Hindsight, Foresight, and Insight: An Experimental Study of a Small-Market Investment Game with Common and Private Values

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Abstract

We experimentally test an endogenous-timing investment model in which subjects privately observe their cost of investing and a signal correlated with the common investment return. Subjects overinvest, relative to Nash. We separately consider whether subjects draw inferences, in hindsight, and use foresight to delay profitable investment and learn from market activity. In contrast to Nash, cursed equilibrium, and level-k predictions, behavior hardly changes across our experimental treatments. Maximum likelihood estimates are inconsistent with belief-based theories. We offer an explanation in terms of boundedly rational rules of thumb, based on insights about the game, which provides a better fit than QRE.

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The theoretical literature on herding with endogenous timing, pioneered by Christophe Chamley and Douglas Gale (1994), explores the important issue of how market activity aggregates and transmits private information. Will firms with favorable private information about the investment climate act on that information, thereby providing benefits to others, or will they postpone investment, to acquire information by observing other firms' investment activity? Experimentally testing the theoretical implications of the endogenous timing herding literature is important for several reasons. Of course, it is worthwhile to compare the Nash equilibrium outcomes with what actually occurs in the lab. Perhaps more importantly, since (unlike, say, in an auction) there are no payoff externalities in this class of investment games, we can test separately (i) whether a subject understands the expected profits of investing, (ii) whether a subject draws inferences from the other's behavior, and (iii) whether a subject delays profitable investment in order to gain information. This distinction is particularly important because experimental subjects often fail to pick actions in accordance with the relevant Nash equilibrium. Because interactions are purely informational, the setting offers a sharp and novel test of various behavioral theories aiming to explain discrepancies from Nash equilibrium, such as the *level-k* model (see Dale O. Stahl and Paul W. Wilson (1995), Rosemarie Nagel (1995), and Vincent P. Crawford and Nagore Iriberri (2007)), *cursed equilibrium* (see Erik Eyster and Matthew Rabin (2005)), and *quantal response equilibrium* (see Richard D. McKelvey and Thomas R. Palfrey (1995, 1998)). In addition, the dynamic structure of the interaction introduces new issues of how subjects gather information from, or anticipate gathering information from, others' behavior over time–issues which do not arise in the mentioned behavioral theories.

Our analysis centers around three behavioral rules of thumb that can be used to classify subjects: An "*S*"(self-contained) subject does not draw inferences from the other subject's decisions, but otherwise chooses optimally. An "*M* " (myopic) subject draws inferences from the other subject's past decisions, in hindsight, not taking into account the option value of waiting to observe future decisions, but otherwise deciding optimally. An "*F*" (foresight) subject invests when profitable, unless valuable information may be revealed by waiting (whether or not waiting would be justified by a computation of expected profits). These rules of thumb reflect insight about the key components of rational play, updating in hindsight and foresight about option values, but does not require the mathematical sophistication to form beliefs and best respond as implied by cursed equilibrium or the level-k model.[1] In our experimental design, the set of strategies implied by S, M, and F rules of thumb contains the strategies consistent with Nash equilibrium, cursed equilibrium, and level-k beliefs.[2]

Our main findings can be summarized as follows. We find that subjects are quite good at determining whether investment is profitable, based on their private information, so this basic aspect of rationality is satisfied. We find that the frequency of investment is higher and overall profits are lower than those predicted by the Nash equilibrium. Comparing our two main treatments, we find that the patterns of investment remain remarkably similar, even though the Nash equilibrium predicts different behavior. Maximum likelihood estimation on the proportions of S, M, and F subjects are nearly identical–roughly 25-30 percent for S, 10 percent for M, and 60-65 percent for F.

Stable proportions of S, M, and F subjects across the two main treatments is consistent with our interpretation of behavior as rules of thumb. However, this finding is also consistent with an asymmetric version of cursed equilibrium and with a version of the level-k model. With a view towards distinguishing between our insight-based rule-of-thumb, cursed equilibrium, and level-k belief explanations of behavior, we introduce Treatment 3. In this treatment, postponing profitable investment is strictly dominated, so strategy F is inconsistent with any theory of behavior in which subjects best respond to beliefs about the other subject's behavior. Despite this, the estimate of F subjects remains above 50 percent. This provides support in favor of bounded rationality along the lines of insight-based rules of thumb, and evidence against belief-based theories. Another possible explanation of behavior is provided by quantal response equilibrium (QRE), in which subjects are assumed to have correct beliefs but make mistakes in forming best responses. We find that, although the standard logit specification of QRE fits the aggregate data quite well, it does not perform as

[1]In cursed equilibrium and the level-k model, players form beliefs as specified in the theory and choose best responses accordingly.

[2]We will also use S, M, and F to refer to the *strategies* corresponding to the three rules of thumb, even when discussing alternative behavioral interpretations of those strategies.

well as a model in which the population consists of S, M, and F subjects.

We provide a cognitive underpinning for our insight-based rules of thumb. In two sessions of each treatment, after playing the investment game, subjects were given lottery problems, with each lottery corresponding to a given decision in the game, but with strategic uncertainty eliminated. The lotteries are designed to test the propensity/ability to think ahead through the various scenarios, i.e., they examine foresight. Indeed, we find a strong correlation, between subjects with this type of foresight in the investment game and in the lottery task.

After the lottery problems, subjects were given a questionnaire related to the game. The questionnaire responses help to further clarify the nature of subjects' insights regarding hindsight and foresight. We find that subjects do not simply make mistakes in estimating conditional probabilities - rather, many do not seem to incorporate probabilistic thinking. Responses to questions addressing various qualitative aspects of insight predict actual behavior in the game. Responses to questions about probability assessments have no predictive power at all.

Section I provides a review of the literature on cursed equilibrium, level-k, and QRE. Section II defines the games and solves for the Nash equilibria. In section III, we discuss our behavioral rules of thumb and show the predictions of cursed equilibrium and the level-k model. The experimental design is explained in section IV, and the results are presented in section V. Section VI discusses the literature on herding experiments and the robustness of our insight-based model of rules of thumb. Section VII concludes.

I Behavioral Literature Review

There is considerable evidence that experimental subjects fail to pick actions in accordance with the relevant Nash equilibrium. Such discrepancies are particularly acute in tasks that require players to make inferences and update their priors based on other players' actions in games with incomplete information.[3] There are also several studies

[3]Leading examples from laboratory studies include failures in the *takeover game* (see Sheryl B. Ball and Max H. Bazerman (1991) and Gary Charness and Dan Levin (2005)), and systematic overbidding and the winner's curse in common-value auctions (see Bazerman and William F. Samuelson (1983), John H. Kagel and Levin (1986), Charles A. Holt and Roger Sherman (1994), Levin, Kagel,

claiming such failure in real markets.[4] Faced with such overwhelming evidence, it is not surprising that there were several attempts to explain these discrepancies. Stahl and Wilson (1995) and Nagel (1995) use a non-equilibrium model of "level-k" beliefs, where L_0 players behave in some pre-determined way (usually randomly). In the simplest version of the theory, for $k = 1, 2, \ldots$, the L_k players choose a best response to the strategy chosen by the L_{k-1} players. See Crawford and Iriberri (2007) for a survey and an explanation for the winner's curse in auctions, based on level-k beliefs. Eyster and Rabin (2006) propose an alternative theory, which they call "cursed equilibrium." Players are assumed to best respond to the other players' strategies in a certain sense. In a $\chi-$cursed equilibrium, players believe that with probability χ, each other player j chooses an action that is type-independent, and whose distribution is given by the ex ante distribution of player j's actions. Also, players believe that with probability $1 - \chi$, each other player j chooses an action according to player j's type-dependent strategy. Here we consider an asymmetric version of cursed equilibrium, where a fraction of the population, p_1, is fully cursed with $\chi = 1$, and draws no inferences about other players' types.[5] The remaining fraction, $1 - p_1$, is uncursed with $\chi = 0$. These players understand the equilibrium strategies played by the cursed and uncursed players, and rationally best respond using Bayes' rule. Both level-k beliefs and cursed equilibrium weaken the "usual" requirements of correct beliefs regarding other players' strategies, while insisting on players rationally choosing best responses to the more flexible belief structures that are allowed.

In Quantal Response Equilibrium (see McKelvey and Palfrey (1995, 1998)), subjects understand the equilibrium choices of other players and properly update beliefs using Bayes' rule, but make mistakes in choosing best responses. Subjects choose

and Jean-Francois Richard (1996), and Kagel and Levin (2002)).

[4]Leading examples include oil and gas lease auctions (see Edward C. Capen, Robert V. Clapp, and William M. Campbell (1971), Walter J. Mead, Asbjorn Moseidjord, and Philip E. Sorensen (1983, 1984), and the opposite conclusions reached in Kenneth Hendricks, Richard H. Porter, and Bryan Boudreau (1987)), baseball's free agent market (see James Cassing and Richard W. Douglas (1980) and Barry Blecherman (1996)), book publishing (see John P. Dessauer (1981)), initial public offerings (see Kevin Rock (1986) and Mario Levis (1990)), and corporate takeovers (see Richard Roll (1986)).

