Innovate versus Imitate:
Theory and Experimental Evidence

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Abstract

We model and experimentally evaluate the trade-off between innovation and imitation commonly faced by firms and individuals. Innovation involves searching for a high payoff opportunity, but paying a cost to do so. Imitation involves avoiding the search cost and copying the most successful payoff opportunity uncovered thus far. We formulate a novel model of sequential innovation versus imitation decisions made by a group of \( n \) regret minimizing agents. We analyze the consequences of complete versus incomplete information about the distribution of payoffs from innovation on agent’s decisions. We then study these predictions in a laboratory experiment where we find evidence in support of our theoretical predictions.

Keywords: Innovation, Imitation, Risk, Ambiguity, regret minimization, experimental economics

JEL Codes: C91, C92, D21, D81, O31.

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1 Introduction

In many contexts where agents or firms face uncertainty, they do so in an environment that is novel to them. The first firm to enter a market does so when the returns to their research and development are unclear. The first time agents encounter a new item they must decide whether or not to acquire it. On a personal level, we face this scenario when we choose how to order off a menu in a restaurant that we have never been to before.

For those who follow the first mover (the “innovator”), the decision space is doubled: “followers” must decide whether to imitate the innovator or to further innovate themselves and perhaps push the frontier forward. The standard procedure, as in all of economic decision making, is to weigh the benefits and costs of further innovation versus imitation. However, there are many different types of uncertainty and incentive structures that can affect how agents make such decisions. For example, individuals might know the distribution of possible outcomes from further innovation and so behave as expected payoff maximizers in choosing between innovation or imitation. More realistically, they may not know the shape of the distribution from innovation (ambiguity) in which case they might act as regret minimizers. A further complication is whether innovation precludes imitation, or whether imitation is always possible independently of whether an agent chooses to innovate or not. If one can simply abandon failed innovations, i.e., those leading to payoffs that are worse than the current best innovation, and instead imitate the currently best available innovation, then that incentive structure will change the dynamics of innovation, even when agents are placed in an ambiguous setting.

In this paper, we use theory and experiments to address the innovate versus imitate decision in four different settings. Specifically, we consider cases where the distribution of innovation payoff outcomes is known or is unknown to agents, who are always informed of the best innovation payoff uncovered in the game thus far. In these two environments, we further consider the case where individuals can choose to imitate or “recall” the currently best innovation payoff in the event that their innovation payoff is lower, as well as the case where individuals cannot recall that best innovation payoff outcome in the event of unsuccessful innovation, that is, the case where innovation precludes imitation. We characterize agents as regret minimizing, which, in our case, degenerates into utility maximizing when the distribution of innovation opportunities is known.

Our theory predicts that agents behave differently when incentive and informational
structures vary. Specifically, agents are predicted to play probabilistically in situations where they face ambiguous innovation payoff distributions, but deterministically when the distribution of payoffs from innovation is known. Further, the expected maximum innovation value (or draw) increases when we allow for recall (imitation following unsuccessful innovation). The four different conditions also give rise to four different values for the expected number of innovation attempts (or draws) and the expected maximum draw. We test the predictions of our novel, sequential innovate versus imitate model using an experiment that elicits subjects’ probabilities of innovating.

Our experimental results reveal that behavior is closest to the predictions of the model in the case where subjects cannot recall the current best innovation payoff in the event of worse innovation outcomes, and furthest from model predictions when subjects have the ability to recall. Our evidence is based on analysis of subjects’ deviations from model predictions, specifically, their innovation stopping behavior, the expected number of innovations and the expected maximum payoff value from innovation. We further analyze individual level correlates of innovation decisions and find that, across all treatments, males are more likely to innovate than females and that those with higher grade point averages tend to be less willing to innovate. We also find that elicited risk preferences play no role in innovation choices. Overall, we find evidence that agents act as regret minimizers, and that the evidence for our model’s predictions is strongest in the case of no recall, i.e., where innovation precludes imitation. We speculate that the inability to imitate the current best available innovations (the absence of recall) makes subjects think harder about the choice problem they face, which results in a closer accordance between subjects’ behavior and the predictions of our model.

This study is connected to theoretical work in several areas: evolutionary innovation versus imitative behavior, ambiguity aversion, strategic experimentation and search. We often see innovative and imitative behavior featured in the theoretical literature in the context of research and development and changes in productivity (König et al. 2016), development of new products (Ofek & Turut 2008), in the composition of industrial structure (Iwai 2000), and as coexisting behaviors among firms in evolutionary models (Hommes and Zeppini (2014)). In these models, firms are typically considering a continuous strategy space, instead of a binary strategy space as in this paper. Firms in these models also have beliefs about the payoff distribution, or how the stochastic elements are
distributed, allowing for utility maximization. Our model features utility maximization as a special case of a more general regret minimization specification for preferences.

Our study is influenced by the literature on ambiguity aversion, or aversion to unknown risks, which occurs when some aspect(s) of the distribution of possible states of the world are unknown, so that agents are not able to assign probabilities to states of the world. This notion dates back to the work of David Hume (1738). Knight (1921) made a distinction between risk, where the probabilities of all possible states of nature are known (distributional information is complete), and uncertainty where this is not the case. Ellsberg (1961) added the term ‘ambiguity’ to describe settings in between “complete ignorance” and risk, where decision makers have less than perfect confidence in their estimates of relative likelihoods.\footnote{Uncertainty is now used as an umbrella term to describe both risk and ambiguity.} Decision making under ambiguity has been formalized in models of maxmin expected utility (Gilboa & Schmeidler 2004), Choquet expected utility (Schmeidler & Gilboa 1994), and models that allow violations of the reduction of compound lotteries axiom (Halevy 2007). Ambiguity preferences have been studied extensively in the laboratory, with findings that point to high levels of ambiguity aversion, ambiguity prudence, and ambiguity temperance (Adbellaoui et al. 2015, Baillon et al. 2017). We model ambiguity averse individuals as regret minimizers, or agents who apply minimax strategies, similar to the work of Bergemann & Schlag (2011) and Renou & Schlag (2010), where agents encounter uncertainty about the distribution of stochastic elements and seek to minimize their regret given the state of the world that is the least favorable. Again, our study focuses on a simplified version of these models, where agents do not need to consider a continuum of strategies. This results in a simple minimax mixed strategy prediction when the distribution over payoffs is ambiguous and a unique threshold prediction when that ambiguity is resolved.

Our model is also related to the literature on strategic experimentation. In this literature, agents face double-armed bandit problems and must decide how to divide their decisions between a safe option and a risky option with a true payoff plus noise (Bolton & Harris 1999, Keller et al. 2005). Over time, agents learn the true payoff by witnessing the realized payoffs of other agents who “experiment”, or receive payoffs from the risky strategy. Our game has a similar flavor to it, though agents who play in the unknown distribution setting have limits on their information sets that are not present in the
standard strategic experimentation framework. Namely, our agents only see the current maximum payoff value obtained, and the game is one-shot, so no learning is possible. In a laboratory setting, it is possible that subjects may learn about the distribution of payoffs through their own payoffs resulting from strategic experimentation, though recall complicates this process by censoring the observation of payoffs that fall below the current maximum.

Finally, our model is also reminiscent of certain types of search models in that there is an optimal stopping rule for further innovation. For example, in labor search models (see, e.g. Lippman and McCall (1976)) a worker with a current wage offer in hand has to repeatedly consider whether to accept that offer or to pay the opportunity cost of waiting to sample again from the distribution of possible wage offers. In that literature, a distinction is usually made between the case where wage offers not immediately accepted are lost, and the case where past wage offers are retained, which are referred to as sampling without or with recall. We adopt this same recall/no recall terminology in our innovate-versus-imitate model. The main difference between our model and labor search models is that the search process for the best innovation in our model is a sequential move game played by \( n \) different agents (firms), and not a model of repeated, individual decision-making. Firms in our model only get a single opportunity to innovate, and they take as given the value of the current best innovation as determined earlier in the game by another firm. Further, we study the case of both known distributions and unknown distributions (ambiguity) for the distribution of rewards to innovation.

This paper takes elements from each of these different strains of the literature and combines them to ask how an agent or firm might approach the risky task of innovating where the payoff to further innovation is either known or unknown within the context of a single-shot innovate or imitate game. Our model provides a rational choice explanation as to why firms’ innovation efforts may not lead to the best of all possible products; if the distribution of rewards from innovations is known and stationary, then at some point, the costs of further innovation cannot be rationalized and firms switch to imitating one another. It is less clear what happens in a world where the distribution of rewards from innovation are unknown (ambiguity). Indeed, central to our study is our evaluation of the reasonableness of modeling agents as regret minimizers. Further, we examine whether the ability to copy the best outcome of another individual, an explicit choice of imitation,
increases the likelihood that an agent obtains the maximum payoff possible in a game. Indeed, there is much anecdotal evidence that costless imitation, rather than retarding innovation, actually fosters further innovation (see, e.g. Raustiala and Sprigman (2012)).

The rest of the paper is organized as follows. Section 2 presents the game and our theoretical predictions; section 3 describes our experimental design; section 4 presents our experimental hypotheses; section 5 reports on the results of the experiment and tests of our hypotheses; finally, section 6 concludes with a summary of the main findings and some suggestions for future research.

2 Theory

2.1 Known Distribution

Consider the following sequential move, $n$-player game. Agent $i$ must choose between a costly lottery or simply accepting the highest lottery payoff realization achieved by agents who have moved earlier in the game. We interpret the former choice as "innovation" and the latter as "imitation". The lottery is a random draw from a continuous and differentiable probability distribution $F(\theta)$. Specifically, let $X$ denote a random variable with distribution $F(\theta)$, and let $x_i$ denote agent $i$’s realization of that random variable (lottery draw). We denote the full prior history of lottery realizations up to round $t$ by $H_t = \{x_1, \ldots, x_{t-1}\}$ and the maximum of this set by $x_{\text{max}} = \max \{H_t\}$. We assume that an agent’s index, $i \in I$, the set of all $n$ agents, also denotes the time period, or order, in which agents make their decision. We further assume that the cost to choosing the lottery in any time period is fixed and equal to $c$. Each agent begins the game with an endowment, $e$, which may be used to purchase lotteries.

