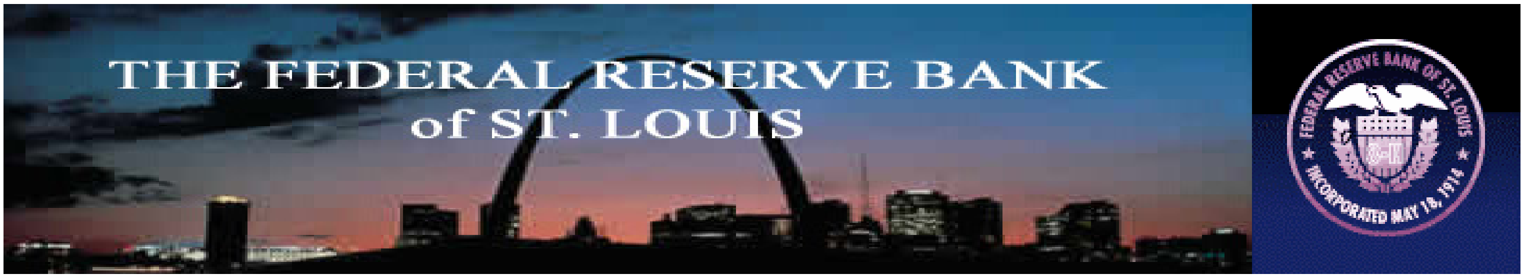

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TESTS OF RATIONAL EXPECTATIONS
IN A STARK SETTING

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ABSTRACT

We test the hypothesis that forecasts by participants in a stark experimental setting are the same as the rational expectation. At least for a process as simple as a random walk, relatively sophisticated as well as relatively unsophisticated participants' forecasts can be characterized as consistent with rational expectations. We find no support for the proposition that one-step-ahead forecasts are predictably wrong and substantial support for the converse proposition. The variance of forecast errors, though, is greater than for the rational expectation. Some participants have differences between two-step-ahead and one-step-ahead forecasts that are statistically significant, but the direction of bias is not systematic across individuals.

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> Some type of expectation lies at the base of every dynamic model in economics, and the rational-expectation approach eases the problem of the specification of expectations, despite the lack of any empirical justification. (Cyert and DeGroot 1987, p. x).

I. INTRODUCTION

While rational expectations has been the usual way of specifying expectations for some time, it still is not well supported in terms of evidence consistent with tighter definitions of rational expectations. There are at least three alternative ways of viewing rational expectations. One of them is in terms of the informal definition given by Grossman (1980, p. 10) that rational expectations is the proposition "that private economic agents gather and use information efficiently." While this proposition arguably is the basis of rational expectations' popularity, it also is sufficiently vague as to be generally untestable and sufficiently broad that it excludes only purposeful mis-forecasting contrary to the agent's interest. Muth provided another definition in the context of firm's forecasting: "expectations of firms (or more generally, the subjective probability distribution of outcomes) tend to be distributed, for the same information set, about the prediction of the theory (or the 'objective' probability distribution of outcomes)." (Parentheses in original. Muth 1961, p. 316). Naturally, this tighter definition can be considered a possible implication of the first: a sufficiently rich information set can (but need not) make it possible for agents' forecasts to approximate the conditional mathematical expectation. With such an information set, agents may behave as if the objective and subjective parameters which characterize the environment are exactly the same, a more precise statement of the hypothesis of rational expectations which was first made by Lucas and

Prescott (1971). This last definition of rational expectations, equal objective and subjective parameters characterizing the environment, is the one which we test in this paper and what we mean by the term "rational expectations" in the rest of this paper.

Substantial evidence has accumulated which is inconsistent with rational expectations. For example, Caskey (1985) finds that a Bayesian learning mechanism is necessary to adequately characterize the Livingston data on price expectations. This analysis and many others such as Zarnowitz's (1985) find evidence inconsistent with the hypothesis. The findings inevitably are somewhat tenuous. Is rational expectations wrong, did the economy change, did knowledge of the economy's structure change, or did both the economy and knowledge of it change?[1] This quandary highlights a major problem with many examinations of the rational-expectations hypothesis.

For any model, there is no clear distinction between rejection of the model or rejection of rational expectations. This problem is not unique to rational expectations. If the estimated demand function for a normal good indicates that households will buy more when the price is higher, is it demand theory or the maintained hypotheses of the estimated equation that are inconsistent with the data?

Just as for demand theory, controlled experiments can be used to sort out hypotheses concerning rational expectations.[2] There have been some experiments which involve forecasts of stochastic variables by participants

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1 Webb (1987) surveys the problems with non-experimental tests of rational expectations.

2 Battalio, Dwyer, and Kagel (1987) examine demand theory and related propositions using data from controlled experiments.

in experiments and comparison of the forecasts with the outcomes. The results of these experiments generally are interpreted as inconsistent with rational expectations and consistent with adaptive expectations (Schmalensee 1976; Garner 1982; Williams 1987; Bolle 1988; Smith, Suchanek and Williams 1988). While these results are not universal (Mason 1987; Daniels and Plott 1988), at best rational expectations does not find much support, and a stronger conclusion of inconsistency between rational expectations and the experimental results might well seem warranted. Nonetheless, the asset-market experiments presented by, among others, Forsythe, Palfrey and Plott (1982), Plott and Sunder (1982), and Smith, Suchanek and Williams (1988) indicate that experimental asset markets converge to rational expectations equilibria. This contrast is puzzling. In recent work (Daniels and Plott 1988; Williams 1987; Smith, Suchanek and Williams 1988), participants simultaneously learn a market environment and make forecasts which, if acted on, influence the market outcomes. Characterizing the outcome of this learning process with endogenous prices is a complex problem (Jordan 1985; Lucas 1986, pp. S411-16; Cyert and DeGroot 1987, Ch. 13). We lessen the complexity by removing this complication from the scene: agents forecast data which we generate using a data generating mechanism known to us and exogenous to the participants.[3] This does mean though that we do not test one aspect of rational expectations: forecasts "are essentially the same as

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3 Removing these initial tests from a market setting also gives us greater flexibility in determining the earnings function than we would have otherwise. The greater flexibility arises because there need be no worry about a trade-off of possible manipulation and saliency relative to the payment earned in market trading. That is, if the payment received for forecasts is too large relative earnings from the market, there is an incentive to alter the market outcome to equal the forecast.

the predictions of the relevant economic theory" (Muth 1961, p. 316).[4]

The purpose of this paper is to test the hypothesis that participants' forecasts are the same as rational expectations in some experiments with a stark (and therefore easily understood by observers) environment. In the next section, we describe the experimental environment. Because we generate the data to be forecast, we know the underlying distribution. This leads to substantial differences between our tests and those commonly available. For example, because we know the mechanism used to generate the data to be forecast each period, we can directly compare the participants' forecasts to the forecasts implied by rational expectations. In Section III, we discuss the tests and present the results. In this section, we use statistical significance to determine inconsistency between the forecasts and rational expectations. In section IV, we examine the relationship between earnings and the moments of the distribution of the forecast errors and the consistency of the overall results with rational expectations. In section V, we explore some simple aspects of characteristics of the adjustment of forecasts to the distribution implied by data observed by the participants. The final section is a brief conclusion.

