Learning and Success in Entrepreneurship

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Abstract

New venture competitions offer a laboratory to study high-growth entrepreneurship. I use novel application and judging data from nearly 100 competitions to examine which founder and venture characteristics are associated with success. I focus on whether the ability to learn is important. Two exercises demonstrate that judge ranks are relevant information for entrepreneurs. First, independently of winning, ranks predict subsequent venture external financing and employment. Second, a quasi-experimental design finds that negative feedback increases the probability that an entrepreneur abandons his venture. I then show that learning, measured as raw score or rank improvement, predicts success. These findings are consistent with a view of entrepreneurship as experimentation. Ventures likely to have a lower cost of experimentation, such as software and student-run ventures, learn more. However, founders with degrees from highly ranked schools are less responsive to feedback than their counterparts. This behavior appears rational for elite college graduates, but seems to reflect overconfidence among elite MBA graduates.

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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.[1] In parallel, a recent strand of the literature on entrepreneurship emphasizes the importance of experimentation and adaptability (Manso 2016 and Kerr et al. 2014).[2]

Yet there is little empirical evidence of managerial learning. Further, it is not obvious that adapting to feedback is important for entrepreneurs. Calculations have found that even among founders of venture capital-backed startups, the returns to entrepreneurship are quite low (Moskowitz & Vissing-Jørgensen 2002).[3] A prominent explanation for low returns is that entrepreneurs may suffer from cognitive biases, in particular overconfidence. This behavioral view of entrepreneurship suggests that entrepreneurs enter irrationally and fail to update their priors in light of new information.[4] One example is the contracting model in Landier & Thesmar (2009), in which entrepreneurs receive nothing if the venture fails because they assign this event zero probability.[5] A second example is Bergemann & Hege (2005), who motivate their model of R&D investment with agency conflicts by pointing out that "entrepreneurs express a strong preference for continuation regardless of present-value considerations."

This paper uses new venture competitions to study predictors of early

[1] Additional examples of theoretical work that relies on learning assumptions include Lucas (1978), Jovanovic & Lach (1989), Cagetti & De Nardi (2006), Vereshchagina & Hopenhayn (2009), and Poschke (2013).

[2] See also Dillon & Stanton (2016), McGrath (1999), and Stern (2006).

[3] See also Hamilton (2000) and Hall & Woodward (2010).

[4] For example, Camerer & Lovallo (1999), Arabsheibani et al. (2000), and Koellinger, Minniti & Schade (2007) find evidence of overconfidence among entrepreneurs. 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.

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

stage success in high-growth entrepreneurship, with a focus on learning. I provide the first empirical evidence that on average, nascent entrepreneurs are quite responsive to feedback, and furthermore that the ability to learn is an important determinant of success. This by no means precludes overconfidence from playing an important role in explaining why people forego valuable outside options to become entrepreneurs. In fact, I find suggestive evidence that founders with degrees from elite schools, particularly elite MBA programs, exhibit overconfidence.

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 raw scores and their translation into ordinal rankings, which determine winning. The sample consists largely of first-time entrepreneurs seeking external finance in order to grow quickly. This is an important group to study, as young, high-growth startups drive innovation, employment, and productivity growth (Haltiwanger, Jarmin & Miranda 2013).

My data permit new descriptive statistics about venture and founder characteristics associated with early stage entrepreneurial success. For example, prior job experience and holding a top 10 college degree predict success, but being older or having an MBA do not. Although there is little data or empirical literature on startups prior to their first external financing, I provide rough evidence that the data are representative of early stage startups and founders.

Managerial learning is challenging to study rigorously because it is abstract and often subjective. New venture competitions are well suited to the task. Feedback from judges is the new, external information that entrepreneurs receive. It is codified in ranks observable to the econometrician. The participating ventures, however, observe only mappings of the ranks; in some cases, they learn their overall rank in the round, and in other cases, they learn only that they won or lost.

I measure learning as improvement in rank. To be a valid measure of venture quality, ranks must be relevant to venture outcomes. The first step is to establish that ranks are informative about outcomes, and that winning a competition is causally useful. In a regression discontinuity design, I show that conditional on win status, rank robustly predicts measures of success like subsequent financing, employment, and survival. Winning positively affects these outcomes as well as 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. Since winning is useful, founders should be expected to try to improve their scores. A tangential benefit of this analysis is that it provides, to my knowledge, the first formal evaluation of new venture "pitch" competitions. Such competitions have proliferated in the past decade, and many are publicly funded.[6]

In the second step, I assess the causal effect of especially negative feedback on the entrepreneur's long term decision to abandon the venture. About 1/3 of the 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 the probability that the venture is abandoned by about 12%.

Together, these findings imply that the competitions are a valid setting to examine learning measured as improvement in judge scores. This is akin to an educator measuring student learning as improvement in test scores over the semester. Among ventures that participate in multiple competitions (on average 215 days apart), I find that improvement in rank across competitions predicts subsequent angel/VC investment and employment, controlling for the venture's rank in the last competition and round fixed effects. To understand the type of learning, I compare venture descriptions across the competitions. The

[6]Two examples of such public support in my data are the Arizona Innovation Challenge, which awards $3 million annually, and the the U.S. Department of Energy's National Clean Energy Business Plan Competition, with $2.5 million in allocated funding.

description changes associated with improvements in rank are a greater focus on solving a perceived customer problem or need, and greater focus on the product's competitive advantage. A greater focus on making money or substantial changes to the product itself do not predict learning.

The final analysis focuses on 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. As in Bernstein, Korteweg & Laws (2015) the strongest criterion predictor of success is the team (management quality) rank. 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.

Overall, my results are consistent with early stage entrepreneurship being a process of experimentation. Rather than passively receive type shocks, the firms seem to actively acquire and adapt to new information, as in Ericson & Pakes (1995). In the experimentation view, the option to abandon the venture is valuable. In support of this theory, I show a causal relationship between receiving especially negative feedback and abandoning the venture. Further, 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.[7] Unincorporated ventures and student founders are more sensitive to feedback. These results are consistent with the option value of abandoning entrepreneurship declining as the firm and founder age.

