Prizing Innovation: Do Competition Grants Help Start-ups Succeed?

Geoffrey Barrows*

October 1, 2016

Preliminary and Incomplete. Please do not cite.

Abstract

Many organizations around the world hope to catalyze innovation from start-ups through grant funding, but if capital markets are working properly, such policies merely crowd out private investment (at best) or extend funding to businesses with little chance of succeeding (at worst). In this paper, we present evidence from the first large-scale, quasi-experimental study of whether grant funding increases start-up business innovation for early stage firms. We employ a regression discontinuity design to test whether winners of start-up business plan competitions perform better ex-post than losers, where the threshold rank for winning the competition provides exogenous variation in access to start-up funding. With 460 competitions across 113 countries and over 20,000 competing firms, we find that the causal impact of winning a business plan competition is approximately to double the chance of business survival, and more than double some web-based metrics of success. We also find that impacts are strongest for firms in the clean technology sector, firms from countries with high costs of business formation, and firms competing for mid-size prizes. These results suggest that capital market frictions indeed prohibit start-up innovation in precisely the areas we would expect them to.

Keywords: Start-ups, Credit Constraints, Grants
JEL codes: G24, L26, M13, O16

*CNRS – École Polytechnique.

1 Introduction

Governments, NGOs, and private organizations all over the world advocate policies to help start-up businesses succeed.[1] A popular strategy is to offer cheap (or free) capital for promising entrepreneurial ideas; but, many argue that such policies fail to promote growth because they crowd out private investment (at best), or extend funding to businesses with little chance of succeeding (at worst). The extent to which alternative finance programs such as grants, angel investors, crowd sourcing platforms, etc. increase start-up success depends on the efficiency of pre-existing credit markets, but estimating causal impacts is challenging because (1) control firms who might have received funding but did not are usually unobserved, and (2) funding is usually endogenous to firm quality. In this paper, we exploit a large-scale quasi-natural experiment that allows us to overcome these empirical challenges and offer the first empirical evidence of how alternative financing (i.e., financing from outside the private credit market) causally impacts early-stage start-up firms – and hence, innovation.

The quasi-natural experiment we study in the paper owes to hundreds of business plan competitions held in various parts of the world in recent years. Competitions offer cash prizes to winners, usually in the form of grants, for the stated purpose of incentivizing innovation. Competition entrants are judged and ranked according to quality, and winners are determined based on relative rank. Thus, for each competition, some pre-specified number of firms with rank less than x (where x may vary by competition) receive funding as a result of the competition, and the rest do not. This competition structure delivers exogenous variation in access to funding between similar firms – those on either side of the threshold rank – with which the causal impact of alternative financing on start-up success can be estimated.

Critically for the analysis, the dataset includes firms from many different countries and industries all over the world competing for start-up funding. As a result, we are able to test for not only *whether* competition grants improve start-up outcomes, but *where* start-ups benefit most and in what industries. Heterogeneous impacts speak to the efficiency of markets for early-stage funding in different places in the world. If credit markets are segmented, we would expect impacts to be highest where firms have less access to traditional financing vehicles – i.e. the developing world. Additionally, standard theory would predict that firms operating in industries where start-up capital is particularly constrained would see the largest impacts from alternative financial sources. With significant coverage across

[1] See Kerr et al. (2014) for a review of research on entrepreneurship

regions and industries, we are able to test for this pattern of heterogeneity.

The dataset for this paper was built in collaboration with the San Francisco-based Internet firm YouNoodle, Inc., which organizes and judges competitions for many donor organizations. Applicants submit business plans (and/or other requested materials) and are then judged by industry experts. A weighted average of judge scores delivers a ranked ordering of firms in each competition from which donor organizations select "winners." Donors are not bound to follow the YouNoodle (henceforth "YN") ranking explicitly, but the YN rankings have strong predictive power over how firms place in the competition. While YN did not previously keep records on which firms won each competition, we were able to identify competition winners from donor publicity materials. After determining competition winners and losers, we then collected several "success" metrics for firms around the critical thresholds, including subjective evaluations of firm websites and general web presence, and objective metrics such as unique web visitors, follow-on financing, facebook likes, employee count, etc from the data analytics firm Mattarmark.

All together, we analyze data from over 20,000 start-up firms from more than 100 countries competing in 460 competitions between 2010 and 2015. In the first stage, we find that receiving a rank just to the left of the threshold (being ranked just high enough to beat the competition-specific cutoff for winning) generates a discontinuous jump in probability of winning the competition by about 20 percentage points, on a base level of 20 percent – or roughly double the chance of winning the competition. Furthermore, placing left of the threshold increases the probability of firm survival by 19.3%, web score by 19.2%, and overall web presence by 23.0%. While we lack sufficient coverage in the Mattarmark dataset to deliver precise RD estimates in terms of objective metrics, we find that these metrics are approximately linearly increasing in both subjective metrics, and that the point estimates are highly statistically significant. Based on this result, we project the RD estimates from the subjective measures onto the objective metrics and calculate that winning a competition generates 86% follow-on funding, 120% more facebook likes, and 214% more unique web visitors (in addition to other impacts).

In terms of heterogeneity, we find that the overall impact is driven by mid-size competitions, NGO donors, firms in the clean technology industry, and firms in less-developed countries. These heterogeneous impacts are consistent with expectations, since firms operating in markets with greater financial imperfections see greatest impact. Additionally, since impacts are driven by mid-size prizes, it appears that mere signaling can not explain the effects. I.e., it seems the actually funds received as a result of winning the competition

matter for the effects.

This paper contributes to a small group of papers that similarly estimate returns to alternative financial vehicles. Early work by Kortum & Lerner (2000) and Lelarge et al. (2010) estimates the impact of venture capital and government grants, respectively, on firm success. Lerner et al. (2015) estimate by RD the returns to angel investing across different markets, finding that in general angel investments increase the probability of firm survival and the quantity of future funding received by the firms. However, Lerner et al. (2015) fail to reject a null of no difference in impact depending on relative robustness of financial markets. Gonzalez-Uribe & Leatherbee (2015) also estimate by RD the return to business competition grants for 7 competitions held by the government of Chile. In fact, Gonzalez-Uribe & Leatherbee (2015) also use YN data to define treatment and controls. But with only 7 competitions, Gonzalez-Uribe & Leatherbee (2015) are severely underpowered. By contrast, in our dataset, there are 460 competitions, which yields enough power to precisely estimate heterogeneous effects. Finally, Howell (2016) studies US government grants for clean technology innovation and finds that government grants increase future venture capital funding. Relative to Howell (2016), we investigate more sectors of the economy and more countries, which allows us to test whether the impacts found by Howell (2016) extend to other contexts. Furthermore, none of the existing literature examines very early stage firms. For example, in Lerner et al. (2015) and Howell (2016) the average age of firms are 8 and 9 years respectively, where as firms in our dataset are often not even a year old. Thus, ours is the first paper in this literature – or any literature, to our knowledge – that studies firms at this crucial early stage.

In what follows, Section 2 presents the unique database constructed in collaboration with YN and the identification strategy. Section 3 presents results. Section 4 presents robustness. And section 5 concludes.

2 Data

The data for this paper come from 387 "super competitions" adjudicated by YN between 2010 and 2015, where a "super competition" may comprise multiple mutually exclusive simultaneous competitions. All firms that enter the same super competition submit requested materials (usually a business plan) to YN, and are subsequently judged by multiple experts along pre-determined dimensions (e.g., strength of team, market potential, etc.). YN aggregates individual judge scores using a pre-determined weighting rule so each firm

Table 1: Super Competitions and Entrants by Year

	# Super Competitions	# Entrants	Entrants/Application Group		
			Mean	Min	Max
	(1)	(2)	(3)	(4)	(5)
2010	16	1206	75.38	1	199
2011	53	3569	67.34	2	259
2012	69	5237	75.90	2	558
2013	105	6445	61.38	3	209
2014	135	9572	70.90	3	260
2015	9	827	91.89	1	212
All Years	387	26856	69.40	1	558

Notes: "super competition" may comprise multiple simultaneous competitions

is assigned a single raw score from which a complete ordered ranking can be computed for each super competition. The number of super competitions and entrants are reported by year in Table 1. The bulk of the competitions were held between 2012-2014, with 26,854 firms in total entrants over the period.

The YN judge data establish the rankings of start-up firms within super competitions, but they do not identify the winners of the competitions nor the cutoff rank thresholds. Also, in many cases, a super competition contains multiple individuated competitions. For example, a given super competition may include a "clean energy track" and a "social enterprise" track, with firms actually competing in only one of the tracks, though they were all judged by the same YN procedures. We assume that firms do not compete with each other across tracks, and thus we break apart these super competitions into individual competitions to have like-for-like comparisons. The procedure for individuating competitions, identifying winners and thresholds is described in Appendix A.

After individuation competitions and computing thresholds, we have a total of 460 competitions with 20,828 entrants.[2] The distribution of competitions and entrants by threshold rank is reported in Table 2. Thresholds range from 1 to 150, but the bulk of the competitions have threshold ranks in the single digits. In fact, 80% of competitions have thresholds under 10.

