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The Market Value of Information: Some Experimental Results*

I. Introduction

A rational individual values information to the extent that the expected utility he or she obtains from making an optimal informed decision exceeds the expected utility obtained from an optimal uninformed decision. In a competitive economy the market value of a message that can be privately purchased is the monetary equivalent of its information value to a marginal individual. This much is conceptually straightforward. Matters become interesting when the trading behavior of an individual purchasing the message may partially or fully reveal its contents to nonpurchasers, as may be the case in competitive asset markets.

Unfortunately, it is difficult to obtain direct empirical evidence on the extent to which private information is revealed in ongoing asset markets, since by its very nature private information is not observable by the econometrician. In contrast, laboratory experimental techniques in economics (e.g., Smith 1976, 1982; Plott 1982) allow the

We examine the price and allocation of purchased information and of the underlying asset in eight double-auction asset market experiments. Observed outcomes support fully revealing rational expectations in simple environments in which uninformed traders can easily infer the private information of informed traders but support nonrevealing rational expectations in more complex environments. The private value of information is positive in the more complex (noisy) environments, but competition forces the information price to its Nash equilibrium value, and the net gain by purchasers is approximately zero.

creation of an asset market in which the timing and content of private information (purchased or not) can be observed and controlled. Constraints on research budgets dictate that fewer traders participate over shorter time periods in laboratory markets than in major ongoing markets in the field, but budgets certainly allow traders to be experienced and profit motivated.

This article investigates the market value of information in an experimental asset market. Three theories of equilibrium behavior are used to predict the value of information. Their predictions differ, so comparisons to observed outcomes shed light on trader behavior. The first theory, which we call *fully revealing rational expectations* (FRE), assumes strong-form informational efficiency in the Fama (1970) sense. That is, asset price or trading behavior is assumed to fully reveal all relevant private information. In FRE equilibrium, the value of information will be zero, as shown by Grossman and Stiglitz (1976). The argument is that asset prices adjust instantaneously to all information, private as well as public, and therefore no action can be taken to profit from information acquisition. At the opposite extreme is a *private information* (PI) equilibrium where it is assumed that individuals make decisions based exclusively on their own private information and are unable to infer anything from observing asset prices. We shall demonstrate in a private information equilibrium that information has a positive market value. A third theory, embodying semistrong informational efficiency, is called *nonrevealing rational expectations* (NRE).[1] Market participants are assumed to combine their own private information with public knowledge of state-contingent prices in order to refine their conditional expectations, but they cannot infer the private information of any other participants. The value of information in NRE equilibrium will be shown to be positive but less than the value in PI equilibrium.

Our work is closely related to other experimental work reported in three recent articles. Sunder (1988) examines a 1-period economy where prices are established in an oral double auction. Competing traders know that one or two states of nature (good or bad for all traders) will be announced at the end of each trading round. A trader who obtains information knows with certainty what the final equilibrium price will be, because there is a simple one-to-one mapping between the two possible information signals and the two possible final

equilibrium prices. In this simple environment, Sunder finds that the value of information falls to zero when information is sold to three or more traders. Alternatively, when the price of information is fixed at some positive value, the number of traders bidding for it falls toward zero but becomes unstable at the single monopolist case. Sunder (1988) also reports two follow-up experiments featuring a computerized double auction. Except in allowing an additional state of the world but one fewer trader type, the design is quite similar to that of his earlier experiments, and the results are also similar.

Copeland and Friedman (1987) study a computerized double-auction asset market in more informationally complex environments. Traders always begin a trading period uncertain of the current state of nature, and at some point during the trading period each trader receives costless notification of his own payoff (''news''). Traders may all receive news simultaneously (the Sim environment) or sequentially (Seq), and the news may be the same for all (the Hom environment) or may be different for different traders (Het). The study concludes that the evidence favors FRE (strong-form efficiency) over the PI and NRE alternatives, even in the more complex environments. It does not consider the market value of information, but if FRE adequately characterizes behavior, then the value of information should fall to zero even in the more complex environments.

This article extends Copeland and Friedman (1987) by reporting eight new experiments that all have a pretrade auction for information: traders bid to receive their news messages before each trading period opens. The Sim:Hom environment is similar to Sunder's (1988) environment, and here we confirm his finding that the market value of information (the price set at auction) falls to zero, as in the FRE forecast. However, we find that the value of information remains positive in the more complex (Het) environments. We derive Nash equilibrium forecasts for the information auction price and allocation under alternative assumptions of FRE, NRE, and PI behavior in the subsequent asset market trading period. It turns out that the Nash equilibrium forecasts based on NRE are much more accurate than the alternatives. Moreover, traders' incemental profits when they purchase the information closely approximate its purchase price, confirming the decision-theoretic underpinnings of the Nash equilibrium forecasts. We conclude that our results support the NRE view that private information is not fully revealed by market signals.

The third related paper, Copeland and Friedman (1991), attempts to reconcile the support for nonrevelation (NRE) in the information auctions with the support for revelation (FRE) in asset prices. That paper does not derive Nash equilibrium predictions for the information auction, nor does it develop in any detail the statistical tests for the information price and allocation data. However, it does formalize an

alternative asset market model, called partial revelation (PRE), which is at least partially successful in reconciling previous findings.

The plan of this article is as follows. We briefly review our experimental procedures and design in Section II. In Section III, we use decision theory together with the alternative theories of information revelation (PI, NRE, and FRE) to provide alternative forecasts of the Nash equilibrium value of information in our asset markets.[2] In Section IV, we briefly describe the data from our eight experiments and present the highlights of our data analysis. Section V summarizes our findings and offers interpretations and suggestions for further work. More details of our procedures can be found in our working paper (1988) and in our previous study (1987); the working paper also contains a more complete data analysis.

II. Experimental Procedures

The key aspect of our design is the repetition of an information market followed by an asset market. The asset market is a continuous-time double auction (DA) run on a Hewlett Packard HP 3000 computer system at the University of California, Los Angeles (site A), and a virtually identical implementation at the University of California, Santa Cruz (site C), on a network of VAXen operating under UNIX-B. Prior to each computerized trading period, an information market is conducted in which three messages about traders' payouts are sold in a (noncomputerized) uniform-price sealed-bid auction: the top three bidders pay the fourth-highest bid price. The identities of the top bidders are kept secret, and all subjects receive envelopes containing pieces of paper. All envelopes reveal the market price of the information, but only the three top bidders receive a message revealing their own actual payout for the forthcoming asset market.

As explained in Copeland and Friedman (1987), we use nine experienced traders (undergraduates at site C and MBA students at site A) in each experiment, and each trader is endowed each period with three shares (indivisible asset units) and ample cash. Table 1 shows typical state-contingent per-share payouts for each of the three trader types. Note that traders ("clones") of type I have the highest payout in the "good" state of nature (G), while type III clones have the highest payout in the "bad" state (B). Type II clones have the highest expected payout.

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2. The exercise of writing out these theories explicitly is necessary because the original models (e.g., in Grossman and Stiglitz [1976]) are not adapted to concrete, laboratory-implementable settings with discrete units for the asset, finite numbers of traders, etc.

TABLE 1   Parameter Set No. 1

| Trader Type | Number of Traders | Starting Inventory | | Payout/Share ($) | |
		Cash ($)	Shares	G	B
I	3	20.00	3	2.00	.30
II	3	20.00	3	1.70	.80
III	3	20.00	3	1.20	1.00

NOTE.—The prior probability of each state (G and B) is 0.5 for each trader type; G is the payout in the "good" state of nature; B is the payout in the "bad" state.

