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Information Cascades with Financial Market Professionals: An Experimental Study*

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Abstract:
In settings where there is imperfect information about an underlying state of nature, but where inferences are made sequentially and are publicly observable, information cascades can lead to rational herding. Cascade phenomena may be seen in a variety of areas including technology adoption, financial market behavior, as well as in social processes such as mate selection or fads and fashions. Theories of rational herding have found a natural testing ground in experimental environments since the character of private and public information can be readily controlled. In previous experimental studies, behavior consistent with Bayesian benchmarks has been observed in simple contexts, but there are substantial reductions in experimental environments that introduce relevant complications such as costly information. In this paper we make use of a unique subject pool, that of financial market professionals from the floor of the Chicago Board of Trade, to investigate the role of market experience on herding behavior. We find that market professionals behave differently than a control group of college student subjects. In particular the Bayesian behavior of those with market experience does not differ significantly across the gain and loss domains. Cascade formation also differs across the subject pools with market professionals entering fewer reverse cascades.

Introduction

In economic environments where 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 on what are believed to be more informative public signals. In particular, if decisions are made sequentially and the earlier decisions become public information, herding behavior or "information cascades" where individuals choose identical actions despite having different private information, can result. Information cascades may be important in a variety of settings including technology adoption, medical treatment choices, responses to environmental hazards, as well as decisions in financial markets, where bubbles and crashes may be examples of cascade behavior[1].

Herding behavior can be suboptimal, since the private information of herd followers is not revealed. As a result a small amount of information revealed early in a sequence has a large impact. Cascades thus are idiosyncratic, with their welfare effects depending on chance revelation of information in early rounds. One consequence is that cascades are often fragile as well, with abrupt shifts or reversals in direction when new information becomes available (Bannerjee, 1992; Bhikchandani, Hirshleifer, and Welch, (BHW) 1992). Indeed some argue that volatility induced by herding behavior can increase the fragility of financial markets and destabilize the broader market system (Eichengreen et al. 1998; see also Bikhchandani & Sharma 2000)[2].

[1] 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), Bannerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992,1998), Kuran and Sunstein (1999) and Welch (1992) discuss a variety of examples.
[2] The distinction between technical and fundamental approaches to trading illustrates one avenue through which herding behavior may be introduced into financial markets. Technicians ignore underlying supply and demand

Empirical tests of cascade behavior have used both field and experimental methods. Bikhchandani and Sharma review the extant field results for herding in financial markets but note the difficulty of controlling for underlying fundamentals. A result of this difficulty, they argue, is that 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." The laboratory environment allows for better control of public and private information and so explicit tests of theory are made more easily. An important debate exists however about the relevance of experimental findings for understanding phenomenon in the field.

In this study we make a contribution to this debate, addressing the importance of laboratory results on cascade formation for field behavior by using a unique subject pool- that of financial market professionals from the floor of the Chicago Board of Trade (CBOT), in a controlled setting. The behavior of the market professionals is compared with that of college students in treatments that vary over both the gain and loss domains, and over the strength of private signals. Differences in behavior over the domain of earnings has been an important subject in both the behavioral finance and behavioral decision theory literature (Kahneman and Tversky 1979; Odean 1998; Shefrin and Statman 1985; Tversky and Kahneman 1992), since asymmetric responses to gains and losses represent important deviations from normative utility theory. The treatments that vary over signal strength yield direct evidence on whether individuals use information in accord with Bayes rule.

We find interesting differences between the subject pools, both with respect to Bayesian decisionmaking in general, and the specific Bayesian decisions that result in cascade formation. Further, we find that market experience seems to be correlated with symmetric responses to the gain and loss domains. This latter result is consistent with several previous studies that have found market experience to be important in reducing deviations from expected utility theory that are associated with reference dependent preferences (Genesove and Mayer, 2001; List, 2003; Locke and Mann, 2000).[3]

Literature Review

Initial formalizations of the cascade phenomenon were developed by Banerjee (1992) and Bikchandani, Hirshleifer, and Welch (1992). These models assume Bayesian updating of information in order to demonstrate the rationality of cascade formation. They also explore the idiosyncratic or path-dependent nature of cascade formation and the resulting fragility of herd behavior. The empirical validity of these theories thus depends to a great extent on whether people exercise Bayesian rationality.

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conditions and assume that more informed trader's signal their understanding through price changes. Herding may also arise from agency problems, such as those associated with the management of pension or mutual funds when compensation derives from relative performance or from payoff externalities, as in bank runs.

[3] By contrast, experimental work that investigates responses to ambiguity by market professionals finds that deviations from expected utility theory are maintained (Sarin and Weber,1993; Fox et al., 1993).

The cascade phenomenon, however, raises interesting questions beyond whether humans update information in a way that is consistent with Bayes rule, a subject on which there is a large literature[4]. The formation of informational cascades also forces us to address the question of how people think about the rationality of others, and specifically, how people respond to uncertainty about the quality of information that arises due to potential deviations from Bayesian rationality by others.

Anderson (1994), and Anderson and Holt (1997) presented a seminal experimental study to investigate these issues, using a subject pool of undergraduate students. In their experimental setting each individual receives a private but noisy signal regarding the underlying state of nature in an exogenously determined order. The strength of private signals varies across treatments. After receiving their signal each subject announces their belief about the state of nature. Decision makers after the first have the opportunity to observe the announcements of players who preceded them. Rational herding can develop when public announcements provide evidence for a specific state that overwhelms the informational content of the private draw[5].

Extensions to the literature have introduced relevant complications to the cascade process, such as costly information, and endogenous sequencing of choice order, as well as collective decision-making (Hung and Plott, 2001; Kraemer, Noth, and Weber, 2000; Kubler and Weizsacker, 2002). In general, as complications are introduced, significant deviations from normative rationality are observed.