To measure firm success, we use two types of outcome variables. First, we collected "subjective" metrics that include:

- alive {0,1} – an indicator for whether we could find a working website for the firm

[2]Several super competitions were dropped because we could not find a list of winners

- web score (0-5) – a subjective evaluation of the quality of a firm's internet home page
- general score (0-5) – a subjective evaluation of the firm's overall web presence

We call these variables "subjective" because in each case, a subjective evaluation was rendered by a researcher with respect to each variables. We adhered to some general guidelines for scoring web sites and web presence (described in Appendix A), but of course, there could be differences in how the guidelines were applied. To minimize measurement bias, all firms within the same competition were scored by the same researcher. Hence, any level differences in scoring tendencies between researchers will be absorbed by the competition fixed effect.

Second, we collected "objective" metrics from the data analytics company Mattarmark, Inc. for all the firms that we could match in their database (about 1/3rd of the firms we looked for). Mattarmark variables include:

- Employee count
- Unique web visits
- Facebook likes
- Funding
- Twitter followers
- LinkedIn connections

Both subjective and objective measures are snap shots in time taken between June 2015 - April 2016. Subjective metrics give a general picture of the overall progress of the start-up. Objective metrics are clearly more specific, and presumably reflect less measurement error. However, we have much broader coverage with the subjective metrics, which we will see allows for much more precise estimation of impacts.

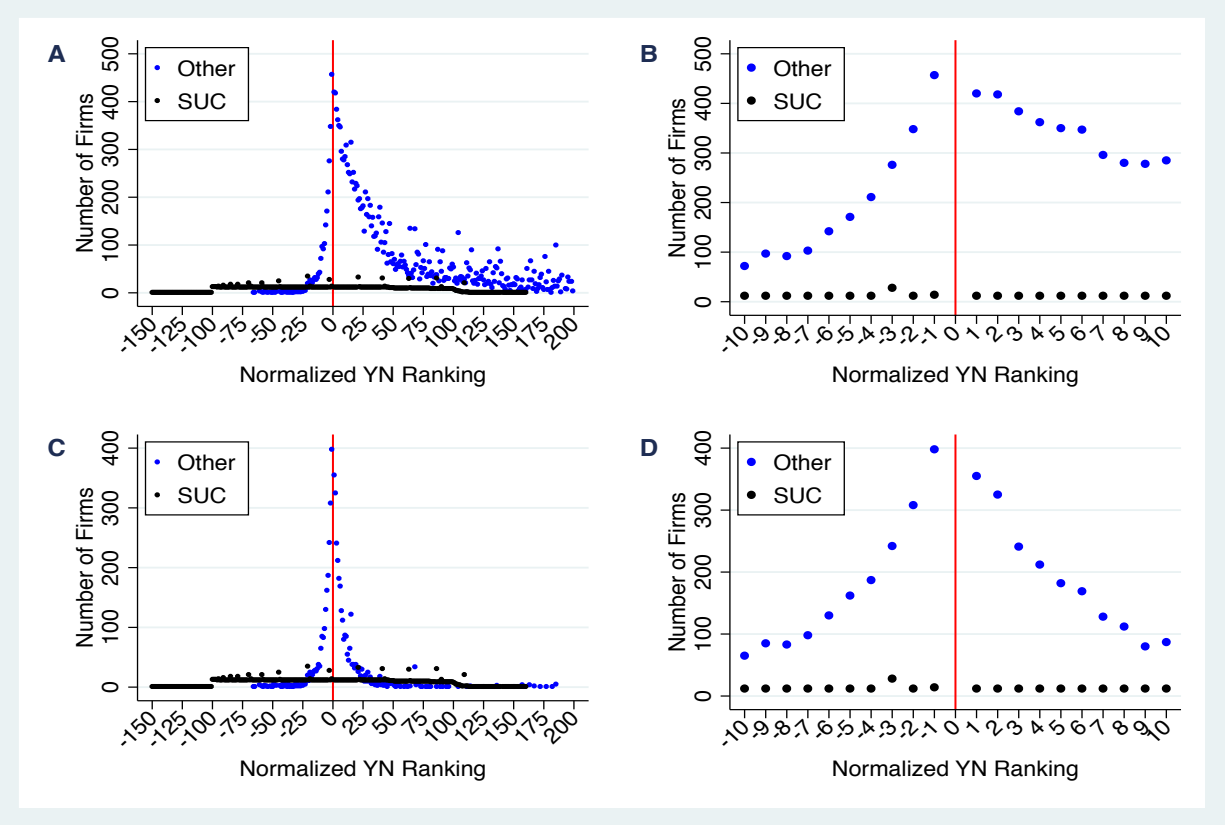
We refer to both the subjective and objective metrics of firm success as "outcome" data. While in principle we could collect outcome data for all competition entrants (at least for subjective metrics), we concentrated research efforts on collecting data for firms around the threshold, since only firms within a certain bandwidth around the threshold will be used in the RD estimation anyway. Thus, we only collected outcome data for 7,883 firms. The distribution of these firms with outcome data by thresholds and competitions can be

Table 2: Competitions and Entrants by Threshold

	Competitions		# Entrants (All)				# Entrants (w/ Outcome Data)			
Threshold	Number	Cumulative	Count	Mean	Min	Max	Count	Mean	Min	Max
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	57	0.124	1226	21.5	2	201	212	3.7	2	29
2	98	0.337	1652	16.9	3	200	509	5.2	3	29
3	81	0.513	2415	29.8	5	193	628	7.8	3	18
4	23	0.563	1199	52.1	6	202	201	8.7	5	14
5	38	0.646	1466	38.6	6	194	412	10.8	5	20
6	27	0.704	1426	52.8	8	150	325	12.0	7	20
7	15	0.737	829	55.3	12	204	187	12.5	7	20
8	16	0.772	575	35.9	12	64	240	15.0	12	18
9	13	0.800	646	49.7	21	200	233	17.9	14	21
10	23	0.850	1878	81.7	15	217	424	18.4	15	25
11	6	0.863	387	64.5	19	199	108	18.0	16	20
12	10	0.885	725	72.5	25	198	257	25.7	23	37
13	3	0.891	141	47.0	37	61	64	21.3	13	33
14	3	0.898	307	102.3	19	209	57	19.0	18	20
15	2	0.902	237	118.5	107	130	65	32.5	32	33
16	6	0.915	547	91.2	30	206	170	28.3	22	32
17	2	0.920	186	93.0	31	155	59	29.5	29	30
18	3	0.926	333	111.0	63	200	89	29.7	26	33
19	2	0.930	212	106.0	99	113	82	41.0	38	44
20	4	0.939	299	74.8	66	85	153	38.3	37	40
21	3	0.946	131	43.7	37	51	100	33.3	28	41
23	2	0.950	307	153.5	108	199	98	49.0	45	53
24	2	0.954	165	82.5	53	112	93	46.5	40	53
25	1	0.957	200	200.0	200	200	47	47.0	47	47
26	1	0.959	29	29.0	29	29	29	29.0	29	29
28	1	0.961	199	199.0	199	199	45	45.0	45	45
29	1	0.963	56	56.0	56	56	56	56.0	56	56
40	1	0.965	162	162.0	162	162	70	70.0	70	70
51	1	0.967	78	78.0	78	78	78	78.0	78	78
58	1	0.970	92	92.0	92	92	90	90.0	90	90
66	1	0.972	99	99.0	99	99	80	80.0	80	80
100	12	0.998	2424	202.0	146	261	2422	201.8	146	260
150	1	1.000	200	200.0	200	200	200	200.0	200	200
Total	460	1.000	20828	45.3	2	261	7883	17.1	2	260

Notes: The threshold reported in column 1 corresponds to the number of firms that advance in the competition as a result of YN judging. Columns 4-7 report descriptive statistics for all entrants, while columns 8-11 restricts to observations with non-missing outcome data.

Figure 1: Distribution of Firms by Normalized YN Rank



Notes: Top row (panels A and B) presents data from all competition entrants (20,594 entrants across 460 competitions), while bottom row (panels C and D) restricts to observations with outcome data (7,649 entrants across 460 competitions). Panels A and C include the entire range of the running variable, while panels B and D restrict to bandwidths of 10 ranks on either side of the cutoff. Blue dots indicate competitions other than Start-up Chile (447) while black dots indicate Start-up Chile (13)

seen in columns 8 - 11 of Table 2. Overall, we have a little over 17 firms per competition with outcome data.

Figure 1 presents the distribution of firms by normalized YN rank, where the threshold rank has been normalized to 0 for each competition. A firm with normalized YN rank of -1 (i.e., left of the threshold) just barely beat the threshold, while a firm with normalize rank of 1 just barely missed the threshold. Subfigures A and B present the distribution of all 20,594 entrants from the 460 competitions in Table 2, while subfigures C and D present only firms with both ranking and outcome data (7,649).[3] Subfigures A and C present the distributions for the entire range, while subfigures B and D present only firms within a bandwidth of 10 ranks of the threshold. We see in subfigure C that most of the mass with outcome data is clustered around the threshold, and in subfgure D that the distribution is fairly smooth across the threshold.

Descriptive statistics by winners and losers of the competitions are presented in Table 3. Competition ranks are described above. "Competition outcomes" refers to how the firm placed in the competition. Winning vs losing is a binary variable, but we also know final competition place (e.g., 1st, 2nd, 3rd, etc) as well as the dollar value of the prize won. "Normalized competition Place" enumerates competition place normalized to the winning threshold.[4] The average prize awarded is $25,370 USD with the highest prize being $1,000,000 USD.

