Referral Programs for Platform Growth: Evidence from a Randomized Field Experiment

Rodrigo Belo*, Ting Li†

July 12, 2019

Abstract

We study referral programs that reward users with access to premium features in exchange for new referrals. We leverage data from a field experiment in an online dating platform. In this platform, users get access to premium features by inviting new users or by paying a monthly fee. During the experiment, each user was randomly allocated to a referral policy — referral policies determine the required number of successful referrals to access premium features. Our findings suggest that referral programs can work as a double-edged sword. Stricter policies increase both the number of referrals and total revenue. Yet, these benefits appear to come at a cost. Users become less engaged, contributing to a decrease in the value of the platform for all users. Two mechanisms may be at play. First, stricter policies may induce a delayed access to premium features. Second, stricter policies push some users to become payers. These users are less likely to enjoy the benefits of having their friends in the platform. We discuss the contributions for literature and implications for business.

Keywords: referral program, field experiment, platform strategy

1 Introduction

Stimulating platform growth can be challenging, especially in early stages, when the number of users is still small and the value of joining for each prospective user is still uncertain (Goldenberg et al., 2010). Platforms have at their disposal a wide range of strategies to overcome the adversities of initial growth. Examples of these strategies include the introduction of specific features that

*Rodrigo Belo, Rotterdam School of Management, Erasmus University, rbelo@rsm.nl.
†Ting Li, Rotterdam School of Management, Erasmus University, tli@rsm.nl.

decrease barriers to entry for new users (e.g., Biyalogorsky et al., 2001; Parker and Van Alstyne, 2005), the deployment of viral marketing campaigns and seeding strategies that target influential users to bring new users to the platform (e.g., Aral et al., 2013; Dou et al., 2013), and the creation of incentives for existing users to bring new users to the platform, i.e., referral programs (e.g., Godes and Mayzlin, 2009; Biyalogorsky et al., 2001). There are some notable examples of well-known platforms that have successfully implemented some of these latter strategies and that experienced fast initial growth. For example, Dropbox has implemented several referral programs to incentivize users to invite other users.[1] It is worth noting, however, that the effectiveness of a specific strategy is highly dependent on its design and on the targeted population.

Referral programs are especially important in contexts in which existing users do not feel compelled to spontaneously talk about the product to their friends. This can happen either because users do not anticipate benefits from inviting their friends to the platform (no networks effects), or because the costs of inviting are high. This is especially true when direct externalities are relatively low or negative.[2]

So far, the literature on referral programs has followed two main streams. A stream of theoretical work has focused on the design of optimal referral programs (e.g. Lobel et al., 2016; Kornish and Li, 2010), while an empirical set of studies have focused on assessing the value of referral programs from the perspective of the platform. Our study is the first to combine both theoretical and empirical perspectives to study a type of referral programs previously not studied before.

We study the dynamics of referral programs in freemium platforms in which referrals are re-

[1]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 25GB of extra space in their Dropbox account by inviting new members from their university. Each successful referral would yield points to the university, which would yield extra space to all members of the university that participated in the campaign. Even though the product itself exhibited no strong network effects, this campaign created such effects resulting in almost 640,000 new users registering from the top 100 universities listed on Dropbox's web site.

[2]From an efficiency perspective, referral programs can be important when externalities are negligible at a local level (i.e., direct connections), but important at a global level (i.e., indirect connections). Note that referral programs can be useful even if there are no global network externalities. Referrals programs can help in the acquisition of new users by, for example, reducing uncertainty about the product for the receiver, provided they trust the sender.

warded with free access to premium features. These programs are common practice in the industry but have received limited attention in the literature. These rewards allow users to become premium members by recruiting new users, i.e., without explicitly paying for them, which can be beneficial in contexts in which some users do not value the premium feature enough to pay the full price, but are willing to recruit new members to do so. In particular, we study threshold programs that require users to recruit a minimum number of new users to access the premium features. We show that, in line with optimal referral program design, it is possible to design incentives such that members self select into the conditions most convenient for them, without compromising the firm's profit. There are two types of tradeoffs a firm faces when putting these referral programs in place. First, allowing for referral programs will generate more invites in exchange for having fewer users paying, and the higher the requirements for invites, the more users pay and the less users invite. Second, individuals that end up inviting their friends become more engaged with the platform, when compared to those that pay for premium membership.

We work with an exclusive online dating platform collecting data from a randomized field experiment spanning multiple years in which different referral policies were used to invite individuals to join the platform. Our findings show that referral programs can work as a double-edged sword. On the one hand, asking users to invite more new users provides benefits in terms of increased number of successful referrals and total payment. On the other hand, these benefits appear to come at the cost of reduced level of user engagement. More specifically, policies that require existing users to get one additional referral can lead to an *increase* of about 2% of a standard deviation in the number of successful referrals ($p < 0.01$) and to an *increase* of 2.6% of a standard deviation in total payment ($p < 0.01$). On the other hand, policies that require existing users to get one additional referral can lead to an *decrease* of 5.4% of a standard deviation in user engagement, as measured by the number of visits to the platform ($p < 0.01$). These results are robust to different specifications. The effects we observe are also economically significant. In our platform, moving from a referral policy that requires only one referral to a policy that requires three referrals for accessing full functionality would result in an overall increase of about 1.13 EUR in payment per user over the first eight weeks, including the payment from users' referrals, which represents an increase of about 26% (1.13/4.34) of the average payment per user. This leads to an increase of more than 50,000 EUR of revenue for the platform for the studied market during the first eight weeks of users' tenure.

To better understand how referral programs affect user behavior, we first develop a stylized model that explains the effect of stricter policies on platform growth and revenue. Then we provide suggestive empirical evidence for two mechanisms that can explain the decline in user engagement. On the one hand, users with stricter policies take longer to access some premium features, thus engaging less with the platform and providing lower value to other users as well. Second, users with stricter policies are likely to have fewer friends and acquaintances on the platform, leading to a lower platform engagement.

The remaining of the article is organized as follows. Section 2 discusses prior literature and explains the contributions of our paper. Section 3 presents the research context, the field experiment, the data and variables, randomization checks, and the model-free evidence. Section 4 develops a stylized model that explains the effects of the changes in referral programs. Section 5 explains our empirical strategy in terms of estimating the effects of referral policies on user behavior and how we address endogeneity. Section 6 presents the results and robustness checks, and explains the mechanisms. Section 7 concludes the paper.

2 Platform Strategy and Referral Programs

2.1 Platform Growth

One of the main challenges that platforms face, is to achieve and maintain a critical mass of users – the so called cold-start problem. This problem is usually attributed to the existence of network effects, in which users value the platform in proportion to the total number of users in the platform (Katz and Shapiro, 1985; Sundararajan, 2007; Kauffman et al., 2000). For example, social networks such as Facebook or Twitter are more useful as more people join the network.

We distinguish between *local network effects* and *global network effects*. A platform can exhibit *local network effects* — i.e., network effects operate at a local scale — and/or *global network effects* — i.e., network effects operate at a global scale. There is a limited body of literature focusing on platforms that exhibit simultaneously strong global network effects and weak local network effects. In such cases, the usual strategies to foster growth under network externalities — such as lowering participation costs and suggesting new connections to existing users and new users — may not be enough. In the absence of local network effects users do not benefit from having their close connections in the platform, leading to an under-supply of invited new users.

Platforms can employ multiple strategies to overcome this problem. Prior studies have looked at how platforms can redesign the participation rules (e.g. Parker and Van Alstyne, 2017) and how platforms can target an initially restricted set of users with an attractive offer (i.e., seeding) (e.g. Hinz et al., 2011) for growth. Contributing to this literature, our paper focuses on how platforms, especially those in which local network effects are weak, can employ referral programs that motivate existing users to invite their friends in the platform in exchange of free access to premium functionality.

2.2 Theoretical Work on Referral Programs

A stream of theoretical work on referral programs has provided guidance on the conditions in which rewards should be offered.[3] These conditions include the customers' valuation of the product (e.g. Biyalogorsky et al., 2001; Lobel et al., 2016), what triggers them to make the referral (e.g. Biyalogorsky et al., 2001; Lobel et al., 2016; Kornish and Li, 2010), their network of friends and acquaintances (e.g. Lobel et al., 2016), their costs of making referrals (e.g. Kamada and Öry, 2017), and whether they value their friends' benefits (e.g. Kornish and Li, 2010).

Biyalogorsky et al. (2001) are among the first to model consumer incentives in referring other users to buy a product (or service). They define a delighted consumer as a consumer that is so happy with the product (i.e., high consumer surplus) that they recommend the product to their friends. They find that the optimal strategy depends on how demanding consumers are. If consumers are easy to delight, the best strategy is to lower prices below what they would be without referrals, so that more consumers are delighted with the product and recommend it to their friends. If consumers are moderately demanding, then both prices and rewards should increase. Finally, if consumers are very demanding, the firm should forgo referrals and revert to normal pricing. Kornish and Li (2010) explore another dimension of consumer heterogeneity: consumers have private information about their friends' tastes, and rather than taking into account only their own delight, they also care about their friends' satisfaction with the product. Under these assumptions consumers' recommendations serve as a way to reduce referrals' uncertainty about the product and foster their purchase.