The payoff function is given by:

$$\pi_i = \begin{cases} 
\max \{x_i, x_{\text{max}}\} - c + e & \text{if innovate} \\
x_{\text{max}} + e & \text{if imitate}
\end{cases}$$

(1)

We refer to this payoff function as the “recall” version in that if innovation is unsuccessful, agent $i$ can always recall (receive) the imitation payoff $x_{\text{max}}$, but in that case agent $i$ must still pay the cost of innovating, $c$. We will also consider the case where such recall is not
allowed.

We characterize our agents as expected regret minimizers. However, in the case where the distribution of $X$ is objective, our problem reduces to the utility maximization. To see that this is the case, let $r(x_{\text{max}}, y, j)$ be the regret resulting from action $j$ when the payoff from imitating is $x_{\text{max}}$ and the innovation payoff draw is $y$. Regret is then a piecewise defined function:

$$r(x_{\text{max}}, x, j) = \begin{cases} 
\max\{x - c, x_{\text{max}}\} - x_{\text{max}} & \text{if imitate} \\
\max\{x - c, x_{\text{max}}\} - (x - c) & \text{if innovate} 
\end{cases} \quad (2)$$

A regret minimizer’s objective is to pick the strategy that produces the minimum expected regret, which is

$$E[r(x_{\text{max}}, X, j)|X > x_{\text{max}}] = \begin{cases} 
E[\max\{X - c, x_{\text{max}}\}|X > x_{\text{max}}] - x_{\text{max}} & \text{if imitate} \\
E[\max\{X - c, x_{\text{max}}\}|X > x_{\text{max}}] - (E[X|X > x_{\text{max}}] - c) & \text{if innovate.} 
\end{cases}$$

Our agent will choose to innovate when

$$E (X|X \geq x_{\text{max}}) - x_{\text{max}} \geq c. \quad (3)$$

This condition for when to innovate under recall, as well as a similar condition for when to innovate under no recall (discussed below), are equivalent to an agent making a payoff maximizing decision. Thus, the decision to participate in a lottery in round $t$ depends on the expected value of that lottery, conditional on the draw being larger than the current maximum of lottery outcomes. Specifically, (??) states that the expected increase in the outcome over the current maximum of lottery draws must exceed the cost of innovation. Thus, the expected increase in the payoff from an additional lottery being accepted must be larger than the cost associated with taking that additional lottery.

**Proposition 1.** In the case where agents are allowed to recall, there will be some agent/period $k \in I$ such that all agents $i < k$ will innovate and all agents $j \geq k$ will imitate. Furthermore, the $k - 1^{\text{th}}$ or $k^{\text{th}}$ agent will determine $x_{\text{max}} = E(X|X > x_{\text{max}}) - c$ for all future agents.

**Proof.** Under the assumption that agents play rationally, they will continue to choose to
pay for lotteries (innovate) so long as $E(X|X \geq x_{\text{max}}) - x_{\text{max}} \geq c$. Assuming that $F(\theta)$ is a well-behaved continuous probability distribution, the expression $E(X|X \geq x_{\text{max}}) - x_{\text{max}}$ will be decreasing in $x_{\text{max}}$ and approaches 0 as $x_{\text{max}}$ approaches the upper bound of the distribution.

By the intermediate value theorem, there exists an $x_{\text{max}}$ such that $E(X|X \geq x_{\text{max}}) - x_{\text{max}} = c$, for a $c$ small enough. Thus, there is some $j \in I$ for which $E(X|X \geq x_{\text{max}}) - x_{\text{max}} = c$ or $E(X|X \geq x_{\text{max}}) - x_{\text{max}} < c$. The $j^{th}$ agent will be either indifferent between imitating and innovating or strictly prefer to imitate. If the $j^{th}$ agent innovates, then the first agent who will imitate will be $k = j + 1$ and if the $j^{th}$ agent imitates, the first agent who will imitate will be $k = j$. For all agents $i > k$, we have that $E(X|X \geq x_{\text{max}}) - x_{\text{max}} < c$, and these agents will all choose to imitate. \qed

As noted, the payoff function (1) allows an innovator to imitate the current best payoff, $x_{\text{max}}$, less the innovation cost, $c$, in the event that his/her innovation is unsuccessful ($x_i < x_{\text{max}}$). We can relax this ability to recall the maximum prior payoff and consider payoff functions without such recall:

$$
\pi_i = \begin{cases} 
    x_i - c + e & \text{if innovate} \\
    x_{\text{max}} + e & \text{if imitate}
\end{cases}
$$

which states that agent $i$ faces the decision of either taking the lottery draw, $x_i \sim F(\theta)$ at cost $c$ or taking the highest of the previous innovations (imitation). This “no recall” case can be given the following interpretation. In addition to the cost of innovating, $c$, choosing to innovate is so costly in terms of time that switching, ex-post, after a failed innovation to a strategy of imitation is simply not possible. With this new payoff function, the decision calculus is somewhat changed. Agents should choose to innovate whenever $E(X) - x_{\text{max}} \geq c$, and imitate otherwise. What makes this second setup different from the first is that since agents are no longer are guaranteed $x_{\text{max}}$, they will not condition their expectations on $x_i$ being greater than $x_{\text{max}}$. The model makes the following prediction:

**Proposition 2.** In the case where agents are not allowed to recall, for some $k \in I$, agent $k$ will be the first to imitate and all agents $i > k$ will also choose to imitate. Furthermore, the $k - 1^{th}$ or $k^{th}$ will determine $x_{\text{max}} = E(X) - c = \mu - c$ for all future agents.

The proof of Proposition 2 follows a logic similar to Proposition 1 and is omitted.

In many environments there are legal restrictions, e.g., patents and copyrights, that
prevent firms from imitating other firms or that make it costly for a firm to choose to imitate. On the other hand, there are also industries where there is effectively no cost to imitation. For example, for historical and legal reasons, imitation is common and effectively costless in the fashion and restaurant food industries (Raustiala and Sprigman (2012)). Assuming that the costs of imitation are not infinite, we can easily allow for costly imitation by requiring agents to pay a cost, \( d \), if they choose to imitate.\(^2\) This new cost changes the decision criteria in (??) to:

\[
E (X|X \geq x_{\text{max}}) - x_{\text{max}} \geq c - d. \tag{5}
\]

Adding a cost to imitation decreases the number of agents who play imitate and increases \( k \) in expectation, \textit{ceteris paribus}. Without loss of generality, we will focus on a single cost, \( c \), for innovation rather than a cost \( d \), for imitation, though one can also think of our innovation cost as the net cost of the two actions, i.e., \((c - d)\).

### 2.2 Unknown Distribution

There are many cases in which an agent or firm does not know the distribution of possible payoffs from innovation. In such a setting, expected utility maximization and expected regret minimization are no longer equivalent since the relevant distributional information is not fully available. We do suppose that agents know something about innovation prospects. Specifically, we suppose that the support, \([a, b]\), of the unknown distribution from innovation is perfectly (and commonly known), a setting that corresponds to ambiguity as discussed earlier.\(^3\) In such a setting, we conjecture that agents adopt a minimax regret strategy instead of expected utility maximization.

As before, let \( r(x_{\text{max}}, x, j) \) be the regret resulting from action \( j \) with the payoffs from imitating being \( x_{\text{max}} \) and innovating being the draw \( x \). Regret is then modeled as it was in equation (??) previously.

**Proposition 3.** In the case where agents are not allowed to recall, agents will play the mixed strategy \( p^* = \frac{x_{\text{max}} - a + c}{b - a} \), where \( p^* \) is the equilibrium probability that an agent imitates.

**Proof.** We start by finding the distribution \( F \) that maximizes regret in our framework. To

\(^2\)We set \( d \) to 0 in our experiment, though changing it only changes a constant in our theory.

\(^3\)That is, we do not consider the case of complete ignorance!
this end, we examine the expected regret function $r(p, F, x_{\text{max}})$, where $p$ is the probability that an agent chooses to imitate.

$$r(p, F, x_{\text{max}}) = \int_{a}^{b} \left[ pr(x_{\text{max}}, x, Im) + (1 - p)r(x_{\text{max}}, x, In) \right] dF(x) \quad (6)$$

It is assumed that $b - c > x_{\text{max}} \geq a$ so that imitation does not dominate. We examine the two *degenerate* distributions where all mass lies at the boundaries of the support, which maximizes regret, i.e., $F = \delta_b$ and $F = \delta_a$, where payoffs from innovation are at their most extreme.

In the case where $F = \delta_b$, the expected regret is

$$p \left[ \max \{ b - c, x_{\text{max}} \} - x_{\text{max}} \right] + (1 - p) \left[ \max \{ b - c, x_{\text{max}} \} - (b - c) \right]$$

which simplifies to

$$p [b - c - x_{\text{max}}] + (1 - p)0 = p [b - c - x_{\text{max}}].$$

In the second case, where $F = \delta_a$, expected regret is found to be

$$(1 - p) [ x_{\text{max}} - a + c ].$$

It follows that the regret from $F = \delta_b$ will be higher than the regret from $F = \delta_a$ when

$$p [b - c - x_{\text{max}}] \geq (1 - p) [ x_{\text{max}} - a + c ] ,$$

which simplifies to

$$\frac{x_{\text{max}} - a - c}{b - a} \leq p.$$

Similarly for the case where $F = \delta_a,$

$$\frac{x_{\text{max}} - a - c}{b - a} \geq p.$$

Let $p^* = \frac{x_{\text{max}} - a - c}{b - a}$. Then we return to our regret minimization problem, where we wish to minimize
We minimize this function by finding the mixing probabilities for our agents.

\[
\frac{\partial (MR)}{\partial p} = \begin{cases} 
    a - c - x_{\text{max}} & \text{if } p < p^* \\
    b - c - x_{\text{max}} & \text{if } p > p^*
\end{cases}
\]

This function reaches a minimum at \( p^* \).

