation, we assume that access to tier 2 premium functionality implies access to tier 1 premium functionality as well (as it is always the case in our context), and thus, the y -axis represents *additional* requirements on top of those to access tier 1 functionality. Each point in the lower left quarter of this space (i.e., in the *referrals* region) corresponds to a referral program with the area of the corresponding gray circle representing the number of users in each referral plan in our experiment. The number of users in each of these plans is detailed in Table A.1 in the paper. In this region, moving one unit along the x -axis—the movement labeled β_1 in the figure—corresponds to increasing access requirements for both tier 1 and 2 premium functionality. Similarly, a movement along the y -axis—labeled β_2 in the figure—corresponds to increasing requirements exclusively for tier 2 functionality. These movements correspond to the estimated effects from our main results, “Number of referrals for tier 1” and “Number of additional referrals for tier 2,” respectively (Table 5).

Appendix F. Customer Lifetime Value

Whereas our main results unequivocally show that referral programs with higher requirements lead to an increase in revenue to the platform in the first eight weeks of tenure, they do not provide us with a long-term perspective of the customer value as a function of the referral threshold requirements. We address this by performing a CLV analysis.

We start by plotting the survival rate based on whether users stop using the platform for four consecutive weeks. Figure F.1(a) shows the survival rate for the first eight weeks of users' tenure. The pattern observed resembles an exponential decay function with about 40% of the users remaining active after eight weeks of tenure. This number seems reasonable for an online dating platform in which it is expected that users decrease their use in the platform as they find a suitable match.

Figure F.1. (Color online) Survival Rate and Average Payment Fit as a Function of User Tenure