Lobel et al. (2016) propose another model that (1) incorporates the network structure at a local level, and (2) models consumers as being able to strategically anticipate how many of their friends will adopt the product, based on how much they value it. They find that from the platform's point

[3] Referral programs consist of incentives laid out to both existing and prospective customers, so that existing users attract new users to the platform. Consistent with prior literature, we use the term "referrer" to denote the existing user who brings in another user, and "referral" to denote the referred user whom the existing user brings in.

of view, the optimal incentive scheme may be non-monotonic 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.

Kamada and Öry (2017) study the optimal referral incentive scheme in a scenario in which existing customers benefit from recruiting new customers through word-of-mouth (WoM) either because (1) they get a referral reward from the platform, or because (2) they benefit directly from having their referrals in the platform (referral externalities). The platform can give referral rewards to existing customers, or provide free products to new customers, in order to increase their likelihood of being a customer and to increase the benefits from externalities to existing customers. Their model predicts that referral rewards should be used when externalities accrued from recruiting new users to the platform are low, and free products can substitute referral rewards only when the fraction of premium users is low.

In this paper we focus on yet a different type of referral programs. The platform we study operates under a freemium model in which the rewards for a successful referral correspond to getting access to additional features in the platform. In our context, users start by using a limited set of features of the platform for free. They can get access to the full set of features by either paying a monthly fee or inviting a pre-determined number of friends. Unlike Kamada and Öry (2017), we study a scenario in which freemium is a given, and thus, not part of the firm's strategy space. Similar to Lobel et al. (2016) and Kamada and Öry (2017), we focus on users' reactions to different intensities of these referral programs. In our case, the platform determines how many successful referrals an existing user must bring to get a reward, but the referral rewards are constant (i.e. access to full functionality). Our paper is different from prior theoretical work on referral programs in the following ways. First, it is different from Biyalogorsky et al. (2001) (but similar to Kamada and Öry (2017), Lobel et al. (2016), and Kornish and Li (2010)) in that we assume WoM is costly and users do not automatically talk about the product if they don't benefit from doing so. Our paper is also distinct from Kornish and Li (2010) as we do not directly consider the possibility of users taking their friends' well-being into account. Finally, unlike Lobel et al. (2016) — that focus on rewards that are proportional to the number of successful referrals — in our paper the reward is fixed and referrals are costly, making users selective about whom to refer, so they maximize the likelihood of each referral joining the platform.

2.3 Empirical Work on Referral Programs

From an empirical perspective, most effort in the literature on referral programs has focused on assessing the quality of referrals and their loyalty (e.g. Schmitt et al., 2011; Van den Bulte et al., 2017; Garnefeld et al., 2013), on assessing 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), and which types of messages work the best (e.g. Jung et al., 2018).

Several studies have documented significant economic post-acquisition benefits from referral consumers, including a higher contribution margin, a higher retention rate, a higher customer lifetime value (e.g. Van den Bulte et al., 2017; Schmitt et al., 2011). However, most of these studies use observational data, and do not explicitly account for potential endogeneity issues. For example, Schmitt et al. (2011), studying referrals in a German bank, find that referrals (customers that were referred by other customers) have a higher retention rate and are more valuable in both the short and long run. The average value of a referred customer is at least 16% higher than that of a non-referred customer. However, the observational nature of the study does not allow us to know whether, in the absence of the referral program, the referred customers would join as well. Similarly, Van den Bulte et al. (2017) show that higher-margin referrals are associated with referrers with more experience with the firm. The authors, again, assume that in the absence of the referrer, referrals would not join, which may not be the case.

Garnefeld et al. (2013) go a step further in the direction of assessing the causal effects of referral programs on customers. The authors focus on how referral programs affect existing customers' loyalty. They use data from a telecommunications provider and compare referrers with non-referrers using propensity score matching. They find that referrers are associated with having lower churn rates and higher average monthly revenue. Nevertheless, propensity score matching is not a perfect substitute for a randomized experiment. The authors are unable to control for potential unobservables (which cannot be matched on) that may be correlated with being a loyal customer and with being a referrer.

Our paper is the first to make use of data from a large-scale randomized control trial to causally assess how existing customers react to different referral programs in terms of new customer acquisition, payments, and engagement with the platform. Our work provides empirical evidence that stricter referral programs contribute for platform growth in terms of referrals and payments. It also provides empirical evidence that stricter policies lead to lower user engagement, which may have a negative effect on the value of the platform.

3 Context, Experiment, and Data

3.1 Research Context

We use data from a large-scale randomized field experiment in collaboration with an exclusive online dating platform. This platform focuses on young professionals and has a screening process for new member approval: all registered new users need to go through a screening process before getting approved to join. This is a manual process that aims at ensuring individuals provide truthful information about themselves, including gender, age, and an adequate profile picture. Individuals are also required to connect their profile on the platform to either Facebook or LinkedIn. This screening process ensures a basic level of quality of members' profiles and discourages false profiles.

Individuals that register but do not get approved stay in a probation state until they provide adequate information.

On the platform, approved users can freely perform four types of activities: view (visit other users' profiles), message (write messages to other users), wink (click on a wink button to express their interest in other users), and like (click on a like button to express their stronger interest in other users). A match occurs when two users like each other. On the receiving end, to access information about views, messages, winks, and likes they have received, users are required either to recruit new users to the platform or to pay a monthly fee. Accessing information on received profile views and messages is considered basic functionality, while accessing information on winks and matches is considered advanced functionality.

In our setting, a successful recruitment of a new user 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*). We use the term "recruit" to denote a referrer's successful recruitment of one or more referrals who have been approved by the platform.

3.2 Experimental Setup

For its new roll-out in a major European city in 2015, our partner platform introduced a referral program aiming to grow its user base. To do so, the platform employed a large-scale randomized field experiment to assess the effectiveness of different referral policies. A referral policy is determined by how many new users (successful referrals) each existing user is required to recruit in order to get a full membership in the platform itself (i.e., gain access to the platform's basic functionality and advanced functionality). An example of a referral policy is: a user is required to recruit two new users in order to access basic functionality, and one additional user to access advanced functionality. Note that paying a monthly membership fee is always an option, irrespective of the referral policy.

Table 1: Referral program experimental conditions (frequency)

		# Approvals for Adv. Functionality			
		0	1	2	Total
# Approvals for Basic Functionality	0	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

Note: # Approvals for Basic Functionality represents how many new successful referrals are necessary for a user to have access to basic functionality. # Approvals for Basic Functionality represents how many additional new successful referrals (on top of those required to access basic functionality) are necessary for a user to have access to advanced functionality.

We use data from the experiment between March 2015 and February 2017. For each week of the experiment, the platform determined a set of two or three referral policies that were active in that week, and randomly assigned each new user to one of the active policies at the moment of user registration. The policy that a new user is assigned to does not change over time.

Table 1 shows how many new users were assigned to each referral policy for accessing basic functionality and advanced functionality. For example, a total of 20,254 users were assigned to a policy that requires the recruitment of one successful referral for accessing basic functionality. Out of these, 8,265 users were requested to recruit one additional successful referral to access advanced functionality, and 4,526 users were requested to recruit two additional successful referrals to access advanced functionality.

3.3 Data and Variables

Our data include all 52,782 new users that 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 dataset. 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 degree and 33% reported having a Master degree. Among the 45% of the users that reported their height, the average is 174cm; out of the 35% of the users that provided information about whether they smoke, 5% responded affirmatively; and out of the 39% of the users that provided information about having children, 2% said yes.

Table 2: Summary statistics for user demographics

Var	N	Mean	Median	S.D.	Min	Max
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

Dating platforms usually exhibit high turnovers, 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 a lot of 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 due to a successful outcome. Figure 1 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 their approval, as most user activities happen during the first eight weeks.[5]

We evaluate three outcome variables when assessing the impact of referral policies 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*

[4]The platform does not perform any personalization regarding which profiles to promote, or which profiles to show to other users. Users could 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 that were recently online, "Nearby", shows members that 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.

