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Professional Traders as Intuitive Bayesians

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We compare the behavior of laboratory markets populated by experienced commodity and stock traders with the behavior of markets populated by MBA student traders. Unlike previous research, subject experience is a treatment variable in our experiment. Trading experience is found to be an important determinant of how well market outcomes approximate equilibrium predictions. Markets with student traders exhibit biases consistent with the prior literature; bias levels in markets with experienced traders are substantially reduced and trend toward zero. These market level results are confirmed with individual level tests. However, we cannot unambiguously determine whether the market outcomes with experienced traders are better organized using Bayes' rule or by a heuristic–base rate neglect. © 1995 Academic Press, Inc.

Researchers in judgment and decision making have largely abandoned normative models as descriptors of human behavior (De Bondt & Thaler, 1994). This abandonment is largely based on empirical results since Simon's (1955) work, suggesting that man has limited rationality. This contrasts with the model of economic man used both to derive the equilibrium predictions of markets and as a standard against which individual behavior is judged.

In this paper we explore the possibility that the failure of intuition in particular laboratory environments may coexist with the development of Bayesian responses with experience. Our controlled double oral auction markets with student subjects exhibit price biases consistent with prior results in the literature. However, market outcomes with experienced professional traders do move toward Bayesian predictions. Seen in conjunction with prior results, our experiments do not support the proposition that the actions of market participants are *inevitably* non-Bayesian. While we cannot reject particular alternative hypotheses, our results suggest that market outcomes with experienced professional traders are not inconsistent with the axioms of probability theory.

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THEORY AND PRIOR EVIDENCE

Since Simon (1955), a large body of research claims that man is not a good intuitive statistician (Kahneman, Slovic, & Tversky, 1982; Nisbett & Ross, 1980). Simon (1955) suggests that unaided human cognition is constrained by a limited capacity to store, retrieve, and attend to information. Given such constraints, and the complexity of most natural environments, decision makers are not likely to be able to optimize. Instead, they will satisfice—do the best they can under any given set of conditions—which often means an inability to consider the optimal action.

Support for this view of decision makers is not universal. Christensen-Szalanski and Beach (1984) argue that much of the published literature is biased toward reporting suboptimal behavior. They point out that many of the studies detailing "inappropriate" performance have relied on student subjects. Studies using professional subjects have generally reported better performance (Bonner & Pennington, 1991). To the extent that divergences in behavior are observed, doubts arise about the equivalence of the student and professional populations, an assumption implicit in much of

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the research using student subjects (Frederick & Libby, 1986). Further, the equivalence assumption is ultimately inconsistent with the bounded rationality hypothesis since the latter assumes adaptation over time by the decision maker (Simon, 1955).

A central issue is the extent to which propositions based on individual behavior generalize to aggregate market settings (Camerer, 1987a). Markets are characterized by economic incentives and provide feedback about the consequences of one's actions, affording individuals the opportunity to learn from their mistakes. Further, market behavior is not a simple aggregation of individual behavior. It does not follow that biased individual behavior implies biased aggregate market outcomes. Becker (1962) argues that it is behavior at the margin, not the mean, that drives market outcomes. Conscious optimization by individuals is not a prerequisite for observing optimal behavior in markets. Gode and Sunder (1993) and Jamal and Sunder (1994) report computer simulations of markets populated by nonrational or boundedly rational robots, which, given a budget constraint, converge to theoretical equilibria.

Nonetheless, theoretical and empirical results on market behavior are inconclusive. Russell and Thaler (1985, 1987) reject the proposition that individual biases would have no impact on market behavior. Kahneman (1988) argues that the claim that individually biased behavior does not impact market level outcomes must be subject to empirical test and validation. Debondt and Thaler (1994) argue that both real-world and laboratory markets may deviate from "rationally expected outcomes" under certain conditions.

On the other hand, Grether and Plott (1977) and Grether (1980) found that the presence of economic incentives attenuates the preference reversal phenomenon and the effect of the representativeness heuristic. Duh and Sunder (1986, 1993) found that laboratory market prices were most consistent with Bayes' rule (resource allocation was better described by the base rate neglect model). Camerer (1987a, 1987b) and Camerer, Loewenstein, and Weber (1988) suggest that heuristics can be reasonable predictors of market outcomes, but the degree of deviation from normative expectations is attenuated relative to non-market settings. These findings are consistent with those of Plott and Wilde (1982); while characterizing their market outcomes as consistent with Bayesian predictions, they noted a surprising degree of representativeness bias in prices. Results in the literature suggest that observed market prices can, at most, noisily approximate theoretical predictions (Friedman & Sunder, 1994).

Tversky and Kahneman (1987) argue that some aspect of the decision process, such as the decision maker's focal attention, must be altered by any incentive. Jamal and Sunder (1991) assessed flat versus salient (output related) incentive payment schemes and found that salient payments are more likely to cause markets to reach theoretical equilibria. However, prior experience in a market setting was important to observed outcomes. Ganguly, Kagel, and Moser (1994) manipulated data presentation and context and found that both market prices and allocations were best described by a heuristic model–base rate neglect. Alm, McClelland, and Schulze (1988), on the other hand, found no effect of framing or context on market behavior.

The research leaves several issues unresolved, including the role of experience in a market. While market outcomes are not a simple aggregation of individual behavior, they *are* an aggregation of participant behavior. Thus, the composition of those participants may be important. Camerer et al. (1988) conjecture that the activity of more rational traders appears to make their markets work effectively. Conversely, the work with "noise" traders and the results of Jamal and Sunder (1994) and Gode and Sunder (1993) suggest that rational behavior is not a prerequisite for rational equilibria in a market.

Few studies have employed professional traders in market settings, though there are reasons to suspect that professionals' behavior may differ from students' (Burns, 1985; Holt & Villamel 1986). The effect of training and legal barriers to entry, such as the regulation of traders, may serve to limit those who gain market experience. Understanding the nature of potential deviations in behavior and likely causes is important to our understanding of both market and individual processes. We test the following hypotheses relative to Bayesian expectations:

H1. Market prices are consistent with Bayesian predictions.

H2. Prices of markets with professional trader subjects are more consistent with Bayesian predictions than prices in markets with student traders as subjects.

H3. Market allocations are consistent with Bayesian predictions.

H4. Allocations of markets with professional trader subjects are more consistent with Bayesian predictions than are outcomes in markets with student traders as subjects.

Laboratory market prices and allocations are assessed relative to the predictions of Bayes rule and a heuristic model—representativeness.[1] We also investi-

[1] Tversky and Kahneman define representativeness as "a relation between a process or a model, M, and some instance or event, X, associated with that model . . . a value and a distribution, an instance and a category, . . . a sample and a population . . . (1974, 1982).

gate the behavior of individual subjects during various parts of the experiments.

METHOD

Model Predictions and Trading

Economic analyses of market outcomes—prices and resources exchanged or allocated—are based on Bayes Rule. In our markets, there were two states of nature, X and Y, with state probabilities $P(X) = 1 - P(Y)$. S_i ($i = 1, \ldots n$) describes n signals about the state occurrence with likelihoods $P(S_i \mid X)$ and $P(S_i \mid Y)$ for each signal. Then, the Bayesian posterior probability of each state, conditional on signal S_i being observed is

$$P(X \mid S_i) = \frac{P(S_i \mid X) \cdot P(X)}{P(S_i \mid X) \cdot P(X) + P(S_i \mid Y) \cdot P(Y)}. \quad (1)$$

An alternative model for developing the likelihood of state outcomes is the representativeness heuristic. "According to (this heuristic) the subjective probability of an event, or a sample, is determined by the degree to which it: (i) is similar in essential characteristics to its parent population; and (ii) reflects the salient features of the process by which it is generated" (Kahneman & Tversky, 1972, p. 430). This definition and subsequent research does not specify criteria for identifying characteristics or features that are to be regarded as essential. In order to make direct comparisons between Bayes' rule and the representativeness heuristic, specific interpretations of the heuristic must be used. We discuss three—the base rate neglect (NBR) model, exact representativeness (ER), and similarity (SIM). Two interpretations, NBR and SIM, are used in this paper.

The SIM model is based on Tversky (1977). Tversky defines an interval metric S(a,b) of similarity between two objects, A and B, as

$$S(A,B) = \theta f(A \cap B) - \alpha f(A - B) - \beta f(B - A)$$
$$\text{for some constants } \theta, \alpha, \beta \geqslant 0, \quad (2)$$

where $A \cap B$ are features common to A and B, $A - B$ are features of A not present in B, $B - A$ are features of B not present in A. The θ, α and β are constants, which serve as indices of the degree to which each component of S impacts the degree of similarity of A and B.

