

INFORMATION CASCADES IN THE LABORATORY

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Abstract

When a series of individuals with private information announce public predictions, initial conformity can create an “information cascade” in which later predictions match the early announcements. This paper reports an experiment in which private signals are draws from an unobserved urn. Subjects make predictions in sequence and are paid if they correctly guess which of two urns was used for the draws. If initial decisions coincide, then it is rational for subsequent decision makers to follow the established pattern, regardless of their private information. Rational cascades formed in most periods in which such an imbalance occurred.

In many economic situations, agents observe private signals of some underlying state and make public decisions. Subsequent decision makers face a dilemma if their own private signal is indicative of a state that is unlikely given the previously observed decisions. An “information cascade” occurs when initial decisions coincide in a way that it is optimal for each of the subsequent individuals to ignore their private signals and follow the established pattern. For example, suppose that a worker is not hired by several potential employers because of poor interview performances. Knowing this, an employer approached subsequently may not hire the worker even if the employer’s own assessment is favorable, since this information may be dominated by the unfavorable signals inferred from previous rejections.¹ Sushil Bikhchandani, David Hirshleifer, and Ivo Welch (1992) discuss other examples and some simple models of the cascade process. They point out that the conformity of followers in a cascade contains no informational value, and in this sense, the cascade is fragile and can be upset by the arrival of new public information.

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¹ Steve Stern (1990) presents an econometric study based on a model in which a longer duration of job search is interpreted by employers as evidence that a worker has low skills.

As indicated above, an information cascade can result from rational inferences that others' decisions are based on information that dominates one's own signal. Particularly interesting is the possibility of a reverse cascade; the initial decision makers are unfortunate to observe private signals that indicate the incorrect state, and a large number of followers may join the resulting pattern of "mistakes", despite the fact that their private signals are more likely to indicate the correct state.² Even a qualified worker will sometimes make a bad impression in an interview, and a series of rejections can create a reverse cascade that eliminates many future job opportunities.³ Cascade-like behavior might also arise in financial markets, where trading decisions come across a ticker tape in sequence. Even if early traders have no inside information, others may incorrectly infer that the previous trades reveal private information. These followers may then trade in a manner that suggests inside information, drawing in others. In this way, some randomness in initial trades might create a price movement that is not supported by fundamentals, as in a reverse cascade. Colin Camerer and Keith Weigelt (1991) report some trading sequences in laboratory experiments that seem to fit this pattern.

problem

There are several reasons to doubt that cascades develop in this way. First, human subjects frequently deviate from rational Bayesian inferences in controlled experiments, especially when simple rule-of-thumb heuristics are available.⁴ Second, with sequential announcements, decision makers must make inferences about others' rationality. Third, much of the evidence offered in support of the rational view of cascades consists of anecdotes about patterns in fashion, papers getting rejected by a sequence of journals, the risk of entering the academic job market too early, etc. Laboratory experiments can provide more decisive evidence on the validity of the rational view of cascades.

Several alternatives to the Bayesian view of conformity have been suggested. Psychologists and decision theorists have found a tendency for subjects to prefer an alternative that maintains the "status quo". For example, William Samuelson and Richard Zeckhauser

² Cf. John Dryden: "Nor is the people's judgement always true; the most may err as grossly as the few."

³ Other examples and applications are discussed in A. V. Bannerjee (1992) and Welch (1992).

⁴ See Daniel Kahneman and Amos Tversky (1973) and David Grether (1980 and 1992). Camerer (1995) and Doug Davis and Charles Holt (1993, chapter 8) review this literature and provide additional references.

(1988) gave subjects hypothetical problems with several alternative decisions. When one of the alternatives was distinguished as being the status quo, it was generally chosen more often than when no alternative was distinguished.⁵ This systematic preference for the status quo is an irrational bias if the decision maker's private information is at least as good as the information available to the people who established the status quo. In answering a question about an unfamiliar decision problem, however, it can be rational for a subject to select the status quo option if it is reasonable to believe that this status quo was initially established on the basis of good information or bad experiences with alternatives. Even in non-hypothetical decision-making situations, it may be very difficult for a researcher to infer what people think about the quality of others' sources of information. It is possible to control information flows in the laboratory by drawing balls from urns, and therefore, to determine whether subjects tend to follow previous decision(s) only when it is rational.

Another non-Bayesian explanation of patterns of conformity is that people derive utility from herding together or that they are averse to the risk of standing alone.⁶ For example, a forecaster may prefer the chance of being wrong with everybody else to the risk of providing a deviant forecast that turns out to be the only incorrect guess.⁷ These other interpersonal factors can be minimized in a laboratory experiment with anonymity and careful isolation of subjects.⁸

⁵ The status-quo version of question 2 from Samuelson and Zeckhauser (1988, pp. 52-53) is: "You are a serious reader of the financial pages but until recently have had few funds to invest. That is when you inherited a portfolio of cash and securities from your great uncle. A significant portion of this portfolio is invested in moderate-risk Company A. You are deliberating whether to leave the portfolio intact or to change it by investing in other securities. (The tax and broker commission consequences of any change are insignificant.) Your choices are (check one): ____ a) Retain the investment in moderate-risk Company A. Over a year's time, the stock has a .5 chance of increasing 30% in value, a .2 chance of being unchanged, and a .3 chance of declining 20% in value. ____ b) Invest in high-risk Company B. Over a year's time, the stock has a .4 chance of doubling in value, a .3 chance of being unchanged, and a .3 chance of declining 40% in value. ____ c) Invest in treasury bills. Over a year's time, they will yield a nearly certain return of 9%. ____ d) Invest in municipal bonds. Over a year's time, these will yield a *tax-free* rate of return of 6%."

⁶ "To do *exactly as your neighbors* do is the only sensible rule...." (Emily Post, 1922, chapter 33).

⁷ John Maynard Keynes (1965, p.158) notes that "Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally."

