Learning in Entrepreneurship

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Abstract

Evidence of low returns to entrepreneurship is puzzling. Cognitive biases like overconfidence, non-pecuniary benefits, or extreme risk preferences 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. I use novel data from nearly 100 new venture competitions to show that negative feedback causally increases the chances a venture is abandoned. Further, learning in the sense of improvement is predictive of subsequent financing and employment. I find heterogeneity relevant to theories of 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, but founders with degrees from elite schools and social impact ventures do not learn in ways that suggest they, respectively, suffer from cognitive biases 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, entry and exit occur when managers respond to new information about the net present value of the enterprise relative to their outside option. The models contain an explicit or implicit learning process that is in general rational and homogenous.[1]

Empirical evidence of low returns to entrepreneurship has led to explanations of entry at odds with these theories, and to a tension between two strands of thought.[2] One argues that non-pecuniary benefits or cognitive biases like overconfidence explain why people forego valuable outside options to become entrepreneurs. In this view, entrepreneurs enter irrationally and fail to update their priors in light of new information.[3] The cognitive bias explanation gives rise to contracting models such as Landier & Thesmar (2009), 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 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) pro-

[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.

pose 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 and experimentation views imply different reactions to new signals. The former points to entrepreneurs persisting despite the arrival of negative information about the venture's commercial prospects. The latter requires entrepreneurs to recognize and value the abandonment option, and also to adapt their strategies to new information. This paper provides the first causal evidence that new ventures and founders do, in fact, learn from interim signals. More importantly, it identifies 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 ventures and their founders are not representative of the universe of entrepreneurs. 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). This is an important group to study. Young, high-growth startups drive innovation, employment, and productivity growth (Haltiwanger, Jarmin & Miranda 2013).

The first step in the analysis is to establish that the competitions generate valuable, informative signals. In a regression discontinuity design, I show that

[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.

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; further, it is useful independently of a cash award, suggesting a certification mechanism. Regressions include competition-round-panel fixed effects, which control for the date and geographic location. I also control for whether the judge or the judge's company invested in the venture. Rank itself and learning continue to predict success in models with judge fixed effects.

I next ask whether ventures that receive especially negative feedback are more likely to fail. This measures "learning" in the narrow sense of responsiveness. I exploit an institutional difference across competitions: 35 inform ventures of their ranks within a round, while the remaining 61 do not. Within the sample of losers, I compare the effect of being below median in a round after which the venture is informed of its rank, relative to being below median rank in a round after which the venture is not informed of its rank. I show that receiving this negative, structured feedback increases by about 15% the probability that the venture is ultimately abandoned.

Third, I examine learning measured as improvement across rounds, which all ventures wish to achieve (selection into participation indicates a desire to win). Ventures may change their pitch across rounds through learning-by-doing, or in response to informal feedback. "Learning" is a vague term that applies to a broad range of behavior. Henceforth, I refer to "learning" in the sense of three measures, which (a) capture whether ventures improve in judges' eyes in response to judge feedback; and (b) are predictive of firm outcomes.

The first measure is the change in decile rank between a pre-competition written business plan phase and the first round of the competition.[6] 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,

[6]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.

employment, and survival.[7]

Founders are more likely to abandon their venture in response to negative feedback when the venture at the time of the competition had no external financing, was unincorporated, or was not from a VC hub state. Yet ventures with previous financing and those with formal IP rights learn more across rounds. More interesting, software ventures and student-run ventures are much more likely to fail in response to negative feedback, and they learn more across rounds. Older ventures and older founders learn less.[8] These results are indicative of early stage experimentation. As the venture reaches the milestones of incorporation and initial funding, or as the cost of experimentation rises across sectors, the options to change strategies or abandon decline in value.

Founders that received any degree from the top three universities for entrepreneurship (Harvard, Stanford, and MIT) and founders with 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.[9] While elite school founders are more likely to succeed in terms of subsequent financing, employment, and survival, consistent with Gompers, Mukharlyamov & Xuan (2016), they are *less* likely to experience the top-tail outcomes of an acquisition or IPO. Also, the causal effect of winning on financing is larger for elite founders. Therefore, rational elite founders should learn, making these facts consistent with such founders being overconfident.

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 they are using the competition to mobilize a

[7]Since winning is useful, participating ventures should seek improvement across rounds regardless of the relationship between rank and success. I find that in the competitions with structured feedback, improvement across rounds is more predictive of success.

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

[9]A related result is that individuals trained in entrepreneurship and management (whether undergraduate or MBA) learn more, but this course of study is associated with success at only the undergraduate level.

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.

There are two mechanisms that might explain improvement across rounds: firms may refine how they sell their idea, or they may alter the idea itself.[10] Criteria scores illuminate the type of learning.[11] Consistent with Bernstein, Korteweg & Laws (2015), the strongest predictor of success is a higher team (leadership quality) rank. 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, rather than dramatic pivots to a new idea. Founders also vary in their benefit from learning. One characteristic associated with greater benefit from learning is a degree in computer science or engineering, even though founders with such degrees 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.

In this sample, behavior is consistent with the experimentation view on average. Founders are sensitive to negative feedback, and learning is strongly predictive of success. My findings support theories such as Ericson & Pakes (1995), in which firms actively acquire new information rather than passively receive type shocks. However, my results suggest that contrary to most existing models, firms do not learn from new information homogeneously. For example, entrepreneurs in clean energy and "social impact" sectors, who likely derive large non-pecuniary benefits, tend to learn less. Such heterogeneity in learning about future profits might be responsible for inefficient stickiness and for the long right tail of seemingly poor ideas that turn out to be wildly successful.

[10] I am also examining whether business descriptions change across competitions; results coming soon.

[11] The dimensions are team (leadership quality), financials (sound fundraising and cash flow strategy), business model (plan for commercial viability), market attractiveness, technology/product quality, and presentation (polish of the in-person pitch). Criteria scores, where competitions use them, are aggregated to generate the overall ranks that are used elsewhere.

Temporal heterogeneity suggests that successful founders become more sensitive to new information in hard times. I find that during the financial crisis, winners learned more across rounds. Entrepreneurs may pursue many poor ideas during expansions, when financing is relatively cheap, leading to resource misallocation. As financing availability declines, persisting with a poor idea is increasingly costly. Faster learning may be one mechanism for the cleansing effect of recessions in Caballero et al. (1996).

More broadly, faster learning - and churning - can improve resource allocation in the economy. In their study of Italian entrepreneurs, 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: skill and overconfidence among CEOs and entrepreneurs (Malmendier & Tate 2005, Bertrand & Schoar 2003); 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 new resources for startups (Fehder & Hochberg 2014, Scott, Shu & Lubynsky 2015).[12]

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.

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

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, 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.[13] 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.[14]

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, 353 also raised seed or angel investment, 195

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

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

raised VC investment, and 114 exited via an acquisition or IPO. The overall number of new venture competitions has grown dramatically in the past decade.

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 winning ventures.[15]
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).[16] 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

[15]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.

[16]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.

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 some competitions, ventures receive handwritten, non-numeric feedback. In all competitions, ventures receive questions and usually some type of informal, verbal feedback from the judges. However, feedback only includes rankings relative to other firms in the structured feedback competitions. Also, in no competitions do ventures receive judge-specific feedback.

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. Neither other judges nor the ventures observe a specific judge's rank.

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 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.[17] Ventures in these states have access to richer networks of investors, advisers, and other resources. The indicator for being located in one of these three VC hub states is 1 with probability .35 in the overall sample. The competitions take place in 17 U.S. states. From a sector, geographic, and entrepreneur background perspective, 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 companies 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.[18] 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

[17] 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).

[18] I do not observe hiring events.

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. Through researching the ventures, 765 name changes were identified. Ventures were matched to private investment on both the original and changed names.

Table 1 Panel 3 describes the venture founders, using data from the competitions and from LinkedIn profiles. Of the 3,643 team leaders (listed first as leader or CEO on application) researched, 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 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).[19] I also divide the sample by major; for example, 130 founders list their major as economics or finance, while 169 list their major as management, entrepreneurship or marketing.[20]

Judges participate in order to source deals, clients, or job opportunities. All these types also sometimes describe judging as a way to "give back" to the

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

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

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 examination of each funded venture and the judges that observed that venture 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.

One challenge the literature has faced is that the survey or population data typically used (the SCF, NLSY79, or BDS) contain relatively few high-growth entrepreneurs, as Levine & Rubinstein (2013) point out. For example, the non-military, ever-worker size of the NLSY79 is roughly 5,400 individuals, only about 10% of which were ever self-employed. Further, it is difficult to distinguish high-growth, young firms from local small businesses with limited growth potential (e.g. restaurants, plumbers, and self-employed accountants). Startups are in the former category; through a new technology or business model, they aim to become large, valuable, and transformational to their industry. The data in this paper consist of individuals considering founding or having just founded potentially high-growth ventures. Among the unique aspects of the data is that there are no subsistence businesses or sole proprietorships. Effectively all have high-growth ambitions; when already founded, they are primarily c-corps, and nearly all seek external finance to fund growth. A second unique aspect is that I observe ventures and their founders at a much earlier stage, with much greater granularity and in a larger sample than any extant study in entrepreneurship.

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 from

aggregated judge ranks about their future prospects. 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:

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

Here, i indicates a venture, and j a competition-round (e.g. the MIT Clean Energy Prize Semifinals). 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. In most specifications, I simply control for a linear decile rank, but in the baseline estimation I estimate separate decile ranks among losers of a round and among winners. Y_i^{Post} is a binary outcome variable. The coefficient of interest is on $DecileRank_{i,j}$. The best decile is 1, and the worst is 10. Therefore, a negative coefficient on $DecileRank_{i,j}$ indicates that judge ranks are positively correlated with the success metrics, after controlling for whether the venture one or lost.