II. THE EXPERIMENTAL DESIGN AND PROCEDURES

In this section, we present the data to be forecast by the participants, the incentive system, the information structure of the problem, and a general description of the participants themselves. The

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4 Examination of this related hypothesis is appropriate for later experiments if the simpler hypothesis is not rejected in the experiments without these complications.

overall setup is designed to give the hypothesis of rational expectations a clean test independent of ancillary complications. To accomplish this, the data series chosen is filtered to be characteristic of the population; participants do not have any simultaneous activity such as participating in a market and their only source of earnings in the experiment is forecasting; and participants are given enough information that an econometrician plausibly could identify the linear stochastic process generating the data. In addition, the setup is designed to provide a base for further analysis if rational expectations is generally inconsistent with the forecasts. Important components of the experimental design largely motivated by this objective are initial forecasts made by the participants and forecasts one-step and two-steps ahead.

A. *The Data To Be Forecast*

The basic data to be forecast are a random walk with increments built from quasi-random numbers from a linear congruential generator.[5] These numbers are then transformed into a discrete approximation of a normal distribution with 11 mass points. The probabilities on left side of the distribution and the probability of the peak are

.01 .02 .05 .12 .19 .22.

The right side of the distribution is the mirror image of the left side. The value of the random variable associated with the mode is 0 and the value associated with each mass point changes by .05 as one moves away from the mode. For example, there is a 19 percent chance of drawing a value of -.05

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5 Knuth (1981, Ch. 3) provides a clear and concise discussion of quasi-random number generators.

and a one percent chance of drawing a value of -.25. By symmetry, there is a 19 percent chance of drawing a value of .05 and a one percent chance of drawing a value of .25. This distribution is sufficiently simple that, if the hypothesis of rational expectations is inconsistent with the forecasts, it is possible to use an urn with draws from a known distribution to show participants the distribution in a concrete way.

The theoretical probability distribution function for the 100 observations generated and the empirical one are presented in Figure 1. The agreement is close, with a Pearson chi-square goodness-of-fit test statistic of 10.342 with 10 degrees of freedom, which has a marginal significance level of 41.1 percent. The numbers also appear to be serially uncorrelated, with a Box-Pierce chi-square test statistic of 4.121 with 10 degrees of freedom at the 10th lag. For the 100 observations, the largest serial correlation coefficient is -.133 for the fifth lag. This serial correlation coefficient has a standard error of 0.10. A runs test has a marginal significance level of 36.8 percent.[6]

The series which we use is a random walk generated by these innovations. The initial value of the variable to be forecast, simply called an "event", is 5.00. The evolution of the event is determined by the sequence of numbers drawn from the approximate normal distribution. Permitted forecasts varied by as little as 0.01. The evolution of the random walk is shown in Figure 2. Participants make forecasts during two

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6 We also ran the same tests for the first 70 observations, which is the set of data available to the participants when they begin the second forecasting interval (explained below). The results of all of these tests are consistent with the theoretical distribution function and a lack of serial correlation.

intervals in the evolution of the series: the two periods denoted "first interval" and "second interval" in Figure 2.

B. *The Incentive System*

The payment rule, which declines linearly from the peak to zero, is

(1) $$\text{payment} = \max(\$.25 - |e|, 0)$$

where $|e|$ is the absolute value of the forecast error.[7] The only exception is the first interval with the first set of participants in which the payment rule has a base of \$.50 instead of \$.25.[8] In the second interval, the payment rule is the same for all participants. Notice that the largest magnitude of an actual possible change in a single period is .25 with the probability distribution function used.

With this (or any other) payment rule and the distribution of events to be forecast, we can calculate the expected value of participants' earnings relative to the expected value based on an unbiased forecast. For example, suppose that a participant has a biased expectation in which the forecast is always off by .05, .10, .15, etc. Based on the population distribution, the ratio of expected earnings for these biased forecasts relative to earnings from unbiased forecasts is given in Table 1. As the numbers in Table 1 indicate, a payment rule that was not truncated at zero

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7 Losses are excluded because evidence from various experiments indicates that crossing zero often introduces discontinuities in responses. In addition, losses would complicate the experimental design by making negative balances and bankruptcy possible.

8 Not surprisingly, this higher base increases earnings substantially.

would be little different than one without truncation unless the forecasts are biased by .20 or more. Because of the symmetry of the whole problem, the cost of being too high by .05 is the same as the cost of being too low by .05. Because of the built-in peakedness of the distribution function, the cost of being off by a little is relatively small.

C. *The Information Structure*

The participants make the forecasts seated at computer terminals. All of the experiments are conducted at Indiana University on the PLATO computer network using procedures developed by Mason (1987).[9] The computer collects forecasts and displays actual and forecasted events, forecast errors, and earnings to date. Each participant makes a series of one-step-ahead and two-step-ahead forecasts of the event at two different intervals in the evolution of the 100 values of the series. The first interval is for the 20 observations at the start of the series. The participants are given the value of the event in period 0, 5.00, and forecast the values in periods 1 and 2. They have no information about the series other than this initial value and what is suggested by the instructions. After they forecast these values, the participants then are told the actual value in period 1. They then forecast the values for periods 2 and 3. This sequential forecasting and revelation of the value in a period continues for a total of 20 periods. The participants then are given a handout revealing the next 50 events. The second interval then begins, in which the participants sequentially forecast for 30 observations with an actual value revealed each period. In all,

9 Copies of the instructions and the screens available to participants are in an appendix available on request.

participants make forecasts for a total of 50 observations on the random walk.

In each of the two forecasting intervals, participants have some information readily available. A table with the sequence of the levels of the events through the current period as well as the sequence of the participant's one-step-ahead and two-step-ahead forecasts is on the terminal screen. Graphs of the level of the events and the participant's forecast errors also are available by single-keystroke requests.

Because the information available to participants is quite different in the first and second intervals, we observe the participants at two quite different points in their forecasting. In the first interval, participants have relatively little information. They have one observation on the event before making the first forecast and only 20 observations at the end of this interval. The primary value of these data for this paper is to provide information on relatively uninformed forecasting if the hypothesis of rational expectations is rejected. At the start of the second interval, the participants have 70 observations on the event, which would be enough to do a statistical analysis on the data using standard econometric procedures and reach what generally would be regarded as moderately reliable results. Such an analysis, with the usual procedure of setting estimated statistically-insignificant coefficients to zero, would result in the conclusion that the series is a random walk.[10]

The participants are told little about the process generating the events. Before beginning to forecast, among other things, instructions on

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10 In an experiment with graduate students, the two forecasting intervals were run on separate days. One graduate student put the 70 observations then available up on a computer, ran Box-Jenkins procedures and some simple regressions, and concluded that the series was a random walk.

the terminal indicate that "[y]our task is to forecast the event that will occur in the next periods, based on the information available in the current period." At a later point, the instructions indicate that "[D]uring the experiment you will be asked to use this information [a table with the events and one-step-ahead and two-step-ahead forecasts to date] to forecast what the event will be in the next TWO periods." These statements are the extent of the information provided about the process generating the events beyond the to-date sequence of values and forecast errors themselves.

The participants are permitted to take as long as they wish. There is no interaction between participants and there is no reason to force simultaneous choices. The total time taken for the first and second intervals is about 3 hours.