A trader's *gross profits* are the sum of (1) status quo profit = payout per share × endowed number of shares, and (2) gross trading profit = (payout per share − purchase price) summed over share purchases + (sale price − payout per share) summed over shares sold. Traders are paid their net profit, in which the price of information in the sealed-bid auction is deducted from the gross profit of the three information purchasers. In this way, we induce (information contingent) asset values and potential gains from trade in the Smith (1976) sense.

During the asset trading period, we send private news messages notifying each trader of her actual payout (G or B). All three "clones" (traders of the same type) receive news at the same time. For example, in a given period, the news arrival times might be $t = 60$, 120, and 180 seconds for traders of type II, III, and I in a sequential (Seq) experiment with 240-second trading periods. In the simpler simultaneous (Sim) treatment, traders of all types receive news regarding their realized payout for that period at the same time, for example, at $t = 120$ seconds. The realized state is the same (G or B) for all trader types in our simpler homogeneous (Hom) experiments, but in our more complex heterogeneous (Het) experiments the realized payouts are determined independently for each trader type, so there are $2^3 = 8$ equally likely aggregate states in this case. Our Sim:Hom environment resembles the Sunder (1988) setup in that there is an obvious one-to-one mapping between an individual traders' news or purchased information (G or B) and the final equilibrium prices, but other environments (Sim:Het and Seq:Het, and possibly Seq:Hom) are significantly more complex.

The experiments follow a factorial design, with each combination of Infocontent (Hom or Het) and Infoarrival (Sim or Seq) performed twice, once at each site. We can use each of these treatment variables to split the sample of trading periods and then compare outcomes in the two subsamples. Similarly, we can detect learning effects occurring with experiments by comparing earlier trading periods (say the first eight) to later trading periods, pooled across experiments.

III.   Theoretical Predictions

We begin with some notational conventions. Let Z be the set of payout-relevant states, so $Z = \{G, B\}$ for Hom experiments, and $Z = \{GGG, GGB, \ldots, BBB\}$ for Het experiments; in the latter case, $z = GBG$, for instance, means the "good" (high-payout) state for clone types I and III, and the "bad" (low payout) for type II. Let $\pi(z)$ denote the unconditional (or prior) probability of final equilibrium state z, so $\pi(z) = 1/8\ (1/2)$ for all z in Het (Hom) experiments. For $i = $ I, II, III, let $p_i(z) = $ trader type i's per-share payout in state z.

   Information at time t in the trading period $[0, T]$ can be represented by an "event" $A_t \subset Z$. The interpretation is that the true state $z \in A_t$ with probability 1, so the conditional probability distribution is $\pi(z|A_t) = \pi(z)/\pi(A_t)$ if $z \in A_t$ and is 0 otherwise, where $\pi(A_t) = \Sigma_{z \in A_t}\pi(z)$. The number of shares held by trader type i at time t is denoted by x_{it}; note that, at any instant in time, $\Sigma_i x_{it} = 27$ in our experiments.

   We define an *information structure* as a partition $M = \{A_1, \ldots, A_k\}$ of Z with associated probabilites $\{q_1, \ldots, q_k\}$. That is, the realized message m is A_j with ex ante probability q_j, where $q_j > 0$ and $\Sigma q_j = 1$. An expected utility-maximizing individual i will choose some optimal action $\hat{a}$ in the absence of information, that is, $\Sigma \pi(z) U_i(\hat{a}, z) \geq \Sigma \pi(z) U_i(a, z)$ for all feasible actions a. However, given an information structure with some message m to be received before taking an action, the individual can choose a set of optimal contingent actions $a^*(m)$, that is, for each $m \in M$, $\Sigma \pi(z|m) U_i(a^*(m), z) \geq \Sigma \pi(z|m) U_i(a, z)$ for all feasible a. The value of the information structure M for individual i is

$$V_i(M) = \sum_{m \in M} q(m) \sum_{z \in Z} \pi(z|m)\{U_i(a^*(m), z) - U_i(\hat{a}, z)\} \geq 0. \quad (1)$$

This definition emphasizes that the value of information generally reflects an agent's ability to find more beneficial actions when informed. We can apply the definition after specifying the relevant preferences and actions.

   We assume successful "induced valuation" so that traders care only about wealth at the end of the trading period, that is, about $W_i(\cdot, z) = x_{iT}P_i(z) + \Sigma_{t>0}^{T} \delta_{it}P(t) + \delta_{i0}C$, where x_{iT} is trader i's final share holdings and $p_i(z)$ is his or her per-share payout in state z, $P(t)$ is the transaction price at time t, and $\delta_{it} = \pm 1$ if trader i purchased a share $(-)$ or sold a share $(+)$ at time t and is zero otherwise for $t > 0$, while $\delta_{i0} = -1$ if trader i purchased information (at cost C) before trade began and is zero otherwise. We assume that traders are risk neutral, so expected utility in equation (1) is expected wealth $\Sigma \pi(z|A_t)W_i(a, z)$, and traders choose actions a so as to maximize it.

   A general specification of feasible actions including bids, asks, and acceptances is quite complex; see Friedman (1984) for one approach

and a survey of other approaches. Fortunately a very simple version is sufficient for purposes of testing equilibrium theories.[3] In deriving testable predictions from equation (1), we assume that the price of a share, $P(t)$, is always precisely at the level determined by a specified equilibrium theory and that feasible actions consist of the purchase or sale of as many shares as desired, subject to nonnegativity constraints.

Equilibrium asset prices and, hence, the values of $V_i(M)$ generally depend on the purchase decisions of other traders $j \neq i$, so a game-theoretic definition is required for the equilibrium value of information V^* in the sealed-bid auction. Specify the *information purchase game* (IPG) payoff to trader i (whose strategy selection is a bid v_i) as the expected increment in trading profit net of information cost. That is, for cost defined as the fourth-highest bid, $C = \max_4 v_j$, the payoff is $V_i(M) - C$. For the parameter schedules in our experiments, each Nash equilibrium of the IPG yields the same value C^* for the fourth highest bid. We therefore define the equilibrium value of information as $V^* = C^*$.

A. Asset Market Equilibria

We now are prepared to define specific asset market equilibria and thus derive alternative forecasts for V^* as well as for asset prices, allocations, and trading profits. If the true state is known to be z, then the final equilibrium (FE) price is the maximum payout among clone types:

$$p(\text{FE}, z) = \max \{p_i(z): i = \text{I}, \text{II}, \text{III}\}. \tag{2}$$

All equilibrium models we use (or know about) predict that the asset market price $P(t)$ equals $p(\text{FE}, z)$ in the last subperiod of any trading period, because then all traders know their actual payout.[4] The corresponding prediction for share allocation x_{iT} is unique up to trader (clone) type, but not up to individual trader: $x_{iT} = 0$ unless $p_i(z) = p(\text{FE}, z)$. More generally, all our equilibrium models predict that all

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3. In our view, it is not yet productive to forecast price variations within subperiods, because theoretical guidance regarding learning and signaling within a subperiod is lacking. Hence, we neglect potentially interesting issues of short-run dynamics to focus sharply on the explanatory power of equilibrium theories.