[5]In a previous version of this paper, we considered a symmetric cursed equilibrium in which all players have the same value of χ, which can be strictly between zero and one. The present formulation provides a better comparison to the alternative theories, by allowing for heterogeneity across subjects.

"better responses," in the sense that strategies yielding higher expected payoffs are more likely to be chosen. The usual approach is to use a logit quantal response function that treats all players symmetrically. Colin F. Camerer, Palfrey, and Brian W. Rogers (2006) and Christoph Brunner and Jacob K. Goeree (2008) have developed heterogeneous versions of QRE, in which players differ in their response functions and their beliefs about others' response functions. This approach combines elements of QRE and level-k beliefs. Brunner and Goeree (2008) apply their heterogeneous QRE to a herding experiment, and find strong evidence of heterogeneity, as we do. However, none of these models can easily explain our finding that more than half of our subjects choose to postpone profitable investment in Treatment 3, which is a strictly dominated action.

Other notions of bounded rationality have been studied which bear some relation to the rules of thumb we consider.[6] Stahl (2000) proposes a theory in which players assign probability weights to behavioral rules, by evaluating their relative performance and assigning more weight to better-performing rules.[7] The games studied in these papers are normal-form games, and the behavioral rules are unrelated to our emphasis on hindsight and foresight in extensive form games.[8] While we have something to say about learning, it is not our main focus. Behavioral rules in extensive form games are studied in Philippe Jehiel (2001, 2005).[9] The equilibrium notions in these papers are consistent with some of our rules of thumb (like S), but not with the presence of F subjects in Treatment 3.

[6]For other theories of bounded rationality, see Herbert A. Simon (1972) and Ariel Rubinstein (1998), including references therein.

[7]Stahl (2001) develops a closely related theory of population rule learning, in which the population distribution of rules adjusts based on relative performance.

[8]The rules in Stahl (2000, 2001) include level-1, level-2, Nash, and "follow the herd." See also Stahl and Ernan Haruvy (2008) for a study of how players' beliefs respond to the other player having a dominated strategy. In our Treatment 3, the players themselves are playing a dominated strategy.

[9]Jehiel (2001) models limited foresight in repeated games. In Jehiel (2005), players group nodes at which other players may act into classes, and best respond to the average behavior. See also David Ettinger and Jehiel (2008).

II Theoretical Framework

Our theoretical framework is based on the general model studied in Levin and James Peck (forthcoming). There are 2 risk-neutral players or potential investors. Let $Z \in \{0, 10\}$ denote the true investment return, common to all investors, with $pr(Z = 0) = pr(Z = 10) = 1/2$. Each player $i = 1, 2$ observes a signal correlated with the investment return, $X_i \in \{0, 1\}$, which we call the (common-value) signal of player i. We assume that signals are independent, conditional on Z. The accuracy of the signal is 0.7, so we have

$$pr(Z = 0 \mid X_i = 0) = pr(Z = 10 \mid X_i = 1) = 0.7. \tag{1}$$

Each player i also privately observes a second signal, representing the idiosyncratic cost of undertaking the investment, c_i. Depending on the treatment, either (i) each player's cost is independently drawn to be either high or low with equal probability, or (ii) both players have the same cost, and this cost is common knowledge.

Impatience is measured by the discount factor, $\delta < 1$. If player i has cost c_i and the state is Z, her profits are zero if she does not invest, and $\delta^{t-1}(Z - c_i)$ if she invests in round t. We now describe the game. First, each player observes her signals, (X_i, c_i). For $t = 1, 2, ...$, each player observes the history of play through round $t - 1$, and players not yet invested simultaneously decide whether to invest in round t. A strategy for player i is a mapping from signal realizations and histories (including the null history) into a decision of whether to invest following that history. We require that a player can invest at most once. Our treatments are based on the following games.

Game 1 (two costs):

This game corresponds to our Random Two-Cost Treatment (R2CT). The discount factor is $\delta = 0.9$ and there are two equally likely cost realizations, $L = 3.5$ and $H = 6.5$. Thus, we have four possible types of players, based on the common-value signal and the cost: $(0, H)$, $(0, L)$, $(1, H)$, and $(1, L)$. Equilibrium path play is uniquely determined, and involves pure strategies. A type $(0, H)$ player will never invest under any circumstances, because her expected profits from investing are negative even if she knows that the other player has the high common-value signal.[10] Similarly, a type $(1, L)$ player finds it profitable to invest even if she knows that the other player has the low common-value signal, and therefore invests in round 1. A type $(0, L)$ player will not invest in round 1, because the expected return is 3, while her cost is 3.5. However, since we have established that investment in round 1 must come from a player with the high common-value signal, a type $(0, L)$ player will invest in round 2 if the other player invests in round 1, because her conditional expected return becomes 5.

The remaining type, $(1, H)$, is the most interesting. Investment in round 1 yields positive expected profits of 0.5, but profits are slightly higher by taking advantage of the option value of waiting, investing in round 2 if and only if the other player invests in round 1. If all other type $(1, H)$ players wait, profits from waiting are 0.5085.[11] Thus, we have characterized the equilibrium path, which is given in Table 1.[12] To simplify the discussion, denote the choice to invest in round 1 as "1", denote the choice never to invest as "N", and denote the choice to wait and invest immediately following investment by the other player as "W".

Game 2L (low cost):

The discount factor is $\delta = 0.9$ and there is only one possible cost realization, 3.5. Thus, we have two possible types of players, $(0, L)$ and $(1, L)$. It is easy to see that a type $(1, L)$ player would want to invest, no matter what she believes about the other player's type, so she invests in round 1. A type $(0, L)$ player finds it unprofitable to invest in round 1, but will invest in round 2 if the other player invests in round 1 (implying a high common-value signal).

Game 2H (high cost):

The discount factor is $\delta = 0.9$ and there is only one possible cost realization, 6.5. Thus, we have two possible types of players, $(0, H)$ and $(1, H)$. It is easy to see that

[10] In such a case, her conditional expected return would be 5, but her cost is 6.5.

[11] If some other type $(1, H)$ players would invest in round 1, the advantage of waiting is even greater.

[12] Several specifications of behavior and beliefs off the equilibrium path are consistent with sequential equilibrium, all yielding the same equilibrium path. After no one invests in round 1 and one player invests in round 2, beliefs about the investor's common-value signal can affect the the remaining player's decision. However, the beliefs and subsequent decision do not affect the original investor's profit, so the equilibrium path is unaffected.

	R2CT	**A1CT**	**Treatment 3**
type $(0, H)$	N	N	N
type $(0, L)$	W	W	W
type $(1, H)$	W	1 with prob. 0.4916 W with prob. 0.5084	1
type $(1, L)$	1	1	1

Table 1: Nash equilibrium characterization in each treatment

a type $(0, H)$ player would not want to invest, no matter what she believes about the other player's type, so she never invests. A type $(1, H)$ player mixes, choosing "1" with probability 0.4916 and choosing "W" with probability 0.5084.

In our Alternating One-Cost Treatment (A1CT), the subjects alternate between Game 2L and Game 2H. Because matching is random and anonymous, folk theorem issues do not arise, so the equilibrium characterization combines the equilibria of Game 2L and Game 2H, as given in Table 1.

Game 3L:

The discount factor is $\delta = 0.8$ and there is only one possible cost realization, 3.5. In the Nash equilibrium, a type $(1, L)$ player chooses "1" and a type $(0, L)$ player chooses "W".

Game 3H:

The discount factor is $\delta = 0.8$ and there is only one possible cost realization, 5.7. A type $(1, H)$ player has a dominant strategy to invest in round 1, because the expected profits from investing in round 1 are greater than the expected profits of waiting, even if waiting would reveal the other player's type. In the Nash equilibrium, a type $(1, H)$ player chooses "1" and a type $(0, H)$ player chooses "N".

In our Treatment 3, the subjects alternate between Game 3L and Game 3H. The equilibrium combines the equilibria of Game 3L and 3H, as given in Table 1.

III Behavioral Considerations

In the investment games we study here, interactions between players are purely informational, with no direct payoff consequences. This simple structure isolates situations in which updating is important, and situations in which foresight is important; these different aspects of rationality would be more difficult to disentangle in auctions or other games with strategic interaction.[13] For our investment games, a small but nonzero proportion of type $(0, H)$ subjects invests in round 1, which is a mistake indicating a lack of understanding of the game. If mistakes like this occur, perhaps less extreme departures from Nash behavior reflect a lack of insight about some of the fine points of the game.

Let us elaborate on the insights we have in mind. Investment in round 1 is profitable for types $(1, H)$ and $(1, L)$, and not for the other types. We start with the notion that subjects have the basic insight that the expected revenue is 7 when receiving the high common-value signal and 3 when receiving the low common value signal.[14] We refer to the insight about updating, that a type $(0, L)$ subject understands that investing is profitable after the other subject invests in round 1, as Insight 1. Insight 1 can be subdivided into components:[15]

Insight 1a: If the other subject invests in round 1, then she is likely to have the high signal,

Insight 1b: If the other subject is likely to have the high signal, then investment is profitable.