There are some important differences between these forecasts and survey data or data on expectations embedded in a maintained model. We know the rational expectation (in the strict sense of equal moments of objective and subjective distributions) of the event each period. In every period, the rational expectation for an event generated by a random walk simply is the event in the previous period. Because we know the rational expectation, we can compare the forecasts given by the participants to the rational expectation. It is hard to ask participants to do better than a participant maximizing the expected payment based on the exact linear process generating the data.[11] In addition, if the one-step-ahead forecast errors are substantially predictable, then the forecasts for the first uninformed

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11 If the participants knew the exact nonlinear process generating the data and the seed, there will be no errors. After all, these are quasi-random (namely deterministic, chaotic) numbers.

interval and the two-step-ahead forecasts are likely to be informative about why the hypothesis is rejected.

D. *Participants*

All of the participants are students at Indiana University. The participants denoted "sg" are graduate students with formal training in econometrics. We began with a relatively sophisticated set of participants because, based on prior work, we would not have been surprised if other participants, if not these, generally forecasted in ways clearly inconsistent with rational expectations. The participants denoted "su" are sophomore, junior, and senior undergraduate students. We call these participants the "intermediate participants" in the rest of the paper. The participants denoted "sp" are students in a Freshman Honors section of Introductory Microeconomics who have not taken any college-level statistics courses. We call these participants the "inexperienced participants" in the rest of the paper.

III. THE INFORMED FORECASTS

In this section, we focus on the one-step-ahead forecasts after the participants have seen 70 values of the event, a point at which the participants can be regarded as possibly informed about the underlying stochastic process generating the data. The first thing we do is show that the usual way of analyzing the forecasts is wrong for forecasts of a random walk. After this, we analyze the data for the last 30 periods in a way that generates reliable statistical results. Finally, we examine the two-step-ahead forecasts for deviations from rational expectations.

A. *The Usual Test for Unbiasedness Is Biased*

It is almost natural to run regressions such as

(2) $$y_{t+1} = \alpha_i + \beta_i \, {}_t f_{t+1,i} + \epsilon_{t+1,i}$$

where y_{t+1} is the actual outcome in period t+1, ${}_t f_{t+1,i}$ is the value forecasted in period t for period t+1 by participant i, $\epsilon_{t+1,i}$ is the residual in period t+1 for participant i, and α_i and β_i are parameters to be estimated. If expectations are rational, α_i=0 and β_i=1 in (2). In addition,

(3) $$E\epsilon_{t+1,i} = 0, \; E\epsilon_{t+1,i}\epsilon_{i,s+1} = 0, \quad t \neq s.$$

The ordinary-least-squares estimates of β for each participant in the second forecasting interval are summarized in Figure 3. All but 4 of the 39 estimated slope coefficients are less than one, which suggests a systematic factor producing an estimated coefficient less than one. The force of this observation is not negated by the failure to reject the hypothesis that the constant equals zero and the slope coefficient equals one for all but two of the 39 participants. Suppose that the true slope coefficients are all one and the probability of an estimated coefficient greater or less than one is one half. The joint probability of 35 or more estimated coefficients less than one out of 39 is about 1.7 x 10^{-5} percent. On the other hand, even for the rational expectation forecasts, the estimated coefficient is .928, which is not far from many of the other estimated coefficients. Is the rational expectation of this series inconsistent with rational expectations or is it a peculiarity of the sequence of events in our sample?

If the forecasts are rational expectations of a random walk, the ordinary least squares estimator is biased downward. Under the null hypothesis of rational expectations, ${}_tf_{t+1,r}=y_t$ (where the subscript r denotes the rational expectation) and equation (3) is

$$y_{t+1} = \alpha_r + \beta_r y_t + \epsilon_{t+1,i}. \tag{4}$$

Equation (4) is the first-order autoregressive representation for a random walk. As Fuller (1976, pp. 366-70) shows, the implications for the ordinary least squares estimator of β are hardly appealing. With a true value of β_r equal to 1, the estimator's distribution is skewed to the left and, for sample sizes typical in experiments, this skewness is large.[12] With 25 observations, there is a 10 percent probability of an estimated coefficient of 0.592 or less, and there is a 90 percent probability of an estimated coefficient of 0.972 or less. There is only a 5 percent probability of an estimated coefficient of 1.0004 or more. Rejection of the hypothesis of rational expectations based on these test statistics is of no value.[13]

B. *Do The Forecasts Have the Same Distribution as the Data?*

Despite the impossibility of using equation (2) for generating the usual test statistics, a different and in some ways more appealing procedure

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12 The pertinent results of the Monte Carlo study by Dickey (1976) are presented in Fuller (1976, p. 371-73).

13 It might seem that simply adjusting for bias would solve the problem. The usual estimated test statistics do not, however, have the usual distributions.

is open to us. We systematically test whether: 1. the moments of the distribution of the forecasts are the same as the moments of the distribution of the rational-expectations forecasts; and 2. the participants' forecasts are related to the information set in the same way that the rational expectation is related to the information available. In this section, we use statistical significance as the metric to determine whether the forecasts are different than the forecasts from a random walk.

The Tests

The first implications for the distribution of the forecasts concern the existence of unit roots. If expectations are rational, there should be a unit root in the forecasts.[14] Assume that the forecast is the same as the rational expectation, that is,

$$ {}_{t}f_{t+1,i} = y_t \tag{5} $$

for participant i. We know that the difference equation characterizing the events has a unit root because the events are a random walk and a random walk is a special case of a difference equation with a unit root. If (5) is correct, then the forecasts should have a unit root as well. If the

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14 A unit root can be defined the following way. Assume that a series has representation such as

$$ [1-\gamma(L)]x_t = \epsilon_t $$

where x is the data series and $\gamma(L)$ is a polynomial in the lag operator. This always can be rewritten as

$$ (1-\gamma_1)[1-\gamma^*(L)]x_t = \epsilon_t $$

where γ_1 is a root of the polynomial in the lag operator. A test for a unit root is a test whether there is *a* root γ_1 which equals unity.

forecasts do not have a unit root, then the distribution of the forecasts has a constant long-run mean even though the distribution of the events does not revert to a constant mean. Clearly, this would be a dramatic inconsistency between the distribution of the outcomes (the events) and the forecasts.

The existence of a unit root in the forecasts is necessary but not sufficient to rule out the existence of unit roots in the forecast errors.[15] If expectations are rational, then the forecast error e^f_{t+1} in period t+1 is

$$e^f_{t+1,i} = y_{t+1} - {}_tf_{t+1,i} = y_{t+1} - y_t = \epsilon_{t+1}. \tag{6}$$

By construction, ϵ is a serially uncorrelated series with a constant variance and an approximate normal distribution. A unit root in the forecast errors would indicate that the distribution of the forecast errors has a random walk component which has no counterpart in the innovations in the events being forecast. This would indicate an egregious inconsistency between the objective and subjective distributions of the events. If this and the prior test is passed, then further tests are of interest.

The approximate normality of the innovations in the events and the stationarity of the forecast errors mean that we can use standard statistical tests on the moments of the forecast errors. Because the distribution of the innovations is approximately normal, we examine the first two moments. First we test the hypothesis that the variance of the forecast errors for each participant is the same as the variance of the

15 In terminology due to Granger, the actual values and the forecasts may not be cointegrated (Engle and Granger 1987).

forecast errors implied by the objective distribution. This implication obviously follows from (6). Then we test whether the means of the forecast errors are the same.[16]

Last but not least, we examine the response of changes in forecasts to past forecasts, forecast errors, and events. More precisely, given a unit root in forecasts and the lack of one in forecast errors, we test whether the error correction mechanism that characterizes the change in forecasts is the same as the one implied by rational expectations.[17] The general form of such an equation is

$$(7) \qquad \Delta_t f_{t+1,i} = a + b(y_t - {}_{t-1}f_{t,i}) + c_1(L)\Delta_{t-1}f_{t,i} + c_2(L)\Delta y_t + \eta_{t+1,i},$$

where $c_j(L)=\Sigma c_{j,k}L^k$ is a polynomial in the lag operator, j=1,2, with summation over k and $\eta_{t+1,i}$ is the error term.

