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Incentives, Learning and Processing of Information in a Market Environment: An Examination of the Base-Rate Fallacy

INTRODUCTION

There are at least two traditions in analyzing how people process information. Psychologists start with the premise that the human capacity to store and process information is finite. Cognitive limitations lead people to use heuristics or rules of thumb to make decisions. Heuristics may serve as efficient decision tools, but they sometimes lead to decisions which deviate from the theoretical optimum defined for a world without cognitive limitations [Nisbett and Ross, 1980].[1] Several empirical studies support this proposition [e.g., Kahneman and Tversky, 1972, 1973; Tversky and Kahneman, 1974, 1980; Bar-Hillel, 1980].

Economists, on the other hand, focus their attention on motivations or incentives of people, both pecuniary and nonpecuniary. Individuals are postulated to be driven by incentives to achieve the optimum solution within the constraints of their environment. Cognitive constraints that receive so much attention from the psychologists are often omitted from economic analysis.[2] Psychologists, in turn, tend to pay less attention to incentives.

Besides selective attention to incentives and cognitive limits, there is a second difference between the economic and psychological traditions in human decision-making. Economists tend to focus on the aggregate manifestations of individual behavior, such as allocations and prices in a competitive market. Psychologists, on the other hand, are interested in the individual behavior per se. Accordingly, the settings in which they choose

We have benefited from discussions with many of our colleagues at Minnesota. Comments by Gene Borgida, Matt Anderson, Joyce Berg, Lane Daley, John Dickhaut, Gordon Duke, Paul Fox, Doris Holt, Ed Joyce and Chandra Kanodia were particularly useful. Helpful comments were also provided by several participants at the Conference. Financial support for this research was provided by the Accounting Research Center and the Dayton Hudson Foundation.

to conduct their experiments tend to be quite different. While psychologists may examine the behavior of individuals in isolation, economists may place them in a market where close interaction occurs among individuals.

This paper is an attempt to bring the two traditions of research into human information processing together by explicitly recognizing, rather than ignoring, their mutual differences.[3] Such integration of perspective has pragmatic significance in accounting which is often described as a source of information for making decisions [Libby, 1981]. On one hand, most accounting phenomena occur in incentive rich environments and results obtained in nonincentive environments have, at most, limited significance to accountants. On the other hand, the *raison d'etre* of accountants is the cognitive limitation of man: absent the finiteness of cognitive capacity, everyone would know all there is to know in the public domain at all times. Who would need the accountants? Both incentives and cognitive limitations are essential parts of accounting phenomena; neither can be ignored. Furthermore, accounting phenomena include not only individual behavior in isolation, but also individual behavior in close interactive environments, and aggregate behavior in market and other settings. We must understand behavior in all three settings, and their mutual relationships, in order to understand accounting.

To begin such an exploration, we have chosen for study the phenomenon of the base-rate fallacy which has been examined by psychologists, mostly at the individual level, in non-interactive settings and without explicit performance-based incentives. Base-rate fallacy refers to the tendency of people to deviate from Bayes' theorem when combining information from base-rates with sample data [Kahneman and Tversky, 1972; Bar-Hillel, 1980]. With a few notable exceptions, the base-rate fallacy literature in psychology, economics and accounting pays little attention to performance-based incentives, interaction, feedback and learning. Our study examines the aggregate manifestation of individual behavior in market environments which are rich in incentive, interaction, feedback and opportunities for learning.

Many interesting classes of decisions are made in situations where incentives for normative judgments, learning from environments, and pressures from competitive markets are present. Winkler [1982] suggested that situations with multiple decision makers were sufficiently widespread and important to warrant studies: "the competitive nature of the situation adds many complexities not found in decision making against nature, and the work done to date has involved fairly simple situations." (p. 528). Einhorn [1976] suggested that it is extremely important to study how sub-optimal individual behavior can lead to "rational" behavior at the aggregate level. In addition, previous studies suggest that people's decision behavior is contingent on the task environment [Payne, 1982]. Whether the base-rate fallacy persists in a market setting is an important and open question.

This paper is organized as follows. The rest of the introductory section reviews the relevant literature in psychology, accounting and economics. The next section presents the research design, structure of the market parameters and procedures. The third section outlines the competing models of behavior [Bayesian model, base-rate-only (BRO) model, and no-base-rate (NBR) model] and the hypotheses to be tested. The predictions of each model are also presented. The last section includes the experimental results and discussion.

The Base-Rate Fallacy

The phenomenon of base-rate neglect was first identified by Kahneman and Tversky [1972]. In their "taxi cab problem," subjects were given the base rates of two cab companies (Blue and Green) operating in a city. They were told that a cab was involved in a hit-and-run accident at night. A witness later identified the cab to be a Green cab. The subjects were given the positive and negative hit rates and were asked to estimate the probability that the hit-and-run cab was indeed Green as the witness claimed. Most subjects ignored the base rates. In another study, Kahneman and Tversky [1973] told one group of subjects that a panel of psychologists had administered personality tests to 70 engineers and 30 lawyers; for a second group of subjects, the relative proportion of engineers and lawyers was reversed. Kahneman and Tversky also presented the subjects with individuating information in the form of five paragraph-length personality sketches. Subjects were then asked to estimate the probability that a specific respondent was one of the 70 (30) engineers. Kahneman and Tversky found that, relative to the Bayesian predictions, subjects underutilized base rates and overweighted the individuating information.

Following Kahneman and Tversky [1972], researchers examined the conditions under which base rates are used or neglected [see a review by Borgida and Brekke, 1981]. For example, Nisbett and Borgida [1975] suggested that base rates might be underutilized because they were abstract and pallid. Ajzen [1977] proposed that causal base rates had more impact than non-causal base rates in judging the probability of passing an examination or of choosing a course. Bar-Hillel [1980] suggested that relevancy (specificity) of information would determine the utilization of information. Ginosar and Trope [1980] found that when given inconsistent or irrelevant individuating information, people tended to use base rates and make a relatively normative probability judgment. Fischhoff and Bar-Hillel [1984] suggested that the effect of base rates depended on the neutrality of individuating information relative to the categories for prediction.

The phenomenon of base-rate fallacy has also been the concern of accounting research [e.g., Gibbins, 1977; Holt, 1984a,b; Joyce and Biddle, 1981; Libby, 1981: Swieringa et al., 1976]. In general, auditors were found to react to base rates but their probability judgments deviated from the Bayesian norm.

The above studies seem to omit the effect of learning on probability judgments.[4] One of the exceptions is Holt [1984a]. She assumed, based on her pilot study, that the auditors' environment was more favorable than the bank-lenders environment for probability learning. She hypothesized that auditors would be more Bayesian than the bank-lenders in their risk assessments and that the assessments of the former would improve with experience. The field data supported her hypothesis.

The effect of incentive systems on probability judgments has not been encouraging in the psychology literature [Slovic and Lichtenstein, 1971; Tversky and Kahneman, 1974]. However, Eger and Dickhaut [1982] devised an incentive compatible payoff system, as represented by making book, and found that subjects' inferred probability assessments were more Bayesian than under traditional elicitation procedures. Grether [1980] operationalized probabilities by drawing balls from bingo cages to test the representativeness hypothesis. He found that the phenomenon of base-rate fallacy was confirmed for inexperienced or financially unmotivated subjects, but for others the evidence was less clear.

The environment of probability judgments is frequently characterized not only by learning but also by incentives to make judgments whose outcomes are more desirable and by the competitive pressures of a market environment.[5] Grether [1980] considered the sensistivity of market equilibria to the information search strategies used by individuals, though subjects in his experiment could not participate in market trading activities. Tests of the base rate fallacy presented in our paper are conducted in a double oral auction market environment.[6] Previous work with experimental markets suggests that in such an environment the market behavior is consistent with the revision of subjective beliefs by the participants on the basis of information they can learn from the market process [see Plott and Sunder, 1982, 1984; Sunder 1984]. An oral double auction provides more interaction among market participants than the other market institutions. Smith [1982, Propositions 15 and 19] also suggests that double auctions tend to be more efficient than posted price or sealed-bid auctions. Furthermore, to facilitate learning from experience, at the end of each period the realized state of nature was announced to the subjects as feedback. This is a favorable condition for learning because the subjects were supplied with not only the confirmatory feedback but also the disconfirmatory feedback. Lack of disconfirmatory feedback has been suggested as a source of overconfidence in judgment which is detrimental to learning [see Einhorn and Hogarth, 1978; Einhorn, 1980]. Thus the environment included an oral double auction market in which the subjects could interact with and learn from one another, receive feedback about whether they made a correct decision, and receive payoffs based on their decisions.

