Learning in Entrepreneurship

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Abstract

Evidence of low returns to entrepreneurship is puzzling. Overconfidence or non-pecuniary benefits may explain why people start firms. An alternative view emphasizes the real option value of launching or abandoning a new firm, and characterizes entrepreneurship as rational experimentation. These perspectives have different predictions for whether and how entrepreneurs learn from new information; in the experimentation view, founders should be more responsive to new information. I use novel data from nearly 100 new venture competitions to show that negative feedback causally increases the chances a venture is abandoned. Learning in the sense of improvement predicts measures of venture success. Ventures likely to have a lower cost of experimentation, such as those with software-based technologies, learn more. The results support the experimentation view, but elite-school founders appear overconfident.

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1 Introduction

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

At odds with these canonical models is empirical evidence of low returns to entrepreneurship, even among founders of venture capital-backed startups.[2] A prominent explanation for why people forego valuable outside options to become entrepreneurs is that they suffer from cognitive biases or reap large non-pecuniary benefits. An alternative view is that entrepreneurship is a process of rational experimentation. I use data from new venture competitions to provide the first causal evidence of entrepreneurs learning from new information. I then explore the learning mechanisms. The results help to micro-found theories of firm dynamics, and shed light on the two explanations for entrepreneurial entry.

The "behavioral entrepreneurship" view suggests that entrepreneurs enter irrationally and fail to update their priors in light of new information.[3] One example is Landier & Thesmar (2009)'s contracting model, in which entrepreneurs receive nothing if the venture fails because they assign this event zero probability. Investors correctly believe that it is quite possible.[4] A second example is

[1] Additional examples of the large body of theoretical work that rely on learning assumptions include Lucas (1978), Jovanovic & Lach (1989), 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), Arabsheibani et al. (2000), and Koellinger, Minniti & Schade (2007) find 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), Hvide & Møen (2010) and Giannetti & Simonov (2009) suggest that non-pecuniary benefits - like being one's own boss or a warm glow from providing a social good - explain the low returns in entrepreneurship. See Astebro et al. (2014) for a review.

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

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

The alternative view is that entrepreneurship may arise from rational expectations of future cash flows if starting a venture and abandoning it are considered real options. Manso (2016) and Kerr, Nanda & Rhodes-Kropf (2014) propose that the process of founding a high-growth new venture is one of experimentation.[5] This real options lens 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.

In extreme interpretations of the behavioral view, entrepreneurs should persist in the face of negative information about the venture's prospects. The experimentation view, in contrast, requires entrepreneurs to recognize and value the abandonment option, and also to adapt their strategies to new information. This paper examines three kinds of learning relevant to short, medium, and long term decisions that are crucial to many entrepreneurial ventures. Specifically, I use novel data on 4,328 new ventures participating in 96 competitions in 17 states between 1999 and 2016. In the competitions, founders present their businesses to a panel of expert judges. I observe judge identities and all scores at each round. Sponsored by universities, governments, and non-profit organizations, the competitions award cash prizes to winners.

The sample consists largely of first-time entrepreneurs seeking external finance in order to grow quickly. While the data are are not necessarily representative of entrepreneurs or startups, they allow observation of a set of nascent entrepreneurs at risk of founding high-growth startups much earlier than most existing data sources permit. Young, high-growth startups drive innovation, employment, and productivity growth (Haltiwanger, Jarmin & Miranda 2013).

The competitions generate valuable, informative signals. In a regression discontinuity design, I show that conditional on win status, rank robustly predicts

[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.

measures of success like subsequent financing, employment, and survival. Winning positively affects these outcomes and the chances of an IPO or acquisition. Regressions include round or judge 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.

Having established that rank is informative, I assess the causal effect of especially negative feedback on the entrepreneur's long term decision to abandon the venture. I exploit the fact that some competitions inform ventures of their ranks within a round, while others do not. Within the sample of losers, I estimate the effect of a very low rank with knowledge of that rank, relative to a very low rank without such knowledge. This is akin to a difference-in-differences specification. The first difference is within round, comparing below median and above median losers. The second difference is across rounds, comparing ventures that were informed of their rank with those that were not. I show that receiving this negative, structured feedback increases by about 15% the probability that the venture is ultimately abandoned. This provides initial evidence in favor of the experimentation view.

The experimentation view also demands adaptability to new information, which I examine through learning in the sense of improvement across rounds (much as an educator might measure student learning as improvement in test scores over the semester). Among ventures that participate in multiple competitions on average 215 days apart), I use the change in rank (relative score) as a measure of learning. Improvement in rank across competitions predicts subsequent angel/VC investment and employment. To understand what kind of learning is occurring, I compare venture descriptions across the competitions. The changes in descriptions that are associated with learning in the sense of improvement are a greater focus on solving a perceived customer problem or need, and greater focus on the product's competitive advantage. Irrelevant changes include a greater focus on making money or dramatic changes in the product itself.

Third, I examine venture improvement across rounds within competitions. This short term improvement (there are 17 days on average between rounds) also strongly predicts subsequent venture success. Criteria scores illuminate the mechanism. Learning is only relevant to venture outcomes for financial and presentation criteria. Learning along product, business model, or team dimensions, for example, are not relevant to outcomes. As in Bernstein, Korteweg & Laws (2015), however, the strongest criterion predictor of success is the team rank.

On average, ventures in my data on average behave consistently with the experimentation view. Rather than passively receive type shocks, the firms seem to actively acquire and adapt to new information, as in Ericson & Pakes (1995). However, I find heterogeneity in learning itself and in the benefit of learning that helps to unify the two strands of thought. I find that firms with a lower cost of experimentation do more of it. Software ventures are much more likely to be abandoned in response to negative feedback, and they learn more across rounds.[6] The earliest stage firms and founders are more responsive. Founders are more likely to abandon their venture in response to negative feedback when the venture is unincorporated or student-run at the time of the competition. Student-run ventures learn more across rounds than non-students, while older ventures and older founders learn less.[7] This is consistent with the option value of entrepreneurship declining as the firm and founder age.

Founders with elite college degrees or top 10 MBA degrees learn less, and the former are much less likely to abandon their ventures in the face of negative feedback. These results suggest that elite-school founders are overconfident. The latter result is also consistent with rational Bayesian updating among elite-school founders if they have more precise priors. However, as all participating ventures wish to win, there is no obvious rational reason for them to learn less across rounds. This result for startup founders complements the literature on CEO overconfidence (Malmendier & Tate 2005, Ben-David, Graham & Harvey 2013).

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

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

Using the number of judges to proxy for signal precision, I find suggestive evidence that the type of overconfidence among elite founders is over-optimism, not over-precision.[8] Over-optimistic CEOs have been shown to be more innovative (Hirshleifer et al. 2012), and over-precise ones less so (Herz, Schunk & Zehnder 2014). Entrepreneurs with radical technologies may be less responsive to feedback than those with incremental ideas. Theoretical models of industry dynamics could micro-found technological discontinuities in the small fraction of entrepreneurs that enter without regard to signals about future cash flows, and occasionally transform the industry. The mass of entrants could remain rational and responsive to new information.

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

During the financial crisis, winners of competitions in my data tended to improve more across rounds. This might reflect the cost of persisting with a poor idea being higher during the crisis. Faster learning may be one mechanism for the cleansing effect of recessions in Caballero et al. (1996). More generally, faster learning could improve resource allocation in the economy. Guiso, Pistaferri & Schivardi (2015) argue that if entrepreneurship can be learned, government efforts to spur entrepreneurship can focus on learning opportunities. I cannot speak to the relative social welfare benefits of different types of learning, but my results suggest that competitions are a successful learning intervention for participating

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

ventures. I provide several results pertinent to program design.

Competitions provide nascent entrepreneurs with failure-tolerant, timely feedback. While they reward top performers, they do not penalize especially poor performance, as ranks are not public information.[9] This relates to Manso (2011)'s model of innovation as learning through a series of experiments. To encourage greater exploration, the optimal contract rewards long term success but tolerates early failure, and reduces the cost of experimentation by providing timely feedback about performance. To the degree that competitions are useful, they potentially offer additional support for Manso's channel, in a similar vein as Lerner & Wulf (2007), Azoulay et al. (2011), and Tian & Wang (2014).

This paper also contributes to the literatures on the relationship of executive characteristics and corporate decisions (Bertrand & Schoar 2003, Graham, Harvey & Puri 2013); financial constraints facing startups and the evaluation of policies to alleviate them (Howell 2016, Ozmel, Robinson & Stuart 2013, Schmalz, Sraer & Thesmar 2015); human capital networks (Ewens & Rhodes-Kropf 2015, Hochberg, Ljungqvist & Lu 2007); peer effects in entrepreneurship (Nanda & Sørensen (2010), Lerner & Malmendier (2013)), and predicting startup success (Scott, Shu & Lubynsky 2015).[10]

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

2 Data on New Venture Competitions

New venture competitions permit us to observe new ventures around the time of their birth. The competitions (some of which describe themselves as accel-

[9]Overall ranks are never publicized. They are aggregated from judge ranks. Judges do not know others' ranks, though it is possible that they converse after the competition.