Tests based on this regression are likely to be more powerful than the usual regression of forecast errors on readily-available information because this error correction regression is closely related to a regression of the participant's forecast errors *minus the rational expectation forecast error* on the readily available-information. To see this, note that by definition

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16 We do the variance test first because the results could affect the test statistic used in the tests on means.

17 Hendry (1986) and Engle and Granger (1987) discuss error correction mechanisms and their relationship to the unit root tests and cointegration. We do not estimate a cointegrating regression between the events and the forecasts. The tests for unit roots in the forecast errors are cointegration tests with the cointegrating coefficient set equal to one rather than estimated. As a result, the table in Fuller (1976, p. 373) is the correct one for the cointegration tests, not the tables in Engle and Granger (1987) or Engle and Yoo (1987) based on estimated linear relationships of the cointegrated variables.

$$e^f_{t+1,i} = \Delta y_{t+1} - \Delta_t f_{t+1,i} + e^f_{t,i}$$

Substitution of this equation into (7), rearrangement, and use of $\Delta y_{t+1} = \epsilon_{t+1}$ results in

$$-(e^f_{t+1,i} - \epsilon_{t+1}) = a + (b-1)(y_t - {}_{t-1}f_{t,i}) + c_1(L)\Delta_{t-1}f_{t,i} + c_2(L)\Delta y_t + \eta_{t+1,i},$$

If the estimate of b in equation (7) is constrained to equal one, equation (7) is a regression of the difference between the participant's forecast error and the rational-expectation forecast error on readily-available information. As a result, the error term in (7) does not include the unpredictable part of the event; it includes only the unpredictable part of the participant's forecast error over and above that associated with the rational expectation of a random walk. Both rational expectations and adaptive expectations are special cases of the general error correction mechanism (7).

We examine the restrictions implied by rational expectations and then consider the implications of adaptive expectations. If expectations are rational, then equation (5) implies

$$(8) \qquad \Delta_t f_{t+1,i} = \Delta y_t.$$

This equation characterizes the change in forecasts if expectations are rational. Equation (8) also can be used to determine the restrictions on (7) necessary for (7) to be restricted to equal (8). With (8) substituted for the changes in forecasts in the right-hand side of (7), equation (7) becomes

(9) $$\Delta_t f_{t+1,i} = a + b\Delta y_t + c_1(L)\Delta y_{t-1} + c_2(L)\Delta y_t + e_{t,i},$$

It is obvious that Δy_t appears in two different places on the right-hand side of equation (9). One set of restrictions which makes the right-hand sides of (8) and (9) the same is

(10) $$a = 0,\ b = 1,\ \text{and } c_{j,k} = 0 \text{ for all } j \text{ and } k.$$

In addition, equations (8) and (9) also are the same if

(11) $$a = 0,\ b = 0,\ c_{2,1} = 1,$$
$$\text{and } c_{j,k} = 0 \text{ for all } j \text{ and } k \text{ except } c_{2,1}.$$

In addition, any linear combination of these restrictions also is consistent with equating the right-hand-sides of equations (8) and (9). This set of restrictions is

(12) $$a = 0,\ b + c_{2,1} = 1$$
$$c_{j,k} = 0 \text{ for all } j \text{ and } k \text{ except } c_{2,1}.$$

The restrictions (10) and (11) are special cases of (12).

The error correction mechanism also can be consistent with adaptive expectations. If

(13) $$a = 0,\ b < 1,\ \text{and } c_{1,k}=c_{2,k}=0 \text{ for all } j \text{ and } k,$$

then equation (7) is consistent with adaptive expectations. Because b is restricted to an open interval bounded by 1, any test result consistent with the first set of restrictions consistent with rational expectations (10) almost surely is consistent with the restrictions implied by adaptive expectations (13). Consistency with the more general restrictions for rational expectations (12) though is not necessarily close to consistency with (10) or (13); therefore, the data can be consistent with rational expectations (12) and not with adaptive expectations (13). As a result, it is worthwhile to test the restrictions implied by adaptive expectations (13).

At this point, we will have tested equality of the moments of the distribution of each participant's forecast errors with the moments based on the exact linear process generating the data. In addition, we will have tested whether data available to the participants can be used to forecast deviations of the forecasts from the rational expectation. In other words, the usual regression tests are subsumed in the tests which we present. We will have tested interesting additional hypotheses as well, in particular whether the second moments of the distributions are the same.

The Test Results for One-step-ahead Forecasts

Based on Dickey and Fuller (1979), the hypothesis that the forecasts have the unit root in the data can be tested with the results of the regression

$$(14) \qquad \Delta_t f_{t+1,i} = \delta_0 + \delta_1 \; {}_{t-1}f_{t,i} + \eta_{t,i},$$

where $\Delta_t f_{t+1,i}$ is the first difference of the expectation and ${}_{t-1}f_{t,i}$ is the participant's forecast in the previous period. On the null hypothesis that the forecasts have a unit root, δ_1 is zero.[18] If the first-order difference equation that characterizes the evolution of ${}_tf_{t+1,i}$ does not have a unit root, then δ_1 is negative and equal to the first-order autoregressive coefficient minus one. The usual tabulated t-values do not apply because the ratio of the ordinary least squares estimate of δ_1 to its standard error does not have a t-distribution. The values instead can be compared to those presented in Fuller (1976, p. 373). The appropriate t-ratio for rejecting the null hypothesis of a unit root is about -2.63 at the 10 percent significance level, -3.00 at the 5 percent level, and -3.75 at the 1 percent level.

The test statistics for testing the null hypothesis that the forecasts have unit roots are presented in Table 2. The hypothesis of a unit root in the forecasts is not rejected for any of the participants.[19] This means that the time-series behavior of the forecasts is similar in this respect to the time-series behavior of the variable being forecasted.

The null hypothesis that *forecast errors* have unit roots is the converse of the hypothesis that *forecasts* have unit roots. Under the maintained hypothesis of rational expectations, the forecasts have unit roots and forecast errors do not. A unit root of the forecast errors would be a gross violation of the hypothesis of rational expectations. The t-ratios for testing the null hypothesis that the forecast errors have unit roots are presented in Table 3. The appropriate t-ratios for rejecting the null

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18 We do not impose a null hypothesis that the constant terms are zero in the reported tests; we test the consistency of the mean values of the forecasts and forecast errors with rational expectations below. In any case, the conclusions are exactly the same with constant terms deleted.

19 The hypothesis of a second unit root is easily rejected at usual significance levels.

hypothesis of a unit root are the same as those for the previous table. For each participant, the data are inconsistent with the hypothesis that the forecast errors have a unit root. In other words, the results of this test also are consistent with hypothesis that participants' forecasts are the same as the rational expectation.

