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# Dynamic Stock Markets with Multiple Assets: An Experimental Analysis

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## ABSTRACT

We study the performance of the rational expectations hypothesis in multiperiod experimental markets with multiple assets. We find that the markets are generally inefficient from the point of view of full information aggregation. However, arbitrage relationships hold, and it is not possible to detect the informational inefficiency by using some standard tests of market efficiency. These findings suggest that the lack of arbitrage opportunities and the failure of common tests to reject inefficiency are not sufficient to conclude that a market is informationally efficient.

A GROWING BODY OF research has investigated whether the rational expectations hypothesis provides a reasonable description of behavior observed in laboratory markets. In this paper, we continue this investigation by examining information aggregation in fairly complex multiperiod markets with multiple stocks and experienced traders. We find strong evidence against information aggregation. However, we also find that conventional econometric tests are unable to reject the hypothesis of an informationally efficient market.

Our study consists of two markets, one with three stocks and one with four. In each market, each stock has a two-period life. A stock pays a dividend at the end of each period, and the underlying distribution of endowments is common knowledge. Traders are given private information about the dividends.

Important features of our laboratory markets are: (a) trading takes place in continuous time in a computerized market; (b) multiple units of the same asset can be traded in a single transaction; (c) the same dividends are paid to all owners of a stock; (d) the distribution of private information is not common knowledge; and, (e) borrowing and short sales are allowed.

We analyze the data obtained from the experimental sessions in several ways. First, we study how efficiently our markets aggregate information by measuring the extent to which market prices reflect all available information. Since a stock pays dividends in both periods, the aggregation problem in the first period is more difficult than in the second (since the rational expectations price must correctly forecast the sequence of dividends). We find

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that the rational expectations model does not perform well in the first period, but does better in the second period. This conclusion does not seem to depend on the number of securities in the market.

Second, we ask whether some standard tests of market efficiency detect the deviations from rational expectations. In applying these tests, we assume the role of an econometrician who can only observe market data, not the underlying fundamentals.[1] We find that, despite the lack of informational efficiency, the econometric tests do not allow us to reject market efficiency.

The features described above allow us to focus on arbitrage relationships which cannot be examined in simpler environments. By introducing correlation across stocks and across time, we can induce both cross-sectional and intertemporal arbitrage relationships, and we can examine the extent to which these relationships hold. In the experiments we conduct, the arbitrage relationships are independent of information aggregation, so we can analyze them independently of the issue of information aggregation. Somewhat surprisingly, we find that the arbitrage relationships in our markets hold quite well in spite of the inability of the market to fully aggregate information.

Finally, we examine the extent to which a heuristic learning model is consistent with observed price dynamics. We show that a simple model of learning by frequency distribution captures virtually all of the price dynamics. We also find that this model accurately predicts both future bids and asks and also future transaction prices.

The next section contains a review of the literature on asset market experiments. Section II contains a description of the experimental design, while the results of the experiments are given in Section III. A summary and concluding remarks are given in Section IV.

## I. Review of the Literature

Much of the previous experimental literature on stock markets has focused on information aggregation. These studies have been concerned largely with the conditions required to ensure convergence to a rational expectations equilibrium.

Tests of the information aggregation properties of prices in double auction asset markets have met with mixed success. In simple environments where a subset of multiple traders face no state uncertainty for a particular security, price converges to the rational expectations price (e.g., Plott and Sunder (1982), and the Arrow-Debreu markets in Plott and Sunder (1988)). In similar environments, but where the arrival time of the information was manipulated, support for the rational expectations equilibrium was obtained by Copeland and Friedman (1987). However, in environments for which it is common knowledge that the market as a whole has complete information but no trader has perfect information, information aggregation has been more

[1] This approach is similar to that of LaLonde (1986). We thank a referee for bringing this reference to our attention.

difficult to attain. For example, in the initial tests of this type of environment with multiple trader types, price failed to aggregate information (Plott and Sunder Series A (1988)). Successful aggregation has required either trader types to be homogeneous (Plott and Sunder (1988)), or have required common knowledge about the types of all traders (Forsythe and Lundholm (1988)). In environments where traders have different privately induced risk preferences and a common dividend distribution, information aggregation was sensitive to the risk preferences of the marginal traders, and the disclosure of the realized dividend (O'Brien (1989)). Finally information aggregation has also been less successful when there exists aggregate uncertainty and the number of traders is increased (Lundholm (1989)).

A second stream of the literature examines information aggregation with futures markets (e.g., Forsythe, Palfrey, and Plott (1982); Forsythe, Palfrey, and Plott (1984); Friedman, Harrison, and Salmon (1984)). The introduction of a futures market increased the speed of convergence.

Most of the experiments described above were conducted manually. The original automated market experiments were conducted by Williams (1980), using a PLATO double auction market. These markets were single dividend state markets, and trading was restricted to one unit at a time. The current bid or ask could be accepted by other traders at any time, and confirmation of a trade was required by the trader with the current active quote, before a trade was consummated. Finally the screen display for these markets was designed to mimic the single dividend state oral double auction markets. Variations of the original PLATO double auction markets have been used in subsequent experiments (e.g., Williams and Smith (1984); Smith, Suchanek, and Williams (1988)). Additional automated markets experiments using a different system have been reported by Copeland and Friedman (1987). In these markets confirmation by the trader with the active quote was not required and screens were designed to display current (and past) market information. Trading was restricted to one unit at a time, and there were two possible dividend states for each trader type each period.

In contrast to these studies, we are explicitly interested in studying behavior in complex markets with experienced subjects. Our markets are designed to make information aggregation difficult, as opposed to finding conditions under which aggregation occurs. Further, our focus is on issues which can be studied independently of information aggregation, such as arbitrage relationships and empirical tests of efficiency.

## II. Description of the Markets

The experiments reported in this paper were conducted using the Simulab Automated Market Laboratory. The Simulab system allows the operation of real time, multiperiod markets with multiple assets, and a detailed description of the system is available upon request. Briefly, the system consists of a group of 80386 based personal computers linked in series. All computers simultaneously process all market information (i.e., trades are not executed or processed by a "central" computer). However, only information selected by the experimenters is displayed on the high resolution color monitor of each trader. The traders are physically isolated and have no means of communication except through market activity.

The experiments were broken down into two sets of markets which we call Market 3 and Market 4. All subjects were experienced as described below, and were divided into two groups: group 1 participated only in Market 3, and group 2 participated only in Market 4, each for 32 trading periods.

Market 3 contains three stocks. Each stock has a two-period life, and the stocks pay dividends in each period. Each two-period market is called a *trial.* In each trial, dividends are realized by rolling five dice before the start of the first period. The relationship between dice rolls and dividends is reproduced in Table I, and all the information in the table was read out publicly to all traders. There were 16 traders in this market. Note that before any information is given out, there are three times as many (dividend) states for each stock in period 1 that in period 2, since stocks pay dividends in both periods, and there are three possible first period dividends.

Market 4 contains four stocks, each with a two-period life, and dividend information relating dice rolls to dividends in Market 4 is given in Table II. Again, all the information in Table II was given to each trader, and was read out publicly to all traders. There were 12 traders in this market. Again, there is a much larger state space in the first period than in the second.

All traders gained experience in a two-period market with two stocks using the Simulab system, and, after an initial practice session, had at least twenty-four periods of experience lasting over two sessions. The data analyzed here are taken from sessions *after* the initial practice session and the twenty-four training periods. The traders were Master's students at Carnegie Mellon's Graduate School of Industrial Administration. During the training sessions, the traders were compensated in exactly the same way as in our experiments and faced comparable information conditions. In fact, except for the number of stocks and the parameters of the distribution of dividends, the training sessions were indistinguishable from our main experiments.

During a period, each trader can submit bids (offers to buy), asks (offers to sell), accept an existing bid (sell), and accept an existing ask (buy). In addition, traders must specify the *quantities* they wish to trade. Once an offer or a trade is sent to the market, it cannot be recalled or canceled. Orders are processed on a first come first serve basis. Since the Simulab system can handle approximately twenty transactions per second, trading is virtually instantaneous.

The rules of the market are as follows.

### *A. Price Rules*

If there is an existing bid for a stock, called the current bid, any subsequent bid must be at least as high as the current bid. If there is no current bid, then any positive price is a valid bid. Once a market clears in that all the

**Table I**

**Dividend Structure for Market 3**

Market 3 has three two-period lived stocks, and dividends paid by each stock are generated by rolls of a dice. One dice roll determines the dividend for stock 1 in period 1. A second dice roll simultaneously determines the dividends for stocks 2 and 3 in period 1. There are three dice rolls to determine dividends in period 2, one for each stock. The total number of dice rolls is 5: two for period 1 and 3 for period 2.

| | Stock 1 | | | |
|---|---|---|---|---|
| | | Dividends in Period 2 if Period 1 Dividend Is: | | |
| Dice Roll | Dividends in Period 1 | 0 | 12 | 24 |
| 1 | 0 | 0 | 0 | 12 |
| 2 | 0 | 0 | 0 | 12 |
| 3 | 12 | 0 | 12 | 24 |
| 4 | 12 | 0 | 12 | 24 |
| 5 | 24 | 12 | 24 | 24 |
| 6 | 24 | 12 | 24 | 24 |

| | Stock 2 | |
|---|---|---|
| Dice Roll | Dividends in Period 1 | Dividends in Period 2 |
| 1 | 0 | 8 |
| 2 | 0 | 8 |
| 3 | 12 | 8 |
| 4 | 12 | 12 |
| 5 | 24 | 18 |
| 6 | 24 | 18 |

| | Stock 3 | |
|---|---|---|
| Dice Roll | Dividends in Period 1 | Dividends in Period 2 |
| 1 | 24 | 0 |
| 2 | 24 | 0 |
| 3 | 12 | 0 |
| 4 | 12 | 12 |
| 5 | 0 | 36 |
| 6 | 0 | 36 |

units outstanding at the current bid are bought, then there is no existing bid. In case a market clears, the previous highest bid does not become the current bid.

