Learning in Entrepreneurship

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Abstract

Why do people become entrepreneurs? Evidence of low returns to entrepreneurship is puzzling. Cognitive biases like overconfidence or non-pecuniary benefits may explain why people start firms. An alternative view emphasizes the real option value of launching or abandoning a new firm, and characterizes entrepreneurship as rational experimentation. These perspectives have different predictions for whether and how entrepreneurs learn from new information; in the experimentation view, founders should be more responsive to new information. I use novel data from nearly 100 new venture competitions to show that negative feedback increases the chances a venture is abandoned. Further, learning in the sense of improvement is predictive of subsequent financing and employment. I find heterogeneity that is relevant to understanding innovation and firm dynamics. The cost of experimentation, the stage of the venture and its founder in their respective lifecycles, geography, and the founder's personal background are all important determinants of learning. The results are broadly consistent with the experimentation view. However, founders with degrees from elite schools and social impact ventures are unresponsive to feedback and may, respectively, be overconfident and garner large non-pecuniary benefits.

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1 Introduction

Canonical models of firm dynamics rest on assumptions about how firms learn (e.g. Jovanovic 1982, Hopenhayn 1992, Ericson & Pakes 1995, Aghion & Howitt 2006). In these and other models, entrepreneurs enter an industry and incumbent managers exit in response to new information about the net present value of the enterprise. The models contain an explicit or implicit learning process that is in general rational and homogenous.[1]

At odds with these canonical models is empirical evidence of low returns to entrepreneurship.[2] Two prominent explanations for entry despite low returns are in some tension with one another: a cognitive bias view and an experimentation view. I use data from new venture competitions to provide the first causal evidence of entrepreneurs learning from new information. I then use heterogeneity in learning to shed light on theories of firm dynamics, and in particular the two explanations for entrepreneurial entry.

The cognitive bias approach suggests that overconfidence or non-pecuniary benefits explain why people forego valuable outside options to become entrepreneurs. In this perspective, entrepreneurs enter irrationally and fail to update their priors in light of new information.[3] One example of a theory premised on this view is the Landier & Thesmar (2009) contracting model, in which entrepreneurs receive nothing if the venture fails because they assign this event zero probability, while investors correctly believe that it is quite possible.[4] A second example is

[1]The literature on occupational choice makes analogous assumptions for individuals and includes Lucas (1978), Cagetti & De Nardi (2006), Vereshchagina & Hopenhayn (2009), and Poschke (2013).

[2]Hamilton (2000), Moskowitz & Vissing-Jørgensen (2002), and Hall & Woodward (2010), among others, find evidence of a "private equity premium puzzle" in which the returns to entrepreneurship are extremely low.

[3]For example, Camerer & Lovallo (1999) and Koellinger, Minniti & Schade (2007) find evidence that entrepreneurs are extremely overconfident. Astebro, Jeffrey & Adomdza (2007) finds that inventors are over-optimistic and fail to respond to negative feedback. Hurst & Pugsley (2011) and Giannetti & Simonov (2009) argue that non-pecuniary benefits - like being one's own boss or a warm glow from providing a social good - explain the low returns in entrepreneurship. See Astebro et al. (2014) for a review.

[4]Landier and Thesmar (2009) assume a form of Bayesian updating in which the entrepreneur ignores negative feedback at an interim stage.

Bergemann & Hege (2005), who motivate their model of R&D investment with agency conflicts by pointing out that "entrepreneurs express a strong preference for continuation regardless of present-value considerations."

The other strand argues that entrepreneurial entry should be viewed through a real options lens. Manso (2016) and Kerr, Nanda & Rhodes-Kropf (2014) propose that the process of founding a high-growth new venture is one of experimentation.[5] Entrepreneurship may arise from rational expectations of future cash flows if starting a venture and abandoning it are considered options. This experimentation view casts a different light on the skewness of the outcome distribution; rather than decreasing risk-adjusted expected returns, high outcome variance increases the option's value.

The cognitive bias view points to entrepreneurs persisting despite the arrival of negative information about the venture's commercial prospects. The experimentation view requires entrepreneurs to recognize and value the abandonment option, and also to adapt their strategies to new information. I find that new ventures and founders are quite responsive to interim signals, consistent with the experimentation view. However, I find heterogeneity in learning itself and in the benefit of learning that helps to unify the two strands of thought.

I use novel data on 4,328 new ventures participating in 96 competitions in 17 states between 1999 and 2016. Each competition consists of one or more rounds (e.g. semifinals) in which ventures present their ideas to a panel of expert judges. I observe judge identities and all scores at each round. Sponsored by universities, federal and local governments, and non-profit organizations, the competitions award cash prizes to winners and do not take equity stakes.

The sample consists largely of first-time entrepreneurs seeking external finance in order to grow quickly. It is weighted towards hardware (especially clean energy technology) and away from the major clusters (35% of ventures are from the VC hub states of California, Massachusetts and New York). While the data are are not representative of the universe of entrepreneurs, they are an

[5] See also Dillon & Stanton (2016), McGrath (1999), and Stern (2006). An important piece of evidence for this view is that most entrepreneurship spells are short.

important group to study for at least two reasons. First, young, high-growth startups drive innovation, employment, and productivity growth (Haltiwanger, Jarmin & Miranda 2013). Second, there is evidence that startups outside of the major clusters and those with hardware or clean energy technologies have especially large positive externalities and are also challenging to fund privately.[6]

The first step in the analysis is to establish that the competitions generate valuable, informative signals. In a regression discontinuity design, I show that conditional on win status, rank robustly predicts measures of success like subsequent financing, employment, and survival. Winning positively affects these outcomes and the chances of an IPO or acquisition. Regressions include competition-round-panel fixed effects, which control for the date and geographic location, or judge fixed effects. I also control for whether the judge or the judge's company invested in the venture.

Having established that rank is informative, I next show that ventures do respond to these signals. Specifically, I ask whether entrepreneurs that receive especially negative feedback are more likely to abandon their ventures. I exploit the fact that some competitions inform ventures of their ranks within a round, while others do not. Within the sample of losers, I estimate the effect of a very low rank with knowledge of that rank, relative to a very low rank without such knowledge. This is akin to a difference-in-differences specification. The first difference is within round, comparing below median and above median losers. The second difference is across rounds, comparing ventures that were informed of their rank with those that were not. I show that receiving this negative, structured feedback increases by about 15% the probability that the venture is ultimately abandoned. This provides initial evidence in favor of the experimentation view.

The experimentation view also demands adaptability to new information, which I examine through learning in the sense of improvement across rounds (much as an educator might measure student learning as improvement in test scores over the semester). The first measure is the change in decile rank be-

[6]See Howell (2016), Nanda et al. (2015), and Chatterji et al. (2013).

tween a pre-competition written business plan phase and the first round of the competition.[7] The second is the change in decile rank across competitions for ventures in more than one. The last measure, the change in rank across rounds, is the primary focus of the heterogeneity analysis. All three measures strongly predict subsequent financing, employment, and survival, which is evidence that successful entrepreneurs adapt to new signals. Henceforth, I refer to "learning" in the sense of these measures.

As the cost of experimentation rises across sectors, I expect that the options to change strategies or abandon decline in value. Indeed, I find that firms with a lower cost of experimentation do more of it. Software ventures are much more likely to be abandoned in response to negative feedback, and they learn more across rounds.[8]

Recent decades have seen a decline in new firm entry that is troubling in light of evidence that new, young businesses drive employment growth (Pugsley & Sahin 2015, Decker et al. 2014). At the same time, however, the cost of launching software or internet-based companies declined dramatically (Ewens et al. 2015). It is likely that the cost of adapting to new information has also fallen for these companies. If underlying costs or new resources like accelerators and competitions are making learning more efficient, entry-exit dynamics may shift to entry-pivot dynamics. That is, entrepreneurs may increasingly change strategies rather than fail.[9] Anecdotal evidence from industry suggests this is common and even desirable. Paul Graham, founder of the well-regarded Y Combinator accelerator, wrote, "Don't get too attached to your original plan, because it's probably wrong. Most successful startups end up doing something different than they originally intended."

The earliest stage firms and founders are more responsive. Founders are

[7] Business plan scores are explicitly intended for learning and are not used in the competition. However, this measure exists for a small subset of the data.

[8] This result is not explained by correlation between software and other characteristics, like expected non-pecuniary benefits.

[9] One indicator of such changes is that 18% of the ventures in my sample changed their names after the competition.

more likely to abandon their venture in response to negative feedback when the venture was unincorporated or was run by a student at the time of the competition. Student-run ventures learn more across rounds than non-students, while older ventures and older founders learn less.[10] This is consistent with the option value of entrepreneurship declining as the firm and founder age.

I find evidence that elite founders are overconfident. Founders that received any degree from the top entrepreneurship universities or a top ten MBA learn less on average, and the former are much less likely to abandon their ventures in the face of negative feedback.[11] This does not seem to reflect higher quality ventures learning less; for example, ventures with previous financing learn more. As the effect of winning on financing is larger for elite school founders, there is no obvious rational reason for them to learn less. This result for startup founders complements the literature on CEO overconfidence (Malmendier & Tate 2005, Ben-David, Graham & Harvey 2013).

Using the number of judges to proxy for signal precision, I find suggestive evidence that the type of overconfidence among elite founders is over-optimism, not over-precision.[12] Over-optimistic CEOs have been shown to be more innovative (Hirshleifer et al. 2012), and over-precise ones less so (Herz, Schunk & Zehnder 2014). Entrepreneurs with radical technologies may be less responsive to feedback than those with incremental ideas. Theoretical models of industry dynamics could micro-found technological discontinuities in the small fraction of entrepreneurs that enter without regard to signals about net discounted expected cash flows, and occasionally transform the industry. The mass of entrants could remain rational and responsive to new information.

Criteria scores illuminate the learning mechanism. Ventures could improve across rounds by changing the idea, or by changing how they sell the idea. The

[10] While some of these characteristics are correlated, they are independently predictive.

[11] A related result is that individuals trained in entrepreneurship and management (whether undergraduate or MBA) learn more. The top entrepreneurship universities are Harvard, Stanford, and MIT.

[12] Over-optimism, or the "above average effect," implies the agent overestimates his expected mean performance, while over-precision implies he underestimates the volatility of his performance (also called "judgmental overconfidence" or "miscalibration").

strongest predictor of success is a higher team (leadership quality) rank, as in Bernstein, Korteweg & Laws (2015). A better technology/product rank predicts exit and survival. Learning, however, is only relevant to venture outcomes for the financial and presentation criteria. Adjustments to the financing plan and the pitch are most useful, therefore, rather than dramatic pivots to a new idea.

Geographic variation provides related insights into how learning is useful. The competitions draw ventures from diverse geographic locations, but judges are mostly very local. While winning and learning are useful to ventures regardless of geographic location, learning is much more predictive of success when the venture and competition are in the same, non-VC hub state. Learning is most productive in this setting for entrepreneurs without strong educational or geographic advantages, *and* when the competition helps mobilize a local network of advisors and investors. Through this channel, competitions may promote local entrepreneurship, which Glaeser, Kerr & Kerr (2015) and Gennaioli et al. (2013) show is strongly correlated with local economic growth.

Ventures in my data on average behave consistently with the experimentation view. Rather than passively receive type shocks, the firms seem to actively acquire new information, as in Ericson & Pakes (1995). I demonstrate heterogeneity in learning about future profits that might be responsible for resource misallocation and for stylized facts that contradict rational models of entry and exit. For example, clean energy and "social impact" entrepreneurs, who likely derive large non-pecuniary benefits, tend to learn less. A second example is that during the financial crisis, winners learned more across rounds (i.e. successful founders adapted more to new information). Faster learning may be one mechanism for the cleansing effect of recessions in Caballero et al. (1996). Entrepreneurs may pursue many poor ideas during expansions, when financing is relatively cheap, leading to resource misallocation. As financing availability declines, the cost of persisting with a poor idea increases.

Faster learning could improve resource allocation in the economy. Guiso, Pistaferri & Schivardi (2015) argue that if entrepreneurship can be learned, government efforts to spur entrepreneurship can focus on learning opportunities. My results suggest that competitions are a successful learning intervention for participating ventures, and I provide several results pertinent to program design.

This paper draws from and contributes to the following literatures, beyond the works cited thus far: the relationship of executive characteristics and corporate decisions (Bertrand & Schoar 2003, Graham, Harvey & Puri 2013) financial constraints facing startups and the evaluation of policies to alleviate them (Howell 2016, Ozmel, Robinson & Stuart 2013, Schmalz, Sraer & Thesmar 2015); human capital networks (Ewens & Rhodes-Kropf 2015, Hochberg, Ljungqvist & Lu 2007); and predicting startup success (Scott, Shu & Lubynsky 2015).[13]

The paper proceeds as follows. Section 2 describes the competitions and summarizes data. Section 3 explains the empirical approach, and Section 4 contains the results. Section 5 concludes, with a focus on policy implications.

2 Data on New Venture Competitions

Novel data on new venture competitions between 1999 and 2016 provide a window into the earliest stages of entrepreneurship. The competitions (sometimes called business plan competitions or competitive accelerators) are an intermediary between entrepreneurs and investors; they act as certifiers, conveners, and perhaps educators. The competitions in my data are one- or two-day programs in which new ventures present their technologies and business models to a panel of judges. The ventures are either recently founded startups, or teams of individuals deciding whether to move forward with a startup idea. Essentially all seek external finance of some kind.

New venture competitions have proliferated over the past decade, sponsored by universities, corporations, foundations, governments at the federal, state,

[13]The large literature on the first topic also includes Gabaix & Landier (2008), Gompers, Kovner, Lerner & Scharfstein (2010), Lazear (2005), Kaplan, Klebanov & Sorensen (2012), Lindquist, Sol & Van Praag (2015) and Shane et al. (2010). Also relevant is the nascent literature on new startup resources, including Yu (2014), Winston Smith, Hannigan & Gasiorowski (2013), and Hallen, Bingham & Cohen (2014).

and city level, angel investor groups, and others. There is no formal count of the competitions, but one website that provides resources to founders, F6S, contained 4,623 competitive events as of September, 2016.[14] More specifically, in 2015 a different website provided information about 260 business plan competitions in 50 U.S. states with $23 million in prize money, and a further 122 international events with $25 million in prize money.[15]

There is little empirical analysis of startups prior to their first external funding event, and thus there is also little evidence about what types of startups participate in new venture competitions. It is difficult to assess whether the ventures examined here are "representative" of early stage startups in general. An examination of the most comprehensive early stage financing database for recently founded startups indicates that new venture competitions are an important piece of the startup ecosystem. The CB Insights database contains 15,850 firms that got their first early stage financing between 2009 and 2016, of which 2,298 have received cash prizes from a new venture competition or competitive accelerator. Among these competition winners, 114 exited via an acquisition or IPO.

The sample of 96 competitions in this paper is not accidental; it offers enough variation to glean insights into heterogeneity among places and venture types while containing enough commonalities across programs that they can reasonably be evaluated together. All the competitions have the following characteristics:

1. They include a pitch event, where the company presents its business plan;

2. They involve formal judging, in which volunteer judges score the company and these scores are recorded;

3. Specific participants are publicly announced as winners, but no loser ranks are made public;

4. The sponsoring organization does not take equity in the participating or

[14]See https://www.f6s.com/.

[15]See http://www.bizplancompetitions.com.

winning ventures.[16]

5. The sponsoring organization explicitly seeks to enable winners to access subsequent external finance.

The data are summarized in Table 1, and the individual competitions are listed in Appendix Table A1. As Table 1 Panel 1 describes, there are 214 rounds (where a round might be the semifinals in a given competition).[17] A few competitions divide preliminary rounds into panels. For example, the roughly 40 startups participating in the first round of each year's Rice Business Plan Competition are divided into about seven panels of six startups each. About 25 judges are assigned to each panel, and rank the startups within the panel. In the baseline empirical analyses, I include competition-round-panel fixed effects. Where a competition does not divide its preliminary rounds into panels, this is simply a fixed effect at the round level. The data include 543 competition-round-panels. On average there are 44 ventures in a preliminary round, and 18 ventures in a final round. The average number of winners is 4.5, and the average award amount conditional on receiving a cash prize is $66,000.

