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Information Cascades: Evidence from a Field Experiment with Financial Market Professionals

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ABSTRACT

Previous empirical studies of information cascades use either naturally occurring data or laboratory experiments. We combine attractive elements from each of these lines of research by observing market professionals from the Chicago Board of Trade (CBOT) in a controlled environment. Analysis of over 1,500 individual decisions suggests that CBOT professionals behave differently from our student control group. For instance, professionals are better able to discern the quality of public signals and their decisions are not affected by the domain of earnings. These results have implications for market efficiency and are important in both a positive and normative sense.

IN ECONOMIC AND FINANCIAL ENVIRONMENTS in which decision makers have imperfect information about the true state of the world, it can be rational to ignore one's own private information and make decisions based upon what are believed to be more informative public signals. In particular, if decisions are made sequentially and earlier decisions are public information, "information cascades" can result. Information cascades arise when individuals rationally choose identical actions despite having different private information.[1] Cascades may arise

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[1] Herding is a more general phenomenon than an informational cascade though both result in behavioral conformity. The homogeneity of a herd may arise through other than informational means such as payoff externalities, preferences for conformity, or sanctions. A comprehensive taxonomy of herd behavior is developed by Hirshleifer and Teoh (2003) and Smith and Sorenson (2000). Devenow and Welch (1996) and Bikhchandani and Sharma (2000) also discuss alternative sources of herd behavior and review the extant literature.

in myriad settings, including technology adoption, medical treatment, and environmental hazard response. Arguably, however, the most well-known herds or cascades occur in financial markets, where bubbles and crashes may be examples of such behavior.[2]

Since the private information of cascade followers is not revealed, information cascades can be suboptimal. Moreover, because the small amount of information revealed early in a sequence has a large impact on social welfare, cascades can be fragile, with abrupt shifts or reversals in direction when new information becomes available (Bikhchandani, Hirshleifer, and Welch (1992, 1998; hereafter BHW), Gale (1996), Goeree et al. (2004)). Indeed, some argue that the volatility induced by herding behavior can increase the fragility of financial markets and destabilize the broader market system (Eichengreen et al. (1998), Bikhchandani and Sharma (2000), Chari and Kehoe (2004)).

Previous empirical approaches that examine cascade behavior can be divided into two classes; regression-based tests that use naturally occurring data and laboratory experiments that use data gathered from student subjects. In a review of the extant regression-based results for herding in financial markets, Bikhchandani and Sharma (2000) note the difficulty of controlling for underlying fundamentals, and argue that as a result of this difficulty there is often "a lack of a direct link between the theoretical discussion of herding behavior and the empirical specifications used to test for herding."[3] The laboratory environment, in contrast, allows one to control for public and private information and thus to make explicit tests of theoretical predictions more easily. Yet an important debate exists about the relevance of experimental findings from student subjects for understanding phenomena in the field. For example, professional behavior in the field might differ from student behavior in laboratory experiments due to training or regulatory considerations, which may affect the development of decision heuristics, as well as the overall naturalness of the experimental environment (see, e.g., Harrison and List (2004)). Locke and Mann (2005) argue that financial market research that ignores the effect of professional expertise is likely to be received passively because "ordinary" individuals, as opposed to professional traders, are too far removed from the price discovery process. Bikhchandani and Sharma (2000, p. 13) also argue that "to examine herd behavior, one needs to find a group of participants that trade actively and act similarly."

We find these arguments compelling and therefore combine the most attractive aspects of these two classes of empirical research, that is, we observe professionals in a controlled environment, and extend the literature in several new directions. First, we compare the behavior of market professionals from the floor of the Chicago Board of Trade (CBOT) with that of college students in an experimental setting in which the underlying rationality of herd behavior

[2] It has been argued, also, that information cascades can explain a large variety of social behaviors such as fashion, customs, and rapid changes in political organization. Anderson (1994), Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992, 1998), and Welch (1992) discuss a variety of interesting examples. A number of historical anecdotes can be found in MacKay (1980) and Garber (2000).

[3] Fama (1998) discusses the interpretation of empirical results as evidence of irrational behavior.

can be identified. Second, given the vast normative implications of work that has established the importance of the domain of earnings for decision making under risk (Kahneman and Tversky (1979), Shefrin and Statman (1985), Odean (1998)), we examine the behavior of each group in the gain and loss domain. We further examine whether, and to what extent, cascade formation is influenced by both private signal strength and the quality of previous public signals, as well as decision heuristics that differ from Bayesian rationality. Finally, within the group of market professionals, we examine the extent to which differences in cascade formation are associated with individual characteristics such as whether the participant is a day trader.

Empirical findings gained from an examination of more than 1,500 individual decisions lend some interesting insights into cascade behavior. A key finding is that market professionals tend to make use of their private signal to a greater degree and base their decisions on the quality of the public signal to a greater extent, than do students. As a result, the professionals are involved in weakly fewer overall cascades and significantly fewer *reverse cascades* (cascades that lead to inferior outcomes). This result is novel to the literature and has important implications for financial markets.[4] Furthermore, while the behavior of students is consistent with the notion that losses loom larger than gains, market professionals are unaffected by the domain of earnings. This finding is consistent with Locke and Mann (2005), Genesove and Mayer (2001), and List (2003, 2004), who find, in varying environments, that market experience is associated with a decline in deviations from classical assumptions.

Note that we observe behavioral differences not only across subject pools, but also within the market professional group. For example, Bayesian play is correlated with market experience and day traders are much more likely to join an informational cascade than are non-day traders. Finally, we present data on the prevalence of non-Bayesian decision heuristics, an area in which the two subject pools demonstrate similarities.

The remainder of the study is crafted as follows. Section II outlines the basic theory and experimental design. Section III presents our empirical results. Section IV considers implications of our results for financial markets and briefly discusses the use of professionals in experimental practice more broadly. Section V concludes.

I. Theory and Experimental Design

Imitative behavior associated with herding has often been viewed as the product of irrational decision making (Keynes (1936), Shleifer and Summers (1990), Hirshleifer (2001)). Alternatively, models such as Banerjee (1992), BHW (1992), and Welch (1992) consider the conditions under which it is rational to join a cascade. The model we present below, and the experimental environment we implement, is consistent with the work of this second set of authors

[4] Combined with the insights gained from the models of Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrhamanyam (2001), and Hirshleifer (2001), our results indicate that the ability of the strength and weight of the evidence to have a differential impact on asset pricing is a potentially powerful phenomenon.

in that it is predicated on Bayesian updating of beliefs, given private signals and a history of observable actions.[5] The empirical investigation of the cascade phenomenon raises interesting questions beyond whether agents update information in a manner that is consistent with Bayes's rule.[6] Since the formation of informational cascades is a social phenomenon, individual behavior may depend on how agents view the rationality of others. Accordingly, we examine how our two subject pools respond to uncertainty about the quality of information that arises due to potential deviations from Bayesian rationality by others. We adopt two approaches. First, we use a model in which the null hypothesis is that Bayesian rationality is universally applied and is common knowledge. Second, we estimate a quantal response equilibrium (QRE) model that assumes decision error (McKelvey and Palfrey (1998), Goeree et al. (2004).

A. Theoretical Model and Predictions

Consider an environment in which there are two possible underlying states of nature $\Omega = \{A, B\}$, with the true state denoted by $\omega \in \Omega$. Each of a set of $I = \{1, 2, \ldots, n\}$ agents receives an independent private signal, $s_i \in \{a, b\}$, that is informative in the sense that $\Pr(A \mid a) > \Pr(B \mid a)$ and $\Pr(A \mid b) < \Pr(B \mid b)$. Signal precision, given by $\Pr(s = \omega \mid \omega)$, is identical for all agents. After receiving their signal, each agent chooses either A or B with their choice, c_i. If $c_i = \omega$, individual i receives a reward normalized to one. If $c_i \neq \omega$, individual i receives zero. Each individual receives their signal in an exogenously determined choice order. Along with their private signal s_i, each agent observes the history of choices, $H_i = \{c_1, \ldots, c_{i-1}\}$. The prior probability of an underlying state, given by $\Pr(\omega = A) = p$ and $\Pr(\omega = B) = 1 - p$, is common knowledge. If all individuals update beliefs according to Bayes's rule and this updating is common knowledge, the posterior probability $\Pr(\omega \mid H_i, s_i)$ is easily derived. We demonstrate the formation of an information cascade in this setting via a simple example, parameterized with the probabilities from one of our experimental treatments.

Let $\Pr(\omega = A) = \Pr(\omega = B) = p = 1/2$ be the prior probability, with the precision of the symmetric signal given by $\Pr(a \mid A) = \Pr(b \mid B) = 2/3$, with complementary probabilities $\Pr(b \mid A) = \Pr(a \mid B) = 1/3$. Suppose that $s_1 = a$. Bayes' rule implies that

$$\Pr(\omega = A \mid s_1 = a) = \frac{\Pr(a \mid A)\Pr(A)}{\Pr(a \mid A)\Pr(A) + \Pr(a \mid B)\Pr(B)} = \frac{2}{3}. \tag{1}$$

[5] As we discus below, our experimental environment makes use of a binary signal, binary state, and fixed payoff regardless of the history of announcements. Avery and Zemsky (1998), Lee (1998), Chari and Kehoe (2004), and Cipriani and Guarino (2005a) explore more general settings in which variable pricing reduces but does not eliminate the potential for information cascades. Chamley (2004) provides a comprehensive review of rational herding models.

[6] The ability of humans to reason in a Bayesian manner seems to depend on how information is presented. Studies that present base rates as percentages often show that we are poor “intuitive statisticians” (Tversky and Kahneman (1974)). Decisions tend to be more consistent with Bayesian rationality when individuals experience probability distributions through repeated exposure (see Gigerenzer and Murray (1987)). Our experiment is consistent with protocols that have been shown to give Bayesian decision making its best chance.

