

Learning from Feedback:

Evidence from New Ventures

Sabrina T. Howell*

January, 2018

Abstract

This paper explores how new venture competitions are helpful to entrepreneurs. In a regression discontinuity design using data from 87 competitions in 17 U.S. states, I show that winning is useful. While cash awards matter, winning is independently valuable in ways inconsistent with certification. Competitions instead seem to facilitate learning. I isolate learning by comparing lower and higher ranked non-winners across competitions in which they did and did not observe their standing. There is an economically large effect of negative feedback on venture abandonment. Cross-sectional variation suggests that founders treat their ventures as real options and are Bayesian updaters.

*New York University Stern School of Business. 44 West 4th St KMC 9-93, NY NY 10012; Phone: +1-917-519-8052; Email: sabrina.howell@nyu.edu. This project was funded by the Kauffman Foundation. For especially useful comments, I thank Manuel Adelino, Tom Åstebro, Shai Bernstein, Edward Glaeser, Will Gornall, Boyan Jovanovic, Saul Lach, Augustin Landier, Josh Lerner, Song Ma, Ramana Nanda, David Robinson, Rick Townsend, Annette Vissing-Jørgensen, and participants at the NBER Entrepreneurship Working Group, Yale Junior Finance Conference, IDC Herzliya Eagle Labs Conference, Queens University Economics of Entrepreneurship and Innovation Conference, UC Berkeley-Stanford Innovation and Finance Conference, Georgia State CEAR Conference, and the Tech Scheller seminar. Finally, I thank Adam Rentschler of Valid Evaluation, and all the others who provided the data, including Lea Lueck, Allison Ernst, and Catherine Cronin. Lucy Gong, Sreyoshi Mukherjee, and Jack Reiss provided excellent research assistance.

“It has been assumed here that learning takes place only as a by-product of ordinary production. In fact, society has created institutions, education and research, whose purpose it is to enable learning to take place more rapidly. A fuller model would take account of these as additional variables.”

– Arrow (1962)

1. Introduction

New venture competitions have become a ubiquitous feature of the high-growth entrepreneurship ecosystem. In these competitions, early stage startup founders present their businesses to a panel of expert judges. This paper explores whether and how new venture competitions are useful to entrepreneurs. To my knowledge, it is the first to do so with a large, administrative dataset from the developed world. It thus contributes to a nascent literature on competitions, including McKenzie (2017)’s analysis of one in Nigeria.¹

I use novel data on 4,328 new ventures participating in 87 competitions in 17 states between 2007 and 2015. I link the ventures to employment, financing, and survival outcomes, taking care to account for name changes. The ventures are roughly representative of the U.S. startup population, with no local subsistence businesses – such as restaurants or landscapers – that often contaminate efforts to study high-growth entrepreneurship (Levine & Rubinstein 2016). I also identify founders’ education and career histories. I shed light on the characteristics associated with success. For example, founder job experience or having a software venture are associated with success, while having an MBA or a hardware venture are not.

Next, I employ a regression discontinuity design to assess the effect of winning and the informativeness of judge ranks. I find that winning is useful; after controlling for any cash award, winning a round increases a venture’s chances of subsequent external finance by about 13 percentage points, relative to a mean of 24 percent. Winning also increases employment. There are three primary ways that competitions may be useful for startups: cash prizes,

¹In contemporaneous related working papers, Xu (2017) and Wagner (2017) examine feedback in crowdfunding and the Startup Chile accelerator program, respectively. Other recent work studies related programs, including Hallen et al. (2014), Fehder & Hochberg (2014), Scott, Shu & Lubynsky (2016), Fehder (2016), and Gonzalez-Uribe & Leatherbee (2016).

certification, and learning. The cash prizes are valuable; an additional \$10,000 is associated with about a 1 percentage point increase in financing probability. This is somewhat higher than the effect of U.S. Department of Energy SBIR grants found in Howell (2017).

However, the effect of the cash prize is economically small relative to the independent effect of winning and the predictive power of judge scores. Percentile rank and z-score robustly predict external financing, employment, and acquisition or IPO. Ranks predict startup outcomes even when ventures do not learn their ranks and thus cannot be affected by them. Further, dimension scores are differentially predictive. Team scores are the strongest predictor of initial success, while technology/product scores are strongly predictive – and are the only predictor – of long run, high-level success (acquisition/IPO).

Score informativeness indicates that the competitions provide useful signals. Yet certification, where winning is a signal to the market about venture quality, does not seem to be the primary mechanism. Winning is more useful in preliminary rounds, where certification should be weaker, than in final rounds. Winning is also just as useful in non-selective competitions as selective competitions, and just as useful for elite college graduates as other founders. This points to learning.

I test for learning, in the sense of entrepreneur type revelation, by isolating the effect of feedback. In 53 of the competitions, ventures are informed only that they won or lost, and otherwise do not learn where they stand relative to their peers. In 34 of the competitions, ventures are privately informed of their overall and dimension ranks in the round (but never individual judge ranks). The competitions are otherwise similar, and in the feedback competitions neither ventures nor judges are informed that structured feedback would be provided.

The effect of negative feedback on venture continuation is identified with a difference-in-differences model among non-winning ventures. The first difference is within round, comparing below-median and above-median non-winners. The second difference is across rounds, comparing ventures that were informed of their rank with those that were not. That is, I estimate the effect of a very low rank with knowledge of that rank, relative to a very low rank without such knowledge. Receiving negative feedback significantly increases abandonment. Specifically, it reduces the chances a venture has at least one employee besides the founder as of August 2016 by about nine percentage points, equivalent to a 14 percent increase in abandonment (the mean is 66 percent). The effect occurs quickly, mostly in the first six

months. It is also roughly symmetrical among winners without cash awards.

The empirical concern is whether this effect reflects systematically different distributions among non-winners in the two types of competitions (differences in levels are absorbed). To address this concern, I use three tests and five robustness exercises. The three tests show that the distributions of observables across the two types of competitions are similar ex-ante, and that entrepreneurs do not seem to select into feedback.

The first robustness test shows that the results persist in exact and propensity score matching estimators. The second measures the effect of feedback as the difference between ordinal and nominal scores, within the feedback competitions. The intuition is that two ventures in different competitions may have the same rank but different distances in score to the next highest rank. After accounting for the venture’s quality in the eyes of the judges, I continue to find a strong effect of feedback. The third finds a similar result within a single competition that gave feedback in one year but not others. The fourth interacts feedback with competition characteristics likely associated with participant diversity, signal quality, and venture survival, as well as venture characteristics associated with ex-ante quality. These interactions do not affect the main finding. Finally, the results are robust to including polynomials in z-score and to estimation within relevant subsamples, such as student founders.

Understanding how and which entrepreneurs learn can help inform the theory of entrepreneurship. The data reject models in which entrepreneurs have static types, or equivalently models in which entrepreneurs are so overconfident that they ignore new information. This is consistent with the idea of entrepreneurship as a process of experimentation, as in Kerr, Nanda & Rhodes-Kropf (2014) and Manso (2016). While it may seem obvious that people learn, in the context of entrepreneurship it is not. Instead, there is a strong paradigm that entrepreneurs do not learn about their own probability of success (Bernardo & Welch 2001, Bergemann & Hege 2005, Landier & Thesmar 2009). This behavioral view emphasizes the role of cognitive biases such as over-precision and optimism in entrepreneurial decision-making.² In contrast, learning plays a pivotal role in many models of firm dynamics, including Jovanovic (1982), Aghion, Bolton, Harris & Jullien (1991), and Ericson & Pakes

²See Cooper et al. (1988), Camerer & Lovo (1999), Arabsheibani et al. (2000), Astebro, Jeffrey & Adomdza (2007), Koellinger et al. (2007), Kogan (2009), and Bloom, Lemos, Sadun, Scur & VanReenen (2014). More broadly, financial contracting theory focuses on information asymmetry, and typically assumes that the entrepreneur knows his type or has static beliefs about it (e.g. Admati & Pfleiderer 1994, Clementi & Hopenhayn 2006, Sørensen 2007, Hellmann 1998, Cagetti & De Nardi 2006).

(1995). New information determines entry and exit decisions in these models, implying that entrepreneurs should be sensitive to external signals about their project quality, as they are in my data.

To speak more specifically to theory, some ventures may have higher real option values from delaying abandonment, as in Manso (2016). An option’s value increases in its uncertainty and in its asset specificity. Consistent with this, when judges are uncertain about a venture, the founder is less responsive to negative feedback. Ventures that are not yet incorporated, have no prior external private financing, or are software- rather than hardware-based are more responsive. These characteristics are associated with less irreversible investment.

Founders also behave consistently with Bayesian updating. They are less responsive when there are fewer judges, suggesting that they dismiss imprecise signals. They also update less when they have more information about their own type. Over-precision and optimism biases should concentrate the effect of negative feedback in the lowest ranked founders. Instead, the effect is broadly linear. Feedback induces near-winners to continue as much or more than it encourages the poorest performers to exit. Motivated by this evidence, I use a Bayesian framework to model and calibrate sensitivity to feedback.

In Odean (1999) and Hanna, Mullainathan & Schwartzstein (2014), people do not learn because of noisy or multi-dimensional signals. On the other hand, recent work outside of firm settings has found that individuals can learn about their ability through performance (Seru, Shumway & Stoffman 2010, Hochberg, Ljungqvist & Vissing-Jørgensen 2013). Whether entrepreneurs learn better from certain types of signals is a promising avenue for future research.³

The paper proceeds as follows. The data are introduced in Section 2. The effect of winning and the predictive power of scores are in Section 3. The effect of feedback is in Sections 4 and 5. Section 6 uses cross-sectional evidence to explore variation in learning.

2. New venture competition data

This section first introduces the new venture competition data. Section 2.2 presents summary statistics. Startups and founders in the data are compared to the U.S. startup ecosystem in

³Also related to this paper is the literature on peer effects in entrepreneurship, including Nanda & Sørensen (2010), Lerner & Malmendier (2013), and Guiso et al. (2015).

Section 2.3.

2.1. *The competitions*

New venture competitions, sometimes called business plan or “pitch” competitions, have proliferated in the past decade. In a competition, new venture founders present their technologies and business models to a panel of judges. New venture competitions are now an important part of the startup ecosystem, particularly for first-time founders. For example, among the 16,000 ventures that the data platform CB Insights reports received their first seed or Series A financing between 2009 and 2016, 14.5 percent won a competition. Sponsored universities, foundations, governments, and corporations, among other institutions, competitions aim to serve convening, certification, education, and financing functions.

Data from these competitions permit observing startups and their founders at an earlier stage, with greater granularity, and in a larger sample than prior studies. Further, unlike many data sources commonly used to study entrepreneurship, such as the Survey of Consumer Finances or the Panel Study of Income Dynamics, local subsistence businesses do not appear.

This paper uses data from 87 competitions between 2007 and 2016.⁴ Competitions consist of rounds (e.g. semifinals), and sometimes panels within round. The number of ventures in a preliminary (final) round averages 45 (19). There are 558 ventures that participate in multiple competitions. The mean award amount is \$73,000. The data are summarized in Table 1, and the individual competitions are listed in Online Appendix Table A1. The competitions are usually open to the public, but typically there are few people besides the judges in the room, except in the final round.

All the competitions have the following features: (1) They include a pitch event, where the company takes five to 15 minutes to present its business plan; (2) Volunteer judges formally and privately score participants, and venture ranks in the round determine which ventures win; (3) Ranks and scores are secret, except when a feedback competition informs a venture of its rank; (4) The organizer does not take equity in any participating ventures; (5) The organizer explicitly seeks to enable winners to access subsequent external finance. In most competitions, judges score or rank based on six dimensions (or “criteria”): Team,

⁴The data were obtained individually from program administrators and from Valid Evaluation.

Financials, Business Model, Market Attractiveness, Technology/Product, and Presentation. These dimension scores or ranks are aggregated into a judge-specific venture score or rank. When scores are used, they are ordered to produce ranks. Judge ranks are then averaged to create an overall rank, which determines round winners.

The econometrician observes all ranking and scoring information. This includes overall ranks and individual judges' scores and ranks. In no case do founders observe individual judge scores or ranks. Judges score independently and observe only their own scoring, and never overall ranks.⁵ There is time for questions and usually dedicated networking (e.g., post-competition reception), providing for informal, verbal feedback. Only winning participants are typically listed on a program website, and my understanding is that judges and outside investors do not closely monitor competitions to identify non-winners. To the best of my knowledge, neither entrepreneurs nor judges perceive a penalty from losing.

I use three transformations of the rank and score data. First, I use decile ranks calculated within non-winners and winners separately. That is, I divide non-winners in a round into ten equal bins, with the best ranks in 1, and the worst in 10. Second, I use judge decile ranks, calculated among ventures that the judge scored. Third, I use z-scores for the subset that begin with raw scores. The z-score indicates how far, in terms of standard deviations, a given absolute score falls relative to the sample mean. A higher z-score is better.⁶

2.2. *Summary statistics*

The ventures are described in Table 1 panel 2. The average age of the ventures is 1.9 years.⁷ Forty-four percent of the ventures were incorporated at the round date as a C- or S-corp. Ventures are matched to investment events and employment using CB Insights, Crunchbase, AngelList, and LinkedIn.⁸ In researching the ventures, 765 name changes were identified.

⁵Judges could in theory report their scores to each other. This is unlikely, as 17 judges score a venture on average.

⁶The number of ventures varies across rounds, and to determine which ventures win a round, most of the competitions use ordinal ranks while a few use scores. I cannot, therefore, use the raw rank or score data provided.

⁷Age is determined by the venture's founding date in its application materials. Ventures that describe themselves as "not yet founded" are assigned an age of zero.

⁸For LinkedIn, I only use public profile data as a non-logged-in user, based on Google searches for person and school or firm.

Ventures were matched to private investment on both original and changed names.

Venture survival is a binary indicator for the venture having at least one employee besides the founder on LinkedIn as of August 2016. Among ventures that are abandoned, time to abandonment is the number of days between the competition and the founder’s next job start date. While some startups may not appear on LinkedIn, if they are ultimately successful, they almost certainly will, because their employees will identify themselves as working at the company. That is, companies rarely remain in “stealth” mode forever. Websites are a poor survival measure because they often stay active long after a startup has failed. Founders are described in Table 1 panel 3, using data from the competitions and LinkedIn profiles. Founders are mostly first-time entrepreneurs. Twenty-one percent of founders are women, and 72 percent are men (the remaining seven percent had ambiguous names and no clear LinkedIn match).⁹ Elite degree status is tabulated using the university ranking in Table A2.

Judges participate to source deals, clients, job opportunities, or as volunteer work. There are 2,514 unique judges, described in Table A3, of whom 27 percent are VCs, 20 percent are corporate executives, and 16 percent are angel investors. Ventures and judges are assigned to 16 sectors. Ventures sector assignments come from competition data, and each venture is assigned only one sector. Judge sectors are drawn from LinkedIn profiles or firm webpages, and judges may have expertise in multiple sectors. Ventures and competitions are sorted by state in Table A4. There is concern that the judges investing themselves might contaminate any impact of the competitions on venture financing. Careful comparison of funded ventures’ investors and judges revealed 95 instances of a judge’s firm invested in the venture, and three instances of the judge personally investing.

2.3. *Sample representativeness*

There is little empirical analysis of startups prior to their first external funding event, but the data are roughly representative of first-time, early stage startups and their founders in the U.S.. Table A5 compares the distribution of ventures in my data to overall U.S. VC investment. The share of software startups in my data, 37 percent, is close to the national average (40 percent) in deals and dollars. In part because VC investment in clean energy

⁹Genders were assigned to founder names using the Blevins & Mullen (2015) algorithm, based on gender-name combinations from the U.S. Social Security Administration. Unclear cases, such as East Asian names, were coded by hand.

has declined dramatically in recent years (Saha & Muro 2017), as well as the presence of the Cleantech Open in my sample, the data are skewed towards clean energy.

The competitions take place in 17 U.S. states. With the exception of Arizona, the top twenty states for venture location in the data almost entirely overlap with the top twenty states for VC investment, though the data has fewer ventures from California and more from Massachusetts. This may be expected from such early stage firms, as startups often move to Silicon Valley to raise VC.

The probability of an IPO or acquisition in my sample, 3 percent, is comparable to the 5 percent found in Ewens & Townsend (2017)’s sample of AngelList startups. Each venture team averages three members. This is similar to Bernstein, Korteweg & Laws (2017), 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. This is roughly representative of startup founders.¹⁰

Associations between venture characteristics and success also accord with common knowledge. I regress two measures of success, subsequent angel/VC investment and having at least 10 employees as of August 2016, on venture and founder characteristics. The results are in Table A6 panel 1. More founder job experience, being an IT/software (rather than hardware) venture, being located in a VC hub state, and having prior financing are all strongly associated with both measures of success. Having an MBA is weakly negatively associated with success. Attending a top 10 college is associated with a higher likelihood of investment. Kaplan et al. (2012) find a similar relationship between college selectivity and success for CEOs of VC-backed companies. Associations between sector and success are in Table A6 panel 2. Software and education ventures are more likely to succeed, while social enterprise and biotech ventures are less so. Media and entertainment ventures are far more likely to raise Angel/VC.¹¹

¹⁰The average Y-Combinator founder is just 26, and the average entrepreneur age at company founding among startups with at least a \$1 billion valuation between 2003 and 2013 was 34 (<https://techcrunch.com/2010/07/30/ron-conway-paul-graham/> and <https://techcrunch.com/2013/11/02/welcome-to-the-unicorn-club/>).

¹¹A similar exercise using founder college majors does not find strong variation. Majoring in either entrepreneurship or political science/international affairs is weakly associated with success.

2.4. *Feedback*

I selected competitions for analysis that are otherwise similar but provided systematically different feedback. Interestingly, competition organizers generally do not treat explicit feedback as a program goal. Instead, they are concerned with facilitating networking and identifying the “best” ventures as winners. However, 34 of the programs I study used a third party, Valid Evaluation, to manage their judging software. Valid Evaluation believed that formal feedback might be useful, and sent each venture an email after the round containing their overall rank and dimension ranks (dimensions include “Team” and “Technology”). Ventures learned only their own ranks, and not those of other participants. Interviews with competition organizers indicated that they do not share an interest in feedback, and in fact sometimes discontinued use of Valid Evaluation in part because it seemed more concerned with feedback than with features the organizers valued more, such as the user interface.

The remaining 53 no-feedback competitions used different software, and participants did not observe any rank information. There are no systematic differences in the way judges scored or in the services provided (e.g. mentoring, networking, or training) across the two competition types. In no case did a competition with feedback advertise itself as providing relative ranks or more feedback in general, so ventures with greater informational needs could not have selected into them (a test is also below). Judges were not informed that feedback would be provided, so there is no reason to believe judges would put greater effort into scoring in the feedback competitions. Judges cannot learn from the feedback, as they observe only their own scoring.

3. **Effect of winning and signal informativeness**

This section first presents the empirical strategy for estimating the effect of winning (Section 3.1). The results are in Section 3.2. Section 3.3 discuss the predictive power of the scores. This analysis provides, to my knowledge, the first evaluation of the effect of winning new venture competitions in the developed world. This is relevant for policy, as many competitions are publicly funded. 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. Two examples of government-funded competitions in my data are the Arizona Innovation

Challenge, which awards \$3 million annually, and the National Clean Energy Business Plan Competition, with \$2.5 million in allocated funding.