Using a similar method we can find a solution to the regret minimization problem faced by agents who have the ability to recall \( x_{\text{max}} \) in the event of a worse payoff from innovation. Here, the only thing that changes is when we consider the case where \( F = \delta_a \). In that case, when there is recall, agents know they cannot do worse than the current maximum draw, thus the expected regret under \( F = \delta_a \) will be \((1 - p)c\) instead of \((1 - p)[x_{\text{max}} - a + c]\).

**Proposition 4.** In the case where agents are allowed to recall, they will play the mixed strategy \( p^* = \frac{c}{b - x_{\text{max}}} \), where \( p^* \) is the equilibrium probability that an agent imitates.

The proof follows the same form as the proof provided for proposition ??, noting the change mentioned above regarding the case where \( F = \delta_a \).

Propositions ??-?? provide sharp testable predictions as to the strategies that agents should play in our innovate versus imitate game. In the next section, we describe our experimental design for evaluating these theoretical predictions.

3 Experimental Design

The model makes distinct predictions about stopping rules, innovation probabilities, and how they differ depending on whether the distribution is known as well as on the ability to recall prior payoffs in the event of an unsuccessful innovation. Thus our experiment employs a \( 2 \times 2 \) experimental design where the two treatment variables are: 1) knowledge/lack of knowledge about the distribution of possible payoffs from innovation and 2) the presence or absence of the ability to recall the maximum prior payoff from innova-
tion in the event that an innovation choice leads to a lower payoff. Table 2 provides a summary.

<table>
<thead>
<tr>
<th>Known Distribution</th>
<th>No Recall</th>
<th>Recall</th>
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<tbody>
<tr>
<td>Unknown Distribution</td>
<td>KDNR</td>
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<td>UDNR</td>
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Table 1: Four treatments of the experiment

In each of these four treatments, subjects participated in 4 different stages: the main decision consisting of 1) ten, 10-round, 10-player innovate/imitate games, 2) a risk elicitation task, 3) a cognitive reflection task, and 4) a short demographic survey.

3.1 The main task

In the first and main stage, subjects participate in ten, 10-round “games” with a fixed group of $n = 10$ subjects. At the start of each game, the subjects were assigned a random number from 1 to 10 indicating the order of moves for the current game. Then, for each round of each game, one of the 10 subjects took a turn deciding whether to take a draw from a payoff distribution (known or unknown) or copy the highest payoff drawn in the current game thus far by subjects who had drawn before them in the game, i.e., $x_{\text{max}}$. For the first player to draw in round 1 of each game, $x_{\text{max}}$ was set to 0.

The distribution we used in both treatments (known and unknown) was a discrete approximation of the symmetric triangular distribution, with support $[0, 100]$ and a modal peak of 50. Draws from that distribution were truncated at the hundredths place. Though unlikely, it was possible for subjects to draw the same number more than once.

In the known distribution (KD) treatments, subjects were told about the distribution of innovation payoffs, while in the unknown treatment subjects were only informed of the support of the unknown distribution $[0, 100]$. Specifically, in the KD treatments, subjects were shown a graph of the distribution they were drawing from featuring the finite range of the support as well as the triangular distribution, the modal peak of that distribution and its value. Figure 1 displays a screen shot of the main decision screen for the known distribution treatment. In both the KDNR and KDR treatments a dashed line on the graph of the distribution function revealed to each subject the current value of $x_{\text{max}}$. In the unknown distribution (UD) treatments, subjects were only told the support of the distribution $[0, 100]$ and were not provided with any information characterizing the shape
of the distribution; indeed, they were explicitly told that the distribution of payoffs from choosing to draw (innovate) was unknown to them and could be any distribution.

In both treatments, subjects knew their payoff function and the value of $x_{\text{max}}$ at the time they were asked to make a choice. Specifically, they were asked to decide how likely they were to take a draw (innovate) from the payoff distribution. This likelihood also determined the probability that they did not take a draw, and instead copied the highest payoff received by previous subjects. Options for the likelihood to take a draw included two buttons, Do Not Draw and Draw which indicated either a 0% or 100% chance to take a draw. In addition, we provided subjects with input box in which they could choose a probability in between these two extremes, to better compare behavior with the mixed strategy predictions in our UD treatments—see again Figure ??.

Figure 1: The main decision screen for the known distribution treatment.

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4We realize that subjects might update their pessimistic priors using observations of the current maxima across multiple games. However, subjects were never told that the distribution did not change from game to game (which was in fact the case), no history of draws (other than $x_{\text{max}}$ was shown to them, and density estimation with small sample sizes is unlikely to update the prior in a significant manner.

5For the unknown distribution treatments, the choice screen eliciting subjects’ probabilities of innovating looks the same as in Figure ??, but the distribution of innovation payoffs is not shown.
In each game, subjects were endowed with $e = 10$ points and were informed that taking a draw in that game would cost them this 10 point endowment, i.e., in terms of the theory, we set $c = e = 10$. If they did not take a draw (did not innovate), then they would keep their 10 point endowment, and get the payoff from imitation, $x_{\text{max}}$. In sessions where recall was available, when a subject took a draw and that draw was below the current maximum, $x_{\text{max}}$, their draw was automatically replaced by the current maximum, $x_{\text{max}}$, for payoff calculation purposes. In neither case did a draw below the current maximum change the current maximum. That is, the current maximum was determined at the 10 player game level and would always be defined as the current maximum draw taken in a game up until that round; this means that the value of $x_{\text{max}}$ was non-decreasing over the 10 rounds of a game. Prior to the start of each new game, $x_{\text{max}}$ was reset to 0.

After subjects submitted the likelihood with which they would like to take a draw (innovate), the computer program drew a number from 0 to 100 with uniform probability. If the number was less than or equal to the submitted likelihood, then the computer drew a value from the payoff distribution and calculated payoffs in the manner specified on the decision screen and displayed the results on the page that followed directly after the decision screen.

Subjects took turns in making these decisions. At the beginning of a session, each subject received a number that denoted the order in which they would make their decision. When the program advanced to the round number that matched their order, that subject was asked to make their decision. The number denoting the subject’s ordering was never disclosed to the subject and could not be inferred from any information displayed on the decision screen.

Every session consisted of 10 subjects, and each subject made only one decision in the decision stage. Therefore one decision stage lasted 10 rounds. The subjects played 10 decision stages and one was picked at random for payment.

### 3.2 Risk Elicitation Stage

After 10 games were played, each subject advanced to the risk elicitation stage. In the risk elicitation stage, subjects were presented with 6 gambles, as in Eckel & Johnson (2010). The subject was told to pick the gamble they most preferred and the computer would randomly determine a payoff, conditional on their choice. The risk elicitation stage
can be seen in Figure ??.

Figure 2: The risk elicitation screen.

Assuming subjects exhibit CRRA risk preferences, we can find ranges of the coefficient of relative risk aversion, \( r \), by comparing adjacent lotteries in the table of possibilities. This further allows us to classify subjects as risk-averse, risk-neutral, or risk-loving in our analysis. We report the modal range of coefficient of relative risk aversion in Table ??, below.

3.3 Cognitive Reflection Task and Survey Stages

After completion of the risk elicitation stage, subjects proceeded to the survey stage. In this stage, subjects first answer three cognitive reflection questions and then proceeded to answer demographic questions. These questions covered nationality, ethnicity, age, major, and GPA. An illustration of the cognitive reflection task question screen is shown in Figure ??.
Following the survey stage, subjects were informed of their experimental earnings, risk elicitation earnings, the show-up payment, and their grand total earnings. Subjects were then paid discreetly.

### 3.4 Subjects and Data Collection

The experiments were conducted at the University of California, Irvine at the Experimental Social Sciences Laboratory (ESSL). Subjects were undergraduate students at UC Irvine with no prior experience with the game. These subjects were recruited using the SONA systems software.

We collected data from 5 groups of 10 players for each of the four treatments (cells) of our experimental design. Thus we have data on the behavior of $5 \times 10 \times 4 = 200$ subjects. For the first task, we chose one game randomly from all games played and converted subjects’ point earnings in that game into money earnings at a fixed and known rate $1 \text{ point} = $0.15 \text{ USD}$. For the second stage, subjects earned money in an incentivized risk elicitation following the design of Eckel & Grossman (2010). Subjects could earn between $0.20$ and $7.00$ in this stage. The CRT and demographic survey questions in the final stage were unincenitized.

The total average payment was $\sim$22, including a $7 \text{ show up payment}$. On average, subjects spent about an hour in the laboratory, and of that time about 20 minutes were spent reviewing instructions verbally and taking a comprehension quiz. The remaining 40 minutes were devoted to the experiment, which used a web browser and was programmed
in Python using the oTree package (Chen et al. 2016).

Some statistics on our subject population, as taken from our demographic survey, are provided in Table 2.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>19.94</td>
</tr>
<tr>
<td></td>
<td>(1.94)</td>
</tr>
<tr>
<td>GPA</td>
<td>3.01-3.50</td>
</tr>
<tr>
<td>CRT score</td>
<td>1.13</td>
</tr>
<tr>
<td></td>
<td>(1.15)</td>
</tr>
<tr>
<td>CRRA coef.</td>
<td>0.50 &lt; r &lt; 0.71</td>
</tr>
<tr>
<td>% female</td>
<td>70%</td>
</tr>
</tbody>
</table>

Table 2: Descriptive statistics regarding subject population

4 Hypotheses

Based on our theory and experimental design, we have several related hypotheses about behavior in our four different treatments – known distribution without recall (KDNR), known distribution with recall (KDR), unknown distribution without recall (UDNR), and unknown distribution with recall (UDR).

