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

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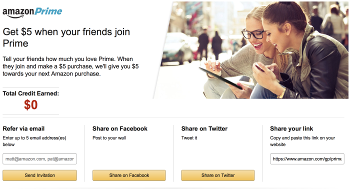
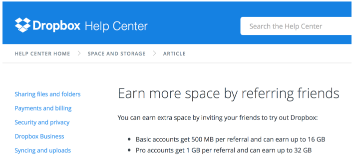
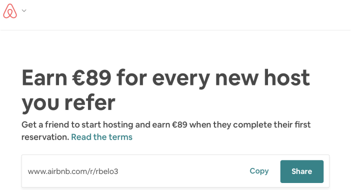
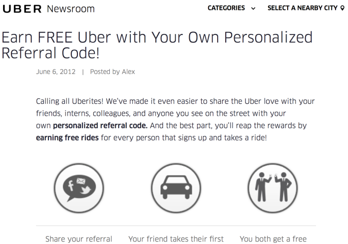
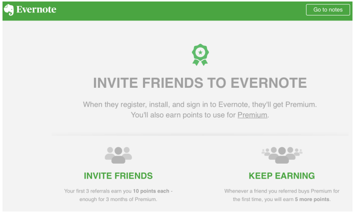
Many platforms offer incentives for inviting friends









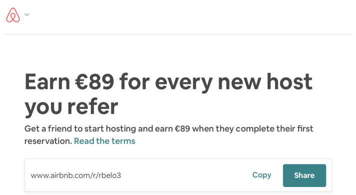


. . . but others not so much

Network Effects and Costs of Inviting

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

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



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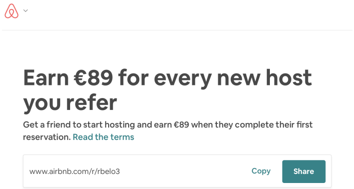
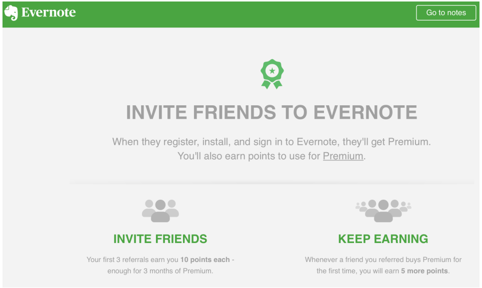


Platforms that exhibit **network effects** and **low costs of inviting** are less likely to request referrals as users have direct benefits from inviting their friends to the platform

Referral Programs in Freemium Models

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 what are the mechanisms at play?
3. Are referrals on average **more valuable** than the average users?

Research Questions

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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

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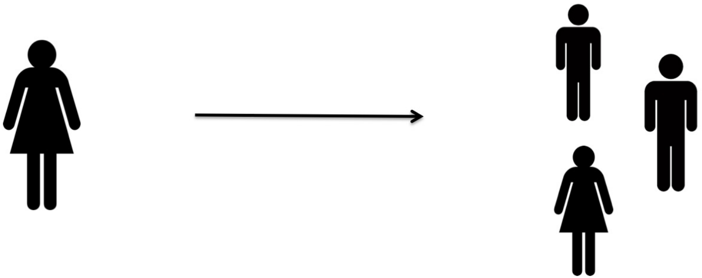

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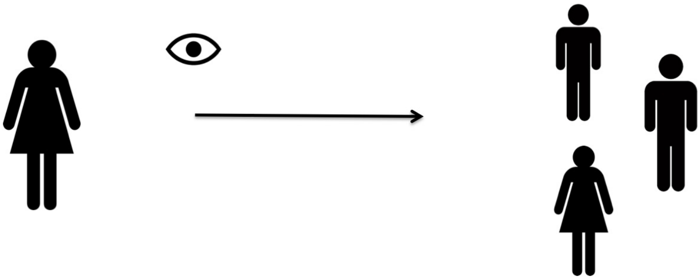

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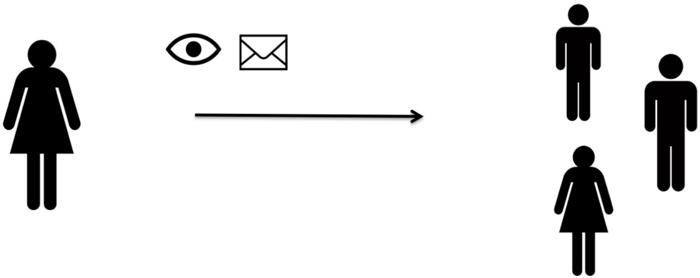