Firm outcomes and Mattarmark outcomes are described above. Column 11 tests for equality of means between winners and losers. We see that winners have a live website 61.7% of the time, while losers only have live websites 46.6% of the time. This difference is statistically significant at the 1% level. In addition, winners have higher web scores and general scores, both statistically significant. Looking at the Mattarmark data, we find much lower coverage in terms of non-missing data. Here, with the smaller dataset, the difference between winners and losers is not statistically significant.

Finally, in addition to ranking data and outcome data, we also collected data on firm location, industry, and product type. We present aggregate groupings in Table 3 for ease of viewing, but in fact we assign firms to one of 113 countries, 21 industries, and 17 product types. In Table 3, we can see that the distribution of firms is skewed towards North America, South America and Europe.

As described above, we have two sets of outcome metrics, both of which are meant to

[3]The total number of entrants drops from 20,828 to 20,594 and scored firms from 7,883 to 7,649 because 234 firms have outcome data but no ranking data

[4]This threshold is different from the YN threshold.

Table 3: Firm-level Descriptive Statistics

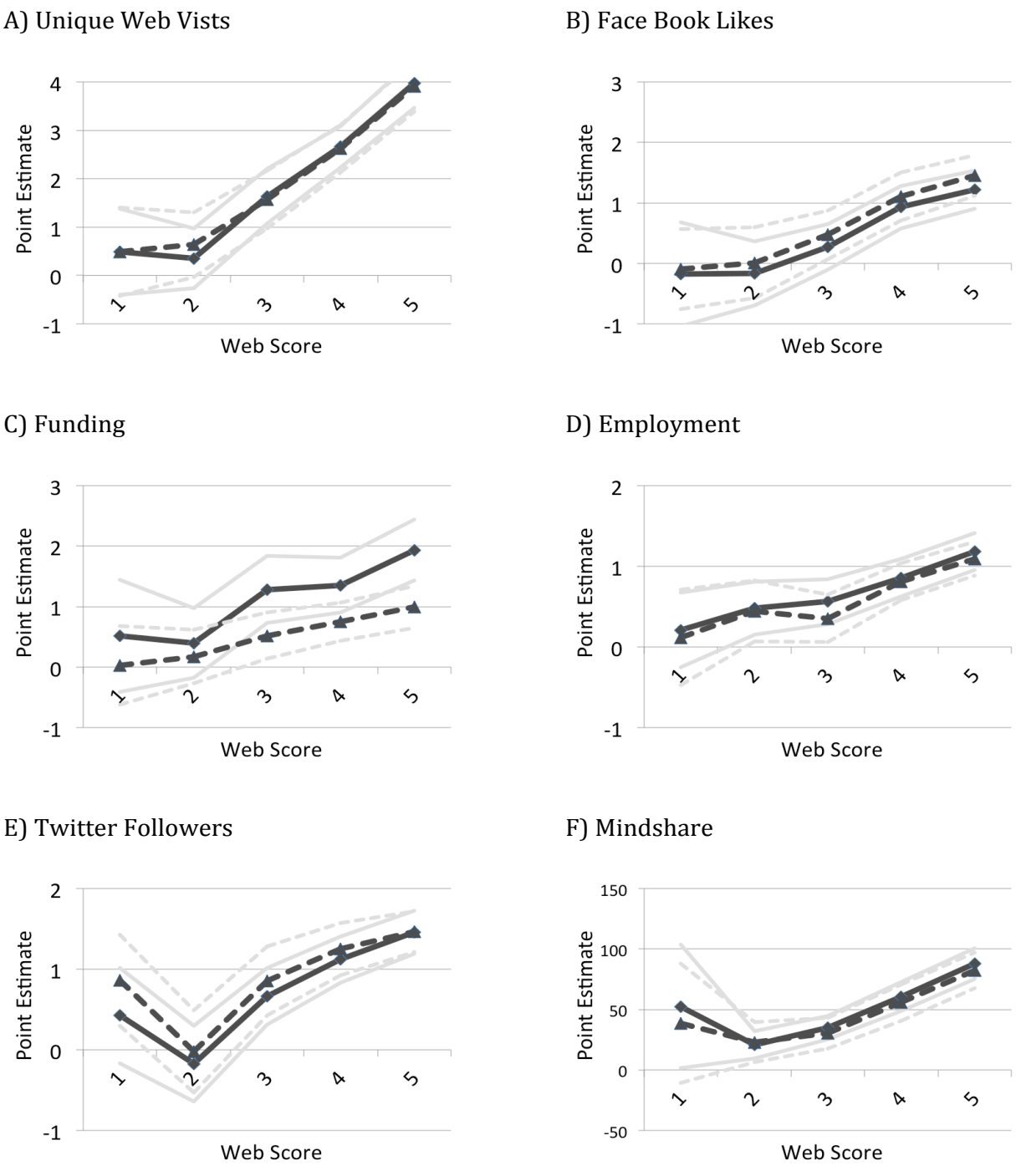
	Winners					Losers					Diff
	Mean (1)	Sd (2)	Min (3)	Max (4)	Obs (5)	Mean (6)	Sd (7)	Min (8)	Max (9)	Obs (10)	(11)
Comp Ranks											
Raw YN Rank	43.88	51.30	1	396	2720	52.85	60.61	1	464	4931	***
Norm YN Rank	-15.65	43.26	-150	185	2720	12.23	34.08	-129	185	4931	***
Comp Outcomes											
Norm Comp Place	1.124	0.420	1	3	2870	-1.342	0.580	-3	-1	5013	***
Value (Ths USD)	25.37	45.38	0	1000	2870						
Cat Prize (0,1)	0.021	0.143	0	1	2870	0.018	0.132	0	1	5013	
Val CP	10.93	7.29	0.500	30	35	5.59	6.20	0.100	30	51	***
Firm Outcomes											
Alive (0,1)	0.617	0.486	0	1	2870	0.466	0.499	0	1	5013	***
Web	3.741	1.164	1	5	1771	3.649	1.189	1	5	2335	**
General	2.378	1.930	0	5	2870	1.808	1.911	0	5	5013	***
Mattarmark											
Mmark (0,1)	0.442	0.497	0	1	2870	0.281	0.449	0	1	5013	***
Employees	12.72	27.4	1	345	526	16.25	40.29	1	611	697	*
Uniques (Ths)	33.02	194.5	0.001	3241	856	39.13	163.0	0.001	2235	1061	
FB Likes (Ths)	9.404	34.95	0.001	590.1	678	13.31	66.40	0.002	1271	923	
Funding (mil)	2.616	14.41	0.011	204.3	366	4.391	13.06	0.005	149.5	318	*
Twitter (Ths)	2.671	12.95	0.001	249.7	771	3.127	20.58	0.001	411.1	1032	
Mindshare	48.25	96.98	-314.0	758.0	894	56.40	111.0	-336	970	1156	*
Linked-in (Ths)	0.156	0.554	0.001	10.46	568	0.210	0.680	0.001	13.35	760	
Firm Location											
NAmerica	0.346	0.476	0	1	2870	0.360	0.480	0	1	5013	
SAmerica	0.285	0.452	0	1	2870	0.241	0.428	0	1	5013	***
Europe	0.238	0.426	0	1	2870	0.242	0.428	0	1	5013	
Asia	0.099	0.299	0	1	2870	0.106	0.308	0	1	5013	
Africa	0.025	0.155	0	1	2870	0.028	0.164	0	1	5013	
Unknown	0.008	0.089	0	1	2870	0.023	0.151	0	1	5013	***
Industry											
Clean Tech	0.106	0.308	0	1	2870	0.106	0.308	0	1	5013	
Services	0.309	0.462	0	1	2870	0.297	0.457	0	1	5013	
Products	0.188	0.391	0	1	2870	0.203	0.403	0	1	5013	*
Web	0.194	0.395	0	1	2870	0.176	0.381	0	1	5013	**
Life Sciences	0.125	0.330	0	1	2870	0.115	0.320	0	1	5013	
Product Type											
Services	0.252	0.434	0	1	2870	0.248	0.432	0	1	5013	
Products	0.240	0.427	0	1	2870	0.232	0.422	0	1	5013	
Software/Apps	0.410	0.492	0	1	2870	0.354	0.478	0	1	5013	***

Notes: Column 11 tests for equality of means between winners and losers. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

proxy for firm success. Lacking profit data, we cannot know for sure how well these proxies track the bottom line. However, we can use the two reports to cross check each other and build some confidence. If both objective and subjective metrics track firm success, then they should be positively correlated. In Figure 2, we test non-parametrically for the relationship between 6 Mattarmark outcome measures and the subjective web score. In each subfigure, we regress the log of the reported Mattarmark variable on a dummy for each positive web score (solid lines) and included controls (dashed lines). In all cases, web score of 0 is the omitted category (firms for which we could not find a live web site). Non-parametric point estimates are plotted against the web score in black and 95% confidence intervals are plotted in gray. As we can see, the objective scores are strongly positively associated with the web score and the point estimates are highly statistically significant. In addition, it appears the relationship is approximately linear in almost all cases. We will rely on this result later in translating RD results form the subjective metrics into objective outcomes.