Given that the forecast errors do not have a unit root, standard statistical tests on the moments of the distribution of these errors are valid.[20] We first test the hypothesis that the variance of each participant's forecast error equals the variance of the forecast errors using the rational expectation. Table 4 presents the statistics for these tests.[21] The appropriate test, given the approximate normality of the underlying data, is a chi-square test with degrees of freedom equal to the number of observations less the one degree of freedom used to estimate the mean. We use a two-tailed test because too high a variance or too low a variance is inconsistent with the hypothesis that the variance is the same as the variance based on the rational expectation. It is possible for a participant to have a forecast error variance less than the variance based on the rational expectation for a finite period, even though it is hard to see how this can be done systematically.[22] Even at the 25 percent marginal significance level, none of

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20 For a discussion of the tests used and the relevant references, see Mood, Graybill, and Boes (1974) and Kendall and Stuart (1961).

21 In this table and later in the paper, we always discuss the magnitude of the second moment in terms of the standard deviation because the standard deviation is in terms of the units of the data being forecast rather than their square and therefore is simpler to relate to the magnitude of the events.

22 Of the 39 participants in our sample, one has a variance that is almost statistically significantly smaller than the variance based on the rational expectation.

the variances of forecast errors for the graduate students fails to be consistent with the variance based on the rational expectation. One of the 10 variances for intermediate participants is too large at the 5 percent marginal significance level. At the 10 percent marginal significance level, 5 of the 20 inexperienced participants have variances that are too large and 1 has a variance that is too small. At the more stringent 5 percent marginal significance level, 1 of the 20 variances for the inexperienced participants is too large to be consistent with the hypothesis that the variance equals the variance based on the rational expectation.

It is worthwhile to compare these variances to a less stringent standard than the variance of forecast errors based on the random walk. One standard would be fixed-length autoregressions updated with the addition of each new observation to the data set. For these observations, the standard deviation of the forecast errors is 0.100 based on a 5th-order autoregression updated before each forecast and 0.102 based on a 10th-order autoregression similarly updated.[23] These standard deviations can be compared to the standard deviations in Table 4 for each of the participants. A more concise comparison is possible with the standard deviations for the groups of participants in Table 5, which range from 0.102 for the graduate participants to 0.112 for the intermediate participants. The standard deviations for the autoregressions are virtually the same as the standard deviation for the graduate participants and less than the standard deviations for the other participants.

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23 It is not surprising that these forecast-error variances are larger than from the random walk: forecasts based on equations with nonzero estimates of coefficients that really are zero are inefficient.

In addition to these tests for equality of each variance to the rational-expectation variance, we can perform standard tests for equality of the participants' variances to each other and then test whether the overall variance is the same as the one implied by rational expectations. The results of such tests within each group of participants are presented in Table 5. In order to keep degrees of freedom and therefore power the same in the tests, the data for the two groups of 10 inexperienced participants are used in separate tests. The first test in Table 5 is a test whether the variances of the participants' forecast errors are the same. This hypothesis cannot be rejected at even the 40 percent marginal significance level for any of the groups of participants. The second test is a test whether the overall variances are the same as the variance for the rational expectation. At the 1 percent marginal significance level, this hypothesis is rejected for the groups other than the graduate participants. On the basis of these and the prior tests on the variances, we conclude that there is evidence that the participants with less experience have excess variance of the forecast errors relative to forecasting with a random walk. Later, we examine the impact of this excess variance on earnings.

This apparent excess variance of forecast errors is not inconsistent with the hypothesis that the forecasts are unbiased. This can be seen from the test statistics in Tables 6 and 7. At the 5 percent marginal significance level, only the mean forecast errors for two inexperienced participants are different than the rational-expectation mean forecast error.[24] For none of

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24 The statistics are based on the rational expectation standard deviation, which is less than the subject's actual standard deviation for each of the participants except sp4, sp8, and sp13. The standard deviations are trivially less for sp4 and sp8. With these three exceptions, this test is more stringent than using the participants' actual standard deviations of the forecast errors.

the groups can the hypothesis that the mean forecast error is the same across participants be rejected. In addition, three of the four normally-distributed test statistics for testing the null hypothesis that the group mean forecast error equals the rational-expectation mean are less than 1.0 in absolute value. For the first group of inexperienced participants, the statistic for testing the hypothesis that the group mean forecast error equals the rational-expectation mean is 1.93. This statistic can be contrasted with the statistic for the other group of inexperienced participants, which is -0.29, the smallest in magnitude for any of the four groups. We conclude that there is no evidence of bias in the forecast errors for any of these groups.

Taken together, these results suggest that, in general, any excess variance of forecast errors is stochastic and not simply a constant added to or subtracted from the forecasts. This excess variance may reflect an unpredictable element added to the forecasts for whatever reason. Alternatively, the excess variance of the forecast errors may be a systematic response to past forecast errors and events which introduces predictable errors into the forecasts. The error correction mechanism provides a means of examining this issue.

Table 8 presents the test statistics for testing whether a general error correction mechanism can be reduced to either one consistent with rational expectations or adaptive expectations. The most general error correction mechanism estimated has a constant, two lags of the change in the forecast and two lags of the change in the event. The first column in Table 8 presents the F-ratio for testing the hypothesis that the estimated coefficients which are superfluous according to the rational expectations hypothesis are zero. The four coefficients which are set to zero are the constant term, the two coefficients of lagged changes in forecasts, and the coefficient of the second lag of changes in the event. This set of restrictions is rejected at the 5 percent marginal significance level for two of the 39 participants. We conclude that these restrictions are consistent with the data.

The t-ratios for testing the hypothesis that the sum of the coefficients of the lagged forecast error and the change in the event equals one are presented in the second column of Table 8.[25] At the 5 percent marginal significance level, this hypothesis is inconsistent with the data for 12 of the 39 participants. These rejections are at best loosely related to the participants' experience. This hypothesis is rejected at the 5 percent marginal significance level for 2 of the 9 graduate students, 3 of the 10 intermediate participants, and 8 of the 20 inexperienced participants. At this level of detail, there is a clear indication for some participants of an inconsistency between the equation which characterizes the forecasts and the random walk generating the data. Nonetheless, about two-thirds of the participants forecast in a way that is consistent with rational expectations.

Even for the participants with some inconsistency between the determinants of their forecasts and the mechanism generating the underlying data, adaptive expectations does not provide an alternative way of organizing the data. The restriction to zero of the coefficient of the lagged change in the event is inconsistent with the data at the 5 percent marginal significance level for 16 of the 39 participants. This hypothesis is rejected for 9 of the 13 participants whose simplified error correction mechanism is inconsistent

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25 These test statistics are conditional on the restriction that the four superfluous (according to rational expectations) coefficients are zero.

with the rational expectation. In addition, the point estimate of the estimated coefficient of the lagged error is less than one for only 12 of the 39 participants, which is fewer than would be expected if the true coefficient is less than one.

The Test Results for Two-step-ahead Forecasts

We focus on an interesting aspect of the results for the two-step-ahead forecasts and the one-step-ahead forecasts. Based on a random walk, the difference between an unbiased two-step-ahead forecast and an unbiased one-step-ahead forecast is exactly zero always.[26] This condition holds for three of the 39 participants for all 30 observations in the second interval. The other participants often forecast some change one and two steps ahead, and for some of the subjects, there is systematic bias in terms of the individual forecasts.[27] Table 9 contains t-statistics for testing the hypothesis that the mean one-step-ahead and two-step-ahead forecasts are the same. This hypothesis can be rejected for 3 of the 9 graduate students, 2 of the 10 intermediate students, and 6 of the 20 inexperienced participants.