If there is an existing ask for a stock, called the current ask, any subsequent ask must be no higher than the current ask. If there is no existing ask, then any positive price is a valid ask. Once a market clears in that all the units outstanding at the current ask are sold, then there is no current ask. When a market clears, the previous lowest ask does not become the current ask.

**Table II**

## Dividend Structure for Market 4

Market 4 has four two-period lived stocks, and dividends paid by each stock are generated by rolls of a dice. There are two separate dice rolls for stocks 1 and 2 *each* period. The first two rolls determine first period dividends and the second two determine the second period dividends. There is only *one* dice roll for each period to determine the dividends for stocks 3 and 4. The first dice roll determines the first period dividend for both stocks 3 and 4. The second dice roll determines the second period dividend for both stocks 3 and 4. The total number of dice rolls for all stocks is 6: 4 dice rolls for stocks 1 and 2, and 2 dice rolls for stocks 3 and 4.

| | Stock 1 | | | |
|---|---|---|---|---|
| | | Dividends in Period 2 if Period 1 Dividend Is | | |
| Dice Roll | Dividends in Period 1 | 0 | 12 | 24 |
| 1 | 0 | 0 | 0 | 12 |
| 2 | 0 | 0 | 0 | 12 |
| 3 | 12 | 0 | 12 | 24 |
| 4 | 12 | 0 | 12 | 24 |
| 5 | 24 | 12 | 24 | 24 |
| 6 | 24 | 12 | 24 | 24 |

| | Stock 2 | | | |
|---|---|---|---|---|
| | | Dividends in Period 2 if Period 1 Dividend Is | | |
| Dice Roll | Dividends in Period 1 | 0 | 12 | 24 |
| 1 | 0 | 12 | 0 | 0 |
| 2 | 0 | 12 | 0 | 0 |
| 3 | 12 | 24 | 12 | 0 |
| 4 | 12 | 24 | 12 | 0 |
| 5 | 24 | 24 | 24 | 12 |
| 6 | 24 | 24 | 24 | 12 |

| | Stock 3 | | | |
|---|---|---|---|---|
| | | Dividends in Period 2 if Period 1 Dividend Is | | |
| Dice Roll | Dividends in Period 1 | 0 | 15 | 30 |
| 1 | 0 | 24 | 24 | 12 |
| 2 | 0 | 24 | 24 | 12 |
| 3 | 15 | 24 | 18 | 12 |
| 4 | 15 | 18 | 18 | 18 |
| 5 | 30 | 18 | 12 | 18 |
| 6 | 30 | 12 | 12 | 24 |

| | Stock 4 | | | |
|---|---|---|---|---|
| | | Dividends in Period 2 if Period 1 Dividend Is | | |
| Dice Roll | Dividends in Period 1 | 0 | 15 | 30 |
| 1 | 30 | 12 | 12 | 24 |
| 2 | 30 | 12 | 12 | 24 |
| 3 | 15 | 12 | 18 | 24 |
| 4 | 15 | 18 | 18 | 18 |
| 5 | 0 | 18 | 24 | 18 |
| 6 | 0 | 24 | 24 | 12 |

### *B. Trading Rules*

A trader can, at any time, buy at the current ask or sell at the current bid. These trades can involve quantities up to the amounts offered for trade. We allowed a limited degree of borrowing and unlimited short sales in all the markets.

### *C. Trader Displays*

The screen in front of a trader is divided into several boxes. One box displays the current bids, asks, and quantities. Only the highest bid and the lowest ask are displayed. A second box shows the last three traded prices, but not the quantities traded. A third box displays the trader's portfolio. Before the start of the first period, each trader is given an initial endowment of experimental cash and of the stocks. Once a trade is executed, the computer automatically updates the trader's portfolios. A fourth box displays the information received by the trader. All information is sent at the beginning of the period. The distribution of information is described below.

At the end of the first period, first period dividends are paid out. The resulting cash, and the holdings of the stocks at the end of the period, are carried over to the second period. The second period then begins. At the end of the second period, period 2 dividends are paid out and the total experimental cash of the trader is computed. This total cash determines whether or not a trader wins any money as described next.

In all the experiments, we induced risk neutrality using the binary lottery technique (Roth and Malouf (1979); Berg et al. (1986).[2] This was done as follows for every trial. Let $C$ be the end of trial experimental cash of a trader. We drew a number between 0 and 999, say $B$, from a bingo cage containing 10 balls labeled 0 to 9 (with replacement). If $C \geq B$, the trader was awarded a cash prize. If $C < B$, the trader was awarded nothing. This implies a linear relationship between $C$ and the probability of winning the cash prize, and induces risk neutrality as described in Berg et al. (1986). The value of the cash prize was common to all traders, and was common knowledge.

Much of our analysis is independent of whether we successfully induced risk neutrality.[3] However, the use of the binary lottery technique allowed us to permit borrowing and short sales without exposing us to large potential payouts since the maximum payout in a trial was limited to the cash prize. In

[2] Experimental evidence on the performance of the binary lottery technique in stock market contexts is contained in O'Brien (1990). This evidence strongly supports the risk preference inducing technique in a double auction stock market. As we note below, much of our analysis is independent of whether we induced risk neutrality. In particular, the computation of the equilibrium price in most of the trials is independent of risk preferences.

[3] Note that, since the number drawn from the bingo cage ranges from 0 to 999, a trader who has, for example, accumulated a long position in all stocks and has a cash balance exceeding 1000, is guaranteed to win the cash prize. Across the 16 traders in 16 trials in Market 3, 6 out of 256 were in the position of either winning for sure or not winning for sure. In Market 4, the number was 9 out of 256.

our computerized markets, limiting experimental liability is an important issue because the ease by which trades can be conducted usually leads to large trading volumes, even within short periods of time. Borrowing and short sales were made operational as follows. If a trader ended a trial with negative total experimental cash, the trader had zero probability of winning the cash prize. If a trader held a short position in a stock at the end of a period, say $-X$, and the dividend on the stock was $D$, the amount $XD$ was subtracted from the trader's cash position. Of course, if the trader had sold the stock at price $P$, he had previously received $XP$ from the sale.

The experiments were conducted in two sessions usually consisting of eight trials each, and in each of the sessions, we randomly assigned traders to different endowment groups, each of which had the same ex ante probability of winning the cash prize under rational expectations. Cash earning averaged about \$16 for a two-hour session.

### D. Information

In all the experiments, we gave the traders some information about dividends. This information always took the form of eliminating one or more possible dividends in one or more periods. For example, the information window could display the following at the beginning of period 1 in Market 3.

| | Period 1 | Period 2 |
|---|---|---|
| Stock 3 | 0 12 24 | 12 36 |

Thus, no information is given about period 1, but this trader knows that the period 2 dice roll for stock 3 was not 1, 2, or 3. If we gave out information about period 2 at the beginning of period 1, then this information was repeated at the beginning of period 2. In each trial, we chose whether or not to give the market complete information about dividends in any of the periods. Once this decision was made, the possible clues consistent with this decision were assigned randomly to subsets of traders.

Next, we note what is and is not common knowledge in the trials. As mentioned above, the information contained on the stock certificate relating dice rolls to dividends is announced to all traders before the start of the experiment. All traders also know the number of trials in an experimental session and the length of each period. Information about how experimental cash is converted into the dollar cash prize is privately told to each trader (although it is the same for all traders). Thus, each trader knows only his own preferences. No information is given about the preferences of other traders or about the number of trader types. The distribution of endowments was also not common knowledge. Traders were told that some subset would receive private information, but no trader was ever told whether or not the market had complete information.

### *E. Experimental Design*

The parameters of the markets were chosen in order to examine issues such as information aggregation and arbitrage relationships.

Consider first the problem of information aggregation. Suppose, in Market 3, that we give the market the following information. Half the traders are told that the period 2 dividend for stock 1 is 12 or 24, while the other half is told that the period 2 dividend is either 0 or 12. Given the intertemporal correlation depicted in Table I, the rational expectations equilibrium price in period 1 is 24 (12 with probability 1/3, 24 with probability 1/3, and 36 with probability 1/3). If the first period dividend is revealed as being, say 0, the rational expectations price in period 2 is 12.

In Market 4, the information aggregation problem can be even more difficult. Suppose that a quarter of the market is told that the period 2 dividend for stock 3 is either 18 or 24, a quarter is told that this dividend is either 12 or 24, a quarter is told that stock 4 will pay either 0 or 15 in period 1, and the last quarter are told that stock 4 will pay either 0 and 30. Then, the market as a whole has complete information about *both* stocks in both periods.