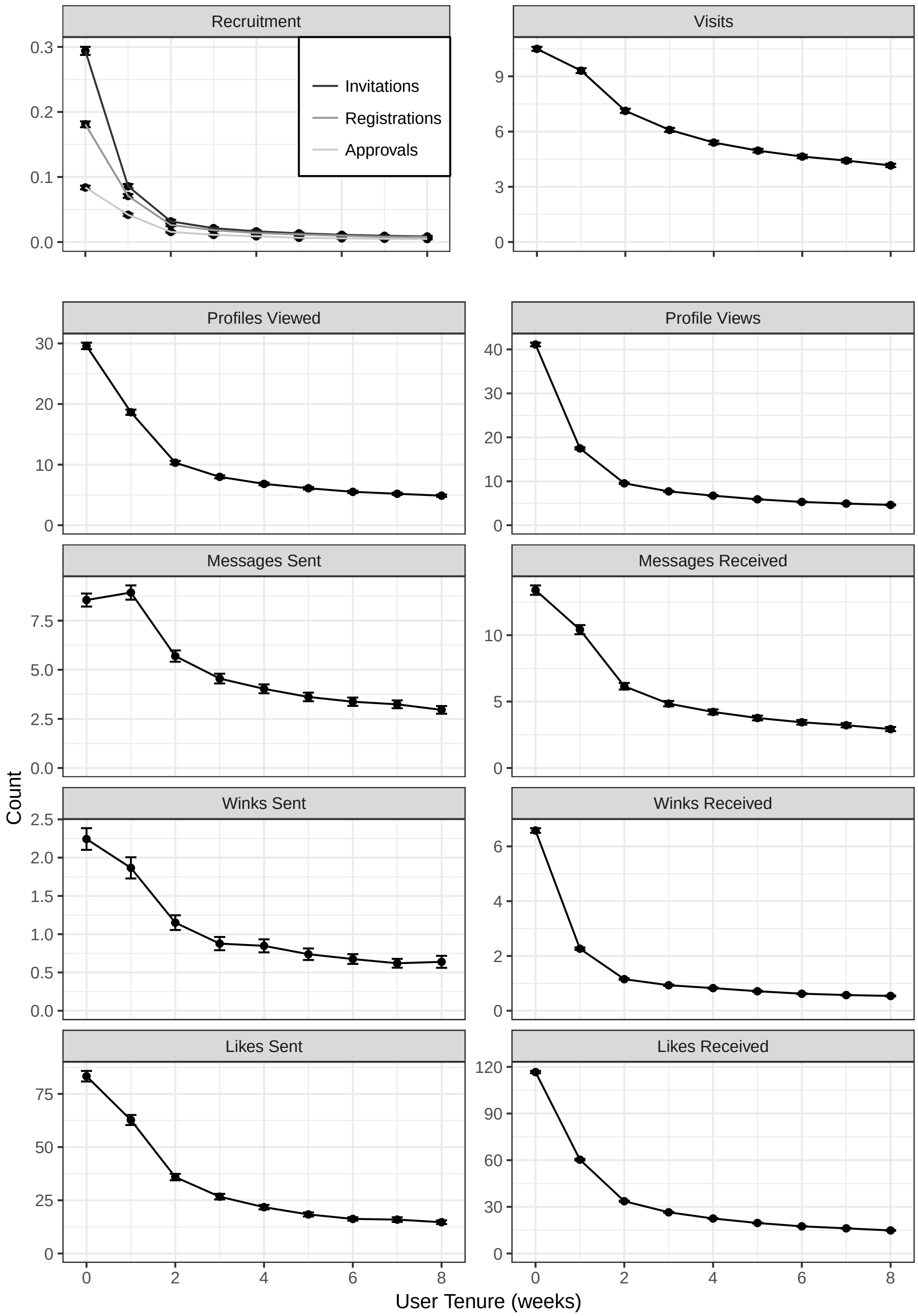


Figure 1: User behavior over time

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 0.5 referrals to the platform and are able to successfully recruit 0.18 referrals during their first 8 weeks. An average user visits the platform 56 times and pays 4.3 EUR during their first eight weeks.

Table 3: Summary statistics for key outcome variables (first 8 weeks)

Var	N	Mean	Median	S.D.	Min	Max
Invitations	52,782	0.489	0	1.100	0	74
Registrations	52,782	0.344	0	0.895	0	70
Approvals	52,782	0.181	0	0.573	0	24
Payment (Eur)	52,782	4.345	0	13.677	0	370
Visits	52,782	55.525	17	87.388	0	1,562

3.4 Randomization Checks

On this platform, new users are randomly allocated to one of the referral policies active at the moment of registration. In order to evaluate whether the policy allocation was indeed random, we regressed demographics on referral policy assignment using age and week fixed-effects. We use age fixed-effects because during a certain period of time the platform had different referral policies for users that are 27 years old or younger. We use week fixed-effects because different sets of referral policies were available in different weeks. The results are shown in Table 4. We see no significant relationship between referral policy and our demographic variables (i.e., education, gender, height, whether a user reported being a smoker or having children).

3.5 Model-Free Evidence

To evaluate the impact of referral policies on platform growth, we first look at how the three key dependent variables (total number of successful referrals, total payment, and user engagement) change during the first eight weeks on the platform across different referral policies. See Figure 2.

Table 4: Randomization check: demographics as a function of referral policies

	Dependent variable:				
	education	female	height	smoker	children
	(1)	(2)	(3)	(4)	(5)
# Referrals for Basic	−0.006	0.006	0.048	−0.003	−0.002
	(0.016)	(0.005)	(0.148)	(0.004)	(0.002)
# Referrals for Advanced	−0.016	0.006	−0.042	−0.0004	−0.001
	(0.017)	(0.005)	(0.142)	(0.004)	(0.002)
Observations	36,698	52,782	23,765	18,702	20,908
R^2	0.029	0.028	0.026	0.010	0.131
Adjusted R^2	0.026	0.025	0.021	0.002	0.125
Note:					*p<0.1; **p<0.05; ***p<0.01 Fixed effects: Age, Time Standard Errors clustered at the user level

Plots on the left-hand side — Figures 2(a), 2(c), and 2(e) — represent differences among policies regarding basic functionality, while plots on the right-hand side — Figures 2(b), 2(d), and 2(f) — represent differences among policies regarding advanced functionality.

Figure 2(a) shows the differences in the total number of approvals between the baseline policy, permitting access without requesting any referral or paying a fee, and the referral policies that require one, two or three referrals to access basic functionality. The figure shows that requesting users to recruit referrals (i.e., 1, 2 or 3) leads to a higher number of total successful referrals when compared to the baseline policy. Requiring a single referral seems to yield better results in the long term compared to requiring two or three referrals, however the confidence intervals overlap significantly.

Figure 2(c) shows the differences in total payment between the baseline policy and referral policies that require one, two or three referrals to access basic functionality. In general requiring existing users to recruit more referrals to access functionality increases total payment when compared to the baseline policy.

Figure 2(e) shows the cumulative differences in the number of visits between the baseline policy, and the other referral policies. Requiring users to register other users results in a general decrease

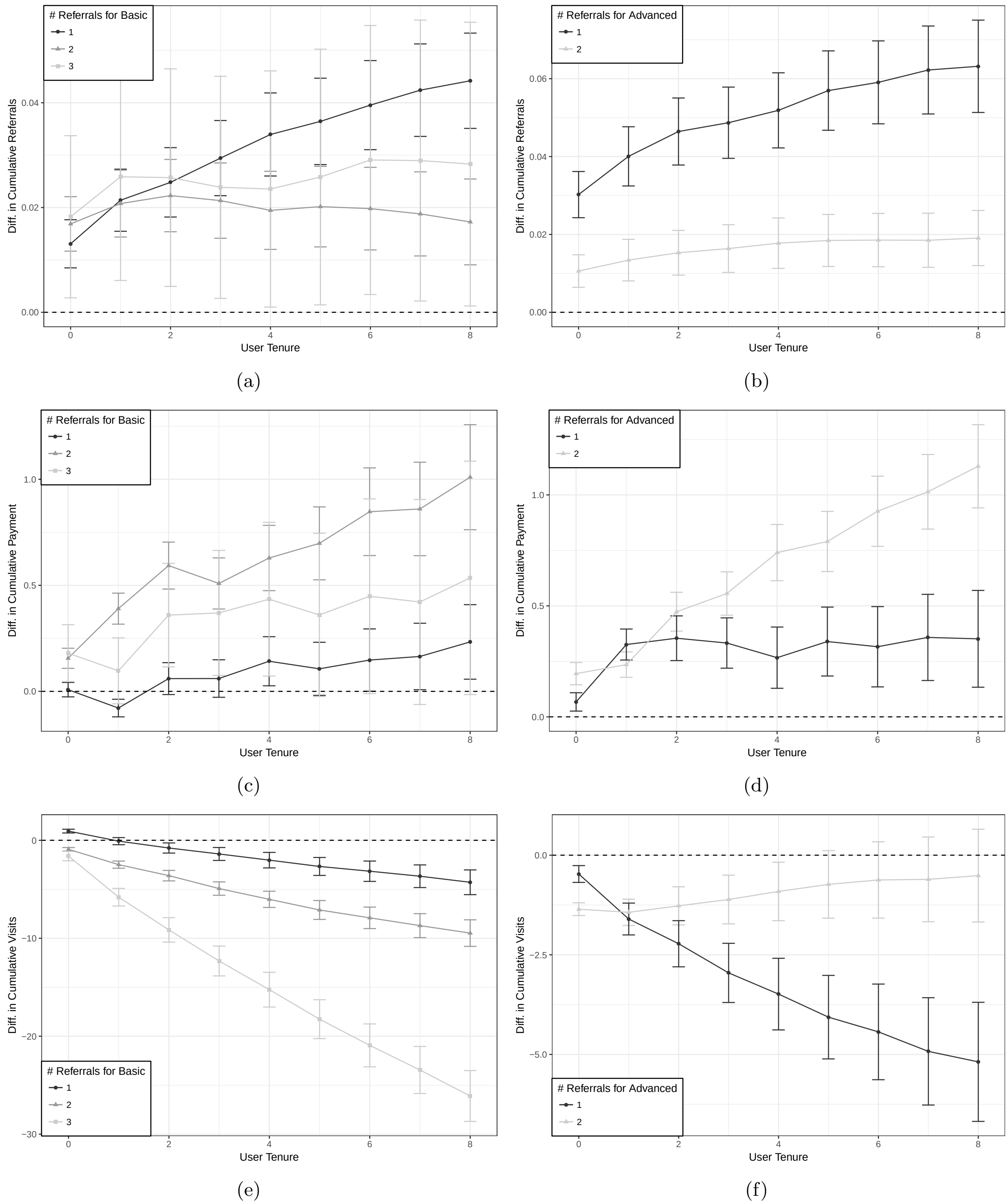


Figure 2: Differences in user behavior across referral policies over time.

on their visits to the platform over time. This decrease is more severe for referral policies that request more referrals, but tends to be linear over time.