The next step has two pieces. First, I ask whether whether ventures that receive especially negative feedback are more likely to fail. I can causally estimate the effect of negative feedback by comparing the 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 the combined effect on the entrepreneur of losing, receiving a below-median score among losers, and knowing that he received a low score on continuation (the measures of survival) in Equation 2:

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

Here, the coefficient of interest 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. The first learning measure is based on feedback provided to ventures about their written business plans prior to the competition. Ventures are explicitly told to incorporate this feedback, which includes dimension and overall scores aggregated across judges, into their pitches in the actual competition. The business plan scores do not count towards winning. Letting j denote the business plan phase in the competition and j' the competition's first round, the learning metric is the change in 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 non-competitive business plan phase occurs in two programs (the Massachusetts CEC Catalyst competition and the Rice Business Plan Competition), so the sample is small. As there are only two competitions, 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 in the 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 (some ventures participated in three or more competitions).

The third learning metric is improvement across rounds within a competition. This yields the largest sample, so it is the primary metric for studying heterogeneity. 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, with both the overall rank and the dimension-specific rank, which permits initial evidence about the learning mechanism. In robustness tests, I also examine learning from the first to final round, skipping intermediate rounds where they exist.

Improvement in ranking across rounds is a measure of learning because all ventures seek to improve in the eyes of the judges, else they would not participate in the competition. 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. 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 predict venture success and thus are valuable signals; and (b) learning predicts venture success and is thus useful to ventures. I can then 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:

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

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 establish 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 com-

paring 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 III-IV). Similarly, using judge fixed effects and controlling for the judge's rank of a venture among ventures that the judge scored, 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.[21]

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

[21]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.

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%.

As this analysis is limited to ventures participating in a set of competitions, it is possible that the positive effect of winning could instead be 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 is certainly possible; however, it 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.

The learning metrics are based on judge ranks being meaningful signals about startup quality in two ways: 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 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 columns III, VI, and VIII confirm the strong predictive power of rank. I rely on OLS models in the remaining analysis. Not only do OLS models have a simpler interpretation, but logit models drop groups without positive outcomes, leading them to typically overestimate models with 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.

4.2 Effect of Feedback on Continuation

The first type of learning I consider is whether ventures that receive especially negative feedback are more likely to fail. 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.

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. Columns I-V show that this interaction has an effect of -7 to -13 pp on employment. Thus this 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 clearly highly specific to this context, this provides the first causal estimate of the effect of feedback on venture abandonment. Founders respond to negative feedback by being more likely to abandon their venture. 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 (which increases the sample), 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. The cost of experimentation (or pivoting) should be lower for IT/software ventures than for hardware startups. To more closely isolate ventures whose founders are more likely to derive large non-pecuniary benefits, I create an indicator for the firm being in a capital-intensive or social impact-driven sector; it is 1 for ventures that are in social impact, energy, manufacturing, air/waste, transportation, education, and biotech. As Appendix Table A6 columns II, V, and VII show, this indicator is indeed a strong negative predictor of success (while columns I and IV show that software-based ventures are much more likely to succeed). I also examine only ventures that self-identify as social impact or clean technology/renewable energy ventures. Both the hard-to-fund and social/clean tech indicators include some software startups but are are negatively correlated with the IT/software indicator (see the correlation matrix in Appendix Table A8 Panel 2).

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 (experimentation is cheaper for software ventures) appears to make abandonment a more attractive option, and this does not seem to be linked to higher non-pecuniary motivations for hardware founders. Founders with especially strong social motivations are no more likely to abandon their startup than their more profit-oriented counterparts.

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 number of and early stage funding to web- and software-based startups in the mid- and late-2000s 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, hardware technologies should have a lower option value of entrepreneurship. Resolving uncertainty about their viability will require more time and more money than software ventures.

Column VII shows that ventures from the three VC hub states are less responsive, suggesting either that they have more access to resources for continuing, or that the feedback is less relevant for them. Some evidence for the latter hypothesis is in Appendix Table A9, which shows that while the rank signal is informative about success for these ventures (an additional decile increases the probability of subsequent financing by 1.3 pp, significant at the 1% level), it is substantially more predictive for ventures from other states (the analogous coefficient is 2.1 pp, also significant at the 1% level).

Uncertainty among judges (measured by the standard deviation in their ranks) is a measure of the venture's riskiness. 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. I examine whether consensus among judges affects how ventures respond to feed-

back. I use an indicator for whether the standard deviation of judge ranks within a competition-round-panel is above or below median. Ventures are unaware of this uncertainty; they receive only their aggregated rank in the structured feedback competitions. 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 6 column VIII). This is consistent with more confident founders choosing risky business models. At the same time, 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 to attributing the uncertainty effect to venture type is that founders pay less attention to the rank when they know there was no consensus among judges.

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. Note that 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.

There is a strong positive relationship between measures of elite education and most of the outcome measures. 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). Among the majors, only entrepreneurship/managing/marketing predicts success; this major increases the probability of subsequent financing by 6.3 pp. 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.

Surprisingly, elite education is negatively associated in this sample with the top tail outcome of undergoing an acquisition or IPO. We see this in the fully controlled regressions in Table 7, but independent examination provides more insight into the distribution of outcomes for these founders.[22] Figure 3 contains coefficients from regressions of each outcome on the two indicators for elite education and competition fixed 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).

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. This is evidence in favor of the experimentation view. Students may also weight judges' advice highly since they have little per-

[22]The Table 7 result does not simply reflect a lack of power; while only 3% of the sample experiences such an event, note that other variables in Table 7 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.

sonal experience. Consistent with this, founders with more previous jobs are less responsive to feedback (column II).

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 has any effect (columns IV and V). This is the first indication of a broad finding in this paper: the most elite individuals do not seem to respond to or learn from feedback. As Section 4.3 will explore further, the absence of learning is consistent with these founders being overconfident, since they are less likely than other founders to achieve the top tail outcome of an IPO or acquisition.

Similar 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 et al. (2008) theorize that good leaders make an initial assessment of their environment, and then persist in their strategy regardless of new information. They argue that "a key attribute of a good leader is a form of overconfidence, which we shall refer to as resoluteness. A resolute leader has a strong prior and is slow to change his mind in the face of new information about the environment in which the organization operates." The coordination problem that Bolton et al. (2008) focus on is quite relevant to the startup founder; as Rajan (2012) describes, a central task of the early stage entrepreneur is to convince collaborators to join the venture and personally coordinate their efforts.

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 the case that the most successful founders enter with strong business models and pitches, and do not adjust to feedback along the way. This would be consistent with entrepreneurs being

extremely overconfident. Perhaps more important, however, establishing that learning predicts success is essential to analyzing heterogeneity; if this 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; as explained in Section 3. Improvement in ranking between these two phases strongly 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; strikingly, a quintile improvement increases the probability of having at least 10 employees in 2016 by 4.1-4.6 pp, relative to a mean of 20%.

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 strongly 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 much of 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 a number of

tests to ensure the robustness 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[23], 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 primary measure for a person's subsequent success is whether they have an executive title after the round (CEO, CTO, VP, COO, or President). 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. Interestingly, 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. However, these are 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%.

Since winning is useful, participating ventures should seek improvement across rounds regardless of the relationship between rank and success. They may change their pitch across rounds on the basis of learning-by-doing, or because of either informal verbal or written feedback. To confirm that learning is occurring and that ventures respond to judge feedback, 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. Specifically, column I indicates 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), but the effect of learning on the operating as of 2016 survival metric is not different across

[23] Includes whether the company received investment before the round, award amount if any, sector indicator variables, company age, and the number of founders/team members

the two types of competitions (column VI).

Heterogeneity in Learning

Having established that decile rankings are predictive of success, and further that measures of learning using improvement in decile rankings are also predictive of success, I now turn to examining 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 will 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 venture characteristics included, neither the hard-to-fund nor social/clean tech indicators are statistically significant. However, when I include only the three sector-focused variables in column II, it becomes clear that social/clean tech ventures learn much less. 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 at the same time, a lower cost of experimentation leads to more improvement, independently of whether the sector is challenging to finance or not.

The next characteristics address venture stage. In combination, columns I and III indicate that ventures with previous external financing learn more. However, ventures that were incorporated at the time of the round learn less than unincorporated ventures, and older ventures learn less than younger ventures. Ventures learn the most from feedback at their earliest stages, suggesting that interventions like competitions or accelerators will be most useful if targeted to ventures at the time they are founded. 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 more overconfident and less receptive to new information.

Column IV confirms that software startups learn more, social/clean tech startups learn less, and that neither of these effects are explained by location in a VC hub. Founders motivated by non-pecuniary benefits are, as we might expect, less likely to succeed commercially, and they also learn less. Consistent with the structured feedback analysis, where ventures from VC hub states were less likely to fail in response to negative feedback, this specification 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. Founders of riskier ventures may be more overconfident and learn less. 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. 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.

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 average MBA effect grows stronger than in column 1, increasing learning by 1.1 deciles. The effect of having a top ten MBA is to *decrease* learning by 0.8 deciles.[24]

Recall from the structured feedback analysis that elite graduates were 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 simplistic story in which higher quality ventures and founders learn more. Elite founders may be less responsive because, conditional on venture quality, their private knowledge is more accurate, they have superior advice networks, they have better access to financing, or they have personal wealth that reduces the cost of failure.