Founders with elite college degrees are much less likely to abandon their ventures in the face of negative feedback. This is consistent with rational Bayesian updating among elite school founders if they have more precise priors. Indeed, on average elite college graduates are more likely to succeed by all outcome measures, and among losers, they are far more likely to raise angel or VC investment. Both elite college and top 10 MBA program graduates learn less across rounds.

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

Within elite founder subsamples, rank and winning robustly predict success. As all participating ventures wish to win, there is no obvious rational reason for elite founders to learn less across rounds. In contrast with the elite college graduates, top 10 MBA graduates are not more likely to succeed on average. The sum of the evidence is most consistent with substantial overconfidence among elite MBA graduates. This result for startup founders relates to the literature on CEO overconfidence (Malmendier & Tate 2005, Ben-David, Graham & Harvey 2013).

Using the number of judges to proxy for signal precision, I find suggestive evidence that the type of overconfidence among elite founders is over-optimism, not over-precision.[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.

Guiso, Pistaferri & Schivardi (2015) argue that if entrepreneurship can be

[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").

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 ventures. Manso (2011) models innovation as learning through a series of experiments. The optimal contract to encourage exploration rewards long term success but tolerates early failure, and it reduces the cost of experimentation by providing timely feedback about performance. Competitions provide nascent entrepreneurs with failure-tolerant, timely feedback. While they reward top performers, they do not penalize especially poor performance, as ranks are private.[9] The large positive effect of winning that I find supports Manso's theory, 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. It summarizes the data and discusses its representativeness. Section 3 explains the empirical approach, and Section 4 contains the results. Section 5 concludes.

[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).

2 The new venture competition context

This paper contributes to the entrepreneurship literature by introducing a new source of data. I observe new ventures and their founders at an earlier stage, with greater granularity, and in a larger sample than extant studies. Survey or population data sources such as the Survey of Consumer Finances, the National Longitudinal Survey of Youth (NLSY79), or the Business Dynamics Statistics 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).

In contrast, the participants in new venture competitions are effectively never subsistence businesses or sole proprietorships. They are deciding whether to found a startup or have very recently founded a startup. By definition, a startup is a temporary entity that aims to grow quickly, and usually to transform an industry. While most will fail, the few that do succeed will be very valuable.

Description of the sample

New venture competitions, which sometimes describe themselves as competitive accelerators or business plan competitions, are an intermediary between entrepreneurs and investors; they act as certifiers, conveners, and sometimes educators. They are sponsored by universities, corporations, foundations, governments at the federal, state, and city level, angel investor groups, and others. In a competition, new ventures present their technologies and business models to a panel of judges.

New venture competitions are an important part of the startup ecosystem, particularly for first-time founders. 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. There is no formal count of new venture competitions, 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]

The sample of 96 competitions in this paper is not accidental; they are similar enough to be evaluated together, but offer variation in the feedback they give to participants, in location, and in venture characteristics.[13] 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 winning ventures.[14]
5. The sponsoring organization explicitly seeks to enable winners to access subsequent external finance.

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

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

[13]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.

[14]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.

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).[15] 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.

An advantage of this context is that the econometrician observes more than the agents under study. I observe overall firm ranks in a round, as well as the judge-specific ranks from which overall ranks are derived. Some competitions calculate the judge-specific rank as an average of judge-dimension specific ranks. The main dimensions are Team, Financials, Business Model, Market Attractiveness, Technology/Product, and Presentation. 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. (See Appendix Table 2 for statistics on the various levels of scores.)

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.[16] Forty-four percent of the ventures were

[15] 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.

[16] Age is determined by the venture's founding date in its application materials. Ventures

incorporated at the round date as a C- or S-corp.

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.[17] The probability of subsequent financing is 0.24, relative to 0.16 before the competition-round. 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. I proxy for continuation with whether a venture has at least two employees as of August, 2016 (mean 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 truncation concerns. Three percent of ventures were acquired or went public.

Founders are described in Table 1 Panel 3, 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 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 4). 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.[18]

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

that describe themselves as "not yet founded" are assigned an age of zero.

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

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

trepreneurial 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.

Representativeness of the data

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 5 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 non-profit 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.

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.[19] 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

[19]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).

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.

The average number of team members in my data 3. This is similar to Bernstein et al. (2015), who note that on the AngelList platform, the average number of founders is 2.6. The median founder age, 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.[20] Wadhwa et al. (2009), on the other hand, find that the average age of entrepreneurs of successful, high-growth startups is 40. Analysis of startups valued at $1 billion or above between 2003 and 2013 by Cowboy Ventures found the average entrepreneur age at company founding was 34 (Lee 2013).

Which venture and founder characteristics predict success?

The data permit descriptive statistics that are, to my knowledge, new to the world on the relationship between early stage entrepreneur and venture characteristics and subsequent success. Table 3 Panel A contains estimates of projecting success proxies on vectors of characteristics. The dependent variables are subsequent angel/VC investment, and having at least 10 employees as of August, 2016.[21] Columns 2 and 4 exclude 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 5-6 pp increase in the probability of angel/VC, but is only noisily associated with having at least 10 employees. In contrast, more founder job experience, being an IT/software (rather than hardware) venture, being located in a VC hub state, and having

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

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

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 much more likely to succeed. Figure 2 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 has no association with success.

Table 3 Panel B shows the association between 17 venture sectors and success. The base sector is "Air/water/waste/agriculture". Software and education ventures are relatively more likely to succeed for both outcomes, while social enterprise and biotech ventures are not. Media and entertainment ventures are far more likely to raise Angel/VC, but are not measurably more likely to reach 10 employees. A similar exercise using college majors does not find robust differences in success rates across majors. Majoring in either entrepreneurship or political science/international affairs are weakly associated with success.

3 Analytical approach to learning

Managerial learning is challenging to study rigorously because it is abstract and often subjective. New venture competition data are well-suited to this task. The new, external information that entrepreneurs receive is feedback from judges about the quality of their ventures. I define learning in this context as responsiveness and adaptation to judge feedback about venture quality. This feedback is codified in scores or ranks. I observe these scores but the entrepreneurs observe only mappings of the scores; in some cases, they learn their overall rank in the round, and in other cases, they learn only that they won or lost.