4. That the final equilibrium price is the maximum payout (or, more generally, that the equilibrium price at any time is the maximum reservation price across clone types) follows from traditional supply and demand theory (demand is infinitely elastic up to at least 40 shares at $p(\text{FE}, z)$ and supply is fixed at 27 shares), from English auction theory (second-highest price among traders = highest price among types, since there are more than two clones of each type), as well as from the game-theoretic approaches to the double auction surveyed in Friedman (1984). Occasionally we encounter the case where traders of the same clone type have different information because of endogenous information purchase decisions, and the highest reservation price is held by a single trader. In this "information monopolist" case, we revert to the English auction view and define the equilibrium price as the second-highest reservation price across individual traders.

shares will be held by traders of the type with highest reservation price.

In fully revealing rational expectations (FRE), traders are assumed to behave as if they each know the aggregate of all private information. That is, if $A_{it} \subset Z$ represents trader i's information (purchased information as well as "news" received by time t), so that $A_t = \cap_i A_{it}$ represents aggregate information, then traders each employ the reservation price $E_t p(\text{FE}, z) = \Sigma \pi(z|A_t) p(\text{FE}, z)$, anticipating resale opportunities in the final subperiod at the FE price. Hence, FRE predicts the equilibrium price

$$P(t) = p_t(\text{FRE}) = E_t p(\text{FE}, z). \tag{3}$$

Such strong-form information aggregation is plausible when traders have learned the contingent prices $p(\text{FE}, z)$, know the objective probabilities $\pi(z)$ of states of nature, and are able to make very rapid and accurate inferences about privately held information by observing market signals such as price changes and trading volume. As theorized by Grossman and Stiglitz (1976), transaction prices under FRE respond immediately to purchased information, so that it has no private value. That is, $V^* = V_i(M) = 0$ under FRE because information is a pure public good; once purchased by anyone, it is available to all, and so in equation (1) the optimal uninformed action, $\hat{a}$, coincides with $a^*(m)$, the optimal action given purchased information. Since all traders have the same reservation price whether or not they purchase information, FRE provides no allocation forecasts for information purchases or for asset holdings.

Rational expectations theory suggests that traders will behave as if they know the contingent prices $p(z|\text{FE})$ and the objective state probabilities $\pi(z)$ since these data are essentially public information in a repetitive experiment. However, it may be reasonable to suppose that traders are unable to make reliable inferences about other traders' private information; market signals may just be too noisy to be useful. In this case, privately held information is not revealed by the behavior of informed traders. If we assume that each trader conditions only on messages he or she personally has received, summarized by A_{it}, then we have trader type-specific expected final equilibrium prices $E_{it}p(\text{FE}, z)$ as reservation prices. The highest such reservation price is the nonrevealing rational expectations (NRE) equilibrium price forecast

$$P(t) = p_t(\text{NRE}) \equiv \max_i \dot{E}_{it} p(\text{FE}, z). \tag{4}$$

As usual, the asset allocation forecast is that all shares will be held by traders with the highest reservation price.

In order to compute the market value of information from equation (1), we need the probabilities of messages $q(m)$, the probabilites of states given messages $\pi(z|m)$, and the state-contingent wealth gains under NRE. We begin with the simplest environment, Sim:Hom. Here,

$q(G) = q(B) = 0.5$, and $\pi(z|m) = 1$ if $z = m$ ($=B$ or G) and is 0 if $z \neq m$, since the two messages G and B are conclusive regarding the state and are equally likely. By equation (4), the transaction price immediately rises to $\max_i E_{it} p(\text{FE}, G)$ if $m = G$ but remains at $P(t) = \max_i E_{it} p(\text{FE}, z) = \Sigma \pi(z) p(\text{FE}, z) = .5p(\text{FE}, B) + .5p(\text{FE}, G)$ if $m = B$ during the initial subperiod (e.g., $0 \leq t \leq 140$ seconds). An informed trader cannot benefit from $m = G$ because (by eq. [4]) competition from other informed traders in NRE will immediately force the equilibrium price to $\max_i E_{it} p(\text{FE}, G)$. However, when $m = B$ an informed trader can sneak out of the market, selling all three endowed shares in the initial subperiod for a contingent wealth gain of $W^*(B) = 3[P(t) - p(\text{FE}, B)]$. For the parameters in our experiments, $P(t) - p(\text{FE}, B) = \$0.50$. Hence, $V_i(M) = q(G)W^*(G) + q(B)W^*(B) = (0.5)\$0 + (0.5)3(\$0.50) = \$0.75$ for each trader i. Thus, if NRE is valid, all traders would bid $\$0.75$ in the information purchase game, so this is the market value of information under NRE in the Sim:Hom environment.

Now consider a Sim:Het environment.[5] Here $m = G$ or B refers to not a single state, but a subset of four equally likely states; for example, $m = G$ signals the event $A_{IG} = \{GGG, GGB, GBG, GBB\}$ if the trader is of type I. Thus, $q(G) = q(B) = .5$ as before, but $\pi(z|m) = .25$ if $z \in A_{im}$ and is zero if $z \notin A_{im}$. In the initial subperiod, $P(t)$ will remain at the unconditional reservation price $\Sigma \pi(z) p(\text{FE}, z)$ if $m = B$ for all purchasers of information but will rise to the (second-) highest conditional reservation price $\Sigma \pi(z|A_{im}) p(\text{FE}, z)$ if some traders receive $m = G$. The expected per-share gains then are the absolute difference between the conditional reservation price and $P(t)$. When the former is higher, the informed trader optimally will buy up all 24 shares, and when the latter is higher, he will sell his three shares. Thus, $V_i(M)$ can then be calculated directly from equation (1) for any pattern of information purchases.

Tedious but reasonably straightforward computations for all relevant patterns of information purchases disclose that $\$0.45$ is the Nash equilibrium market value of information in the Sim:Het environment: the fourth highest bid, tendered by a type I or type II trader will be $\$0.45$ in NRE equilibrium. In this information purchase game (IPG), all Nash equilibria have at least two type I, at most one type II, and no type III traders purchasing information; the three purchasers all value the information at $\$0.45$, that is, all are marginal. It follows that in NRE

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5. The Seq:Hom (or Seq:Het) environment coincides with that of Sim:Hom (or Sim:Het) for the initial ($0 < t \leq 60$) and final ($180 < t \leq 240$) subperiods but contains two intermediate subperiods that may present an informed trader with additional opportunities for gain. It turns out that the additional opportunities, although numerous, are individually and in aggregate quite small. Hence, we use the same numerical forecasts for Seq environments as for the corresponding Sim environments. Complete NRE calculations of V^* for the Sim:Het environment are available on request from the second author.

purchasers' expected gain in trading profit net of the cost of informa-
tion is zero.