3.1. Empirical design

I use a regression discontinuity design to evaluate the effect of winning. In Equation 1, the dependent variable Y_i^{Post} is a binary measure of venture success.

$$Y_i^{Post} = \alpha + \beta_1 WonRound_{i,j} + f(Rank/Zscore_{i,j}) + \beta_2 AwardAmt + \gamma' \mathbf{f.e.}_{j/k} + \delta' \mathbf{X}_i + \varepsilon_{i,j} \quad (1)$$

The vector $\mathbf{f.e.}$ includes competition-round-panel or judge fixed effects. The former absorb the date and location. Controls \mathbf{X}_i include whether the judge or judge’s company ever invested in the venture, whether the company previously raised external financing, and the number of team members. I cluster standard errors by competition-round-panel or by judge.

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 and typically only score a subset of participating ventures.

3.2. Effect of winning

I find that winning itself and cash awards are useful to startups. Visual evidence is in Figure 1. The top two graphs use local polynomials to show the probability of subsequent external financing in preliminary and final rounds. The venture’s percentile rank in the round is on the x-axis, with vigntile ranks (five percentile bins) for preliminary rounds, and decile (ten percentile bins) for final rounds. The lines overlap because the share of participants that win varies across rounds.¹² The bottom two graphs repeat this exercise for having at least ten employees. In all four cases, the winner line lies above the non-winner line, indicating a substantial raw effect of winning.

Estimates of Equation 1 are in Table 2. After controlling for any cash award won, my preferred specification finds that winning a round increases a venture’s chances of subsequent external finance by 13 percentage points (pp), relative to a mean of 24 percent (Table 2 panel 1 column 1). The effect falls with venture controls, although these reduce the sample

¹²There are no losers in the top bin in either case. Winners are truncated at the sixth vigntile and fifth decile for preliminary and final rounds, respectively.

size (column 2). A logit model in column 3 finds roughly a doubling, because it drops groups without successes (panels without financing events). The effect is a bit larger at the judge-venture level with judge fixed effects (column 4). Remaining columns examine other outcomes. Winning increases a venture’s chances of survival and having at least 10 employees in 2016 by about 5 pp, relative to means of 34 percent and 20 percent, respectively (columns 5-6). In the specification used here, the effect on acquisition or IPO (column 7) is not statistically significant, though it is in alternative models, such as when the separate control for cash award amount is omitted.

The cash award is also useful. An extra \$10,000 increases the probability of financing by about 1 pp (Table 2 panel 1 columns 1-2). This effect seems small in economic magnitude relative to the overall effect of winning and the predictive power of rank, discussed below.¹³ It is similar to the effect of U.S. Department of Energy SBIR grants found in Howell (2017). The effect of an additional \$10,000 in SBIR grants on the probability of subsequent financing is 0.66 pp, or 8 percent of the sample mean, while the effect of a prize here is 1 pp, or 4 percent of the sample mean.¹⁴

Winning is most impactful in preliminary rounds, and when it does not involve prize money. The effect is 14 pp in preliminary rounds (Table 2 panel 2 column 1), and just 9 pp in final rounds (column 4). Within preliminary rounds, column 2 omits ventures that ultimately won any cash award are omitted. The effect increases slightly, to 15 pp. To emphasize the causality of this effect, column 3 restricts the sample to the two quintiles around the cutoff for winning in a preliminary round, and finds again an effect of 9.8 pp.¹⁵

A larger effect in preliminary rounds is the opposite of what we would expect if certification were the mechanism. Two further tests for certification are whether winning is more useful in selective competitions, and is less useful for founders with elite backgrounds. In Table A7, all covariates besides the panel fixed effects are interacted with an indicator for whether the competition was selective or prestigious.¹⁶ I find no differential effect of winning

¹³Depending 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.

¹⁴A \$150,000 SBIR grant increased the probability a venture subsequently received external financing by about 10 pp. Thus an extra \$10,000 in SBIR grants was associated with a 0.66 pp increase in financing, while in the competition context an extra \$10,000 is associated with about a 1 pp increase. The sample means are eight and 24 percent, respectively.

¹⁵In unreported regressions, I found no difference in the effect of winning across university-hosted and non-university competitions.

¹⁶I include HBS’ New Venture Competition, because while the competition itself is not selective, partici-

or the award (column 1). I next interact with an indicator for whether the founder graduated from a top ten college. Again, I find no differential effect of winning, but I do find that the cash award is significantly less useful for elite founders (column 2). The same is true using an indicator for whether the founder had a previous venture (column 3). The results thus far indicate that competitions are useful for reasons beyond certification or prize money, though cash awards are more useful to founders who likely have less access to resources. Competitions therefore operate differently from the SBIR grants in Howell (2017), which were found to be useful because the cash award funded prototyping.

3.3. *Signal informativeness*

A striking finding from Table 2 is the large and significant coefficients on rank. The regressions control for the decile rank among winners and among non-winners separately. Particularly within non-winners – a much larger sample – rank and z-score strongly predict success, after controlling for winning and competition fixed effects. A one decile improvement in rank increases the probability of external financing by 1.8 pp, significant at the .01 level (Table 2 panel 1 column 1). Rank is also predictive within judge (column 3). Importantly, it persists within the no-feedback competitions, where it is impossible that the judge’s ranks directly affect venture outcomes (Table 2 panel 2 columns 7-8).¹⁷

Thus, competitions generate valuable signals, suggesting that winning – and perhaps participation more broadly – may be useful because of the opportunity to learn from the judges’ expert opinions. Note that if the judges did not have predictive power, in expectation it would not be clear why ventures participate. In a rational market, there should be no positive effect of winning separate from the cash award if judges were choosing winners at random. This is the opposite of SBIR grant ranks, which were uninformative about outcomes. There are a number of differences between the SBIR grant process and new venture competitions. One is that the competition judges are expert market participants. Unreported regressions examine the predictive power of rank by judge occupation. There is little difference across investor, lawyer/consultant/accountant, and corporate executive

pating teams must include at least one HBS MBA student, and of course attending HBS is quite selective. The competition is also regarded as prestigious by local venture capitalists.

¹⁷Table A8 uses indicator variables for each decile of rank, while also controlling for winning. The top decile dummy is omitted, and the others all have large, negative coefficients that increase stepwise from -.065 for the second decile to -.18 for the tenth decile. All are significant at the .01 or .05 level.

judges. Perhaps surprisingly, entrepreneur judge scores have no predictive power.

The dimension ranks that are aggregated to form overall ranks are also informative. Table 3 shows the association between dimension ranks and outcomes, controlling for win status. A higher team rank is the strongest predictor of success for all outcomes other than IPO/acquisition. For IPO/acquisition, the only dimension with predictive power is product/technology, and this is quite robust. ? and Gompers, Gornall, Kaplan & Strebulaev (2016) find that early stage investors care most about information regarding founder team quality. Here, team matters for low-level, earlier stage success, while technology matters for high-level successes, such as IPO. This speaks to the “horse vs. jockey” debate, suggesting that the team matters initially, but the business matters in the long run. It is consistent with Kaplan, Sensoy & Strömberg (2009), who examine 50 public firms and find that business lines but not management remain stable from startup to IPO.

4. Responsiveness to feedback: Estimation strategy

Thus far, we have seen that winning a competition is useful, and much of the benefit of winning is not well-explained by either the prize money or certification. Furthermore, the judges generate informative signals in their scoring. This raises the possibility that competitions are useful because they create learning opportunities. Winning is a binary transformation of the underlying ranking information, which is not observed in the no-feedback competitions, where it is still informative about startup outcomes. Winners may push forward with their ventures because they correctly interpret winning as a positive signal. To test this possibility, it is necessary to isolate the effect of the rank signal. This section first proposes the main design for estimating the effect of feedback on venture continuation (Section 4.1). It then addresses the challenge to causal identification (Section 4.2).

4.1. *Analytical approach*

I compare competitions where ventures receive feedback – they learn their rank relative to other participating ventures – with competitions where ventures learn only that they won or lost. This feedback is relative: ventures are learning their order statistic, and thus the peer group matters. The analysis asks whether founders that receive especially negative feedback about their position relative to their peers are more likely to abandon their ventures.

The empirical design in Equation 2 is a difference-in-differences model among non-winners, which comprise 75 percent of the data. The first difference is between above- and below-median non-winners in a given competition ($Low\ Rank_{i,j}$). The second difference is across feedback and no-feedback competitions ($Feedback_j$).

$$Y_i^{Post} = \alpha + \beta_1 Low\ Rank_{i,j} \cdot Feedback_j + \beta_2 Low\ Rank_{i,j} + \beta_3 Feedback_j + \gamma' \mathbf{f.e.}_{j'/k} + \delta' \mathbf{X}_i + \varepsilon_{i,j} \text{ if } i \in Losers_j \quad (2)$$

Here, i indexes ventures, and j indexes competition rounds. The dependent variable is continuation, measured as having at least one employee besides the founder as of August 2016. I include year fixed effects, which address censoring issues with the survival outcome. The controls are sector dummies, whether the founder is a student at the time of the competition, and whether the venture is incorporated at the time of the competition. Some models include company age and whether the company received investment before the round. When a venture participated in multiple competitions, only the first instance is included.

4.2. Identification challenge

In Equation 2, above-median non-winners comprise the control group. Therefore, average differences across the types of competitions are differenced out. The concern is that the distribution of non-winners around the median may be systematically different in the two types of competitions, even though applicants did not know whether the competition would inform them of their rank in the round. The problem is if the mapping from quality to rank is systematically different. There are two main sources of bias. First, suppose that ranks in the feedback competitions better correlate to true quality than ranks in the no-feedback competitions. Then feedback might be inherently correlated with continuation without any effect of information. Second, feedback competitions could have diverse participants while the no-feedback competitions have participants with similar quality. This could also lead to more abandonment in response to a lower rank in the feedback competitions.

To address these concerns, I use three tests and five robustness exercises. The three tests are: (1) Test for ex-ante differences in the distributions of observables across the two types of competitions; (2) Test whether rank reflects measures of ex-ante quality equally in both types of competitions; (3) Exploit ventures in multiple competitions to test for selection

into feedback. The five robustness exercises are: (1) Use matching estimators in lieu of the difference-in-differences strategy in which participants are matched on characteristics likely to predict survival; (2) Measure the effect of feedback as the difference between ordinal and nominal scores; (3) Interact feedback with competition characteristics likely associated with participant diversity, signal quality, and venture survival, as well as venture characteristics associated with ex-ante quality; (4) Estimate the effect of feedback within a single competition that gave feedback in one year but not others; (5) Include polynomials in z-score, and ensure that the results persist within relevant subsamples.

The first part of the Online Appendix describes the three tests. They demonstrate that across the two types of competitions, the distributions are not meaningfully different, rank reflects observable quality at the time of the competition equally, and that there is no evidence of selection into feedback. The five robustness tests are in Section 5.

5. Responsiveness to feedback: Results

The main effect of negative feedback on abandonment is in Section 5.1. Section 5.2 contains five robustness tests. Section 5.3 explores whether learning is efficient.

5.1. *Main results*

Entrepreneurs who receive especially negative feedback about their ventures are more likely to abandon them. The raw effect is in Figure 2. Rank and score are far more predictive of continuation in the feedback competitions. They are also, however, predictive in the no-feedback competitions, as shown in the regression discontinuity analysis. This is important, as it demonstrates that ranks are inherently informative about outcomes. The higher average probability in feedback competitions reflects that feedback induces highly ranked non-winners to continue, and that ventures are more likely to be incorporated on average in the feedback competitions. This average difference is eliminated by Equation 2.

Equation 2 is estimated in Table 4. The main specification in panel 1 column 1 finds that negative feedback reduces the likelihood of continuation by 8.6 pp, relative to a mean of 34 percent, significant at the .05 level. This effect size is economically large, especially given the subtle, low stakes nature of the feedback. It translates to a 14 percent increase

in the probability of failure.¹⁸ Summing the three coefficients gives a total average effect of *Low Rank · Feedback* of 8.4 pp. The effect is slightly larger within preliminary rounds (column 4). To ensure that the higher average venture maturity in feedback competitions does not somehow explain the effect, column 5 restricts the sample to unincorporated ventures, and finds an effect of 12 pp. An alternative story is that highly ranked non-winners with feedback are better able to raise financing than their uninformed counterparts. Perhaps they tell prospective funders about their relatively high ranking. However, in unreported tests I find that negative feedback has no effect on subsequent external financing.¹⁹

The effect is roughly linear, but somewhat larger at the higher end of the non-winner distribution, suggesting that feedback induces near-winners to persevere as much as or more than it encourages the poorest performers to exit. In column 6, “low rank” is one if the venture is in the bottom three deciles among non-winners. In column 7, it is one for the bottom seven deciles. In column 8, “low rank” is defined as deciles 5-8, and the bottom two deciles are omitted. The effect is not driven by the bottom deciles, and is strongest in column 7. Supporting the hypothesis that relatively positive feedback induces continuation, the effect is symmetrical among round winners that did not ultimately win the overall competition. I show the effect of positive feedback in Table 5 panel 1 column 10. Having an above median rank but not winning is associated with a 11 pp increase in the probability of survival. However, this effect is less robust than the negative feedback effect, possibly reflecting the smaller sample.

The effect occurs quickly. When the dependent variable is an indicator for abandoning within six months, the effect is 7.9 pp, relative to a mean of 51 percent (Table 4 panel 2 column 1). In columns 2 and 3, the effect increases to 8.7 and 8.9 pp within 1 and 2 years, respectively, relative to means of 57 and 64 percent. The main effect therefore occurs within the first two years.

The large effect of subtle, low-stakes feedback shows that entrepreneurs can learn about their types. This offers a mechanism for competitions to be useful, and it also rejects

¹⁸The coefficient on *Low Rank · Feedback* (-.086) is relative to above median non-winners in no-feedback competitions. The coefficient on *Low Rank* is -.062, implying that in no-feedback competitions low-ranked non-winners are 6.2 pp less likely to continue than high ranked non-winners. The coefficient on feedback is 0.066, as there is a higher probability of survival in feedback competitions.

¹⁹In further unreported tests, I find that the result remains roughly similar when competitions held at universities are excluded, and when ventures can enter the sample multiple times.

the hypothesis that entrepreneurs are characterized by extreme overconfidence. Showing that entrepreneurs learn is not as obvious as it might appear. There is in fact a strong paradigm in the literature that entrepreneurs do not learn about their own probability of success (Bernardo & Welch 2001, Bergemann & Hege 2005, Landier & Thesmar 2009). This behavioral view emphasizes the role of cognitive biases such as over-precision and optimism in entrepreneurial decision-making.²⁰ My results are more consistent with models of firm dynamics in which learning plays a pivotal role, including Jovanovic (1982), Aghion, Bolton, Harris & Jullien (1991), and Ericson & Pakes (1995). New information determines entry and exit decisions in these models, implying that entrepreneurs should be sensitive to external signals about their project quality.

5.2. *Robustness tests*

5.2.1. *Matching estimators*

Exact and propensity score matching estimators adjust for “missing” potential outcomes by matching subjects in a treatment group to their closest counterparts in the untreated group. The difference between observed and predicted outcomes is the average treatment effect. I compare continuation for these matched groups to the above-median matched group. The first method is exact matching, which is preferable as there is no conditional bias in the estimated treatment effect (Abadie & Imbens 2006). The samples of above- and below-median non-winners were matched exactly on 13 sectors, competition year, student status, and company incorporation status. I conduct balance tests of variables not used in matching in Table A9; the match dramatically reduces the differences. The result is in Table 4 panel 2 column 6. Exact matching yields nearly the full sample result, at 7.6 pp, significant at the .01 level.

The second method is propensity-score matching, which first estimates the probability of treatment using a logit model. It then identifies, for each treated participant, the untreated participant with the closest probability of treatment.²¹ Table A10 shows that the matching

²⁰See Astebro, Jeffrey & Adomdza (2007), Cooper et al. (1988), Camerer & Lovallo (1999), Arabsheibani et al. (2000), Koellinger et al. (2007), Kogan (2009), and Bloom et al. (2014). Financial contracting theory typically assumes that the entrepreneur knows his type or has static beliefs about it (Aghion & Bolton 1992, Admati & Pfleiderer 1994, Clementi & Hopenhayn 2006, Sørensen 2007, Hellmann 1998, Cagetti & De Nardi 2006, and Ewens, Jones & Rhodes-Kropf 2013).

²¹I try to eliminate bias in several ways. First, I match without replacement, so that once an untreated

brings the samples almost entirely in line. The effect falls somewhat in the propensity-score matching, to 5.6 pp, significant at the .05 level (Table 4 panel 2 column 7).

5.2.2. *Exploiting nominal scores*

In all but two of the competitions, the conference organizers arrive at ranks by ordering nominal scores. These nominal scores are never revealed to ventures. I exploit them to better approximate the random allocation of feedback. To illustrate the approach, consider a pair of ventures with ranks five and six, and a second pair in a different round that also has ranks five and six. Now suppose that the first pair had very similar scores, while the second pair had more distant scores. As perceived by the judges, the quality difference of the second pair is larger than that of the first pair. If all four ventures are informed of their rank, their feedback is the same but their quality is different. The venture ranked sixth in the second pair got randomly higher feedback relative to its true quality.

If scores measure latent quality, then residual variation in rank reflects noise in transforming nominal scores to forced ranks. Table 4 panel 2 column 8 confirms that score strongly predicts survival. Column 9 replicates the main specification with a control for score. The effect of *Low Rank · Feedback* strengthens somewhat, to 9.3 pp. The effect of interest is in column 10, which restricts the sample to feedback competitions, and estimates the effect of rank after controlling for nominal score. It finds that increasing a venture’s rank by one decile reduces the probability of abandonment by 1.4 pp, significant at the .1 level. This is strong evidence that ex-ante quality distributional differences do not explain the main result.

5.2.3. *Interacting feedback with competition and ex-ante quality characteristics*

There is a risk that the distribution of participants is correlated with feedback. Feedback could be more informative or impactful in competitions with feedback if ventures in those competitions have inherently more precise signals. I add interactions between feedback

participant is matched, it cannot be considered as a match for subsequent treated participants. Since each subject appears no more than once, variance estimation is uncomplicated by duplicates. Second, I match only on binary covariates; I use the covariates from the exact match plus several others, such as prior external financing. Abadie & Imbens 2006 note that the matching estimator’s bias increases in the number of continuous covariates used to match. Third, I omit matches without common support, which reduces the matched sample by 408 ventures.

and characteristics likely associated with signal quality, venture survival, and participant diversity.

Competition signal quality proxies are whether the competition is at a university, the number of ventures, the number of judges, and the location.²² For likelihood of venture survival, I use the share of founders that attended a top ten college, the share of incorporated ventures, and the share of ventures that previously received external financing. Competition diversity might affect the slope in rank. I proxy for it with the number of venture sectors (out of a total possible 16 sectors), the share of ventures that are software-based, and the share of ventures that are clean energy based. The results are in Table A11 panels 1-3. The effect of *Low Rank · Feedback* persists, and even grows somewhat larger (about 9 pp). I conduct a similar exercise at the venture level in Table A11 panel 4, interacting feedback with venture characteristics associated with ex-ante quality.²³ The effect of feedback persists, though it is attenuated to 6.7 pp. Thus distributional differences do not seem to drive the effect.