[10]The literature on the first topic also includes Lazear (2005), Gabaix & Landier (2008), Gompers, Kovner, Lerner & Scharfstein (2010), Shane et al. (2010), Kaplan, Klebanov & Sorensen (2012), and Lindquist, Sol & Van Praag (2015). Also relevant is the nascent literature on new resources for startups, including Winston Smith, Hannigan & Gasiorowski (2013), Yu (2014), Hallen, Bingham & Cohen (2014), and Eesley & Wu (2016).

erators, and some as business plan competitions) 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.

New venture competitions are an important part of the startup ecosystem, particularly for first-time founders. New venture competitions are sponsored by universities, corporations, foundations, governments at the federal, state, and city level, angel investor groups, and others. There is no formal count, but one startup resource provider listed 4,623 competitive events as of September, 2016.[11] Another listed 382 business plan competitions with $48 million in prize money in 2015 alone.[12] CB Insights (the most comprehensive early stage financing database for recently founded startups) contains about 16,000 ventures that got their first early stage financing between 2009 and 2016, of which 14.5% won a new venture competition or competitive accelerator. Bernstein et al. (2015) note that on the AngelList platform, 57% of their experimental sample and 30% of all startups listed on AngelList have been through an accelerator or incubator.

The sample of 96 competitions in this paper is not accidental; they are similar enough to be evaluated together, but offer variation in location and venture characteristics. All the competitions have the following features:

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

[11] See https://www.f6s.com/.
[12] See http://www.bizplancompetitions.com.

winning ventures.[13]

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 1. Competition dates range from 1999 to 2016. As Table 1 Panel 1 describes, there are 214 rounds (where a round might be the semifinals in a given competition).[14] A few competitions divide preliminary rounds into panels. For example, the roughly 40 startups participating in the first round of each year's Rice Business Plan Competition are divided into about seven panels of around six startups and 25 judges each. On average there are 44 ventures in a preliminary round, and 18 ventures in a final round. The average number of winners is 4.5, and the average award amount conditional on receiving a cash prize is $66,000.

Thirty-five of the programs provide structured feedback through software from Valid Evaluation, a private company. These competitions inform ventures of their ranking relative to other ventures in their round. In the remaining competitions, ventures learn only that they won or lost, not their rank or score. In all competitions, judges verbally ask questions and usually give some type of informal feedback. Feedback only includes rankings relative to other firms in the structured feedback competitions. None of the competitions inform ventures which judge gave them a specific score, nor may judges observe each other's scores.

This paper is a rare instance in which the econometrician observes more than the agents studied. I observe overall firm ranks in a round, judge-specific

[13]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.

[14]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.

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 (see Appendix Table 2 for statistics on the various levels of scores). Different competitions use different score ranges, and the number of of ventures varies across rounds. For much of the analysis, I convert raw scores to percentile ranks; primarily deciles.

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 3). There are 558 ventures that participate in multiple competitions. In the main analysis, I consider only a venture's first competition. The average age of the ventures is 1.9 years.[15] Forty-four percent of the ventures were incorporated at the round date as a C- or S-corp. Incorporation is a good indication of high-growth ambitions, as self-employed and local subsistence businesses typically do not incorporate. The average number of team members is 3. This is similar to Bernstein et al. (2015), who note that on the AngelList platform, the average number of founders is 2.6.

There is little empirical analysis of startups prior to their first external funding event or of new venture competitions, so it is difficult to assess the representativeness of the sample. Appendix Table 4 compares the distribution of ventures in my data to overall U.S. VC investment, based on the National Venture Capital Association's (NVCA) 2016 yearbook. The share of software startups in my data, 37%, is very close to the national average for both deals and dollars of 40%. However, in part because of data from the Cleantech Open, a national nonprofit competition focused on clean energy startups, the data skews somewhat towards clean energy. With the exception of Arizona, which is oversampled in my data due to the presence in my data of the large Arizona Innovation Challenge, the top twenty states in my data almost entirely overlap with the top twenty states for VC investment.

[15] Age is determined by the venture's founding date in its application materials. Ventures that describe themselves as "not yet founded" are assigned an age of zero.

The competitions take place in 17 U.S. states. 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.[16] Ventures in these states - 35% of the sample - have access to richer networks of investors, advisers, and other resources. Relative to the NVCA data, my data under-samples California and over-samples Massachusetts. Many successful startups that raise VC move to Silicon Valley, so this is perhaps to be expected from earlier stage firms. Nonetheless, the location and sector statistics suggest the sample may be biased towards more marginal ventures than the universe of startups at hazard of VC investment.

I matched ventures to investment events and employment using CB Insights, Crunchbase, AngelList, and LinkedIn. These yielded 752, 638, 1,528, and 1,933 unique company matches, respectively. The probability of subsequent financing is 0.24, relative to 0.16 before the competition (based on the round date). I focus on subsequent angel investment and initial venture capital (VC Series A rounds) 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.[17] The probability that a venture has at least two employees as of August, 2016 is 0.34. The probability that a venture has an active website as of September, 2016 is 0.63. Note that in the analysis, competition fixed effects will control for date, obviating concerns about ventures in more recent competitions having less time. Three percent of ventures were acquired or went public.

Table 1 Panel 3 describes the venture founders, using data from the competitions and LinkedIn profiles. Of the 3,643 team leaders (listed either as CEO or team leader on the competition application), 2,554 matched to a LinkedIn profile that contains data on experience, education, or both. The median founder age,

[16]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).

[17] I do not observe hiring events. In researching the ventures, 765 name changes were identified. Ventures were matched to private investment on both original and changed names.

based on subtracting 22 from the college graduation year, is 29 years. Whether the sample is representative of startup founders in terms of age depends on the comparison set. The founders in my data are older than the average Y-Combinator founder, who is just 26.[18] Wadhwa et al. (2009), on the other hand, find that the average age of entrepreneurs of successful, high-growth startups is 40. Analysis of companies valued at $1 billion or above between 2003 and 2013 by Cowboy Ventures found the average founder age was 34 (Lee 2013).

The average founder had 4.4 jobs prior to the round, in 2.7 locations. The probability of having an executive title (at any company) after the round is 0.35, lower than before the round, reflecting founders abandoning entrepreneurship for salaried employment. Forty-eight percent of founders have an MBA, a little more than half of which are from top 10 programs (based on U.S. News & World Report rankings in Appendix Table 5). Twenty-seven percent of founders graduated from a top 20 college. I also divide the college majors into groupings; the largest is engineering, with 484 founders.[19]

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

This paper contributes to the entrepreneurship literature by introducing a new source of data, in which I observe ventures and their founders at an earlier stage, with greater granularity, and in a larger sample than extant studies. Survey

[18]See https://techcrunch.com/2010/07/30/ron-conway-paul-graham/

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

or population data sources such as the SCF, NLSY79, or BDS contain relatively few high-growth entrepreneurs, as Levine & Rubinstein (2013) point out. For example, the NLSY79 has roughly 5,400 workers, only about 10% of which were ever self-employed. Further, in these databases it is difficult to distinguish high-growth, young firms from local small businesses (e.g. restaurants, plumbers, and self-employed accountants). The data in this paper consist of individuals considering founding or having just founded startups. Through a new technology or business model, startups aim to become large, valuable, and transformational to their industry. One unique aspects of the data is that there are no subsistence businesses or sole proprietorships.

3 Empirical Approach

Establish that signals are informative

New venture competitions permit me to quantify and isolate learning, a novel and challenging exercise. The learning I am interested in is the responsiveness and adaptation to feedback about the venture quality. Feedback will address various aspects of the venture, including the product itself, the business model, and the presentation style. The first step in identifying learning is to observe codified, informative feedback. The primary feedback I examine are aggregated judge scores. I therefore must show that this signal is informative about venture outcomes independently of winning. Then rational founders should incorporate it into their own expectations about the venture's probability of success. If the judges cannot predict success, rational founders have nothing to "learn" from their feedback.

I establish that the competitions generate valuable, informative signals by estimating variants of Equation 1, which essentially is a regression discontinuity design:

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

$$\mathbf{X}_i = [Prev.\ Financing,\ Judge/Judge\ Comp\ Invested,\ Sector\ Dummies,$$
$$Venture\ Age,\ \#\ team\ members,\ award\ amt]$$

Here, i indicates a venture, and j a competition-round-panel (e.g. the MIT Clean Energy Prize Semifinals). Y_i^{Post} is a binary outcome variable. In the baseline empirical analyses, I include competition-round-panel fixed effects.[20] In other cases I use judge fixed effects. I cluster standard errors by competition-round-panel or by judge. Note that competition-round-panel effects absorb the date and location.

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

This initial analysis also provides the first causal evaluation of whether it is useful for ventures to win a competition. The primary empirical concern along this policy dimension 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

[20] Where a competition does not divide its preliminary rounds into panels, this is a fixed effect at the round level.

to happen ex-ante.

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

Learning in the Long Term: Real Outcome Responsiveness

The first learning analysis asks whether whether ventures that receive especially negative feedback are more likely to be abandoned. This long term "learning" measure is in the sense of the entrepreneur ultimately deciding to exit in response to feedback that his venture quality is poor. I causally estimate the effect of negative feedback by comparing competitions where ventures receive structured feedback - they learn their rank relative to other participating ventures - with competitions where ventures learn only that they won or lost. In the latter competitions, feedback is much less precise: it is informal and disconnected from peer performance.