If judge ranks are valid tools to study learning, the ranks must relevant to firm outcomes, and further entrepreneurs should respond to the signals they receive. In a regression discontinuity design, I show that judge scores are informative about venture outcomes, and that winning a competition is useful. Since winning is useful, founders should be expected to try to improve across rounds within a competition, and across competitions when they compete in more than one.

In the second step, I exploit a quasi-experiment to show that entrepreneurs respond to feedback. That is, I demonstrate a causal effect of judge rankings on the entrepreneur's decision to abandon his venture. Together, these findings imply that the competitions are a valid setting to examine learning, when learning is measured as improvement in judge scores. I then show that improvement across competitions and rounds predicts success, independently of rank and winning. I examine which venture and founder characteristics are associated with learning.

Signal informativeness

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, essentially a regression discontinuity design:

$$
\begin{aligned}
Y_i^{Post} &= \alpha + \beta_1 WonRound_{i,j} + f\left(DecileRank_{i,j}\right) + \beta_2 AwardAmt + \gamma' \mathbf{f.e.}_{j'/k} + \delta' \mathbf{X}_i + \varepsilon_i \qquad (1) \\
& \mathbf{X}_i = [Prev.\ financing,\ Judge/Judge\ comp\ invested,\ Sector\ dummies, \\
& Venture\ age,\ \#\ team\ members]
\end{aligned}
$$

Here, i indicates a venture, and j a competition-round-panel (e.g. the MIT Clean Energy Prize Semifinals). Y_i^{Post} is a binary outcome variable, and $WonRound_{i,j}$ is an indicator for whether the venture was a winner in the round. In the baseline empirical analysis, I include competition-round-panel or judge fixed effects.[22] The

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

former absorb the date and location. I cluster standard errors by competition-round-panel or by judge.

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. I control either for linear decile rank separate decile ranks among losers of a round and among winners. Some specifications use judge decile ranks, which is the venture's decile rank among ventures the judge scored. The best decile is 1, and the worst is 10. A negative coefficient on $DecileRank_{i,j}$ indicates that judge ranks are positively predictive of the success metric.

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

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

Unfortunately, this is beyond the scope of the present study.

Responsiveness to feedback

The ideal experiment to assess responsiveness is to randomly allocate feedback across ventures within rounds. I try to approximate this 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. I ask whether ventures that receive especially negative feedback are more likely to be abandoned.

The empirical design is a difference-in-differences model 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. That is, I estimate among losers the combined effect on the entrepreneur of receiving a below-median score, and knowing that he received a low score:

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

The coefficient of interest in Equation 2 is β_1. I similarly estimate whether there is a symmetric effect for especially positive feedback among winners. I am able to study 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. First, note that the estimation is within round. 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 is systematically different along dimensions that are not captures by the controls,, 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 this approach is not the , it provides the closest approximation in the literature to date.

Learning as improvement across competitions

A different type of learning is in the sense of improvement. 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 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. I define the learning metric $\Delta_{i,j,j'(deciles)}$, where j denotes the first competition and j' the last competition, as $\Delta_{i,j,j'(deciles)} = Decile\ Rank_{i,j} - Decile\ Rank_{i,j'}$. When $\Delta_{i,j,j'(deciles)} > 0$, the venture improved, whereas when $\Delta_{i,j,j'(deciles)} < 0$, the venture's relative rank declined.

I first focus on the sub-sample of ventures that participate in multiple competitions. I estimate a version of Equation 3, using the preliminary round in both:

$$Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j'(deciles)} + \beta_2 Won\ Round_{i,j'} + \beta_3 Decile\ Rank_{i,j'} + \gamma' \mathbf{f.e.}_{j'/k} + \varepsilon_{i,j'}. \quad (3)$$

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 as 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. Using raw scores obviates concern that the changing composition of ventures across rounds may affect the results. To be consistent with the $\Delta_{i,j,j'(deciles)}$, the raw score change is measured as $\Delta_{i,j,j'(raw)} = Raw\ Score_{i,j'} - Raw\ Score_{i,j}$. For both, a positive Δ indicates improvement.

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. 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.[23]

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:

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

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

4.1 Signal informativeness and the benefit of winning

The learning metrics require judge ranks to be meaningful signals about startup quality. If ventures seek to improve in the judges' estimation, then improvement in rankings reflect venture learning regardless of whether the ventures observes their scores. It is crucial that rank predicts subsequent success independently of win status. Figure 1 demonstrates visually the effects of winning and the predictive power of rank on either side of the cutoff for subsequent financing.

Estimates of Equation 1 in Tables 4 and 5 show that the competitions generate valuable signals. Across all the success proxies, the coefficients on rank

[23]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.

are negative and highly significant, even when separated on either side of the cutoff (e.g. Table 5 column 1). As an example of the interpretation, the coefficient on decile rank in round in Table 5 column 4 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 5 column 3), and increases he probability of financing by 1.4 pp (Table 4 column 7). Logit specifications in Table 3 columns 3, 6, and 8 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.

Table 4 columns 1-2 show that within final rounds of a competition, winning increases a venture's probability of subsequent external private finance by 12 pp, relative to a mean of 24%. There is an independent effect of winning a preliminary round, at 4-8 pp using OLS (columns 4-5). Columns 1, 7, and 10 include the cash award amount; interestingly, as the large effect of winning a preliminary round foreshadowed, winning is useful independently of the award. An extra $10,000 in cash prize increases the probability of financing by at most 1 pp. Controlling for this award effect, winning increases the probability of financing by 8-12 pp using competition-round-panel fixed effects, and 16-23 pp using judge fixed effects.[24] Models with judge fixed effects have larger samples because an observation is a judge-venture-round, rather than a venture-round.

