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Public Leaderboard Feedback in Innovation Contests: A Theoretical and Experimental Investigation*

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Abstract

We investigate the role of performance feedback, in the form of a public leaderboard, in innovation competition that features sequential search activity and a range of possible innovation qualities. We find that in the subgame perfect equilibrium of contests with a fixed ending date (i.e., finite horizon), providing public performance feedback results in lower equilibrium effort and lower innovation quality. We conduct a controlled laboratory experiment to test the theoretical predictions and find that the experimental results largely support the theory. In addition, we investigate how individual characteristics affect competitive innovation activity. We find that risk aversion is a significant predictor of behavior both with and without leaderboard feedback and that the direction of this effect is consistent with the theoretical predictions.

JEL classification: *D90, O31, C90, D83*

Keywords: Innovation Competitions, Experiments, Contests

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1 Introduction

Innovation contests play an increasingly important role in research and development applications ranging from algorithmic design problems, to graphic design and marketing, to scientific breakthroughs. For example, in 2009, Netflix ran a crowd-sourcing contest, the Netflix Prize, with a $1 million reward and the objective to "substantially improve the accuracy of predictions about how much someone is going to enjoy a movie based on their movie preferences." One key feature of this contest was a real-time leaderboard that provided information regarding performance of the top submitted algorithms. Since then, leaderboards have become a common feature of crowd-sourcing contests (e.g., Kaggle.com, drivendata.org, challenge.gov). However, the extent to which leaderboards contribute to innovation quality and innovation effort is not well understood.

In this paper, we theoretically and experimentally examine sequential-search innovation competition with a public leaderboard and a fixed ending date (i.e. finite horizon) and compare it to innovation competition with private performance feedback. In each period of the innovation contest, participants have the opportunity to engage in a costly innovation search. The search yields –a priori uncertain– innovation quality. We refer to the maximum of the innovation qualities among all of the opportunities that she has developed in previous periods as the *score*. At the fixed end of the contest, the participant with the highest score wins a prize. In this context, our focus is on the effects of information disclosure in the form of a public leaderboard on effort provision and innovation quality. We provide new results on the characterization of the subgame perfect equilibrium for searched-based innovation competition with public-leaderboard feedback, and compare that to the case of private performance feedback without a leaderboard as characterized by Taylor (1995). We then use a controlled laboratory experiment to test the theoretical predictions on effort provision and innovation quality with and without public leaderboard feedback.

In our sequential-search environment, information disclosure in the form of public leaderboard feedback generates incentives that are reminiscent of the dollar auction and the penny auction.[1] The dollar auction is a dynamic ascending-price auction with public feedback of the highest standing bid (i.e. a leaderboard) and the following features: (i) the auction opens with a standing bid of zero, (ii) the standing bid may only be increased by a fixed bid increment (iii) bidding continues until no bidder is willing to increase the standing bid (by the fixed bid increment), (iv) the highest bidder wins the item up for auction, and (v) both the highest and the second highest bidders pay their bids. Escalation arises in this setting because the losing bidder would always be better off if she incrementally increased the standing bid and won the auction. Our sequential-search contest with public leaderboard feedback presents a similar opportunity for escalation. In particular, at each stage of the contest, each

[1] See, for example, Hinnosaar (2016) on the penny auction and Shubik (1971) and O'Neill (1986) on the dollar auction.

participant (i) has a sunk research cost, (ii) knows whether he or she is in the lead, and (iii) the trailing player can try to take the lead by expending an incremental search cost. We show that, in equilibrium, participants who trail in the competition provide more effort. However, we also show that, in equilibrium, both participants who are ahead and participants who are behind strategically reduce their effort as the leader's existing innovation quality increases.

The main takeaway from our theoretical analysis is that despite the potential for leaderboard feedback to escalate the competition, we find that the presence of a leaderboard generates both lower equilibrium expected effort and lower equilibrium expected innovation quality than would be achieved without the leaderboard. The results of our experiment largely confirm these theoretical predictions. In particular, the experiment consist of two main treatments of the competition with the leaderboard (*leaderboard feedback* treatment) and without the leaderboard (*private feedback* treatment). We find that the private-feedback treatment results in more effort and a higher quality of the winning innovation than the leaderboard-feedback treatment. We also experimentally confirm that current leaders tend to exert less effort than followers and that both leaders and followers become less willing to exert effort as the innovation quality increases.

Our paper contributes to several active streams of literature. First, we contribute to the literature on innovation competitions. The existing approaches include but are not limited to variations on the all-pay auctions (e.g., Che and Gale, 2003; Chawla, Hartline and Sivan, 2015), the exponential-bandit contests (e.g., Halac, Kartik and Liu, 2017; Bimpikis, Ehsani and Mostagir, 2019), two-stage difference-form contests (e.g., Aoyagi, 2010; Klein and Schmutzler, 2017; Goltsman and Mukherjee, 2011; Gershkov and Perry, 2009; Yildirim, 2005), crowdsourcing contests (e.g,. Terwiesch and Xu, 2008; DiPalantino and Vojnovic, 2009; Erat and Krishnan, 2012; Ales, Cho and Körpeoğlu, 2017), and dynamic contests (e.g., Lang, Seel and Strack, 2014; Seel and Strack, 2016). In terms of studies that focus on feedback in contests, our work is closely related to Mihm and Schlapp (2018) who examine a two-period contest with leaderboard feedback, private feedback, and no feedback. The authors show that the level of uncertainty may interact with the designer's objective (i.e., average effort or best performance) and lead to feedback being optimal for some combination(s) of uncertainty and objective. Regarding models on search-based innovation competitions, our work is most closely related to Taylor (1995), Fullerton and McAfee (1999), and Baye and Hoppe (2003). In particular, although the existing literature on search-based innovation competition has considered the case of private feedback, our study is the first (to our knowledge) to provide equilibrium predictions for dynamic contests with the leaderboard feedback in a finite-horizon setting.

Second, we contribute to the experimental literature on feedback in contests. Relevant recent experimental work shows that feedback may not always be desired include Kuhnen and Tymula (2012), Ludwig and Lünser (2012), and Deck and Kimbrough (2017). Deck and Kimbrough (2017) experimentally confirm that in Halac, Kartik and Liu (2017) setting, withholding information leads to better innovation outcomes. This result arises from the fact that the information that your opponents have not procured the zero-one innovation lowers your own belief about the probability that innovation is possible. That is, information may be discouraging and, thus, hiding information may be valuable. In the dynamic effort provision setting in which there is range of possible outcomes Kuhnen and Tymula (2012) and Ludwig and Lünser (2012) find that feedback influences the dynamics of effort provision but not total effort. Our experimental results are consistent with some of the findings on the dynamics of effort provision observed in these papers. In particular, we find that leaders tend to reduce their effort, whereas followers tend to increase their effort. It is important to note, however, that these findings are not generalizable to all contest settings. In fact, in a recent survey, Dechenaux, Kovenock and Sheremeta (2015) highlight that in some cases feedback may result in the trailing player dropping out (e.g., Fershtman and Gneezy, 2011).

Finally, our work is related to the literature on factors that motivate individuals to innovate. In particular, on the experimental side, recent studies have examined the role of incentives (Ederer and Manso, 2013), preferences (Herz, Schunk and Zehnder, 2014; Rosokha and Younge, 2017), and biases (Herz, Schunk and Zehnder, 2014). On the empirical side, two recent surveys by Astebro et al. (2014) and Koudstaal, Sloof and Van Praag (2015) highlight that entrepreneurs are typically less risk and loss averse. In the current paper, we consider the extent to which risk aversion, loss aversion, and sunk-cost fallacy play a role in a search-based innovation competition.[2] Specifically, as part of our experiment, we elicited those three measures with incentivized multiple-price list tasks. In addition, we asked subjects to complete several unincentivized personality questionnaires. We find that risk aversion is a significant predictor of the number of costly innovation actions in the contest, with more risk-averse subjects taking fewer actions. However, we did not find that loss aversion, sunk-cost fallacy, or unincentivized measures of personality were predictive of subjects' behavior in the contest.

The rest of the paper is organized as follows: in section 2, we present the theoretical model. In section 3, we provide details of the experimental design. In section 4, we develop predictions for our environment and organize them into four hypotheses. In section 5, we present main results of the experiment. Finally, in section 6, we conclude.

[2]We focus on risk aversion and loss aversion as characteristics that have been documented to matter in the lab (e.g., Herz, Schunk and Zehnder, 2014; Rosokha and Younge, 2017) and field (Astebro et al., 2014; Koudstaal, Sloof and Van Praag, 2015) settings. In addition, we consider the sunk-cost fallacy because it has been shown to affect behavior in a related setting of penny auctions (Augenblick, 2015). Penny auctions are auctions in which agents pay to bid and the value of the item decreases after each bid. Augenblick (2015) shows theoretically how the sunk cost fallacy can lead to auctioneers making profit and finds empirical support for the sunk-cost fallacy in online penny auction data. Although our environment shares elements similar to the penny auction, we do not find evidence of the sunk-cost fallacy.

2 Theory

Consider a two-player T-period dynamic innovation contest, along the lines of Taylor (1995). In this model, innovation activity takes the form of a search process with perfect recall. In each period $t \in \{1, \ldots, T\}$, each player $i \in \{1, 2\}$ has the opportunity to exert effort at a cost of $c > 0$. If player i exerts effort, she obtains an innovation, with quality level $s_{i,t}$, a random variable that is distributed according to F, where F has a continuous and strictly positive density everywhere on its support, which is assumed to be a convex subset of $\mathbb{R}_+$ with a lower bound of 0.[3] In the event that player i does not exert effort in period t, let $s_{i,t} = 0$. Player i's innovation "score" at the end of period t is denoted by $\overline{s}_{i,t} \equiv \max\{s_{i,1}, \ldots, s_{i,t}\}$. After T periods, the contest ends and the player with the higher innovation score at the end of period T, that is, the player i with $\overline{s}_{i,T} = \max\{\overline{s}_{1,T}, \overline{s}_{2,T}\}$, is awarded a prize with value $v \geq 2c$.[4] In the case of a tie, the winner is randomly chosen.

We examine two levels of feedback in the dynamic-innovation contest: (i) private feedback and (ii) leaderboard feedback. With the private-feedback innovation contest, at the beginning of each period t, each player i knows her current score ($\overline{s}_{i,t-1}$) and at the end of period t, player i observes her period t innovation quality $s_{i,t}$. With the leaderboard-feedback innovation contest, at the beginning of each period t, each player i knows, in addition to her own private feedback, the current max score,[5] $\max\{\overline{s}_{1,t-1}, \overline{s}_{2,t-1}\}$. In the following subsection, we characterize the subgame perfect equilibrium for the public-feedback innovation contest.

Throughout the rest of the paper, we use the convention, due to Taylor (1995), of referring to each draw of an innovation quality $s_{i,t}$ as a new innovation. Note, however, that an equivalent interpretation is that player i is working on one specific innovation and that each draw of an innovation quality $s_{i,t}$ is in regards to searching over quality improvements to that particular innovation. Depending on the application, this second interpretation may be more natural.

2.1 Subgame Perfect Equilibrium in Innovation Contests

Private Feedback

The subgame perfect equilibrium for the private-feedback innovation contest is characterized by Taylor (1995). In particular, Proposition 2 of that paper establishes that the unique subgame perfect equilibrium takes the form of a stopping rule in which each player i continues

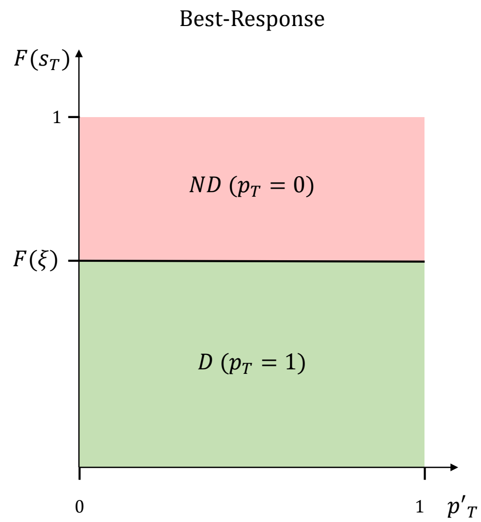
[3] In the experiment, we assume that innovations are exponentially distributed ($F(x; \lambda) = 1 - e^{-\lambda x}$ and $f(x; \lambda) = \lambda e^{-\lambda x}$, where $\lambda > 0$ is the rate parameter).

[4] Our analysis can be extended to the case of $v \in [c, 2c)$, but for the sake of brevity, we focus here on the case in which $v \geq 2c$.

[5] Note that the game in which, at the beginning of each period, each player observes both of the players' current scores is theoretically equivalent to the game in which, at the beginning of each period, each player observes her own score and the maximum of the players' scores.

to exert effort until her max score hits a threshold – denoted by ξ_i – and she stops exerting effort.

Figure 1: Period T Local Best Response for Private Feedback



Notes: s_T – own score in period T; $F(.)$ – distribution of innovation quality; p'_T – probability that the other player draws in period T; $ND(p_T = 0)$ – decision not to draw; $D(p_T = 1)$ – decision to draw; ξ – threshold determined by equation (1).

The equilibrium value of the threshold ξ_i is determined by the equation

$$v \int_{\xi_i}^{\infty} (1 - F^T(\xi_i)) \frac{F(x) - F(\xi_i)}{1 - F(\xi_i)} dF(x) - c = 0. \tag{1}$$

For example, in our experiment, we assume that when a player exerts effort in a given period the quality of the innovation in that period is a random variable that is distributed according to $F(x; \lambda) = 1 - e^{-\lambda x}$ with $\lambda = 0.125$, which implies that for $T = 10$, the unique subgame perfect equilibrium stopping rule has a threshold of $\xi = 12.16$.

