Public Leaderboard Feedback in Sampling Competition: An Experimental Investigation*

July 2020

Stanton Hudja[†] Brian Roberson[†] Yaroslav Rosokha[†]

Abstract

We investigate the role of performance feedback, in the form of a public leaderboard, in a sequential-sampling contest with costly observations. The player whose sequential random sample contains the observation with the highest value wins the contest and obtains a prize with a fixed value. We show theoretically that in the subgame perfect equilibrium of contests with a fixed ending date (i.e., finite horizon), providing public performance feedback may result in fewer expected observations and a lower expected value of the winning observation. 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 sequential-sampling 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

† Krannert School of Management, Purdue University • Emails: shudja@purdue.edu, brobers@purdue.edu, yrosokha@purdue.edu

∗ This paper benefited from comments by participants at the 2018 Southern Economics Association Annual Meeting, 2019 American Economic Association Annual Meeting, 2019 Purdue-IU Experimental and Behavioral Mini Conference and seminar participants at Purdue University.

1 Introduction

Sequential sampling is a classic statistical problem in which a decision-maker, using the information from previous observations, chooses whether to make an additional costly observation.[1] This problem provides a framework for examining the trade-off between continued exploration and stopping to exploit the value of a given sequential random sample—a trade-off that is clearly relevant for a range of applications involving innovation activity.[2] In this paper, we examine a model of sequential-sampling competition[3] with a public leaderboard – a feature that has become prevalent among innovation-contest platforms such as Kaggle.com, drivendata.org, and challenge.gov. In particular, we demonstrate that, in the subgame perfect equilibrium of the sequential-sampling competition with a fixed ending date (i.e., finite horizon), the public leaderboard feedback competition may not always generate a higher expected quality of the winning innovation than the corresponding private-feedback competition. We conduct a controlled laboratory experiment to test this theoretical prediction and find that the experimental results largely support the theory.

To understand how leaderboard feedback affects the competition, note that the presence of a leaderboard generates two distinct effects on the dynamics of effort provision that are not present with private feedback. With a leaderboard the trailing competitor (henceforth, *follower*) may condition her choice of whether or not to make an additional costly observation on the leader's score. When the leader's score is low, the follower is more likely to be able to overtake the leader, and thus, leaderboard feedback may encourage followers to continue searching. Conversely, when the leader's score is high, a follower is less likely to be able to overtake the leader, and thus, leaderboard feedback may discourage followers from continuing to search. We show that in equilibrium: (i) followers who trail in the competition are more likely to invest in additional search than leaders, and (ii) all competitors reduce their search efforts as the leader's existing innovation quality increases. The results of our experiment confirm these theoretical predictions that current leaders tend to exert less search effort than followers and that both leaders and followers become less willing to exert search effort as the leader's innovation quality increases.

[1]This problem appears to have been first formulated in Wald (1947). Early work includes Robbins (1952), Bradt and Karlin (1956), Feldman (1962), and Berry (1972). In economics, early applications include Stigler (1961) and the following literature on search, and Rothschild (1974) and the following literature on two-armed bandits.

[2]For an introduction to sequential-sampling problems, see DeGroot (1970). In addition to innovation competition, which we discuss in more detail below, recent applications include, among others, dynamic public-goods problems (Keller, Rady and Cripps, 2005), long-term contracts (Halac, Kartik and Liu, 2016), moral hazard in teams (Bonatti and Hörner, 2011), voting for reforms (Strulovici, 2010; Khromenkova, 2015), and decision timing (Fudenberg, Strack and Strzalecki, 2018).

[3]In sequential-sampling competition, each draw of an innovation quality may be thought of as a new innovation, and then each competitor submits their best innovation. An alternative interpretation is that each competitor is working on one specific innovation and that each draw of an innovation quality is in regards to searching over quality improvements to that particular innovation.

The dynamics of innovation effort provision help provide insight as to why leaderboard feedback may result in a lower expected value of the winning innovation for contests with a fixed ending date. Beginning with the case of an infinite horizon, leaderboard feedback generates a higher equilibrium expected value of the winning innovation than private feedback does.[4] However, a fixed ending date (i.e., a finite horizon) presents an additional obstacle for a follower that is attempting to overtake the leader. As a result, the leader score at which leaderboard feedback changes from encouraging effort by followers to discouraging effort by followers decreases as the length of the contest decreases. Because contest length has a less pronounced discouragement effect on the private-feedback contest, we find that there exist fixed contest lengths that, given the other model parameters, are sufficiently short as to result in leaderboard feedback generating a lower equilibrium expected quality for the winning innovation than the corresponding private-feedback contest.

An additional consideration with leaderboard feedback is its potential to generate an escalation of commitment (i.e., sunk-cost fallacy) that is reminiscent of the dollar auction and the penny auction.[5] That is, with a leaderboard, the follower knows that he or she is not in the lead and may consider his or her sunk research costs when deciding whether to try to take the lead by making an incremental investment in additional research effort. We investigate how individual characteristics, including sunk-cost fallacy, affect competitive sequential-sampling activity. Despite the fact that players engaged in sequential-sampling competition make escalating research investments, we find that performance on a sunk-cost-fallacy elicitation task is not a significant predictor of behavior with the leaderboard, or without the leaderboard. However, risk aversion is a significant predictor of behavior both with and without leaderboard feedback, and we find that the direction of this effect is consistent with the theoretical predictions.

Our paper contributes to several active streams of literature. First, we contribute to the experimental literature on feedback in innovation contests. There are several recent examples of experimental work that examine potential drawbacks of providing feedback in related contest environments, including Kuhnen and Tymula (2012), Ludwig and Lünser (2012), and Deck and Kimbrough (2017). Most closely related is Deck and Kimbrough (2017) who experimentally examine the exponential-bandit based innovation competition in Halac, Kartik and Liu (2017). In that setting, Deck and Kimbrough (2017) find that 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 only be discouraging, and thus, hiding information may be valuable. In a variation of a two-stage difference-form contest, Ludwig and Lünser (2012) find that feedback influences the dynamics of effort pro-

[4] For further details on the infinite horizon version of the model, see Appendix A.2

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

vision but not total effort. Kuhnen and Tymula (2012) find a similar result in an experiment that is modeled as a single-stage difference-form contest that is repeatedly played and feedback affects ego utility which may evolve over time. Lastly, In a recent survey, Dechenaux, Kovenock and Sheremeta (2015) highlight that in environments where it is difficult for the follower to overtake the leader, feedback may result in the trailing player dropping out (e.g., Fershtman and Gneezy, 2011). In the case of sequential-sampling competition, 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 followers who trail in the competition are more likely to continue to search than leaders, and all competitors reduce their search effort as the leader's existing innovation quality increases and it becomes more difficult for the follower to overtake the leader.

Second, 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 the sunk-cost fallacy play a role in sequential-sampling competition.[6] 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, the sunk-cost fallacy, or unincentivized measures of personality were predictive of subjects' behavior in the contest.

Finally, we contribute to the literature on innovation competition. Existing approaches include but are not limited to variations of all-pay auctions (e.g., Che and Gale, 2003; Chawla, Hartline and Sivan, 2015), 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; Mihm and Schlapp, 2018; Yildirim, 2005), crowdsourcing contests (e.g,. Terwiesch and Xu, 2008; DiPalantino and Vojnovic, 2009; Erat and Krishnan, 2012; Ales, Cho and Körpeoğlu, 2017), dynamic contests (e.g., Lang, Seel and Strack, 2014; Seel and Strack, 2016), and structural/empirical models of innovation contests (e.g. Gross (2017); Lemus and Marshall (Forthcoming)). For example, Lemus and Marshall (Forthcoming) examine Markov Perfect

[6]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).

equilibrium in a variation of continuous-time sequential-sampling competition which includes features such as: (i) new contestants exogenously entering the competition at a constant rate over time and (ii) for each contestant innovation opportunities arrive stochastically over time. In this framework, Lemus and Marshall (Forthcoming) find that the effect of leaderboard feedback is theoretically ambiguous.[7]

In contrast, our work is most closely related to classic sequential-sampling competition, as in Taylor (1995), Fullerton and McAfee (1999), Baye and Hoppe (2003), and Rieck (2010), which readily lends itself to both multi-period competition and standard exploration versus exploitation considerations. Within this line of research, Fullerton and McAfee (1999) and Baye and Hoppe (2003) consider the case of no feedback and Taylor (1995) considers the case of private feedback. Our focus in this study is on leaderboard feedback in a setting with an arbitrary, but fixed, number of periods and in which the contestants may have general utility functions. The special case of our model with risk-neutral players and two periods is examined in Rieck (2010), who find that private feedback generates a higher equilibrium expected value of the winning innovation. Conversely, we find that with an infinite horizon, leaderboard feedback makes for a more engaging competition that generates a higher expected value of the winning innovation than private feedback does. In the remaining case of a fixed contest length between the extremes of 2 periods and an infinite horizon, we find that there exist a range of finite contest lengths that are sufficiently short that leaderboard feedback generates a lower equilibrium expected value for the winning innovation than the corresponding private-feedback 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 the main results of the experiment. Finally, in section 6, we conclude.

