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

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Many platforms offer incentives for inviting friends:

**Amazon Prime**
Get $5 when your friends join Prime
Tell your friends how much you love Prime. When they join and make a $5 purchase, we'll give you $5 towards your next Amazon purchase.

**Dropbox**
Earn more space by referring friends
You can earn extra space by inviting your friends to try out Dropbox.
- Basic accounts get 500 MB per referral and can earn up to 16 GB
- Pro accounts get 1 GB per referral and can earn up to 32 GB

**Uber Newsroom**
Earn FREE Uber with Your Own Personalized Referral Code!
Calling all Uberites! We've made it even easier to share the Uber love with your friends, interns, colleagues, and anyone you see on the street with your own personalized referral code. And the best part, you'll reap the rewards by earning free rides for every person that signs up and takes a ride!

**Evernote**
INVITE FRIENDS TO EVERNOTE
When they register, install, and sign in to Evernote, they'll get Premium. You'll also earn points to use for Premium.
... but others not so much

WhatsApp

Facebook

WeChat
Network Effects and Costs of Inviting

Referral programs are especially useful in contexts in which existing users are not compelled to spontaneously invite their friends:

- **No network effects** - users do not anticipate benefits from inviting their friends to the platform
- **High costs of inviting**
Referral programs are especially useful in contexts in which existing users are not compelled to spontaneously invite their friends:

- **No network effects** - users do not anticipate benefits from inviting their friends to the platform
- **High costs of inviting**

Platforms that exhibit **network effects** and **low costs of inviting** are less likely to request referrals as users have direct benefits from inviting their friends to the platform.
Most common types of referral programs are linear programs and threshold programs.

- Threshold referral programs are adequate for **freemium models**, when rewards correspond to free access to premium membership (which may be harder to split).

We set out to explore one dimension of threshold referral programs:

- **How many friends** to ask for in exchange for free access to premium features?
Research Questions

1. How does changing the **threshold** of the required number of referrals affect users’ decisions to invite their friends?

2. How does **engagement** change as a function of whether individuals have their friends in the network, and what are the mechanisms at play?

3. Are referrals on average **more valuable** than the average users?
Research Questions

1. How does changing the **threshold** of the required number of referrals affect users’ decisions to invite their friends?

2. How does **engagement** change as a function of whether individuals have their friends in the network, and what are the mechanisms at play?

3. Are referrals on average **more valuable** than the average users?

We leverage data from a **randomized field experiment** on referral programs that allows us to answer these questions.
Preview of the Results

Stricter referral policies are more effective at contributing both for platform growth and paid memberships.

Stricter policies lead to a decrease in engagement with the platform.

- Such decrease is driven by users that become paying members.
- Users may value having their friends in the platform, which leads to higher engagement when they do.

No change the type of users that get invited or their behavior in the platform.
Our Context

Exclusive online dating platform focused on providing its services in metropolitan areas around the world

- Members can sign up for the platform spontaneously or as a result of an invitation
- Each new member is manually approved by the platform
  - Ensures ‘high quality’ profiles (e.g., profile is connected to LinkedIn or Facebook; has a picture with a face)
Our Context
Our Context
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Basic Functionality
Our Context

Basic Functionality → Advanced Functionality

- Eye
- Mail
- Smile
- Heart

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Field Experiment

For its roll-out on a new city in 2015, the platform randomized how many new users each member is required to refer in order to access each type of functionality.

- Each of the 53,000 new members joining between late 2015 and early 2017 was randomly assigned one of two (or three) permission plans active in that specific week.