However, we established above that rank is predictive of success for elite founders, and we can assume that all ventures selecting into participating in these competitions wish to win and thus try to improve across rounds. Thus if the elite founders were rational they would exhibit learning. We also showed above that elite founders are less likely to experience the top tail outcome of acquisition or IPO. Together, these facts are consistent with overconfidence among these founders, in contrast to the rest of the sample, which is very responsive to feedback.

Table 15 Column III shows that learning is much higher (about the same effect as having an MBA) when the founder is a student at the time of the competition, consistent with the greater responsiveness of students from Table 8.

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

Columns IV and V include indicators for the founder's college major (area of study). I have aggregated these into four groupings: liberal arts (which includes economics and finance), entrepreneurship/management/marketing, computer science/engineering, and other sciences (including math and physics). Across specifications (including many not shown here), the entrepreneurship major is strongly associated with learning. In case some people 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 learn the most. At the college level, this course of study is positively associated with subsequent success, but 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 and at least 9,000 faculty members teaching entrepreneurship, and in recent years, some colleges have made entrepreneurship courses core requirements (Morelix 2015). I show that entrepreneurship education is associated with greater adaptability. While not causal, this provides 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 only are correlated with subsequent success for entrepreneurship education at the college level, not for MBAs.

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, none of these characteristics interacts with learning.

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 will shed light on *why* learning is useful, and exactly *what type* of learning is observed here.

Heterogeneity over time provides some insight into why learning is valuable. 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). I do not find any statistically significant relationship between learning and outcomes. 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 literature on larger firms showing a positive correlation between good managerial practices and productivity (Bloom et al. (2012), Bloom et al. (2016),Guiso et al. (2015)) and the importance of the startup's management team to VC investors (Gompers, Gornall, Kaplan & Strebulaev (2016)). Presentation strongly predicts financing but does not predict any other outcome. A better technology or product strongly 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, in particular 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, interestingly, 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.

The dimensions that predict success are not, in general, the same as the dimensions that matter for learning. 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 distract ventures from concrete, near-term objectives. That learning is most useful in terms of financials suggests that between rounds, ventures are not dramatically pivoting to a new idea, but instead are adjusting their financing strategy. 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 subsequent investment is consistent with the pitch being a key fundraising component, and with competitions helping new ventures to refine their pitch.

In general, the judges are based in the same geographic location as the competition, but participating ventures are typically drawn from diverse locations.[25] Appendix Table A9 shows that the competitions are useful to ventures regardless of the venture's home state. 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 the major hubs (column VI). I find analogous results for other outcomes (not reported). None of the differences across these regions

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

are statistically significant. 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).

The positive same state effect is for ventures from states besides the three VC hubs. Appendix Table A16 shows that in the overall sample, 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. Subsequent columns show positive effects of being local on employment and survival. 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 very useful for ventures outside the primary entrepreneurial ecosystems; the competitions serve as an important convening mechanism. While winning is useful across locations, the competitions do not have the same convening power for startups from VC hub states.

This sets the stage for understanding how this convening power interacts with learning.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.[26] Note again from the individual VC hub effects that ventures from these two states have much higher average probabilities of success.

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. It is clear that separate from an elite school effect, the benefit of local networks within the context of the competition is much smaller in the VC hub states. This implies that judge feedback is most helpful when the judge is local in places with fewer entrepreneurial resources.

Chatterji et al. (2013) point out that the top tail of high-growth startups tend to flock to Silicon Valley, but that substantial evidence exists about the importance of a region's local supply of entrepreneurs to the region's tendency to establish an innovation cluster and its attending economic benefits. 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 provides micro-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, the most elite founders do not exhibit such location-specific benefits.

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

Finally, Tables 20 and 21 interacts learning with characteristics to determine which types of ventures and founders benefit more than their counterparts from learning. For example, it could be the case 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. These tables include characteristics with strong learning-related findings below, 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.

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 a 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 different in signal strength, as the coefficient on the rank is roughly equal across these types.

The second important finding from Table 20 is that founders whose majors are computer science or engineering benefit much more than those with other majors (column VII). I did not find that these individuals learned more than their counterparts; here it appears that when they do learn, it is very useful. This is consistent with them having technical skills related to the venture's product, but needing help with the presentation and financial sides of the startup, which are the dimensions that I found to be most useful (Table 18).

The channel through which productive learning occurs in this competition setting appears to be through improved financing strategies and better presentations mobilizing a local network of investors. The evidence is most consistent with elite individuals and those located in VC hubs being less responsive and learning less *not* because of overconfidence or another behavioral explanation, but because their private knowledge is more accurate, they have better advice networks, or they have greater access to financing (conditional on venture quality).

5 Conclusion and Policy Discussion

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. 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."

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.

Recent decades have seen a decline in new firm entry that is troubling in light of evidence that new, young businesses drive increases in employment

(Pugsley & Sahin 2015, Decker et al. 2014). The cost of launching a new firm has simultaneously declined dramatically, particularly for software and web-based technologies (Ewens et al. 2015). It seems likely that the cost of adapting to new information is also much lower for software ventures than it was in the early 2000s. I show that software ventures are more responsive to feedback and learn more. If learning is becoming more efficient, ventures may change strategies more often. It is noteworthy that in researching individual venture outcomes, 765 of the 4,300 startups in my data changed their names after the competition. That is, entry-exit dynamics may be to some extent replaced with entry-pivot dynamics. Anecdotal evidence suggests that pivoting 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."

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.[27] 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.[28] 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

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

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

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 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		*Judge Professions*	
	# unique ventures		*# 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		.0032	.0089		-.011**	-.071***	-.0062	-.071***		
among winners		(.0066)	(.031)		(.0049)	(.025)	(.0056)	(.021)		
Decile rank in round		-.021***	-.13***		-.017***	-.13***	-.014***	-.13***		
among losers		(.0044)	(.026)		(.0031)	(.022)	(.0032)	(.017)		
Judge decile rank in									-.0065***	-.0061***
round									(.0011)	(.0014)
Award Amount ($,							.0093***			.011***
10,000s)							(.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:

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

. 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, rank, and award (cash prize) on indicators for various outcomes, using variants of:

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

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:	≥ 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:

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

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††	Std dev of judge ranks above median
	I	II	III	IV	V	VI	VII	VIII
Below median rank among losers· Structured feedback· C_i	.4*** (.04)	.13*** (.029)	-.088* (.05)	-.14*** (.033)	.022 (.038)	-.045 (.047)	.14* (.074)	.082** (.037)
Below median rank among losers· Structured feedback	.076*** (.028)	.0079 (.053)	-.11** (.053)	.088*** (.032)	.09** (.036)	.062** (.031)	.11*** (.037)	.038 (.04)
Structured feedback· C_i	.42*** (.043)	.28*** (.034)	.097* (.053)	.33*** (.039)	.12** (.047)	.021 (.067)	.44*** (.075)	.21*** (.042)
Below median rank among losers· C_i	.36*** (.046)	.16*** (.037)	.044 (.066)	.1*** (.038)	-.07** (.035)	-.092*** (.035)	-.0088 (.038)	-.015 (.036)
Below median rank among losers	-.021 (.026)	-.04 (.028)	-.066 (.054)	-.029 (.028)	-.038 (.034)	-.057* (.03)	-.004 (.038)	-.089** (.036)
Structured feedback	.22*** (.036)	.076 (.1)	.0074 (.064)	.19*** (.04)	.27*** (.041)	.22*** (.035)	.24*** (.041)	.22*** (.05)
C_i	.44*** (.059)	.21*** (.053)	.065 (.078)	.21*** (.057)	-.022 (.044)	-.1** (.049)	.064 (.044)	-.0092 (.044)
Year f.e.	Y	Y	Y	Y	Y	Y	Y	Y
N	3264	3264	1815	3264	3264	3264	3264	3264
R^2	.11	.059	.023	.051	.043	.044	.041	.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

Dependent Variable:	*Panel 3: Other Outcomes* ≥ 3 employees as of 8/2016	≥ 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 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):	Founder is student	Founder number of previous jobs	Founder has Harvard/MIT/Stanford degree	Founder attended top 20 college	Founder has MBA
	I	II	III	IV	V
Below median rank among losers· Structured feedback· C_i	-.3***	.13**	.69***	.17	.084
	(.028)	(.054)	(.027)	(.37)	(.17)
Below median rank among losers· Structured feedback	.096***	.12*	.07**	.069**	.06**
	(.028)	(.068)	(.028)	(.028)	(.029)
Structured feedback· C_i	0	.27***	.69***	.66***	.25
	(.)	(.057)	(.027)	(.028)	(.16)
Below median rank among losers· C_i	.078**	.02	-.088*	-.065	-.074
	(.037)	(.054)	(.048)	(.053)	(.046)
Below median rank among losers	-.049*	-.024	-.037	-.042	-.05*
	(.028)	(.059)	(.027)	(.027)	(.028)
Structured feedback	.25***	.3***	.22***	.22***	.21***
	(.033)	(.095)	(.033)	(.032)	(.033)
C_i	.14**	.066	.013	-.0016	-.057
	(.059)	(.057)	(.065)	(.082)	(.058)
Year f.e.	Y	Y	Y	Y	Y
N	3264	3264	3264	3264	3264
R^2	.045	.039	.04	.039	.039

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			≥ 3 employees as of 8/2016	≥ 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:

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

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. Note that competition f.e. control for a specific date. †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: $Y_i^{Post} = \alpha + \beta_1 \left(\mathbf{1} \mid WonRound_{i,j}\right) + f\left(DimensionDecileRank_{i,j}/JudgeDimQuintileRank_{i,j,k}\right) + \gamma' \left(\mathbf{1} \mid f.e._{j/k}\right) + \varepsilon_{i,j,/k}$. 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*			≥ 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: $Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j'(deciles)} (\mathbf{1} \mid SameState_{i,j'}) + \beta_2 \Delta_{i,j,j'(deciles)} + \beta_3 (\mathbf{1} \mid SameState_{i,j'}) + \beta_4 (\mathbf{1} \mid WonRound_{i,j'}) + f(DecileRank_{i,j'}) + \gamma' (\mathbf{1} \mid f.e._{j'/k}) + \varepsilon_{i,j'}$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)

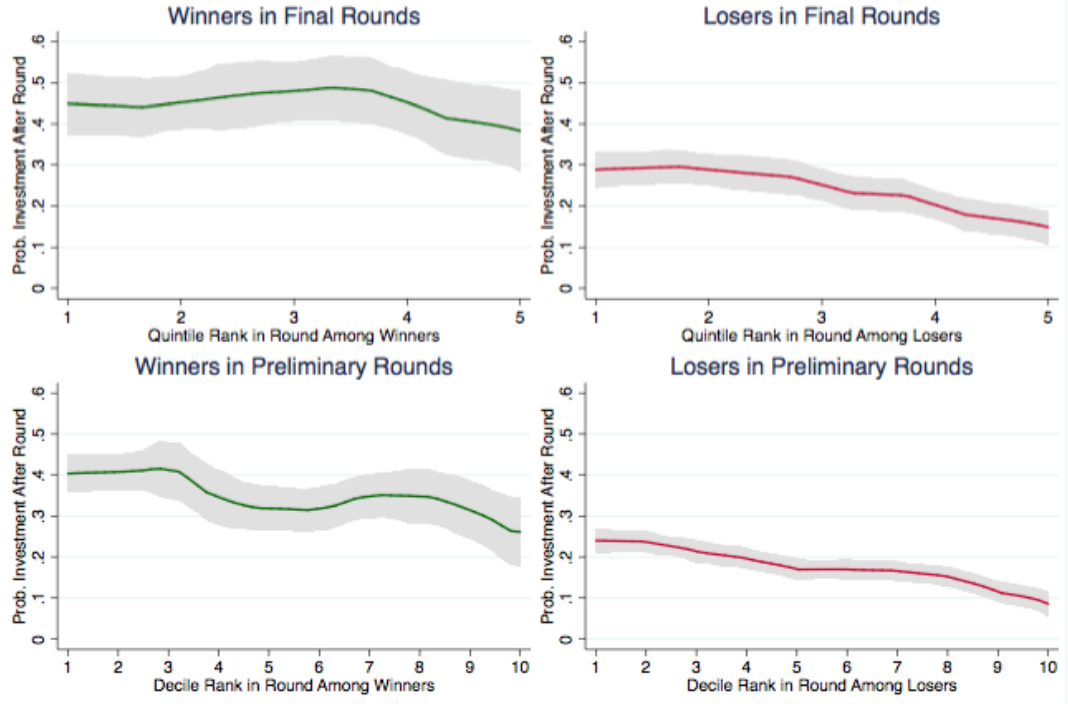


Figure 2: Probability venture had ≥ 3 employees as of 8/2016 (rank 1 is best)

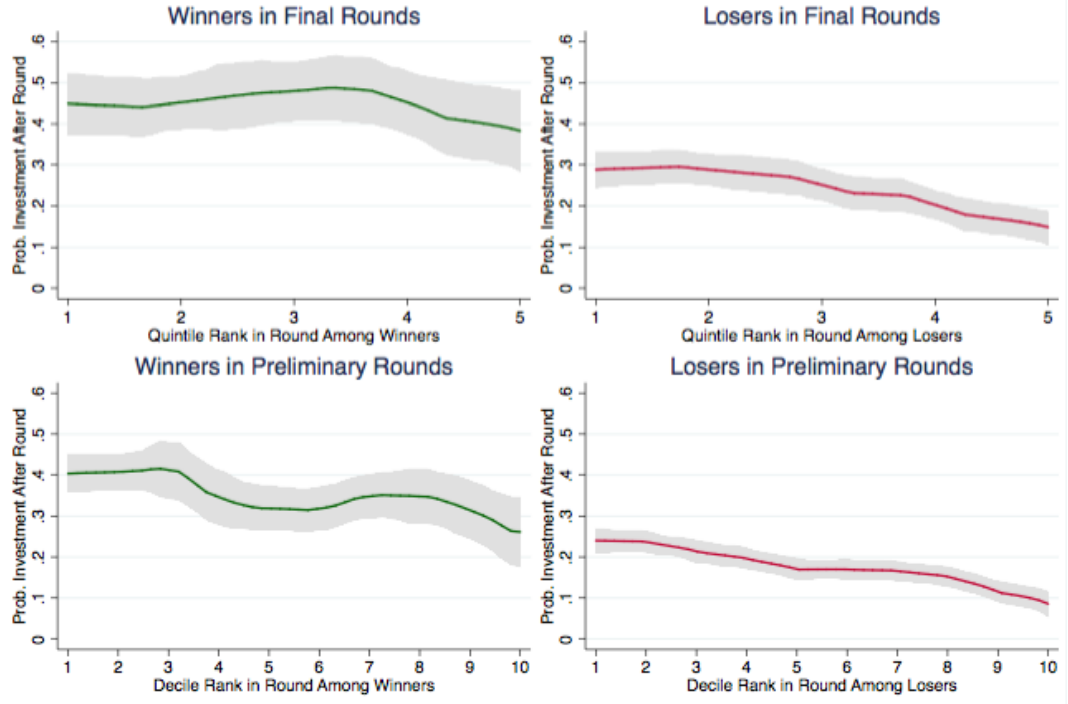
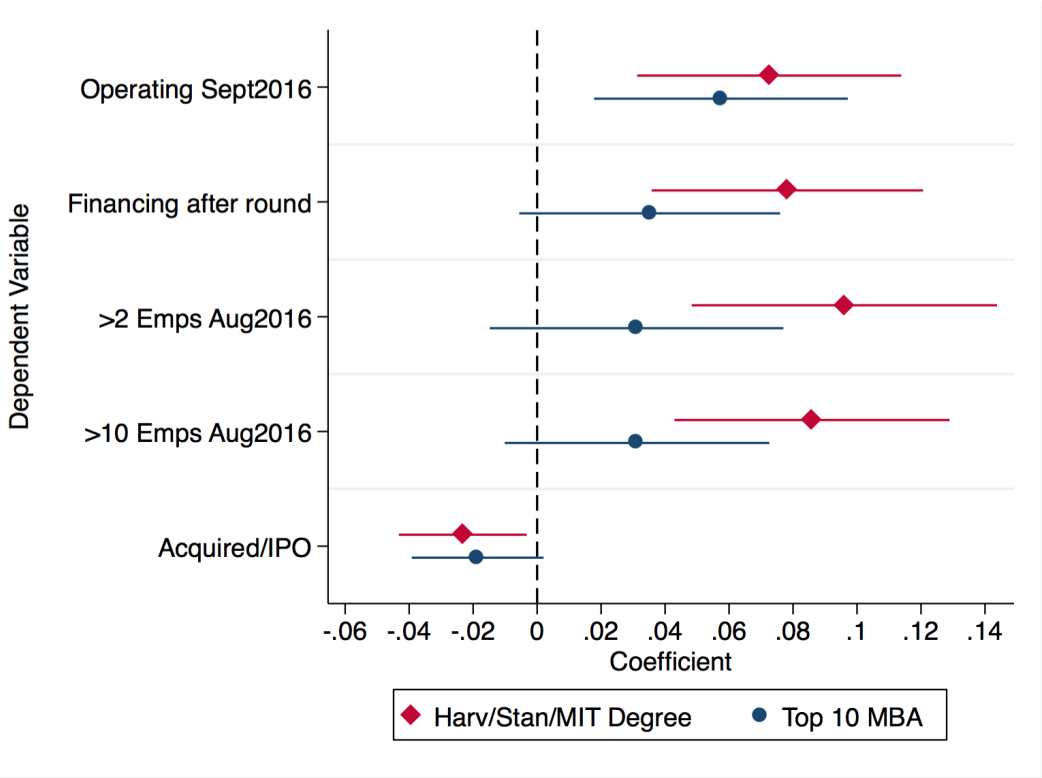


Figure 3: Elite Founders and Success; Coefficients from Regressing Outcome on Elite Status within Competition



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

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

, 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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Appendix