The analytical approach is a difference-in-differences design within the population of losers. The first difference is between above- and below-median losers in a given competition. The second difference is across structured feedback and non-structured feedback competitions. Specifically, I estimate among losers the combined effect on the entrepreneur of receiving a below-median score, and knowing that he received a low score:

$$\begin{aligned} Y_i^{Post} = {} & \alpha + \beta_1 \left(\mathbf{1} \mid LostRound \;\&\; BelowMedRank_{i,j}\right)\left(\mathbf{1} \mid StructuredFeedback_j\right) \\ & + \beta_2 \left(\mathbf{1} \mid LostRound \;\&\; BelowMedRank_{i,j}\right) + \beta_3 \left(\mathbf{1} \mid StructuredFeedback_j\right) \\ & + \gamma' \mathbf{f.e.}_{j'/k} + \delta' \mathbf{X}_i + \varepsilon_{i,j} \end{aligned} \tag{2}$$

if $i \in Losers_j$

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

A concern with this approach is that the structured feedback and non-structured feedback competitions may be different, for example attracting different types of ventures. However, note that the estimation is within round. That is, the control group is the above-median losers in both types of competitions. Therefore, average differences across the types of competitions are differenced out. However, if the distribution of losing ventures around the median are systematically different in unobserved characteristics, the estimates may be biased. Appendix Table 6 uses t-tests to compare key venture outcomes and competition statistics for the two types of competitions. They are broadly similar, and importantly the number of ventures, winners, and judges are not statistically different across the two groups. Therefore, while the empirical design is not the ideal experiment in which new ventures randomly receive feedback, it provides the closest approximation in the literature to date.

Learning in the Medium Term: Improvement Across Competitions

A different type of learning is in the sense of improvement. I use the change in the venture's rank across competitions and rounds, which has the advantages of being codified and common to participating ventures (since they wish to win, they must value improving across rounds). An analogous learning metric is when an educator measures student learning as the difference between beginning- and end-of-semester test results.

My empirical approach is to ask whether learning is useful for real outcomes, and then to examine how and which ventures learn. If successful entrepreneurship is the result of random draws among the extremely over-confident,

or is driven by innate talent or technology, then, learning from feedback in competitions should not be strongly associated with success. Conversely, finding that learning is relevant to success supports the experimentation view of entrepreneurship.

I first focus on learning in the medium term using the sub-sample of ventures that participate in multiple competitions. I estimate a version of Equation 3, where j denotes the first competition and j' the last competition, using the preliminary round in both:

$$\begin{aligned} Y_i^{Post} &= \alpha + \beta_1 \Delta_{i,j,j'(deciles)} + \beta_2 Won\ Round_{i,j'} + f\left(Decile\ Rank_{i,j'}\right) \\ &\quad + \gamma' \mathbf{f.e.}_{j'/k} + \varepsilon_{i,j'} \end{aligned} \tag{3}$$

The coefficient of interest is on the change in overall decile ranks between the two competitions: $\Delta_{i,j,j'deciles}$. The dependent variable Y_i^{Post} is a measure of venture success, such as whether it had 10 or more employees by August, 2016, or whether it raised angel/VC series A investment after the round. To understand the type of learning that is occurring, I coded the venture descriptions that founders submit when they apply to the competitions (usually two or three sentences). Among the 413 ventures that competed in multiple competitions and for which the data include descriptions for at least two competitions, I coded six aspects of the description changes.

Learning in the Short Term: Improvement Across Rounds

In the preliminary round of a competition, 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 estimate versions of Equation 3 to show that learning across rounds predicts venture success, where j and j' are the first and second round within a competition, respectively. I use both decile rank changes and raw score changes. The latter obviates concern that the changing composition of ventures

across rounds may affect the results.

I also examine scores of written business plans prior to the competition. Ventures are explicitly told to incorporate this feedback, which they receive about two weeks before the competition, into their pitches in the actual competition. The business plan scores do not count towards winning, and include dimension and overall scores aggregated across judges. This measure is useful because it is explicitly intended for learning. Further, the sample of ventures is static across the business plan and preliminary rounds, so there is no concern about changing composition. However, the business plan phase occurs in just two programs, so the sample is small.[21]

Having demonstrated that (a) judge ranks are valuable signals; and (b) learning predicts venture success, I examine which types of ventures and founders learn. I estimate variants of Equation 4, where the dependent variable is the change in rank or raw score across rounds.

$$\Delta_{i,j,j'(raw\ score/decile)} = \alpha + \beta' \mathbf{C}_i + \gamma' \mathbf{f.e.}_{j,k} + \varepsilon_{i,j'} \tag{4}$$

Here, $\mathbf{C}_i$ is a vector of venture and founder characteristics. In the final part of the analysis, I use the change in decile rank across rounds learning metric to explore variation in learning across dimensions (e.g. team, technology, business plan), location, and over time.

4 Results

Ranks are informative signals

Estimates of Equation 1 in Tables 3 and 4 show that the competitions generate valuable signals. The learning metrics require judge ranks to be meaningful signals about startup quality. If ventures seek to improve in the judges' estimation,

[21] The two programs are the Massachusetts CEC Catalyst competition and the Rice Business Plan Competition. I use quintiles because in the Rice competition, business plans are judged within panels of five to eight ventures.

then improvement in rankings reflect venture learning regardless of whether the venture observes judges' scores. It is crucial that rank predicts subsequent success independently of win status.

Across all the success proxies, the coefficients on rank are negative and highly significant, even when separated on either side of the cutoff (e.g. Table 4 column I). 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. An extra decile of rank among losers increases the probability of at least three employees by about 2 pp (Table 4 column III), and increases he probability of financing by 1.4 pp (Table 3 column VII).

Logit specifications in Table 3 columns III, VI, and VIII confirm the strong predictive power of rank. I rely on OLS models in the remaining analysis. Not only does OLS have a simpler interpretation, but logit drops groups without positive outcomes, leading to overestimation when there are many fixed effects. Finally, 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.

Winning is useful

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

Column VII includes the cash award amount; interestingly, as the large effect of winning a preliminary round foreshadowed, winning is useful indepen-

dently of the award. An extra $10,000 in cash prize increases the probability of financing by about 1 pp. Controlling for this award effect, winning increases the probability of financing by 8 pp.[22]

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

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

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

Venture and founder characteristics

Which types of ventures and founders learn will be more interesting if we first know which types are unconditionally associated with greater subsequent success. Table 5 uses as dependent variables the best "right-tail" success proxies: subsequent angel/VC investment, and having at least 10 employees.[23] I project the success proxy on a vector of characteristics. Columns 2 and 4 expand the sample by excluding venture and founder age, which are not available for many ventures.

The associations differ across the two outcome metrics, sometimes dramatically. For example, attending a top 10 college is associated with a 5 pp increase in the probability of angel/VC, but has no association with the employment metric. In contrast, more founder job experience, being an IT/software (rather than hardware) venture, being located in a VC hub state, and having prior financing are all strongly associated with both measures of success. Having an MBA is weakly negatively associated with success. Ventures that identify their sectors as social impact or clean technology are much less likely to raise angel/VC, but are only slightly less likely to reach at least 10 employees.

When considered independently, founders from top 10 colleges are more likely to succeed. Figure 3 contains coefficients from regressions of each outcome on the two indicators for elite education and competition fixed effects. Having a top 10 college degree is strongly associated with success, recalling a similar relationship between college selectivity and success for CEOs of VC-backed companies in Kaplan et al. (2012). However, having a top 10 MBA degree is not independently associated with success.

[23] Too few ventures have thus far exited through IPO or acquisition for this to be a useful variable.

4.1 Learning in the Long Term: Real Outcome Responsiveness

The first type of learning I consider is whether ventures that receive especially negative feedback are more likely to be abandoned. This measures learning in the sense of a real outcome response to new information. Equation 2 is estimated in Table 6. The coefficient of interest gives the effect of having a below median rank among losers in a round where the venture is informed of its rank, relative to having a below median rank among losers in a round where the venture is *not* informed of its rank, after controlling for the two individual effects of below median rank and receiving structured feedback. The control group is above-median losers in both types of competitions.

The dependent variable, having at least two employees in 2016, measures continuation. I find that negative feedback reduces the likelihood of continuation by 8-14 pp, relative to a mean of 34%. This implies, conservatively, that this negative feedback increases failure by 12%. While specific to this context, this provides the first causal estimate of the effect of feedback on venture abandonment. This suggests that on average, ventures are not so overconfident as to give zero probability to the failure state; interim signals do matter.

This effect is weakly symmetrical for winners. Appendix Table 7 examines whether receiving particularly positive feedback makes winners of a round more likely to continue. The sample is smaller, as most rounds have far fewer winners than losers. With judge fixed effects, there is a strong positive effect on continuation of extremely good feedback. However, this effect disappears when I use the standard sample of one venture-round observation.