Winning increases the probability of subsequent angel or series A VC investment by 11-15 pp, relative to a mean of 15% (Table 5 columns 1-2). 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% (Table 5 columns 3-6). The effect on having at least two employees is virtually identical to having at least three employees. Winning increases the likelihood the

[24]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 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, there should be little demand for competitions. Instead, the programs are typically oversubscribed. For example, the Rice Business Plan Competition receives between 400 and 500 applications for 40 places in its annual competition. The results in Table 4 indicate that winning a preliminary round is useful even when the venture ultimately loses, and that among losers, a higher rank is predictive of success. Thus competitions may well be useful for a majority of participants.

4.2 Responsiveness to feedback

This section shows that entrepreneurs who receive especially negative feedback about their ventures are more likely to be abandon them. This finding both demonstrates that ranks contain meaningful information for the entrepreneurs, and also offers some of the first empirical evidence of managerial 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%. Conservatively, this translates to a 12% increase in the probability of failure. Thus on average, the entrepreneurs in this setting are not so overconfident as to give zero probability to the failure state; interim signals do matter.[25]

The effect of negative feedback on abandonment persists within important subsamples. Three models in Appendix Table 8 show that the effect persists within the population of founders with MBAs, among ventures from VC hub states, and among student-led ventures. Yet there is also substantial heterogeneity in responsiveness. 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. 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.

These results could reflect earlier stage ventures having less private information about their own potential, leading them to update more when they receive negative feedback. Yet the lack of a result for venture age suggests that if anything judge feedback is less informative for the youngest ventures. 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. In sum, these results are consistent with the option to abandon becoming less valuable as the venture reaches the milestones of incorporation and initial funding.

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

[25] 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.

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. Students may place greater weight on judges' advice because they have little personal experience and thus a less precise private prior. Yet I find no effect of prior jobs or founding a prior venture (Panel 2 columns 5 and 6).

Panel 3 columns 4 and 5 show that founders with elite college degrees are 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. Figures 2 and 3 suggest this may reflect rational behavior. The graphs show coefficients from regressing outcome measures on an indicator for elite status, with competition-round fixed effects. Founders with top college degrees are significantly more likely to succeed on average (Figure 2), and within the sample of losers, they are much more likely to raise angel/VC but not more likely to reach at least 10 employees (Figure 3). A top 10 MBA degree has no association with any of the success measures. In Section 4.5 below, I discuss the implications of these findings for overconfidence.

One measure of venture risk is uncertainty among judges.[26] 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.[27] The triple interaction has a positive effect (Panel 2 column 3); when judges are uncertain, founders are less sensitive to their overall rank. 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 was no consensus among judges.[28] 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).

4.3 Learning as improvement across competitions

I next examine whether the ability to learn predicts success. I first measure learning as improvement across competitions. 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. Improving a decile increases

[26]Appendix Table 9 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.

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

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

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.[29]

Broadly, there are three mechanisms for score improvement. First, founders may improve their salesmanship. 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.

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 customer problem that the product solves. 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 learning measure 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 description changes across competitions. All three models in Table 10 find that learning is driven by focusing more on solving a problem and on competitive advantage. Changing or re-targeting the product do not explain the improvement. Learning across competitions does not reflect wholesale pivoting to a new idea, but rather what practitioners sometimes call "product-market fit."

[29]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.

4.4 Learning as improvement across rounds

The last measure of learning is the change in rank across rounds. 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 strong ventures earn high ranks in all rounds. These ventures will have learning measures that are either zero or 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 across rounds increases the chances of subsequent success across all the outcome variables. Panel 1 uses the change in decile rank across rounds. Increasing a decile in rank increases the probability of at least two employees by 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.

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. I use judge fixed effects, so the unit of observation is a judge-specific score. The effect on having at least 10 employees loses significance. 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 10-11). I add founder and venture characteristics in Appendix Table 12, using both rank and raw score changes. The associations with success shown unconditionally in Table 3 remain (for example, software ventures are more likely to raise financing). Controlling for these characteristics, the effect of the learning metrics retain their magnitude and significance.

At the founder level, I also find that learning within a competition predicts success. In Appendix Table 13, 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. 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 reflects learning, it should be more predictive of success when ventures are aware of their rank than when they are not, because they receive more information from judges. I interact the learning across rounds measure with whether the competition provided structured feedback. Estimates in Appendix Table 14 find that the effect of learning on subsequent financing and employment is significantly higher in structured feedback than in non-structured feedback competitions.

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 15 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.

Who Learns?

The above sections found that, at least among the founders in my data, adapting to feedback is important for nascent entrepreneurs to be successful. Heterogeneity sheds light on the relationship between learning and theories of entrepreneurial entry. In Table 12, I project the learning metrics (decile rank and raw score changes across round) on venture and founder characteristics. Not all characteristics are available for all ventures and founders, so the sample size changes across the regressions. Note that if some ventures are systematically highly ranked across all rounds, they cannot "learn" using the decile rank change metric. To mitigate this problem, I control for the rank in the first round and also use raw score changes, which can increase for all ventures.

Across specifications, students and founders with software-based products tend to learn more. I find mixed results for some characteristics. Ventures that were incorporated at the time of the round or are from a VC hub state learn appear to learn more with raw scores, but not with rank changes. There is more movement in ranks and an overall increase in raw scores when there is more time between the rounds (columns 7-8).

Evidence of Overconfidence among Elite-School Founders

Elite degrees both at the MBA and undergraduate level are associated with less learning. For example, in columns 4 and 8 a single rank improvement in the college rankings (among the top 20 colleges) reduces learning measured as improvement in raw scores by .2 of a point, relative to a mean of -1.2 (this negative mean implies that raw scores decrease on average between preliminary to final rounds). Assuming all ventures wish to win, rational founders should try to improve across rounds. That elite-school founders do not learn is potentially consistent with overconfidence. Conversely, it may be that winning is not useful and/or ranks are not informative for this subsample. To test this possibility, I estimate Equation 1 within subsamples of elite-school founders in Appendix Table 16. Among top 20 college graduates, top 10 college graduates, and top 10 MBA graduates, winning and rank are roughly as predictive of success as in the whole sample. Thus it does not seem that the competitions and the information they generate are less useful for these founders.