5.2.4. *Effect of feedback within a single competition*

A single program in my data, the Cleantech Open (CTO), gave feedback in 2011 but in no other year. As the CTO did not otherwise change in 2011, there is no reason that the distribution of quality among non-winners was different in 2011. Comparing the effect of having a low rank in 2011 relative to other years provides a useful robustness test. The results are in Table A12. I limit the sample to 2010-12, and also estimate the effect using all years for which I have CTO data (2008-14). Negative feedback reduces the probability of survival by 11-13 pp in 2011 relative to the surrounding years. This is quite similar to the main specification.

5.2.5. *Functional form and subsamples*

Table 4 panel 2 column 4 controls for the first and second moment in z-score. Column 5 uses a logit specification. The main effect is robust to both approaches, significant at the .05 level. A final set of tests ensures that the results are robust to subsamples. The effect

²²For location, I use indicators for the nine U.S. Census divisions.

²³These are whether the venture was incorporated at the time of the round, whether it had previous external financing, whether the founder attended a top 10 college, whether the founder has a PhD from a top 20 university, and whether the founder is a student at the time of the competition.

persists within the population of founders with MBAs, among ventures from VC hub states, and among student-led ventures (Table A13).

5.3. *Is learning efficient?*

Private, costless, informative signals at an early stage might enable poor quality startups to fail faster, making innovation more efficient. The main result implies that had the 1,603 unique below-median non-winners in the no-feedback competitions received feedback, an additional 137 would have been abandoned, beyond the 1,186 that were abandoned. While I cannot assess the welfare impacts of feedback, I examine three ways that learning might not be efficient.

First, inducing abandonment could be socially costly if a few highly successful outcomes are foregone. Among below-median ventures in the feedback competitions, 2.1 percent were acquired, compared to 3.2 percent in the no-feedback competitions. All appear to be minor acquisitions, as valuation data is in no case available. There were no IPOs in either group. Thus, if there is a cost in right-tail outcomes, it seems small.

Second, learning may be privately inefficient if abandoning after negative feedback leads to poorer long run labor market performance. In the absence of earnings data, I create an indicator for whether the latest job title of founders who abandoned their ventures implies a leadership role.²⁴ Founders have a revealed taste for leadership, so leadership in other domains is a reasonable proxy for non-entrepreneurial success. In unreported regressions, I find no evidence that receiving any feedback or negative feedback is related to subsequent non-entrepreneurial leadership among founders that abandoned their ventures. Therefore, feedback does not seem to cost abandoners ultimate leadership positions.

Third, even if learning is on average efficient, there may be many cases in which ventures are randomly assigned especially lenient or harsh judges, leading to inaccurate signals. I look for such “noisy” learning using a version of the leave-one-out judge leniency in Dobbie & Song (2015). Let S_{ij} be an indicator for the highest score a venture received across judges. Let j denote a judge, and let n_j be the count of ventures that the judge scored. The leave-one-out leniency measure at the venture-judge pair level is then $L_{ij} = \frac{1}{n_j - 1} \left(\sum_{k=1}^j S_k - S_i \right)$. For a venture i , it is the number of times one of its judges gave a high

²⁴Indicator for the title containing any of the following words: CEO, CFO, CTO, Chief, Managing Director, Manager, Senior, President, Partner, Director.

score to other ventures, divided by the number of other ventures the judge scored. L_{ij} is summarized in Table A3 panel 3. In Table A14, I show that leniency predicts scores (columns 1-2), but that there is no effect of leniency on responsiveness (column 5). Lenient judges do not influence a venture’s overall rank enough to affect the abandonment decision. In sum, I find no evidence of large private or social costs to feedback, suggesting that it is weakly more efficient. However, this will not be true if encouraging more entrepreneurial entry is always socially beneficial, regardless of startup quality.

6. Who learns?

Section 5 demonstrated that on average, entrepreneurs are quite sensitive to informative feedback, and incorporate it into their strategic decisions. This raises the questions of which entrepreneurs learn and under what circumstances. I add an interaction for a cross-sectional characteristic. A nice aspect of this heterogeneity analysis is that it permits including competition fixed effects, which address any remaining concerns about systematic differences across competitions.

I begin by showing that variation in overconfidence does not explain the results well (section 6.1). Instead, I find cross-sectional evidence consistent with two mechanisms. First, some ventures have higher real option value from delaying abandonment (Section 6.2). Second, founders behave consistently with Bayesian updating (Section 6.3).

6.1. *Overconfidence*

Being male is the characteristic most robustly associated with overconfidence, in the sense of both over-optimism and an excessively precise prior (e.g. Barber & Odean 2001, Beyer & Bowden 1997). Thus if overconfidence affects responsiveness, I expect to find a difference along gender lines. Conversely, women, who comprise 21 percent of the sample, are not more responsive. This is shown in Table 5 panel 1. In column 1, female is added as a third interaction to Equation 2. In column 2, competition fixed effects are included. Notably, the effect of low rank interacted with feedback (now identified within male founders) is almost exactly the same as in the main specification, at 8.3 pp. This is true for many of the heterogeneity analyses, confirming that differences across competition types do not explain the results.

6.2. The venture as a real option

If founders treat their ventures as real options, they should be less responsive – delaying abandonment despite negative feedback – when the venture is more uncertain and has more asset specificity, or irreversibility of investment (Dixit & Pindyck 1994). First, software-based ventures are more responsive than hardware-based ventures (Table 4 Panel 1 columns 3-4). This does not seem to relate to non-pecuniary motivations among hardware founders, as columns 5-6 find no effect for social impact ventures. Second, ventures with prior external financing are 15 pp more likely to continue after receiving especially negative feedback than those without prior financing (Table 5 panel 1 columns 7-8). Third, unincorporated ventures are 11 pp more responsive, relative to a mean of 44 percent (Table 5 panel 2 columns 1-2). These three types of ventures likely have higher sunk costs and thus greater investment irreversibility.²⁵ These results also indicate that learning about type is most important before firm boundaries form. In some models, including Cornelli & Yosha (2003) and Schmidt (2003), firms update their beliefs after initial investment and business operation. My results support these models but also show that type revelation can occur before entry, at *de minimis* cost.²⁶

A good proxy for risk is disagreement among judges. When the standard deviation of judge ranks within a competition-round-panel is above median, the triple interaction yields a positive effect (Table 5 panel 2 columns 7-8).²⁷ However, this could reflect signal precision, if founders learn from verbal interactions with judges that they lacked consensus. To tests this, I instrument for the standard deviation using the judge leniency measure described above. I find no effect using the instrument, indicating that the result likely reflects venture risk.²⁸

²⁵These characteristics could also be associated with more private information, but older ventures and non-student founders are not more or less responsive than their counterparts (Table 5 panel 2 columns 3-6, 11-12). These groups may have more information, but have not necessarily generated more specific assets.

²⁶In unreported results, I find no variation among future serial entrepreneurs (founders that abandon this venture but found a subsequent one). I also find no variation by founder age or whether he founded a prior venture.

²⁷Recall that founders do not observe individual judge ranks, but they do know how many judges there are. When there are more judges, the standard deviation is measured with greater accuracy, but it does not get smaller in expectation.

²⁸When a venture is assigned an especially lenient and an especially harsh judge, the standard deviation of judge ranks should be higher independently of the venture's risk. I consider two measures: $V_{i,\sigma}^{high}$ is the standard deviation of the lenience measure L_{ij} , and $V_{i,\sigma}^{ext}$ is the standard deviation of L_{ij} among only

Venture resemblance to a call option should increase with the personal wealth of the founder. More personal wealth should make it less costly to continue with the venture and also reduce downside risk in the event the venture ultimately fails, as in Vereshchagina & Hopenhayn (2009). Founders with top college degrees are likely richer (Chetty et al. 2017). Table 5 panel 2 columns 13-16 shows that they are less responsive. In unreported tests, I find that rank is equally predictive among elite school founders as in the broader sample.

6.3. *Bayesian updating*

Bayes’ rule dictates how rational agents update their beliefs.²⁹ Three cross-sectional findings are consistent with Bayesian updating. First, founders are more responsive when the signal is more precise, measured as having more judges. (Founders can observe the number of judges.) In the strongest heterogeneity result, the effect of negative feedback on continuation is 29 pp greater when the number of judges is above median (Table 5 panel 2 columns 9-10).³⁰ Second, feedback should matter less when the prior is more precise. Consistent with this, ventures that have received external financing are less responsive.

Relatedly, Bayesians should update less when they have more information about their own type. The short pitch duration and judge backgrounds suggest that information asymmetry will tilt in the judges’ favor more on business viability (e.g. market demand) than on technology viability. That is, founders likely have better private knowledge about the quality of their product or technology than judges do. In Table 6, “low rank” is defined along a specific dimension. Negative feedback impacts continuation most along the financials, business model, market, and team dimensions. There is no effect for product/technology.³¹

the four most extreme judges that scored a venture (the most lenient, least lenient, harshest, and least harsh). These measures are summarized in Table A3 panel 3. When variation in leniency is high, the venture randomly receives a particularly noisy signal. Table A15 shows that variation in leniency predicts the standard deviation of judge scores quite well. The F-statistics in first-stage regressions range from 14 to 31. In a naive instrumentation approach, I replace the standard deviation with the leave-one-out variation measures. Columns 5-6 show no effect of the triple interaction between having a low rank, receiving feedback, and having judges with high expected variation in leniency.

²⁹Given a prior belief and a new signal, the posterior belief of the Bayesian updater is a precision-weighted average of the two.

³⁰Precision might also be higher when there are more ventures in a round, but I do not find that responsiveness varies significantly with the number of participants.

³¹There is also no effect for presentation. Presentation scores may not affect survival because there is more scope for improvement (or perceived scope for improvement) along this dimension. I do not find substantial variation by judge occupation

Non-linearity in the effect could be consistent with cognitive biases, because rank predicts success in a linear way. Excessively elevated or precise priors should prevent founders from updating downward enough when they receive a middling rank among non-winners. Instead, the effect is roughly linear, and persists among winners (see Section 5.1). In sum, founders behave like Bayesians, though I cannot rule out other models.

A simple model of how a Bayesian updater responds to feedback is in Appendix Section 2. It assumes the founder interprets his rank as the result of a series of Bernoulli trials, where the number of signals is the number of judges. This allows the Beta distribution as the conjugate prior. Hewing closely to the information structure and main results from the preceding sections, I calibrate the model to show how feedback affects a founder’s success probability distribution. Figure 3 shows the results of the calibration exercise. The interim prior is in Figure 3A. The posteriors after negative feedback (below-median non-winner) and positive feedback (above-median non-winner) are in Figure 3B and 3C. Finally, I interpret one of the heterogeneity results through the Bayesian calibration. Figure 4 depicts how having an above-median number judges affects the posterior by improving signal precision.

7. Conclusion

This paper shows how new venture competitions are useful to startups. Winning and cash awards are useful, but competitions are also valuable because they facilitate entrepreneur learning in the sense of type revelation. Founders seem to treat the venture as a real option, and they behave consistently with Bayesian updating. In Manso (2011)’s optimal contract, feedback should be timely and tolerant of failure. New venture competitions with feedback implement this guidance: While they reward top performers, they do not penalize especially poor performance. Under conditions in which it is not socially costly to deter low quality startups, the data indicate that giving entrepreneurs private, expert feedback may improve resource allocation and the efficiency of innovation.

The substantial heterogeneity raises questions about how learning interacts with innovation. Risky ventures and those with elite degree founders are less responsive to negative feedback. This hints that even as most entrants are rational and responsive to new information, a small subset may have ambitious, radical ideas and also may be imperviousness to negative feedback. Ventures in this subset may be the ones with the potential to transform

industries, and the overconfidence of their founders may be crucial to coordinating other stakeholders. Theoretical models of industry dynamics could micro-found technological discontinuities in the small fraction of entrepreneurs that enter without regard to signals about expected cash flows. A promising avenue for future research is whether the most innovative, risky new firms tend to have founders who ignore negative feedback.

References

- Abadie, A. & Imbens, G. W. (2006), ‘Large sample properties of matching estimators for average treatment effects’, *Econometrica* **74**(1), 235–267.
- Admati, A. R. & Pfleiderer, P. (1994), ‘Robust financial contracting and the role of venture capitalists’, *The Journal of Finance* **49**(2), 371–402.
- Aghion, P. & Bolton, P. (1992), ‘An incomplete contracts approach to financial contracting’, *The Review of Economic Studies* **59**(3), 473–494.
- Aghion, P., Bolton, P., Harris, C. & Jullien, B. (1991), ‘Optimal learning by experimentation’, *The review of economic studies* **58**(4), 621–654.
- Arabsheibani, G., De Meza, D., Maloney, J. & Pearson, B. (2000), ‘And a vision appeared unto them of a great profit: evidence of self-deception among the self-employed’, *Economics Letters* **67**(1), 35–41.
- Arrow, K. J. (1962), ‘The economic implications of learning by doing’, *Review of Economic Studies* **29**(3), 155–173.
- Astebro, T., Jeffrey, S. A. & Adomdza, G. K. (2007), ‘Inventor perseverance after being told to quit: The role of cognitive biases’, *Journal of Behavioral Decision Making* **20**(3), 253–272.
- Barber, B. M. & Odean, T. (2001), ‘Boys will be boys: Gender, overconfidence, and common stock investment’, *The Quarterly Journal of Economics* **116**(1), 261–292.
- Bergemann, D. & Hege, U. (2005), ‘The financing of innovation: Learning and stopping’, *RAND Journal of Economics* pp. 719–752.
- Bernardo, A. E. & Welch, I. (2001), ‘On the evolution of overconfidence and entrepreneurs’, *Journal of Economics & Management Strategy* **10**(3), 301–330.
- Bernstein, S., Korteweg, A. & Laws, K. (2017), ‘Attracting early-stage investors: Evidence from a randomized field experiment’, *The Journal of Finance* **72**(2), 509–538.
- Beyer, S. & Bowden, E. M. (1997), ‘Gender differences in self-perceptions: Convergent evidence from three measures of accuracy and bias’, *Personality and Social Psychology Bulletin* **23**(2), 157–172.
- Blevins, C. & Mullen, L. (2015), ‘Jane, John... Leslie? A historical method for algorithmic gender prediction’, *Digital Humanities Quarterly* **9**(3).
- Bloom, N., Lemos, R., Sadun, R., Scur, D. & VanReenen, J. (2014), ‘The new empirical economics of management’. NBER Working Paper.
- Cagetti, M. & De Nardi, M. (2006), ‘Entrepreneurship, frictions, and wealth’, *Journal of political Economy* **114**(5), 835–870.

- Camerer, C. & Lovallo, D. (1999), ‘Overconfidence and excess entry: An experimental approach’, *The American Economic Review* **89**(1), 306–318.
- Chetty, R., Friedman, J. N., Saez, E., Turner, N. & Yagan, D. (2017), ‘Mobility report cards: The role of colleges in intergenerational mobility’.
- Clementi, G. L. & Hopenhayn, H. A. (2006), ‘A theory of financing constraints and firm dynamics’, *The Quarterly Journal of Economics* **121**(1), 229–265.
- Cooper, A. C., Woo, C. Y. & Dunkelberg, W. C. (1988), ‘Entrepreneurs’ perceived chances for success’, *Journal of business venturing* **3**(2), 97–108.
- Cornelli, F. & Yosha, O. (2003), ‘Stage financing and the role of convertible securities’, *The Review of Economic Studies* **70**(1), 1–32.
- Dixit, A. K. & Pindyck, R. S. (1994), *Investment under uncertainty*, Princeton university press.
- Dobbie, W. & Song, J. (2015), ‘Debt relief and debtor outcomes: Measuring the effects of consumer bankruptcy protection’, *The American Economic Review* **105**(3), 1272–1311.
- Ericson, R. & Pakes, A. (1995), ‘Markov-perfect industry dynamics: A framework for empirical work’, *The Review of Economic Studies* **62**(1), 53–82.
- Ewens, M., Jones, C. M. & Rhodes-Kropf, M. (2013), ‘The price of diversifiable risk in venture capital and private equity’, *The Review of Financial Studies* **26**(8), 1854–1889.
- Ewens, M. & Townsend, R. R. (2017), ‘Investors and the entrepreneurship gender gap’. Working Paper.
- Fehder, D. (2016), ‘Startup accelerators and ecosystems: Substitutes or complements?’. Working Paper.
- Fehder, D. C. & Hochberg, Y. V. (2014), ‘Accelerators and the regional supply of venture capital investment’, *Available at SSRN 2518668*.
- Gompers, P., Gornall, W., Kaplan, S. N. & Strebulaev, I. A. (2016), ‘How do venture capitalists make decisions?’. National Bureau of Economic Research.
- Gonzalez-Uribe, J. & Leatherbee, M. (2016), ‘The effects of business accelerators on venture performance: Evidence from start-up chile’. Working Paper.
- Guiso, L., Pistaferri, L. & Schivardi, F. (2015), ‘Learning entrepreneurship from other entrepreneurs?’.
- Hallen, B. L., Bingham, C. B. & Cohen, S. (2014), Do accelerators accelerate? a study of venture accelerators as a path to success?, in ‘Academy of Management Proceedings’, Vol. 2014, Academy of Management, p. 12955.

- Hanna, R., Mullainathan, S. & Schwartzstein, J. (2014), ‘Learning through noticing: Theory and evidence from a field experiment’, *The Quarterly Journal of Economics* **129**(3), 1311–1353.
- Hellmann, T. (1998), ‘The allocation of control rights in venture capital contracts’, *The Rand Journal of Economics* pp. 57–76.
- Hochberg, Y. V., Ljungqvist, A. & Vissing-Jørgensen, A. (2013), ‘Informational holdup and performance persistence in venture capital’, *The Review of Financial Studies* **27**(1), 102–152.
- Howell, S. T. (2017), ‘Financing innovation: Evidence from R&D grants’, *The American Economic Review* **107**(4), 1136–1164.
- Jovanovic, B. (1982), ‘Selection and the evolution of industry’, *Econometrica: Journal of the Econometric Society* pp. 649–670.
- Kaplan, S. N., Klebanov, M. M. & Sorensen, M. (2012), ‘Which CEO characteristics and abilities matter?’, *The Journal of Finance* **67**(3), 973–1007.
- Kaplan, S. N., Sensoy, B. A. & Strömberg, P. (2009), ‘Should investors bet on the jockey or the horse? evidence from the evolution of firms from early business plans to public companies’, *The Journal of Finance* **64**(1), 75–115.
- Kerr, W. R., Nanda, R. & Rhodes-Kropf, M. (2014), ‘Entrepreneurship as experimentation’, *The Journal of Economic Perspectives* **28**(3), 25–48.
- Koellinger, P., Minniti, M. & Schade, C. (2007), ‘I think I can, I think I can: Overconfidence and entrepreneurial behavior’, *Journal of economic psychology* **28**(4), 502–527.
- Kogan, S. (2009), ‘Distinguishing the effect of overconfidence from rational best-response on information aggregation’, *Review of Financial Studies* **22**(5), 1889–1914.
- Landier, A. & Thesmar, D. (2009), ‘Financial contracting with optimistic entrepreneurs’, *Review of financial studies* **22**(1), 117–150.
- Lerner, J. & Malmendier, U. (2013), ‘With a little help from my (random) friends: Success and failure in post-business school entrepreneurship’, *Review of Financial Studies* **26**(10), 2411–2452.
- Levine, R. & Rubinstein, Y. (2016), ‘Smart and illicit: Who becomes an entrepreneur and does it pay?’, *The Quarterly Journal of Economics* .
- Manso, G. (2011), ‘Motivating innovation’, *The Journal of Finance* **66**(5), 1823–1860.
- Manso, G. (2016), ‘Experimentation and the returns to entrepreneurship’, *Review of Financial Studies* p. hhw019.
- McKenzie, D. (2017), ‘Identifying and spurring high-growth entrepreneurship: experimental evidence from a business plan competition’, *American Economic Review* **107**(8), 2278–2307.