In our experiments, subjects saw a sample of 5 balls, drawn one at a time with replacement, without knowing if the sample came from Cage B (which contained 16 red and 4 white balls), or from Cage C (which contained 12 red, 8 white balls) as in Fig. 1. We regarded the number of balls of each color in a given sample and in the populations (Cages B and C) as the "essential characteristics" in this case, and applied Tversky's

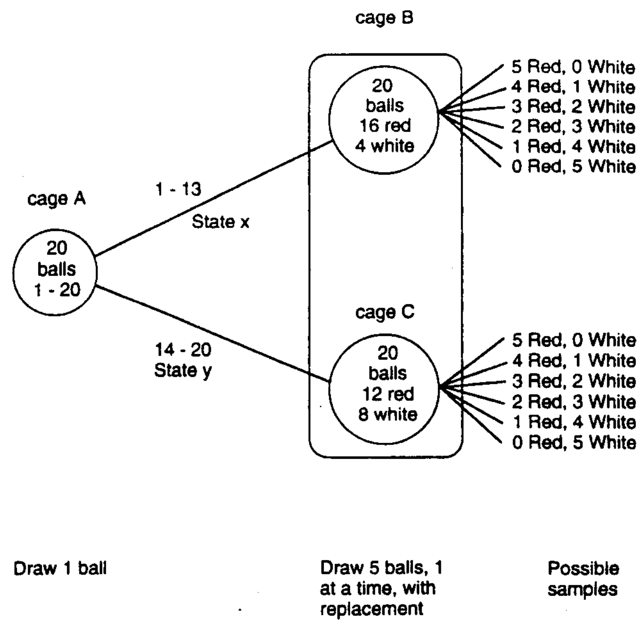

FIG. 1. The state of nature was determined by first selecting a numbered ball from cage A. Depending on the number selected, a sample of 5 balls was drawn, with replacement, from the relevant cage (B or C) and shown to subjects. The source cage of the sample was announced to subjects *after* trading.

metric, by choosing constants θ, α, and β. Because the metric is defined over an interval scale, it cannot be used to determine relative weights or unique probability measures for a given sample. We assumed that subjects using the SIM model will act as if a sample is drawn with certainty from the population to which it is most similar. The relative similarity scores are invariant to the choice of parameters θ, α, $\beta \geqslant 0$.

Exact representativeness (ER) is an incomplete special case of Tversky's similarity measure and is used in Camerer (1987a). Under ER, subjects are assumed to infer Cage B from a 4-Red sample and Cage C from a 3-Red sample as they represent exact proportionate analogs to the respective bingo cage distributions. There are no exact proportionate state analogs to other potential sample outcomes. no inference can be made on the basis of these "disproportionate" samples (which can be expected to constitute 39% of all samples). We use predictions derived from Tversky's similarity measures because they are complete and coincide with the ER predictions for 3-Red and 4-Red samples.

The base rate neglect (NBR) model implies that subjects place total reliance on the sample evidence and none on the cage proportions (base rates), effectively replacing the given base rates by equal base rates to arrive at posterior probabilities. Substituting $P(X) = P(Y)$ in Eq. (1) yields:

$$p^{NBR}(X \mid S_i) = \frac{P(S_i \mid X)}{P(S_i \mid X) + P(S_i \mid Y)}. \quad (3)$$

This equation is used to derive NBR model predictions. The effect of base rate neglect is to lower the posterior probabilities of state X for all possible samples.

Model predictions are given in Table 1 for each of the six possible samples. In deriving predictions, we use the following maintained hypotheses: (1) Market participants are risk neutral, (2) the double oral auction market with six or more participants yields a reasonable approximation of perfect competition (Gresik & Satterthwaite, 1983; Jamal & Sunder, 1991; Smith, 1982), and (3) prices and quantities of these markets are given by the point of intersection of the market supply and demand functions (Smith, 1982; Plott, 1987).

The design of laboratory markets is based on the concept of induced values (Smith, 1976; Friedman & Sunder, 1994). In our markets, subjects were assigned a role of either of two trader types, I and II. The two trader types differed in the amount of state-dependent payoffs they received from certificates held at the end of a trading period. For example, if state X occurred, a Type I trader would receive a payoff of 550 "francs" for each certificate held, while a Type II trader would receive only 75 francs for each certificate held. If the traders believed the state to be "X," this difference in dividends induced an incentive for Type I traders to buy and for Type II traders to sell at some price between 75 and 550 francs. These relationships were reversed if state Y occurred; Type II traders had the higher "Y" payoff. The payoffs (or expected payoffs) serve as the reservation or aspiration values[2] of the particular traders.

Parameters of the markets (dividends, prior and posterior state probabilities) were chosen so that Bayes' rule and the representativeness heuristic yields distinct predictions of prices and allocations. For example, for a 3-Red sample, Bayes' rule predicts a price of 312 francs, and all certificates should be held by Type I traders. Both the NBR and SIM models predict the allocation of certificates to Type II traders, with prices of 263 and 375, respectively. The prediction of certificate holdings at the end of trading (allocations) is distinct only for the 3-Red sample.

[2] The reservation wage for a trader is the minimum acceptable price for a trade. It is consistent with the psychological concept of aspiration level.

TABLE 1

Predicted Market Prices and Trader Type Expected to Hold Certificates after Trading Given a Signal Sample of Five Balls

	Markets 1, 1a, 2, and 2a			Market 3		
	Model prices and trader type			Model prices and trader type		
Signal	BAYES	NBR	SIM	BAYES	NBR	SIM
R0	360 II	366 II	375 II	68	50	50
R1	335 II	352 II	375 II	97	90	50
R2	288 II	320 II	375 II	152	113	50
R3	312 I	263 II	375 II	233	180	50
R4	423 I	356 I	550 I	311	264	400
R5	493 I	454 I	550 I	360	334	400

Note. R, red; combination is the number of red balls in a sample. Bayes, Bayesian price; SIM, similarity price; NBR, base rate neglect price.

Participants

Subjects were either MBA students majoring in finance or professional stock, bond, or commodity traders. The MBA students were solicited from two large state universities. All had taken several finance courses and had been exposed to statistical methods and risk analysis (a few had also done some stock market trading). Twelve and 11 students participated in Markets 2 and 2a, respectively. Eight student subjects participated in Market 3. The average student was in the second year of an MBA program and was approximately 26 years of age. About 1 in 6 had some experience with buying, selling, or owning stock. None were stock traders.

Professional traders were solicited from several stock and bond underwriting houses and from the Minneapolis Commodity Exchange. These individuals were involved in both research and actual trading on an ongoing basis. This can be contrasted with stockbrokers, who tend to act as salespersons for brokerage firms. Twelve and 9 traders, respectively, participated in Markets 1 and 1a. The average trader was 30 years of age and had about 5 years of professional experience.

Procedure

A three-fourth's replication of a 2 × 2, between-subjects, factorial design was used in this study.[3] The design is shown in Table 2, and follows Duh and Sunder (1986, 1993), and Camerer (1987a). The manipulated variables were subjects' market experience (student vs professional trader) and the market dividend type (uniform vs nonuniform). Subjects were randomly assigned to trader type in all markets. In the uniform dividend experiments, the dividends of both types of traders were identical.

Each experimental session began with the random assignment of subjects to either of the two trader types. Each subject was given an experimental packet which contained a trader identification number, information about his or her *private* payoffs, and other experimental materials. Talking between traders was not allowed. The probability devices (bingo cages) and other

[3] All cells were repeated with the exception of the uniform dividend market.

TABLE 2
Research Design and Market Payoffs by Realized State and Trader Type

State	Payoffs: Uniform X	Uniform Y	Nonuniform X	Nonuniform Y
Trader type				
Professional				
Type I	—	—	550	50
Type II	—	—	75	375
Student				
Type I	400	50	550	50
Type II	400	50	75	375

Note. Market traders generally held differing, or nonuniform payoffs. Payoffs are expressed in francs. The uniform cell was not done for professionals due to a lack of subjects.

experimental procedures were then introduced in a step by step process.

The first step of this process consisted of 10 trials where subjects guessed whether a ball drawn from a bingo cage (A) containing 20 numbered balls came from the sequences 1–13 (representing state X) or 14–20 (representing state Y) (see Fig. 1). The instructions and a partial response sheet for this exercise appears in the Appendix as Instructions #1.