Thirty-five of the programs provide structured feedback through software from Valid Evaluation, a private company. These competitions inform ventures of their ranking relative to other ventures in their round. In the remaining competitions, ventures learn only that they won or lost, not their rank or score. In all competitions, judges verbally ask questions and usually give some type of informal, verbal feedback. In some competitions, ventures receive handwritten, non-numeric feedback. However, feedback only includes rankings relative to

[16]Some accelerators take a small equity stake in their companies, including some of the most well-known programs, like Y-Combinator and Techstars. These programs have become an additional source of seed investment, and the networking and mentorship resources they provide are not unlike those traditionally provided by conventional investors. While interesting, these programs are not the focus of this study. They should instead be evaluated alongside their counterpart investors, angel and early stage VC. By design, none of the programs examined here take equity investments in participating firms. Since the primary outcome that I examine is fundraising, it would be challenging to evaluate such programs in the same analysis.

[17]The data were obtained individually from program administrators and from Valid Evaluation. In most cases, the author signed an NDA committing not to share or publish venture/judge/founder identifying information.

other firms in the structured feedback competitions. Also, in no competitions do ventures receive judge-specific feedback, nor do judges observe each other's scores.

I observe overall firm ranks in a round, judge-specific ranks, and judge-dimension specific ranks. The main dimensions are Team, Financials, Business Model, Market Attractiveness, Technology/Product, and Presentation. In competitions where dimensions are used, judge-specific and overall scores are aggregated from judge-dimension scores. Appendix Table A2 shows that there 6,051 observations of unique company-round ranks, and 47,065 judge-specific ranks. The original data are in the form of raw scores or ranks. Different competitions use different score ranges, and the number of of ventures varies across rounds. I convert raw scores to ranks for competitions that do not provide ranks, and then calculate percentile ranks. I primarily use deciles. For metrics where preliminary panels are important, I use quintiles, as these are more appropriate for groups of less than ten ventures.

The 4,328 unique ventures in the data are described in Table 1 Panel 2, and are categorized by sector and technology type in Table 2 (and by state in Appendix Table A3). There are 558 ventures that participate in multiple competitions. The average age of the ventures is 1.9 years, where age is determined by the self-identified date of founding. I assign ventures that respond "not yet founded" an age of zero. Forty-four percent of the ventures were incorporated at the round date, lending support to my contention that the sample consists of startups with growth ambitions.

The VC industry is concentrated in California, New York, and Massachusetts; in 2015, these states accounted for 77% of total U.S. VC investment, and 80% of VC deals.[18] Ventures in these states - 35% of the sample - have access to richer networks of investors, advisers, and other resources. The competitions take place in 17 U.S. states. From a sector, geographic, and entrepreneur background per-

[18]VC investment totaled $34, $6.3, and $5.8 billion in these three states, respectively, relative to a national total of about $60 billion. The fourth state had only $1.2 billion. They had 2,748 deals, relative to a national total of 3,448 (source: PWC MoneyTree 2016 report).

spective, the sample is likely biased towards more marginal ventures than the universe of VC-backed startups. In part because of data from the Cleantech Open, a national non-profit competition focused on clean energy startups, the data skews somewhat towards clean energy.

I matched ventures to investment events and employment using CB Insights, Crunchbase, AngelList, and LinkedIn. These yielded 752, 638, 1,528, and 1,933 unique company matches, respectively. The probability of subsequent financing is 0.24, relative to 0.16 before the competition (based on the round date). I focus on subsequent external private financing as a success metric because it is a good indicator of commercial potential for high-growth startups, about which data are otherwise sparse.

In addition to financing, I use success metrics based on employment and survival as of 2016.[19] The probability that a venture has at least two employees as of August, 2016 is 0.34. The probability that a venture has an active website as of September, 2016 is 0.63. Note that in the analysis, competition fixed effects will control for date, obviating concerns about ventures in more recent competitions having less time. Three percent of ventures were acquired or went public. For a small subsample of rounds, I observe the percent of the venture owned by the presenting team and whether the venture has formal rights to its intellectual property (IP) through patents or trademarks. In researching the ventures, 765 name changes were identified. Ventures were matched to private investment on both original and changed names.

Table 1 Panel 3 describes the venture founders, using data from the competitions and LinkedIn profiles. Of the 3,643 team leaders (listed either as CEO or in the first space on the competition application), 2,155 have thus far been successfully matched to a LinkedIn profile that contains data on experience, education, or both. The median founder age, based on subtracting 22 from the college graduation year, is 28 years. The average founder had 4.5 jobs prior to the round, in 2.7 locations. The probability of having an executive title (at any

[19] I do not observe hiring events.

company) after the round is 0.13, which is higher than before the round, at 0.38, reflecting founders abandoning entrepreneurship for salaried employment.

Nineteen percent of founders have an MBA, and among these 76% have an MBA from a top 10 business school. Twenty-seven percent of founders graduated from a top 20 college, and 6% have a computer science degree from a university ranked in the top 10 for computer science (based on U.S. News & World Report rankings in Appendix Table A4). Fourteen percent of the sample has a degree from at least one of the three high-growth entrepreneurship powerhouse universities (Stanford, Harvard, or MIT).[20] I also divide the college majors (areas of study) into four groupings: liberal arts (which includes economics and finance), entrepreneurship/management/marketing, computer science/engineering, and other sciences (including math and physics).[21]

Judges participate in order to source deals, clients, or job opportunities. They also sometimes describe judging as a way to "give back" to the entrepreneurial ecosystem. There are 2,514 unique judges, whom I have parsed by profession where I have the judge name, job title, and company. I consider nine occupations, listed in Table 2. The largest group is venture capital investors, with 676 judges. There is concern that any impact of the competitions on venture financing might be contaminated by the judges themselves investing. Careful comparison of funded ventures' investors and judges revealed 95 instances in which a judge's firm invested in the venture, and 3 instances in which the judge personally invested, relative to more than 51,000 judge-venture pairs.

This paper contributes to the entrepreneurship literature by introducing a new source of data, in which I observe ventures and their founders at an earlier stage, with greater granularity, and in a larger sample than extant studies. Survey or population data sources such as the SCF, NLSY79, or BDS contain relatively few high-growth entrepreneurs, as Levine & Rubinstein (2013) point out. For example, the NLSY79 has roughly 5,400 workers, only about 10% of which were

[20]U.S. News & World Report 2016 ranks these three highest for entrepreneurship education among research universities.

[21]The data are not always clean; one founder identified his/her major as "Persuasion - The Science and Art of Effective Influence."

ever self-employed. Further, in these databases it is difficult to distinguish high-growth, young firms from local small businesses (e.g. restaurants, plumbers, and self-employed accountants). The data in this paper consist of individuals considering founding or having just founded startups. Through a new technology or business model, startups aim to become large, valuable, and transformational to their industry. One unique aspects of the data is that there are no subsistence businesses or sole proprietorships.

3 Empirical Approach

New venture competitions permit me to quantify and isolate learning, a novel and challenging exercise. The key ingredient is the signal that ventures receive about their future prospects from aggregated judge ranks. The first step is, therefore, to establish that the competitions generate valuable, informative signals. If the judges cannot predict success, rational founders have nothing to "learn" from their feedback. I therefore begin by estimating variants of Equation 1, essentially a regression discontinuity design:

$$\begin{aligned} Y_i^{Post} &= \alpha+\beta_1\left(\mathbf{1} \mid WonRound_{i,j}\right)+f\left(DecileRank_{i,j}\right)+\gamma'\left(\mathbf{1} \mid f.e._{\cdot j}\right)+\delta' X_i+\varepsilon_{i,j} \quad (1)\\ & X_i=[Prev.\ Financing,\ Judge/Judge\ Comp\ Invested,\ Sector\ Dummies,\\ & Venture\ Age,\ \#\ team\ members] \end{aligned}$$

Here, i indicates a venture, and j a competition-round-panel (e.g. the MIT Clean Energy Prize Semifinals). Y_i^{Post} is a binary outcome variable. Fixed effects are either indicators for the competition-round-panel, in which case I cluster standard errors by competition-round-panel, or indicators for the judge, in which case I cluster standard errors by judge. When other fixed effects are used, I cluster by competition-round-panel. I also include the award amount in some specifications. Note that competition-round fixed effects control for the specific date.

The coefficient of interest is on $DecileRank_{i,j}$. This is the venture's overall rank in the round, so there is one observation per venture-round. Some specifications use judge decile ranks, which is the venture's decile rank among ventures the judge scored. The best decile is 1, and the worst is 10. Therefore, a negative coefficient on $DecileRank_{i,j}$ indicates that judge ranks are positively predictive of the success metric. In most specifications, I control for a linear decile rank, but in the baseline estimation I estimate separate decile ranks among losers of a round and among winners.

The next step has two pieces. First, I ask whether whether ventures that receive especially negative feedback are more likely to be abandoned. I causally estimate the effect of negative feedback by comparing competitions where ventures receive structured feedback - they learn their rank relative to other participating ventures - with competitions where ventures learn only that they won or lost. In the latter competitions, any specific feedback is informal and, critically, not connected to how other ventures performed. It is therefore much less precise. Specifically, I estimate among losers the combined effect on the entrepreneur of receiving a below-median score, and knowing that he received a low score:

$$\begin{aligned} Y_i^{Post} = {} & \alpha + \beta_1 \left(\mathbf{1} \mid LostRound\ \&\ BelowMedRank_{i,j}\right)\left(\mathbf{1} \mid StructuredFeedback_j\right) \\ & + \beta_2 \left(\mathbf{1} \mid LostRound\ \&\ BelowMedRank_{i,j}\right) + \beta_3 \left(\mathbf{1} \mid StructuredFeedback_j\right) \\ & + \gamma' \left(\mathbf{1} \mid f.e._{\cdot j}\right) + X_j + \varepsilon_{i,j} \\ & \text{if } i \in Losers_j \end{aligned} \tag{2}$$

The coefficient of interest in Equation 2 is β_1. I similarly estimate whether there is a symmetric effect for especially positive feedback among winners. I then examine heterogeneity by adding a venture characteristic as a third interaction, controlling for the three individual effects and the three two-way interactions.

Second, I test whether measures of learning predict success. Of course, "learning" is a vague term that applies to a broad range of behavior. I focus on learning in the sense of improvement, and measure improvement as the change in the venture's rank across rounds. The advantages of this measure are that it is observable and common to all participating ventures; since they wish to win, they wish to improve across rounds. This measures learning much as an educator might measure student learning as the difference between test results at the end of the semester and at the end of the first month of class. In the preliminary round, ventures receive questions, informal verbal feedback, and sometimes written or numeric feedback. They also experience learning-by-doing through the act of pitching and in some cases, observing other ventures.

The first learning measure uses scores of written business plans prior to the competition. Ventures are explicitly told to incorporate this feedback, which they receive about two weeks before the competition, into their pitches in the actual competition. The business plan scores do not count towards winning, and include dimension and overall scores aggregated across judges.

Letting j denote the business plan phase in the competition and j' the competition's first round, the learning metric is the change in overall quintile ranks between the two phases: $\Delta_{i,j,j'quintiles}$. I estimate Equation 3:

$$\begin{aligned} Y_i^{Post} &= \alpha + \beta_1 \Delta_{i,j,j'quintiles} + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j}\right) + f\left(QuintileRank_{i,j}\right) \\ &\quad + \gamma' \left(\mathbf{1} \mid f.e._{j/k}\right) + \varepsilon_{i,j} \end{aligned} \tag{3}$$

This measure is useful because it is explicitly intended for learning. Also, the number of ventures does not change across the two phases, so there is no concern about a change in rankings due to a changing composition of participants. However, the business plan phase occurs in just two programs (the Massachusetts CEC Catalyst competition and the Rice Business Plan Competition), so the sample is small. I use either year or judge fixed effects. I also use quintiles (rather than deciles elsewhere) because in the Rice competition, business plans are judged within panels of five to eight ventures.

The second learning metric is across competitions, for the sub-sample of ventures that participate in multiple competitions. I estimate a version of Equation 4 where j denotes the first competition and j' the last competition, using the preliminary round in both:

$$\begin{aligned} Y_i^{Post} &= \alpha + \beta_1 \Delta_{i,j,j'(deciles)} + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) \\ &\quad + \gamma' \left(\mathbf{1} \mid f.e._{j'/k}\right) + \varepsilon_{i,j'} \end{aligned} \tag{4}$$

In alternative approaches, I use the maximum round the venture reached in both competitions, or use the first and second competition rather than first and last (a few ventures participated in three or more competitions).

The third learning metric is improvement across rounds within a competition. This yields the largest sample. Letting j denote the first round in the competition and j' the second round, the learning metric is the change in decile ranks between the first and second rounds of a competition ($\Delta_{i,j,j'(deciles)}$). I use variants of Equation 4. I also examine whether learning is more predictive of success when ventures are aware of their rank than when they are not. I do this by interacting Equation 4 with the indicator for receiving structured feedback.

Thus far, the empirical approach demonstrates that (a) judge ranks are valuable signals; and (b) learning predicts venture success and is thus useful to ventures. I next examine which types of ventures and founders learn. I estimate variants of Equation 5, where the dependent variable is the change in deciles across rounds:

$$\Delta_{i,j,j'(deciles)} = \alpha + \gamma' \mathbf{C}_i + \beta_1 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) + \varepsilon_{i,j'} \tag{5}$$

Here, $\mathbf{C}_i$ is a vector of venture characteristics. To ease reading, I describe the characteristics and their economic context when presenting the results in the following section. The earlier specifications used competition-round-panel fixed effects, and established that the relationship between improvement across rounds and subsequent success is not spuriously associated with a single competition. In the heterogeneity analysis, I omit these fixed effects to maximize power in the considerably smaller sample.

The primary empirical concern is that judges are sorting firms on unobservables around the cutoff. This is unlikely. Although the number of awards is known ex-ante, judges score independently - and typically only score a subset of the participating ventures - so they cannot sort the firms around the cutoff. The judges' scores are averaged to form the overall score, which determines which firms move forward and win. Sometimes the judges discuss which among the teams they observed to send forward, but this occurs after they have independently entered scores electronically or on score-sheets. Judges individually do not rank or score candidates; they provide numeric scores or ranks and do not know what the "high score" in a competition will be. Thus there is little means for sorting to happen ex-ante.

One limitation of this study from a policy perspective is that the evaluation is limited to participating firms. Accelerators may have region- or sector-wide effects beyond the companies that participate. For example, the mere presence of a business plan competition at a university might make students more likely to become entrepreneurs. Fehder & Hochberg (2014) address this issue by comparing regions with and without accelerators. They find that the presence of an accelerator in a region increases financing events for non-accelerated firms. Unfortunately, this is beyond the scope of the present study.

4 Results

4.1 Signal Informativeness

I first establish that the competitions generate valuable signals. I begin by describing results from estimating the regression discontinuity design in Equation 1. Table 3 columns I and II show that within final rounds of a competition, winning increases a venture's probability of subsequent external private finance by 12-16 percentage points (pp), relative to a mean of 24%. The effect of winning is somewhat larger, at 21-22 pp, when I consider preliminary rounds (columns IV-V). Similarly, using judge fixed effects and controlling for the judge decile rank, winning increases the probability of financing by 23 pp. This specification, in column IX, has a much larger sample because an observation is a judge-venture-round, rather than a venture-round.

Column VII includes the cash award amount; interestingly, as the large effect of winning a preliminary round foreshadowed, winning is useful independently of the award. An extra $10,000 in cash prize increases the probability of financing by about 1 pp. Controlling for this award effect, winning increases the probability of financing by 8 pp.[22]

Table 4 considers other outcomes, pooling across rounds. Winning increases the probability of subsequent angel or series A VC investment (a subset of the dependent variable in Table 3) by 11-15 pp, relative to a mean of 15% (columns I-II). It increases the probability the venture has at least three and at least 10 employees in 2016 by 9-15 and 7-12 pp, respectively, relative to means of 30% and 20%. The effect on having at least two employees is virtually identical to having at least three employees. Winning increases the likelihood the venture experienced a successful exit by 2 pp, relative to a mean of 3%. Finally, winning increases the survival probability (whether the venture had an active website in 2016) by 5-12 pp, relative to a mean of 63%.

The learning metrics require judge ranks to be meaningful signals about startup quality. I assume ventures seek to improve in the judges' estimation, and further that improvement in rankings, regardless of whether the venture observes its ranks, reflects venture learning. It is critical, therefore, that the venture's rank predict subsequent success, independently from the effect of winning or losing.