There are two arbitrage relationships implied by the distribution of dividends, one in each market.

In Market 4, stocks 3 and 4 were perfectly negatively correlated in each period and across time. It can be seen that taken together, these stocks pay a dividend of 30 in period 1 and 36 in period 2 *independent of the dice* rolls. Hence we must have $p_3 + p_4 = 66$, $q_1 + q_2 = 36$ no matter what the realized dividends are, where $p$ and $q$ denote the first and second period prices of the stocks. This arbitrage relationship is independent of both information aggregation and risk preferences.

In Market 3, the period 1 dividends of stocks 2 and 3 sum to 24 independent of the dice roll. If no additional information regarding period 2 dividends is supplied to the market between periods, then the price difference between period 1 and period 2 of a portfolio consisting of one unit of each stock is predicted to be 24. This prediction depends on risk neutrality and also on information aggregation. For example, if traders fail to aggregate second period information in the first period but do so in the second period, we would not expect this relationship to hold.

## III. Experimental Results

In this section, we describe the results from our experiments. We will describe the results in three parts. The first part will concentrate on the degree to which the participants in our markets aggregated information. The second will examine the extent to which deviations from rational expectations can be captured based on some "standard" market efficiency tests. Finally, we will present a heuristic learning model which captures market behavior and examine the implications of this learning model for bid-ask behavior.

### A. Information Aggregation

It is easy to compute rational expectations equilibrium prices in our markets if all traders are risk neutral.[4] In period 2, the rational expectations price is simply the expectation of the dividend at the end of the period conditional on the information of the market as a whole. In the first period, the price is the expected dividend in period 1 plus the expected dividend in period 2, again conditional on the information available to the market as a whole. In either period, the expectation takes account of any correlation across stocks or across time.

We present in Figures 1–4 the rational expectations equilibrium predictions of the model and actual transaction prices. A preliminary examination of the figures shows that there was a significant difference between period 1 and period 2, in that the market aggregated information much better in period 2. This is not surprising, since the information aggregation problem in the second period is much simpler than in the first. We note that the essential difference between periods 1 and 2 is the complexity of the market, but that the structure of common knowledge is exactly the same. It is also interesting that the pattern of prices between Market 3 and Market 4 is not very different. We also note that the figures do not provide any evidence that trader's systematically under- or overestimate capital gains (as was the case in Smith et al. (1988). Their paper focused on the complexity induced by many periods, whereas we focus on complexity induced by the number of stocks and the number of states within a period).

In order to obtain some nonvisual evidence on the issue of information aggregation, we examined the data in two ways.

(i) First, we investigated whether the prior information equilibrium is a better explanation of the transaction prices than the rational expectations equilibrium.[5]
(ii) Second, we regressed dividends on price to see the extent to which the rational expectations hypothesis provides a good prediction of observed behavior, and also examined the arbitrage relationships discussed above.

[4] In most of our trials, the market as a whole has complete information. In these trials, the rational expectations equilibrium is independent of risk preferences.

[5] See Forsythe, Palfrey, and Plott (1982); Plott and Sunder (1982); and Friedman, Harrison, and Salmon (1984) for further discussions of this concept. The prior information equilibrium price for a security in any period is simply the highest prior expectation among all traders taking into account all correlations. Here, the idea is that the trader(s) with the highest expected value will bid up prices to this expected value, and will end up holding all the units of the stock. (Note that we have unlimited short sales but a borrowing constraint, so that such an equilibrium is well defined.)

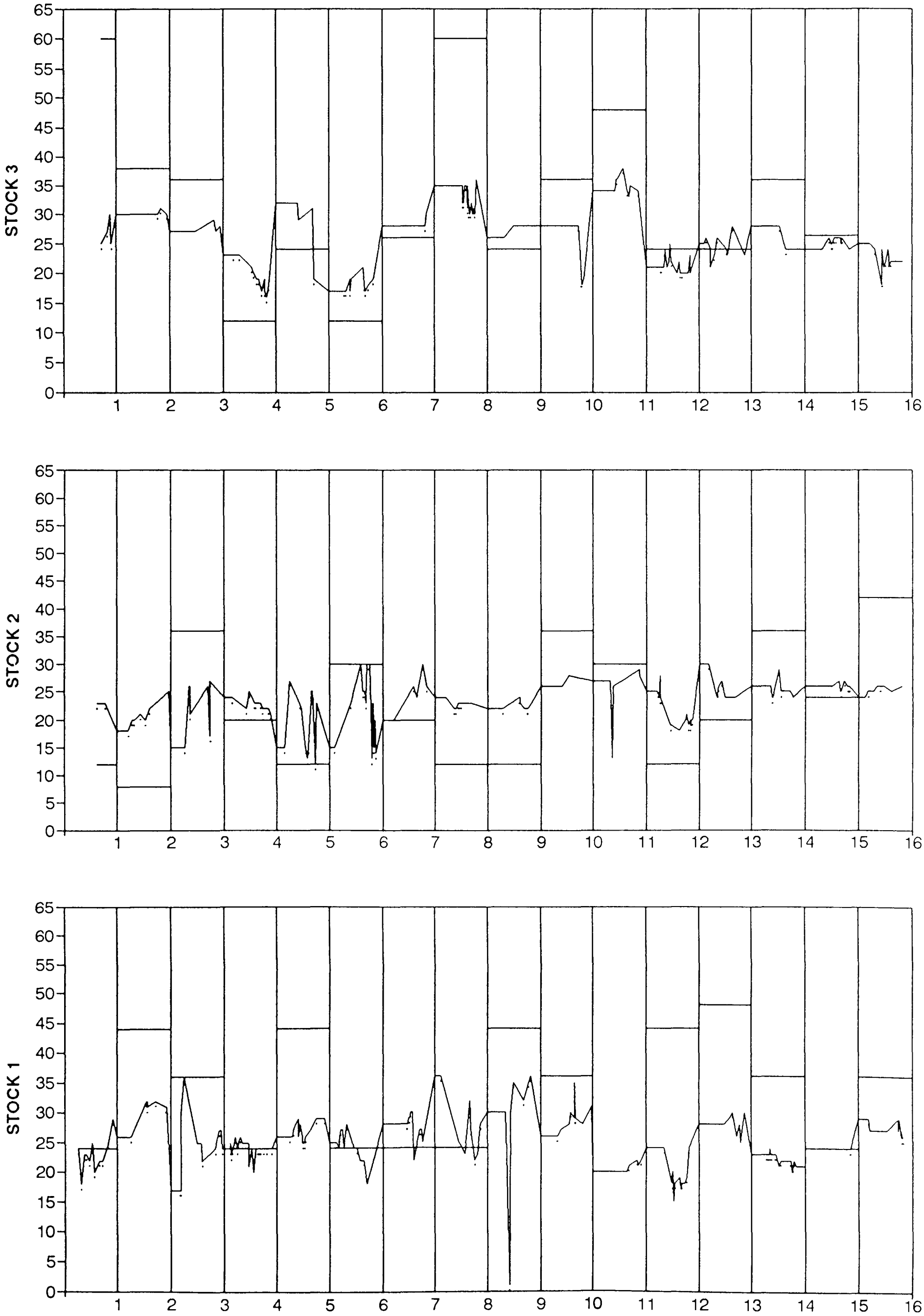


**Figure 1. Transaction prices and the rational expectations equilibrium prices in the first period of Market 3, Trials 1 to 16.** Market 3 has three two-period lives stocks. A trade occurred at the price above the dot. The vertical lines separate the trials, and within each trial, the dots are plotted in real time. The horizontal lines are the rational expectations equilibrium (REE) prices.