An expected utility maximizer would therefore predict A as the state of nature since expected profits for announcing A, π_A, exceed those for announcing B, π_B.[7] If the second subject also receives an a signal, updating according to Bayes's rule yields

$$\Pr(\omega = A \mid H_2 = A, s_2 = a) = \frac{\Pr(a \mid A)^2}{\Pr(a \mid A)^2 + \Pr(a \mid B)^2} = \frac{4}{5}. \quad (2)$$

That is, two consecutive identical announcements yield a posterior probability of 0.80 in favor of the indicated urn.[8] As a result, the third decision maker should "follow the herd" and choose $\omega = A$ regardless of her signal, as can be seen by examining the posterior in which an opposing b signal is the private draw of the third player after two consecutive A announcements:

$$\Pr(\omega = A \mid H_3 = A, A, s_3 = b) = \frac{\Pr(a \mid A)^2 \Pr(b \mid A)}{\Pr(a \mid A)^2 \Pr(b \mid A) + \Pr(a \mid B)^2 \Pr(b \mid B)} = \frac{2}{3}. \quad (3)$$

We classify a decision of this type—consistent with Bayesian rationality, but inconsistent with one's own private signal—as a *cascade decision*. In this example, the decision maker in the third position reveals nothing about their private information and thus the positive externality associated with learning from others' choices is blocked by a cascade. The analysis implies that, with this parameterization, public announcements are uninformative whenever the number of public signals of one type exceeds the other by two or more. As a result, if a cascade has not started, two consecutive low probability draws can result in a *reverse cascade* whereby everyone rationally herds on the incorrect state.

B. Experimental Design

Anderson and Holt (1997) present a seminal experimental investigation of cascade formation using a subject pool of undergraduates. To ensure comparability of our results to the extant literature, we use experimental protocols that

[7] In the gain treatments, $\pi_A - \pi_B = \frac{\$W}{3}$ after an initial a signal, where \$W is the win amount. Treatments over gains and losses yield identical predictions (i.e., expected losses are minimized by picking the most probable urn).

[8] A second A announcement could arise in this setting if the second subject receives a b signal. We consider an announcement of A given the history Ab to be inconsistent with Bayesian rationality, although alternative interpretations are possible. Since the posterior probability is 0.5 in this case, a tie-breaking rule must be invoked. We follow Anderson and Holt (1997) in assuming that individuals who are indifferent announce their own signal. This is sensible if individuals recognize the possibility of decision error in previous announcements. Alternative tie-breaking rules include random choice as in BHW (1992) and a "nonconfident" rule in which one ignores one's own information (Koessler and Zieglemeyer (2000)). In our treatments the Anderson and Holt rule is followed 81% of the time, with most of the deviations occurring in the early rounds of play.

are closely related to those of their work.[9] The parameterization in the example above is consistent with their symmetric treatment ($\Pr(a \mid A) = \Pr(b \mid B)$). The experimental sessions we conduct comprise 15 *rounds* of the basic game for a group of either five or six players whose choice order in each round—either first, second, third, . . . , sixth—is determined by a random draw.

A round begins with the experimental monitor selecting the state of nature with a roll of a die that is unobserved by the subjects. Subjects gain information about the state by drawing a single ball out of an unmarked bag into which the contents of the selected urn have been transferred. The draw is made while the subject is isolated from the other players. The monitor is informed of the choice of the state, and announces it publicly. After all subjects have made their choices, the true state is revealed.

To provide exogenous variation in the informational content of the private signal across treatments, we use two urn types. In the symmetric treatment, Urn A contains two type-a balls and one type-b ball, while Urn B contains two type-b balls and one type-a ball. To create the *asymmetric* treatment, we add four a balls to both urns, yielding 6 (5) a signals and 1 (2) b signal in the A (B) state. This modification results in a significant dilution of the strength of an a signal, the relative weakness of which can be observed in Table I, which provides posterior probabilities for all possible signal histories for both the symmetric and asymmetric urn types. As an example, the two-thirds probability that arises after a single a draw in the symmetric treatment arises after four consecutive a draws in the asymmetric setting. One consequence of the change in signal strength is that in the asymmetric treatment, a cascade on the B state should take place after one b signal even with either one or two a signals in the game's history.

The difference in signal strength across urn types allows us to investigate the relationship between Bayesian updating and a choice heuristic based on a counting rule. In the symmetric treatment, the optimal decision is always consistent with choosing the state with the most informative signals. In the asymmetric case, four sequences violate this counting rule in that it is optimal to choose B even when there are fewer b signals; these *noncounting rule* sequences are $(a, b) \in \{(2, 1), (3, 1), (3, 2), (4, 2)\}$, as indicated by bold type in Table I. Thus, the asymmetric treatment allows us to gain insights into the extent to which decisions are better characterized as following a counting heuristic rather than Bayesian updating.

To provide exogenous variation in the earnings domain, we randomly place subjects in either a *gain* or a *loss* treatment for all 15 rounds. The treatment

[9] Our experimental instructions are available upon request. Note that Anderson and Holt (1997) find that cascades form in roughly 70% of the rounds in which they are possible. Deviations from Bayesian cascade formation occur most often when a simple counting rule gives a different indication of the underlying state. Extensions to the experimental literature introduce relevant complications to the cascade process that include costly information, endogenous sequencing of choice order, collective decision making, expanded signal spaces, and payoff externalities (Celen and Kariv (2004, 2005), Cipriani and Guarino (2005b), Drehmann, Oechssler, and Roider (2005), Huck and Oechssler (2000), Hung and Plott (2001), Kubler and Weizsacker (2004), Noth and Weber (2003), Sgroi (2003), Willinger and Ziegelmeyer (1998)).

Table I

Posterior Probabilities: Symmetric (upper) and Asymmetric (*lower*) Urns

Entries represent the posterior probabilities for all possible sequences of draws for both symmetric (upper) and asymmetric (*lower*) treatments based on choice histories (a, b). The prior probability of an urn is 0.5 in (0,0). Bold entries for the asymmetric urn are those in which counting and the posterior probability make different predictions about the state.

b a	0	1	2	3	4	5	6
0	0.500	0.330	0.200	0.110	0.060	0.030	0.020
	0.500	*0.333*	*0.200*	*0.111*	*0.059*	*0.030*	*0.015*
1	0.670	0.500	0.330	0.200	0.110	0.060	
	0.545	*0.375*	*0.231*	*0.130*	*0.070*	*0.036*	
2	0.800	0.670	0.500	0.330	0.200		
	0.590	***0.419***	*0.265*	*0.153*	*0.083*		
3	0.890	0.800	0.670	0.500			
	0.633	***0.464***	***0.302***	*0.178*			
4	0.940	0.890	0.800				
	0.675	*0.509*	***0.341***				
5	0.970	0.940					
	0.713	*0.554*					
6	0.980						
	0.749						

is implemented so that in gain (loss) space a correct (incorrect) inference about the underlying state results in positive (negative) earnings of $1 for students and $4 for market professionals.[10] An incorrect (correct) choice in gain (loss) space results in no earnings. To generate similar monetary outcomes across treatments, in the loss treatments students and market professionals are endowed with $6.25 and $25.00, respectively.[11] We believe that this is the first study to vary the gain/loss domain in cascade games.

Experimental subjects in a particular session consist entirely of one of the two subject types, students or market professionals. The experimental sessions with market professionals are conducted at the CBOT and the student data are gathered from undergraduates at the University of Maryland in College Park. The CBOT (student) subject pool includes 55 (54) subjects recruited from the floor of CBOT (the university). The resulting experimental design is a $2 \times 2 \times 2$ factorial across urn type (symmetric (S) or asymmetric (A)), domain type (gains (G) or losses (L)), and subject type (college undergraduates (C) or market professionals (M)). Each experimental session consists of a group of either five

[10] CBOT officials suggest that designing a 30-minute game with an expected average payout of approximately $30 is more than a reasonable approximation of an average trader's earnings for an equivalent amount of time on the floor. In our experiments the median earnings for the market professionals are slightly in excess of this amount and therefore likely to be salient.

[11] To ensure that subjects depart with positive money balances we have both subject pools participate in other unrelated games during the experimental session.

Table II

Experimental Design

Panel A (B) shows that Market Professionals (Students) are exposed to either the Symmetric or Asymmetric urn and play the game in either the gain or the loss domain. The symmetric urn consists of three balls—two a and one b in Urn A, and one b and two a in Urn B. The Asymmetric urn consists of seven balls—six a and one b in Urn A, and five a and two b in Urn B. The number of decisions is a function of the number of players, the number of games, and the number of rounds in each game.

	Symmetric Urn		Asymmetric Urn	
	Gains	Losses	Gains	Losses
Panel A: Ten Market Professional Sessions				
Number of Sessions	3	1	3	3
Participants in Session	5	5	One with 5, two with 6	6
Total Decisions	225	75	255	270
Average Earnings	\$43.20	−\$20.80	\$39.06	−\$22.89
Panel B: Ten Student Sessions				
Number of Sessions	3	1	3	3
Participants in Session	One with 5, two with 6	5	One with 5, two with 6	5
Total Decisions	267	75	255	225
Average Earnings	\$11.61	−\$2.80	\$11.00	−\$6.40

or six participants making decisions within the same treatment type over 15 rounds. Table II summarizes our experimental sessions.

II. Experimental Results

Table III, Panel A presents descriptive statistics from the experiment. We report the rate of Bayesian decision making and the rate of cascade formation, with a Bayesian decision defined assuming common knowledge of Bayesian rationality (no decision error). Pooled, the 20 experimental sessions yield a total of 1,647 decisions, 1,284 (78%) of which are consistent with a perfect Bayesian equilibrium.[12] Cascade decisions (i.e., Bayesian decisions inconsistent with the private signal) occur in 15% of the choices. Of these, just under one-quarter (55 out of 245) are “reverse” cascades, resulting in the wrong inference about the underlying state.

Perhaps more revealing than the aggregate number of cascades is the proportion of cascade decisions made when the opportunity arises. Recall that a cascade decision is possible only when the private draw is inconsistent with the probability weight derived from the choice history and one’s own private signal. In our data, cascade formation is possible in 441 of the decisions, representing 27% of the total; cascades are realized in 245 (56%) of these cases. These

[12] In the discussion that follows we use the term “Bayesian decision” to mean that the decision is consistent with the predictions of perfect Bayesian equilibrium.

results are presented in the *potential* and *realized* cascades columns of Table III, Panel A.