MARKET DESIGN

Four experiments were conducted. Subjects were: two graduate students and five undergraduate students in Experiment 1; eleven undergraduate students in Experiment 2; nine undergraduate students in Experiment 3; and twelve undergraduate students in Experiment 4. Subjects in the first three experiments had no prior experience with market experiments; subjects in Experiment 4 did. All undergraduate students were drawn from sections of introductory accounting courses for freshmen and sophomores.

Each experiment involved the operation of a market for several periods. In each period, securities which had one-period lives were traded. Dividends were paid to the security holders at the end of the period. These dividends differed across the traders and depended on the realized state of nature. The inter-subject difference in dividends and in their judgments about the state of nature created opportunities for gains from trade.

Parameters and Information

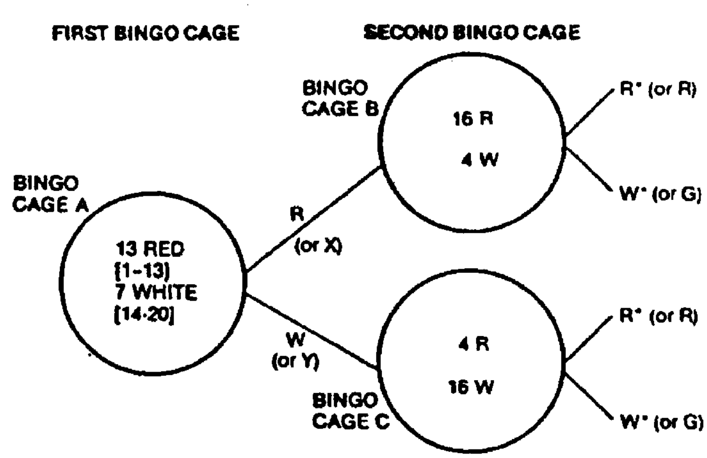
Three parameters, base rates, diagnosticity of individuating information, and dividends for each experiment were as follows.

In Experiment 1, subjects, all sitting in a classroom, were told that at the beginning of each period a ball would be drawn from a bingo cage, labelled A, containing twenty balls numbered 1 through 20. If the ball drawn was numbered 1 through 13, the outcome of the draw was called "Red" (R); if the ball drawn was numbered 14 through 20, the outcome was called "White" (W). The outcome of this draw determined the payoff of the security traded but the outcome was not announced to the subjects. The mechanism for making the draw was explained and exhibited to them. The implicit base rates were P(W) = 0.35 and P(R) = 0.65, though neither the term base rates nor probability were used in the conduct of the experiment. All explanations were presented in operational terms. The same procedure was used in Experiments 2-4, except that the base rates were changed and the labels used to describe the outcomes of the first and the second draws were changed for Experiments 3 and 4. In Experiments 3 and 4, W and R, and W* and R* were labelled Y and X, and G and R, respectively.

In all four experiments, diagnosticity of individuating information was the same as that in the taxi-cab problem (i.e., 0.80/0.20 = 4).[7] Subjects were told that if the draw from the first bingo cage was red (R), a second ball would be drawn from a second bingo cage labelled B which contained 16 red and 4 white balls. If, on the other hand, the ball drawn from the first bingo cage (bingo cage A) was white (W), the second ball would be drawn from yet another bingo cage, labelled C, which contained 16 white and 4 red balls. The outcome of the second draw constituted the individuating information; and it was announced to the subjects. An asterisk on W and R in the following discussion designates individuating information. This chance mechanism was shown to the subjects by a transparency of Figure 1.

FIGURE 1

Mechanism of Drawing Balls



Subjects knew that different traders might have different dividends, but they did not know how many types of traders there were in the market and what others' dividends were. Half of the subjects were randomly assigned to be "type I" traders, the other half were "type II" traders. Each trader knew his or her own dividends under states W and R and was to keep this dividend information private. Dividend parameters were designed so the price and allocations predicted by the competing models of human information processing might be as distinct from each other as possible.

Dividends per certificate for each type of trader in each state of nature are given in Table 1. The base rates and the diagnosticity of individuating information are summarized in Table 2.

TABLE 1

Dividends per Certificate for Each Type of Traders in Each State of Nature

		State of Nature	
	Type of Traders	W	R
Experiment 1	I	150	200
	II	40	230
Experiment 2	I	100	360
	II	160	300
Experiment 3	I	340	120
	II	120	300
Experiment 4	I	325	145
	II	165	365

Note: In Experiments 3 and 4, W and R are labelled by Y and X, respectively.

TABLE 2

Base Rates and Diagnosticity of Individuating Information

	P(W)	P(R)	P(W*/W)	P(R*/W)	P(R*/R)	P(W*/R)
Experiment 1	.35	.65	.80	.20	.80	.20
Experiment 2	.25	.75	.80	.20	.80	.20
Experiment 3	.15	.85	.80	.20	.80	.20
Experiment 4	.25	.75	.80	.20	.80	.20

Note: W and R are the states of nature. W* and R* are the individuating information about the state of nature. In Experiments 3 and 4, W and R were labelled by Y and X, respectively; and W* and R* were called by G and R, respectively.

TABLE 2 (continued)

Base Rates and Diagnosticity of Individuating Information

Bayesian posterior odds = likelihood ratio × prior odds

	$\frac{P(W/W^*)}{P(R/W^*)}$	=	$\frac{P(W^*/W)}{P(W^*/R)}$	×	$\frac{P(W)}{P(R)}$
Expt. 1	2.15		4		.538
Expt. 2	1.33		4		.33
Expt. 3	0.71		4		.176
Expt. 4	1.33		4		.33
	$\frac{P(R/R^*)}{P(W/R^*)}$	=	$\frac{P(R^*/R)}{P(R^*/W)}$	×	$\frac{P(R)}{P(W)}$
Expt. 1	7.4		4		1.85
Expt. 2	12.0		4		3.0
Expt. 3	22.8		4		5.7
Expt. 4	12.0		4		3.0

Preferences and Assets

Each trader, i, was assigned a dollar redemption function of the form:

$$R_i^t = r\,[a + d_i(\theta_t)x_i^t + \sum_s P_s^{it} - \sum_\varrho P_\varrho^{it} + C]$$

$$a < 0,\ d_i(\theta_t) > 0,\ r > 0,\ x_i^t \geqslant 0.$$

$i \epsilon I$ = the set of traders.

$\theta_t \epsilon \Theta$ = set of states of nature.

R_i^t = dollar earnings of trader i in period t.

x_i^t = Number of securities held by trader i at the end of period t is the initial endowment of securities z plus purchases less sales in period t.

$d_i(\theta_t)$ = the dividend rate of security in francs for trader i expressed as a function of the state of nature θ.

$\sum_s P_s^{it}$ = revenue from sales of securities during period t.

$\sum_\varrho P_\varrho^{it}$ = cost of securities purchased during period t.

C = initial endowment of cash in francs.

a = fixed cost in francs.

r = conversion rate of francs into U.S. dollars.

If traders have a positive, nonsatiating utility for money, they would like R_i^t as large as possible. Derived demand induces values on securities which, in turn, can be used as parameters in the models of market behavior [Smith, 1976, 1982].

Constraints on decisions by traders were as follows. At the beginning of each period, all traders were given an initial endowment of cash (C) which was sufficiently large not to be binding. Additionally, each trader was given an initial endowment of z securities. Short positions were not permissible. Thus, the supply of securities was fixed at z times the number of traders.

Procedures

Several periods of training were conducted to familiarize the subjects with the drawing mechanism.[8] Subjects were given all the parameters except the dividend information. In each training period, the experimenter drew a ball from the first bingo cage. Following the announcement of the outcome of the draw from the second bingo cage, subjects were asked to predict the state of nature (i.e., the outcome of the first draw). After subjects circled their prediction, the realized state of nature was announced to them. Subjects won $0.25 if their prediction was correct, and lost $0.10 if wrong. Thirteen to seventeen trials were carried out. Instruction Set 1 in the Appendix describes the procedure.

When the market trading began, subjects were supplied the information and parameters as described before. In addition, each subject was endowed with cash and one (in Experiment 1) or two (in Experiments 2-4) certificates. Subjects were free to make bids (to buy) or offers (to sell) after the announcement of the outcome of the second draw. At the end of each five-minute trading period the state of nature (outcome of the first draw) was announced to them. Each subject earned the appropriate dividend (see Table 1) for each certificate he or she held at the end of trading. The initial cash endowment of the subjects was taken away in the form of a fixed cost ($C+a=0$) and their net profits for the period R_i^t derived from dividends, sales of certificates, and trading profits were calculated.[9] Instruction Set 2 in the Appendix describes the procedure.

THEORY AND HYPOTHESES

Competing Models of Behavior

Four models are examined as candidate explanations for the behavior of these markets. They are: the Bayesian model, the base-rate-only model (BRO), the no-base-rate-1 (NBR1) model, and the no-base-rate-2 (NBR2) model. Predictions of the Bayesian, the base-rate-only, and the no-base-rate-2 models for the market behavior are derived under the assumption that the participants are risk-neutral expected utility maximizers. Th following explanations are based on the parametric design for Experiment 1 Predictions for Experiments 2-4 are similarly derived.