Table A.1: List of Programs

Panel 1

Competition Name	*City*	*State*	*Years*	*# unique ventures*	*# unique judges*	*# rounds per comp.*	*Judges score*$^{\ominus}$	*Judges rank*	*Dimension scores*	*Structured feedback*
1M Cups Denver	Denver	CO	2014	6	2	1	Yes	No	Yes	Yes
Arizona Innovation Challenge Fall	Phoenix	AZ	2012-2015	551	90	2	Yes	No	Yes	Yes
Arizona Innovation Challenge Spring	Phoenix	AZ	2012-2015	640	87	2	Yes	No	Yes	Yes
Angel Capital Summit	Denver	CO	2014-15	195	55	1	Yes	No	Yes	Yes
BRF Entrepreneur Accelerator Program (EAP)	Shreveport	LA	2014	22	4	1	Yes	No	Yes	Yes
CU CleanTech New Venture Challenge	Boulder	CO	2012-13	27	35	1	Yes	No	Yes	Yes
Clean Energy Challenge	Chicago	IL	2013	50	55	2	Yes	No	Yes	Yes
Cleantech Open: California	Redwood City	CA	2009-14	231	163	2	Yes	No	Yes	Only 2011
Cleantech Open: North Central	Minneapolis	MN	2010-13	109	103	2	Yes	No	Yes	Only 2011
Cleantech Open: Northeast	Boston	MA	2009-13	233	137	2	Yes	No	Yes	Only 2011
Cleantech Open: Pacific Northwest	Portland	OR	2009-13	62	38	2	Yes	No	Yes	Only 2011
Cleantech Open: Rocky Mountain	Denver	CO	2009-13	133	61	2	Yes	No	Yes	Only 2011
Cleantech Open: South Central	Austin	TX	2011-13	11	12	2	Yes	No	Yes	Only 2011
Cleantech Open: Southeast	Atlanta	GA	2011-13	24	37	2	Yes	No	Yes	Only 2011
Colorado Capital Conference 2013	Denver	CO	2013	52	23	2	Yes	No	Yes	Yes
Colorado Digital Health Challenge	Denver	CO	2014	33	46	2	Yes	No	Yes	Yes
DOE Cleantech Business Plan Competition	Washington	D.C.	2013	6	5	2	Yes	No	Yes	Yes
Energize 2013	Snowbird	UT	2013	22	12	1	Yes	No	Yes	Yes
Energy Security Prize, EIA Track	Washington	D.C.	2013	16	18	2	Yes	No	Yes	Yes
Galvanize Pitches and Pitchers	San Francisco	CA	2013	4	6	1	Yes	No	Yes	Yes

Competition Name	*City*	*State*	*Years*	*Panel 2* # *unique ventures*	# *unique judges*	# *rounds per comp.*	*Judges score*$^{\ominus}$	*Judges rank*	*Dimension scores*	*Structured feedback*
Harvard Business School New Venture Competition	Boston	MA	1999-2015	837	563	2‡	Yes$^{\oslash}$	Yes	No	No
Illinois Clean Energy Student Challenge	Chicago	IL	2013	6	9	1	Yes	No	Yes	Yes
Imagine H2O Infrastructure Challenge	San Francisco	CA	2013-15	160	31	3	Yes	No	Yes	Yes
Innosphere Admissions	Fort Collins	CO	2013-15	32	46	1	Yes	No	Yes	Yes
MIT Clean Energy Prize	Cambridge	MA	2013-15	156	80	2-3$^{\diagdown}$	Yes	No	Yes	No
Missouri Clean Energy Student Challenge	St. Louis	MO	2013	14	9	1	Yes	No	Yes	Yes
OEDIT Advanced Industries Accelerator Energy and Natural Resources	Denver	CO	2015	16	7	1	Yes	No	Yes	Yes
Ohio Clean Energy Student Challenge	Cleveland	OH	2012-13	12	8	1	Yes	No	Yes	Yes
SESP Training - Colorado Springs Technology Incubator	Colorado Springs	CO	2012-14	7	2	1	Yes	No	Yes	Yes
TransTech Energy Conference 2012	Morgantown	WV	2012	20	25	1	Yes	No	Yes	Yes
Venture Madness 2015	Scottsdale	AZ	2015	82	38	3	Yes	No	Yes	Yes
Massachusetts Clean Energy Center Catalyst Grant Program	Boston	MA	2012-15	250	134	2	Yes	No	Yes	No
Rice University Business Plan Competition	Houston	TX	2004-2015	480	694	3†	No	Yes	No$^{\mp}$	No

Notes: $^{\ominus}$In the main data file, I have transformed scores to ranks (and all ranks to percentile ranks). Therefore, two ventures may have the same rank. ‡First round done in panels of 4-8 ventures and 5-15 judges per panel, varies somewhat year to year (note: there is small finals for top three teams, all of which win a cash prize. Do not have data for this final round) †First round, challenge round, and semifinal rounds all "tracked" into panels (what RBPC calls "flights"). First round tracked by sector, then firms randomized across panels. Losers of first round go on to "Challenge" round. There is also pre-competition business plan stage. *Have in hand: 2012-16. Hopefully more coming. $^{\mp}$But used in pre-competition business plan stage, and I have those scores. $^{\oslash}$ Main data file includes only ranks. I also have scores for HBS NVC. $^{\diagdown}$Depends on year.

Table A.2: Rank and Learning Metrics Summary Statistics

Panel 1: Venture's Overall Rank in Round/Panel						
	N	Mean	Median	S.d.	Min	Max
Decile rank in round	6051	5.13	5	2.87	1	10
Decile rank in final round	1605	5.22	5	2.89	1	10
Decile rank in preliminary round	4394	5.1	5	2.87	1	10
Decile rank in final round among winners	407	4.57	5	2.84	1	10
Decile rank in final round among losers	1198	5.12	5	2.89	1	10
Decile rank in preliminary round among winners	1126	4.17	4	2.98	1	10
Decile rank in preliminary round among losers	3268	4.94	5	2.85	1	10
Dimension decile rank in round						
Team	4904	5.09	5	2.9	1	10
Financials	3691	5.07	5	2.9	1	10
Business Model	4024	5.08	5	2.89	1	10
Market Attractiveness	4024	5.09	5	2.9	1	10
Technology/Product	4848	5.09	5	2.89	1	10
Presentation	2799	5.04	5	2.93	1	10
Legal/IP/Regulatory	1537	4.94	5	2.89	1	10
Traction/Validation	1809	5.01	5	2.86	1	10
Risk/Cost Management	550	4.65	5	2.81	1	10
Panel 2: Judge's Rank of Venture (Among Ventures Judge Scored)						
	N	Mean	Median	S.d.	Min	Max
Judge decile rank in round	47065	4.75	5	2.83	1	10
Judge dimension quintile rank in round						
Team	27603	2.22	2	1.34	1	5
Financials	23070	2.21	2	1.32	1	5
Business Model	24127	2.24	2	1.34	1	5
Market Attractiveness	24167	2.25	2	1.33	1	5
Technology/Product	27346	2.26	2	1.34	1	5
Presentation	12644	2.26	2	1.37	1	5
Legal/IP/Regulatory	12779	2.15	2	1.34	1	5
Traction/Validation	13978	2.22	2	1.36	1	5
Risk/Cost Management	2776	2.17	2	1.26	1	5
Panel 3: Learning Metrics						
	N	Mean	Median	S.d.	Min	Max
$\Delta_{quintiles}$ business plan to first round	510	0.29	0	1.47	-4	4
$\Delta_{quintiles}$ business plan to final round	154	-0.93	-1	1.52	-4	4
$\Delta_{deciles}$ prelim round to second round	1252	-1.45	-1	3.63	-9	8
$\Delta_{deciles}$ prelim round to final round	761	-2.62	-2	3.08	-9	8
$\Delta_{quintiles}$ prelim round to second round	1252	-0.72	-1	1.79	-4	4
$\Delta_{deciles}$ first to last competition (among ventures in > 1 competition), using preliminary rounds in both	484	0.29	0	3.09	-8	9
$\Delta_{deciles}$ first to second competition (among ventures in > 1 competition), using preliminary rounds in both	499	0.15	0	3.01	-8	9
$\Delta_{deciles}$ first to second competition (among ventures in > 1 competition), using final rounds in both	538	0.01	0	3.19	-9	9

Note: This table contains summary statistics about the ranks and learning metrics used in analysis.

Table A.3: Company & Competition States

State	# competitions in state	# ventures located in state	State	# competitions in state	# ventures located in state
Arizona	8	665	Idaho		9
California	7	298	Kentucky		13
Massachusetts	34	1,146	Michigan		24
Colorado	16	250	Rhode Island		9
New York		85	Arkansas		14
Minnesota	2	46	North Carolina		14
Utah	3	48	Montana		7
Washington		40	Florida		16
Illinois		62	Hawaii		6
Nevada		28	Indiana		21
Texas	14	70	Missouri	1	19
Oregon	3	21	South Carolina		4
Wisconsin		28	Vermont		4
Connecticut		20	DC		4
Iowa		17	Kansas		9
Maryland		23	Alaska		2
Maine		8	Tennessee		10
New Jersey		14	New Hampshire		5
Ohio	2	28	South Dakota		3
Pennsylvania		26	Delaware		3
Virginia		20	Wyoming		5
North Dakota		7	Louisiana		13
New Mexico		10	West Virginia	1	2
Georgia		18	Mississippi		1
Oklahoma		4	Foreign		26

Note: This table lists the number of competitions and unique ventures by state. Companies that changed states are assigned their earliest state.

Table A.4: University Rankings

Top Twenty U.S. Universities		*Top Ten MBA Programs*		*Top Ten Universities for Computer Science*	
Rank	Name	Rank	Name	Rank	Name
1	PRINCETON	1	HARVARD	1	MIT
2	HARVARD	2	STANFORD	2	STANFORD
3	YALE	3	CHICAGO	3	HARVARD
4	COLUMBIA	4	UPENN	4	UC BERKELEY
5	STANFORD	5	MIT	5	TSINGHUA
6	CHICAGO	6	NORTHWESTERN	6	UT AUSTIN
7	MIT	7	UC BERKELEY	7	PRINCETON
8	DUKE	8	DARTMOUTH	8	UC SAN DIEGO
9	UPENN	9	YALE	9	UCLA
10	CALTECH	10	COLUMBIA	10	GEORGIA TECH
11	JOHNS HOPKINS				
12	DARTMOUTH				
13	NORTHWESTERN				
14	BROWN				
15	CORNELL				
16	VANDERBILT				
17	WASH ST LOUIS				
18	RICE				
19	NOTRE DAME				
20	UC BERKELEY				

Note: This table describes the university rankings used in analysis. Source: US News & World Report 2016 Rankings.