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 $t \in \{1, \dots, T\}$, each player $i \in \{1, 2\}$ has the opportunity to exert effort at a cost of $c > 0$. For simplicity, the discussion in this section is for the case of risk-neutral players, and the case of a general utility function that allows for risk aversion, loss aversion, and/or sunk-cost fallacy considerations is addressed in Appendices A and B. If player i exerts effort, she obtains an innovation, with quality level $s_{i,t}$, a random variable that is distributed

[7] Lemus and Marshall (2019) estimate their model on data obtained from kaggle.com for competitions with public leaderboard. The authors then run a series of counterfactual simulations to show a positive effect of leaderboard on the number of submissions and the quality of winning submission. The authors also conduct a set of student competitions on kaggle.com to experimentally support their results.

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.[8] 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 $v \geq 2c$.[9] 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,[10] $\max\{\overline{s}_{1,t-1}, \overline{s}_{2,t-1}\}$. 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. Recall 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

In Appendix A, we characterize the SPNE in the leaderboard-feedback innovation contest for the case of a general utility function that allows for risk aversion, and in Appendix B, we address the modeling of loss aversion and sunk-cost fallacy considerations. For simplicity, we focus here on the case of risk neutral players. Note that for the special case of risk-neutral players, the analysis of the final stage T coincides with the analysis of the second stage of the two-stage model in Rieck (2010).

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

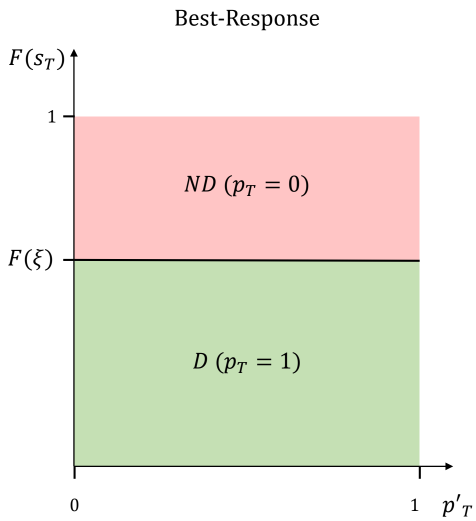
[8] In the experiment, we assume that innovations are exponentially distributed ($F(x;\lambda) = 1 - e^{-\lambda x}$ and $f(x;\lambda) = \lambda e^{-\lambda x}$, where $\lambda > 0$ is the rate parameter).

[9] For the remaining cases of $v \in [0, 2c)$, note that if $c > v$ then the contest is trivial, and it is straightforward to extend our analysis to the case of $v \in [c, 2c)$.

[10] Note that the characterization of the subgame perfect equilibrium of the leaderboard feedback game in Section 2.1, also applies to the variation of the game in which at the beginning of each period, each player observes both players' scores.

subgame perfect equilibrium takes the form of a stopping rule in which each player i continues 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

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. Given a leader score of s_T at the beginning of the final stage T, note that the probability that a stage T random draw by the follower does [does not] overtake a leader who does not draw in stage T is $1 - F(s_T)$ [$F(s_T)$]. Similarly, the probability that a stage T random draw by the follower does [does not] overtake a leader who also draws in stage T is $F(s_T)(1 - F(s_T)) + \frac{(1-F(s_T))^2}{2} = {}^{(1-(F(s_T))^2)}/_2$

$[{}^{(1+(F(s_T))^2)}/_2]$. 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:

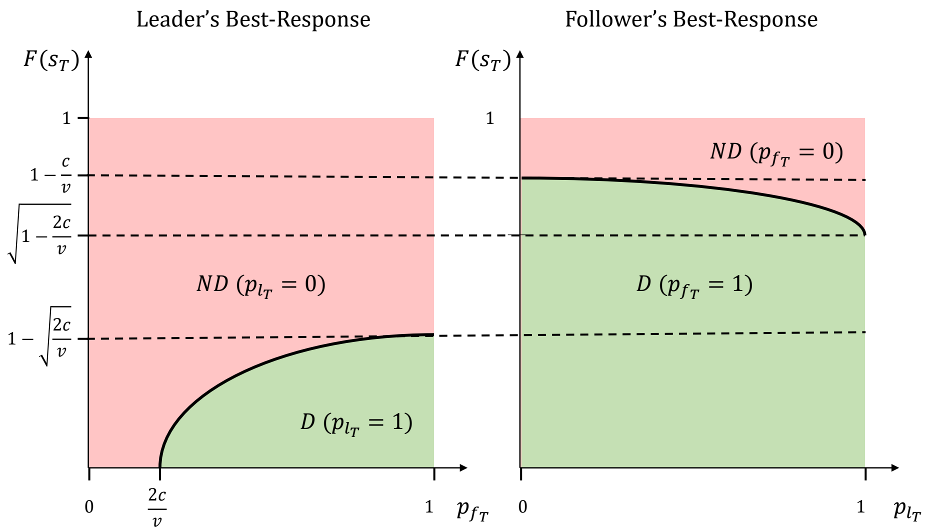
Table 1: Period T Local Subgame

		Follower (f_T)	
		D	ND
Leader (l_T)	D	$\frac{v\left(1+(F(s_T))^2\right)}{2} - c$, $\frac{v\left(1-(F(s_T))^2\right)}{2} - c$	$v - c$, 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 $\frac{v(1-F(s_T)^2)}{2} - c$. 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 $D(p_{l_T}=1)$ is a best response for the the leader. 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 Table 1.

Regarding intuition for the final-stage local equilibrium strategies, recall that the probability that a random draw by the follower overtakes a leader who does not draw $(1-F(s_T))$, is decreasing in the leader's score (s_T). If the leader's score at the beginning of the final period is not sufficiently high ($1 - F(s_T) \geq \frac{c}{v}$), then the marginal gain to the follower from making an additional draw is greater than the cost of making that draw. The follower's decision to draw, in turn, generates a strictly positive probability that the follower overtakes the leader. To counter this probability, the leader will draw, but only if the current score is sufficiently low ($1 - F(s_T) \geq \sqrt{\frac{2c}{v}}$). However, if the leader's score is above this threshold ($1 - F(s_T) < \sqrt{\frac{2c}{v}}$), then the marginal gain to the leader from making an additional draw is sufficiently low that the leader's best response is to not draw even if the follower draws.

To calculate the (closed-form) 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 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 private-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.