Leaderboard Feedback

In Appendix A, we characterize the SPNE in the leaderboard-feedback innovation contest for the case of a general utility function that may allow for risk aversion, loss aversion, and sunk-cost fallacy considerations to be modeled. For simplicity, we focus, here, on the case of risk neutral players. Let f_t (l_t) denote the follower (leader) in an arbitrary period t. We begin by characterizing the final-stage local equilibrium strategies and corresponding equilibrium expected payoffs, and then make our way back through the game tree. In the final period T, if the max score at the beginning of period T is s_T, then we have the following matrix game:

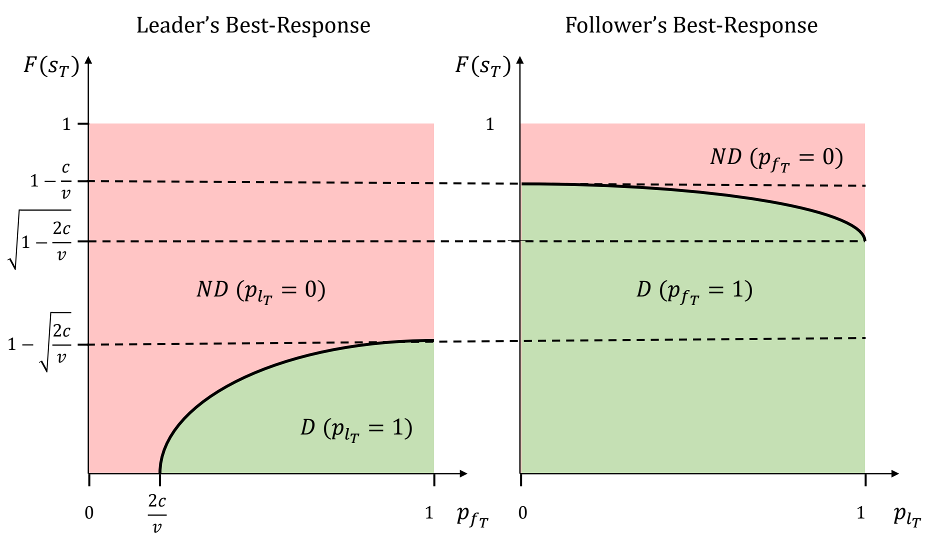
Table 1: Period T Local Subgame

		f_T (follower) D	ND
l_T (leader)	D	$\frac{v(1+F(s_T)^2)}{2} - c$, $\frac{v(1-F(s_T)^2)}{2} - c$	$v - c$, 0
	ND	$vF(s_T)$, $v(1 - F(s_T)) - c$	v, 0

From Table 1, we see that the period T follower's (f_T's) final-stage local expected payoff from choosing to draw (D) when the period T leader (l_T) chooses not to draw (ND) is $v(1 - F(s_T)) - c$. Similarly, f_T's expected payoff from choosing D when l_T chooses D is $vF(s_T)(1 - F(s_T)) + \frac{v(1-F(s_T))^2}{2} - c = \frac{v(1-F(s_T)^2)}{2} - c$. Regardless of l_T's period T action, the payoff to f_T from choosing ND in period T is 0. The expected payoffs for the period T leader (l_T) follow along similar lines.

To calculate the final-stage local equilibrium, let p_{l_T} (p_{f_T}) denote the probability that the period T leader l_T (period T follower f_T) draws in period T. Figure 2 presents the players' best-response correspondences as a function of the leader's max score at the beginning of period-T, s_T, and of the probability that the opponent draws in period T and receives a stochastic period-T innovation quality distributed according to $F(\cdot)$.

Figure 2: Period T Local Best Responses for Leaderboard Feedback



Notes: s_T – score in period T; $F(.)$ – distribution of innovation quality; p_{f_T} – probability that follower draws in period T; p_{l_T} – probability that the leader draws in period T; $ND(p_{i_T} = 0)$ – decision not to draw by player $i \in \{leader, follower\}$; $D(p_{i_T} = 1)$ – decision to draw by player $i \in \{leader, follower\}$;

Proposition 1 characterizes the final-stage local equilibrium strategies and expected payoffs that follow directly from the best-response correspondences given in Figure 2. In particular, if $1-\sqrt{\frac{2c}{v}} \geq F(s_T)$ and $p_{f_t}=1$ then we see from the Leader's Best-Response panel of Figure 2 that the leader's best response is $D(p_{l_T}=1)$. Similarly, if $1-\sqrt{\frac{2c}{v}} \geq F(s_T)$ then we see from the Follower's Best-Response panel of Figure 2 that for any value of $p_{f_t} \in [0,1]$ the follower's best response is $D(p_{f_T}=1)$. The remaining cases of values of $F(s_T)$ follow along similar lines.

Proposition 1. *The final-stage local equilibrium strategies are characterized as follows:*

$$\begin{cases} \text{Both draw} & \text{if } 1-\sqrt{\frac{2c}{v}} \geq F(s_T) \\ \text{only follower draws} & \text{if } 1-\frac{c}{v} \geq F(s_T) > 1-\sqrt{\frac{2c}{v}} \\ \text{neither draws} & \text{if } F(s_T) > 1-\frac{c}{v} \end{cases}.$$

The corresponding final-stage local equilibrium expected payoffs for the leader and follower are given in Figure 1.

To calculate the subgame perfect equilibrium strategies, we may take the Proposition 1 final-stage local expected payoffs and work back through the game tree to stage $T-1$. The only (computational) issue in continuing the backward induction process all the way to the root of the game in stage 1 is the calculation of the expected continuation payoffs in the period t local subgame. We provide details on these calculations in Appendix A.

3 Experimental Design

In this section, we describe the experimental design and provide predictions for our experiment using the theory developed above. In particular, the primary goal of the experiment is to address the role of feedback in sequential-search innovation competition. To this end, the main part of our experiment consists of two within-subject treatments: (i) a public feedback treatment and (ii) a leaderboard feedback treatment. In addition to the primary goal, our aim is to better understand factors that may influence individuals to innovate. To this end, our design includes an individual search task that removes the strategic aspect present in the two competitions and the elicitation of individual (e.g., risk aversion) and personality (e.g., grit) characteristics that may be important in an innovation setting. Next, we elaborate on details of the design and our implementation of the experiment.

3.1 Private-Feedback and Leaderboard-Feedback Contests

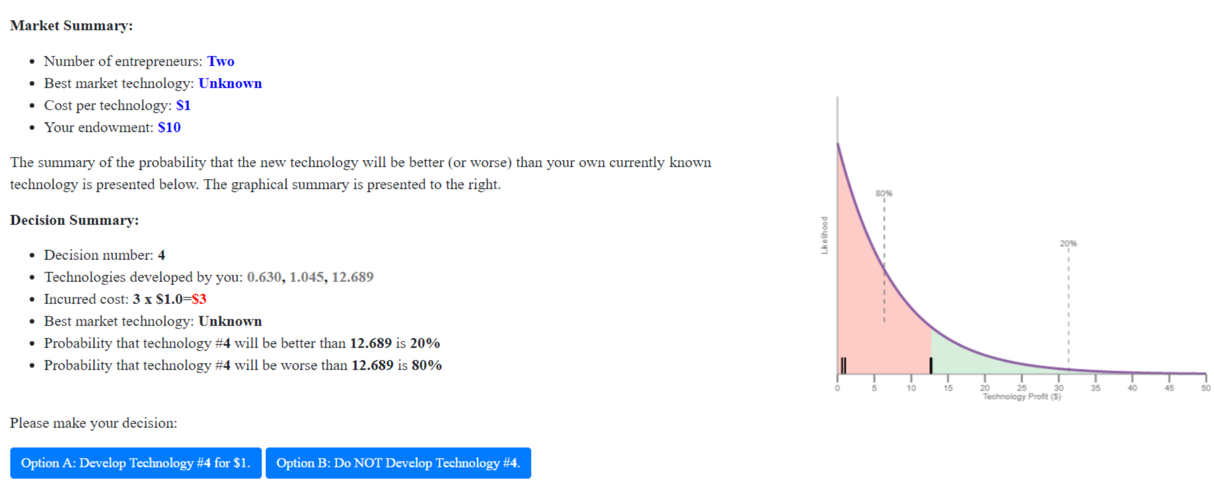
At the beginning of the experiment, each subject individually reads instructions that are displayed on their computer screen. In particular, we implemented a within-subject design, whereby each subject starts the experiment with either eight private-feedback contests or eight leaderboard-feedback contests and then switches to the other feedback type for contests 9 through 16. Thus, before contests 1 and 9, subjects are provided with detailed instructions and practice tasks that explain the setting of the upcoming eight contests. During the practice tasks, subjects were matched with a computer that made decisions randomly, and subjects were informed about the random behavior of the opponent in the practice task. A copy of the instructions used in the experiment and the practice tasks is provided in Appendix C.

Each contest consists of two subjects matched for 10 periods of decision-making. Prior to the first period, each subject is given an endowment of \$10.00. Within each period, subjects have the opportunity to pay a cost $c = \$1.00$ to draw an innovation quality from an exponential distribution with parameter $\lambda = 0.125$. At the end of 10 periods, the contest ends and the subject with the highest-quality innovation (the highest score) wins the prize of $v = \$10.00$. Each subject keeps any money left over from her endowment. These parameters were chosen to simplify the environment and were the same for the private and leaderboard treatments as well as for the individual search task described in section 3.2.

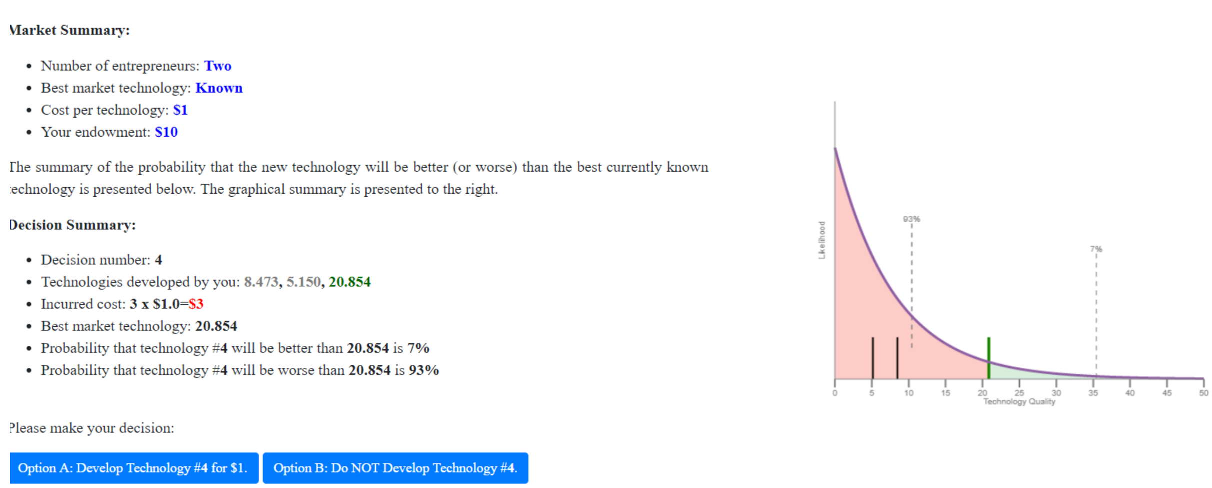
The first treatment is a two-player pravate-feedback contest in which each subject only receives feedback on their own innovations. Specifically, in each period, subjects decide whether to innovate. Although subjects know the quality of their own innovation, they do not know whether they are winning or losing until all decision periods are over. That is, the winning innovation is revealed only at the end of the contest. A screenshot of the private-feedback treatment is presented in Figure 3(a). In particular, during each period, each subject has access to the number of times she has drawn, the quality of each of the past innovations she has drawn, and her current innovation score (her innovation with the highest quality). To simplify decision-making, subjects are told the probability that an additional draw will result in a higher individual innovation score. At the end of the contest, subjects are informed of the winner of the contest and the amount of money they have earned for the contest.

The second treatment is a two-player leaderboard-feedback contest in which each subject receives feedback on hew own innovation as well as the innovation that is currently leading the contest. Specifically, similar to the private-feedback contest, in each period of the leaderboard-feedback contest, subjects decide whether to innovate; however, the contest's best innovation is now revealed at the start of each period. Thus, each participant knows whether she is a leader or a follower. A screenshot of the leaderboard-feedback treatment is presented in Figure 3(b). Although most aspects of the leaderboard-feedback treatment are the same as in the private-feedback treatment, subjects receive additional feedback regarding the current highest score in the contest. That is, subjects always know whether they are currently winning or losing the contest and the probability that their next draw will result in their score being higher than the current maximum score.[6]

Figure 3: Screenshots of the Experimental Interface



(a) Private Feedback



(b) Leaderboard Feedback

3.2 Individual Tasks and Questionnaires

After completing both treatments, subjects were presented with several individual tasks. In particular, subjects completed three elicitation tasks: (i) a risk-aversion task, (ii) a loss-aversion task, and (iii) a sunk-cost-fallacy task. In each of these three tasks, subjects chose one of two options for each of the 20 decisions. The decisions were organized into a multiple

[6]Subjects are no longer shown the probability that an additional draw will result in a higher individual innovation score.

price list as is common in the literature (e.g., Holt and Laury, 2002; Rubin, Samek and Sheremeta, 2018). In particular, the first task was the risk-aversion task. In this task each participant chose between a risky option (50% chance of \$10.00 and a 50% percent chance of \$0.00) and a safe option that was varied across decisions (started at \$0.50 and increased by \$0.50 in each subsequent decision). The second task was the loss-aversion task. In this task each participant chose between a safe option of \$0.00 and a risky option had a 50% chance at \$0.00 and a 50% chance of a loss (varied from −\$0.50 to −\$10.00 in increments of \$0.50). The third elicitation task was the sunk-cost-fallacy task. In this task, subjects were given an endowment of \$15.00 and were required to pay \$5.00 to initiate a project. Each subject then decided whether to complete the project at various completion costs. Completing the project was always worth \$7.50; however, the cost varied between decisions. The completion cost started at \$0.50 and increased by \$0.50 in each subsequent decision. The sunk-cost fallacy occurs if the subject completes the project at a cost greater than \$7.50. Screenshots of the three individual elicitation tasks are presented in Figures D1-D3 in the Appendix.

In addition to the above elicitation tasks, each subject participated in eight individual search tasks. The individual search tasks were similar to the two contests except that the human opponent was replaced with an existing innovation of a known quality. In particular, the existing innovation took on five values: 15.177, 16.832, 18.421, 20.205, and 23.966.[7] Each subject saw all five values and the values 15.177, 18.421, and 23.966 were repeated twice. The five values were displayed in random order. If the subject ends the period with an innovation of greater quality than the existing innovation, she won \$10.00. Thus, these tasks allow us to analyze individual behavior in a similar environment but without competition against another human subject. A screenshot of the individual search task is presented in Figure D4 in the Appendix.