Subjects then moved on to the next phase, an exercise consisting of five trials designed to introduce subjects to the actual probability procedures to be used in the laboratory markets. Subjects were shown a sample of five balls, drawn one at a time with replacement from a pair of hidden bingo cages, and asked to guess from which bingo cage the sample had been drawn—Cage B (state X) or Cage C (state Y). The source cage was chosen based on an undisclosed draw from Cage A, as shown in Fig. 1. After subjects made their state choices, the state was announced and payoffs were calculated. Subjects earned 25¢ for correct guesses during both of these two exercises and were penalized 10¢ for incorrect guesses. The number of trials in either stage was not known in advance to subjects. Instructions and a partial response sheet for Exercise 2 appears in the Appendix as Instructions #2.

Subjects were next introduced to the market trading procedures. This began with an experimenter reading aloud the detailed trading instructions. Subjects were encouraged to ask questions at any time. A dry run, or "zero" period, was then used to familiarize subjects with the actual market trading procedures. Trading began when subjects were comfortable with the procedures. A sample of the trading instructions and certificate (trading record) form appears in the Appendix as Instructions #3.

The market trading procedure was a double oral auction. In a double oral auction, any trader can, at any time, transmit (to the auctioneer) one of two possible messages: "x bids y" or "x offers y," where x is the identification number of the subject, and y is the price at which the trader is willing to buy (a bid) or sell (an offer). In order to be valid, a current bid must exceed any previous bid, and a current offer must be less than any previous offer. Only the highest bid and the lowest offer are valid. A trader can accept a valid bid or offer from another trader by saying "x accepts y," and a transaction is completed. All other bids and offers are erased with a completed transaction, and the process starts again.

The number of trading periods in a given laboratory market session was unknown to subjects. In each experimental packet was a set of 20 period sheets giving the holder the right to the "use" of two certificates *each period* in any way (s)he saw fit (buy, sell, or simply hold the certificates). Certificates had value for only the particular period they were "in play." Each trader was also given a "cash credit"[4] each period which permitted them to trade without fear of bankruptcy. At the beginning of each period, a sample was drawn and announced, and trading commenced. All bids, offers, and completed transactions were publicly displayed by the experimenter (auctioneer). After 5 min, the period ended, the actual state was revealed, and subjects repaid their cash credit, computed, and recorded their profit (dividends plus net proceeds from trading) for the period. Each market continued for 13 or 14 periods. At the conclusion of the market trading sessions, subjects completed a manipulation check and debriefing questionnaire. Profits were then converted into U.S. dollars at a conversion rate announced in advance and paid to the subjects in cash. Total earnings ranged from $6 to $65 for individual subjects. A typical session lasted 3 h. A sample profit record form appears in the Appendix.

Finally, subjects were allowed to sell short (sell certificates not actually owned at the time of sale) within a period as long as any certificates sold short were covered prior to the end of the period. This feature permitted confident or aggressive traders to "drive the market." Failure to make up any deficit balance was subject to a penalty which was sufficiently high in order to make it unprofitable for the traders to violate the short-sale rule.[5]

[4] The credit given is subtracted out at the end of each period. The currency generally used in laboratory markets is francs. This permits the use of larger certificate values and increases the incentive to trade. Subjects also do not know exactly how much is made per transaction, which helps to preserve the desired magnitude effect.

[5] Compared to previous studies, subjects could make relatively small amounts of money by simply holding on to their certificates and refusing to trade.

RESULTS

Hypotheses H1 and H2: Prices and Bias

Figures 2 through 6 show the average and range of transaction prices for each period of five markets. Markets 1 and 1a used professional subjects; markets 2, 2a, and 3 used students. The averages of all transactions and of the last three transactions are shown. We show the latter since market prices are construed to be consistent with marginal behavior and the former because the literature generally reports average prices. Horizontal markers depict the price predictions of the three models given a period's signal sample.

Market price data are limited to a graphical presentation. Statistical comparison of prices with theoretical predictions is complicated by (1) the inadequacy of static price predictions for changing prices, (2) the absence of a defined theory of the market convergence process, (3) the presence of statistical dependence in transaction prices, and (4) the effect of learning over time among traders (for a further discussion, see Davis & Holt, 1993; Friedman & Sunder, 1994).

For Market 1 (Fig. 2), there were no periods with extreme samples of 0-Red or 5-Red. For all but one period average prices were below both the Bayesian and NBR predictions, reflecting a conservative bias. The mean and marginal prices tend to move toward the Bayesian and NBR predictions over time. Market 1a generally replicates the Market 1 behavior, with the exception that more of the prices are above the Bayesian and NBR predictions, consistent with a slight representativeness bias (Fig. 3). Figures 2 and 3 suggest that both Bayes' rule and the NBR model yield reasonable predictions of transaction prices. Neither model can be rejected as a descriptive alternative.

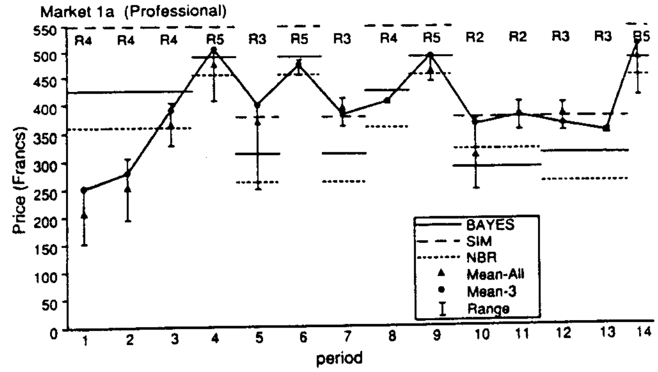

FIG. 3. Average market transaction prices each period. Horizontal lines reflect the predicted price given a pricing model and a signal sample. Mean-All = average price for all transactions. Mean-3 = average price for the last 3 transactions. Range = low to high price distribution each period. R(#) = the number of red balls in the signal sample.

Markets 2 and 2a (Figs. 4 and 5, student traders) on the other hand, presents quite different price behavior. In virtually every period, the mean and marginal prices are well above the Bayesian and NBR prices. Both models predict student pricing behavior poorly. The average and marginal prices tend to approach the extreme SIM model predictions—regardless of signal and period.

Only students participated in the uniform dividend market (Fig. 6). The uniform dividend condition provides a baseline measure of the extent to which subjects differed in terms of their beliefs about which state was indicated by a given sample outcome. Since all subjects had identical information and payoffs, we interpreted the pricing and trading activity as indicators of subjects' confidence in their beliefs.

The uniform dividend market had fewer trades, and the number decreased over time. No trading at all occurred in the latter stages of most periods; trading ac-

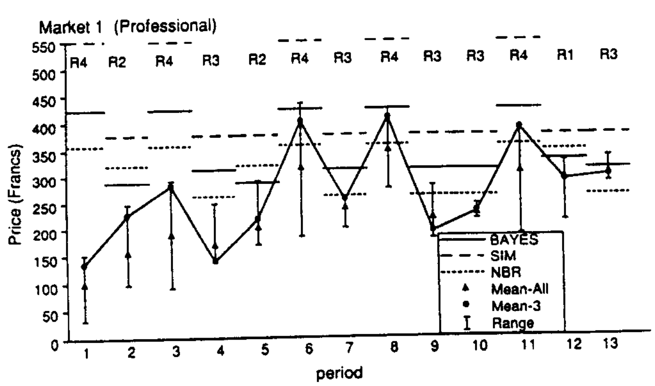

FIG. 2. Average market transaction prices each period. Horizontal lines reflect the predicted price given a pricing model and a signal sample. Mean-All = average price for all transactions. Mean-3 = average price for the last 3 transactions. Range = low to high price distribution each period. R(#) = the number of red balls in the signal sample.

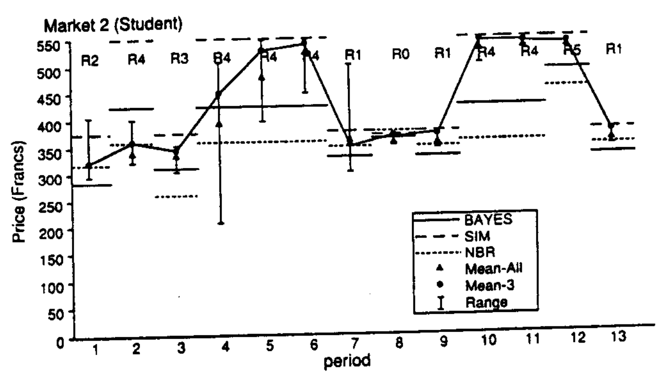

FIG. 4. Average market transaction prices each period. Horizontal lines reflect the predicted price given a pricing model and a signal sample. Mean-All = average price for all transactions. Mean-3 = average price for the last 3 transactions. Range = low to high price distribution each period. R(#) = the number of red balls in the signal sample.