It is perhaps not surprising to find evidence of overconfidence among elite school founders. Landier & Thesmar (2009) find that entrepreneur overconfidence increases with the entrepreneur's outside option. Elite school founders likely have better outside options. At the same time, they may have personal wealth that reduces the cost of failure.

Theory suggests that in certain leadership contexts, failing to learn may be optimal. Bernardo & Welch (2001) and Goel & Thakor (2008) theorize that the few entrepreneurs or CEOs who do succeed benefit from their overconfidence. 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. Related empirical work by Kaplan et al. (2012) finds that better performing CEOs are characterized by less openness to criticism and feedback. These points apply best in my context to elite college graduates; as Figures 2 and 3 show, they are unconditionally more likely to succeed than their counterparts. Top 10 MBA degree holders, however, are not, making it much more difficult to rationalize their failure to learn.

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. Relative to unbiased entrepreneurs, over-precise ones should put less weight on a noisy signal than a precise signal. That is, they should weigh their own signal more heavily if they believe it is more precise. Entrepreneurs without this bias should differentiate less between noisy and precise signals. Over-precise founders should be relatively more responsive to a more precise signal than un-

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

biased founders.

Appendix Table 17 interacts elite status with the indicator for whether the number of judges is above median. The coefficient on the interaction is small and insignificant. This test by no means establishes that elite founders are not over-precise, but it provides some evidence 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 VC 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).

This analysis is suggestive rather than conclusive. It raises interesting questions, however, about how learning and overconfidence interact with innovation. New entrants with radical technologies may be less responsive to feedback, while those with more incremental ideas are more adaptable. 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 VC quote above.

Learning by Criteria

I showed in Section 4.3 that learning across competitions most often consists of greater focus on how the product solves a customer problem, and on the product's competitive advantage. As explained in Section 2, overall scores are in most competitions aggregated dimension (criteria) scores. I now use these to explore the type of learning that occurs across rounds. 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 Bernstein et al. (2015) and Gompers et al. (2016), who find that early stage investors most value information about startup teams. Related work find a positive correlation between good managerial practices and productivity in large firms (Bloom et al. 2012, Bloom et al. 2016, Guiso et al. 2015).

Presentation ranks predict financing but no other outcome. A better technology or product rank 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 18.

Learning within these dimension ranks provides a somewhat different picture. Estimates in Table 14 find that improvement in the financials rank is most predictive of success. 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 predicts subsequent financing, but not employment. The importance of learning how to present better in order to access investment is consistent with the pitch being key to the startup fundraising process, and with competitions helping new ventures to refine it.[31]

Learning by Geography

The competitions take place in 17 states. In general, judges are based in the same geographic location as the competition, but participating ventures are typically

[31] At the individual level, Appendix Table 13 shows that learning along the presentation dimension (and no other dimension) predicts whether the founder will found a subsequent venture or have a subsequent executive title.

drawn from diverse locations.[32] Competitions may be most useful when they serve as convening mechanisms to help nascent entrepreneurs build local networks. They seek to match entrepreneurs with local resources, both in terms of relevant feedback and more tangible resources like investment. Supporting this hypothesis, I find that learning is most useful when the venture is local *and* when the locality in question is not a VC hub state.

Specifically, in Table 15 column 1, I show 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.

Next, I add being from a VC hub state as a third interaction (Table 15 columns 2, 3, 5 and 6). The coefficient on the triple interaction represents, for example, the effect of learning for a venture from Massachusetts in a Massachusetts competition. It is negative and precisely estimated, and robust to controlling for whether the founder has a degree from Harvard, MIT, or Stanford.[34] Thus adapting to judge feedback is most helpful when the judge is local in places with fewer entrepreneurial resources.

Chatterji et al. (2013) point out that while the top tail of high-growth

[32] 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.

[33] Variation in the benefit of learning across locations might reflect variation in the competitions' usefulness. To rule this out, Appendix Table 19 shows that winning is useful to ventures regardless of the venture's home state. I also find no systematic differences in the learning measures across states. 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 (Appendix Table 20). There may be a fixed effect of participating in a local competition in a non-VC hub state, or higher quality ventures may tend to participate in local competitions.

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

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, founders from out of town benefit less.

5 Conclusion

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 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 new information. If such a learning process is occurring, we know little about it. This paper offers the first evidence that learning among nascent entrepreneurs is strongly predictive of success, and that new ventures respond to feedback.

I also show that certain types of startups learn more than others. A strong result is that software-based ventures are more responsive to feedback and learn more. Pugsley & Sahin (2015) and Decker et al. (2014) document a troubling secular decline in new firm entry. 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.[35] 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."

A final comment relates to the program evaluation aspect to this paper, which is tangential to the main research agenda but important in its own right. Many new venture competitions are publicly funded, both in the U.S. and abroad. 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. The White House "Startup America" initiative, launched in 2011, champions the public sponsorship of acceleration and competition programs.[36]

Despite the recent burgeoning of support, it is not obvious that competitions are useful. Since participation in a competition is typically public information, 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 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 even in preliminary rounds with no prize. Further, learning is useful independently of winning. Thus 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. While it is well-established that high-growth startups tend to co-locate, we know little about

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

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

which policies cost-effectively foster innovation 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. New venture competitions may be such an activity. I cannot address how the benefits of competitions compare to other policies like tax credits or incubator sponsorship. However, competitions appear to be relatively cheap, exploiting convening power and private sector expertise.

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 4 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	
Retail/apparel/consumer goods	139	judge's firm invested in venture	95
Social enterprise	42	# judge-venture pairs in which	
Transportation	136	judge's 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: Unconditional association between characteristics and success

Panel A

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 panel contains the unconditional association of characteristics and success, using the OLS regression: $Y_i^{Post} = \alpha + \beta' \mathbf{C}_i + \varepsilon_{i,j}$ where $\mathbf{C}$ is a vector of characteristics. Standard errors clustered by competition-round. Columns 2 and 4 have a much larger sample because they omit venture and founder age, which are not available for many ventures. *** indicates p-value<.01.