To describe a private information (PI) equilibrium model suppose
that, contrary to rational expectations assumptions, traders do not
know (and do not learn) the contingent FE prices $p(\text{FE}, z)$. If each
trader i pursues a buy-and-hold strategy based only on private informa-
tion received, summarized by A_{it}, then his reservation price is $E_{it}p_i(z)$
and the PI equilibrium price is

$$P(t) = p_t(\text{PI}) \equiv \max_i E_{it}p_i(z). \tag{5}$$

The formal calculation of V^* under PI is at least as complicated as
that under NRE and requires many arbitrary assumptions (regarding
how many shares traders expect to be able to purchase, how they
regard the expected final subperiod price, and so forth) that are con-
trary to the naive spirit of PI equilibrium. Hence (before any experi-
ments were performed), we chose a simplified approach that yields
value for V^* that seem representative of values obtained from more
sophisticated calculations. Each trader i supposes he can transact at
his (uninformed) initial period reservation price $\overline{p}_i = .5[p_i(G) + p_i(B)]$
and will be able to gain $|\overline{p}_i - p_i(z)|$ per share if he purchases the infor-
mation. He assumes he can sell his three shares if $z = B$ and purchase
three if $z = G$. Hence, $V_i(M) = 3|\overline{p}_i - p_i(z)|$, and as usual V^* is the
fourth-highest $V_i(M)$ under PI. Our parameters lead to a forecast value
of \$1.35 for both Hom and Het environments, with the three type I
traders purchasing the messages and enjoying a substantial net gain in
trading profit of \$1.20.

It is perhaps worth emphasizing that these numerical information
price forecasts (\$0 for FRE, \$0.75/\$0.45 for NRE [Sim/Seq], and \$1.35
for PI) were computed before any information market experiments
were performed, that is, these are true a priori forecasts.

B.   Summary of Predictions

Each of the equilibrium concepts (FRE, NRE, PI) makes forecasts
concerning the Nash equilibrium value of information in the sealed-bid
auction, the type of traders who will purchase the information, the
profits earned by each type of trader, and asset prices and allocations.
Theory and intuition suggest the following general predictions:

1. In the simple Hom environments, the market value of information
will approach the FRE forecast of zero because asset prices will be
fully revealing. In the more complex Het environments, the observed
market value of information will approximate the NRE forecast
(\$0.45). The PI forecast (\$1.35) will be too high, except perhaps in
early trading periods where traders have not yet learned the contingent
FE prices and probabilities. The FRE forecast will be too low.

2. Information allocations will also converge to those forecast by
FRE in Hom environments and by NRE in Het environments. That

is, in Het environments the high bid will be tendered by two type I clones with the third bidder being another type I or a type II, while in Hom environments information will be purchased at random by traders of all clone types.

3. In environments where the value of information is positive, the gross trading profits of informed traders will be greater than those of the uninformed, but profits net of information costs will be the same. As noted above, this prediction is consistent with the NRE implementation of decision theory, but not the PI implementation.

4. Except perhaps in early trading periods, the FRE and NRE forecasts of asset price and allocation will outperform the PI forecasts. The FRE forecasts will outperform the corresponding NRE forecasts in environments for which the market value of information is near zero.


IV. Results

Our eight experiments gave us over 120 trading periods (or *reps* as we often call them) in which to observe the price and allocation of purchased information and trading profits, as well as the associated asset prices and allocations. The first two subsections below will review the raw data, emphasizing graphs and qualitative impressions, in order to provide a context for the statistical tests to follow. In each of our experiments, the same set of subjects participates in consecutive trading periods, and their previous experiences and expectations affect the outcomes. Consequently, the trading periods in a given experiment reflect learning behavior and are not truly independent. There is no simple corrective that deals properly with this problem.[6] Therefore, we offer our statistics in the last four subsections as a summary of the evidence, rather than as definitive formal tests.

A. Asset Market Outcomes

The value of information arises from its use in asset market trading, so we begin with a description of the basic asset market data. For brevity, we look at four trading periods in our most complicated environments, Seq:Het, as shown in figure 1. The dash in the upper left corner of the first panel (Experiment: C1, Rep: 1) indicates that no

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6. The most obvious manifestation would be positive first-order serial correlation in prices across trading periods or subperiods. (Possible negative correlation in transaction prices due to the bid-ask spread should disappear when the data are aggregated by subperiods.) We tested the mean squared error (MSE) data (see Subsection *F* below) from experiments C1–4 by subperiod and in aggregate and obtained *negative* point estimates of ρ in nine of 16 cases. Only four of the 16 estimates were significant at the 10% level, and only one estimate exceeded 0.3 in absolute value. We conclude that autocorrelation is not an important problem in our data, but nevertheless we cannot assume true independence. No consensus has yet emerged among experimentalists despite some recent attempts, noted in Friedman (1988), to address the issue.

Experiment: C1   Rep: 1
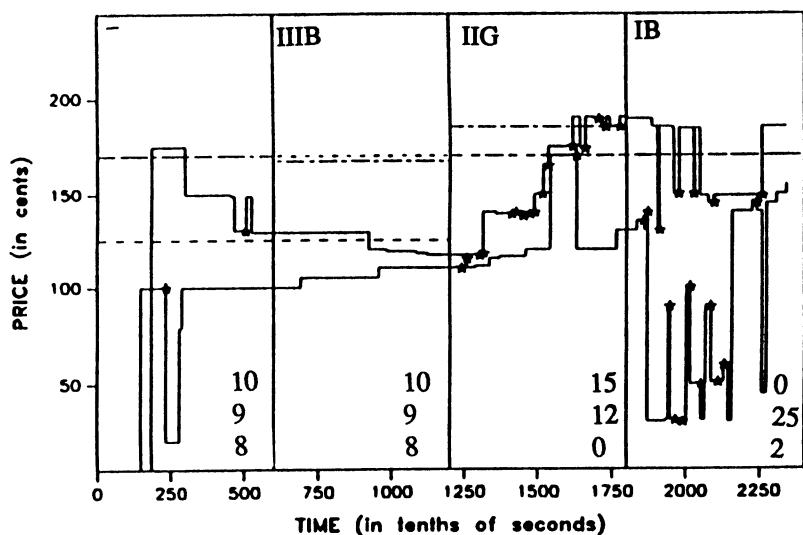
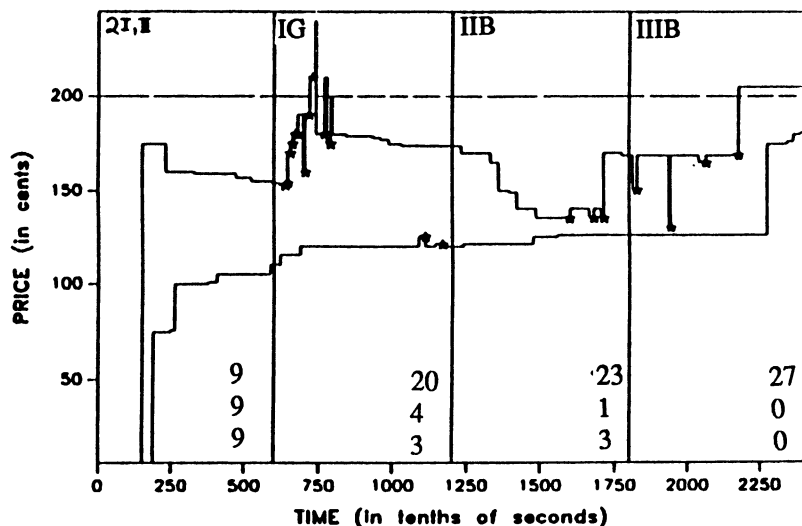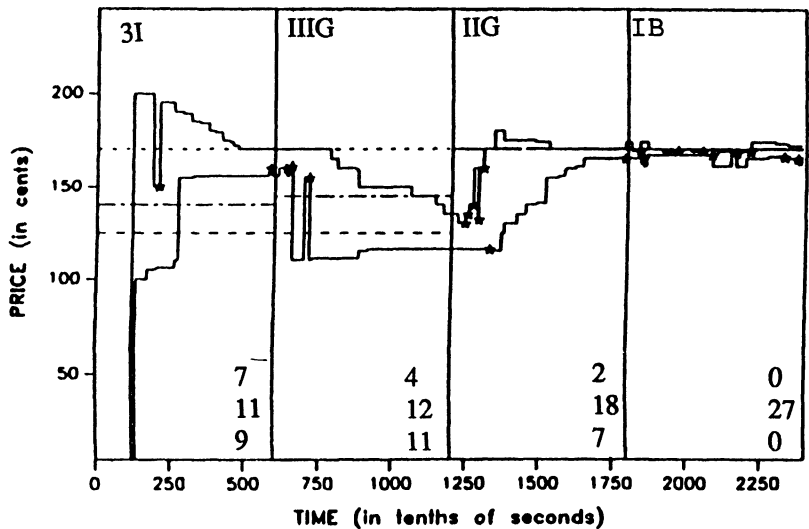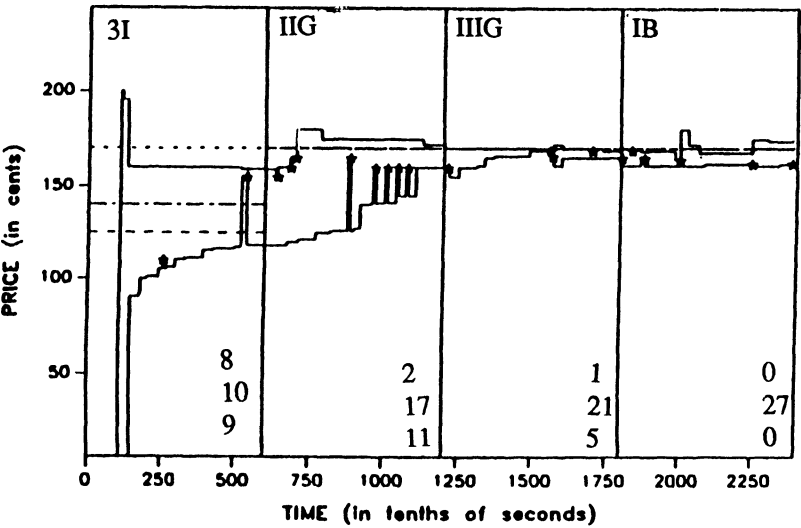