Across all these outcomes, as well as for financing in Table 3, the coefficients on decile rank are negative and highly significant. A decile rank of 1 is best, and 10 worst. When I separate the decile rank on either side of the cutoff (as, for example, in Table 4 column I) the slopes are generally negative and significant on either side of the cutoff. In some cases, the slope among winners (particularly

[22]Depending on the specification, winning is separately identified because of the variation in award amount, because not all competitions have prizes, and because in some competitions not all winners receive cash prizes.

when rounds are separated by type, as in Table 3) is not statistically significant; this is in part because there are few winners in final rounds and the regression cannot distinguish the effects of winning from the slope in ranks. As an example of the interpretation, the coefficient on decile rank in round in Table 4 column IV implies that being ranked one decile higher increases the probability a venture has at least three employees by about 1 pp. In general, the relationships are stronger among losers, as they are a larger group and the effect of rank is uncontaminated by the indicator for winning. An extra decile of rank among losers increases the probability of at least three employees by about 2 pp (Table 4 column III), and increases he probability of financing by 1.4 pp (Table 3 column VII).

Logit specifications in Table 3 columns III, VI, and VIII confirm the strong predictive power of rank. I rely on OLS models in the remaining analysis. Not only does OLS have a simpler interpretation, but logit drops groups without positive outcomes, leading to overestimation when there are many fixed effects. Last, Figures 1 and 2 demonstrate visually the effects of winning and the predictive power of rank on either side of the cutoff for two important outcomes: subsequent financing and having at least three employees in 2016.

It is possible that the positive effect of winning actually reflects a negative effect of losing. Perhaps it is costly in time and travel expense for the venture to compete, or perhaps losing generates a negative signal about venture quality. This would require substantial irrationality on the ventures' part. If the downside of losing - which is much more likely given that only a small share of competitors win - were much larger than the upside of winning, no ventures should participate. Instead, many of the competitions observed here are oversubscribed. For example, the Rice Business Plan Competition receives between 400 and 500 applications for 40 places in its annual competition. I show that winning a preliminary round is useful even when the venture ultimately loses, and that among losers, a higher rank is predictive of success. These finding suggest that competitions may well be useful for a large majority of participants.

4.2 Effect of Feedback on Continuation

Learning means "to become informed." The first type of learning I consider is whether ventures that receive especially negative feedback are more likely to be abandoned. This measures learning in the sense of observing a real outcome response to new information.

Equation 2 is estimated in Table 5. The coefficient of interest gives the effect of having a below median rank among losers in a round where the venture is informed of its rank, relative to having a below median rank among losers in a round where the venture is *not* informed of its rank, after controlling for the two individual effects of below median rank and receiving structured feedback. The control group is the above-median losers in both types of competitions.

I use two outcome measures to proxy for continuation (not failing): having at least two employees in 2016, and having an active website (operating) in 2016. Table 5 columns I-V show that negative feedback increases the probability of failure by 7-13 pp; note the sample mean that does continue is 34%, so the effect is about a 15% increase in the likelihood of failure. Columns VI-VIII show an effect of 6-10 pp on operating, relative to a mean of 63%. While specific to this context, this provides the first causal estimate of the effect of feedback on venture abandonment. This suggests that on average, ventures are not so overconfident as to give zero probability to the failure state; interim signals do matter.

This effect is weakly symmetrical for winners. Appendix Table A5 examines whether receiving particularly positive feedback makes winners of a round more likely to continue. The sample is smaller, as most rounds have far fewer winners than losers. With judge fixed effects, there is a strong positive effect on continuation of extremely good feedback. However, this effect disappears when I use the standard sample of one venture-round observation.

Heterogeneity in Responsiveness

There is strong heterogeneity across venture types in responsiveness to negative feedback. Table 6 adds a venture characteristic as a third interaction. The option to abandon should be most valuable at an earlier stage. If entrepreneurs are experimenting, and value the abandonment option, the response should be strongest among earlier stage firms. Further, earlier stage ventures likely have less private information about their own potential, leading them to update more when they receive negative feedback. I examine three proxies for firm stage: receiving prior external financing, being incorporated, and age in years.

Column I shows that ventures with previous private financing are much less responsive to the negative signal; they are 40 pp more likely to continue (using the positive employees metric) after receiving especially negative feedback. Column II shows that incorporated ventures are similarly less responsive. These results suggest that very early stage founders treat entrepreneurship as an option, valuing the ability to abandon a venture when they receive negative feedback. As the venture reaches the milestones of incorporation and initial funding, the option to abandon becomes less valuable. Note that the regressions control for the average higher likelihood of continuation for previously funded and incorporated startups. Appendix Table A6 asks what venture characteristics predict success, controlling for winning, rank, and competition-round-panel fixed effects. As we might expect, startups that previously raised external finance or were incorporated at the time of the round are much more likely to succeed.

Table 6 column III shows that older (above median age) ventures fail somewhat *more* in response to negative feedback than younger ventures. One explanation is that judges' feedback is less informative for very young ventures (recall the median age is about 9 months). The youngest ventures may have too short of a track record, or may not have settled on their final business model. Indeed, Appendix Table A7 columns II-III show that when Equation 1 is estimated separately for below- and above-median age ventures, the predictive power of rank triples for financing and almost doubles for positive employment. This is evidence that the signal is more precise for somewhat older ventures.

Technology type is related to a firm's cost of pivoting and to external financing availability. I consider three sector variables. First, the cost of experimentation (or pivoting) should be lower for IT/software ventures than for hardware startups. Second, ventures more likely to be financially constrained are in capital-intensive or social impact-driven sectors. I create a “hard-to-fund” indicator for for the following sectors: social impact, energy, manufacturing, air/waste, transportation, education, or biotech. As Appendix Table A6 columns II, V, and VII show, this indicator is indeed a strong negative predictor of financing (while columns I and IV show that software-based ventures are much more likely to be financed). The third indicator is more narrowly associated with large non-pecuniary benefits; ventures that self-identify as social impact or clean technology/renewable energy ventures.[23]

Table 6 column IV shows that IT/software startups are much more responsive; they are 14 pp more likely to fail after receiving especially negative feedback than hardware startups. However, I find no such significant effect of the triple interaction for the hard-to-fund or social/clean tech indicators. A lower cost of launching a startup appears to make abandonment a more attractive option, and this does not seem to be linked to higher non-pecuniary motivations for hardware founders.

This supports the argument in Kerr et al. (2014) and Ewens et al. (2015) that the cost of resolving initial uncertainty about whether a new technology or business model will work helps determine which projects are funded and thus the direction of innovation in the economy. They attribute the dramatic increase in web- and software-based startups in the 2000s in part to the dramatic fall in computing power and storage costs. One implication is that new ventures with high initial capital intensity have become relatively higher cost experiments. In particular, the option value of entrepreneurship is lower for a hardware technology. Resolving uncertainty about their viability will require more time and more money than software ventures.

Last, column VII shows that ventures from the three VC hub states are

[23]Both the hard-to-fund and social/clean tech indicators include some software startups but are negatively correlated with the IT/software indicator (see the correlation matrix in Appendix Table A8 Panel 2).

less responsive. Feedback may be less relevant for them; Appendix Table A9 shows that the coefficient on rank is smaller for ventures from hub states.

Before examining founder heterogeneity, it is useful to know which founder characteristics predict success. Table 7 shows that the number of jobs a founder lists having held prior to the round is strongly predictive of subsequent financing (Panel 1), as well as the other outcomes (Panel 3). The number of geographical locations a founder reports having worked strongly negatively predicts success. This is the first indication of a broad finding in this paper that founders who invest in building a local network of resources are more likely to succeed. Being student at the time of the competition is strongly predictive of subsequent success (Panel 1 column V). Consistent with this, founder age at the time of competition is negatively associated with success. I do not include all characteristics in a single model as some characteristics, like founder age, are available for only a small subset of the data.

Any degree from Harvard, Stanford or MIT increases the probability of subsequent financing by 15 pp and the probability of having at least 10 employees in 2016 by 21 pp, significant at the 5% and 1% levels, respectively (Table 7 Panel 1 columns III and IV). Among founders with a computer science degree from a top ten computer science university, an additional rank within that top ten (that is, attending a school ranked, say, seven rather than eight) increases the probability of subsequent financing by 4.2 pp, quite a large effect (Table 7 Panel 2 column I). There is also a positive effect of attending a higher ranking college among the top 20 (Table 7 Panel 2 column II). These results recall a similar relationship between college selectivity and success for CEOs of VC-backed companies in Kaplan et al. (2012).

Elite education is negatively associated with the top tail outcome of undergoing an acquisition or IPO.[24] Figure 3 contains coefficients from regressions of each outcome on the two indicators for elite education and competition fixed

[24]Table 7 provides some evidence of this; note that variables other than elite education do have statistically significant predictive power over acquired/IPO, and recall from Table 4 that both rank and winning significantly impact the probability of a successful exit.

effects. The effect of having an elite education is largest and most significant for the survival metrics (operating and having at least two employees as of 2016), at about 8 pp. The effect on having at least 10 employees is similar for the Harvard/Stanford/MIT metric, but declines to 3 pp for the top 10 MBA program indicator. The effect of both metrics on acquired/IPO is *negative* (about -2 pp). However, the highest performing startups may not have had time to exit; a manual check indicates that most of the exits are relatively small value, early stage acquisitions.

Among the majors, only entrepreneurship/managing/marketing predicts success. There is no statistically significant effect of having an MBA, but holding a non-MBA master's degree negatively predicts subsequent financing as well as the probability the company remains active in 2016.

Table 8 then turns to heterogeneity in the effect of receiving negative feedback. I interact the specification in Table 6 with various founder characteristics. Column I shows that students are much more responsive; the effect of negative feedback is 30 pp higher for students than non-students. Students are deciding whether to enter entrepreneurship; the option to abandon the idea is perhaps most valuable for this group. Students may also place greater weight on judges' advice because they have little personal experience. Consistent with this, founders with more previous jobs are less responsive to feedback (column II). The fact that more experienced founders are less responsive may also relate to the amount of private information they have; these founders could have a more informative private signal, but as in Oskamp (1965), their overconfidence (in the sense of over-precision or miscalibration) might be increasing with age.

The abandonment option might be especially valuable for elite individuals. Surprisingly, having any degree from Harvard, Stanford, or MIT makes a founder much *less* responsive to feedback; this difference is large in magnitude at 69 pp. Yet neither graduating from a top 20 college nor having an MBA have any effect (columns IV and V). The most elite individuals do not seem to respond to feedback, a finding discussed further below.

One measure of venture risk is uncertainty among judges.[25] When I interact the effect of negative feedback with an indicator for whether the standard deviation of judge ranks within a competition-round-panel is above median.[26] The triple interaction has a strong positive effect; when judges are uncertain, founders are more likely to reject the negative information and pursue their venture (Table 8 column VI). This is suggestive evidence that more confident founders choose riskier business models, consistent with the findings among CEOs in prior work, including Hirshleifer et al. (2012) and Graham et al. (2013). However, it should be interpreted with caution. A lack of consensus in judge ranks could manifest during the competition through questions and verbal feedback. An alternative explanation is that founders pay less attention to the rank when they know there was no consensus among judges.

While the venture does not observe each judge's score, the entrepreneur does know the number of judges. Thus the signal (observing their rank, which is the average of judge individual ranks) is more precise when the sample of judges is larger.[27] If entrepreneurs are updating their beliefs in an approximately rational way, I expect that they will update more when the signal is more precise. Table 8 column VII interacts the effect of negative feedback with an indicator for whether the number of judges on the panel was above median. The coefficient is is large and negative, though significant only at the 10% level. This provides some evidence that updating reflects signal precision, consistent with experimental evidence in Poinas et al. (2012) and survey evidence inBen-David et al. (2013).

[25] Appendix Table A10 suggests that judge uncertainty - after controlling for rank and winning - predicts angel/VC series A financing, consistent with these types of investors targeting risky ventures.

[26] Ventures are unaware of this uncertainty; they receive only their aggregated rank in the structured feedback competitions.

[27] The quality of judges may vary across competitions, but Appendix A18, which shows the predictive power of ranks by judge profession, suggests that a variety of judge types' scores are predictive of success.

4.3 Value of Improvement

I next turn to measures of learning in the sense of improvement, rather than in the sense of determining entry or exit based on new information. I first ask whether learning predicts success. It may be that successful founders enter with the strongest business models and pitches. If the measure of learning is not useful, then it will not be interesting to examine which founders exhibit it.

The first measure is the change in rank between the business plan and first round of the competition. Improvement in ranking between these two phases predicts success across all outcomes. Estimates of Equation 3 in Table 9 find that improving a quintile from the business plan to the preliminary round increases the probability of subsequent financing by 5.5 pp relative to a mean of 24%; improving a quintile from the business plan to the final round increases the financing probability by 11 pp. The remaining specifications show similarly strong effects on other outcomes.

The second measure is learning across competitions. Estimates of Equation 4, in Table 10, show that for the subset of ventures that compete in multiple competitions, improving across preliminary rounds between their first and last competition is also predictive of success. Depending on the specification, Panel 1 columns I-III show that improving a decile increases the probability of subsequent financing by about 1.8-3.4 pp, and increases the probability of having at least 10 employees in 2016 by 2.9-3.9 pp. Appendix Table A11 uses the first and second competition, rather than first and last, and Appendix Table A12 uses the highest round the venture reached, rather than the preliminary round. Both tables provide similarly strong positive effects of improvement on all outcomes.

The last measure, which I rely on for the heterogeneity analysis, is the change in rank across rounds. Table 11 shows that improving a decile across rounds increases the chances of subsequent private financing by 1.8 pp, and the probability of having at least 10 employees by 1.5 pp. These estimates control for competition-round-panel fixed effects, and the predictive power of rank is quite similar with models using judge fixed effects. The Appendix conducts robustness tests of this measure's importance to outcomes. First, Appendix Table A13 uses quintile changes and finds similar results. Second, Appendix Table A14 column I-IV include venture controls, and columns V-VIII use the decile change between the first and final rounds, rather than first and second rounds.

Table 12 predicts success at the founder level with the change in decile across rounds measure. My measures for a person's subsequent success is whether they have an executive title after the round (CEO, CTO, VP, COO, or President) in the venture or any other company, and whether they founded a new venture. Columns I and IV show that a one decile improvement across rounds increases the probability of a subsequent executive title, or of founding a subsequent venture, by about half a percentage point, albeit significant only at the 10% level. When I examine the decile changes in dimension scores, only presentation score changes are predictive of a founder having an executive title or founding a subsequent venture. This is highly predictive: a decile improvement in presentation score across rounds increases the probability an individual has an executive title by nearly 1%, relative to a mean of 13%.

Structured feedback makes learning more valuable. I interact the learning across rounds measure with whether the competition provided structured feedback. Table 13 shows that when ventures are informed of their rank in the round, the effect of improving across rounds on subsequent success is relatively larger. Column I finds that the effect of learning on subsequent financing is 24 pp higher in structured feedback than in non-structured feedback competitions. Similar differences exist for three and 10 employees (columns IV and V).

Heterogeneity in Learning

Having established that decile rankings are predictive of success, and that measures of learning using improvement in decile rankings are also predictive of success, I now turn to which ventures learn. Tables 14 and 15 estimate variants of Equation 5, where I regress the learning measure (change in deciles) on characteristics as well as winning and overall rank in the latter round.

I expect that software ventures have lower costs of experimentation, but as mentioned above, such ventures may also be associated with founders that place relatively more value on pecuniary benefits. Columns I and II show that software ventures learn much more. With all characteristics included, the hard-to-fund and social/clean tech indicators are not significant. However, social/clean tech ventures learn much less in regressions with fewer controls (columns II and IV). The estimates indicate that, controlling for the separate effects of winning and rank, social/clean tech ventures on average decrease by half a decile (5 pp) in ranking across rounds, while software ventures improve by 6 pp. These differences suggest that non-pecuniary motivations are associated with less learning, and a lower cost of experimentation leads to more improvement.