- We look at the first eight weeks of each user and look at their behavior in terms of visits to the site or mobile app, number of successful referrals and payments.
Empirical Strategy

Pooled OLS

\[ \text{Outcome}_{it} = \beta_1 \text{BasicReferrals}_i + \beta_2 \text{ExtraAdvReferrals}_i + \ldots + \varepsilon_{it} \]

Outcomes
- Referrals
- Revenue (Payment)
- Engagement (Visits)

Controls
- User tenure
- Gender
- Age fixed-effects (FE)
- Education FE
- Week FE
Results
### Main Results

**Dependent variable:** Referrals, Payment, Visits

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td># Referrals for Basic</td>
<td>0.009***</td>
<td>0.026***</td>
<td>−0.054***</td>
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**Observations:** 463,470 463,470 463,470  
**R²:** 0.025 0.020 0.079  
**Adjusted R²:** 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

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**Stricter policies lead to:**

- Increase in referrals
### Main Results

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**Stricter policies lead to:**

- Increase in referrals
- Increase in payment
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Stricter policies lead to:
- Increase in referrals
- Increase in payment
- Decrease in visits to the platform
How do referral policies affect consumer decisions?
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Stricter policies imply more paying users and more users lurking; but unclear effect on total registrations.
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Stricter policies imply **more paying users** and **more users lurking**; but unclear effect on total registrations
How referral policies affect engagement level?
Engagement as a function of consumer decisions

\[ Visits_{it} = \beta_0 + \beta_1 Payer_{it} + \beta_2 Lurker_{it} + \ldots + \varepsilon_{it} \]
**Engagement as a function of consumer decisions**

\[ \text{Visits}_{it} = \beta_0 + \beta_1 \text{Payer}_{it} + \beta_2 \text{Lurker}_{it} + \ldots + \varepsilon_{it} \]

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Observations 463,470

- Payers are more active than recruiters

*Note:*

* p < 0.1; ** p < 0.05; *** p < 0.01

Fixed effects: Education, Age, Gender, Tenure, Time

Standard errors clustered at the user level
Engagement as a function of consumer decisions

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- Payers are more active than recruiters
- Lurkers are less active than recruiters
How referral policies affect engagement level?

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Heterogeneous responses to policy changes

- Which individuals comply with the treatment?
How referral policies affect engagement level?

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Heterogeneous responses to policy changes

- Which individuals comply with the treatment?

IV approach

- Instrument pay and lurk conditions with the referral policy randomly assigned
- Regress engagement level on instrumented pay and lurk
### IV Results - Visits

**Dependent variable:** Visits Payer Lurker

<table>
<thead>
<tr>
<th></th>
<th>OLS (1)</th>
<th>2SLS (2)</th>
<th>1st Stage (3)</th>
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<td>−0.707***</td>
<td>−0.217</td>
<td>(0.025)</td>
<td>(0.202)</td>
</tr>
</tbody>
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- 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:**
- OLS: 463,470
- 2SLS: 463,470
- 1st Stage: 463,470
- 1st Stage: 463,470

**Note:**
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Fixed effects: Education, Age, Gender, Tenure, Time

Standard errors clustered at the user level

Users that move from **Recruiter** to **Payer** decrease their engagement when compared to those that stay as Recruiters.
### IV Results - Profile Views, Messages, Winks, Likes

This also applies to other activities: profile views, messages, winks, likes:

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Visits</th>
<th>Profiles Viewed</th>
<th>Profile Views</th>
<th>Messages Sent</th>
<th>Messages Received</th>
<th>Winks Sent</th>
<th>Winks Received</th>
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<td></td>
</tr>
<tr>
<td></td>
<td>−1.450***</td>
<td>−0.706***</td>
<td>−0.308**</td>
<td>−0.432***</td>
<td>−0.557***</td>
<td>−0.301*</td>
<td>−0.345**</td>
<td>−0.656***</td>
<td>−0.945***</td>
</tr>
<tr>
<td></td>
<td>(0.233)</td>
<td>(0.154)</td>
<td>(0.136)</td>
<td>(0.147)</td>
<td>(0.143)</td>
<td>(0.162)</td>
<td>(0.140)</td>
<td>(0.159)</td>
<td>(0.162)</td>
</tr>
<tr>
<td>Lurker</td>
<td>−0.217</td>
<td>−0.238*</td>
<td>−0.017</td>
<td>0.044</td>
<td>−0.035</td>
<td>−0.461***</td>
<td>0.226*</td>
<td>−0.127</td>
<td>−0.085</td>
</tr>
<tr>
<td></td>
<td>(0.202)</td>
<td>(0.139)</td>
<td>(0.130)</td>
<td>(0.155)</td>
<td>(0.146)</td>
<td>(0.158)</td>
<td>(0.133)</td>
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*Note:* *p<0.1; **p<0.05; ***p<0.01

Fixed effects: Education, Age, Gender, Tenure, Time

Standard errors clustered at the user level
Why do recruiters stay relatively more engaged?