Bayesian Model. The Bayesian probability judgments incorporate botl base rates and signal information. The Bayesian posterior probabilities ar P(W/W*) = 0.683, P(R/W*) = 0.317, P(W/R*) = .0119, and P(R/R*) = 0.881 in Experiment 1.

If the subjects are assumed to be risk-neutral expected-utility maximizers predictions of the Bayesian model can be obtained by using their expectec payoffs as reservation prices to construct the demand and supply functions The Bayesian expected payoffs given each signal for each type of trader are summarized in Table 3. This model, supplemented by the principles of demand and supply and assumption of perfect competition, predicts that th equilibrium price will be 165.9 francs and that the securities will be held by type I traders (marked by &), if the signal is W*. If, on the other hand, the signal is R*, this model predicts that the equilibrium price will be 207.4 francs, and that the securities will be held by type II traders (marked by &).

Base-Rate-Only Model (BRO). The extreme hypothesis that only base rates are considered by traders with no consideration given to the signal provides a useful benchmark to evaluate the data. The expected payoffs, given different information for different types of traders, are presented in Table 3. Given the assumptions of risk-neutral expected-utility maximizing traders, this model, supplemented by principles of demand and supply and assumption of perfect competition, predicts that the equilibrium price will be 182.5 francs, and that the securities will be held by type I traders regardless of whether the signal is W* or R*.

No-Base-Rate Model (NBR). The base-rate fallacy has been described as the tendency of subjects to ignore (or underutilize) base rates in favor of individuating information. The no-base-rate model captures the extreme form of this idea. There are at least two ways to operationalize this idea. One interpretation would be that people ignore base rates in the sense that the base rates are not incorporated into decision processes and that the diagnosticity of individuating information is regarded as perfect. Kahneman and Tversky's [1973] explanations for the results of their profession and graduate specialization studies seem to support this interpretation of the no-base-rate model.

However, there is another interpretation: people may ignore base rates in the sense that they replace the given base rates by diffuse priors, although they do incorporate these diffuse priors into decisions. In other words, base rates are considered to be equal among all states of nature. According to this interpretation, the posterior probability for the taxi-cab problem is 0.80. Bar-Hillel's [1980] and Kahneman and Tversky's [1972] studies seem to support this second interpretation since subjects' modal response was 0.80. Libby [1981], by reference to Joyce and Biddle [1981], suggests that if subjects completely ignore base rates, their probability judgment will be 0.952 which is exactly the same as that derived by following this second interpretation.[10]

Thus, there are at least two interpretations for the idea of "ignoring base rates"; both have some support in the literature. Because it is not clear

TABLE 3
Expected Payoffs by Four Models

		Individuating Information							
		W*				R*			
	Type of Traders	Bayes	BRO	NBR1	NBR2	Bayes	BRO	NBR1	NBR2
Expt. 1	I	165.9&	182.5&	150&	160&	194.1	182.5&	200	190
	II	100.2	163.5	40	78	207.4&	163.5	230&	192&
Expt. 2	I	211.4	295.0&	100	152	340.0&	295.0&	360&	308&
	II	220.0&	265.0	160&	188&	289.2	265.0	300	272
Expt. 3	I	220	153	340&	296&	129	153	120	164
	II	225&	273&	120	156	292&	273&	300&	264&
Expt. 4	I	222	190	325&	289&	159	190	145	181
	II	251&	315&	165	205	350&	315&	365&	325&

Note: 1. In Experiments 3 and 4, W* and R* were replaced by G and R, respectively.
2. & Indicates the predicted price and allocation under the specified individuating information and model of information processing.

which interpretation is to be adopted, we use both in the following discussion and label them the NBR1 model and NBR2 model, respectively.

According to the NBR1 model, subjects will only look at the outcome of the second draw (i.e., W^* or R^*) to infer the state of nature. Specifically, if the outcome of the second draw is W^*, subjects will infer that the state of nature is W. If, on the other hand, the outcome of the second draw is R^*, subjects will infer that the state of nature is R with certainty.

Under each state of nature, different types of traders have different preferences for the securities. Those receiving higher dividends will bid a higher price to the extent that the price is not greater than the dividends. Thus, supplemented with the standard principles of demand and supply in competitive conditions, this model predicts that the equilibrium price will be 150 francs, and that the securities will be held by type I traders, if the outcome of the second draw is W^*. On the other hand, this model predicts that the equilibrium price will be 230 francs, and that the securities will be held by type II traders, if the outcome of the second draw is R^* (see numbers marked & in Table 3).

According to the NBR2 model, the base rates are treated as if they are diffuse: $P(W) = P(R) = \frac{1}{2}$. Given the diffuse priors and the diagnosticity of individuating data, subjects' posterior probabilities would be $P(W/W^*) = 0.80$, $P(R/W^*) = 0.20$, $P(W/R^*) = 0.20$, and $P(R/R^*) = 0.80$.

If the subjects are assumed to be risk-neutral expected-utility maximizers, predictions of this model can be obtained by using expected payoffs as reservation prices to construct the demand and supply functions. The expected payoffs are summarized in Table 3. This model supplemented by the principles of demand and supply predicts that the equilibrium price will be 160 francs and that the securities will be held by type I traders, if the individuating information is W^*. If, on the other hand, the individuating information is R^*, this model predicts that the equilibrium price will be 192 francs, and that the securities will be held by type II traders.

The price and allocation predictions of all four models discussed above are marked by & in Table 3.

Conditions Under Which Base Rates May be Utilized

In addition to the four quantified models of information processing mentioned above, the data we collected pertain to several qualitative ideas in the literature: extremity of base rates, experience of subjects, and confusion among signals and states of nature."[11]

The Base-Rate Extremity Argument. Kahneman and Tversky [1973] suggested that base rates might be used in a Bayesian manner when they are extreme. Studies which directly manipulated the extremity of base rates yielded equivocal results [Wells and Harvey, 1975; Lyon and Slovic, 1976]. We used three different base rates: (0.35, 0.65), (0.25, 0.75) and (0.15, 0.85) to test the Kahneman and Tversky's [1973] hypothesis that when the subjects are given extreme base rates, the observed behavior is more Bayesian.

The Experience Argument. We hypothesize that the behavior of subjects who have had prior experience with the experimental task will be closer to the Bayesian prediction than the behavior of the inexperienced subjects. The market environment provides a supportive environment for learning.

The Confusion Argument. This argument concerns the experimental design. One might argue that if the designation of the state of nature (the outcome of the first draw) is similar to that of the signal (the second draw), subjects would be confused and therefore behave less normatively. To test this hypothesis, in the first two experiments, outcomes of the two draws were given similar designations (W and R for the first draw, W* and R* for the second), but in the last two experiments, they were designated differently (Y and X for the first draw, G and R for the second).

RESULTS AND DISCUSSION

Comparisons of the Four Models of Behavior

Three aggregate manifestations of market behavior, security allocations, transaction prices and profit distributions, are employed to infer the ability of the four models to predict market behavior.

The ability of each model to predict the allocation of securities is measured by comparing the identity of actual buyers to the identity of the traders predicted to be buyers by that model, and by comparing the identity of the actual sellers to the identity of the traders predicted to be sellers by that model. For example, if a model predicts type I traders to be buyers and type II traders to be sellers under a given signal, the following comparisons are made and scored:

Actual trade	Consistency of Buyer	Consistency of Seller	No. of Comparisons Consistent with the model
Type I buys Type II sells	yes	yes	2
Type I buys Type I sells	yes	no	1
Type II buys Type II sells	no	yes	1
Type II buys Type I sells	no	no	0

Table 4 shows the number of comparisons which are consistent with each of the four models. Overall, the NBR1 and NBR2 models predict best (915 out of 1104 are consistent comparisons), followed by the Bayesian model (793 consistent comparisons), and a distant fourth, the BRO model (719 consistent comparisons). When the signal information is R* (or R), three models (NBR1, NBR2 and Bayesian) predict equally well (651 out of 762 are consistent comparisons) and are better than the BRO model (641 consistent comparisons). When the signal information is W* (or G), the NBR1 and NBR2 models predict best (264 out of 342 are consistent comparisons), followed by the Bayesian model (142 consistent comparisons), and the BRO model (78 consistent comparisons).

Transaction prices in the four markets are given in Figures 2-5. For markets 2, 3 and 4, prices move around the Bayesian and NBR1 predictions when the individuating information is R* (or R). When the individuating information is W* (or G) prices move around the Bayesian and NBR2 (NBR1 in market 2) predictions. Market 1 had so few transactions that no clear trend can be discerned.