Table III, Panel A also reports statistics disaggregated by subject and treatment type. In aggregate, 81% (75%) of the students' (market professionals') decisions are consistent with Bayesian Nash equilibrium. Decisions of individual subjects range from 38% to 100% Bayesian (these results are not shown to conserve space), and of the 14 subjects perfectly consistent with Bayesian

Table III

Aggregate Decision Making

The *Bayesian* column represents the total proportion and number of decisions consistent with a perfect Bayesian equilibrium. *Cascade* decisions (those that are Bayesian but for which private information is ignored) and *reverse* cascades (cascades in which the wrong inference of the underlying state occurs) occupy the next two columns. The *potential* cascades category represents the proportion (and number) of cascades that could have occurred when it was possible to make one, and the *realized* cascades category represents the proportion of those potential cascades that were actually realized. "n" = number of decisions. Treatment codes are S = symmetric, A = asymmetric, G = gain, L = loss, C = college student, and M = market professional. Panel A includes all decisions and Panel B restricts attention to those sequences in which the Bayesian posterior and a counting rule make different predictions.

Treatment	Bayesian	Cascades (Total)	Reverse Cascades	Potential Cascades	Realized Cascades
Panel A: Decision Making Pooled and by Treatment					
Pooled Data					
C&M	0.780	0.149	0.033	0.268	0.556
$n = 1{,}647$	1,284	245	55	441	245/441
College Student Treatments (C)					
C	0.814	0.178	0.045	0.292	0.608
$n = 822$	669	146	37	240	146/240
SGC	0.940	0.157	0.041	0.172	0.913
$n = 267$	251	42	11	46	42/46
SLC	0.960	0.067	0.013	0.080	0.833
$n = 75$	72	5	1	6	5/6
AGC	0.682	0.251	0.051	0.451	0.557
$n = 255$	174	64	13	115	64/115
ALC	0.764	0.155	0.053	0.324	0.480
$n = 225$	172	35	12	73	35/73
Market Professional Treatments (M)					
M	0.745	0.120	0.021	0.244	0.493
$n = 825$	615	99	18	201	99/201
SGM	0.818	0.098	0.022	0.142	0.688
$n = 225$	184	22	5	32	22/32
SLM	0.867	0.147	0.067	0.213	0.688
$n = 75$	65	11	5	16	11/16
AGM	0.714	0.133	0.008	0.275	0.486
$n = 255$	182	34	2	70	34/70
ALM	0.681	0.133	0.022	0.307	0.385
$n = 270$	184	32	6	83	32/83

(*continued*)

Table III—*Continued*

Treatment	Bayesian	Cascades (Total)	Reverse Cascades	Potential Cascades	Realized Cascades
Panel B: Decision Making by Counting Rule Predictions (Asymmetric Treatments)					
Pooled Data					
C&M	0.709	0.164	0.033	0.339	0.477
$n = 1{,}005$	712	165	33	341	165/341
Count = Baye	0.759	0.152	0.024	0.267	0.565
$n = 843$	640	128	20	225	128/225
Count $\neq$ Baye	0.444	0.228	0.080	0.716	0.313
$n = 162$	72	37	13	116	37/116
College Student Treatments (C)					
C	0.721	0.206	0.052	0.392	0.527
$n = 480$	346	99	25	188	99/188
Count = Baye	0.760	0.189	0.036	0.325	0.582
$n = 412$	313	78	15	134	78/134
Count $\neq$ Baye	0.485	0.309	0.147	0.794	0.389
$n = 68$	33	21	10	54	21/54
Market Professional Treatments (M)					
M	0.697	0.126	0.015	0.291	0.431
$n = 525$	366	66	8	153	66/153
Count = Baye	0.759	0.116	0.011	0.211	0.550
$n = 431$	327	50	5	91	50/91
Count $\neq$ Baye	0.415	0.170	0.032	0.660	0.258
$n = 94$	39	16	3	62	16/62

rationality, 10 were students.[13] In situations in which Bayesian behavior requires that one ignore private information, fewer agents are Bayesian: The final column of Table III, Panel A shows that 61% (49%) of students (market professionals) ignore their signal when doing so leads to a cascade. Interestingly, rates of cascade formation and Bayesian decision making are lower in the asymmetric treatments for both subject pools.

The final set of descriptive statistics is presented in Table III, Panel B, which displays results from the asymmetric treatments first pooled and then parsed by subject pool and sequence type, where the type is either a counting rule or a noncounting rule sequence.[14] Table III, Panel B demonstrates that both Bayesian decision making and cascade formation decline when the rules are not reinforcing: The proportion of Bayesian decisions by students (market professionals) declines from 76% (76%) to 49% (42%), and the rate at which cascades obtain declines from 58 percent (55%) to 39% (26%). These results suggest that the noncounting rule sequences pose a challenge for both subject pools.[15]

[13] Thirteen of the 14 who are perfectly consistent with Bayesian rationality are in the symmetric urn treatment. One market professional is perfectly Bayesian in the asymmetric setting.

[14] We will see below that there are differences between the symmetric and asymmetric treatments even after controlling for the counting rule sequences. As a result, we do not pool the symmetric results in this table.

[15] Anderson and Holt (1997) find that the rate of Bayesian behavior in the noncounting rule sequences is 50%, comparable to our student population rate of 49% and close to the pooled rate of 44%.

To permit more formal inference, we apply a variety of parametric and nonparametric statistical techniques and group our results into five categories. Three of the categories compare students and market professionals to consider differences in (1) Bayesian decision making, (2) cascade formation, and (3) behavior across the gain/loss domain. A fourth category concentrates on data from market professionals by making use of additional demographic data collected during the experiment. The fifth category considers the exogenous alteration of signal strength through the use of the symmetric and asymmetric urns. Our analysis leads to the following insight:

RESULT 1: *Market professionals are less Bayesian than students. Despite this behavioral discrepancy, earnings are not significantly different across subject pools.*

To provide evidence of this result we employ both unconditional and conditional statistical tests. When using unconditional tests, we account for the data dependencies within an experimental session by using session-level aggregates to yield the most conservative statistical tests. Our unconditional test used to support Result 1 is a nonparametric Mann-Whitney U-test, which indicates that the rate of Bayesian decision making differs across subject pools at a level of significance of $p = 0.052$.[16]

To complement this analysis, we employ conditional tests that recognize the panel nature of our data; in particular, we use a random effects probit specification of the form

$$Baye_{it} = \beta' X_{it} + e_{it}, \quad e_{it} \sim N[0, 1], \tag{4}$$

where $Baye_{it}$ equals unity if agent i is a Bayesian in round t under the assumption of no decision error by preceding players, and zero otherwise, and X_{it} includes treatment effects (*gain*, *sym*, and *trader*) and other variables predicted to influence play (*order_x*, *diff*, and *heurist*). The treatment variables are as defined above: *gain* equals one (zero) for sessions in the domain of gains (losses), *sym* equals one (zero) for the symmetric (asymmetric) sessions, and *trader* equals one (zero) for the market professionals (students).

The remaining variables are defined as follows. The categorical variable *order_x* ($x = 2, \ldots, 6$) indicates the positional order in which the individual choice is made. The posterior probability is incorporated in the variable *diff,* which is calculated as $|\Pr(\omega = A \mid H, s) - 0.5|$ and measures the accrued public and private information at the disposal of each decision maker; note that *diff*, therefore, varies from zero to one-half, increasing with evidence of the underlying state.[17] The variable *heurist* is equal to one (zero) for noncounting rule (counting rule) sequences. In a perfect Bayesian equilibrium, the coefficients of these latter two variables should not differ from zero.

We specify $e_{it} = u_{it} + \alpha_i$, where the two components are independent and normally distributed with mean zero: $\mathrm{Var}(e_{it}) = \sigma_u^2 + \sigma_\alpha^2$. We estimate equation (4)

[16] There are 10 session-level observations for each subject pool as summarized in Table II.

[17] The posterior, and thus the *diff* variable, remains constant once a cascade has formed, unless a decision breaking the cascade is observed.

using the maximum likelihood approach derived in Butler and Moffitt (1982). Estimation of this model is amenable to Hermite integration. To estimate the model, we use a 12-point quadrature and the method of Berndt et al. (1974) to compute the covariance matrix.

Empirical results are reported in Table IV, which presents the marginal effects associated with a change in each of the regressors computed at the overall sample means.[18] Concerning subject pool effects, results from both a likelihood ratio test and the *trader* dummy variable in the pooled regression model (Panel 4a) support the nonparametric finding that market professionals are less Bayesian than students.[19] The estimated marginal effect in the pooled model suggests that traders are 6% less likely to be Bayesian, and this effect is significant at the $p < 0.05$ level.

Despite the noisier environment (fewer professionals are Bayesian), market professionals and students choose the correct underlying state at similar rates. Indeed, using a Mann-Whitney U-test, we find that we cannot reject the homogenous null that success rates are similar at conventional levels ($p = 0.29$), leading to the result that earnings are similar across the subject pools. To dig a level deeper into this finding, we estimate a model similar in spirit to equation (4), but make the dependent variable *win* be dichotomous and equal to unity (zero) if the individual chooses correctly (incorrectly). We also include an additional independent variable, *round,* to identify learning during the course of the session; *round* is a time trend and increases from 1 to 15 within a session.[20]

The empirical results summarized in Table V support the nonparametric finding concerning earnings and provide more formal evidence of the second half of Result 1. In particular, the *trader* variable in Table V, Panel 5a is not significantly different from zero at conventional levels ($p = 0.27$). This result suggests that traders and students choose the correct urn at similar rates. The two groups differ in their temporal play, however, as evidenced by the significant (insignificant) and positive marginal effect of *round* for the traders (students), consistent with learning effects among traders.