Hypothesis: Users derive value from **having their friends on the platform**

**Strategy 1:**
- Check if users become more engaged after their referrals get approved (controlling for invitation effort)

**Strategy 2:**
- Focus on 10,000 users that got referred by existing members
- Regress engagement on whether referrer has dropped from the platform (4 weeks of inactivity)
Why do recruiters stay relatively more engaged?

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Results from both strategies consistent with our hypothesis
We study referral programs in **freemium platforms** that reward recruiters with access to premium features of the platform.

We leverage data from a randomized field experiment to empirically assess how user behavior changes with **referral policy strictness**.

Stricter referral policies can lead to **higher revenue** and to an **increase in growth**.

Stricter policies lead to a **decrease in engagement** with the platform.

- Users may value having their friends in the platform.

No change the **type of users that get invited** or their **behavior** in the platform.
Thank you

Rodrigo Belo
rbelo@rsm.nl
S1: Why do recruiters stay relatively more active

<table>
<thead>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2SLS (1)</td>
</tr>
<tr>
<td>Payer</td>
<td>−1.063***</td>
</tr>
<tr>
<td></td>
<td>(0.204)</td>
</tr>
<tr>
<td>Basic Access</td>
<td>0.064***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
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<tr>
<td>Advanced Access</td>
<td>0.769***</td>
</tr>
<tr>
<td></td>
<td>(0.206)</td>
</tr>
<tr>
<td>First Approved Referral</td>
<td>3.696**</td>
</tr>
<tr>
<td></td>
<td>(1.521)</td>
</tr>
<tr>
<td># Registrations</td>
<td>0.111***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
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<td>Observations</td>
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Fixed effects: Education, Age, Gender, Tenure, Time
Standard errors clustered at the user level

- Referrals approvals explain user engagement
### S2: Why do recruiters stay relatively more active?

**Dependent variable:**

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<th>Visits</th>
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<th>Messages Sent</th>
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<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
</tr>
<tr>
<td>Referrer Dropped</td>
<td>−0.130***</td>
<td>−0.021*</td>
<td>−0.067***</td>
<td>−0.035***</td>
<td>−0.049***</td>
<td>0.021</td>
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<td></td>
<td>(0.018)</td>
<td>(0.012)</td>
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<td>(0.009)</td>
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<tr>
<td># Referrals for Basic</td>
<td>−0.086***</td>
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<td>−0.042***</td>
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R² 0.138 0.114 0.282 0.051 0.063 0.061 0.262 0.070 0.444

Adjusted R² 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

- Having referrer drop leads to a decrease in activity levels
S2: Why do recruiters stay relatively more active?

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<td>(0.015)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.018)</td>
<td>(0.015)</td>
<td>(0.014)</td>
<td>(0.015)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th># Referrals for Advanced</th>
<th>Visits</th>
<th>Profiles Viewed</th>
<th>Profile Views</th>
<th>Messages Sent</th>
<th>Messages Received</th>
<th>Winks Sent</th>
<th>Winks Received</th>
<th>Likes Sent</th>
<th>Likes Received</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.065</td>
<td>-0.034**</td>
<td>-0.023</td>
<td>-0.035***</td>
<td>-0.044***</td>
<td>-0.037*</td>
<td>-0.012</td>
<td>-0.037***</td>
<td>-0.040***</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.023)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.015)</td>
</tr>
</tbody>
</table>

Observations: 53,565
R²: 0.138
Adjusted R²: 0.125

**Note:**
* p<0.1; ** p<0.05; *** p<0.01

Fixed effects: Education, Age, Gender, Tenure, Time
Standard errors clustered at the user level