To acquire Insight 1a, a subject can reason that investment would be unprofitable for the other subject if she had the low signal. For Insight 1b, a type $(0, L)$ subject can reason that her low signal and the other subject's high signal cancel, so the expected investment return is 5.[16] Insight 1 entails updating, but not explicit use of Bayes'

[13]For example, Rod Garratt and Todd Keister (2006) experimentally test a model of bank runs, where a player's decision to withdraw deposits simultaneously involves Bayesian updating, considering the option of withdrawing in the future, and anticipating the strategies of the other players.

[14]To the extent that some subjects do not even have this basic insight, this only strengthens bounded rationality as an explanation for behavior, rather than misspecified beliefs.

[15]This approach is inspired by Ken Binmore et al. (2002), who break backwards induction into components, subgame consistency and truncation consistency.

[16]Even allowing for the chance that some subjects with the low signal will invest (unprofitably),

rule.

We refer to the insight about foresight, that a type $(1, H)$ subject understands that waiting provides a valuable option, as Insight 2, which can be subdivided into components:

Insight 2a: If a subject waits, she will find out whether the other subject invested in round 1,

Insight 2b: If the other subject does not invest in round 1, then the likelihood that the other subject has the low signal increases substantially,

Insight 2c: If the other subject does not invest in round 1, (and therefore is much more likely to have the low signal), then investment for a type (1,H) subject is not profitable.

Given the instructions and practice trials, we feel that Insight 2a can be stipulated. For Insight 2b, a type $(1, H)$ subject can reason that the other subject might invest with the high signal, but not with the low signal, so seeing the other subject not invest substantially increases the likelihood that the other subject has the low signal. For Insight 2c, a type $(1, H)$ subject can reason that profits were only slightly positive before observing the other subject not invest, so any negative inference should be enough to make investment unprofitable.

We refer to 1a-1b and 2a-2c as insights, because they reflect basic understanding that does not require much computation. It is our contention that the game is too complex for subjects to form beliefs and compute best-responses, so they instead choose a rule of thumb based on which of these two insights are acquired. If a subject does not have either insight, then she is an S (for *self-contained*), and disregards the behavior of the other subject. Such a subject chooses the type-dependent strategy $S \equiv (N, N, 1, 1)$.[17] If a subject has Insight 1 but not Insight 2, then she is an M (for *myopic*), and is able to draw inferences from market activity, in *hindsight*, but does not look with *foresight* to the informational benefits of waiting. Such a subject chooses the type-dependent strategy $M \equiv (N, W, 1, 1)$. If a subject has Insight 1

a type (1,L) subject can reason that the decision was very close before observing the other subject invest, so any favorable inference that the other subject has the high signal should make investment profitable.

[17]The type-dependent strategy, (A, B, C, D), means that type $(0, H)$ players choose A, type $(0, L)$ players choose B, type $(1, H)$ players choose C, and type $(1, L)$ players choose D.

and Insight 2, then she is an F (for *foresight*), and looks with *foresight* to the useful information that can be gained by waiting when her type is $(0, L)$ or $(1, H)$.[18] Note that this *foresight* does not necessarily mean that she actually calculates the value of waiting, or even that such a calculation would justify waiting. Such a subject chooses the type-dependent strategy $F \equiv (N, W, W, 1)$. If subjects choose insight-based rules of thumb as described above, the difference between the R2CT and A1CT in how costs are determined should not affect the generation of these insights. The new parameter values in Treatment 3 should not affect the ability of subjects to generate these insights, so one would expect similar behavior across treatments.

A word of qualification is in order. It is possible that a type $(1, H)$ subject has Insight 2 and clearly understands the benefit to waiting, but feels that investment in round 1 is the better choice. While this is certainly possible, few subjects seem to fit in this category. One indication is that our maximum likelihood estimate for the population fraction of F subjects in Treatment 3 is close to our estimates for the R2CT and the A1CT, even though the tradeoff between investing and waiting is dramatically different. Another indication (elaborated in section C) is that questionnaire responses regarding Insight 2c are a strong indicator of whether the subject will invest in round 1 when she is type $(1, H)$.

As it turns out, we can characterize the Nash equilibrium, level-k behavior, and the cursed equilibrium, all in terms of the three strategies, S, M, and F, although the interpretation and implications for behavior across treatments differs from our rule-of-thumb interpretation. For our R2CT (Game 1), A1CT (Games 2L and 2H), and Treatment 3 (Games 3L and 3H), the Nash equilibrium, level-k behavior, and the cursed equilibrium are characterized in Table 2, all in terms of the three strategies, S, M, and F.[19] The cursed equilibrium is based on a population fraction p_1 being fully cursed ($\chi = 1$) and the remaining fraction uncursed ($\chi = 0$). The probability given in Table 2, q^{alt}, is defined as follows.

[18] A type $(0, H)$ subject does not receive useful information by waiting, because the expected profits from investment are always negative. A type $(1, L)$ subject also does not receive useful information by waiting, because the expected profits from investment are always positive.

[19] We are being a little loose when we refer to F, M, and S as strategies, because behavior is not uniquely determined after unexpected contingencies that do not affect play in the NE, the cursed equilibrium, or under level-k beliefs. In our maximum likelihood estimation (section B), we are careful to specify the decisions following investment by the other subject in round 2 (after not investing in round 1), and following a tremble that is inconsistent with the strategy itself.

	Game 1 (R2CT)	Games 2L&2H (A1CT)	Games 3L&3H (Treatment 3)
Nash Equilibrium			
	F	M with prob. 0.4916 F with prob. 0.5084	M
Level-k			
L_1	S	S	S
L_2	F	F	M
L_3	F	M	M
Cursed Equilibrium			
$0 \leq p_1 < \frac{500}{1017}$			
cursed ($\chi = 1$)	S	S	S
uncursed ($\chi = 0$)	F	M with prob. q^{alt} F with prob. $1 - q^{alt}$	M
$\frac{500}{1017} \leq p_1 \leq 1$			
cursed ($\chi = 1$)	S	S	S
uncursed ($\chi = 0$)	F	F	M

Table 2: Nash, Level-k, and Cursed Equilibrium

(2) $$q^{alt} = \frac{500 - 1017p_1}{1017(1 - p_1)}.$$

IV Experimental Design

The experiment consisted of the R2CT, the A1CT, and Treatment 3. We conducted four sessions of the R2CT (78 participants), four sessions of the A1CT (96 participants), and three sessions of Treatment 3 (72 participants).[20]

In the R2CT, subjects played Game 1 in each trial, so that each subject's private cost of investment was randomly selected to be either 3.5 or 6.5. In the A1CT, subjects played Game 2L in odd numbered trials and Game 2H in even numbered trials, so that each subject's cost alternated between 3.5 and 6.5 from trial to trial (but was the same for all subjects within a trial). Treatment 3 was the same as our A1CT, except that the discount factor was given by $\delta = 0.8$ and the costs alternated between 3.5 and 5.7 (i.e., subjects alternated between games 3L and 3H). To guarantee that the

[20]We also conducted a pilot session for the R2CT (14 participants).

trials ended, without changing the equilibria, subjects were told that the trial ended after either both subjects had invested or there were two consecutive rounds with no investment.

Each session in all treatments consisted of two practice trials and 24 trials in which subjects played for real money. At the start of each trial, subjects were randomly and anonymously matched in pairs to form separate two-player markets which bore no relation to each other. There was a new random matching from trial to trial. Subjects were given an initial cash balance of 20 experimental currency units (ECU). In addition, they could gain (lose) ECU in each trial, which were added to (subtracted from) their cash balances. At the end of the session, ECU were converted into dollars at a rate of 0.6 $/ECU in the R2CT and A1CT, and 0.5 $/ECU in Treatment 3. Subjects were paid the resulting dollar amount or $5, whichever was greater. If a subject's cash balances fell below 0 at any point during the session, that subject was paid $5 and was asked to leave.[21]

In order to test our interpretation of behavior, for 2 sessions of each treatment, we followed up the investment game with some lottery problems and a questionnaire (explained later).

Average earnings for the R2CT, the A1CT, and Treatment 3 were $26.04, $26.49, and $24.13 respectively. Including the reading of instructions, sessions lasted between 1 hour 45 minutes and 2 hours.

Subjects in the experiment were undergraduate students at The Ohio State University. The sessions were held at the Experimental Economics Lab at OSU. Before starting the trials, the experimenter read the instructions aloud as subjects read along, seated at their computer terminals. Subjects were invited to ask questions, including after the practice trials. Once the real trials began, no more questions were allowed.

The experiment was programmed and conducted with the software z-Tree (Urs Fischbacher (2007)).

[21]This occurred for three subjects in the R2CT, for three subjects in the A1CT, and for two subjects in Treatment 3. After a subject goes bankrupt, if the number of subjects in a session is no longer even, one subject is randomly selected to sit out during each trial.