Besides providing empirical support for Result 1, the models in Tables IV and V reveal some of the important effects of the other independent variables. For example, the *diff* and *heurist* coefficient estimates in the pooled model of Table IV indicate that a marginal change in the posterior probability has a large positive effect (66%), while decisions in the *counting rule* sequences are 23% less likely to be Bayesian than those in which counting and Bayesian posterior imply the same result. Similar insights arise when we split the sample by

[18] The alternative approach of computing the marginal effects for each observation and taking the means yields very similar results. Results are also robust to the inclusion of a time trend for round or time dummies (categorical time dummy variables for each round of play). We discuss our evidence of learning further, below.

[19] A Chow test rejects the null hypothesis of no differences across the subject pools at the $p < 0.01$ level.

[20] We test several specifications of the model of Bayesian decision making for learning and find no such effect.

Table IV

Bayesian Decisions: Probit Model

The dichotomous dependent variable in all three probit models (pooled, student, and market professional) is coded one for a decision consistent with the Bayesian posterior and zero otherwise. Independent variables include *diff*, which is $|\text{prob}(\text{urn} = A) - 0.5|$, where $\text{prob}(\text{urn} = A)$ is the posterior probability arising from the combination of public and private information at the disposal of each decision maker. The variables *gain*, *sym*, and *trader* (in the case of the pooled model) are dichotomous and distinguish the treatments. *Heurist* is a dummy variable equal to one for the noncounting rule sequences and zero for all others. *Order_x* (where $x = 2, \ldots 6$) is a categorical variable indicating where in the round of play the decision was made. The Wald statistic tests the null hypothesis that all coefficients are zero.

Dependent Variable: *baye*	4a. Pooled Model $n = 1{,}647$ $\Pr(baye = 1) = 0.818$			4b. Student Model $n = 822$ $\Pr(baye = 1) = 0.868$			4c. Market Professionals Model $n = 825$ $\Pr(baye = 1) = 0.772$		
Ind. Variables:	Marginal Effect	z stat	$p > \|z\|$	Marginal Effect	z stat	$p > \|z\|$	Marginal Effect	z stat	$p > \|z\|$
Diff	0.655	5.53	0.000	0.769	5.06	0.000	0.546	3.11	0.002
Heurist	−0.232	−4.95	0.000	−0.161	−2.51	0.012	−0.284	−4.47	0.000
Gain	−0.030	−1.13	0.259	−0.060	−2.19	0.028	0.015	0.34	0.737
Sym	0.102	3.64	0.000	0.145	4.88	0.000	0.037	0.79	0.430
Trader	−0.060	−2.32	0.020	–	–	–	–	–	–
Order_2	−0.023	−0.66	0.507	0.019	0.54	0.590	−0.084	−1.42	0.157
Order_3	−0.041	−1.06	0.291	0.017	0.42	0.673	−0.120	−1.86	0.063
Order_4	−0.120	−2.91	0.004	−0.052	−1.13	0.261	−0.205	−3.12	0.002
Order_5	−0.035	−0.95	0.343	0.017	0.46	0.649	−0.107	−1.71	0.087
Order_6	−0.040	−0.83	0.408	−0.035	−0.56	0.577	−0.080	−1.05	0.294
	Log Likelihood: −766.49, Wald $\chi^2_{(10)} = 141.03$, Prob $> \chi^2_{(10)} = 0.000$			Log Likelihood: −328.95, Wald $\chi^2_{(9)} = 87.77$, Prob $> \chi^2_{(9)} = 0.000$			Log Likelihood: −427.28, Wald $\chi^2_{(9)} = 68.91$, Prob $> \chi^2_{(9)} = 0.000$		

Table V

Winning Decisions: Probit Model

The dichotomous dependent variable in all three probit models (pooled, student, and market professional) is coded one for a decision that correctly predicts the underlying state and zero otherwise. Independent variables include *diff*, which is $|\text{prob}(\text{urn} = A) - 0.5|$, where prob(urn $= A$) is the posterior probability arising from the combination of public and private information at the disposal of each decision maker. The variables *gain*, *sym*, and *trader* (in the case of the pooled model) are dichotomous and distinguish the treatments. *Heurist* is a dummy variable equal to one for the non-counting rule sequences and zero for all others. *Round* represents a time trend that increases from 1 to 16 with each completed play of the cascade game. *Order_x* (where $x = 2, \ldots 6$) is a categorical variable indicating where in the round of play the decision was made. The Wald statistic tests the null hypothesis that all coefficients are zero.

Dependent Variable: *win*	5a. Pooled Model $n = 1{,}647$ $\Pr(win = 1) = 0.702$			5b. Student Model $n = 822$ $\Pr(win = 1) = 0.729$			5c. Market Professionals Model $n = 825$ $\Pr(win = 1) = 0.670$		
Ind. Variables:	Marginal Effect	z stat	$p > \|z\|$	Marginal Effect	z stat	$p > \|z\|$	Marginal Effect	z stat	$p > \|z\|$
Diff	1.070	7.85	0.000	1.039	5.51	0.000	1.053	5.55	0.000
Heurist	−0.008	−0.19	0.846	−0.009	−0.14	0.886	−0.050	−0.31	0.754
Gain	0.083	2.65	0.008	0.113	2.52	0.012	0.158	1.26	0.207
Sym	−0.028	−0.81	0.418	−0.013	−0.31	0.759	−0.122	−0.86	0.388
Trader	−0.033	−1.10	0.272	–	–	–	–	–	–
Round	0.005	1.95	0.051	0.003	0.68	0.499	0.022	2.06	0.040
Order_2	0.008	0.22	0.824	0.014	0.29	0.774	0.008	0.05	0.960
Order_3	0.019	0.49	0.627	0.016	0.30	0.767	0.073	0.45	0.656
Order_4	0.048	1.26	0.206	−0.001	−0.02	0.988	0.293	1.79	0.074
Order_5	0.057	1.53	0.126	0.081	1.64	0.102	0.010	0.62	0.534
Order_6	0.063	1.33	0.184	0.046	0.63	0.528	0.192	0.96	0.337
	Log Likelihood: −964.06, Wald $\chi^2_{(11)} = 99.52$, Prob $> \chi^2_{(11)} = 0.000$			Log Likelihood: −462.25, Wald $\chi^2_{(10)} = 54.39$, Prob $> \chi^2_{(10)} = 0.000$			Log Likelihood: −498.55, Wald $\chi^2_{(10)} = 48.30$, Prob $> \chi^2_{(10)} = 0.000$		

subject type, as summarized in Panels 4b and 4c of Table IV. In addition, the effect of *diff* is statistically significant for both subject pools in the Table V *win* models.

Interestingly, urn symmetry, as captured by the *sym* dummy variable, is not significant for the market professionals in either model, implying that, for the traders, the difference across urn types is captured by the counting rule distinction. In contrast, the urn difference has a significant influence on students, who are much more likely to be Bayesians in the symmetric treatment (see Table IV, Panel 4b).

A final important difference across subject pools is that the *order_x* variables indicate a decline in Bayesian behavior among market professionals who choose in the third through fifth positions. The magnitude of the effect is rather large, having from one-third to two-thirds of the effect of the counting rule sequences as represented in the *heurist* variable (Table IV, Panel 4c). In contrast, the students show no such effect. The behavior reflected in this finding is consistent with the idea that the market professionals recognize that no new additional information is added by choices once a herd has been formed.

Given the significance of the *diff* and *heurist* variables, we explore the individual data further in a QRE model, which examines the degree to which incentives affect error rates in decision making. Following Anderson and Holt (1997), we focus on data from our symmetric sessions and make use of the QRE model developed by McKelvey and Palfrey (1995, 1998); (see also Goeree et al. (2004), Goeree, Holt, and Palfrey (2005)). The QRE model assumes that the probability of choosing an urn is increasing in its expected value. Given the positive and significant coefficient on the *diff* variable in Table IV, the usefulness of such a model for both the students and market professionals appears evident. For parsimony, we reserve detailed discussion of the QRE model for the Appendix. However, we briefly describe the results below.

Table AI in the Appendix reports estimates of the lambda parameter in the QRE model. The lambda parameter indicates the extent to which noise affects decision outcomes; as $\lambda \rightarrow \infty$, the choice converges to the Bayesian outcome; as $\lambda \rightarrow 0$, the decisions become purely random. Significant differences in lambda across the subject pools are observed at choice orders one, two, and five as reflected in the p-values in column "p" of Table AI. Particularly notable is the difference at choice order two, where the students exhibit few errors. The differences in noise in the first two choice orders lead to quite different behaviors in choice order three, despite the fact that estimates of the lambda parameter are indistinguishable.

The lambda estimates imply that the two subject pools have similar deviations from Bayesian rationality at choice order three. Thus, the market professionals' tendency to rely on their own signal due to errors in earlier rounds is as rational as the students' decision to ignore theirs and join the cascade. Table AII clarifies the meaning of this result by examining in detail the impact of the noisy decision process on revealed public information and choice probabilities for the first three rounds of play. For comparison, we present the posteriors and choice probabilities assuming a perfect Bayesian equilibrium, as well as the actual individual decisions.

Consider the posterior probability for choice order three in Table AII, the first choice at which a cascade may form in the symmetric treatment, when the signal history is AAb (or BBa). In this case, the posterior probability of urn A has dropped from 0.67 for the most likely urn to 0.51 (0.59) for the market professionals (students). Thus, while ignoring one's private information is optimal for both groups, the noise in prior decisions dilutes the strength of the signals, with the market professionals facing essentially a random choice. The probability that urn A is chosen is 0.54 (0.83) for the market professionals (students). The differences across the sequences in choice order three highlights the fact that noise in the decision-making process dilutes the value of the public signal.

Despite the evidence from the QRE estimation of the noisier environment for the market professionals we find that the two groups do not differ significantly in their earnings. Further exploration into this observation leads to the following two results:

RESULT 2a: *In aggregate, the rate of cascade formation is not significantly different for students and market professionals; however, market professionals enter into fewer reverse cascades in the asymmetric treatments.*

RESULT 2b: *Market professionals are better able to discern the quality of the signal associated with other players' announcements than are students.*

Evidence in favor of Results 2a and 2b follows from both nonparametric and parametric statistical tests. Even though the rate at which cascades are realized is roughly 60% for the students and only 50% for the market professionals (see Table III, Panel A), using a Mann-Whitney test the homogeneous null cannot be rejected at conventional levels (Mann-Whitney $p = 0.33$).