TABLE 4

Number of Comparisons on Security Transactions Consistent With Each of the Four Models

Experiment	Signal Info.	Total No. of Comparisons	No. of Comparisons Consistent With Bayesian	BRO	NBR1	NBR2
	W*	24	12	12	12	12
1	R*	34	22	12	22	22
	Total	58	34	24	34	34
	W*	100	82	18	82	82
2	R*	248	212	212	212	212
	Total	348	294	230	294	294
	G	80	17	17	63	63
3	R	196	176	176	176	176
	Total	276	193	193	239	239
	G	138	31	31	107	107
4	R	284	241	241	241	241
	Total	422	272	272	348	348
Combined-all periods	W*(G)	342	142	78	264	264
	R*(R)	762	651	641	651	651
	Total	1104	793	719	915	915
Combined-last period	W*(G)	92	39	21	79	79
	R*(R)	86	78	76	78	78
	Total	178	117	97	157	157

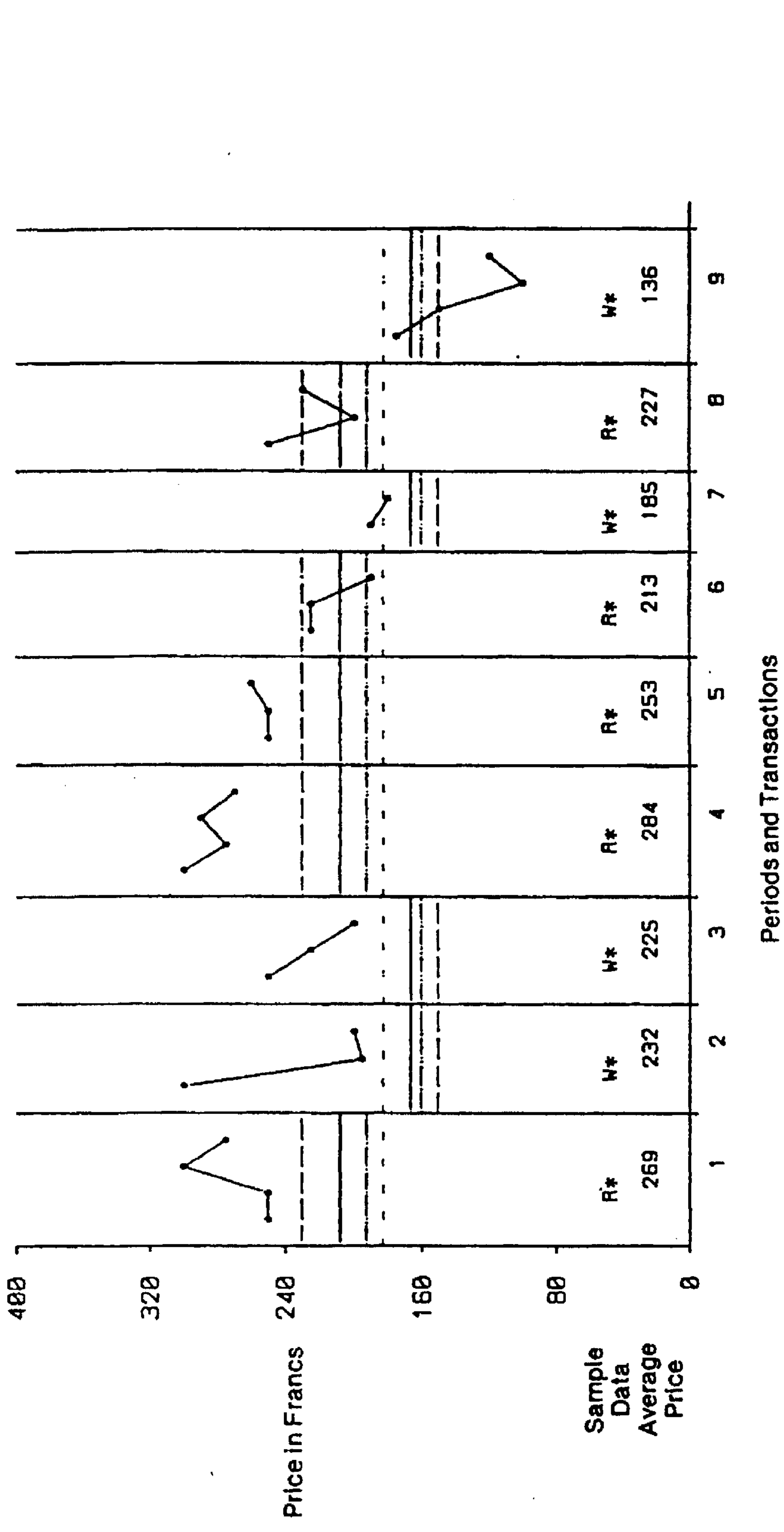
Note: Data for periods 1 and 2 in Experiment 2 are excluded.

To test the ability of the four models to predict transaction prices, mean absolute deviations of actual prices from the predicted prices were calculated and Wilcoxon signed-rank tests were conducted [Conover, 1980].[12]

Table 5 provides Wilcoxon signed-rank statistics and the results. Overall, the Bayesian model predicts best, followed by the NBR2 and NBR1 models, and distant fourth, the BRO model. When the individuating information is R* (or R), the Bayesian model predicts best, followed by the NBR1 and NBR2 models, and the BRO model predicts poorest. When the individuating information is W* (or G), the Bayesian model predicts best, followed by the NBR2 and NBR1 models, and the BRO model poorest. But the difference between the Bayesian and the NBR2 models, and that between the Bayesian and the NBR1 are not statistically significant ($\alpha = .10$).

The ability of each model to predict the distribution of profits is measured by comparing the average actual profit made by investers in each class with the average theoretical profit predicted by that model for the members of that class under the realized signal and the state of nature.