In this paper we implement experimental treatments that are closely related to the original work of Anderson and Holt, but extend the investigation in ways that may be significant for understanding the importance of cascade formation in financial markets. Bikhcandani and Sharma (2000) note that, "To examine herd behavior, one needs to find a group of participants that trade actively and act similarly." Further, herding is more likely among a group if the trading activity of others is easily observable. The CBOT floor traders comprise a group that is arguably unique in meeting Bikhchandani and Sharma's requirements. In particular, the trading decisions of other group members are readily observable for local traders in the futures market "pits." Introducing these individuals into the experimental environment, while using student subjects as a control group, allows us to investigate whether those with market experience respond differently to situations in which information cascades may form.

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[4] The ability of humans to reason in a Bayesian manner seems to depend strongly on how new information is represented. Studies that present base rates as percentages often imply that we are poor "intuitive statisticians." Decisions tend to be more consistent with Bayesian rationality when individuals experience probability distributions through repeated exposure (see eg. Gigerenzer and Murray 1987). The experiments presented here are consistent with protocols that have been shown to give Bayesian decision-making its best chance.

[5] Anderson and Holt found that cascades form in roughly 70% of the periods in which they were possible. Deviations from Bayesian cascade formation occurred most often when a simple counting rule gave a different indication of the underlying state than that of the Bayesian posterior. In these cases subjects tended to use the simpler counting rule. Huck and Oechssler (2000) provide additional discussion of this behavior and suggest that deviations from Bayesian rationality are likely to remain important in the field.

Experimental Protocol[6]:

In the experimental investigation of cascade behavior, we examine a situation in which two potential states of the world exist and are represented by two urns, Urn A and Urn B, containing golf balls. The urns differ in their composition, containing different numbers of balls of type *a* and type *b*[7]. The unobserved "state of the world" in each round of play is the urn selected by a random process, the roll of a die. Each urn has a 50% chance of being selected. Subjects gain information about the state of the world by drawing a single ball out of an unmarked bag into which the contents of the selected urn has been transferred. This draw is made while isolated from the other experimental subjects so that the outcome of the draw remains private information. The subject then decides which urn they believe was selected by the random process and their decision is announced to the other subjects by the experimental monitor. Each subject's inference therefore becomes public information for those who make decisions later in the round. The experimental sessions include 15 rounds of this game in which each of the participants draws a ball and announces their urn choice. Sessions consist of either five or six players who participate in all 15 rounds.

Experimental subjects in a particular session consisted entirely of one of the subject pools, either students or market professionals[8]. In addition to the treatments over subject type we also followed Anderson and Holt's design by varying the informational content of the private signal across treatments. In the *symmetric* treatment Urn A contained two *a* type balls and one *b* type. Urn B contained two of type *b* and one type *a*. In the *asymmetric* treatment both urns contained seven balls with Urn A holding six of type *a* and Urn B 5 of type *a*. As a result of this change the *a* signal is weakened and the *b* signal strengthened in the asymmetric treatment. The variation in signal strength was implemented in order to differentiate between Bayesian decision-making and the use of a counting heuristic, in which the signal observed most often would indicate the most probable urn. In the symmetric treatment the counting heuristic and Bayesian decisions yield the same predictions. In the asymmetric condition they do not. The experiment thus consisted of a 2x2x2 factorial design across urn type, either symmetric (S) or asymmetric (A), the domain of earnings, either gains (G) or losses (L), and trader type, either college students (C) or market professionals (M).

The treatment condition over gains and losses was implemented so that in gain space a correct inference about the underlying state resulted in positive earnings of $1 for students and $4 for the market professionals[9]. An incorrect choice resulted in no earnings. In loss space, a correct choice

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[6] Instructions for the symmetric gain treatment for students are included in Appendix.

[7] The balls used were golf balls of two types. Type *a* was a golf ball with visible stripes. Type *b* had the University Maryland Terrapin mascot clearly visible.

[8] The 54 subjects recruited from the floor of the CBOTconsisted of locals, brokers, clerks and an exchange employee. We found no statistical difference among the different types of floor participants and collectively call them the "market professionals." This finding is intuitively sensible since the average non-trader had accumulated approximately 9 years of floor experience and many reported experience as either brokers or local traders.

[9] CBOT officials suggested that designing a 30-minute game with an expected average payout of approximately $30 was more than a reasonable approximation to an average trader's earnings for an equivalent amount of time on the floor. In our experiments the median trader's earnings were slightly in excess of this amount and therefore likely to

resulted in no earnings and an incorrect one in a loss of either \$1 or \$4 depending on the subject pool. In the loss treatments, students and market professionals were endowed with \$6.25 and \$25.00 respectively. All subjects, whether in the gain or loss treatments, also participated in two other unrelated games during their experimental session. The cascade game was the last of the three to be played. Average earnings for the cascade treatments, not including endowments for loss treatments, are included in Table 1.

The experimental sessions with market professionals were conducted at the Chicago Board of Trade (CBOT) in the spring of 2002 and with students, at the University of Maryland College Park in the spring and summer of 2002. Each experimental session consisted of a group of either five or six participants making decisions over 15 rounds. Table 1 provides an overview of the experimental sessions that were conducted.

Theoretical Predictions:

The formal examination of cascade behavior presented by BHW (1992) assumes that individuals update beliefs about underlying states in accordance with Baye's rule. Consider an environment in which there are two possible underlying states, *A* and *B*. Each individual receives a private signal either, *a* or *b,* indicating the probability of a state where $p(A \mid a) > p(B \mid a)$ and $p(A \mid b) < p(B \mid b)$. Signal strength is symmetric in the initial formulation we consider which means that $p(A \mid a) = p(B \mid b)$. After receiving their signal each individual takes a publicly observable action which, if the agent maximizes expected earnings, reveals their belief about the state of nature. Subsequent decisionmakers take action based on previously revealed public information and their own private signal. Bayesian rationality implies that the initial decisionmaker reveals their signal.