Heterogeneity in Responsiveness

There is strong heterogeneity across venture types in responsiveness to negative feedback. Table 7 adds a venture characteristic as a third interaction; for brevity, panels 2 and 3 do not report control coefficients. 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 1 of Panel 1 shows that ventures with previous private financing are much less responsive to the negative signal; they are 18 pp more likely to continue after receiving especially negative feedback. Panel 2 shows that incorporated ventures are similarly much less responsive. I find no result for venture age, possibly because judges' feedback is less informative for very young ventures. Indeed, unreported tests find that when Equation 1 is estimated separately for below- and above-median age ventures (median age is about 9 months), the predictive power of rank on having at least two employees almost doubles for the older ventures. 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.

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. Table 7 Panel 1 column 2 shows that IT/software startups are more responsive; they are 11 pp more likely to fail after receiving especially negative feedback than hardware startups. This does not seem to relate to non-pecuniary motivations among hardware founders, as column 3 finds no effect for social impact/clean technology ventures. A lower cost of launching a startup appears to make abandonment a more attractive option.

This supports the argument in Kerr et al. (2014) and Ewens et al. (2015) that the cost of resolving initial uncertainty about whether a new technology or business model will work helps determine which projects are funded and thus

the direction of innovation in the economy. They attribute the dramatic increase in web- and software-based startups in the 2000s in part to the dramatic fall in computing power and storage costs. One implication is that new ventures with high initial capital intensity have become relatively higher cost experiments. In particular, the option value of entrepreneurship is lower for a hardware technology. Resolving uncertainty about their viability will require more time and more money than software ventures.

I also find that students and younger founders are more responsive (Panel 2 column 4 and Panel 3 column 6); the option to abandon the idea is perhaps most valuable for this group. It is also possible that students place greater weight on judges' advice because they have little personal experience and thus a less precise private prior. Inconsistent with this interpretation, I find no effect of prior jobs or founding a prior venture (Panel 2 columns 5 and 6). The abandonment option might be especially valuable for elite individuals. Surprisingly, Panel 3 columns 4 and 5 show that elite college degrees make founders much less responsive to feedback; for example, founders with top 10 college degrees are 23 pp less likely to fail in response to negative feedback. I find no such effect for MBAs.

One measure of venture risk is uncertainty among judges.[24] I interact the effect of negative feedback with an indicator for whether the standard deviation of judge ranks within a competition-round-panel is above median.[25] The triple interaction has a strong positive effect (Panel 2 column 3); when judges are uncertain, founders are more likely to reject the negative information and pursue their venture. This is suggestive evidence that more confident founders choose riskier business models, consistent with the findings among CEOs in prior work, including Hirshleifer et al. (2012) and Graham et al. (2013). An alternative explanation is that the higher standard deviation reflects a less precise signal, and interactions with judges during the competition inform founders that there

[24] Appendix Table 8 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.

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

was no consensus among judges.[26] In this case, the finding suggests that updating reflects signal precision, consistent with experimental evidence in Poinas et al. (2012) and survey evidence inBen-David et al. (2013).

4.2 Learning in the Medium Term: Improvement Across Competitions

I next examine whether learning predicts success, first using learning in the sense of improvement across competitions. Showing that learning is useful is suggestive evidence in favor of the experimentation view and against hypotheses about high growth entrepreneurship in which either innate talent or extreme overconfidence are responsible for entry, and some combination of talent and luck explain the few successes. Both of these perspectives are inconsistent with a strong link between learning and success.

Estimates of Equation 3, in Table 8, show that for the subset of ventures that compete in multiple competitions, improving across preliminary rounds between their first and last competition is predictive of success. Outcome variables are angel/VC series A investment and having at least 10 employees as of August, 2016. In the context of very early stage startups, the former is substantial success, and the latter is right-tail success. Columns 1-3 show that improving a decile increases the probability of angel/VC by about 1.6-2.5 pp, and increases the probability of having at least 10 employees in 2016 by 2.9-3.9 pp.[27]

Broadly, there are three mechanisms for score improvement. First, founders may improve their salesmanship; nothing about the business may change. Second, the underlying product or technology may be constant but the founders may change their strategy, perhaps targeting a different market. Third, founders may pivot to an entirely new idea.

[26] A lack of consensus in judge ranks could manifest during the competition through questions and verbal feedback.

[27] In unreported tests, I use the first and second competition, rather than first and last, and the highest round the venture reached, rather than the preliminary round. Both approaches provide similarly strong positive effects of improvement on outcomes.

Venture descriptions from competition applications provide insight into the type of learning that is occurring. Table 9 Panel 1 shows the coded changes in venture descriptions among ventures that competed in multiple competitions. Only 8.5% of the ventures changed their product or technology significantly, but 25.2% targeted their product to a more specific market or use, and 45.5% focused more on a problem or need that the product solves or fills. While only 12.6% focused more on how the venture will make money, 28.8% focused more on the product's competitive advantage. Panel 2 shows correlations across outcomes and these changes (the sample is not big enough for meaningful regression analysis). Receiving angel/VC investment is most correlated with improving clarity and focusing more on solving a problem. Having more than 10 employees is most correlated with targeting the product to a more specific market or use.

In Table 10, I regress the the overall learning measure from Table 8 on the coded description changes. The dependent variable, learning in the sense of score improvement across competitions, is derived from judge scores in the competitions. Judges do not observe descriptions or their changes across competitions. Across multiple specifications, Table 10 shows that learning is driven by focusing more on solving a problem and on competitive advantage explain learning in the sense of score improvement across competitions. Changing or re-targeting the product do not explain the improvement. In general, this evidence suggests that learning in this context takes the form primarily of improved salesmanship and a refined sense of what is sometimes referred to by practitioners as "product-market fit."

4.3 Learning in the Short Term: Improvement Across Rounds

The last measure of learning is the change in rank across rounds. This offers the largest sample and thus is the focus of heterogeneity in learning because this measure provides the largest sample. One concern is that the composition of ventures changes across rounds as ventures are eliminated. The average venture rank increases (i.e., worsens) as it proceeds from a preliminary round (which have

44 ventures on average) to a final round (which have 18 ventures on average). The learning measure is therefore inherently biased against correlation with success, to the degree that a few ventures enter the competition as the strongest, and earn high ranks throughout all rounds. These ventures will have learning measures that are either zero or just slightly negative. The ventures with large positive learning measures are those that barely made it from a preliminary round, and then shone in a subsequent round.

Table 11 shows that improving a decile across rounds increases the chances of subsequent success across all the outcome variables. Panel 1 uses my preferred metric, the change in decile rank across rounds, using competition-round-panel fixed effects. For angel/VC investment and having at least two employees, I also show specifications with judge fixed effects. Panel 2 uses the change in raw scores to confirm that the effect is not due to a spurious correlation between success and the changing composition across rounds. Across all specifications, increasing a decile in rank increases the probability of at least two employees by 1.3-1.7 pp; this implies that a standard deviation increase in rank leads to a roughly 4.5 pp increase in the survival measure. I also find a consistently strong positive effect on financing after the round. However, the effect on angel/VC is not statistically significantly positive with competition-round-panel f.e., and the effect on having at least 10 employees, while very strong in Panel 1, loses significance in Panel 2. Using quintile changes instead of decile changes, adding venture controls, and using the decile change between the first and final rounds, rather than first and second rounds, all yield similar results (Appendix Tables 9-10).

At the founder level, I also find that learning within a competition predicts success. In Appendix Table 11, the dependent variables are whether the founder had an executive title after the round (CEO, CTO, VP, COO, or President) in the venture or any other company, and whether they founded a new venture. Columns 1 and 4 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.

To confirm that the change in deciles across rounds does indeed measure learning from feedback, I conduct two additional tests. First, If the change in decile rank is truly a measure of learning, it should be more predictive of success when ventures are aware of their rank than when they are not. I interact the learning across rounds measure with whether the competition provided structured feedback. Estimates in Appendix Table 12 shows 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.

Second, I construct an alternative learning measure using the change in rank between the business plan and first round of the competition. Improvement in ranking between these two phases predicts success across all outcomes. Estimates in Appendix Table 13 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.

4.4 Who Learns?

The above sections established that venture ranks and improvement in ranks (the learning measure) predict success. This is broadly consistent with adapting to feedback being important for nascent entrepreneurship, but examining heterogeneity will shed further light on the relationship between learning and theories of entrepreneurial entry.

In Table 12, I project the learning metrics on venture and founder characteristics. I use changes in decile ranks with year fixed effects, and changes in raw scores with judge fixed effects. Founder characteristics are in columns 1-2, founder elite school status in columns 3-4, venture characteristics in columns 5-6, and all characteristics together in columns 7-8. (Not all characteristics are available for all ventures and founders, so more characteristics tends to reduce the sample.) Across specifications, students tend to learn much more, again consis-

tent with greater experimentation in this group. With a larger sample and fewer controls, founders with MBAs appear to learn more.[28]

As in the responsiveness analysis above, software ventures learn much more (Table 12 columns 5-8), consistent with them having lower costs of experimentation. I find somewhat mixed results for other characteristics. Ventures that were incorporated at the time of the round learn appear to learn less, but only using raw scores. Ventures from a VC hub state learn less, but this is statistically significant only in column 5. The raw score measure permits examining whether on average all ventures improve with more time between rounds. Indeed, an extra day between rounds has a small positive effect on learning (columns 4 and 5).