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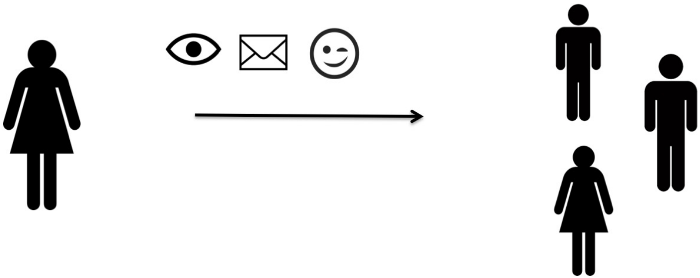

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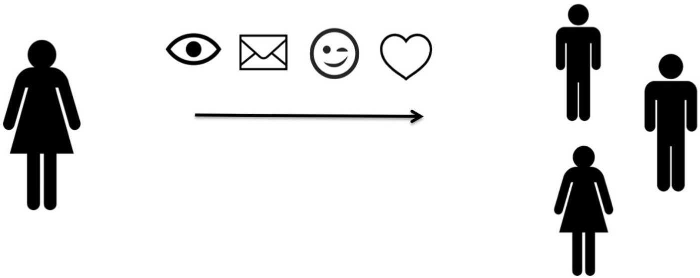

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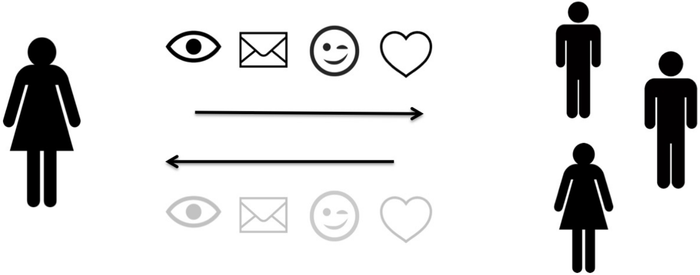

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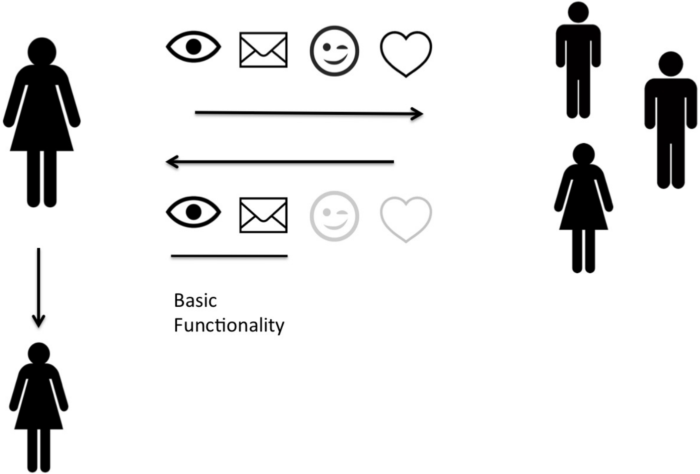

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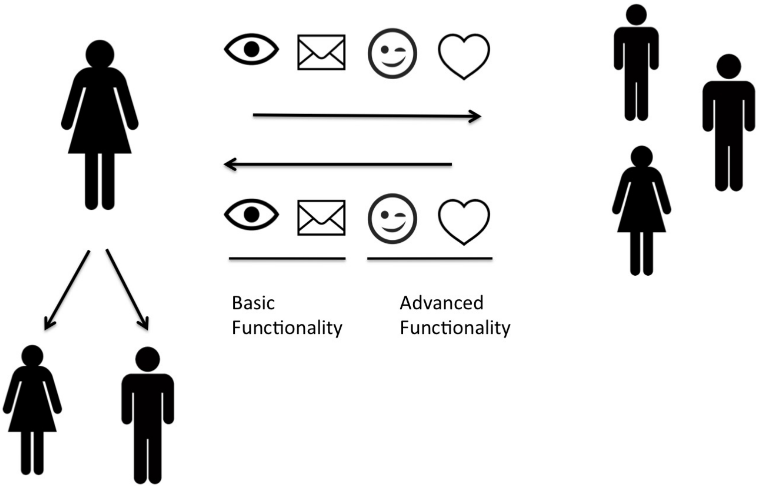

