forthcoming in *Economic Inquiry*

PAYOFF EFFECTS IN INFORMATION CASCADE EXPERIMENTS

Lisa R. Anderson
Department of Economics
The College of William and Mary
phone: 757.221.2359
fax: 757.221.2390
e-mail: lrande@wm.edu

revised May 2000

JEL Classification Code: C91, Design of Experiments (Laboratory, Individual Behavior)

ABSTRACT

Error rates are estimated using data from “information cascade” experiments. The econometric estimation assumes a logistic error structure and error rates are compared across three experimental treatments that differ only with respect to payoff structure. In a “no payoff” treatment subjects receive a fixed payment for participating in the experiment and earnings do not vary with decisions. In “payoff” and “double payoff” treatments earnings depend on each subject's decisions. The results indicate that rewarding correct decisions reduces the amount of decision error. However, increasing the payment for a correct decision does not reduce errors over the range of payoffs considered.

PAYOFF EFFECTS IN INFORMATION CASCADE EXPERIMENTS

Lisa R. Anderson*

I. Introduction

This paper examines payoff effects in "information cascade" experiments.[1] Cascade experiments provide a unique environment to study errors because decisions are made publicly and in sequence, allowing people to learn from the decisions of others. However, there are no payoff interdependencies, so subjects are only concerned with maximizing their own expected payoffs which cannot be directly affected by the actions of others. This feature simplifies the analysis of the decision making process and makes it possible to focus more clearly on how subjects draw inferences from public decisions. Furthermore, errors are recursive in the sense that mistakes made by initial decision makers influence the decisions of those that come later in the sequence. This study focuses on learning and errors by analyzing data econometrically in a logistic error model.

Econometric methods have gained popularity as a way to examine errors in experimental data. Harless and Camerer (1994) present a maximum likelihood estimation method to test the predictive power of various utility theories using data from 23 different experiments. McKelvey and Palfrey (1995 and 1998) use the logistic structure to estimate error rates with data from a variety of games. Palfrey and Prisbrey (1997) use a similar structure with a probit model to estimate error rates in a public goods experiment. The analysis presented here differs from these previous econometric studies of experimental data in the following way: In this model, errors are analyzed in a sequential structure

---

* This research was supported in part by grants from the National Science Foundation (SES 9320617 and SES 9709530). I wish to thank (without implicating) Charles Holt, Roger Sherman, Sarah Stafford, Steven Stern, Chris Swann and two anonymous referees for assistance and suggestions.

[1] Information cascades are discussed extensively in Bikhchandani, Hirshleifer, and Welch (1992) and Anderson and Holt (1997).

so the errors of others must be taken into account, but there is no strategic element in the decision making process.

This study expands on the error analysis presented in Anderson and Holt (1997) by examining error rates under different payoff conditions. Smith and Walker (1993a) present a model of decision making in which the effort of contemplating a decision is balanced against potential gains in payoffs. In addition, they survey the experimental literature in economics and psychology addressing the issue of payoff effects, and they find mixed results. Some studies report a decrease in error rates as payoffs increase. Others show little difference in results under payoff and no payoff treatments. However, there is a consensus that higher payoffs reduce the variance of decisions from the predicted outcome. Testing their own theory in the context of a first price auction experiment, Smith and Walker (1993b) report that the amount and severity of error decreases as payoffs increase. Interestingly, behavior is not random, even when there is no monetary reward for a correct decision. Using data from lottery choice experiments, Wilcox (1993) finds that higher monetary payoffs affect behavior in complex situations, but not in relatively simple decision making environments. Harless and Camerer (1994) use econometric methods to compare error rates in experiments with real losses to those with hypothetical losses. They find that error rates are lower and variances are reduced in data with real losses. This paper adds to the literature on the saliency of rewards by analyzing behavior in a different experimental framework and by using the logistic model to generate econometric estimates of error rates under no payoff, payoff, and double payoff conditions. The underlying behavioral model is an extension of the cascade model presented in Bikhchandani, Hirshleifer, and Welch (1992). Experimental procedures are discussed in section II. Section III discusses econometric details. Section IV reports results and section V concludes.