The next characteristics address venture stage. Ventures with previous external financing learn more (column I). However, ventures that were incorporated at the time of the round learn less than unincorporated ventures, and older ventures learn less than younger ventures. Thus ventures appear to learn the most from feedback at their earliest stages, suggesting that competitions and possibly other interventions are most useful if targeted to ventures at roughly the time of founding. Previous financing - like learning itself - is perhaps an indicator of venture quality that trumps previous financing's small positive correlation with age and incorporation (see Appendix Table A8 Panel 2). These results support an "entrepreneurship as experimentation" hypothesis for the earliest stages of a venture; in later stages, entrepreneurs may become less receptive to new information.

Consistent with the structured feedback analysis, where ventures from VC hub states were less likely to fail in response to negative feedback, column IV shows that being from a hub state reduces learning substantially. For a small group of the founders, the competition data include whether the venture possesses formal IP rights - usually a patent - and the percent of the company owned by the presenting team. The indicator for the team owning more than 90% of the venture in column II is negatively associated with learning (column IV). This provides confirmation of the previous financing result from a different source. Possessing IP rights is more difficult to interpret. It is an indicator that the venture intends to profit from its technology and is also positively associated with hardware startups (see Appendix Table A8 Panel 2). Like previous external financing, it is likely also a proxy for venture quality and founder commitment. The indicator for possessing IP rights is strongly positively associated with learning (column V). This supports the inference above that when ventures are oriented toward future profits, they learn more.

I also find that uncertainty among judges is negatively associated with learning, as it was associated with less responsiveness to negative feedback. Founders of riskier ventures may be more overconfident and learn less.[28] Landier & Thesmar (2009) find that entrepreneur overconfidence increases with the entrepreneur's outside option and decreases with the quality of his signal. Here, analogously, responsiveness increases with signal precision. I do not find a relationship between the number of judges and learning.

Learning varies with founder characteristics as well. Table 15 column I combines the key founder characteristics, and shows that two have particular significance. First, founders with MBAs learn much more; having an MBA increases the change in deciles between rounds by .84, or nearly one decile. Second, receiving any degree from one of the three elite universities has a strong negative effect on learning; this indicator is associated with the venture decreasing in rank by 5.8 pp. In column II, I include only whether the founder has an MBA and whether the MBA was from a top 10 program. The MBA effect increases to 1.1 deciles. The effect of having a top ten MBA is to *decrease* learning by 0.8 deciles.[29]

Recall from the structured feedback analysis that elite graduates are much less likely to abandon their venture when they received especially negative feedback (Table 8). Similarly, Table 15 columns I and II show that graduates from the very top schools - for college and MBAs - learn less. This contrasts with a

[28]As above, this result could also be explained by more muddled feedback, to the degree that ventures are improving across rounds in response to specific feedback from judges.

[29]The other characteristics, like the number of prior jobs or having a PhD, are not statistically significant in this specification or when considered independently.

simplistic story in which higher quality ventures and founders learn more. All ventures selecting into participating wish to win and thus try to improve across rounds. Thus if the elite founders were rational they would exhibit learning. Therefore, they appear to be overconfident, in contrast to the rest of the sample, which is very responsive to feedback.

Elite school founders are more likely to raise venture capital investment and hire ten or more employees. They are less likely to experience an acquisition or IPO, but this may reflect truncation of the sample; given that most of the data is post-2010, it seems likely that the top performing VC-funded startups in the data have not yet exited. Particularly if there is a wage premium for failed entrepreneurs, as Manso (2016) suggests, elite founders' failure to learn is not necessarily suboptimal. The few that do succeed may benefit from their overconfidence, an evolutionary explanation for overconfidence explored by Bernardo & Welch (2001) and Goel & Thakor (2008). Related evidence exists in both theory and empirical work for large firm CEOs. Kaplan et al. (2012) find that better performing CEOs are characterized by less openness to criticism and feedback. Bolton, Brunnermeier & Veldkamp (2013) theorize that good leaders make an initial assessment of their environment, and then persist in their strategy regardless of new information.[30]

Overconfidence is often refined into two more specific biases. Over-optimism implies the individual overestimates his mean chance of success, while over-precision (also called "miscalibration" or "judgmental overconfidence") implies the individual overestimates the precision of his information. Whether elite founders are over-precise or over-optimistic matters for firm outcomes. Galasso & Simcoe (2011) and Hirshleifer et al. (2012) Hirshleifer et al (2012) show that over-optimistic CEOs invest in more innovation, while Herz et al. (2014) show that over-precise CEOs invest less.[31]

I showed above that ventures are more responsive to negative feedback

[30]Elite founders may also be less responsive because, conditional on venture quality, they have personal wealth that reduces the cost of failure.

[31]Both types are associated with greater executive risk-taking and leverage (Malmendier et al. 2011, Ben-David et al. 2013).

when the signal is more precise, where signal precision is measured by the number of judges. While I do not find that this signal precision measure has correlates with learning, it is useful for teasing apart the type of overconfidence among elite founders. Relative to unbiased entrepreneurs, over-precise ones should put less weight on a noisy signal than a precise signal; that is, they should weight their own signal more highly if they believe it is more precise. Entrepreneurs without this bias should differentiate less between noisy and precise signals. I expect that this differences-in-differences construct will show over-precise founders to be relatively more responsive to a more precise signal than unbiased founders.

Appendix Table A15 interacts elite status (top three schools in column I, and top ten MBA in column II) with the indicator for whether the number of judges is above median. The coefficient on the interaction is small and insignificant. This test by no means establishes that elite founders are not over-precise, but it provides some evidence that the dominant form of overconfidence among elite founders is over-optimism. The ambiguous relationship between these founders and ultimate success is consistent with the literature, which has generally found overoptimism to be widespread among CEOs but to have a mixed or non-monotonic relationship with value creation (Puri & Robinson 2007,Malmendier & Tate 2008,Goel & Thakor 2008). In the startup industry, it tends to be viewed favorably. For example, a well-known venture capitalist wrote: "Genetic or not, there are certain classic characteristics of the entrepreneur. The most important of these are certain kind a visionary optimism; tremendous confidence in oneself that can inspire confidence in others" (Bussgang 2011).

While suggestive, this provides some basis for how learning and overconfidence interact with innovation. New entrants with radical technologies may be those that are less responsive to feedback, while those with more incremental ideas learn more. Theoretical models of industry dynamics could micro-found technological discontinuities in the small fraction of entrepreneurs that enter without regard to signals about net discounted expected cash flows, while the mass of entrants remain rational and responsive to new information. The former group are potentially transformative, and their overconfidence is crucial to coordinating others, as emphasized in Rajan (2012), Bolton et al. (2013), and the venture capitalist quote above.

Table 15 Column III shows that learning is higher when the founder is a student at the time of the competition, consistent with the greater responsiveness of students from Table 8. Columns IV and V include indicators for the founder's college major. Across specifications (including many not shown here), the entrepreneurship major is strongly associated with learning. In case some founders use the "Major" field to describe their MBA studies, in column V I add controls for having an MBA and a top 20 college degree. The effect of the entrepreneurship major retains its large magnitude and statistical significance. Individuals trained in entrepreneurship and management, whether as undergraduates or MBAs, learn the most. At the college level, this course of study is positively associated with subsequent success. Unfortunately, if there is any relationship between having an MBA and subsequent success, Table 7 (especially Panel 3) suggests it may be negative.

There has been a massive rise in entrepreneurship education since the early 1980s, when only a handful of colleges offered any entrepreneurship courses. In 2008, there were at least 5,000 such courses, with some colleges making them core requirements (Morelix 2015). I show that entrepreneurship education is associated with greater adaptability. While not causal, this is some validation of educators' intent to teach nascent founders the ability to learn from feedback about their ventures. However, I find that such education *and* the associated greater learning are correlated with subsequent success for entrepreneurship education only at the college level.

It is interesting to note that some characteristics strongly predict success yet seem unrelated to learning. For example, founders with more job experiences (including, potentially, internships) prior to the competition are much more likely to succeed in their ventures, yet founder age is negatively associated with subsequent success. Founders with job experiences in more locations are less likely to succeed, perhaps because they have not built a local support network where they are launching the venture. Having non-MBA Master's degree is also negatively associated with success. As we might expect, a higher ranking computer science degree is strongly associated with success. However, these characteristics do not interact with learning.

Who Benefits from Learning?

Finally, Tables 20 and 21 interact learning with characteristics to determine which types of ventures and founders benefit more than their counterparts from learning. For example, it may be that elite school founders are overconfident and in general learn less, but when they do learn, it is helpful for them. Table 21 columns I and III suggest this is not the case; while as above both learning and elite degrees predict success, there is no interaction between the two. [32]

The most surprising heterogeneity in the value of learning is across age; for both company age (Table 20 columns III and IV) and founder age (Table 21 column VII), I find a robust positive relationship between age and the value of learning. Improving a decile when the company (founder) is one year older increases the probability of financing by 0.22 pp (0.16 pp). The value of learning is also higher when the individual founded a previous enterprise. This is perhaps contrary to intuition that students or younger people gain more from learning. Note that above I showed that younger people and students learn more; here I find that when older people learn, it is relatively more valuable to them. This may reflect a higher cost of failure for older founders. It does not seem to reflect a difference in signal strength, as the coefficient on rank is roughly similar across these types.

The second important finding from Table 20 is that founders with a degree in computer science or engineering benefit more from learning (column VII),

[32]These tables include characteristics with strong learning-related findings or where the relationship between learning and the characteristic is statistically significant. I find that the value of learning does not vary systematically across most of the characteristics, like being a student, the founder's number of previous jobs, or being from a VC hub.

even though they do not learn more on average than their counterparts. These founders may have technical skills related to the venture's product, but need help with their pitch and financial approach. Those are the dimensions along which learning was most predictive of success (Table 18).

4.4 Learning mechanisms

We have established that learning is valuable, but that there is substantial heterogeneity in which types of ventures and founders learn. Now I examine evidence that sheds light on *why* learning is useful, and exactly *what type* of learning is observed here.

Heterogeneity over time suggests that learning is valuable because it leads to more efficient allocation of human capital resources. I examine whether winners of final rounds were more likely to have improved in certain years. Table 16, using this small sample of final round winners where I have a change in decile metric, offers striking evidence that learning increased during the financial crisis. In columns I-III, I use dummies for pre-crisis (omitted), crisis (9/15/2008 to the end of 2010), and post-crisis. Relative to the pre-crisis period, there was much more learning among winners. Column II, which controls for rank, finds that improvement across rounds was 6.7 pp higher during the crisis. Learning also seems to have subsequently declined; relative to the pre-crisis period, learning has been 7.6 pp less in the post-crisis period. Column IV uses indicators for two-year periods, confirming the greater learning during the crisis (2008-09).

Column V shows what share of firms competing in each two-year increment subsequently received financing. There is relatively little variation, except that the 2010-11 population was about 10 pp more likely to receive subsequent financing (38% relative to a mean of 24%). Since the median firm age is about 9 months, it is possible that firms founded during the crisis, and competing in 2010-11, were of higher quality.

When times are hard, founders become more open to feedback. As financing availability and the value of the founder's outside option both decline, persisting with a bad idea becomes increasingly costly. These results suggest an interesting interaction between high-growth entrepreneurship and capital market cycles. Entrepreneurs may pursue many bad ideas during expansions, when financing is relatively cheap, leading to resource misallocation. During recessions, learning quickens as financing becomes more expensive. This provides a mechanism for one aspect of the increased destruction, or cleansing effects of recessions, observed and theorized in Caballero et al. (1996). It also supports Fort et al. (2013), who find that young, small businesses are more sensitive to contractions than older, small businesses.

There are two general mechanisms that might explain improvement across rounds. First, firms may refine how they present their idea, but the underlying technology and business model may not change. Alternatively, firms may change their strategy or pivot to an entirely new idea. I use two approaches to understanding the type of learning: examining which dimension of learning across rounds predicts success, and examining whether business descriptions change across competitions.

Different dimensions predict different kinds of success. Table 17 shows that for all outcomes other than IPO/acquisition, a higher team rank is the strongest predictor of subsequent success. This is consistent with the literatures showing a positive correlation between good managerial practices and productivity in large firms(Bloom et al. 2012, Bloom et al. 2016, Guiso et al. 2015), and on the importance of a startup's management team to prospective VC investors (Gompers et al. 2016).

Presentation ranks predict financing but not any other outcome. A better technology or product predicts IPO/acquisition and survival. The financials rank, which reflect a venture's recent and planned fundraising, as well as near-term cost management, is especially important to survival and to having a large number of employees. The business model rank, an indicator of a venture's long term plan to make a profit, does not predict success. This may be an excessively vague criterion with which judges cannot effectively discriminate. For a small sample, the data include scores for two additional dimensions, which confirm the value of specificity. Having IP protection and a solid legal footing predicts survival, and traction or having validated the technology predicts subsequent financing. These are shown in Appendix Table A15.

Table 18 shows that learning on the financials dimension matters most for financing and employment. Presentation improvement matters a great deal for subsequent financing and IPO/acquisition, but is not statistically significant for the other outcomes. Improvement in business model scores, interestingly, negatively predict IPO/acquisition, and have negative but insignificant coefficients for the other outcomes. It may be that focusing on long term, abstract plans distracts ventures from concrete, near-term objectives. Managing financing effectively is crucial for startups, as this type of firm typically sustains initial losses to achieve high growth before ultimately realizing returns for founders and investors. The importance of presentation for investment is consistent with the pitch being a key fundraising component, and with competitions helping new ventures to refine it.

In general, the judges are based in the same geographic location as the competition, but participating ventures are typically drawn from diverse locations.[33] Appendix Table A9 shows that the competitions are useful to ventures regardless of the venture's home state.[34] Column VII shows that when the competition is in the venture's home state, the venture's unconditional probability of subsequent financing is 10 pp higher. However, there is no additional benefit from winning when the venture is local (the interaction Won round·Same state is near zero and insignificant).

Ventures from states besides the three VC hubs are responsible for the positive same state effect. Appendix Table A16 shows that in the overall sample,

[33]An exception is the HBS New Venture Challenge, where all teams have at least one member who is an active Harvard student (at any Harvard school). However, even in the HBS program, some ventures are not from Massachusetts.

[34]Columns I and II show that when the sample is restricted to VC hub states, the effect of winning and the predictive power of rank are slightly smaller than when these states are excluded. Restricting the sample to Arizona or Colorado (columns III and IV) also yield similar results, as does excluding all major clusters (column VI). I find analogous results for other outcomes (not reported). None of the differences across these regions are statistically significant.

being local increases the probability of financing by 11 pp. This regression, in column I, is the same as that in Table A9 column VII except it excludes the interaction.[35] This confirms the importance of local networks for high-growth entrepreneurs. The effect disappears when the sample is restricted to ventures from VC hub states (column II). In columns IV, VI, VIII and X I interact the indicators for VC hub state and the venture and competition being in the same state. As we might expect, VC hub ventures are on average 24 pp more likely to raise private financing. The same state effect remains strongly positive. The interaction between the two, however, is -21 pp, significant at the 1% level. This suggests that participating in a local competition is much more useful for ventures outside the primary entrepreneurial ecosystems, where the competitions serve as important convening mechanisms.

While I find no differences in learning across states, I do find that on average learning is more valuable for ventures when the venture is in the same state as the competition. Table 19 column I shows that the interaction between improvement across rounds and an indicator for the venture being from the same state as the competition increases the probability of subsequent financing by 1.5 pp. Note that this specification controls for these two individual effects, winning, rank, and whether the judge or the judge's company invested in the venture. Column IV shows an analogous effect for having at least three employees in 2016. In columns II, III, V and VI I additionally interact the specification with an indicator for being from a VC hub state. The triple interaction effect on subsequent financing in column III is -4 pp, significant at the 5% level (this triple interaction represents, for example, the effect of learning for a venture from Massachusetts in a Massachusetts competition). Column V shows essentially the same result for employment.[36] Note again from the individual VC hub effects that ventures from these two states have much higher average probabilities of success.

[35] Subsequent columns show positive effects of being local on employment and survival.

[36] Not shown, I find similar and also statistically significant effects for the other employment outcome metrics.

Columns III and VI control for whether the founder has a degree from Harvard, MIT, or Stanford, the elite schools in these hubs. Recall from Table 15 that entrepreneurs from elite schools, while being more likely to succeed, learn less. Since these schools are in the VC hub states, it could be that the negative hub state effect reflects these founders. However, the negative relationships grow stronger with this control. Separate from an elite school effect, judge feedback is most helpful when the judge is local in places with fewer entrepreneurial resources.