Experiment: C1   Rep: 2

Fig. 1.—Asset market outcomes

Experiment: C1 Rep: 19

Experiment: C1 Rep: 20

sealed-bid auction was held in this experiment prior to the first trading period. The vertical lines at 600, 1,200, and 1,800 indicate news arrival times (in tenths of a second); the notation at the upper end of these lines indicates the news content of low payout for type III traders, high for type II, and low for type I, respectively. The asset allocations at the time of news arrival are indicated at the lower end of the vertical lines; for example, the allocation at $t = 60$ seconds is 10 shares held by type I traders, nine by II's, and eight by III's. The continuous stepwise lines indicate that the opening bid of $1.00 appeared at $t = 15$ seconds, and the opening ask appeared a few seconds later at a price of about $1.75. The stars indicate transactions: the first transaction consisted of some trader accepting the $1.00 bid about 24 seconds into the trading period, and a second transaction consisted of an accepted ask of about $1.30 at about 45 seconds. (Given the single-share net change in this first subperiod from the initial allocation of nine shares for each type, one concludes that two traders of the same type were involved in one of the transactions.) In the second subperiod, no transactions were consummated, but the bid-ask spread narrowed. Shortly after the type II traders received the good news that their payout would be $1.70 per share, a flurry of transactions arose, initially the acceptance of the best bid but mostly thereafter acceptances of best asks. This prompted higher ask prices and eventually higher bids. By the end of this subperiod, we see that type III traders had sold all shares to the informed type II traders and also to the uninformed type I's. In the final subperiod, the latter got the bad news of a low payout and unceremoniously dumped their holdings, some at such low prices that the shares (two of them) were purchased by type III traders. The horizontal long-dash lines, short-dash lines, and dash-dot lines indicate the PI, NRE, and FRE asset price forecasts, respectively. None of the forecasts is accurate in this initial trading period.

The second panel of figure 1 shows that in rep 2 information was purchased at auction by two type I traders and one type II trader. The bid-ask spread was wide in the first subperiod, and no transactions occurred. A few seconds after all type I traders learned their payout would be $2.00, a flurry of accepted asks drove the ask price briefly above this level. All forecasts called for $2.00 prices since the two informed type I traders presumably had reservation prices at this level all along. Nevertheless, bid price remained low for most of the rest of the experiment, and ask price was mostly under $1.75. The closing bid and ask, however, bracketed the $2.00 forecast, and the final allocation coincided with the FE forecast.

The remaining panels show that the forecasts (particularly FRE) do much better in later reps. In rep 19, we see that three type I traders purchased information that revealed that their payout would be low. The asset price forecasts conditioned on this pattern of information

purchase were \$1.70 (NRE), \$1.40 (FRE), and \$1.25 (PI) in the first subperiod. All transactions in the first two subperiods appear to be sales by these informed traders as they snuck out of the market by accepting relatively attractive bids. At $t = 120$ seconds, type II traders *receive good news, provoking a flurry of accepted asks and generally* rising prices. In the final subperiod, the remaining transactions take place within a narrow and stable bid-ask spread near the FE (= FRE = NRE = PI) price forecast of \$1.70. Likewise, in rep 20 prices and allocations converge nicely to the FE forecast, and the behavior in the middle two subperiods seems generally consistent with the FRE forecast.

Graphs for the remaining 100+ trading periods are available on request. At the end of this section, we will briefly review the summary statistics comparing the forecasts of asset price and allocation. We will see that the asset market results are generally consistent with those of Copeland and Friedman (1987) and that prediction 4 is mostly supported.

B. Information Market Outcomes

Figure 2 and table 2 present the outcomes of our sealed-bid auctions for information. One can see that the PI forecast gives a reasonably good description of the actual prices observed in early trading periods but that these prices soon decline. In the Hom environments, the price declines typically seem to begin sooner and go further; indeed, the observed price in the last few periods of C2 and C3 was under \$0.10. In experiment A9, the price does not fall much below the NRE forecast, but the trend was still downward when this Seq:Hom experiment ended after only 12 reps. Thus, the data appear to support our first prediction that information values converge to the FRE forecast value of zero in noiseless environments. In the noisier Het environments, the price of information does not fall to zero, but rather remains near the \$0.45 NRE forecast, again supporting our first prediction.

The allocation data in table 2 likewise seem to support our second prediction. Information is usually purchased as predicted in NRE, that is, by two or more type I traders and at most one type II. Exceptions seem to take the form of random purchases and seem more common in earlier periods (contrary to the PI forecast) and in late reps of Hom experiments (as in the FRE forecast). We will offer statistical confirmation of these qualitative impressions in Subsections *D* and *E* below.