While the rate of cascade formation indicates that there is only weak evidence that students enter into a greater number of cascades than do professionals, there are significant differences across subject pools in the rate of cascade formation in the asymmetric urn treatment. Table III, Panel A reveals that in the asymmetric treatment only 12% (8 of 66) of the cascades entered by market professionals are reverse cascades. This is roughly half of the rate observed for students (25 of 99), a difference that is statistically significant at the $p < 0.05$ level using a Mann-Whitney test.

To complement these nonparametric insights, we estimate models similar to equation (4), but set the dependent variable equal to one when a cascade is formed and zero otherwise. To conserve space, we do not formally tabulate these results since they reinforce the nonparametric insights gained above. We find that in the model that pools the symmetric and asymmetric data cascade formation is similar across the students and market professionals. When we focus, instead, on reverse cascades and use only the data from the asymmetric urn treatments, we find that students enter significantly more reverse cascades than do professionals.

These results cannot be explained by our model of decision making based on posterior probabilities derived from signals and actions. We therefore investigate the hypothesis that market professionals use auxiliary information that the students ignore in order to avoid reverse cascades. To do so, we augment the cascade formation model discussed above by considering whether subjects use information specific to individuals selecting prior to them in the current round.

Specifically, we construct two variables that each provides an indication of the Bayesian decision making of subjects who preceded each player in a particular round: *othb*_max (*othb*_min) measures the extent of previous Bayesian decisions by the most (least) Bayesian players. For example, for player i whose choice order is x in round t, we calculate *othb*_min as

$$othb\_\min{}_{it}^{x} = \min\left[\frac{\sum_{t=1}^{t-1} baye_{jt}}{t-1}\ \forall j : x_{jt} < x_{it}\right]. \tag{5}$$

In this case, the proportion of Bayesian decisions for the individual with the

Table VI

Cascade Formation: Probit Model

The dichotomous dependent variable in all three probit models (pooled, student, and market professional) is coded one for a cascade decision and zero otherwise. Independent variables include *diff*, which is $|\text{prob}(\text{urn} = A) - 0.5|$, where $\text{prob}(\text{urn} = A)$ is the posterior probability arising from the combination of public and private information at the disposal of each decision maker. The variables *gain* and *trader* (in the case of the pooled model) are dichotomous and distinguish the treatment/subject type. *Othb*_min is the proportion of Bayesian decisions by the individual with the lowest proportion among all agent preceding the decision maker, and is calculated in each round of the game to include only those decisions that have already occurred. *Heurist* is a dummy variable equal to one for the noncounting rule sequences and zero for all others. *Order_x* is a categorical variable indicating where in the round of play the decision was made. Note: Because the *othb* variable is not applicable for those in the first round or first in choice order in subsequent rounds (they do not observe others' decisions in the current round), these observations are excluded. This results in the exclusion of 25 of the 441 potential cascades. The *order_6* dummy variable is also excluded and choice order two serves as the baseline to which others are compared. The Wald statistic tests the null hypothesis that all coefficients are zero.

Dependent Variable: *cascade*	6a. Pooled Model $n = 416$ Pr(*cascade* = 1) = 0.588			6b. Student Model $n = 226$ Pr(*cascade* = 1) = 0.676			6c. Market Professionals Model $n = 190$ Pr(*cascade* = 1) = 0.493		
Ind. Variables:	Marginal Effect	z stat	$p > \|z\|$	Marginal Effect	z stat	$p > \|z\|$	Marginal Effect	z stat	$p > \|z\|$
Diff	0.861	0.75	0.453	−0.136	−0.08	0.939	1.689	1.13	0.259
Othb_min	−0.014	−0.09	0.924	−0.572	−2.54	0.011	0.469	2.11	0.035
Heurist	−0.354	−4.35	0.000	−0.331	−2.49	0.013	−0.394	−3.95	0.000
Gain	0.133	1.67	0.095	0.021	0.19	0.846	0.120	1.12	0.261
Sym	0.126	1.03	0.303	0.389	4.09	0.000	−0.200	−1.16	0.246
Trader	−0.111	−1.44	0.151	–	–	–	–	–	–
Order_2	−0.146	−1.13	0.260	0.064	0.39	0.696	−0.332	−2.33	0.020
Order_3	0.078	0.72	0.469	0.167	1.24	0.214	0.039	0.24	0.810
Order_4	0.042	0.39	0.696	0.048	0.33	0.744	0.066	0.44	0.658
Order_5	0.233	2.35	0.019	0.169	1.21	0.225	0.308	2.13	0.033
	Log Likelihood: −245.22, Wald $\chi^2_{(10)} = 46.24$, Prob > $\chi^2_{(10)} = 0.000$			Log Likelihood: −125.20, Wald $\chi^2_{(9)} = 27.78$, Prob > $\chi^2_{(9)} = 0.001$			Log Likelihood: −111.06, Wald $\chi^2_{(9)} = 27.42$, Prob > $\chi^2_{(9)} = 0.012$		

lowest proportion among all j agents preceding the current decision maker is used as the independent variable, although the empirical results are robust to other specifications including replacing the min operator with the mean or max. In the case of *othb*_max, we simply replace "min" with "max" in equation (5). Note that these variables are calculated for each t (round of the game) so that they include only those decisions that have already occurred. The variables *diff*, *heurist*, and *gain* are also included, and are defined as in the previous models.

Empirical results are presented in Table VI. Since the results across models yield similar insights concerning the nature of interpreting signals, we focus on the *othb*_min results. Although *othb*_min is insignificant in the pooled specification in Panel 6a, this result masks a difference in how the two subject pools respond to the announcements of others. Results in Table VI, Panel 6c suggest that cascade formation for the market professionals is significantly and substantially associated with the *quality* of the others' signals. The marginal effect of a higher minimum in the preceding players' share of Bayesian decisions is 47%, which is the largest of the variables that are statistically significant and is an indication of the impact of the inferred signal quality on the willingness to make a decision that relies on others. This variable is significant and negative in the student sample (Panel 6b).

Using *othb*_max in the regression yields an insignificant effect for the students, while the market professionals again respond positively, with a marginal effect of 57% (detailed results omitted).[21] We therefore conclude that the market professionals make better use of available public information, incorporating evidence on others' rationality in their decision making in a way that is payoff relevant.[22] Note also that, in contrast with what we found with respect to all decisions (Table IV), the *diff* variable is not significant for either group when we restrict our attention to the subset on cascade formation.

One may wonder whether the result on signal quality is due to market professionals having a greater level of previous interaction with one another than students, or, alternatively, whether there is evidence of learning in the experiment. To explore this issue, we again examine changes in behavioral patterns during an experimental session. The evidence is consistent with the view that market professionals learn over these 15 rounds. Comparing behavior from the first and last three rounds of a session, we find that market professionals: (1) significantly reduce the rate at which they join reverse cascades (from 13% to 2%), and (2) increase the rate at which they join cascades with good outcomes (from 24% to 46%). Both results are statistically significant in probit specifications that include the cascade type as the dependent variable and the temporal variable along with the control variables as independent variables (full results omitted to conserve space). By contrast, there are no significant changes in the rate of cascade formation for either type of cascade for the student subjects.

Our final insight concerning the comparison between students and professionals concerns the domain of earnings of the game:

RESULT 3: *Bayesian behavior of the student population is affected by whether earnings are in the gain or loss domain, while market professionals are unaffected.*

Summary evidence in favor of this result can be found in Table III, Panel A, where we observe that professionals exhibit a similar degree of Bayesian

[21] We estimated six models that included variables designed to measure the quality of previous agents' decision making on cascade formation. In addition to the three that used other Bayes variables (*othb*_min, *othb*_max, and *othb*_mean) we considered whether individuals who had previously revealed their private signal were followed when cascades were possible. These *other*_*reveal* models also tested the min, max, and mean operators. In all six cases market professionals followed those with higher levels of reliability into cascades. Among the students, in five of six cases there was no significant effect of signal quality, with *othb*_min the sole exception as reported in Table VI, Panel 6b.

[22] Support for the significant differences between subject pools found in the parametric results is also found in nonparametric (Mann-Whitney) tests.

decision making across the gain and loss domains (roughly 75%), whereas for students Bayesian play increases in the loss domain. For example, considering the asymmetric treatments, we find that a Mann-Whitney test indicates that college students are less Bayesian in the gain treatment than in the loss treatment, while market professionals are unaffected by the domain of earnings (students: $p < 0.08$; traders: $p = 0.61$).[23]

Empirical estimates in Table IV provide additional evidence of this result. In the pooled data (Panel 4a), the dummy variable *gain* is not significant at conventional levels, and it remains insignificant for the market professionals' specification (Panel 4c). For the students, however, the parameter estimate is both significant ($p = 0.028$) and negative, indicating a 6% increase in Bayesian behavior in the loss domain. This result is consistent with the notion that, for the student population, losses loom larger than gains. This result is consonant with results in List (2003, 2004), who explore loss aversion in a much different environment. Nevertheless, consistent with the notion that repetition might attenuate such anomalies (see, e.g., Knez et al. (1985), Coursey et al. (1987)), analysis of the data from the student sessions provides some evidence that the effect of the domain is mitigated via repetition.

While Results 1–3 highlight differences between the professional and student subjects, we also find important differences within the group of market professionals that are relevant for understanding their decision processes. We supplement our data with a survey implemented at the end of the experimental session. Upon exploring these data more closely, we find:

RESULT 4: *Behavioral differences exist within the professional subject pool.*

Evidence of this result can be obtained by augmenting equation (4) using the additional demographic data collected from the CBOT floor personnel after the experiment. We focus on data collected from a group of 28 of the 55 traders who reported information on *intensity* (the average number of contracts traded per day), *gender* (one for female, zero otherwise), *yrs* (years of experience), *income,* and *overnight* (a dichotomous variable that equals one if the trader takes overnight positions and zero otherwise). Panel A of Table VII reports on the Bayesian decision making and Panel B reports on the cascade formation for these traders.