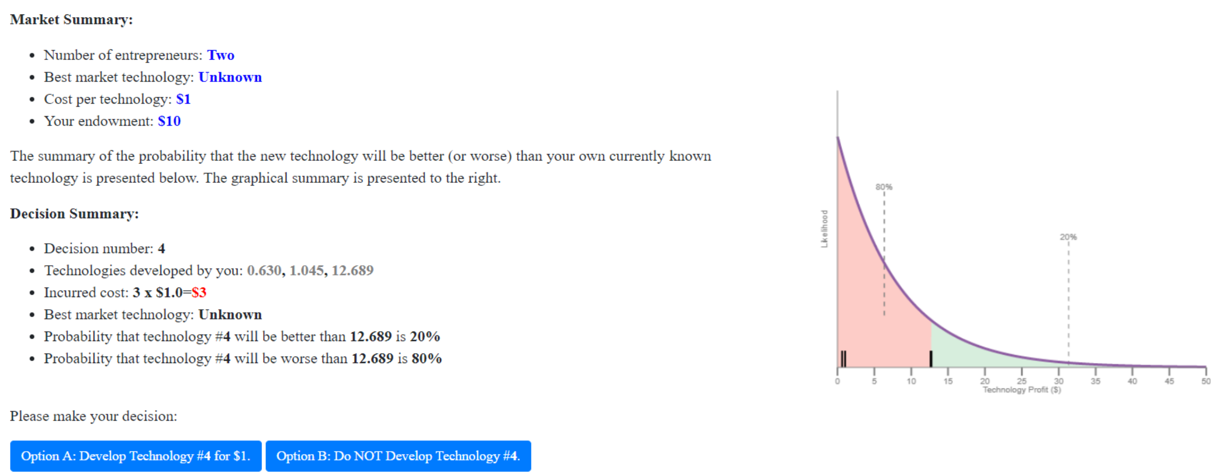
Each contest consists of two subjects matched for 10 periods of decision-making. Prior to the first period, each subject is given an endowment of \$10.00. Within each period, subjects have the opportunity to pay a cost $c = \$1.00$ to draw an innovation quality from an exponential distribution with parameter $\lambda = 0.125$. 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. We chose these parameters because they provide interesting qualitative model predictions in a simple 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 private-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.

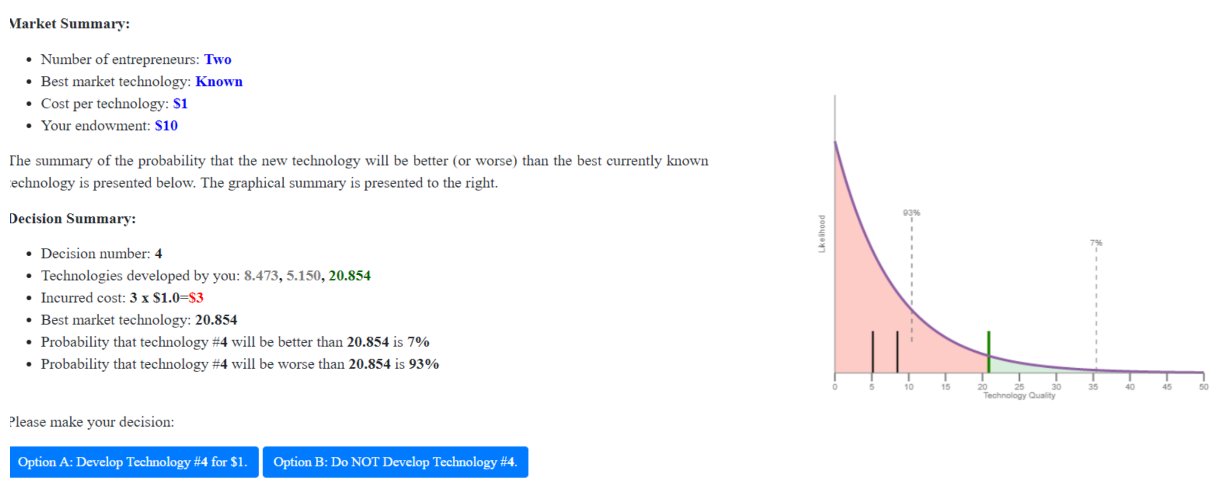
The second treatment is a two-player leaderboard-feedback contest in which each subject receives feedback on her own innovation as well as the innovation that is currently leading the contest. Specifically, similar to the private-feedback contest, in each period of the leaderboard-feedback contest, subjects 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.[11]

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

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 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 that 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.[12] 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 ended 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.[13]

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 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

[12] These values correspond to the 85th, 88th, 90th, 92nd, and 95th 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.

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

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.

We recruited 96 students 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, whereas the other half of the sessions started out with eight leaderboard-feedback contests. The experiment 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 solving for the closed-form subgame-perfect equilibrium described in section 2 for the particular model parameters specified in the experiment. In particular, using the model, 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. Note that these hypotheses are for the particular model parameters specified in the experiment ($v = \$10$, $c = \$1$, $T = 10$, and an exponential distribution of innovation quality with $\lambda = 0.125$), which we chose because they provide interesting qualitative model predictions in a simple environment. Furthermore, it is straightforward to provide examples of parameter configurations that generate qualitatively different model predictions.[14]

[14]For example, if the number of periods, which is set at $T = 10$ in the experiment, becomes arbitrarily large, then the prediction of which level of feedback leads to more draws and a higher winning innovation switches from private-feedback to leaderboard-feedback.

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).[15] 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 time subjects chose to draw an innovation. The proportions are broken down by the period of the contest (presented as a triple of the 2nd/6th/10th periods), the current score (grouped into ranges 0–15 and 15–25), and whether the player was a leader or a follower.[16] 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.[17] We summarize this prediction with Hypothesis 2.

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

[15]We used a simulation approach to obtain moments presented in Table 2. In particular, we simulate one million contests for two players following equilibrium strategies derived in Appendix A.1.

[16]Figures D6 in Appendix D present further evidence on the proportion of draws obtained in the simulations.

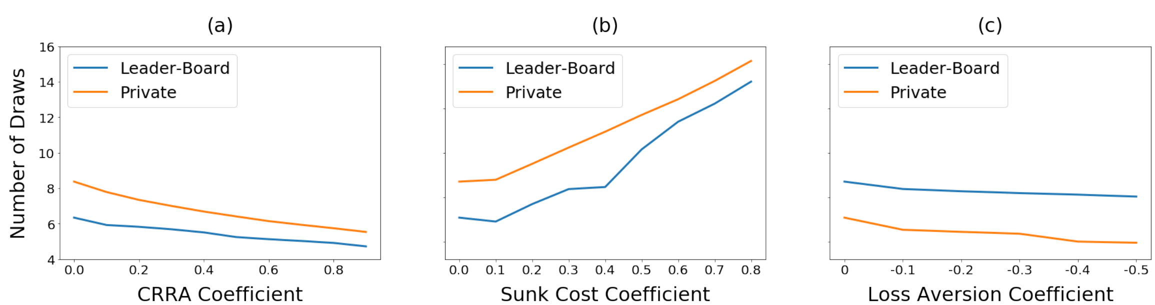
[17]Overall, leaders draw 8.73% of the time in the simulated contests and followers draw 39.20% of the time in the simulated contests.

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, each player becomes less willing to draw. This decrease in willingness to draw 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.[18] 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) the sunk-cost fallacy, and (c) loss aversion. The orange line is the private-feedback treatment, and 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, and (c) an increase in the sunk-cost fallacy.*

[18]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 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.[19]

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 occur 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 percentiles 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.

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, the average number of draws (8.50) and the average value of the winning innovation (22.87)

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

are not significantly different from the theoretically predicted values (8.36 draws, p-value 0.67; score of 23.42, p-value 0.36).[20] 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.[21] We find that this difference is significant (p-value=0.000).[22] Similarly, Table 3 shows that the winning technology is greater in a private-feedback contest (22.87) than in 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).[23] Table D4 in the Appendix shows that our conclusions are robust when we control for the order in which the two contests were presented as well as when we restrict the analysis to the first contest faced by the participant. 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. Although 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.[24]