C. Trading Profits

Table 3 presents evidence on how information purchase affects trading profit. For example, the first line reports that, in the 11 trading periods of experiment A7 in which three traders purchased valid information (there was inadvertent misinformation in rep 10), these traders aver-
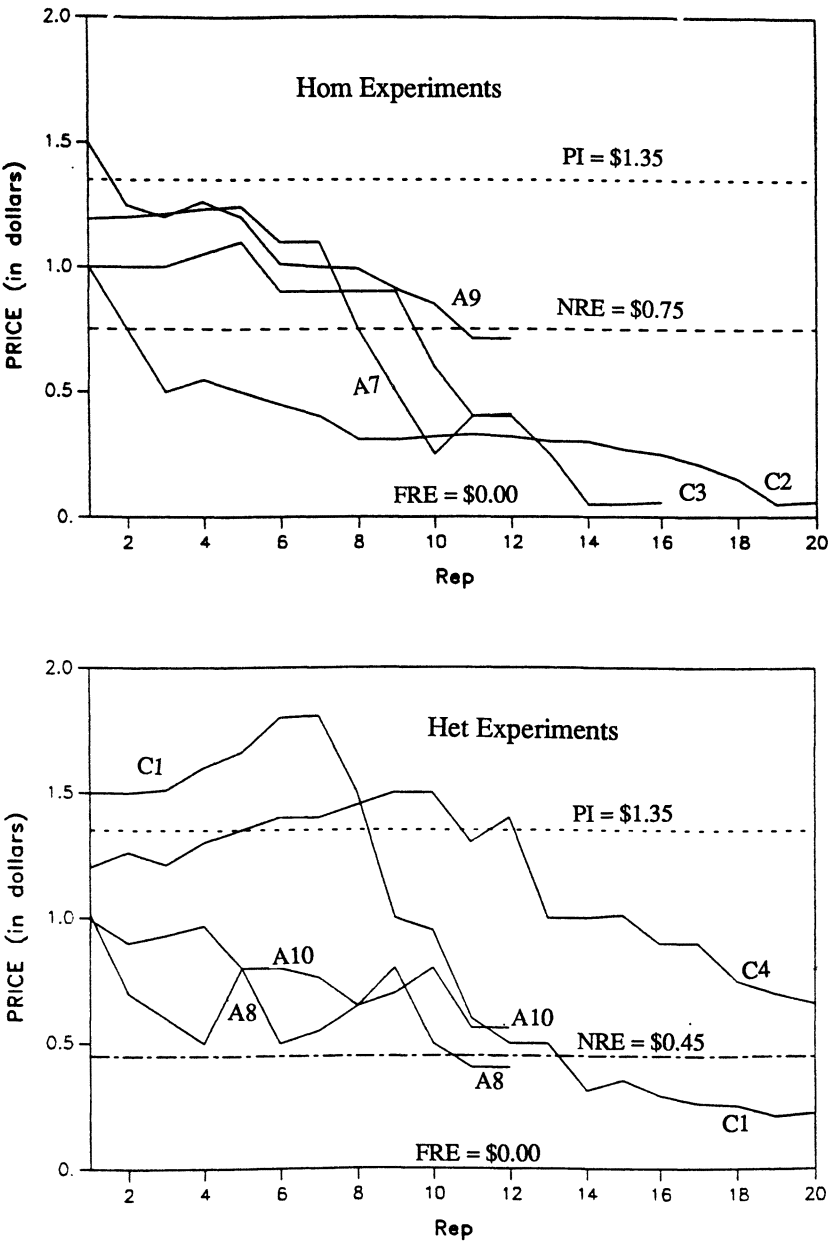
FIG. 2.—The market value of information

TABLE 2   Information Prices and Informed Traders

Rep No.	Sim:Hom A7 Info Price	Held by	Sim:Het A8 Info Price	Held by	Seq:Hom A9 Info Price	Held by	Seq:Het A10 Info Price	Held by	Seq:Het C1 Info Price	Held by	Seq:Hom C2 Info Price	Held by	Sim:Hom C3 Info Price	held by	Sim:Het C4 Info Price	Held by
1	1.19	1, 2 II	1.01	1, 2 II	1.50	1, II, III	.99	2 1, III	..	..	1.00	1, II, III	..	..	1.20	1, II, III
2	1.20	1, 2 II	.70	1, 2 II	1.25	1, 2 III	.90	2 1, II	1.50	2 1, II	.75	2 II, III	1.00	1, II, III	1.26	2 1, III
3	1.21	1, II, III	.60	2 1, II	1.20	1, 2 III	.93	2 1, II	1.51	3 1	.50	2 1, II	1.00	1, II, III	1.21	3 1
4	1.23	3 1	.50	3 II	1.26	2 1, II	.97	2 1, II	1.60	2 1, II	.55	1, 2 II	1.05	1, II, III	1.30	2 1, II
5	1.24	3 1	.80	1, 2 II	1.20	3 1	.80	1 1, 2 II	1.66	2 1, II	.50	1, 2 II	1.10	1, II, III	1.35	2 1, II
6	1.10	2 1, II	.50	1, 2 II	1.01	2 1, II	.80	2 1, II	1.80	2 1, II	.45	1, 2 III	.90	2 1, II	1.40	2 1, II
7	1.10	2 1, II	.55	1, 2 II	1.00	2 1, II	.76	1 1, 2 II	1.81	3 1	.40	2 1, III	.90	2 1, II	1.40	3 1
8	.75	1, II, III	.65	1, 2 II	.99	2 1, III	.65	2 1, II	1.50	1, 2 II	.31	2 1, II	.90	2 1, II	1.45	2 1, III
9	.50	1, 2 III	.70	2 1, II	.91	2 1, III	.80	2 1, II	1.00	2 1, II	.31	2 1, II	.60	1, 2 II	1.50	2 1, III
10	.25	II, 2 III	.80	2 1, III	.85	3 1	.50	2 1, II	.95	2 1, II	.32	1, 2 II	.40	1, II, III	1.50	2 1, II
11	.40	2 1, III	.56	2 1, II	.71	1, II, III	.40	2 1, II	.60	2 1, II	.33	1, II, III	.40	1, II, III	1.30	1, II, III
12	.41	2 1, III	.56	2 1, II	.71	1, II, III	.40	2 1, II	.50	2 1, II	.32	1, 2 III	.40	1, II, III	1.40	1, 2 II
13	..	..	..	..	..	..	..	..	.50	2 1, II	.30	2 1, II	.25	1, II, III	1.00	1, 2 III
14	..	..	..	..	..	..	..	..	.31	2 1, II	.30	2 1, II	.05	2 1, II	1.00	2 1, III

TABLE 3   Average Trading Profits

Experiments	Number of Observations All Periods (Late Periods)	Purchasers ($)			Nonpurchasers ($) GP = NP	Differences in NP ($) Mean (and t-Statistic)	
		GP	C	NP		All Periods	Late Periods
A7	11 (3)	1.18	.94	.24	.91	−.67 (−2.51)	−.52 (−.85)
A8	11 (4)	2.18	.67	1.51	1.60	−.09 (−.26)	−.34 (−.62)
A9	12 (4)	1.70	1.06	.65	.56	.09 (.27)	−.50 (−1.55)
A10	12 (4)	2.05	.74	1.31	1.17	.14 (.72)	.28 (.70)
C1	20 (12)	1.98	.76	1.22	1.47	−.25 (−.78)	.46 (1.15)
C2	20 (12)	1.67	.37	1.30	.65	.65 (1.21)	1.33 (1.68)
C3	10 (2)	1.27	.45	.82	.90	−.08 (−.18)	.26 (.25)
C4	18 (11)	2.24	1.18	1.06	1.66	−.60 (−1.62)	−.67 (−1.45)
All	114 (52)	1.82	.77	1.05	1.12	−.07 (−.51)	.21 (.82)

Difference in GP ($) Mean (and t-Statistic)	
All Periods	Late Periods
.69 (5.00)	.77 (3.23)

NOTE.—See text for explanation of abbreviations.

aged $1.18 in gross trading profits (GP) and $0.24 net profit given (NP) the $0.94 average information cost (C). The remaining six traders in each rep averaged $0.91 in trading profits, significantly better as indicated by the t-statistic of −2.51. The last column restricts the comparison to later periods, defined as reps 9–20. For A7 the difference in mean net profit was somewhat smaller at $0.52, suggesting a decreasing tendency to overpay for information, but the number of relevant observations is rather small as indicated by the insignificant t-statistic of −0.85.