The experiment concluded with three unincentivized personality questionnaires. In particular, the first questionnaire measured the psychological construct of grit through the 12-item Grit Scale (Duckworth et al., 2007). The second questionnaire measured the big five characteristics (agreeableness, extraversion, neuroticism, openness, and conscientiousness) through the 44-item big-five inventory (John and Srivastava, 1999). The third questionnaire measured achievement-striving and competitiveness through the 10- and 6-item scales obtained from the International Personality Item Pool.[8]

3.3 Experimental Administration

All parts of the experiment, including instructions, innovation contests, individual elicitation tasks, and personality questionnaires, were implemented in oTree (Chen, Schonger and

[7] These values correspond to 85, 88, 90, 92, and 95 percentiles of the exponential distribution, respectively. In particular, the risk-neutral agent would be indifferent between drawing and not drawing if the existing innovation was 18.421.

[8] https://ipip.ori.org/

Wickens, 2016). In total, subjects participated in 27 compensation-relevant tasks. Specifically, the compensation-relevant tasks included the eight private-feedback contests, the eight leaderboard-feedback contests, the risk-aversion elicitation task, the loss-aversion elicitation task, the sunk-cost-elicitation task, and the eight individual search tasks. At the end of the experiment, two of these 27 tasks were chosen at random by the computer for payment.

In total, 96 students were recruited on the campus of Purdue University using ORSEE software (Greiner, 2015). Participants were split into 12 sessions, with eight participants per session. As mentioned above, to ensure that the order of treatments did not affect the main results, half of the sessions started out with eight private-feedback contests, while the other half of the sessions started out with eight leaderboard-feedback contests. The experimental lasted under 60 minutes, with average earnings of $19.91.

4 Predictions

In this section, we present predictions for the experiment that were obtained by computationally solving for the sequential equilibrium described in section 2. In particular, using the model, 1 million contests were simulated and the resulting predictions were organized into four hypotheses: the first hypothesis pertains to the comparison of the private- and leaderboard-feedback contests; the second hypothesis pertains to the comparison of leader and follower behavior; the third hypothesis pertains to the dynamics of the draws in the two contests; and the fourth hypothesis pertains to the role of individual characteristics such as risk aversion, loss aversion, and the sunk-cost fallacy.[9]

[9] One million contests were simulated for each value of each bias parameter.

Table 2: Summary of Predictions

	Private Feedback	Leaderboard Feedback
Winning Innovation	23.42	21.84
Aggregate Draws	8.36	6.34
Proportion of Draws		
Leader		
Known Score 0–15	0.67/0.30/0.03	0.59/0.04/0.00
Known Score 15–25	0.11/0.02/0.00	0.00/0.00/0.00
Follower		
Known Score 0–15	0.90/0.62/0.37	0.59/0.55/1.00
Known Score 15–25	0.58/0.19/0.08	0.14/0.38/0.32

Notes: Aggregate draws refers to the predicted number of draws that occurs in a contest in each treatment. Winning innovation refers to the predicted quality of the winning innovation in each treatment. Known score refers to the individual score in the private-feedback treatment and the maximum score in the leaderboard-feedback treatment. The third row displays the draw rate of the leader and the follower in periods 2, 6, and 10 of the experiment. The fourth row displays the draw rate in periods 2, 6, and 10 of the experiment for known scores in the 20th-80th percentiles for that period. The fifth row displays the difference in draw rates for known scores in the lower half and the upper half of the known score distribution for periods 2, 6, and 10.

The top part of Table 2 shows that a contest with private feedback is predicted to induce more draws (8.36) and result in a greater winning innovation score (23.42) than a contest with leaderboard feedback (6.34 draws; winning innovation of 21.84). We summarize this prediction with Hypothesis 1.

Hypothesis 1. *The private-feedback contest leads to more draws and a higher winning innovation than the leaderboard-feedback contest.*

The bottom part of Table 2 presents the proportion of draws broken down by the period of the contest (presented as a triple of 2nd/6th/10th period), the current score (grouped into ranges 0–15 and 15–25), and whether the player was a leader or a follower.[10] By comparing the proportion of draws between leaders and followers, the follower is clearly predicted to be at least as likely to draw as the leader across most of the ranges of innovation scores and periods.[11] We summarize this prediction with Hypothesis 2.

Hypothesis 2. *Followers draw more frequently than leaders.*

The bottom part of Table 2 also provides an insight regarding the dynamics of decision-making. In the private-feedback treatment, as the individual innovation score increases,

[10]Figures D6 and D7 in Appendix D present further evidence on the proportion of draws obtained from our computational model using simulations.

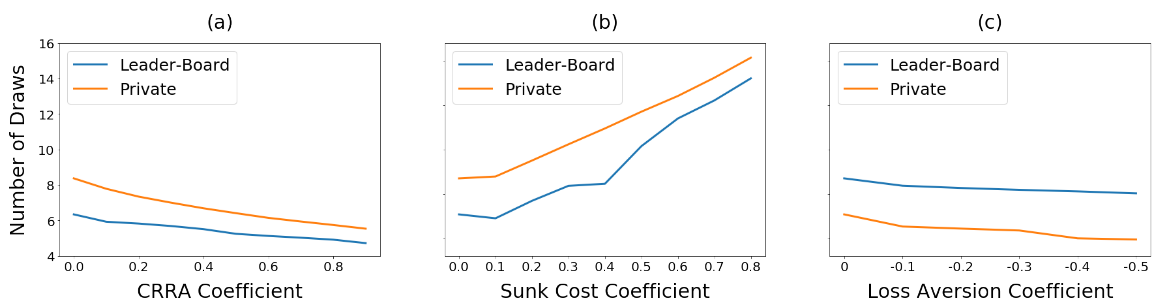
[11]Overall, leaders draw 8.73% of the time in the simulated contests and followers draw 39.20% of the time in the simulated contests.

each player becomes less willing to draw. This can be seen by comparing the proportion of draws between relatively low individual scores (0–15) and relatively high individual scores (15–25) for both leaders and followers. Additionally, in the leaderboard-feedback treatment, as the maximum score increases, each player becomes less willing to draw. This can be seen by comparing the proportion of draws between relatively low maximum scores (0–15) and relatively high maximum scores (15–25) for both leaders and followers. We summarize this prediction with Hypothesis 3.

Hypothesis 3. *Players become less willing to draw as their individual score increases in the private-feedback treatment and as the maximum score increases in the leaderboard-feedback treatment.*

Lastly, we incorporate three behavioral characteristics: risk aversion, loss aversion, and the sunk-cost fallacy.[12] The three panels of Figure 4 present the comparative statics as we vary these characteristics one at a time. For example, to vary risk aversion, we model both players as having a CRRA utility function with parameter γ, and we vary this parameter across a range of values typically observed in the experimental literature.

Figure 4: Decision to Draw and Comparative Statics



Notes: This figure displays equilibrium predictions under different levels of (a) risk aversion, (b) sunk cost fallacy, and (c) loss aversion. The orange line is the private-feedback treatment, while the blue line is the leaderboard-feedback treatment.

Figure 4 shows that as risk aversion and loss aversion increase, the number of total draws made in the contest decreases. The sunk-cost fallacy, however, has an opposite effect. In particular, as the sunk-cost fallacy increases, we observe more total draws. We summarize these predictions with Hypothesis 4.

Hypothesis 4. *The number of draws increases with (a) a decrease in risk aversion, (b) a decrease in loss aversion, (c) an increase in sunk-cost fallacy.*

[12]Specifications of the three utility functions as well as the general procedure for obtaining predictions are provided in Appendix B.

5 Results

In this section, we present the results of our experiment. In particular, first, in section 5.1 we compare the outcomes of the private and leaderboard treatments. Next, in section 5.2, we test for differences in behavior between the leader and the follower. Then, in section 5.3 we consider the dynamics observed in the experimental data. Finally, in section 5.4, we discuss the role of individual characteristics in determining innovation-contest outcomes.

5.1 Private vs Leaderboard Contests

The columns of Table 3 display the summary statistics from the two treatments. In particular, the table is divided down into two parts. In the top part, we present the aggregate results on the final innovation quality and the total number of draws that we observed in each of the treatments, on average. In the bottom part, we present the results on the proportion of draws conditional on the period in the game (periods 2, 6, and 10 are separated by "/"), current score (we group scores into two ranges 0–15 and 15–25), and whether the decision-maker was a leader or a follower.[13]

Table 3: Contest Results

	Private Feedback	Leaderboard Feedback
Winning Innovation	22.87	21.47
Aggregate Draws	8.50	7.54
Proportion of Draws		
Leader		
Known Score 0–15	0.59/0.60/0.33	0.37/0.36/0.20
Known Score 15–25	0.16/0.16/0.11	0.08/0.08/0.07
Follower		
Known Score 0–15	0.61/0.64/0.40	0.60/0.59/0.63
Known Score 15–25	0.45/0.41/0.38	0.49/0.50/0.49

Notes: Aggregate draws refers to the predicted number of draws that occurs in a contest in each treatment. Winning innovation refers to the predicted quality of the winning innovation in each treatment. The third row displays the draw rate of the leader and the follower in periods 2, 6, and 10 of the experiment. The fourth row displays the draw rate in periods 2, 6, and 10 of the experiment for scores that range in the 20th-80th percentile for that period. The fifth row displays the difference in draw rates for scores in the lower half and the upper half of the score distribution for periods 2, 6, and 10. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The top part of Table 3 shows the average number of contest draws and the average value of the winning innovation in each treatment. In particular, in the private-feedback treatment,

[13]Recall that while the role of leader/follower is known to the decision-making in the leaderboard treatment, it is not known to the decision-makers in the private feedback.

the average number of draws (8.50) and the average value of the winning innovation (22.87) are not significantly different from the theoretically predicted values (8.36 draws, p-value 0.67; score of 23.42, p-value 0.36).[14] In terms of the leaderboard feedback, we also find no difference in the value of the winning innovation between theory and the experiment (21.84 vs. 21.47, p-value 0.42). However, we do find a difference between theory and the experiment in terms of the number of draws for the leaderboard-feedback treatment (6.34 vs. 7.54, p-value 0.000).

The main focus of the aggregate results is on the comparison between private and leaderboard feedback (i.e., Hypothesis 1). Table 3 shows that in our experiment, the number of draws in the private-feedback contest (8.50) is greater than in the leaderboard-feedback contest (7.54). We test whether this difference is significant using a random-effects regression with session-level effects. We find that this difference is significant (p-value=0.000). Similarly, Table 3 shows that the winning technology is greater in a private-feedback contest (22.87) than a leaderboard-feedback contest (21.47). Again, using a random-effects regression with session-level effects, we find that this difference is significant (p-value=0.029). We summarize these tests with Result 1.

Result 1. *A private-feedback contest results in more draws and a greater winning innovation value than a leaderboard-feedback contest (evidence supporting Hypothesis 1).*

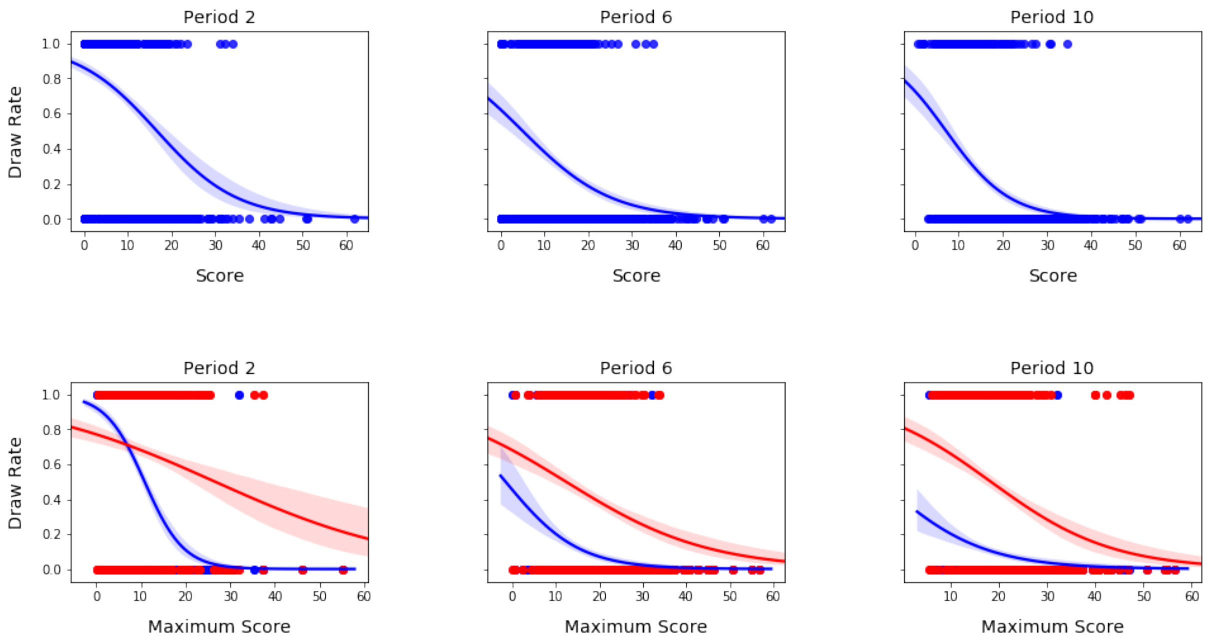
5.2 Leaders vs. Followers

The bottom part of Table 3 shows that the proportion of time that a follower draws is greater than the proportion of time that a leader draws. While the difference is observed in both the private and leaderboard treatments, the difference is much larger in the latter. Figure 5 presents further evidence regarding this comparison. Formally, each panel of the figure shows a panel data logistic regression of the decision to draw on the maximum score. The bottom row of the figure presents the comparison of of the leader's decision (blue) and the follower's decision (red). The figure clearly shows that in almost every combination of period and maximum score, followers are more likely to draw than leaders. Thus, Figure 5 suggests that Hypothesis 2 holds.[15]

[14]Hypothesis tests in this subsection are conducted using bootstrapped regressions, with 5,000 bootstrap samples, on the session-level averages.

[15]Figure B5 provide similar figures for the remaining periods.

Figure 5: Decision to Draw in the Leaderboard-Feedback Treatment



Notes: This figure displays two sets of graphs. The first set of graphs display logistic regressions of the decision to draw in the pravate-feedback treatment for periods 2, 6, and 10. The second set of graphs display logistic regressions of the leader's decision (blue) to draw and the follower's decision (red) to draw in the leaderboard-feedback treatment for periods 2, 6, and 10.

To formally test the difference between leader and follower behavior, we use a panel data logistic regression. In particular, we regress the decision to draw on an indicator variable for whether the subject was a leader, while accounting for subject-level random effects and clustering standard errors at the session level.[16] The coefficient on the leader variable is negative and significant at the 1% level. We summarize these observations with Result 2.