We find similar results for referral policies for accessing advanced functionality. Figures 2(b), 2(d), and 2(f) show differences between the baseline policy and other referral policies (i.e., requiring one or two extra referrals) to access advanced functionality. These figures show that, in general, referral policies that require extra referrals to access advanced functionality lead to more approvals, higher payment, and fewer visits.

4 A Stylized Model

We present a stylized model that provides intuition on how referral policies that reward referrers with free membership on the platform itself may affect user behavior. The model also sets the stage for our empirical strategy.

Consider a set of individuals that vary across two dimensions: (1) how much they value the platform, V; and (2) how much it costs them to recruit one additional referral to the platform, $c(\cdot)$. Some individuals 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 individuals to reach others and successfully recruit them to the platform. While some individuals may be able to easily tap in their social network to recruit new users, 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 recruiting referrals to the platform or paying a price p for the full membership, users choose the option that yields the highest utility. The utility of a user can be defined as:

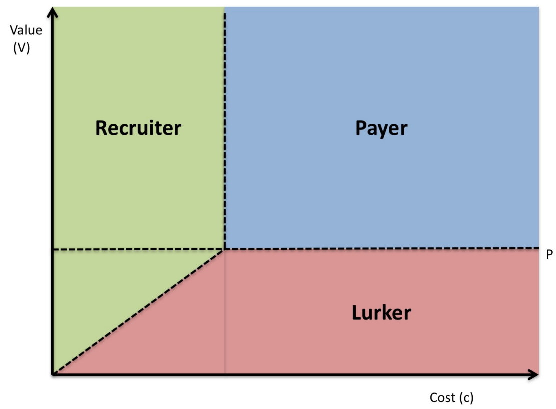
$$u_i = V_i - min\{c_i(r), p\} \tag{1}$$

where $V_i \equiv V + v_i$ in which v_i is an error term with mean zero, and r represents the number of new users an individual needs to recruit to get a full membership. We assume $c_i(\cdot)$ in an increasing function in its argument. Users will use the platform if their valuation is higher than the minimum between the cost of recruiting the required number of referrals and the price they need to pay to get the full access. Otherwise, they will either use the restricted version of the platform or stop using it. Thus, the utility of a user can be defined as:

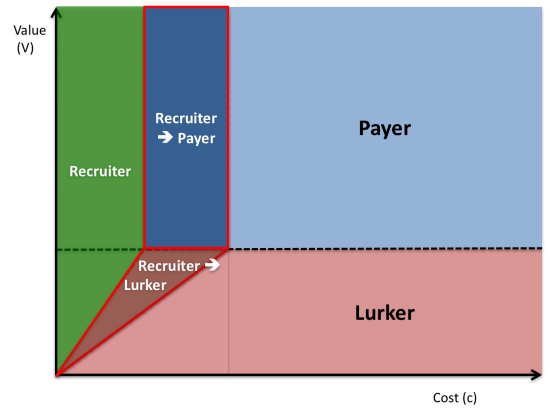
$$u_i = \begin{cases} V_i - c_i(r), \text{ for } V_i \geq c_i(r) \leq p & \text{(recruiter)} \\ V_i - p, \text{ for } V_i \geq p < c_i(r) & \text{(payer)} \\ 0, \text{ for } V_i < c_i(r) \text{ and } V_i < p & \text{(lurker)} \end{cases} \tag{2}$$

Figure 3 shows the decision regions as a function of an individual's platform valuation and her cost of recruiting referrals. Figure 3(a) shows the decision regions for a policy that requires existing users to either recruit one new user or pay a fee to get access to the full membership. 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").

Figure 3(b) shows the decision regions for a referral policy that requires existing users to recruit two new users. Changing from an easier policy (e.g. recruit one referral) to a stricter policy (e.g. recruit two referrals) increases the cost of recruiting, as users now need to recruit more new users in order to get the full membership. As a result, some users previously labeled as recruiters will become either payers or lurkers. The region marked with "recruiter → payer" includes users that decide to pay, because they find it too costly to get one additional referral and prefer to pay the fee to get the full membership. The region marked with "recruiter → lurker" includes users that



(a) Users are required to invite one user.



(b) Users are required to invite two users.

Figure 3: 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)

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 that are payers and lurkers increase as well, while the share of individuals that are recruiters decreases. Appendix A contains the derivations for these expressions using comparative statics.

In summary, stricter policies always result in an increase in the number of payers and in total payments. A fraction of the existing users, who would self-select to be recruiters under a more lenient policy, become payers under a stricter policy, as they find it harder to recruit the required number of referrals and less costly to pay for the full membership. Also, under stricter policies fewer existing users self-select to become recruiters, leading to fewer users recruiting referrals but each with a higher number of referrals. However, whether or not the total number of successful referrals increases under stricter policies is determined by the functional form of $c(\cdot)$, which is mostly an empirical question. Finally, we are interested in assessing the effects of stricter policies on user engagement. Our model is agnostic about it, and there's no clear theoretical prediction on whether engagement would increase or decrease. We explain how we empirically examine the impact of referral policies on successful referrals, total payments, and user engagement in the next section.

5 Empirical Strategy

5.1 Estimating The Effects of Referral Programs on User Behavior

We start by estimating the effects of referral policies on three types of user behavior, namely the number of successful referrals, total payment, 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 referral policy strictness — which linear models readily provide — and because we use instrumental variables in some specifications, for which linear models are more suitable (Angrist and Pischke, 2008). To do so we regress our dependent variables on referral policy, using age, gender, education, time, and user tenure fixed effects. We use the equation

$$y_{it} = c_i(r_i) + \boldsymbol{x}_i + \boldsymbol{w}_t + v_{it} \tag{3}$$

in which y_{it} represents one of our dependent variables, and vectors $\boldsymbol{x}_i$ and $\boldsymbol{w}_t$ represent individual characteristics and time covariates that we use as fixed-effects. We are unable to use individual fixed effects in our setting because policy 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

$$r = \delta_b r_b + \delta_a r_a$$

in which r_b represents how many referrals an existing user needs to recruit to access the basic functionality, and r_a represents how many additional referrals she needs to recruit to access the advanced functionality.

$$y_{it} = \beta_b r_{bi} + \beta_a r_{ai} + \boldsymbol{x}_i + \boldsymbol{w}_t + \varepsilon_{it} \tag{4}$$

where $\beta_b \equiv \gamma\delta_b$ and $\beta_a \equiv \gamma\delta_a$ are our main parameters of interest, representing how much requiring an existing user to recruit a referral to access basic and advanced functionality, 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.

5.2 Addressing Endogeneity in Estimating The Effect on User Engagement

A major challenge in identifying the effect of referral policies on user engagement from our data is that it is the existing user who decides to increase or decrease her engagement levels on the platform when she is assigned to a different referral policy. Figure 3 shows that not all users change their user status as a result of a policy change. Some users self-select into a given user status independently of the referral policy they are assigned to, while other users change their user status as a function of the policy they get. As a result, the coefficient we estimate from the linear probability model could be biased by the endogeneous selection of the user status. To strengthen our empirical identification and causal interpretation for the estimated effects of referral policies on user engagement, we use an instrumental variable approach.

We are interested in understanding whether users change their behavior (engagement) as a function of the status they are in (recruiter, payer, lurker):

$$y_{it} = \varphi_1 Payer_{it} + \varphi_2 Lurker_{it} + \varphi_3 Recruiter_{it} + \boldsymbol{x}_i + \boldsymbol{w}_t + \varepsilon_{it} \tag{5}$$

in which $Payer_{it}$, $Lurker_{it}$, and $Recruiter_{it}$ are dummy variables indicating whether a user i belongs to each of these status at time t. Given the three status are mutually exclusive, we can rewrite this equation as

$$y_{it} = \varphi_1 Payer_{it} + \varphi_2 Lurker_{it} + \varphi_3(1 - Payer_{it} - Lurker_{it}) + \boldsymbol{x}_i + \boldsymbol{w}_t + \varepsilon_{it} \tag{6}$$

or

$$y_{it} = (\varphi_1 - \varphi_3) Payer_{it} + (\varphi_2 - \varphi_3) Lurker_{it} + \boldsymbol{x}_i + \boldsymbol{w}_t + \varepsilon_{it} \tag{7}$$

As shown in our model, whether a user chooses to be a recruiter, a payer, or a lurker, is, at least in part, determined by unobserved factors that may also determine user engagement levels. For example, users that have a high value towards the platform may be simultaneously more likely to pay and more likely to use the platform frequently, making these variables endogenous. Thus, estimating equation (5) directly would yield biased estimates for the coefficients of interest.