In the rest of table 3, one sees about as many positive as negative mean differences in net profit between informed and uninformed traders and no "significant" t-statistics despite reasonably large sample sizes. The largest positive mean difference occurs in C2, but the low average information value in that experiment of $0.37 indicates that the PI prediction is off the mark. The bottom line is that for the 114 relevant reps[7] the mean difference in net trading profit was $0.07, with a t-statistic of −0.51 indicating statistical as well as economic insignificance. By contrast, the mean overall difference in gross trading profit was $0.69, with a highly significant t-statistic of 5.00. Results for the subsample of later reps are qualitatively similar: the mean gross difference is $0.77 with a t-statistic of 3.23. Overall, we conclude that the gross and net profit data are quite consistent with the NRE and FRE implementations of decision theory and our third general prediction is supported.

D. Test of Forecasts: Information Price

To detect regularities in the information price data that may have escaped visual scrutiny, we first transform the data by computing absolute forecast error. We then use three statistical tests to compare forecast errors. The first counts the number r (respectively w) of times forecast Y has a smaller (respectively larger) error than forecast X in a given sample of reps. Under the null hypothesis that the forecasts are equally good (more specifically that errors are independently and identically distributed across trading periods and that X and Y are equally likely to produce smaller error), the "signs" statistic $z = (r - w)/\sqrt{r + w}$ has a binomial distribution with mean zero and unit variance.[8] We also employ another popular nonparametric statistic, the Wilcoxon rank-sum, which measures the overall tendency of Y to produce smaller forecast errors than X. Finally, we compute the

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7. In some experiments the first trading period has no information auction, and in a few cases errors were made in sending the information; we excluded these reps from the sample. In the latter case, misinformed traders were paid average gross trading profits.

8. The formula is easy to verify from the definition of z as $V^{-1/2}(r - n/2)$, where $n = r + w$ is the sample size and $V = n^{-1}(n/2)(n/2)$ is the binomial sample variance.

differences in forecast errors for each trading period and compute the
t-statistic associated with the null hypothesis that these differences
have a normal distribution with mean zero. (If the differences were
normal, then this t-statistic would be the more powerful measure, but
unfortunately the distribution seems far from normal.)

Table 4 reports the three t-statistics for some of the more interest-
ing data subsamples. The middle three columns indicate that only in
the case of E-reps (periods 1–8) in Het experiments do $Y = $ PI fore-
casts outperform $X = $ NRE forecasts, with "significant" Wilcoxon
and t-statistics of 2.51 and 2.31 and a positive signs statistic of 1.46.
Clearly NRE outperforms PI in L-reps (periods 9–20), especially in
Hom experiments; for the full sample the absolute value of all three
statistics is over 3.0. Perhaps the most important comparison in table
4 is between $X = $ FRE and $Y = $ NRE. The performance of the NRE
forecasts is far superior in early reps, but this merely reflects the usual
"convergence from above" pattern. Negative statistics (indicating a
superior performance by FRE) arise for the later trading periods of
Hom experiments, but at -1.57, -1.17, and -0.54 these are insig-
nificant at conventional levels. Overall, the NRE forecasts strongly
outperform the FRE forecasts according to the statistics of 7.30, 6.71,
and 11.29 and also do better in the pooled later reps. Finally, the last
three columns report that PI strongly outperforms FRE in early periods
but not in later periods; indeed, FRE has a highly significant edge in
later periods of Hom experiments.[9]

We conclude that the information price data weakly favors FRE
over NRE in later trading periods in the relatively noiseless Hom envi-
ronment and weakly favors PI over NRE in early trading periods.
Otherwise (and overall), the NRE forecasts are clearly superior. Thus,
the evidence supports our first general prediction.

E. Tests of Forecasts: Information Allocation

To test the information purchase forecasts we focus on Q, the fraction
of the total information purchases by traders of type I. Recall that
FRE forecasts random purchases and PI forecasts all purchases by
type I traders. The NRE forecasts are for either (a) all type I, or (b)
two I's and one II, with informal logistical considerations suggesting
that (a) is the more likely case. Thus, the forecasts are $Q_I(\text{FRE}) = 1/3$,
$Q_I(\text{NRE}) \geq 2/3$, and $Q_I(\text{PI}) = 1$. We compare these forecasts to the
actual fractions $\hat{Q}_I$ observed in relevant samples of our data.

Regarding the purchase decision by a trader of type I as an indepen-

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9. Our working paper reports test results on another 10 subsamples, but none is of
any consequence. We detect differences across sites, but closer examination strongly
suggests that these differences are attributable to differences between earlier and later
trading periods: over three-quarters of the L-reps subsample is associated with site C.

TABLE 4   Tests of Information Price Forecasts

Sample	Number of Observations	FRE vs. NRE			NRE vs. PI			PI vs. FRE		
		Signs	Wilcoxon	t	Signs	Wilcoxon	t	Signs	Wilcoxon	t
E-reps:										
Hom	31	5.21	6.21	14.15	-.73	-.13	-1.09	-3.41	-5.58	-5.36
Het	31	5.57	3.70	∞	1.46	2.51	2.31	-3.41	-5.89	-6.30
L-reps:										
Hom	26	-1.57	-1.17	-.54	-5.10	-5.32	-31.89	3.14	5.50	5.96
Het	32	4.95	4.13	13.22	-2.19	-3.57	-2.93	-.35	-.29	-.42
All	120	7.30	6.71	11.29	-3.16	-3.14	-3.06	-2.01	-3.62	-2.88

NOTE.—Positive entries favor the second model; e.g., for FRE vs. NRE, positive entries indicate that prediction errors are larger for FRE, and so NRE is favored.

TABLE 5   Tests of Information Allocation Forecasts

| | | | | z-Statistic | | |
Sample	Number of Observations	Purchases by Type I's	Q	PI	NRE	FRE
E-reps:						
Hom	31	48	.52	−5.71	−1.78	2.16
Het	31	54	.58	−4.95	−1.02	2.92
L-reps:						
Hom	26	36	.46	−5.82	−2.22	1.39
Het	32	62	.65	−4.25	−.25	3.75
All:						
Hom	57	84	.49	−8.15	−2.81	2.53
Het	68	116	.61	−6.50	−.89	4.72
All:						
E-reps	62	102	.55	−7.54	−1.98	3.59
L-reps	58	98	.56	−7.06	−1.67	3.71
Both	120	200	.56	−10.33	−2.58	5.17

dent Bernoulli random variable with parameter $Q_I(X)$, the statistic

$$z = \frac{\hat{Q}_I - Q_I(X)}{\{Q_I(X)[1 - Q_I(X)]/N\}^{1/2}}$$

is asymptotically unit normal under the null hypothesis that X is the correct model when $0 < Q_I(X) < 1$. For X = FRE or NRE the denominator of z is $\sqrt{2/N}/3$, but it is zero for X = PI. To maintain comparability (and to give PI a better chance at a good performance) we redefine this z-statistic for the PI forecast to have the same denominator as in FRE and NRE.