Result 2. *Leaders draw less frequently than followers in the leaderboard-feedback treatment (evidence supporting Hypothesis 2).*

5.3 Dynamics of Decision Making

Figure 5 suggests that subjects are less willing to draw as the individual score increases in the private-feedback treatment and as the maximum score increases in the leaderboard-feedback treatment. To formally test Hypothesis 3, we run panel data logisitic regressions, with subject-level random effects and session-level clustered standard errors, of the decision to

[16]Note that the regression is run on the observations where the score is greater than zero (and thus there is a leader and a follower).

draw on the individual score. We run these regressions for the last nine periods of the private-feedback treatment. We find that in each of the regressions, the coefficient on the individual score is negative and significant at the 1% level. Additionally, we run similar regressions for the leaderboard-feedback treatment with the difference being that the decision to draw is regressed on the maximum score. Again, for each of the regressions, the coefficient on the maximum score is negative and significant at the 1% level. We summarize these results with Result 3.

Result 3. *Subjects are less willing to draw as their individual score increases in the private-feedback treatment and as the maximum score increases in the leaderboard-feedback treatment (evidence supporting Hypothesis 3).*

5.4 Role of Individual Characteristics

In our experiment, subjects completed various elicitation tasks. We used these tasks to shed light on factors that may influence subjects' decision to draw. Table 4 displays three sets of regressions that analyze the decision to draw on the elicited characteristics.[17] In particular, the regressions are carried out using a panel data logistic regression with subject-level random effects, and standard errors are obtained by clustering at the session level.

Table 4 shows that the regression analyses yield results consistent with our prior analysis in terms of the role of the treatments and leader/follower behavior. In terms of elicited individual characteristics, we find that risk aversion has a significantly negative effect across a number of specifications. At the same time, we find that our measures of loss aversion and sunk-cost fallacy are not significant in any of the specifications. We summarize these results with Result 4.

Result 4. *Risk aversion leads to a lower likelihood of drawing an innovation (evidence supporting Hypothesis 4a).*

Recall that in addition to the incentivized elicitation of risk aversion, loss aversion, and the sunk-cost fallacy, we conducted a number of non-incentivized personality questionnaires that addressed personality characteristics. In particular, in addition to a broad questionnaire (i.e., Big 5), we selected a few characteristics as potentially important to behavior in an innovation-contest setting (i.e., Grit and Competitiveness). Table 4 shows that virtually no personality characteristics are significant in explaining drawing behavior for any of the regression specifications.[18]

[17] We relegate regressions on the individual search task to the appendix as the results are similar to the results found in Table 4.

[18] Table D1 in the Appendix provides an alternative specification of this regression in which we first carry out factor analysis to identify orthogonal factors present in the questionnaire. The regression results stay largely the same.

Table 4: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	Pooled		Private			Leaderboard	
Draw Decision		All	Leader	Follower	All	Leader	Follower
L-Board	-0.70***	—	—	—	—	—	—
	(0.20)	—	—	—	—	—	—
Priv. x Score	-0.17***	-0.21***	-0.25***	-0.18***	—	—	—
	(0.01)	(0.02)	(0.04)	(0.02)	—	—	—
L-Board x MaxScore	-0.11***	—	—	—	-0.11***	-0.23***	-0.11***
	(0.01)	—	—	—	(0.01)	(0.02)	(0.01)
Period	-0.12***	-0.13***	-0.19***	-0.11***	-0.10***	-0.24***	-0.03
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)
Risk Aversion	-1.13**	-1.41**	-1.50	-1.20**	-1.05**	-1.01	-0.31
	(0.50)	(0.72)	(1.32)	(0.56)	(0.46)	(0.87)	(1.15)
Loss Aversion	-0.22	-0.10	1.15	-0.83	-0.30	-1.12	-0.43
	(0.65)	(0.83)	(1.01)	(0.70)	(0.63)	(1.09)	(0.89)
Sunk Cost Fallacy	0.06	0.14	-1.07	0.25	-0.12	-0.55	0.02
	(0.61)	(0.94)	(0.87)	(0.96)	(0.45)	(0.87)	(0.94)
Grit	-0.15	-0.28	-0.53	-0.05	-0.02	-0.17	-0.20
	(0.24)	(0.39)	(0.47)	(0.33)	(0.16)	(0.40)	(0.47)
Competitiveness	-0.18	0.12	0.00	0.42	-0.43	-0.07	-0.27
	(0.31)	(0.43)	(0.47)	(0.42)	(0.28)	(0.38)	(0.36)
Achievement Striving	0.38	0.18	0.06	-0.18	0.57	0.66	0.08
	(0.39)	(0.54)	(0.68)	(0.49)	(0.36)	(0.46)	(0.70)
Extraversion	0.04	-0.03	0.09	-0.07	0.09	-0.21	0.13
	(0.10)	(0.13)	(0.17)	(0.11)	(0.11)	(0.23)	(0.13)
Agreeableness	0.19	0.09	0.03	0.00	0.27	0.20	0.26
	(0.22)	(0.28)	(0.35)	(0.29)	(0.22)	(0.32)	(0.33)
Neuroticism	0.06	0.07	-0.14	0.12	0.04	0.13	-0.08
	(0.13)	(0.17)	(0.22)	(0.15)	(0.13)	(0.22)	0.26
Openness	-0.18	-0.18	-0.27	-0.25	-0.23	-0.46	-0.23
	(0.17)	(0.26)	(0.33)	(0.25)	(0.15)	(0.33)	(0.26)
Conscientiousness	0.04	0.30	0.43	0.10	-0.24	-0.34	-0.41
	(0.28)	(0.49)	(0.46)	(0.45)	(0.17)	(0.60)	(0.34)
Constant	0.83	0.91	5.38**	1.03	0.58	2.62**	4.24*
	(1.44)	(2.00)	(2.46)	(1.95)	(1.26)	(1.13)	(2.46)
Observations	15,360	7,680	3,451	3,451	7,680	3,411	3,411

Notes: The regression pools the data from the individual search tasks, the private-feedback treatment, and the leaderboard-feedback treatment. *,** , and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

6 Conclusion

In this paper, we investigate the role of leaderboard feedback in sequential-search innovation competition. In particular, our contribution is threefold. First, we contribute to the existing theoretical literature by developing a model of dynamic scoring contests with a finite horizon and perfect recall. Our work is the first (to our knowledge) to formally provide an equilibrium prediction for the environment with leaderboard feedback. Specifically, we show that leaderboard feedback may result in lower effort as captured by the number of costly innovation decisions, which in turn yields worse innovation quality of the innovation competition than providing private feedback.

Second, we contribute to the experimental literature that investigates contest and innovation competitions. Our experiment yields several results that support theory. Specifically, we find that for a two-player finite-horizon contest, leaderboard feedback yields less effort and lower innovation quality than private feedback. We also find that the internal dynamics present in the data are consistent with the model. In particular, when feedback is provided, leaders of the contest reduce their effort, whereas followers do not. In addition, as the quality of innovation increases, agents become less likely to invest resources to generate a new innovation.

Finally, our work also contributes to a stream of literature that studies the role of individual characteristics in determining an individual's propensity to innovate. In particular, we elicit three individual characteristics that have been shown to be important in the innovation and contest setting: risk aversion, loss aversion, and the sunk-cost fallacy. We find that among these individual characteristics, risk aversion stands out as being an important driver of behavior in our experiment. At the same time, loss aversion and sunk cost fallacy are not significant in explaining the data. In addition, we find no evidence that personality characteristics are predictive of behavior in the dynamic contests studied in this paper.

Our work has several shortcomings that open interesting avenues for future research. First, our theoretical model and laboratory experiment investigate a finite-horizon innovation competition. Comparing it to the an infinite-horizon setting would be interesting. Second, we considered a two-player contest, the extent to which these results translate to a setting with more than two players is not known. Finally, subjects in our experiment participated in the contest (although they had an option not to draw). Investigating the extent to which our results hold if subjects could select to withdraw from the contests entirely would be interesting.

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Appendices

A SPNE for Finite-horizon Leaderboard-Feedback Innovation Contest

In this appendix, we describe the process for characterizing the subgame perfect Nash equilibria of the finite horizon leaderboard-feedback innovation contest. Recall that f_t (l_t) denotes the follower (leader) in an arbitrary period t. We begin by characterizing the final-stage local equilibrium strategies and corresponding equilibrium expected payoffs, and then make our way back through the game tree. We assume that: (i) utility is time separable and (ii) the utility $u(\cdot)$ in each period displays constant absolute risk aversion (CARA), where for convenience we set $u(x) = {}^{(1-e^{-xR})}/_{R}$ for $R > 0$ and $u(x) = x$ for $R = 0$. Although our focus in this appendix is on a utility function that displays risk aversion, it is straightforward to extend the analysis below to allow for loss aversion and sunk-cost fallacy considerations.

Period T

Let p_{l_T} [p_{f_T}] denote the probability that the period T leader l_T [period T follower f_T] draws in period T, and let $\pi_{f_T}(D, p_{l_T}|s_T)$ denote the the payoff to the period T follower f_T from drawing in period T given p_{l_T} and the score s_T. In the final period T, if the max score at the beginning of period T is s_T, then the benefit to the period T follower from drawing (i.e. $p_{f_T} = 1$) when the period T leader does not draw (i.e. $p_{l_T} = 0$) is

$$\pi_{f_T}(D, p_{l_T} = 0|s_T) = (1 - F(s_T))u(v - c) + F(s_T)u(-c). \tag{2}$$

Next, the benefit to the period T follower from drawing when the period T leader does draw is

$$\pi_{f_T}(D, p_{l_T} = 1|s_T) = \left[\frac{1 - [F(s_T)]^2}{2}\right] u(v - c) + \left[\frac{1 + [F(s_T)]^2}{2}\right] u(-c). \tag{3}$$

Thus, at the beginning of period T and given any $p_{l_T} \in [0, 1]$, we have that

$$\pi_{f_T}(D, p_{l_T}|s_T) = (1 - p_{l_T})\pi_{f_T}(D, p_{l_T} = 0|s_T) + p_{l_T}\pi_{f_T}(D, p_{l_T} = 1|s_T). \tag{4}$$

For all $p_{l_T} \in [0, 1]$, the payoff to the period T follower from not drawing in period T, denoted $\pi_{f_T}(ND, p_{l_T}|s_T)$, is 0.

For the characterization of when player f_T is indifferent between drawing and not drawing as a function of the beginning of period T leader score s_T and the leader's final-stage-local strategy p_{l_T}, it will be convenient to refer to the change in player f_T's payoff in moving from drawing to not drawing given that either $p_{l_T} = 0$ or $p_{l_T} = 1$, which we denote by

$\Delta\pi_{f_T}(p_{l_T}=0|s_T)$ and $\Delta\pi_{f_T}(p_{l_T}=1|s_T)$ respectively, where

$$\Delta\pi_{f_T}(p_{l_T}=0|s_T)=\pi_{f_T}(ND,p_{l_T}=0|s_T)-\pi_{f_T}(D,p_{l_T}=0|s_T) \tag{5}$$

and

$$\Delta\pi_{f_T}(p_{l_T}=1|s_T)=\pi_{f_T}(ND,p_{l_T}=1|s_T)-\pi_{f_T}(D,p_{l_T}=1|s_T) \tag{6}$$

If

$$\frac{\pi_{f_T}(D,p_{l_T}=0|s_T)}{\pi_{f_T}(D,p_{l_T}=0|s_T)-\pi_{f_T}(D,p_{l_T}=1|s_T)}\in[0,1]$$

then for

$$\begin{aligned} p_{l_T}^{indiff} &= \frac{\Delta\pi_{f_T}(p_{l_T}=0|s_T)}{\Delta\pi_{f_T}(p_{l_T}=0|s_T)-\Delta\pi_{f_T}(p_{l_T}=1|s_T)} \\ &= \frac{(1-F(s_T))u(v-c)+F(s_T)u(-c)}{(u(v-c)-u(-c))\,\frac{1}{2}\,(1-[F(s_T)]^2)} \end{aligned} \tag{7}$$

it follows from equation (4) that

$$\pi_{f_T}(D,p_{l_T}^{indiff}|s_T)=\pi_{f_T}(ND,p_{l_T}^{indiff}|s_T)=0$$

and the period T follower is indifferent between drawing and not drawing. Because $\Delta\pi_{f_T}(p_{l_T}=0|s_T)\leq\Delta\pi_{f_T}(p_{l_T}=1|s_T)$, it follows that if $\Delta\pi_{f_T}(p_{l_T}=0|s_T)=-\pi_{f_T}(D,p_{l_T}=0|s_T)>0$, then player f_T would have incentive to not draw for all $p_{l_T}\in[0,1]$. Similarly, if $\Delta\pi_{f_T}(p_{l_T}=1|s_T)=-\pi_{f_T}(D,p_{l_T}=1|s_T)<0$, then player f_T would have incentive to draw for all $p_{l_T}\in[0,1]$. Thus, it follows that for the term $p_{l_T}^{indiff}$ defined by equation (7) to take values in the interval $[0,1]$, it must be the case that $\Delta\pi_{f_T}(p_{l_T}=0|s_T)=-\pi_{f_T}(D,p_{l_T}=0|s_T)\leq 0$ and $\Delta\pi_{f_T}(p_{l_T}=1|s_T)=-\pi_{f_T}(D,p_{l_T}=1|s_T)\geq 0$, or equivalently, $F(s_T)\in\left[\sqrt{\frac{u(v-c)+u(-c)}{u(v-c)-u(-c)}},\frac{u(v-c)}{u(v-c)-u(-c)}\right]$.[19]

For the purpose of stating player f_T's final-stage-local best-response correspondence as a function of $(p_{l_T},s_T)\in[0,1]\times\mathrm{supp}(F)$, let

$$\Sigma_{f_T}^{indiff}=\left\{s_T\middle|\Delta\pi_{f_T}(p_{l_T}=0|s_T)\leq 0 \text{ and } \Delta\pi_{f_T}(p_{l_T}=1|s_T)\geq 0\right\}$$

denote the set of period T beginning scores s_T such that $p_{l_T}^{indiff}\in[0,1]$. Similarly, let

$$\Sigma_{f_T}^{1}=\left\{s_T\middle|\Delta\pi_{f_T}(p_{l_T}=1|s_T)<0\right\}$$

[19] Note that in the case of risk neutrality, the equation (7) expression for $p_{l_T}^{indiff}$ becomes $p_{l_T}^{indiff}=\frac{v(1-F(s_T))-c}{\frac{v}{2}(1-F(s_T))^2}$ which takes values in $[0,1]$ when $F(s_T)\in\left[\sqrt{1-\frac{2c}{v}},1-\frac{c}{v}\right]$.