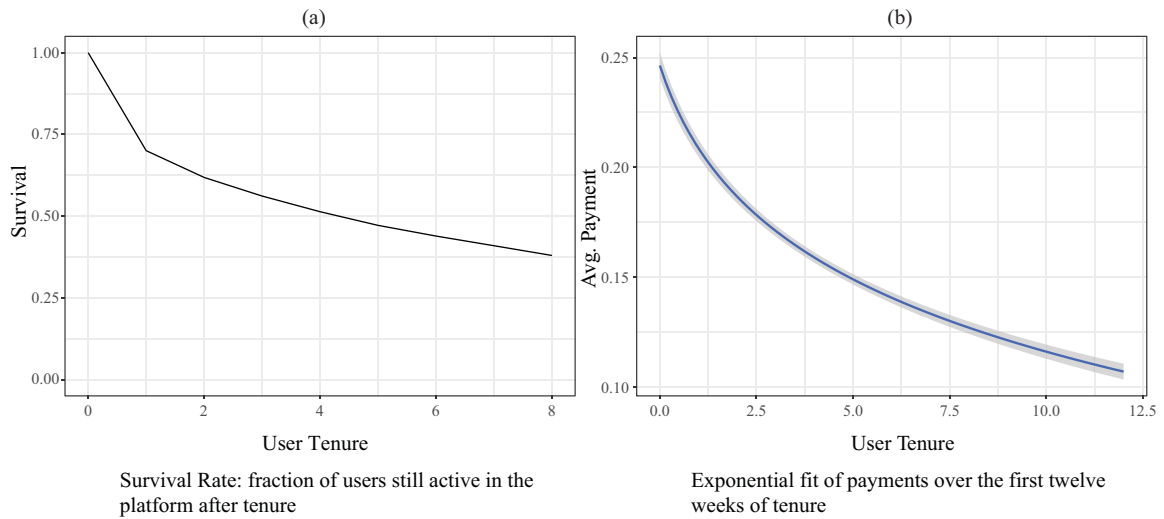
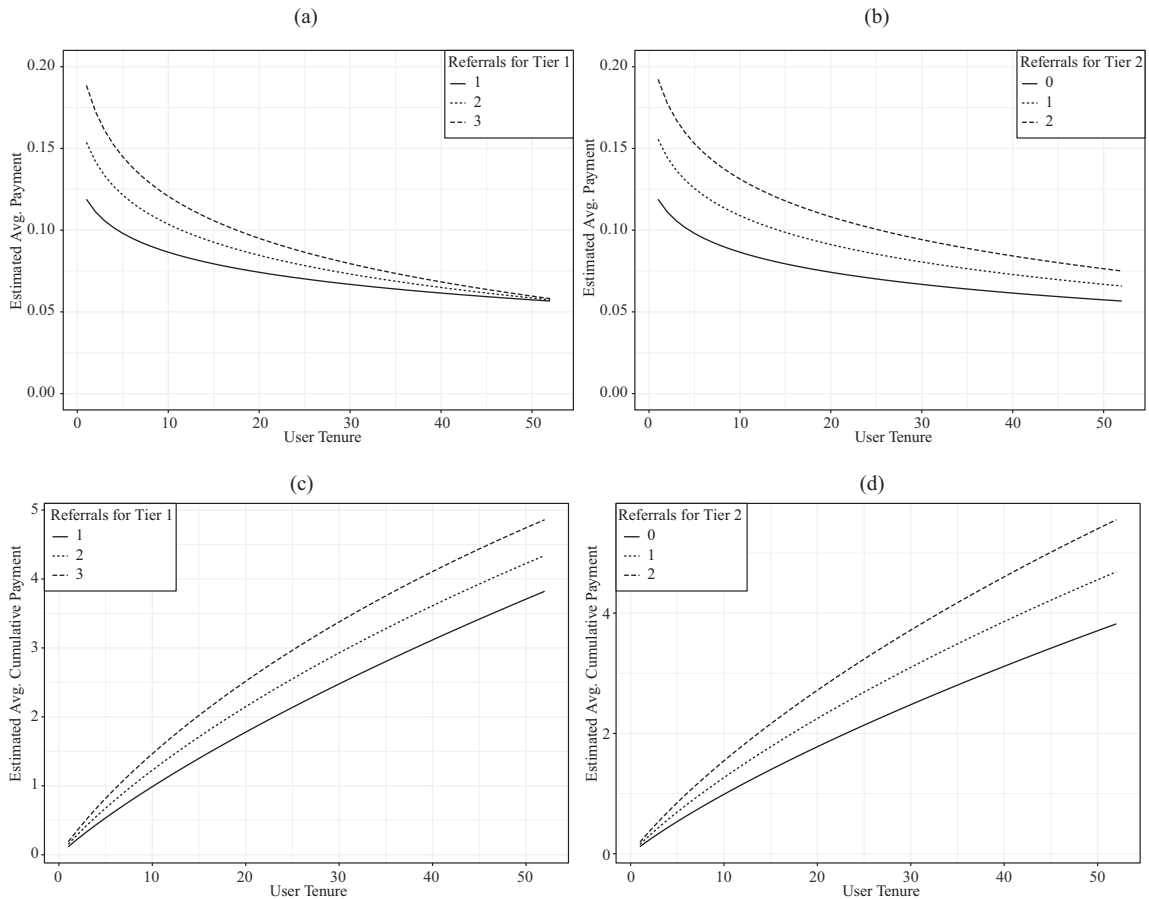


Figure F.2. Estimated Average Payment ((a) and (b)) and Cumulative Payment ((c) and (d)) over 52 Weeks of User Tenure for Different Requirements for Access to Tier 1 and 2 Features



Note. When not visible, referral requirements for tier 1 and 2 features are assumed one and zero, respectively.

To perform a CLV analysis, we could extrapolate this survival rate over a longer period and multiply it by the average revenue per active user during our period of observation. Alternatively, we can directly predict the cumulative payment amount over time based on the first 12 weeks of a user's tenure and then extrapolate it over time. We follow the second alternative as it is more straightforward and does not require calculating two separate estimates (i.e., survival rate and average revenue per active user). Given the exponential form of the actual survival rate in the first eight weeks (Figure F.1(a)), we plot an exponential fit of the average payment over the first 12 weeks of tenure (measured in standard deviations). Figure F.1(b) shows this fit. We move on to estimate payment as a function of user tenure and referral requirements, assuming payment changes exponentially with user tenure. We also allow different trends for different referral requirements. Figure F.2 shows estimates of this model over a period of one year (52 weeks) for different values of referral requirements for access to both tier 1 and 2 features. When not visible, referral requirements for tier 1 and 2 features are assumed one and zero, respectively. Panels (a) and (b) of Figure F.2 show estimates for average payment per user over the first year of tenure, whereas panels (c) and (d) show estimates of cumulative effects. A general trend is that, consistent with our main results, higher referral requirements lead to higher revenue per user. For panel (c), requiring users to recruit three new members to access tier 1 functionality leads to an estimated cumulative revenue about 27% higher than requiring users to recruit only one new member. Similarly, for panel (c), requiring users to recruit two additional members to access tier 2 functionality leads to an estimated cumulative revenue about 45% higher than requiring users to recruit no additional members.