There is no evidence of systematic bias within the groups of participants: some of the participants forecast values that are falling on average and some forecast values that are increasing on average. Table 10 presents tests of the hypothesis that the mean two-step-ahead minus one-step-ahead forecasts are equal across subjects and that these mean forecast errors

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26 Garner (1982) and Mason (1987) also examine two-step-ahead forecasts.

27 Preliminary tests indicate that the two-step-ahead forecasts have one unit root and that the two-step-ahead forecast errors do not. In addition, the two-step-ahead forecasts are cointegrated with the one-step-ahead forecasts. These results are necessary, but are hardly sufficient, for rational expectations to be consistent with these forecasts.

equal zero on average. With the exception of the intermediate participants, the data are inconsistent with the hypothesis that the mean differences between two-step-ahead and one-step-ahead forecasts are equal within each group of participants. This is consistent with the prior result that some participants have nonzero mean differences and others do not. The mean forecasts within each group are, nonetheless, all zero within the precision of the forecasts. (Participants entered at most two digits after the decimal point.) The apparently statistically significant mean for the second group of inexperienced participants is rounding error.

Given the results for the one-step-ahead forecasts, it is not clear how to evaluate these results for two-step-ahead forecasts. A possibly important reason for the difference between the results obtained between the one-step-ahead forecasts and the two-step-ahead forecasts may be because the two-step-ahead forecasts relative to the one-step-ahead forecasts require the application of the chain rule of forecasting in addition to what is required for a one-step-ahead forecast consistent with rational expectations. The iterative substitution necessary to make forecasts that are the conditional expected value is a different type of mental process that may well require more experience. The delayed reinforcement, smaller expected earnings relative to the one-step-ahead forecasts, or the lower frequency of positive reinforcement when forecasting consistent with rational expectations also may account for these results. We are inclined to reserve judgment on the implications of these tests until further results are available.

IV. OVERALL EVALUATION OF THE STATISTICAL TESTS

Some variance in results across participants is to be expected and we find this. Participants are not told the process generating the events and must infer it in a noisy environment, a nontrivial problem. Some indication of the range of forecasts can be gained from the distribution of one-step-ahead forecasts at each observation of the event. Figure 4 shows the rational expectation of the event and the distribution for each of the groups for each period, with the inexperienced participants included in one graph. The distribution does not appear to be characterized by a stable distribution function across periods, which is not surprising since the identity of the participants making high and low forecasts changes over time. Nonetheless, the distributions generally are centered on the forecasts in the sense that the median and mode deviation from the rational expectation generally are zero.

There are some statistically significant deviations from rational expectations in this distribution. In terms of one-step-ahead forecasts, the evidence indicates that the variance of the forecast errors for the groups of participants is greater than from a random walk. In addition, the simplified error-correction mechanism that characterizes the changes in forecasts is inconsistent with the rational expectation of a random walk for about one-third of the participants. In terms of two-step-ahead forecasts, there is some evidence of bias at the individual level. All of these conclusions are based on statistical significance, which may or may not be associated with any economically significant differences in earnings.

A. *Earnings and Forecasts*

One way of examining the economic significance of the deviations from rational expectations is to see how these deviations are related to earnings across participants. Table 11 presents each participants' earnings from their forecasts for the last 30 observations and indicates by a plus which earnings are greater than are earned by the rational expectation and by an asterisk which of the various test statistics is different than is implied by rational expectations at the 5 percent marginal significance level. The earnings of the graduate students in economics appear to be greater than the intermediate or inexperienced participants' earnings, but little significance can be attached to this. The graduate students had the first 70 observations on the event for 22 hours before the session at which they forecast these last 30 events. This may have given the graduate students some advantage in forecasting, but the hypothesis that mean earnings are the same across the groups cannot be rejected.

Some idea of the importance of rejection of various hypotheses is indicated by regressions presented in Table 12. The variables included in the regressions which reflect one-step-ahead forecasting include the absolute value of the mean forecast error minus the mean rational-expectation forecast error and the standard deviation of the forecast error. The absolute value of the deviation of the mean forecast error from the rational expectation is a measure of forecasting performance relative to the rational expectation.[28] The standard deviation of the forecast errors is an absolute measure of forecasting performance in the sense that beating the rational expectation is possible and is done in the sample, which by itself suggests a negative relationship between earnings and the standard error. The regressions also include the absolute value of $1 - (b + c_{2,1})$ in the error correction mechanism with the change in the event and the most recent change in the forecast. This

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28 This is the absolute value of the difference between the means, not the mean absolute value, in which case it would be the same as the payment rule except for the truncation of payments at zero.

variable is the deviation of the estimated sum of the coefficients in the rational-expectations error correction mechanism from the sum implied by rational expectations. In addition, the regressions include measures of deviations of two-step-ahead forecasts from rational expectations. These measures are the absolute value of the mean difference between two-step-ahead and one-step-ahead forecasts and the standard deviation of the difference. These measures are conditional on the one-step-ahead forecasts and therefore should be included in the regression for two-step-ahead earnings in addition to the one-step-ahead variables.

In both the regressions for earnings from the one-step-ahead forecasts and the two-step-ahead forecasts, it is clear that the deviation from one of the sum of coefficients in the rational-expectations error correction mechanism is not important in terms of explaining why some participants' earnings were lower. In both cases, the variable is not statistically significant and it has the wrong sign for it to indicate that deviating from the rational-expectations error correction mechanism are associated with lower earnings. The point estimates suggest that deviating from the theoretical sum of one increases earnings, at least holding constant the other statistics summarizing the distribution of forecasts. This conclusion holds up for the one-step-ahead forecasts when the measures of deviations of two-step-ahead forecasts from the rational expectation are excluded from the regression.

Overall, the results indicate that a higher standard deviation of forecast errors explains most of the variance of earnings from one-step-ahead forecasts across participants. An increase in the standard deviation by .01 decreases average earnings from each forecast by about .8 cents. The absolute deviation of the mean forecast errors from the rational-expectation mean also is important, with an increase in this absolute value by .01 lowering average earnings by .25 cents.[29]

The results for earnings from the two-step-ahead forecasts are ambiguous: two estimated coefficients are marginally statistically significant if the absolute value of $1 - (b + c_{2,1})$ is included but not if it is left out. Perhaps the most interesting aspects of these regressions are the importance of the standard deviation of one-step-ahead forecast errors and the statistical significance at the 5 percent level of the absolute value of the difference between the two-step-ahead and one-step-ahead forecasts in some of the regressions in the table. The estimated coefficient of the absolute value is about -.25 and the absolute value of the largest difference between the one-step-ahead and two-step-ahead forecasts for any participant is .070. With this coefficient estimate, this largest deviation of the forecasts from the rational expectation cost this participant 1.75 cents on average from each two-step-ahead forecast.