We address the above-mentioned concern by following a two-stage least squares approach (2SLS) in which we regress user engagement on the user status they self-select into (i.e., recruiter, payer, or lurker), and instrument these user status with the referral policy randomly assigned to them. As depicted in Figure 3(b), stricter policies lead some users to switch from the recruiter status to the payer status and other users to switch to the lurker status. This, together with the fact that policies were assigned randomly, makes the referral policies good candidate instruments for *Payer* and *Lurker*. A valid instrument should be correlated with the potentially endogeneous independent variable (in our case, user status), but it should not have an effect on the dependent variable except through the endogeneous variable (engagement). Using this strategy allows us to assess the extent to which user engagement is affected, when a user "moves" from a given status to another status as a function of the policy assigned to her. The obtained results are valid only for the subset of users that are affected by changes in referral policies, i.e., the compliers. In other words, this strategy allows us to estimate the local average treatment effects (LATE) of "being forced" to move from a recruiter status to a payer or a lurker status in terms of user engagement.

Moreover, given that the baseline for these comparisons are users who stay in the recruiter status, and are also affected by the policy change, the obtained coefficients should be interpreted as the difference in behavior between staying in the recruiter status (and being required to recruit more referrals) and moving to a payer or a lurker status. Equation (7) depicts these comparisons.

6 Results

Following our empirical strategy, we first present the main results related to the effects of referral policies on user behavior. Next, we focus on explaining why we observed a decreased level of user engagement in the presence of stricter policies. In addition, we present a set of robustness checks of our main results by using alternative measures of our dependent variables.

6.1 Main Results of The Effects of Referral Programs on User Behavior

We start by looking at the impact of different referral policies 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 basic functionality and advanced functionality in a referral policy: (1) how many referrals are required by the policy for accessing basic functionality and, (2) how many additional referrals are required for accessing advanced functionality. We use fixed effects for education, age, gender, user tenure, and week, 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. The coefficients of this table corroborate the general trends discussed above in Figure 2.

Referral policies 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 stricter policies tend to increase the number of successful referrals. Requiring an additional approval in order to access basic

Table 5: Main results: effect of referral policies on user behavior

	Dependent variable:				
	Invitations	Registrations	Approvals	Payment	Visits
	(1)	(2)	(3)	(4)	(5)
# Referrals for Basic	0.020***	0.014***	0.009***	0.026***	−0.054***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
# Referrals for Advanced	0.025***	0.019***	0.012***	0.022***	−0.029***
	(0.003)	(0.003)	(0.003)	(0.003)	(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

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard Errors clustered at the user level

(advanced) functionality leads to an increase of 2% (2.5%) of a standard deviation in the number of invited new 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 were invited, and their approval is conditional on their platform registration. Requiring an additional referral to access basic (advanced) functionality 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 stricter policies lead to an increase in payment. This effect is visible for both policy changes regarding access to basic functionality and access to advanced functionality. Column (4) shows that requiring an additional referral to access basic (advanced) functionality leads to an increase of 2.6% (2.2%) of a standard deviation in the amount paid ($p < 0.01$). This happens likely because some users may find it hard to invite enough referrals and decide to pay in order to access the desired functionality.

Surprisingly, stricter policies lead users to decrease their platform engagement, as measured by the number of visits. Column (5) shows that requiring users to recruit an additional referral to access basic (advanced) functionality leads to a decrease of 5.4% (2.9%) of a standard deviation

($p < 0.01$).

We also test for the existence of non-linear effects. It is unlikely that the positive effect of referral policies 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 will have a smaller effect on their behavior. We test the existence of non-linear effects of referral policy requirements on user behavior. As expected, requiring an additional referral in order to gain basic functionality 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 2 and 3 referrals to access basic functionality. We do not observe a non-linear effect of referral policies on user engagement. The results of this analysis are provided in Appendix C.

In addition, we test for the existence of heterogeneous effects across users' demographics. We take advantage of the referral policies' random assignment to assess potential heterogeneity in the effects of policy strictness 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 policy strictness with each of these controls. Overall we find some degree of heterogeneity across users, but always with the same directions as the main results, meaning that there are no specific advantages in providing different treatments to users based on their demographics. The results of this analysis are provided in Appendix D.

6.2 Instrumental Variable Analysis on User Engagement

Even though we observe a decrease in user engagement for stricter policies, such a decrease may not be uniform across all users. Some users are not affected by the policy they are assigned to. For example, as shown in Figure 3(b), users with high valuation and high recruitment cost will always be payers, and users with low valuation and high recruitment cost will always be lurkers.

In our setting, we consider users to be payers from the moment they perform their first pay-

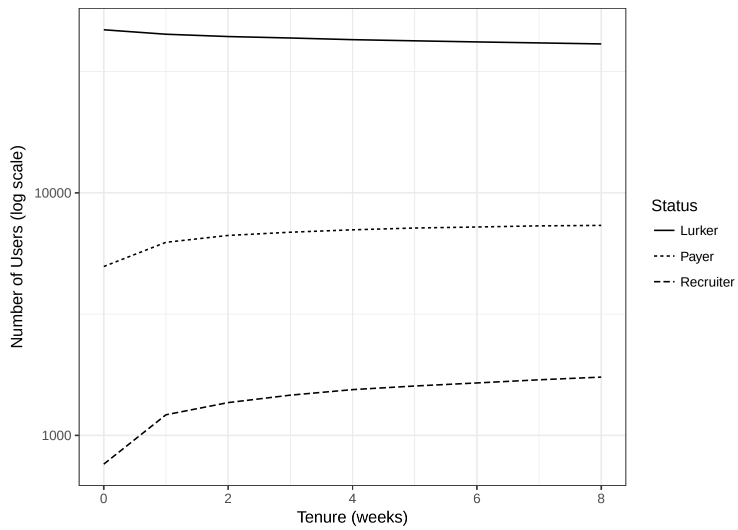


Figure 4: User status over time

ment to the platform; otherwise, in case they have referred enough new users they are considered recruiters; and all the remaining users are considered lurkers.[6] Figure 4 shows how the number of users within each of the user status changes with user tenure. Among the 50,216 users for which we observe their first eight weeks, about 82% (41,135) of the users are lurkers, 3% (1,739) are recruiters and 15% (7,342) are payers.

We first regress engagement on user status. Column (1) of Table 6 shows that payers tend to be more active than recruiters, and that lurkers are less active than recruiters. These results are consistent with our main model, in which users that value more of the platform also end up using it more. However, as mentioned above, these results rely on user self-selection, which is endogenous and are not representative of the effects of different policies on user behavior. Our goal is to understand how users whose status is determined by their policy, i.e. compliers, change their engagement with the platform. Therefore, we follow the 2SLS approach mentioned in section 5 and regress user engagement on user status (i.e., payer or lurker), using the randomly assigned referral

[6] We have also used alternative criteria for assigning users to payer, recruiter and lurker status. For example, we have defined that a user is a payer only if they have made a payment over the previous 4 weeks (members can lose access to full functionality if they stop paying and have not recruited enough referrals). All results remain qualitative the same, so we decided to use the simpler definitions. Results using alternative definitions are available from the authors upon request.

policies as instruments for user status.

Column (2) of Table 6 shows a 2SLS estimate for user engagement as a function of whether users move to being payers or lurkers as a result of stricter policies, as compared to users that remain as recruiters. Columns (3) and (4) show the first stages, which go in the expected direction: stricter policies regarding access to basic functionality contribute to an increase in the likelihood of becoming a payer, but to a decrease in the likelihood of becoming a lurker; and stricter policies regarding access to advanced functionality contribute to an increase in the likelihood of both becoming a payer and lurker. Column (2) shows the second stage regression. The negative coefficient in *Payer* means that moving from being a recruiter in an easier policy to being a payer in a stricter policy contributes to a decrease in user engagement of about 1.5 standard deviations ($p < 0.01$). Similarly, the negative coefficient in *Lurker* suggests that moving from being a recruiter in an easier policy to being a lurker in a stricter policy contributes to a decrease in the level of engagement of about 0.2 of a standard deviation, but the estimate is imprecise. Note that both of these numbers are a comparison with a 'moving' baseline: users that remain as recruiters also change their user engagement as a function of the policy they are assigned to.

We also checked the robustness of our results using alternative measures of user engagement. We used 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). These results, presented in Appendix B, are consistent with our main findings.

6.3 Mechanisms for Decreased User Engagement

Our stylized model helps us understand why stricter policies increase both successful referrals and total payments, but it does not explain why, on average, users with stricter policies become less engaged. We delve further into the data to better understand which mechanisms may justify the

Table 6: 2SLS results for user engagement

	Dependent variable:			
	Visits		Payer	Lurker
	OLS	2SLS	1st Stage	1st Stage
	(1)	(2)	(3)	(4)
Payer	0.167***	−1.450***		
	(0.029)	(0.233)		
Lurker	−0.707***	−0.217		
	(0.025)	(0.202)		
1 Approv. for Basic			0.056***	−0.048***
			(0.006)	(0.006)
2 Approv. for Basic			0.058***	−0.014**
			(0.006)	(0.006)
3 Approv. for Basic			0.094***	−0.040***
			(0.009)	(0.010)
1 Approv. for Advanced			0.034***	0.034***
			(0.005)	(0.006)
2 Approv. for Advanced			0.058***	0.011*
			(0.006)	(0.006)
Observations	463,470	463,470	463,470	463,470

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard errors clustered at the user level

decrease in user engagement for stricter policies.