Our main hypothesis is that subjects will behave in accordance with our theoretical predictions. That is, a subject’s propensity to draw (innovate) will match the deterministic or probabilistic predictions of the theory. Further, when the distribution is known, we hypothesize that subjects will draw up to the maximum predicted threshold and imitate thereafter in the manner characterized by either proposition 1 when there is recall or proposition 2 when there is no recall.

Hypothesis 1. The probabilities of drawing from the distribution will match those predicted by the theory. When the distribution is known, subjects will choose to draw if $x_{max}$ is below a certain threshold and will imitate otherwise. When the distribution is unknown, subjects will employ probabilistic regret minimizing strategies that are functions of $x_{max}$.

For the parameterization of the model we implement, the threshold or probability values are shown in the first two rows of Table 2. Note in particular that the threshold for KDNR < KDR. The probability in UDNR is linear in $x_{max}$ and nonlinear in UDR, an in expectation, for a given $x_{max}$ the probability of innovation is higher in UDR than in UDNR.
In addition to considering individual subject behavior we also simulated theoretical play by 10 agents, playing according to theoretical predictions in all four treatments of our experiment 100,000 times. We use these simulated distributions to make additional aggregate, game-level distributional hypotheses.

**Hypothesis 2.** The mean number of draws and the expected maximum draw will correspond to the simulation results reported on in Table ??.

From our simulation results, the mean number of draws and the expected maximum draw across our four treatments should follow the order KDNR < UDNR < UDR < KDR.

We note that our theory, in the case of known distributions, makes use of risk neutral risk preferences. However, we note that empirically many subjects are not risk-neutral and so we predict that any deviations away from risk-neutral preferences might influence a subject’s propensity to draw or innovate. Specifically, those who are risk-averse might stop innovating before our predicted thresholds or exhibit lower probabilities of drawing. Conversely, a risk-loving subject might stop drawing (innovating) after our predicted thresholds or exhibit high probabilities of drawing. To the extent that our subjects are risk-neutral, deviations from the theory should be minimal. Other attributes that might explain departures from risk neutral predictions include subjects’ cognitive abilities, which we measure using GPA and CRT scores.

**Hypothesis 3.** Deviations from risk-neutral play are correlated with individual risk preferences or other personal attributes.
5 Experimental Results

The theory makes predictions about a few main outcome measures. Each measure we look at will be related to the theory’s predictions on subjects’ deterministic or probabilistic propensity to innovate given the current, realized maximum reached in the game, i.e. the actual value of $x_{\text{max}}$ when they made their choice. First, we look at individual level predictions versus behavior across the four different conditions in which our subjects could find themselves. These analyses make significant use of deviations from theoretical predictions. We next compare behavior within a game (10 subjects playing for 10 rounds) with the numerical results we generated from large simulations of agents all playing the exact strategies dictated by our theory. Here we compare the number of draws expected within a game, the expected maximum draw, and indifference thresholds (in the case where distributional information is known). When possible we compare these measures across the different treatments as well as with the predicted values for each treatment.

5.1 Deviation analysis

We analyze predicted behavior by examining the root mean squared error between the probabilities of drawing, as generated by our model, and subject’s actual decisions. The model predictions are a function of the current maximum in a game resulting from subject’s actual decisions. From the data we have subject’s elicited probabilities of taking a draw from the distribution and the theory makes predictions about the probabilities that a risk neutral agent would make when confronted with different levels of $x_{\text{max}}$, the current maximum value drawn in a game. We compute the squared deviations from predicted probabilities using the metric

$$\text{dev}_{i,t} = (p_{i,t} - \hat{p}_{i,t})^2$$

where $p_{i,t}$ is the subject’s reported probability and $\hat{p}_{i,t}$ is the predicted probability of risk-neutral agent drawing. We take the square root of these squared deviations to create round-averaged probabilities, which are reported in Figure ??, separated into the four different treatments. Subjects follow the predictions made by the model most closely when recall is not a factor in the decision making process. Specifically, the root mean squared error (RMSE) of deviations from predictions in the no recall treatments are significantly
smaller than those of the recall treatments \((p < 0.01\), two-tailed Mann-Whitney U-test). Figure ?? also supports the notion that subjects’ decisions are consistent with the predictions of our regret minimization model in the UDNR treatment, but less consistent in the UDR treatment.

![Graphs showing average deviations from regret minimizing model](image)

Figure 4: Average deviations from regret minimizing model

We further decompose our sample into early rounds (games) versus later rounds to see whether subjects are updating their beliefs about the payoff distribution from their initial, regret minimizing beliefs, which are conjectured to be most prevalent in the early rounds before learning can take full force. We define early rounds as the first five rounds, when there are few observations for a subject to condition on to form accurate beliefs about the payoff distribution. Figure ?? demonstrates that, though differences are minor in most cases, that subjects tend to follow the model predictions a little better over time, suggesting that learning is taking place. Thus, it seems that it may take many repetitions of the game for subjects to learn the payoff distribution and to behave in a manner consistent with regret minimization. This same figure also supports the notion that subjects in the KDR and UDR treatments fail to take advantage of the recall opportunity, even after many games have been played.
5.1.1 Bifurcated drawing sequence

We define a “bifurcated drawing sequence” as a 10-round game in which there is a one-time-only switch-over from innovation to imitation. Our theory predicts that when the distribution is known, as in our KD treatments, all games should involve such bifurcated drawing sequences. In neither the no recall nor the recall condition of the KD treatments do subjects bifurcate perfectly \( (p < 0.01, \text{two-tailed Mann-Whitney U-test}) \). However, when subjects do bifurcate, the maximum draw achieved within a game is significantly higher than when they do not bifurcate \( (p < 0.01, \text{two-tailed Mann-Whitney U-test}) \). This finding indicates that when the theory is followed more closely, payoff outcomes are

\[\text{Theory predictions are based off the actual current maximum values in an experimental game.}\]
better. Indeed, when subjects adhere to the predicted bifurcating behavior, their payoffs are, on average, \( \sim 2.30 \) higher than when they do not, a significant difference. Moreover, there is a significant negative correlation between earnings and the root mean squared error \( (p < 0.01, \text{two-tailed Mann-Whitney U-test}) \). These two facts indicate that when subjects act consistently with the model, they stand to earn considerably more than if they act inconsistently.

### 5.2 Threshold Analysis

#### 5.2.1 Known Distribution

Before proceeding with threshold estimation for the cases where such analyses are appropriate (i.e., those scenarios where distributional information is known), we present our estimation strategy. For each subject \( i \), we estimate a threshold indifference point using logit regressions of the form

\[
\text{Innovation}_i = \alpha + \beta \text{CurrentMax}_i + \varepsilon_i, \]

where \( \text{Innovation}_i \) is an indicator variable for whether a subject attempted to innovate (draw=1) or not (imitate=0). After estimating this equation, we then take the ratio of the estimated values \( \frac{-\hat{\alpha}}{\hat{\beta}} \), which indicate the threshold of indifference between drawing and not drawing. Errors are clustered at the subject level. We estimate thresholds at both the game and treatment level.

![Figure 6: Estimated threshold in games by treatment](image)

Figure 6 shows the average of the estimated thresholds in every game for KDNR and KDR treatments and time trends. Figure ?? supports the notion that subjects behavior is consistent with the model when they are in the no recall condition. In the
KDR treatment, where recall is enforced, subjects perform well below predictions, under-leveraging the benefits of recall. However, it is worth noting that in the KDR treatment, the trend is positive, and that subjects in the KDR treatment had marginally significantly higher estimated indifference points in the last five games as compared with the first five games \((p = .10,\) two-tailed Mann-Whitney U-test), indicating that subjects are adjusting their behavior with experience.

<table>
<thead>
<tr>
<th>Prediction</th>
<th>KDR Games 1-5</th>
<th>Games 6-10</th>
<th>All Games</th>
<th>KDR Games 1-5</th>
<th>Games 6-10</th>
<th>All Games</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>42.00</td>
<td>40.00</td>
<td>40.00</td>
<td>70.00</td>
<td>70.00</td>
<td>70.00</td>
</tr>
<tr>
<td>(s.d)</td>
<td>(3.47)</td>
<td>(3.49)</td>
<td>(2.73)</td>
<td>(4.61)</td>
<td>(1.81)</td>
<td>(2.75)</td>
</tr>
</tbody>
</table>

Table 4: Thresholds by treatment

Table ?? shows the estimated thresholds at which subjects are predicted to be indifferent between drawing and not drawing in each treatment and their associated standard errors. We average over the first five and last five games to show the effects of learning. We acquire standard errors using 1000 repetitions of nonparametric bootstrapping of the logit regression stated above.

Table ?? shows that KDNR is statistically significantly different from KDR, which is predicted by the model. These findings indicate that our model of innovate versus imitate provides reasonable predictions about the order of the estimated thresholds. However, we note that the estimates of the thresholds is statistically significantly different from the predicted thresholds in the KDR case.