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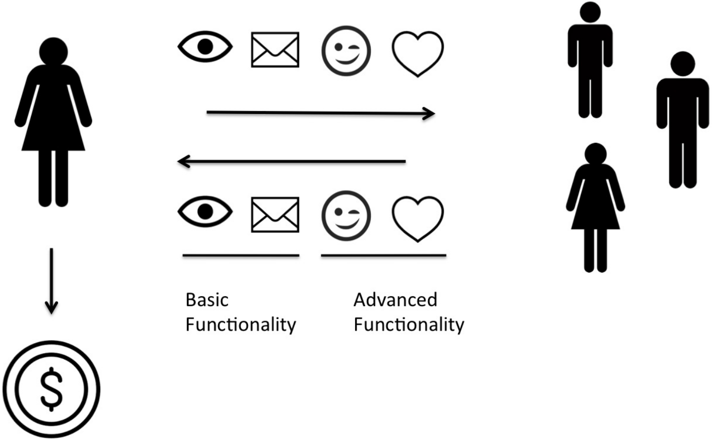

Field Experiment

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

$$Outcome_{it} = \beta_1 BasicReferrals_i + \beta_2 ExtraAdvReferrals_i + \ldots + \varepsilon_{it}$$

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
	(1)	(2)	(3)
# Referrals for Basic	0.009^{***}	0.026^{***}	-0.054^{***}
	(0.003)	(0.003)	(0.005)
# Referrals for Advanced	0.012^{***}	0.022^{***}	-0.029^{***}
	(0.003)	(0.003)	(0.005)
Observations	463,470	463,470	463,470
R^2	0.025	0.020	0.079
Adjusted R^2	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

Stricter policies lead to:

- Increase in referrals

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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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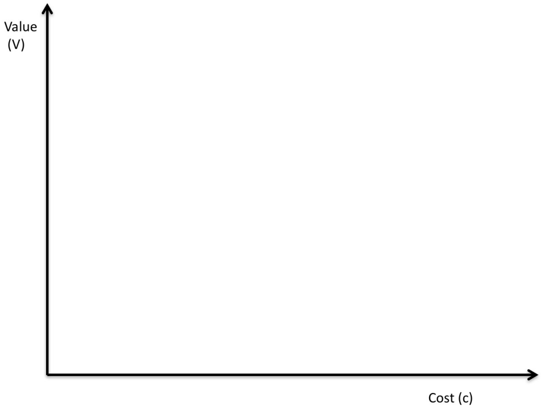

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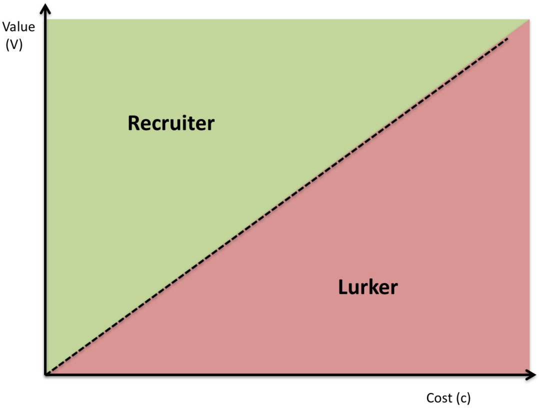

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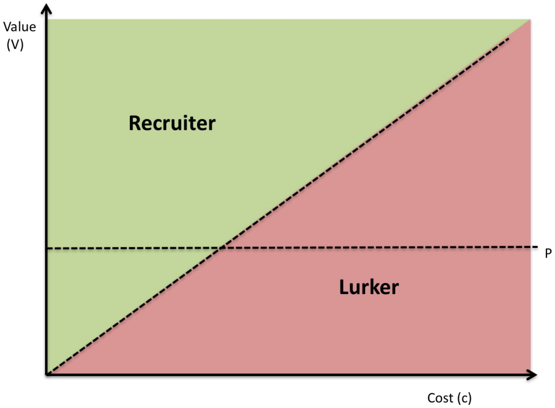