Evidence of Overconfidence among Elite-School Founders

A robust and consistent result across models (including columns 7-8) is that elite degrees both at the MBA and undergraduate level are associated with less learning. A single rank improvement in the college rankings (among the top 20 colleges) reduces learning by 0.2 deciles, indicating that going from the number 10 college (Caltech) to the number one college (Princeton) reduces learning by 20 pp. Having a degree from a top 10 MBA program, controlling for having any MBA, also reduces learning dramatically, by around 20 pp.

Recall from the structured feedback analysis that elite graduates are also much less likely to abandon their venture when they received especially negative feedback. If we presume that by virtue of participating in a competition, a venture wishes to win, then rational founders should try to improve across rounds in order to increase their chances of winning. The fact that elite-school founders do not learn is consistent with overconfidence in this subgroup, in contrast to the rest of the sample, which is very responsive to feedback. This is especially true for elite-school MBAs, who figure 3 shows are not more likely to succeed on average. For elite-college founders, elite founders' failure to learn is not necessarily suboptimal. This is particularly true if there is a wage premium for failed entrepreneurs, as

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

Manso (2016) suggests. As theorized in Bernardo & Welch (2001) and Goel & Thakor (2008), the few that do succeed may benefit from their overconfidence. Related evidence exists in both theory and empirical work for large firm CEOs. Kaplan et al. (2012) find that better performing CEOs are characterized by less openness to criticism and feedback. Bolton, Brunnermeier & Veldkamp (2013) theorize that good leaders make an initial assessment of their environment, and then persist in their strategy regardless of new information.[29] Landier & Thesmar (2009) find that entrepreneur overconfidence increases with the entrepreneur's outside option and decreases with the quality of his signal.

Overconfidence is often refined into two more specific biases. Over-optimism implies the individual overestimates his mean chance of success, while over-precision (also called "miscalibration" or "judgmental overconfidence") implies the individual overestimates the precision of his information. Whether elite founders are over-precise or over-optimistic matters for firm outcomes. Galasso & Simcoe (2011) and Hirshleifer et al. (2012) Hirshleifer et al (2012) show that over-optimistic CEOs invest in more innovation, while Herz et al. (2014) show that over-precise CEOs invest less.[30]

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

Appendix Table 14 interacts elite status with the indicator for whether

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

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

the number of judges is above median. The coefficient on the interaction is small and insignificant. This test by no means establishes that elite founders are not over-precise, but it provides some evidence for over-optimism rather than miscalibration. The literature has found overoptimism to be widespread among CEOs but to have a mixed relationship with value creation (Puri & Robinson 2007,Malmendier & Tate 2008,Goel & Thakor 2008). In the startup industry, it tends to be viewed favorably. For example, a well-known venture capitalist wrote: "Genetic or not, there are certain classic characteristics of the entrepreneur. The most important of these are certain kind a visionary optimism; tremendous confidence in oneself that can inspire confidence in others" (Bussgang 2011).

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

Learning by Criteria

The above sections established that learning is valuable, and found that learning across competitions most often consists of greater focus on how the product solves a problem or need, and greater focus on the product's competitive advantage. Now I use dimension (criteria) scores to explore the type of learning in the short term, across rounds. First, I find that different dimensions predict different kinds of success. Table 13 shows that for all outcomes other than IPO/acquisition, a higher team rank is the strongest predictor of subsequent success. This is consistent with the literatures showing a positive correlation between good managerial

practices and productivity in large firms(Bloom et al. 2012, Bloom et al. 2016, Guiso et al. 2015), and on the importance of a startup's management team to prospective VC investors (Gompers et al. 2016).

Presentation ranks predict financing but not any other outcome. A better technology or product predicts IPO/acquisition and survival. The financials rank, which reflect a venture's recent and planned fundraising, as well as near-term cost management, is especially important to survival and to having a large number of employees. 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 15.

Table 14 shows that learning on the financials dimension is strongly associated with subsequent financing and employment. 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. Presentation improvement matter for subsequent financing, but is not statistically significant for the other outcomes. Appendix Table 11 shows that only presentation score changes are predictive of a founder having an executive title or founding a subsequent venture. This is highly predictive: a decile improvement in presentation score across rounds increases the probability an individual has an executive title by nearly 1%, relative to a mean of 13%. The importance of presentation for investment is consistent with the pitch being a key fundraising component, and with competitions helping new ventures to refine it.

Learning by Geography

As the competitions take place in 17 states, examining whether learning is more valuable in certain locations will help illuminate the learning mechanism. In general, judges are based in the same geographic location as the competition,

but participating ventures are typically drawn from diverse locations.[31]

Variation in the benefit of learning across locations might reflect variation in the competitions' usefulness. To rule this out, Appendix Table 16 shows that winning is useful to ventures regardless of the venture's home state.[32] However, I find that independently of winning and rank, when the venture is from the same state as the competition, this "same state" effect is strongly associated with all measures of success. For example, being local increases the probability of having at least 10 employees by 5.4 pp. Ventures from non-VC hub states drive this average effect (Appendix Table 17). This is initial evidence that competitions are most useful when they serve as convening mechanisms to help nascent entrepreneurs build local networks. However, an alternative explanation is that higher quality ventures tend to participate in local competitions.

Supporting the hypothesis that competitions match entrepreneurs with local resources, both in terms of relevant feedback and more tangible resources like investment, I find that learning is most useful when the venture is local *and* when the locality in question is not a VC hub state. First, Table 15 column 1 shows that learning is more valuable for ventures when the venture is in the same state as the competition.[33] 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 4 shows an analogous effect for having at least three employees in 2016.

When being from a VC hub state is added as a third interaction (Table 15 columns 2, 3, 5 and 6), the triple interaction is negative and significant across

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

[32] Appendix Table 16 shows 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 3 and 4) also yields similar results, as does excluding all major clusters (column 6). I find analogous results for other outcomes (not reported). None of the differences across these regions are statistically significant.

[33] I find no differences in learning across states.

models. This triple interaction represents, for example, the effect of learning for a venture from Massachusetts in a Massachusetts competition).[34] The negative hub state effect might reflect elite-school founders. However, when I control for whether the founder has a degree from Harvard, MIT, or Stanford (columns 3 and 6), the negative relationships grow stronger. Therefore, separate from an elite school effect, judge feedback is most helpful when the judge is local in places with fewer entrepreneurial resources. '

Entrepreneurs disproportionately locate near where they were born.[35] Chatterji et al. (2013) point out that while the top tail of high-growth startups tend to flock to Silicon Valley, a region's local supply of entrepreneurs is important for establishing an innovation cluster. They suggest that policies promoting entrepreneurship among locals may be more effective than seeking to attract outside entrepreneurs. This paper offers evidence that a local network of investors and advisors enable the most useful learning for marginal entrepreneurs outside of clusters, while, as Chatterji et al. (2013) hypothesize, founder from out of town benefit less.

Learning in the Financial Crisis

Valuable learning in entrepreneurship should lead to more efficient allocation of human capital resources. I expect that during the financial crisis, ventures faced lower availability of external financing and lower quality outside options. Both imply that persisting with a bad idea became more costly. In turn, the ability to adapt to feedback should be relatively more valuable.

I examine whether winners of final rounds were more likely to have improved in certain years. Table 16, offers striking evidence (despite a small sample) that winning and learning were more strongly associated during the financial crisis. In columns 1-3, I use dummies for pre-crisis (omitted), crisis (9/15/2008 to the end of 2010), and post-crisis. Column 2, which controls for rank, finds that

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

[35]See Figueiredo et al. (2002), Glaeser et al. (2010), and Audretsch et al. (2012).

improvement across rounds was 6.7 pp higher during the crisis. Also, relative to the pre-crisis period, learning seems o have become less associated with winning post-crisis. Column 4 uses indicators for two-year periods, confirming the greater learning during the crisis (2008-09).[36]

It seems that within these competitions, there was greater churning during the crisis, with winners improving more across rounds relative to their peers. This is suggestive of an interaction between high-growth entrepreneurship and capital market cycles that deserves further study. 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.

5 Conclusion

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

Yet in many theoretical models of firm dynamics and occupational choice, entry and exit occur when entrepreneurs or firm managers rationally learn from

[36]Column 5 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%).

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.

Recent decades have seen a decline in new firm entry that is troubling in light of evidence that new, young businesses drive employment growth (Pugsley & Sahin 2015, Decker et al. 2014). At the same time, however, the cost of launching software or internet-based companies declined dramatically (Ewens et al. 2015). It is likely that the cost of adapting to new information has also fallen for these companies. If underlying costs or new resources like accelerators and competitions are making learning more efficient, entry-exit dynamics may shift to entry-pivot dynamics. That is, entrepreneurs may increasingly change strategies rather than fail.[37] Anecdotal evidence from industry suggests this is common and even desirable. Paul Graham, founder of the well-regarded Y Combinator accelerator, wrote, "Don't get too attached to your original plan, because it's probably wrong. Most successful startups end up doing something different than they originally intended."