To understand the mechanics of cascade formation, we consider an example parameterized in accordance with the symmetric experimental treatment discussed above and presented in Figure 1. For the initial decisionmaker $p(a \mid A) = p(b \mid B) = 2/3$, and therefore, $p(b \mid A) = p(a \mid B) = 1/3$. Suppose that in fact the first draw is *a.* According to Baye's rule the probability that the underlying state is *A* is given by $p(A \mid a) = \dfrac{p(a \mid A)p(A)}{p(a \mid A)p(A) + p(a \mid B)p(B)} = \dfrac{(2/3)(1/2)}{(2/3)(1/2) + (1/3)(1/2)} = \dfrac{2}{3}$. An expected utility maximizer would choose *A* as the state of nature since expected profits for announcing *A*, π_A, exceed those for announcing *B*, π_B.[10] Suppose that the second subject also draws signal *a* from

be salient. Indeed post-experimental discussions with the traders, and a review of the accuracy with which they recorded payoff relevant experimental data indicated that the stakes warranted the trader's attention.

[10] $\pi_A - \pi_B = \dfrac{\$W}{3}$ in the gains treatment, after an initial *a* signal, where \$W is the win amount, either \$1 for students or \$4 for professionals. Note also that treatments over gains and losses do not yield different predictions. Expected losses are minimized by picking the most probable urn.

the urn. Updating according to Bayes rule yields,

$$p(A \mid A, a) = \frac{p(a \mid A)^2}{p(a \mid A)^2 + p(a \mid B)^2} = \frac{(2/3)^2}{(2/3)^2 + (1/3)^2} = \frac{4}{5}.$$

Thus two consecutive identical announcements yield a posterior probability of .80 in favor of the urn announced. As a result the third decisionmaker should “follow the herd” and announce in accordance with the two preceding announcements regardless of their own private draw. This can be seen by examining the case where an opposing *b* signal is the private draw of the third player after two consecutive *A* announcements yielding the posterior probability

$$p(A \mid A, A, b) = \frac{p(a \mid A)^2\, p(b \mid A)}{p(a \mid A)^2\, p(b \mid A) + p(a \mid B)^2\, p(b \mid B)} = \frac{(2/3)^2 (1/3)}{(2/3)^2 (1/3) + (1/3)^2 (2/3)} = \frac{2}{3}.$$

As a result $\pi_A > \pi_B$, and it is optimal to announce A as the underlying state. A decision of this type; one consistent with Bayesian rationality but in which one’s own private information is ignored, we call a *cascade decision*. Naturally the cascade decision may result in either a correct or incorrect inference about the underlying state. It is entirely possible, in the example above, that the true underlying state is B. As in the earlier literature we call a cascade decision in which the wrong underlying state is announced a *reverse cascade* (Anderson and Holt). Regardless of the underlying state, the theoretical analysis of cascade formation in the symmetric treatment implies that private information is uninformative whenever the number of public signals of one type exceeds the other by two or more.

In the asymmetric treatment, presented in Figure 2, there are 6 *a* signals and 1 *b* signal in *A* and 5 *a* and 2 *b* in *B*. Relative to the symmetric treatment *a* signals are weakened and *b* signals are strengthened in the asymmetric case. Table 2 provides posterior probabilities for all possible sequences of draws for both the symmetric and asymmetric treatments. As an example, the 2/3 probability of urn *A* that arises after a single *a* draw in the symmetric treatment is matched in the asymmetric case only by 4 consecutive *a* draws.[11]

As Anderson and Holt discuss, one of the interesting differences between the symmetric and asymmetric treatments is that the optimal Bayesian decision in the symmetric treatment corresponds to a simple counting rule. Choosing the event with the most signals maximizes expected earnings. In the asymmetric case a number of sequences violate this counting rule in that it is optimal to choose B even when there are fewer *b* signals than *a* signals. The asymmetric treatment therefore allows us to distinguish Bayesian behavior from heuristics that may mimic Bayesian behavior in simple settings. The sequences that are of interest in making this determination are highlighted in Table 2.

While the expected utility formulation implies that it is rational to always choose the most probable urn, previous experimental results suggest that there are deviations from this strategy. One explanation for this behavior derives from theories that incorporate decision costs in the choice of urns (Smith and Walker 1993; Anderson and Holt, 1997). Consider the case where the posterior probability is only slightly in favor of one urn. Here the expected return from choosing

[11] An initial *a* signal yields Pr(urn=A)=54.5% in the asymmetric treatment and Pr(urn=A)=67% in the symmetric.

the most probable urn is positive but small. Deviations from the Bayesian predictions may be rational if the cost of optimizing is greater than the expected benefits. Thus we expect more Bayesian decisions when the posteriors move away from ½ and the expected utility of a correct choice increases. In this setting, we can investigate indirectly a prediction of prospect theory, by examining whether decisions are more or less Bayesian over gains than over losses of equal magnitude. The notion that losses loom larger than gains would suggest more Bayesian decision making in the loss domain, if decision costs across the domains are assumed to be constant within a subject pool[12].

Experimental Results

We investigate whether differences in cascade formation and Bayesian decisionmaking exist across treatments using both non-parametric tests and a random effects probit model. These results indicate that there are important differences across the treatment variables of signal strength, domain of earnings, and subject type.

I. Descriptive Statistics and Non-Parametric Tests

Table 3a presents descriptive statistics on Bayesian decisionmaking and cascade formation in aggregate and Table 3b presents the same statistics for each treatment variable. A total of 1647 decisions were made over all sessions and Bayesian decisions, reflecting urn choices consistent with the posterior probability derived from Bayes rule occurred 79% of the time. Cascade decisions, defined as one that was Bayesian but in which the private signal was ignored, took place 16% of the time. One quarter of the cascades formed were reverse cascades, resulting in the wrong inferences about the underlying state.

More revealing perhaps than the number of cascades in aggregate is the proportion of cascade decisions made when it was possible to make one. Recall that a cascade decision is only possible when the private draw is inconsistent with the posterior probability. For four hundred and sixty-six decisions, representing 28% of the total, cascade formation was possible. Cascades were realized 56% of the time. These results are presented in the *potential* and *realized* cascades columns of Table 3a. Table 3b reports the same statistics on decisionmaking for each of the treatment variables. Bayesian decisionmaking was dramatically reduced in the asymmetric treatment with only 70% of decisions consistent with Baye's rule. In the symmetric treatment 91% of the decisions were Bayesian. In addition cascade formation when measured as the proportion of possible cascades was significantly different over both the domain of earnings and urn type[13]. These figures are presented in Table 3b in the column *Realized Cascades,* which

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[12] To properly investigate this hypothesis we must control for the posterior probability, or rather the difference between the posterior and one half, where expected utility maximizers are indifferent between urn types. We control for the posterior probability in the probit model that follows.