Finally, in addition to firm-level variables, we also collect competition-level variables which we will use to estimate heterogeneous impacts. These variables are summarized in Table 4. Each competition is assigned to one of three competition size groups (small, mid, big), depending on the dollar value of the largest prize offered in each competition. Competitions are also categorized in terms of the type of donor organization (firm, government, NGO, university). Finally, the type of prize offered is identified as grant, accelerator, idea, incubator, pitch/other.

Figure 2: Mattarmark



Notes: Each subfigure reports point estimate and 95% confidence intervals from regressing the log of the dependent variable on category variables for each value of web score and (solid lines) and controls for competition, industry, firm country, and product type (dashed lines). In each case, web score = 0 is the omitted category (no website found). The number of observations range form a minimum of 685 (panel C) to a maximum of 2050 (panel F).

Table 4: Competition-level Variables

	# Competitions (1)	Percentage (2)
Comp Prize Size		
Small ($x \leq$ 1,000 USD)	120	0.261
Mid (1,000 USD $< x \leq$ 10,000 USD)	212	0.461
Big (10,000 USD $< x$)	128	0.278
Total	460	1.000
Donor Organization Type		
Firm	64	0.139
Government	51	0.111
NGO	239	0.520
University	106	0.230
Total	460	1.000
Competition Prize Type		
Idea	84	0.183
Accelerator	25	0.054
Grant	273	0.593
Incubator	32	0.070
Pitch/Other	46	0.100
Total	460	1.000

3 Results

3.1 RD estimates

With the data described in section 2, we aim to exploit the discontinuous jump in funding around the YN threshold to estimate the return to alternative financing in different countries and industries around the world. The identification assumption is that unobservable determinants of firm success are balanced across the threshold, within a reasonable bandwidth. That is, firms with similar ranks that happen to lie on opposite sides of the threshold can be considered similar in terms of unobservable ability.

Conditional on this assumption, impacts can be recovered by the standard RD estimating equation:

$$y_{ic} = \alpha + \tau * [\mathbb{1}|Rank_{ic} < 0] + f(Rank_{ic}) + X_{ic}\Gamma + \delta_c + \epsilon_{ic} \quad , \quad \text{with} \quad -r < Rank_{ic} < r \tag{1}$$

where y_{ic} is outcome for firm i entering competition c, $[\mathbb{1}|Rank_{ic} < 0]$ is an indicator for firm i's YN normalized rank lying to the left of the threshold, X_{ic} is a vector of firm-level controls that might include country fixed effects, industry fixed effects, and product-type fixed effects, $f(Rank_{ic})$ is a polynomial control for normalized rank, δ_c is a competition fixed effect, r is the bandwidth, and ϵ_{ic} is the idiosyncratic error term. The parameter of interest is τ. When y_{ic} is a dummy for winning the competition or the normalized competition place, then τ represents the first stage impact. When y_{ic} represents one of the subjective or objective outcome variables, then τ reports the reduced form effect.

To begin, we present evidence in support of the identification assumption in Table 5. If firms are as good as randomly assigned to either side of the threshold, then covariates should be approximately equal across the threshold. In Table 5, we report means of dummy variables for country, industry, and product type within different bandwidths on either side of the threshold. Column 7 tests for difference in means. First, setting $r = 1$, we have 295 firms to the left of the threshold and 266 firms to the right. We find no statistically difference in means for any of the covariates. Next, we expand the bandwidth to $r = 5$ and $r = 10$, respectively. With the wider bandwidth, precision increases and a few mean differences become statistically significant, but not many. We take Table 5 as supporting evidence of covariate balance.

Next, in Figure 3, we present visual evidence of the discontinuity in competition place

Table 5: Covariate Balance Across Threshold

	Rank<0			Rank>0			Diff
	Mean (1)	Sd (2)	# Obs (3)	Mean (4)	Sd (5)	# Obs (6)	(7)
Bandwidth==1							
NAmerica	0.386	(0.488)	295	0.376	(0.485)	266	0.011
SAmerica	0.088	(0.284)	295	0.064	(0.245)	266	0.024
Europe	0.424	(0.495)	295	0.455	(0.499)	266	-0.031
Asia	0.071	(0.258)	295	0.060	(0.238)	266	0.011
Africa	0.017	(0.129)	295	0.019	(0.136)	266	-0.002
Unknown	0.014	(0.116)	295	0.026	(0.160)	266	-0.013
Clean Tech	0.108	(0.312)	295	0.102	(0.303)	266	0.007
Services	0.254	(0.436)	295	0.244	(0.431)	266	0.010
Products	0.217	(0.413)	295	0.237	(0.426)	266	-0.020
Web	0.180	(0.385)	295	0.143	(0.351)	266	0.037
Life Sciences	0.149	(0.357)	295	0.162	(0.369)	266	-0.013
Services	0.217	(0.413)	295	0.214	(0.411)	266	0.003
Products	0.342	(0.475)	295	0.316	(0.466)	266	0.027
Software/Apps	0.312	(0.464)	295	0.263	(0.441)	266	0.049
Bandwidth==5							
NAmerica	0.440	(0.497)	1241	0.408	(0.492)	1322	0.032
SAmerica	0.122	(0.327)	1241	0.116	(0.321)	1322	0.005
Europe	0.305	(0.461)	1241	0.340	(0.474)	1322	-0.034 *
Asia	0.085	(0.278)	1241	0.087	(0.282)	1322	-0.002
Africa	0.029	(0.168)	1241	0.025	(0.156)	1322	0.004
Unknown	0.019	(0.138)	1241	0.024	(0.154)	1322	-0.005
Clean Tech	0.136	(0.343)	1241	0.117	(0.322)	1322	0.019
Services	0.250	(0.433)	1241	0.270	(0.444)	1322	-0.020
Products	0.222	(0.416)	1241	0.207	(0.405)	1322	0.015
Web	0.154	(0.361)	1241	0.140	(0.347)	1322	0.014
Life Sciences	0.161	(0.368)	1241	0.159	(0.366)	1322	0.002
Services	0.222	(0.415)	1241	0.231	(0.422)	1322	-0.010
Products	0.314	(0.464)	1241	0.297	(0.457)	1322	0.018
Software/Apps	0.305	(0.460)	1241	0.269	(0.444)	1322	0.035 **
Bandwidth==10							
NAmerica	0.436	(0.496)	1794	0.414	(0.493)	1961	0.022
SAmerica	0.146	(0.353)	1794	0.130	(0.336)	1961	0.016
Europe	0.278	(0.448)	1794	0.318	(0.466)	1961	-0.041 ***
Asia	0.082	(0.275)	1794	0.087	(0.281)	1961	-0.004
Africa	0.030	(0.169)	1794	0.025	(0.156)	1961	0.005
Unknown	0.028	(0.165)	1794	0.026	(0.159)	1961	0.002
Clean Tech	0.134	(0.341)	1794	0.115	(0.319)	1961	0.019 *
Services	0.255	(0.436)	1794	0.270	(0.444)	1961	-0.015
Products	0.218	(0.413)	1794	0.209	(0.406)	1961	0.009
Web	0.159	(0.366)	1794	0.161	(0.368)	1961	-0.002
Life Sciences	0.153	(0.360)	1794	0.143	(0.350)	1961	0.010
Services	0.222	(0.416)	1794	0.234	(0.424)	1961	-0.012
Products	0.295	(0.456)	1794	0.292	(0.455)	1961	0.003
Software/Apps	0.314	(0.464)	1794	0.282	(0.450)	1961	0.032 **

Notes: Column 7 tests for equality of means between firms above and below the threshold at different bandwidths. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