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.[38] The White House "Startup America" initiative, launched in 2011, champions the public sponsorship of acceleration and competition programs.[39]

Despite the recent burgeoning of support, it is not obvious that competitions are useful. Since participation in a competition is typically public infor-

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

[38]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 (see http://energy.gov/eere/articles/energy-department-announces-25-million-inspire-collegiate-clean-energy-entrepreneurs). Nearly every state hosts a competition. For example, the Arizona Innovation Challenge, one of the competitions in my data, awards $3 million annually.

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

mation, losing might generate a negative signal. Participating could also lead to a loss of intellectual property (IP). Further, competitions may not be useful 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. Further, learning is useful independently of winning. My results suggest that competitions should consider focusing on their convening power - that is, enabling useful social interactions - 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
Days between rounds within competition	88	23	17	31	0	127
# 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 (stats on # of competitions if $\# > 1$)	558	2.52	2	0.98	2	9
Days between competitions among ventures in >1	978	302	215	289	1	2562
# 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 external private investment after round	7099	0.24	0	0.43	0	1
Prob. angel/VC series A investment before round	7099	0.09	0	0.29	0	1
Prob. angel/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	3228					
# founders matched to LinkedIn profile	2554					
Prob. is student at round	2554	0.2	0	0.4	0	1
Age (years) at event (college graduation year-22)	1702	32.8	29	10.2	17	75
Number of total jobs	2554	6.63	6	3.93	0	50
Number of jobs before round	2547	4.41	4	2.66	0	10
Number of locations	2554	2.71	2	2.27	0	29
Founded previous venture before round	2554	0.53	1	0.5	0	1
Founded subsequent venture after round	2554	0.02	0	0.13	0	1
Executive title before round (CEO, CTO, VP, COO, President)	2554	0.56	1	0.5	0	1
Executive title after round	2554	0.35	0	0.48	0	1
Prob. graduated from top 20 college	2554	0.27	0	0.44	0	1
Prob. graduated from top 10 college	2554	0.18	0	0.39	0	1
Prob. degree from Harvard, Stanford, MIT	2554	0.1	0	0.3	0	1
Prob. has MBA	2554	0.48	0	0.5	0	1
Prob. has MBA from top 10 business school	2554	0.33	0	0.47	0	1
Prob. has Master's degree	2554	0.17	0	0.37	0	1
Prob. has PhD	2554	0.13	0	0.34	0	1
Major:						
Other Science/Math	191					
Engineering	484					
Bio/Medical	194					
Comp Sci	151					
Poli-Sci/Int'l	139					
Economics/Finance	346					
Entrepreneurship	89					
Business	391					
Other Arts	156					

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

Table 2: Venture Sectors & Judge Professions

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

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

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

Dependent variable: Financing after round*										
	Final rounds			Preliminary rounds			All rounds			
Model:	OLS	OLS	Logit	OLS	OLS	Logit	OLS	Logit	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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

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	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Won Round	.11***	.15***	.089***	.15***	.071***	.12***	.019*	.023***	.053**	.12***
	(.022)	(.02)	(.027)	(.027)	(.027)	(.038)	(.011)	(.0084)	(.023)	(.023)
Decile rank in round among winners	-.009**		-.0089**		-.0048		-.0029*		-.0092***	
	(.0039)		(.0043)		(.0043)		(.0017)		(.0034)	
Decile rank in round among losers	-.011***		-.021***		-.017***		-.0011		-.019***	
	(.0019)		(.0028)		(.0023)		(.001)		(.0026)	
Judge decile rank in round		-.0058***		-.0093**		-.0087***		-.00047		-.0071**
		(.00057)		(.0038)		(.0032)		(.00057)		(.0029)
Competition-round-panel f.e.	Y	N	Y	N	Y	N	Y	N	Y	N
Judge f.e.	N	Y	N	Y	N	Y	N	Y	N	Y
N	6046	47065	6046	47065	6046	47065	6046	47065	6046	47065
R^2	.15	.11	.16	.11	.14	.083	.083	.047	.29	.17

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

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

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. All rounds included. *** indicates p-value<.01.

Table 5: Unconditional association between characteristics and success, and relative effect of winning by characteristic

Dependent Variable:	Angel/VC series A investment | ≥ 10 employees as of 8/2016			
	(1)	(2)	(3)	(4)
Founder student at round	-.023	.016	.029	.043
	(.047)	(.028)	(.042)	(.028)
Founder top 10 college	.061*	.051***	.035	.032
	(.035)	(.018)	(.037)	(.022)
Founder has MBA	-.052	-.0095	-.061	-.054***
	(.034)	(.017)	(.038)	(.018)
Founder top 10 MBA	-.034	-.029	.042	.028
	(.041)	(.021)	(.046)	(.023)
Venture age > median	-.023		.0091	
	(.028)		(.025)	
Venture in VC hub state	.093**	.088***	.057*	.09***
	(.038)	(.018)	(.034)	(.019)
Financing before round	.088**	.19***	.15***	.16***
	(.038)	(.028)	(.036)	(.023)
Venture incorp. at round	-.0049	.021	.033	.07***
	(.036)	(.018)	(.032)	(.017)
Founder # jobs before round	.029***	.014***	.023***	.0091***
	(.0056)	(.0027)	(.0059)	(.0026)
Founder age > median	-.02		-.063**	
	(.029)		(.031)	
Venture social/ clean tech	-.14***	-.13***	-.024	-.044**
	(.039)	(.015)	(.047)	(.017)
Venture tech type IT/software	.14***	.12***	.068*	.074***
	(.039)	(.021)	(.038)	(.021)
Venture # team members	.03**	.0087	.035***	.017***
	(.014)	(.0063)	(.01)	(.0058)
N	1184	3346	1184	3346
R^2	.072	.1	.06	.061

Note: This table contains the unconditional association of characteristics and success. By omitting venture and founder age, columns 2 and 4 have a much larger sample. *** indicates p-value<.01.

Table 6: 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

	(1)	(2)	(3)	(4)	(5)
Below median rank among losers·Structured feedback	-.1***	-.14***	-.081***	-.1***	-.079***
	(.037)	(.044)	(.02)	(.02)	(.026)
Below median rank among losers	-.046**	-.034	-.053***	-.038***	-.026
	(.02)	(.022)	(.013)	(.015)	(.022)
Structured feedback	.22***	.25***	.28**	.32**	-.031
	(.034)	(.037)	(.11)	(.15)	(.14)
Round type	All	Prelim.	All	Prelim.	All
Venture controls[†]	N	N	N	N	Y
Year f.e.	Y	Y	N	N	N
Judge f.e.	N	N	Y	Y	Y
N	4136	2983	29553	19336	14937
R^2	.044	.046	.13	.11	.29

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 7: 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)

Panel 1

Dependent Variable: ≥ 2 employees as of 8/2016				
Venture characteristic C_i (all binary):	Financing before round	Tech type IT/software	Social/ clean tech	VC hub state[††]
	(1)	(2)	(3)	(4)
Below median rank among losers· Structured feedback· C_i	.18**	-.11*	.078	-.091
	(.088)	(.061)	(.092)	(.13)
Below median rank among losers· Structured feedback	-.12***	-.05	-.11***	-.13***
	(.042)	(.046)	(.042)	(.043)
Structured feedback· C_i	-.22***	-.015	-.13	.13
	(.066)	(.053)	(.084)	(.087)
Below median rank among losers· C_i	-.06	.013	.018	-.073*
	(.071)	(.04)	(.05)	(.04)
Below median rank among losers	-.027	-.058**	-.048**	-.0065
	(.02)	(.026)	(.024)	(.029)
Structured feedback	.21***	.21***	.23***	.24***
	(.036)	(.037)	(.038)	(.039)
C_i	.43***	.13***	-.069	.069*
	(.054)	(.037)	(.044)	(.037)
Year f.e.	Y	Y	Y	Y
N	4136	4136	4136	4136
R^2	.1	.058	.049	.046

Panel 2 (control coefficients not reported)

Dependent Variable: ≥ 2 employees as of 8/2016						
Characteristic C_i (all binary):	(1) Venture incorp. at round	(2) Venture age > median	(3) Venture has high judge rank s.d.‡	(4) Founder age above median	(5) Founder # previous jobs > median	(6) Founded prior venture
Below median rank among losers· Structured feedback· C_i	.13***	-.053	.064*	.34**	.034	.067
	(.031)	(.092)	(.036)	(.14)	(.09)	(.073)
N	4136	2224	4136	1778	4136	4136
R^2	.067	.046	.046	.048	.047	.056

Panel 3 (control coefficients not reported)

Dependent Variable: ≥ 2 employees as of 8/2016						
Characteristic C_i (all binary):	(1) Founder has MBA	(2) Founder has top 10 MBA	(3) Founder attended top 20 college	(4) Founder attended top 10 college	(5) Founder attended Harvard/ Stanford/ MIT	(6) Founder is student
Below median rank among losers· Structured feedback· C_i	-.068	-.18	.11	.23*	.31*	-.43***
	(.11)	(.19)	(.11)	(.12)	(.16)	(.12)
N	4136	4136	4136	4136	4136	4136
R^2	.045	.046	.046	.047	.045	.051

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. ‡Standard deviation of judge ranks for the venture is above median, among ventures in round. ‡‡Number of judges in round is above median. *** indicates p-value<.01.