- Nanda, R. & Sørensen, J. B. (2010), ‘Workplace peers and entrepreneurship’, *Management Science* **56**(7), 1116–1126.
- Odean, T. (1999), ‘Do investors trade too much?’, *The American Economic Review* **89**(5), 1279–1298.
- Saha, D. & Muro, M. (2017), ‘Cleantech venture capital: Continued declines and narrow geography limit prospects’, *Brookings Institution Report* .
- Schmidt, K. M. (2003), ‘Convertible securities and venture capital finance’, *The Journal of Finance* **58**(3), 1139–1166.
- Scott, E. L., Shu, P. & Lubynsky, R. (2016), ‘Are ‘better’ ideas more likely to succeed? an empirical analysis of startup evaluation’.
- Seru, A., Shumway, T. & Stoffman, N. (2010), ‘Learning by trading’, *Review of Financial studies* **23**(2), 705–739.
- Sørensen, M. (2007), ‘How smart is smart money? a two-sided matching model of venture capital’, *The Journal of Finance* **62**(6), 2725–2762.
- Vereshchagina, G. & Hopenhayn, H. A. (2009), ‘Risk taking by entrepreneurs’, *The American Economic Review* **99**(5), 1808–1830.
- Wagner, R. (2017), ‘Does feedback to business-plans impact new ventures? fundraising in a randomized field experiment’. Working Paper.
- Xu, T. (2017), ‘Learning from the crowd: The feedback value of crowdfunding’. Working Paper.

Table 1: Summary Statistics

<i>Panel 1: Competitions</i>						
	N	Mean	Median	S.d.	Min	Max
# competitions	87					
# competition-rounds	176					
# competition-round-panels	454					
# competitions with feedback	34					
# rounds per competition	87	2	2	.69	1	3
# ventures in preliminary rounds	113	45	35	43	6	275
# ventures in final rounds	86	19	12	21	4	152
# winners	176	8.4	6	7.2	1	37
Award amount Award > 0 (thousand nominal \$)	167	73	30	86	2	275
Days between rounds within competition	88	23	17	31	0	127
# judges in round-panel	543	17	9	23	1	178
<i>Panel 2: Ventures*</i>						
	N	Mean	Median	S.d.	Min	Max
# unique ventures	4,328					
# unique ventures in feedback competitions	1,614					
Venture age at first competition (years)	2073	1.9	0.77	3	0	20
Incorporated at round	4328	0.44	0	0.5	0	1
In hub state (CA, NY, MA)	4,328	.35	0	.48	0	1
Survival (Has ≥ 2 employees as of 8/2016)	4328	0.34	0	0.47	0	1
Abandoned within 6 months [†]	3228	0.51	1	0.5	0	1
Abandoned within 1 year	3228	0.57	1	0.5	0	1
Abandoned within 2 years	3228	0.64	1	0.48	0	1
Has ≥ 3 employees as of 8/2016	4328	0.3	0	0.46	0	1
Has ≥ 10 employees as of 8/2016	4328	0.2	0	0.4	0	1
Raised external private investment before round	7099	0.16	0	0.36	0	1
External private investment after round	7099	0.24	0	0.43	0	1
Angel/VC series A investment before round	7099	0.09	0	0.29	0	1
Angel/VC series A investment after round	7099	0.15	0	0.36	0	1
Acquired/IPOd as of 9/2016	4328	0.03	0	0.18	0	1
Ventures in multiple competitions ($\# > 1$)	558	2.52	2	0.98	2	9
# founders/team members at first competition	2305	3.1	3	1.6	1	8

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

	N	Mean	Median	S.d.	Min	Max
# founders	3228					
# founders matched to LinkedIn profile	2554					
Age (years) at event (college graduation year-22)	1702	32.8	29	10.2	17	75
Female [±]	3,228	0.21	0	0.41	0	1
Male	3,228	0.72	0	0.45	0	1
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 worked in	2554	2.71	2	2.27	0	29
Days to abandon venture if abandoned**	1190	313	148	420	1	4810
Is student at round	2554	0.2	0	0.4	0	1
Graduated from top 20 college	2554	0.27	0	0.44	0	1
Graduated from top 10 college	2554	0.18	0	0.39	0	1
Degree from Harvard, Stanford, MIT	2554	0.1	0	0.3	0	1
Has MBA	2554	0.48	0	0.5	0	1
Has MBA from top 10 business school	2554	0.33	0	0.47	0	1
Has Master's degree	2554	0.17	0	0.37	0	1
Has PhD	2554	0.13	0	0.34	0	1
Founder or CEO of subsequent venture after round, if abandoned venture	1190	0.39	0	0.49	0	1

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). [†]1 if the number of days between the competition's end date and the first subsequent new job start date for the founder is less than 180, among ventures that did not survive and where the founder was matched to a LinkedIn profile. [‡]From LinkedIn profiles. Not all competitions retained founder data, so the number of venture leaders is less than the number of ventures. [±]Gender coding by algorithm and manually; sexes do not sum to one because some names are both ambiguous and had no clear LinkedIn match. **This is the number of days between the competition's end date and the first subsequent new job start date, among ventures that did not survive.

Table 2: Effect of Rank and Winning on Subsequent External Financing

<i>Panel 1</i>							
Dependent variable:	Financing after round*				Survival*	10+ employees	Acquired/IPO
	Venture controls	Logit	Judge f.e.				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Won Round	.13*** (.026)	.077** (.037)	.71*** (.14)	.16*** (.015)	.047* (.028)	.051* (.027)	.018 (.012)
Decile rank winners	-.011*** (.0044)	-.0062 (.0056)	-.069*** (.021)		-.006 (.0043)	-.0041 (.0044)	-.0028* (.0017)
Decile rank non-winners	-.018*** (.0025)	-.014*** (.0032)	-.13*** (.017)		-.023*** (.0028)	-.017*** (.0023)	-.0011 (.001)
Within-judge decile rank				-.0061*** (.0014)			
Award Amount (10,000\$)	.0085*** (.0024)	.0093*** (.003)	.036*** (.011)	.011*** (.0023)	.0062* (.0032)	.0074*** (.0026)	.0002 (.0013)
Venture controls ^{††}	N	Y	N	Y	N	N	N
Comp.-round- panel f.e.	Y	Y	Y	N	Y	Y	Y
Judge f.e.	N	N	N	Y	N	N	N
Year f.e.	N	N	N	Y	N	N	N
N	6023	3367	5484	23785	6023	6023	6023
R ²	.16	.4	.12	.43	.17	.14	.083

Note: This table contains OLS regression estimates of the effect of winning, rank, and award (cash prize) on whether the venture raised external financing after the competition. OLS used except column 3. 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 only the two quintiles around the cutoff for winning a preliminary round (no final rounds included). ^{††}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 whether the founder is a student. Note that competition f.e. control for a specific date. *** indicates p-value<.01.

Panel 2

Dependent variable: Financing after round*

	Prelim rounds only			Final rounds	Z-scores		No feedback only	
	No award	Quintiles around cutoff [‡]						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Won Round	.14*** (.03)	.15*** (.04)	.098*** (.026)	.089* (.05)	.13*** (.023)	.098*** (.026)	.13*** (.034)	.15*** (.02)
Decile rank winners	-.015*** (.0052)	-.016** (.0066)		.0031 (.0066)			-.0091 (.0061)	
Decile rank non-winners	-.018*** (.0032)	-.017*** (.0036)		-.021*** (.0044)			-.011*** (.0033)	
Z-score winners					.027 (.019)			.0064 (.023)
Z-score non-winners					.041*** (.01)			.031*** (.011)
Z-score ² winners					.019 (.014)			.013 (.016)
Z-score ² non-winners					.000056 (.0073)			.0097 (.0084)
Within-judge z-score						.027*** (.0063)		
Award Amount (10,000 \$)	.012*** (.0032)		.013** (.0057)	.0053 (.0034)	.0089*** (.0029)	.0056* (.0029)	.011** (.0055)	.012** (.0055)
Venture controls ^{††}	N	N	N	N	Y	Y	N	N
Comp.-round- panel f.e.	Y	Y	Y	Y	Y	N	Y	Y
Judge f.e.	N	N	N	N	N	Y	N	N
Year f.e.	N	N	N	N	N	Y	N	N
N	4394	3404	1945	1605	3529	13285	3429	3980
R ²	.16	.12	.23	.17	.41	.4	.2	.19

Note: This panel is a continuation of Table 2. [‡]Includes only the two quintiles around the cutoff for winning a preliminary round (no final rounds included). *** indicates p-value<.01.

Table 3: Effect of Dimension Rank on Venture Outcomes

Dependent variable:	Financing after round		3+ Employees		10+ Employees		Acquired/IPO	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Percentile rank in round: [†]								
Team	-.021*** (.0057)	-.023*** (.0053)	-.014*** (.0051)	-.021*** (.0052)	-.0091 (.0063)	-.017*** (.0049)	.00069 (.0026)	-.0012 (.0024)
Financials	-.014** (.0067)	-.0079 (.005)	-.03*** (.0094)	-.027*** (.0058)	-.036*** (.0083)	-.026*** (.0057)	.0034 (.0031)	.0023 (.0027)
Business Model	.0032 (.016)	.002 (.011)	.0091 (.016)	.012 (.012)	.0024 (.014)	.0035 (.011)	.0046 (.0074)	-.0059 (.0074)
Market ^{††}	.01 (.015)	-.0091 (.011)	.002 (.015)	-.022* (.012)	.0075 (.013)	-.011 (.011)	-.00047 (.0072)	.0039 (.0074)
Tech./Product	.0098 (.0078)	.0031 (.0054)	-.0043 (.0075)	-.0093* (.0055)	-.0015 (.0069)	-.0081 (.0054)	-.0062** (.0024)	-.0056** (.0024)
Presentation	-.015** (.0059)	-.0098** (.0043)	-.0023 (.0083)	-.0041 (.0048)	.0074 (.0071)	.008 (.0052)	-.0032 (.0024)	-.0013 (.0022)
Won Round	.14*** (.024)	.2*** (.013)	.12*** (.035)	.21*** (.014)	.1*** (.032)	.17*** (.015)	.011 (.013)	.023*** (.0068)
Judge/judge co invested	.47*** (.11)	.56*** (.027)						
Competition-round- panel f.e.	Y	N	Y	N	Y	N	Y	N
Judge f.e.	N	Y	N	Y	N	Y	N	Y
N	1926	8794	1926	8794	1926	8794	1926	7043
R ²	.15	.14	.16	.15	.13	.12	.065	.066

Note: This table contains OLS regression estimates of the effect of dimension-specific ranks on indicators for various outcomes. 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. [†]Decile rank in round or quintile rank within judge. A smaller rank is better (1 is best decile, 10 is worst decile). Note that competition f.e. control for a specific date. ^{††}The attractiveness and size of the market. *** indicates p-value<.01.

Table 4: Effect of Negative Feedback on Venture Continuation

Panel 1

Dependent variable: Survival*

				Prelim rounds only	No incorp. ventures	Low rank among non-winners defined as:			Positive feedback among winners
	(1)	(2)	(3)	(4)	(5)	Bottom 3 deciles	Bottom 7 deciles	Deciles 5-8 (9-10 omitted)	(9)
Low rank-Feedback	-.086** (.036)	-.084*** (.02)	-.079*** (.026)	-.12*** (.044)	-.12** (.058)	-.062** (.029)	-.097** (.04)	-.079* (.046)	
Low rank	-.062*** (.021)	-.051*** (.014)	-.026 (.022)	-.051** (.023)	-.036 (.048)	-.065*** (.019)	-.048** (.022)	-.025 (.025)	
Feedback	.066* (.04)	.17* (.092)	-.03 (.14)	.11** (.045)	.09* (.053)	.032 (.028)	.073* (.043)	.075* (.043)	-.032 (.068)
High rank-Feedback									.11* (.06)
High rank									.029 (.046)
Venture controls [†]	Y	Y	Y+ [‡]	Y	Y	Y	Y	Y	Y
Year f.e.	Y	N	N	Y	Y	Y	Y	Y	Y
Judge f.e.	N	Y	Y	N	N	N	N	N	N
N	3751	26443	14915	2689	1962	3751	3751	2372	1335
R ²	.082	.18	.29	.083	.051	.081	.081	.097	.14

Note: This table shows estimates of the effect of negative feedback within the sample of non-winners (having a below-median rank among non-winners when non-winners learn their ranks, relative to competitions where they do not learn their ranks). “Low rank” is 1 if the venture’s rank is below median among non-winners. Errors clustered by competition-round or judge, depending on fixed effects. Sample restricted to non-winners of round, except in column 10. * Survival is 1 if the venture had ≥ 1 employee besides founder on LinkedIn as of 8/2016. [†]Includes sector indicator variables, student and company incorporation status. [‡]Also includes company age and whether the company received investment before the round. *** indicates p-value<.01.

<i>Panel 2</i>										
Dependent variable:	Abandoned within...			Survival*						
	.5 year	1 year	2 years	Z-scores	Logit	Exact matching [±]	Propensity score matching**	Nominal score Feedback only		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Low rank-Feedback	.079* (.041)	.085** (.041)	.087** (.039)	-.086** (.036)	-.32** (.16)	-.076*** (.027)	-.056** (.022)		-.093** (.04)	
Low rank	.056*** (.021)	.06*** (.022)	.058*** (.022)	-.065*** (.021)	-.31** (.16)				-.047* (.026)	
Feedback	-.0074 (.042)	-.031 (.042)	-.056 (.04)	.07* (.039)	.23 (.17)				.082 (.05)	
Z-score				.04 (.029)						
Z-score ²				-.013** (.0067)						
Nominal score								.0052** (.0024)	.0027 (.0022)	.073*** (.02)
Decile rank										-.014* (.0073)
Venture controls [†]	Y	Y	Y	Y	Y	-	Y	Y	Y	Y
Year f.e.	Y	Y	Y	N	Y	-	Y	Y	Y	Y
Judge f.e.	N	N	N	N	N	N	N	N	N	N
N	3751	3751	3751	3751	3751	2484	3357	3305	2974	2028
R ²	.061	.06	.073	.084	0.065	-	.095	.071	.086	.085

Note: This table shows estimates of the effect of negative feedback as in the previous panel, but with alternative samples.
 *Survival is 1 if the venture had ≥ 1 employee besides founder on LinkedIn as of 8/2016. The dependent variable in columns 1-3 is 1 if the venture was abandoned within the given time frame after the competition (see Table 1 for definition).
[±]Causal effect via exact matching between “treated” group (low-ranked non-winners who received feedback) and control group (low ranked non-winners who did not receive feedback) on sector (there are 16 sectors), year, student and company incorporation status. **Causal effect via propensity score (logit prediction of treatment) matching of treated and control groups. [†]Includes sector indicator variables, student and company incorporation status. *** indicates p-value<.01.

Table 5: Heterogeneity in Effect of Negative Feedback

<i>Panel 1</i>								
Dependent variable: Survival*								
Characteristic C_i :	Founder female		IT/software		Social/clean tech		Financing before round	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low rank·Feedback· C_i	-.1 (.096)	-.057 (.094)	-.1* (.062)	-.097 (.063)	.072 (.088)	.085 (.095)	.15* (.087)	.15* (.088)
Low rank·Feedback	-.093** (.039)	-.083** (.042)	-.015 (.043)	-.016 (.043)	-.1** (.042)	-.1** (.042)	-.1** (.041)	-.1** (.042)
Feedback· C_i	.12 (.073)	.11 (.072)	-.00096 (.058)	-.016 (.057)	-.089 (.08)	-.08 (.087)	-.19*** (.067)	-.19*** (.066)
Low rank· C_i	.071 (.045)	.037 (.042)	-.0035 (.038)	-.0021 (.039)	.028 (.047)	.036 (.047)	-.033 (.069)	-.052 (.069)
Low rank	-.079*** (.025)	-.058** (.023)	-.038* (.023)	-.04* (.023)	-.051** (.023)	-.052** (.023)	-.047** (.022)	-.031 (.02)
Feedback	.059 (.045)		.057 (.038)		.1** (.041)		.11** (.042)	
C_i	-.11*** (.039)	-.079** (.037)	.09** (.037)	.11*** (.038)	-.098** (.042)	-.13*** (.042)	.37*** (.054)	.39*** (.053)
Year f.e.	Y	Y	Y	Y	Y	Y	Y	Y
Sector f.e.	Y	N	N	N	N	N	Y	N
Competition f.e.	N	Y	N	Y	N	Y	N	Y
N	3048	4121	4136	4136	4136	4136	3765	4136
R^2	.1	.084	.12	.14	.077	.092	.13	.13

Panel 2

Dependent variable: Survival*

C_i :	Incorp. at round		Venture age > median		Founder age > median		Judge rank s.d. > median [†]		# judges > median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Low rank·Feedback· C_i	.11*** (.033)	.13* (.069)	.026 (.067)	.034 (.064)	-.11 (.089)	-.094 (.093)	.12*** (.044)	.1** (.046)	-.29*** (.11)	-.31*** (.1)
N	3765	4136	2119	2224	1594	1778	3765	4136	3765	4136
R^2	.084	.086	.082	.1	.1	.1	.086	.088	.088	.087
C_i :	Founder is student		Founder top 10 college		Founder Harvard/ Stanford/MIT		Founder has MBA		Founder had prior venture	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Low rank·Feedback· C_i	-.02 (.089)	-.087 (.094)	.24** (.11)	.19 (.12)	.31** (.14)	.26* (.16)	.11* (.066)	.076 (.063)	.063 (.073)	.066 (.076)
N	3765	4136	3765	4136	3765	4136	3765	4136	4136	4136
R^2	.083	.086	.087	.088	.085	.086	.085	.086	.077	.091
Year f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector f.e.	Y	N	Y	N	Y	N	Y	N	Y	N
Competition f.e.	N	Y	N	Y	N	Y	N	Y	N	Y

Note: This table shows estimates of how the effect of negative feedback on venture survival varies by characteristics C_i . Control coefficients not reported for brevity. *This measure for venture continuation is 1 if the venture had at least one employee besides founder on LinkedIn as of 8/2016. Errors clustered by competition-round. [†]Standard deviation of judge ranks for the venture is above median, among ventures in round. [‡]The fraction of judges in a given occupation/sector who scored the venture is above median, relative to that fraction for all ventures. *** indicates p-value<.01.