and let

$$\Sigma^0_{f_T} = \left\{ s_T \middle| \Delta\pi_{f_T}(p_{l_T} = 0|s_T) > 0 \right\}$$

and note that $\Sigma^{indiff}_{f_T}$, $\Sigma^1_{f_T}$, and $\Sigma^0_{f_T}$ form a partition of supp(F). Player f_T's final-stage-local best-response correspondence is given by:

$$BR_{f_T}(p_{l_T}|s_T) = \begin{cases} p_{f_T} = 1 & \text{if } s_T \in \Sigma^1_{f_T} \\ & \text{or } s_T \in \Sigma^{indiff}_{f_T} \text{ and } p_{l_T} < p^{indiff}_{l_T} \\ & \\ p_{f_T} \in [0,1] & \text{if } s_T \in \Sigma^{indiff}_{f_T} \text{ and } p_{l_T} = p^{indiff}_{l_T} \\ & \\ p_{f_T} = 0 & \text{if } s_T \in \Sigma^0_{f_T} \\ & \text{or } s_T \in \Sigma^{indiff}_{f_T} \text{ and } p_{l_T} > p^{indiff}_{l_T} \end{cases} \tag{8}$$

Moving on to the period T leader's problem, the payoff to the period T leader from not drawing when the period T follower draws is

$$\pi_{l_T}(ND, p_{f_T} = 1|s_T) = F(s_T)u(v)$$

verses a payoff of

$$\pi_{l_T}(D, p_{f_T} = 1|s_T) = \left[\frac{1 + [F(s_T)]^2}{2}\right] u(v-c) + \left[\frac{1 - [F(s_T)]^2}{2}\right] u(-c).$$

when both the period T and the period T follower draw. Similarly, the payoff to the period T leader from not drawing when the period T follower does not draw is

$$\pi_{l_T}(ND, p_{f_T} = 0|s_T) = u(v)$$

verses a payoff of

$$\pi_{l_T}(D, p_{f_T} = 0|s_T) = u(v-c)$$

from drawing. Thus, the payoff to the period T leader from drawing in period T given any $p_{f_T} \in [0,1]$, denoted $\pi_{l_T}(D, p_{f_T}|s_T)$ is

$$\pi_{l_T}(D, p_{f_T}|s_T) = (1 - p_{f_T})\pi_{l_T}(D, p_{f_T} = 0|s_T) + p_{f_T}\pi_{l_T}(D, p_{f_T} = 1|s_T) \tag{9}$$

and the payoff to the period T leader from not drawing in period T, denoted $\pi_{l_T}(ND, p_{f_T}|s_T)$ is

$$\pi_{l_T}(ND, p_{f_T}|s_T) = (1 - p_{f_T})\pi_{l_T}(ND, p_{f_T} = 0|s_T) + p_{f_T}\pi_{l_T}(ND, p_{f_T} = 1|s_T). \tag{10}$$

To define $p_{f_T}^{indiff}$, we use the expressions $\Delta\pi_{l_T}(p_{f_T}=0|s_T)$ and $\Delta\pi_{l_T}(p_{f_T}=1|s_T)$ where

$$\Delta\pi_{l_T}(p_{f_T}=0|s_T)=\pi_{l_T}(ND,p_{f_T}=0|s_T)-\pi_{l_T}(D,p_{f_T}=0|s_T) \tag{11}$$

and

$$\Delta\pi_{l_T}(p_{f_T}=1|s_T)=\pi_{l_T}(ND,p_{f_T}=1|s_T)-\pi_{l_T}(D,p_{f_T}=1|s_T). \tag{12}$$

It follows from equations (9) and (10), that if

$$\frac{\pi_{l_T}(ND,p_{f_T}=0|s_T)-\pi_{l_T}(D,p_{f_T}=0|s_T)}{[\pi_{l_T}(ND,p_{f_T}=0|s_T)-\pi_{l_T}(D,p_{f_T}=0|s_T)]-[\pi_{l_T}(ND,p_{f_T}=1|s_T)-\pi_{l_T}(D,p_{f_T}=1|s_T)]}\in[0,1]$$

then for

$$\begin{aligned} p_{f_T}^{indiff} &= \frac{\Delta\pi_{l_T}(p_{f_T}=0|s_T)}{\Delta\pi_{l_T}(p_{f_T}=0|s_T)-\Delta\pi_{l_T}(p_{f_T}=1|s_T)} \\ &= \frac{u(v)-u(v-c)}{(1-F(s_T))u(v)-(u(v-c)-u(-c))\,\frac{1}{2}\,(1-[F(s_T)]^2)} \end{aligned} \tag{13}$$

it follows from equations (9) and (10) that

$$\pi_{l_T}(D,p_{f_T}^{indiff}|s_T)=\pi_{l_T}(ND,p_{f_T}^{indiff}|s_T)=0$$

and the period T leader is indifferent between drawing and not drawing.

Next, because $\Delta\pi_{l_T}(p_{f_T}=0|s_T)\geq\max\{0,\Delta\pi_{l_T}(p_{f_T}=1|s_T)\}$, it follows that if $\Delta\pi_{l_T}(p_{f_T}=1|s_T)>0$ then for all $p_{f,T}\in[0,1]$ player l_T would have incentive to not draw. For the term p_{f_T} defined by equation (13) to take values in the interval $(0,1)$, it must be the case that $\Delta\pi_{l_T}(p_{f_T}=1|s_T)\leq 0$.

In a manner similar to that used above for player f_T's final-stage-local best-response correspondence, we let

$$\Sigma_{l_T}^{indiff}=\left\{s_T\middle|\Delta\pi_{l_T}(p_{f_T}=1|s_T)\leq 0\right\}$$

denote the set of period T beginning scores s_T such that $p_{l_T}^{indiff}\in[0,1]$. Similarly, let

$$\Sigma_{l_T}^{0}=\left\{s_T\middle|\Delta\pi_{l_T}(p_{f_T}=1|s_T)>0\right\}$$

and note that $\Sigma_{f_T}^{indiff}$ and $\Sigma_{f_T}^{0}$ form a partition of supp(F). Then, the period T leader's final-stage local best-response correspondence as a function of $(p_{f_T},s_T)\in[0,1]\times\text{supp}(F)$

may be written as,

$$BR_{l_T}(p_{f_T}|s_T) = \begin{cases} p_{l_T} = 1 & \text{if } s_T \in \Sigma_{l_T}^{indiff} \text{ and } p_{f_T} > p_{f_T}^{indiff} \\ \\ p_{l_T} \in [0,1] & \text{if } s_T \in \Sigma_{l_T}^{indiff} \text{ and } p_{f_T} = p_{f_T}^{indiff} \\ \\ p_{l_T} = 0 & \text{if } s_T \in \Sigma_{l_T}^{0} \\ & \text{or } s_T \in \Sigma_{l_T}^{indiff} \text{ and } p_{f_T} < p_{f_T}^{indiff} \end{cases} \tag{14}$$

Combining the period T follower's final-stage-local best-response correspondence from equation (8) with the period T leader's final-stage-local best-response correspondence from equation (14), we can now solve for the subgame perfect final-stage-local equilibrium strategies.

First note that because $\Delta\pi_{f_T}(p_{l_T} = 1|s_T) \geq 0$ implies that $\Delta\pi_{l_T}(p_{f_T} = 1|s_T) \geq 0$, it follows that $\Sigma_{l_T}^{indiff} \cap \Sigma_{f_T}^{indiff} = \emptyset$ and thus, there exists no non-degenerate final-stage-local equilibrium. Futhermore, note that $\Sigma_{l_T}^{indiff} \subset \Sigma_{f_T}^{1}$ and that $\Sigma_{f_T}^{indiff} \subset \Sigma_{l_T}^{0}$. For final-stage-local pure-strategy equilibria, we have the following:

$$\begin{cases} \text{Both draw} & \text{if } s_T \in \Sigma_{l_T}^{indiff} \subset \Sigma_{f_T}^{1} \\ \text{only follower draws} & \text{if } s_T \in \Sigma_{l_T}^{0} \cap \Sigma_{f_T}^{1} \\ \text{neither draws} & \text{if } s_T \in \Sigma_{l_T}^{0} \cap \left(\Sigma_{f_T}^{0} \cup \Sigma_{f_T}^{indiff}\right) \end{cases}$$

Note that there exists an $\overline{s}_{B,T} \in [0,1]$ such that the set $\Sigma_{l_T}^{indiff} \subset \Sigma_{f_T}^{1}$ is equivalent to $[0, \overline{s}_{B,T}]$. Similarly, there exists a $\underline{s}_{N,T} \in [0,1]$ such that the set $\Sigma_{l_T}^{0} \cap \left(\Sigma_{f_T}^{0} \cup \Sigma_{f_T}^{indiff}\right)$ is equivalent to $[\underline{s}_{N,T}, 1]$. The remaining set $\Sigma_{l_T}^{0} \cap \Sigma_{f_T}^{1}$ is equivalent to $[\overline{s}_{B,T}, \underline{s}_{N,T}]$. At the points where there exist multiple equilibria (i.e. $\overline{s}_{B,T}$ and $\underline{s}_{N,T}$) we will make the simplifying assumption that the player that is indifferent between drawing and not drawing chooses to draw. That is, at $s_T = \overline{s}_{B,T}$ we focus on the final-stage-local equilibrium in which both player's draw and at $s_T = \underline{s}_{N,T}$ we focus on the final-stage-local equilibrium in which player f_T draws. Given $\overline{s}_{B,T}$ and $\underline{s}_{N,T}$, the final-stage-local equilibria may be characterized as:

$$\begin{cases} \text{Both draw} & \text{if } s_T \in [0, \overline{s}_{B,T}] \\ \text{only follower draws} & \text{if } s_T \in (\overline{s}_{B,T}, \underline{s}_{N,T}] \\ \text{neither draws} & \text{if } s_T \in (\underline{s}_{N,T}, 1] \end{cases}$$

The corresponding subgame perfect final-stage local equilibrium expected payoffs for the leader and follower, respectively, are

$$\begin{cases} \pi_{l_T}(D, p_{f_T} = 1|s_T) \ \& \ \pi_{f_T}(D, p_{l_T} = 1|s_T) & \text{if } s_T \in [0, \overline{s}_{B,T}] \\ \pi_{l_T}(ND, p_{f_T} = 1|s_T) \ \& \ \pi_{f_T}(D, p_{l_T} = 0|s_T) & \text{if } s_T \in (\overline{s}_{B,T}, \underline{s}_{N,T}] \\ \pi_{l_T}(ND, p_{f_T} = 0|s_T) \ \& \ \pi_{f_T}(ND, p_{l_T} = 0|s_T) & \text{if } s_T \in (\underline{s}_{N,T}, 1] \end{cases}$$

Periods 1 to $T-1$

In moving from period T to any period $t \in \{1, \ldots, T-1\}$, the procedure for calculating the subgame perfect period-t-local equilibrium strategies and payoffs follows along the exact same lines as in period T given the changes to the expressions $\pi_{f_t}(p_{f_t}, p_{l_t}|s_t)$ and $\pi_{l_t}(p_{l_t}, p_{f_t}|s_t)$ respectively. In particular, for each period $t \in \{1, \ldots, T-1\}$ we take the period $t+1$ continuation payoffs as given and then calculate $\pi_{f_t}(p_{f_t}, p_{l_t}|s_t)$ and $\pi_{l_t}(p_{l_t}, p_{f_t}|s_t)$. Note that in the case of $t \in \{1, \ldots, T-1\}$, there are twelve possible transitions to consider:

Outcome	in $t+1$			s_{t+1} is such that:
	State	Leader $[l_{t+1}]$	Draws $\vert s_{t+1}$	
O_1	$s_{t+1} = s_t$	l_t	Neither	$BR_{l_{t+1}}(ND\vert s_{t+1}) = ND$ & $BR_{f_{t+1}}(ND\vert s_{t+1}) = ND$
O_2	$s_{t+1} = s_t$	l_t	f_{t+1}	$BR_{l_{t+1}}(D\vert s_{t+1}) = ND$ & $BR_{f_{t+1}}(ND\vert s_{t+1}) = D$
O_3	$s_{t+1} = s_t$	l_t	l_{t+1}	$BR_{l_{t+1}}(ND\vert s_{t+1}) = D$ & $BR_{f_{t+1}}(D\vert s_{t+1}) = ND$
O_4	$s_{t+1} = s_t$	l_t	Both	$BR_{l_{t+1}}(D\vert s_{t+1}) = D$ & $BR_{f_{t+1}}(D\vert s_{t+1}) = D$
O_5	$s_{t+1} > s_t$	l_t	Neither	$BR_{l_{t+1}}(ND\vert s_{t+1}) = ND$ & $BR_{f_{t+1}}(ND\vert s_{t+1}) = ND$
O_6	$s_{t+1} > s_t$	l_t	f_{t+1}	$BR_{l_{t+1}}(D\vert s_{t+1}) = ND$ & $BR_{f_{t+1}}(ND\vert s_{t+1}) = D$
O_7	$s_{t+1} > s_t$	l_t	l_{t+1}	$BR_{l_{t+1}}(ND\vert s_{t+1}) = D$ & $BR_{f_{t+1}}(D\vert s_{t+1}) = ND$
O_8	$s_{t+1} > s_t$	l_t	Both	$BR_{l_{t+1}}(D\vert s_{t+1}) = D$ & $BR_{f_{t+1}}(D\vert s_{t+1}) = D$
O_9	$s_{t+1} > s_t$	f_t	Neither	$BR_{l_{t+1}}(ND\vert s_{t+1}) = ND$ & $BR_{f_{t+1}}(ND\vert s_{t+1}) = ND$
O_{10}	$s_{t+1} > s_t$	f_t	f_{t+1}	$BR_{l_{t+1}}(D\vert s_{t+1}) = ND$ & $BR_{f_{t+1}}(ND\vert s_{t+1}) = D$
O_{11}	$s_{t+1} > s_t$	f_t	l_{t+1}	$BR_{l_{t+1}}(ND\vert s_{t+1}) = D$ & $BR_{f_{t+1}}(D\vert s_{t+1}) = ND$
O_{12}	$s_{t+1} > s_t$	f_t	Both	$BR_{l_{t+1}}(D\vert s_{t+1}) = D$ & $BR_{f_{t+1}}(D\vert s_{t+1}) = D$

Note that although O_3, O_7 and O_{11} do not arise in equilibrium [i.e. there exists no t with a period-t-local equilibrium in which only the leader draws], we include that here as a possibility. Also observe that in states O_5-O_8 it must be the case that l_t draws and in states O_9-O_{12} it must be the case that f_t draws.