We look at two mechanisms that may be at play in our setting. First, stricter policies may prevent some users from getting access to basic/advanced functionality and may lead others to get access later, as they may need more time to acquire the additional required referrals or to decide to pay. This may lead to a lower overall engagement, as engagement is likely determined in part by whether users have access to the full functionality of the platform. Second, we explore the social enrichment hypothesis, i.e. that users derive more value from the platform when their referrals are also active in the platform (Van den Bulte et al., 2017). Users with friends in the platform may end up interacting more with whom they invite, either on the platform or through alternative channels, increasing their valuation and engagement. The presence of a friend in the platform may provide functional benefits for users even if they haven't anticipated it, by, for example, talking with other users about their experiences in the platform. Being assigned to a stricter policy may also prompt users to exert more effort to meet the stated policy requirements, with some users deciding to invite referrals (recruiters), and others deciding to become paying members (payers).

The latter are more likely to end up with fewer friends on the platform and, according to the social enrichment hypothesis, less engaged. We assess to what extent each of these mechanisms plays a role in our setting.

6.3.1 Mechanism #1: Delayed Access to Full Membership

To test the hypothesis that stricter policies lead to lower engagement because they restrict access to some functionality, we start by testing whether users with stricter policies are less likely (or take longer) to get access to basic/advanced functionality.

We regress access to basic/advanced functionality on referral policy strictness. Table 7 shows these results. Stricter policies with respect to basic functionality, i.e. policies that require users to recruit more referrals for accessing basic functionality, decrease users' likelihood of getting access to basic functionality, but do not seem to affect their likelihood of getting access to advanced functionality. Conversely, stricter policies concerning advanced functionality, i.e. policies that require users to recruit more referrals for accessing advanced functionality, increase users' likelihood of getting access to basic functionality and decrease their likelihood of getting access to advanced functionality.

Table 7: Mechanism #1 testing: stricter policy restricts access to functionality

	Dependent variable:	
	Basic Access	Adv. Access
	(1)	(2)
# Referrals for Basic	-0.267^{***}	-0.003
	(0.002)	(0.002)
# Referrals for Advanced	0.175^{***}	-0.016^{***}
	(0.002)	(0.002)
Observations	463,470	463,470
Adjusted R^2	0.493	0.055
Note:		*p<0.1; **p<0.05; ***p<0.01
		Fixed effects: Education, Age, Gender, Tenure, Time
		Standard errors clustered at the user level

These results are consistent with the above-stated hypotheses: setting higher standards to access a given functionality is likely to lead to fewer users reaching the required threshold. This justifies the negative coefficients for the requirements associated with the respective functionality. Also, being assigned to a stricter policy may prompt some users to exert a greater effort to meet the stated policy requirements, leading to more referrals overall. This also justifies why we see an increase in the likelihood of getting access to basic functionality as a function of advanced functionality requirements (column (1) of Table 7): users apply more effort to get access to advanced functionality, and as a side effect get access to basic functionality.

Next, we assess whether getting access to basic/advanced functionality does indeed lead to more engagement. We start by plotting the number of visits for users that get access to basic/advanced functionality during their first eight weeks in the platform, as a function of time relative to the moment each user gets access to the respective functionality. Figure 5 shows that the average number of visits to the platform remains fairly constant up to the moment users get access to basic or advanced functionality. Once users get access to more functionality, their visits to the platform increase. This jump is more pronounced when users acquire access to advanced functionality, with most of this 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 basic/advanced functionality.

As shown above, stricter policies could indeed result in lower engagement due to users requiring more time to get access to the respective functionality. This, by itself, could justify the negative coefficient observed in column (2) of Table 6. In order to assess to what extent this mechanism explains the decrease in user engagement, we regress user engagement on user status (payer or lurker), but this time controlling for whether a user has access to basic/advanced functionality or not. To do so, we instrument whether a user has access to basic/advanced functionality with the policy assigned to them. Table 8 shows the results. Similar to Table 6, columns (1)-(3)

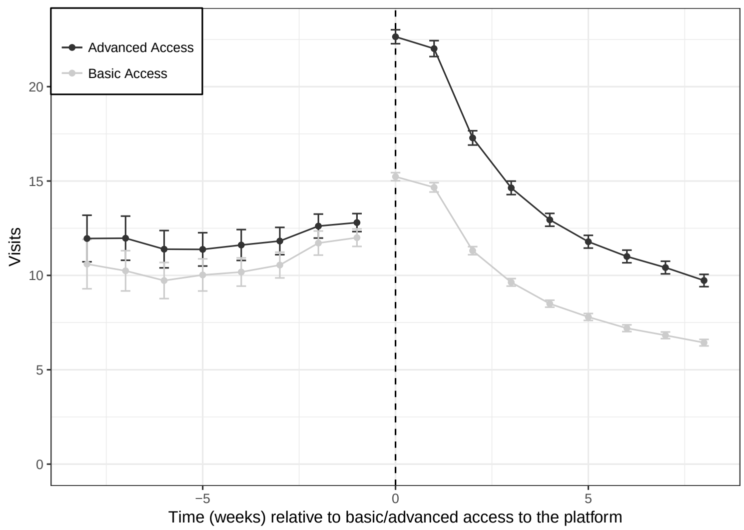


Figure 5: User engagement (visits) relative to access to basic/advanced functionality

show OLS results, suggesting that payers are more active than recruiters and that lurkers are less active. In addition, users with access to basic or advanced functionality are more active than those without access to that functionality (lurkers). Columns (4)-(6) show 2SLS results. Column (4) replicates column (2) in Table 6. Column (5) shows that access to basic/advanced functionality leads users to be more engaged with the platform, even when using instruments: getting access to basic functionality leads users to increase their activity by 9% of a standard deviation ($p < 0.01$), while that effect is ten times as high (90% of a standard deviation) for access to advanced functionality ($p < 0.01$). Column (6) shows that even taking into account whether users have access to basic/advanced functionality, being a payer reduces engagement in about 1 standard deviation ($p < 0.01$), when compared with users that stay as recruiters.

In summary, stricter policies do contribute to a decrease in the likelihood of getting access to basic/advanced functionality (or delay the access timing) and consequently to a decrease in user engagement. However, access to basic/advanced functionality does not fully explain the decrease in engagement: compliers who become payers as a function of their (randomly assigned) policy, become less engaged with the platform even after controlling for access to basic/advanced functionality.

Table 8: Mechanism #1 testing: 2SLS results for decreased user engagement

	Dependent variable:					
	Visits					
	OLS	OLS	OLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Payer	0.167***		0.226***	−1.450***		−1.063***
	(0.029)		(0.029)	(0.233)		(0.204)
Lurker	−0.707***			−0.217		
	(0.025)			(0.202)		
Basic Access		0.253***	0.260***		0.090***	0.064***
		(0.008)	(0.008)		(0.012)	(0.014)
Advanced Access		0.708***	0.520***		0.919***	0.769***
		(0.013)	(0.026)		(0.179)	(0.206)
Observations	463,470	463,470	463,470	463,470	463,470	463,470
Note:	*p<0.1; **p<0.05; ***p<0.01					
	Fixed effects: Education, Age, Gender, Tenure, Time					
	Standard errors clustered at the user level					

6.3.2 Mechanism #2: Social Enrichment

Continuing with our task of understanding why, on average, users become less active upon being presented with stricter policies, we test the social enrichment hypothesis: users derive more value from the platform when their referrals are also active in the platform.

To test the social enrichment hypothesis, we follow two strategies. First, we assess how getting a first successful referral affects user engagement. The main assumption is that, conditional on having friends registered for the platform, their approval (and the timing of approval) is a decision made by the platform itself, and is out of the control of the referrer. This is indeed the case in this platform as new members are approved through a manual process. We regress user engagement on whether a user got their first referral approved, controlling for the number of registrations, for whether the user has access to basic/advanced functionality, and for whether they got their full membership through payment or not. Table 9 shows the results. Column (1) replicates the 2SLS results in column (6) of Table 8 for reference. Column (2) adds an indicator of whether a user got their first referral approved. As before, we instrument each of these variables (including the new indicator) with the policy randomly assigned to the user. Results show that having the first referral approved is associated with a significant increase in engagement ($p < 0.05$).

Table 9: Mechanism #2: the importance of the first referral

	Dependent variable:			
	Visits			
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Payer	-1.063^{***}	-0.721^{**}	-1.135^{***}	-0.600
	(0.204)	(0.365)	(0.205)	(0.419)
Basic Access	0.064^{***}	0.055^{***}	0.064^{***}	0.055^{**}
	(0.014)	(0.021)	(0.014)	(0.022)
Advanced Access	0.769^{***}	0.628^{*}	0.792^{***}	0.588^{*}
	(0.206)	(0.331)	(0.204)	(0.342)
First Approved Referral		3.696^{**}		3.948^{**}
		(1.521)		(1.655)
# Registrations			0.111^{***}	-0.150
			(0.009)	(0.110)
Observations	463,470	463,470	463,470	463,470

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard errors clustered at the user level

This result suggests that users are more engaged with the platform when their friends join. On the contrary, payers, who by definition, have fewer friends in the platform and thus are less engaged. In columns (3) and (4), we also control for the number of registered users invited by the referrer, which can be viewed as a proxy for user effort in recruiting referrals. The results show that, when controlling for the number of registrations, the negative effect of being a payer on user engagement disappears and is transferred to the coefficient associated with having a first referral. This suggests that having a first successful referral increases user engagement, while being a payer has no effect, after controlling for recruitment effort.