II. Procedures[2]

For each session of this experiment, seven subjects were recruited from undergraduate economics courses at the University of Virginia. One subject was randomly chosen to be a monitor, and the remaining six subjects were decision makers. At the beginning of each period, the monitor threw a six-sided die to determine which of two urns was to be used for that period. If the throw of the die was 1, 2, or 3, urn A, which contained two *a* marbles and one *b* marble, was used. Otherwise urn B, which contained one *a* marble and two *b* marbles, was used.[3] After the die throw, the monitor placed the contents of the appropriate urn in an unmarked container. Subjects were chosen in a random order to see one private draw from the container, with replacement. After seeing a private draw, the subject would record it and make a decision, which was a prediction about what urn was being used for the period. This prediction, but not the signal, was announced out loud once it was made. Hence, each subject knew his or her own private draw and all previous decisions, if any, before making a decision. Once all subjects made decisions the monitor announced which urn had been used and the period ended. This process was repeated 15 times with each group of six subjects.

Nine sessions of the experiment were conducted, involving a total of 54 decision makers. Three sessions were conducted for each of the three payoff treatments summarized in the table below. Notice from table I that in each treatment subjects were paid $5 for showing up for the experiment. In the no payoff treatment, subjects were told that they would all be paid $20 at the end of the experiment. In the payoff and double payoff treatments, earnings varied depending on the accuracy

---

[2] A more detailed description of procedures and a copy of the instructions can be found in Anderson and Holt (1997). The notable differences between the two experiments are that there are no public draws and payoff conditions vary in the experiment discussed here.

[3] The marbles were actually called light and dark in the experiment, but they will be referred to as *a* and *b* signals in this paper to facilitate discussion. The urns were actually cups marked "Urn A" or "Urn B."

of predictions. Earnings for the $2 treatment (including the $5 for showing up) averaged $24.54.[4] In the double payoff treatment, subjects were paid $4 for a correct prediction, in addition to the $5 show up fee, and earnings averaged $45.39.

Table I. Payoff Treatments

Payoff Treatment	Number of Sessions	Payment for Showing Up	Payment for a Correct Decision	Fixed Payment	Average Earnings
no payoff	3	$5	$0	$20	$25.00
payoff	3	$5	$2	$0	$24.54
double payoff	3	$5	$4	$0	$45.39

III. Econometric Details

Information cascades are defined as patterns of decisions that are both consistent with Bayes' rule and inconsistent with private information. To identify cascades in the experimental data, posterior probabilities must be calculated for each decision made. Further, since decisions are made in sequence and the underlying model assumes that people can make errors, the calculation of posteriors requires a consideration of the error distribution for all previous rounds.[5] Hence, the econometric model specifies that decisions made in any given round depend on the error distributions for all previous rounds.[6] Additionally, the econometric analysis is structured in such a way that the error distribution that determines beliefs is used to calculate expected payoffs, and errors are more

---

[4] The fixed payment in the no payoff treatment was set at $20 so that average earnings were approximately the same for the no payoff and payoff treatments.

[5] This calculation is described in Anderson (1994).

[6] The estimation described in this section is an extension of the analysis in Chapter 7 of Anderson (1994), which is reported in Anderson and Holt (1997).

likely when expected payoffs for the two decisions are not too different. This feature of the model is consistent with the decision cost explanation for errors proposed by Smith and Walker (1993a).

Since errors are assumed to be logistically distributed, the probability that a subject's decision in round i is urn A, denoted D_i = A, can be expressed in terms of the logistic error function:

$$(1) \qquad Pr(D_i = A) = \frac{e^{\lambda(\pi_i^A - \pi_i^B)}}{1 + e^{\lambda(\pi_i^A - \pi_i^B)}} = \frac{1}{1 + e^{-\lambda(\pi_i^A - \pi_i^B)}},$$

where π_i^A is the expected payoff for choosing urn A, π_i^B is the expected payoff for choosing urn B and λ is a precision parameter. Notice that $\lambda = 0$ implies that the $Pr(D_i = A) = 1/2$. This complete randomization is the most severe form of decision error. At the other extreme, with $\lambda = \infty$, the $Pr(D_i = A) = 0$ if $\pi_i^A < \pi_i^B$, and the $Pr(D_i = A) = 1$ if $\pi_i^A > \pi_i^B$. Hence, $\lambda = \infty$ implies that there is no decision error.