⁸ Cascade-like behavior is sometimes observed in asset market experiments in which some investors are informed about a state of nature and others are not (Charles Plott and Shyam Sunder, 1982). In these markets, the uninformed tend to follow the trading patterns of the insiders well enough to minimize earnings differences between the two groups.

This paper reports a cascade experiment that is based on a specific parametric model taken from Bikhchandani, Hirshleifer, and Welch (1992). This model is outlined in section I. Section II describes the experimental procedures, and sections III, IV, and V contain an analysis of the results. The final section contains a conclusion.

I. A SYMMETRIC MODEL

Consider the inference problem for an individual who observes a private signal that reveals information about which of two equally likely events has occurred. The events are denoted by A and B, and the signal is either a or b . The signal is informative in that the probability is $2/3$ that the signal will match the label of the event. This setup can be implemented by putting balls labeled a or b in urns labeled A and B, as shown in figure 1. Since the events (urns) are equally likely, each of the 6 balls in the figure are, *ex ante*, equally likely to be drawn. Notice that 2 of the 3 balls labeled a are in urn A, and therefore, the posterior probability of event A given signal a is $2/3$. Similarly, the posterior probability of event A given signal b is $1/3$.⁹

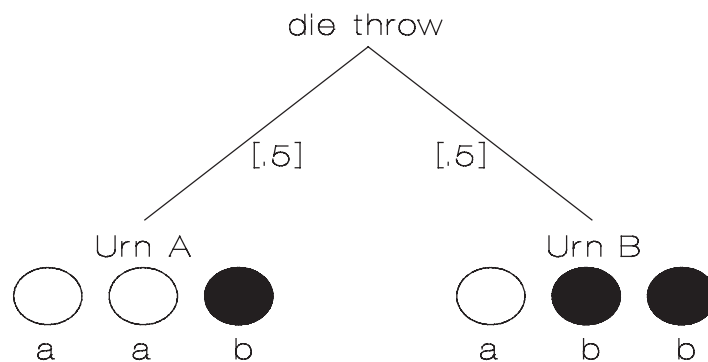


Figure 1. The Physical Setup

Suppose that individuals are approached in a random order to receive a signal and make a decision. The decisions (but not the signals) are announced publicly when they are made. If each individual earns a fixed cash payment for a correct decision (nothing otherwise), then an

⁹ This counting heuristic can be generalized to cover cases in which the prior probabilities are not $1/2$. Holt and Lisa Anderson (1996) discuss how this generalization can be used in the classroom to teach Bayes' rule.

expected-utility maximizer will always choose the urn with the higher posterior probability. The first decision maker in the sequence, whose only information is the private draw, will predict event A if the signal is a and will predict event B if the signal is b . Hence, the prediction made by the first person will reveal that person's private draw.

If the second person's draw matches the label of the first person's prediction, then the second person should also follow the first person's prediction. But suppose that the first person predicts A and the second person draws b . The second person should infer that the first draw was a . This inference, combined with the b signal, results in posterior probabilities of $1/2$ since the priors are $1/2$ and the sample is balanced. In our initial discussion, we assume that the second person will choose the event that matches the label of the private draw when this label differs from the first decision.¹⁰ This assumption is reasonable when there is a positive probability that the first person makes an error (e.g., draws a and predicts B). This assumption is also supported by an econometric analysis of the error rates to be reported below.

Suppose that each subsequent individual assumes that others use Bayes' rule to make predictions. For example, if the first two decisions are A and the third person observes a b signal, then this person is responding to an inferred sample of a on the first two draws, and b on the third draw. Since the events are equally likely *a priori*, and since the sample favors event A, the posterior probability of A is greater than $1/2$. In this case, the third person should predict event A in spite of the private b signal. Hence, the first two decisions can start a cascade in which the third and subsequent decision makers ignore their own private information. Whenever the first and second individuals make the same prediction, all subsequent decision makers should follow, regardless of their own private information. A cascade can also form, for example, if the first two decisions differ and the next two match. In all cases, it takes an imbalance of two decisions in one direction to overpower the informational content of subsequent individual signals.

If individuals recognize that decisions made after the beginning of a cascade are not informative, they will ignore these "irrelevant" decisions in their probability assessments. But

¹⁰ When the posterior probabilities are $1/2$, we could make an alternative assumption that the decision is random, i.e., that it matches the label of the private signal with probability $1/2$. This would not alter the analysis of cascade formation that follows, but it would alter some of the numerical probability calculations, as indicated in the next footnote.

Table I. Posterior Probability of Event A

		number of b signals			
		0	1	2	3
number of a signals	0	1/2	1/3	1/5	1/9
	1	2/3	1/2	1/3	1/5
	2	4/5	2/3	1/2	1/3
	3	8/9	4/5	2/3	1/2

if someone breaks out of a cascade pattern and predicts the other event, then it is reasonable to assume that this deviant decision reveals a private signal that is contrary to the cascade, because the expected cost of deviating would be higher if the signal matched those inferred from previous decisions.¹¹ Therefore relevant signals are those inferred from decisions made before a cascade starts, from the two decisions that start a cascade, and from non-Bayesian deviations from a cascade. Let n be the number of relevant a signals and let m be the number of relevant b signals. Then Bayes' rule can be used to calculate the posterior probability of event A, given any sequence of sample draws:

¹¹ Of course, even the “irrelevant” decisions of followers in a cascade will convey some information in a model with the possibility of decision error, so the probability calculations in this section should be interpreted as appropriate in the limit as errors are reduced to zero. The econometric analysis of errors in section IV explicitly incorporates the relationship between the expected costs of each type of error and the resulting informational content of the error.

$$\begin{aligned}
Pr(A|n, m) &= \frac{Pr(n, m|A)Pr(A)}{Pr(n, m|A)Pr(A) + Pr(n, m|B)Pr(B)} \\
(1) \qquad &= \frac{(2/3)^n(1/3)^m(1/2)}{(2/3)^n(1/3)^m(1/2) + (1/3)^n(2/3)^m(1/2)} \\
&= \frac{2^n}{2^n + 2^m}.
\end{aligned}$$

Table 1 can be used to determine the posterior probability of event A for any combination of draws. Notice that when the signals are balanced, the posterior equals the prior of 1/2; it is the difference in the number of *a* and *b* signals that determines the posterior. In this manner, Bayes' rule corresponds to a simple counting heuristic. Section VI reports results with an asymmetric design in which Bayes' rule and counting can give different predictions.