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

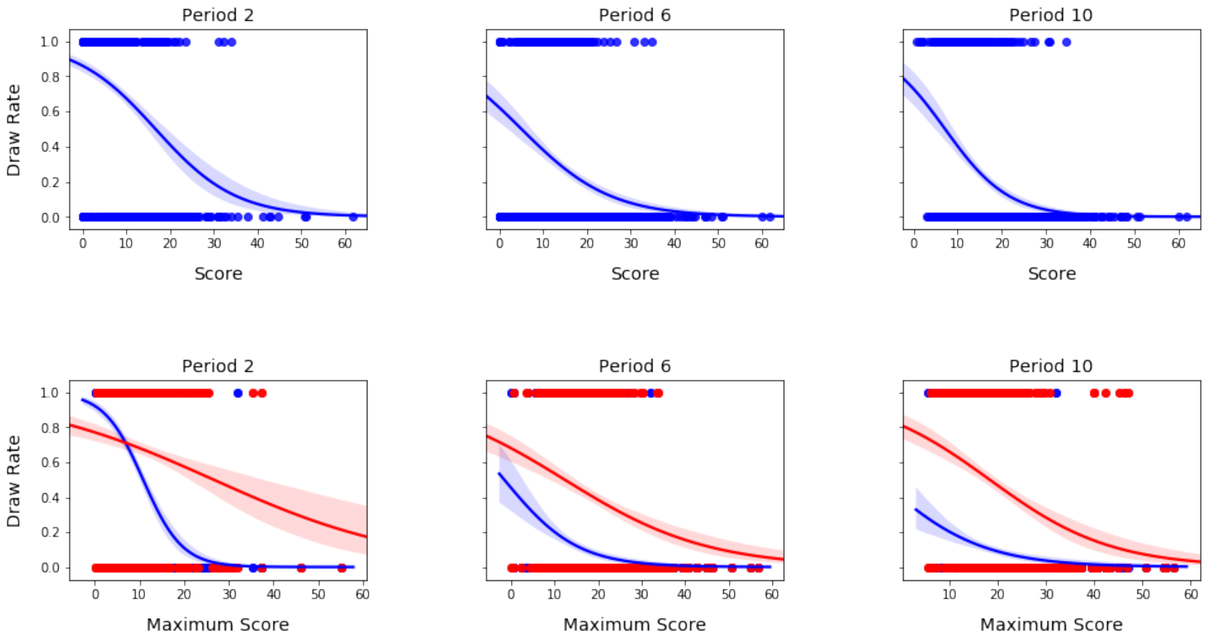
[21]We use random effects instead of fixed effects throughout this section because time-invariant factors will drop out using fixed effects and because random effects is more efficient. Among recent papers that use random-effects regressions are Embrey, Fréchette and Yuksel (2018), Noussair, Trautmann and van de Kuilen (2014), and Anderson, Friedman and Oprea (2010).

[22]The p-value is 0.000 if we utilize a fixed-effects regression with session-level effects.

[23]The p-value is 0.030 if we utilize a fixed-effects regression with session-level effects.

[24]Figure B5 provides 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 private-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.[25] 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 logistic regressions, with subject-level random effects and session-level clustered standard errors, of the decision to

[25] 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.[26] 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.

[26]Results for the individual search task are similar (see regression results presented in Table D2 of the Appendix).

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)	(1.02)	(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	-0.08	-0.15	-0.29	-0.03	-0.01	-0.09	-0.11
	(0.13)	(0.21)	(0.25)	(0.18)	(0.08)	(0.22)	(0.25)
Competitiveness	-0.10	0.07	0.00	0.24	-0.24	-0.04	-0.15
	(0.18)	(0.24)	(0.26)	(0.23)	(0.16)	(0.21)	(0.20)
Achievement Striving	0.18	0.08	0.03	-0.09	0.27	0.31	0.04
	(0.19)	(0.26)	(0.32)	(0.24)	(0.17)	(0.22)	(0.33)
Extraversion	0.03	-0.03	0.07	-0.06	0.08	-0.18	0.11
	(0.09)	(0.11)	(0.14)	(0.10)	(0.10)	(0.19)	(0.11)
Agreeableness	0.11	0.06	0.02	0.00	0.16	0.12	0.16
	(0.13)	(0.17)	(0.22)	(0.18)	(0.14)	(0.20)	(0.20)
Neuroticism	0.05	0.05	-0.12	0.10	0.03	0.11	-0.07
	(0.11)	(0.14)	(0.18)	(0.12)	(0.11)	(0.18)	(0.22)
Openness	-0.10	-0.11	-0.16	-0.14	-0.13	-0.27	-0.14
	(0.10)	(0.15)	(0.19)	(0.14)	(0.09)	(0.19)	(0.15)
Conscientiousness	0.02	0.18	0.25	0.06	-0.14	-0.20	-0.24
	(0.17)	(0.29)	(0.27)	(0.26)	(0.10)	(0.35)	(0.20)
Constant	1.67***	1.98**	4.41***	1.32	1.00*	2.01**	1.75**
	(0.60)	(0.81)	(0.82)	(0.85)	(0.51)	(0.83)	(0.69)
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. Personality characteristics are standardized to have mean 0.00 and standard deviation of 1.00. *,** , 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 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 may yield 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.

Second, 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 the 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.

Finally, we contribute to the existing theoretical literature by examining equilibrium in a model of sequential-sampling competition with a finite, or infinite, horizon and perfect recall. We find that with a finite horizon, leaderboard feedback may result in lower search effort as captured by the number of costly innovation decisions, which in turn yields lower expected quality of the winning innovation with leaderboard feedback than with private feedback.

Our work has several shortcomings that open interesting avenues for future research. First, our laboratory experiment investigates a finite-horizon innovation competition. Comparing it to with 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.

References

Ales, Laurence, Soo-Haeng Cho, and Ersin Körpeoğlu. 2017. “Optimal award scheme in innovation tournaments.” *Operations Research*, 65(3): 693–702.

Anderson, Steven, Daniel Friedman, and Ryan Oprea. 2010. “Preemption Games: Theory and Experiment.” *American Economic Review*, 100: 1788–1803.

Aoyagi, Masaki. 2010. “Information feedback in a dynamic tournament.” *Games and Economic Behavior*, 70(2): 242–260.

Astebro, Thomas, Holger Herz, Ramana Nanda, and Roberto A Weber. 2014. “Seeking the roots of entrepreneurship: Insights from behavioral economics.” *Journal of Economic Perspectives*, 28(3): 49–70.

Augenblick, Ned. 2015. “The sunk-cost fallacy in penny auctions.” *The Review of Economic Studies*, 83(1): 58–86.

Baye, Michael R, and Heidrun C Hoppe. 2003. “The strategic equivalence of rent-seeking, innovation, and patent-race games.” *Games and economic behavior*, 44(2): 217–226.

Berry, Donald A. 1972. “A Bernoulli two-armed bandit.” *Annals of Mathematical Statistics*, 43: 871–897.

Bimpikis, Kostas, Shayan Ehsani, and Mohamed Mostagir. 2019. “Designing dynamic contests.” *Operations Research*, 67(2): 339–356.

Bonatti, Alessandro, and Johannes Hörner. 2011. “Collaborating.” *American Economic Review*, 101: 632–663.

Bradt, Russell N, and Samuel Karlin. 1956. “On the design and comparison of certain dichotomous experiments.” *Annals of Mathematical Statistics*, 27: 390–409.

Chawla, Shuchi, Jason D Hartline, and Balasubramanian Sivan. 2015. “Optimal crowdsourcing contests.” *Games and Economic Behavior*.

Chen, Daniel L, Martin Schonger, and Chris Wickens. 2016. “oTree—An open-source platform for laboratory, online, and field experiments.” *Journal of Behavioral and Experimental Finance*, 9: 88–97.

Che, Yeon-Koo, and Ian Gale. 2003. “Optimal design of research contests.” *American Economic Review*, 93(3): 646–671.

Dechenaux, Emmanuel, Dan Kovenock, and Roman M Sheremeta. 2015. "A survey of experimental research on contests, all-pay auctions and tournaments." *Experimental Economics*, 18(4): 609–669.

Deck, Cary, and Erik O Kimbrough. 2017. "Experimenting with contests for experimentation." *Southern Economic Journal*, 84(2): 391–406.

DeGroot, Morris H. 1970. *Optimal Statistical Decisions.* Wiley New York.

DiPalantino, Dominic, and Milan Vojnovic. 2009. "Crowdsourcing and all-pay auctions." 119–128, ACM.

Duckworth, Angela L, Christopher Peterson, Michael D Matthews, and Dennis R Kelly. 2007. "Grit: perseverance and passion for long-term goals." *Journal of personality and social psychology*, 92(6): 1087.

Ederer, Florian, and Gustavo Manso. 2013. "Is pay for performance detrimental to innovation?" *Management Science*, 59(7): 1496–1513.

Embrey, Matthew, Guillaume Fréchette, and Sevgi Yuksel. 2018. "Cooperation in the Finitely Repeated Prisoner's Dilemma." *Quarterly Journal of Economics*, 133: 509–551.

Erat, Sanjiv, and Vish Krishnan. 2012. "Managing delegated search over design spaces." *Management Science*, 58(3): 606–623.