5.2.2 Unknown Distribution

When analyzing decisions under unknown distributional information, we can no longer use the logit analysis, since each \(p\) represents the probability that minimizes regret given a certain \(x_{max}\). Thus, when a regret minimizing agent plays \(p = 0.5\), it does not represent indifference between innovating and imitating. Instead, it is the mixing probability that minimizes regret given “worst-case” priors on the distribution of \(x\). Therefore, the analysis we find appropriate is the analysis between \(x_{max}\) and the associated probability of taking a draw. This analysis is shown in Figure ?? below. We interpret these probabilities to draw as the average \(p\) which minimizes regret subject to each subject’s subjective payoff.
This analysis also shows the predicted regret minimizing probabilities as well as a quadratic trend for the data. Using t-tests of coefficients, we find that there is no significant difference in probabilities to draw predicted by the model and the experimental data ($p = 0.79$) in the no recall condition, but that the difference is large in the treatment with recall ($p < 0.01$). As in the case of the known distributions, subjects have difficulty incorporating the incentive structure of the recall condition into their decisions. Turning to the quadratic fit of the data, our theory is supported in both treatments by the result that decision probabilities are only influenced linearly by the current maximum draw ($p = 0.06$, two-tailed t-test) in UDNR and only by the quadratic term in UDR ($p = 0.08$, two-tailed t-test). This finding is important because our theory of regret minimization shows that decisions should be linear in the current maximum in UDNR and non-linear in the current maximum in UDR.

5.2.3 Subjective Expected Utility

It is possible that instead of minimizing regret, subjects instead chose to maximize subjective expected utility. Though we gave the subjects no information at all about the nature of the unknown distribution, a subject may have chosen an uninformed prior to use as the basis for their decisions. That is, for the UDNR and UDR treatments, subjects might
have assumed that the distribution was uniform with parameters $a = 0$ and $b = 100$. Under such a distributional assumption, subjects would be predicted to stop at $x_{\text{max}} = 40$ in the UDNR treatment and $x_{\text{max}} = 80$ in the UDR treatment. Instead, using the same estimation strategy outlined in Section ??, we find the empirical stopping thresholds in the experimental data to be 48.14 and 52.31, respectively. Using a two-tailed $z$-test, we find that these values are both significantly different from the predicted values (under the assumption of a uniform prior) at the $p = 0.001$ level. This finding suggests that subjects did not believe the distribution being drawn from was uniform and that our instructions were successful in creating some ambiguity about the actual distribution.

Finding 1. We find support for Hypothesis 1. The probabilities of drawing from the distribution match those predicted by the theory, especially in the case of KDNR and UDNR. When considering the case of known distributions, subjects follow the threshold stopping rule (KDNR) or trend toward the threshold (KDR). When the distribution is unknown, subjects employ probabilistic strategies which resemble closely the regret minimizing theoretical strategies.

We find evidence that subjects’ behavior is reasonably approximated by our model predictions in cases when there is no recall. From our deviation analysis, we find evidence suggesting that subjects deviate much further from the model predictions in the recall treatments. We find corroborating evidence in the threshold and expected draws analysis. We speculate that without recall, subjects may be incentivized to think harder about the trade-offs between innovation and imitation and, as a consequence, their predictions are closer to the rational choice predictions of the theory.

In general, subjects follow the predicted ordering of thresholds in the known distribution treatments. Specifically, we find that the order of the thresholds is KDNR < KDR and that behavior is closest to theoretical threshold predictions in KDNR than in KDR. Though we cannot use a threshold analysis to judge the results of the UDNR and UDR treatments, we do find that subjects make probabilistic decisions consistent with our regret minimization model. We again find that subjects’ decisions are a close match to the model in the UDNR treatment and less so in the UDR treatment. We also find that subjects in the UDNR and UDR treatments follow the linear and (respectively) non-linear predicted relationships between the probability of innovating and the value of $x_{\text{max}}$. Finally, we find that an alternative, SEU model with a naive uniform prior, cannot explain well the behavior of subjects in our UD treatments.
5.3 Expected Maxima Analysis

In the next two sections, we use numerical analyses to test our theory. Specifically we compare our experimental data with 100,000 independent simulations of our 10 round innovation/imitation game in which the simulated agents play strategies in accordance with the deterministic or probabilistic strategies predicted by our theory. For each simulated game we collect a maximum draw and the total number of draws, and we use the distribution of these 100,000 simulations for comparisons with our experimentally generated data.

We first investigate subject behavior via the expected maxima, taking the maximum draw within a game in each treatment as our measure of interest.

![Figure 8: Average maximum draws in games by treatment](image)

Figure 8 shows the experimental data, a linear trend, and a flat line indicating the mean maximum draw from our 100,000 simulations. Figure 8 shows that, while the maxima within a game increased within treatments with unknown distributions, it remained mostly flat in treatments with known distributions. Table reports the results of pairwise comparisons of maximum draws in a game between treatments using t-tests, Mann-Whitney U-tests, and Kolmogorov-Smirnov tests. We also compare how close our

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These distributions can be found in the appendix.
subjects perform to what is predicted by our model\textsuperscript{8}. The results are reported in Table ??.

<table>
<thead>
<tr>
<th>Known Dist.</th>
<th>Prediction</th>
<th>Average</th>
<th>(p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Recall</td>
<td>Games 1-5</td>
<td>60.90</td>
<td>(0.01)</td>
</tr>
<tr>
<td></td>
<td>Games 6-10</td>
<td>60.90</td>
<td>(0.01)</td>
</tr>
<tr>
<td></td>
<td>All Games</td>
<td>60.90</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Recall</td>
<td>Games 1-5</td>
<td>77.33</td>
<td>(0.01)</td>
</tr>
<tr>
<td></td>
<td>Games 6-10</td>
<td>77.33</td>
<td>(0.01)</td>
</tr>
<tr>
<td></td>
<td>All Games</td>
<td>77.33</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Unknown Dist.</td>
<td>Prediction</td>
<td>72.61</td>
<td>(0.12)</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>72.61</td>
<td>(0.974)</td>
</tr>
<tr>
<td></td>
<td>(p-value)</td>
<td>72.61</td>
<td>(0.282)</td>
</tr>
</tbody>
</table>

Table 6: Predicted versus real maximum values by treatment

Table ?? shows that subjects behave remarkably similar to what is predicted by the model, but only in the cases where the distribution is unknown. Columns (2) and (5) of Table ?? also show that the average maximum draw is increased by the ability to recall, but only in the case where the distribution is unknown.

5.4 Expected Draws Analysis

We take advantage of the fact that the expected maxima simulation also provides estimates of the expected number of times subjects will draw during a 10 round game. Figure ?? shows the average number of draws within a game by treatment and their respective trends. In no treatment are the trends significant and the first and last five games of a treatment are never significantly different.

\textsuperscript{8}While we do not report the standard deviations from the 100,000 simulations, our t-tests make use of these simulated standard deviations. Further, we compare the simulated and empirical distributions of maximum draws in a game using Kolmogorov-Smirnov and Mann-Whitney U-tests. In the following section we use these same tests to examine the expected number of draws.
<table>
<thead>
<tr>
<th></th>
<th>KDNR</th>
<th>KDR</th>
<th>UDNR</th>
<th>UDR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Games 1-5</td>
<td>Games 6-10</td>
<td>All Games</td>
<td>Games 1-5</td>
</tr>
<tr>
<td>t-test</td>
<td>0.096</td>
<td>0.498</td>
<td>0.405</td>
<td>0.284</td>
</tr>
<tr>
<td></td>
<td>0.720</td>
<td>0.698</td>
<td>0.647</td>
<td>0.892</td>
</tr>
<tr>
<td></td>
<td>0.994</td>
<td>0.966</td>
<td>0.864</td>
<td>0.994</td>
</tr>
<tr>
<td>U-test</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>KS-test</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td></td>
<td>0.444</td>
<td>0.002</td>
<td>0.274</td>
<td>0.338</td>
</tr>
<tr>
<td></td>
<td>0.554</td>
<td>0.347</td>
<td>0.901</td>
<td>0.587</td>
</tr>
<tr>
<td></td>
<td>0.699</td>
<td>0.408</td>
<td>0.864</td>
<td>0.408</td>
</tr>
<tr>
<td></td>
<td>0.247</td>
<td>0.045</td>
<td>0.032</td>
<td>0.204</td>
</tr>
<tr>
<td></td>
<td>0.281</td>
<td>0.281</td>
<td>0.112</td>
<td>0.281</td>
</tr>
</tbody>
</table>

Table 5: Differences in maximum draws in a game between treatments.
Table ?? presents the mean number of draws from the simulations along with the average and standard deviation from the experimental data. Table ?? reports the results of all pairwise comparisons between the different treatments using a variety of statistical tests. The only statistically or marginally significant differences exist between KDNR/KDR and KDNR/UDR. In both cases KDNR is lower, which is in line with the predictions of the model.

Table 7: Predicted versus real number of draws by treatment

However, in no treatment condition does the model accurately predict the number of draws. In every case, using t-test, U-tests, and KS-tests, we can reject the null hypothesis that the number of draws in a simulated game is the same as in the experimental data at the 0.01 level. However, we do find that deviations from the predictions are significantly higher when subjects are in a condition where recall is present. This is in line with the finding from the deviation analysis, suggesting that subjects are under utilizing the
benefits of recall.

**Finding 2.** We find mixed support for Hypothesis 2. Regarding expected maxima, subjects match closely with the simulated distributions of maximum draws in the UDNR and UDR treatments, but are significantly different from the predictions of the KDNR and KDR treatments. Regarding the expected number of draws, in all treatments but KDNR, subjects significantly underdraw from the distributions, and only in the KDNR treatment do they overdraw.

We find that the distributions of maximum draws in the UDNR and UDR treatments are statistically insignificantly different from those produced by the theory. By contrast, we can reject the null hypothesis that the expected maxima match those predicted by our model for the KDNR and KDR treatments - the maxima are higher than predicted in the KDNR treatment and lower than predicted in the KDR treatment.