II. PROCEDURES

The 72 subjects in this experiment were recruited from undergraduate economics courses at the University of Virginia and had no previous experience with this experiment. A \$5 participation fee was paid upon arrival, and subsequent earnings, which averaged about \$20, were paid privately in cash when the subjects were released. In each session, six subjects were decision makers and one was randomly chosen to serve as a “monitor” to assist the experimenters with rolling dice and drawing marbles. The instructions in the Appendix were read aloud to participants, and the monitor was asked to ensure that the procedures in the instructions were followed. Then subjects were taken to their seats, which were separated by large foam board partitions.¹²

A session consisted of 15 periods and lasted for about one and a half hours. At the start of each period, the monitor threw a die to determine which of two urns would be used for the period. As shown in figure 1, urn A contained two *a* balls and one *b* ball, and urn B contained

¹² These partitions extended three feet beyond the desk on each side, and effectively isolated the subjects. The room has three rows of desks and one subject was seated at either end of each row, so subjects were at least 10 feet apart. The monitor was isolated behind a partition at the front of the room, making it impossible for participants to see either the throw of the die that determined the urn or the private draws of other subjects.

two b balls and one a ball.¹³ The experimenters took great care to assure that all marbles were uniform in size, color, and weight. The “urns” were envelopes marked A and B containing the appropriate marbles. Urn A was used if the throw of the die was one, two, or three; urn B was used otherwise. Once the urn was selected, the contents were emptied into an unmarked container. Unintended visual clues were prevented by using the same container, regardless of the urn used.

In each period, subjects were chosen in a random order and were approached by an experimenter to see one private draw from the container, with replacement. After seeing a private draw, the subject would record it and write the urn decision, A or B, on a record sheet. The experimenter reported the decision to an announcer, who did not know either the urn in use or the subject’s private draw.¹⁴ When the decision was announced, other subjects recorded this decision on their record sheets. In this way, each subject knew his or her own private draw and the prior decisions of others, if any, before making a prediction. This process continued until all subjects had made decisions. Then the monitor announced which urn had been used, and subjects recorded their earnings: \$2 for a correct prediction and nothing otherwise. The session was terminated after 15 periods.^{15,16} Three sessions followed this procedure, and three other

¹³ The a balls were actually light marbles and the b balls were actually dark marbles. The draws were referred to as light and dark. In our discussion of the results, it is convenient to have the labels of the balls indicate the more likely urn, but this would have been too suggestive for the actual experiment.

¹⁴ In an admittedly uncontrolled demonstration experiment in an experimental economics class, students seemed to use visual and voice cues in an attempt to discern whether the person making a prediction was agonizing over a sample draw that seemed unlikely given the pattern of earlier public predictions. In fact, a reverse cascade was broken in this manner.

¹⁵ Several practice periods were conducted at the beginning of each session to familiarize the subjects with the procedures; we continued with practice periods until each urn had been selected at least once. In the practice periods, the subjects observed as the monitor threw the dice and emptied the contents of the appropriate urn into the container. Draws from the container were not private in the practice session and subjects were not asked to make decisions, precluding any reputation effects. This public demonstration of the mechanics of the drawing process was added after a pilot session in which one of the subjects made a pattern of mistakes that suggested misunderstanding or distrust. Cascades were nevertheless observed in the pilot, but it is not included since it had a slightly different structure from the sessions reported here.

¹⁶ At the conclusion of the first session, subjects were asked if there was any confusion or bias in procedures and if they had suggestions for improving the experiment. None of the subjects reported any difficulty understanding the instructions or the procedures. The only suggested improvement in the instructions was to eliminate some of the repetition in the oral instructions across periods.

sessions introduced public draws into the decision sequence in a manner to be described below. In addition, we report results of six sessions with an asymmetry in the content of the two urns in section VI.

III. RESULTS

An information cascade is possible if an imbalance of previous inferred signals causes a person's optimal decision to be inconsistent with their private signal. Cascade behavior was observed in 41 of the 56 periods in which such an imbalance occurred.¹⁷ Table 2 shows the longest sequence of periods with cascade behavior in any of the sessions. Consider period 5 in the top row of this table. Although urn B was used, the first-round decision maker (subject S12) saw an a signal and predicted A. The second person saw a b and predicted urn B, so these two predictions effectively canceled each other out. In the third and fourth rounds, the subjects saw private b signals and predicted B, thereby creating the imbalance that can dominate the information contained in a single private draw. The imbalance resulted in a cascade as the final two decision makers followed the pattern of B predictions, despite their private a signals. The shading in the boxes indicates decisions that were consistent with Bayes' rule and inconsistent with private information. Similar cascades formed in periods 6 and 7. Finally, the bottom row shows a reverse cascade in which urn B was used, but the first two decision makers saw a signals and predicted urn A. All four subsequent decision makers followed this pattern, despite their private b draws.