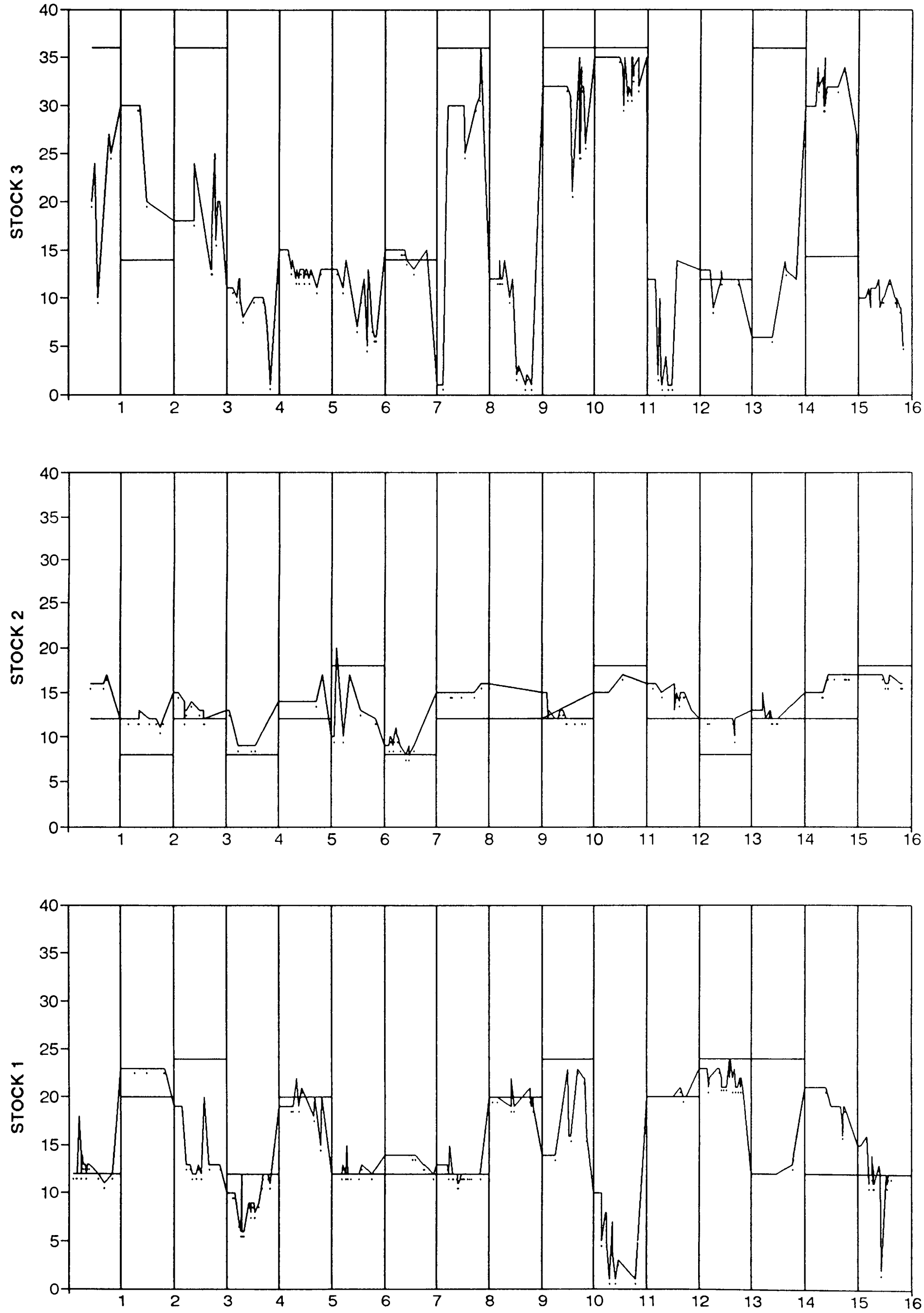


**Figure 2. Transaction prices and the rational expectations equilibrium prices in second period of Market 3, Trials 1 to 16.** Market 3 has three two-period lives stocks. A trade occurred at the price above the dot. The vertical lines separate the trials and, within each trial, the dots are plotted in real time. The horizontal lines are the rational expectations equilibrium (REE) prices.

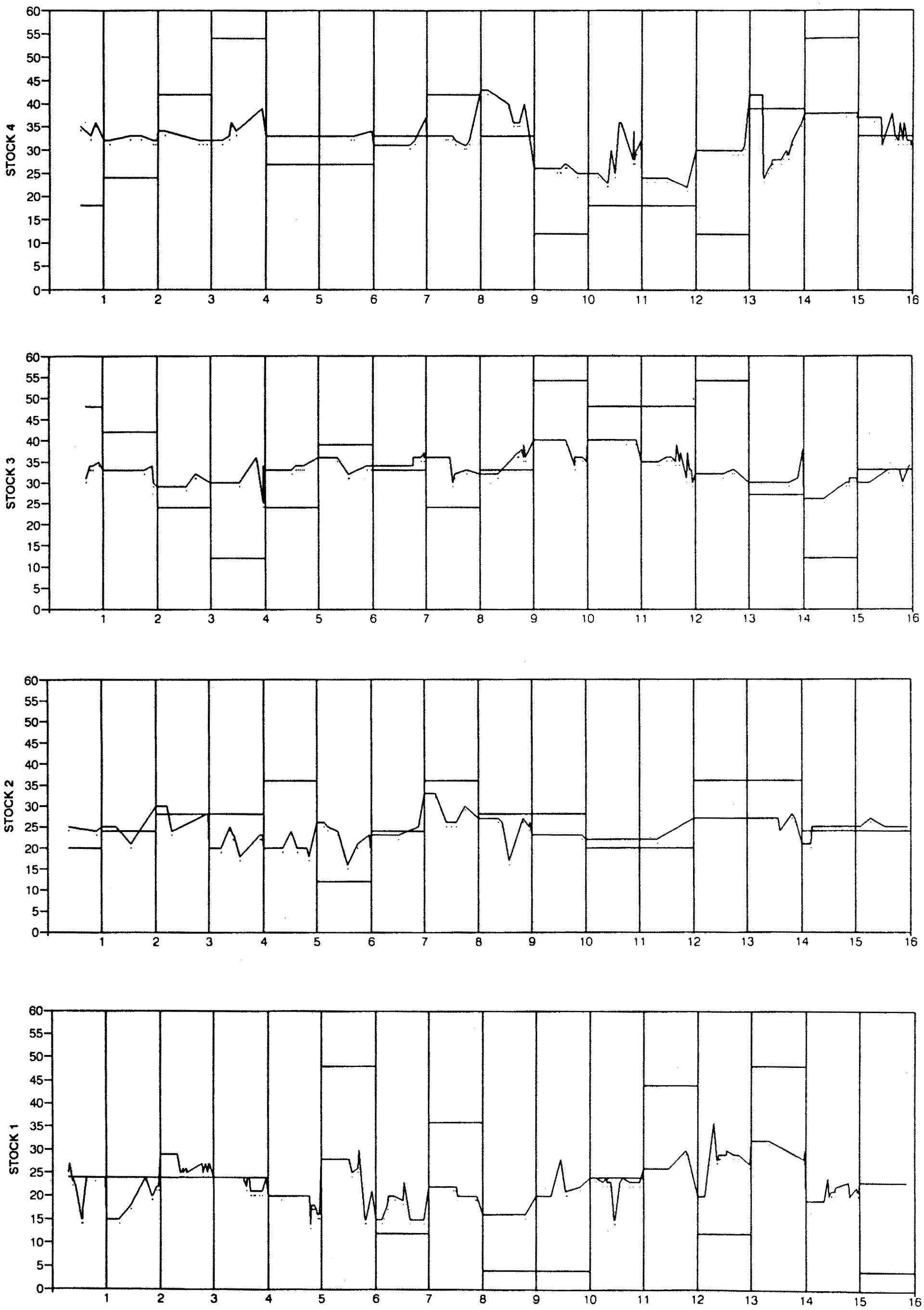


**Figure 3. Transaction prices and the rational expectations equilibrium prices in first period of Market 4, Trials 1 to 16.** Market 4 has four two-period lived stocks. A trade occurred at the price above the dot. The vertical lines separate the trials and, within each trial, the dots are plotted in real time. The horizontal lines are the rational expectations equilibrium (REE) prices.