Concerning Bayesian decision making, we find that *diff* is not significantly different from zero. Indifference to the magnitude of the posterior, for the Bayesian models, does not occur elsewhere in our study, and as we discussed previously is consistent with Bayesian rationality and inconsistent with theories of decision error. Variables that are significant include *heurist, intensity*, and *overnight*. As with the previous results reported in Table IV, *heurist* has a strong negative effect (−39.1%). Trading intensity increases Bayesian behavior slightly (0.4%) and overnight trade has a significantly negative impact on the rate of Bayesian decision making (−17.8%). The probit estimates in Panel B

[23] Due to the small number of sessions at the individual treatment level, p-values for the Mann-Whitney test are reported for observations aggregated at the individual participant level.

Table VII

Bayesian and Cascade Behavior of Traders

The dichotomous dependent variable in Panel A is coded one for a decision consistent with the Bayesian posterior and zero otherwise. For Panel B cascade formation is indicated by a one and cascade failure by a zero. Independent variables include *diff*, which is $|\text{prob(urn} = A) - 0.5|$, where prob(urn $= A$) is the posterior probability arising from the combination of public and private information at the disposal of each decision maker. The variables *gain* and *sym* are dichotomous and distinguish the treatments. *Heurist* is a dummy variable equal to one for the noncounting rule sequences and zero for all others. *Order_x* (where $x = 2, \ldots 6$) is a categorical variable indicating where in the round of play the decision was made. *Intensity* reflects the level of trading intensity among participants, measured as the number of contracts traded per day. *Gender* is one for female and zero for male. *Experience* (years), *income* (dollars), and *overnight* (one for holding overnight positions, zero for daytrader) are additional control variables.

	7a. Trader Subset of CBOT Market Professionals $n = 227$ Dependent Variable: *baye* Pr(*baye* = 1) = 0.745			7b. Trader Subset of CBOT Market Professionals $n = 66$ Dependent Variable: *cascade* Pr(*cascade* = 1) = 0.388		
Ind. Variables	Marginal Effect	z stat	$p > \|z\|$	Marginal Effect	z stat	$p > \|z\|$
Diff	0.467	1.34	0.181	3.710	0.65	0.517
Heurist	−0.391	−3.05	0.002	0.001	0.05	0.997
Gain	−0.023	−0.24	0.81	0.163	0.59	0.552
Sym	0.009	0.08	0.938	0.498	0.79	0.432
Order_2	0.061	0.64	0.523	n/a	n/a	n/a
Order_3	−0.029	−0.28	0.778	−0.185	−0.48	0.629
Order_4	−0.095	−0.86	0.392	−0.219	−0.68	0.498
Order_5	−0.024	−0.22	0.828	0.474	1.22	0.221
Order_6	0.089	0.67	0.504	0.229	0.36	0.721
Intensity	0.004	2.44	0.015	−0.029	−1.91	0.056
Gender	0.069	0.58	0.561	−0.955	−0.2	0.838
Experience (yrs)	−0.001	−0.18	0.859	0.011	0.34	0.735
Income	0.013	0.55	0.582	0.394	1.58	0.115
Overnight	−0.173	−2.03	0.042	−0.804	−2.24	0.025
	Log Likelihood: −93.93, Wald $\chi^2_{(14)} = 52.74$, Prob > $\chi^2_{(14)} = 0.0000$			Log Likelihood: −15.62, Wald $\chi^2_{(13)} = 34.20$, Prob > $\chi^2_{(13)} = 0.0011$		

reveal that day traders are much more likely to join an informational cascade, as are traders with lower trading intensity, with marginal effects of −80% on *overnight* and −2.9% on *intensity*.

For those making consequential trading decisions, the link between trading intensity and Bayesian rationality is consistent with the empirical results of Locke and Mann (2005), Genovese and Mayer (2001), and List (2003, 2004), who find similar results in diverse settings that include financial, housing, and memorabilia markets. We believe that the result on trading style is novel, and we offer some thoughts on its implications in the discussion section below.

Table VIII

Posterior Probability Urn Is *A* and Proportion of Bayesian Decisions

The amount of information associated with urns A and B is given in the first row and first column, respectively. The pairs of numbers within an (a,b) pair represent the Bayesian posterior (upper number) and the proportion of Bayesian decisions (*lower number*). Those in bold type are the sequences in which counting and the Bayesian posterior make different predictions. Thus (2,1) has a posterior probability of 42% that the urn is *A* (diff = 0.08). Forty-six percent made the Bayesian decision in this case. By contrast the (2,0) sequence (in which diff = 0.09) has a posterior probability of 0.59, and 87% of those decisions were Bayesian.

b / a	0	1	2	3	4	5	6
0	0.50	0.33 *0.85*	0.20 *1.00*	0.11 *1.00*	0.06 *1.00*	0.03 *0.89*	0.02 *1.00*
1	0.55 *0.76*	0.38 *0.56*	0.23 *0.72*	0.13 *0.64*	0.07 *0.95*	0.04 *0.63*	
2	0.59 *0.87*	**0.42** ***0.46***	0.26 *0.63*	0.15 *0.69*	0.08 *0.79*		
3	0.63 *0.84*	**0.46** ***0.30***	**0.30** ***0.52***	0.18 *0.58*			
4	0.67 *0.76*	0.51 *0.76*	**0.34** ***0.29***				
5	0.71 *0.87*	0.55 *0.78*					
6	0.75 *0.80*						

Results 1–4 highlight differences in cascade formation and Bayesian decision making across subject types, and include the exogenous alteration of signal strength due to urn type through the *heurist* variable. Our final result looks more closely at the impact of signal strength:

RESULT 5: *Deviations from Bayesian norms are greatest when the counting rule and Bayesian updating make different predictions.*

Our probit specifications reveal that when counting and Bayesian rationality yield different predictions, both market professionals and students are less Bayesian. Table VIII presents all of the observed signal patterns for the asymmetric treatment. Those in which the counting rule and Bayesian posteriors yield different predictions are in bold type. Statistical tests confirm what a visual scan of the data suggests: Bayesian behavior is significantly reduced in the noncounting rule sequences.[24] In fact, the four noncounting rule sequences

[24] We use a Wilcoxon matched pairs test with the variable of interest equal to the proportion of Bayesian decisions aggregated at the session level. The *diff* variable for the *counting rule* sequences is in the range from 0.0 to 0.2, and all other sequences with *diff* variables in this range are included for the paired comparison. Using data from the 12 asymmetric sessions we find that the *counting rule* sequences reflect less Bayesian decision making despite roughly equivalent diff scores at $p < 0.01$.

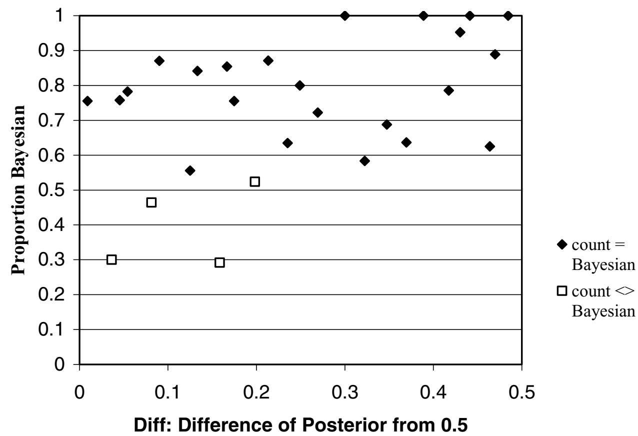

Figure 1. Counting rule heuristic, signal history and Bayesian behavior. The proportion of Bayesian decisions for every realized posterior probability is presented as a data point. The choice histories in which the counting rule and Bayesian posterior yield different predictions are presented as open squares. All other sequences are presented as black diamonds. Note that the sequences in which Bayesian behavior and the counting rule heuristic make different predictions have a uniformly lower proportion of Bayesian decisions than the others.

have lower rates of Bayesian decision making than any of the other sequences, despite the fact that others have smaller *diff* values.

Figure 1 illustrates this insight by presenting the proportion of Bayesian decisions for all observed histories of play as a function of the posterior probability. The noncounting rule sequences (square entries) are uniformly lower than the other choice histories, represented as black diamonds. Compiling the results from Figure 1, we find that Bayesian behavior occurs at a rate of 44% in the noncounting rule choice histories and at a rate of 81% in the remaining choice histories in the asymmetric treatments. There is an important difference in the rate of Bayesian behavior in noncounting rule sequences that depends on whether one's decision involves choosing to join a cascade. The difference is best explained by considering whether individuals rely on their private signal. Restricting attention to noncounting rule sequences, we find that individuals are Bayesian in 31% of the cases when the decision involves choosing to enter a cascade. Therefore, 69% follow their own signal. By contrast 74% of decisions are Bayesian when there is no potential cascade and the decision is consistent with one's private information (see Table IX). Thus, when the signal history requires that Bayesian agents ignore their own signal, agents generally fail to do so. As a result, the failure of cascade decisions implies that 69% rely on their own information—a result statistically indistinguishable from the 74% who rely on their own signal when doing so is optimal. We conclude that for the noncounting rule sequences, a Bayesian perspective provides a less accurate description of decision making than the simple rule of using private information.

Table IX

Bayesian Behavior According to Cascade Potential (Asymmetric Treatments)

The proportion of Bayesian decisions both when a cascade is possible and when one is not for both counting rule and noncounting rule sequences in the asymmetric treatments is provided in the table. When there is no potential cascade the proportion of Bayesian decisions (0.74) is the proportion in which one follows the private signal. When there is a potential cascade ($1 - 0.31 = 0.69$) is the proportion of decisions that follow the private signal.

	No Potential Cascade	Potential Cascades	Total
All	0.82	0.48	0.70
$n = 1{,}005$	541/657	166/348	707/1,005
Noncounting Rule	0.83	0.57	0.76
$n = 843$	512/618	128/225	640/843
Counting Rule	0.74	0.31	0.41
$n = 162$	29/39	38/123	67/162

III. Discussion

Our cascade game data yield interesting evidence of heterogeneity both across the two subject pools and within the market professional group. Simple measures of performance indicate that the students outperform the market professionals. Controlling for learning about signal quality, however, makes clear that the market professionals use a more sophisticated decision process, more finely parsing the quality of public information and relying on their own signal more frequently. Within the market professional group, trading style has a strong effect on behavior, with those taking overnight positions entering cascades much less frequently.