R2CT

History	(0,H)		(0,L)		(1,H)		(1,L)	
{}	33	(0.07)	47	(0.11)	164	(0.35)	334	(0.77)
{0}	18	(0.06)	28	(0.11)	43	(0.23)	37	(0.60)
{1}	25	(0.22)	52	(0.45)	76	(0.68)	33	(0.89)
{0,1}	7	(0.14)	10	(0.36)	16	(0.53)	6	(1.00)
{1,0}	7	(0.08)	24	(0.38)	12	(0.33)	2	(0.50)
{0,1,0}	1	(0.02)	2	(0.11)	3	(0.21)	0	N/A
no {0}	242		197		116		19	
no {1,0}	84		39		24		2	
no {0,1,0}	42		16		11		0	
Total	459		415		465		433	

A1CT

History	(0,H)		(0,L)		(1,H)		(1,L)	
{}	28	(0.05)	72	(0.13)	207	(0.38)	447	(0.78)
{0}	25	(0.05)	32	(0.11)	66	(0.26)	29	(0.52)
{1}	16	(0.16)	105	(0.51)	53	(0.66)	59	(0.83)
{0,1}	13	(0.21)	12	(0.33)	14	(0.82)	4	(0.80)
{1,0}	13	(0.15)	44	(0.44)	11	(0.41)	7	(0.58)
{0,1,0}	4	(0.08)	9	(0.38)	2	(0.67)	1	(1.00)
no {0}	371		218		175		22	
no {1,0}	74		57		16		5	
no {0,1,0}	45		15		1		0	
Total	589		564		545		574	

Treatment 3

History	(0,H)		(0,L)		(1,H)		(1,L)	
{}	23	(0.06)	66	(0.15)	214	(0.46)	317	(0.79)
{0}	10	(0.04)	27	(0.12)	57	(0.32)	19	(0.51)
{1}	26	(0.28)	88	(0.57)	41	(0.59)	38	(0.83)
{0,1}	6	(0.16)	13	(0.43)	13	(0.52)	2	(0.50)
{1,0}	18	(0.27)	22	(0.33)	15	(0.54)	1	(0.13)
{0,1,0}	6	(0.19)	4	(0.24)	1	(0.08)	0	(0.00)
no {0}	222		172		98		14	
no {1,0}	48		45		13		7	
no {0,1,0}	26		13		11		2	
Total	385		450		463		400	

Table 3: Aggregate Actions and Frequency of Investment at each History

V Results

A Aggregate-Level Analysis

Table 3 presents aggregate-level decisions in the R2CT, A1CT, and Treatment 3. There are only six possible histories after which a subject can invest: the null history, $\{\}$; the history following no investment in round 1, $\{0\}$; the history following one subject investing in round 1, $\{1\}$; the history following no investment in round 1 and one subject investing in round 2, $\{0, 1\}$; and so on. The first six rows of each panel in the table show, for each type and history, how many times a subject facing a decision in that situation invested. There are only three possible histories after which no investment would end the game: $\{0\}$, $(1, 0\}$, and $\{0, 1, 0\}$. Rows 7-9 show, for each type and history for which no investment would end the game, how many times a subject in that situation made the final decision *not* to invest. The numbers in parenthesis show what proportion of decisions made at a particular history were decisions to invest. For example, in the R2CT, the 52 times a type $(0, L)$ subject invested after history $\{1\}$ represent 45 percent of all decisions taken at that history. The last line of each panel shows the total number of realizations of each type (the sum of all previous rows).

To correct for the problem of dependence between the investment decisions and profits of the two subjects in any trial, in our statistical tests we will arbitrarily call one subject in each market a Group 1 (or G1) subject (the one with the lower subject ID) and the other subject a G2 subject. Then we will perform the relevant test separately for G1 subjects and G2 subjects. In this way, each test will be based on observations, no two of which were from the same market trial.[22]

Let us start by checking if subjects' aggregate behavior satisfies some basic requirements on rationality. First note that, in the aggregate, subjects in all three treatments respond to their own information (common value signal and investment cost). This can be seen when we consider investment in round 1, and when we consider investment in any round.

The higher the expected profit from investment, given a subject's type, the more likely she is to invest in round 1. In particular, the frequencies with which subjects of type $(0, H)/(0, L)/(1, H)/(1, L)$ invest in round 1 are 7/11/35/77 percent in the R2CT, 5/13/38/78 percent in the A1CT, and 6/15/46/79 percent in Treatment 3.

The higher the expected payoff from investment, given a subject's type, the more

[22]There is no dependence between both subjects' decisions to invest conditional on any particular history, so we do not have to split the sample when we test behavior after any particular history.

likely she is to invest during some round. In particular, the frequencies with which subjects of type $(0, H)/(0, L)/(1, H)/(1, L)$ invest are 20/39/68/95 percent in the R2CT, 17/49/65/95 percent in the A1CT, and 23/49/74/94 percent in Treatment 3.[23] The data suggest that subjects understand when investment is profitable and when it is not profitable, based on their signals.

We now move on to the question of whether subjects respond to the behavior of the other subject in their trial. For each type in each treatment, we find that subjects are considerably more likely to invest in round 2 after seeing the other subject invest in round 1 than after seeing the other subject not invest in round 1 (compare the frequencies of investment after history {1} and {0} in Table 3).

Now that we have established that behavior satisfies some basic requirements on rationality, let us turn to the question of how actual investment and profit outcomes compare with those in the NE.

	(0,H)	**(0,L)**	**(1,H)**	**(1,L)**	**Overall**
R2CT Actual	20	39	68	95	55
R2CT NE	0	21	29	100	38
A1CT Actual	17	49	65	95	56
A1CT NE	0	42	64	100	51
Treatment 3 Actual	23	49	74	94	61
Treatment 3 NE	0	42	100	100	61

Table 4: Investment frequencies (percent)

Table 4 shows, for each treatment, the actual frequency of investment as well as the ex ante expected frequency of investment in the NE. In the R2CT and A1CT treatments, the actual frequency of investment exceeds the NE frequency for all types, except type $(1, L)$, where the actual frequency comes close to the NE frequency of 100 percent. In both treatments, the actual overall frequency of investment is higher than the NE frequency. This overinvestment is both economically (especially in the R2CT) and statistically significant ($p < 0.001$ for both G1 and G2 subjects in the R2CT and $p = 0.03/p < 0.001$ for G1/G2 subjects in the A1CT Treatment[24]). In Treatment 3,

[23] These numbers are obtained from Table 3 by dividing the sum of the first six numbers in a column (the number of times that type invested) by the last number in the column (the total number of times that type occurred).

[24] These p-values are obtained in the following way. In order to account for possible dependence

the actual and NE frequencies of investment are equal, probably because investment in the NE is already quite high. Summarizing:

Result 1 *In the R2CT and the A1CT, the actual overall frequency of investment is significantly higher than the NE frequency of investment. In the R2CT, overinvestment is especially pronounced.*

	(0,H)	(0,L)	(1,H)	(1,L)	Overall
R2CT Actual	-0.61	0.00	0.18	3.73	0.80
R2CT NE	0	0.28	0.51	3.50	1.07
A1CT Actual	-0.34	-0.12	0.39	3.16	0.77
A1CT NE	0	0.57	0.50	3.50	1.14
Treatment 3 Actual	-0.31	-0.09	0.87	3.03	0.86
Treatment 3 NE	0	0.50	1.30	3.50	1.33

Table 5: Average Profits per Period (in ECU)

Table 5 shows, for each treatment, the average actual profits per period as well as the NE expected profits per period. We have:

Result 2 *In all treatments, actual average profits are lower than the NE expected profits. This difference is significant in the A1CT and in Treatment 3.*[25]

The reason that profits are lower than the NE prediction is primarily due to unprofitable investment by subjects with the low common-value signal, and the ensuing unprofitable investment by subjects drawing the wrong inference.

Inspection of Tables 3 and 4 indicates that behavior in all three treatments is remarkably similar. We employ random effects probit estimation with treatment

between investment decisions made by the same player, we perform a random effects probit estimation with only a constant as a right-hand-side variable. Then we test the hypothesis that the predicted probability of investment for the average person (i.e. for someone with subject-specific random effect equal to 0) equals the NE ex ante probability of investment.

[25] $p = 0.004/p = 0.042$ for G1/G2 subjects in the A1CT and $p < .001$ for both G1 and G2 subjects in Treatment 3. These p-values are obtained in the following way. In order to account for possible dependence between profits earned by the same player in different periods, we perform a random effects regression with only a constant as a right-hand-side variable. Then we test the hypothesis that the predicted profits for the average person (i.e. for someone with subject-specific random effect equal to 0) equal the NE profits. Due to the high variance of realized profits, the difference between actual and NE profits is not significant in the R2CT ($p = 0.203/p = 0.146$ for G1/G2 subjects).

dummies as right-hand side variables and we cannot reject the hypothesis that there is no treatment effect (meaning that the coefficients on all three dummies are equal) on key history and type-contingent investment choices.