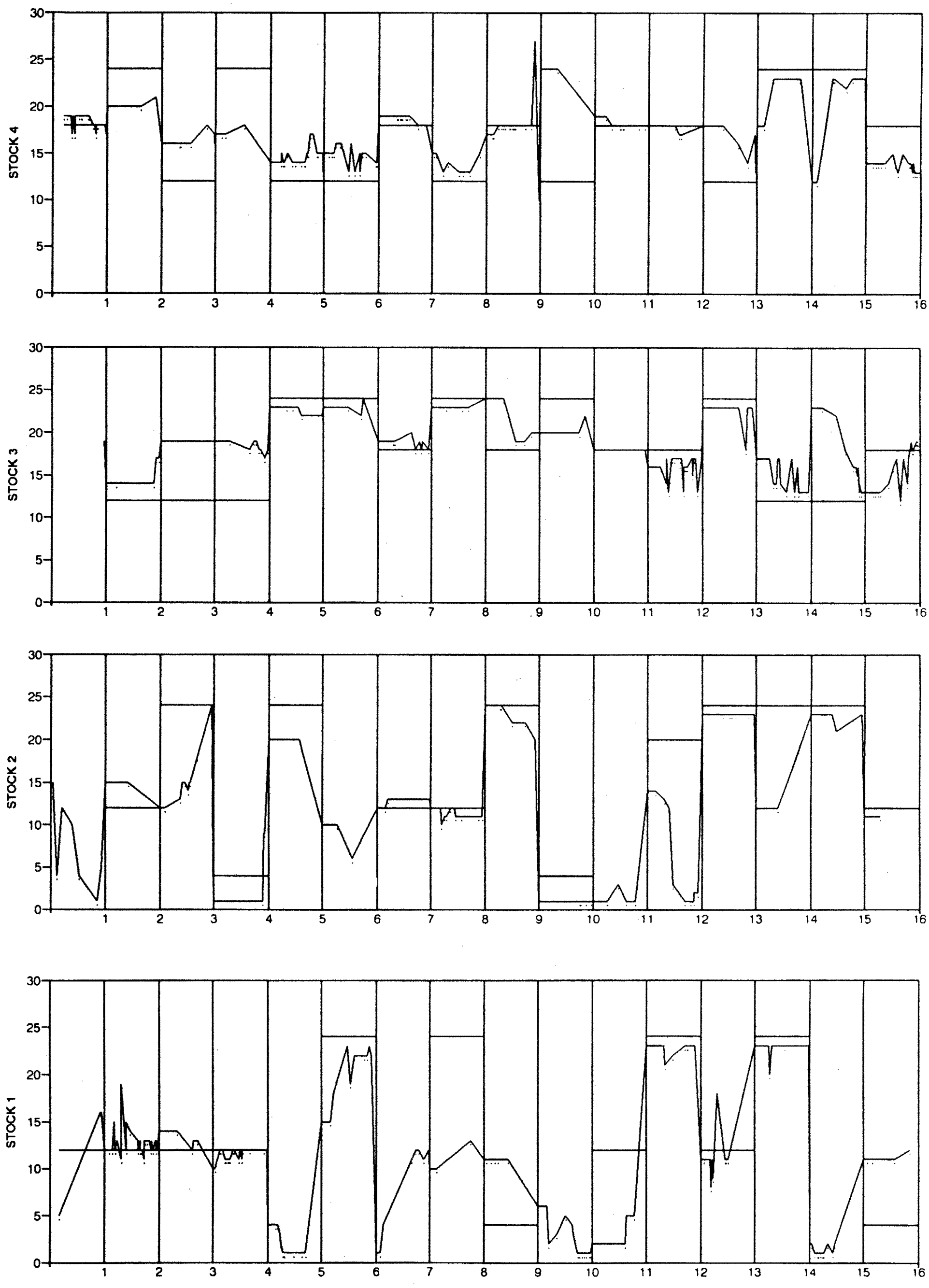


**Figure 4. Transaction prices and the rational expectations equilibrium prices in second period of Market 4, Trials 1 to 16.** Market 4 has four two-period lived stocks. A trade occurred at the price above the dot. The vertical lines separate the trials and, within each trial, the dots are plotted in real time. The horizontal lines are the rational expectations equilibrium (REE) prices.

We compared the mean absolute deviation between the transaction prices and the predicted rational expectation prices with the mean absolute deviation between the prior information equilibrium prices and the transaction prices. Table IX shows the outcome of this comparison based on the last five transaction prices in any period. On the basis of this table, it is clear that at least on the basis of mean absolute deviations, rational expectations does not perform very well relative to prior information in the first period. In the second period, it does slightly better than the prior information equilibrium. One can interpret the fact that the prior information equilibrium outperforms the rational expectations equilibrium as indicating the presence of significant informational inefficiency.

To get some further insight into the issue of information aggregation, we regressed the following model:

$$d_t = \alpha + \beta p_{i,t} + \varepsilon_t$$

where $d_t$ is the expected *stream* of dividends from period $t$ onward given the information available to the market as a whole, and $p_{i,t}$ is the $i$th transaction price in period $t$. If the traders aggregate information, we expect $\alpha = 0$ and $\beta = 1$. Table III contains the regression results, by stock and by period.

The regression results confirm the impression that the market tended to aggregate information better in the second period, and also that there was not much difference in the behavior in Market 3 and Market 4. We remark that weighting the observations by volume did not change the qualitative nature of the estimates.

An interesting observation which emerges from the table is the negative relationship between the estimate of the intercept and that of the slope. We find that without exception, an estimate of $\beta$ greater than 1 has a negative estimate of $\alpha$. We believe this is due to the fact that in a high dividend state, prices tend to rise (although not necessarily to the rational expectations equilibrium), while in the low dividend states, prices tend to fall.

In summary, we have found that the rational expectations model does not perform very well in relatively more complex setting of period 1. Note that the only essential difference between the first and second period is the size of the state space, but there is no difference in what is made common knowledge. Since the market aggregates information much better in the second period, we believe that the complexity of the first period problem contributes to the difficulty of the market to aggregate information. This conclusion is quite consistent with the findings from previous studies that increasing the dividend state space (e.g., the number of trader types, the studies of perfect versus imperfect information) is associated with decreased information aggregation.

In view of these results and the fact that the rational expectations model is used to model behavior in extremely complex markets, we believe that a promising direction for future research is whether the addition of derivative securities, such as options, helps in the dissemination of information. We will address this issue in a subsequent paper. Of course, we could also reduce the

**Table III**

## Regressions of Prices on Dividends

The model is $d_t = \alpha + \beta p_{i,t} + \varepsilon_t$, where $d_t$ is the expected stream of dividends from period $t$ onward, and $p_{i,t}$ is the $i$th transaction price in period $t$. The results are presented by market, by stock, and by period (Per). Market 3 has three two-period lived stocks, and Market 4 had four two-period lived stocks. NOB is the number of observations, and standard errors are in parentheses.

| | | Market 3 | | | |
|---|---|---|---|---|---|
| Stock | | $\alpha$ | $\beta$ | $R^2$ | NOB |
| 1 | Per 1 | 20.15 | 0.48 | 0.036 | 200 |
| | | (10.50) | (0.175) | | |
| 1 | Per 2 | 1.72 | 0.94 | 0.59 | 190 |
| | | (4.07) | (0.056) | | |
| 2 | Per 1 | 1.46 | 0.90 | 0.11 | 128 |
| | | (10.25) | (0.232) | | |
| 2 | Per 2 | 2.68 | 0.68 | 0.34 | 133 |
| | | (2.42) | (0.083) | | |
| 3 | Per 1 | −35.67 | 2.54 | 0.60 | 130 |
| | | (11.64) | (0.181) | | |
| 3 | Per 2 | −5.17 | 1.11 | 0.53 | 178 |
| | | (10.91) | (0.079) | | |
| | | Market 4 | | | |
| Stock | | $\alpha$ | $\beta$ | $R^2$ | NOB |
| 1 | Per 1 | 2.37 | 0.77 | 0.06 | 139 |
| | | (13.44) | (0.263) | | |
| 1 | Per 2 | −1.55 | 1.06 | 0.77 | 158 |
| | | (3.88) | (0.047) | | |
| 2 | Per 1 | 12.73 | 0.58 | 0.07 | 63 |
| | | (6.91) | (0.271) | | |
| 2 | Per 2 | 4.84 | 0.82 | 0.45 | 76 |
| | | (6.95) | (0.105) | | |
| 3 | Per 1 | −31.46 | 1.97 | 0.20 | 89 |
| | | (11.82) | (0.417) | | |
| 3 | Per 2 | 4.80 | 0.70 | 0.28 | 134 |
| | | (3.24) | (0.097) | | |
| 4 | Per 1 | −7.28 | 1.19 | 0.19 | 104 |
| | | (10.83) | (0.241) | | |
| 4 | Per 2 | 4.39 | 0.72 | 0.32 | 177 |
| | | (3.09) | (0.079) | | |

complexity and see what maximal degree of complexity is consistent with aggregation, but we believe that such an exercise, while of theoretical interest, would not shed much light on whether the rational expectations model provides an adequate description of real world markets.

### *B. Test of Arbitrage Relationships*

As discussed in Section II, there are two arbitrage relationships, one in each market. In Market 3, a portfolio consisting of one unit of each stock should have a price difference of 24 between period 1 and period 2. In Market 4, a portfolio of 1 each of stocks 3 and 4 should have a price of 66 in the first period and 36 in the second. Figure 5 shows that the arbitrage relationship in Market 4 held almost without any deviation. In this figure, the 32 periods (i.e., 16 two-period trials) are numbered 1 to 32.

For Market 3, letting $p_j$ be the price of a portfolio of one stock each of stocks 2 and 3, we expect $p_1 = p_2 + 24$ under risk neutrality and assuming that all information is aggregated in the first period. Analysis of this is difficult since we generally have many different prices in each period, and it can be the case that some period 2 information is only aggregated in the second period. However, some insight is provided by the following regression:

$$p_2 = \alpha + \beta p_1 + \varepsilon$$

where $p_j$ is the average price of the portfolio in period $j$. Under risk neutrality, and assuming that the effects due to aggregation in the second period average out to zero *across* trials, we would expect $\alpha = -24$, $\beta = 1$. The estimated coefficients were $\alpha = -24.485$ with a standard error of 9.58, and $\beta = 1.10$ with a standard error of 0.44. On the basis of this regression, we cannot reject the relationship.