Table 6: Effect of Negative Dimension Feedback on Venture Continuation

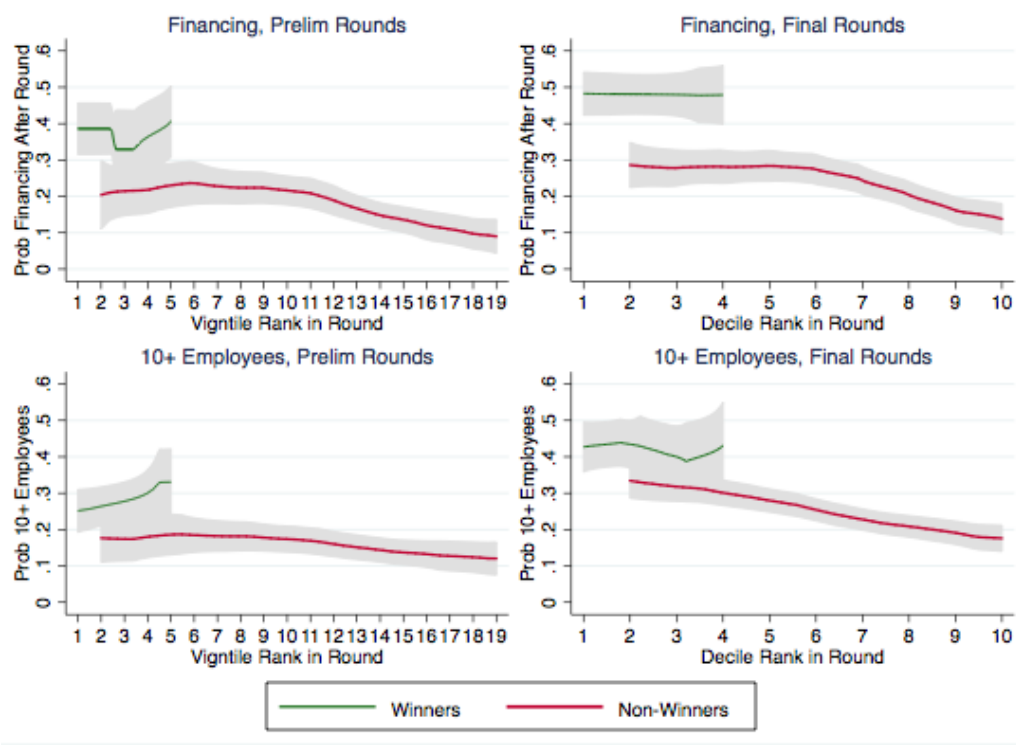
Sample restricted to non-winners of round

Dependent variable: Survival

Criteria (dimension= D):	Presentation	Team	Product/ tech	Market ^{††}	Financials	Bus model
	(1)	(2)	(3)	(4)	(5)	(6)
Low rank in D -Feedback	.0036 (.062)	-.09** (.038)	-.052 (.033)	-.089** (.04)	-.11*** (.038)	-.097** (.04)
Low rank in D	-.0096 (.059)	.01 (.037)	-.026 (.029)	.087** (.04)	-.0013 (.032)	.097** (.04)
Feedback	.17** (.071)	.058 (.038)	.04 (.034)	.07* (.042)	.071 (.053)	.072* (.042)
Overall decile rank	-.034*** (.0059)	-.019*** (.0046)	-.017*** (.0045)	-.031*** (.0048)	-.016*** (.0054)	-.032*** (.0049)
Venture controls [†]	Y	Y	Y	Y	Y	Y
N	2147	3147	3126	2538	2240	2538
R^2	.084	.089	.085	.089	.096	.09

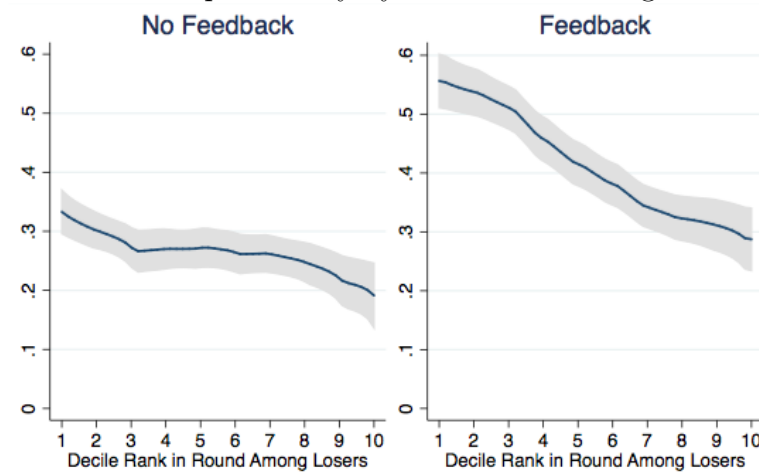
Note: This table shows estimates of the effect of negative feedback within dimensions. Errors clustered by competition-round. [†]Includes sector dummies, whether venture incorporated, and whether founder is student. ^{††}Market attractiveness and size. *** indicates p-value<.01.

Figure 1: Effect of winning (Lower percentile rank is better)



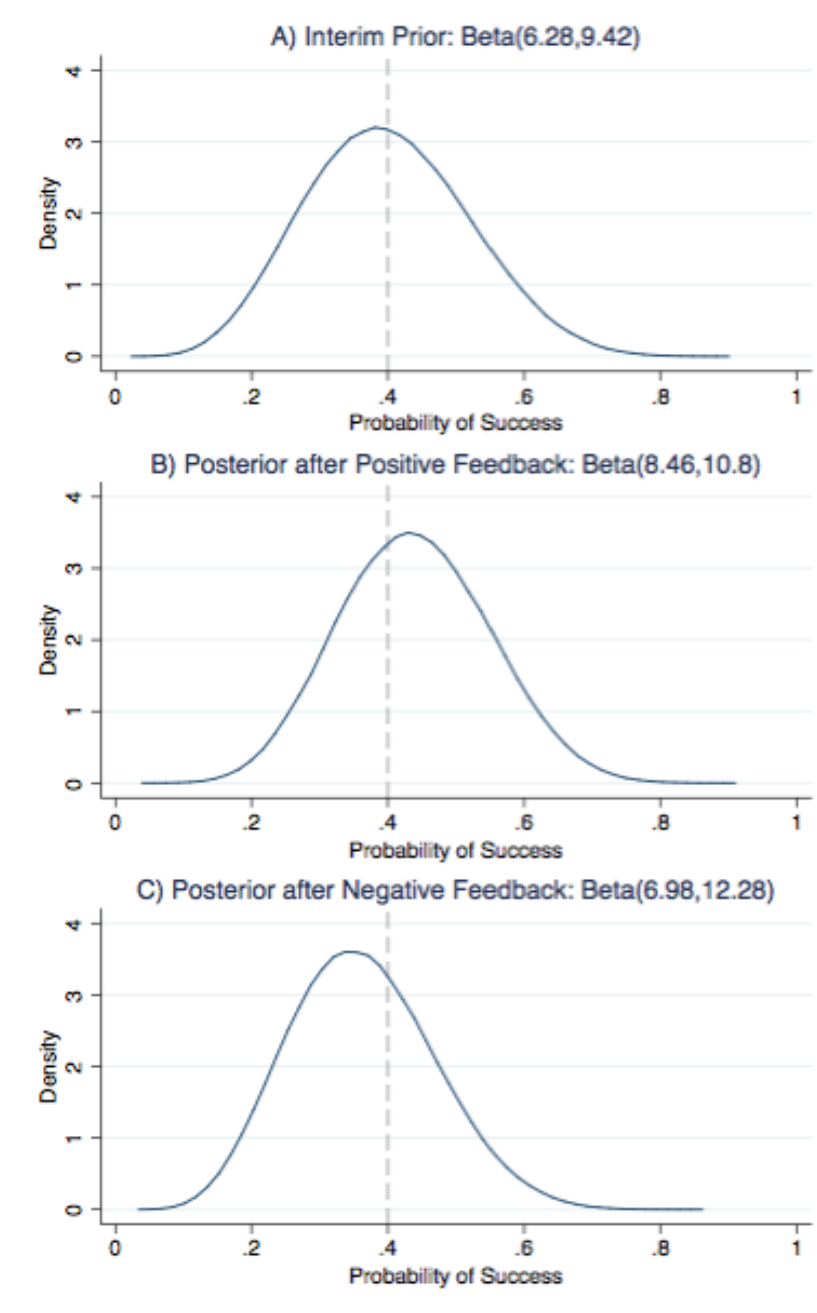
Note: This figure shows probabilities of any subsequent financing (top) and having 10+ employees (bottom) by percentile rank in the round. Local polynomial with Stata's optimal bandwidth; 95% CIs shown.

Figure 2: Survival probability by decile rank among non-winners



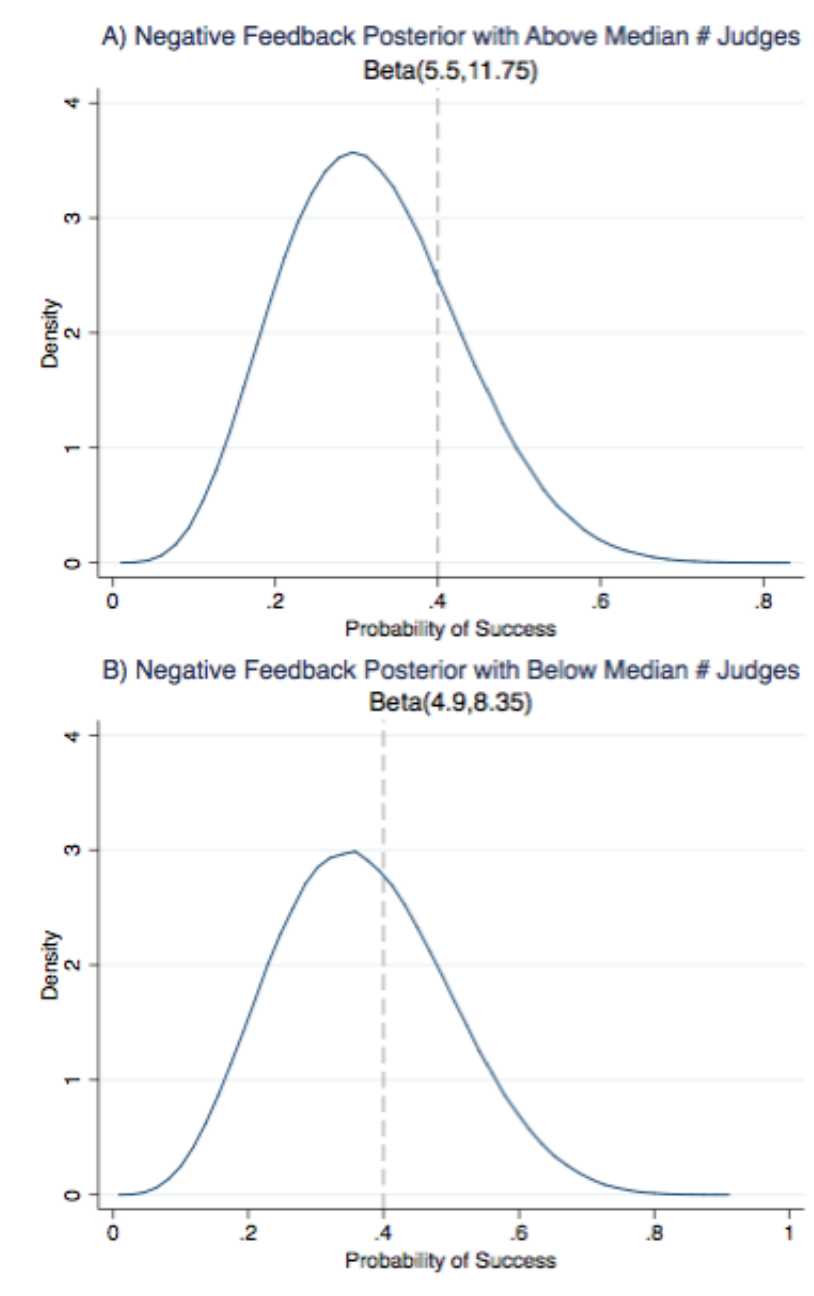
Note: This figure shows the probability of survival among non-winners in preliminary rounds, by percentile rank in the round. Local polynomial with Epanechnikov kernel; 95% CIs shown.

Figure 3: PDFs of interim prior and average posteriors after positive and negative feedback



Note: This figure is based on Equation 4 in the Online Appendix. It simulates Beta distributions using 1 million randomly generated numbers. The prior mean is the realized outcome for uninformed exactly matched losers (losers in the no-feedback competitions matched on observables to losers in the feedback competitions). The shape parameters in the bottom two figures reflect average k_i and J_i (success signals and number of judges) among above median losers (positive feedback) and below-median losers (negative feedback).

Figure 4: PDFs of interim prior and average posteriors after positive and negative feedback



Note: This figure simulates Beta distributions using 1 million randomly generated numbers. The prior mean is the realized outcome for uninformed exactly matched losers (losers in the no-feedback competitions matched on observables to losers in the feedback competitions). The shape parameters in the bottom two figures reflect average k_i and J_i (success signals and number of judges) among above median losers (positive feedback) and below-median losers (negative feedback).

Online Appendix to “Learning from Feedback”

Sabrina T. Howell

1. Tests for differences across competition types

1.1. *Tests for ex-ante distributional differences*

Two types of visual evidence and a formal test find that the distributions of observable characteristics are similar across the two types of competitions. While the levels of observables are not always similar, the demeaned distributions are never measurably different.

First, I show the probability of three characteristics that I expect to predict survival as a function of decile rank in Figure A1: whether the founder attended a top 10 college, whether the venture was incorporated at the time of the round, and whether the venture received external financing before the round. All limit the sample to non-winners. There are no obvious differences around the medians between feedback and no-feedback competitions. However, there are level differences. For example, ventures are more likely to be incorporated in the feedback competitions. This is largely due to the difference between the Arizona Innovation Challenge, a large feedback competition that caters to more advanced ventures, and the HBS New Venture challenge, a large no-feedback competition whose participants are typically teams of students deciding whether to enter entrepreneurship. I match on incorporation below, in case it makes rank a more informative signal of quality.

Second, I present histograms of the distributions, and find no obvious differences in skewness or kurtosis across the two types of competitions.¹ Figures A2 and A3 contain spikes representing the fraction of ventures within narrow

¹Greater skewness means that the data are more concentrated on one side of the distribution, and greater kurtosis (or peakedness) means that the data are more concentrated around the middle, as opposed to being more spread out (fatter-tailed).

z-score bandwidths for observables in feedback and no-feedback competitions.² Figure A2 shows venture characteristics, including company incorporation, prior financing, technology type, whether the company is in a VC hub state, and whether the company is social impact-oriented or clean technology. Figure A3 shows founder characteristics, including whether the founder is a student at the time of the round, ever received an MBA, attended a top-20 college, and is of above median age (in years). The distributions are not the same, but in no case does the distribution of non-winners (left tail) appear meaningfully lopsided.

I test for distributional differences around the median among non-winners in Table A16. I calculate each variable's mean above and below the median among non-winners in each round, and subtract the below median mean from the above median mean. Then I conduct a t-test across rounds with and without feedback. Among the nine observables at the time of the round considered in Table A16, the only significant difference is in the probability that the venture is located in a VC hub state. In the no-feedback competitions, above median non-winners are 4 pp more likely than below median non-winners to be in a hub state, while this difference is -1 pp for feedback competitions. Any bias should act against my main result, since ventures in hub states are unconditionally more likely to succeed (Table A6). Note a Kolmogorov-Smirnov test for equality of distribution functions is not appropriate here, as it tests for stochastic dominance rather than differences in shape.

The two types of competitions are also broadly similar. In Table A17, I use t-tests to compare overall competition and round characteristics. The number of ventures, winners, and judges are not statistically different across the two groups. The award amount is higher in the feedback competitions, but this should not engender differences between below and above median non-winners.

²For example, I sum the total number of incorporated companies in feedback competitions. Then, again for only feedback competitions, I sum within a 0.1 z-score bandwidth the number of incorporated companies. I divide the second sum by the first. Thus, if Inc_i is an indicator for a company being incorporated, the bar height for 0.1 z-score band z in feedback competitions is: $\frac{\sum_{z, SF} Inc_i}{\sum_{SF} Inc_i}$.

1.2. *Rank reflects quality consistently*

I next test whether rank reflects measures of quality observable at the time of the competition. In Table A18, I regress whether the founder attended a top 10 college, whether the venture was incorporated at the time of the round, and whether the venture received external financing before the round on *Low Rank*, within the sample of non-winners.

The sample is restricted to the no-feedback competitions in columns 1, 3, and 5. These regressions find strong, negative, and statistically significant coefficients on *Low Rank*. I include all competitions and interact *Low Rank* with *Feedback* in columns 2, 4, and 6. The coefficients on the interaction term are uniformly zero. These regressions are within round, so the independent effect of feedback is absorbed. This exercise demonstrates that the mapping between observable quality and rank is not different across the two types of competitions.

1.3. *Selection into feedback*

There may be concern that founders with more uncertainty about their project quality select into feedback competitions, even though competitions did not advertise this feedback explicitly. I test for such selection using ventures that participated in multiple competitions: Among founders that compete in a second competition, I expect high information need founders to disproportionately sort into feedback competitions.

To proxy for information need, I use a low average score or a highly dispersed score in the first competition. Table A19 panel 1 contains summary statistics for the sample used in the test. Panel 2 shows t-tests for whether information need, measured in the first round of the first competition, is associated with participation in a second competition with feedback. None are significant. It is therefore unlikely that founder selection into competition type is affected by information needs.

2. Bayesian theory and calibration

This section presents a simple model of how a Bayesian updater responds to feedback. The modeling choices are designed to hew as closely as possible to the information structure and main results from the preceding sections. Section 1.1 contains the model, and Section 1.2 calibrates it to show how feedback affects a founder’s success probability distribution.

2.1. Theory

Consider a potential entrant with a business idea. With probability θ , it will succeed and produce value $y = 1$. It will fail ($y = 0$) with probability $1 - \theta$. The founder i has a prior about his probability of success, $\mu_i(\theta) \in [0, 1]$. The venture has not yet paid an irreversible entry cost c . The prospective founder’s expected payoff is

$$v_i = -c + \mu_i(\theta \mid info_i). \quad (1)$$

The founder’s decision problem, regardless of whether he is rational or biased, is to go forward if the expected payoff exceeds the entry cost, and drop out otherwise. Here, I assume founders are rational Bayesian updaters, consistent with the evidence in Section 6.3.

Recall the following institutional details: A known number of judges have each independently ranked a set of ventures. The average of these judge-specific ranks becomes a rank for a given venture. Ventures in feedback competitions learn only their own rank, and do not observe judge-specific ranks. The empirical approach coarsened the information into a binary signal: negative feedback (below median rank among non-winners), and relatively positive feedback (above median rank among non-winners).

I model signal precision through the number of judges, not the number of ventures. This corresponds to my result that responsiveness is sensitive to the former but not the latter, and simplifies matters. Suppose the founder interprets his rank as the result of a series of Bernoulli trials, where the number of signals

is the number of judges (J). Each judge $j \in J$ independently reports a positive or negative signal for each venture. These signals are summed across J and ordered, creating a ranking of the ventures in the round. Let k be the number of positive signals that judges report about a venture, or the number of judges who ranked a venture above median. Then, the observed rank and the presence of “negative feedback” (below median rank) are monotone functions of k . In practice, I find that both responsiveness and venture continuation are roughly linear in rank, suggesting that this monotonicity assumption is plausible.

The conjugate prior for the Bernoulli distribution is the Beta distribution, which is defined by shape parameters α and β , and is defined on the interval $[0, 1]$.³ The venture begins with a prior distributed $\mathcal{B}[\alpha^{all}, \beta^{all}]$, which has mean $\frac{\alpha^{all}}{\alpha^{all} + \beta^{all}}$. I assume all founders have the same α and β , but discuss below how heterogeneity in responsiveness may reflect different parameters.