We view these results as having potentially interesting implications for financial markets, although care must be taken with the interpretation, in part because of the fixed payoff that subjects received in our experiment.[25] However, fixed prices are not irrelevant in financial markets as variability in order size means that prices need not change with each transaction. Thus, it is reasonable to study cascade decisions occurring at a constant price as well as those that lead to a change in price.

We believe it is plausible that the heterogeneity among traders regarding cascade formation may be related to differences in their trading practices, including those around fixed prices. Local floor traders who do not take overnight positions typically specialize as market makers and are more likely to face

[25] There is a long and important debate on the relevance of cascade models for financial markets (Vives (1996)). Avery and Zemsky (1998) show that the introduction of variable prices to the BHW model can eliminate informational cascades (herding in their terminology) under certain conditions. Lee (1998), Chari and Kehoe (2004), and Cipriani and Guarino (2005a) demonstrate the potential for informational cascades in the variable price setting by introducing transaction costs, endogenous timing, and preference heterogeneity.

situations in which herding, including herding at a constant price, is part of their trading practice. This type of herding may occur, for example, when several floor traders each take a portion of a large institutional order. Manaster and Mann (1999) provide evidence that market makers are willing to give up their advantage in executions, narrowing or eliminating the bid–ask spread, when they have an informational advantage over the outside order. If information is dispersed among traders heterogeneously, the situation is similar to the cascade environment we study here. A crucial difference is that timing and transaction size in the market is endogenous, and ultimately, of course, prices do change.[26]

Avery and Zemsky (1998) introduce flexible pricing into the BHW model and find that for cascades to form, the *value uncertainty*, which we implement in our experimental protocol, needs to be accompanied by *event uncertainty* (the possibility of a change in asset value) and *composition uncertainty* (which implies that the distribution of trader types is not common knowledge). Our results on the discernment of the quality of public announcements suggest that experienced professionals are better able to estimate the composition of the distribution of trader types, and so may act to mitigate price bubbles and crashes.[27] Clearly, while additional research regarding the impact of trader specialization is warranted, our findings highlight the benefits of controlled experimentation with nonstudent subject pools.

We believe that our findings may also shed light on other types of cascade behavior. Consider Welch's (1992) interesting model of initial public offerings (IPOs), for example, which addresses cascade formation at a fixed price due to regulatory requirements for IPOs. Welch finds that issuing firms have an interest in pricing to generate an informational cascade in order to increase the probability of a successful offering. Our results that emphasize the potential for cascade fragility arising from variation in the ability to interpret signal quality may be important in this context. One possible implication is that when underpricing of offerings is optimal in the Welch model, heterogeneity in signal strength and interpretation might play an instrumental role since reverse cascades in which no investment occurs will be fragile. The welfare implications, however, are not immediately obvious given that the resulting cascades are of shorter duration. Furthermore, the importance of the effect may differ across firms or industries depending on the economies of scale of the investment and thus the need to have full or only partial subscription (Welch (1992), p. 709).

[26] One mechanism through which cascades might arise is, in the jargon of the trading floor, when local traders "lean on" large orders by trying to enter the market on the same side and at the same price. Locals who trade alongside an institutional order accumulate a position knowing that they can transact with the institution and avoid a loss. The decision process associated with deciding to trade with the institution has the character of a fixed price cascade. In the context of option markets Berkman (1996) discusses how market makers supply liquidity in the presence of large fixed price orders. Chamley and Gale (1994) introduce endogenous timing in a cascade model that predicts the least informed would trade later, and potentially face adverse prices.

[27] Drehmann, Oechssler, and Roider (2005) test experimentally a version of the Avery and Zemsky (1998) model that omits event and composition uncertainty and find behavior fairly consistent with its predictions, though subject to decision error and contrarian behavior.

Both the differences due to specialization and the heterogeneity in signal quality and processing abilities suggest fruitful directions for future research. How the specialized skills of market participants interact in price discovery could be explored in experiments that move toward a full market setting, but in which liquidity and informational conditions are varied in a controlled manner. A natural part of this research program would be to extend the current environment to study the impact of heterogeneity on the IPO model of Welch (1992). In a recent study that provides evidence from asset market experiments with student subjects Dufwenberg, Lundqvist, and Moore (2005) find that mixed experience levels can reduce the incidence of bubbles and crashes. Heterogeneous subject pools that include professionals would shed crucial light on this issue, and help to identify the mechanisms underlying cascade formation and fragility in settings that mix fixed and variable prices.

IV. Concluding Comments

In this study, we introduce market professionals from the CBOT floor to a controlled experimental environment. Making use of information cascades games, we report several insights. While student subjects more closely follow Bayes's rule, they do not perform significantly better than the market professionals along the important dimension of earnings. This puzzle is explained by the fact that professionals are more sophisticated in their use of public information, as manifested over the course of the decision process: Market professionals are less Bayesian when making decisions later in the choice order in a cascade game, consistent with recognizing that the quality of initial announcements is variable, altering the payoffs of joining cascades.

While market professionals learn over the course of an experimental session to account for the quality of others' decisions, student subjects fail to do so. A further insight is that market professionals are consistent in behavior over the gain and loss domains, while in aggregate, students' behavior is consistent with the notion of loss aversion. Perhaps most provocatively for the operation of markets, we find an important heterogeneity among the market professionals that depends on their trading style. In summary, our data reveal that the decisions of market professionals are consistent with behaviors that may mitigate informational externalities in market settings, and thus reduce the severity of price bubbles due to informational cascades.

Besides revealing both positive and normative insights, our work also offers a methodological contribution. For example, it highlights the potential for experiments with students and professionals to be complementary inputs to research when field data are suggestive but inconclusive. Indeed, in transferring the insights gained in the laboratory with student subjects to the field, a necessary first step is to explore how market professionals behave in strategically similar situations. In this spirit, we focus on the representativeness of the sampled population to lend insights into which empirical results are similar across subject pools. A related issue concerns the representativeness of the environment, which also merits serious consideration. For example, before we can begin to make reasonable arguments that behavior observed in the lab is a good indicator of behavior in the field, we must explore whether the other dimensions of the laboratory environment might cause differences in behavior, including the abstract task, the stakes, the good, and the institution. While our research represents a necessary first step in the discovery process, we hope that future efforts will explore more fully other potentially important dimensions of the controlled laboratory experiment.

Appendix: QRE Estimation Results

Results in Table IV lead us to investigate a modification of the quantal response equilibrium (QRE) developed by McKelvey and Palfrey (1995, 1998). By accounting for the noise associated with the probabilistic choice rule, the QRE yields alternative measures of the public belief. Our approach invokes a rational expectations assumption for the error distribution. There is mixed evidence for this assumption (see Goeree et al. (2004) and Kubler and Weizsacker (2004, 2005)), but several alternative specifications yield similar insights (these results are available upon request).

Let the probability of choosing urn A be given by

$$\mathrm{pr}(c_i = A \mid H_i, s_i) = \mathrm{pr}\big(\pi_i^A + \varepsilon_i^A > \pi_i^B + \varepsilon_i^B\big) = \mathrm{pr}\big(\varepsilon_i > 1 - 2\pi_i^A\big),$$

where $\pi_i^A = \mathrm{pr}(A \mid H_i, s_i) * \$W = \$W - \pi_i^B$, and $\varepsilon_i = \varepsilon_i^A - \varepsilon_i^B$. For comparability across subject pools we normalize so that $\$W = 1$ for both subject pools. If the errors have an extreme value distribution, then the conditional probability of the urn choice is given by the logistic distribution yielding

$$\mathrm{pr}(c_i = A \mid H_i, s_i) = \frac{1}{1 + \exp\big(\lambda_i\big(1 - 2\pi_i^A(\lambda^{1\ldots i-1})\big)\big)}.$$

The lambda parameter indicates the extent to which noise affects decision outcomes. As $\lambda \to \infty$, the choice converges to the Bayesian outcome; as $\lambda \to 0$, the decisions become purely random. Note that the posterior probability that the urn is A, π_i^A, is a function of the lambda estimates from previous choice orders, with $(\lambda^{1\ldots i-1})$ representing the vector of previous estimates.

In our estimation, we follow Anderson and Holt (1997) and focus on the symmetric data. The QRE results using these data are displayed in Tables AI and AII. Our results emphasize the fact that not only the numbers of each signal, but also the order in which they are revealed have an important impact on behavior. For example, note the posterior probability for order choice three in Table AI, the first choice where a cascade may form in the symmetric treatment, when the signal history is AAb (or BBa) (since the AAb and BBa are symmetric, Table AI reports the results from these sequences as one choice history (AAb); all other symmetric choice sequences are treated similarly). In this case the posterior probability of urn A has dropped from 0.67 for the most likely urn to 0.51 (0.59) for the market professionals (students). Thus, while

Table AI

Lambda Estimate for Quantal Response Equilibrium, Symmetric Gain Treatment

Columns M and C report the lambda parameter for market professionals and college students. Column p reports the one-tailed p-value for the null hypothesis that the lambda parameter does not differ across the two groups. All lambda estimates differ significantly from zero.

Choice Order	M	C	p
1	4.59	7.12	0.094
2	4.56	27.75	0.012
3	8.67	8.62	0.505
4	3.90	4.99	0.258
5	2.48	6.34	0.026

Table AII

Posterior Probabilities and Choice Probabilities with QRE Decision Error

Calculations are for the first three choices of the symmetric gain treatment for market professionals (M) and college students (C), with the choice probability and the posterior probability adjusted for decision error. For comparison, the probabilities assuming a perfect Bayesian equilibrium (Bayes) are also presented as are the actual decisions. Due to the symmetry of the treatment, the history and signal combination also represents its complement. For example the row reporting history and signal “ABa” also includes the “BAb” sequences.