B. *How Close Would Aggregate Forecasts Be To Rational Expectations?*

Another way of examining the results overall is in terms of some approximation of an aggregate. The distribution of forecasts relative to rational expectations is summarized in Figure 5. The figure includes graphs for both the one-step-ahead and two-step-ahead forecasts for the groups of participants (with the inexperienced participants again included in one graph). The horizontal axis in each graph is the rational expectation of the

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29 The highest standard deviation is .126, which is .029 greater than the rational-expectation standard deviation. The largest deviation of the mean forecast error from the rational-expectation mean is .043.

event and the vertical axis is the forecast by the participants. Each square drawn on a graph represents one or more forecasts with the rational expectation equal to the value on the horizontal axis. The diagonal line drawn on each graph is the line along which the rational expectation and the forecast are the same.[30]

The forecasts do appear to be distributed along the line bisecting the rectangles.[31] Given the evidence against bias, a simple way of seeing this is in terms of estimated slopes of regressions of the forecasts on the rational expectation.[32] The estimated slope coefficients in each figure is equal to 1.00, which is the same as being exactly equal to 1 within the precision of the data.[33]

C. *An Overall Evaluation of the Second-Interval Forecasts*

A model of the one-step-ahead forecasts that is generally consistent with the results above is

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30 There are 9 graduate participants with 270 one-step-ahead forecasts and 261 two-step-ahead forecasts. There are 10 intermediate participants with 300 one-step-ahead forecasts and 290 two-step-ahead forecasts. There are 20 inexperienced participants with 600 one-step-ahead forecasts and 580 two-step-ahead forecasts. There is one less two-step-ahead forecast per participant because there is no event two steps ahead in the last period.

31 The two-step-ahead forecasts for the intermediate participants do suggest that "a little knowledge is a dangerous thing." The figures suggest that graduate education can rectify this adverse effect of a little knowledge. But see Bryan and Gavin (1987).

32 This is a well-defined regression equation. Under the hypothesis of rational expectations, the error term is orthogonal to the right-hand-side variable because the right-hand-side variable is the lagged value of the event which is available to participants.

33 We do not test whether the estimated coefficients equal one because the "t-ratios" do not have a t-distribution. Such a test is unnecessary anyway.

Under the hypothesis of rational expectations, this agreement of the true value and the coefficient estimate is not improbable. Estimated coefficients in cointegrating regressions converge more rapidly than estimated coefficients in regressions with stationary variables (Phillips 1987; Stock 1987).

$$(15) \qquad {}_tf_{t+1,i} = E[y_{t+1}|\Omega_t] + \xi_{t+1,i}, \qquad E[\xi_{t=1,i}] = E[\xi_{t+1,i}|\Omega_t] = 0.$$

where Ω_t is all of the information available and ξ is, in effect, a random error added onto the mathematical conditional expectation. Although equation (15) characterizes the majority of the participants, it is implausible at best that this is what they perceive themselves to be doing. They would have to be calculating the mathematical expected value and then adding an error term on that reduces their earnings! As Muth noted in 1961, the hypothesis of rational expectations itself "*does not* assert that the scratch work of entrepreneurs resembles the system of equations in any way; nor does it state that the predictions of entrepreneurs are perfect or that their expectations are all the same." (Emphasis in original. Muth 1961, p. 317).[34] In order for the forecasts to be different and unbiased, something like equation (15) must hold. There are only three participants who have ξ exactly equal to zero for all periods in the second interval. The rest of the participants have a positive variance of ξ, although this variance generally is not large.

Even in a stark environment such as this, further reductions in this variance around the rational expectation may occur slowly, if at all. Suppose that learning occurs by continuing behavior that is followed by an increase in earnings and changing behavior that is followed by a decrease in earnings. If some number is added onto the rational expectation in a period, say .05, then this deviation by .05 will decrease earnings sometimes and increase earnings other times. The largest standard deviation of the forecast errors

34 Muth (no date) introduces a model like (15) when he analyzes forecasts by individual firms.

for any participant is .126, which is about .03 greater than the rational-expectation standard deviation of .097. Based on the regressions above, this increase in variance reduces expected earnings by .75 cents per period. Not only may it be hard for a participant to detect this deviation from the maximum expected earnings, but the small magnitude of the decrease in earnings indicates that many forecasts different than rational expectations are being rewarded.

V. A PRELIMINARY ANALYSIS OF THE INITIAL FORECASTS

A detailed analysis of the initial forecasts is beyond the scope of this paper. In addition, such an analysis would require more data and data on different sequences. Nonetheless, a preliminary analysis of the first couple of forecasts is suggestive.

What do the participants forecast when they know that the first event is 5 and they know nothing else? A natural response might be that they can do little besides forecast the number 5. After all, this is suggested both if the data are generated by constant mean and if the data are generated by a random walk. The one-step-ahead forecasts for the first period for each group are summarized on the left-hand side of Figure 6. Most of the graduate participants do forecast 5, but the other participants generally do not. There is a wide dispersion of the forecasts relative to the subsequent outcomes (which they do not know of course).

This dispersion decreases dramatically when the participants know two observations: 5.00 and 5.15. The distributions of the forecasts for the second period are shown on the right-hand side of Figure 6. With an unknown mean and a diffuse prior on a variance from a normal distribution, two observations are sufficient to begin to calculate a posterior distribution using Bayesian analysis. This means that two observations are enough to begin to think about what type of prior underlies the forecasts. If we allow for a range of forecasts in a classification, all but one of the forecasts can be interpreted in terms of some simple prior. We can call the forecast of 5.00 a "complete reversion" prior; a range of 5.05 to 5.10 a "constant mean" prior; a value of 5.15 a "random walk" prior; a range of 5.20 to 5.30 a "trend" prior; and a value greater than 5.30 a "super-trend" prior. Five of the 9 graduate participants assume a constant mean. This prior clearly is not predominant in the other groups of participants. Both the intermediate and the inexperienced participants assume that the data are characterized by further increases beyond the increase of 0.15 from the first to the second observation on the event. This preliminary analysis suggests that a much richer data set than ours will make it possible to characterize participants' processing of information in a way that may be fruitful.

How fast do the participants converge to forecasts that are closely related to the data? One way of looking at this issue is in terms of the standard deviations of the forecast errors relative to the actual rational-expectations standard deviation. Figure 7 shows the distribution of the standard deviations of the forecast errors for each participant relative to the rational-expectation standard deviation for forecasts 2-10 and each subsequent set of 10 forecasts.[35] The mean relative standard deviations for all participants are: 1.257 with a standard deviation of 0.331 for

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35 Given the information on the range of initial forecasts above, it is obvious that some of the participants' standard deviations are far larger when the initial forecast is included in the calculation of the standard deviation of the forecast errors.

observations 2-10; 1.105 with a standard deviation of 0.217 for observations 11-20; and 1.105 with a standard deviation of 0.104 for periods 71-100. The decreases in the mean values of the standard deviations of forecast errors and in the range across participants from the initial intervals (2-10 and 11-20) to the later intervals suggest that participants do gain additional information from having more than a few observations. This decrease also suggests that our results might not have been the same had we only analyzed data for periods 1 to 20 or 5 to 20, a common procedure in previous work and especially tempting when the forecasts are in a market which takes more time per observation than does our stark experiment.[36]

VI. CONCLUSION

In this paper, we have examined the consistency of participants' expectations of events based on a process for which we know the exact mechanism generating the data. We find no evidence which suggests obviously strange forecasts or inefficient use of the available information. We also find no evidence that one-step-ahead forecasts are systematically biased. The major evidence which is inconsistent with the strict equality of the participant's one-step-ahead forecasts and the objective distribution is a higher variance of forecast errors than the variance based on a rational expectation. In addition, we find evidence of bias at the individual level in two-step-ahead forecast errors. These results suggest that a detailed analysis of forecasts for more than one period would be informative. This analysis is on our agenda for future research.

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36 Tests for unit roots in the forecasts and forecast errors are however the same for this initial interval.