FIGURE 2
Transaction Prices
Market No. 1



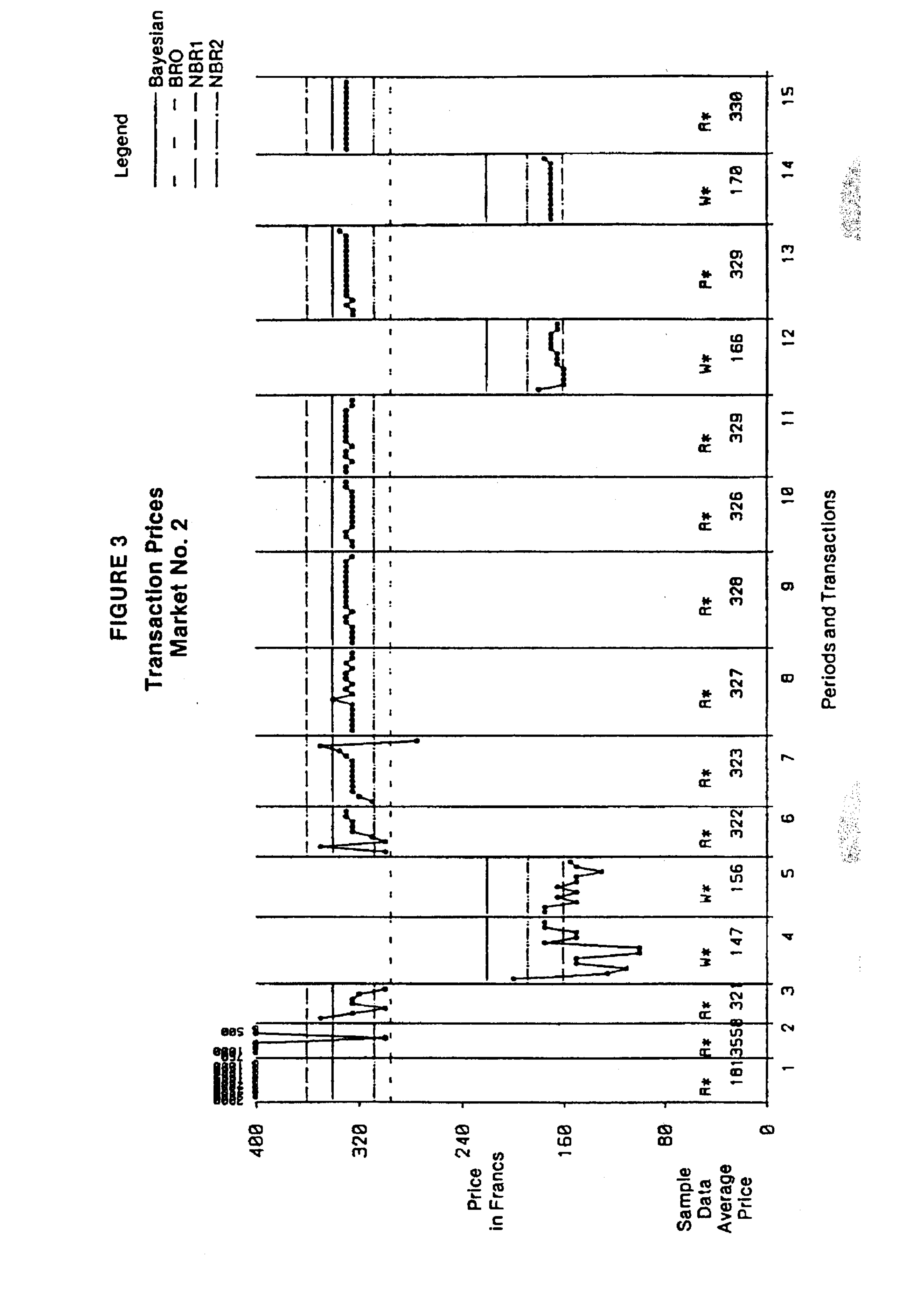


FIGURE 3
Transaction Prices
Market No. 2

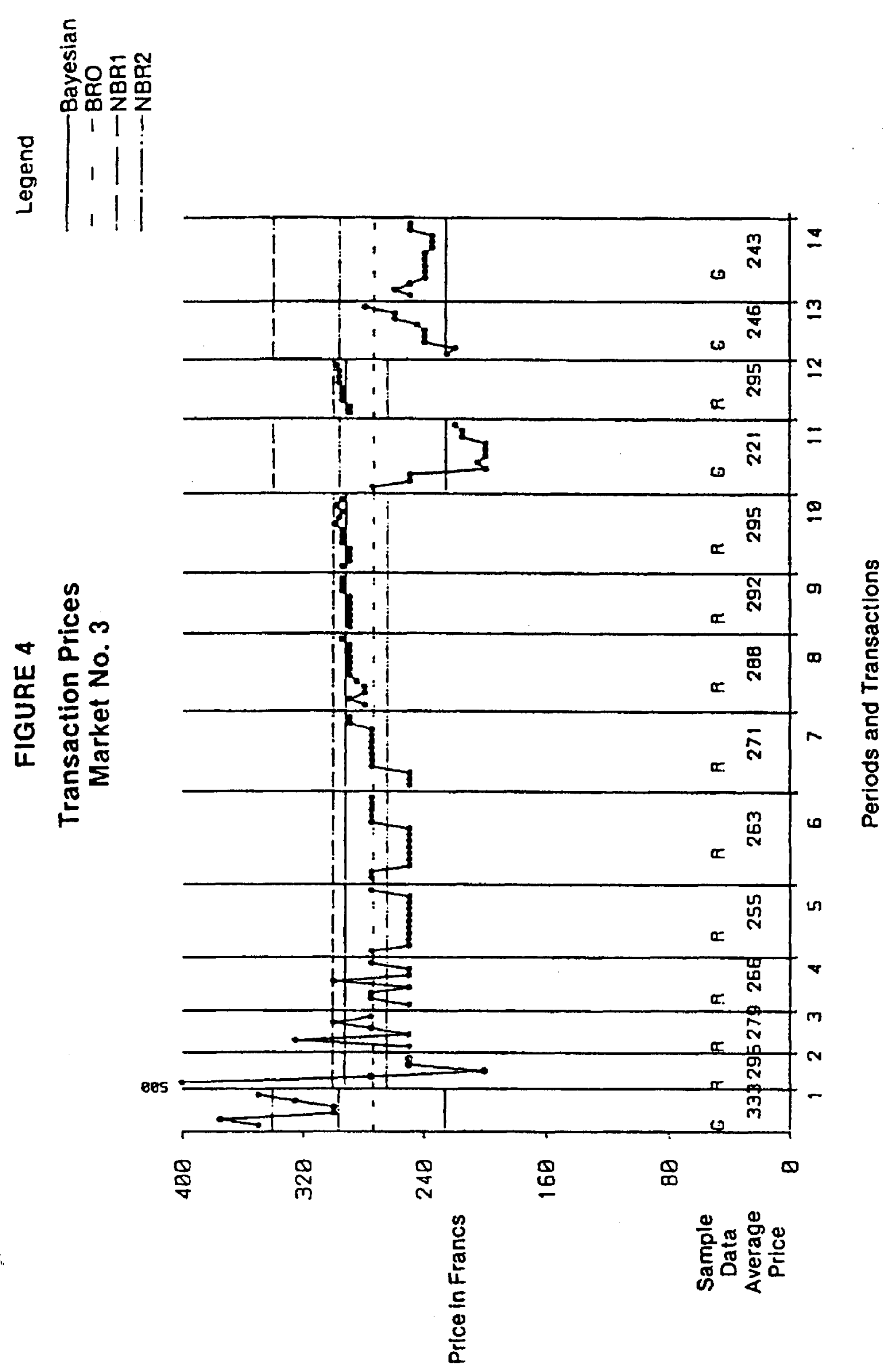


FIGURE 4
Transaction Prices
Market No. 3

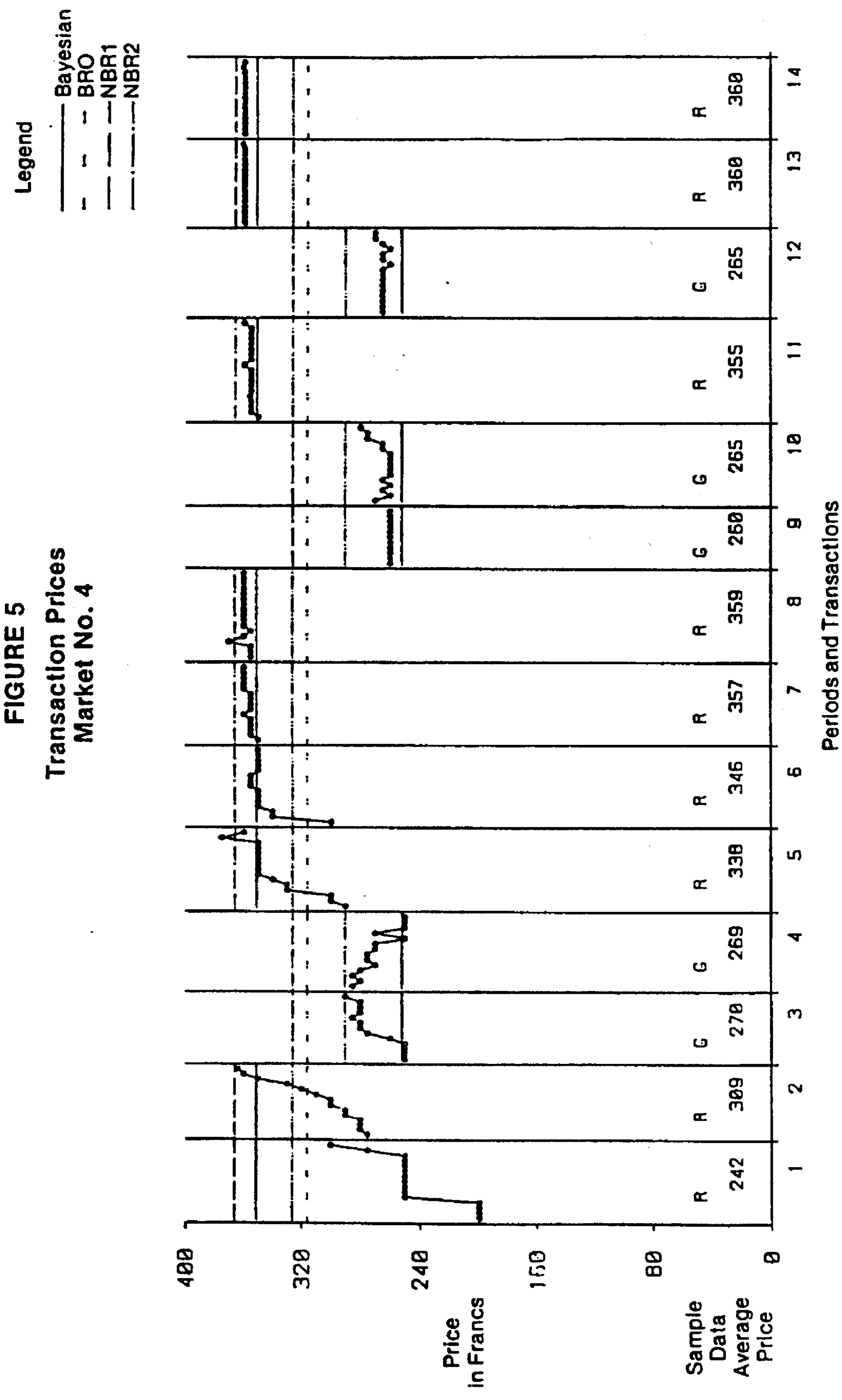


FIGURE 5
Transaction Prices
Market No. 4

TABLE 5

Wilcoxon Signed-Rank Statistics—Mean Absolute Deviations of Actual Prices from Model-Predicted Prices