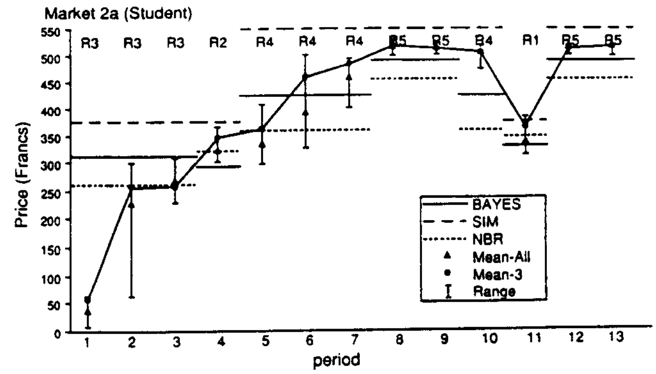

FIG. 5. Average market transaction prices each period. Horizontal lines reflect the predicted price given a pricing model and a signal sample. Mean-All = average price for all transactions. Mean-3 = average price for the last 3 transactions. Range = low to high price distribution each period. R(#) = the number of red balls in the signal sample.

tivity apparently provides an early, rapid indication of the market judgment about likely outcomes. By the last period, only two trades occur.

Transaction prices of Market 3 are similar to those of Markets 2 and 2a in the sense that there is not much deviation from SIM predictions. There is a high degree of representativeness bias in prices. Since all traders have the same information, they are merely shifting from one extreme to the other in response to the signal sample. Nonetheless, the informational environment of uniform dividend markets is simpler, and subjects appear to learn (eventually) that they all have similar information. There is movement toward Bayesian and NBR predictions in the last two periods of the market.

Figure 7 depicts the deviation of observed prices from predicted model prices (or bias), using the last three trades of each period for both professionals and students. Bias is defined as $(P_t - P_B)$, where P_t is the

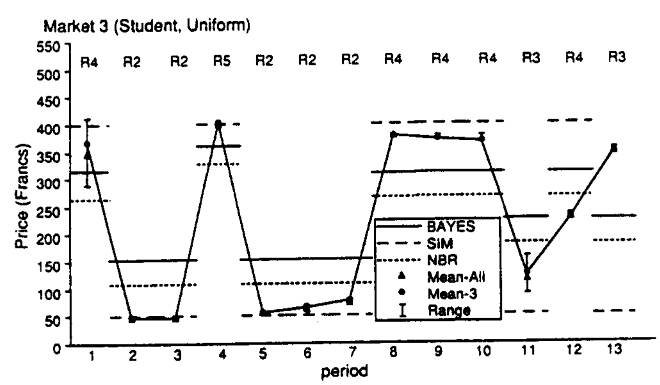

FIG. 6. Average market transaction prices each period. Horizontal lines reflect the predicted price given a pricing model and a signal sample. Mean-All = average price for all transactions. Mean-3 = average price for the last 3 transactions. Range = low to high price distribution each period. R(#) = the number of red balls in the signal sample.

observed transaction price and P_B is the Bayesian *or* NBR market price prediction given the observed signal. Statistical results are provided using nonparametric procedures. An alpha level of .05 was used for all tests.

Sample-conditioned average bias tends to decline across time for the professionals (Fig. 7). Paired comparisons using the Wilcoxon test suggests that the Bayesian model results in smaller bias in Market 1a ($n = 14$; $p < .00$). The NBR model results in smaller bias in Market 1 ($n = 13$; $p < .00$).

The student responses present an interesting contrast. The level of bias is relatively constant across periods, except when the sample composition is extreme (e.g., 0-Red or 5-Red) and thus limits possible error by the trader. Further, the bias tends to be in the opposite direction from that of the professional markets—particularly in the latter periods (see Figs. 2–6). The Bayesian and NBR models are poor predictors of student behavior. Student behavior is best described using the highly representative SIM model.

The extent of differences in behavior between the students and professionals is more clearly seen using relative bias, given by $(P_t - P_B)/(D_M - P_B)$. Here P_t and P_B are as defined before, and D_M is the maximum possible price of the security in the state which has the highest Bayesian or NBR posterior probability. For example, the maximum possible price error (or bias), given a 5-Red sample, is 550–493 = 57, conditional on the Bayesian choice. On the other hand, given a 3-red sample, the maximum possible error is 550–312 = 238. These amounts are used to scale *observed bias*. Since the magnitude of possible price error varies significantly, relative bias provides a scale free, sample-dependent frame of reference for judging subject behavior. Relative bias was computed for both the Bayesian and NBR models.

Figure 8 depicts large differences between the behavior of professional and student subjects using this measure. The relative bias in student markets remains generally unchanged across periods. Relative bias in the professional markets declines with time across all samples. Using the Wilcoxon test, both the magnitude and direction of effects differed significantly between the professionals and students for both the Bayesian ($n = 26$; $p < .00$) and NBR models ($n = 26$; $p < .00$).

The relative bias from the Bayesian and NBR models does not differ for Market 1 ($n = 13$; $p > .31$). However, in Market 1a, the Bayesian model produces smaller bias levels ($n = 14$; $p < .00$). Students were not assessed relative to the NBR and Bayesian models. Student behavior was best described using the SIM model.

Figure 9 depicts the changes in relative bias (pricing behavior) of both students and professionals given repeated exposure to the various samples. Absolute val-