I separate the information that ventures receive into two stages.⁴ In the first stage, the founder learns that he lost, yielding an interim prior that is the rational expectation for success conditional on losing. Let the interim prior be $\mu_i(\theta | lost_i) = E[\mathcal{B}(\alpha, \beta) | lost_i] = \frac{\alpha}{\alpha + \beta} < \frac{\alpha^{all}}{\alpha^{all} + \beta^{all}}$.⁵ In the second stage, ventures in feedback competitions learn their ranks, while ventures in no-feedback competitions learn nothing. An informed founder i observes that he had J_i judges, of whom k_i reported positive signals (ranked him above median). His posterior is distributed $\mathcal{B}[\alpha + k_i, \beta + J_i - k_i]$. My choice of posterior is the mean.⁶ This

³Beta distributions are useful because they represent a distribution of probabilities. Conjugate prior means that if the prior is a Beta distribution, so is the posterior, and thus the posterior simply alters the parameters of the prior. There is then a closed-form expression for the posterior. The pdf of the Beta distribution is $\frac{(\alpha + \beta - 1)!}{(\alpha - 1)!(\beta - 1)!} \theta^{\alpha - 1} (1 - \theta)^{\beta - 1}$.

⁴From the perspective of Bayes’ rule, the order in which the information is received is irrelevant. In practice, ventures learn whether they lost immediately upon conclusion of the competition, and are subsequently informed of their rank by email.

⁵Note that the interim prior should reflect precision; ventures in both types of competitions can observe the number of judges. However, the goal of the analysis is to focus on differences in signals to non-winners, and the number of judges does not differ systematically between feedback and no-feedback competitions (see Section 4.2.1). Thus there is no loss in omitting the number of judges from consideration in the first stage.

⁶The posterior pdf is then $\frac{(\alpha + \beta + J - 1)!}{(\alpha + K - 1)!(\beta + (J - k) - 1)!} \theta^{\alpha + k - 1} (1 - \theta)^{\beta + (J - k) - 1}$. The alternative to using the mean is the mode, which is only defined if α and β are > 1 . This is $Mo[\mathcal{B}(\alpha, \beta)] = \frac{\alpha - 1}{\alpha + \beta - 2}$.

is:

$$\mu_i(\theta \mid lost_i, k_i, J_i) = \frac{\alpha + k_i}{\alpha + k_i + \beta + J_i - k_i} = \frac{\alpha + k_i}{\alpha + \beta + J_i}. \quad (2)$$

The posterior for the uninformed ventures is unchanged from the interim prior, at $\mu_i(\theta \mid lost_i) = \frac{\alpha}{\alpha + \beta}$.

Given the rank transformation assumptions, negative feedback is when a majority of judges report negative signals for a venture, or $k_i < \frac{J_i}{2}$. Since judges must force-rank ventures, this permits dividing ventures in no-feedback competitions around the median, as in the empirical exercise. If there are I losing ventures in a feedback round, the effect of negative feedback on the probability of success is thus:

$$\begin{aligned} & \mu_i\left(\theta \mid lost_i, k_i, k_i < \frac{J_i}{2}\right) - \mu_i\left(\theta \mid lost_i, k_i, k_i \geq \frac{J_i}{2}\right) = \\ & \left[\frac{2}{I} \sum_{i=1}^{\frac{I}{2}} \frac{\alpha + k_i}{\alpha + \beta + J_i} \mid k_i < \frac{J_i}{2} \right] - \left[\frac{2}{I} \sum_{i=\frac{I}{2}}^I \frac{\alpha + k_i}{\alpha + \beta + J_i} \mid k_i \geq \frac{J_i}{2} \right] \end{aligned} \quad (3)$$

Note that because the interim prior does not change for uninformed ventures, the second difference (the control) in the difference-in-differences estimator cancels out (i.e. $\frac{\alpha}{\alpha + \beta} - \frac{\alpha}{\alpha + \beta} = 0$).

2.2. Calibration

The first object that I need is the interim prior expectation of success. The best proxy is realized outcomes in the no-feedback competitions, within the subsample matched to ventures in the feedback competitions.⁷ The mean continuation probability among non-winners in no-feedback competitions exactly matched on observables to non-winners in feedback competitions is 0.4. (Note this is 0.06 higher

⁷This is because the actual distribution of venture continuation is selected on information. It is truncated, or left-censored, in the informed group. At the same time, it is inappropriate to use the raw mean from the no-feedback competitions, because the level probability of success is different across the two types of competitions, even though the demeaned distributions are not different.

than the whole-population probability, reflecting the match.) Then $\frac{\alpha}{\alpha+\beta} = .4$, or $\beta = 1.5\alpha$.

The difference-in-differences estimate found that negative feedback reduces the probability of success by 8.6 percentage points (Table 4 Panel 1 column 1). In practice, there are 53 no-feedback rounds, which I index by r . After replacing $\beta = 1.5\alpha$, the Bayesian updating calculation for the difference-in-differences estimate in Equation 3 becomes:

$$\frac{1}{53} \sum_{r=1}^{54} \left\{ \left[\frac{2}{I_r} \sum_{i=1}^{\frac{I_r}{2}} \frac{\alpha + k_i}{2.5\alpha + J_i} \mid k_i < \frac{J_i}{2} \right] - \left[\frac{2}{I_r} \sum_{i=\frac{I_r}{2}}^{I_r} \frac{\alpha + k_i}{2.5\alpha + J_i} \mid k_i \geq \frac{J_i}{2} \right] \right\} = -.086 \quad (4)$$

I demean k_i and J_i to make their magnitude more consistent across rounds.

Equation 4 is easily solved by iterating, yielding $\alpha = 4.5$. Thus $\beta = 6.75$. The interim prior, distributed $\mathcal{B}[4.5, 6.75]$, is shown in Figure 3A in the main text. To arrive at the posterior after negative feedback, I consider only the first bracketed object in Equation 4. Taking the “population” shape parameters as given, in the subsample receiving negative feedback the average k_i and J_i are 0.70 and 4.3, respectively. Thus the average posterior after negative feedback is:

$$\mu_i \left(\theta \mid lost, k_i, k_i < \frac{J_i}{2} \right) \sim \mathcal{B}[\alpha + 0.70, \beta + 4.3] = \mathcal{B}[5.2, 10.35].$$

The corresponding k_i and J_i in the positive feedback group (above median non-winners; right-hand bracketed term in Equation 4) are 2.2 and 4.3, yielding a positive feedback posterior of:

$$\mu_i \left(\theta \mid lost, k_i, k_i \geq \frac{J_i}{2} \right) \sim \mathcal{B}[\alpha + 2.2, \beta + 4.3] = \mathcal{B}[6.7, 8.85].$$

These are shown in Figure 3B and 3C.

We can interpret the heterogeneity results through this Bayesian calibration. Greater responsiveness within a given group, such as among women, could reflect a lower or a less precise prior. Holding β fixed, a lower α corresponds to

a lower prior and a lower variance.⁸ For some variables, I am able to distinguish between the two moments. In particular, I find that ventures are much more responsive when there are more judges (Table 5 Panel 2 column 9). A similar exercise to the one above, using the average number of judges when it is above and below median and the corresponding average number of success signals yields the two graphs in Figure 4.⁹

⁸ $Var[\mathcal{B}(\alpha, \beta)] = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$

⁹For negative feedback, the average k_i and J_i with an above median number of judges in the round are 1 and 6, respectively. This delivers a posterior distributed $\mathcal{B}[5.5, 11.75]$. The average k_i and J_i with a below median number of judges in the round are 0.4 and 2, respectively. This delivers a posterior distributed $\mathcal{B}[4.9, 8.35]$.

Table A.1: List of Programs

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

<i>Competition Name</i>	<i>City</i>	<i>State</i>	<i>Years</i>	<i>Panel 2</i> # <i>unique</i> <i>ven-</i> <i>tures</i>	# <i>unique</i> <i>judges</i>	# <i>rounds</i> <i>per</i> <i>comp.</i>	<i>Judges</i> <i>score</i> [⊖]	<i>Judges</i> <i>rank</i>	<i>Dimension</i> <i>scores</i>	<i>Feedback</i>
Harvard Business School New Venture Competition	Boston	MA	1999-2015	837	563	2 [‡]	Yes [⊖]	Yes	No	No
Illinois Clean Energy Student Challenge	Chicago	IL	2013	6	9	1	Yes	No	Yes	Yes
Imagine H2O Infrastructure Challenge	San Francisco	CA	2013-15	160	31	3	Yes	No	Yes	Yes
Innosphere Admissions	Fort Collins	CO	2013-15	32	46	1	Yes	No	Yes	Yes
MIT Clean Energy Prize	Cambridge	MA	2013-15	156	80	2-3 [^]	Yes	No	Yes	No
Missouri Clean Energy Student Challenge	St. Louis	MO	2013	14	9	1	Yes	No	Yes	Yes
OEDIT Advanced Industries Accelerator Energy and Natural Resources	Denver	CO	2015	16	7	1	Yes	No	Yes	Yes
Ohio Clean Energy Student Challenge	Cleveland	OH	2012-13	12	8	1	Yes	No	Yes	Yes
TransTech Energy Conference 2012	Morgantown	WV	2012	20	25	1	Yes	No	Yes	Yes
Massachusetts Clean Energy Center Catalyst Grant Program	Boston	MA	2012-15	250	134	2	Yes	No	Yes	No
Rice University Business Plan Competition	Houston	TX	2004-2015	480	694	3 [‡]	No	Yes	No [‡]	No

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

Table A.2: University Rankings

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

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

Table A.3: Sector and Judge Data

<i>Panel 1: Sectors</i>			<i>Panel 2: Judge Professions</i>		
	# unique ventures			# unique judges	
Hardware	245		All	2,514	
Software	1,404		Venture Capital Investor	676	
	Sectors [‡]		Elite VC [†] (by IRR/Multiple)	21	
	Ventures	Judges	Angel Investor*	397	
Air/water/waste/agriculture	146	31	Mean (med) AngelList investments	12.8 (8)	
Biotech	182	64	Professor/Scientist	44	
Clean tech/renewable energy	712	273	Business Development/Sales	83	
Defense/security	64	66	Corporate Executive	498	
Education	37	118	Founder/Entrepreneur	240	
Energy (fossil)	61	373	Lawyer/Consultant/Accountant	369	
Fintech/financial	53	522	Non-Profit/Foundation/Government	164	
Food/beverage	88	24	Other	193	
Health (ex biotech)	270	291			
IT/software/web	1,404	586	# judge-venture pairs in which judge personally invested in venture	3	
Manuf./materials/electronics	323	96	# judge-venture pairs in which judge's firm invested in venture	95	
Media/ads/entertainment	57	157			
Real estate	61	82			
Retail/consumer goods	139	159			
Social enterprise	42	42	Total # judge-venture score pairs	47,066	
Transportation	136	51	# judge-venture pairs in same sector	8,139	

<i>Panel 3: Judge Disagreement and Leniency Measures</i>						
	N	Mean	Median	S.d.	Min	Max
Judge disagreement (std dev of within-panel judge decile ranks of a venture)	5997	1.88	1.02	1.97	0	6.36
Venture leave-one-out leniency score	3788	0.33	0.25	0.32	0	2
Venture leave-one-out harshness score	3779	0.33	0.29	0.28	0	2
$V_{i,\sigma}^{high}$ (venture leave-one-out leniency variation based on propensity to give highest score)	3770	0.21	0.19	0.13	0	0.96
$V_{i,\sigma}^{ext}$ (venture leave-one-out leniency variation based on four most extreme judges)	3788	0.31	0.29	0.13	0	1.15

Note: This table lists the number of ventures by technology type, the number of judges by profession, and the leniency measures. [†]Preqin top 20 VC firm by either IRR or Multiple, as of 2016. *Identifies as angel investor in competition data, or has AngelList profile and at least one investment (160 judges). [‡]Venture sectors from competition data; each venture assigned to one sector. Judge sectors based on LinkedIn profile or firm webpage; judges may have expertise in multiple sectors.

Table A.4: Company & Competition States

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

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

Table A.5: Representativeness of Sample

<i>Panel 1: Venture Sectors</i>			
	% ventures in data	% U.S. VC deals	% U.S. VC deal amt
Air/water/waste/agriculture	3.9%		
Biotech	4.8%	10.8%	12.9%
Clean tech/renewable energy	18.9%	3.3%	2.0%
Defense/security	1.7%		
Education	1.0%		
Energy (fossil)	1.6%		
Fintech/financial	1.4%	1.9%	5.4%
Food/beverage	2.3%		
Health (ex biotech)	7.2%	8.8%	6.1%
IT/software/web	37.2%	40.4%	39.8%
Manuf./materials/electronics	8.6%	7.4%	6.0%
Media/ads/entertainment	1.5%	9.6%	8.0%
Real estate	1.6%		
Retail/apparel/consumer goods	3.7%	6.8%	9.9%
Social enterprise	1.1%		
Transportation	3.6%		

Panel 2: Venture States (top 20 states in data)

	% ventures in data	% U.S. VC deals	% U.S. VC deal amt
Massachusetts	35.5%	9.7%	9.6%
Arizona	20.6%	0.6%	0.2%
California	9.2%	40.6%	57.3%
Colorado	7.8%	2.0%	1.3%
New York	2.6%	10.6%	10.6%
Texas	2.2%	3.7%	2.0%
Illinois	1.9%	2.2%	1.9%
Utah	1.5%	1.3%	1.2%
Minnesota	1.4%	0.7%	0.6%
Washington	1.2%	2.6%	2.0%
Nevada	0.9%	0.1%	0.0%
Wisconsin	0.9%	0.5%	0.2%
Ohio	0.9%	1.6%	0.4%
Pennsylvania	0.8%	4.6%	1.1%
Michigan	0.7%	0.1%	0.6%
Maryland	0.7%	1.6%	1.5%
Oregon	0.7%	1.0%	0.4%
Indiana	0.7%	0.4%	0.1%
Connecticut	0.6%	1.3%	0.8%
Virginia	0.6%	1.7%	0.7%

Note: This table compares the frequency of ventures in my sample with U.S. VC deals from the National Venture Capital Association's 2016 Yearbook.

Table A.6: Unconditional association between characteristics and success

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

<i>Panel 2</i>		
Dependent Variable:	Angel/VC series A investment	≥ 10 employees as of 8/2016
	(1)	(2)
Air/water/waste/agriculture	-	-
Biotech	.053 (.036)	-.012 (.047)
Clean tech/renewable energy	.026 (.026)	.026 (.027)
Defense/security	.14 (.05)	.11 (.062)
Education	.17 (.063)	.18 (.075)
Energy (fossil)	.12 (.073)	.11 (.071)
Fintech/financial	.073 (.039)	.23 (.073)
Food/beverage	.12 (.039)	.11 (.048)
Health (ex biotech)	.2 (.04)	.12 (.043)
IT/software/web	.24 (.035)	.19 (.035)
Manuf./materials/electronics	.18 (.043)	.13 (.043)
Media/ads/entertainment	.27 (.065)	.11 (.069)
Real estate	.053 (.041)	-.0049 (.044)
Retail/apparel/consumer goods	.18 (.046)	.081 (.046)
Social enterprise	-.03 (.085)	.14 (.1)
Transportation	.075 (.031)	.13 (.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: $Y_i^{Post} = \alpha + \beta' Sector\ f.e._i + \gamma' Comp\ f.e._j + \varepsilon_{i,j}$. The base sector is “Air/water/waste/agriculture”. Standard errors clustered by competition-round.

Table A.7: Effect by Characteristic of Rank and Winning on Subsequent External Financing

Dependent variable: Financing after round*

Characteristic C :	Competition selective	Founder graduated from elite college	Founder had prior venture
	(1)	(2)	(3)
Won Round	.13 (.037)	.13 (.028)	.097 (.035)
Won Round $\cdot C$.012 (.053)	-.0027 (.081)	.049 (.058)
Decile rank winners [†]	-.012 (.0055)	-.011 (.0046)	-.0057 (.0059)
Decile rank winners [†] $\cdot C$.0042 (.01)	-.0039 (.013)	-.013 (.0077)
Decile rank non-winners	-.02 (.0029)	-.018 (.0026)	-.015 (.003)
Decile rank non-winners $\cdot C$.0094 (.0054)	.0068 (.0083)	-.0075 (.0048)
Award Amount (\$, 10,000s)	.0076 (.0026)	.0098 (.0024)	.013 (.0029)
Award Amount (\$, 10,000s) $\cdot C$.0079 (.007)	-.013 (.0056)	-.0084 (.004)
C	-	.076 (.049)	.14 (.03)
Comp.-round- panel f.e.	Y	Y	Y
N	6023	6023	6023
R^2	.16	.17	.18

Note: This table contains OLS regression estimates of the effect of winning, rank, and award (cash prize) on whether the venture raised external financing after the competition. OLS used except column 2. 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 only the two quintiles around the cutoff for winning a preliminary round (no final rounds included). [†]Decile rank in round among winners. ^{††}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 whether the founder is a student. Note that competition f.e. control for a specific date.

Table A.8: Effect of Rank and Winning with Decile Rank Indicators

Dependent variable: Financing after round*

	(1)
Won Round	.09
	(.021)
1st decile rank in round	-
2nd decile rank in round	-.065
	(.026)
4th decile rank in round	-.059
	(.025)
5th decile rank in round	-.081
	(.027)
6th decile rank in round	-.078
	(.034)
7th decile rank in round	-.096
	(.027)
8th decile rank in round	-.12
	(.029)
9th decile rank in round	-.13
	(.029)
10th decile rank in round	-.18
	(.029)
Award Amount (\$, 10,000s)	-.22
	(.031)
Competition-round- panel f.e.	Y
N	6046
R^2	.17

Note: This table contains OLS regression estimates of the effect of winning, rank, and award (cash prize). Errors clustered by competition-round. A smaller rank is better (1 is best decile, 10 is worst decile). *All private external investment after round. Note that competition f.e. control for a specific date.

Table A.9: Out-of-Sample Summary Statistics for Exact Match

Sample: non-winners of rounds only								
<i>Panel 1: After Exact Matching</i>								
Variables (not used in first stage)	Treated (Feedback)		Control (No Feedback)		Difference	t	p-value	
	N	Mean	N	Mean				
Venture IT/Software-based	1,050	0.494	1,050	0.494	0.000	0	1	
Venture in VC hub state	1,050	0.054	1,050	0.096	-0.042	-3.65	0	
Venture in same state as competition	1,050	0.550	1,050	0.837	-0.287	-14.99	0	
Venture age (years)	847	2.540	967	2.133	0.407	3.12	0.002	
Venture received financing before round	1,050	0.193	1,050	0.293	-0.100	-5.37	0	
Founder has MBA	1,050	0.086	1,050	0.056	0.030	2.64	0.008	
Founder age above median	255	0.776	198	0.838	-0.062	-1.65	0.1	
Founder attended top 10 college	1,050	0.026	1,050	0.034	-0.009	-1.15	0.25	
<i>Panel 2: Before Exact Matching</i>								
	Treated (Feedback)		Control (No Feedback)		Difference	t	p-value	
	N	Mean	N	Mean				
Venture IT/Software-based	1,075	0.487	3,061	0.452	0.035	1.96	0.05	
Venture in hub state (CA/MA/NY)	1,075	0.054	3,061	0.453	-0.400	-25.4	0	
Venture in same state as competition	1,075	0.548	3,061	0.514	0.034	1.9	0.057	
Venture age (years)	862	2.552	1,362	1.337	1.215	9.75	0	
Venture received financing before round	1,075	0.193	3,061	0.136	0.058	4.55	0	
Founder has MBA	1,075	0.085	3,061	0.361	-0.276	-17.82	0	
Founder age above median	263	0.760	1,515	0.481	0.280	8.56	0	
Founder attended top 10 college	1,075	0.025	3,061	0.156	-0.131	-12.89	0	
<i>Note:</i> This table contains summary statistics about out-of-sample covariate balance for the treated and control samples used in the exact matching analysis. The samples of above- and below-median non-winners were matched exactly sector (there are 16 sectors), competition year, student status, and company incorporation status. Note that IT/software, a larger category than the sectors, is exactly balanced after the match.								