For the period-t follower we have:

$$
\begin{aligned}
\pi_{f_t}(D, p_{l_t} = 0|s_t) = \text{Prob}(O_1|s_t, D, p_{l_t} = 0)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 0|s_{t+1})|O_1\right) \\
\text{Prob}(O_2|s_t, D, p_{l_t} = 0)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 0|s_{t+1})|O_2\right) \\
+ \text{Prob}(O_3|s_t, D, p_{l_t} = 0)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 1|s_{t+1})|O_3\right) \\
+ \text{Prob}(O_4|s_t, D, p_{l_t} = 0)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 1|s_{t+1})|O_4\right) \\
+ \text{Prob}(O_9|s_t, D, p_{l_t} = 0)E\left(\pi_{l_{t+1}}(ND, p_{f_{t+1}} = 0|s_{t+1})|O_5\right) \\
\text{Prob}(O_{10}|s_t, D, p_{l_t} = 0)E\left(\pi_{l_{t+1}}(ND, p_{f_{t+1}} = 1|s_{t+1})|O_6\right) \\
+ \text{Prob}(O_{11}|s_t, D, p_{l_t} = 0)E\left(\pi_{l_{t+1}}(D, p_{f_{t+1}} = 0|s_{t+1})|O_7\right) \\
+ \text{Prob}(O_{12}|s_t, D, p_{l_t} = 0)E\left(\pi_{l_{t+1}}(D, p_{l_{t+1}} = 1|s_{t+1})|O_8\right)
\end{aligned}
\tag{15}
$$

$$
\begin{aligned}
\pi_{f_t}(D, p_{l_t} = 1|s_t) = \text{Prob}(O_1|s_t, D, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 0|s_{t+1})|O_1\right) \\
\text{Prob}(O_2|s_t, D, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 0|s_{t+1})|O_2\right) \\
+ \text{Prob}(O_3|s_t, D, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 1|s_{t+1})|O_3\right) \\
+ \text{Prob}(O_4|s_t, D, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 1|s_{t+1})|O_4\right) \\
+ \text{Prob}(O_5|s_t, D, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 0|s_{t+1})|O_5\right) \\
\text{Prob}(O_6|s_t, D, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 0|s_{t+1})|O_6\right) \\
+ \text{Prob}(O_7|s_t, D, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 1|s_{t+1})|O_7\right) \\
+ \text{Prob}(O_8|s_t, D, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 1|s_{t+1})|O_8\right) \\
+ \text{Prob}(O_9|s_t, D, p_{l_t} = 1)E\left(\pi_{l_{t+1}}(ND, p_{f_{t+1}} = 0|s_{t+1})|O_5\right) \\
\text{Prob}(O_{10}|s_t, D, p_{l_t} = 1)E\left(\pi_{l_{t+1}}(ND, p_{f_{t+1}} = 1|s_{t+1})|O_6\right) \\
+ \text{Prob}(O_{11}|s_t, D, p_{l_t} = 1)E\left(\pi_{l_{t+1}}(D, p_{f_{t+1}} = 0|s_{t+1})|O_7\right) \\
+ \text{Prob}(O_{12}|s_t, D, p_{l_t} = 1)E\left(\pi_{l_{t+1}}(D, p_{l_{t+1}} = 1|s_{t+1})|O_8\right)
\end{aligned}
\tag{16}
$$

$$
\begin{aligned}
\pi_{f_t}(ND, p_{l_t} = 0|s_t) = \text{Prob}(O_1|s_t, ND, p_{l_t} = 0)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 0|s_{t+1})|O_1\right) \\
\text{Prob}(O_2|s_t, ND, p_{l_t} = 0)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 0|s_{t+1})|O_2\right) \\
+ \text{Prob}(O_3|s_t, ND, p_{l_t} = 0)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 1|s_{t+1})|O_3\right) \\
+ \text{Prob}(O_4|s_t, ND, p_{l_t} = 0)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 1|s_{t+1})|O_4\right)
\end{aligned} \tag{17}
$$

$$
\begin{aligned}
\pi_{f_t}(ND, p_{l_t} = 1|s_t) = \text{Prob}(O_1|s_t, ND, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 0|s_{t+1})|O_1\right) \\
\text{Prob}(O_2|s_t, ND, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 0|s_{t+1})|O_2\right) \\
+ \text{Prob}(O_3|s_t, ND, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 1|s_{t+1})|O_3\right) \\
+ \text{Prob}(O_4|s_t, ND, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 1|s_{t+1})|O_4\right) \\
+ \text{Prob}(O_5|s_t, ND, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 0|s_{t+1})|O_5\right) \\
\text{Prob}(O_6|s_t, ND, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 0|s_{t+1})|O_6\right) \\
+ \text{Prob}(O_7|s_t, ND, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(ND, p_{l_{t+1}} = 1|s_{t+1})|O_7\right) \\
+ \text{Prob}(O_8|s_t, ND, p_{l_t} = 1)E\left(\pi_{f_{t+1}}(D, p_{l_{t+1}} = 1|s_{t+1})|O_8\right)
\end{aligned} \tag{18}
$$

Given the expressions in equations (15)-(18) for the period-t follower and the corresponding calculations for the period-t leader, the period-t-local equilibrium can be calculated by: (i) forming the period-t version of the 'Δ' expressions in equations (5), (6), (11), and (12), (ii) using the period-t version of the 'Δ' expressions to form the period t indifference conditions (7) and (13) and construct each player's period-t-local best-response correspondences as in equations (14) and (8), and (iii), using the player's period-t-local best-response correspondences characterize the period-t-local equilibrium.

As an example, consider the case of $t = T - 1$. Recall the characterization of the final-stage-local pure-strategy equilibrium:

$$
\begin{cases}
\text{Both draw} & \text{if } s_T \in [0, \overline{s}_{B,T}] \\
\text{only follower draws} & \text{if } s_T \in (\overline{s}_{B,T}, \underline{s}_{N,T}] \\
\text{neither draws} & \text{if } s_T \in (\underline{s}_{N,T}, 1]
\end{cases}
$$

Note that in period $T - 1$, we know that there exists no period T equilibrium in which only l_T draws. Thus, there is no possible transition from state $T - 1$ to state T in the form of outcomes O_3, O_7, and O_{11}.

If the max score at the beginning of period $T-1$ is s_{T-1}, then the probabilities $\text{Prob}(O_j|\cdot)$, for $j = 1, \ldots, 12$ in equation (15) are given by:

$$\text{Prob}(O_1|s_{T-1}, D, p_{l_{T-1}} = 0) = \begin{cases} F(s_{T-1}) & \text{if } s_{T-1} \in (\underline{s}_{N,T}, 1] \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Prob}(O_2|s_{T-1}, D, p_{l_{T-1}} = 0) = \begin{cases} F(s_{T-1}) & \text{if } s_{T-1} \in (\overline{s}_{B,T}, \underline{s}_{N,T}] \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Prob}(O_3|s_{T-1}, D, p_{l_{T-1}} = 0) = 0$$

$$\text{Prob}(O_4|s_{T-1}, D, p_{l_{T-1}} = 0) = \begin{cases} F(s_{T-1}) & \text{if } s_{T-1} \in [0, \overline{s}_{B,T}] \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Prob}(O_9|s_{T-1}, D, p_{l_{T-1}} = 0) = \begin{cases} 1 - F(\underline{s}_{N,T}) & \text{if } s_{T-1} \in [0, \underline{s}_{N,T}] \\ 1 - F(s_{T-1}) & \text{if } s_{T-1} \in (\underline{s}_{N,T}, 1] \end{cases}$$

$$\text{Prob}(O_{10}|s_{T-1}, D, p_{l_{T-1}} = 0) = \begin{cases} F(\underline{s}_{N,T}) - F(\overline{s}_{B,T}) & \text{if } s_{T-1} \in [0, \overline{s}_{B,T}] \\ F(\underline{s}_{N,T}) - F(s_{T-1}) & \text{if } s_{T-1} \in (\overline{s}_{B,T}, \underline{s}_{N,T}] \\ 0 & \text{if } s_{T-1} \in (\underline{s}_{N,T}, 1] \end{cases}$$

$$\text{Prob}(O_{11}|s_{T-1}, D, p_{l_{T-1}} = 0) = 0$$

$$\text{Prob}(O_{12}|s_{T-1}, D, p_{l_{T-1}} = 0) = \begin{cases} F(\overline{s}_{B,T}) - F(s_{T-1}) & \text{if } s_{T-1} \in [0, \overline{s}_{B,T}] \\ 0 & \text{if } s_{T-1} \in (\overline{s}_{B,T}, 1] \end{cases}$$

The corresponding probabilities for equations (16)-(18) follow directly. This completes the description of the process for characterizing the subgame perfect Nash equilibria of the finite horizon leaderboard-feedback innovation contest.

B Incorporating Behavioral Characteristics

We obtain predictions for risk aversion, loss aversion, and the sunk cost fallacy using the following procedure:

- First, for a maximum score in the leader-board feedback treatment and an individual score in the private feedback treatment, we calculate the expected utility from drawing or not drawing in the last period. At this stage, we incorporate the relevant behavioral characteristic (risk aversion, loss aversion, sunk cost fallacy) into that calculation and repeat this process for various scores in each treatment.

- We then calculate the expected utility, and the optimal decisions, in the penultimate period for the same scores. We calculate the expected utility of drawing and not drawing in the penultimate period through backward induction as we have solved for the last period.
- We continue this process using backward induction. Once we have solved for the optimal decisions for each score and period, we use simulations to make contest predictions.

We use the following specifications:

- **Risk aversion** is modeled using CRRA utility, that is, $u(x) = \frac{x^{1-r}}{1-r}$.
- **Loss aversion** is modeled as an individual being reference dependent around losses. Let TC be the total cost an agent has spent in the contest and E be the agent's endowment. When an individual loses the contest, her utility is given by $E - \lambda * TC$, where $\lambda > 1$. Note that an individual can never lose money when she wins the prize in our experiment. When an individual wins the contest, her utility is given by $E + V - TC$, where V is the prize value.
- The **sunk cost fallacy** is modeled as an individual having a preference for drawing when she has accumulated sunk costs in the contest. An individual's expected utility in the last period from drawing is given by $E - TC + \alpha * TC + p(V) * V$, where $\alpha > 0$ and $p(V)$ is the probability that she wins the contest.

Figure B1: Effect of Risk Aversion on Period T Local Best Responses for Leaderboard Feedback

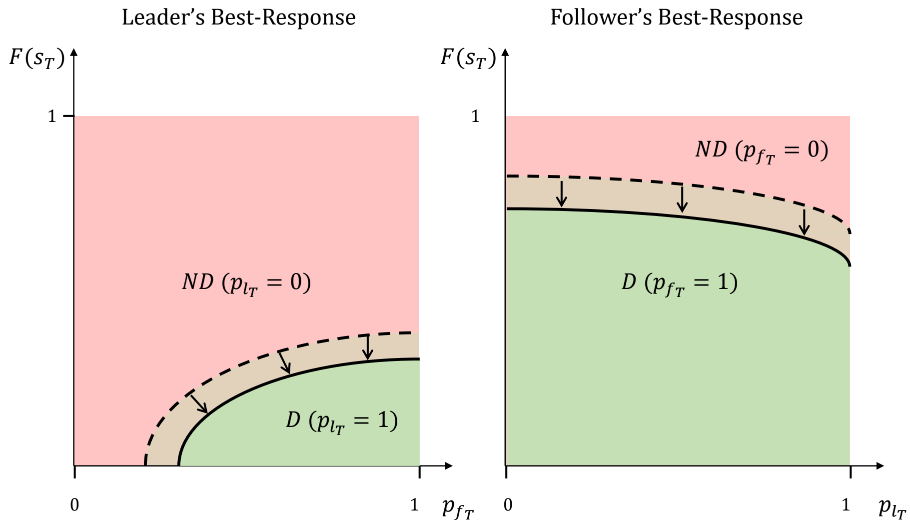
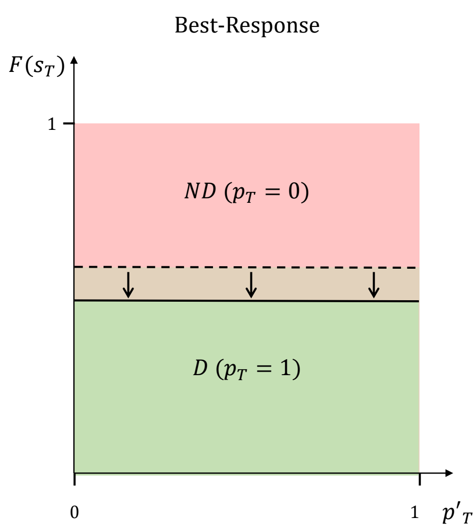


Figure B2: Effect of Risk Aversion on Period T Local Best Responses for Private Feedback



C Experimental Instructions

C.1 Introduction

Welcome and thank you for participating! Today's experiment will last about 60 minutes. Everyone will earn at least \$5. If you follow the instructions carefully, you might earn even more money. This money will be paid at the end of the experiment in private and in cash.

It is important that during the experiment you remain silent. If you have a question or need assistance of any kind, please raise your hand, but do not speak - and an experiment administrator will come to you, and you may then whisper your question. In addition, please turn off your cell phones and put them away during the experiment. Anybody that violates these rules will be asked to leave.

In this experiment you will face 27 tasks in which you will take the role of an entrepreneur. Prior to each task, you will be provided with the information regarding the task. At the end of the experiment, two of the tasks will be chosen randomly to determine your actual money earnings. Thus, your decisions in one task will not affect your earnings in any other task. In addition, at the end of the 27 tasks, you will be asked to fill out several questionnaires.

Next, you will be provided detailed information pertaining to Task #1-8 of the experiment. Before starting with the actual tasks, you will face one practice task. Your compensation for the experiment will not depend on the practice task

C.2 Tasks #1–8: Description

In Tasks #1–8 of the experiment, you will be given an endowment of \$10 and choose whether to develop up to 10 technologies at a cost of \$1 per technology. The quality of each technology is uncertain and will be determined randomly using the probability distribution to the right. However, only the best technology can be brought to the market and yield revenue.