Our second strategy is to examine changes in engagement when a user's referrer leaves the platform, i.e., when they significantly reduce their level of participation. We consider that a user leaves the platform if they did not visit for at least four consecutive weeks. Table 10 shows that when referrers leave the platform, the engagement of the referrals is reduced significantly. This table shows regressions over the 9,622 users that 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 policy of the referral and include fixed effects for education, age, gender, tenure and week. Consistent with the social enrichment hypothesis, having their referrers leave, leads a user to decrease all types of activity in the platform.

Table 10: Mechanism #2: social enrichment

	Dependent variable:								
	Visits	Profiles Viewed	Profile Views	Messages Sent	Messages Received	Winks Sent	Winks Received	Likes Sent	Likes Received
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Referrer Dropped	−0.130***	−0.021*	−0.067***	−0.035***	−0.049***	0.021	−0.064***	−0.009	−0.119***
	(0.018)	(0.012)	(0.012)	(0.009)	(0.010)	(0.024)	(0.013)	(0.014)	(0.012)
# Referrals for Basic	−0.086***	−0.034**	−0.042***	−0.044***	−0.052***	−0.024	−0.031**	−0.012	−0.059***
	(0.020)	(0.015)	(0.015)	(0.013)	(0.013)	(0.018)	(0.015)	(0.014)	(0.015)
# Referrals for Advanced	−0.065***	−0.034**	−0.023	−0.035***	−0.044***	−0.037*	−0.012	−0.037***	−0.040***
	(0.020)	(0.014)	(0.014)	(0.013)	(0.014)	(0.023)	(0.014)	(0.014)	(0.015)
Observations	53,565	53,565	53,565	53,565	53,565	53,565	53,565	53,565	53,565
R^2	0.138	0.114	0.282	0.051	0.063	0.061	0.262	0.070	0.444
Adjusted R^2	0.125	0.100	0.271	0.036	0.049	0.046	0.251	0.056	0.435

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard errors clustered at the user level

6.4 Examining Sustained Effects for Network of Users

Our main results have shown that stricter policies lead to an increased number of successful referrals and to higher average payments. We run additional analyses to assess if such effects are passed on to a user's referrals. In other words, we look at whether stricter referral policies contribute to increasing the value of the referrals. The policy assigned to a referrer could condition the observed behavior for their referrals, even though policy assignment was random. This could happen if, for example, individuals assigned to stricter policies invite different users from those they would have if they were assigned easier policies (as suggested in Van den Bulte et al., 2017; Schmitt et al., 2011), or if their behavior influences their referrals' behavior as well (e.g. Iyengar et al., 2015; Bapna and Umyarov, 2015).

Table 11 shows that none of the above mechanisms is likely at play in our case. This table shows the effect of policy assignment on the total number of referrals, payment, and engagement from users that joined the platform as a result of an invitation from the referrer. Columns (1)-(2) show effects on referrals, and columns (3)-(4) show effects on payments, and columns (5)-(6) show effects on engagement as measured by visits to the platform. Columns (1), (3) and (5) show the effects on the referrals (friends) 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 policy assignment on referrals' behavior, either in terms of total number of referrals, total payment, or engagement. If anything, column (3) shows that requiring an additional referral to access advanced functionality leads the users' referrals to increase their total payment by 0.9% 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 basic functionality leads to a small decrease in total engagement when considering the whole network of users (1.2% of a standard deviation, $p < 0.05$).

Table 11: Results of sustained effects on network of users

	Dependent variable:					
	Frd. Referrals	Agg. Referrals	Frd. Payment	Agg. Payment	Frd. Visits	Agg. Visits
	(1)	(2)	(3)	(4)	(5)	(6)
# Referrals for Basic	0.002	−0.002	0.004	−0.001	0.003	−0.012**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
# Referrals for Advanced	0.004	−0.002	0.008**	0.003	0.00000	−0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(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

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard Errors clustered at the user level

7 Conclusion

We investigate the effectiveness of referral programs in stimulating platform growth. Using a randomized field experiment in an online dating platform, we assess the effectiveness of referral policies that require users to recruit new users to access premium features in the platform. Our findings suggest that referral programs act like a double-edged sword. While stricter policies can increase platform user base and total payment, these benefits come at the cost of reduced level of user engagement. Our paper contributes to the broader literature on platform strategy by focusing on platforms that exhibit strong network effects at a global level, but weak network effects locally. Whereas the majority of prior work on platform strategy has considered pricing and seeding strategies to solve the cold-start problem, we focus on referral programs that reward referrers with free access to the platform itself. Furthermore, our paper contributes to the theoretical and empirical literature on referral programs. We develop a stylized model that explains how referral policies contribute to both user and revenue growth. Not all users are affected in the same way by stricter policies. Some users decide to recruit new users, while others decide to pay a monthly fee to access premium features. We also assess how such referral policies affect the value of new referrals. We find no evidence that stricter policies contribute to an increase in the quality of the pool of invited users. These findings have important managerial implications. We show that despite the conventional wisdom that there is a tension between growth and revenue, referral policies can allow users to self select into the role that best suits them, reconciling these two goals, possibly at the expense of other measures, such as engagement.

References

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion.* Princeton university press.

Aral, S., Muchnik, L., and Sundararajan, A. (2013). Engineering social contagions: Optimal network seeding in the presence of homophily. *Network Science*, 1(02):125–153.

Bapna, R. and Umyarov, A. (2015). Do your online friends make you pay? a randomized field experiment on peer influence in online social networks. *Management Science*, 61(8):1902–1920.

Biyalogorsky, E., Gerstner, E., and Libai, B. (2001). Customer referral management: Optimal reward programs. *Marketing Science*, 20(1):82–95.

Dou, Y., Niculescu, M. F., and Wu, D. (2013). Engineering optimal network effects via social media features and seeding in markets for digital goods and services. *Information Systems Research*, 24(1):164–185.

Garnefeld, I., Eggert, A., Helm, S. V., and Tax, S. S. (2013). Growing existing customers' revenue streams through customer referral programs. *Journal of Marketing*, 77(4):17–32.

Godes, D. and Mayzlin, D. (2009). Firm-created word-of-mouth communication: Evidence from a field test. *Marketing Science*, 28(4):721–739.

Goldenberg, J., Libai, B., and Muller, E. (2010). The chilling effects of network externalities. *International Journal of Research in Marketing*, 27(1):4–15.

Hinz, O., Skiera, B., Barrot, C., and Becker, J. U. (2011). Seeding strategies for viral marketing: An empirical comparison. *Journal of Marketing*, 75(6):55–71.

Iyengar, R., Van den Bulte, C., and Lee, J. Y. (2015). Social contagion in new product trial and repeat. *Marketing Science*, 34(3):408–429.

Jung, J., Bapna, R., Golden, J., and Sun, T. (2018). Words matter! towards pro-social call-to-action for online referral: Evidence from two field experiments.

Kamada, Y. and Öry, A. (2017). Contracting with word-of-mouth management.

Katz, M. L. and Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American economic review*, 75(3):424–440.

Kauffman, R. J., McAndrews, J., and Wang, Y.-M. (2000). Opening the "black box" of network externalities in network adoption. *Information Systems Research*, 11(1):61–82.

Kornish, L. J. and Li, Q. (2010). Optimal referral bonuses with asymmetric information: Firm-offered and interpersonal incentives. *Marketing Science*, 29(1):108–121.

Lobel, I., Sadler, E., and Varshney, L. R. (2016). Customer referral incentives and social media. *Management Science*, 63(10):3514–3529.

Parker, G. and Van Alstyne, M. (2017). Innovation, openness, and platform control. *Management Science*.

Parker, G. G. and Van Alstyne, M. W. (2005). Two-sided network effects: A theory of information product design. *Management Science*, 51(10):1494–1504.

Ryu, G. and Feick, L. (2007). A penny for your thoughts: Referral reward programs and referral likelihood. *Journal of Marketing*, 71(1):84–94.

Schmitt, P., Skiera, B., and Van den Bulte, C. (2011). Referral programs and customer value. *Journal of Marketing*, 75(1):46–59.

Sundararajan, A. (2007). Local network effects and complex network structure. *The BE Journal of Theoretical Economics*, 7(1).

Van den Bulte, C., Bayer, E., Skiera, B., and Schmitt, P. (2017). How customer referral programs turn social capital into economic capital. *Journal of Marketing Research*.

A 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:

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

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

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

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 policies on user behavior. Thus, we use comparative statics to assess how users behave as a function of a change in the referral policy they are assigned to. We start by checking how payments ($\alpha_p p$) change as a function of policy strictness, r:

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

This means that stricter policies always result in an increase in the number of payers and in total payments. A fraction of the existing users, who would self-select to be recruiters under a more lenient policy, becomes payers under a stricter policy, as they find it harder to recruit the required number of referrals and less costly to pay for the full membership.