Table A.10: Propensity Score Matching Summary Statistics

Panel 1: After Propensity Score Matching

	Treated (Feedback)		Control (No Feedback)		Difference	t	p-value
	N	Mean	N	Mean			
Venture incorporated	1,064	0.866	2,701	0.866	0.000	0	1
Venture received financing before round	1,064	0.250	2,701	0.253	-0.003	-0.13	0.899
Founder is student	1,064	0.027	2,701	0.029	-0.002	-0.17	0.868
Air/water/waste/ag	1,064	0.023	2,701	0.023	0.000	0	1
Biotech	1,064	0.061	2,701	0.058	0.003	0.23	0.816
Clean tech/renewable	1,064	0.204	2,701	0.204	0.000	0	1
Defense/security	1,064	0.014	2,701	0.018	-0.005	-0.66	0.51
Education	1,064	0.006	2,701	0.006	0.000	0	1
Energy (fossil)	1,064	0.011	2,701	0.012	-0.002	-0.26	0.795
Fintech/financial	1,064	0.003	2,701	0.002	0.002	0.58	0.564
Food/beverage	1,064	0.020	2,701	0.018	0.002	0.2	0.84
Health (ex biotech)	1,064	0.053	2,701	0.053	0.000	0	1
Mobile/IT/software	1,064	0.453	2,701	0.456	-0.003	-0.11	0.912
Manuf/materials/electronics	1,064	0.104	2,701	0.101	0.003	0.18	0.855
Media/ads/entertainment	1,064	0.002	2,701	0.002	0.000	0	1
Apparel/consumer goods	1,064	0.014	2,701	0.008	0.006	1.07	0.283

Panel 2: Before Propensity Score Matching

	Treated (Feedback)		Control (No Feedback)		Difference	t	p-value
	N	Mean	N	Mean			
Venture incorporated	1,075	0.464	3,061	0.367	0.098	34.94	0
Venture received financing before round	1,075	0.194	3,061	0.151	0.043	3.19	0.001
Founder is student	1,075	0.022	3,061	0.218	-0.196	-15.15	0
Air/water/waste/ag	1,075	0.030	3,061	0.044	-0.014	-1.97	0.049
Biotech	1,075	0.086	3,061	0.033	0.053	6.92	0
Clean tech/renewable	1,075	0.133	3,061	0.236	-0.102	-7.03	0
Defense/security	1,075	0.028	3,061	0.010	0.018	4.01	0
Education	1,075	0.007	3,061	0.009	-0.002	-0.6	0.547
Energy (fossil)	1,075	0.010	3,061	0.019	-0.008	-1.79	0.074
Fintech/financial	1,075	0.005	3,061	0.012	-0.008	-2.08	0.038
Food/beverage	1,075	0.015	3,061	0.025	-0.010	-1.9	0.058
Health (ex biotech)	1,075	0.040	3,061	0.100	-0.059	-5.96	0
Mobile/IT/software	1,075	0.484	3,061	0.302	0.182	10.67	0
Manuf/materials/electronics	1,075	0.123	3,061	0.066	0.057	5.74	0
Media/ads/entertainment	1,075	0.004	3,061	0.009	-0.005	-1.65	0.099
Apparel/consumer goods	1,075	0.011	3,061	0.043	-0.032	-4.84	0

Note: This table contains summary statistics before and after propensity score matching across feedback and no-feedback groups within non-winners. The samples were also matched on year, which I do not report. There are three additional sectors that I did not match on as there were too few observations (transportation, social enterprise, and real estate).

Table A.11: Effect of Negative Feedback with Competition-type Interactions

Panel 1: Competition signal quality measures

Dependent variable: Survival*

	(1)
Low rank·Feedback	-.095 (.038)
Low rank	-.047 (.019)
Held at university·Feedback	-.21 (.19)
Held at university	.04 (.042)
# ventures participating·Feedback	-.00061 (.00071)
# ventures participating	.00015 (.00067)
# judges participating·Feedback	-.0011 (.0011)
# judges participating	-.00029 (.00023)
Indicators for 9 geographic regions (Census divisions)·Feedback	Y
Indicators for 9 geographic regions (Census divisions)	Y
Feedback	.26 (.073)
Year f.e.	Y
N	4136
R^2	.076

Note: This table shows estimates of the effect of negative feedback, from Equation 2, where feedback is also interacted with characteristics likely to be associated with participant diversity, signal quality, and survival probability. Sample restricted to non-winners of round, all rounds included.

Panel 2: Competition participant success likelihood measures

Dependent variable: Survival*

	(1)
Low rank·Feedback	-.098 (.038)
Low rank	-.047 (.02)
Share founders attended top 10 colleges·Feedback	.81 (.74)
Share founders attended top 10 colleges	-.029 (.11)
Share ventures received prior financing·Feedback	-.11 (.3)
Share ventures received prior financing	.69 (.24)
Share ventures incorporated at round·Feedback	-.28 (.13)
Share ventures incorporated at round	-.043 (.063)
Feedback	.32 (.12)
Year f.e.	Y
N	4136
R^2	.078

Note: This table shows estimates of the effect of negative feedback, from Equation 2, where feedback is also interacted with characteristics likely to be associated with participant diversity, signal quality, and survival probability. Sample restricted to non-winners of round, all rounds included.

Panel 3: Competition participant diversity measures

Dependent variable: Survival*

	(1)
Low rank·Feedback	-.09 (.039)
Low rank	-.056 (.021)
# sectors (out of 16) represented by ventures ·Feedback	-.016 (.012)
# sectors (out of 16) represented by ventures	.0013 (.006)
Share ventures software/web/IT·Feedback	-.13 (.18)
Share ventures software/web/IT	.021 (.085)
Share ventures clean energy·Feedback	-.5 (.28)
Share ventures clean energy	.05 (.064)
Feedback	.38 (.17)
Year f.e.	Y
N	3796
R^2	.071

Note: This table shows estimates of the effect of negative feedback, from Equation 2, where feedback is also interacted with characteristics likely to be associated with participant diversity, signal quality, and survival probability. Sample restricted to non-winners of round, all rounds included.

Panel 4: Founder success likelihood measures

Dependent variable: Survival*

	(1)
Low rank·Feedback	-.067
	(.035)
Low rank	-.05
	(.02)
Venture incorporated at round ·Feedback	-.072
	(.061)
Venture incorporated at round	.17
	(.025)
Venture received prior financing·Feedback	-.091
	(.045)
Venture received prior financing	.34
	(.034)
Founder attended top 10 college·Feedback	.14
	(.079)
Founder attended top 10 college	.0024
	(.026)
Founder attended top 20 PhD·Feedback	-.43
	(.12)
Founder attended top 20 PhD*	.045
	(.041)
Founder student at round·Feedback	.0081
	(.086)
Founder student at round	.096
	(.025)
Feedback	.14
	(.063)
Year f.e.	Y
N	3765
R^2	.13

Note: This table shows estimates of the effect of negative feedback, from Equation 2, where feedback is also interacted with characteristics likely to be associated with participant diversity, signal quality, and survival probability. Sample restricted to non-winners of round, all rounds included. *University ranks in top 20 according to US News & World 2016.

Table A.12: Effect of Negative Feedback within Cleantech Open

Sample restricted to non-winners of round in the Cleantech Open Competitions 2010-12						
Dependent variable: Survival*						
Sample:	2010-12		All years		2010-12	All years
					Logit	
	(1)	(2)	(3)	(4)	(5)	(6)
Low rank·Feedback	-.13	-.11	-.13	-.11	-.65	-.6
	(.081)	(.053)	(.069)	(.05)	(.39)	(.32)
Low rank	-.061	-.064	-.056	-.055	-.32	-.3
	(.051)	(.025)	(.037)	(.02)	(.26)	(.19)
Feedback	.072	-.04	.11	.024	.33	.52
	(.092)	(.072)	(.086)	(.068)	(.43)	(.39)
Venture controls [†]	Y	Y	Y	Y	Y	Y
Judge f.e.	N	Y	N	Y	N	N
N	575	2601	739	3247	571	735
R^2	.15	.3	.12	.26		
Pseudo- R^2					.11	.092

Note: This table shows estimates of the effect of negative feedback; specifically, the effect of a below-median rank among non-winners when non-winners learn their ranks, (“Feedback”), relative to competitions where they do not learn their ranks. The sample is limited to the Cleantech Open Competition. Columns 1 and 2 further limit the sample to the years 2010-2012. Feedback only occurred in 2011. Models are OLS in columns 1-4 and logit in columns 5-6. “Low rank” is one if the venture’s rank is below median among non-winners, and 0 if it is above median among non-winners. * This measure for venture continuation is 1 if the venture had at least one employee besides founder on LinkedIn as of 8/2016. Errors clustered by competition-round or judge, depending on fixed effects. Feedback varies by event, so competition-round f.e. are not used. [†]Includes sector indicator variables, whether the company is incorporated, and whether the founder is a student.

Table A.13: Effect of Negative Feedback in Subsamples

Dependent Variable: Survival*			
Sample restricted to:	Founders with MBAs	Ventures in VC hub state [†]	Founder is student
	(1)	(2)	(3)
Low Rank· Feedback	-.16 (.091)	-.17 (.1)	-.39 (.1)
Low Rank	-.018 (.03)	-.09 (.028)	-.042 (.046)
Feedback	.015 (.036)	.088 (.043)	.35 (.074)
Year f.e.	Y	Y	Y
N	1135	1396	612
R^2	.076	.12	.16

Note: This table shows estimates of the effect of negative feedback as in Table 6, but with alternative samples. * Survival is 1 if the venture had ≥ 1 employee besides founder on LinkedIn as of 8/2016. [†]Includes sector indicator variables, student status and company incorporation statuses. [†]Venture state is California, New York, or Massachusetts.

Table A.14: Leave-one-out leniency measure predictive power

Dependent variable:	Judge's score		Survival*	Financing after round	Survival*
	(1)	(2)	(3)	(4)	(5)
Leave one out leniency (L_{ij})	2.2 (.075)	2.1 (.081)	-.06 (.032)	.0069 (.027)	-.051 (.061)
Low rank·Feedback· L_{ij}					.0044 (.081)
Low rank·Feedback					-.095 (.06)
Feedback· L_{ij}					.12 (.086)
Low rank· L_{ij}					.014 (.055)
Low rank					-.067 (.045)
Feedback					.15 (.06)
Venture controls	N	N	N	N	Y
Year f.e.	N	N	N	N	Y
Competition-round-panel f.e.	Y	Y	Y	Y	N
N	20517	14514	5412	5412	3998
R^2	.86	.85	.14	.12	.044

Note: This table shows leniency scores predict real scores, weakly predict success outcomes, and do not interact with feedback. The leave-one-out leniency measure is calculated as: $L_{ij} = \frac{1}{n_j-1} \left(\sum_{k=1}^j S_k - S_i \right)$. The sample is limited to non-winners. * This measure for venture continuation is 1 if the venture had at least one employee besides founder on LinkedIn as of 8/2016. Errors clustered by competition-round.

Table A.15: Instrumenting for score variation with leave-one-out leniency measures (first stage and naive second stage)

Dependent variable:	Standard deviation of venture's scores [†]				Survival*	
	(1)	(2)	(3)	(4)	(5)	(6)
High variation in L_{ij} ($V_{i,\sigma}^{high}$)	2.5 (.96)	2.5 (.88)				
Extreme values of L_{ij} ($V_{i,\sigma}^{ext}$)			2.4 (1.1)	2.4 (1)		
Low rank·Feedback· $V_{i,\sigma}^{high}$.023 (.32)	
Low rank·Feedback· $V_{i,\sigma}^{ext}$.063 (.23)
6 individual effects and interactions	N	N	N	N	Y	Y
Venture controls	N	N	N	N	Y	Y
Year f.e.	N	Y	N	Y	Y	Y
Competition-round-panel f.e.	N	N	N	N	N	N
N	3770	3770	3943	3943	3810	4087
R^2	.023	.039	.022	.038	.041	.047
First stage F-test [±]	28	31	14	16		

Note: This table shows that receiving “randomly” noisier feedback by virtue of having high variation in judge leniency does not seem to affect responsiveness. First, columns 1-2 demonstrate that the leniency measure does predict the judge’s score. This leave-one-out leniency measure is calculated as: $L_{ij} = \frac{1}{n_j-1} \left(\sum_{k=1}^j S_k - S_i \right)$. Columns 3-6 show that variation in leniency predict the standard deviation of judge scores. Finally, in columns 7-8, I use the leave-one-out measures as naive instruments, and interact them with the effect of receiving negative feedback. [†]Standard deviation of within-panel judge decile ranks of a venture. $V_{i,\sigma}^{high}$ is the venture leave-one-out leniency variation based on propensity to give highest score. $V_{i,\sigma}^{low}$ is the venture leave-one-out leniency variation based on propensity to give lowest score. $V_{i,\sigma}^{ext}$ is the venture leave-one-out leniency variation based on four most extreme judges. [±]F-statistic for the excluded instrument (standard deviation of scores) being significantly different from zero. “Low rank” is one if the venture’s rank is below median among non-winners, and 0 if it is above median among non-winners. Regressions are OLS. * This measure for venture continuation is 1 if the venture had at least one employee besides founder on LinkedIn as of 8/2016. Errors clustered by competition-round.

Table A.16: Effect of Negative Dimension Feedback on Venture Continuation

Sample restricted to non-winners of round

Dependent variable: Survival

Criteria (dimension= D):	Presentation	Team	Product/ tech	Market ^{††}	Financials	Bus model
	(1)	(2)	(3)	(4)	(5)	(6)
Low rank in D -Feedback	.0036 (.062)	-.09 (.038)	-.052 (.033)	-.089 (.04)	-.11 (.038)	-.097 (.04)
Low rank in D	-.0096 (.059)	.01 (.037)	-.026 (.029)	.087 (.04)	-.0013 (.032)	.097 (.04)
Feedback	.17 (.071)	.058 (.038)	.04 (.034)	.07 (.042)	.071 (.053)	.072 (.042)
Overall decile rank	-.034 (.0059)	-.019 (.0046)	-.017 (.0045)	-.031 (.0048)	-.016 (.0054)	-.032 (.0049)
Venture controls [†]	Y	Y	Y	Y	Y	Y
N	2147	3147	3126	2538	2240	2538
R^2	.084	.089	.085	.089	.096	.09

Note: This table shows estimates of the effect of negative feedback within dimensions. Errors clustered by competition-round. [†]Includes sector dummies, whether venture incorporated, and whether founder is student. ^{††}Market attractiveness and size.

Table A.17: Round-level test for distributional differences around median among non-winners

	Feedback			No Feedback			Difference P-value	
	N	Mean	S.d.	N	Mean	S.d.		
Venture characteristics								
Incorporated	127	0.03	0.24	48	0.06	0.20	-0.04	0.35
Financing before round	127	0.05	0.25	48	0.11	0.31	-0.06	0.21
IT/Software-based	127	-0.02	0.24	48	0.00	0.29	-0.02	0.68
Hub state (CA/MA/NY)	127	-0.01	0.17	48	0.04	0.17	-0.06	0.05
Social impact/cleantech	127	-0.02	0.28	48	-0.06	0.24	0.03	0.46
Founder characteristics								
Student at round	127	-0.03	0.14	48	0.00	0.09	-0.03	0.23
Has MBA	127	0.05	0.36	48	0.10	0.37	-0.04	0.51
Attended top 20 college	127	0.03	0.31	48	0.01	0.19	0.02	0.66
Age above median	99	0.05	0.37	26	0.08	0.25	-0.03	0.68
<i>Note:</i> This table compares the difference between above- and below-median non-winners across feedback status. Specifically, for each round the below- and above-median means are calculated. Then the below median mean is subtracted from the above median mean. Finally, a t-test is conducted across rounds with and without feedback.								

Table A.18: Competition Characteristics by Feedback Status

	No feedback			Feedback			Difference P-value	
	N	Mean	S.d.	N	Mean	S.d.		
# ventures in round	77	31.81	21.07	53	40.53	46.08	-8.72	0.15
# winners	77	8.38	7.08	53	11.14	11.46	-2.76	0.09
# judges on panel	233	18.51	26.53	55	17.62	14.05	0.89	0.81
Award amount	94	42181	40650	55	183400	89941	-141219	0.00
<i>Note:</i> This table compares the difference between competition rounds by whether they have feedback or not.								

Table A.19: Relationship between rank and observable quality

Sample restricted to non-winners of round						
Dependent variable:	Founder attended top 10 college		Venture externally financed before competition		Venture incorporated by competition date	
Sample:	No- feedback		No- feedback		No- feedback	
	(1)	(2)	(3)	(4)	(5)	(6)
Low rank	-.0047 (.0026)	-.0047 (.0025)	-.025 (.0023)	-.025 (.0022)	-.012 (.0031)	-.012 (.003)
Low rank·Feedback		.0035 (.0026)		.000058 (.0038)		-.00032 (.0043)
Comp.-round- panel f.e.	Y	Y	Y	Y	Y	Y
N	2453	4513	2453	4513	2453	4513
R^2	.28	.3	.21	.15	.36	.66

Note: This table shows correlations between rank and characteristics expected to predict venture survival, observable at the time of the competition. “Low rank” is 1 if the venture’s rank is below median among non-winners. Errors clustered by competition-round. Competition-round fixed effects absorb the independent effect of feedback.