[13] Because of the dependence among individual observations we use session level aggregates to yield the most conservative estimates of treatment effects. The statistical test used is the Mann Whitney U test. Significant differences in Bayesian behavior exist at $p<.001$ across urn types. Cascade formation also differs across urn type at $p<.001$ and across earnings domain at the $p<.05$ level.

shows that 81% of potential cascades were realized in the symmetric treatment but only 48% in the asymmetric case. The results on gains and losses are confounded by the pooling of symmetric and asymmetric treatments in the sessions since fewer symmetric treatments were conducted in the loss domain. Table 4 clarifies these results.

Table 4 presents a disaggregated view of the eight treatments implemented within the 2x2x2 factorial design. Treatments are designated with a three letter code; the first indicating urn type, the second the domain of earnings, and the third the subject type. AGM then is the asymmetric treatment over gains with market professionals, SLC the symmetric loss treatment with college student subjects. The strong treatment differences in Bayesian behavior across urn type remain at this level. Two other findings of particular interest are the rate of Bayesian behavior over gains and losses, and the rate of reverse cascade formation. For the domain of earnings, the aggregate figures reported in Table 3 are roughly equivalent, with 80% of decisions Bayesian over gains and 77% over losses. Restricting attention to the asymmetric treatments, however, shows that college students are less Bayesian in the gains treatment while market professionals are unaffected by the domain of earnings (AGC v. ALC p=.085; AGM v. ALM p=.607). Looking at cascade formation we find market professionals involved in significantly fewer reverse cascades in both the gain and loss domains (AGC v. AGM p=.028; ALC v. ALM p= .057). These results provide an initial indication the effect of market experience on herding behavior which is further explored econometrically.

II. Econometric Models

We estimate two parametric models with the experimental cascade data to better characterize the treatment effects. Both use a random effects probit specification which provides consistent estimates given that unobserved individual differences are random (Hsiao). The first model examines the extent of Bayesian decisionmaking and the second cascade formation.

Estimation results for Bayesian decsionmaking are presented in Table 5. The dependent variable, *baye*, is dichotomous and coded one for a decision consistent with the Bayesian posterior and zero otherwise. Independent variables include: choice order which is labeled *order* in Table 5 and is a categorical variable indicating where in the round of play the decision was made, *diff* is calculated as $|prob\,(urn = A) - .5|$, where the $prob\,(urn = A)$ is the posterior probability arising from the combination of public and private information at the disposal of each decision maker. The absolute value of the difference of the posterior probability from one half is an indication of the magnitude of the accrued public and private information. The *diff* variable thus varies from zero to one half, increasing with the evidence for a specific urn type. Theories of noisy decision predict that the parameter on this variable would be positive, with decisions more Bayesian as the posterior probability of a specific urn type increases. The variables *gain*, *sym*, and *trader*, are categorical and represent the experimental treatments, with *gain* equal to one for treatments over gains and zero over losses, and *sym* equal to one for the symmetric and zero for the asymmetric treatments. In the specification pooling subject types, *trader* is equal to one for the market professionals and zero for the students.

The maximum likelihood results on the pooled data, in Table 5a, supplement those of the non-parametric tests and suggest that subject pool and urn type have a significant impact on Bayesian behavior while the domain of earnings is not statistically significant. Market professionals are less Bayesian than the college student subject pool, although the magnitude of the effect, -.189, is the smallest of the variables that are statistically significant. The posterior probability (*diff*) has the greatest impact on Bayesian choice with the coefficient equal to 1.22. As expected, the larger is the divergence from a posterior of one half the more likely the choice will be consistent with Bayesian rationality. Choice order is also important, with Bayesian behavior significantly reduced in rounds three through six. The fact that the later choice orders have a consistently negative coefficient implies less Bayesian decision making by the players who have the most information, later in each round. The decline in Bayesian behavior as the round proceeds is statistically significant in the pooled data, and is also visually obvious, particularly in the asymmetric treatments with market professionals presented in Figure 3. The magnitudes of these effects are also large, ranging from -.282 for the third choice to -.505 for the sixth, effects that are roughly one-third to one-half the size of the urn symmetry treatment effects.

A plausible explanation for the *order* result, consistent with the theoretical work of Bikhchandani and others, is that the players recognize that later announcements are uninformative after a cascade has formed and they assess the likelihood that they are in a reverse cascade. Alternatively, deviations may be sensible if it is believed that previous decisions in a round have been in error, that is, they are non-Bayesian.

The regression by subject type reveals that students are more sensitive to treatment differences than the market professionals. Student subjects respond more dramatically to the urn symmetry and are more sensitive to the information presented by in the posterior probabilities as represented in the *diff* variable. In fact the magnitude of the coefficients for sym and diff, in the student subject pool, are almost exactly double those of the market professionals with the estimates for *sym* 1.076 and .533 for students and market professionals respectively. The coefficients on *diff* are 1.692 and .863 for the two subject pools. Consistent with the findings in the non-parametric tests, the Bayesian decision making of students is also sensitive to the domain of gains and losses, with significance at better than the 5% level. The magnitude of the increase in Bayesian behavior in the loss treatments is approximately one quarter of the size of the symmetry effects (-.245). By contrast the behavior of market professionals does not differ over the earnings domains. The market professionals' Bayesian behavior also declines more consistently with choice order than does the students, an effect which is visible in Figure 3. This latter result is consistent with the finding that trader's enter fewer reverse cascades than do the students. Traders apparently recognize that they are in a noisy environment with less Bayesian decision-making in the early rounds. As a result they are less likely to follow the uninformative signals.