Table 8: Learning Across Competitions and Success (Effect of improvement between first and last competitions among ventures in > 1 competition, using preliminary round in both)

Dependent variable:	Angel/VC series A investment			≥ 10 employees as of 8/2016		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{deciles}$ 1st to last competition	.025***	.023*	.016*	.039***	.029***	.033***
	(.0094)	(.012)	(.0086)	(.0086)	(.0097)	(.01)
Decile rank in last competition	-.025***	-.027***	-.016*	-.05***	-.04***	-.044***
	(.0092)	(.0097)	(.0087)	(.0085)	(.01)	(.01)
Won Round	.036	.06	-.0076	.05	.089	.0039
	(.065)	(.084)	(.06)	(.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	.19	.45	.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) †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 9: Venture Description Changes Across Competitions

Panel 1: Frequency of changes

	No	Yes
Relative to the first competition, in the last competition did the description....		
...indicate a significant change in the product? (Product changed)	91.5%	8.5%
...of the product become more targeted or specific to a certain market or use? (More targeted)	74.8%	25.2%
...become clearer in terms of conveying the nature of the product? (Improved clarity)	26.9%	73.1%
...focus more on a customer problem/need that the product solves/fills? (New focus on solving problem)	54.5%	45.5%
...focus more on the product's competitive advantage or key distinguishing attribute? (New focus on competitive advantage)	71.2%	28.8%
...focus more on how the venture will make money? (New focus on profit)	87.4%	12.6%

Total N = 413

Panel 2: Correlations among changes, and between success outcomes and changes

	Angel/VC	$\geq$ 10 employees	Product changed	More targeted	Improved clarity	New focus on solving problem	New focus on comp. adv.
$\geq$ 10 employees	0.21	-					
Product changed	0.00	0.03	-				
More targeted	0.05	0.20	0.14	-			
Improved clarity	0.11	0.01	0.02	0.16	-		
New focus on solving problem	0.11	-0.15	-0.04	0.11	0.18	-	
New focus on comp. adv.	-0.11	-0.06	0.06	0.01	0.29	0.20	-
New focus on profit	0.08	-0.15	0.01	-0.01	0.09	0.09	0.07

Note: Panel 1 of this table shows the results of coding venture descriptions from application materials, among ventures that participated in multiple competitions and where descriptions are available for at least two competitions. Of the 588 ventures that competed in multiple competitions, 387 competed in just two. For the other ventures, the coding uses the first and last competitions.Ventures are included once. Panel 2 shows correlations across the changes, and between changes and two success outcomes.

Table 10: Venture Description Changes and Learning Across Competitions

Dependent variable: $\Delta_{deciles}$ 1st to last competition			
	(1)	(2)	(3)
Product changed	.42	.36	1
	(.72)	(.73)	(.76)
More targeted	.065	.07	-.3
	(.54)	(.54)	(.58)
Improved clarity	-.042	.0038	.072
	(.55)	(.55)	(.56)
New focus on solving problem	1**	1**	.92*
	(.49)	(.5)	(.53)
New focus on comp. adv.	1.2**	1.1*	1.2**
	(.56)	(.57)	(.57)
New focus on profit	.47	.64	.74
	(.76)	(.77)	(.81)
Venture controls†	N	N	Y
Year f.e.	N	Y	N
N	134	134	134
R^2	.086	.11	.16

Note: This table contains OLS regression estimates of the association between changes in the venture's description and learning. 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. †Includes whether the company received investment before the round, sector indicator variables, 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

Panel 1: Decile rank change						
Dependent variable:	Financing after round*	Angel/VC Series A Investment		≥ 2 employees as of 8/2016		≥ 10 employees as of 8/2016
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{deciles}$ prelim round to second round**	.018***	.0083	.01*	.017**	.013**	.015**
	(.0066)	(.0051)	(.0052)	(.0076)	(.0067)	(.0067)
Decile rank in first round	-.025***	-.013*	-.028***	-.029***	-.036***	-.025***
	(.0077)	(.0069)	(.009)	(.0099)	(.011)	(.0094)
Won round	.14***	.1***	.089***	.028	.039	.066*
	(.043)	(.033)	(.032)	(.043)	(.052)	(.039)
Judge f.e.	N	N	Y	N	N	Y
Competition-round-panel f.e.	Y	Y	N	Y	N	Y
N	1252	1252	1252	1252	1252	1252
R^2	.22	.18	.17	.22	.22	.2
Panel 2: Raw score change						
Dependent variable:	Financing after round*	Angel/VC Series A Investment		≥ 2 employees as of 8/2016		≥ 10 employees as of 8/2016
	(1)	(2)	(3)	(4)	(5)	(6)
Raw score Δ prelim round to second round**	.028***	.017*	.064**	.016*	.061***	.024
	(.01)	(.0089)	(.024)	(.0091)	(.016)	(.026)
Score in first round	.00087	-.0024	.0072	.0083**	.0043	.0023
	(.0046)	(.0037)	(.0073)	(.0038)	(.011)	(.0094)
Won round	.062	.071	-.089	.055	-.0021	.23**
	(.11)	(.11)	(.16)	(.071)	(.11)	(.087)
Judge f.e.	Y	Y	Y	Y	Y	Y
Venture controls†	N	N	Y	N	Y	Y
N	3456	3456	2185	3456	2185	2185
R^2	.22	.2	.4	.27	.39	.37

Note: This table contains OLS regression estimates of the effect of learning on subsequent venture measures of success. Letting j denote the first round in the competition and j' the second round, I use variants of:

$$Y_i^{Post} = \alpha + \beta_1 \Delta Score_{i,j,j'} + \beta_2 (\mathbf{1} \mid WonRound_{i,j'}) + \beta_2 Score_{i,j} + \gamma' \mathbf{Judge}_k + \delta_1' \mathbf{Sector}_j + \delta_2' \mathbf{X}_j + \varepsilon_{i,j'}$$

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. **When competition has two rounds, 2nd round is final round. Note that competition f.e. control for a specific date. †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 fixed effects, company age, and the number of founders/team members. Controls not available for all ventures. *** indicates p-value<.01.

Table 12: Who learns? (Learning measured as relative improvement between first and second rounds in a competition)

Dependent Variable:	$\Delta_{deciles}$	Δ_{raw}	$\Delta_{deciles}$	Δ_{raw}	$\Delta_{deciles}$	Δ_{raw}	$\Delta_{deciles}$	Δ_{raw}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Founder has MBA	-.49	-.63	.61*	.34			-.075	1.1
	(.32)	(.6)	(.33)	(.41)			(.37)	(.7)
Founder has PhD	-.021	-.49					.095	-.16
	(.38)	(.65)					(.39)	(.79)
Founder age	.023	.095**					.015	.036
	(.016)	(.037)					(.016)	(.023)
Founder is student at round	2.5***	2.4*					2.1***	.8
	(.49)	(1.2)					(.58)	(.73)
Number of jobs before round > median	-.18	.61					-.22	.05
	(.36)	(.53)					(.37)	(.48)
Founded previous venture	-.39	1.1*					-.37	.79
	(.33)	(.62)					(.33)	(.56)
Founder has top 10 MBA			-1.6***	-2.2**			-.75*	-2**
			(.48)	(.83)			(.44)	(.81)
Founder college rank in top 20 (1 best)			.0053	-.19*			-.065**	-.2*
			(.027)	(.095)			(.031)	(.1)
Tech type IT/software					1.1***	.6**	.23	.96**
					(.29)	(.28)	(.4)	(.46)
In VC hub state†					-.7**	-.0062	-.2	-.36
					(.32)	(.51)	(.31)	(.57)
In social/clean tech sector					.57**	.62	.22	1.8**
					(.29)	(.66)	(.35)	(.75)
Raised financing before round					-.11	.16	.26	.73
					(.26)	(.28)	(.37)	(.52)
Incorporated at round					-.43	2**	-.084	2.8**
					(.35)	(.9)	(.35)	(1.1)
Days between rounds							-.0056	.051***
							(.0043)	(.016)
Year f.e.	Y	N	Y	N	Y	N	Y	N
Judge f.e.	N	Y	N	Y	N	Y	N	Y
N	618	1320	893	2123	1252	3456	618	1097
R^2	.16	.2	.08	.17	.1	.17	.18	.46

Note: This table contains OLS regression estimates of the relationship between venture characteristics and learning across rounds, measured as the change in decile rank ($\Delta_{deciles}$), or the raw change in scores (Δ_{raw}) between the first and second rounds of a competition. Errors clustered by competition-round. **When competition has two rounds, 2nd round is final round. Note that judge f.e. are within-competition control for a specific date. †Venture state is California, New York, or Massachusetts. *** indicates p-value<.01.