Table A.5: Effect of Positive Feedback (Effect of above-median rank within winners when founders informed of rank, relative to above-median rank winners *not* informed of rank)

Sample restricted to winners of round	$\geq$ 2 employees as of 8/2016					Operating as of 9/2016		
Dependent Variable:								
	I	II	III	IV	V	VI	VII	VIII
Above median rank among winners$\cdot$ Structured feedback	.02	-.03	.12***	.13**	.12**	-.071	-.022	.027*
	(.065)	(.077)	(.046)	(.053)	(.052)	(.067)	(.076)	(.016)
Above median rank among winners	.082	.069	-.037	-.025	-.045	.098*	.032	-.0035
	(.051)	(.056)	(.033)	(.035)	(.037)	(.058)	(.063)	(.01)
Structured feedback	.21***	.25***	.49***	.23	.087	.24***	.2**	-.012
	(.065)	(.074)	(.12)	(.26)	(.28)	(.065)	(.079)	(.058)
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	1147	844	8361	5403	5376	1147	1173	5376
R^2	.064	.058	.29	.26	.42	.071	.16	.34

Note: This table contains OLS regression estimates of the effect of having a above-median rank among winners 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. 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 A.6: Venture Characteristics' Association with Success (All rounds)

Dependent Variable:	Financing After Round			≥ 3 employees as of 8/2016		Acquired/IPO	
	I	II	III	IV	V	VI	VII
Number of team members	.063***		.059	.024		.021*	
	(.021)		(.041)	(.021)		(.012)	
Incorporated at round	.11**			.15***		-.038	
	(.044)			(.04)		(.025)	
Tech type IT/software, not hardware	.18***		.089	.17***		-.027	
	(.052)		(.2)	(.047)		(.023)	
External financing before round	.16***			.16***		.13***	
	(.035)			(.038)		(.026)	
Hard-to-fund sector†		-.21***			-.13***		-.04***
		(.016)			(.013)		(.0047)
Possessed formal IP rights at round			.17**				
			(.067)				
Decile rank in round	-.008	-.019***	-.028**	-.018***	-.022***	-.00081	-.002**
	(.0075)	(.0025)	(.014)	(.006)	(.0028)	(.0026)	(.00096)
Won Round	.14***	.11***	.07	.066*	.062***	-.00066	.0025
	(.042)	(.016)	(.074)	(.036)	(.016)	(.015)	(.0064)
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y
N	1072	6046	284	1072	6046	1072	6046
R^2	.23	.13	.28	.2	.12	.28	.036

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 A.7: Effect of Rank and Winning Across Venture Age and Technology Types (All Rounds)

	*Panel 1: Dependent variable is financing after round**								
		Venture age above median		Tech type		Hard-to-fund†		Identify as social or clean tech	
	Baseline	No	Yes	Software	Hardware	Yes	No	Yes	No
	I	II	III	IV	V	VI	VII	VIII	IX
Won Round	.11***	.095**	.14***	.17***	.074***	.05**	.14***	.015	.13***
	(.018)	(.04)	(.033)	(.037)	(.019)	(.024)	(.028)	(.026)	(.022)
Decile rank in round	-.02***	-.011*	-.028***	-.028***	-.016***	-.016***	-.022***	-.013***	-.019***
	(.0027)	(.0064)	(.0055)	(.0053)	(.0026)	(.0034)	(.0043)	(.0041)	(.0033)
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	6046	1762	1765	2112	3934	2552	3494	1215	4831
R^2	.16	.39	.31	.27	.19	.23	.23	.3	.18
	Panel 2: Dependent variable is ≥ 2 *employees as of 8/2016*								
		Venture age above median		Tech type		Hard-to-fund†		Identify as social or clean tech	
	Baseline	No	Yes	Software	Hardware	Yes	No	Yes	No
	I	II	III	IV	V	VI	VII	VIII	IX
Won Round	.049***	.044	.083**	.048**	.052*	.049*	.044	.049**	.039
	(.019)	(.044)	(.033)	(.023)	(.031)	(.027)	(.03)	(.021)	(.049)
Decile rank in round	-.025***	-.021***	-.035***	-.015***	-.042***	-.03***	-.016***	-.027***	-.011*
	(.0031)	(.0073)	(.0056)	(.0034)	(.0046)	(.0042)	(.004)	(.0034)	(.0065)
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	6046	1762	1765	3934	2112	3494	2552	4831	1215
R^2	.17	.32	.24	.17	.27	.26	.16	.2	.2

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

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

Errors clustered by competition-round in I-V, and judge in VI-VII. 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. †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 A.8: Correlations among Outcomes, Venture Characteristics, and Founder Characteristics

Panel 1: Outcomes

	Financing after round	Angel/seed/VC series A investment after round	Has ≥ 2 employees as of 8/2016	Has ≥ 3 employees as of 8/2016	Has ≥ 10 employees as of 8/2016	Operating as of 9/2016
Financing after round	1.00					
Angel/seed/VC series A investment after round	0.75	1.00				
Has ≥ 2 employees as of 8/2016	0.37	0.31	1.00			
Has ≥ 3 employees as of 8/2016	0.38	0.32	0.91	1.00		
Has ≥ 10 employees as of 8/2016	0.34	0.31	0.69	0.76	1.00	
Operating as of 9/2016	0.32	0.26	0.52	0.47	0.37	1.00
Acquired/IPOd as of 9/2016	0.24	0.13	0.09	0.09	0.12	0.11

Panel 2: Ventures

	Financing before round	Incorporated at round	Venture age at first competition (years)	# founders/team members at first competition	Tech type IT/software, not hardware	Hard-to-fund sector†	% venture owned by presenting team at round
Incorporated at round	0.06	1.00					
Venture age at first competition (years)	0.14	-0.01	1.00				
# founders/team members at first competition	-0.17	0.09	-0.20	1.00			
Tech type IT/software, not hardware	0.08	-0.04	-0.11	-0.20	1.00		
Hard-to-fund sector†	0.05	0.24	-0.23	0.25	-0.48	1.00	
% venture owned by presenting team at round	0.03	-0.18	-0.06	-0.03	0.18	-0.17	1.00
Possesses formal IP rights at round	-0.07	0.02	-0.19	0.04	-0.13	0.19	0.11

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

	Executive title after	Founded venture after	Age	# total jobs	# jobs before	# locations	Degree from H/S/M	Top 20 college	MBA	MBA from top 10	Master's	PhD
Founded venture after round	0.49	1.00										
Age (years) at event (college graduation year-22)	-0.12	-0.10	1.00									
# total jobs	0.18	0.15	-0.01	1.00								
# jobs before round	-0.13	-0.10	0.17	0.71	1.00							
Number of locations	0.05	0.02	-0.01	0.55	0.49	1.00						
Any degree Harvard, Stanford, MIT	0.13	0.08	-0.23	0.08	-0.07	0.06	1.00					
Top 20 college	0.08	0.06	-0.13	0.13	-0.01	0.01	0.34	1.00				
Has MBA	0.11	0.07	-0.15	-0.05	-0.14	-0.04	0.45	0.08	1.00			
Has MBA from top 10	0.12	0.02	-0.15	-0.01	-0.11	0.03	0.74	0.25	0.66	1.00		
Master's	0.00	0.03	-0.01	0.05	0.02	0.05	-0.07	-0.01	-0.20	-0.17	1.00	
Has PhD	0.06	-0.01	-0.06	0.08	-0.01	0.05	-0.12	-0.05	-0.33	-0.21	0.11	1.00
Has CS degree from top 10 CS univ	-0.01	-0.06	-0.04	0.04	0.04	0.05	0.17	0.11	-0.05	-0.01	0.07	0.13

Note: This table contains correlations of variables used in analysis.†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.

Table A.9: Effect of Rank and Winning Across Venture States (All Rounds)

Dependent variable: Financing after round*							
Sample:	VC hub state (venture in CA, NY, or MA)	Excluding VC hub states	AZ	CO	NY, TX & IL	Excluding MA, CA, CO, NY, TX, IL	All
	I	II	III	IV	V	VI	VII
Won round	.097***	.12***	.093**	.13*	.14	.11***	.096***
	(.036)	(.022)	(.041)	(.069)	(.11)	(.024)	(.025)
Decile rank in round	-.013***	-.021***	-.03***	-.0024	-.012	-.021***	-.019***
	(.0047)	(.0032)	(.0066)	(.012)	(.019)	(.0036)	(.0027)
Won round·Same state†							.013
							(.029)
Same state							.11***
							(.02)
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y
N	1977	4069	1378	343	388	3474	6046
R^2	.28	.17	.12	.22	.55	.17	.17

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

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

Errors clustered by competition-round in I-V, and judge in VI-VII. A smaller rank is better (1 is best decile, 10 is worst decile). †Venture's state and competition state are same. *All private external investment after round. Note that competition f.e. control for a specific date. *** indicates p-value<.01.

Table A.10: Judge Uncertainty Association with Success (All rounds)

Dependent variable:	Financing After Round	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
Std dev of judge ranks above median	.017	.018**	.012	.013	.0022	.021**
	(.01)	(.0077)	(.01)	(.0089)	(.0038)	(.01)
Judge/judge company invested		.51***				
		(.1)				
Decile rank in round	-.021***	-.013***	-.026***	-.023***	-.0019*	-.019***
	(.0029)	(.0023)	(.0032)	(.0028)	(.0011)	(.0028)
Won Round	.11***	.085***	.075***	.062***	.0023	.049***
	(.02)	(.017)	(.02)	(.021)	(.0073)	(.018)
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y
N	4226	4226	4226	4226	4226	4226
R^2	.092	.084	.11	.09	.019	.15

Note: This table contains OLS regression estimates of the relationship between the standard deviation of judge ranks, across unique judges that scored a specific venture, and that venture's outcomes. I use variants of:

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

Errors clustered by competition-round. Note that competition f.e. control for a specific date. *** indicates p-value$<$.01.