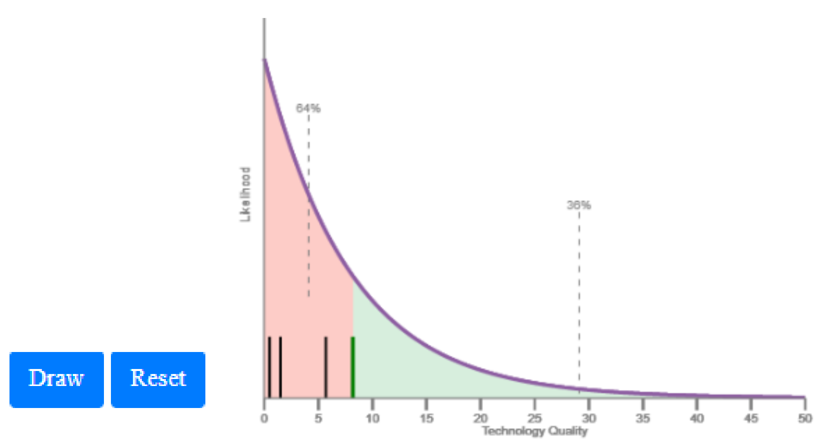
The decisions whether to develop a technology will be made sequentially. In particular, you will first decide whether to develop technology #1. If you decide to do so, you will incur a cost of \$1 and observe the quality of technology #1. Next, you will decide whether to develop technology #2. If so, you will incur a cost of \$1. And so on. Each new technology will be obtained using an independent draw from the distribution to the right. That is, quality of technology #2 does not depend on technology #1, quality of technology #3 does not depend on technology #2, etc. At each decision, you will be provided with the summary information in the graphical and text forms.

For example, suppose you have developed 4 technologies. Each of them will be marked on the graph with a line. At the time of each decision, you will be provided with the probability that a new technology will be better (or worse) than the best known technology. For example, suppose you are deciding whether to develop technology #5, then the probability that technology #5 will be better than the best known technology is shaded in green, and is equal to 36%. The probability that technology #5 will be worse than the best known technology is shaded in red, and is equal to 64%.

For each task, you will be randomly matched with another participant in this room. Each of you will simultaneously and independently decide whether to develop up to 10 technologies (one technology at a time). At the time of each decision you will not know the technology that has the best quality among all of the technologies developed so far (either by you or by the participant that you are matched with). After all of the decisions have been made, the best technology developed in during the task (either by you or by the participant that you are matched with) will be revealed. The best technology will be adopted by the market and yield $10 revenue.

At this time you can get some experience of drawing from the distribution. You can click 'Draw' to draw a random number from the distribution. You can also click 'Reset' to clear all the draws. Reminder, each draw is independent from all other draws. Note, that although the diagram shows domain to be [0,50], the domain is unbounded and there is a small chance (less than a quarter of one percent) that a draw from the distribution will exceed 50. When you are done drawing random numbers from the distribution, please click 'Continue to Practice Task'.

Figure C1: Screenshots of Distribution Presented in Instructions



C.3 Tasks #1–8: Practice Task

Figure C2: Screenshots of the Practice Task

For each of the Tasks #1-8, you will be randomly matched with another participant in this room. That is, there will be new random rematching at the beginning of each task, but the matching will stay fixed within a task. Each participant will be given an endowment of \$10 and able to develop up to 10 technologies at the cost of \$1 per technology. At the time of each decision you **will not** know the technology that has the best quality among all of the technologies developed so far (either by you or by the participant that you are matched with). Note that only the best technology among the two of you can be brought to the market and yield revenue. **The best technology will generate a revenue of \$10.**

For the practice task, you will make a sequence of decisions in this setting, however, unlike the actual tasks, for the practice tasks you will be matched with a computer that chooses randomly.

Market Summary:

- Number of entrepreneurs: **Two**
- Best market technology: **Unknown**
- Cost per technology: **\$1**
- Your endowment: **\$10**

You will make a sequence of 10 decisions. Each decision is a choice between two options:

- Option A: develop another technology at a cost of \$1
- Option B: do NOT develop another technology

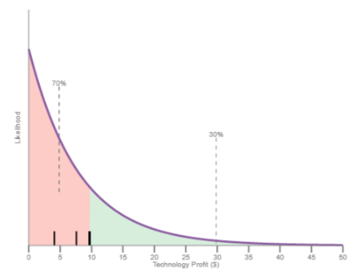
The summary of the most current information is presented below.

Decision Summary:

- Decision number: **6**
- Technologies developed by you: 9.690, 7.572, 4.079
- Incurred cost: **3 x \$1=\$3**
- Best market technology: **Unknown**
- Probability that technology #**6** will be better than **9.690** is **30%**
- Probability that technology #**6** will be better than **9.690** is **70%**

Please make your decisions:

Option A: Develop Technology #6 for \$1. | Option B: Do NOT Develop Technology #6.



D Additional Tables and Figures

Figure D1: Screenshots of the Risk Aversion Elicitation Task

Please make a choice for **each of the 20 decisions** in this task.

Decision	Option A	Option B	Your Choice
#1	**$10** with 50% chance; **$0** with 50% chance	$0.5	A
#2	**$10** with 50% chance; **$0** with 50% chance	$1	A
#3	**$10** with 50% chance; **$0** with 50% chance	$1.5	A
#4	**$10** with 50% chance; **$0** with 50% chance	$2	A
#5	**$10** with 50% chance; **$0** with 50% chance	$2.5	A
#6	**$10** with 50% chance; **$0** with 50% chance	$3	A
#7	**$10** with 50% chance; **$0** with 50% chance	$3.5	A
#8	**$10** with 50% chance; **$0** with 50% chance	$4	A
#9	**$10** with 50% chance; **$0** with 50% chance	$4.5	A
#10	**$10** with 50% chance; **$0** with 50% chance	**$5**	B
#11	**$10** with 50% chance; **$0** with 50% chance	**$5.5**	B
#12	**$10** with 50% chance; **$0** with 50% chance	**$6**	B
#13	**$10** with 50% chance; **$0** with 50% chance	**$6.5**	B
#14	**$10** with 50% chance; **$0** with 50% chance	**$7**	B
#15	**$10** with 50% chance; **$0** with 50% chance	**$7.5**	B
#16	**$10** with 50% chance; **$0** with 50% chance	**$8**	B
#17	**$10** with 50% chance; **$0** with 50% chance	**$8.5**	B
#18	**$10** with 50% chance; **$0** with 50% chance	**$9**	B
#19	**$10** with 50% chance; **$0** with 50% chance	**$9.5**	B
#20	**$10** with 50% chance; **$0** with 50% chance	**$10**	B

Submit Decisions

Figure D2: Screenshots of the Loss Aversion Elicitation Task

Please make a choice for **each of the 20 decisions** in this task.

Decision	Option A	Option B	Your Choice
#1	-$0.5 with 50% chance; $5.00 with 50% chance	$0.00	A
#2	-$1 with 50% chance; $5.00 with 50% chance	$0.00	A
#3	-$1.5 with 50% chance; $5.00 with 50% chance	$0.00	A
#4	-$2 with 50% chance; $5.00 with 50% chance	$0.00	A
#5	-$2.5 with 50% chance; $5.00 with 50% chance	$0.00	A
#6	-$3 with 50% chance; $5.00 with 50% chance	$0.00	A
#7	-$3.5 with 50% chance; $5.00 with 50% chance	$0.00	A
#8	-$4 with 50% chance; $5.00 with 50% chance	$0.00	A
#9	-$4.5 with 50% chance; $5.00 with 50% chance	$0.00	A
#10	-$5 with 50% chance; $5.00 with 50% chance	$0.00	B
#11	-$5.5 with 50% chance; $5.00 with 50% chance	$0.00	B
#12	-$6 with 50% chance; $5.00 with 50% chance	$0.00	B
#13	-$6.5 with 50% chance; $5.00 with 50% chance	$0.00	B
#14	-$7 with 50% chance; $5.00 with 50% chance	$0.00	B
#15	-$7.5 with 50% chance; $5.00 with 50% chance	$0.00	B
#16	-$8 with 50% chance; $5.00 with 50% chance	$0.00	B
#17	-$8.5 with 50% chance; $5.00 with 50% chance	$0.00	B
#18	-$9 with 50% chance; $5.00 with 50% chance	$0.00	B
#19	-$9.5 with 50% chance; $5.00 with 50% chance	$0.00	B
#20	-$10 with 50% chance; $5.00 with 50% chance	$0.00	B

Submit Decisions

Figure D3: Screenshots of the Sunk Cost Fallacy Elicitation Task

Please make a choice for **each of the 20 decisions** in this task. Reminder: Uncompleted Project Payoff = [Endowment -$5]; Completed Project Payoff= [Endowment -$5]+[$7.5- Project Completion Cost].

Decision	Completion Cost	Option A	Option B	Your Choice
#1	$0.5	Complete	Do Not Complete	A
#2	$1.0	Complete	Do Not Complete	A
#3	$1.5	Complete	Do Not Complete	A
#4	$2.0	Complete	Do Not Complete	A
#5	$2.5	Complete	Do Not Complete	A
#6	$3.0	Complete	Do Not Complete	A
#7	$3.5	Complete	Do Not Complete	A
#8	$4.0	Complete	Do Not Complete	A
#9	$4.5	Complete	Do Not Complete	A
#10	$5.0	Complete	Do Not Complete	B
#11	$5.5	Complete	Do Not Complete	B
#12	$6.0	Complete	Do Not Complete	B
#13	$6.5	Complete	Do Not Complete	B
#14	$7.0	Complete	Do Not Complete	B
#15	$7.5	Complete	Do Not Complete	B
#16	$8.0	Complete	Do Not Complete	B
#17	$8.5	Complete	Do Not Complete	B
#18	$9.0	Complete	Do Not Complete	B
#19	$9.5	Complete	Do Not Complete	B
#20	$10.0	Complete	Do Not Complete	B

Submit Decisions

Figure D4: Screenshots of the Individual Search Task

In Task # 20, you will be the sole entrepreneur. You are able to develop up to 10 technologies at the cost of $1 per technology.

Market Summary:

- Number of entrepreneurs: **One**
- Existing market technology: **Known (Shown in red)**
- Cost per technology: **$1**
- Your endowment: **$10**

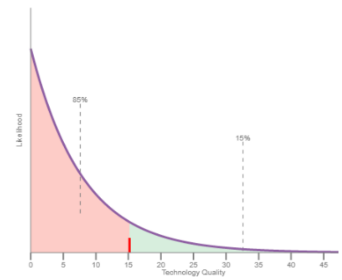
You will make up to 10 decisions. Each decision is a choice between two options:

- Option A: develop another technology at a cost of $1
- Option B: do NOT develop another technology

The summary of the probability that the new technology will be better (or worse) than the existing technology is presented below. The graphical summary is presented to the right.

Decision Summary:

- Decision number: **1**
- Technologies developed by you: **None**
- Incurred cost: **0 x $1= $0**
- Existing market technology: **15.177**
- Probability that technology #1 will be better than **15.177** is **15%**
- Probability that technology #1 will be worse than **15.177** is **85%**



Please make your decisions for task # 20.

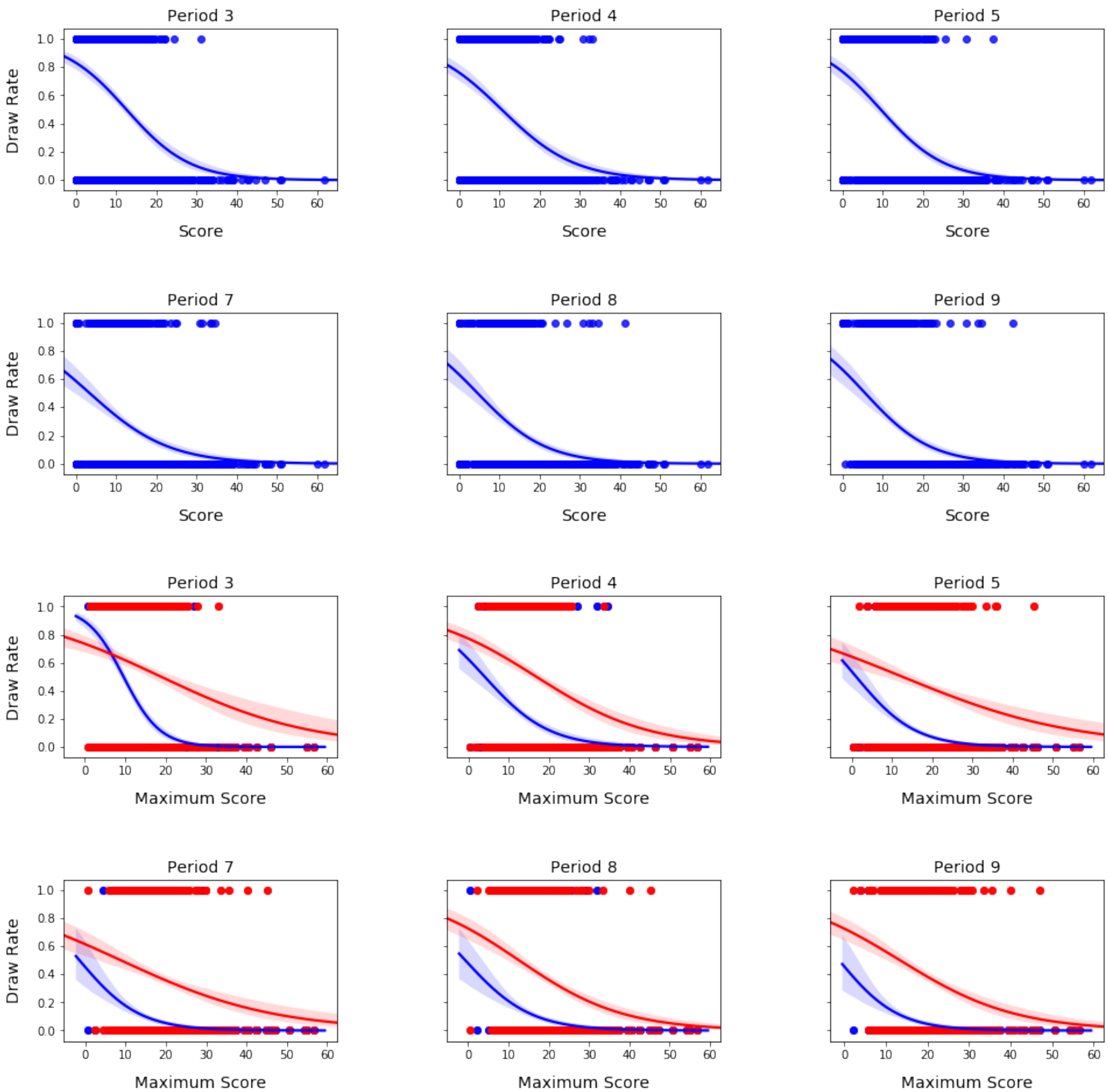
Option A: Develop Technology #1 for $1. | Option B: Do NOT Develop Technology #1.