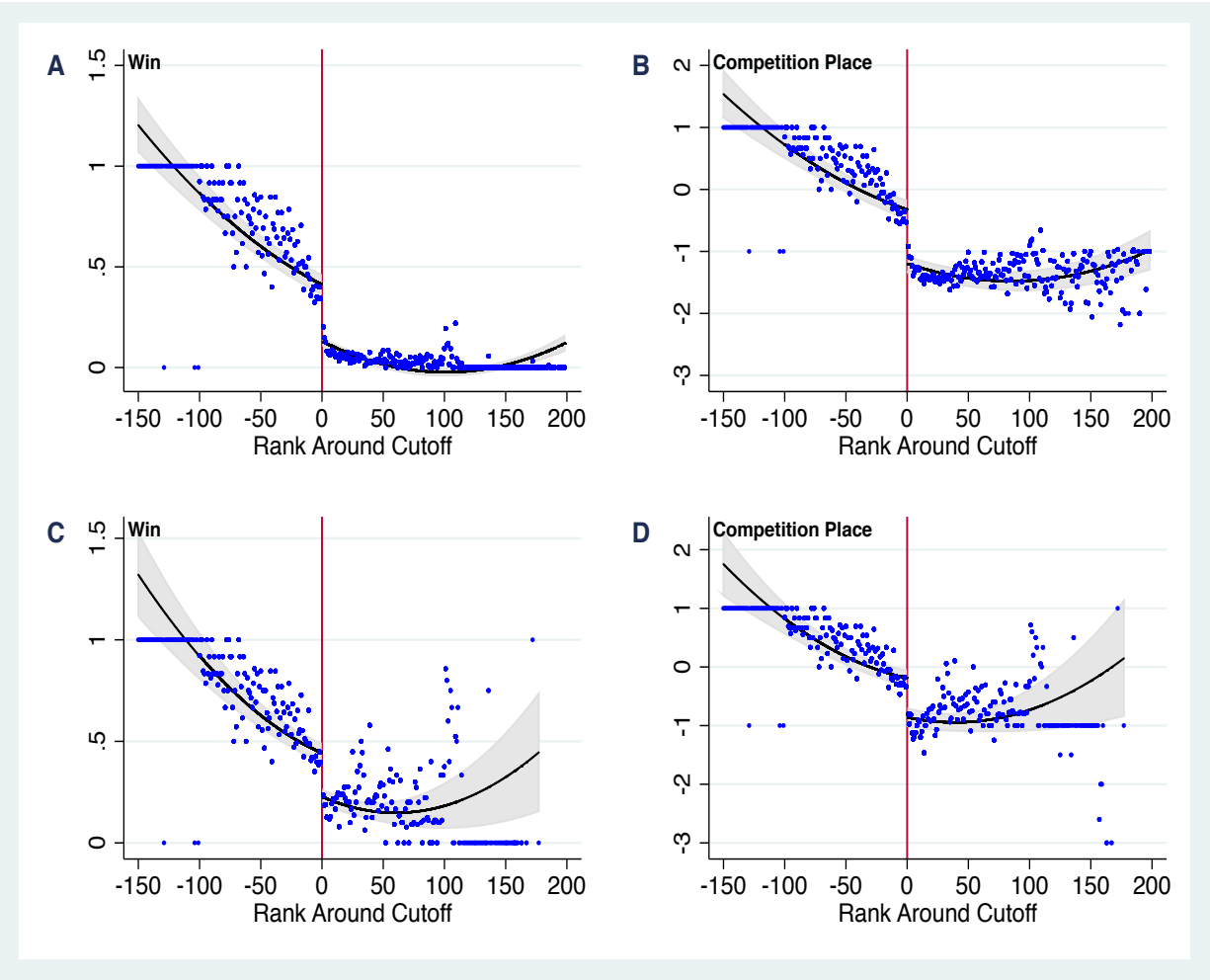
around the threshold. Each subfigure presents bin averages of competition place (win vs lose in subfigures A and C, normalized competition place in subfigures B and D) against normalized rank. Regression lines and 95% confidence intervals are included from regressing the outcome measure on rank and rank squared. The top row (subfigures A and B) include information for all competition entrants, while bottom row (subfigures C and D) include only firms for which we also have outcome data. Starting in subfigure A, we see that the probability of winning the competition is clearly decreasing in $Rank_{ic}$, and that there is a discontinuous jump at the threshold of about 20 percentage points. This same pattern holds in the other subfigures, though in C and D the probability becomes quite noisy at high values of $Rank_{ic}$. This is mostly due to having deliberately neglected to collect outcome data for firms with ranks far from the threshold.

In a sharp RD design, the probability of winning the competition would be 1 to the left of the threshold and 0 to the right. There are two reasons this is not the case in our setting. First, in many cases, donor organizations held "finals" rounds subsequent to YN judging. That is, the donor organization used YN rankings to determine a group of "finalists", from which the organization ultimately selected a subset as "winners" of the competition. In this case, winning the competition is based partially on YN rankings (you cannot win unless you make it into the finals) but it is also based on unobserved evaluations that take place subsequent to YN judging. Given this structure, the YN rankings are deterministic for placing into the finals round, but not necessarily for winning the competition. While this feature weakens the first stage, it should not introduce any bias into the estimation.

The second reason that we have a fuzzy RD instead of a sharp RD is that donor organizations sometimes deviate from the YN rankings. Again, as long as the threshold is truly exogenous and there is no manipulation of the raw YN judge rankings, deviations from the donor organizations merely weaken the first stage effect.

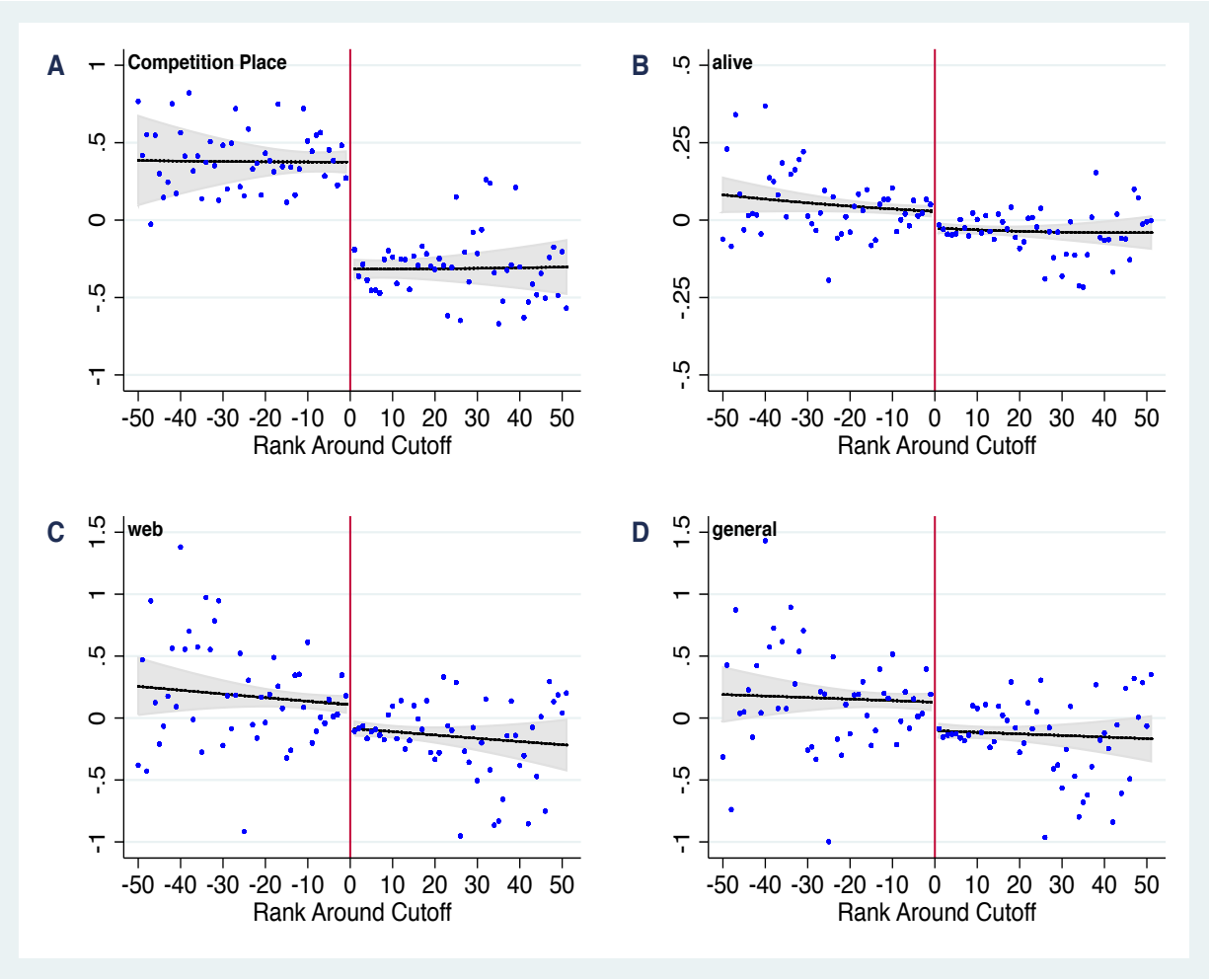
In Figure 4, we present first stage and reduced form regression results after stripping out fixed effects for competition, country, industry, and product type. Again, regression lines and 95% confidence intervals are included based on projecting the residuals (after subtracting fixed effects) on rank and rank squared and an indicator $[\mathbb{1}|Rank_{ic} < 0]$. Subfigure A presents results taking normalize competition place as the outcome (i.e., the first stage), while sub figures B-D take the three subjective metric outcome variables as the dependent variables (reduced forms). Here, we allow a wide bandwidth ($r = 50$) in order to see the patterns in the data. In the regression tables below, we restrict to tighter bandwidths. In each case, a clear discontinuity is visible at the threshold.

Figure 3: First Stage



Notes: Top row (panels A and B) presents data from all competition entrants, while bottom row (panels C and D) restricts to observations with outcome data. In all cases, only competitions with observations both to the right and left of the threshold are included. Top row includes 19,706 observations (3,739 to the left of the threshold and 15,967 to the right) across 449 competitions. Bottom row includes 7450 observations (3,469 to the left of the threshold and 3,981 to the right) across 437 competitions. Y-axis reports average of dependent variable by normalized YN rank (panels A and C report the binary variable "Win", which indicates whether or not the firm was named as a winner, and panels B and D report the Normalized Competition Place). All subfigures include regression lines and 95% confidence intervals based on linear regressions with controls for running variable and running variable squared.

Figure 4: Regression Discontinuity Results



Notes: Figure includes only observations with both ranking data and outcome data, and only competitions with observations both to the right and left of the threshold – 6,036 observations across 437 competitions, 2,756 observations left of threshold and 3,280 observations right of threshold. Each panel first subtracts averages by competition, industry, firm country, and product type from the dependent variable. Regression lines and 95% confidence intervals are then computed based on linear projections of these residuals on controls for running variable and running variable squared. Dots represent bin average of the residual by value of the running variable.