	T(a-b)	T(a-c)	T(a-d)	T(b-c)	T(b-d)	T(c-d)
Expt. 1 Overall	-1.25	0.89	-2.57##	0.89	-0.18	-1.25
W*	1.46	-1.47	-1.51	-1.47	-0.73	1.51
R*	-2.06##	-2.06##	-2.06##	2.06##	2.24##	-2.06##
Expt. 2 Overall	-3.19##	0.04	-0.38	1.22	3.20##	1.71#
W*	-2 ##	1.83#	1.89#	1.82#	1.89#	-1.10
R*	-2.67##	-2.75##	-2.07##	-0.65	2.71##	2.67##
Expt. 3 Overall	0.46	-2.48##	-0.97	-1.66#	-1.75#	1.60
W*	-0.36	-0.73	-0.37	-1.47	-0.55	1.51
R*	0.46	-2.80##	-0.45	-1.27	-1.72#	0.66
Expt. 4 Overall	-3.19##	-2.60##	-3.31##	0.47	2.87##	1.41
G	-2.02##	-2.02##	-1.75#	-2.12##	2.12##	2.06##
R	-1.98##	-1.36	-1.98##	1.25	1.83#	-0.89
Combined-all periods						
Overall	-4.06##	-2.27##	-1.92#	0.65	3.13##	1.32
G	-2.15##	-1.38	-0.46	-0.02	2.30##	2.35##
R	-3.35##	-2.21##	-2.25##	1.38	3.48##	-0.41
Combined-last period						
Overall	-2.52##	-0.42	-1.40	1.26	1.54	0
G	-1.83#	-0.73	-0.36	0.36	1.46	0.73
R	-1.83#	0	-1.83#	1.83#	1.09	-1.46

Note: 1. a = Bayesian; b = BRO; c = NBR1; and d = NBR2

2. #: significant at α = .10, ##: significant at α = .05.

3. The general form of conducting hypothesis testing: HO: d = 0 and H1: d ≠ 0.

where d denotes the difference in mean absolute deviations between a pair of models.

Table 6 presents the statistics and results of Wilcoxon signed-rank tests to compare the ability of the four models to predict the distribution of profits. Overall, the NBR2 model predicts best followed by the Bayesian and NBR1 models, the BRO model predicts poorest. When the individuating information is R*(R), the Bayesian model predicts best, followed by the NBR2 and BRO models; the NBR1 model predicts the poorest. When the individuating information is W* (G), the NBR2 model predicts best, followed by the NBR1 and Bayesian models, the BRO model predicts poorest.

The above observations and statistical analyses were conducted using data for all the periods. Because of the importance of learning in experimental markets, data of the last period in which W* (G) or R* (R) occurs are analyzed in the bottom panels of Tables 4, 5 and 6. Overall, the NBR1 and NBR2 models predict security transactions best (157 out of 178 are consistent comparisons), the Bayesian model next (117 consistent comparisons), and the BRO model predicts poorest (97 consistent comparisons). When the signal is R* (R), the NBR1, NBR2 and Bayesian models predict equally well (78 out of 86 are consistent comparisons) and are better than the BRO model (76 consistent comparisons). When the signal is W* (G), the NBR1 and NBR2 models predict best (79 out of 92 are consistent comparisons), the Bayesian model next (39 consistent comparisons) and the BRO model predicts poorest (21 consistent comparisons). This result is essentially the same as the result obtained from the data for all periods.

When the individuating information is R* (R), the Bayesian and NBR1 models predict transaction prices best, the NBR2 model next, and the BRO model poorest. When the individuating information is W* (G), the Bayesian model predicts best, followed by the NBR2 and NBR1 models, the BRO model predicts poorest. Overall, the Bayesian model predicts best, followed by the NBR1 and NBR2 models, the BRO model predicts poorest. The result is similar to the previous one except that when the individuating information is R* (R), the NBR1 model is no longer poorer than the Bayesian model.

When the signal is R* (R), the Bayesian model predicts profit distributions best, followed by the NBR1 and NBR2 models, and the BRO model predicts poorest. The difference between the Bayesian and the NBR1 model is not statistically significant ($\alpha = .10$). When the signal is W* (G), the NBR2 model predicts best, followed by the NBR1 and Bayesian models, the BRO model predicts poorest. Overall, the NBR2 and NBR1 models predict profit distributions best, the Bayesian model next, and the BRO model poorest. The result is different from the previous in that, overall, the Bayesian model does not predict better than the NBR1 model. Again, the results using profit distributions are different from those using transaction prices, especially when the signal is W* (G).

The choice data gathered in the training part of the experiments conducted to familiarize the subjects with the stochastic mechanism to determine the state of nature and the signal (see Instruction Set 1 in the Appendix) were also analyzed. In Experiments 1, 2 and 4, the choice predictions of the Bayesian, NBR1 and NBR2 models were identical and the data supported these predictions over the predictions of the BRO model. In Experiment 3, the data supported the predictions of the NBR1 and NBR2 models over the predictions of the Bayesian and BRO models.

TABLE 6

Wilcoxon Signed-Rank Statistics—Mean Absolute Deviations of Actual Profits from Average Model-Predicted Profits

	T(a-b)	T(a-c)	T(a-d)	T(b-c)	T(b-d)	T(c-d)
Expt. 1 Overall	-0.53	1.43	-1.25	1.31	0.06	-1.84#
W*	-1.47	1	1.51	1.51	1.51	-0.38
R*	0.13	0.94	-2.06##	0.54	0.94	-1.75#
Expt. 2 Overall	-2.06##	-2.63##	0.73	0.87	2.69##	2.83##
W*	-1.76#	-0.67	0.94	1.75#	1.75#	1.75#
R*	-0.98	-2.41##	-0.28	-0.84	1.96#	2.03##
Expt. 3 Overall	0.81	-0.66	1.42	0.16	0.73	1.92#
G	1.13	1.83#	1.83#	1.46	1.83#	1.89#
R	0.36	-2.74##	-0.28	-1.38	-1.50	0.56
Expt. 4 Overall	-1.28	1.01	1.52	1.79#	2.83##	1.44
G	0	2.02##	2.02##	2.02##	2.02##	1.89#
R	-1.28	-1.83#	-0.73	0.17	1.81#	0.18
Combined-all periods						
Overall	-1.96#	-0.75	1.78#	2.23##	3.82##	2.78##
W*(G)	-1.24	2.48##	3.29##	3.28##	3.59##	2.35##
R*(R)	-1.24	-3.76##	-1.10	-0.48	1.00	0.54
Combined-last period						
Overall	-1.78##	1.12	0.42	2.52##	2.10##	0.70
W*(G)	-0.53	1.82#	1.82#	1.82#	1.82#	1.46
R*(R)	-1.82#	-1.09	-1.82#	1.82#	0.73	-0.73

Note: 1. a = Bayesian; b = BRO; c = NBR1; and d = NBR2.
2. #: significant at α = .10, ##: significant at α = .05.
3. The general form of conducting hypothesis testing: HO: d = 0 and H1: d ≠ 0
where d denotes the difference in mean absolute deviations between a pair of models.

In summary, the analysis using all-period and last-period data seem to support the following conclusions (see Table 7). In terms of predictability on security transactions, the NBR1 and NBR2 models are best, and the BRO model is the poorest among the four models. In terms of price and profit predictability, the Bayesian model seems the best, and the BRO model poorest when the individuating information is R* (R). But, when the individuating information is W* (G), these two measures lead to different results. Because the profit distribution incorporates both security allocations and transaction prices, and leads to the same conclusions as security allocations do, we conclude that when the individuating information is W* (G) the NBR2 model predicts best among the four models.[13]

Qualitative Hypotheses

The Extremity Hypothesis. To test the base-rate extremity hypothesis, we compare the results of Experiment 1 (Base rates: 0.35, 0.65) with those of Experiment 2 (0.25, 0.75). Results of Experiments 2 and 3 (0.15, 0.85) are also compared.

In terms of predictability of security transactions, results of Experiments 1 and 2 are essentially the same (see Table 4). The Bayesian model does not predict better than the NBR1 and NBR2 models when the base rates become more extreme. A comparison of results from Experiment 2 with those from Experiment 3 shows that the Bayesian model predicts even worse when the base rates become more extreme.

In terms of predictability of transaction prices, the effect of base-rate extremity is mixed (see Table 5). A comparison of Experiment 1 with Experiment 2 suggests that when base rates are more extreme, the Bayesian model performs better relative to the other three models, given that the individuating information is R*; however, the Bayesian model performs worse if the individuating information is W*. Comparing Experiment 2 with Experiment 3 indicates a different result. When the base rates are more extreme, the Baysian model improves relative to the other three models, given that the individuating information is W* (G); and has no improvement when the sample data is R* (R).