A number of decisions did not follow this pattern of rational inferences about other's signals. In period 8, for example, the formation of a cascade was delayed as the third decision maker (S12) failed to follow the pattern of A decisions by making a decision consistent with private information. This type of deviation, indicated by an *, occurred in 26 percent of the cases when the optimal Bayesian decision was inconsistent with a decision based only on private

¹⁷ In sessions with public draws, a cascade is possible if an imbalance of previous inferred signals causes a person's optimal decision to be inconsistent with a decision based on both the public draw(s) and their private signal.

information. Over all six sessions, about 4 percent of the decisions were inconsistent with both Bayes' rule and private information.¹⁸

Table 2. Data for Selected Periods of Session 2

Period	Urn Used	Subject Number: Urn Decision (private draw)						Cascade Outcome
		1st	2nd	3rd	4th	5th	6th	
		round	round	round	round	round	round	
5	B	S12: A (a)	S11: B (b)	S9: B (b)	S7: B (b)	S8: B (a)	S10: B (a)	cascade
6	A	S12: A (a)	S8: A (a)	S9: A (b)	S11: A (b)	S10: A (a)	S7: A (a)	cascade
7	B	S8: B (b)	S7: A (a)	S10: B (b)	S11: B (b)	S12: B (b)	S9: B (a)	cascade
8	A	S8: A (a)	S9: A (a)	S12: B* (b)	S10: A (a)	S11: A (b)	S7: A (a)	cascade
9	B	S11: A (a)	S12: A (a)	S8: A (b)	S9: A (b)	S7: A (b)	S10: A (b)	reverse cascade

Key: Shading -- Bayesian decision, inconsistent with private information.

* -- Decision based on private information, inconsistent with Bayesian updating.

One question of

interest is the extent to which errors cause actual earnings to be lower than the earnings that would result from Bayesian decisions in a theoretical model with no errors. The *Bayes distribution* for subject Si in a particular round is defined to be the Bayesian posterior distribution on the urn used, assuming that others are Bayesians and that an obvious deviation from a Bayesian decision by someone else reveals that person's private information. For example,

¹⁸ A complete data appendix is available from the authors on request.

consider the Bayesian calculations for the top row of table 2. Subject S12 drew an a in the first round, so the Bayes distribution at this point was $2/3$ for A. After split decisions of A and B in the first 2 rounds of this period, the Bayes distribution for S9 with a b signal in the third round was $2/3$ for urn B. Expected-utility-maximizing decisions based on the Bayes distribution will be called *optimal*. The optimal decision is A if and only if the Bayesian posterior for urn A is greater than or equal to $1/2$. As noted above, the shading in the table indicates rounds in which the decision was optimal but inconsistent with private information.

We will use expected payoff calculations to measure both the extent to which subjects do worse than choosing optimally and the extent to which they do better than just choosing randomly. The expected payoff for a particular decision depends on the information used to make decisions, and all expected payoffs are calculated on the basis of the Bayes distribution *at the time the decision was made*. The *optimal expected payoff* is the expected earnings for a person who makes an optimal urn decision at each stage using the appropriate Bayes distribution. The *random-choice expected payoff* is the expected earnings for a person who makes decisions randomly in each period. The *private-information expected payoff* is the expected earnings for a person who makes a decision only on the basis of the private draw. Finally, the *actual expected payoff* is the expected earnings for the person's actual decision. The sums of the expected payoffs for all 15 periods will be denoted by π_O , π_R , π_P , and π_A for the optimal, random-choice, private-information, and actual expected payoffs respectively.

These expected payoffs are used to construct measures of how efficiently people use relevant information to make decisions. We will normalize the efficiency measure so that optimal decisions are 100 percent efficient and random choices are 0 percent efficient:

$$actual\ efficiency = \frac{100(\pi_A - \pi_R)}{(\pi_O - \pi_R)}.$$

The *actual efficiency* is the difference between the actual expected payoff and the random-choice payoff expressed as a percentage of the difference between the optimal expected payoff and the random-choice payoff.¹⁹ As a benchmark, we also calculate the *private information efficiency*

¹⁹ Even a random chooser may get a measure above zero if they are lucky in their choices.

as the difference between the private-information expected payoff and the random-choice payoff expressed as a percentage of the difference between the optimal expected payoff and the random-choice payoff:

$$\text{private information efficiency} = \frac{100(\pi_P - \pi_R)}{(\pi_O - \pi_R)}.$$

This measure is also between 0 and 100 and is useful as a basis of comparison with actual efficiency, to determine the extent to which a person used information inferred from public decisions.

Actual efficiency, averaged over all subjects in the symmetric design being discussed here, was 91.4 percent, and private-information efficiency was 72.1 percent. Of the 36 subjects, about two-thirds (22) obtained actual efficiencies of 100 percent, indicating perfect conformity with Bayes' rule.²⁰ About two-thirds of the others (9 of 14) also did better than they would have with decisions based solely on private information. Several subjects seemed to disregard the information in others' previous predictions, which is a plausible reaction to the possibility that others are making errors. The next section uses a logit model to analyze the effects of decision errors, caused by independent additive shocks, on posterior probabilities.

IV. AN ECONOMETRIC ANALYSIS OF ERRORS²¹

This section presents a dynamic model in which people calculate posteriors allowing for the possibility of errors in earlier decisions. Error rates are econometrically estimated assuming a logistic distribution of independent shocks to expected payoffs. The first step in the analysis is the calculation of expected payoffs. Suppose that the first person in the sequence sees a draw of a , and therefore has a posterior of 2/3 for urn A and 1/3 for urn B. The expected payoff for choosing A is 2/3 times the reward of \$2 for a correct prediction, and the expected payoff for choosing B is 1/3 times \$2. Let these expected payoffs be denoted by π^A and π^B respectively, and let the probability that the decision maker in round i chooses urn A be denoted by $\Pr(D_i =$

²⁰ However, four of these subjects also had a private information efficiency of 100; these people faced a series of choices in which relying only on private information resulted in the optimal decisions.

²¹ This section summarizes the econometric analysis in Chapter 7 of Anderson's (1994) doctoral dissertation.