First, let us compare behavior across treatments for some key types, after the history, $\{\}$, and after the history, $\{1\}$. In the R2CT/A1CT/Treatment 3, type $(1, L)$ subjects invest in round 1 77/78/79 percent of the time ($p = 0.854$). In the R2CT/A1CT/Treatment 3, type $(1, H)$ subjects invest in round 1 35/38/46 percent of the time ($p = 0.145$).[26] In the R2CT/A1CT/Treatment 3, type $(1, H)$ subjects invest after the history $\{1\}$ 68/66/59 percent of the time ($p = .567$). In the R2CT/A1CT/Treatment 3, type $(0, L)$ subjects invest after history $\{1\}$ 45/51/57 percent of the time ($p = 0.115$).

As can be seen from Table 4, the frequency of investment is also very similar across treatments: 55/56/61 percent in the R2CT/A1CT/Treatment 3.

B Evaluating the Behavioral Theories

To evaluate which behavioral theory best explains the data, we first consider a model in which subjects are drawn from a population of subjects who play one of the strategies, F, M or S (with error). Cursed equilibrium, level-k beliefs, and insight-based rules of thumb imply different behavior across treatments, which will allow us to distinguish between these interpretations. Later, we will compare the values of the likelihood functions, of our behavioral model and an extensive form QRE model.

We proceed as follows. For each treatment, for $j \in \{F, M, S\}$, the probability of a subject being drawn from class j is denoted by p_j. We estimate, via maximum likelihood, the parameters p_F, p_M , and p_S. Before proceeding to the maximum likelihood estimation, we must specify the strategies F, M and S off the equilibrium path. The basic principle we use is that each of these strategies prescribes correcting one's own departures, and choosing each action with probability 1/2 following an unexpected choice by the other subject (i.e. after history $\{0, 1\}$).[27]

[26] The p-value for the hypothesis that the coefficients on the dummies for the R2CT and Treatment 3 are equal (rather than the coefficients on all three dummies) is 0.06. R2CT and Treatment 3 are the treatments where the NE predictions for type $(1, H)$ differ the most (0 percent vs. 100 percent).

[27] Our estimates are robust to the specification of strategies off the equilibrium path. For example, we estimated a model in which, after a subject makes a mistake, she chooses to invest or not invest in each subsequent round with probability one half. The estimates of p_F, p_M, and p_S are practically

	R2CT	**A1CT**	**Treatment 3**
p_F	0.653	0.6	0.527
	(0.059)	(0.053)	(0.067)
p_M	0.103	0.112	0.249
	0.054	(0.041)	(0.067)
p_S	0.244	0.288	0.224
	(0.063)	(0.050)	(0.058)
ε	0.175	0.167	0.193
	(0.007)	(0.006)	(0.007)
log-likelihood	-1618.5638	-1982.1826	-1586.1104

Table 6: Maximum Likelihood Estimates

Our model of behavior is that, each time a subject of class $j \in \{F, M, S\}$ has to make a decision to invest or not invest, given her type and the observed history of the other subject's behavior, she makes the decision prescribed by strategy j with probability $1 - \varepsilon$ and makes an "error" with probability $\varepsilon \in [0, 0.5]$. Errors are assumed to be i.i.d. across types and histories, trials, and subjects.[28]

For each treatment, we estimate the vector of parameters $\boldsymbol{\theta} = (p_F, p_M, p_S, \varepsilon)$, by maximizing the likelihood function (see the online appendix). Table 6 shows our estimates, along with estimated standard errors.

As can be seen from Table 6, in all three treatments, the population frequency of class F is estimated to be more than one half; the population frequency of class S is estimated to be around 1/4; the population frequency of class M is estimated to be quite small in the R2CT and A1CT and around 1/4 in Treatment 3. Also note that estimated error rates are not very high.

Perhaps the most striking aspect of the estimates in Table 6 is their similarity across treatments. Using likelihood-ratio tests, we test hypotheses about whether certain elements of $\boldsymbol{\theta}$ are the same in different pairs of treatments, as well as across all three treatments. Entry (i, j) in Table 7 shows the resulting p-value, under the null hypothesis that the parameters in row i are the same across all treatments in

identical. Other specifications following an unexpected choice by the other subject also yield similar results (because a subject is faced with history $\{0, 1\}$ infrequently).

[28]For the precise derivation of the likelihood function see the online appendix. This statistical framework is similar to that in many experimental papers, especially David W. Harless and Camerer (1994) and Miguel Costa-Gomes, Crawford and Bruno Broseta (2001). The main difference is that, in our context, subjects are making a sequence of decisions in each game.

	R2CT & A1CT	R2CT & Treatment 3	A1CT & Treatment 3	All three treatments
p_F	0.510	0.166	0.400	0.382
p_M	0.888	0.090	0.073	0.134
p_S	0.592	0.818	0.417	0.697
ε	0.327	0.079	0.005	0.018
p_F, p_M, p_S	0.798	0.197	0.199	0.329
p_F, p_M, p_S, ε	0.708	0.088	0.009	0.041

Table 7: Hypotheses tests: p-values.

column j.

There is no strong evidence of differences in behavior across treatments. The only p-values below 5 percent are due to the higher estimate of ε in Treatment 3.[29] Most notably, any differences in the estimates of p_F across treatments are not significant.[30] Let us summarize:

Result 3 *(i) In all three treatments, the estimate of* p_F *is more than* $1/2$*; the estimate of* p_S *is around* $1/4$*; the estimate of* p_M *is quite small in the R2CT and A1CT and is around* $1/4$ *in Treatment 3.*

(ii) The estimates of $\boldsymbol{\theta}$ *are very similar across treatments. In particular, any differences in the estimates of* p_F *across treatments are not significant.*

How well do the various behavioral theories explain our estimation results for the R2CT and A1CT treatments? (We will consider Treatment 3 shortly.) First, consider the cursed equilibrium framework. Asymmetric cursed equilibrium, with $p_1 = 0.35$, predicts that $(p_F, p_M, p_S) = (0.65, 0, 0.35)$ in the R2CT and $(p_F, p_M, p_S) = (0.51, 0.14, 0.35)$ in the A1CT, which is close to our estimates.[31]

Next, consider the level-k framework. Recall that, in the R2CT and A1CT, L_1 plays S and L_2 plays F. According to our estimates, the majority of the population is indeed F or S. The estimates of p_F and p_S are nearly the same across treatments,

[29]The difference in the estimate of ε in Treatment 3 may be statistically significant but it is hardly economically significant.

[30]Note that the similarity of our maximum likelihood estimates for $\boldsymbol{\theta}$ across treatments is in line with the similarity in behavior at key histories (see section A).

[31]In a previous version of this paper we considered a symmetric cursed equilibrium with a cursedness parameter, $0 < \chi < 1$, common to all subjects. Our MLE estimates, showing the simultaneous presence of F and S subjects, are inconsistent with any value of χ.

which is what one would expect if the proportions of L_1 and L_2 players in the population are stable across the treatments. Therefore, our estimates based on the R2CT and A1CT are consistent with the level-k framework.

Finally, consider the framework in which each subject uses a rule of thumb prescribing either F, M or S. Because the R2CT and A1CT are essentially the same, in terms of the nature and difficulty of the insights discussed above, one would expect to see nearly identical behavior across the two treatments. This is indeed the case. Therefore, our estimates based on the R2CT and A1CT are consistent with the framework in which subjects use a rule of thumb, based on the various insights discussed above.

Our purpose for including Treatment 3 was to distinguish between the belief-based theories and insight-based rules of thumb. With the new parameters, a type $(1, H)$ subject has a dominant strategy to invest in round 1, so the strategy F is never the optimal strategy for a risk-neutral subject within the expected utility framework, regardless of her beliefs. If behavior in our R2CT and A1CT is driven by cursed equilibrium or level-k beliefs, the resulting maximum likelihood estimation for Treatment 3 should show a collapse of p_F.

On the other hand, suppose behavior is driven by rules of thumb based on insights about the game. The new parameters in Treatment 3 should not affect the difficulty of acquiring these insights. Therefore, one would expect to see a similar proportion of F subjects as in the other two treatments. We don't want to claim that behavior should be completely insensitive to the new parameters. Due to the reductions of the high investment cost and the discount factor, some subjects with *foresight* may decide to invest in round 1 when their type is $(1, H)$. However, to the extent that behavior is mainly driven by our insights rather than based on a computation, we would see no large drop in the estimate of p_F in Treatment 3.

As we saw, the estimate of p_F in Treatment 3 is above 50 percent[32] and is very similar to the estimates in the R2CT and A1CT (any differences are not significant). *This supports the view that behavior in our experiment is, to a large extent, driven by boundedly rational rules of thumb, rather than by beliefs about the behavior of the other subject.*

[32]In fact, we can reject the hypothesis that $p_F \leq 0.4$ (0.4 is 1.96 standard errors from the estimate of p_F).