Feldman, Dorian. 1962. "Contributions to the "two-armed bandit" problem." *Annals of Mathematical Statistics*, 33: 847–856.

Fershtman, Chaim, and Uri Gneezy. 2011. "The tradeoff between performance and quitting in high power tournaments." *Journal of the European Economic Association*, 9(2): 318–336.

Fudenberg, Drew, Phillip Strack, and Tomasz Strzalecki. 2018. "Speed, Accuracy, and the Optimal Timing of Choices." *American Economic Review*, 108: 3651–3684.

Fullerton, Richard L, and R Preston McAfee. 1999. "Auctionin entry into tournaments." *Journal of Political Economy*, 107(3): 573–605.

Gershkov, Alex, and Motty Perry. 2009. "Tournaments with midterm reviews." *Games and Economic Behavior*, 66(1): 162–190.

Goltsman, Maria, and Arijit Mukherjee. 2011. "Interim performance feedback in multistage tournaments: The optimality of partial disclosure." *Journal of Labor Economics*, 29(2): 229–265.

Greiner, Ben. 2015. "Subject pool recruitment procedures: organizing experiments with ORSEE." *Journal of the Economic Science Association*, 1(1): 114–125.

Gross, Daniel P. 2017. "Performance feedback in competitive product development." *RAND Journal of Economics*, 48: 438–466.

Halac, Marina, Navin Kartik, and Qingmin Liu. 2016. "Optimal Contracts for Experimentation." *Review of Economic Studies*, 83: 1040–1091.

Halac, Marina, Navin Kartik, and Qingmin Liu. 2017. "Contests for experimentation." *Journal of Political Economy*, 125(5): 1523–1569.

Herz, Holger, Daniel Schunk, and Christian Zehnder. 2014. "How do judgmental overconfidence and overoptimism shape innovative activity?" *Games and Economic Behavior*, 83: 1–23.

Hinnosaar, Toomas. 2016. "Penny auctions." *International Journal of Industrial Organization*, 48: 59–87.

Holt, Charles A, and Susan K Laury. 2002. "Risk aversion and incentive effects." *American economic review*, 92(5): 1644–1655.

John, Oliver P, and Sanjay Srivastava. 1999. "The Big Five trait taxonomy: History, measurement, and theoretical perspectives." *Handbook of personality: Theory and research*, 2(1999): 102–138.

Keller, Godfrey, Sven Rady, and Martin Cripps. 2005. "Strategic Experimentation with Exponential Bandits." *Econometrica*, 73: 39–68.

Khromenkova, Daria. 2015. "Collective Experimentation with Breakdowns and Breakthroughs." *Working Paper.*

Klein, Arnd Heinrich, and Armin Schmutzler. 2017. "Optimal effort incentives in dynamic tournaments." *Games and Economic Behavior*, 103: 199–224.

Koudstaal, Martin, Randolph Sloof, and Mirjam Van Praag. 2015. "Risk, uncertainty, and entrepreneurship: Evidence from a lab-in-the-field experiment." *Management Science*, 62(10): 2897–2915.

Kuhnen, Camelia M, and Agnieszka Tymula. 2012. "Feedback, self-esteem, and performance in organizations." *Management Science*, 58(1): 94–113.

Lang, Matthias, Christian Seel, and Philipp Strack. 2014. "Deadlines in stochastic contests." *Journal of Mathematical Economics*, 52: 134–142.

Lemus, Jorge, and Guillermo Marshall. 2019. "Dynamic Tournament Design: An Application to Prediction Contests." Mimeo.

Lemus, Jorge, and Guillermo Marshall. Forthcoming. "Dynamic tournament design: evidence from prediction contests." *Journal of Political Economy.*

Ludwig, Sandra, and Gabriele K Lünser. 2012. "Observing your competitor–The role of effort information in two-stage tournaments." *Journal of Economic Psychology*, 33(1): 166–182.

Mihm, Jürgen, and Jochen Schlapp. 2018. "Sourcing innovation: On feedback in contests." *Management Science*, 65(2): 559–576.

Noussair, Charles, Stefan Trautmann, and Gijs van de Kuilen. 2014. "Higher Order Risk Attitudes, Demographics, and Financial Decisions." *The Review of Economic Studies*, 81: 325–355.

O'Neill, Barry. 1986. "International escalation and the dollar auction." *Journal of Conflict Resolution*, 30(1): 33–50.

Rieck, Thomas. 2010. "Information disclosure in innovation contests." *Bonn Graduate School of Economics Working paper.*

Robbins, Herbert. 1952. "Some aspects of the sequential design of experiments." *Bulletin of the American Mathematical Society*, 58: 527–535.

Rosokha, Yaroslav, and Kenneth Younge. 2017. "Motivating Innovation: The Effect of Loss Aversion on the Willingness to Persist." *Review of Economics and Statistics*, 1–45.

Rothschild, Michael. 1974. "A two-armed bandit theory of market pricing." *Journal of Economic Theory*, 9: 185–202.

Rubin, Jared, Anya Samek, and Roman M Sheremeta. 2018. "Loss aversion and the quantity–quality tradeoff." *Experimental Economics*, 21(2): 292–315.

Seel, Christian, and Philipp Strack. 2016. "Continuous time contests with private information." *Mathematics of Operations Research*, 41(3): 1093–1107.

Shubik, Martin. 1971. "The dollar auction game: A paradox in noncooperative behavior and escalation." *Journal of conflict Resolution*, 15(1): 109–111.

Stigler, George J. 1961. "The economics of information." *Journal of Political Economy*, 69: 213–225.

Strulovici, Bruno. 2010. "Learning While Voting: Determinants of Collective Experimentation." 78: 933–971.

Taylor, Curtis R. 1995. "Digging for golden carrots: An analysis of research tournaments." *The American Economic Review*, 872–890.

Terwiesch, Christian, and Yi Xu. 2008. "Innovation contests, open innovation, and multiagent problem solving." *Management science*, 54(9): 1529–1543.

Wald, Abraham. 1947. *Sequential Analysis.* Wiley New York.

Yildirim, Huseyin. 2005. "Contests with multiple rounds." *Games and Economic Behavior*, 51(1): 213–227.

Appendices

A Theory Appendix: Equilibrium

In this appendix we examine equilibrium strategy profiles for sequential-sampling competition with and without leaderboard feedback in a setting with an arbitrary number of periods and general utility functions. In subsection A.1, we consider the case of a finite horizon.[27] In subsection A.2, we consider the infinite-horizon case.

A.1 Finite-Horizon Leaderboard-Feedback Sampling Competition

In this subsection of Appendix A, we describe the process for characterizing the subgame perfect Nash equilibria of the finite horizon leaderboard-feedback innovation contest. For the corresponding case of the private-feedback innovation contest, it is straightforward to extend the analysis of Taylor (1995) to allow for a general utility function, and hence we omit the discussion of that case. 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. As risk aversion is found to be an important driver of behavior in the experiment, we focus here on a specification of utility that allows for risk aversion. In particular, we assume that: (i) total utility is time separable and (ii) the utility within a given stage, denoted by $u(\cdot)$, satisfies $u(-c) < 0$ and $u(v - c) > 0$. Risk-aversion may then be modeled via $u(\cdot)$, the utility within a given stage. In Appendix B, we provide additional details on the specifications of utility that we use to model risk aversion, loss aversion and sunk-cost fallacy considerations. Lastly,

[27] Recall that the special case of our model with risk-neutral players and two periods is examined in Rieck (2010).

the following analysis focuses on the case that $u(v-c)+u(-c)\geq 0$, which in the case of risk neutrality requires that $v\geq 2c$.[28]

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

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

[28]Note however, that it is straightforward to extend the analysis to the case of $u(v-c)+u(-c)<0$.

then for

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

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, $F(s_T) \in \left[\sqrt{\frac{u(v-c)+u(-c)}{u(v-c)-u(-c)}}, \frac{u(v-c)}{u(v-c)-u(-c)}\right]$.[29]

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

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

and let

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

and note that $\Sigma_{f_T}^{indiff}$, $\Sigma_{f_T}^{1}$, and $\Sigma_{f_T}^{0}$ form a partition of supp(F). Player f_T's final-stage-local

[29]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 $F(s_T) \in \left[\sqrt{1-\frac{2c}{v}}, 1-\frac{c}{v}\right]$.