Panel B

Dependent Variable:	Angel/VC series A investment	$\geq$ 10 employees as of 8/2016
	(1)	(2)
Air/water/waste/agriculture	-	-
Biotech	.053	-.012
	(.036)	(.047)
Clean tech/renewable energy	.026	.026
	(.026)	(.027)
Defense/security	.14***	.11*
	(.05)	(.062)
Education	.17***	.18**
	(.063)	(.075)
Energy (fossil)	.12	.11
	(.073)	(.071)
Fintech/financial	.073*	.23***
	(.039)	(.073)
Food/beverage	.12***	.11**
	(.039)	(.048)
Health (ex biotech)	.2***	.12***
	(.04)	(.043)
IT/software/web	.24***	.19***
	(.035)	(.035)
Manuf./materials/electronics	.18***	.13***
	(.043)	(.043)
Media/ads/entertainment	.27***	.11
	(.065)	(.069)
Real estate	.053	-.0049
	(.041)	(.044)
Retail/apparel/consumer goods	.18***	.081*
	(.046)	(.046)
Social enterprise	-.03	.14
	(.085)	(.1)
Transportation	.075**	.13***
	(.031)	(.047)
Competition f.e.	Y	Y
N	3519	3519
R^2	.12	.076

Note: This panel contains the unconditional association of venture sectors and success, using the OLS regression: $Y_i^{Post} = \alpha + \beta' Sector\ f.e._i + \gamma' Comp\ f.e._j + \varepsilon_{i,j}$. Standard errors clustered by competition-round. *** indicates p-value<.01.

Table 4: 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	.12***	.12**	.6***	.045**	.083***	1***	.077**	.8***	.23***	.16***
	(.043)	(.048)	(.23)	(.022)	(.03)	(.2)	(.037)	(.14)	(.019)	(.015)
Won Competition				.21***	.22***	.47***				
				(.038)	(.041)	(.17)				
Decile rank in round	-.022***			-.017***						
	(.0049)			(.003)						
Decile rank in round among winners		.0032	.0089		-.011**	-.071***	-.0062	-.071***		
		(.0066)	(.031)		(.0049)	(.025)	(.0056)	(.021)		
Decile rank in round among losers		-.021***	-.13***		-.017***	-.13***	-.014***	-.13***		
		(.0044)	(.026)		(.0031)	(.022)	(.0032)	(.017)		
Judge decile rank in round									-.0065***	-.0061***
									(.0011)	(.0014)
Award Amount ($, 10,000s)	.0057*						.0093***			.011***
	(.0032)						(.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:

$$Y_i^{Post} = \alpha + \beta_1 WonRound_{i,j} + f\left(DecileRank_{i,j}\right) + \beta_2 AwardAmt + \gamma' \mathbf{f.e.}_{j'/k} + \delta' \mathbf{X}_i + \varepsilon_{i,j}$$

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 5: Effect of Rank and Winning on Additional Outcomes

Dependent variable:	Angel/VC series A investment		$\geq$ 3 employees as of 8/2016		$\geq$ 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:

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

Errors clustered by competition-round or judge, depending on f.e. A smaller rank is better (1 is best decile, 10 is worst decile). Note that competition f.e. control for a specific date. All rounds included. *** 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:

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

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						
	(1)	(2)	(3)	(4)	(5)	(6)
Characteristic C_i (all binary):	Venture incorp. at round	Venture age > median	Venture has high judge rank s.d.‡	Founder age above median	Founder # previous jobs > median	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						
	(1)	(2)	(3)	(4)	(5)	(6)
Characteristic C_i (all binary):	Founder has MBA	Founder has top 10 MBA	Founder attended top 20 college	Founder attended top 10 college	Founder attended Harvard/ Stanford/ MIT	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. †Venture state is California, New York, or Massachusetts. ‡Standard deviation of judge ranks for the venture is above median, among ventures in round. *** 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 the venture's first competition j and last competition j' ($\Delta_{i,j,j'(deciles)}$). Sample restricted to ventures participating in multiple competitions. I use variants of:

$$Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j'(deciles)} + \beta_2 Won\ Round_{i,j'} + \beta_3 Decile\ Rank_{i,j'} + \mathbf{X}_i + \gamma' \left(\mathbf{1} \mid f.e._{j'/k}\right) + \varepsilon_{i,j}$$

. Errors clustered by competition-round or judge, depending on f.e. A smaller rank is better (1 is best decile, 10 is worst decile) †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	$\geq$ 2 employees as of 8/2016	$\geq$ 10 employees as of 8/2016
	(1)	(2)	(4)	(6)
$\Delta_{deciles}$ first to second round**	.018***	.0083	.017**	.015**
	(.0066)	(.0051)	(.0076)	(.0067)
Decile rank in first round	-.025***	-.013*	-.029***	-.025***
	(.0077)	(.0069)	(.0099)	(.0094)
Won round	.14***	.1***	.028	.066*
	(.043)	(.033)	(.043)	(.039)
Competition-round- panel f.e.	Y	Y	Y	Y
N	1252	1252	1252	1252
R^2	.22	.18	.22	.2

Panel 2: Raw score change				
Dependent variable:	Financing after round*	Angel/VC Series A Investment	$\geq$ 2 employees as of 8/2016	$\geq$ 10 employees as of 8/2016
	(1)	(2)	(4)	(6)
Δ_{raw} first to second round**	.028***	.017*	.016*	.024
	(.01)	(.0089)	(.0091)	(.026)
Raw score in first round	.00087	-.0024	.0083**	.0023
	(.0046)	(.0037)	(.0038)	(.0094)
Won round	.062	.071	.055	.23**
	(.11)	(.11)	(.071)	(.087)
Judge f.e.	Y	Y	Y	Y
N	3456	3456	3456	2185
R^2	.22	.2	.27	.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:

$$Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j'(deciles/raw)} + \beta_2 Won\ Round_{i,j'} + \beta_3 Decile\ Rank/Raw\ Score_{i,j'} + \gamma' f.e. + \varepsilon_{i,j}$$

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. *** indicates p-value<.01.