These results are confirmed by the regressions results reported in Tables 6 and 7. Each panel in Tables 6 and 7 estimates equation 1 for a different dependent variables for different bandwidths ($r \in \{1, 5, 10, max\}$), with and without controls. First, considering only firms exactly one rank to the right and left of the threshold, we find that beating the YN threshold increases both normalized competition place (panel A) and the probability of winning (panel B) both statistically significant at the 1% level. Standard errors are reported below the point estimates and allow for arbitrary correlation within super competitions. The point estimates remain nearly unchanged when controls are added, as we would expect given covariate balance from Table 5. As we expand the bandwidth, we add controls for rank and rank squared. Point estimates remain fairly constant, and always significant at the 1% level. If we set $r = 10$ and include controls, we find that beating the YN threshold increases the probability of winning the competition by 20.5 percentage points on a mean of 20 percent for firms right of the threshold, or roughly doubling the probability of winning the competition.

Next, in Table 7, we find that beating the YN threshold increases the probability of having a live website (panel A), web score (panel B), and the general web presences score (panel C). Regardless of specification, point estimates are always highly statistically significant. In the preferred specification ($r = 10$ with controls) we find that live websites increase 9.3 percentage points on a base of 48.2%, web scores increase 0.339 points on a base of 1.770, and general scores increase 0.430 points on a base of 1.868, or roughly 19 -23% for the subjective metrics.

These results are summarized in Table 9. Column 1 reports the average value of the dependent variable for firms to the right of the threshold. Column 2 reports $\hat{\tau}$ from Tables 6 and 7. Column 4 presents a Wald estimator of winning the competition, in which the reduced form impact is divided by the first stage impact $\tau_{\hat{win}}$. Finally, column 5 reports the estimated causal impact of winning a competition in the subjective metrics. We find that winning a competition increases these metrics between 93 - 112%.

Finally, in Table 8, we present reduced form impacts on the objective outcomes from Mattarmark. Just as in the previous tables, we run specifications at various bandwidths both with and without controls, though we omit description of the controls for ease of viewing. We find that beating the YN threshold tends to increase objective metrics, but that the impact is often statistically insignificant. The lack of precision is likely due to the drop in sample size (in comparison to the subjective metrics), but we include the results for completeness.

Table 6: First Stage

	No Controls				With Controls			
Bandwidth:	1	5	10	All	1	5	10	All
Panel A: NCP								
$1\|Rank < 0$	0.640***	0.767***	0.811***	0.882***	0.616***	0.494***	0.605***	0.717***
	(0.120)	(0.067)	(0.062)	(0.061)	(0.122)	(0.135)	(0.097)	(0.070)
$Rank$						-0.049**	-0.024**	-0.003***
						(0.021)	(0.010)	(0.001)
$Rank^2$						-0.002	0.001	0.000***
						(0.003)	(0.001)	(0.000)
R squared	0.107	0.113	0.120	0.152	0.320	0.166	0.165	0.193
Mean Dep. Var	-0.490	-0.626	-0.652	-0.465	-0.490	-0.626	-0.652	-0.465
Panel B: Win								
$1\|Rank < 0$	0.237***	0.248***	0.254***	0.336***	0.228***	0.180***	0.205***	0.214***
	(0.043)	(0.025)	(0.024)	(0.031)	(0.045)	(0.043)	(0.033)	(0.028)
$Rank$						-0.011	-0.005	-0.002***
						(0.007)	(0.004)	(0.000)
$Rank^2$						-0.001	0.000	0.000***
						(0.001)	(0.000)	(0.000)
R squared	0.106	0.087	0.088	0.132	0.308	0.141	0.132	0.191
Mean Dep. Var	0.348	0.295	0.289	0.357	0.348	0.295	0.289	0.357
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Product FE	No	No	No	No	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	Yes	Yes	Yes	Yes
# Observations	561	2563	3755	7450	561	2563	3755	7450
# Competitions	266	410	427	437	266	410	427	437

Notes: Panel A takes the normalized competition place as the dependent variable, while Panel B takes the binary "Win" variable as dependent. Each column corresponds to 2 regressions (one for each panel) with the indicated bandwidth and controls. In all cases, only competitions with observation both to the left and to the right of the threshold are included. Standard errors are clustered to allow for arbitrary correlation within super competition. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 7: Reduced Form

	No Controls				With Controls			
Bandwidth:	1	5	10	All	1	5	10	All
Panel A: Alive								
$1\|Rank < 0$	0.094**	0.095***	0.075***	0.109***	0.080**	0.089**	0.093***	0.057***
	(0.040)	(0.020)	(0.016)	(0.012)	(0.040)	(0.042)	(0.030)	(0.016)
$Rank$						0.000	0.003	-0.001***
						(0.007)	(0.003)	(0.000)
$Rank^2$						-0.002	0.000	-0.000
						(0.001)	(0.000)	(0.000)
R squared	0.021	0.013	0.008	0.014	0.227	0.125	0.108	0.092
Mean Dep. Var	0.504	0.494	0.501	0.516	0.504	0.494	0.501	0.516
Panel B: Web Score								
$1\|Rank < 0$	0.469***	0.327***	0.270***	0.430***	0.418**	0.449**	0.339***	0.188***
	(0.167)	(0.081)	(0.066)	(0.050)	(0.169)	(0.179)	(0.126)	(0.065)
$Rank$						0.028	0.011	-0.004***
						(0.027)	(0.012)	(0.001)
$Rank^2$						-0.006	0.000	-0.000
						(0.004)	(0.001)	(0.000)
R squared	0.033	0.010	0.006	0.013	0.212	0.127	0.100	0.085
Mean Dep. Var	1.750	1.773	1.805	1.901	1.750	1.773	1.805	1.901
Panel C: Gen Score								
$1\|Rank < 0$	0.502***	0.372***	0.310***	0.428***	0.476***	0.502***	0.430***	0.208***
	(0.153)	(0.076)	(0.065)	(0.051)	(0.160)	(0.173)	(0.118)	(0.062)
$Rank$						0.029	0.016	-0.004***
						(0.026)	(0.011)	(0.001)
$Rank^2$						-0.006	0.000	-0.000
						(0.004)	(0.001)	(0.000)
R squared	0.041	0.015	0.010	0.014	0.171	0.126	0.100	0.083
Mean Dep. Var	1.868	1.889	1.924	1.992	1.868	1.889	1.924	1.992
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Product FE	No	No	No	No	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	Yes	Yes	Yes	Yes
# Observations	561	2563	3755	7450	561	2563	3755	7450
# Competitions	266	410	427	437	266	410	427	437

Notes: Each panel takes the indicated variable as dependent. Columns corresponds to 3 separate regressions (one for each panel) with the indicated bandwidth and controls. In all cases, only competitions with observation both to the left and to the right of the threshold are included. Standard errors are clustered to allow for arbitrary correlation within super competition. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 8: Reduced Form Mattarmark

	No Controls				With Controls			
Bandwidth:	1	5	10	All	1	5	10	All
Panel A: Twitter								
$1\|Rank < 0$	1.284*	-0.185	0.066	-0.006	0.254	0.254	-0.206	-0.047
	(0.716)	(0.139)	(0.117)	(0.073)	(0.461)	(0.461)	(0.252)	(0.115)
Number of Observations	80	452	686	1477	452	452	686	1477
Comps	68	202	228	248	202	202	228	248
R squared	0.251	0.005	0.001	0.000	0.283	0.283	0.183	0.105
Mean Dep. Var	3.658	3.680	3.690	3.613	3.680	3.680	3.690	3.613
Panel B: employees								
$1\|Rank < 0$	0.767	0.152	0.359***	0.096	0.376	0.376	0.361	0.142
	(0.521)	(0.169)	(0.121)	(0.085)	(0.386)	(0.386)	(0.223)	(0.121)
Number of Observations	73	357	555	1182	357	357	555	1182
Comps	62	176	204	228	176	176	204	228
R squared	0.177	0.004	0.023	0.002	0.426	0.426	0.262	0.116
Mean Dep. Var	1.982	1.927	1.965	1.800	1.927	1.927	1.965	1.800
Panel C: wuniques								
$1\|Rank < 0$	2.512*	0.116	0.716**	0.161	1.895**	1.895**	0.366	0.445*
	(1.272)	(0.360)	(0.277)	(0.178)	(0.951)	(0.951)	(0.523)	(0.247)
Number of Observations	97	523	807	1857	523	523	807	1857
Comps	77	206	232	253	206	206	232	253
R squared	0.178	0.000	0.011	0.001	0.224	0.224	0.186	0.139
Mean Dep. Var	5.039	5.006	5.116	4.866	5.006	5.006	5.116	4.866
Panel D: Linked-IN								
$1\|Rank < 0$	0.898	0.134	0.380**	0.147	0.302	0.302	0.212	0.182
	(0.679)	(0.227)	(0.171)	(0.098)	(0.704)	(0.704)	(0.356)	(0.157)
Number of Observations	71	371	581	1291	371	371	581	1291
Comps	58	180	204	229	180	180	204	229
R squared	0.142	0.002	0.015	0.002	0.258	0.258	0.191	0.096
Mean Dep. Var	4.402	3.863	3.924	3.736	3.863	3.863	3.924	3.736
Panel E: Facebook								
$1\|Rank < 0$	0.946	-0.136	0.125	0.013	0.336	0.336	0.049	-0.054
	(0.808)	(0.262)	(0.220)	(0.164)	(0.650)	(0.650)	(0.358)	(0.191)
Number of Observations	89	463	695	1549	463	463	695	1549
Comps	73	206	231	255	206	206	231	255
R squared	0.091	0.001	0.001	0.000	0.278	0.278	0.212	0.164
Mean Dep. Var	7.087	6.774	6.893	6.926	6.774	6.774	6.893	6.926