- Having referrer drop leads to a decrease in activity levels
Reduced level of activity could have been originated by payers that leave the platform because they find a match and stop using the platform.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Payer</td>
<td>-0.996</td>
<td>-0.881</td>
<td>-0.829</td>
<td>-0.792</td>
</tr>
<tr>
<td>Lurker</td>
<td>-0.440</td>
<td>-0.199</td>
<td>-0.195</td>
<td>-0.191</td>
</tr>
</tbody>
</table>

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
IV Results - Matches

Reduced level of activity could have been originated by payers that leave the platform because they find a match and stop using the platform

- We assess whether payers get more matches in the platform as measured by mutual likes and exchanged messages

<table>
<thead>
<tr>
<th></th>
<th>Dependent variable:</th>
<th>Mut. Like 3</th>
<th>Messages 5</th>
<th>Messages 7</th>
<th>Messages 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Payer</td>
<td></td>
<td>-0.996**</td>
<td>-0.881**</td>
<td>-0.829**</td>
<td>-0.792**</td>
</tr>
<tr>
<td>Lurker</td>
<td></td>
<td>-0.440**</td>
<td>-0.199</td>
<td>-0.195</td>
<td>-0.191</td>
</tr>
</tbody>
</table>

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
Reduced level of activity could have been originated by payers that leave the platform because they find a match and stop using the platform

We assess whether payers get more matches in the platform as measured by mutual likes and exchanged messages

<table>
<thead>
<tr>
<th></th>
<th>Mut. Like</th>
<th>3 Messages</th>
<th>5 Messages</th>
<th>7 Messages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Payer</td>
<td>−0.996***</td>
<td>−0.881***</td>
<td>−0.829***</td>
<td>−0.792***</td>
</tr>
<tr>
<td></td>
<td>(0.185)</td>
<td>(0.167)</td>
<td>(0.165)</td>
<td>(0.163)</td>
</tr>
<tr>
<td>Lurker</td>
<td>−0.440***</td>
<td>−0.199</td>
<td>−0.195</td>
<td>−0.191</td>
</tr>
<tr>
<td></td>
<td>(0.160)</td>
<td>(0.171)</td>
<td>(0.167)</td>
<td>(0.162)</td>
</tr>
<tr>
<td>Observations</td>
<td>463,470</td>
<td>463,470</td>
<td>463,470</td>
<td>463,470</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
Fixed effects: Education, Age, Gender, Tenure, Time
Standard errors clustered at the user level
## Non-linear Effects of Referral Policies on User Behavior

### Dependent variable:

<table>
<thead>
<tr>
<th></th>
<th>Invitations (1)</th>
<th>Registrations (2)</th>
<th>Approvals (3)</th>
<th>Payment (4)</th>
<th>Visits (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td># Referrals for Basic</td>
<td>0.044***</td>
<td>0.038***</td>
<td>0.026**</td>
<td>0.057***</td>
<td>−0.055***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.017)</td>
</tr>
<tr>
<td># Referrals for Basic Sq.</td>
<td>−0.009**</td>
<td>−0.009**</td>
<td>−0.007*</td>
<td>−0.011***</td>
<td>0.0004</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td># Referrals for Advanced</td>
<td>0.045***</td>
<td>0.031**</td>
<td>0.027**</td>
<td>0.044***</td>
<td>−0.038*</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.012)</td>
<td>(0.022)</td>
</tr>
<tr>
<td># Referrals for Advanced Sq.</td>
<td>−0.007</td>
<td>−0.003</td>
<td>−0.005</td>
<td>−0.007</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.010)</td>
</tr>
</tbody>
</table>

| Observations          | 463,470         | 463,470           | 463,470       | 463,470     | 463,470    |
| R²                    | 0.077           | 0.048             | 0.025         | 0.021       | 0.079      |
| Adjusted R²           | 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
Activity by gender

- Profiles Viewed
- Profile Views
- Messages Sent
- Messages Received
- Winks Sent
- Winks Received
- Likes Sent
- Likes Received

Graphs showing activity by gender over tenure (weeks) with counts for each category.