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

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

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

Under stricter policies fewer existing users self-select to become recruiters, leading to fewer users recruiting referrals but each with a higher number of referrals. However, whether or not the total number of successful referrals increases under stricter policies 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 policy 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 policy strictness, r:

$$\frac{\partial \alpha_l}{\partial r} = (1-p)\Big(1 + p\frac{c'(r)}{c(r)^2}\Big) - \frac{1}{2}p^2\frac{c'(r)}{c(r)^2}$$

$$= (1-p) + p(1 - \frac{3}{2}p)\frac{c'(r)}{c(r)^2} > 0$$

Thus, the fraction of lurkers always increases with policy strictness.

B Alternative User Engagement Measures

In this section we use other types of platform activities as measures of user engagement, 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 12 shows that users assigned to stricter policies have much lower levels of engagement as measured by profile views, messages, winks, and likes. Table 13 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 3, 5 of 7 messages, with at least 1, 2, and 3 messages in each direction, respectively. All these results are consistent with our main results. Tables 14 and 15 show the respective instrumental variable analyses for all alternative measures of user engagement. The results are again consistent with our main findings.

Table 12: Alternative measures of user engagement: profile views, messages, winks, and likes

	Dependent variable:								
	Visits	Profiles Viewed	Profile Views	Messages Sent	Messages Received	Winks Sent	Winks Received	Likes Sent	Likes Received
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# Referrals for Basic	-0.054^{***}	-0.026^{***}	-0.017^{***}	-0.020^{***}	-0.023^{***}	-0.005	-0.018^{***}	-0.015^{***}	-0.035^{***}
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
# Referrals for Advanced	-0.029^{***}	-0.018^{***}	-0.012^{***}	-0.004	-0.012^{***}	-0.017^{***}	-0.012^{***}	-0.015^{***}	-0.016^{***}
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(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

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard Errors clustered at the user level

Table 13: Alternative measures of user engagement: matches

	Dependent variable:			
	Mut. Like	3 Messages	5 Messages	7 Messages
	(1)	(2)	(3)	(4)
# Referrals for Basic	-0.029^{***}	-0.035^{***}	-0.033^{***}	-0.031^{***}
	(0.005)	(0.004)	(0.004)	(0.004)
# Referrals for Advanced	-0.023^{***}	-0.019^{***}	-0.018^{***}	-0.017^{***}
	(0.005)	(0.005)	(0.005)	(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

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard errors clustered at the user level

Table 14: 2SLS results for alternative measures of user engagement: profile views, messages, winks, and likes

	Dependent variable:								
	Visits	Profiles Viewed	Profile Views	Messages Sent	Messages Received	Winks Sent	Winks Received	Likes Sent	Likes Received
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Payer	-1.450^{***}	-0.706^{***}	-0.308^{**}	-0.432^{***}	-0.557^{***}	-0.301^{*}	-0.345^{**}	-0.656^{***}	-0.945^{***}
	(0.233)	(0.154)	(0.136)	(0.147)	(0.143)	(0.162)	(0.140)	(0.159)	(0.162)
Lurker	-0.217	-0.238^{*}	-0.017	0.044	-0.035	-0.461^{***}	0.226^{*}	-0.127	-0.085
	(0.202)	(0.139)	(0.130)	(0.155)	(0.146)	(0.158)	(0.133)	(0.133)	(0.147)
Observations	463,470	463,470	463,470	463,470	463,470	463,470	463,470	463,470	463,470

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard errors clustered at the user level

Table 15: 2SLS results for alternative measures of user engagement: matches

	Dependent variable:			
	Mut. Like	3 Messages	5 Messages	7 Messages
	(1)	(2)	(3)	(4)
Payer	-0.996^{***}	-0.881^{***}	-0.829^{***}	-0.792^{***}
	(0.185)	(0.167)	(0.165)	(0.163)
Lurker	-0.440^{***}	-0.199	-0.195	-0.191
	(0.160)	(0.171)	(0.167)	(0.162)
Observations	463,470	463,470	463,470	463,470

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard errors clustered at the user level

C Non-linear Effects of Referral Policies on User Behavior

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 effect on their behavior. Table 16 shows regressions that test for the existence of non-linear effects of referral policy requirements on user behavior. In our setting, requiring an additional referral in order to gain basic membership leads to an increase in invitations (column (1)), registrations (column (2)), approvals (column (3)), and payment (column (4)), but only up to a point. In our specifications, the maximum benefit is attained when requiring between 2 and 3 referrals to access basic functionality. We do not observe a non-linear effect in the required number of referrals to get access to advanced functionality. This means that, at least in the studied region of this parameter, stricter policies always lead to more invitations, registrations, approvals and payments. Finally, we do not see non-linear effects of referral policies on user engagement as measured by the number of visits to the platform.

Table 16: (Non-linear) Effects of referral policies on user behavior

	Dependent variable:				
	Invitations	Registrations	Approvals	Payment	Visits
	(1)	(2)	(3)	(4)	(5)
# Referrals for Basic	0.044^{***}	0.038^{***}	0.026^{**}	0.057^{***}	-0.055^{***}
	(0.012)	(0.012)	(0.011)	(0.010)	(0.017)
# Referrals for Basic Sq.	-0.009^{**}	-0.009^{**}	-0.007^{*}	-0.011^{***}	0.0004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
# Referrals for Advanced	0.045^{***}	0.031^{**}	0.027^{**}	0.044^{***}	-0.038^{*}
	(0.013)	(0.013)	(0.014)	(0.012)	(0.022)
# Referrals for Advanced Sq.	−0.007	−0.003	−0.005	−0.007	0.005
	(0.006)	(0.006)	(0.007)	(0.006)	(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

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard Errors clustered at the user level

D Heterogeneous 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 policies' random assignment to assess potential heterogeneity in the effects of policy strictness 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 policy strictness with each of these controls.

Table 17 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 new users to the platform for advanced functionality has a larger effect on invitations, registrations, approvals, and payments for users older than 27.

Table 17: Heterogeneous effects: age

	Dependent variable:				
	Invitations	Registrations	Approvals	Payment	Visits
	(1)	(2)	(3)	(4)	(5)
# Referrals for Basic	0.019***	0.015***	0.009**	0.023***	−0.054***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.006)
# Referrals for Advanced	0.020***	0.016***	0.008**	0.015***	−0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Age > 27	−0.010	−0.012	−0.027**	0.089***	0.190***
	(0.011)	(0.012)	(0.011)	(0.013)	(0.021)
# Referrals for Basic * (Age > 27)	0.008	0.003	0.004	0.020***	−0.003
	(0.006)	(0.006)	(0.005)	(0.006)	(0.010)
# Referrals for Advanced * (Age > 27)	0.015***	0.010*	0.011**	0.026***	−0.008
	(0.005)	(0.005)	(0.005)	(0.006)	(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
Note:					*p<0.1; **p<0.05; ***p<0.01
					Fixed effects: Education, Gender, Tenure, Time
					Standard errors clustered at the user level

Table 18 shows the results of heterogeneous treatment effects across gender. We explicitly control for gender, and interact the referral policy 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 recruit new users to the platform for advanced functionality has an effect on women's engagement, but not on men's.

Table 18: Heterogeneous effects: gender

	Dependent variable:				
	Invitations	Registrations	Approvals	Payment	Visits
	(1)	(2)	(3)	(4)	(5)
# Referrals for Basic	0.015***	0.011**	0.010**	0.020***	−0.060***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.008)
# Referrals for Advanced	0.021***	0.018***	0.013***	0.017***	−0.011
	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)
Female	0.028***	0.011	0.018*	−0.054***	−0.151***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.020)
# Referrals for Basic * Female	0.007	0.004	−0.002	0.010*	0.010
	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)
# Referrals for Advanced * Female	0.006	0.002	−0.002	0.007	−0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(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
Note:					*p<0.1; **p<0.05; ***p<0.01
					Fixed effects: Education, Age, Tenure, Time
					Standard errors clustered at the user level

Table 19 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 to have a Master's degree of 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 new users to the platform has in general a higher effect for users with a Master's degree, especially in terms of invitations, approvals and payments.

Even though these results show some degree of heterogeneity across users, all the directions

Table 19: Heterogeneous effects: education

	Dependent variable:				
	Invitations	Registrations	Approvals	Payment	Visits
	(1)	(2)	(3)	(4)	(5)
# Referrals for Basic	0.003	0.001	-0.001	0.038^{***}	-0.056^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
# Referrals for Advanced	0.007	0.005	0.0001	0.010^{**}	-0.041^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)
Masters Degree	0.008	0.007	0.002	0.001	0.104^{***}
	(0.013)	(0.014)	(0.014)	(0.015)	(0.028)
# Referrals for Basic * Masters Degree	0.015^{**}	0.012^{*}	0.006	-0.0002	-0.018
	(0.007)	(0.007)	(0.007)	(0.008)	(0.013)
# Referrals for Advanced * Masters Degree	0.017^{**}	0.012^{*}	0.014^{**}	0.031^{***}	0.017
	(0.007)	(0.007)	(0.007)	(0.008)	(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

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Gender, Age, Tenure, Time
Standard errors clustered at the user level

remain the same as for the main results, meaning that there are no specific advantages in providing different treatments to users based on their demographics. If anything, men do not seem to have their engagement affected by policy strictness with respect to advanced functionality. The platform could use this information to increase policy strictness for men, leading to mode approvals and payments, and without hurting engagement.