In terms of profit distribution, when the base rates are changed from 0.65 to 0.75, the Bayesian model does not improve given either R* or W*. When the base rates are changed from 0.75 to 0.85, the Bayesian model becomes poorer than the NBR1 and NBR2 models given W* (G), and has no improvement given R* (R) (see Table 6).

In summary, the above analysis does not support the hypothesis that people may be more Bayesian when the base rates are extreme.

The Experience Hypothesis. To test the experience hypothesis, Experiments 2 and 4 were conducted with the same base rates but different subjects: inexperienced with the experimental task in the former and experienced in the latter.

The results of these two experiments are different in that the Bayesian model predicts security transactions poorer when the subjects are experienced (3 percent) than when subjects are inexperienced (72 percent), given the individuating information is W* (G).

Analysis of the price data indicates that, relative to the other three

TABLE 7

Ranking of Models by Prediction Criteria

	Transactions	Prices	Profit Distribution
All Observations			
Overall	NBR1&2>Bay>BRO	Bay>NBR1&2>BRO	NBR2>Bay,NBR1>BRO
Signal W*(G)	NBR1&2>Bay>BRO	Bay,NBR1&2>BRO	NBR2>NBR1,Bay>BRO
Signal R*(R)	NBR1&2,Bay>BRO	Bay>NBR1&2>BRO	Bay>NBR2,BRO>NBR1
Last Occurrence of each signal			
Overall	NBR1&2>Bay>BRO	Bay>NBR1&2>BRO	NBR2&1,Bay>BRO
Signal W*(G)	NBR1&2>Bay>BRO	Bay,NBR1&2>BRO	NBR2>NBR1,Bay>BRO
Signal R*(R)	NBR1&2,Bay>BRO	Bay,NBR1>NBR2>BRO	Bay>NBR1&2>BRO

models, the experienced subjects behave more Bayesian than the inexperienced subjects no matter what the individuating information is. Comparisons of the profit yield a different result. When the individuating information is G, the experienced subjects behave less Bayesian than the inexperienced.

In summary, the above analysis does not provide clear evidence in favor of the experience hypothesis.

The Confusion Hypothesis. To test whether subjects are confused in the first two markets, the combined data of Experiments 1 and 2 are compared with the combined data of Experiments 3 and 4.

In the first two markets, the Bayesian model predicts as well as the NBR1 and NBR2 models do. When the signal information is R*, 234 out of 282 comparisons are consistent with the three models. When the signal information is W*, 94 out of 124 comparisons are consistent with the three models. Overall, 328 out of 406 comparisons are consistent with the three models. In the last two markets, the Bayesian model predicts as well as the NBR1 and NBR2 models do (417 out of 480 are consistent comparisons) when the signal information is R. But, the Bayesian model predicts poorer (48 out of 218 are consistent comparisons) than the NBR1 and NBR2 models do (170 consistent comparisons) when the signal information is G. Overall, 465 out of 698 comparisons are consistent with the Bayesian model, and 587 comparisons are consistent with the NBR1 and NBR2 models.

The price data suggest that, compared to the other three models, the Bayesian model predicts better in the last two experiments than in the first two experiments, especially when the individuating information is W* (G). However, the profit distribution data indicate just the opposite: when the individuating information is W* (G), the Bayesian model performs worse than before.

In summary, the above analyses, at best, provide equivocal evidence for supporting the confusion hypothesis.

Discussion

The results of the four experiments suggest that the observed market behavior is closer to the Bayesian model than the other three models, especially when the individuating information is R* (R). The results of the four markets provide some supportive evidence for the proposition that individuals will learn the normative rule over time through incentives and interactions with the environment.

However, this position cannot be taken too far. Although the Bayesian model performs best among the four models in its ability to predict transaction prices, the observed market behavior still deviates from the Bayesian prescription. The Bayesian model is noticeably weaker in predicting security transactions when the individuating information is W* (G). This leads to two conjectures: (1) in general, the subjects might have used a heuristic which may approximate the Bayesian model but requires less cognitive capacity, and (2) the degree of learning is different under different individuating information.

The first conjecture is similar to the position taken by many psychologists. Because of cognitive limitations of human beings and cognitive demands of the Bayesian rule, the subjects might have used some satisficing rather than normative rule to make decisions [Simon, 1981]. Therefore, the observed market behavior does not exactly conform to the Bayesian prediction.

The second conjecture concerns the relative frequency of occurrence of signals W* (G) and R* (R). Because the base rate of W (or Y) has been lower than that of R (or X) and the positive hit rate has been kept at 0.80, P(W*) [or P(G)] was less than P(R*) [or P(R)] in all four markets. Thus, the subjects experienced, and perhaps learned, more about R* (R) than about W* (G) occurrence. Consequently, the advantage that the Bayesian model has in predicting market behavior under R* (R) is diminished or reversed under W* (G). Given equal amounts of experience with trading under W* (G), this conjecture would hold that the Bayesian model would do just as well as it did under R* (R). This conjecture could be tested by using equal base rates. However, the use of equal base rates would eliminate the distinction between the predictions of the Bayesian and the NBR2 models.

Finally, there are several remarks on the experimental design and implications for future studies:

(1) In the above experiments, subjects were assumed to be risk neutral. It would be desirable to control subjects' risk attitude. Berg et al's [1983] risk-preference inducing mechanism may be used for this purpose.

(2) The purpose of conducting training sessions is to make subjects familiar with the chance mechanism. To determine if training sessions have any effect on market trading behavior (other than familiarization with the chance mechanism), an experiment without training sessions should be conducted.

(3) Bayes' theorem has been considered as a way of revising subjective beliefs (in terms of prior probabilities) by incorporating additional information into decisions [Winkler, 1972]. In the base-rate fallacy literature, subjects are often given particular prior probabilities. Researchers assume that subjects will take the given (objective) priors as their own subjective beliefs regardless of whether or not the given priors are consistent with the subjects' own.[14] This may contribute to the phenomenon of base-rate fallacy when subjects have strong beliefs on the case under study and when their beliefs are different from those given to them. In our study, the base rates were objective and explicitly defined by the proportions of balls of various colors.

(4) With the exception of Grether [1980], little attention has been paid in the base-rate fallacy literature to designing a metric for measuring how much weight people place on base rates versus the individuating information. Grether used logit (probit) analysis to estimate the coefficients for each type of information. Comparing the Bayesian-predicted coefficients with the estimated coefficients, he was able to determine whether people underutilize base rates. The applicability of this or other similar metrics to the market environment is under study.

NOTES

[1]Also see Hogarth [1981].

[2]Herbert Simon [1955, 1981] is an exception.

[3]Camerer [1985] is another study on similar lines.

[4]In most accounting studies, subjects were expert auditors. It seemed reasonable to assume that for these subjects learning had already occurred. Choice of experts over student subjects is often motivated by the researcher's desire to by-pass the learning process.

[5]The effect of competitive pressure on integration of base-rate information is not available in the psychology literature. One might regard competitive pressure as a motivational factor for improving performance [cf. Broadbent, 1971]. On the other hand, one might look at competitive pressure as a stressor which would be detrimental to task performance because of cognitive overload [cf. Cohen, 1978]. Furthermore, one might argue that the presence of coactors might lead to social facilitation [see Zajonc, 1965; Martens and Landers, 1972; Bond and Titus, 1983]. Whatever argument is adopted, its applicability to the market setting is not clear because of (1) the way that stress is defined and (2) the tasks that subjects perform are different.

[6]An oral double auction is conducted as follows. After the market opens an auction for a unit of certificate begins with the announcement of a price bid by any buyer or a price offer by any seller. Any subsequent bid (offer) must be higher (lower) than the previous one. Once a bid offer has been made public, it cannot be withdrawn. A binding contract occurs when any buyer (seller) accepts the offer (bid) of any seller (buyer). The auction ends with a contract. Following a contract a new auction begins when a new bid (offer) is announced. The new bid (offer) may be at any level. This process continues until a prespecified amount of time has elapsed and the market period ends.

[7]Diagnosticity of datum is represented by the likelihood ratio. If the ratio is different from one, the datum is called "diagnostic" [see Fischoff and Beyth-Marom, 1983]. In statistical terms:

$$\frac{P(H/D)}{P(\overline{H}/D)} = \frac{P(D/H)}{P(D/\overline{H})} \cdot \frac{P(H)}{P(\overline{H})} \quad \text{i.e.,} \quad \begin{array}{c}\text{Posterior}\\ \text{odds}\end{array} = \begin{array}{c}\text{Likelihood}\\ \text{ratio}\end{array} \times \begin{array}{c}\text{Prior}\\ \text{odds}\end{array}$$

where H denotes hypothesis

$\overline{H}$ denotes the complement of H

D denotes datum

[8]Thirteen periods of training in Experiment 1, seventeen periods in Experiment 2, thirteen periods in Experiment 3 and six periods in Experiment 4 were conducted.