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

Dependent Variable:	$\Delta_{deciles}$ (1)	Δ_{raw} (2)	$\Delta_{deciles}$ (3)	Δ_{raw} (4)	$\Delta_{deciles}$ (5)	Δ_{raw} (6)	$\Delta_{deciles}$ (7)	Δ_{raw} (8)
Founder has MBA	-.081	-.42	.33	.28			-.12	.86***
	(.27)	(.28)	(.25)	(.23)			(.31)	(.28)
Founder has PhD	.21	-.11					-.24	-.33
	(.31)	(.34)					(.23)	(.36)
Founder age	.015	.087***					.012	.046***
	(.012)	(.014)					(.012)	(.0099)
Founder is student at round	.79***	1.9***					1.8***	.65
	(.29)	(.43)					(.45)	(.39)
Number of jobs before round > median	-.067	.84**					-.16	.12
	(.3)	(.38)					(.24)	(.37)
Founded previous venture	-.041	.91***					-.36*	.83***
	(.26)	(.29)					(.21)	(.28)
Founder has top 10 MBA			-1.4***	-2***			-.93***	-1.5***
			(.37)	(.39)			(.35)	(.38)
Founder college rank in top 20 (1 best)			-.0051	-.21***			-.059***	-.25***
			(.019)	(.044)			(.018)	(.05)
Tech type IT/software					.26**	.37***	.32	.79***
					(.13)	(.12)	(.25)	(.24)
In VC hub state†					-.27*	1***	.1	.73*
					(.16)	(.29)	(.22)	(.38)
In social/clean tech sector					-.27	1.3***	.81***	2.2***
					(.19)	(.37)	(.23)	(.4)
Raised financing before round					.46**	.2*	-.095	.87***
					(.22)	(.11)	(.24)	(.23)
Incorporated at round					-.0042	2***	-.16	2.4***
					(.19)	(.37)	(.25)	(.46)
Days between rounds							-.0088**	.038***
							(.0035)	(.0062)
Rank/score in first round	.76***	-.22***	.85***	-.17***	.83***	-.2***	.77***	-.16***
	(.046)	(.049)	(.042)	(.027)	(.046)	(.033)	(.048)	(.043)
Year f.e.	Y	N	Y	N	Y	N	Y	N
Judge f.e.	N	Y	N	Y	N	Y	N	Y
N	618	1248	893	2004	1252	3281	618	1029
R^2	.4	.29	.4	.26	.39	.28	.63	.49

Note: This table contains OLS estimates of the relationship between venture characteristics and learning, which is 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 or judge. †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*		$\geq$ 3 employees as of 8/2016		$\geq$ 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:

$$Y_i^{Post} = \alpha + \beta_1 Won\ Round_{i,j} + \delta' DimDecileRank_{i,j}/JudgeDimQuintileRank_{i,j,k} + \gamma' f.e._{j/k} + \varepsilon_{i,j,/k}$$

. All rounds are included. Note that dimension scores are generally averaged to produce the overall ranks used in other tables. Errors clustered by competition-round or judge, depending on f.e. [†]Regressions use 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* (1)	Angel/VC Series A Investment (2)	≥ 2 employees as of 8/2016 (3)	≥ 10 employees as of 8/2016 (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:

$$Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j'(deciles)} + \beta_2 Won\ Round_{i,j'} + \delta' DimDecileRank_{i,j} + \gamma' \mathbf{f.e.}_{j'/k} + \varepsilon_{i,j'}$$

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*			$\geq$ 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:

$$Y_i^{Post} = \alpha + \beta_1 \Delta_{i,j,j'(deciles)} \left(\mathbf{1} \mid SameState_{i,j'}\right) + \beta_2 \Delta_{i,j,j'(deciles)} + \beta_3 \left(\mathbf{1} \mid SameState_{i,j'}\right)$$
$$+ \beta_4 Won\ Round_{i,j'} + \beta_5 DecileRank_{i,j'} + \gamma' \mathbf{f.e.}_{j'/k} + \varepsilon_{i,j'}$$

I also add an indicator for the venture's state being California or Massachusetts as a third interaction in 2 and 4. 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.