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 $p^{indiff}_{f_T}$, 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 $\mathrm{supp}(F)$. Then, the period T leader's final-stage local best-response correspondence as a function of $(p_{f_T},s_T)\in[0,1]\times\mathrm{supp}(F)$

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	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.

A.2 Infinite-Horizon Sampling Competition

In the following analysis of the infinite-horizon game we focus on stationary Markov equilibria in which both players use a stopping rule. Recall that a stationary Markov strategy ignores all of the details of a history except the current state. In the case of leaderboard-feedback, the state is the leader's score. Similarly, in the case of private feedback, the state for each player is their own score. Lastly, recall that any subgame-perfect equilibrium strategy profile in which each player utilizes a stationary Markov strategy forms a stationary Markov equilibrium.

Case of Leaderboard Feedback

Let ξ^L denote the threshold for the equilibrium stopping rule with leaderboard feedback. The threshold ξ^L is solved by setting the marginal gain from additional search equal to its marginal cost. Given that at the start of an arbitrary period t, $\max\{s_{i,t}, s_{-i,t}\} \leq \xi^L$ and that the opponent uses a stationary Markov strategy in which they continue to search until at least one player hits the threshold ξ^L, the continuation payoff from searching in period t, denoted $V(\max\{s_{i,t}, s_{-i,t}\})$, is calculated as

$$
\begin{aligned}
V(\max\{s_{i,t}, s_{-i,t}\}) = \left(F(\xi^L)\right)^2 \left(V(\max\{s_{i,t+1}, s_{-i,t+1}\}) + u(-c)\right) \\
+ \left(F(\xi^L)(1 - F(\xi^L)) + \frac{(1 - F(\xi^L))^2}{2}\right) \left(u(v-c) + u(-c)\right).
\end{aligned} \tag{19}
$$

Player i wins the contest in period t and receives a utility of $u(v-c)$ at the end of period t if in period t player i draws an innovation above the threshold ξ^L but player $-i$ does not draw above the threshold ξ^L, which occurs with probability, $F(\xi^L)(1 - F(\xi^L))$, or if both players draw an innovation above the threshold and player i has the higher of the two scores, which occurs with probability, $\frac{(1-F(\xi^L))^2}{2}$. Player i loses the contest in period t and receives a utility of $u(-c)$ at the end of period t if in period t player $-i$ draws an innovation above the threshold ξ^L but player i does not draw above the threshold ξ^L, which occurs with probability, $F(\xi^L)(1-F(\xi^L))$, or if both players draw an innovation above the threshold and player i has the lower of the two scores, which occurs with probability, $\frac{(1-F(\xi^L))^2}{2}$. Lastly, if both players draws are below ξ^L, which occurs with probability $(F(\xi^L))^2$, then player i incurs a period t payoff of $u(-c)$ from searching in period t but the game continues and the continuation payoff in state $\max\{s_{i,t+1}, s_{-i,t+1}\} \leq \xi^L$ is $V(\max\{s_{i,t+1}, s_{-i,t+1}\})$.

In a stationary Markov equilibrium, if $\max\{s_{i,t+1}, s_{-i,t+1}\} \leq \xi^L$, then it must be the case that $V(\max\{s_{i,t}, s_{-i,t}\}) = V(\max\{s_{i,t+1}, s_{-i,t+1}\})$. Furthermore, because the continuation payoff from stopping search is 0, it follows that if $\max\{s_{i,t}, s_{-i,t}\} \leq \xi^L$ then $V(\max\{s_{i,t}, s_{-i,t}\}) = 0$. Thus, it follows from equation (19) that

$$
(F(\xi^L))^2 u(-c) + \left(\frac{1 - (F(\xi^L))^2}{2}\right) \left(u(v-c) + u(-c)\right) = 0 \tag{20}
$$

or equivalently

$$
F(\xi^L) = \sqrt{\frac{u(v-c) + u(-c)}{u(v-c) - u(-c)}}. \tag{21}
$$

Case of Private Feedback

The case of private feedback follows along similar lines. Let ξ^P denote the threshold for the equilibrium stopping rule with private feedback. The threshold ξ^P is solved by setting the marginal gain from additional search equal to its marginal cost. Given that $s_{i,t} \leq \xi^P$ and that the opponent uses a strategy in which they continue to search until they hit the threshold ξ^P, the continuation payoff from searching is

$$V(s_{i,t}) = F(\xi)\left(V(s_{i,t+1}) + u(-c)\right) + \frac{(1 - F(\xi))}{2}\left(u(v - c) + u(-c)\right). \tag{22}$$

In a stationary Markov equilibrium, if $s_{i,t+1} \leq \xi^P$, then it must be the case that $V(s_{i,t}) = V(s_{i,t+1})$. Furthermore, because the continuation payoff from stopping search is 0, it follows that if $s_{i,t} \leq \xi^P$ then $V(s_{i,t}) = 0$. Thus, it follows from equation (22), that

$$F(\xi^P) = \frac{u(v - c) + u(-c)}{u(v - c) - u(-c)}. \tag{23}$$

Comparison of Infinite Horizon with Leaderboard Feedback to that of Private Feedback

Now we compare the expected value of the winning innovation with leaderboard feedback to that of private feedback. First, note that from equations (21) and (23) it follows that $(F(\xi^L))^2 = F(\xi^P)$. Then, to compare the expected value of the winning innovation with leaderboard feedback to that of private feedback, note that with feedback it can be shown that the distribution of the winning innovation, denoted by $\phi^L(x)$, is, for $x \geq \xi^L$, given by:

$$\phi^L(x) = \frac{(F(x))^2 - (F(\xi^L))^2}{1 - (F(\xi^L))^2}, \tag{24}$$

whereas with private feedback, the distribution of the winning innovation, denoted by $\phi^P(x)$, is, for $x \geq \xi^P$, given by:

$$\phi^P(x) = \left(\frac{F(x) - F(\xi^P)}{1 - F(\xi^P)}\right)^2. \tag{25}$$

Because $(F(\xi^L))^2 = F(\xi^P)$, it follows that $\phi^L(x)$ first-order stochastic dominates $\phi^P(x)$, and thus the leaderboard feedback contest has a higher expected value for the winning innovation.

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 obtain moments of interest and make contest predictions.

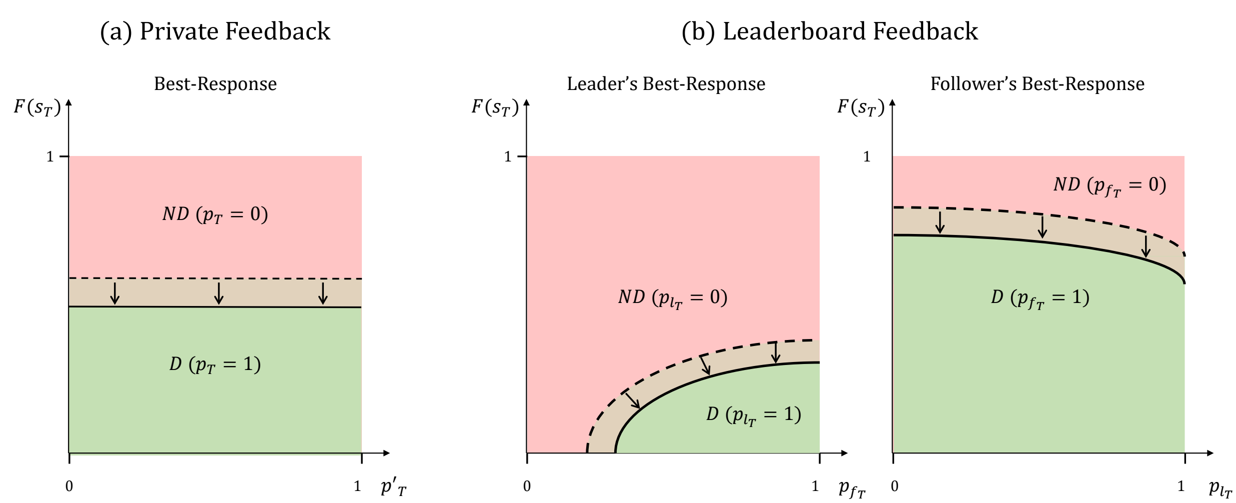
We use the following specifications:

- **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



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.