[9]A few subjects did earn negative profits for single periods. But the total profit of every subject in every experiment was comfortably positive.

[10]In one of Joyce and Biddle's [1981] experiments, subjects were asked to assess the posterior probability that a key manager who received a "fraud" test signal was actually involved in fraudulent activities. The base rate of fraud, the positive hit rate, and the false positive rate were 0.01, 0.80, and 0.04, respectively. That is $P(H) = .01$, $P(D/H) = .80$, $P(D/\overline{H}) = .04$. According to Bayes theorem,

$$P(H/D) = \frac{P(D/H)\,P(H)}{P(D/H)\,P(H) + P(D/\overline{H})\,P(\overline{H})}$$

$$= \frac{.80 \times .01}{(.80 \times .01) + (.04 \times .99)} = .168$$

However, according to the NBR2 model, P(H) is replaced by the diffuse base rate and therefore

$$P(H/D) = \frac{.80 \times .50}{(.80 \times .50) + (.04 \times .50)} = .952$$

[11]The relevancy argument is not tested because the market is operationalized such that the dividends of securities are dependent on the base rates of the states of nature. It is clear that the base rates are relevant to the task under consideration. The saliency argument is not tested because both the base rates and the individuating information are presented to the subjects in operational terms and they appear to be equally salient.

[12]As can be seen from Figure 3, the subjects clearly had a misunderstanding about dividends in periods 1 and 2. The data for these periods in Experiment 2 are excluded.

[13]We discount the fact that when only last-period data are analyzed, the NBR1 model is better than the NBR2 model given W^* (G), because the prices converge to the NBR2 model.

[14]In Kahneman and Tversky's [1973] "profession" study, subjects seemed to accept the given priors as their own.

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APPENDIX

Instruction Set 1

At the beginning of each year we will draw a ball from a bingo cage containing twenty balls numbered one through twenty. If the ball drawn is number one through thirteen, outcome of the draw is called "Red" (R); if the ball drawn is number fourteen through twenty, the outcome is called "White" (W). This outcome is not announced to you until you make a decision on the Decision Sheet.

In order to help you with your decision, each period you will receive a clue as to which event (W or R) occurred. If the ball drawn from the first bingo cage is red (R), we will go to a second bingo cage which has 16 red balls and 4 white balls. A draw from this cage is made and announced to you.

If, on the other hand, the ball drawn from the first bingo cage is white (W), we go to a second bingo cage which has 16 white and 4 red balls. A draw is made from this bingo cage and announced to you.

Note that in each case two balls are drawn from two bingo cages. The first bingo cage is the same for all periods, and draw from the first bingo cage determines which of the other two cages is chosen for the second draw. The second cage chosen has 16 balls of the same color as the color of the first draw. There are only two possible colors—white and red and you learn only the outcome of the second draw.

You have to guess the outcome of the first draw in each period before it is announced. If your decision is correct, you win $0.25; if wrong, you lose $0.10. Before the outcome of the first draw is announced, record your decision by circling either W or R in the first row of the Decision 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 table. If your decision is correct, circle the amount shown in the Win Column, otherwise circle the amount in the Lose Column.

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

Instruction Set 2

General: This is an experiment in the economics of market decision making. The instructions are simple, and if you follow them carefully and make good decisions, you might earn a considerable amount of money which will be paid to you in cash.

In this experiment we are going to have a market in which you will buy and sell certificates in a sequence of market years. Attached to the instructions you will find a sheet, labeled Information and Record Sheet, which helps determine the value to you of any decisions you might make. You are not to reveal this information to anyone. It is your own private information.

The type of currency used in this market is francs. All trading and earnings will be in terms of francs. Each franc is worth $0.003 to you. At the end of the experiment your francs will be converted to dollars at this rate, and you will be paid in dollars. Notice that the more francs you earn, the more dollars you earn.

Specific Instructions: Your profits come from two sources—from collecting certificate earnings on all certificates you hold at the end of the year *and* from buying and selling certificates. During each market year you are free to purchase or sell as many certificates as you wish, provided you follow the rules below. For each certificate you hold at the end of the year you will be given one of the two numbers of francs listed in the margin of your Information and Record Sheet. Note that earnings may be different for different investors. The method by which one of the two numbers is selected each year is explained later in these instructions. Compute your total certificate earnings for a period by multiplying the earnings per certificate by the number of certificates held. That is, (number of certificates held) x (earnings per certificate) = total certificate earnings. Suppose for example that you hold five certificates at the end of year one. If for that year your earnings are one hundred francs per certificate (that is, the number selected from the margin of your information and record sheet is 100) then your total certificate earnings in the year would be 5 × 100 = 500 francs. This number should be recorded on row 26 at the end of the year.

Sales from your certificate holdings increase your francs on hand by the amount of the sale price. Similarly, purchases reduce your francs on hand by the amount of the purchase price. Thus you can gain or lose money on the purchase and resale of certificates. After calculating your profits at the end of each year all your holdings are automatically sold to the experimenter at a price of zero.

At the beginning of each year you are provided with an initial holding of certificates. This is recorded on row 0 of the year's information and record sheet. You may sell these if you wish or you may hold them. If you hold a certificate, then you receive "earnings per certificate" at the end of the year. Notice therefore that for each certificate you hold you can earn *at least* the amount shown as "earnings per certificate." You earn this amount if you do not sell that certificate during the year.

In addition, at the beginning of each year you are provided with an initial amount of francs on hand. This is also recorded on row 0 of each year's information and record sheet. You may keep this if you wish or you may use it to purchase certificates.

Thus at the beginning of each year you are endowed with holdings of certificates and francs on hand. You are free to buy and sell certificates as you wish according to the rules below. Your francs on hand at the end of the year are determined by your initial amount of francs on hand, earnings on certificate holdings at the end of the year, and by gains and losses from purchases and sales of certificates. All francs on hand at the end of a year in excess of 10,000 francs are yours to keep.

Information About Dividends: Whether the dividend you receive from the certificates you hold is the W dividend or R dividend, shown in the margin of your Information and Record Sheet, is determined by the outcome of the first draw of each year. At the beginning of each year we draw a ball from a bingo cage containing twenty balls numbered one through twenty. If the ball drawn is number one through thirteen, the outcome of the draw is called "Red" (R); "White" (W). This outcome is not announced to you until the end of the trading for the period.

If the ball drawn from the first bingo cage is red, we go to a second bingo cage which has sixteen red balls and four white balls. A draw from this cage is made and announced to you.

If, on the other hand, the ball drawn from the first bingo cage is white, we go to a second bingo cage which has sixteen white and four red balls. A draw is made from this bingo cage and announced to you.

Note that in each case two balls are drawn from two bingo cages. The first bingo cage is the same for all periods, and the draw from the first cage determines which of the other two cages is chosen for the second draw. The second cage chosen has 16 balls of the same color as the color of the first draw. There are only two possible colors—white and red and you learn only the outcome of the second draw.

Trading and Recording Rules:

(1) All transactions are for one certificate at a time. After each of your sales or purchases you

must record the TRANSACTION PRICE in the appropriate column depending on the nature of the transaction. The first transaction is recorded on row (1) and succeeding transactions are recorded on subsequent rows.

(2) After each transaction you must calculate and record your new holdings of certificates and your new francs on hand. Your holdings of certificates may never go below zero. Your francs on hand may never go below zero.

(3) At the end of the year record your total certificate earnings in the last column of row 26. Compute your end of period totals on row 27 by listing certificate holdings and adding total certificate earnings to your francs on hand.

(4) At the end of the year, subtract from your francs on hand the amount listed in row 28 and enter this new amount on row 29. This is your profit for the market year and is yours to keep. At the end of each market year, record this number on your Profit Sheet.

(5) At the end of the experiment add up your total profit on your profit sheet and enter this sum on row 21 of your profit sheet. To convert this number into dollars, multiply by the number on row 22 and record the product on row 23. The experimenter will pay you this amount of money.

Market Organization: The market for these certificates is organized as follows. The market will be conducted in a series of years. Each period lasts for five minutes. Anyone wishing to purchase a certificate is free to raise his or her hand and make a verbal bid to buy one certificate at a specified price, and anyone with certificates to sell is free to accept or not accept the bid. Likewise, anyone wishing to sell a certificate is free to raise his or her hand and make a verbal offer to sell one certificate at a specified price. Any subsequent bid (offer) must be at a higher (lower) price to be admissible. If a bid or offer is accepted, a binding contract has been closed for a single certificate, and the contracting parties will record the transaction on their information and record sheets. Any ties in bids or acceptance will be resolved by random choice. Except for the bids and their acceptance you are not to speak to any other subject. There are likely to be many bids that are not accepted, but you are free to keep trying. You are free to make as much profit as you can.