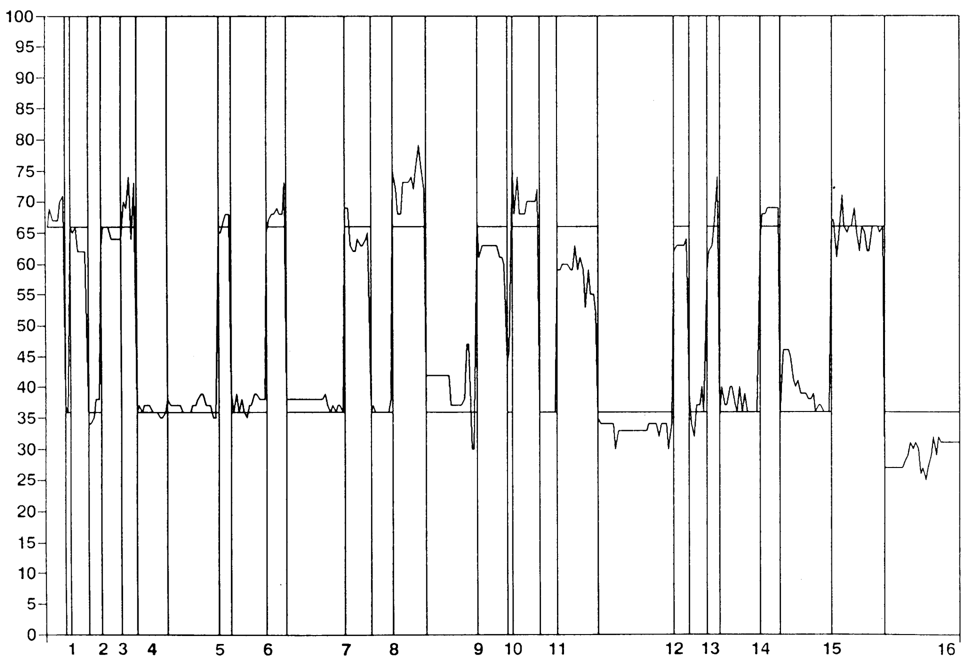


**Figure 5. Arbitrage Relationship in Market 4.** Market 4 has four two-period lived stocks. The figure shows the price of a portfolio of one unit of stock 3 and one unit of stock 4 and the rational expectations price of this portfolio in Market 4 for all periods and all trials. The vertical lines represent the periods (two per trial), and the horizontal lines are the rational expectations predictions.

### C. Detecting Deviations from Rational Expectations

Given that the rational expectations model does not perform very well in our markets, we examined whether some common tests of market efficiency would detect these deviations. The first of these is the random walk, or unbiasedness, hypothesis. It is sometimes asserted that in an informationally efficient market (especially with risk-neutral traders), the current price is the best predictor of the next price.

For all the trials, we examined the following model, adjusted for period changes:

$$p_{t+1} = \alpha + \beta p_t + \varepsilon_t.$$

We tested the hypothesis ($\alpha = 0, \beta = 1$) using the method proposed by Dickey and Fuller (1981) to test for a unit root. The outcomes of the tests are presented in Table IV.

The table shows that there is overwhelming evidence against rejection of the null hypothesis. On the basis of this evidence alone, it is difficult to reject the implied hypothesis of an informationally efficient market. We find this result especially interesting in that we already know that our markets are not informationally efficient.

Investigators of the efficient markets hypothesis have also examined the behavior of bid-ask spreads. One group of studies investigates whether the bid-ask spread depends on the volume of trade (see, e.g., Glosten and Harris (1988)). The motivation for these studies is that information aggregation is less likely in thinly traded stocks, resulting in a higher bid-ask spread than in thickly traded stocks. A related argument (see, e.g., Copeland and Galai (1983)) is that the bid-ask spread is likely to be wider when traders face more uncertainty.[6]

We investigated the relationship between volume and the bid-ask spread in two ways. First, we compared the relationship between volume and the bid-ask spread across stocks. Second, we compared the bid-ask spread to the mean absolute deviation from rational expectations. If the volume of trade facilitates information aggregation, we would expect lower absolute deviations to be associated with lower bid-ask spreads. In conducting this analysis, we encountered two types of data problems: (i) Sometimes, the bid exceeded the ask. This occurred infrequently, and when it did, it occurred because the bids and asks were made at approximately the same time. If the bid exceeded the ask, we eliminated the observation. (ii) Occasionally, there was an outstanding bid (ask) but no ask (bid). We only accepted observations for which both a bid and ask were outstanding at the time of a trade. In addition, we eliminated cases when the bid-ask spread exceeded 50 (this usually occurred when an initial high ask was entered by some trader with no subsequent ask activity).

[6] Copeland and Friedman (1987) provide experimental evidence in support of this hypothesis.

**Table IV**

## Dickey-Fuller Unit Root Tests

The fitted model is

$$P_t - P_{t-1} = \gamma_0 + \gamma_1 P_{t-1} + \gamma_2(P_{t-1} - P_{t-2}) + \gamma_3(P_{t-2} - P_{t-3}) + \gamma_4(P_{t-3} - P_{t-4}) + \varepsilon_t,$$

where $P_t$ is the $t$th transaction price. The underlying model under the null hypothesis of a random walk is

$$P_t = \gamma_0 + (1 + \gamma_1) P_{t-1} + v_t.$$

Under the null, $(1 + \gamma_1) = 1, \gamma_0 = 0$. The alternative hypothesis is $(1 + \gamma_1) < 1, \gamma_0 > 0$. The results are presented by market and by stock. Market 3 has three stocks, and Market 4 has four stocks. NOB is the number of observations.

| | $\gamma_0$ | $\gamma_1$ | NOB | $\Phi_1$ | Critical Value[a] |
|---|---|---|---|---|---|
| Market 3 Stock 1 | 0.009 | −0.000 | 263 | 0.001 | 4.61 |
| Market 3 Stock 2 | 0.651 | −0.053 | 145 | 1.982 | 4.63 |
| Market 3 Stock 3 | −0.187 | 0.003 | 184 | 0.199 | 4.63 |
| Market 4 Stock 1 | 0.312 | −0.027 | 181 | 1.101 | 4.63 |
| Market 4 Stock 2[b] | 0.071 | −0.018 | 83 | 0.399 | 4.71 |
| Market 4 Stock 3 | 0.044 | −0.006 | 106 | 0.164 | 4.63 |
| Market 4 Stock 4 | 0.045 | 0.000 | 168 | 0.049 | 4.63 |

[a] The critical values are taken from Table IV of Dickey and Fuller (1981), where they provide critical values for a small range of sample sizes. Since these critical values are decreasing in the sample size, the value reported above is that for the next largest sample size in their table. For example, with 263 observations, we report the critical value for a sample of 500. The model is rejected at the 5% significance level if $\Phi_1 >$ critical value.

[b] For Stock 2, Market 4, only one lag term could be fitted given the number of available observations.

Table V provides evidence in this regard by stock and market. One interesting fact that emerges from this table is that there is always a positive correlation between the average bid-ask spread and the mean absolute deviation from rational expectations. This correlation is significantly different from zero in four out of the seven cases, indicating that large bid-ask spreads are associated with large deviations for rational expectations. As argued above, this finding is quite intuitive. On the other hand, volume does not seem to be correlated with either the extent of information aggregation or the average bid-ask spread.

In terms of the relationship between uncertainty and the bid-ask spread, we would expect the bid-ask spread in period 1 to be wider than that in period

Table V

**Correlation of Deviations from Rational Expectations, Volume of Trade, and the Average Bid-Ask Spread**

DEV is the mean absolute deviation from rational expectations based on the last five traded prices, QTY is the average quantity traded in the market, BA is the average bid-ask spread. The figure in parentheses is 1 minus the probability that the correlation is significantly different from zero. The results are given by market and by stock. Market 3 has three stocks while Market 4 has four stocks.

| Stock/Market | DEV vs. QTY | DEV vs. BA | QTY vs. BA |
|---|---|---|---|
| 1/3 | −0.261 | 0.199 | −0.043 |
| | (0.149) | (0.276) | (0.814) |
| 2/3 | 0.095 | 0.626 | 0.155 |
| | (0.610) | (0.000) | (0.406) |
| 3/3 | 0.112 | 0.039 | 0.019 |
| | (0.542) | (0.834) | (0.916) |
| 1/4 | −0.390 | 0.262 | −0.259 |
| | (0.027) | (0.147) | (0.152) |
| 2/4 | −0.166 | 0.443 | −0.074 |
| | (0.389) | (0.016) | (0.703) |
| 3/4 | 0.080 | 0.425 | 0.265 |
| | (0.670) | (0.017) | (0.150) |
| 4/4 | −0.198 | 0.483 | −0.043 |
| | (0.286) | (0.006) | (0.817) |

2. This is because traders face more uncertainty in period 1 since the distribution of information in our markets is *not* common knowledge, and the set of possible distributions is greater in the first period than in the second. Examining the average bid-ask spread given (i) and (ii) above; we found support for this hypothesis, as shown in Table VI. Our results thus complement those of Copeland and Friedman (1987), who examined the role of sequential information arrival on the bid-ask spread.

The next test we performed was a variance bounds test (see LeRoy and Porter (1981); Shiller (1981)). In an efficient market, if prices reflect the present discounted value of future dividends, then the variance of prices should not exceed the variance of dividends. This relationship should hold in our model, both within periods and across periods. Within one of our trading periods, the variance of the rational expectations dividend is zero. However, since all information can, in theory, be transmitted through bids and asks, one prediction is that there should be no price volatility in a period. This is clearly violated by our data, as can be seen from Figures 1–4. Comparing across periods, however, we expect price volatility since realized dividends change. In practice, variance bound tests are conducted on the basis of realized dividends. In our markets, we are also able to compare the variance of dividends conditional on rational expectations. This is not observable in practice. Table VII contains information about variances of prices and dividends, by stock and period.