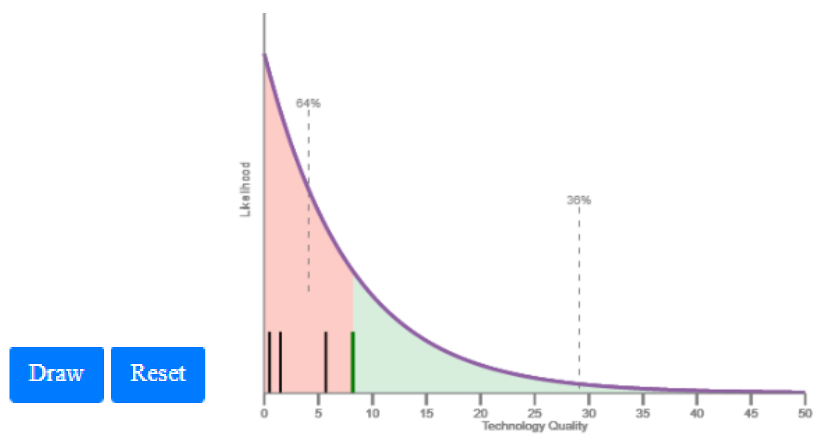
The decisions whether to develop a technology will be made sequentially. In particular, you will first decide whether to develop technology #1. If you decide to do so, you will incur a cost of \$1 and observe the quality of technology #1. Next, you will decide whether to develop technology #2. If so, 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

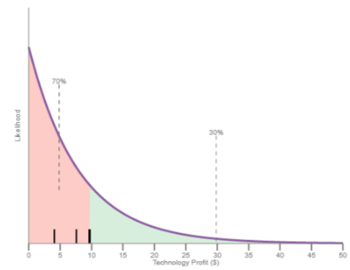
The summary of the most current information is presented below.

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**

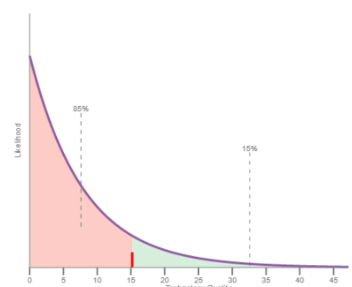
You will make up to 10 decisions. Each decision is a choice between two options:

- 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:

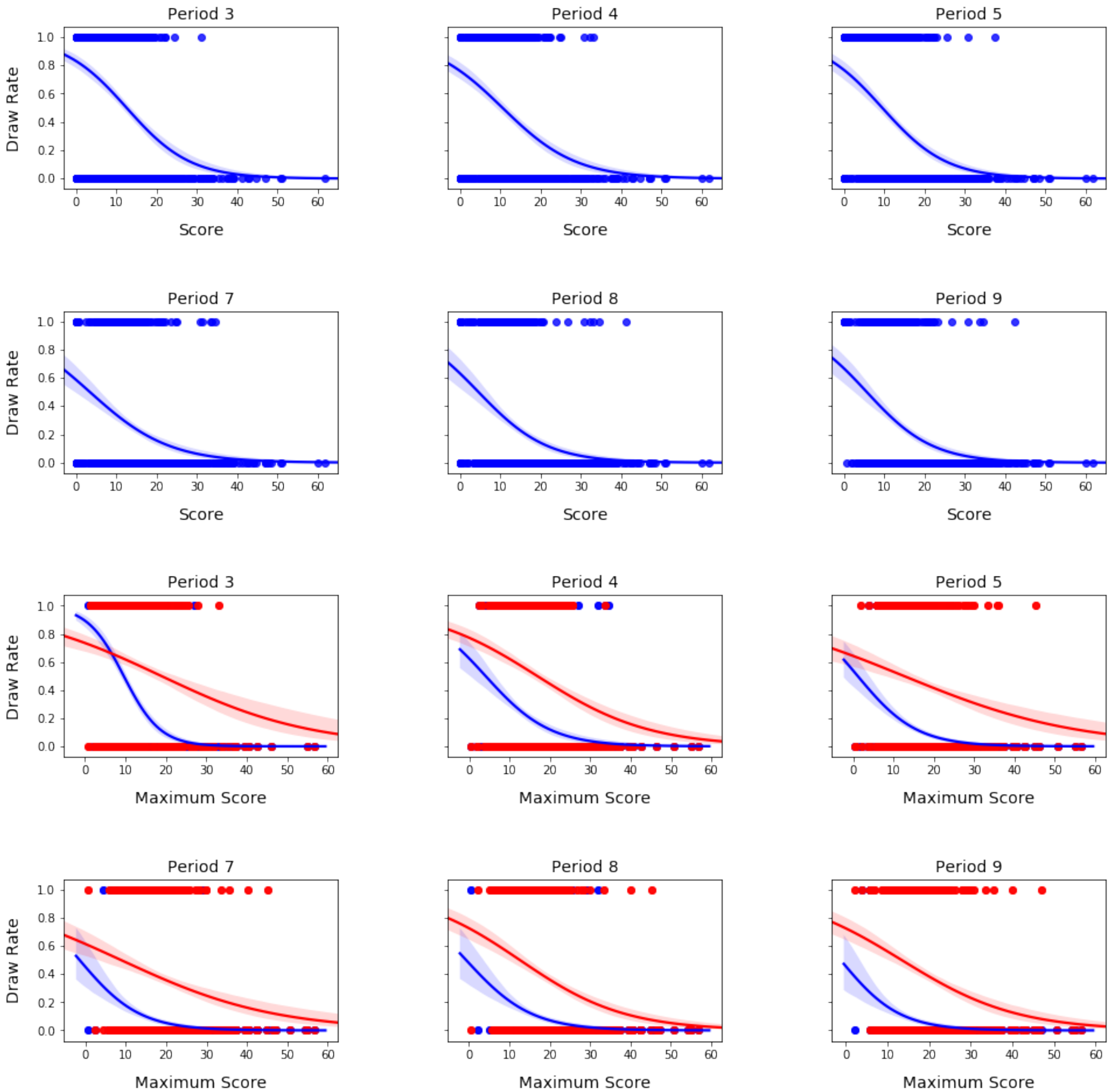
- Decision number: **1**
- Technologies developed by you: **None**
- Incurred cost: **0 x $1= $0**
- Existing market technology: **15.177**
- Probability that technology **#1** will be better than **15.177** is **15%**
- Probability that technology **#1** will be worse than **15.177** is **85%**



Please make your decisions for task # 20.