Also notice from equation (1) that a subject's decision depends on the difference in the expected payoffs for the two decisions:

$$(2) \qquad \pi_i^A - \pi_i^B = R*P_i - R*(1 - P_i) = R*(2P_i - 1),$$

where R is the payoff for a correct decision and P_i is the posterior probability of urn A. Error rates are estimated for each of the three payoff conditions (*R*=0, 2, 4), using the difference in probabilities ($2P_i$ - 1) as the explanatory variable. Bayes' rule is used to calculate the P_i's for every possible combination of private signal and previous decisions. For example, there are two possible values of private signal (*a* or *b*) that round one decision makers use to calculate P_i, there are four possible combinations of first rounds decisions and private signals that round two decision makers use to calculate P_i, there are eight possible combinations of first round decisions, second round decisions, and private signals that round three decision makers use to calculate P_i, etc.

The λ's are estimated using a maximum likelihood routine in GAUSS.[7] The estimation is complicated by the fact that P_i depends on the λ's for all previous rounds. Therefore, the independent variable, which is a function of P_i, changes with different estimates of λ. The estimation algorithm takes these interdependencies into account by defining P_i as a variable that depends on the individual's signal, previous decisions, and λ's from previous rounds.

Table II. Econometric Results

Payoff For a Correct Decision	constrained λ (standard errors)	λ's by round (standard errors)					
		1	2	3	4	5	6
$0	4.47 (.44)	5.59 (1.36)	5.50 (1.59)	6.09 (1.86)	3.61 (.96)	3.52 (.97)	3.88 (1.02)
$2	6.59 (.71)	4.73 (1.01)	10.60 (2.83)	11.83 (3.86)	4.01 (1.13)	5.90 (1.80)	8.45 (2.96)
$4	6.25 (.61)	4.88 (1.10)	5.38 (1.15)	11.08 (4.62)	16.13 (7.72)	4.95 (1.25)	6.99 (2.09)

IV. Results

Summary statistics from the estimation are presented in table II. In one specification, λ is constrained to be the same over all six rounds of the experiment. These results are presented in the second column of table II. In another specification, λ is allowed to vary over rounds. These results are listed in the remaining six columns of table II. All of the λ's are statistically significant, indicating that the difference in probabilities alone is a significant variable in determining a person's prediction. Specifically, notice in the top row of this table that λ is equal to 4.47 with no payoff for a correct prediction. This suggests that subjects attach some non-monetary value to making a correct prediction, which is consistent with the finding of Smith and Walker (1993b). Likelihood ratio tests

[7] The estimation program is available from the author upon request.

indicate that the restriction that λ is the same for all rounds cannot be rejected under any of the three payoff conditions. Hence, the discussion that follows pertains to the constrained λ's from table II.

Notice from the second column of table II that λ increases as the payoff for a correct decision increases from $0 to $2, indicating that the effect of a positive payoff is a reduction in decision error. Also note that increasing the payoff from $2 to $4 has no significant effect on the amount of decision error. This result is consistent with Wilcox's (1993) finding that higher payoffs matter when decision tasks are complex. The cascade setup is a relatively complex decision making environment in the sense that inferences drawn from the decisions of other people rely on assumptions about how those people processed public and private information. Hence, adding some monetary incentive increases interest in the problem and reduces error. However, the problem is sufficiently complicated that doubling payoffs is not enough to further reduce error rates.

The magnitude of the λ's from table II translates into decision probabilities in the following manner: There is an 81 percent chance that a first round decision maker who sees *a* will predict urn A in the no payoff treatment. This probability increases to 90 percent in the payoff and double payoff treatments. These probabilities are listed as information set 1 in table III below.

Table III presents estimated values of the probability that a subject will predict urn A using the λ's from table II. This table demonstrates how these error rates affect decision probabilities for a variety of information sets (private signal, "s_i," and observed decisions, "D_i's"). As noted above, information set 1 characterizes a first round decision maker who sees an *a* signal. Some information sets in the table show sequences where the current decision maker's signal matches previous decisions (e.g., A, A, *a*), and other examples show sequences where the current decision maker's signal differs from the previous pattern of decisions (e.g., A, A, *b*). Also, some sequences show all conforming decisions (e.g., A, A, A) and others include deviations from the established pattern (e.g., A, A, B).

Table III. Pr (D=A) for Selected Combinations of Information

Information Set	Available Information											Pr(D=A)	
	D_1	D_2	D_3	D_4	D_5	s_1	s_2	s_3	s_4	s_5	s_6	\$0 payoff	\$2 payoff & \$4 payoff
1						*a*						.81	.90
2	A						*a*					.92	.97
3	A						*b*					.36	.38
4	A	A						*a*				.94	.98
5	A	A						*b*				.56	.61
6	A	A	A						*a*			.95	.99
7	A	A	A						*b*			.62	.72
8	A	A	B						*a*			.87	.94
9	A	A	B						*b*			.25	.17

Notice that differences in decision probabilities across the three payoff conditions are relatively small when the private signal matches a series of observed decisions. With information set 6, the first three decision makers predict urn A and the fourth decision maker sees an *a* signal. In this case, the private signal confirms previous predictions, suggesting that errors are less likely to have occurred. With this combination of information, subjects in the no payoff condition predict urn A 95 percent of the time and subjects in the payoff conditions predict urn A 99 percent of the time.