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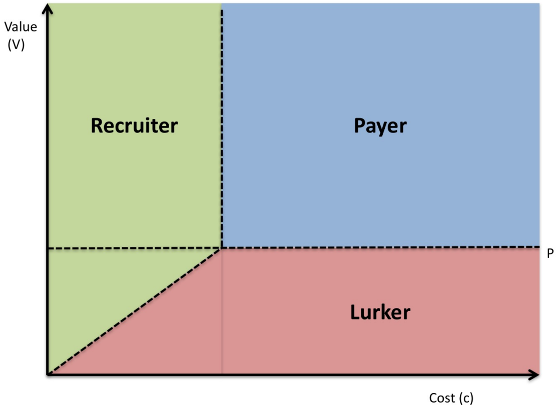

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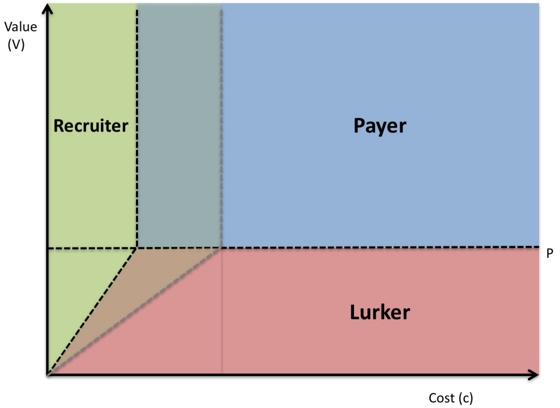

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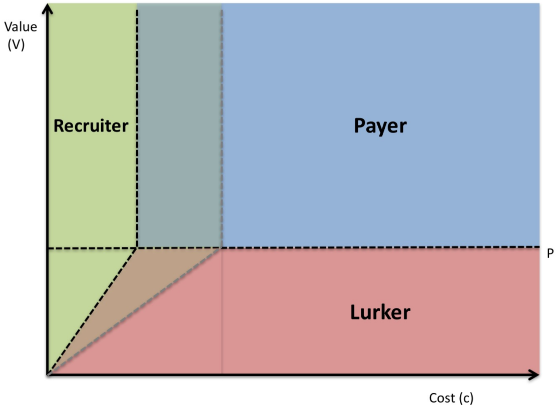

Stricter policies imply **more paying users** and **more users lurking**; but unclear effect on total registrations

How referral policies affect engagement level?

Engagement as a function of consumer decisions

$$Visits_{it} = \beta_0 + \beta_1 Payer_{it} + \beta_2 Lurker_{it} + ... + \varepsilon_{it}$$

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Payer	0.167^{***}
	(0.029)
Lurker	-0.707^{***}
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Observations	463,470
Note:	*p<0.1; **p<0.05; ***p<0.01
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- Payers are more active than recruiters

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- Payers are more active than recruiters
- Lurkers are less active than recruiters

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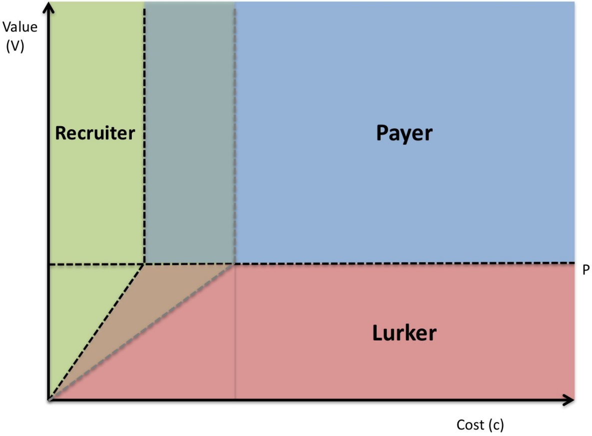

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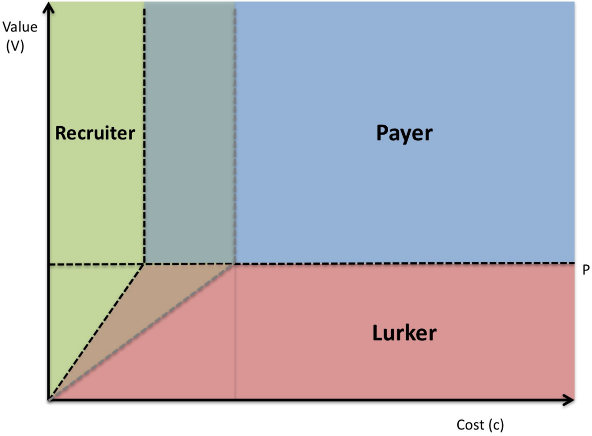

Heterogeneous responses to policy changes

- Which individuals comply with the treatment?