Our maximum likelihood estimation assumes that the strategy classes F, M, and S are drawn from the population at the beginning of the experiment, and do not evolve as the trials progress. This specification was made for simplicity, and because learning issues are not our main focus. However, there seems to be some learning going on, which sheds light on our interpretation of behavior as rules of thumb. Random effects probit estimation is used to study the effect of the trial number on the probability that a type $(1, H)$ subject invests in round 1 (see equation B1 in the online appendix). In the R2CT, the marginal effect is -0.0149 ($p < 0.001$); in the A1CT, the marginal effect is -0.0105 ($p = 0.003$); in Treatment 3, the marginal effect is 0.0037 ($p = 0.344$). The negative marginal effect in the R2CT and A1CT indicates that subjects are "learning" to wait and observe the behavior of the other subject.[33] This learning moves behavior towards the NE in the R2CT, but moves behavior away from the NE in the A1CT. This learning could be due to a "Eureka" effect, where some subjects suddenly acquire the insight that waiting gives them useful information about the other subject. Why is learning absent in Treatment 3 (the estimated marginal effect is insignificant and of the wrong sign)? Perhaps while some subjects acquire the insight that waiting gives them useful information, other subjects realize that the benefits are not adequate to compensate for the discounting.[34] These two opposing effects may offset each other.

Treatment 3 addresses the potential criticism that the incentives of a type $(1, H)$ subject are weak, so that drawing conclusions about behavior is problematic. It is true that, in the R2CT and A1CT, the differences in the ex ante expected payoff of playing F, M, and S are quite small (both in the NE and given the empirical frequencies of play).[35] However, in Treatment 3, the expected payoff of playing $F/M/S$, given the empirical frequencies is 1.155/1.294/1.2 ECU. Therefore, the advantage of M over F in Treatment 3 is quite substantial. Over 24 trials, the expected profit gain of playing

[33] This effect is large in the R2CT and A1CT. The predicted probability of investment in round 1 by a type $(1, H)$ player decreases from 0.48 in trial 1 to 0.15 in trial 24 in the R2CT and from 0.47 in trial 1 to 0.23 in trial 24 in the A1CT.

[34] After all, even if the other subject is revealed to have the low common-value signal, the expected loss is only 0.7 ECU in Treatment 3, while it is 1.5 ECU in the other treatments. Also, the other subject may choose to wait with the high common-value signal, thereby weakening the inference.

[35] The expected payoff of playing $F/M/S$, given the empirical frequencies of play, is 1.084/1.057/1 ECU in the R2CT and 1.09/1.10/1 ECU in the A1CT. The expected payoff of playing $F/M/S$, given NE beliefs, is 1.073/1.071/1 ECU in the R2CT and 1.142/1.142/1 ECU in the A1CT.

	Game 2L	Game 2H	Game 3L	Game 3H
λ	1.834	0.931	1.775	1.042
log-likelihood	-1055.3309	-975.6769	-794.98	-838.772

Table 8: QRE - Maximum Likelihood estimates

M rather than F is 3.336 ECU or \$1.668.

Let us now turn attention to Quantal Response Equilibrium. We compare how well QRE explains the data relative to our model in which the population consists of subjects each of which plays (with error) one of the three strategies F, M, or S. In QRE, subjects best-respond with error to the equilibrium behavior of other players. The likelihood of a particular error depends on how costly that error is as well as on a precision parameter λ which (in a symmetric QRE) is common to all players. We employ the agent-form of QRE which is relevant for extensive-form games (see McKelvey and Palfrey (1998)).

Using the software *Gambit* (McKelvey, Andrew M. McLennan, and Theodore L. Turocy (2007)), we were able to solve numerically for the QRE of the games in the A1CT and in Treatment 3 (games 2L, 2H, 3L, and 3H) for different levels of λ. Then, using maximum likelihood, we estimated λ for each of the four games. Table 8 shows the estimates of lambda along with the maximized value of the log-likelihood function.

In order to compare whether QRE or our model provides the better fit, we employ the Bayesian Information Criterion (Gideon Schwarz (1978)) which compares the maximized values of the log-likelihood functions, adjusting for parameters. Table 9 presents the BIC for QRE and our model. The model with the lower *BIC* provides the better fit.[36] Based on Table 9, we can state:

Result 4 *In the A1CT and in Treatment 3, the model in which the population consists of F, M, and S subjects provides a better fit than QRE (based on BIC).*

Actually, QRE (with the ML estimates of the λs) tracks the aggregate data quite

[36]The *BIC* of a particular model is computed as $BIC = -2(\text{log-likelihood}) + (\text{number of parameters}) \times ln(\text{number of observations})$. The log-likelihood for the QRE model for the A1CT/Treatment 3 is the sum of the log-likelihoods for games 2L&2H/3L&3H. The number of parameters in our model is 3; the number of parameters in the QRE model is 2. We also looked at the Akaike Information Criterion. We present the BIC because it penalizes a larger number of parameters more severely so that it is less favorable to our model.

	A1CT	Treatment 3
QRE	4078.71	3283.59
Our model	3989.40	3196.34

Table 9: Bayesian Information Criteria

well (as does our model). Our model nevertheless provides a better fit because, by allowing for heterogeneity of subjects, it tracks individual-level behavior better.[37]

C Lottery and Questionnaire Results

We have provided evidence that a model based on a population of subjects using the strategies S, M, and F outperforms a QRE model, and that this behavior involves boundedly rational rules of thumb that are not best responses to beliefs about the other subject's behavior. We also provided cognitive underpinnings of these rules of thumb, by interpreting them as being based on insights about updating and looking ahead (Insight 1 and Insight 2 defined earlier). In order to test this interpretation, for 2 sessions of each treatment, we followed up the investment game with some lottery problems and a questionnaire. The lottery problems convert decision situations at different nodes in the game for the crucial types $(1, H)$ and $(0, L)$ into individual-choice decision situations, thus eliminating strategic uncertainty. Although we cannot conclusively determine what thought processes subjects perform, the results support our theory of insight-based rules of thumb as a basis for behavior.

In the lottery problems, subjects choose between different procedures of earning ECU. These procedures are based on six lotteries, each of which corresponds to the decision to invest after a particular history. Suppose that, given a player's type and a particular history in the game, the probability of the high investment return is p.[38] Then, the corresponding lottery pays the profits from investing in the high investment state with probability p, and the profits from investing in the low investment state

[37] A heterogeneous version of QRE might provide a better fit in our experiment than the symmetric QRE we consider. Note however that even a heterogeneous version of QRE could not explain why 54 percent of subjects in Treatment 3 wait in round 1 when type $(1, H)$ even though this is strictly dominated (and hence must be played less than half the time in any QRE).

[38] We compute p via Bayes' rule based on the empirical frequencies of play from our first batch of sessions. This is done for each treatment separately.

with probability $1-p$.[39] Lottery 1/2/3 corresponds to the decision to invest by type $(1,H)$ after history $\{\}/\{0\}/\{1\}$. Lottery 4/5/6 corresponds to the decision to invest by type $(0,L)$ after history $\{\}/\{0\}/\{1\}$.[40]

Procedure A is simply to pay a subject according to Lottery 1.[41] Hence, Procedure A corresponds to the decision by type $(1,H)$ to invest in round 1. To understand Procedure B, let q be the probability that a $(1,H)$ subject observes history $\{1\}$ if she waits until round 2.[42] Procedure B is, with probability q, to let a subject choose between Lottery 3 and getting 0 ECU for sure and, with probability $1-q$, to let a subject choose between Lottery 2 and getting 0 ECU for sure. Hence, Procedure B corresponds to a decision by $(1,H)$ to wait in round 1. Procedure C is analogous to Procedure A, except that it corresponds to the decision by type $(0,L)$ to invest in round 1. Procedure D is analogous to Procedure B, except that it corresponds to the decision by type $(0,L)$ to wait in round 1.[43]

The first set of lottery problems, which we call our "calibration" problems, involve a choice between (i) being paid according to Procedure A plus receiving an amount of money (which increases from -0.75 ECU to 1 ECU) for sure, and (ii) being paid according to Procedure B. By finding the amount of money (the cutoff) at which each subject switches from (ii) to (i), we can quantify by how much she values Procedure B over Procedure A (a higher cutoff indicates a stronger preference for Procedure B). Evaluating Procedure B requires a propensity/ability to think ahead through the various scenarios, i.e., it requires foresight. Therefore, Procedure B is likely to be

[39] Actually, in the lotteries we round off p to the nearest 5 percent.

[40] Let $(X,s;Y,1-s)$ be a lottery which pays X ECU with probability s and Y ECU with probability $1-s$. In the R2CT/A1CT/Treatment 3 Lottery 1 is (-6.5,.3;3.5,.7)/(-6.5,.3;3.5,.7)/(-5.7,.3;4.3,.7); Lottery 2 is (-5.85,.35;3.15,.65)/(-5.85,.35;3.15,.65)/(-4.56,.35;3.44,.65); Lottery 3 is (-5.85,.2;3.15,.8)/(-5.85,.2;3.15,.8)/(-4.56,.2;3.44,.8); Lottery 4 is (-3.5,.7;6.5,.3)/(-3.5,.7;6.5,.3)/(-3.5,.7;6.5,.3); Lottery 5 is (-3.15,.75;5.85,.25)/(-3.15,.75;5.85,.25)/(-2.8,.75;5.2,.25); Lottery 6 is (-3.15,.6;5.85,.4)/(-3.15,.55;5.85,.45)/(-2.8,.6;5.2,.4).