		Choice Probability $\mathrm{pr}(c = A \mid H, s, \lambda)$			Posterior Probability $\mathrm{pr}(\omega = A \mid H, s, \lambda)$			Actual Decisions					
			QRE			QRE		M			C		
Choice Order	History & Signal	Bayes	M	C	Bayes	M	C	A	B	Share A	A	B	Share A
1	A	1.00	0.82	0.92	0.67	0.67	0.67	37	8	0.822	43	4	0.915
2	Aa	1.00	0.91	0.99	0.80	0.76	0.78	23	3	0.885	27	0	1.000
2	Ab	0.00	0.36	0.15	0.50	0.44	0.47	4	15	0.211	3	17	0.150
3	AAa	1.00	0.99	0.99	0.89	0.81	0.85	14	0	1.000	17	1	0.944
3	AAb	1.00	0.54	0.83	0.67	0.51	0.59	7	6	0.538	12	0	1.000
3	ABa	1.00	0.94	0.92	0.67	0.65	0.64	10	0	1.000	8	0	1.000
3	ABb	0.00	0.05	0.03	0.33	0.32	0.31	1	7	0.125	0	9	0.000

ignoring one’s private information is optimal for both groups, the noise in prior decisions dilutes the strength of the signals, with the market professionals facing essentially a random choice with the probability that urn A is chosen being 0.539 (0.833) for the market professionals (students). In comparison the ABa sequence, which has an identical posterior probability when there is no noise, the posterior 0.64 (0.65) for market professionals (students), and the optimal decision is made uniformly by both subject pools. This difference across the sequences in choice order three highlights the fact that noise in the decision-making process dilutes the value of the public signal.

REFERENCES

Anderson, Lisa R., 1994, Information cascades, Dissertation, University of Virginia.

Anderson, Lisa R., and Charles A. Holt, 1997, Information cascades in the laboratory, *American Economic Review* 87, 847–862.

Avery, Christopher, and Peter Zemsky, 1998, Multidimensional uncertainty and herd behavior in financial markets, *American Economic Review* 88, 724–748.

Banerjee, Abhijit V., 1992, A simple model of herd behavior, *Quarterly Journal of Economics* 107, 797–818.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Berkman, Henk, 1996, Large option trades, market makers, and limit orders, *Review of Financial Studies* 9, 977–1002.

Berndt, Ernst, Bronwyn H. Hall, Robert E. Hall, and Jerry A. Hausman, 1974, Estimation and inference in nonlinear structural models, *Annals of Economic and Social Measurement* 3, 653–665.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch, 1992, A theory of fads, fashion, custom, and cultural change as informational cascades, *Journal of Political Economy* 100, 992–1026.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch, 1998, Learning from the behavior of others: Conformity, fads, and informational cascades, *Journal of Economic Perspectives* 12, 151–170.

Bikhchandani, Sushil, and Sunil Sharma, 2000, Herd behavior in financial markets: A review, IMF Working paper 48.

Butler, John S., and Robert Moffitt, 1982, A computationally efficient quadrature procedure for the one-factor multinomial probit model, *Econometrica* 50, 761–764.

Celen, Bogachan, and Shachar Kariv, 2004, Distinguishing informational cascades from herding behavior in the laboratory, *American Economic Review* 94, 484–497.

Celen, Bogachan, and Shachar Kariv, 2005, An experimental test of observational learning under imperfect information, *Economic Theory* 26, 677–699.

Chamley, Christophe P., 2004, *Rational Herds: Economic Models of Social Learning* (Cambridge University Press, Cambridge, UK).

Chamley, Christophe P., and Douglas Gale, 1994, Information revelation and strategic delay in a model of investment, *Econometrica* 62, 1065–1085.

Chari, Varadarajan V., and Patrick J. Kehoe, 2004, Financial crises as herds: Overturning the critiques, *Journal of Economic Theory* 119, 128–150.

Cipriani, Marco, and Antonio Guarino, 2005a, Herd behavior and contagion in financial markets, Working paper, George Washington University.

Cipriani, Marco, and Antonio Guarino, 2005b, Herd behavior in a laboratory financial market, *American Economic Review* 95, 1403–1426.

Coursey, Don L., John L. Hovis, and William D. Schulze, 1987, The disparity between willingness to accept and willingness to pay measures of value. *Quarterly Journal of Economics* 102, 679–690.

Daniel, Kent, David Hirshleifer, and Avandihar Subrhamanyam, 2001, Mispricing, covariance risk, and the cross-section of security returns, *Journal of Finance* 56, 921–965.

Devenow, Andrea, and Ivo Welch, 1996, Rational herding in financial economics, *European Economic Review* 40, 603–615.

Drehmann, Mathias, Jorg Oechssler, and Andreas Roider, 2005, Herding and contrarian behavior in financial markets: An internet experiment, *American Economic Review* 95, 1403–1426.

Dufwenberg, Martin, Tobias Lindqvist, and Evan Moore, 2005, Bubbles and experience: An experiment, *American Economic Review* 95, 1731–1737.

Eichengreen, Barry, Donald Mathieson, Bankim Chandha, Anne Jansen, Laura Kodres, and Sunil Sharma, 1998, Hedge funds and financial market dynamics, *IMF Occasional paper* 172.

Fama, Eugene F., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283–306.

Gale, Douglas, 1996, What have we learned from social learning? *European Economic Review* 40, 617–628.

Garber, Peter, 2000, *Famous First Bubbles: The Fundamentals of Early Manias* (MIT Press, Cambridge, MA).

Genesove, David, and Christopher Mayer, 2001, Loss aversion and seller behavior: Evidence from the housing market, *Quarterly Journal of Economics* 116, 1233–1260.

Gigerenzer, Gerd, and David J. Murray, 1987, *Cognition as Intuitive Statistics* (Erlbaum, Hillsdale, NJ).

Goeree, Jacob K., Charles A. Holt, and Thomas R. Palfrey, 2005, Regular quantal response equilibrium, *Experimental Economics* 8, 347–367.

Goeree, Jacob K., Thomas R. Palfrey, Brian W. Rogers, and Richard D. McKelvey, 2004, Self-correcting information cascades, Working paper, California Institute of Technology.

Harrison, Glenn, and John A. List, 2004, Field experiments, *Journal of Economic Literature* 42, 1009–1055.

Hirshleifer, David, 2001, Investor psychology and asset pricing, *Journal of Finance* LVI, 1533–1597.

Hirshleifer, David, and Siew Hong Teoh, 2003, Herd behavior and cascading in capital markets: A review and synthesis, *European Financial Management* 9, 25–66.

Huck, Steffen, and Jorg Oechssler, 2000, Informational cascades in the laboratory: Do they occur for the right reasons? *Journal of Economic Psychology* 21, 661–671.

Hung, Angela A., and Charles R. Plott, 2001, Information cascades: Replication and an extension to majority rule and conformity-rewarding institutions, *American Economic Review* 91, 1508–1520.

Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–291.

Keynes, John M. 1936, *The General Theory of Employment, Interest and Money* (Macmillan, London).

Knez, Peter, Vernon L. Smith, and Arlington Willliams, 1985, Individual rationality, market rationality, and value estimation, *American Economic Review* 75, 397–402.

Koessler, Frederic, and Anthony Ziegelmeyer, 2000, Tie-breaking rules and informational cascades: A note, Working paper, University Louis Pasteur.

Kubler, Dorothea, and Georg Weizsacker, 2004, Limited depth of reasoning and failure of cascade formation in the laboratory, *Review of Economic Studies* 71, 425–441.

Kubler, Dorothea, and Georg Weizsacker, 2005, Are longer cascades more stable? *Journal of the European Economic Association* 3, 330–339.

Lee, In H. 1998, Market crashes and informational avalanches, *Review of Economic Studies* 65, 741–760.

List, John A. 2003, Does market experience eliminate market anomalies? *Quarterly Journal of Economics* 118, 41–71.

List, John A. 2004, Neoclassical theory versus prospect theory: Evidence from the marketplace, *Econometrica* 72, 615–625.

Locke, Peter R., and Steven C. Mann, 2005, Professional trader discipline and trade disposition, *Journal of Financial Economics* 76, 401–444.

MacKay, Charles, 1980, *Extraordinary Popular Delusions and the Madness of Crowds* (Three Rivers Press, New York).

Manaster, Steven, and Steven C. Mann, 1999, Sources of market making profits: Man does not live by spread alone, Working paper, Texas Christian University.

McKelvey, Richard D., and Thomas R. Palfrey, 1995, Quantal response equilibria for normal form games, *Games and Economic Behavior* 10, 6–38.

McKelvey, Richard D., and Thomas R. Palfrey , 1998, Quantal response equilibria for extensive form games, *Experimental Economics* 1, 9–41.

Noth, Markus, and Martin Weber, 2003, Information aggregation with random ordering: Cascades and overconfidence, *Economic Journal* 113, 166–189.

Odean, Terrance, 1998, Are investors reluctant to realize their losses? *Journal of Finance* 53, 1775–1798.

Sgroi, Daniel, 2003, The right choice at the right time: A herding experiment in endogenous time, *Experimental Economics* 6, 159–180.

Shefrin, Hersh M., and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long, *Journal of Finance* 40, 777–790.

Shleifer, Andrei, and Lawrence H. Summers, 1990, The noise trader approach to finance, *Journal of Economic Perspectives* 4, 19–33.

Smith, Lones, and Peter Sorenson, 2000, Pathological outcomes of observational learning, *Econometrica* 68, 371–398.

Tversky, Amos, and Daniel Kahneman, 1974, Judgment under uncertainty: Heuristics and biases, *Science* 185, 1124–1131.

Vives, Xavier, 1996, Social learning and rational expectations, *European Economic Review* 40, 589–601.

Welch, Ivo, 1992, Sequential sales, learning, and cascades, *Journal of Finance* 47, 695–732.

Willinger, M., and Anthony Ziegelemeyer, 1998, Are more informed agents able to shatter information cascades in the lab? in P. Cohendet, Patrick Llerna, Hubert Stahn, and Gisele Umbhauer, eds.: *The Economics of Networks: Interaction and Behaviours* (Springer-Verlag, London).