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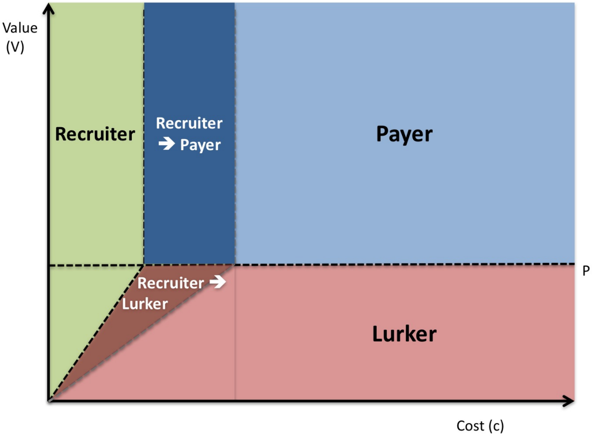

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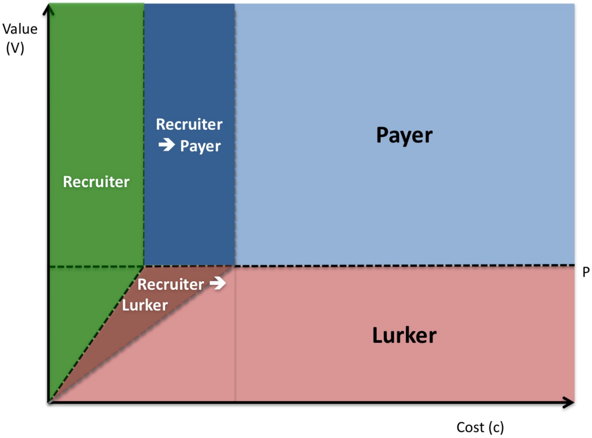

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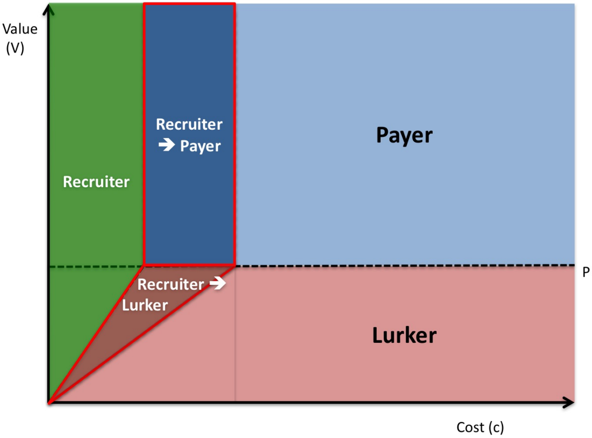

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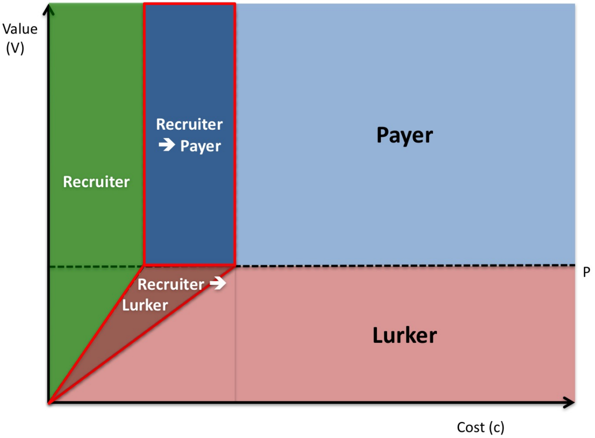

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IV approach

- 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
	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

- 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:

	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: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
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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)

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Results from both strategies consistent with our hypothesis

Summary

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

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Extras

S1: Why do recruiters stay relatively more active

	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

- Referrals approvals explain user engagement

S2: Why do recruiters stay relatively more active?

	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

- Having referrer drop leads to a decrease in activity levels

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	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

- Having referrer drop leads to a decrease in activity levels

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

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

	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

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

Activity by gender