Chatterji et al. (2013) point out that while the top tail of high-growth startups tend to flock to Silicon Valley, a region's local supply of entrepreneurs is important for establishing an innovation cluster. Figueiredo et al. (2002), Glaeser et al. (2010), and Audretsch et al. (2012) show that entrepreneurs disproportionately locate near where they were born. Chatterji et al. (2013) conclude that "policy efforts to build entrepreneurship among a location's existing residents may be more powerful than efforts to attract outside entrepreneurs to the city." This paper offers evidence that a local network of investors and advisors enable the most useful learning for marginal entrepreneurs outside of clusters, while, as Chatterji et al. (2013) hypothesize, founder from out of town benefit less.

5 Conclusion and Policy Discussion

In seeking to explain why entrepreneurs own such large, undiversified stakes in their firms, Bitler, Moskowitz & Vissing-Jørgensen (2005) conclude that "the decision to become an entrepreneur remains somewhat puzzling." It is possible that entrepreneurs are simultaneously endowed with a technology, business model, and beliefs about future profits. Their expectations may be static, changing only when the firm fails, as in in Acemoglu et al. (2013). Such static information is consistent with empirical evidence of low returns to entrepreneurship, and explanations for entrepreneurial entry based on overconfidence, over-optimism, or very high non-pecuniary benefits.

Yet in many theoretical models of firm dynamics and occupational choice, entry and exit occur when entrepreneurs or firm managers rationally learn from new information. If such a learning process is occurring, we know little about it. This paper explores whether and how entrepreneurs respond to new information in the context of new venture competitions. I demonstrate that learning is strongly predictive of success and that new ventures do respond to feedback. Ventures likely to have large non-pecuniary motivations, particularly those that identify as "social impact" or "clean tech," are less responsive. Elite founders are also less responsive in ways consistent with overconfidence.

A tangential benefit of the competition context is that it has a public policy component. Many new venture competitions are publicly funded, both in the U.S. and abroad. Federal and local governments view these programs as a means to foster high-growth entrepreneurship either in a specific region or in a sector perceived to have high social benefits. For example, the U.S. Department of Energy expanded its National Clean Energy Business Plan Competition in 2016 to eight competitions with \$2.5 million in allocated funding.[37] Nearly every state hosts a competition. For example, the Arizona Innovation Challenge, one of the competitions in my data, awards \$3 million annually. The White House "Startup America" initiative, launched in 2011, champions the public sponsorship of acceleration and competition programs.[38] Thus it seems likely that public support for new venture competitions will only increase.

Despite the recent burgeoning of support, it is not obvious that competitions are useful. One aspect of competitions absent from most sources of early stage financing is their public nature. Losing a competition could produce a negative signal about the venture. Also, if a venture believes its idea is good enough to win, then it likely also believes it is good enough to steal. Participating could lead to a loss of intellectual property (IP). Thus ventures competing in such competitions are likely to either (a) be low quality; (b) have defensible IP (e.g. strong patents); or (c) have a non-replicable business model. A third reason

[37] http://energy.gov/eere/articles/energy-department-announces-25-million-inspire-collegiate-clean-energy-entrepreneurs

[38] https://www.whitehouse.gov/startup-america-fact-sheet

competitions may not be useful is if judges do not effectively discriminate because they are uninformed or inadequately incentivized. Finally, if the skills required to win are different from those needed for commercial success, competitions could distract from productive activities.

I find that winning causally increases a venture's probability of success. While a larger cash award is associated with greater success, winning is useful independently of the prize, and learning is useful independently of winning. It seems that these programs engender useful social interactions. My results suggest that competitions should consider focusing on their convening power and on providing structured feedback, rather than on awarding large prizes.

Competitions are useful to winners regardless of their location, but benefits from learning are largest in more marginal geographic locations and for founders that are local and lack an elite degree. Chatterji et al. (2013) note the recent increase in policies promoting high-growth entrepreneurship in specific regions; the goal is to create clusters of innovative activity and economic growth. While startups and innovation do cluster, it is unclear which policies cost-effectively foster clusters. Lerner (2009) points out the ways that government programs supporting new ventures and their investors can fail. He argues that government should focus on "setting the table" activities that improve local institutions rather than target specific firms or industries.

A new venture competition may be a "setting the table" type of program. While this paper cannot address how the benefits of competitions compare to other policies like tax credits or incubator sponsorship, competitions are low cost, exploit government's convening power, and rely on private sector experts rather than officials to determine winners.

Table 1: Summary Statistics

Panel 1: Competitions

	N	Mean	Median	S.d.	Min	Max
# competitions	96					
# competition-rounds	214					
# competition-round-panels	543					
# competitions with structured feedback (venture learns rank relative to other participants)	35					
# rounds per competition	96	1.9	2	.69	1	3
# ventures in preliminary rounds	120	44	36	41	4	275
# ventures in final rounds	94	18	12	20	4	152
# winners in final rounds	94	4.5	5	3.6	1	25
Award amount$\|$ Award>0 (thousand nominal $)	317	66	25	85	750	275
# judges in round-panel	543	17	9	23	1	178
Judge uncertainty (std dev of within-panel judge decile ranks of a venture)	5997	1.88	1.02	1.97	0	6.36
Judge dimension uncertainty (std dev of within-panel judge decile dimension ranks of a venture)	4961	1.37	0.85	1.29	0	5.66

*Panel 2: Ventures**

	N	Mean	Median	S.d.	Min	Max
# unique ventures	4,328					
# ventures in multiple competitions	558					
# founders/team members at first competition	2305	3.1	3	1.6	1	8
Prob. in hub state (CA, NY, MA)	4,328	.35	0	.48	0	1
Venture age at first competition (years)	2073	1.9	0.77	3	0	20
Probability operating as of 9/2016†	4328	0.63	1	0.48	0	1
Prob. acquired/IPOd as of 9/2016†	4328	0.03	0	0.18	0	1
Prob. has ≥ 2 employees as of 8/2016	4328	0.34	0	0.47	0	1
Prob. has ≥ 3 employees as of 8/2016	4328	0.3	0	0.46	0	1
Prob. has ≥ 10 employees as of 8/2016	4328	0.2	0	0.4	0	1
Prob. raised external private investment before round	7099	0.16	0	0.36	0	1
Probability raised external private investment after round	7099	0.24	0	0.43	0	1
Prob. raised angel/seed/VC series A investment before round	7099	0.09	0	0.29	0	1
Prob. raised angel/seed/VC series A investment after round	7099	0.15	0	0.36	0	1
Probability incorporated at round	4328	0.44	0	0.5	0	1
Percent of venture owned by presenting team	420	74.79	85.5	28.91	0	100
Possesses formal IP rights at round	1091	0.48	0	0.5	0	1

Panel 3: Founders (Venture Leader - One Per Venture)‡

	N	Mean	Median	S.d.	Min	Max
# founders	3,228					
# founders matched to LinkedIn profile	2,155					
Age (years) at event (college graduation year-22)	565	29.94	28	7.86	19	59
Number of total jobs	2155	6.48	3.66	6	0	43
Number of jobs before round	2148	4.5	4	2.68	0	10
Number of locations	2155	2.67	2	2.26	0	29
Founded previous venture before round	2155	0.37	0	0.48	0	1
Founded subsequent venture after round	2155	0.11	0	0.31	0	1
Executive title before round (CEO, CTO, VP, COO, President)	2155	0.38	0	0.49	0	1
Executive title after round	2155	0.13	0	0.34	0	1
Prob. graduated from top 20 college (within founders whose college is known)	725	0.27	0	0.44	0	1
Prob. any degree from Harvard, Stanford, MIT	2155	0.14	0	0.35	0	1
Prob. comp sci degree from top 10 comp sci univs	725	.06	0	.24	0	1
Prob. has MBA	2155	0.19	0	0.39	0	1
Prob. has MBA from top 10 business school (within founders with MBAs)	402	0.76	1	0.43	0	1
Prob. has Master's degree	2155	0.06	0	0.23	0	1
Prob. has PhD	2155	0.05	0	0.21	0	1
Prob. is student at round	2155	0.23	0	0.42	0	1
Major:						
Other Science/Math	49					
Engineering	108					
Bio/Med/Pharma	53					
Comp Sci	30					
Poli-Sci/Int'l	30					
Economics/Finance	130					
Entrepr./Management/Marketing	169					
Other Arts	156					

Note: This table contains summary statistics about the competitions (panel 1), ventures (panel 2), and founders/team leaders (panel 3) used in analysis. *Post-competition data from matching to CB Insights (752 unique company matches), Crunchbase (638), AngelList (1,528), and LinkedIn (1,933). †Active website. ‡From LinkedIn profiles. Not all competitions provided me with founder data, so the number of venture leaders is less than the number of ventures. See Appendix Table A4 for university rankings.

Table 2: Venture Sectors & Judge Professions

Venture Sectors	# *unique ventures*	*Judge Professions*	# *unique judges*
Hardware	245	All	2514
Software	1,404		
		Venture Capital Investor	676
Air/water/waste/agriculture	146	Angel Investor	51
Biotech	182	Professor/Scientist	44
Clean tech/renewable energy	712	Business Development/Sales	83
Defense/security	64	Corporate Executive	498
Education	37	Founder/Entrepreneur	240
Energy (fossil)	61	Lawyer/Consultant/Accountant	369
Fintech/financial	53	Non-Profit/Foundation/Government	164
Food/beverage	88	Other	193
Health (ex biotech)	270		
IT/software/web	1,404	*Investment in judged ventures*	
Manuf./materials/electronics	323	# judge-venture pairs in which judge	
Media/ads/entertainment	57	personally invested in venture	3
Real estate	61	# judge-venture pairs in which judge's	
Retail/apparel/consumer goods	139	firm invested in venture	95
Social enterprise	42	# judge-venture pairs in which judge's	
Transportation	136	firm did not invest in venture	51,093

Note: This table lists the number of ventures by technology type, and number of judges by profession.

Table 3: Effect of Rank and Winning on Subsequent External Financing

Dependent variable: Financing after round*	Final rounds			Preliminary rounds			All rounds			
Model:	OLS	OLS	Logit	OLS	OLS	Logit	OLS	Logit	OLS	OLS
	I	II	III	IV	V	VI	VII	VIII	IX	X
Won Round	.16***	.12**	.6***	.21***	.22***	.47***	.077**	.8***	.23***	.16***
	(.037)	(.048)	(.23)	(.038)	(.041)	(.17)	(.037)	(.14)	(.019)	(.015)
Won Competition				.045**	.083***	1***				
				(.022)	(.03)	(.2)				
Decile rank in round	-.02***			-.017***						
	(.005)			(.003)						
Decile rank in round among winners		.0032	.0089		-.011**	-.071***	-.0062	-.071***		
		(.0066)	(.031)		(.0049)	(.025)	(.0056)	(.021)		
Decile rank in round among losers		-.021***	-.13***		-.017***	-.13***	-.014***	-.13***		
		(.0044)	(.026)		(.0031)	(.022)	(.0032)	(.017)		
Judge decile rank in round									-.0065***	-.0061***
									(.0011)	(.0014)
Award Amount ($, 10,000s)							.0093***			.011***
							(.003)			(.0023)
Venture controls†	N	N	N	N	N	N	Y	N	N	Y
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y	N	N
Judge f.e.	N	N	N	N	N	N	N	N	Y	Y
Year f.e.	N	N	N	N	N	N	N	N	N	Y
N	1605	1605	1572	4369	4394	3888	3367	5500	47065	23785
R^2	.17	.17	.14	.17	.17	.11	.4	.12	.13	.43

Note: This table contains OLS regression estimates of the effect of winning, rank, and award (cash prize) on an indicator for whether the venture raised private investment after the competition, using variants of:

$$Y_i^{Post} = \alpha + \beta_1 \left(\mathbf{1} \mid WonRound_{i,j} \right) + f \left(DecileRank_{i,j} \right) + \gamma' \left(\mathbf{1} \mid f.e._{\cdot j} \right) + X_i + \varepsilon_{i,j}$$

. Errors clustered by competition-round or judge, depending on f.e. A smaller rank is better (1 is best decile, 10 is worst decile). *All private external investment after round. †Includes whether the company received investment before the round, whether any of the venture's judges or those judges' firms ever invested in the venture, sector indicator variables, company age, and the number of founders/team members. Note this reduces the sample as these variables are not available for all ventures. Also note that competition f.e. control for a specific date. *** indicates p-value<.01.

Table 4: Effect of Rank and Winning on Additional Outcomes (All Rounds)

Dependent variable:	Angel/VC series A investment		≥ 3 employees as of 8/2016		≥ 10 employees as of 8/2016		Acquired/IPO		Operating as of 9/2016	
	I	II	III	IV	V	VI	VII	VIII	IX	X
Won Round	.11***	.15***	.089***	.15***	.071***	.12***	.019*	.023***	.053**	.12***
	(.022)	(.02)	(.027)	(.027)	(.027)	(.038)	(.011)	(.0084)	(.023)	(.023)
Decile rank in round among winners	-.009**		-.0089**		-.0048		-.0029*		-.0092***	
	(.0039)		(.0043)		(.0043)		(.0017)		(.0034)	
Decile rank in round among losers	-.011***		-.021***		-.017***		-.0011		-.019***	
	(.0019)		(.0028)		(.0023)		(.001)		(.0026)	
Judge decile rank in round		-.0058***		-.0093**		-.0087***		-.00047		-.0071**
		(.00057)		(.0038)		(.0032)		(.00057)		(.0029)
Competition-round-panel f.e.	Y	N	Y	N	Y	N	Y	N	Y	N
Judge f.e.	N	Y	N	Y	N	Y	N	Y	N	Y
N	6046	47065	6046	47065	6046	47065	6046	47065	6046	47065
R^2	.15	.11	.16	.11	.14	.083	.083	.047	.29	.17

Note: This table contains OLS regression estimates of the effect of winning and rank on indicators for various outcomes, using variants of:

$$Y_i^{Post} = \alpha + \beta_1 \left(\mathbf{1} \mid WonRound_{i,j}\right) + f\left(DecileRank_{i,j}\right) + \gamma' \left(\mathbf{1} \mid f.e._{\cdot j}\right) + \varepsilon_{i,j}$$

Errors clustered by competition-round or judge, depending on f.e. A smaller rank is better (1 is best decile, 10 is worst decile). *All private external investment after round. †Includes whether the company received investment before the round, sector indicator variables, company age, and the number of founders/team members. Note this reduces the sample as these variables are not available for all ventures. Also note that competition f.e. control for a specific date. *** indicates p-value<.01.

Table 5: Effect of Negative Feedback on Venture Continuation (Effect of below-median rank within losers when founders informed of rank, relative to below-median rank losers *not* informed of rank)

Sample restricted to losers of round								
Dependent variable:	$\geq$ 2 employees as of 8/2016					Operating as of 9/2016		
	I	II	III	IV	V	VI	VII	VIII
Below median rank among losers· Structured feedback	-.11***	-.13***	-.07***	-.1***	-.082***	-.068*	-.1**	-.061**
	(.041)	(.048)	(.021)	(.025)	(.025)	(.035)	(.042)	(.026)
Below median rank among losers	-.043*	-.038	-.064***	-.041*	-.023	-.024	.0013	.0012
	(.026)	(.029)	(.016)	(.021)	(.02)	(.029)	(.033)	(.014)
Structured feedback	.22***	.25***	.13	.28*	-.11	.3***	.35***	-.075
	(.036)	(.04)	(.084)	(.16)	(.12)	(.031)	(.033)	(.049)
Round type	All	Prelim.	All	Prelim.	All	All	Prelim.	All
Venture controls†	N	N	N	N	Y	N	N	Y
Year f.e.	Y	Y	N	N	N	Y	Y	N
Judge f.e.	N	N	Y	Y	Y	N	N	Y
N	3264	2284	20355	13097	10713	3264	2284	10713
R^2	.038	.042	.14	.12	.31	.091	.095	.26

Note: This table contains OLS regression estimates of the effect of having a below-median rank among losers of a round in a competition where ventures receive feedback that includes their rank within a round ("Structured feedback"), relative to competitions where they do not receive such feedback. Regressions are variants of:

$$\begin{aligned} Y_i^{Post} &= \alpha + \beta_1 \left(\mathbf{1} \mid LostRound\ with\ BelowMedRank_{i,j}\right)\left(\mathbf{1} \mid StructuredFeedback_j\right) \\ &+ \beta_2 \left(\mathbf{1} \mid LostRound\ with\ BelowMedRank_{i,j}\right) + \beta_3 \left(\mathbf{1} \mid StructuredFeedback_j\right) \\ &+ f\left(DecileRank_{i,j}\right) + \gamma' \left(\mathbf{1} \mid f.e._j\right) + X_j + \varepsilon_{i,j} \end{aligned}$$

Errors clustered by competition-round or judge, depending on fixed effects. Structured feedback varies by event, so competition-round f.e. are not used. †Includes whether the company received investment before the round, sector indicator variables, company age, whether the company is incorporated, and the number of founders/team members. Note this reduces the sample as these variables are not available for all ventures. *** indicates p-value<.01.