A). Then the logit model specifies that this probability is an increasing exponential function of π^A :

$$Pr(D_i = A) = \frac{e^{\beta\pi^A}}{e^{\beta\pi^A} + e^{\beta\pi^B}} = \frac{1}{1 + e^{-\beta(\pi^A - \pi^B)}}.$$

Thus the probability of choosing urn A is an increasing function of the payoff difference, $\pi^A - \pi^B$, where β parameterizes the sensitivity to payoff differences.²² The tendency to make errors diminishes as $\beta \rightarrow \infty$, and the probability of making the decision with the highest payoff goes to 1. Conversely, behavior becomes essentially random as $\beta \rightarrow 0$, in which case the decision probabilities approach 1/2, regardless of expected payoffs. When the expected payoffs are equal, the logit function specifies a probability of 1/2 for each decision.

The inference problem becomes more interesting for the decision maker in round 2 if the second person in the sequence knows that the first one may make an error. When such errors are possible, the private draw seen by the second person contains more information than can be inferred from the first person's decision. The estimated value of β for the first round can be used to determine the decision probabilities: $Pr(D_1 = A | s_1 = a)$, $Pr(D_1 = A | s_1 = b)$, etc., where s_1 is the signal seen by the first round decision maker. These probabilities, together with Bayes' rule, can be used to calculate the posterior probabilities for the second person conditional on D_1 and on the second person's signal: $Pr(\text{Urn} = A | D_1, s_2)$.²³ This posterior determines the second person's expected payoff for each prediction. Since the second person may also make an error, we assume that this person's expected payoffs for each prediction determine decision probabilities via the logit choice function given above.

²² The functional form of the logit model can be derived by assuming that there is an independent random shock to each of the expected payoffs, and that these shocks have a logistic distribution.

²³ There are $2^2 (= 4)$ possible combinations of information that a second round decision maker might use to calculate posteriors. These calculations are increasingly tedious for later decision making rounds because of the incorporation of all previous information. For a sixth round decision maker there are $2^6 (= 64)$ possible combinations of previous decisions and private signals that this person might observe. Posteriors for each round depend on the error distributions for all previous rounds, making the calculation more complicated. These calculations can be found in Chapter 6 of Anderson (1994).

Table 3. Econometric Results by Round

Round	1	2	3	4	5	6
β	2.84	8.67	4.95	2.94	3.03	4.29
(standard error)	(0.36)	(2.03)	(1.02)	(0.64)	(0.58)	(1.15)
number of errors	4	3	6	14	13	7

Notice that the error structure is recursive; the β parameter for the first person in the sequence affects the second person's expected payoffs, which are used in turn to estimate a β parameter for the second stage decision. In each round, the β estimates for previous rounds are used to calculate the expected payoffs for each decision (urn A or urn B), conditional on each possible combination of the current draw (a or b) and the decisions observed in previous rounds. Then the difference in expected payoffs for a round constitutes the independent variable in the estimation for that round. Table 3 reports the results of this recursive estimation, using a maximum likelihood routine in GAUSS.²⁴ The model predicts correctly in 493 out of 540 cases. This econometric approach changes the error classification of about 5 percent of the individual decisions, as compared with the previous section's analysis that assumed no error. The inclusion of errors in the expected payoff calculation does not change the cascade outcome classification for any period.

Notice from the round 1 column of the table that there were even some errors in the first round, where the optimal prediction is clearly to reveal one's own draw. Thus the first-round prediction is a noisy signal of the first-round draw, and therefore, the second person in the sequence should not be indifferent when the draw observed in the second round is inconsistent with the first-round prediction. In such cases, the parameter estimate from the first column in table 3 can be used to predict that the second person will make a decision consistent with his/her private draw with a probability of 0.96. In fact, the second person did make a prediction that

²⁴ The estimation used the Newton-Raphson algorithm to minimize the negative of the log likelihood function. An alternative to the recursive method is to constrain β to be the same for all rounds, which resulted in a β of 3.78. However, the recursive method reported in table 3 provides a better fit based on a likelihood ratio test.

matched the private draw in 95 percent of the cases in which there was a conflict between the first-round prediction and the second-round draw.

The logit analysis shows how a cascade can result from rational behavior, even in the presence of decision error. If the first two people predict A and the third person sees a b draw, the parameter estimates in table 3 can be used to show that the third person should still start the cascade, since the posterior for urn A (given two A decision and a b draw) is 0.5745.²⁵ Since the posterior for urn A is higher than the posterior for urn B, the expected payoff for predicting A is higher. Hence the logit probability for decision A is greater than 1/2.

Similarly, the logit analysis of decision errors provides a natural framework in which to interpret irrational deviations from a cascade pattern. For example, suppose that someone announces a B decision that differs from a cascade pattern of A decisions. If the deviator saw an a draw, then the deviation is a more costly error than if the deviator saw a b draw. For this reason, a deviation from a cascade of A decisions should be interpreted as evidence that the deviator was more likely to have seen a b signal. In fact, 15 of the 16 deviations from cascade patterns were made after seeing a private draw that favored the urn that was not predicted by previous decision makers. The information inherent in whether or not someone deviates from a cascade is incorporated into the posteriors that are based on the application of Bayes' rule in a probabilistic choice context.²⁶ Suppose that a person sees an a draw. The estimates in table 3 can be used to calculate a posterior for urn A of 0.84 if the person sees two previous A decisions and no B decisions, and this posterior is only marginally higher (0.85) if the person sees three previous A decision. But if the fourth decision maker sees two A decisions and a (third) B decision, prior to the a draw, then the posterior for urn A falls to 0.73. Thus the deviation from the cascade pattern lowers the probability of urn A by much more than it is increased by the continuation of the cascade pattern.

To summarize, many of the interesting patterns of behavior can be explained when the analysis is modified to include the possibility that others make errors. This model explains why

²⁵ These calculations are provided in Anderson (1994).