Table D1: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	Pooled		Private			Leaderboard	
Draw Decision		All	Leader	Follower	All	Leader	Follower
L-Board	-0.70***	—	—	—	—	—	—
	(0.20)	—	—	—	—	—	—
Priv. x Score	-0.17***	-0.21***	-0.25***	-0.18***	—	—	—
	(0.01)	(0.02)	(0.04)	(0.02)	—	—	—
L-Board x MaxScore	-0.11***	—	—	—	-0.11***	-0.23***	-0.11***
	(0.01)	—	—	—	(0.01)	(0.02)	(0.01)
Period	-0.12***	-0.13***	-0.19***	-0.11***	-0.10***	-0.24***	-0.03
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)
Risk Aversion	-1.10**	-1.61**	-1.71	-1.36*	-0.79*	-0.64	-0.20
	(0.50)	(0.76)	(1.26)	(0.70)	(0.45)	(0.93)	(0.91)
Loss Aversion	-0.13	0.02	1.26	-0.74	-0.22	-1.33	0.07
	(0.63)	(0.78)	(1.11)	(0.65)	(0.66)	(1.11)	(0.96)
Sunk Cost Fallacy	0.11	0.29	-0.93	0.41	-0.15	-0.62	0.01
	(0.63)	(0.97)	(0.85)	(1.00)	(0.51)	(0.87)	(0.96)
Factor 1	0.05	0.17	0.02	0.12	-0.04	-0.05	-0.31***
	(0.09)	(0.13)	(0.14)	(0.13)	(0.09)	(0.18)	(0.12)
Factor 2	—	—	—	—	—	—	—
	—	—	—	—	—	—	—
Factor 3	0.02	-0.03	0.12	-0.07	0.05	-0.23	0.12
	(0.11)	(0.14)	(0.21)	(0.13)	(0.11)	(0.19)	(0.14)
Factor 4	0.06	0.07	-0.01	0.09	0.06	0.08	0.15
	(0.06)	(0.09)	(0.09)	(0.08)	(0.07)	(0.15)	(0.18)
Factor 5	0.16	0.22	0.11	0.15	0.10	0.05	0.20**
	(0.10)	(0.16)	(0.19)	(0.14)	(0.08)	(0.18)	(0.08)
Factor 6	0.18**	0.17	0.09	0.17	0.20**	0.16	0.08
	(0.08)	(0.11)	(0.13)	(0.12)	(0.09)	(0.17)	(0.14)
Factor 7	-0.09	-0.17	-0.22	-0.17	-0.04	-0.06	-0.22
	(0.11)	(0.18)	(0.23)	(0.17)	(0.08)	(0.18)	(0.18)
Factor 8	-0.09	-0.07	0.00	-0.10	-0.12	-0.03	-0.14
	(0.08)	(0.12)	(0.16)	(0.13)	(0.09)	(0.16)	(0.15)
Factor 9	-0.08	-0.08	-0.19	0.02	-0.11	0.04	-0.44**
	(0.12)	(0.16)	(0.17)	(0.16)	(0.10)	(0.22)	(0.22)
Constant	1.69***	1.83**	4.26***	1.17	1.17**	2.17***	1.99***
	(0.57)	(0.81)	(0.77)	(0.86)	(0.51)	(0.74)	(0.76)
Observations	15,360	7,680	3,451	3,451	7,680	3,411	3,411

Notes: The regression pools the data from the individual search tasks, the private-feedback treatment, and the leaderboard-feedback treatment. *,** ,*** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Figure D5: Decision to Draw in the Leaderboard-Feedback Treatment



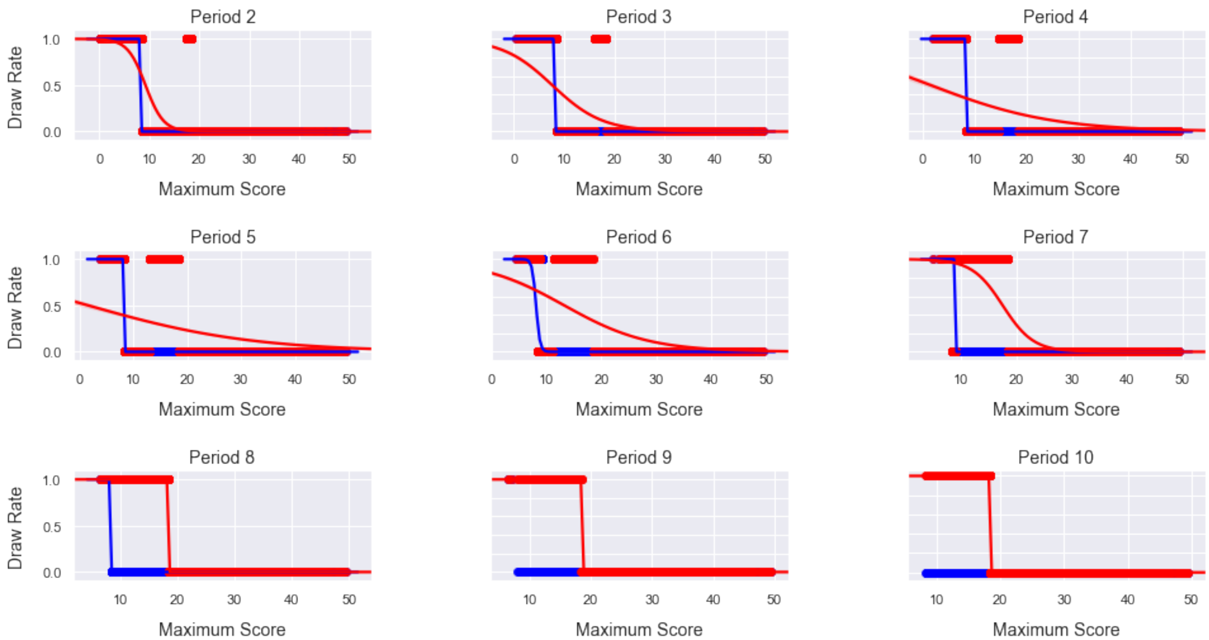
Notes: This figure displays two sets of graphs. The first set of graphs display logistic regressions of the decision to draw in the private-feedback treatment for periods 3, 4, 5, 7, 8, and 9. The second set of graphs display logistic regressions of the leader's decision (blue) to draw and the follower's decision (red) to draw in the leaderboard-feedback treatment for periods 3, 4, 5, 7, 8, and 9.

Table D2: Contest Results

	Priv. Draws	LB Draws	Priv. Innovation	LB Innovation
Session 1	6.53	7.16	24.02	19.20
Session 2	7.78	8.00	21.81	23.46
Session 3	8.97	7.89	19.34	23.16
Session 4	7.28	6.22	22.44	19.24
Session 5	7.41	7.25	21.06	20.84
Session 6	7.22	7.50	20.40	21.48
Session 7	9.19	7.09	26.54	19.82
Session 8	8.59	6.69	24.82	21.21
Session 9	9.28	7.72	21.62	23.91
Session 10	10.16	9.75	22.92	20.54
Session 11	9.03	7.00	24.18	21.58
Session 12	10.59	8.28	25.33	23.18

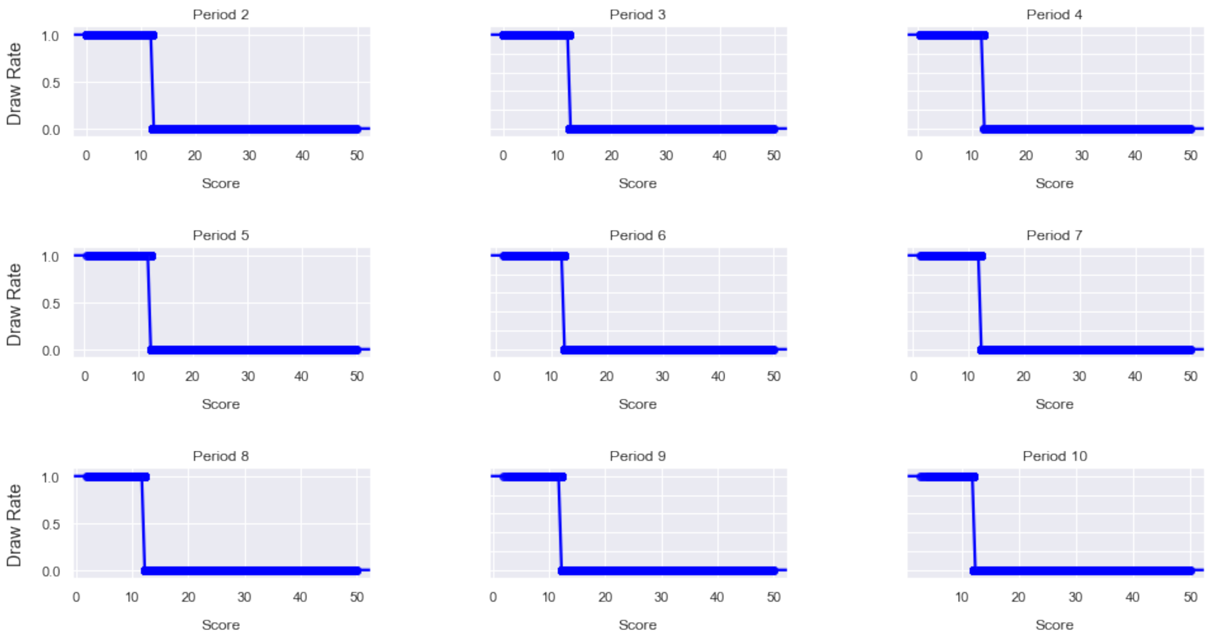
Notes: Priv. Draws refers to the mean number of draws in a contest in a session in the pravate-feedback treatment. LB Draws refers to the mean number of draws in a contest in a session in the leaderboard-feedback treatment. Priv. Innovation refers to the mean value of the winning innovation in a session in the pravate-feedback treatment. LB Innovation refers to the mean value of the winning innovation in a session in the leaderboard-feedback treatment.

Figure D6: Decision to Draw in the Simulated Leaderboard-Feedback Contests



Notes: These graphs display logistic regressions of the leader's decision (blue) to draw and the follower's decision (red) to draw in the simulated leaderboard-feedback treatment contests for periods 2, 3, 4, 5, 6, 7, 8, 9, 10.

Figure D7: Decision to Draw in the Simulated Private-Feedback Contests



Notes: The first set of graphs display logistic regressions of the decision to draw in the simulated pravate-feedback treatment contests for periods 2, 3, 4, 5, 6, 7, 8, 9, 10.

Table D3: Individual Regression Results

	(1)	(2)
Dep. Var.: Draw Decision	Individual	Individual
Individual Score	-0.04***	-0.04***
	(0.01)	(0.01)
Period	-0.15***	-0.15***
	(0.02)	(0.02)
Risk Aversion	-2.70**	-2.72***
	(1.17)	(1.00)
Loss Aversion	-0.80	-0.84
	(1.00)	(1.02)
Sunk Cost Fallacy	-0.13	-0.10
	(0.59)	(0.72)
Grit/Factor 1	-0.57**	-0.08
	(0.23)	(0.14)
Competitiveness/Factor 2	0.05	—
	(0.43)	—
Achievement Striving/Factor 3	0.02	0.27**
	(0.66)	(0.11)
Extraversion/Factor 4	0.17	0.06
	(0.11)	(0.12)
Agreeableness/Factor 5	0.27	0.19**
	(0.24)	(0.08)
Neuroticism/Factor 6	-0.18	-0.10
	(0.23)	(0.12)
Openness/Factor 7	0.05	-0.06
	(0.18)	(0.19)
Conscientiousness/Factor 8	0.09	-0.19**
	(0.24)	(0.08)
Factor 9	—	0.07
	—	(0.22)
Constant	-1.35	-1.48**
	(0.99)	(0.67)
Observations	7,680	7,680

Notes: The regression pools the data from the individual search tasks, the pravate-feedback treatment, and the leaderboard-feedback treatment. *,** ,*** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table D4: Demographics Regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	Pooled		Private			Leaderoard	
Draw Decision		All	Leader	Follower	All	Leader	Follower
L-Board	-0.70***	—	—	—	—	—	—
	(0.20)	—	—	—	—	—	—
Priv. x Score	-0.17***	-0.21***	-0.25***	-0.18***	—	—	—
	(0.01)	(0.02)	(0.04)	(0.02)	—	—	—
L-Board x MaxScore	-0.11***	—	—	—	-0.11***	-0.23***	-0.11***
	(0.01)	—	—	—	(0.01)	(0.02)	(0.01)
Period	-0.12***	-0.13***	-0.19***	-0.11***	-0.10***	-0.24***	-0.03
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)
Risk Aversion	-0.74**	-1.15**	-1.64**	-0.95	-0.60	-0.22	-0.58
	(0.35)	(0.47)	(0.80)	(0.61)	(0.38)	(1.05)	(0.65)
Loss Aversion	-0.72	-0.67	0.52	-1.01*	-0.79	-1.32	-1.00
	(0.50)	(0.59)	(0.72)	(0.56)	(0.62)	(1.06)	(0.91)
Sunk Cost Fallacy	0.40	0.66	-0.47	0.77	0.07	-0.29	0.51
	(0.49)	(0.75)	(0.67)	(0.81)	(0.32)	(0.80)	(0.62)
Gender	-0.15	-0.17	-0.11	-0.03	-0.14	-0.36	0.33
	(0.14)	(0.20)	(0.25)	(0.22)	(0.17)	(0.30)	(0.28)
Age	-0.11***	-0.18**	-0.23***	-0.16**	-0.07	-0.04	-0.22
	(0.04)	(0.07)	(0.08)	(0.07)	(0.05)	(0.13)	(0.13)
Constant	3.09***	3.93**	7.35***	2.78	2.05**	3.56	4.13*
	(0.96)	(1.75)	(1.48)	(1.83)	(0.85)	(2.25)	(2.22)
Observations	15,360	7,680	3,451	3,451	7,680	3,411	3,411

Notes: The regressions analyze how demographics influence the decision to draw. Gender is a dummy variable for male. There are multiple race dummy variables, major dummy variables, school year dummy variables, and high school location dummy variables that are in these regressions, but not included in the tables. *,** ,*** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.