We note that these analyses rely on important functional form assumptions and should be interpreted for their trends and not as precise estimates of the effects of referral requirements on users' CLV.

Endnotes

¹ We use the term *growth* to refer to *customer acquisition* and use these terms interchangeably throughout the paper.

² For example, the Dropbox Space Race campaign, active between October 15 and December 10, 2012, allowed university students, faculty, and staff to earn up to 25 GB of extra space in their Dropbox account by inviting new members from their university. Each successful referral yielded points to the university, which yielded extra space to all members of the university that participated in the campaign. This campaign resulted in almost 640,000 new users registering from the top 100 universities listed on Dropbox's website. It is worth noting, however, that the effectiveness of a specific strategy is highly dependent on its design and on the targeted population.

³ Duolingo—a language learning platform—and Evernote—a productivity platform—are two examples of digital platforms that follow a freemium business model and that have been using such social referrals to encourage users to bring their friends to the platform. Duolingo encourages its users to invite their friends with the call to action “Get one week free of Duolingo Plus [i.e., the premium version] for every friend you refer to the app.” Evernote uses “Your first 3 referrals earn you 10 points each, enough for 3 months of premium.” Additional examples and their calls to action include (1) the

sharing platform Scribd with “Invite one new user, get one month free membership”; (2) the consumer electronics platform Tile with “Get 25 points for every friend who buys a Tile, and receive a free Tile once you have 50 points”; and (3) the virtual presentation platform Prezi with “You can upgrade your account to something better [i.e., one of their premium tiers] for 3 months (free of charge) if you refer 3 people.”

⁴ The platform does not perform any personalization regarding which profiles to promote or which profiles to show to other users. Users can find other users in the platform either by searching based on age range, gender, city, education and interests or by browsing different tabs (i.e., lists of users) that are available to them. These tabs show users filtered by fixed criteria based on a focal user's characteristics. For example, each user can see other users from the opposite sex, registered in the same city, and within an age range according to their own age. There are four tabs: “new members” shows the most recently approved users; “online” shows online members or those who were recently online; “nearby” shows members who recently logged in from a nearby location; and “all,” the default tab, shows a merged list of all users in the previous three tabs.

⁵ We also tested the robustness of our results using 4 and 12 weeks. The results are consistent.

⁶ A “week” in our data is coded as unique identifier for each week in our data (i.e., not week of the year). Note that we have one observation per user per week, which means that week fixed effects is equivalent to having a dummy for each period in our data.

⁷ We also use alternative criteria for assigning users to payer, recruiter, and lurker status. For example, we define that a user is a payer only if the user has made a payment over the previous four weeks (members can lose access to premium features if they stop paying and/or have not met the referral requirement). All results remain qualitatively the same, so we decided to use the simpler definitions. Results using alternative definitions are available from the authors upon request.

⁸ Nevertheless, it is important to note that the coefficients in these regressions are indicative, and we should not interpret them causally as they capture a mixture of the selection effect (some users become payers in referral programs with higher thresholds) and the causal effect (such a program directly changes user engagement).

⁹ Moreover, these users would never be prompted to invite other users as it would not help them accessing premium features (they could still invite their friends; they were just not prompted by the platform to do so).

¹⁰ Note that there is no young version of iteration 9 because iteration 8 for young users ran along both iterations 8 and 9 for regular users, that is, starting on June 19, 2016, the platform changed the referral programs targeted for regular users but kept using the same definition for young users.

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