²⁶ The calculations are straightforward but tedious. See Anderson (1994) for details.

a second-round decision makers almost always makes a prediction consistent with private information, even when this prediction differs from that made in the first round. Most importantly, the error estimates are small enough so that it is still optimal to follow a cascade once it develops even if one's private information indicates otherwise. The information inferred from others' decisions depends on the context in which they are made. In most cases, the possibility of error makes others' decisions less informative. However, when errors by others cause them to break out of a cascade pattern, their decisions are almost always indicative of their private signal, thus providing much information for those later in the decision sequence. In addition to the random errors discussed above, some subjects make systematic deviations from Bayesian decision making. These errors can often be linked to one of biases which is discussed in the next section.

V. BIASES

Unlike the random errors discussed in the previous section, many of the information processing biases of interest to psychologists are systematic in nature. These biases are more likely to show up in environments that are richer than the highly controlled ball-and-urn setting discussed here. Nevertheless, even in this environment, it is possible to identify some patterns of behavior that would be implied by previous research on biases. For simplicity, the posteriors reported in this section are calculated without random decision error and the focus is on other (non-random) biases that might be present.

A. Status Quo and Representativeness Bias

Recall that a cascade is a situation where it is *rational* for subjects to follow the *status quo*. The high actual efficiencies indicate that most subjects followed others when it was rational to do so, and not otherwise. If there is an additional preference to go along with the crowd, then this *status quo* bias should show up most clearly when the Bayes distribution for A is close to 1/2. Posteriors of 1/2 are most common in the second round, i.e. when the second decision maker's signal differs from the signal inferred from the first-round decision. We think that it is reasonable to identify the previous decision as being the status quo, even when there is only one

previous decision.²⁷ Over all 6 sessions with the symmetric design, there were 68 instances in which the Bayes distribution was 1/2 and the private information did not match the label of the previous decision. In 57 of these 68 cases, the subject did not follow the previous decision, but rather made decisions that were consistent with their private information. If there is a systematic bias in favor of following the previous decision(s), it is too weak to show up in these data.²⁸

Another type of bias in decision making that has been suggested is that subjects tend to underweight prior probabilities and focus on the similarity of their sample to a particular population (Kahneman and Tversky, 1973). This notion of similarity or “representativeness” is easiest to explain in the context of drawing balls from urns (Grether, 1980 and 1992). A sample of draws is said to be representative of an urn if the sample proportions match those of the urn. For example, a sample of two *a* signals and one *b* signal is representative of urn A in figure 1.²⁹ By adding two public draws after the fourth round in sessions 4 and 5, we provided the fifth and sixth decision makers with samples of three draws, making representativeness possible. Before seeing the two public draws and their own private draw, these decision makers had priors based on the previous decisions of others. They then formed their posteriors using the three additional draws. The combination of the two public draws and the private draw matched the contents of one urn in thirty-six cases. In ten of these cases, the Bayesian posterior for the urn that the

²⁷ After all, many of the hypothetical questions used in the original Samuelson and Zeckhauser (1988) study explained the status quo to the subjects as being determined by a previous decision, e.g., the investment decision of a recently deceased great uncle. One version of the investment question (2) was phrased so that the subject was told how the money was invested previously, and another version was phrased identically except that no information was given about how the money was previously invested. Although the same investment options were used in both versions, each option was selected more frequently if it was identified as the great uncle’s portfolio, i.e., the status quo.

²⁸ These deviations from the status quo are consistent with an analysis that incorporates decision error. When others make errors, one’s own information becomes more informative. With errors incorporated in the calculations, all of the posterior probabilities in this section (with samples of A and *b* or B and *a*) change so that the urn represented by a subject’s private draw is slightly favored to the urn previously predicted.

²⁹ Grether (1980) showed subjects samples from one of two possible urns, with the urn being selected with a known prior probability. When individual subjects were asked which urn was being used, the frequency of Bayesian decisions was clearly lower when the sample matched the contents of the urn with the lower posterior probability. By altering the prior probabilities, Grether was able to compare decisions made under identical posterior probabilities, but with representativeness either reinforcing or contradicting the Bayesian decision. There were no public, sequential decisions in the Grether experiment, so cascades were not possible.

sample “represented” was less than $1/2$, and the subject made a decision consistent with Bayes’ rule in all ten cases.³⁰ There is no support for representativeness in this context.³¹

B. Counting Heuristic

As discussed above, one implication of the symmetric composition of the two urns in figure 1 is that the optimal Bayesian decision is to predict the urn that receives the greatest number of observed and inferred signals, ignoring those that follow the formation of a cascade. Therefore, we conducted six additional sessions with an asymmetric design in which counting can be distinguished from Bayesian behavior.

Table 4. Physical Setup for the Asymmetric Design

Urn A	Urn B
(used if the die is 1, 2, or 3)	(used if the die is 4, 5, or 6)
6 a Balls	5 a Balls
1 b Ball	2 b Balls

In this asymmetric design, urns A and B are also equally likely to be chosen, but their contents differ, as shown in table 4. As before, the a signal indicates that urn A is more likely, and the b signal indicates that urn B is more likely. The asymmetry is that the b signal is much more informative than the a signal, so that just counting the number of relevant decisions made previously does not necessarily indicate a correct Bayesian decision.

³⁰ Adding random decision error does not change the “correct” Bayesian prediction in any of these ten cases.

³¹ A possible explanation for the apparent lack of attention to representativeness is that priors in the cascade experiment are not in the form of instructions, as in Grether (1980 and 1992). Instead, priors in our setup are based on the subjects’ own inferences about others’ signals.

Table 5. Posterior Probability of Event A for the Asymmetric Design^a

		number of <i>b</i> signals						
		0	1	2	3	4	5	6
number of <i>a</i> signals	0	0.50	0.33	0.20	0.11	0.06	0.03	0.02
	1	0.55	0.38	0.23	0.13	0.07	0.04	
	2	0.59	0.42	0.27	0.15	0.08		
	3	0.63	0.46	0.30	0.18			
	4	0.68	0.51	0.34				
	5	0.71	0.55					
	6	0.75						

^a Shading indicates cases where Bayes' rule and the counting rule make different predictions.