What is more, in the UDNR treatment, subjects follow the probabilistic predictions of the regret minimization model that gives rise to the expected maximum draw predictions. Subjects follow these predictions closely even after playing multiple games, indicating that regret minimization can continue to play a role in behavior even after payoffs have been realized several times and learning can occur. We also find that deviations from predicted behavior are statistically significantly different over only the known/unknown distribution treatments: that is to say, there is no statistically significant difference in deviations between KDNR and KDR or UDNR and UDR (\( p = 0.711, p = 0.544 \) respectively using two-tailed Mann-Whitney U-tests). The remaining pairwise comparisons all show high levels of statistical significance (\( p < 0.01 \), two-tailed Mann-Whitney U-test).

However, the subjects do not follow the predictions of the model in terms of the order of the predictions or matching the distributions generated by the theory. Though we do not find any evidence for the hypothesis that the model would predict the number of draws, our analysis of the expected number of draws reveals a similar effect that we found in the deviations analysis: recall increases deviations from the model’s predictions.

### 5.5 Risk Aversion and Individual Characteristics

We return to deviations from model predictions to explore the relationship between such deviations and individual characteristics. That is, we investigate correlations between individual characteristics and individual deviations that might serve to explain systematic differences across our four experimental treatments. In particular, we examine whether
Table 8: Differences in expected number of draws in a game between treatments

<table>
<thead>
<tr>
<th></th>
<th>KDNR</th>
<th>KDR</th>
<th>UDNR</th>
<th>UDR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Games 1-5</td>
<td>Games 6-10</td>
<td>All Games</td>
<td>Games 1-5</td>
<td>Games 6-10</td>
</tr>
<tr>
<td>t-test</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>KDNR</td>
<td>0.219</td>
<td>0.002</td>
<td>0.003</td>
<td>0.250</td>
</tr>
<tr>
<td>U-test</td>
<td>0.220</td>
<td>0.006</td>
<td>0.005</td>
<td>0.187</td>
</tr>
<tr>
<td>KS-test</td>
<td>0.281</td>
<td>0.155</td>
<td>0.068</td>
<td>0.155</td>
</tr>
<tr>
<td>t-test</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>KDR</td>
<td>0.835</td>
<td>0.036</td>
<td>0.107</td>
<td>0.830</td>
</tr>
<tr>
<td>U-test</td>
<td>0.922</td>
<td>0.050</td>
<td>0.200</td>
<td>0.898</td>
</tr>
<tr>
<td>KS-test</td>
<td>0.906</td>
<td>0.009</td>
<td>0.711</td>
<td>0.922</td>
</tr>
<tr>
<td>t-test</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>UDNR</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>KDNR</td>
<td>0.664</td>
<td>0.830</td>
<td>0.174</td>
<td>0.244</td>
</tr>
<tr>
<td>U-test</td>
<td>0.742</td>
<td>0.898</td>
<td>0.131</td>
<td>0.330</td>
</tr>
<tr>
<td>KS-test</td>
<td>0.964</td>
<td>0.994</td>
<td>0.664</td>
<td>1.00</td>
</tr>
</tbody>
</table>
deviations are systematically different between those who are risk neutral and those who are not. If there is some curvature in the utility function, then the threshold stopping value of a subject may differ from our theory, which assumes risk-neutral risk preferences. A risk-averse subject would be predicted to stop innovating earlier than a risk-neutral agent and a risk-loving subject would be predicted to stop innovating later than a risk-neutral agent. These predictions apply only to the case when the payoff distribution is known and would manifest themselves as deviations from predicted probabilities of innovating in our data.

First we test whether risk averse individuals behaved differently than risk-neutral or risk-loving individuals using OLS. Since we use the elicitation procedure found in Eckel & Johnson (2010), we also follow its prescriptive advice for the classification of subjects as either risk-averse or risk-neutral. That is, we classify a subject as risk-averse if they chose the first, second, third, or fourth option in the elicitation found in Figure ?? and risk-neutral if they chose option five or six. The results of these tests can be found in Table ???. In none of our models do we see any significant effect of risk aversion on subject deviations.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>KDNR &amp; KDR</th>
<th>KDNR</th>
<th>KDR</th>
<th>KDNR &amp; KDR</th>
<th>KDNR</th>
<th>KDR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recall</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>1,771***</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>RiskAverse</td>
<td>493.8</td>
<td>-32.61</td>
<td>751.3</td>
<td>346.2</td>
<td>-32.61</td>
<td>751.3</td>
</tr>
<tr>
<td></td>
<td>(329.1)</td>
<td>(329.3)</td>
<td>(460.8)</td>
<td>(282.2)</td>
<td>(329.3)</td>
<td>(460.8)</td>
</tr>
<tr>
<td>Constant</td>
<td>1,954***</td>
<td>1,300***</td>
<td>2,600***</td>
<td>1,157***</td>
<td>1,300***</td>
<td>2,600***</td>
</tr>
<tr>
<td></td>
<td>(218.9)</td>
<td>(230.8)</td>
<td>(326.9)</td>
<td>(221.2)</td>
<td>(230.8)</td>
<td>(326.9)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,000</td>
<td>500</td>
<td>500</td>
<td>1,000</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.001</td>
<td>0.000</td>
<td>0.006</td>
<td>0.052</td>
<td>0.000</td>
<td>0.006</td>
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</table>

Robust standard errors clustered at the subject level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Risk Aversion’s impact on squared deviations from model predictions.

We next test for relationships between deviations and individual level characteristics, including age, sex, GPA, cognitive reflection test (CRT) score, and quantitative reasoning (QR) score. We impute a QR score by associating the mean GRE quantitative score associated with the major of each subject (such scores can range from 130-170). For undeclared majors, we used the mean GRE quantitative score across all test takers, which

[9] We had data on the major of each subject participant, and we used the mean GRE quantitative score for each major as reported by the Educational Testing Service, which administers the GRE.
The least squares estimates are reported in Table ??.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>All</th>
<th>KDNR</th>
<th>KDR</th>
<th>UDNR</th>
<th>UDR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unknown Dist. -178.7</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>(191.5)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recall 1,820***</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>(290.7)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unknown Dist. x Recall  989.1***</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
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<tr>
<td>(201.7)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Risk Averse</td>
<td>101.0</td>
<td>56.11</td>
<td>431.4</td>
<td>78.80</td>
<td>-106.6</td>
</tr>
<tr>
<td>(170.5)</td>
<td>(285.3) (529.4) (153.9) (249.8)</td>
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<td></td>
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<tr>
<td>Age</td>
<td>-8.926</td>
<td>-40.48</td>
<td>-80.89</td>
<td>96.22</td>
<td>135.9*</td>
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<tr>
<td>(51.66)</td>
<td>(52.88) (145.0) (85.21) (73.91)</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Gender 349.4*</td>
<td>211.4</td>
<td>899.5</td>
<td>15.97</td>
<td>218.9</td>
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<tr>
<td>(193.0)</td>
<td>(312.1) (562.7) (213.4) (346.6)</td>
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<tr>
<td>GPA -158.9**</td>
<td>-437.9**</td>
<td>-96.99</td>
<td>-99.34</td>
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<tr>
<td>(66.61)</td>
<td>(191.9) (180.8) (82.30) (78.40)</td>
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<td>CRTscore 0.536</td>
<td>-346.2***</td>
<td>100.9</td>
<td>57.79</td>
<td>-31.84</td>
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<tr>
<td>(74.19)</td>
<td>(125.0) (212.0) (103.5) (113.0)</td>
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<td></td>
<td></td>
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<tr>
<td>QRscore 7.437</td>
<td>-36.28</td>
<td>66.32</td>
<td>-16.29</td>
<td>-23.65</td>
<td></td>
</tr>
<tr>
<td>(18.14)</td>
<td>(32.69) (56.73) (13.12) (27.32)</td>
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</tr>
<tr>
<td>Constant 690.0</td>
<td>9,609*</td>
<td>-6,007</td>
<td>2,028</td>
<td>3,536</td>
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<tr>
<td>(2,783)</td>
<td>(5,241) (9,929) (2,315) (3,919)</td>
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<tr>
<td>Observations 2,000</td>
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<td>500</td>
<td>500</td>
<td>500</td>
<td></td>
</tr>
<tr>
<td>R-squared 0.072</td>
<td>0.035</td>
<td>0.020</td>
<td>0.011</td>
<td>0.011</td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Determinants of squared deviations from model predictions

Finding 3. We find evidence to support Hypothesis 3. While subjects' attitudes toward risk have an insignificant correlation with their deviations from theoretical predictions whether in the known or unknown distribution treatments, cognitive ability, as measured by GPA and CRT score, correlate to model deviations.

Table ?? shows that, though there is no significant correlation between risk preference and deviations after controlling for confounding factors, both sex and the GPA of the subject matter for differences in the degree to which subjects' deviate from the model's predictions. Specifically, men deviate from the model more than women and those with higher GPAs deviate from the model less than those with lower GPAs. These effects are felt most strongly in the KDNR and KDR treatments. Table 6 also shows, again, that KDNR and UDNR have similarly small deviations, while KDR and UDR generate significantly larger differences in deviations. This finding is consistent with the results of
6 Concluding Remarks

Our study makes several key contributions to the regret minimization and strategic experimentation literatures. First, we merge the two into a model of experimentation in a single shot game, where we model agents as regret minimizing. We predict four distinct behaviors which are influenced by the ability to copy the leader in the case of failed innovation (recall) and knowledge of the payoff distribution. These different conditions mirror aspects of the real world, such as the presence of intellectual property rights and the strength of beliefs on the returns to research and development. Our model predicts differences in the probabilities of a regret minimizing individual to innovate conditional on the current maximum draw, which also influences the expected maximum draw to be obtained within a game.

We develop a novel experimental design to test the implications of the model. To our knowledge, this is the first to measure how well subjects behavior corresponds to the predictions of regret minimization where the states of nature form a continuum. We find that our subjects behavior is consistent with that predicted by regret minimization. We find that the biggest driver of differences between model predictions and behavior in most of our subject and game level measures is recall, while knowledge of the distribution plays a less central role in explaining differences.