Table 13: 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	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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 14: 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*	Angel/VC Series A Investment	≥ 2 employees as of 8/2016	≥ 10 employees as of 8/2016
	(1)	(2)	(3)	(4)
$\Delta_{deciles}$ prelim round to second round:**				
Team	.01	.0055	.0014	-.0002
	(.011)	(.012)	(.011)	(.0086)
Financials	.022**	.0045	.025**	.028**
	(.01)	(.0071)	(.011)	(.011)
Technology/Product	-.0064	-.005	.0066	.011
	(.0061)	(.0063)	(.01)	(.009)
Business Model	-.0073	-.014	-.015	-.011
	(.049)	(.056)	(.044)	(.045)
Presentation	.023**	.018*	.011	.0064
	(.0096)	(.0093)	(.011)	(.014)
Market Attractiveness	-.0068	.0092	.0033	.0036
	(.048)	(.055)	(.046)	(.045)
Won Round	.23***	.16***	.12**	.12**
	(.052)	(.039)	(.057)	(.047)
Dimension decile rank in 1st round	Y	Y	Y	Y
Competition-round- panel f.e.	Y	Y	Y	Y
N	640	640	640	640
R^2	.18	.16	.17	.19

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 15: 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		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{deciles}$ 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 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
	(1)	(2)	(3)	(4)	(5)
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.

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

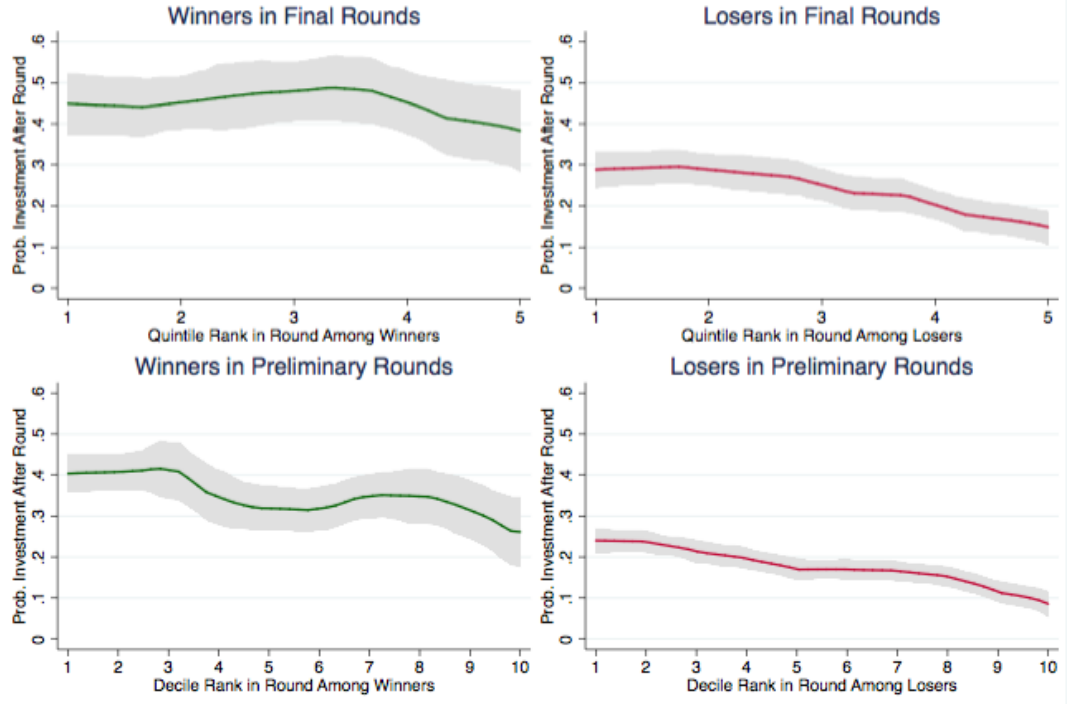


Figure 2: Probability venture had ≥ 3 employees as of 8/2016 (rank 1 is best)

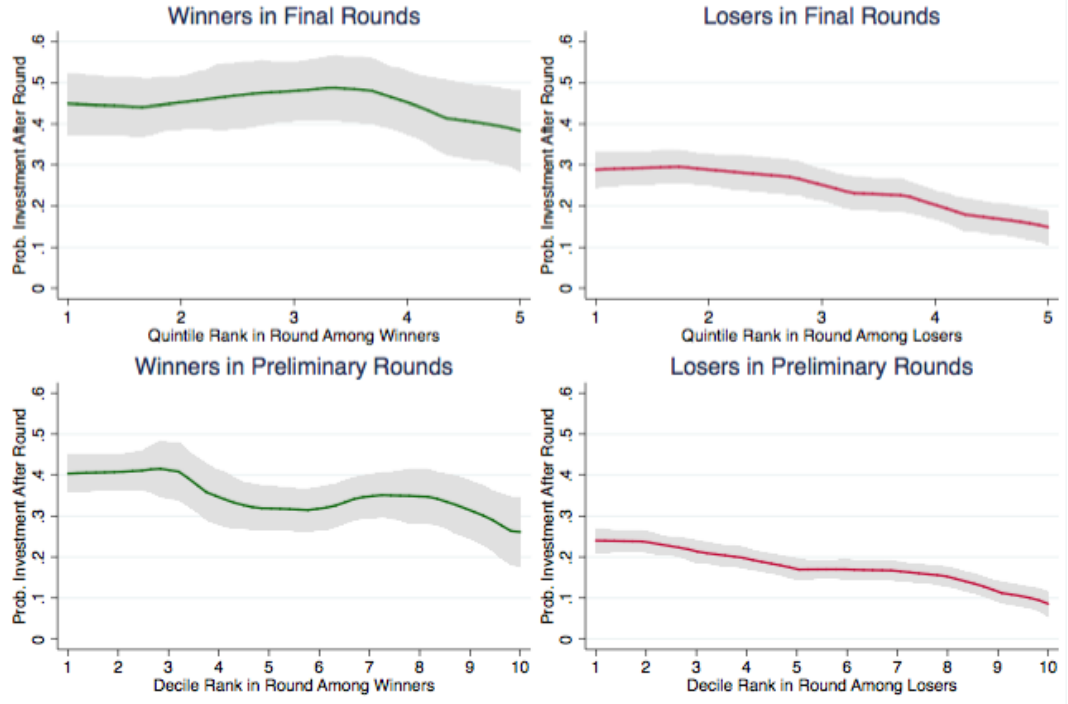
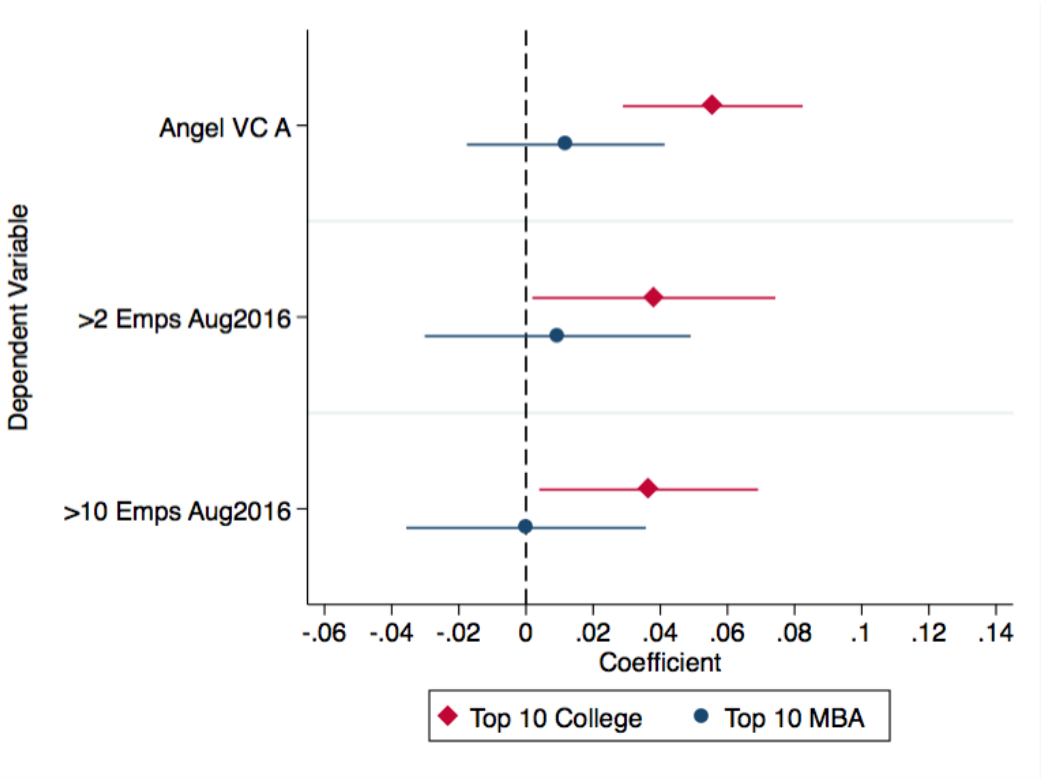


Figure 3: Elite Founders and Success; Coefficients from Regressing Outcome on Elite Status within Competition



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

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

, where C_i is either an indicator for having a top 10 college degree or an indicator for having a degree from a top 10 MBA program (see Appendix Table 4 for rankings). Regression results are in Appendix Table 20.

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