Table A.11: Learning Across Competitions and Success (Effect of improvement between first and second competitions among ventures in > 1 competition, using preliminary round in both)

Dependent Variable:	Financing After Round*		$\geq$ 3 employees as of 8/2016		$\geq$ 10 employees as of 8/2016		Operating as of 9/2016	
	I	II	IV	V	VI	VII	VIII	IX
$\Delta_{deciles}$ 1st to 2nd competition	.025**	.027*	.034***	.037***	.03***	.035***	.023***	.023**
	(.012)	(.016)	(.0093)	(.012)	(.0092)	(.0098)	(.0082)	(.01)
Decile rank in 2nd competition	-.04***	-.044**	-.042***	-.055***	-.041***	-.05***	-.026***	-.023
	(.015)	(.018)	(.0079)	(.014)	(.0084)	(.01)	(.0087)	(.014)
Won Round	.1	.16	.071	.058	.037	.0091	.014	.043
	(.1)	(.12)	(.069)	(.1)	(.073)	(.089)	(.047)	(.043)
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	499	499	499	499	499	499	499	499
R^2	.21	.44	.18	.43	.14	.42	.19	.42

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 second competition, I use variants of:

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

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 A.12: Learning Across Competitions and Success (Effect of improvement between first and subsequent competitions among ventures in >1 competition, using maximum round in both)

	First to last competition				First to 2nd competition			
Dependent variable:	Financing after round*	≥ 3 employees as of 8/2016	≥ 10 employees as of 8/2016	Operating as of 9/2016	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
$\Delta_{deciles}$ 1st to last competition	.026***	.032***	.035***	.024***				
	(.0098)	(.0072)	(.0076)	(.0063)				
$\Delta_{deciles}$ 1st to 2nd competition					.017	.023**	.019*	.021***
					(.011)	(.0087)	(.0096)	(.0062)
Decile rank in last competition	-.036***	-.047***	-.044***	-.024***				
	(.0099)	(.0087)	(.0084)	(.0071)				
Decile rank in 2nd competition					-.036***	-.039***	-.031***	-.021***
					(.013)	(.011)	(.011)	(.0079)
Won Round	.35***	.27***	.22***	.039	.31***	.21**	.19*	.11**
	(.092)	(.055)	(.065)	(.051)	(.075)	(.086)	(.1)	(.046)
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y	N
N	540	540	540	540	538	538	538	538
R^2	.3	.21	.2	.19	.24	.18	.13	.2

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 second or last competition, I use variants of:

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

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 A.13: Learning Across Rounds and Success with Quintile Ranks (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
$\Delta_{quintiles}$ prelim round to second round**	.04***	.037**	.042***	.034**	.036**	.031*	.023*	.014
	(.014)	(.018)	(.015)	(.016)	(.014)	(.017)	(.012)	(.013)
Quintile rank in prelim round	-.046***	-.085***	-.062***	-.074***	-.049**	-.065***	-.038**	-.042***
	(.015)	(.02)	(.019)	(.019)	(.019)	(.019)	(.016)	(.015)
Won Round	.14***	.14***	.054	.067	.061	.062	.019	.045
	(.044)	(.043)	(.043)	(.048)	(.039)	(.039)	(.033)	(.035)
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 quintile ranks between the first and second rounds of a competition ($\Delta_{quintiles}$). I use variants of:

$$Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j+1(quintiles)} + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j}\right) + f\left(DecileRank_{i,j}\right) + \gamma' \left(\mathbf{1} \mid CompetitionRound_j\right) + \varepsilon_{i,j}$$

Errors clustered by competition-round or judge, depending on f.e. A smaller rank is better (1 is best quintile, 10 is worst quintile).*All private external investment after round. **When competition has two rounds, 2nd round is final 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 A.14: Learning Across Rounds and Success with Venture Controls and to Final Rounds Only (Effect of improvement between first and subsequent rounds in a competition on venture outcomes)

	Venture controls				First to final round			
Dependent Variable:	Financing After Round*	≥ 3 employees as of 8/2016	≥ 10 employees as of 8/2016	Operating as of 9/2016	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**	.013**	.014*	.015*	.0072				
	(.0064)	(.0074)	(.0075)	(.0051)				
$\Delta_{deciles}$ prelim round to final round					.019**	.019*	.015	.012**
					(.008)	(.0098)	(.0099)	(.0059)
Decile rank in prelim round	-.017**	-.026**	-.023**	-.011	-.018*	-.02*	-.013	-.018*
	(.0084)	(.01)	(.0094)	(.009)	(.0095)	(.011)	(.012)	(.0097)
Won Round	.11**	.038	.056	.036	.18***	.098	.09*	.042
	(.046)	(.044)	(.043)	(.038)	(.054)	(.06)	(.05)	(.044)
Venture controls	Y	Y	Y	Y	N	N	N	N
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y
N	1162	1162	1162	1162	759	759	759	759
R^2	.35	.28	.26	.36	.2	.21	.19	.28

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 ($\Delta_{deciles}$). I use variants of:

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

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. **When competition has two rounds, 2nd round is final round. †Includes whether the company received investment before the round, award amount if any, 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 A.15: Effect of Legal/IP and Traction/Validation Dimension Ranks 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:†										
	-.0028		-.012*		-.0014		.0018		-.015***	
Legal/IP/Regulatory										
	(.0059)		(.0067)		(.0056)		(.0024)		(.0055)	
Traction/Validation		-.016***		-.0078		-.0033		.0013		.0023
		(.0048)		(.0048)		(.0045)		(.0019)		(.0045)
Won Round	.17***	.18***	.13***	.12***	.15***	.14***	.02	-.0074	.24***	.12***
	(.052)	(.039)	(.046)	(.038)	(.045)	(.042)	(.018)	(.011)	(.037)	(.033)
Judge/judge company invested	.68***	.5**								
	(.11)	(.25)								
Competition-round-Panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1028	1300	1028	1300	1028	1300	1028	1300	1028	1300
R^2	.17	.18	.17	.18	.18	.18	.1	.14	.23	.27

Note: This table contains OLS regression estimates of the effect of dimension-specific ranks on indicators for various outcomes, using variants of: $Y_i^{Post} = \alpha + \beta_1 (\mathbf{1} \mid WonRound_{i,j}) + f(DimensionDecileRank_{i,j}) + \gamma' (\mathbf{1} \mid f.e._{j/k}) + \varepsilon_{i,j,/k}$. 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. 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 A.16: Effect of Rank and Winning When Venture and Competition in Same State (All Rounds)

Dependent variable:	Financing after round*				≥ 3 employees as of 8/2016		≥ 10 employees as of 8/2016		Operating as of 9/2016	
Sample:		Only VC hub states	Excluding VC hub states							
	I	II	III	IV	V	VI	VII	VIII	IX	X
Same state†	.11***	-.041	.15***	.14***	.12***	.14***	.075***	.091***	.079***	.11***
	(.019)	(.056)	(.024)	(.023)	(.02)	(.027)	(.015)	(.019)	(.017)	(.021)
Won round	.1***	.099***	.11***	.11***	.056***	.058***	.053***	.054***	.022	.024
	(.019)	(.037)	(.022)	(.019)	(.018)	(.017)	(.018)	(.018)	(.016)	(.017)
Company in VC hub state				.24***		.2***		.15***		.19***
				(.034)		(.025)		(.027)		(.024)
Company in VC hub state·Same state				-.21***		-.17***		-.12***		-.17***
				(.05)		(.044)		(.043)		(.037)
Decile rank in round	-.019***	-.013***	-.019***	-.019***	-.022***	-.022***	-.018***	-.018***	-.019***	-.018***
	(.0027)	(.0048)	(.0032)	(.0027)	(.0029)	(.0029)	(.0025)	(.0025)	(.0026)	(.0027)
Competition-round- panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	6046	1977	4069	6046	6046	6046	6046	6046	6046	6046
R^2	.17	.28	.18	.18	.17	.18	.15	.15	.29	.3

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

$$Y_i^{Post} = \alpha + \beta_1 \left(\mathbf{1} \mid SameState_{i,j}\right) + \beta_2 \left(\mathbf{1} \mid WonRound_{i,j}\right) + f\left(DecileRank_{i,j}\right) + \gamma' \left(\mathbf{1} \mid f.e._j\right) + X_{i,j} + \varepsilon_{i,j}$$

†Indicator for venture's state and competition state being the same. In IV, VI, VIII, and X $\left(\mathbf{1} \mid SameState_{i,j}\right)$ is interacted with an indicator for the company being in a VC hub state (CA, NY, or MA). Errors clustered by competition-round. 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. *** indicates p-value<.01.