Further, when we compare average propensities to innovate, we find that regret minimization describes patterns in subject behavior well. Again, regret minimization best describes subject behavior when there is no recall, which is again mirrored in results pertaining to the average maximum reached within a game. Regret minimization seems to describe behavior just as well in early rounds as it does in later rounds, which indicates that the beliefs of our subjects are not updated enough to move them away from their regret minimizing behavior. This, in turn, points to the fact that our environment is not similar enough to the classical strategic experimentation paradigm to generate results consistent with its theory. It is likely that there are too few observations for subjects to condition on and estimate the payoff distribution in a meaningful way.

Since recall does not substantially change the propensity to innovate and serves to
increase deviations between our model and the data, we conclude that recall does not help in exploring the payoff distribution. This may be due to the fact that while recall lowers innovation costs, it also lowers the difference in payoffs between innovating and imitating, especially after a sufficiently high maximum has been reached within a game. This smaller differential, compared to the case where there is no recall, may lead to subjects thinking less critically about what their best decision is when attempting to minimize regret under the recall condition. In essence, the reduced salience of decision making brought about by the recall condition leads to less critical thinking about an agent’s optimal strategy.

In future research, it would be of interest to modify our design to explore some more realistic scenarios. Since one innovation often serves as a complement to new innovations (Romer 1994), a simple change would be to make the payoff distribution endogenous by allowing successful innovation to shift the parameters of the distribution. Depending on the differences in the changes to the parameters, innovation may continue indefinitely or stop earlier than it might have if the distribution was static. One could also model changes to the distribution as ambiguous to capture behavior when the changes in the state of nature are not known. Another reasonable modification would be to let subjects play the game for a longer period of time, e.g. cycling through the n-round game multiple times, allowing for a more realistic depiction of the research and development process and transforming the game into one of strategic interaction and repeated play, allowing for more learning to develop. We leave these extensions to future research.
References


Appendices

A Threshold Proofs

The proof below will make extensive use of the generalized form of the triangular distribution,

\[
f(x) = \begin{cases} 
\frac{2(x-a)}{(b-a)(c-a)} & \text{if } a \leq x < c \\
\frac{2}{b-a} & \text{if } x = c \\
\frac{2(b-x)}{(b-a)(b-c)} & \text{if } c < x \leq b \\
0 & \text{elsewhere}
\end{cases}
\]  

(8)

When we parameterize the distribution with \(a = 0\), \(b = 100\), and \(c = 50\), the above definition reduces to

\[
f(x) = \begin{cases} 
\frac{2x}{5000} & \text{if } 0 \leq x < 50 \\
\frac{2}{100} & \text{if } x = 50 \\
\frac{2(100-x)}{5000} & \text{if } 50 < x \leq 100 \\
0 & \text{elsewhere}
\end{cases}
\]  

(9)

A.1 Known Distribution, No Recall

First we consider the case where we have no recall. Thus the decision whether to draw or not for a risk neutral individual is defined as

\[E(X) - x_{\text{max}} \geq 10\]

Since \(E(X) = \mu = 50\), the threshold will be set as \(x_{\text{max}} = 40\).

A.2 Known Distribution, Recall

Here the agent is allowed to condition on the current \(x_{\text{max}}\), which, in effect, raises the lower support of \(X\). This leads to a dynamic reduction in cost that decreases as \(x_{\text{max}}\) increases. Recall that the decision to draw or not for a risk neutral agent is based upon
\[ E(X|X > x_{\text{max}}) - x_{\text{max}} \geq 10. \]

The first term is defined as

\[ E(X|X > x_{\text{max}}) = \frac{\int_{x_{\text{max}}}^{100} x dF(x)}{\int_{x_{\text{max}}}^{100} dF(x)}, \]

which simplifies to

\[ E(X|X > x_{\text{max}}) = \frac{-x_{\text{max}}^3 + 300x_{\text{max}}^2 - 30000x_{\text{max}} + 1000000}{3x_{\text{max}}^2 - 600x_{\text{max}} + 30000}. \]

Subtracting \( x_{\text{max}} \) and setting equal to 10 yields the indifference point for the decision rule. This can be reduced to the equation

\[ -x_{\text{max}}^3 + 270x_{\text{max}}^2 - 24000x_{\text{max}} + 700000 = 0. \]

The positive root of \( x_{\text{max}} \) is equal to 70.
B Laboratory Instructions

We provide our laboratory instructions for the KDNR and UDR treatments, in that order. The KDR instructions are identical to the KDNR instructions, except that they included a full description of recall and how it worked, as is detailed in the UDR instructions. Similarly, the UDNR instructions are changed from the UDR instructions to remove all mention of how recall would work.
Instructions

Overview

Welcome to this experiment in the economics of decision-making. Funding for this experiment has been provided by the UC Irvine School of Social Sciences. We ask that you not talk with one another and that you silence your mobile devices for the duration of today’s session.

For your participation in today’s session you will be paid in cash at the end of the experiment. The amount you earn depends on the choices you make and on the choices made by others. Thus, it is important that you listen carefully and fully understand these instructions before we begin. There will be a short comprehension quiz following the reading of these instructions which you will all need to complete before we can begin the experimental session.

The experiment will make use of the computer workstations and all interactions by you and others will take place through these networked computers. You will interact anonymously with one another and your data records will be stored only by your ID number; your name or the names of other participants will not be revealed at any time during today’s session or in any write-up of the findings from this experiment.

Today’s session consists of two parts. You will receive instructions for part two at the end of part one.

In the first part of the session, you will participate in number of “games.” Each game consists of a number of “rounds.” In each round you will view some information and make a choice. Your choice, and possibly the choices of others determines the amount of points that you earn each round. At the end of the session, we will randomly select one game from all of the games played in today’s session. Your point earnings from the chosen game will be converted into dollars at a conversion rate of $0.15 per point earned. Your earnings from the chosen game and your $7 show-up payment will be paid to you in cash and in private. You will also have the opportunity to earn additional earnings in the second part of the experiment.

Specific Details

There are $N$ individuals in today’s session. At the start of each new game, each individual will be randomly assigned a position number for the game. This position number indicates the round in the game, 1,2,...,$N$, at which you will be called upon to make a choice.

When it is your turn to make a choice you will see the Choice screen (you will see a waiting screen until that time). On the Choice screen you will be asked to make a choice. Specifically, you can decide whether or not to draw a number from a distribution having a a mean of 50.00 and a standard deviation of 26.36. The distribution is shown in the computer screen and depicted below in Figure 1. The horizontal axis shows the numbers (in points) that you could draw, from (0.00 to 100.00) non-inclusive. The vertical axis reveals the probability or likelihood of drawing each possible number. As the distribution reveals,
the most likely outcome is 50.00, with the likelihood of numbers away from 50 declining equally in both directions.

Drawing a number from the distribution is costly. Specifically, a draw costs you 10 points. However, every individual is given an endowment of 10 points at the start of each new game, so the choice you face is whether to spend your endowment of 10 points drawing a number from the distribution.

Prior to making this choice, you are informed of the highest number that has been drawn by another participant in the current game. The choice you face is whether or not you want to try to draw a new number, at a cost to you of your 10 point endowment for the game.

If you choose not to draw a number, then your points for the game will equal the highest number chosen in the game so far plus your 10 point endowment.

If you choose to draw a number, then your points for the game we equal the number you drew for the game minus your 10 point endowment (the cost of drawing a number).

Please note the following:

• First, draws from the distribution are *with replacement* which means that the same number can be drawn more than once. The likelihood of drawing any number, as illustrated in Figure 1 and shown on your computer screen, does NOT change across all games played in today’s session.

• Second, if the highest number drawn in the current game is 0.0, then EITHER you are the first person to make a choice in the current game OR no prior participant has chosen to draw a number in the current game.

• Third, if you choose to draw a number, it is possible that the number you draw is higher or lower than the current highest number drawn by another participant in the current game. The distribution shown in Figure 1 reveals the likelihood of each of the possible numbers you could possibly draw.
Fourth, your earnings from drawing a number can be higher or lower than your earnings from NOT drawing a number. If you choose to draw a number and the number you draw is higher then the current highest number drawn, then your earnings from drawing that number will be higher than your earnings from not drawing a number only if the number you drew is at least 10 more than the current high number, since by drawing a number you lose your endowment of 10 points. On the other hand, if you choose to draw a number, your earnings will be lower than if you had not drawn a number whenever the number you drew is less than the current high number plus 10.

In making a choice of whether or not to draw a number for the current game, you face three options:

1. Do NOT draw
2. Enter a probability to draw
3. Draw

If you choose Do NOT draw, then you definitely DO NOT draw a number for the current game. If you choose Draw, then you definitely DO draw a number for the current game. If you choose Enter a probability to draw a number, then you must also enter a number (an integer) between 1 and 99 representing the probability, in percentage terms, that you will draw a number for the current game. After entering your percent chance of drawing a number, the computer program randomly draws a number (an integer) between 1 and 99 inclusive. If this randomly drawn number is less than or equal to your entered percent chance of drawing a number, then you will draw a number from the distribution for the current game. After entering your percent chance of drawing a number, the computer program randomly draws a number (an integer) between 1 and 99 inclusive. If this randomly drawn number is less than or equal to your entered percent chance of drawing a number, then you will draw a number from the distribution for the current game: it will be automatically drawn for you; otherwise, you will not draw a number for the current game. Thus, the higher (lower) is the percent chance you enter for the probability of drawing a number, the more (less) likely it is that you draw a number in the current game.