Table 6: Venture Heterogeneity in Effect of Negative Feedback (Effect of below-median rank within losers when founders informed of rank, relative to below-median rank losers *not* informed of rank)

Sample restricted to losers of round; all rounds included
Dependent Variable: ≥ 2 employees as of 8/2016

Venture characteristic C_i (all binary):	Financing before round	Incorp. at round	Age above median	Tech type IT/software	Hard-to-fund sector†	Social/ clean tech	VC hub state††
	I	II	III	IV	V	VI	VII
Below median rank among losers· Structured feedback· C_i	.4***	.13***	-.088*	-.14***	.022	-.045	.14*
	(.04)	(.029)	(.05)	(.033)	(.038)	(.047)	(.074)
Below median rank among losers· Structured feedback	.076***	.0079	-.11**	.088***	.09**	.062**	.11***
	(.028)	(.053)	(.053)	(.032)	(.036)	(.031)	(.037)
Structured feedback· C_i	.42***	.28***	.097*	.33***	.12**	.021	.44***
	(.043)	(.034)	(.053)	(.039)	(.047)	(.067)	(.075)
Below median rank among losers· C_i	.36***	.16***	.044	.1***	-.07**	-.092***	-.0088
	(.046)	(.037)	(.066)	(.038)	(.035)	(.035)	(.038)
Below median rank among losers	-.021	-.04	-.066	-.029	-.038	-.057*	-.004
	(.026)	(.028)	(.054)	(.028)	(.034)	(.03)	(.038)
Structured feedback	.22***	.076	.0074	.19***	.27***	.22***	.24***
	(.036)	(.1)	(.064)	(.04)	(.041)	(.035)	(.041)
C_i	.44***	.21***	.065	.21***	-.022	-.1**	.064
	(.059)	(.053)	(.078)	(.057)	(.044)	(.049)	(.044)
Year f.e.	Y	Y	Y	Y	Y	Y	Y
N	3264	3264	1815	3264	3264	3264	3264
R^2	.11	.059	.023	.051	.043	.044	.041

Note: This table contains OLS regression estimates of the effect of having a below-median rank among losers of a round in a competition where ventures receive feedback that includes their rank within a round ("Structured feedback"), relative to competitions where they do not receive such feedback. Regressions are variants of Equation 2, with an additional interaction. Errors clustered by competition-round. Structured feedback varies by event, so competition-round f.e. are not used. †Firms in the following sectors are categorized as being in a capital intensive/difficult-to-finance sector: social impact, energy (clean tech and fossil), manufacturing, air/waste, transportation, education, and biotech. ††Venture state is California, New York, or Massachusetts. *** indicates p-value<.01.

Table 7: Founder Characteristics' Association with Success (All rounds)

	Panel 1				
Dependent Variable: Financing after round					
	I	II	III	IV	V
# jobs before round	.019***	.051***	.05***	.019***	.02***
	(.0036)	(.0085)	(.0085)	(.0036)	(.0036)
# job locations before round	-.0082**	-.028***	-.03***	-.0081**	-.0084**
	(.0038)	(.01)	(.01)	(.0038)	(.0037)
Has MBA	.013	.0061	-.022	-.028	-.031
	(.023)	(.042)	(.041)	(.028)	(.028)
Has Master's	-.058**	-.094**	-.1***	-.067**	-.068**
	(.027)	(.038)	(.037)	(.027)	(.027)
Has PhD	-.014	.077	.064	-.025	-.033
	(.031)	(.047)	(.047)	(.031)	(.031)
Age at round		-.0044**	-.0036**		
		(.0018)	(.0018)		
Any degree from Harvard/Stanford/MIT			.15**	.091**	.073*
			(.064)	(.039)	(.038)
Founded previous venture					-.0052
					(.015)
Is student at round					.15***
					(.039)
Won round	.11***	.19***	.19***	.11***	.1***
	(.022)	(.043)	(.042)	(.022)	(.022)
Decile rank in round	-.017***	-.0018	-.0006	-.017***	-.018***
	(.0031)	(.0069)	(.0067)	(.003)	(.0031)
Competition-round- panel f.e.	Y	Y	Y	Y	Y
N	3368	829	829	3368	3368
R^2	.12	.29	.3	.12	.12

Panel 2

Dependent Variable: Financing after round

	I	II	III
Comp Sci rank|CS major at top 10 CS univ	-.042***		
	(.014)		
Univ rank|College at top 20 univ		-.0064**	
		(.003)	
Major:			
Liberal Arts†		.0035	
		(.029)	
Entrepreneurship/ Management/Marketing		.063**	
		(.031)	
Computer Science/ Engineering		-.004	
		(.03)	
Other Sciences		-.045	
		(.029)	
Won round	.2	.11***	.18***
	(.15)	(.017)	(.041)
Decile rank in round	-.0011	-.019***	-.0082
	(.021)	(.0026)	(.006)
Competition-round- panel f.e.	Y	Y	Y
N	69	6046	1079
R^2	.59	.091	.22

	Panel 3: Other Outcomes			
Dependent Variable:	$\geq$ 3 employees as of 8/2016	$\geq$ 10 employees as of 8/2016	Acquired/ IPO	Operating as of 9/2016
	II	III	IV	V
Number of jobs before round	.043***	.032***	.0036	.042***
	(.0081)	(.0073)	(.0028)	(.0077)
Number of job locations before round	-.025***	-.011	-.0041	-.018**
	(.0095)	(.0089)	(.0026)	(.009)
Has MBA	-.026	-.047	-.015	-.048
	(.047)	(.043)	(.016)	(.037)
Has Master's	.041	.01	-.015	-.081**
	(.047)	(.042)	(.011)	(.039)
Has PhD	.0098	-.016	-.025**	.0078
	(.05)	(.044)	(.011)	(.044)
Age at round	-.0058**	-.0048**	-.0016***	-.0008
	(.0023)	(.0023)	(.00058)	(.002)
Received any degree from Harvard/Stanford/MIT	.2***	.21***	-.013	-.046
	(.058)	(.063)	(.029)	(.063)
Won round	.086**	.078*	.0085	.15***
	(.042)	(.041)	(.014)	(.037)
Decile rank in round	-.0012	-.0074	.0018	.0067
	(.0074)	(.0069)	(.0028)	(.0071)
Competition-round- panel f.e.	Y	Y	Y	Y
N	829	829	829	829
R^2	.28	.27	.18	.37

Note: This table contains OLS regression estimates of the relationship between venture characteristics and successful venture outcomes. I use variants of:

$$Y_{ij} = \alpha + \beta_1 C_i + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j}\right) + f\left(DecileRank_{i,j}\right) + \varepsilon_{i,j}$$

Errors clustered by competition-round. Note that competition f.e. control for a specific date. †Firms in the following sectors are categorized as being in a capital intensive/difficult-to-finance sector: social impact, energy (clean tech and fossil), manufacturing, air/waste, transportation, education, and biotech. *** indicates p-value<.01.

Table 8: Founder And Scoring Heterogeneity in Effect of Negative Feedback (Effect of below-median rank within losers when founders informed of rank, relative to below-median rank losers *not* informed of rank)

Sample restricted to losers of round; all rounds included
Dependent Variable: $\geq$ 2 employees as of 8/2016

	Founder characteristic					Judge distribution	
Characteristic C_i (all binary):	Is student	# previous jobs	Has Harvard/ MIT/Stanford degree	Attended top 20 college	Has MBA	Std dev ranks above median	# judges above median
	I	II	III	IV	V	VI	VII
Below median rank among losers· Structured feedback· C_i	-.3***	.13**	.69***	.17	.084	.082**	-.26*
	(.028)	(.054)	(.027)	(.37)	(.17)	(.037)	(.14)
Below median rank among losers· Structured feedback	.096***	.12*	.07**	.069**	.06**	.038	.14
	(.028)	(.068)	(.028)	(.028)	(.029)	(.04)	(.13)
Structured feedback· C_i	0	.27***	.69***	.66***	.25	.21***	.0064
	(.)	(.057)	(.027)	(.028)	(.16)	(.042)	(.11)
Below median rank among losers· C_i	.078**	.02	-.088*	-.065	-.074	-.015	.078
	(.037)	(.054)	(.048)	(.053)	(.046)	(.036)	(.058)
Below median rank among losers	-.049*	-.024	-.037	-.042	-.05*	-.089**	-.11**
	(.028)	(.059)	(.027)	(.027)	(.028)	(.036)	(.049)
Structured feedback	.25***	.3***	.22***	.22***	.21***	.22***	.2*
	(.033)	(.095)	(.033)	(.032)	(.033)	(.05)	(.11)
C_i	.14**	.066	.013	-.0016	-.057	-.0092	.039
	(.059)	(.057)	(.065)	(.082)	(.058)	(.044)	(.053)
Year f.e.	Y	Y	Y	Y	Y	Y	Y
N	3264	3264	3264	3264	3264	3264	3264
R^2	.045	.039	.04	.039	.039	.041	.042

Note: This table contains OLS regression estimates of the effect of having a below-median rank among losers of a round in a competition where ventures receive feedback that includes their rank within a round ("Structured feedback"), relative to competitions where they do not receive such feedback. Regressions are variants of Equation 2. All variables are interacted with a binary venture characteristic of interest. Errors clustered by competition-round. Structured feedback varies by event, so competition-round f.e. are not used. †Firms in the following sectors are categorized as being in a capital intensive/difficult-to-finance sector: social impact, energy (clean tech and fossil), manufacturing, air/waste, transportation, education, and biotech. *** indicates p-value<.01.

Table 9: Learning and Success with Business Plan Scores (Effect of improvement between pre-competition business plan and competition on venture outcomes)

Panel 1

Dependent variable:	Financing after round*			Operating as of 9/2016	
	I	II	III	IV	V
$\Delta_{quintiles}$ b-plan to prelim round	.051***	.055***		.034**	.039**
	(.014)	(.016)		(.013)	(.016)
$\Delta_{quintiles}$ b-plan to final round			.11***		
			(.04)		
Quintile b-plan rank	-.071***	-.075***	-.14***	-.042***	-.044**
	(.014)	(.016)	(.041)	(.015)	(.019)
Won Round	.42***	.41***	-.089	.18**	.16*
	(.09)	(.1)	(.12)	(.077)	(.096)
Year f.e.	Y	N	Y	Y	N
Judge f.e.	N	Y	N	N	Y
N	510	510	154	510	510
R^2	.16	.22	.25	.31	.16

Panel 2

Dependent variable:	$\geq$ 3 employees as of 8/2016			$\geq$ 10 employees as of 8/2016	
	I	II	III	IV	V
$\Delta_{quintiles}$ b-plan to prelim round	.042**	.04**		.041***	.046***
	(.017)	(.019)		(.013)	(.016)
$\Delta_{quintiles}$ b-plan to final round			.09**		
			(.037)		
Quintile b-plan rank	-.048***	-.053***	-.018	-.044***	-.047***
	(.017)	(.017)	(.047)	(.014)	(.016)
Won Round	.22**	.25**	-.08	.18*	.24**
	(.099)	(.11)	(.11)	(.1)	(.11)
Year f.e.	Y	N	Y	Y	N
Judge f.e.	N	Y	N	N	Y
N	510	510	154	510	510
R^2	.1	.23	.14	.074	.17

Note: This table contains OLS estimates of learning's effect on venture outcomes. The learning metric is the change in quintile ranks between the business plan phase, where scores do not count towards winning, and the competition phase ($\Delta_{quintiles}$). Letting j denote the business plan phase in the competition and j' the second round (either first or final), I use variants of: $Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j' quintiles} + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j}\right) + f\left(QuintileRank_{i,j}\right) + \gamma' \left(\mathbf{1} \mid f.e._{j/k}\right) + \varepsilon_{i,j}$. Errors clustered by competition-round or judge depending on f.e. A smaller rank is better. *All private external investment after round. *** indicates p-value<.01.

Table 10: Learning Across Competitions and Success (Effect of improvement between first and last competitions among ventures in > 1 competition, using preliminary round in both)

			Panel 1			
Dependent variable:	Financing after round*			Operating as of 9/2016		
	I	II	III	IV	V	VI
$\Delta_{deciles}$ 1st to last competition	.034***	.028*	.018*	.022***	.021**	.015*
	(.012)	(.016)	(.0098)	(.0081)	(.0082)	(.0087)
Decile rank in last competition	-.044***	-.04**	-.027***	-.028***	-.026**	-.018*
	(.011)	(.015)	(.0085)	(.0096)	(.013)	(.01)
Won Round	.099	.18*	.056	.021	.013	-.0045
	(.092)	(.11)	(.079)	(.042)	(.043)	(.034)
Venture controls†	N	N	Y	N	N	Y
Competition-round- panel f.e.	Y	N	Y	Y	N	Y
Judge f.e.	N	Y	N	N	Y	N
N	484	484	480	484	484	480
R^2	.26	.5	.41	.18	.4	.25
			Panel 2			
Dependent Variable:	≥ 3 employees as of 8/2016			≥ 10 employees as of 8/2016		
	VII	VIII	IX	X	XI	XII
$\Delta_{deciles}$ 1st to last competition	.037***	.024**	.026***	.039***	.029***	.033***
	(.0088)	(.011)	(.0096)	(.0086)	(.0097)	(.01)
Decile rank in last competition	-.049***	-.045***	-.034***	-.05***	-.04***	-.044***
	(.0075)	(.013)	(.0092)	(.0085)	(.01)	(.01)
Won Round	.13**	.23**	.049	.05	.089	.0039
	(.059)	(.093)	(.063)	(.06)	(.08)	(.059)
Venture controls†	N	N	Y	N	N	Y
Competition-round- panel f.e.	Y	N	Y	Y	N	Y
Judge f.e.	N	Y	N	N	Y	N
N	484	484	480	484	484	480
R^2	.21	.43	.31	.19	.39	.25

Note: This table contains OLS regression estimates of the effect of learning on subsequent venture measures of success. The learning metric is the change in decile ranks across first rounds of two competitions ($\Delta_{deciles}$), among the ventures that participate in multiple competitions. Letting j denote the first competition and j' the last competition, I use variants of: $Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j'(deciles)} + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) + \gamma' \left(\mathbf{1} \mid f.e._{j'/k}\right) + X_i + \varepsilon_{i,j}$. Errors clustered by competition-round or judge, depending on f.e. A smaller rank is better (1 is best decile, 10 is worst decile).*All private external investment after round. †Includes whether the company received investment before the round, sector indicator variables, award amount if any, and whether the company was incorporated. Note this reduces the sample as these variables are not available for all ventures. Also note that competition f.e. control for a specific date. *** indicates p-value<.01.

Table 11: Learning Across Rounds and Success (Effect of improvement between first and second rounds in a competition on venture outcomes)

Dependent variable:	Financing after round*		≥ 3 employees as of 8/2016		≥ 10 employees as of 8/2016		Operating as of 9/2016	
	I	II	III	IV	V	VI	VII	VIII
$\Delta_{deciles}$ prelim round to second round**	.018***	.017**	.017**	.014*	.015**	.013*	.01*	.0064
	(.0066)	(.0082)	(.0072)	(.0072)	(.0067)	(.0077)	(.0056)	(.0058)
Decile rank in second round	-.025***	-.045***	-.032***	-.038***	-.025***	-.032***	-.018**	-.022***
	(.0077)	(.0095)	(.0096)	(.0092)	(.0094)	(.0091)	(.0084)	(.0085)
Won Round	.14***	.13***	.059	.07	.066*	.066	.02	.043
	(.043)	(.043)	(.044)	(.051)	(.039)	(.042)	(.033)	(.034)
Competition-round- panel f.e.	Y	N	Y	N	Y	N	Y	N
Judge f.e.	N	Y	N	Y	N	Y	N	Y
N	1252	1252	1252	1252	1252	1252	1252	1252
R^2	.22	.22	.22	.22	.2	.22	.34	.22

Note: This table contains OLS regression estimates of the effect of learning on subsequent venture measures of success. The learning metric is the change in decile ranks between the first and second rounds of a competition ($\Delta_{deciles}$). Letting j denote the first round in the competition and j' the second round, I use variants of:

$$Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j'(deciles)} + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) + \gamma' \left(\mathbf{1} \mid f.e._{j'/k}\right) + \varepsilon_{i,j'}$$

Errors clustered by competition-round or judge, depending on f.e. A smaller rank is better (1 is best decile, 10 is worst decile).*All private external investment after round. **When competition has two rounds, 2nd round is final round. Note that competition f.e. control for a specific date. *** indicates p-value<.01.