Table 5 shows Bayesian posteriors for urn A (without decision error) as a function of the numbers of *a* and *b* signals.³² The four shaded entries in this table correspond to cases in which there are more *a* signals, but a smaller number of informative *b* signals causes the Bayesian posterior for urn A to be less than 0.5. The asymmetric design was chosen to yield a high probability that the sample sequences will create this conflict (subject to a constraint of keeping the design simple).³³

Table 6 shows partial results for one of the six sessions conducted with this asymmetric design. In period 2, the first three subjects saw *a* signals and correctly predicted urn A. The posterior probabilities for urn A (from table 5) are shown in parentheses to the right of the letter indicating the signal observed by the subject. The fourth decision maker in this period saw the

³² The econometric analysis in section IV was based on the symmetric experimental design. Random error rates were not estimated for this asymmetric design. Hence, the Bayesian posteriors reported in this section do not include random decision error.

³³ We also considered using the symmetric design in figure 1 but with unequal probabilities of selecting the two urns. This approach was not followed since, if a six-sided die is used to make the chances of one urn go from 1/2 to 2/3, then the posterior for the urn with the higher prior is always greater than or equal to 1/2 after only one draw.

Table 6. Data for Selected Periods of Session 10

Period	Urn Used	Subject Number: Urn Decision (private draw, Bayesian posterior)						Cascade Outcome
		1st round	2nd round	3rd round	4th round	5th round	6th round	
2	A	S60: A (a, 0.55)	S59: A (a, 0.59)	S55: A (a, 0.63)	S58: B (b, 0.46)	S56: B (b, 0.30)	S57: B (a, 0.51)**	
3	A	S58: A (a, 0.55)	S55: A (a, 0.59)	S59: A (a, 0.63)	S60: A (b, 0.46)*	S56: A (a, 0.71)	S57: A (a, 0.71)	
4	A	S57: A (a, 0.55)	S58: B (a, 0.59)	S59: E (a, 0.42)	S55: E (a, 0.42)	S60: E (a, 0.42)	S56: B (a, 0.42)	reverse cascade
5	B	S58: B (b, 0.33)	S57: B (b, 0.20)	S59: B (a, 0.38)	S55: E (b, 0.20)	S56: E (a, 0.38)	S60: B (a, 0.38)	cascade

Key:

Shading -- Bayesian decision, inconsistent with private information.

+ -- Bayesian decision, inconsistent with counting.

* -- Decision based on counting, inconsistent with Bayesian updating.

more informative b signal. Using a counting rule, this person would also predict urn A with

three (inferred) a signals and only one (observed) b signal. However, because of the asymmetry in the contents of the urns, the posterior for urn A is only 0.46, and this subject correctly predicted urn B. The subject in the fifth round also made a correct Bayesian decision in a case where counting would have yielded a different prediction. The + marks in the table indicate Bayesian decisions that are inconsistent with counting. The last subject in period 2 made a decision that was inconsistent with both Bayes' rule and counting, as denoted by the ** notation in the table. The third period begins in the same way as the previous period, however the fourth subject in the sequence makes a decision that is inconsistent with Bayes' rule but consistent with counting. This type of error is denoted by a single asterisk in the table. The shading in period 4 shows a reverse cascade that was triggered by an error in the second round. Over all six sessions with the asymmetric design, cascades formed in 46 out of the 66 periods where they were possible, i.e. where an optimal Bayesian decision was inconsistent with a subjects private information. The incidence of reverse cascades was higher in this asymmetric design (18 out of 46) than in the symmetric design (13 out of 41).

While cascades are still prevalent in this asymmetric design, the effect of counting is to reduce the incidence of rational Bayesian cascades from about 73 percent to 70 percent. When Bayes' rule and counting make different predictions in the asymmetric design, people make a correct (Bayesian) decision half of the time (41 out of 82 cases).³⁴ When counting makes no prediction (i.e. there are equal numbers of observed and inferred signals of each type) the percentage of correct decisions increases to 66 percent, as would be expected. In total, 115 of the 540 decisions were inconsistent with Bayes' rule, and over a third of these can be explained by counting.

Besides categorizing decisions, it is useful to calculate the expected gains and losses from alternative decision rules. The previous efficiency calculations can be made with data from this asymmetric design. Averaged over all subjects, actual and private information efficiencies were 67.6 percent and 45.2 percent, respectively. These are lower than the corresponding efficiencies with the symmetric design where counting and Bayes' rule always coincide. In addition to the measures of actual and private information efficiency, we define counting efficiency to be the percentage of the expected payoff gains for using a counting rule over random decision making:

$$\text{counting efficiency} = \frac{100(\pi_C - \pi_R)}{(\pi_O - \pi_R)},$$

where π_C is the expected payoff for making a decision based on counting. Twenty-one out of thirty-six subjects in the asymmetric design did better than counting in the sense that their actual efficiencies exceeded counting efficiencies. Averaged over all subjects, however, counting efficiency is approximately equal to actual efficiency. This is because the gains from Bayesian decision making (instead of counting) were balanced by severe reductions in expected payoffs when subjects made predictions that were inconsistent with both counting and Bayes' rule.

VI. SUMMARY

Information cascades develop consistently in a laboratory situation in which other incentives to go along with the crowd are minimized. Some decision sequences result in reverse cascades, where initial misrepresentative signals start a chain of incorrect decisions that is not

³⁴ A large fraction of these errors (29 out of 41) were made by a third of the subjects.