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

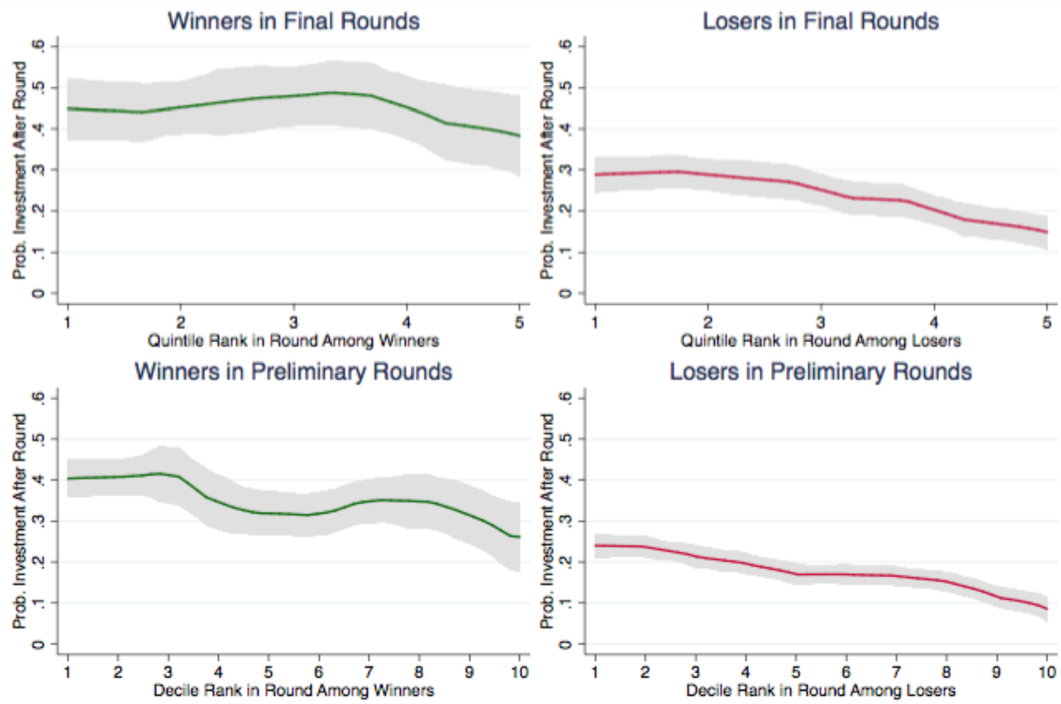
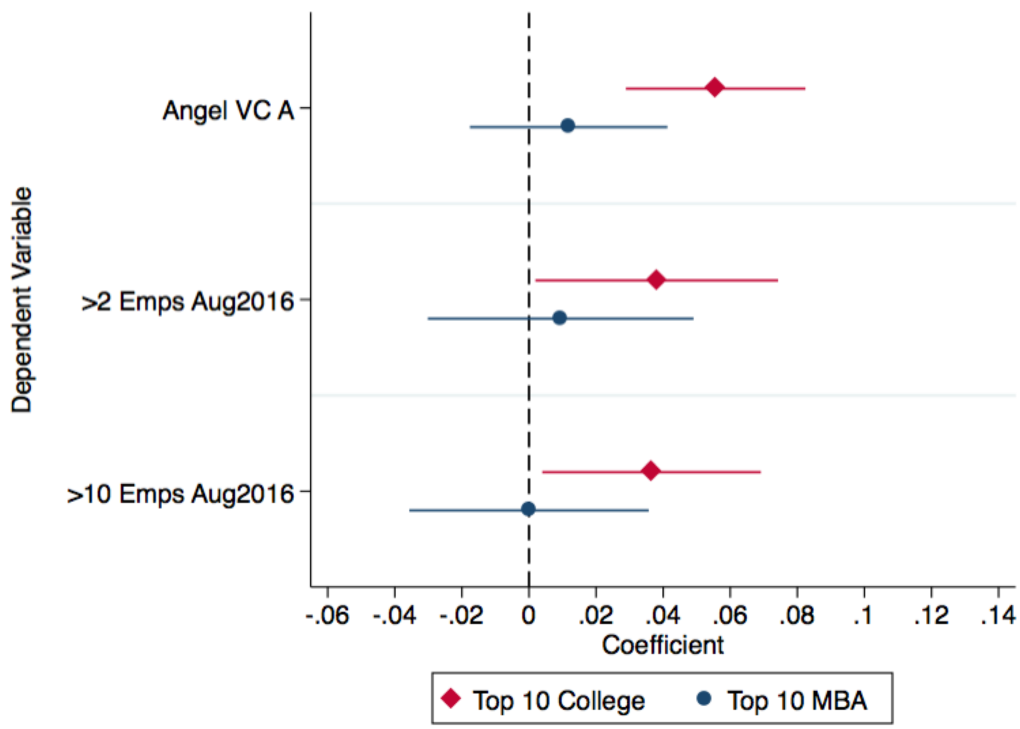


Figure 2: Elite Founders and Success; Coefficients from Regressing Outcome on Elite Status within Competition

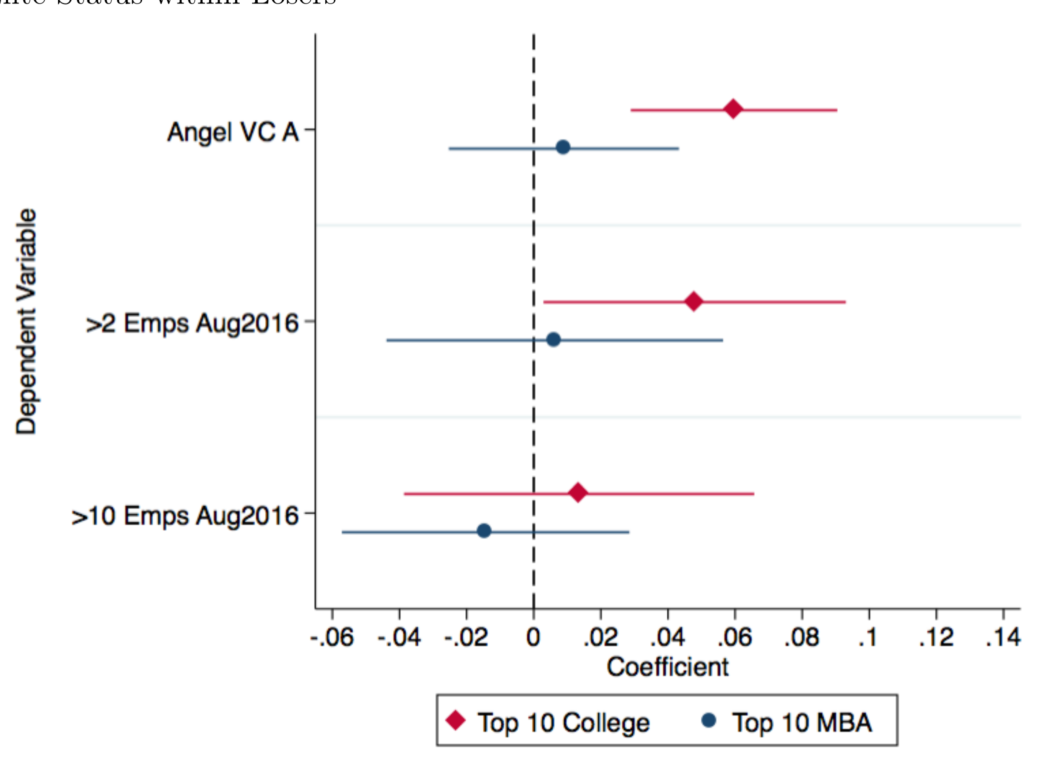


Note: This figure shows coefficients and 95% confidence intervals from six regressions, each of which takes the form:

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

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

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



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

$$\begin{aligned} Y_i^{Post} &= \alpha + \beta_1 \left(\mathbf{1} \mid C_i\right) + \gamma' \left(\mathbf{1} \mid CompRound_j\right) + \varepsilon_{i,j} \\ &if\ i \in Losers_j \end{aligned}$$

, 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).

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