**Table VI**

**Average Bid-Ask Spread**

The average bid-ask spread is given by period, by stock, and by market. Market 3 has three two-period lived stocks, while Market 4 has four two-period lived stocks.

| | Period 1 | Period 2 |
|---|---|---|
| Market 3 | | |
| Stock 1 | 4.92 | 3.71 |
| Stock 2 | 6.07 | 2.08 |
| Stock 3 | 5.55 | 5.41 |
| Market 4 | | |
| Stock 1 | 6.17 | 3.56 |
| Stock 2 | 6.02 | 5.11 |
| Stock 3 | 4.23 | 3.37 |
| Stock 4 | 6.46 | 3.31 |

The table indicates that across periods, our markets cannot be said to be "excessively volatile" since the variance of prices is always below the variance both of actual dividends and of dividends conditional on rational expectations.

The final test we performed consisted of examining whether a price filter trading rule was profitable. The profitability of such rules has been demonstrated by several authors in various markets (see Lehmann (1988) for a recent reference). The particular trading rule we employed was the following: start with an initial price (say the first traded price in a period). If the price exceeds this price, then sell one unit, and if the price falls below this price, buy one unit. Continue this rule, except change the initial price to the price at which you traded. We examined the profitability of this simple rule in three ways.

*Rule 1:* First, we assumed that one could either buy or sell at any transaction price, *irrespective* of whether it was a bid or ask.

*Rule 2:* Second, we assumed that one could only sell (buy) if there *existed* a bid (ask) at the time a trade took place.

*Rule 3:* Finally, we examined the profitability of the rule if one traded whenever there existed a favorable bid (ask), *irrespective* of whether a trade actually took place at that bid (ask).

The results from this trading strategy are given in Table VIII. We find it very interesting that the filter strategy is profitable under Rule 1 for every stock except stock 2 in Market 4. On the other hand, if we adjust for the fact that one can only sell at a bid and buy at an ask, the strategy is quite unfavorable. In practice, the profitability of such strategies are examined assuming Rule 1. This analysis indicates that adjusting for the bid-ask spread may make seemingly profitable strategies quite undesirable.

On the basis of the tests we have performed, we find that our experimental

Table VII

**Variances of Transaction Prices and Dividends**

$V(P)$ is the variance of the last five traded prices, $V(D{:}RE)$ is the variance of dividends given rational expectations, and $V(D)$ is the variance of actual dividends. The results are presented by market and by stock, further disaggregated by period. Market 3 has three two-period lived stocks, and Market 4 has four two-period lived stocks.

| | Market 3 | | |
|---|---|---|---|
| | $V(P)$ | $V(D{:}RE)$ | $V(D)$ |
| Period 1 | | | |
| Stock 1 | 3.837 | 12.393 | 13.660 |
| Stock 2 | 2.664 | 11.020 | 9.338 |
| Stock 3 | 4.568 | 16.366 | 19.100 |
| Period 2 | | | |
| Stock 1 | 5.256 | 6.767 | 7.550 |
| Stock 2 | 2.528 | 3.383 | 4.382 |
| Stock 3 | 10.664 | 16.231 | 18.000 |
| | Market 4 | | |
| | $V(P)$ | $V(D{:}RE)$ | $V(D)$ |
| Period 1 | | | |
| Stock 1 | 4.069 | 16.667 | 18.330 |
| Stock 2 | 2.228 | 6.532 | 7.335 |
| Stock 3 | 2.388 | 13.637 | 13.670 |
| Stock 4 | 3.694 | 14.562 | 13.816 |
| Period 2 | | | |
| Stock 1 | 7.070 | 9.180 | 10.247 |
| Stock 2 | 7.544 | 9.794 | 10.621 |
| Stock 3 | 3.017 | 4.900 | 5.003 |
| Stock 4 | 3.227 | 4.837 | 5.005 |

markets share many of the statistical properties of real world markets, despite the fact that our markets are generally not very efficient.

### D. A Learning Model

It is clear from the results presented above that the transaction prices in the markets do not conform closely to the predictions of rational expectations theory. It is equally clear that to attempt to explain these deviations, we must model the process of expectation formation during a market session. There are formidable difficulties which must be faced in modeling expectation formation. This difficulty is exacerbated by the fact that the type of market we are studying does not fall into the class of models analyzed in the theoretical literature on learning rational expectations (see Marcet and Sargent (1988) for a recent review of the literature). We investigated whether a simple, heuristic learning model could explain the time path of prices. This model also allows us to predict bid and ask behavior for each individual trader. We examined whether learning by frequency distribution captured

**Table VIII**

**Profitability of Filter Trading Strategy**

Rule 1 assumes we could buy or sell at any transaction price. Rule 2 requires a bid (ask) be available to sell (buy) but only at the time a transaction takes place. Rule 3 applies the Rule 2 strategy irrespective of whether a transaction takes place. The outcomes of the strategies are given by stock, by market, and by period. Market 3 contains three two-period lived stocks, and Market 4 has four two-period lived stocks.

| Stock/Market | Rule 1 | Rule 2 | Rule 3 |
|---|---|---|---|
| Period 1 | | | |
| 1/3 | 113 | 2 | -34 |
| 2/3 | 112 | 24 | 106 |
| 3/3 | 81 | 14 | -50 |
| Period 2 | | | |
| 1/3 | 105 | 23 | 5 |
| 2/3 | 35 | 2 | -26 |
| 3/3 | 156 | 9 | -49 |
| Period 1 | | | |
| 1/4 | 93 | 18 | -24 |
| 2/4 | 34 | -4 | -27 |
| 3/4 | 36 | 0 | 9 |
| 4/4 | 23 | -43 | -76 |
| Period 2 | | | |
| 1/4 | 39 | 8 | -46 |
| 2/4 | -34 | -34 | -46 |
| 3/4 | 19 | -19 | -78 |
| 4/4 | 55 | 17 | 10 |

the dynamics of prices in our markets. The learning rule for a trader is simply

$$p_{n+1}^e = \frac{n}{(n+1)} p_n^e + \frac{1}{(n+1)} p_n$$

where $p_{n+1}^e$ is the expectation of the price at the $(n+1)$st trade after $n$ trading prices have been observed, and $p_1^e$ is given by the information in the dividend table assuming Bayesian processing of any information given to the trader at the beginning of the period. In computing $p_1^e$, it is also assumed that any correlation which exists among stocks, either within a period or across time, is also taken into account. At the beginning of period 2, we assume that the prior is again formed in the same way, ignoring any updating which took place in period 1. Finally, if $p_n^e$ was greater (less) than the maximum (minimum) possible dividend, it was set equal to the maximum (minimum) possible dividend.

Figure 6 shows the comparison between the actual price at the $n$th trade and the price predicted by the above learning model after $(n-1)$ trades, both measured in deviations from rational expectations. The solid line shows the actual price, the "+" the expected price given the expectations of the seller, and the "." is the expected price given the expectations of the buyer. The