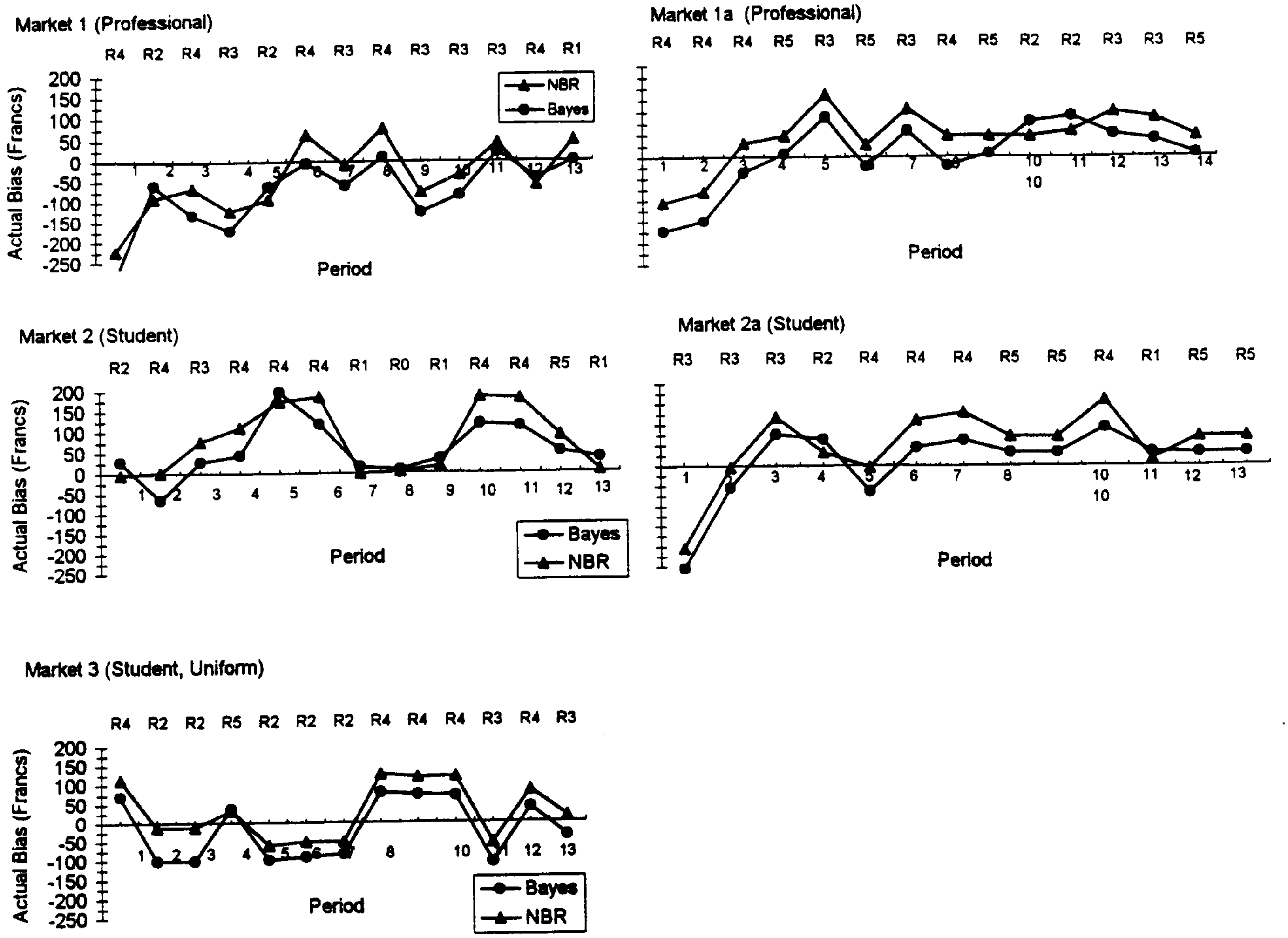

FIG. 7. Market price bias (actual price–predicted price) as a function of the assumed pricing model. Economic theory presumes Bayes' rule. The alternative shown is the NBR model, or base rate neglect.

ues are used for comparison purposes. Only the Bayesian effects are shown since the levels of bias are comparable for the NBR model. The data provide evidence on the issue of learning in this environment. Student behavior appears to be consistently unchanged—and biased. There is little or no evidence of learning or conformity with model predictions by student subjects. On the other hand, the professionals clearly alter their behavior over time. Behavior trends toward model predictions for each signal. The data also suggest, however, that the presence of economic incentives does not, by itself, induce immediate, effective learning. Learning is iterative and apparently dependent on subject experience.

Overall, there is mixed support for H1 and H2. The prices in the professional markets are better described using the Bayesian and NBR models and are poorly described by the SIM model. In the student markets, the situation is reversed. The SIM model dominates in prediction. Generally, the performance of the Bayesian and NBR models are statistically indistinguishable from each other.

Hypotheses H3 and H4: Security Allocations

Markets determine prices and allocate resources. Given the signals and payoffs, particular traders should be expected to buy and sell certificates in equilibrium. Allocations of securities between the two types of traders provides another basis for inferring how well different models predict performance. Allocation predictions of both interpretations of the representativeness heuristic are identical for all samples, and they deviate from the predictions of Bayes' rule for only one of the six possible samples—the 3-Red sample (Table 2).

When the allocation predictions of all models coincide, the number of certificates holdings that are inconsistent with model predictions is close to zero in all periods of all markets except in period 11 of Market 1a

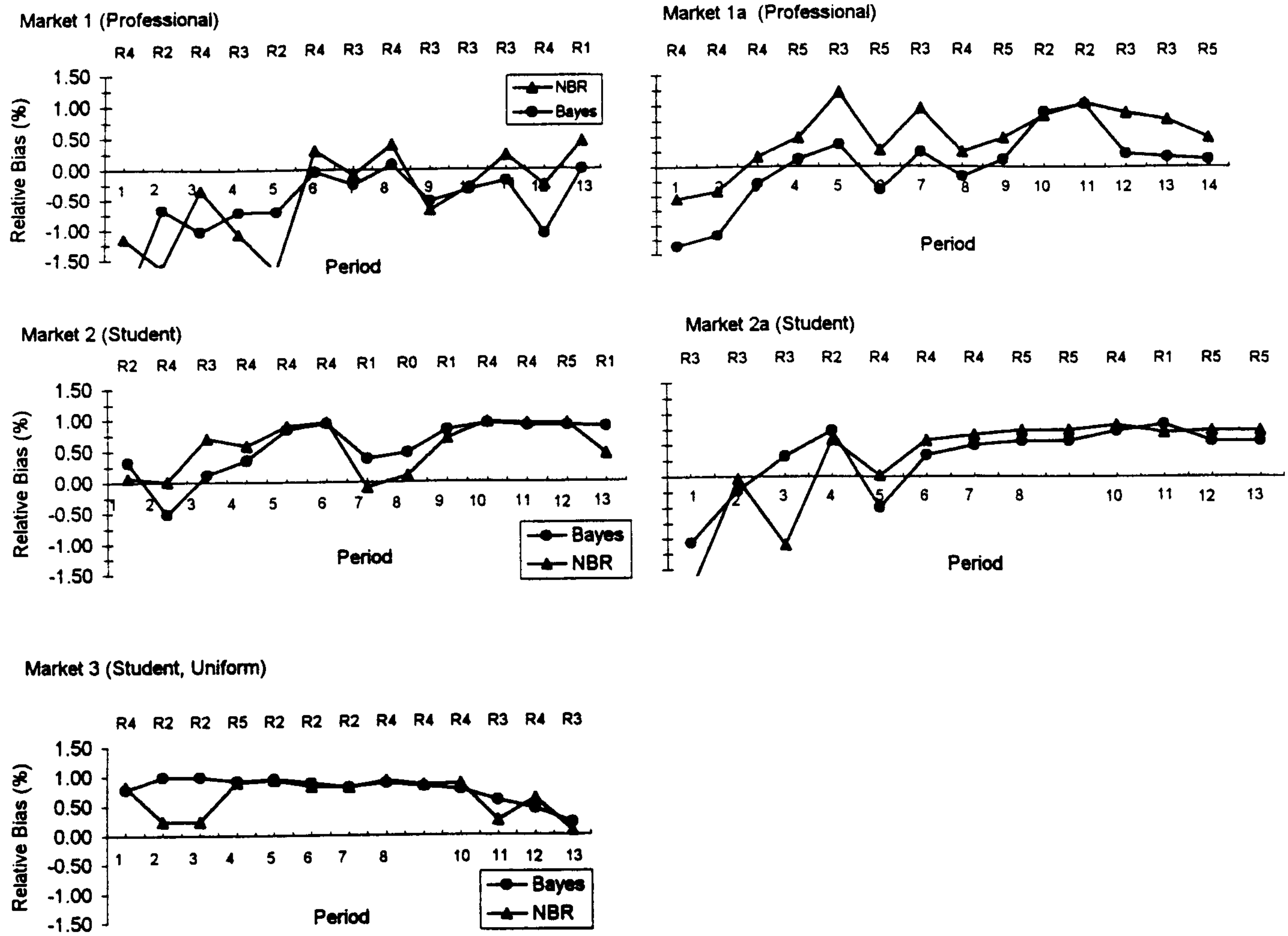

FIG. 8. Relative bias ([actual price–predicted price]/[period's payoff-predicted price]) is the percentage bias of subjects each period. The market payoffs serve to limit the possible amount by which a price can vary.

and period 4 of Market 2a (both are 2-Red samples; Fig. 10). However, for 3-Red sample periods, the observed allocations do not conform closely to the predictions of either theory. There is some indication that in Markets 1, 1a, and 2a, with repetition of the 3-Red sample periods, allocations move toward the predictions of Bayes' rule and away from predictions of the representativeness heuristic (in Markets 2 and 2a, there are fewer occurrences of the 3-Red sample). In general, however, when comparing the same signal, student and professional allocation behavior is indistinguishable. The allocation data do not generally support hypotheses H3 and H4.

Individual Analyses and Manipulation Checks

Recall that as part of the familiarization exercises, subjects were provided a small incentive/penalty function and asked to predict whether a ball drawn from Bingo Cage A (Fig. 1) would correspond to either state X (balls 1–13) or state Y (balls 14–20). All subjects performed well, with 84 percent of the professionals' and 83% of the students' predictions consistent with the expected profit maximizing state (Table 3). Prediction performance was statistically equivalent across the groups.

In the second stage of the experiment, when subjects were shown a sample of 5 draws from a bingo cage and asked to predict the state, professionals made the expected profit maximizing (Bayesian) choice 69% of the time. Students made the Bayesian choice 72% of the time. Overall, the ability of student and professional subjects to predict the state is similar, imperfect, and partially consistent with the representativeness heuristic. Professionals appear to have no advantage at making such predictions. This suggests that it is behavior after the state selection decision which causes the observed difference in pricing behavior.