Table 12: Learning and Founder Success (Learning measured as improvement between first and second rounds in a competition on venture outcomes)

Dependent variable:	Executive title after round†			Founded subsequent venture after round	
	I	II	III	IV	V
$\Delta_{deciles}$ prelim to 2nd round*	.0057*			.0045*	
	(.0032)			(.0024)	
Dimension $\Delta_{deciles}$ prelim round to second round:					
Team		.0012	-.0016		
		(.003)	(.0052)		
Financials		-.0027	-.0028		
		(.0038)	(.0068)		
Business Model		.013	.0031		
		(.015)	(.009)		
Market Attractiveness		-.012	-.0042		
		(.016)	(.0085)		
Technology/Product		-.0031	.0006		
		(.0033)	(.0052)		
Presentation		.0066**	.0099*		.0071**
		(.003)	(.0053)		(.0033)
Founder before round	.056	.042*	.0072	.04	.0088
	(.035)	(.022)	(.031)	(.031)	(.03)
Decile rank in second round	-.0097**		-.0026	-.0052	-.002
	(.0037)		(.0054)	(.0039)	(.0046)
Won Round	.0037		-.02	.011	-.026
	(.025)		(.037)	(.023)	(.03)
N	499	258	258	499	258
R^2	.03	.017	.012	.021	.01

Note: This table contains OLS regression estimates of the relationship between venture characteristics and learning across rounds, where the learning metric is the change in decile ranks between the first and second rounds of a competition ($\Delta_{deciles}$). Letting j denote the first round in the competition and j' the second round, I use variants of:

$$ExecAfter_i = \alpha + \beta_1 \Delta_{i,j,j'(deciles)} + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j'} \right) + f\left(DecileRank_{i,j'} \right) + \varepsilon_{i,j'}$$

Errors clustered by competition-round. *When competition has two rounds, 2nd round is final round. Note that competition f.e. control for a specific date. †LinkedIn profile contains post-round job in which founder self-described as CEO, CTO, VP, COO, or President. *** indicates p-value<.01.

Table 13: Learning Across Rounds and Success with Structured Feedback (Effect of improvement between first and second rounds in a competition on venture outcomes)

Dependent variable:	Financing After Round			$\geq$ 3 employees as of 8/2016	$\geq$ 10 employees as of 8/2016	Operating as of 9/2016
		No structured feedback	Structured feedback			
	I	II	III	IV	V	VI
$\Delta_{deciles}$ prelim to 2nd round**· Structured feedback	.024***			.017**	.022***	.0053
	(.0076)			(.0086)	(.008)	(.0059)
$\Delta_{deciles}$ prelim to 2nd round	.0074	.016**	.035***	.011*	.0073	.01*
	(.0056)	(.0066)	(.01)	(.0062)	(.0054)	(.0058)
Structured feedback	.17***			.3***	.31***	.18***
	(.039)			(.04)	(.038)	(.03)
Decile rank in second round	-.035***	-.021**	-.044***	-.035***	-.03***	-.021***
	(.0068)	(.0095)	(.0098)	(.0076)	(.0068)	(.0065)
Won Round	.14***	.19***	.17*	.065*	.07**	.0012
	(.036)	(.063)	(.08)	(.037)	(.035)	(.03)
Competition-round- panel f.e.	N	Y	Y	N	N	N
Year f.e.	Y	N	N	Y	Y	Y
N	1252	877	375	1252	1252	1252
R^2	.12	.24	.16	.12	.11	.22

Note: This table contains OLS regression estimates of the effect of learning on subsequent venture measures of success. The learning metric is the change in decile ranks between the preliminary (first) and second (sometimes final, sometimes intermediate) rounds of a competition ($\Delta_{deciles}$). Letting j denote the first round in the competition and j' the second round, I use variants of:

$$\begin{aligned} Y_i^{Post} &= \alpha + \beta_1 \Delta_{i,j,j'(deciles)} \left(\mathbf{1} \mid StructuredFeedback_j\right) + \beta_2 \left(\mathbf{1} \mid StructuredFeedback_j\right) \\ &+ \beta_3 \Delta_{i,j,j'(deciles)} + \beta_4 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) + \gamma' \left(\mathbf{1} \mid f.e._{j'/k}\right) + \varepsilon_{i,j'} \end{aligned}$$

Errors clustered by competition-round. *All private external investment after round. **When competition has two rounds, 2nd round is final round. Note that competition f.e. control for a specific date. *** indicates p-value<.01.

Table 14: Venture Characteristics and Learning (Learning measured as improvement between first and second rounds in a competition)

Dependent Variable: $\Delta_{deciles}$ prelim round to second round*

	I	II	III	IV	V	VI
Tech type IT/software, not hardware	.59**	.62***		.52***		
	(.23)	(.17)		(.15)		
Hard-to-fund sector†	-.26	-.21				
	(.25)	(.19)				
Social/clean tech sector	.18	-.52**		-.57***		
	(.3)	(.21)		(.18)		
Financing before round	.39**		.31			
	(.19)		(.19)			
Incorporated at round	-.29		-.37*			
	(.21)		(.19)			
Age	-.069*		-.07*			
	(.037)		(.038)			
Std dev of judge ranks above median	-.46**					
	(.19)					
VC hub state††				-.34**		
				(.14)		
Presenting team owned >90% of venture at round					-.34*	
					(.19)	
Possessed formal IP rights at round						.41**
						(.2)
Decile rank in second round	.95***	.96***	.96***	.95***	1.1***	1***
	(.036)	(.027)	(.036)	(.027)	(.035)	(.038)
Won Round	3.6***	3.7***	3.6***	3.7***	4.6***	4.3***
	(.17)	(.13)	(.16)	(.13)	(.15)	(.19)
N	763	1252	763	1252	392	475
R^2	.61	.59	.6	.59	.75	.66

Note: This table contains OLS regression estimates of the relationship between venture characteristics and learning across rounds, where the learning metric is the change in decile ranks between the first and second rounds of a competition ($\Delta_{deciles}$). Letting j denote the first round in the competition and j' the second round, I use variants of:

$$\Delta_{i,j,j'(deciles)} = \alpha + \gamma'\mathbf{C}_i + \beta_1 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) + \varepsilon_{i,j'}$$

Errors clustered by competition-round. *When competition has two rounds, 2nd round is final round. Note that competition f.e. control for a specific date. †Firms in the following sectors are categorized as being in a capital intensive/difficult-to-finance sector: social impact, energy (clean tech and fossil), manufacturing, air/waste, transportation, education, and biotech. ††Venture state is California, New York, or Massachusetts. *** indicates p-value<.01.

Table 15: Founder Characteristics and Learning (Learning measured as improvement between first and second rounds in a competition)

Dependent Variable: $\Delta_{deciles}$ prelim round to second round*					
	I	II	III	IV	V
Has MBA	.84***	1.1***	.53**		.32
	(.23)	(.27)	(.21)		(.29)
Has Master's	-.094				
	(.3)				
Has PhD	.16				
	(.3)				
Received degree from Harvard/Stanford/MIT	-.58*				
	(.34)				
Top twenty college	.037		-.26		-.22
	(.31)		(.3)		(.32)
Founder before round	.066				
	(.17)				
Number of jobs before round	-.024				
	(.033)				
Number of job locations before round	.059				
	(.038)				
Top 10 MBA		-.77**			
		(.36)			
Student at round			.78***		
			(.14)		
Major:					
Liberal Arts†				.33	.18
				(.33)	(.39)
Entrepreneurship/Management/Marketing				1.1***	.92***
				(.22)	(.32)
Computer Science/Engineering				-.13	-.16
				(.32)	(.33)
Other Sciences				.51	.46
				(.38)	(.39)
Decile rank in second round	.97***	.96***	.91***	.96***	.96***
	(.033)	(.027)	(.028)	(.026)	(.026)
Won Round	3.8***	3.7***	3.7***	3.7***	3.7***
	(.16)	(.14)	(.13)	(.14)	(.14)
N	862	1252	1252	1252	1252
R^2	.62	.59	.6	.59	.59

Note: This table contains OLS regression estimates of the relationship between venture characteristics and learning across rounds, where the learning metric is the change in decile ranks between the first and second rounds of a competition ($\Delta_{deciles}$). Letting j denote the first round in the competition and j' the second round, I use variants of:

$$\Delta_{i,j,j'(deciles)} = \alpha + \beta_1 C_i + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) + \varepsilon_{i,j'}$$

Errors clustered by competition-round. *When competition has two rounds, 2nd round is final round. †Includes economics/finance. *** indicates p-value<.01.

Table 16: Learning Across Rounds During the Financial Crisis (How learning varies over time; learning measured as improvement between first and second rounds in a competition on venture outcomes)

Sample restricted to winners					
Dependent variable:	$\Delta_{deciles}$ prelim round to second round*				Financing after round
	I	II	III	IV	V
Financial crisis period†	2.1**	.67***	1.9**		
	(.8)	(.15)	(.86)		
Post-crisis	-1.1***	-.76***	-1.2***		
	(.41)	(.19)	(.46)		
$\mathbf{1}$ |Year$_{2003-05}$				1.9*	.21**
				(1)	(.092)
$\mathbf{1}$ |Year$_{2006-07}$				1.9**	.016
				(.95)	(.072)
$\mathbf{1}$ |Year$_{2008-09}$				2.7***	.24***
				(.82)	(.08)
$\mathbf{1}$ |Year$_{2010-11}$				1.7***	.38***
				(.58)	(.066)
$\mathbf{1}$ |Year$_{2012-13}$				.49	.25***
				(.48)	(.06)
$\mathbf{1}$ |Year$_{2014-16}$				.49	.23***
				(.47)	(.059)
Tech type is IT/software, not hardware			-1***		
			(.36)		
Received external financing before round			-.12		
			(.41)		
Std dev of judge ranks above median			-1.5***		
			(.31)		
Incorporated at round			.22		
			(.39)		
Decile rank in second round		1.1***			
		(.052)			
N	350	350	350	350	1675
R^2	.043	.63	.12	.052	.024

Note: This table contains OLS regression estimates of the relationship between time period and learning across rounds among winners. The learning metric is the change in decile ranks between the first and second rounds of a competition ($\Delta_{deciles}$). I use variants of:

$$\Delta_{i,j,j'(deciles)} = \alpha + \beta_1 C_i + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) + \varepsilon_{i,j'}$$

Errors clustered by competition-round. *When competition has two rounds, 2nd round is final round. Note that competition f.e. control for a specific date.†Crisis indicator is 1 from 9/15/2008 to end of 2009, and zero otherwise. Post-crisis is 2010-2016. Omitted time dummy in I and II is pre-crisis period (1999 to 9/15/2008). Omitted time period in III is the period 1999-2002. *** indicates p-value<.01.

Table 17: Effect of Dimension Rank on Venture Outcomes

Dependent variable:	Financing after round*		≥ 3 employees as of 8/2016		≥ 10 employees as of 8/2016		Acquired/IPO		Operating as of 9/2016	
	I	II	III	IV	V	VI	VII	VIII	IX	X
Pctile rank in round:†										
Team	-.021***	-.023***	-.014***	-.021***	-.0091	-.017***	.00069	-.0012	-.011***	-.011**
	(.0057)	(.0053)	(.0051)	(.0052)	(.0063)	(.0049)	(.0026)	(.0024)	(.0034)	(.0043)
Financials	-.014**	-.0079	-.03***	-.027***	-.036***	-.026***	.0034	.0023	-.0022	-.0087**
	(.0067)	(.005)	(.0094)	(.0058)	(.0083)	(.0057)	(.0031)	(.0027)	(.0053)	(.0042)
Business Model	.0032	.002	.0091	.012	.0024	.0035	.0046	-.0059	.016	.026**
	(.016)	(.011)	(.016)	(.012)	(.014)	(.011)	(.0074)	(.0074)	(.013)	(.012)
Market††	.01	-.0091	.002	-.022*	.0075	-.011	-.00047	.0039	-.015	-.03**
	(.015)	(.011)	(.015)	(.012)	(.013)	(.011)	(.0072)	(.0074)	(.013)	(.012)
Tech./Product	.0098	.0031	-.0043	-.0093*	-.0015	-.0081	-.0062**	-.0056**	-.013***	-.015***
	(.0078)	(.0054)	(.0075)	(.0055)	(.0069)	(.0054)	(.0024)	(.0024)	(.0048)	(.0048)
Presentation	-.015**	-.0098**	-.0023	-.0041	.0074	.008	-.0032	-.0013	-.0011	-.0079*
	(.0059)	(.0043)	(.0083)	(.0048)	(.0071)	(.0052)	(.0024)	(.0022)	(.004)	(.0041)
Won Round	.14***	.2***	.12***	.21***	.1***	.17***	.011	.023***	-.0095	.061***
	(.024)	(.013)	(.035)	(.014)	(.032)	(.015)	(.013)	(.0068)	(.018)	(.0071)
Judge/judge company invested	.47***	.56***								
	(.11)	(.027)								
Competition-round-panel f.e.	Y	N	Y	N	Y	N	Y	N	Y	N
Judge f.e.	N	Y	N	Y	N	Y	N	Y	N	Y
N	1926	8794	1926	8794	1926	8794	1926	7043	1926	8794
R^2	.15	.14	.16	.15	.13	.12	.065	.066	.2	.2

Note: This table contains OLS regression estimates of the effect of dimension-specific ranks on indicators for various outcomes, using variants of: $Y_i^{Post} = \alpha + \beta_1 \left(\mathbf{1} \mid WonRound_{i,j}\right) + f\left(DimensionDecileRank_{i,j}/JudgeDimQuintileRank_{i,j,k}\right) + \gamma' \left(\mathbf{1} \mid f.e._{\cdot j/k}\right) + \varepsilon_{i,j,/k}$. All rounds are included. Note that dimension scores are generally averaged to produce the overall ranks used in other tables. Errors clustered by competition-round or judge, depending on f.e. †Regressions us decile rank in round or quintile rank within judge. A smaller rank is better (1 is best decile, 10 is worst decile). *All private external investment after round. Note that competition f.e. control for a specific date. ††The attractiveness and size of the market. *** indicates p-value<.01.

Table 18: Learning Across Rounds and Success by Dimension (Effect of improvement between first and second rounds in a competition on venture outcomes, using dimension ranks)

Dependent variable:	Financing after round*	≥ 3 employees as of 8/2016	≥ 10 employees as of 8/2016	Operating as of 9/2016	Acquired/IPO
	I	II	III	IV	V
$\Delta_{deciles}$ prelim round to second round:**					
Team	.01	-.0041	-.0002	.0044	.005
	(.011)	(.0078)	(.0086)	(.0083)	(.0041)
Financials	.022**	.029***	.028**	.0037	-.00068
	(.01)	(.0093)	(.011)	(.0094)	(.005)
Technology/Product	-.0064	.0097	.011	.00034	.0035
	(.0061)	(.0091)	(.009)	(.0073)	(.004)
Business Model	-.0073	-.014	-.011	-.023	-.023***
	(.049)	(.046)	(.045)	(.058)	(.0071)
Presentation	.023**	.0076	.0064	.0029	.01**
	(.0096)	(.011)	(.014)	(.006)	(.0047)
Market Attractiveness	-.0068	.0069	.0036	.0082	.0094
	(.048)	(.048)	(.045)	(.056)	(.0071)
Won Round	.23***	.14**	.12**	.093**	-.012
	(.052)	(.055)	(.047)	(.039)	(.022)
Dimension decile rank in second round	Y	Y	Y	Y	Y
Competition-round- panel f.e.	Y	Y	Y	Y	Y
N	640	640	640	640	640
R^2	.18	.21	.19	.16	.084

Note: This table contains OLS regression estimates of the effect of learning on subsequent venture measures of success. The learning metric is the change in dimension decile ranks between the first and second rounds of a competition ($\Delta_{deciles}$). That is, for example, the change in a venture's ranking using the "Financials" score. Letting j denote the first round in the competition and j' the second round, I use variants of:

$$Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j'(deciles)} + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DimensionDecileRank_{i,j'}\right) + \gamma' \left(\mathbf{1} \mid f.e._{j'/k}\right) + \varepsilon_{i,j'}$$

Errors clustered by competition-round or judge, depending on f.e. A smaller rank is better (1 is best decile, 10 is worst decile).*All private external investment after round. **When competition has two rounds, 2nd round is final round. Note that competition f.e. control for a specific date. *** indicates p-value<.01.