Table A.20: Information Provision Test Among Companies Participating in Multiple Competitions

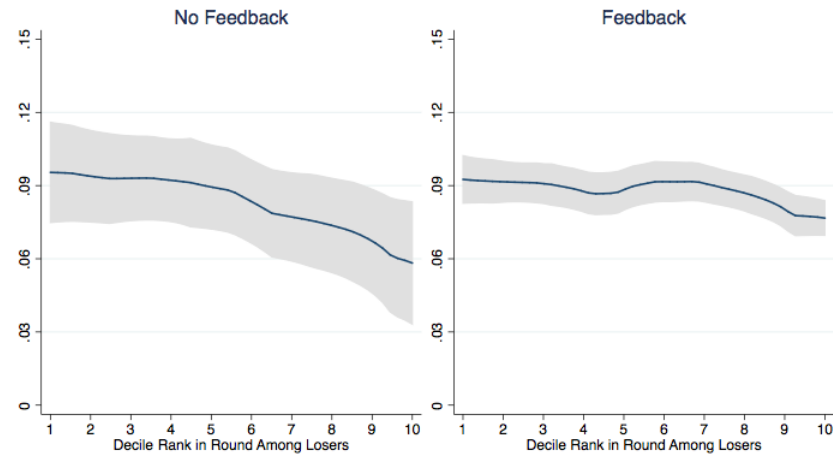
<i>Panel 1: Summary Statistics of Variables used in T-Tests Below</i>								
	N	Mean	Median	S.d.	Min	Max		
Decile rank in 1st competition 1st round	521	5.06	5	2.81	1	10		
Judge score dispersion (uncertainty measure) in 1st competition 1st round	521	1.89	1.92	1.05	0	4.95		
Likelihood 2nd competition has feedback	521	0.7	1	0.46	0	1		

<i>Panel 2: T-tests of propensity to participate in subsequent competition with feedback</i>								
	Above median			Below median			Diff	2-tailed p-value
	N	Mean	S.d.	N	Mean	S.d.		
Decile rank in 1st competition 1st round:								
Likelihood 2nd competition has feedback	238	0.69	0.46	283	0.70	0.46	-0.01	0.81
Judge score dispersion (uncertainty measure) in 1st competition 1st round:								
Likelihood 2nd competition has feedback	224	0.70	0.46	297	0.70	0.46	0.00	0.92

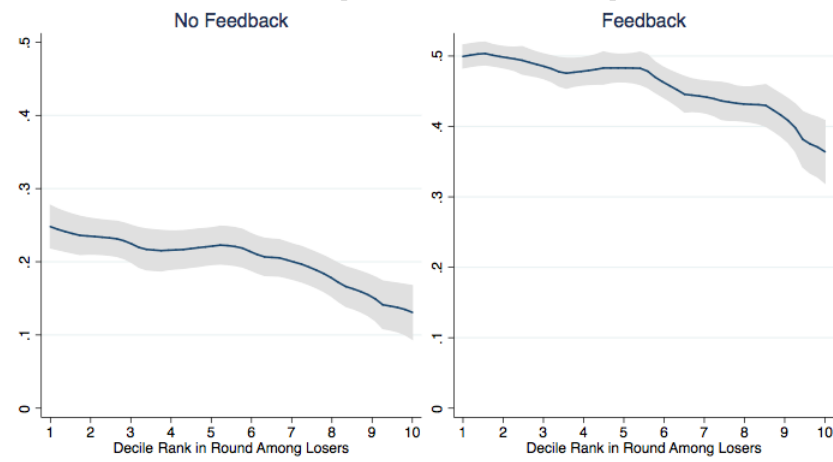
Note: This table tests whether founders with high information needs (below median rank or above median judge score dispersion) are more likely to participate in competitions with feedback. The sample is limited to ventures that participate in multiple competitions. I conduct t-tests for whether the proxies for uncertainty, measured in the first round of the first competition, are associated with a propensity to participate in a second competition that has feedback.

Figure A.1: Ex-ante characteristics among non-winners (decile 1 is best)

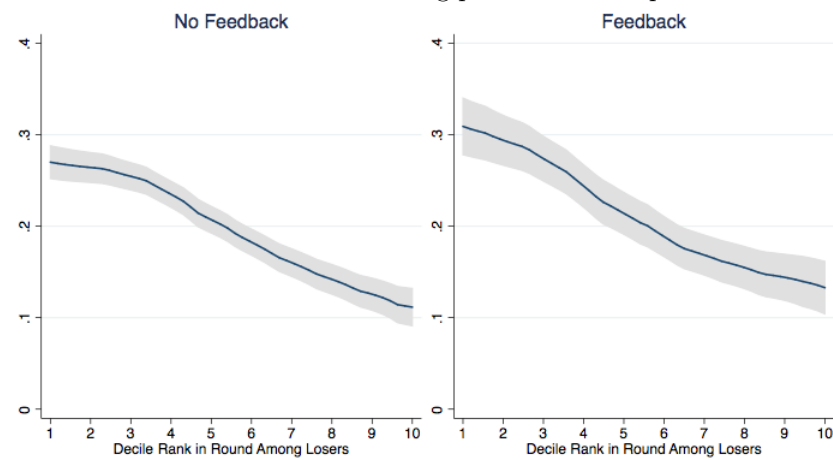
A. Founder attended top 10 college



B. Venture incorporated at time of competition



C. Venture received financing prior to the competition



Note: These figures show a characteristic's probability by venture decile rank among non-winners in the round. Only non-winners in preliminary rounds included. Local polynomial with Epanechnikov kernel using Stata's optimal bandwidth; 95% confidence intervals shown.

Figure A.2: Distributions of Pre-Round Venture Characteristics

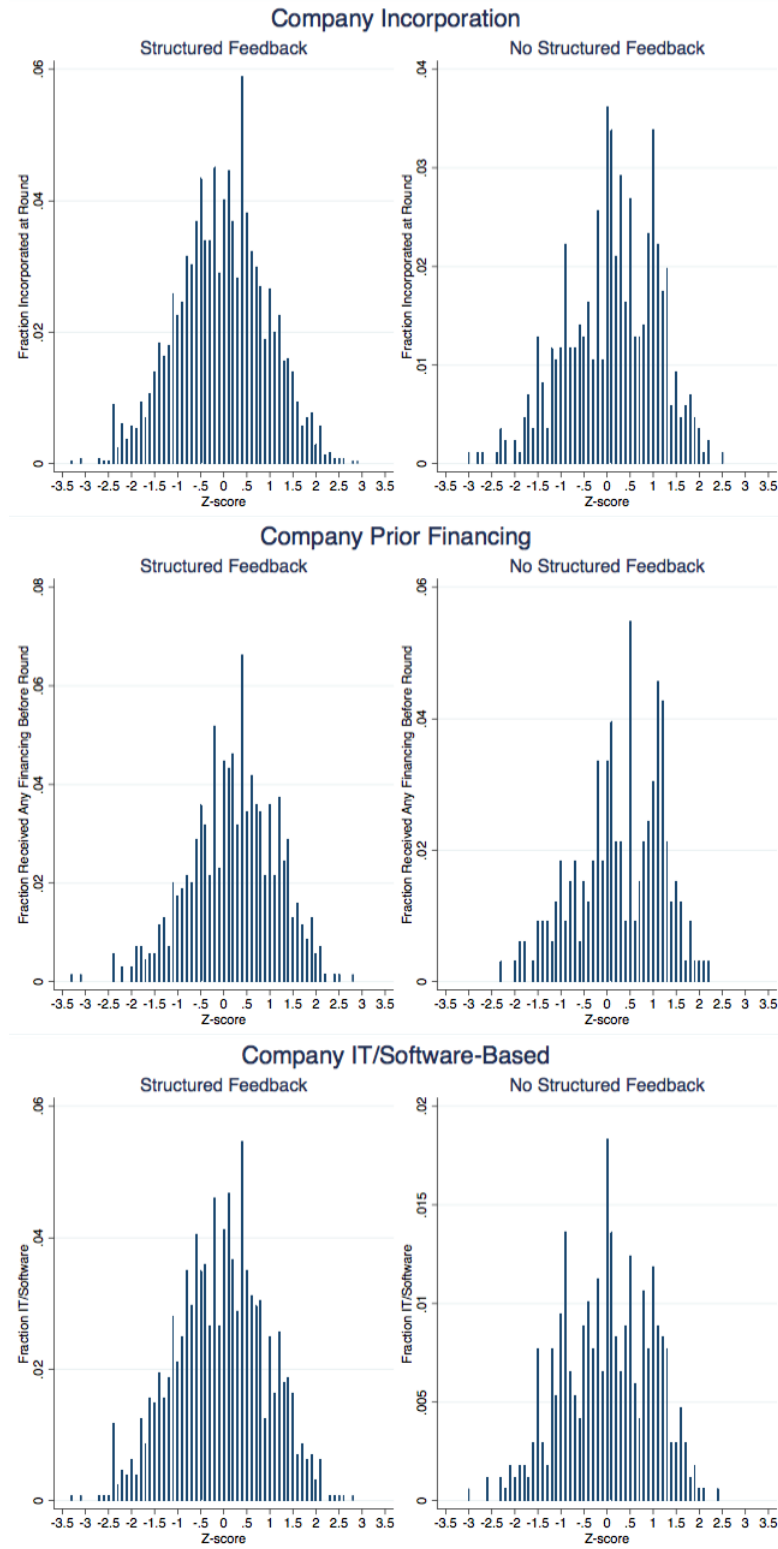
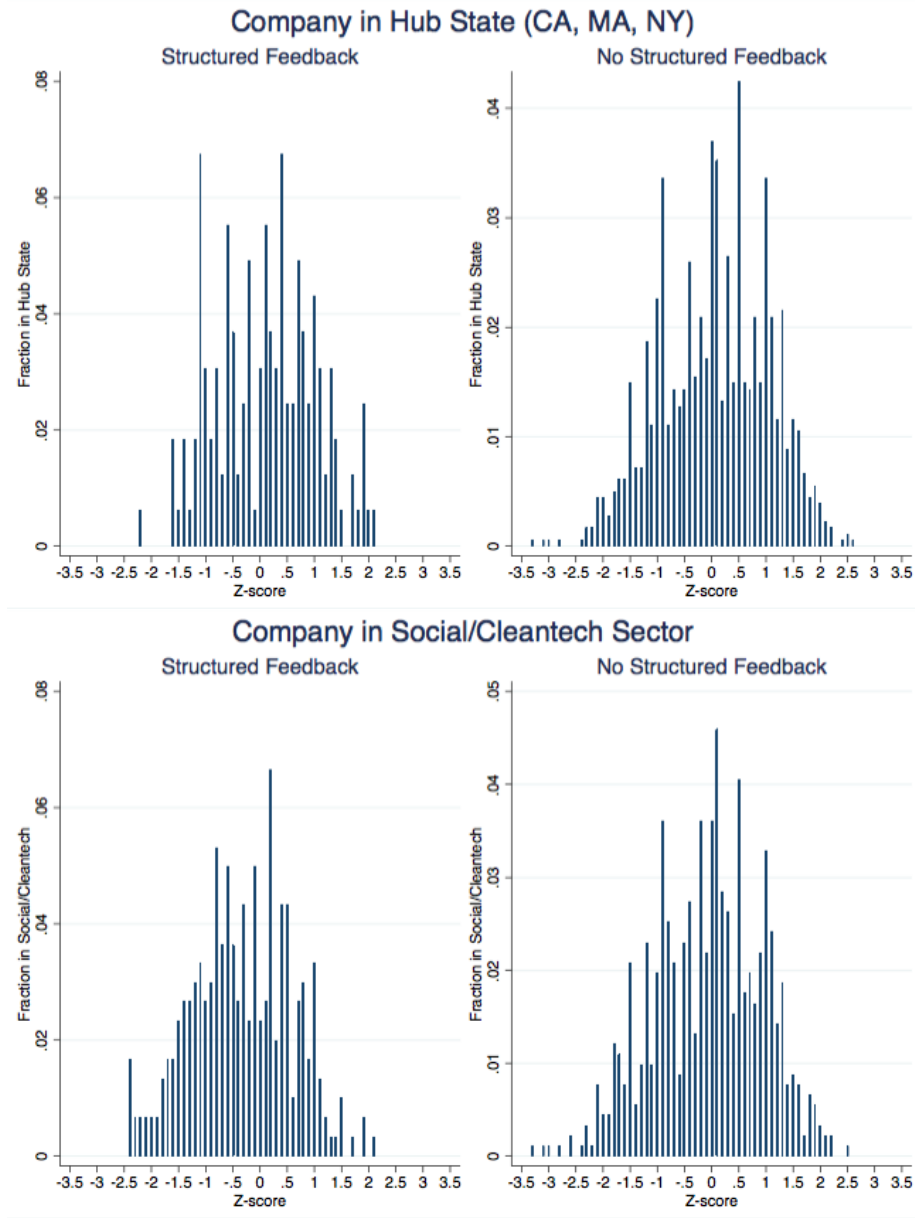


Figure 2 (continued)



Note: This figure shows spikes representing the fraction of all firms within 0.1 z-score bandwidths. For example, for variable X_i , the bar height for a z-score band of z in feedback competitions is: $\frac{\sum_{z, SF} Inc_i}{\sum_{SF} Inc_i}$.

Figure A.3: Distributions of Pre-Round Founder Characteristics

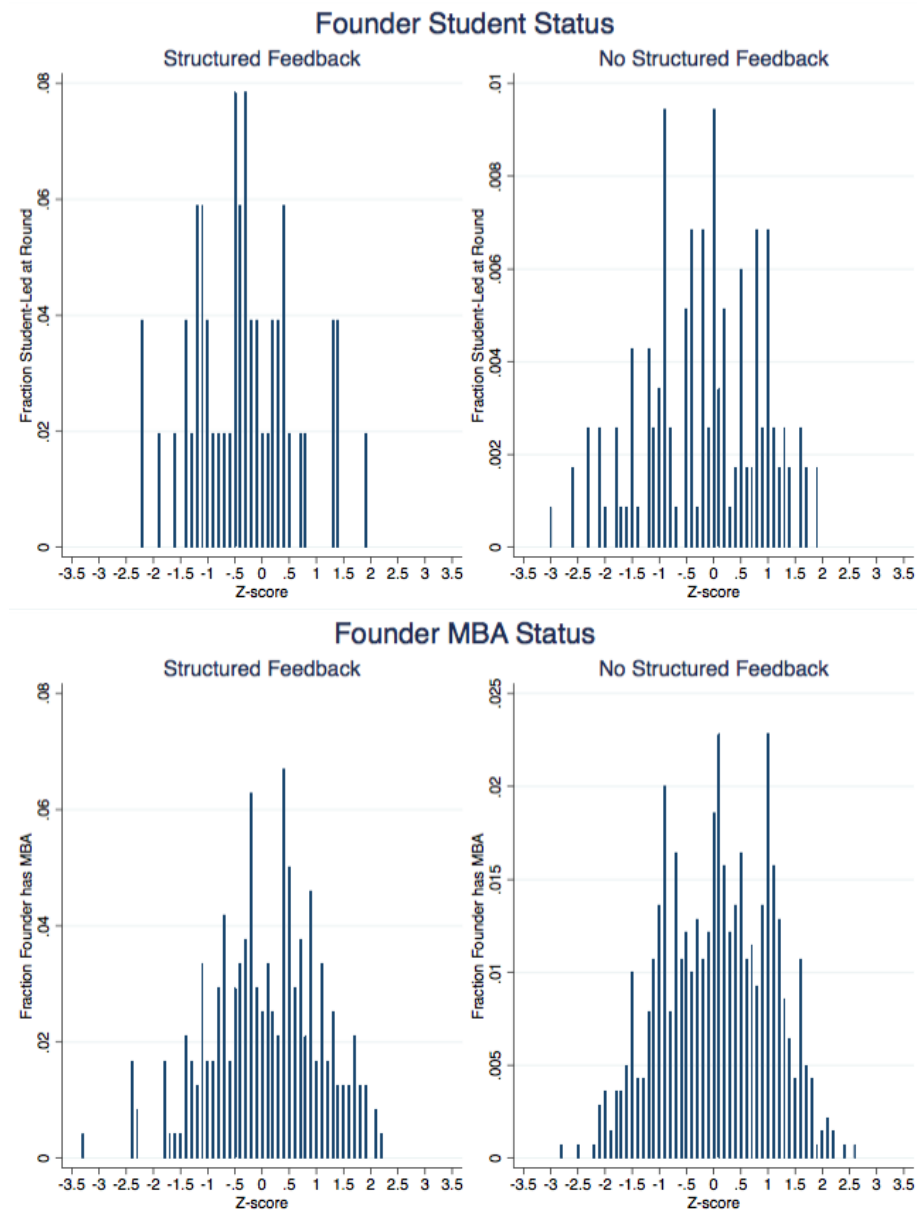
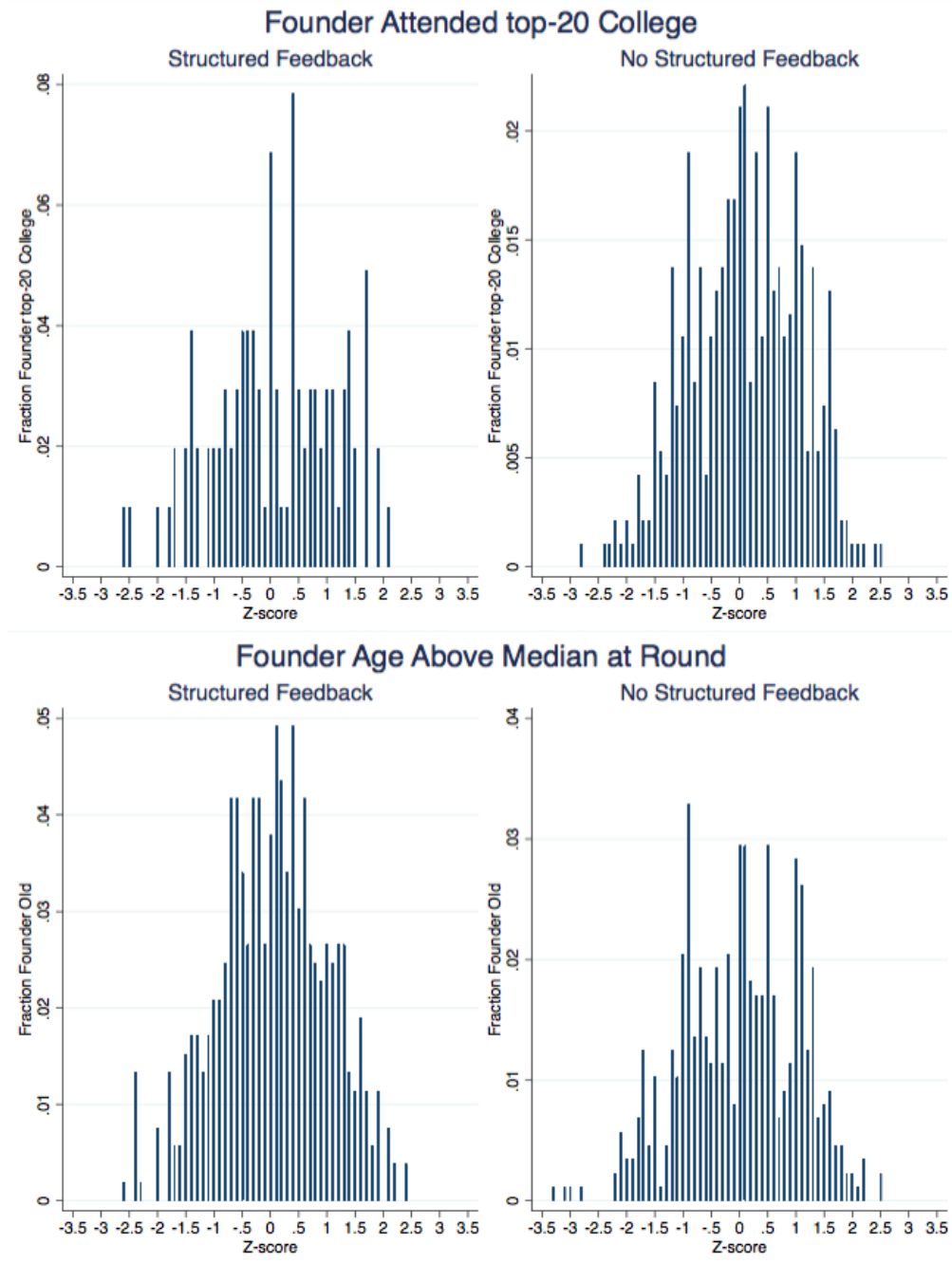


Figure 3 (continued)



Note: This figure shows spikes representing the fraction of all firms within 0.1 z-score bandwidths. For example, for variable X_i , the bar height for a z-score band of z in feedback competitions is: $\frac{\sum_{z, SF} Inc_i}{\sum_{SF} Inc_i}$.