Subjects also differed significantly in their beliefs about their performance during the experimental sessions (Table 4). At the end of market trading, subjects

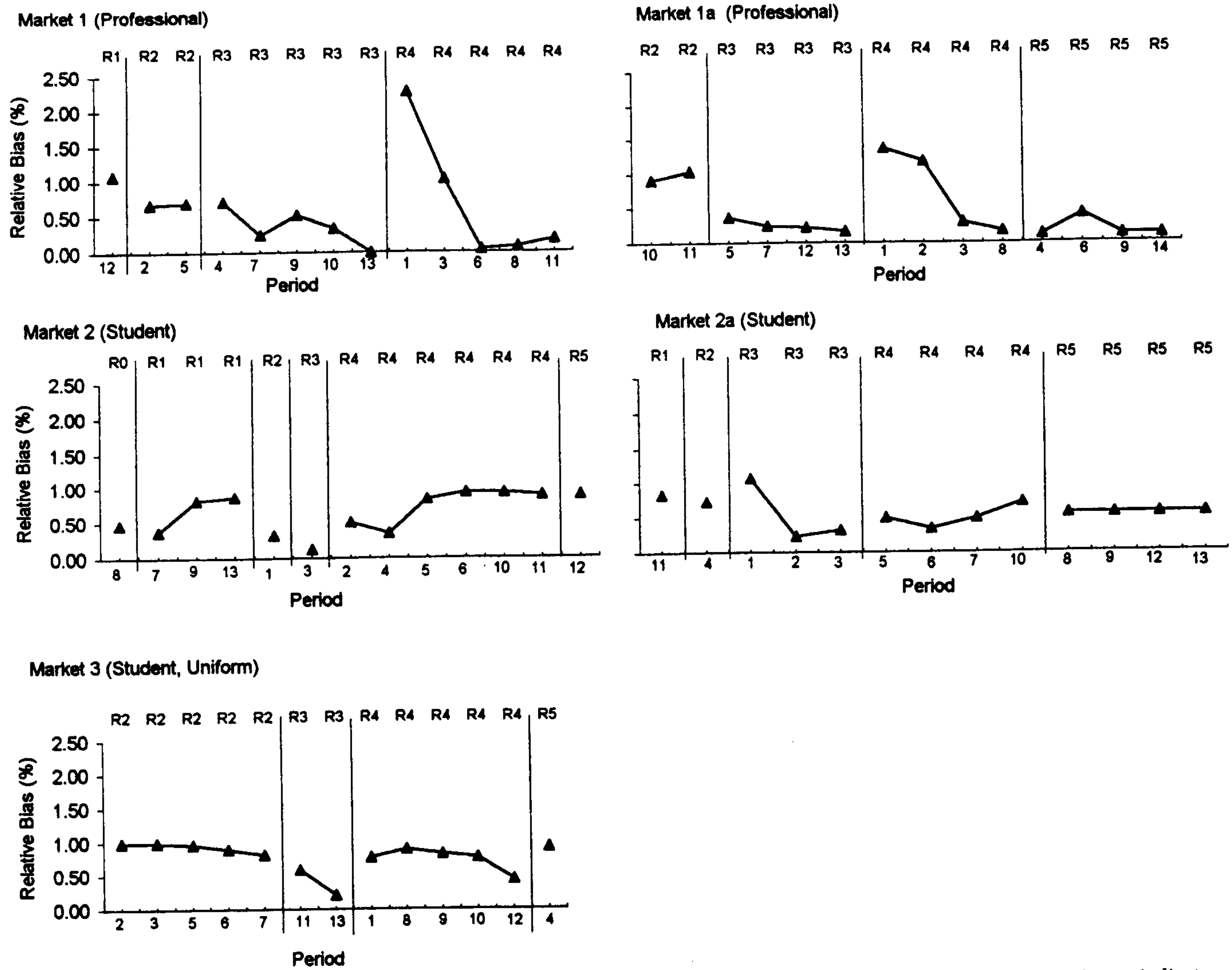

FIG. 9. Relative bias as a function of time, given repeated exposure to a signal. Assuming a pricing model, this provides an indicator of learning in this environment. Absolute value is used to remove the effect of positive and negative deviations from expectations.

were asked to rate on a scale of 1 (minimum) to 7 (maximum) their confidence in their state predictions at the beginning and at the end of the market. Students had significantly greater reported confidence than the professionals, $t(41) = 3.56$, $p < .00$; both groups' reported confidence remained relatively unchanged during the market. Interestingly, approximately three-fourths of the students reported that (s)he had done better than average at the task. Only 40% of the professionals expressed such an opinion.

Finally, subjects also completed a set of "profile sketches" adapted from Tversky and Kahneman (1974). Subjects were randomly divided into two "base rate" groups—a 70% group and a 30% group. Each group was given general descriptions of subjects taken from populations with the given base rates. A typical description follows:

> Jack is a 45 year old man. He is married and has two children. He is generally conservative, careful, and ambitious. He shows little interest in political and social issues. Nonetheless, he has a strong commitment to "traditional" values, and has strong ties to his family, church, and community. He spends most of his free time on his many hobbies which include home carpentry, sailing, and mathematical puzzles.
>
> The probability that Jack is one of the 30 accountants in the sample of 100 is ______.

Subjects then assessed the probability that the target came from the particular base rate group. Results were consistent with those reported by Tversky and Kahneman for student subjects, but not for the professionals (Table 5). Bayes' rule suggests that the mean predicted probability ought to be a function of the different base rates (in fact, equal to the base rates, since the profiles contain no diagnostic information). For the MBA students, the mean assessed probabilities between the two

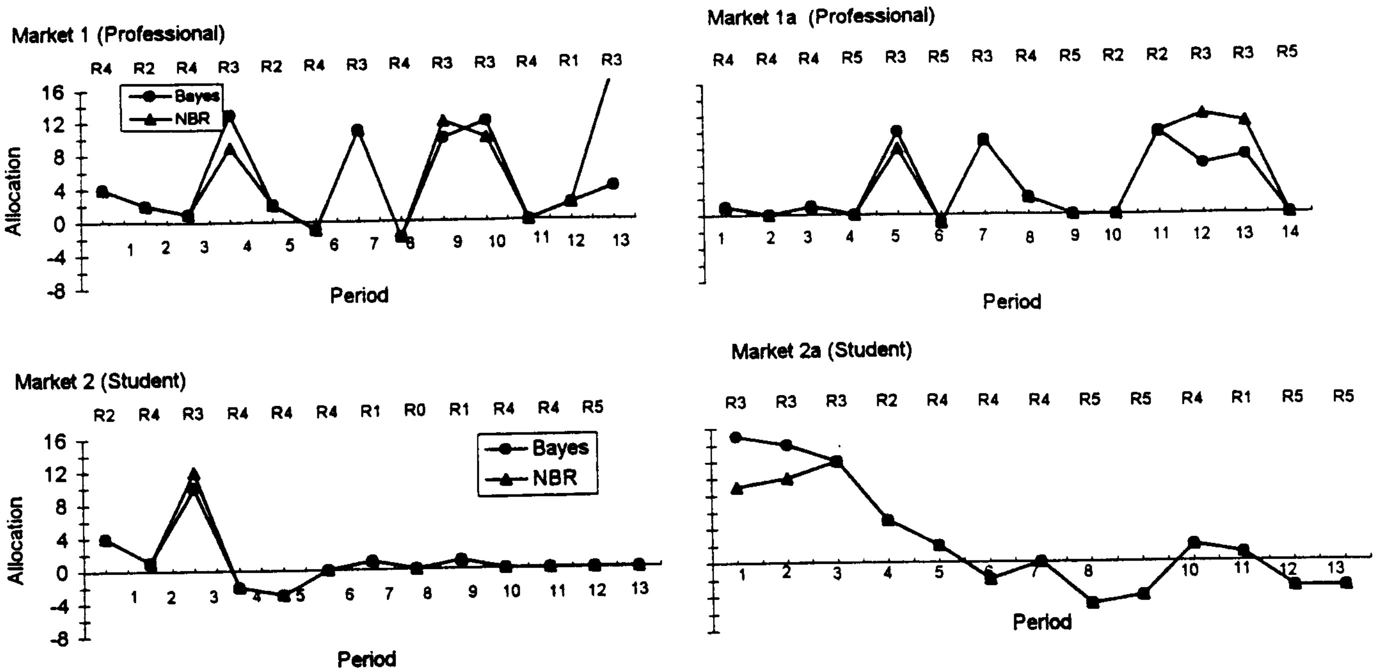

FIG. 10. Market allocations each period. Allocations reflect who ends up holding certificates after trading, given a signal and the payoffs. It is a corollary measure (with price) of how effectively a market is working.

conditions do not differ; $t(21) = .11$, $p > .46$. For the professionals, the means are significantly different; $t(18) = -2.45$, $p < .01$. This result suggests that the professionals utilize sample information better in such tasks. However, note that for both groups the means are too high in the low-base-rate group and too low in the high-base-rate group. Assessing behavior across the profiles (using Friedman's ANOVA) for a given type of subject suggests that both groups react to the information in the profiles. The professionals are simply not as extreme in their reactions [MBAs: $\chi^2(2, 26) = 16.8$, $p < .00$; professionals: $\chi^2(2, 26) = 13.44$, $p < .00$].