Table 19: Learning Across Rounds and Success when Venture is Local (Effect of improvement between first and second rounds in a competition on venture outcomes)

Dependent variable:	Financing after round*			$\geq$ 3 employees as of 8/2016		
	I	II	III	IV	V	VI
$\Delta_{deciles}$ prelim to 2nd round·Same State[†]	.015**	.018*	.018*	.016**	.025**	.025**
	(.0072)	(.01)	(.01)	(.008)	(.011)	(.011)
$\Delta_{deciles}$ prelim to 2nd round·Company in VC hub state·Same State		-.04**	-.042**		-.047**	-.051**
		(.019)	(.019)		(.022)	(.022)
Company in VC hub state·Same state		-.24**	-.24**		-.19*	-.2*
		(.11)	(.11)		(.11)	(.11)
$\Delta_{deciles}$ prelim to 2nd round·Company in VC hub state		.024	.025*		.04**	.042**
		(.015)	(.015)		(.017)	(.017)
Company in VC hub state		.23***	.23***		.18***	.17***
		(.061)	(.061)		(.061)	(.061)
Same state	.057*	.1**	.1**	.1***	.13**	.13**
	(.032)	(.052)	(.052)	(.034)	(.057)	(.056)
$\Delta_{deciles}$ prelim to 2nd round	.0078	.011	.011	.0088	.0038	.0037
	(.0062)	(.007)	(.007)	(.007)	(.0078)	(.0078)
Decile rank in 2nd round	-.036***	-.023***	-.022***	-.036***	-.03***	-.029***
	(.007)	(.0081)	(.0081)	(.0078)	(.0093)	(.0093)
Won Round	.015**	.14***	.14***	.016**	.06	.062
	(.0072)	(.038)	(.038)	(.008)	(.039)	(.039)
Judge/judge company invested	.45***	.39***	.38***			
	(.11)	(.12)	(.11)			
Founder has Harvard/MIT/ Stanford degree			.074			.11*
			(.055)			(.06)
Competition-round- panel f.e.	Y	Y	Y	Y	Y	Y
N	1252	1252	1252	1252	1252	1252
R^2	.11	.24	.24	.082	.23	.23

Note: This table contains OLS regression estimates of the effect of learning on subsequent venture measures of success. I use variants of: $Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j'(deciles)} \left(\mathbf{1} \mid SameState_{i,j'}\right) + \beta_2 \Delta_{i,j,j'(deciles)} + \beta_3 \left(\mathbf{1} \mid SameState_{i,j'}\right) + \beta_4 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) + \gamma' \left(\mathbf{1} \mid f.e._{j'/k}\right) + \varepsilon_{i,j'}$I also add an indicator for the venture's state being California or Massachusetts as a third interaction in II and IV. Errors clustered by competition-round. A smaller rank is better (1 is best decile, 10 is worst decile).*All private external investment after round. **When competition has two rounds, 2nd round is final round. Note that competition f.e. control for a specific date. [†]Venture's state and competition state are same. *** indicates p-value<.01.

Table 20: Which Venture Types Benefit from Learning? (Learning measured as improvement between first and second rounds in a competition)

Dependent Variable: Financing after round

$C_i =$	VC hub state	IT/ Software	Company age	Company age above median	Structured feedback competition
	I	II	III	IV	V
$C_i \cdot \Delta_{deciles}$ prelim to 2nd round	.0052	.0085	.0037**	.022**	.024**
	(.0075)	(.0078)	(.0016)	(.0088)	(.01)
$\Delta_{deciles}$ prelim to 2nd round	.013**	.013**	.0018	-.0015	.0074
	(.0063)	(.0053)	(.0084)	(.0089)	(.0059)
C_i	.037	.29***	.0029	.012	.17***
	(.034)	(.037)	(.0091)	(.035)	(.05)
Decile rank in last round	-.038***	-.034***	-.02**	-.021**	-.035***
	(.007)	(.0066)	(.0094)	(.0093)	(.0064)
Won Round	.14***	.14***	.22***	.22***	.14***
	(.039)	(.036)	(.043)	(.043)	(.038)
Year f.e.	Y	Y	Y	Y	Y
N	1252	1252	763	763	1252
R^2	.1	.18	.19	.19	.12

Note: This table contains OLS regression estimates of the relationship between venture characteristics and learning across rounds, where the learning metric is the change in decile ranks between the first and second rounds of a competition ($\Delta_{deciles}$). Letting j denote the first round in the competition and j' the second round, I use variants of:

$$Y_i = \alpha + \beta_1 C_i \Delta_{i,j,j'(deciles)} + \beta_2 C_i + \beta_3 \Delta_{i,j,j'(deciles)} + \beta_4 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) + \varepsilon_{i,j'}$$

Errors clustered by competition-round. *When competition has two rounds, 2nd round is final round. Note that competition f.e. control for a specific date. There is no significant effect of the other characteristics, including majors. *** indicates p-value<.01.

Table 21: Which Founder Types Benefit from Learning? (Learning measured as improvement between first and second rounds in a competition)

Dependent Variable: Financing after round

$C_i =$	Has MBA	Top ten MBA	Degree from HSM*	Major is Entrepr.†	Major is CS/Eng††	Founder before round	Founder age
	I	II	III	IV	V	VI	VII
$C_i \cdot \Delta_{deciles}$ prelim to 2nd round	.0025	.0067	.016	.0097	.024**	.014*	.0016***
	(.0085)	(.012)	(.016)	(.015)	(.011)	(.0072)	(.00058)
$\Delta_{deciles}$ prelim to 2nd round	.014**	.013**	.013**	.012**	.014**	.0099	-.026
	(.0059)	(.0057)	(.0058)	(.0059)	(.0058)	(.0065)	(.024)
C_i	-.019	-.012	.096	.032	.0093	.033	.0033
	(.04)	(.055)	(.076)	(.058)	(.057)	(.031)	(.0033)
Decile rank in last round	-.039***	-.039***	-.038***	-.038***	-.039***	-.038***	-.038**
	(.007)	(.0069)	(.0068)	(.0071)	(.007)	(.007)	(.017)
Won Round	.14***	.14***	.14***	.14***	.14***	.14***	.28***
	(.038)	(.039)	(.039)	(.039)	(.038)	(.038)	(.084)
Year f.e.	Y	Y	Y	Y	Y	Y	Y
N	1252	1252	1252	1252	1252	1252	231
R^2	.11	.1	.1	.1	.11	.11	.3

Note: This table contains OLS regression estimates of the relationship between venture characteristics and learning across rounds, where the learning metric is the change in decile ranks between the first and second rounds of a competition ($\Delta_{deciles}$). Letting j denote the first round in the competition and j' the second round, I use variants of:

$$Y_i = \alpha + \beta_1 C_i \Delta_{i,j,j'(deciles)} + \beta_2 C_i + \beta_3 \Delta_{i,j,j'(deciles)} + \beta_4 \left(\mathbf{1} \mid WonRound_{i,j'}\right) + f\left(DecileRank_{i,j'}\right) + \varepsilon_{i,j'}$$

Errors clustered by competition-round. *When competition has two rounds, 2nd round is final round. Note that competition f.e. control for a specific date. There is no significant effect of the other characteristics, including majors. *Harvard/Stanford/ MIT. †Entrepreneurship/management/marketing. ††Computer Science/Engineering. *** indicates p-value<.01.

Figure 1: Probability venture raised external finance after round (rank 1 is best)

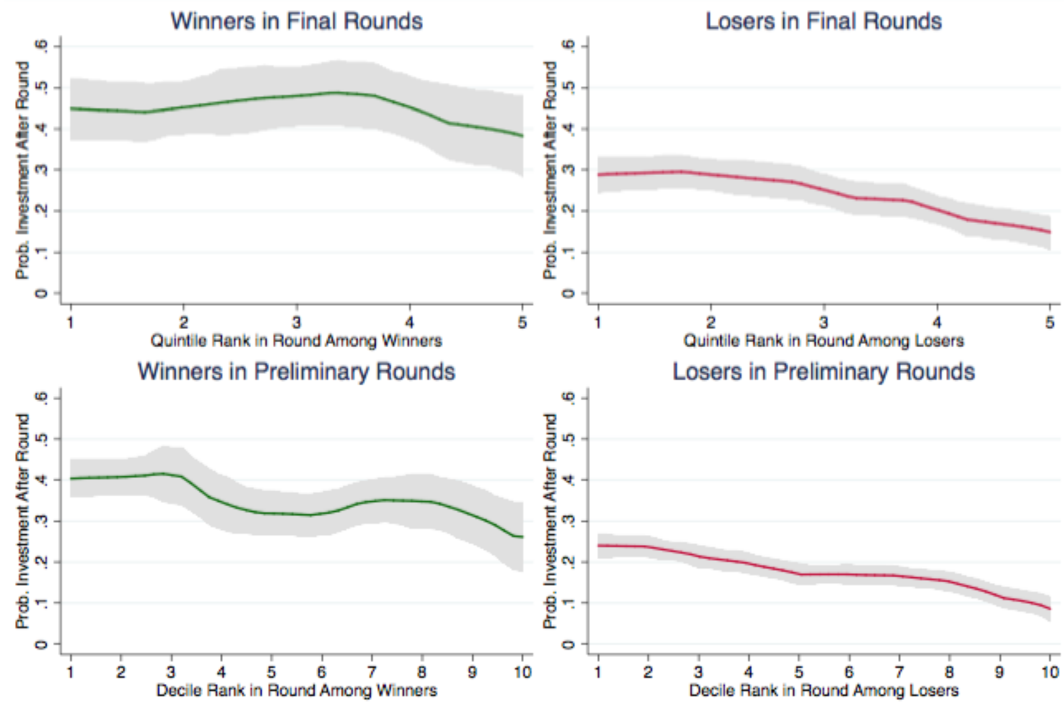


Figure 2: Probability venture had ≥ 3 employees as of 8/2016 (rank 1 is best)

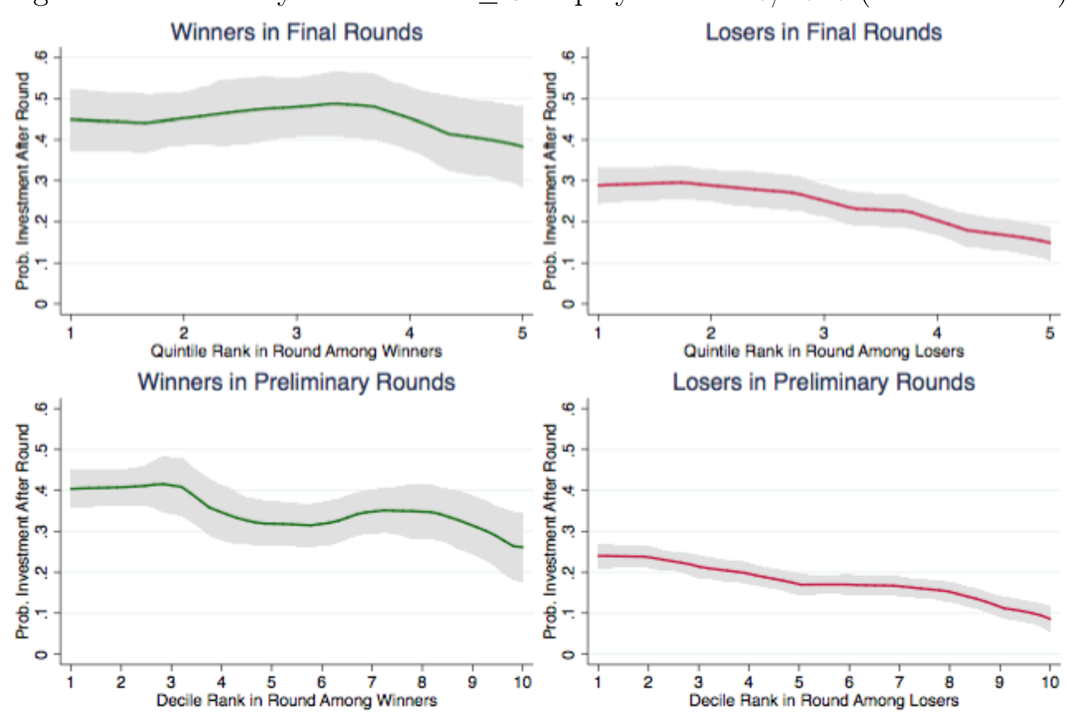
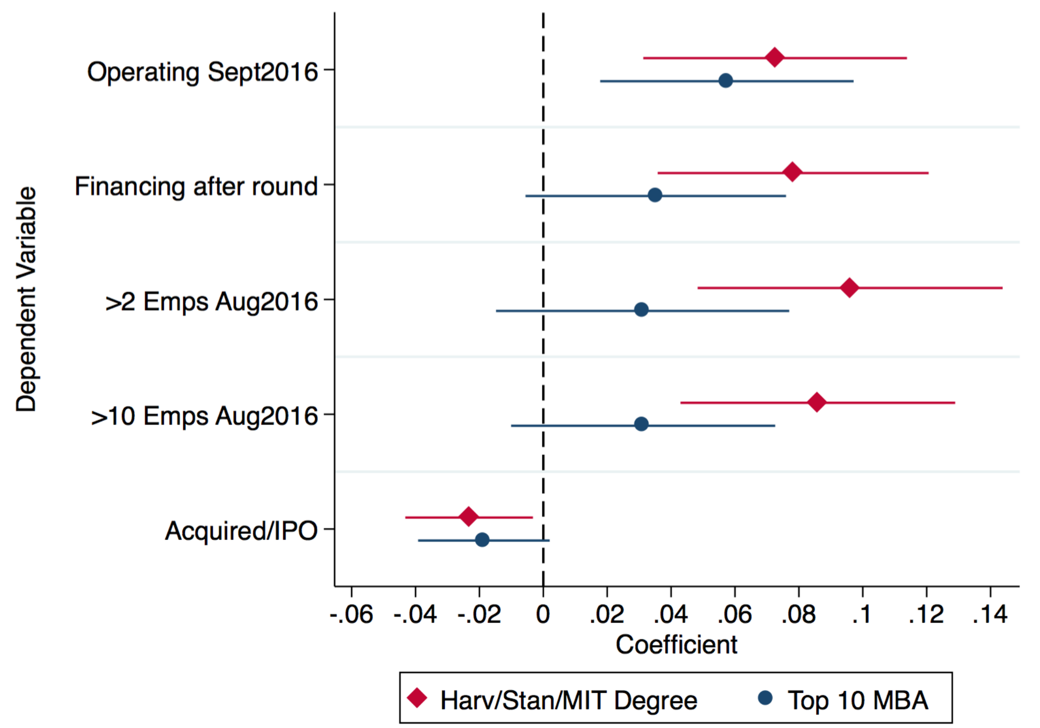


Figure 3: Elite Founders and Success; Coefficients from Regressing Outcome on Elite Status within Competition



Note: This figure shows coefficients and 95% confidence intervals from eight regressions, each of which takes the form:

$$Y_i^{Post} = \alpha + \beta_1 (\mathbf{1} \mid C_i) + \gamma' (\mathbf{1} \mid CompRound_j) + \varepsilon_{i,j}$$

, where C_i is either an indicator for having any degree from an elite school (Harvard, Stanford, MIT) or an indicator for attending a top 10 MBA program (see Appendix Table 4 for rankings). Regression results are in Appendix Table 20.

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