Notes: Each panel takes the indicated variable as dependent. Columns corresponds to 3 separate regressions (one for each panel) with the indicated bandwidth. In all cases, only competitions with observation both to the left and to the right of the threshold are included. Columns denoted "With Controls" control for industry, country, product type, competition, running variable, and running variable squared. Standard errors are clustered to allow for arbitrary correlation within super competition. Asterisks indicate statistical

Table 9: Summary of Impacts

		OLS		IV	
	Avg. Value ($R > 0$) (1)	$\hat{\tau}$ (95% CI) (2)	Impact (95% CI) 100*(2)/(1) (3)	$\hat{\tau}$ (2) $/\hat{\tau}_{win}$ (4)	Impact 100*(4)/(1) (5)
Win	0.202	0.205 (0.139 , 0.271)	101.5% (68.8% , 134.2%)		
Alive	0.482	0.093 (0.033 , 0.153)	19.3% (6.8% , 31.7%)	0.454	94.1%
Web	1.770	0.339 (0.087 , 0.591)	19.2% (4.9% , 33.4%)	1.654	93.4%
General	1.868	0.430 (0.194 , 0.666)	23.0% (10.4% , 35.7%)	2.098	112.3%

3.2 Heterogeneous Impacts

Table 10: Heterogeneity

	Dependent Variable						# Obs		# Comps
	Alive		Web		General		$R_i < 0$	$R_i > 0$	
A: Prize Size									
Small	0.047	(0.085)	0.200	(0.363)	0.244	(0.345)	323	364	109
Medium	0.147 **	(0.059)	0.857 ***	(0.252)	0.902 ***	(0.245)	528	559	196
Large	-0.003	(0.084)	-0.172	(0.330)	-0.092	(0.318)	390	399	105
B: Org Type									
Firm	-0.108	(0.118)	-0.094	(0.448)	0.397	(0.384)	178	185	53
Gov	-0.001	(0.116)	0.020	(0.412)	-0.130	(0.405)	181	175	47
NGO	0.221 ***	(0.063)	1.013 ***	(0.276)	1.008 ***	(0.296)	515	571	209
University	-0.049	(0.075)	-0.138	(0.317)	-0.074	(0.283)	361	384	98
C: Comp Type									
Idea	-0.030	(0.080)	0.095	(0.289)	0.164	(0.253)	224	252	77
Acc	0.116	(0.257)	0.708	(0.847)	0.818	(0.949)	95	93	20
Grant	0.124 **	(0.056)	0.549 **	(0.247)	0.673 ***	(0.239)	704	757	247
Incub	0.369 *	(0.198)	1.975 ***	(0.740)	1.910 ***	(0.679)	90	90	27
Other	0.113	(0.144)	0.306	(0.532)	-0.019	(0.405)	122	123	36
D: Industry									
Clean Tech	0.353 **	(0.139)	1.521 ***	(0.466)	1.510 ***	(0.565)	117	112	58
Services	-0.008	(0.105)	0.004	(0.424)	-0.271	(0.374)	222	256	129
Products	0.043	(0.137)	0.817	(0.502)	1.170 **	(0.520)	165	169	109
Web	0.236	(0.155)	1.246 **	(0.587)	0.829	(0.517)	113	108	69
Life Science	0.126	(0.108)	0.327	(0.395)	0.527	(0.378)	128	155	71
Other	-0.120	(0.107)	-0.444	(0.461)	-0.412	(0.495)	52	64	38
E: Cost									
Low Cost	0.043	(0.054)	0.278	(0.225)	0.211	(0.206)	567	573	182
High Cost	0.141 **	(0.064)	0.665 ***	(0.264)	0.785 ***	(0.263)	633	691	256
F: Product									
Services	0.080	(0.120)	0.788 *	(0.444)	0.756	(0.471)	188	190	119
Products	0.109	(0.093)	0.428	(0.363)	0.768 **	(0.381)	291	278	163
Software/Apps	0.059	(0.093)	0.503	(0.363)	0.190	(0.341)	290	272	141

Notes: Each panel tests for heterogeneous treatment effects along the indicated dimension. Each row reports the point estimate on the threshold indicator variable ($1|Rank < 0$) from three different regressions where the dependent variable varies as indicated above (Alive, Web, or General), and controls are included for industry, country, product type, competition, running variable, and running variable squared. The bandwidth is set at 5 for all regressions, and only competitions with observation both to the left and to the right of the threshold (after imposing all restrictions) are included. Standard errors are clustered to allow for arbitrary correlation within super competition and reported next to point estimates in parenthesis. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 11: Heterogeneity Within Dimensions

	Dependent Variable						# Obs		# Comps
	Alive		Web		General		$R_i < 0$	$R_i > 0$	
A:NGO X Size									
Small	0.070	(0.132)	0.124	(0.616)	0.167	(0.610)	144	186	64
Medium	0.255 ***	(0.077)	1.221 ***	(0.300)	1.279 ***	(0.308)	297	322	127
Large	0.222	(0.152)	1.122	(0.847)	1.080	(1.081)	74	63	18

Notes: Each panel tests for heterogeneous treatment effects along the indicated dimension. Each row reports the point estimate on the threshold indicator variable ($1|Rank < 0$) from three different regressions where the dependent variable varies as indicated above (Alive, Web, or General), and controls are included for industry, country, product type, competition, running variable, and running variable squared. The bandwidth is set at 5 for all regressions, and only competitions with observation both to the left and to the right of the threshold (after imposing all restrictions) are included. Standard errors are clustered to allow for arbitrary correlation within super competition and reported next to point estimates in parenthesis. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

3.3 Estimating Impacts on Objective Metrics

In section 3.1, we found economically and statistically significant impacts on the subjective metrics, suggesting that alternative funding sources can in fact increase start-up success. However, subjective metrics of web scores and web presence are hard to interpret in dollar terms and compare to other findings in the literature. Unfortunately, the RD estimates from the objective metrics are too noisy to draw conclusions. Instead, to connect these findings to the literature, we rely on the results in Figure 2 to perform back of the envelope calculations for what a 93-112% increase in web score and general score mean for these objective metrics.

In Figure 2, we estimated the relationship between objective metrics and web score non-parametrically, founding that objective metrics are approximately linearly increasing in web score. For the calculations below, we will assume that this linear relationship holds, so that an increase in web score of $\hat{\tau}$ increases objective metrics by

$$\beta = \hat{\tau} * \hat{\rho} \tag{2}$$

where $\hat{\rho}$ is the linear estimate of how an increase in subjective metrics translate into an increase in objective metrics.

We estimate $\hat{\rho}$ in Table 12 for both web score and general score and 6 different objective metrics from Mattarmark. All regressions include fixed effects for competition, industry, country, and product type. In all panels, we take the log of the objective metric so point estimates are interpretable as a semi-elasticity. In panel A, we find that a 1 point increase in web score leads to a $e^{0.77} - 1 = 115\%$ increase in unique web visitors. In columns 2 and 3, we find that this relationship holds both for winning firms (column 2) and losing firms (column 3) separately, though the point estimate is a bit smaller for losing firms. Across all 6 objective metrics and both subjective metrics, we find that the linear parameter is always positive and statistically significant at the 1% level.

Table 13 reports the back of the envelope calculations. Columns 2 and 6 reproduces the IV results from Table 9, and columns 3 and 7 report estimates of $\hat{\rho}$. Multiplying the IV impact by the scalar $\hat{\rho}$ yields percentage increases in column 4 and 8 from winning a competition between 86.9 - 342.8 %, depending on the objective-subjective metric pairing. In columns 5 and 9, we evaluate these percent increases at the average objective values for losing firms and find, for example, that winning a competition translates into 83,735 - 134,144 more unique web visits, and between 3.8 - 6.0 million USD more in follow-on

funding.