Another econometric specification, also a random effects probit model, is estimated to investigate the rate of cascade formation, for which differences were found in the nonparametric tests. The dependent variable *cascprop* is dichotomous and equal to one when a cascade forms, and zero when it does not. The dataset is restricted to the observations in which cascade formation is possible. In this model we include a variable, *othwin* that indicates the aggregate performance of other subjects in terms of the proportion of correct urn inferences they have made. This variable includes only observable information since the proportion of correct inferences includes only those from preceding rounds. The measures for all relevant individuals, that is, those choosing ahead of the particular observation in a round, are aggregated, giving a measure of the success of individuals who precede each subject's choice. The variables *gain*, and *sym*, are also included and are defined identically as in the previous model. As with the nonparametric results differences in cascade formation across subject pools is found in the asymmetric treatment, and these results are presented in Table 6.

The results imply that the *othwin* variable is informative for the market professionals. Specifically we see that the students' decisions are not significantly affected by the summary measure of the quality of others decisions (*othwin*: p = .368). Market professionals however, recognize that individuals differ in the quality of their decisions and thus are more willing to ignore their own private information, if the individuals preceding them have proven more reliable (*othwin* p=.075).

Conclusion

The potential for herding behavior arising from informational cascades, has been discussed in a wide variety of economic and social settings ranging from medical treatment choices to mate selection (Bikhchandani et al. 1998). Of particular interest is the potential that herding behavior has to destabilize financial markets. In this study we introduce market professionals from the CBOT floor to a controlled experimental environment in which cascade formation can be carefully studied. Market professionals and student subjects are shown to behave differently in this simple cascade game with perhaps the most important differences found over the domains of gains and losses. While market professionals are unaffected by the domain of earnings student subjects are sensitive to this treatment variable, a finding consistent with other studies that suggest market experience may attenuate anomalies associated with reference dependent preferences. Further there is evidence that traders are cognizant of the fact that the quality of other's decisions can vary and they do a better job of taking this variability into account when choosing to rely on the information disclosed by other's actions. One result of this behavior is that the market professionals end up in significantly fewer reverse cascades than the student population.

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Appendix: Experimental Instructions for Symmetric, Gain, Student (SGS) Treatment

Instructions:

In this experiment, you will be asked to decide from which of two urns balls are being drawn. We will begin by rolling a six-sided die. If the die roll yields a 1,2, or 3, we will draw from Urn A. If the roll of the die yields a 4,5, or 6, we will draw from Urn B. However, the roll of the die will be done behind a screen so that you will not know which urn has been chosen.

The urns differ in the following way:

Urn A (used if die is 1,2,or 3)	Urn B (used if die is 4,5,or 6)
2 Striped Balls	1 Striped Ball
1 Terp Ball	2 Terp Balls

Once an urn is determined by the roll of the die we will empty the contents of that urn into a container. (The container is always the same, regardless of which urn is being used.)

After the urn has been chosen each of you will come behind the screen one at a time and draw a ball from the container. The order in which you will draw has been determined randomly.
The result of your draw is your private information and **MUST NOT** be shared with other participants.

After each draw, we will return the ball to the container before making the next private draw. Each person will have one private draw, with the ball being replaced after each draw.

After each person has seen the results of their own draw, we will ask them to record the letter of the urn (A or B) that they think is more likely to have been used. When the first person to draw has indicated a letter, we will display that letter. After displaying the first person's decision, we will call out the next registration number, and the person with that number will draw a ball and record a letter (A or B). Again, their decision will be displayed on the overhead projector. This process will be repeated until everyone has made a draw and made a decision about which urn they believe is being used. After everyone has made a decision, the monitor will announce which of the urns was actually used. Everyone who chose the correct urn earns $1. All others earn nothing.

This session will consist of 15 rounds of the procedure just described.

Now I will describe the use of the record sheet, which is at the back of these instructions.

The results for each round are recorded on a separate row on the record sheet. Round numbers are listed on the left side of each row. Next to the round number record your draw (S or T) in column "***Own Draw***". In columns "***choice1***" through "***choice10***" record each participants decisions (A or B) as they are displayed. (If there are less than 10 players the last choice columns remain blank.) This means that when you are asked to make a decision about which Urn is being used the decisions of participants who have drawn before you will be available. Write your decision in the appropriate column depending on the order in which you draw, and *circle your decision to distinguish it from other's decisions.*

When all participants have made their choices, the monitor will announce the letter of the Urn that was actually used. Record this letter in the column headed "***Urn***" for that round. If your circled decision matches the letter of the urn used, record your earnings of $1 in the "***Payoff***" column. If your choice does not match the urn used record your earnings of $0. You should keep track of your cumulative earnings in column "***Total Payoff***".

Before we begin we will conduct a demonstration. During the demonstration, the roll of the die and the draw of the ball from the container will be publicly visible. When we move to Round 1 the roll of the die will be visible only to the monitor, and the draw will be visible only to the monitor and the person called behind the screen. Remember that urn A contains 2 striped balls and 1 terp ball. It is used if the throw of the die is 1,2, or 3. Urn B contains 1 striped ball and 2 terp balls, and is used if the throw of the die is 4,5, or 6.

Before we begin, be sure that your registration number is on the Record Sheet.