Payment

The first part of today’s sessions consists of 10 games. At the end of each game you will learn your points earned for the game, which, as explained above, depend on whether or not you draw a number. After all 10 games have been completed, one of the 10 games will be randomly chosen for payment. Each game has an equal chance of being chosen and so you will want to do your best in each game. Your points from the chosen game will be converted into dollars at the rate of 1 point = $0.15 (15 cents). Thus, the more points you earn, the greater are your monetary earnings. In addition, you are guaranteed $7 for showing up to today’s experiment. You will be paid your show-up payment, together with your earnings from the first part of the experiment and your earnings from the second part of the experiment at the end of today’s session. All payments will be made in cash and in private. At then end of this first part of the experiment, you will receive further instructions for how to complete part 2 of the experiment.
Questions?

Now is the time for questions. If you have a question about any aspect of these instructions, please raise your hand and an experimenter will answer your question.

Quiz

Before we start today’s experiment we ask you to answer the following quiz questions that are intended to check your comprehension of the instructions. The numbers in these quiz questions are illustrative; the actual numbers in the experiment may be quite different. Before starting the experiment we will review each participant’s answers. If there are any incorrect answers we will go over the relevant part of the instructions again.

1. Each game consists of _____ rounds. Your position in the game circle one: changes remains the same in each game.

2. Before deciding whether to draw a number you can see the highest number drawn so far in the current game. Circle one: True False

3. If you choose NOT to draw a number, then your point earnings will be equal to: Circle one:
   a. the highest number drawn earlier in the current game, (or 0.00 if no number has been drawn yet)
   b. the highest number drawn earlier in the current game (or 0.00 if no number has been drawn yet) plus your 10 point endowment.
   c. your 10 point endowment.

4. If you choose to draw a number, you lose your 10 point endowment for the current game. Circle one: True False Do you get a new endowment of 10 points for each new game? Circle one: Yes No.

5. Consider the following scenario. The current highest number is 65.56. You choose to draw a number which turns out to be 73.21 What is your payoff in points for the game in this case? _____ What would have been your payoff in points if you did not choose to draw a number? _____

6. Consider the following scenario. The current highest number is 31.03. You choose to draw a number, which turns out to be 56.71. What is your payoff in points this case? _____ What would have been your payoff in points if you did not choose to draw a number? _____

7. At the end of the experiment, one game will be randomly chosen. Your point earnings from that game will be converted into dollars at the conversion rate of 1 point = $_____
Instructions

Overview
Welcome to this experiment in the economics of decision-making. Funding for this experiment has been provided by the UC Irvine School of Social Sciences. We ask that you not talk with one another and that you silence your mobile devices for the duration of today’s session.

For your participation in today’s session you will be paid in cash at the end of the experiment. The amount you earn depends on the choices you make and on the choices made by others. Thus, it is important that you listen carefully and fully understand these instructions before we begin. There will be a short comprehension quiz following the reading of these instructions which you will all need to complete before we can begin the experimental session.

The experiment will make use of the computer workstations and all interactions by you and others will take place through these networked computers. You will interact anonymously with one another and your data records will be stored only by your ID number; your name or the names of other participants will not be revealed at any time during today’s session or in any write-up of the findings from this experiment.

Today’s session consists of two parts. You will receive instructions for part two at the end of part one.

In the first part of the session, you will participate in number of “games.” Each game consists of a number of “rounds.” In each round you will view some information and make a choice. Your choice, and possibly the choices of others determines the amount of points that you earn each round. At the end of the session, we will randomly select one game from all of the games played in today’s session. Your point earnings from the chosen game will be converted into dollars at a conversion rate of $0.15 per point earned. Your earnings from the chosen game and your $7 show-up payment will be paid to you in cash and in private. You will also have the opportunity to earn additional earnings in the second part of the experiment.

Specific Details
There are $N$ individuals in today’s session. At the start of each new game, each individual will be randomly assigned a position number for the game. This position number indicates the round in the game, 1,2,...,$N$, at which you will be called upon to make a choice.

When it is your turn to make a choice you will see the Choice screen (you will see a waiting screen until that time). On the Choice screen you will be asked to make a choice. Specifically, you can decide whether or not to draw a number from from 0 to 100, non-inclusive. The likelihood that you draw any particular number is fixed, but unknown to you. That is, the distribution of numbers you are drawing from could take the shape of ANY valid probability distribution, defined over the interval between 0 and 100, non-exclusive. All numbers drawn within this interval are limited to two decimal places. Thus, the smallest
A possible number you could draw is 0.01 and the largest possible number you could draw is: 99.99.

Drawing a number from the distribution is costly. Specifically, a draw costs you 10 points. However, every individual is given an endowment of 10 points at the start of each new game, so the choice you face is whether to spend your endowment of 10 points drawing a number from the distribution.

Prior to making this choice, you are informed of the highest number that has been drawn by another participant in the current game. The choice you face is whether or not you want to try to draw a new number, at a cost to you of your 10 point endowment for the game.

If you choose not to draw a number, then your points for the game will be equal the highest number chosen in the game so far plus your 10 point endowment.

If you choose to draw a number, then your points for the game will depend on the number you draw. Specifically:

- If the number you draw is greater than the highest number drawn in the game so far, then your points for the game will equal the number that you draw minus your 10 point endowment (the cost of drawing a number).

- If the number you draw is less than or equal to the highest number drawn in the game so far, then your points for the game will equal that highest number drawn in the game so far minus your 10 point endowment (the cost of drawing a number).

Please note the following:

- First, draws from the unknown distribution are with replacement which means that the same number can be drawn more than once. The likelihood of drawing any number does NOT change across all games played in today’s session.

- Second, if the highest number drawn in the current game is 0.00, then EITHER you are the first person to make a choice in the current game OR no prior participant has chosen to draw a number in the current game.

- Third, if you choose to draw a number, it is possible that the number you draw is higher or lower than the current highest number drawn by another participant in the current game. Remember, you don’t know the likelihood of each of the possible numbers you could possibly draw; you only know that the unknown distribution of numbers is constant over time.

- Fourth, your earnings from drawing a number can be higher or lower than your earnings from NOT drawing a number. If you choose to draw a number and the number you draw is higher then the current highest number drawn, then your earnings from drawing that number will be higher than your earnings from not drawing a number only if the number you drew is at least 10 more than the current high number, since by drawing a number you lose your endowment of 10 points. On the other hand, if you choose to draw a number, your earnings will be lower than if you had not drawn a number whenever the number you drew is less than the current high number plus 10.
In making a choice of whether or not to draw a number for the current game, you face three options:

1. Do NOT draw
2. Enter a probability to draw
3. Draw

If you choose Do NOT draw, then you definitely DO NOT draw a number for the current game. If you choose Draw, then you definitely DO draw a number for the current game. If you choose Enter a probability to draw a number, then you must also enter a number (an integer) between 1 and 99 representing the probability, in percentage terms, that you will draw a number for the current game. After entering your percent chance of drawing a number, the computer program randomly draws a number (an integer) between 1 and 99 inclusive. If this randomly drawn number is less than or equal to your entered percent chance of drawing a number, then you will draw a number from the distribution for the current game: it will be automatically drawn for you; otherwise, you will not draw a number for the current game. Thus, the higher (lower) is the percent chance you enter for the probability of drawing a number, the more (less) likely it is that you draw a number in the current game.

Payment

The first part of today’s sessions consists of 10 games. At the end of each game you will learn your points earned for the game, which, as explained above, depend on whether or not you draw a number. After all 10 games have been completed, one of the 10 games will be randomly chosen for payment. Each game has an equal chance of being chosen and so you will want to do your best in each game. Your points from the chosen game will be converted into dollars at the rate of 1 point = $0.15 (15 cents). Thus, the more points you earn, the greater are your monetary earnings. In addition, you are guaranteed $7 for showing up to today’s experiment. You will be paid your show-up payment, together with your earnings from the first part of the experiment and your earnings from the second part of the experiment at the end of today’s session. All payments will be made in cash and in private. At then end of this first part of the experiment, you will receive further instructions for how to complete part 2 of the experiment.

Questions?

Now is the time for questions. If you have a question about any aspect of these instructions, please raise your hand and an experimenter will answer your question.
Quiz

Before we start today’s experiment we ask you to answer the following quiz questions that are intended to check your comprehension of the instructions. The numbers in these quiz questions are illustrative; the actual numbers in the experiment may be quite different. Before starting the experiment we will review each participant’s answers. If there are any incorrect answers we will go over the relevant part of the instructions again.

1. Each game consists of _____ rounds. Your position in the game circle one: changes remains the same in each game.

2. The distribution of numbers you are drawing from: Circle one:
   a. Changes over time.
   b. Is unknown.
   c. Is unknown, but all possible numbers lie between 0 and 100, non-inclusive, and the distribution does not change over time.

3. Before deciding whether to draw a number you can see the highest number drawn so far in the current game. Circle one: True False

4. If you choose NOT to draw a number, then your point earnings will be equal to: Circle one:
   a. the highest number drawn earlier in the current game, (or 0.00 if no number has been drawn yet)
   b. the highest number drawn earlier in the current game (or 0.00 if no number has been drawn yet) plus your 10 point endowment.
   c. your 10 point endowment.

5. If you choose to draw a number, you lose your 10 point endowment for the current game. Circle one: True False Do you get a new endowment of 10 points for each new game? Circle one: Yes No.

6. Consider the following scenario. The current highest number is 65.56. You choose to draw a number which turns out to be 73.21 What is your payoff in points for the game in this case? _____ What would have been your payoff in points if you did not choose to draw a number? _____

7. Consider the following scenario. The current highest number is 56.71. You choose to draw a number, which turns out to be 31.03. What is your payoff in points this case? _____ What would have been your payoff in points if you did not choose to draw a number? _____

8. At the end of the experiment, one game will be randomly chosen. Your point earnings from that game will be converted into dollars at the conversion rate of 1 point = $_____
C Simulations of Behavior

Figure 10: Simulations of behavior of # of draws and maximum draws in a 10 person game.