Table 7. Summary of Cascade Results

	Periods with Cascade Activity		Periods Where Cascades Were Possible But Did Not Form	
	Normal	Reverse	Normal	Reverse
Symmetric Setup	28	13	10	5
Asymmetric Setup	28	18	12	8

broken by more representative signals received later. The first two columns of table 7 show that there were about half as many reverse cascades as there were normal cascades in both the symmetric and asymmetric setups. The two columns on the right summarize periods in which cascades were possible but did not form. Over all twelve sessions, cascades formed in 87 of 122 periods in which they were possible. Individuals generally used information efficiently and followed the decisions of others when it was rational. There were, however, some errors, which tended to make subjects rely more on their own private information, as indicated by an econometric (logit) analysis of decision errors. The most prevalent systematic bias is the tendency for about a third of the subjects to rely on simple counts of signals rather than Bayes' rule in situations where these imply different decisions. Overall, only a third of the deviations from Bayes' rule in the asymmetric design can be explained by counting.

APPENDIX: INSTRUCTIONS FOR SYMMETRIC DESIGN

This is an experiment in the economics of decision making. Various agencies have provided funds for the experiment. Your earnings will depend partly on your decisions and partly on chance. If you are careful and make good decisions, you may earn a considerable amount of money, which will be paid to you, privately, in cash, at the end of the experiment. At this time, we will give you \$5. This payment is to compensate you for showing up today.

Before beginning, we will choose one of you to assist us in the experiment today. This person, who will be called the monitor, will help us by throwing dice and drawing colored balls from a container. The monitor will also observe procedures to insure that the instructions are followed. The monitor will be paid \$15 at the end of the experiment in addition to the \$5 already paid. We will now assign each of you a number, and we will throw a multi-sided die to select the monitor.

In this experiment, you will be asked to predict from which randomly chosen urn a ball was drawn. We will begin by rolling a 6 sided die. If the roll of the die yields a 1, 2, or 3, we will draw from urn A which contains 2 light balls and 1 dark ball. If the roll of the die yields a 4, 5, or 6, we will draw from urn B which contains 1 light ball and 2 dark balls. Therefore, it is equally likely that either urn will be selected.

Urn A

(used if the die is 1, 2, or 3)

2 Light Balls

1 Dark Ball

Urn B

(used if the die is 4, 5, or 6)

1 Light Ball

2 Dark 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.) Then we will come around to each of you and draw a ball from the container. The result of this draw will be your private information and should 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 his or her 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 approached has indicated a letter, we will announce that letter. After announcing the first person's decision, we will approach the second person and ask this person to record a letter (A or B), which will then be announced. This process will be repeated until all remaining people have made decisions. Finally, the monitor will inform everyone of the urn that was actually used. Everyone who correctly recorded the letter of the urn used earns \$2. All others earn nothing.

The experiment will consist of 15 periods. The results for each period are recorded on a separate row on the decision sheet that follows. The period numbers are listed on the left side of each row. Next to the period number is a blank that should be used to record the draw (Light or Dark) that you see when we come to your desk. Write L (for Light) or D (for Dark) in column (0) at the time the draw is made. The columns numbered (1) through (6) should be used to record the decisions as they are announced. When you are asked to record the letter of an urn, you will be able to see the decisions, if any, that have been made previously by other participants. Write your decision in the column, (1) through (6), that corresponds to the order in which you are approached, *and circle your decision to distinguish it from others' decisions*. When all six participants have made their choices, the monitor will announce the letter of the urn that was actually used. Record this letter in column (7). If your (circled) decision matches the letter of the urn used, record earnings of \$2 in column (8). Otherwise, record earnings of zero for this period. You should keep track of your cumulative earnings in column (9).

At this time, we will draw a colored marble for each participant; this color will serve as your identification during the experiment. Please write this color in the blank indicated at the top of your decision sheet. In each period, the order in which decisions are made will be determined by drawing these same colored marbles in sequence.

Before we begin the periods that determine your earnings, we will go through several practice periods. In these practice periods, the monitor will throw the die that determines which urn will be used, and you will each see a draw from that urn. However, unlike in the periods that determine your earnings, you will observe the throw of the die, your draw will not be private, and you will not be asked to make a decision in these practice periods.

At this time the monitor will throw the die that determines which urn is to be used. Remember that urn A is used if the throw is 1, 2, or 3, and urn B is used if the throw is 4, 5, or 6. Now we will draw a colored marble to determine who will see the first draw. The color is _____. We will bring the container to the desk of the person assigned this color and we will draw a ball for this person to see. If this were not a practice period, this person would record the color of this ball (L or D) in column (0), make a decision (A or B), enter it in column (1), and circle it. Then, everyone else would record this decision in column (1), but would not circle this decision since it is not your own.

Now we will draw a colored marble to determine who will see the next draw. The color is _____. We will now draw a ball for this person to see. If this were not a practice period, this person would record the color of this ball (L or D) in column (0), make a decision (A or B), enter it in the appropriate column, and circle it. Then, everyone else would record this decision in the appropriate column.

Are there any questions before we begin the periods that determine your earnings? Please do not talk with anyone during the experiment. We will insist that everyone remain silent until the end of the last period. If we observe you communicating with anyone else during the

experiment we will pay you your cumulative earnings at that point and ask you to leave without completing the experiment.

At this time the monitor will throw the die that determines which urn is to be used. Remember that urn A is used if the throw is 1, 2, or 3, and urn B is used if the throw is 4, 5, or 6. Now we will draw a colored marble to determine who makes the first decision. The color is _____. We will bring the container to the desk of the person assigned this color and we will draw a ball for this person to see. This person should record the color of this ball (L or D) in column (0), make a decision (A or B), enter it in column (1), and circle it. The first decision is _____. Everyone else should now record this decision in column (1), but do not circle this decision since it is not your own.

Now we will draw a colored marble to determine who makes the next decision. The color is _____. We will now draw a ball for this person to see. Record the color of this ball (L or D) in column (0), make a decision (A or B), enter it in the appropriate column, and circle it. This decision is _____. Everyone else should now record this decision in the appropriate column.

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