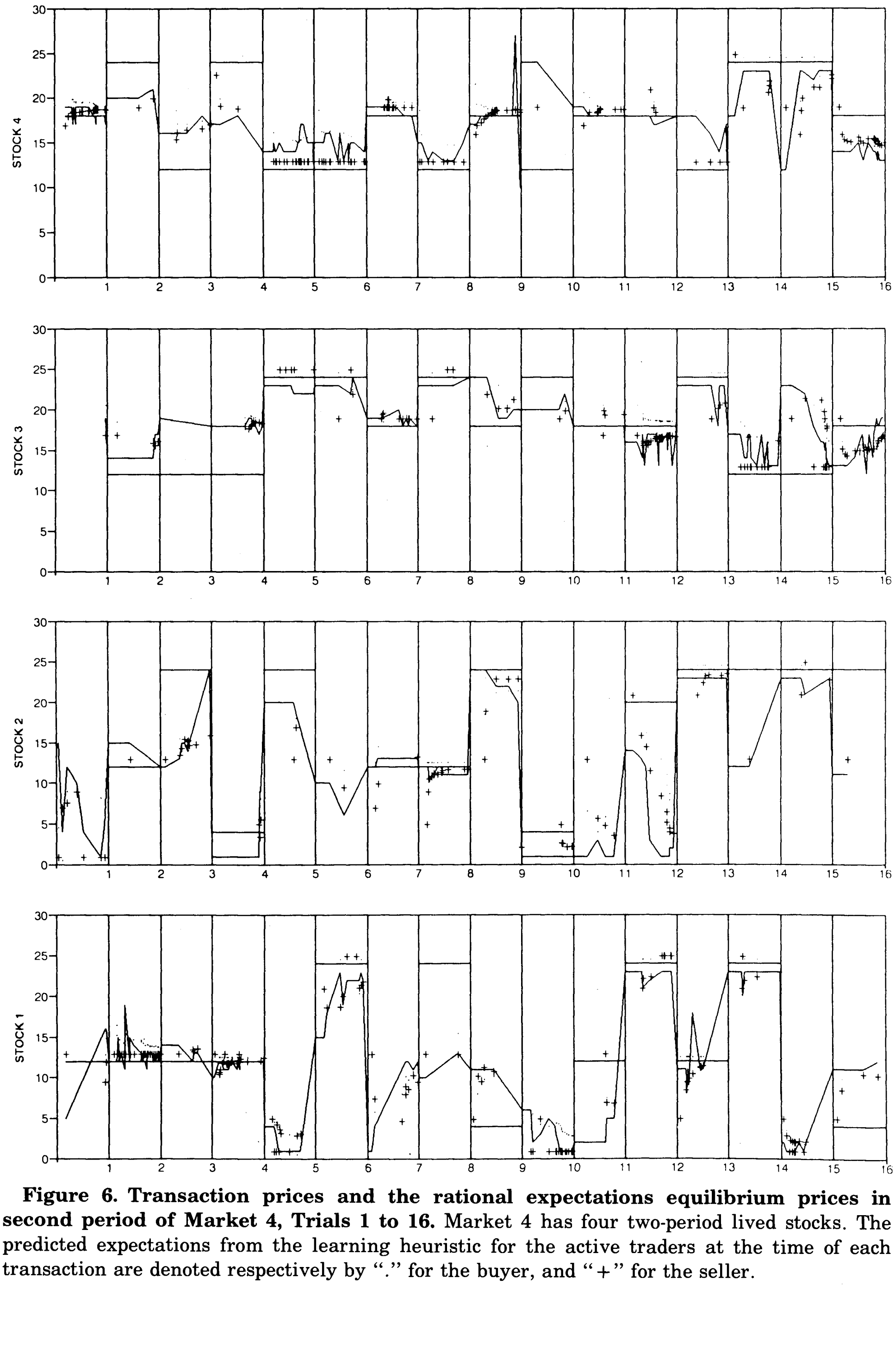


**Figure 6. Transaction prices and the rational expectations equilibrium prices in second period of Market 4, Trials 1 to 16.** Market 4 has four two-period lived stocks. The predicted expectations from the learning heuristic for the active traders at the time of each transaction are denoted respectively by "." for the buyer, and "+" for the seller.

**Table IX**

**Mean Absolute Deviations**

RE is the mean absolute deviations from rational expectations equilibrium, PI is mean absolute deviation from the prior information equilibrium, LEARNING is the mean absolute deviation from learning model. The results are given by period for each market. Market 3 has three stocks, while Market 4 has four stocks.

| | Period 1 Market 3 | Period 2 Market 3 | Period 1 Market 4 | Period 2 Market 4 |
|---|---|---|---|---|
| RE | 9.64 | 4.74 | 9.82 | 3.16 |
| PI | 6.95 | 5.65 | 6.67 | 3.26 |
| LEARNING | 2.05 | 1.99 | 1.93 | 1.78 |

figure contains information about the second period of Market 4, and is representative of the other market and periods.[7]

We find that the simple learning model described above captures the price dynamics surprisingly well. This is confirmed by Table IX, which shows the mean absolute deviation between the actual price and the average of the buyer's and seller's expected prices. For ease of comparison, we have reproduced the mean absolute deviations based on prior information and on rational expectations.

The table confirms the graphical impression that the learning rule tracks market prices to a remarkable degree. Note that even our ad hoc learning rule does only slightly better in the second period than in the first. That is, it provides a good description of market prices even though the problem faced by traders is more complex in the first period.

The learning rule can also be used for predicting bid-ask behavior in the markets. If traders form expectations according to this rule, then any actual bid made by a trader should not exceed the expected price of the stock. Similarly, asks should not be below the expected price. Table X shows the frequency of positive and negative deviations of all bids and asks given the expectations implied by our learning rule. As is evident, the learning model performs exceptionally well in predicting bid and ask behavior. For example, 82.6% of the actual bids in Market 3 and 87.9% in Market 4 are in the predicted range. Of all the asks, 94.6% and 94.5% are consistent with the learning model. Further, of the bids and asks which are inconsistent with the predictions of the learning rule, a significant number are within two (experimental) dollars of the predicted bids and asks.

## IV. Conclusions

In this paper, we have examined the behavior of prices in multiperiod markets with multiple assets. Our aim has been to study the performance of

[7] Graphs for all the markets are available upon request.

Table X

**Actual Bids (Asks) Minus Bids (Asks) Predicted by Learning Model**

DEV is the deviation of actual bid (ask) from predicted bids (asks). The numbers denote the frequency of the deviation. The results are given by period, by stock, and by market. Market 3 has three two-period lived stocks and Market 4 has four two-period lived stocks. Thus, S1/3 refers to stock 1 in Market 3, etc.

| | Market 3 | | | | Market 4 | | | |
|---|---|---|---|---|---|---|---|---|
| | Period 1 | | Period 2 | | Period 1 | | Period 2 | |
| DEV | S1/3 Bid | S1/3 Ask | S1/3 Bid | S1/3 Ask | S1/4 Bid | S1/4 Ask | S1/4 Bid | S1/4 Ask |
| − 30 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| −20 | 5 | 0 | 0 | 0 | 24 | 0 | 0 | 0 |
| −10 | 52 | 1 | 6 | 1 | 73 | 1 | 17 | 0 |
| −5 | 92 | 3 | 26 | 4 | 52 | 0 | 28 | 5 |
| −2 | 77 | 8 | 47 | 4 | 39 | 15 | 62 | 2 |
| 0 | 42 | 16 | 48 | 21 | 26 | 16 | 106 | 14 |
| 2 | 8 | 69 | 32 | 53 | 6 | 41 | 35 | 79 |
| 5 | 5 | 44 | 26 | 41 | 1 | 51 | 6 | 62 |
| 10 | 8 | 42 | 13 | 41 | 2 | 40 | 3 | 50 |
| 20 | 0 | 27 | 0 | 21 | 0 | 34 | 0 | 9 |
| 30 | 0 | 27 | 0 | 4 | 0 | 17 | 0 | 0 |
| DEV | S2/3 Bid | S2/3 Ask | S2/3 Bid | S2/3 Ask | S2/4 Bid | S2/4 Ask | S2/4 Bid | S2/4 Ask |
| − 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| −20 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| −10 | 32 | 1 | 0 | 0 | 37 | 1 | 15 | 0 |
| −5 | 75 | 2 | 4 | 1 | 62 | 5 | 53 | 0 |
| −2 | 82 | 4 | 77 | 2 | 45 | 6 | 28 | 1 |
| 0 | 59 | 7 | 55 | 12 | 23 | 37 | 52 | 7 |
| 2 | 36 | 14 | 31 | 36 | 6 | 32 | 9 | 42 |
| 5 | 16 | 29 | 13 | 61 | 0 | 32 | 1 | 31 |
| 10 | 4 | 33 | 0 | 25 | 0 | 11 | 0 | 38 |
| 20 | 0 | 34 | 0 | 4 | 0 | 23 | 0 | 14 |
| 30 | 0 | 22 | 0 | 11 | 0 | 8 | 0 | 0 |
| DEV | S3/3 Bid | S3/3 Ask | S3/3 Bid | S3/3 Ask | S3/4 Bid | S3/4 Ask | S3/4 Bid | S3/4 Ask |
| − 30 | 24 | 0 | 3 | 0 | 0 | 0 | 0 | 0 |
| −20 | 7 | 0 | 13 | 0 | 11 | 0 | 5 | 0 |
| −10 | 27 | 0 | 44 | 5 | 61 | 0 | 20 | 2 |
| −5 | 39 | 6 | 44 | 5 | 67 | 1 | 35 | 5 |
| −2 | 35 | 4 | 38 | 11 | 53 | 5 | 38 | 18 |
| 0 | 24 | 17 | 59 | 15 | 25 | 3 | 30 | 11 |
| 2 | 10 | 51 | 13 | 35 | 19 | 27 | 16 | 65 |
| 5 | 2 | 52 | 16 | 32 | 26 | 31 | 11 | 34 |
| 10 | 0 | 58 | 4 | 36 | 17 | 24 | 5 | 49 |
| 20 | 1 | 66 | 2 | 17 | 0 | 29 | 5 | 45 |
| 30 | 0 | 22 | 0 | 5 | 2 | 12 | 0 | 19 |

**Table X**—*Continued*

| | Market 3 | | Market 4 | | | |
|---|---|---|---|---|---|---|
| | Period 1 | Period 2 | Period 1 | | Period 2 | |
| DEV | | | S1/4 Bid | S1/4 Ask | S1/4 Bid | S1/4 Ask |
| − 30 | | | 0 | 0 | 0 | 0 |
| −20 | | | 22 | 0 | 0 | 0 |
| −10 | | | 65 | 0 | 6 | 0 |
| −5 | | | 74 | 5 | 21 | 4 |
| −2 | | | 62 | 6 | 101 | 0 |
| 0 | | | 33 | 10 | 92 | 18 |
| 2 | | | 18 | 21 | 17 | 131 |
| 5 | | | 7 | 27 | 2 | 49 |
| 10 | | | 0 | 44 | 1 | 26 |
| 20 | | | 0 | 25 | 0 | 0 |
| 30 | | | 0 | 11 | 0 | 0 |

the rational expectations hypothesis in successively more complex market environments without imposing strong common knowledge conditions. We found that the markets are generally inefficient from the point of view of full information aggregation. As reported, this was especially the case in the more complex setting of period 1. Despite this, the arbitrage relationships implied by the dividend structure held, and it was not possible to detect the informational inefficiency by using some standard tests of market efficiency. These findings suggest that the lack of arbitrage opportunities and the failure of these tests to reject efficiency is not sufficient to conclude that a market is informationally efficient.

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