[41] All randomizations are performed by the computer.

[42] We compute q via Bayes' rule based on the empirical frequencies of play from our first batch of sessions. This is done for each treatment separately. In the R2CT/A1CT/Treatment 3, q equals 0.4/0.25/0.3.

[43] Let r be the probability that a $(0,L)$ subject observes history $\{1\}$ if she waits until round 2 (r is computed via Bayes' rule based on the empirical frequencies of play from our first batch of sessions). Procedure D is, with probability r, to let a subject choose between Lottery 6 and getting 0 ECU for sure and, with probability $1-r$, to let a subject choose between Lottery 5 and getting 0 ECU for sure. In the R2CT/A1CT/Treatment 3, r equals 0.3/0.4/0.5.

unappealing for a subject without foresight.[44] To the extent that waiting in round 1 by types $(1, H)$ is driven by foresight, we may expect a correlation between a subject's propensity to wait in round 1 when $(1, H)$ and her cutoff in the calibration problems. In fact, we find that:

Result 5 *A subject's cutoff*[45] *is a strong predictor of the probability that she waits in round 1 when type* $(1, H)$*: the marginal effect of a 0.25 ECU increase in a subject's cutoff leads to a 12 percent increase in this probability. This effect is strongly significant (*$p < 0.001$*).*[46]

In the next lottery problem, subjects had to choose between Procedure A, Procedure B, or getting 0 ECU for sure. This lottery problem corresponds to the decision situation faced by a $(1, H)$ subject in round 1.[47] The top part of Table 10 shows subjects' choices in each treatment. Notice that the frequency with which Procedure A is chosen in each treatment is very close to the frequency with which type $(1, H)$ subjects invest in round 1. Also, a subject's choice of Procedure A is a strong predictor that she will invest in round 1 when type $(1, H)$: the probability of investing in round 1 is 23 percent ($p = 0.009$) higher for someone who chose Procedure A (see equation B3 in the online appendix). Since the decision in the game and in the lottery problem are framed very differently but both revolve around foresight, this supports the view that behavior in the two settings is largely driven by whether a subject exhibits foresight.

In the last lottery problem, subjects had to choose between Procedure C, Procedure D, or getting 0 ECU for sure. This lottery problem corresponds to the decision situation faced by a type $(0, L)$ subject in round 1. The most interesting aspect of

[44]The evidence supports the view that the choice between (i) and (ii) is driven by a subject's propensity to look ahead, rather than by a computation with errors. For example, we see no tendency for lower cutoffs in Treatment 3, where the percentage of subjects whose cutoff is at least 0.35 ECU is highest. However, the computed advantage of Procedure B over Procedure A is actually lowest in Treatment 3 (and negative).

[45]In the R2CT/A1CT/Treatment 3 27/29/14 percent of subjects had multiple switch points. For these subjects, the cutoff is interpolated.

[46]See equation B2 in the online appendix.

[47]The third choice, receiving 0 for sure, is analogous to a commitment in round 1 never to invest, which is not available in the game. We included this option in the lottery problem because, if a subject lacks foresight, then she should not be expected to see that Procedure B allows her to opt out later. Opting out of the lottery through procedure B requires a certain amount of foresight, but it is obvious in the game that one can choose not to invest by waiting.

	R2CT	A1CT	Treatment 3
Procedure A	29	35	47
Procedure B	59	56	42
0 for sure	12	8	12
Procedure C	10	15	2
Procedure D	39	44	40
0 for sure	51	42	58

Table 10: Frequency of Choices (percent)

behavior in this lottery problem (see the lower part of Table 10) is that about half of the subjects choose to receive 0 ECU for sure. This is despite the fact that Procedure D (i) can guarantee 0 for sure, but (ii) also offers the possibility to get the quite favorable Lottery 6.[48] It is likely that a large proportion of the subjects choosing 0 for sure are exhibiting a lack of foresight–they do not realize that the more complex Procedure D actually gives them a valuable option with no cost. This supports our view that the choice between procedures is largely driven by whether a subject has foresight or not. (For further evidence in support of this view, see footnote 44.)

Let us turn to the questionnaire. Question 1 asks whether a type $(0, L)$ subject would invest, if she found out that the other subject had the high signal; this addresses Insight 1b. Question 2 asks for a type $(0, L)$ subject's probability assessment that the other subject, who invests in round 1, has the high signal; this addresses whether Insight 1a is understood quantitatively. Question 3 asks whether a type $(1, H)$ subject would invest in round 2, if she found out that the other subject does not invest in round 1; this addresses Insight 2c. Question 4 asks for a type $(1, H)$ subject's probability assessment that the other subject, who does not invest in round 1, has the low signal; this addresses whether Insight 2b is understood quantitatively.

The questionnaire results are interesting, both for what we find and what we do not find. First, we find that, for subjects who responded with "not invest" to question 1, only 21 percent of the decisions, after history $\{1\}$ when type $(0, L)$ in the game, were decisions to invest. On the other hand, for subjects who responded with "invest", 61 percent of those decisions were decisions to invest.[49] Thus, a strong predictor

[48]Lottery 6 has expected value 0.45/0.9/0.4 ECU in the R2CT/R1CT/Treatment 3.

[49]These percentages are pooled across treatments. The percentages within each treatment are similar.

of behavior by a type $(0, L)$ subject after history $\{1\}$ is whether she perceives that the other subject having the high signal makes investment profitable. However, the quantitative assessment of the probability that the other subject has the high signal (question 2) does not have a significant effect on the probability of investment by type $(0, L)$ after history $\{1\}$ ($p = 0.153$; see equation B4 in the online appendix).

Second, we find that, for subjects who responded with "not invest" to question 3, only 29 percent of the decisions, in round 1 when type $(1, H)$ in the game, were decisions to invest. On the other hand, for subjects who responded with "invest", 62 percent of the decisions were decisions to invest.[50] Thus, a strong predictor of behavior by a type $(1, H)$ subject in round 1 is whether she believes that there is an option value of waiting (i.e., that investment is no longer profitable if the other subject does not invest in round 1). However, the quantitative assessment of the probability that the other subject has the low signal, after not investing in round 1, (question 4) does not have a significant effect on the probability of investment by type $(1, H)$ in round 1 ($p = 0.592$; see equation B5) in the online appendix).[51] Summarizing:

Result 6 *Question 1 has a large and significant effect on the probability of investment by type* $(0, L)$ *after history* $\{1\}$ *in the game; Question 3 has a large and significant effect on the probability of investment by type* $(1, H)$ *in round 1 in the game. However, questions 2 and 4 have no significant predictive power for behavior in the game.*

This result suggests that insights about updating and foresight play an important role in guiding behavior in the game. However, these insights do not translate into quantitative probability assessments.

Finally, another strong indication that behavior is driven by subjects' ability to acquire various insights about the game comes from a different source. We find that, in the R2CT and A1CT, subjects' SAT scores are a strong predictor of whether they wait in round 1 when type $(1, H)$ (see equation B6 in the online appendix). The

[50]These percentages are pooled across treatments. The percentages within each treatment are similar.

[51]There was also a question 5, which asked what a type $(1, H)$ subject would pay to observe the other subject's signal directly, and then decide whether to invest in round 1. We find that (i) answers are not a significant predictor of behavior in the game and (ii) the average willingness to pay is 0.431 and 0.502 in the R2CT and A1CT (computed value is 0.63), while it is 0.575 in Treatment 3 (computed value 0.29). Although the computed value of the information is much lower in Treatment 3, average willingness to pay is higher. Thus, responses do not respond directly to computed values.

estimated marginal effects on the probability of waiting are 0.0013 ($p < 0.001$) in the R2CT and 0.00075 ($p = 0.021$) in the A1CT.[52] In Treatment 3, there is no significant effect, perhaps because a high SAT score may facilitate both the acquisition of insights as well as the realization that the benefits of waiting are not large enough.[53] We also find that subjects' SATs are a strong predictor of whether they invest in round 2 when type $(0, L)$ after seeing the other player invest in round 1 (see equation B7 in the online appendix). The estimated marginal effect on the probability of following the other subject is 0.00103 ($p = 0.011$).

VI Robustness of insight-based rules of thumb

In this subsection, we discuss how subjects using insight-based rules of thumb in our games–S, M, and F subjects–would play in other experiments in the literature.

The experimental work closest to ours studies investment with endogenous timing, where subjects observe a signal and decide whether to invest or wait. In Daniel Sgroi (2003), subjects receive two draws from one of two urns: a "red" urn which contains two red (R) balls and one white (W) ball, and a "white" urn which contains two W balls and one R ball. The possible signals are either strongly red (RR), strongly white (WW), or neutral (RW or WR). In each round, subjects either guess which urn the draws came from, or wait (at a cost) to observe others' guesses. Roughly 85 percent of subjects with a strong signal guess in round 1 and almost all subjects with a neutral signal wait.