Table 12: Mattarmark and Web Metrics

	Web Score (0-5)			General Score (0-5)		
	All	Winners	Losers	All	Winners	Losers
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unique Visitors						
ρ	0.770***	0.870***	0.641***	0.865***	0.922***	0.747***
	(0.052)	(0.069)	(0.072)	(0.060)	(0.075)	(0.077)
# Observations	1901	1046	855	1901	1046	855
# Comps	264	212	187	264	212	187
R squared	0.285	0.319	0.309	0.307	0.322	0.341
Panel B: Facebook Likes						
ρ	0.313***	0.333***	0.288***	0.394***	0.416***	0.352***
	(0.034)	(0.049)	(0.056)	(0.040)	(0.044)	(0.061)
# Observations	1589	910	679	1589	910	679
# Comps	266	219	176	266	219	176
R squared	0.217	0.285	0.302	0.238	0.308	0.317
Panel C: Funding						
ρ	0.203***	0.305***	0.122***	0.240***	0.384***	0.125***
	(0.033)	(0.086)	(0.036)	(0.037)	(0.090)	(0.039)
# Observations	684	318	366	684	318	366
# Comps	160	123	91	160	123	91
R squared	0.208	0.365	0.235	0.222	0.385	0.234
Panel D: Employment						
ρ	0.229***	0.236***	0.191***	0.297***	0.314***	0.229***
	(0.020)	(0.030)	(0.033)	(0.029)	(0.041)	(0.038)
# Observations	1211	692	519	1211	692	519
# Comps	239	191	156	239	191	156
R squared	0.203	0.267	0.326	0.246	0.312	0.344
Panel E: Twitter Followers						
ρ	0.306***	0.294***	0.307***	0.393***	0.357***	0.390***
	(0.026)	(0.040)	(0.044)	(0.031)	(0.046)	(0.053)
# Observations	1792	1027	765	1792	1027	765
# Comps	268	219	189	268	219	189
R squared	0.154	0.220	0.214	0.180	0.235	0.241
Panel F: LinkedIn						
ρ	0.240***	0.292***	0.200***	0.319***	0.392***	0.248***
	(0.028)	(0.036)	(0.040)	(0.038)	(0.044)	(0.051)
# Observations	1320	758	562	1320	758	562
# Comps	240	192	156	240	192	156
R squared	0.163	0.251	0.210	0.200	0.302	0.227

Notes: Each panel takes the indicated variable as dependent. Columns 1-3 take the web score as the independent variable. Columns 4-6 take the general score as the independent variable. All regressions include fixed effects for competition, industry, country, and product type. Standard errors are clustered to allow for arbitrary correlation within super competition. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 13: Summary of Impacts, Ctd

		Web Score				General Score			
	Avg. Value (Losers)	$\hat{\tau}$	$\hat{\rho}$	% Increase $((\hat{\tau} * e^{\hat{\rho}})$-1)*100	Eval @ Avg	$\hat{\tau}$	$\hat{\rho}$	% Increase $((\hat{\tau} * e^{\hat{\rho}})$-1)*100	Eval @ Avg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unique Web Visitors	39130	1.654	0.641	214.0 %	83,735	2.098	0.747	342.8 %	134,144
Facebook Likes	13310	1.654	0.288	120.6 %	16,052	2.098	0.352	198.3 %	26,396
Funding	4391000	1.654	0.122	86.9 %	3,814,081	2.098	0.125	137.7 %	6,047,924
Employment	16.25	1.654	0.191	100.2 %	16	2.098	0.229	163.8 %	27
Twitter Followers	3127	1.654	0.307	124.8 %	3,904	2.098	0.390	209.9 %	6,563
LinkedIn	210	1.654	0.200	102.0 %	214	2.098	0.248	168.9 %	355

4 Robustness

TBD

5 Conclusion

TBD

References

Allcott, H. & Greenstone, M. (2012). Is there an energy efficiency gap? *The Journal of Economic Perspectives*, 26(1), 3–28.

Gonzalez-Uribe, J. & Leatherbee, M. (2015). Business accelerators: Evidence from start-up chile. *Available at SSRN*.

Howell, S. (2016). Financing innovation: Evidence from r&d grants. *Available at SSRN*.

Kerr, W. R., Nanda, R., & Rhodes-Kropf, M. (2014). Entrepreneurship as experimentation. *The Journal of Economic Perspectives*, 28(3), 25–48.

Kortum, S. & Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *RAND journal of Economics*, (pp. 674–692).

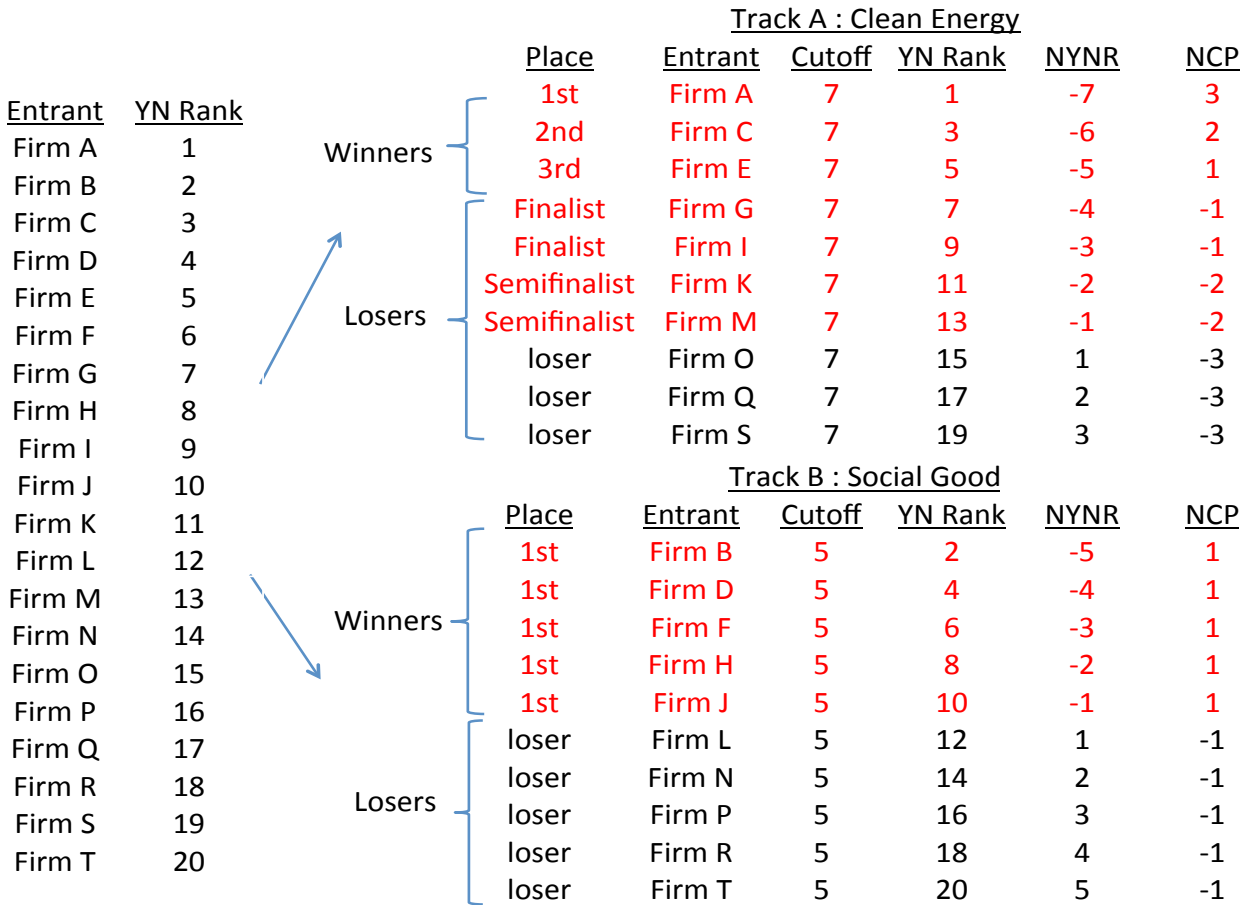
Lelarge, C., Sraer, D., & Thesmar, D. (2010). Entrepreneurship and credit constraints: Evidence from a french loan guarantee program. In *International differences in entrepreneurship* (pp. 243–273). University of Chicago Press.

Lerner, J., Schoar, A., Sokolinski, S., & Wilson, K. (2015). *The Globalization of Angel Investments: Evidence across Countries*. Technical report, National Bureau of Economic Research.

Appendix

A Data Construction

Figure A.1: Hypothetical Super Competition Example



Entrant	YN Rank
Firm A	1
Firm B	2
Firm C	3
Firm D	4
Firm E	5
Firm F	6
Firm G	7
Firm H	8
Firm I	9
Firm J	10
Firm K	11
Firm L	12
Firm M	13
Firm N	14
Firm O	15
Firm P	16
Firm Q	17
Firm R	18
Firm S	19
Firm T	20

Track A : Clean Energy

	Place	Entrant	Cutoff	YN Rank	NYNR	NCP
Winners	1st	Firm A	7	1	-7	3
	2nd	Firm C	7	3	-6	2
	3rd	Firm E	7	5	-5	1
Losers	Finalist	Firm G	7	7	-4	-1
	Finalist	Firm I	7	9	-3	-1
	Semifinalist	Firm K	7	11	-2	-2
	Semifinalist	Firm M	7	13	-1	-2
	loser	Firm O	7	15	1	-3
	loser	Firm Q	7	17	2	-3
	loser	Firm S	7	19	3	-3

Track B : Social Good

	Place	Entrant	Cutoff	YN Rank	NYNR	NCP
Winners	1st	Firm B	5	2	-5	1
	1st	Firm D	5	4	-4	1
	1st	Firm F	5	6	-3	1
	1st	Firm H	5	8	-2	1
	1st	Firm J	5	10	-1	1
Losers	loser	Firm L	5	12	1	-1
	loser	Firm N	5	14	2	-1
	loser	Firm P	5	16	3	-1
	loser	Firm R	5	18	4	-1
	loser	Firm T	5	20	5	-1

Notes: Example of how a single super competition can be subdivided into mutually exclusive competitions. Red highlighting indicates firms that beat the YN cutoff. "NYNR" stands for "Normalized YouNoodle Rank", and "NCP" stands for "Normalized Competition Place".

B Tables