Here is an overview of the procedure that will be followed in each round:

1. The monitor rolls the die to determine which urn is used and transfers balls from that urn to the container.

2. The monitor calls on a participant.

3. The participant goes behind the screen: (Be sure to bring your record sheet)
   a) Makes a draw from the container
   b) records the draw on record sheet in "***Own Draw***" column
   c) records urn choice *and circles their choice*

4. The monitor displays the participant's choice and the other participants record the urn choice on their record form.

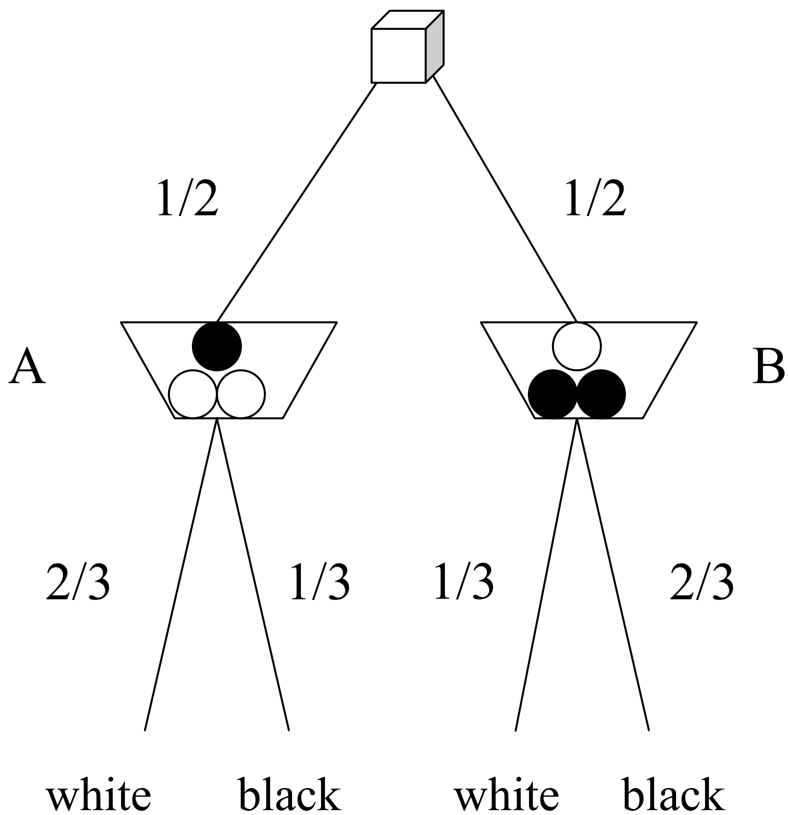
5. Repeat steps 2 – 4 until all participants have made their choice.

6. The monitor reveals the urn used in that round by displaying the balls in the container.

7. Subjects record the urn used in that round and record their earnings, and their cumulative earnings.

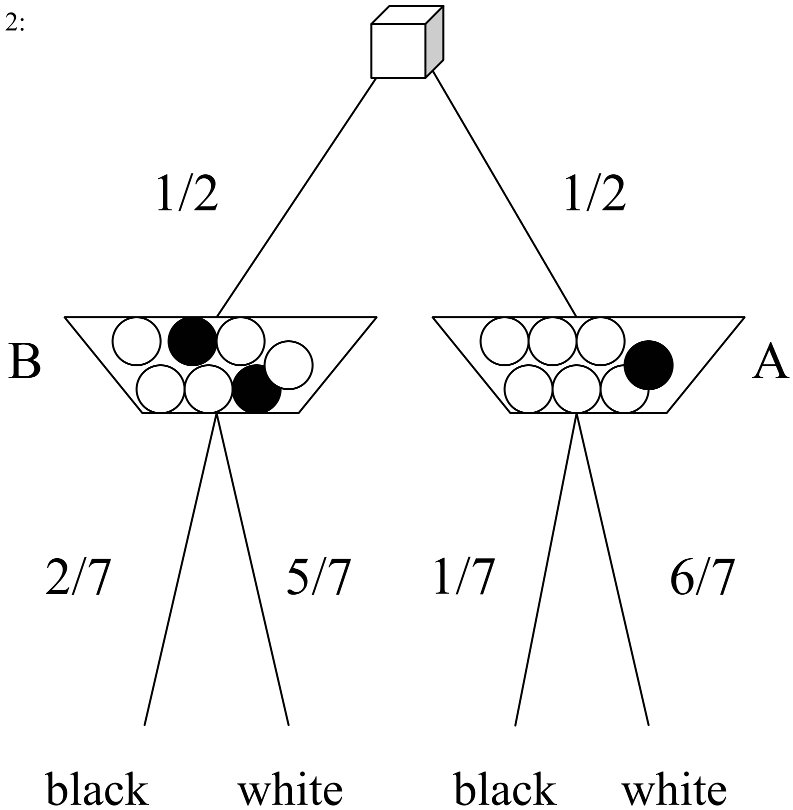
Please refrain from conversation during all rounds of play, and keep the information on your record sheet confidential.

Figure 1:



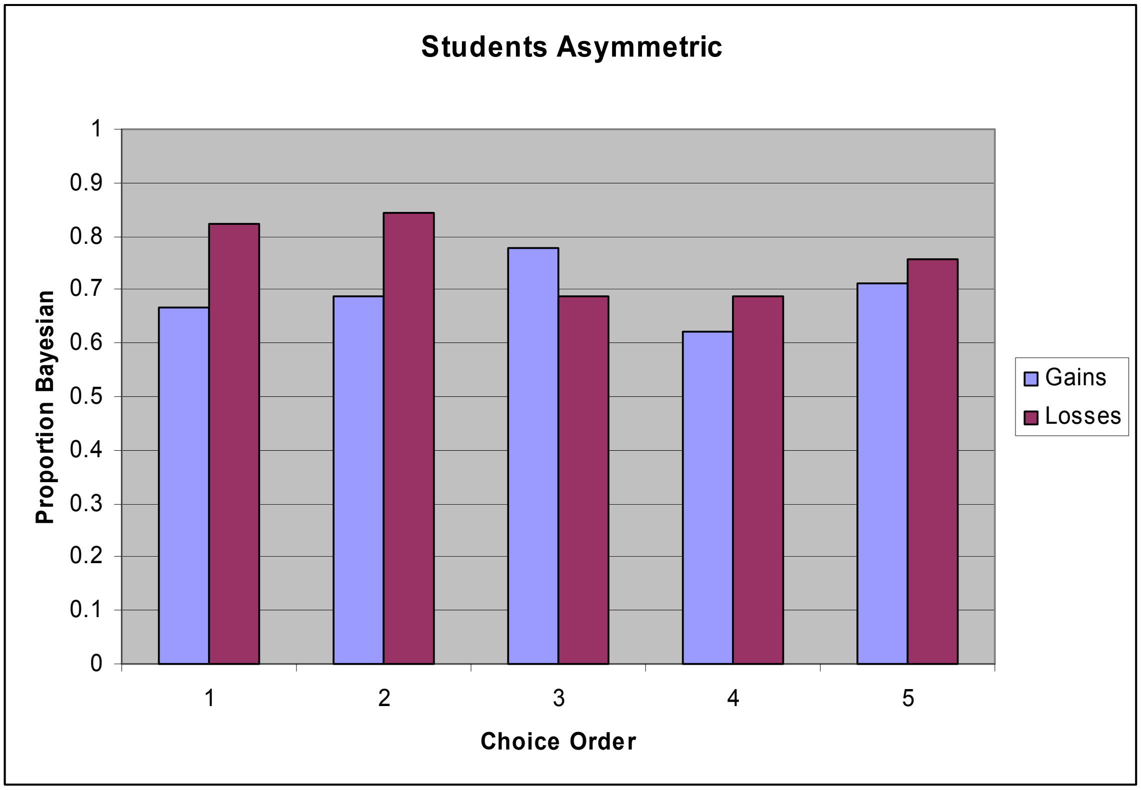
Symmetric Treatment

Figure 2:



Asymmetric Treatment

Figure 3:


Students Asymmetric
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Proportion Bayesian
1
2
3
4
5
Choice Order
Gains
Losses

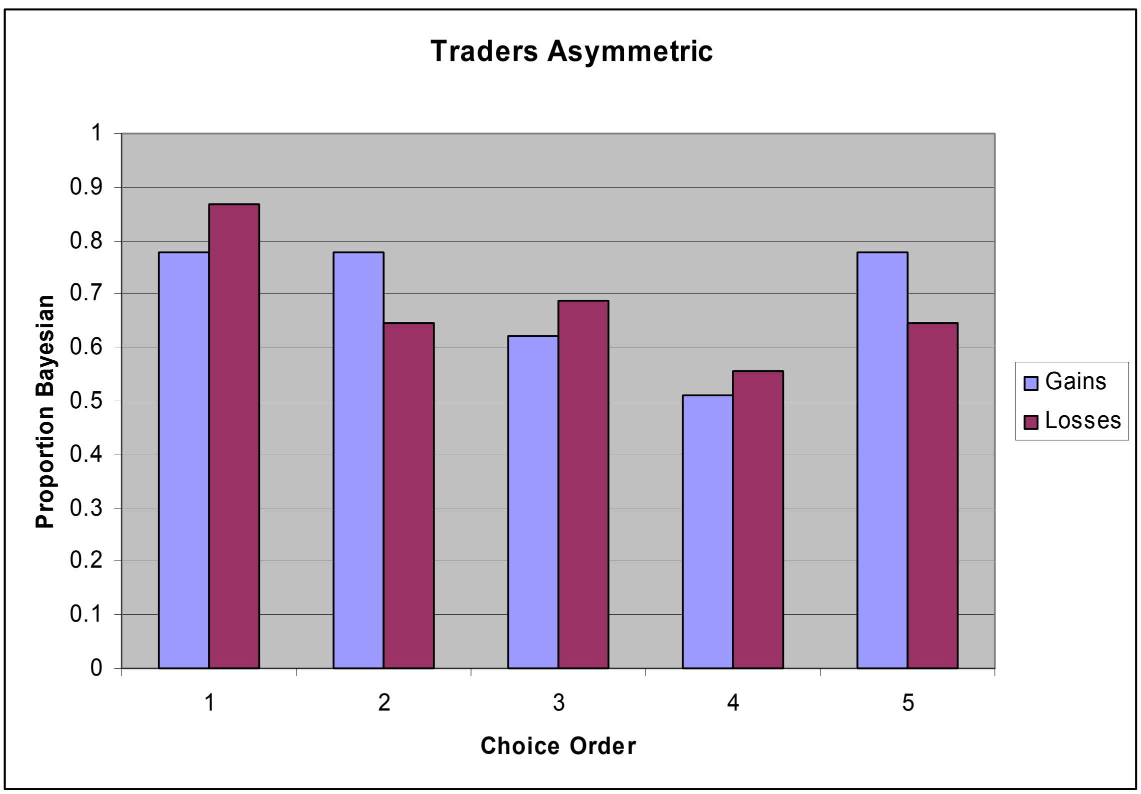

Traders Asymmetric
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Proportion Bayesian
1
2
3
4
5
Choice Order
Gains
Losses

Table 1a: Ten Market Professional Sessions

Urn Type	**Gains**	**Losses**
Symmetric Urn – 3 balls Urn A – Two *a*, one *b* Urn B – One *b*, two *a*	Number of games: 3 Participants in each game: 5 Number of decisions: 225 Avg. earnings: $43.20	Number of games: 1 Participants in a game: 5 Number of decisions: 75 Avg. earnings: -$20.80
Asymmetric Urn – 7 balls Urn A – Six *a*, one *b* Urn B – Five *a*, two *b*	Number of games: 3 Participants in each game: One with 5,two with 6 Number of decisions: 255 Avg. earnings: $39.06	Number of games: 3 Participants in each game: 6 Number of decisions: 270 Avg. earnings: -$22.89

Table 1b: Ten Student Sessions

Urn Type	**Gains**	**Losses**
Symmetric Urn – 3 balls Urn A – Two *a*, one *b* Urn B – One *b*, two *a*	Number of games: 3 Participants in each game: One with 5, two with 6 Number of decisions: 267 Avg. earnings: $11.61	Number of games: 1 Participants in a game: 5 Number of decisions: 75 Avg. earnings: -$2.80
Asymmetric Urn – 7 balls Urn A – Six *a*, one *b* Urn B – Five *a*, two *b*	Number of games: 3 Participants in each game: One with 5, two with 6 Number of decisions: 255 Avg. earnings: $11.00	Number of games: 3 Participants in each game: 5 Number of decisions: 225 Avg. earnings: -$6.40

Table 2:

Posterior Probabilities: Symmetric and Asymmetric Urns

Sym							
a* \ *b	***0***	***1***	***2***	***3***	***4***	***5***	***6***
0	0.500	0.330	0.200	0.110	0.060	0.030	0.020
1	0.670	0.500	0.330	0.200	0.110	0.060	
2	0.800	0.670	0.500	0.330	0.200		
3	0.890	0.800	0.670	0.500			
4	0.940	0.890	0.800				
5	0.970	0.940					
6	0.980						

Asym							
a* \ *b	***0***	***1***	***2***	***3***	***4***	***5***	***6***
0	0.500	0.333	0.200	0.111	0.059	0.030	0.015
1	0.545	0.375	0.231	0.130	0.070	0.036	
2	0.590	*0.419*	0.265	0.153	0.083		
3	0.633	*0.464*	*0.302*	0.178			
4	0.675	0.509	*0.341*				
5	0.713	0.554					
6	0.749						

Table 3a: Aggregate Decision Making

n =1647	Bayesian	Cascades (total)	Reverse Cascades	Potential Cascades	Realized Cascades
Proportion	.79	.16	.04	.28	.56
Number	1293	262	62	466	262/466

Table 3b: Decision Making across treatments

Trader Type		Bayesian	Cascades (total)	Reverse Cascades	Potential Cascades	Realized Cascades
Student	Proportion	.82	.18	.05	.30	.61
n = 822	Number	670	150	39	247	150/247
Market Professional	Proportion	.76	.14	.03	.27	.51
n = 825	Number	623	112	23	219	112/219
Symmetric	Proportion	.91	.15	.05	.18	.81
	Number	586	96	29	118	96/118
Asymmetric	Proportion	.70	.17	.03	.35	.48
	Number	707	166	33	348	166/348
Gain	Proportion	.80	.18	.03	.28	.62
	Number	799	176	38	283	176/283
Loss	Proportion	.77	.13	.03	.28	.47
	Number	494	86	24	183	86/183

Table 4: Non-parametric tests of Bayesian behavior and Cascade Formation (aggregate and reverse)

Treatment :	AGC	ALC	SGC	SLC	AGM	ALM	SGM	SLM
AGC *n* = 17	___	.085 .042 .422	.000 .035 .924	NA	.478 .008 .028	NA	NA	NA
ALC *n* = 15		___	NA	.003 .120 .114	NA	.106 .377 .057	NA	NA
SGC *n* = 17			___	.898 .155 .291	NA	NA	.005 .984 .558	NA
SLC *n* = 5				___	NA	NA	NA	.154 .049 .065
AGM *n* = 17					___	.607 .701 .163	.004 .909 .002	NA
ALM *n* = 18						___	NA	.008 .270 ..039
SGM *n* = 15							___	.476 .675 .327
SLM *n* = 5								___

Treatment codes: First letter S or A indicates the *symmetric* or *asymmetric* treatment. Second letter is G or L for the domain of *gains* or *losses*. Third letter indicates subject type, where P = *pooled*, C = *college students*, and M = *market professionals*. The top number represents the p value associated with differences in Bayesian decisions across treatments. The second number reports p values for cascade formation, and row 3 the p values for reverse cascades. All are tested with the Mann-Whitney U test with an individual's aggregate choice the observation level.

Table 5: Bayesian Decisions: Probit Model

5a. Pooled data

Independent variable: *baye*

Variable	Coeff	z	P>|z|
diff	1.222	3.560	0.000
gain	-0.101	-1.030	0.303
sym	0.780	7.110	0.000
trader	-0.189	-2.000	0.045
order_2	0.041	0.310	0.754
order_3	-0.282	-2.200	0.028
order_4	-0.437	-3.370	0.001
order_5	-0.320	-2.390	0.017
order_6	-0.505	-3.030	0.002
Log likelihood	-779.31649	Wald $\chi^2_{(9)}$ =96.67	Prob > chi2 = 0.0000

5b. Students:

Independent variable: *baye*

Variable	Coeff	z	P>|z|
diff	1.692	3.240	0.001
gain	-0.245	-2.060	0.040
sym	1.076	7.660	0.000
order_2	0.235	1.270	0.206
order_3	-0.014	-0.080	0.939
order_4	-0.329	-1.750	0.080
order_5	-0.206	-1.060	0.289
order_6	-0.621	-2.420	0.016
Log likelihood	-339.32349	Wald $\chi^2_{(8)}$ = 86.93	Prob > chi2 = 0.0000

5c. Market Professionals:

Independent variable: *baye*

Variable	Coeff	z	P>|z|
diff	0.863	1.920	0.055
gain	0.029	0.220	0.825
sym	0.533	3.590	0.000
order_2	-0.138	-0.770	0.441
order_3	-0.516	-2.920	0.003
order_4	-0.589	-3.290	0.001
order_5	-0.460	-2.510	0.012
order_6	-0.538	-2.450	0.014
Log likelihood	-431.50898	Wald $\chi^2_{(8)}$ = 36.66	Prob > chi2 = 0.0000

Table 6: Cascade Formation: Probit Model: Asymmetric Treatment

6a. Pooled

Independent variable:*cascprop* n=281

Variable	Coeff	z	P>|z|
diff	3.508	4.620	0.000
gain	0.360	1.590	0.112
othwin	0.214	0.460	0.645
Log likelihood	-177.37094	Wald $\chi^2_{(3)}$ = 23.85	Prob > chi2 = 0.000

6b. Students

Independent variable:*cascprop* n = 156

Variable	Coeff	z	P>|z|
diff	1.983	1.930	0.054
gain	0.398	1.360	0.175
othwin	-0.553	-0.900	0.368
Log likelihood	-102.96995	Wald $\chi^2_{(3)}$ = 6.12	Prob > $\chi^2_{(3)}$ = 0.1058

6c. Market Professionals

Independent variable:*cascprop* n = 125

Variable	Coeff	z	P>|z
diff	4.956	4.280	0.000
gain	0.331	1.040	0.297
othwin	1.206	1.780	0.075
Log likelihood	-70.302215	Wald $\chi^2_{(3)}$ = 22.53	Prob > $\chi^2_{(3)}$ = 0.0001