Overall, the individual results suggest that the likely source of performance differences between students and professionals is their trading strategies (and by implication, their information weighting behavior). The professionals appear to have learned to be cautious, in effect, to hedge their bets. Students apparently do not understand how to implement strategies which protect them from the possibility of being wrong—even when they have made an appropriate state decision. Given a model, they appear to be able to make the appropriate state selection, but are then unable to appropriately weigh the possibilities. This conclusion is consistent with the results from the analysis of relative bias. The degree of bias of the student subjects is consistent with the application of a relatively high weight to the payoff of the state with the highest posterior probability. This is consistent with Einhorn's (1980) conclusion that decision makers do not appropriately consider the *possibility* of negative, as opposed to positive, outcomes. However, our conclusions are inconsistent with studies that suggest that discipline-based training in statistics may lead subjects to perform better on tasks involving uncertainty (Lehman et

TABLE 3

Percentage of Subjects Making the Bayesian Choice on Exercises 1 and 2

Group	n	Expt 1	Expt 2
MBAs	23	83 [27]	72 [21]
Professionals	20	84 [21]	69 [23]

Note. One subject in each group did not complete exercises. Values in brackets are standard deviations; tests are two-tailed. Groups did not differ significantly at $p < .05$ by t test.

TABLE 4

Subjects' Perceived Confidence in Their Decisions before and after Completing Market Sessions

		Mean confidence score	
Group	n	Before	After
MBA students	23	5.9 [.2]	6.0 [.2]
Professionals	20	4.8 [.3]	4.8 [.3]

Note. One subject in each group did not complete this exercise. Tests are two-tailed; values in brackets are standard deviations. Scores do not differ at $p < .05$ by t test.

TABLE 5

Mean Judged Likelihood of Group Membership Using Kahneman–Tversky Type Profile Tasks

		Condition	
Group	n	30% BR	70% BR
MBAs	23	.56	.57
		[.32]	[.27]
Professionals	20	.50	.66
		[.27]	[.23]

Note. Values enclosed in brackets are standard deviations. BR, base rate; tests are one-tailed. Professionals differed significantly with $p < .01$ by t test; MBAs did not differ significantly at conventional levels.

al., 1988; Medin & Edelson, 1988). The students had more (and more recent) statistical training than did the professionals.

DISCUSSION

Does a subject's prior market experience matter to price and allocation outcomes in markets? Our evidence suggests that the answer is "yes." For the student markets, the representativeness model (SIM) dominates in predicting market prices. Further, the students were highly confident that their work was relatively correct. In this setting, markets do not appear to *necessarily* provide sufficient feedback to encourage effective learning and changed behavior. However, there is some evidence from our uniform dividend market and several prior studies which suggests that market experience does help to move observed behavior in the direction predicted by Bayes' rule (Jamal and Sunder, 1991, 1994). Nonetheless, the tendency toward biased behavior was confirmed using individual tests.

For our experienced professional traders, the Bayesian model is a better predictor of prices. The bias for professionals is substantially lower than in student markets and decreases over time. Yet, as suggested by the performance of the NBR model, the professionals do not utilize appropriate weights in making their decisions. Again, these tendencies toward better performance were confirmed using individual test data.

Market allocations are not predicted well by either model when uncertainty prevails, as with the 3-Red sample. For both the professionals and students, neither model dominates in predicting behavior. However, repeated exposure to uncertain outcomes does suggest that the allocation behavior may move toward Bayesian predictions.

A relevant question is when one could expect decision makers to exhibit biased judgments. Subjects in this study were aware of the probabilistic nature of the process. Students were better trained statistically than the average decision maker and were knowledgeable about markets. These subjects should be capable of more "rational" behavior (Lehman et al., 1988). Nonetheless, student behavior in the markets fails to conform to Bayesian predictions. Experience appears to play an important role in altering behavior.

While our results suggest that real market experience appears to generalize to the laboratory setting, decreasing price (and possibly allocation) bias, they also suggest that these effects may occur gradually over time. Exposure to market forces does not appear to be sufficient in this context, to eliminate bias.[6] Thus, the extent to which the average market participant has a chance to have repeated exposures to target experiences is a relevant question. Many significant events occur rarely or with extended time intervals between occurrences; e.g., a change in one's pension plan, or a home purchase. The effect or extent of learning in such cases remains an open question.

[6] Jamal and Sunder (1994) find that, given sufficient replications, markets populated by heuristic "robots" converge to Bayesian predictions. This suggests that market forces do reduce bias—regardless of the rationality of market participants.

APPENDIX

Experimental materials are presented in the order in which they were given to subjects. Instructions and partial response sheets are provided for Exercises 1 and 2 of the experiment. Instructions for the trading sessions are complete and appear as Instructions #3. An information and record sheet (certificates and profit record) for this phase of the experiment is also provided.

Instructions #1

Each period we draw a ball from a bingo cage containing 20 balls numbered 1 through 20. If the ball drawn is numbered 1 through 13, the outcome of the draw is called 'X'; if the ball is numbered 14 through 20, the outcome is called 'Y'

You have to guess the outcome of each draw before it is announced. If your prediction is correct, you win 25 cents; if your prediction is wrong, you lose 10 cents. Before the first draw is made, record your prediction by circling either X or Y in the first row of your record sheet. After you have encircled one letter the outcome will be announced and you should record the announced outcome in the blank space on the same row of the record sheet. If your prediction is correct, circle the amount shown in the win column; otherwise, circle the amount shown in the lose column.

Once you have recorded your prediction you must not make a change; any erasure will invalidate your prediction. At the end (you will be informed of the end of this phase by the experimenters), add up your total winnings and losses and record the difference (net winnings or losses) at the bottom right corner of the record sheet.

Subject no. ________

Partial
RECORD SHEET
Instructions #1

Number	Circle One: Decision		Outcome X or Y	Circle One: Win ($)	Circle One: Lose ($)
1.	X	Y	______	0.25	−0.10
2.	X	Y	______	0.25	−0.10
3.	X	Y	______	0.25	−0.10
4.	X	Y	______	0.25	−0.10
5.	X	Y	______	0.25	−0.10
17.	X	Y	______	0.25	−0.10
18.	X	Y	______	0.25	−0.10
19.	X	Y	______	0.25	−0.10
20.	X	Y	______	0.25	−0.10

Total winning ____
Total losses ____
Net winnings/losses ____

Instructions #2

Each period we will draw a ball from a bingo cage (we will call it the XY cage) containing 20 balls numbered 1 through 20. If the ball drawn is numbered 1 through 13, inclusive, the period is X. If the ball is numbered 14 through 20, inclusive, the period is Y. You will not be told the number on the ball drawn until the end of the period.

Instead, the ball drawn is used to select a second bingo cage from a pair representing the X and Y periods. If the ball drawn from the first bingo cage (XY) is any of numbers 1 through 13, we will draw a sample of five balls, with replacement, from a second bingo cage (X bingo cage) containing 20 balls, 80% of which (16) are red, 20% white (4). If the ball drawn from the XY bingo cage is any of numbers 14 through 20, then the sample of five balls is drawn from a third bingo cage (Y bingo cage) containing 60% red (12) balls, and 40% white (8) balls. You must keep track of the sample of balls drawn on the record sheet provided. The sample is to be used to guess which period's dividend will be paid (in effect, you guess from which sequence of numbers the ball drawn from the first bingo cage came). If you guess the period or event correctly, you win 25 cents; if you are incorrect, you lose 10 cents.

The balls drawn should be written down in the same sequence as drawn on your record sheet. A sequence might look like R W W R R, for example. This implies that the first ball drawn was red, the second and third white, etc. . This constitutes your clue. This part of the experiment is designed to help you in identifying whether the clue came from the X or Y cage, respectively. For each sample clue, you must record your guess by circling X or Y on the appropriate row of the record sheet. After you have circled your guess, you will be told the actual cage. You should then record your wins and losses. Do not erase after your guess. Any erasures invalidates your guess. Make sure before you write.