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

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



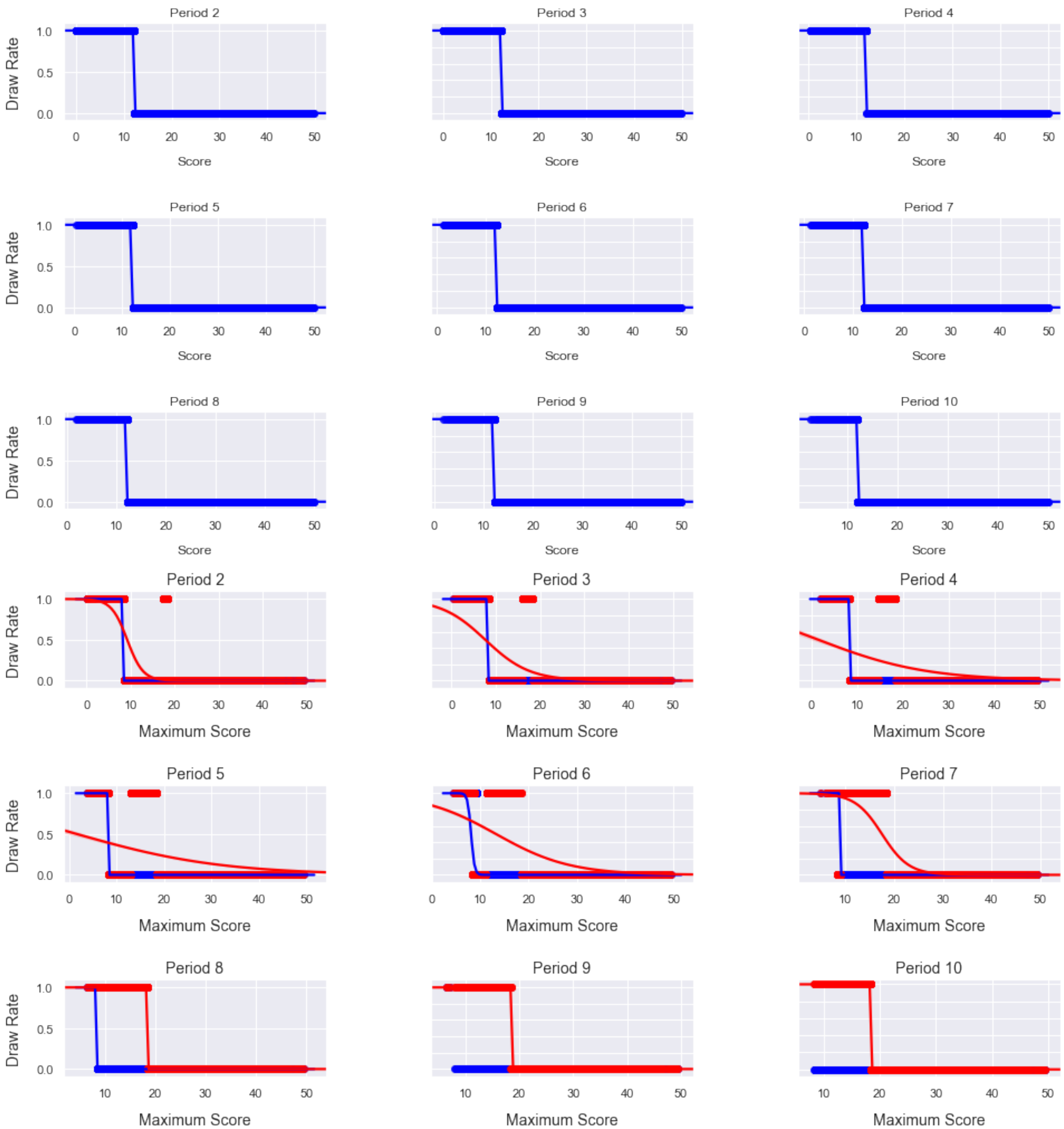
Notes: This figure displays two sets of graphs. The first set of graphs display logistic regressions of the decision to draw in the private-feedback treatment for periods 3, 4, 5, 7, 8, and 9. The second set of graphs display logistic regressions of the leader's decision (blue) to draw and the follower's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

Table D1: 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 private-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 private-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 Contests



Notes: The first set of graphs (rows 1-3) display logistic regressions of the decision to draw in the simulated private-feedback treatment contests for periods 2, 3, 4, 5, 6, 7, 8, 9, 10. The second set of graphs (rows 4-6) 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 2-10.

Table D2: Individual Search Task

Dep. Var.: Draw Decision	Individual
Individual Score	-0.04***
	(0.01)
Period	-0.15***
	(0.02)
Risk Aversion	-2.70**
	(1.17)
Loss Aversion	-0.80
	(1.00)
Sunk Cost Fallacy	-0.13
	(0.59)
Grit	-0.31**
	(0.13)
Competitiveness	0.03
	(0.24)
Achievement Striving	0.01
	(0.31)
Extraversion	0.15
	(0.09)
Agreeableness	0.16
	(0.15)
Neuroticism	-0.15
	(0.19)
Openness	0.03
	(0.11)
Conscientiousness	0.05
	(0.14)
Constant	-1.44**
	(0.71)
Observations	7,680

Notes: This is a logistic regression that analyzes the data from the individual search tasks. The logistic regression has subject level random effects and is clustered at the session level. *,** ,*** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table D3: Decision to Draw (with Demographic Variables)

	(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.

Table D4: Contest Results (Robustness)

(a) Aggregate Draws

Dep. Var.: Aggregate Draws	(1) Pooled	(2) First Half
Private Feedback Treatment	0.96***	2.14***
	(0.25)	(0.40)
Order	1.18***	—
	(0.45)	
Constant	4.81***	5.19***
	(0.80)	(0.64)
Observations	768	384

(b) Winning Innovation

Dep. Var.: Winning Innovation	(1) Pooled	(2) First Half
Private Feedback Treatment	1.40**	3.00***
	(0.64)	(1.04)
Order	1.60**	
	(0.64)	
Constant	17.67***	18.23***
	(1.40)	(1.64)
Observations	768	384

Notes: **(a)** Column (1) presents a regression of the number of aggregate draws in a contest on a dummy variable for the private-feedback treatment and a dummy variable for whether subjects start off with the private-feedback treatment. Column (2) presents a regression of the number of aggregate draws in a contest on a dummy variable for the private-feedback treatment using data from only the first treatment subjects faced. **(b)** Column (1) presents a regression of the winning innovation in a contest on a dummy variable for the private-feedback treatment and a dummy variable for whether subjects start off with the private-feedback treatment. Column (2) presents a regression of the winning innovation in a contest on a dummy variable for the private-feedback treatment using data from only the first treatment subjects faced. All regressions have session level random effects. *,**,*** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table D5: Decision To Draw (Robustness)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	Pooled	Private			Leaderboard		
Draw Decision		All	Leader	Follower	All	Leader	Follower
Order	0.48***	1.04***	1.30***	0.78***	0.073	0.22	0.02
	(0.14)	(0.16)	(0.21)	(0.18)	(0.18)	(0.35)	(0.30)
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	-0.95**	-1.01*	-1.01	-0.90**	-1.02**	-0.93	-0.30
	(0.44)	(0.56)	(1.14)	(0.44)	(0.44)	(0.83)	(1.17)
Loss Aversion	-0.33	-0.35	0.84	-1.03	-0.32	-1.17	-0.44
	(0.67)	(0.88)	(1.07)	(0.73)	(0.62)	(1.12)	(0.88)
Sunk Cost Fallacy	0.06	0.13	-1.12	0.22	-0.12	-0.55	0.02
	(0.63)	(0.94)	(0.72)	(0.97)	(0.46)	(0.87)	(0.94)
Grit	-0.05	-0.09	-0.22	0.02	-0.01	-0.08	-0.10
	(0.13)	(0.21)	(0.26)	(0.17)	(0.08)	(0.22)	(0.26)
Competitiveness	-0.03	0.21	0.17	0.34	-0.23	-0.01	-0.15
	(0.17)	(0.23)	(0.24)	(0.23)	(0.15)	(0.21)	(0.20)
Achievement Striving	0.10	-0.10	-0.20	-0.23	0.26	0.28	0.033
	(0.18)	(0.24)	(0.28)	(0.22)	(0.16)	(0.20)	(0.35)
Extraversion	0.00	-0.09	0.00	-0.10	0.07	-0.19	0.11
	(0.09)	(0.09)	(0.12)	(0.09)	(0.10)	(0.20)	(0.12)
Agreeableness	0.10	0.03	-0.03	-0.02	0.16	0.11	0.16
	(0.12)	(0.14)	(0.18)	(0.15)	(0.13)	(0.20)	(0.20)
Neuroticism	0.09	0.15	-0.01	0.17	0.04	0.12	-0.07
	(0.11)	(0.15)	(0.18)	(0.13)	(0.10)	(0.18)	(0.22)
Openness	-0.08	-0.06	-0.10	-0.10	-0.13	-0.26	-0.14
	(0.09)	(0.14)	(0.17)	(0.14)	(0.09)	(0.18)	(0.15)
Conscientiousness	0.06	0.25	0.36	0.11	-0.13	-0.18	-0.24
	(0.15)	(0.26)	(0.24)	(0.25)	(0.10)	(0.34)	(0.20)
Constant	1.48**	1.58*	3.91***	1.02	0.98*	1.93**	1.75***
	(0.63)	(0.85)	(0.69)	(0.88)	(0.52)	(0.89)	(0.65)
Observations	15,360	7,680	3,451	3,451	7,680	3,411	3,411

Notes: These regressions analyze the data from the private-feedback treatment and the leaderboard-feedback treatment. These regressions are logistic regressions that have subject level random effects and are clustered at the session level. Order is a dummy variable for whether a subject started off with the private-feedback treatment. Personality characteristics are standardized to have mean 0.00 and standard deviation of 1.00. *,** , and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.