Table A.17: Learning Across Rounds and Success by Dimension (Effect of improvement between first and second rounds in a competition on venture outcomes, using independent dimension ranks)

Dependent variable:	Financing after round*						≥ 3 employees as of 8/2016					
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
$\Delta_{deciles}$ prelim round to second round:**												
Team	.019**						.013					
	(.0091)						(.0081)					
Financials		.027***						.034***				
		(.0087)						(.008)				
Technology/Product			.011*						.021**			
			(.0057)						(.0083)			
Business Model				.01						.016*		
				(.0099)						(.0087)		
Presentation					.03***						.021*	
					(.0089)						(.01)	
Market Attractiveness						.01						.017*
						(.0096)						(.0089)
Won Round	.24***	.24***	.3***	.3***	.27***	.22***	.17***	.13**	.21***	.21***	.16***	.17**
	(.051)	(.053)	(.057)	(.059)	(.049)	(.065)	(.052)	(.055)	(.063)	(.063)	(.058)	(.075)
Dimension-specific decile rank in second round	-	-	-	-.013	-	-.011	-	-	-.019*	-	-	-.022
	.026**	.028***	.0066		.031**		.027***	.034***		.022*	.045***	
	(.01)	(.0069)	(.0077)	(.008)	(.011)	(.0079)	(.008)	(.011)	(.0099)	(.013)	(.0088)	(.013)
Competition-round- panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	638	506	628	431	387	431	638	506	628	431	387	431
R^2	.17	.19	.15	.15	.17	.15	.18	.2	.18	.17	.17	.17

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 A.18: Effect of Rank and Winning by Judge Type (All Rounds)

Panel 1

Dependent Variable:	Angel/VC series A investment	Financing after round*	≥ 3 employees as of 8/2016	Operating as of 9/2016	Angel/VC series A investment	Financing after round*	≥ 3 employees as of 8/2016	Operating as of 9/2016
Sample limited to judges:	Angel Investors				Venture Capitalist			
	I	II	III	IV	V	VI	VII	VIII
Won Round	.14**	.088	-.088	-.014	.15***	.11***	.099***	.015
	(.064)	(.056)	(.079)	(.049)	(.033)	(.028)	(.033)	(.03)
Decile rank in round	-.018*	-.012**	-.035***	-.022***	-.017***	-.0086**	-.017***	-.017***
	(.01)	(.005)	(.01)	(.0069)	(.0045)	(.0036)	(.0042)	(.0045)
Judge/judge company invested	.66***	.6***	.59***	.17**	.35**	.3	.39**	.13***
	(.063)	(.13)	(.077)	(.065)	(.16)	(.2)	(.16)	(.035)
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y
N	400	400	400	400	1994	1994	1994	1994
R^2	.24	.21	.17	.16	.16	.15	.2	.33

Panel 2

Sample limited to judges:	Founder/Entrepreneurs				Corporate Executives			
	I	II	III	IV	V	VI	VII	VIII
Won Round	.12	.091*	.11	-.036	.047	.034	.074	.041
	(.072)	(.052)	(.089)	(.066)	(.077)	(.059)	(.079)	(.061)
Decile rank in round	-.0069	-.0053	-.024***	-.026**	-.025***	-.014*	-.021**	-.015*
	(.011)	(.0077)	(.0092)	(.01)	(.0087)	(.0076)	(.0081)	(.0085)
Judge/judge company invested	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y
N	523	523	523	523	566	566	566	566
R^2	.21	.22	.23	.29	.19	.19	.23	.28

Dependent Variable:	Angel/VC series A investment	Financing after round*	≥ 3 employees as of 8/2016	Operating as of 9/2016	Angel/VC series A investment	Financing after round*	≥ 3 employees as of 8/2016	Operating as of 9/2016
	I	II	III	IV	V	VI	VII	VIII
Panel 3								
Sample limited to judges:	Business Development/Sales				Professors/Scientists			
Won Round	-.13	-.09	.021	-.048	-.23***	-.11	.22**	.22
	(.1)	(.084)	(.16)	(.11)	(.064)	(.072)	(.083)	(.13)
Decile rank in round	-.029*	-.0083	-.022	-.028	-.031**	-.017*	-.024	-.016
	(.014)	(.014)	(.02)	(.02)	(.013)	(.0094)	(.014)	(.012)
Judge/judge company invested	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y
N	131	131	131	131	78	78	78	78
R^2	.16	.11	.24	.45	.44	.51	.33	.37
Panel 4								
Sample limited to judges:	Lawyer/Consultant/Accountant				Nonprofit/Government			
Won Round	.064	.048	-.011	.0082	.1	.072	.08	.065
	(.058)	(.04)	(.059)	(.037)	(.081)	(.064)	(.095)	(.073)
Decile rank in round	-.026***	-.016**	-.039***	-.022***	-.02**	-.019**	-.031*	-.025**
	(.008)	(.0061)	(.0088)	(.007)	(.0099)	(.008)	(.016)	(.012)
Judge/judge company invested	0	0	0	0	.37**	.53***	.25	.13*
	(.)	(.)	(.)	(.)	(.15)	(.17)	(.17)	(.076)
Competition-round-panel f.e.	Y	Y	Y	Y	Y	Y	Y	Y
N	743	743	743	743	286	286	286	286
R^2	.18	.17	.18	.24	.28	.34	.3	.3

Note: This table contains OLS regression estimates of the effect of winning and rank on indicators for venture outcomes, restricting the sample to judges in specific professions, using variants of:

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

Errors clustered by competition-round in I-V, and judge in VI-VII. 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. *** indicates p-value<.01.

Table A.19: Elite Founder Association with Success (All rounds)

Panel 1

Dependent Variable:	Operating as of 9/2016	Financing after round	≥ 2 employees as of 8/2016	≥ 10 employees as of 8/2016	Acquired/ IPO
	I	II	III	IV	V
Any degree from HSM*	.073***	.078***	.096***	.086***	-.023**
	(.021)	(.022)	(.024)	(.022)	(.01)
Competition-round f.e.	Y	Y	Y	Y	Y
N	8962	7099	8962	8962	8962
R^2	.19	.049	.1	.051	.025

Panel 2

Dependent Variable:	Operating as of 9/2016	Financing after round	≥ 2 employees as of 8/2016	≥ 10 employees as of 8/2016	Acquired/ IPO
	I	II	III	IV	V
Top 10 MBA	.057***	.035*	.031	.031	-.019*
	(.02)	(.021)	(.023)	(.021)	(.011)
Competition-round f.e.	Y	Y	Y	Y	Y
N	8962	7099	8962	8962	8962
R^2	.19	.048	.098	.049	.057

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

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

where C_i is either an indicator for having any degree from an elite school (*HSM=Harvard, Stanford, MIT) or an indicator for attending a top 10 MBA program (see Appendix Table 4 for rankings). Errors clustered by competition-round. Note that competition f.e. control for a specific date. *** indicates p-value<.01.

Table A.20: Summary of Results

Metric:	Char. predicts success?	Char. predicts failing when get negative new info?	Char. predicts learning?	Learning useful for char.?
	Panel 1: Ventures			
Financing prior to round	Y	N	Y	-
Incorporated at round	Y	N	N	-
IT/Software	Y	Y	Y	-
Social/clean tech/hard-to-fund	N	-	Y	-
Venture in VC hub state	Y	N	N	-
Venture & competition in same state	Y	-	Y	Y
IP rights	Y	-	Y	-
Venture age	-	Y	N	Y
Judge uncertainty (riskiness)	Y	N	N	-
Structured feedback competition	-	-	Y	Y
	Panel 2: Founders			
# jobs before round	Y	N	-	-
# job locations before round	N		-	-
Has MBA	-	-	Y	-
Has Master's	N	-	-	-
Has PhD	-	-	-	-
Age at round	N	-		Y
Any degree from Harvard/Stanford/MIT	Y	N	N	-
Founded previous venture	-		-	Y
Is student at round	Y	Y	Y	-
Top 10 MBA	-	-	N	-
Comp Sci rank|CS major at top 10 CS univ	Y	-	-	-
Univ rank|College at top 20 univ	Y	-	-	-
Major:				
Liberal Arts†	-	-	-	-
Entrepren./Managmt/Marktg	Y	-	Y	-
Computer Science/ Engineering	-	-	-	Y
Other Sciences	-	-	-	-

Note: This table summarizes the main associations between venture and founder characteristics, and success and learning, from the empirical analysis. Code: Y = positive relationship; N = negative relationship; - = no statistically sig relationship

Table A.21: Effect of Rank and Winning Across Founder Characteristics Types (All Rounds)

*Panel 1: Dependent variable is financing after round**

	Student		Has MBA		Degree from HSM		Entrepr. Major		Previous founder	
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
	I	II	III	IV	V	VI	VII	VIII	IX	X
Won Round	.12***	.11***	.24***	.082***	.2***	.1***	.18***	.1***	.047	.12***
	(.042)	(.02)	(.052)	(.025)	(.061)	(.019)	(.068)	(.019)	(.059)	(.019)
Decile rank in round	-.021***	-.019***	.0073	-.022***	.013	-.021***	.00035	-.02***	-.025***	-.018***
	(.0063)	(.0029)	(.0085)	(.0032)	(.0095)	(.0028)	(.013)	(.0027)	(.0066)	(.0031)
Competition f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1186	4860	565	2803	373	5673	272	5774	1344	4702
R^2	.11	.13	.3	.11	.37	.16	.56	.16	.29	.19

Panel 2: Dependent variable is ≥ 2 employees as of 8/2016

	Student		Has MBA		Degree from HSM		Entrepr. Major		Previous founder	
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
	I	II	III	IV	V	VI	VII	VIII	IX	X
Won Round	.018	.064***	.11**	.041*	.11*	.048**	.006	.05**	.061	.053**
	(.045)	(.021)	(.056)	(.024)	(.062)	(.02)	(.085)	(.02)	(.054)	(.021)
Decile rank in round	-.022***	-.024***	.0019	-.023***	.0037	-.025***	-.02	-.025***	-.012*	-.026***
	(.0075)	(.0033)	(.01)	(.0036)	(.011)	(.0032)	(.015)	(.0032)	(.007)	(.0037)
Competition f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1186	4860	565	2803	373	5673	272	5774	1344	4702
R^2	.11	.15	.25	.13	.34	.17	.4	.17	.29	.21

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

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

Errors clustered by competition-round in I-V, and judge in VI-VII. 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. †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.