Trader # ______

Partial
RECORD SHEET
Instructions #2

Period	Clue	Events Circle One		Actual Event	Circle one Win or Lose (Cents)	
1	____________	X	Y	____	25	–10
2	____________	X	Y	____	25	–10
3	____________	X	Y	____	25	–10
4	____________	X	Y	____	25	–10
5	____________	X	Y	____	25	–10
6	____________	X	Y	____	25	–10
7	____________	X	Y	____	25	–10
8	____________	X	Y	____	25	–10
9	____________	X	Y	____	25	–10
10	____________	X	Y	____	25	–10
11	____________	X	Y	____	25	–10
12	____________	X	Y	____	25	–10
13	____________	X	Y	____	25	–10

Instructions #3

This is an experiment in the economics of market decision making. The instructions are provided as a guide to how the market works. If you follow the instructions carefully and make good decisions, you may earn a considerable amount of money. The money you earn will be paid to you in cash.

General Market Organization

The market is conducted over a number of periods (analogous to days, weeks, or years, for example, in a market such as the stock market). In each period you will have the opportunity to buy and sell certificates. You will be given a sheet on which you can record any transactions you enter into during that period. This enables you to keep track of any earnings for the period. These records are yours only and should not be revealed to anyone else.

The currency used in the market will be francs. All transactions (purchases or sales of certificates) will be in terms of francs. Each franc is worth $.003. At the end of the experiment, your francs will be converted into dollars at this rate. You will be paid in dollars. The more francs you earn, the more dollars you earn.

Specific Instructions

(1) General description

Your earnings each period come from two sources–from 'cashing in' certificates you hold at the end of a period for the prescribed value of the certificates (analogous to receiving a dividend), and from buying and selling certificates. During a given market period, you are free to buy or sell as many certificates as you wish, provided you follow the rules below.

For each certificate you hold at the end of a period you will be given an amount (in francs) equal to one of the two numbers (certificate earnings) listed in the margin of your Information and Record Sheet (to the left of line 26). These two numbers may be different for different people. The manner in which one of these two numbers is chosen each period will be described later in these instructions.

Earnings from certificates each period are determined by multiplying the number of certificates held at the end of the period by the certificate earnings number explained above. Line 26 of your Information and Record Sheet explains this procedure. This amount must be computed each period.

Sales from your certificate holdings increase your franc balance by the amount of the sale price. Purchases of certificates reduce your franc balance by the amount of the purchase price. Thus, sales or purchases by you may result in either increasing or reducing your overall franc balance. After calculating your profit or loss at the end of each period, all certificates revert to the experimenter (at zero price).

At the beginning of each period you will be given an initial stake (holding) of certificates. This should already be recorded on line '0' of your period Information and Record Sheet. You may either sell or hold these certificates as you see fit. If you do not sell a certificate, you will receive the 'certificate earnings,' as determined for the period, at the end of the period. In effect, then, this is the minimum amount that you can earn on each certificate during the period.

You will also be provided with an initial stake of francs at the beginning of each period. This initial stake amount should already be recorded on line '0' of your Information and Record Sheet. You may either use this sum to purchase other securities or simply keep it. Francs on hand at the end of the period in excess of 10,000 are yours to keep.

In summary, each period you will receive an initial stake of 2 certificates and francs. You are free to buy and sell certificates as you see fit as long as you follow the rules to be given below. Your francs on hand at the end of each period are determined by the initial sum you receive, earnings from certificate holdings, and profit or loss from purchases or sales of certificates.

(2) Procedures and Trading Rules

The certificate earnings (to the left of line 26 on the Information and Record Sheet) that you will be paid in a given period are determined in the following manner. At the beginning of each period, a sample of one unit is drawn from a bingo cage (we will call this the XY cage). This sample determines the 'type' of a particular period. The cage contains twenty (20) bingo balls numbered 1 to 20. If any of balls 1 to 13 (inclusive) is drawn, we will say that this is an 'X' period, and the X amount of certificate earnings will be paid on all certificates held at the end of the period. If any of balls 14 to 20 (inclusive) is drawn, we will say that this is a 'Y' period, and the Y amount of certificate earnings will be paid on all certificates held at the end of the period.

You will not be told if a period is X or Y until the end of a period. Instead, the outcome of the first sample will be used to select a second bingo cage from which a second sample will be drawn. You will be shown the sample drawn from the second cage. You may use the second sample to infer whether or not the period is X or Y. Note that all of these decisions are made based on random outcomes.

The second sample will be drawn from a bingo cage containing twenty (20) balls. The sample in this case will consist of five balls, drawn one at a time, with replacement. The sample may be drawn from either of two cages. In cage X, the twenty bingo balls consist of 20% (4) white balls, 80% (16) red balls. If the result of the first draw indicates that the period is to be X, then the sample is drawn from cage X. Cage Y contains 40% (8) white balls, 60% (12) red balls. If the result of the first draw indicates that the period is to be Y, then the sample is drawn from cage Y.

In summary, there are two samples drawn–the first consists of one unit, the second consists of five units. Only the outcome of the second sample is revealed to you immediately. The first sample is only revealed to you at the end of the period. The origin of the second sample is dependent on the composition of the first sample.

(2) Trading and Recording Rules

(i) <u>All</u> transactions are for one certificate at a time. After each of your sales or purchases you must record the <u>PRICE</u> at which the deal (transaction) was made on your Information and Record Sheet in the appropriate column. Each deal (transaction) you consummate should be listed in the same order as consummated on the Information and Record Sheet, beginning with row 1.

(ii) After each transaction you must calculate and record your new certificate balance and your new francs-on-hand balance. Each sale should increase this balance, and each purchase should decrease this balance. The francs-on-hand balance must never go below zero.

(iii) At the end of each period, record your total certificate earnings in the last column of line 26 of the Information and Record Sheet. Compute your end of period balances by adding certificate earnings and profit or loss from certificate transactions. This should be entered on line 27.

(iv) Your total earnings for each period (line 29) is computed by subtracting the amount listed on line 28 from your total balance of francs on hand (line 27). This amount should be recorded on the appropriate line (same as the period number) of your sheet marked 'PROFIT SHEET'. This profit is yours to keep. This must be done carefully at the end of each period.

(v) At the conclusion of the experiment you must add your total profit on your PROFIT SHEET. The sum should be placed on line 21 of the sheet. This will serve as the basis for your payment for participating in the experiment. Please convert the franc amount to dollars by following the instructions on the PROFIT SHEET. The computations will be checked by the experimenters prior to payment. You will be paid the amount you earn.

Specific Experimental Organization

You may buy and sell certificates during each period. The transactions will take place in a market organized as follows. The market will be conducted over a number of periods (The experimenter will tell you when the

TRADER NO. _________

INFORMATION AND RECORD SHEET
Instructions #3

PERIOD ___________

	Transaction Number	Transaction Price: Sale	Transaction Price: Purchase	Certificates on Hand	Francs on Hand
Beginning of the Period Holdings	0	///////////	///////////	2	10,000
	1				
	2				
	3				
	4				
	5				
	6				
	7				
	8				
	9				
	10				
	11				
	12				
	13				
	14				
	15				
	16				
	17				
	18				
	19				
	20				
	21				
	22				
	23				
	24				
	25				
X-Dividend ______ Y-Dividend ______	26	Total Certificate Earnings = Dividend Rate × Certificates on Hand at the End of the Period			
	27	Total Francs on Hand at the End of the Period			
	28	Less: Fixed Cost			10,000
	29	End of Period Net Profit			
		(Transfer this amount to your Profit Sheet)			

experiment is over). Each period will last for five minutes. Anyone wishing to buy or sell a certificate must raise his or her hand and make a verbal bid to buy or offer to sell, one certificate at a price he or she specifies. Any subsequent (following) bid to buy must be at a higher price to be admissible in the market. Conversely, any subsequent offer to sell must be at a lower price to be admissible in the market. If a bid or offer is accepted, a binding contract has been closed for a single certificate. The two parties to the transaction must record the transaction on their Information and Record sheets. Any ties in bids, offers, or acceptances will be resolved by random choice among the parties involved.

Except for bids, offers, and acceptances, you are not to speak to anyone else. There may be many bids and offers that are not accepted. You are free to keep trying as often as you like to negotiate a sale or purchase. You are free to make as much profit as you can.

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