Alternatively, when private information differs from a relatively long sequence of conforming decisions, error rates have a more pronounced effect on decisions. When the first three decision makers predict A and the fourth decision maker sees a *b* signal (information set 7), subjects in one of the payoff treatments are 10 percentage points more likely to predict urn A than subjects in the no payoff treatment (72% vs. 62%). Since errors are more likely to occur in the no payoff treatment, the previous A decisions contribute less to the posterior. Therefore, a person observing a *b* signal under the no payoff treatment has a lower posterior for A than a similar person in one of the payoff treatments.

Table IV shows some actual patterns of signals and decisions from session 6 of the experiment, in which subjects were paid $2 for a correct prediction and $0 otherwise. The estimated probabilities that are reported in this table were calculated with the constrained λ for the $2 treatment in table II. In the first period of session 6 the first round decision maker, subject S31, saw an *a* signal and predicted urn A. The second round decision maker, subject S32, saw a *b* signal and predicted urn B. Without decision error, the posterior probability for urn A, with an inferred *a* signal and an observed *b* signal, is .50 for subject S32. However, the possibility for error discounts the inferred information, resulting in an estimated probability of .46 < .50 for the second round decision maker.

The third round decision maker saw an *a* signal and predicted A. The fourth decision maker saw a private *b* signal, and the combination of information resulted in an estimated Bayesian posterior of .45 for A. However, this person predicted urn A, which was inconsistent with private information and with Bayes' rule. These decisions are labeled ** mistakes. The sixth decision maker in period 1 had a posterior of .57 for urn A but predicted that urn B was being used. This was consistent with private information. Decisions that are consistent with private information but inconsistent with Bayes' rule are labeled * mistakes.

The first three decision makers in period 2 saw *b* signals and predicted urn B. These decisions were consistent with Bayes' rule and with private information. The last three decision makers in this round saw *a* signals but predicted urn B. Each of these predictions was consistent with Bayes' rule but inconsistent with private information. These shaded decisions were part of an information cascade started by the early conforming decisions. An incorrect cascade formed in period 3 as the first two decision makers were unlucky to see *b* signals when urn A was actually being used for the draws.

Table IV. Data for Selected Periods of Session 6

Pd	Urn Used	Subject Number: Urn Decision (private draw, estimated probability of urn A) 1st round	2nd round	3rd round	4th round	5th round	6th round	Cascade Outcome
1	B	S31: A (*a*, .67)	S32: B (*b*, .46)	S33: A (*a*, .65)	S34: A** (*b*, .45)	S35: A (*a*, .82)	S36: B* (*b*, .57)	
2	B	S35: B (*b*, .33)	S36: B (*b*, .22)	S34: B (*b*, .18)	S32: B (*a*, .43)	S33: B (*a*, .40)	S31: B (*a*, .38)	cascade
3	A	S32: B (*b*, .33)	S33: B (*b*, .22)	S36: B (*a*, .46)	S34: B (*b*, .16)	S35: B (*b*, .14)	S31: B (*b*, .13)	incorrect cascade

Key: Shading -- Bayesian decision, inconsistent with private information.
* -- Decision based on private information, inconsistent with Bayesian updating.
** -- Decision inconsistent with Bayes rule and private information.

Results from all nine sessions are summarized in table V. The second column of table V lists the number of decisions that are inconsistent with both Bayes' rule and private information (** mistakes). There are 14 ** mistakes in both the $2 and the $4 payoff treatments and exactly twice as many in the no payoff treatment. The third column shows the number of decisions that are consistent with private information but inconsistent with Bayes' rule (* mistakes). There are 13 and 11 of these mistakes in the $2 and $4 treatments, respectively, and 23 of these mistakes in the no payoff treatment. Finally, the fourth column of table V reports the number of cascade decisions made under each payoff treatment and the percentage of cascade decisions made when the combination of observed predictions and private draw made a cascade decision possible. For example, under the no payoff treatment, there were 41 cases where the optimal (Bayesian) decision differed from a decision based solely on private information. In 18 of those 41 cases (44%), the person made a decision that was consistent with Bayes' rule.