In these settings, an F subject would wait in round 1, even with a strong signal (RR or WW). The percentage of F subjects is small (roughly 15 percent), perhaps because there is no cost of guessing and a strong signal is extremely informative. If an S or M subject has no clue that waiting provides a valuable option, no matter how simple the problem, then she would always invest in round 1 (randomizing between urns with the neutral signal). However, such a literal interpretation of S and

[52]These marginal effects are large - in the R2CT/A1CT they imply a 41/23 percent difference in the probability of waiting for two subjects who are two standard errors apart in their SATs.

[53]These findings are similar in spirit to the finding that, as the game progresses, subjects in the R2CT and A1CT learn to wait in round 1 when type $(1, H)$, whereas subjects in Treatment 3 do not (see section B). The similarity arises when one thinks of both higher SATs and more experience in the game as facilitating the acquisition of foresight.

M subjects would be a misreading of our theory, which deals with insights in complex situations. A more appropriate interpretation of S and M subjects in Sgroi's experiment would have them guess in round 1 with a strong signal (the only complex situation), but wait with the neutral signal.[54]

In Anthony Ziegelmeyer et al. (2005), each of two subjects receives a signal that is randomly drawn from the set of integers between -4 and 4, and the subjects have to guess whether the sum of the two signals is positive or negative. Although the Nash equilibrium predicts perfect identification (where signals 4 and -4 guess in round 1, signals 3 and -3 guess in round 2, etc.), a more common strategy is for signals of absolute value 3 or 4 to guess in round 1. The authors interpret these deviations from Nash as a cooperative attempt to internalize informational externalities.

In these settings, an F subject with the signal 3 or -3 would wait in round 1. An S or M subject with the signal 3 or -3 would guess in round 1. Thus, we offer an alternative explanation for why a subject with the signal 3 or -3 might guess in round 1. Rather than an attempt at cooperation, a subject might not have a clear insight that waiting in order to imitate is valuable, and choose a rule of thumb that focuses on the profitability of guessing in round 1.

There is a substantial literature on herding game experiments with exogenous timing. Obviously, these experiments do not address the issue of foresight, but Insight 1 about updating is relevant. In Lisa R. Anderson and Charles A. Holt (1997), just like in Sgroi (2003), subjects have to guess the correct urn based on a draw from that urn and on the observed history of others' guesses. However, subjects make guesses in an *exogenously* determined order. Information cascades, where subjects disregard their private information and follow the majority of previous subjects, occur in 41 of the 56 periods in which an imbalance of previous guesses occurred. Goeree et al. (2007) provide a theoretical result that the QRE of a game with sufficiently many players will have informational cascades eventually reversing themselves and revealing the correct urn with probability arbitrarily close to one. Experimental trials with 20 or 40 decision makers exhibit multiple, temporary cascades. In the context of Anderson and Holt (1997) and Goeree et al. (2007), an M or F subject would go against her

[54]If, say, we were to increase the cost of waiting in Sgroi (2003), at some point the problem for a subject with the neutral signal would become complex. Then S and M subjects might start to invest in round 1.

signal to join a cascade, while an S subject would not. If the population frequency of S subjects is similar to our estimate of about one quarter, one would expect to see cascades occurring after the vast majority of imbalances in Anderson and Holt (1997) (with six subjects per market), and to see frequent cascade reversals in Goeree et al. (2007) (with 20 or 40 subjects per market). Thus, our model provides an alternative explanation to QRE for these experimental findings.[55]

Marco Cipriani and Antonio Guarino (2005) and Mathias Drehmann, Jörg Oechssler, and Andreas Roider (2005) consider herding models where subjects decide in an exogenously determined sequence, but where the choice is whether to buy or sell an asset. What makes this different from the urn experiments is that the asset price, rather than being fixed, is equal to the expected asset value, given the history of trades and the assumption that a buy (sell) decision indicates a good (bad) signal about the asset. The Nash equilibrium is to buy with a good signal and sell with a bad signal, without herding. Both papers find that herding is rare, but a new phenomenon emerges, in which a significant minority of subjects engage in "contrarian" behavior, selling at high prices with the good signal or buying at low prices with the bad signal.

In these experiments, an M or F subject would follow this strategy, but an S subject would be a contrarian.[56] Thus, one explanation for contrarian behavior is that some subjects do not update based on market histories.[57]

Our experimental design allows a fairly clean connection between insights, about updating and foresight, and the corresponding behavioral rules. While it is difficult to say exactly what strategies our S, M, and F subjects would choose in games very different from herding games, our results are consistent with certain findings in the

[55]Goeree et al. (2007) find that the likelihood of abandoning a cascade falls sharply with the length of the cascade, which suggests that even S subjects will respond to clear and compelling information, making the decision far less complex.

[56]One treatment in Drehmann, Oechssler, and Roider (2005) publicly announces previous signals, so that contrarian behavior cannot be due to beliefs about the strategies of earlier traders.

[57]Drehmann, Oechssler, and Roider (2005) find no evidence of heterogeneous behavior across subjects, which would argue against the presence of S subjects. However, each subject only participated in 3 trials, so it was rare for a subject to have more than one or two opportunities for contrarian behavior. Andreas Park and Sgroi (2008) ran an experiment in which contrarian behavior is rational under some circumstances. If subjects update properly, it is still the case that behavior should depend on the signal and not the price. In their questionnaire, when subjects were asked what motivates their decisions, 44 percent said a combination of prices and signals, 31 percent said only price, and 18 percent said only signal. These responses suggest heterogeneity in the population.

auction literature. It is known that many subjects fail to perform contingent reasoning, analogous to the lack of foresight exhibited by S and M subjects. For example, in sealed-bid, second-price private-value auctions, many subjects submit bids exceeding their value, which is a weakly dominated strategy. However, in the payoff equivalent English auction, these subjects have no problem remaining in the auction until the clock price reaches their value, and dropping out immediately thereafter. The reason is that, although the two auctions are theoretically equivalent, the sealed-bid auction requires the foresight to perform contingent reasoning[58], while the English auction does not. The winner's curse in common-value auctions can involve failure to update or failure to use foresight. In an English auction, a bidder needs to update her assessment of the common value based on the drop-out behavior of others. In a sealed-bid auction, a bidder needs to think ahead (with foresight) to the scenario in which she wins, and then, within that scenario, must update her assessment of the common value. Thus, we would expect S subjects to suffer from the winner's curse in both sealed-bid and English auctions, because of their inability to update, and M subjects to suffer from the winner's curse only in sealed-bid auctions, where both updating and foresight are important. Charness and Levin (2007) study the takeover game, and conclude that lack of contingent reasoning is the main cause of the winner's curse.[59]

VII Concluding Remarks

To summarize our main results, we find that subjects are more likely to invest as their signals become more favorable, even for the subtle comparison between type $(0, L)$ and type $(1, H)$. Subjects overinvest relative to the Nash benchmark. Behavior is very similar in all three treatments.

Maximum likelihood estimates for the R2CT and A1CT are consistent with asym-

[58]Subjects who bid above their value in the sealed-bid auction, do not realize that the only scenario in which the higher bid matters is one in which they pay more than their value. See Kagel, Ronald M. Harstad, and Levin (1987) as well as Kagel and Levin (2008).

[59]Charness and Levin show that the winner's curse effect is greatly reduced when the game is replaced with simpler lotteries that eliminate the need for contingent reasoning. The takeover game is static, so contingent reasoning and Bayesian updating are intertwined. Note that our procedures B and D are complex and multi-stage, so that the need for contingent reasoning is not eliminated.

metric cursed equilibrium involving a combination of fully cursed and uncursed subjects. Level-k beliefs can account for these estimates as well. We can also account for these estimates if subjects choose rules of thumb, based on insights about how to understand the game (hindsight and foresight). To separate these explanations, we introduce Treatment 3, in which F is strictly dominated and is inconsistent with any theory of best responding to beliefs. We find that the proportion of F subjects does not decline significantly, and remains above 50 percent.

Our results suggest that many subjects are not best-responding to beliefs in our study, but this conclusion does not detract from the important contributions that cursed equilibrium and level-k beliefs have made. Cursed equilibrium formalizes the notion that subjects do not fully draw inferences about others' types from their behavior. Level-k beliefs allow for heterogeneous beliefs about how sophisticated the other players are, but requires best responding to those beliefs. These theories provide important alternatives to (Bayesian) Nash equilibrium, and can account for many behavioral anomalies. They are particularly plausible when the primary task is to figure out what strategies the other players will choose, and figuring out a best response is fairly easy. In our context, a subject who understands the basic tradeoffs will have difficulty computing a best response. Also, the dynamic structure introduces new issues of how subjects gather information from, or anticipate gathering information from, others' behavior over time, while cursed equilibrium and level-k beliefs are motivated by static games.

Our model of S, M, and F subjects fits the data better than a QRE model. We argue in section VI that insights about updating and foresight suggest corresponding rules of thumb in herding experiments and some other experiments. However, other games might require insights unrelated to the ones we study here. Our rules of thumb inherently cannot provide a complete theory of bounded rationality, but they can accurately capture behavior and perform well in an important class of environments where insights about updating and foresight are important.

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