Table 5 collects the results. Overall, 200 of 360 purchases are of type I, significantly different from any of our forecasts but closest to NRE. More important, 62 of 96 purchasers in later reps of Het experiments are of type I, very close to the 64+ forecast in NRE, as indicated by the z-statistic of −0.25, while the FRE and PI forecasts are convincingly rejected with z-statistics of 3.75 and −4.25. Likewise, the z-statistics for the later reps in Hom experiments (−5.82, −2.22, and 1.39) reject PI and NRE but not FRE.[10] No other dramatic patterns are evident in the data. We conclude that the information allocation data are consistent with our second general prediction.

F.   Tests of Forecasts: Asset Price and Allocation

In Copeland and Friedman (1987), we analyze in some detail the mean forecast price error (root mean squared error, or MSE) and percent of shares misallocated relative to FRE, NRE, and PI forecasts. We

10. A referee kindly points out that, while the TRE forecast $Q_I = 1/3$ is the same as the "random baseline" arising from confusion or noise, the fact that the observed $\hat{Q}$ closest to 1/3 arose in the most orderly environment (L-reps:Hom) and is much lower than $\hat{Q}$ in the more complex Het environment is "one of the most striking bits of evidence for FRE" in the Hom environment. We agree.

conducted similarly detailed statistical tests for the present data set.[11] In the interest of brevity, we present only the highlights in table 6. The first line, for example, indicates that FRE and NRE asset price forecasts differed in 44 subperiods of our four Hom experiments and that the MSE was typically lower for the FRE forecasts, as indicated by strongly negative t-statistics of -5.73, -7.58, and -14.40 for the signs, Wilcoxon, and matched-pair t, respectively. The bottom line indicates that overall FRE beats NRE in predicting asset price, that PI also beats NRE, and that PI has an insignificant edge over FRE. Perhaps more important, we find that the advantage of FRE over NRE is less pronounced in later reps of Het experiments, and the advantage of PI over NRE is much less impressive in later reps of all experiments. We also report in our working paper that the NRE asset allocation forecasts are clearly better than those of PI and (by default) FRE. These findings generally are consistent with the results of Copeland and Friedman (1987) and mostly support prediction 4.

V. Summary and Discussion

We have presented new empirical evidence bearing on the issue of whether strong or semistrong theories of informational efficiency best explain the value of information in an asset market. Theoretical forecasts are compared to the actual outcomes observed in eight controlled laboratory experiments involving several different environments. Specifically, we derive the forecasts (price and allocation of purchased information and trading profits in particular) from a Nash equilibrium analysis given three different market equilibrium theories that embody alternative assumptions regarding traders' information sets. The first market equilibrium theory, fully revealing rational expectations (FRE), assumes that each trader's private information is fully and costlessly revealed to other traders (presumably by price or other observable market signals) and thus embodies strong-form efficiency in the sense of Fama (1970). The second theory, nonrevealing rational expectations (NRE), assumes that traders correctly condition on their own private information and use the correct prior distribution for asset resale values but assumes no revelation of other traders' private information and therefore embodies semistrong efficiency.[12] The third theory, private

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11. The only technical difference is that with the present data we sometimes need to invoke the "information monopolist" convention noted above in n. 4.

12. In Fama (1970), semistrong efficiency implies weak-form efficiency, in particular, that future prices are not predictable using past and current prices. We neglect such standard econometric tests of market efficiency in order to focus on the comparative advantage of the laboratory data, the observability of private information. However, see O'Brien and Srivastava (1989), who conclude that their laboratory asset markets are not informationally efficient even though they pass the standard econometric tests for market efficiency.

TABLE 6   Tests of Asset Price Forecasts

Sample	FRE vs. NRE				NRE vs. PI				PI vs. FRE			
	Number of Observations	Signs	Wilcoxon	t	Number of Observations	Signs	Wilcoxon	t	Number of Observations	Signs	Wilcoxon	t
Hom	44	−5.73	−7.58	−14.40	60	5.42	6.03	6.92	60	3.10	3.89	2.44
Het	56	−3.21	−3.96	−3.73	66	4.68	5.32	5.55	51	−1.82	−1.92	−2.75
E-reps	56	−4.28	−6.45	−6.48	68	6.55	7.48	8.75	62	−.25	−.03	−1.50
L-reps	44	−4.52	−5.64	−6.42	58	3.41	3.82	3.92	49	1.86	2.22	2.06
All	100	−6.20	−8.46	−9.05	126	7.13	8.02	8.74	111	1.04	1.40	.31

NOTE.—Positive entries favor the second model.

information (PI), drops the rational expectations assumption that traders know state-contingent equilibrium prices for asset resale and assumes that traders act solely on the basis of their own private information.

Our central finding is that (a) the strong-form theory (FRE) correctly forecasts that the market value of information approaches zero in simple environments with homogeneous states of nature, but (b) the semistrong theory (NRE) rather accurately predicts the price and allocation of purchased information as well as trading profits in more complex environments with heterogeneous states of nature. In such environments, FRE and PI are rejected. In particular, figure 2 shows that the PI forecast value of purchased information is too high and the FRE forecast value (zero) is too low in these complex environments. We conclude that private information is valuable in noisy markets because uninformed traders are unable (even our relatively simple laboratory markets) to extract it by observing the anonymous behavior of informed traders. Traders in our laboratory markets paid full price for purchased information since profits of uninformed and informed traders, net of the cost of acquiring information, were indistinguishable. Part a above of our finding confirms the Grossman-Stiglitz (1976) theory and the Sunder (1988) test of that theory, while b confirms the Grossman (1976) conjecture.

Although most of our results make theoretical sense, there is an anomaly. Copeland and Friedman (1987) reported that FRE forecasts of asset price are on balance superior to the alternatives (especially to NRE) in all environments, yet NRE generally provided the best forecasts for asset allocation and trading volume. Despite the use of a sealed-bid auction prior to each trading period, we obtain similar results in the asset markets reported here. Our findings regarding information markets widen this discrepancy. Camerer and Weigelt (1990) report another information revelation anomaly; under some conditions traders use market signals to infer nonexistent information—that is, traders sometimes chase a mirage.

We believe that these anomalies are important because they point to shortcomings in existing theories. Clearly FRE asks too much of traders in complex environments. Perhaps NRE asks too little: it assumes the equilibrium asset price is set by traders with the *most* optimistic expectations, even when these expectations are based on inferior information. Consequently, there is an upward bias to NRE price forecasts relative to those of FRE or other conceivable rational expectations (RE) theories. The challenge, then, is to formalize a new theory that can produce better forecasts than either FRE or NRE for prices and allocations of assets and purchased information. Ideally, such a theory would reduce to FRE in a noiseless environment, would be somewhat more sophisticated than NRE in a noisy environment, and

could explain information mirages. Copeland and Friedman (1991) begin this task, but much work remains to be done.

To summarize, our data support the strong-form efficient markets hypothesis in a very simple environment, but a semistrong form of efficiency better characterizes our data for more complex environments. Additional empirical and theoretical work may lead to a model that can adequately characterize informational efficiency in all environments.

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