Table V. Errors and Cascade Decisions

Payoff for a Correct Decision	** Mistake	* Mistake	Cascade Decisions
$0	28	23	18 (44%)
$2	14	13	30 (70%)
$4	14	11	40 (78%)

Key: * mistake -- Decision based on private information, inconsistent with Bayesian updating.
** mistake -- Decision inconsistent with Bayes rule and private information.
cascade decision - Decision consistent with Bayes' rule but inconsistent with private information.

Since a decision in the cascade experiment is constrained to be an A or B prediction, the variance of errors is not directly comparable to variances in experiments in which subjects choose from a range of number (e.g. choosing a bid in an auction experiment). However, since large deviations from optimal behavior are generally more costly than small deviation, variations from optimal behavior can be analyzed in terms of how costly they are in expected payoffs. As discussed above, with posteriors close to 50 percent, errors are less costly than when there are big differences in the posteriors for urn A and urn B. Table VI reports the number of errors by payoff rate for five ranges of Bayesian posteriors. In all three payoff conditions, over half of the mistakes were made when the posterior for the more likely event (urn A or urn B) was between 51 and 60 percent. At the other extreme, no subject failed to predict an urn when it's Bayesian posterior was higher than 90 percent. In the intermediate ranges, there is no consistent pattern of results. In the 71 - 90 percent range more errors were made in the no payoff treatment than in the payoff treatments. However, the percent of total errors made in the intermediate ranges was highest for the $4 payoff treatment. This suggests that increasing payoffs in this context does not have the strong effect on the variance of errors that has been documented in other experiments.

Table VI. Severity of Errors

Bayesian Posterior of More Likely Event (Urn A or Urn B)	Number of Errors by Payoff Rate (percent of total)		
	$0	$2	$4
51 - 60%	32 (63%)	18 (67%)	14 (56%)
61 - 70%	9 (17%)	7 (26%)	6 (24%)
71 - 80 %	6 (12%)	2 (7%)	4 (16%)
81 - 90%	4 (8%)	0 (0%)	1 (4%)
91 - 100%	0 (0%)	0 (0%)	0 (0%)

VI. Summary

In this paper error rates are estimated econometrically using a logistic error structure that highlights the impact of decision error in early rounds on subsequent decisions. Further, error rates are compared under three different payoff conditions. Results are consistent with early theoretical and experimental studies of decision costs and payoff effects. The data reveal that a no (variable) payoff condition results in more decision error than two payoff conditions. Under the assumption that people use Bayes' rule to form posterior probabilities, previous public decisions are less informative when the possibility of decision error is higher. Once a cascade starts, deviant decisions are informative in the sense that they are more likely to reveal a person's private information. However, deviant decisions are also less informative in the no payoff condition since decision error is higher.

References

Anderson Lisa R. (1994) *Information Cascades*, doctoral dissertation, The University of Virginia..

Anderson, Lisa R,, and Charles A. Holt (1997) "Information Cascades in the Laboratory," *The American Economic Review*, 87(5), 847 - 62.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch (1992) "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, 100 (5), 992-1026.

Harless, David W. and Colin F. Camerer (1994) "The Predictive Utility of Generalized Expected Utility Theories," *Econometrica*, 62 (6), 1251-1289.

McKelvey, Richard D. and Thomas R. Palfrey (1998) "Quantal Response Equilibria in Extensive Form Games," *Experimental Economics*, 1(1), 1-41.

McKelvey, Richard D. and Thomas R. Palfrey (1995) "Quantal Response Equilibria for Normal Form Games," *Games and Economic Behavior*, 10, 6-38.

Palfrey, T. R. and J. Prisbrey (1997) "Anomalous Behavior in Linear Public Goods Experiments: How Much and Why?" *American Economic Review*, 87(5), 829-46.

Smith, Vernon L. and James M. Walker (1993a) "Monetary Rewards and Decision Cost in Experimental Economics," *Economic Inquiry*, 31, 245-261.

Smith, Vernon L. and James M. Walker (1993b) "Rewards, Experience, and Decision Costs in First Price Auctions," *Economic Inquiry*, 31, 237-245.

Wilcox, Nathaniel T. (1993) "Lottery Choice: Incentives, Complexity and Decision Time," *The Economic Journal*, 103 (421), 1397-1417.