While it may seem restrictive that the results are conditional on a random walk, this series has certain advantages compared to other alternatives such as a constant mean with a trend. Random walks can be tricky. The forecasts clearly reflect the random walk in the data, which suggests that the participants are not looking for mean reversion that is not in the underlying events being forecast. In other words, these results provide no support for the proposition that most participants in a market in which prices have a unit root (for example a martingale or random walk) would be misled into assuming mean reversion. It almost goes without saying that the evidence cannot be transferred to this very different setting directly. Nonetheless, these results with relatively naive participants with relatively small sums of money compared to markets in the economy provide no support for such behavior.

Our results hardly are a definitive answer to the question: "Are expectations rational?" We have provided evidence which suggests that, at least in a stark setting with sufficient information, the answer generally is "yes." Among other things, it is important to note that the answer to this question is conditional on a single sequence of numbers generating a random walk. We are exploring whether this conclusion carries over to other sequences from similar mechanisms and whether the conclusion carries over to other interesting mechanisms such as a difference equation with a cyclical component similar to business cycles.

An important issue is the extent to which these results carry over to markets. After all, the proposition that forecasts are the same as the predictions of economic theory is embedded in one of Muth's original definitions of rational expectations. The statistical setup for such an analysis may have to be dramatically different than the one which we use in this paper because the variable being predicted by the agents is not exactly the same as the theoretical equilibrium value. The results in this paper suggest that such an exploration will yield informative results.

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Table 1
Expected Receipts for Biased Forecasts

Bias	Expected receipts for biased forecasts relative to expected receipts for unbiased forecasts: Expected value	Without negative earnings
.00	1.000	1.000
.05	.939	.941
.10	.771	.782
.15	.536	.570
.20	.274	.363
.25	.000	.198

The expected value for forecasts with no bias is 17.9 cents per one-step-ahead forecast. The expected payment is the same for unbiased forecasts when negative earnings are clipped from the outcomes because negative earnings cannot occur.

Table 2
Tests for Unit Roots in the Forecasts

Graduate students		Intermediate participants		Inexperienced participants	
Subject	Test statistic	Subject	Test statistic	Subject	Test statistic
sg1	-1.09	su1	-1.97	sp1	-1.91
sg2	-1.19	su2	-1.45	sp2	-1.03
sg3	-1.08	su3	-1.08	sp3	-1.38
sg4	-1.08	su4	-1.31	sp4	-1.07
sg5	-1.58	su5	-1.24	sp5	-1.80
sg6	-1.42	su6	-1.64	sp6	-1.63
sg7	-1.53	su7	-1.48	sp7	-1.22
sg8	-1.08	su8	-1.21	sp8	-1.61
sg9	-1.42	su9	-1.31	sp9	-1.57
		su10	-2.00	sp10	-1.47
				sp11	-1.33
				sp12	-1.11
				sp13	-1.10
				sp14	-1.48
				sp15	-1.00
				sp16	-1.53
				sp17	-1.03
				sp18	-1.50
				sp19	-1.495
				sp20	-1.85

The test statistic is the t-ratio from a regression of the change in the forecast on last period's forecast. The test statistic is the t-ratio on last period's forecast from that regression. The distribution is derived from Dickey's simulations as reported by Fuller (1976, p. 373). For the data, the value of the test statistic is -1.20 and for the rational expectation, it is -1.08.

Table 3
Tests for Unit Roots in the Forecast Errors

Graduate students		Intermediate participants		Inexperienced participants	
Subject	Test statistic	Subject	Test statistic	Subject	Test statistic
sg1	-6.16	su1	-7.02	sp1	-7.90
sg2	-6.86	su2	-7.43	sp2	-4.00
sg3	-5.95	su3	-5.95	sp3	-6.04
sg4	-5.57	su4	-6.95	sp4	-6.04
sg5	-5.47	su5	-4.79	sp5	-5.93
sg6	-7.84	su6	-6.74	sp6	-7.06
sg7	-6.12	su7	-6.14	sp7	-6.05
sg8	-5.95	su8	-5.21	sp8	-5.18
sg9	-5.45	su9	-6.57	sp9	-7.61
		su10	-7.20	sp10	-7.43
				sp11	-5.35
				sp12	-6.62
				sp13	-4.15
				sp14	-6.39
				sp15	-4.94
				sp16	-5.19
				sp17	-5.71
				sp18	-6.80
				sp19	-6.19
				sp20	-6.94

The test statistic is the t-ratio from a regression of the change in the forecast error on last period's forecast error. The test statistic is the t-ratio on last period's forecast error from that regression. The distribution is derived from Dickey's simulations as reported by Fuller (1976, p. 373). For the rational expectation, the value of the test statistic is -5.95.

Table 4
Tests of Equality of Variances of Forecast Errors and Variance of Forecast Errors Under Rational Expectations

Graduate participants			Intermediate participants			Inexperienced participants		
Subject	Standard deviation	Test statistic msl	Subject	Standard deviation	Test statistic msl	Subject	Standard deviation	Test statistic msl
sg1	.098	29.56 .873	su1	.114	39.95 .169	sp1	.126	49.11 .023
sg2	.101	31.25 .707	su2	.108	35.72 .364	sp2	.117	41.98 .113
sg3	.097	29.00 .930	su3	.097	29.00 .930	sp3	.108	35.99 .348
sg4	.099	30.10 .818	su4	.108	35.92 .352	sp4	.096	28.51 .982
sg5	.107	35.40 .383	su5	.101	31.44 .690	sp5	.118	42.95 .092
sg6	.109	36.45 .322	su6	.121	44.69 .063	sp6	.119	43.85 .076
sg7	.111	37.67 .260	su7	.125	47.69 .032	sp7	.105	33.77 .495
sg8	.097	29.00 .930	su8	.118	42.51 .101	sp8	.097	28.72 .960
sg9	.102	32.01 .639	su9	.107	35.26 .392	sp9	.104	33.38 .526
			su10	.115	40.91 .140	sp10	.109	36.63 .312
						sp11	.113	39.24 .194
						sp12	.106	34.44 .447
						sp13	.074	16.65 .065
						sp14	.111	37.87 .251
						sp15	.097	28.74 .958
						sp16	.106	34.27 .459
						sp17	.108	36.15 .339
						sp18	.116	41.68 .120
						sp19	.118	42.60 .099
						sp20	.121	45.33 .055

The standard deviation of the forecast errors for the rational expectation is 0.097. The test statistics are distributed chi-square with 29 degrees of freedom. The "msl" is the marginal significance level.

Table 5
Tests of Equality of Overall Variances

Group	Overall standard deviation	Participants' variances to each other: Test statistic	ndf	msl	Overall variance to rational expectation: Test statistic	ndf	msl
Graduate participants	.102	1.23	8	.996	290.43	261	.204
Intermediate participants	.112	3.15	9	.958	383.10	290	.0004
Inexperienced participants first group	.110	4.32	9	.889	374.87	290	.001
Inexperienced participants second group	.108	9.25	9	.414	356.97	290	.009

The test statistics are distributed chi-square with degrees of freedom indicated by "ndf" and marginal significance level indicated by "msl."

Table 6
Tests of Equality of Subject's and Rational-Expectation Mean Forecast Errors

Graduate participants				Intermediate participants				Inexperienced participants			
Subject	Mean	Test statistic	msl	Subject	Mean	Test statistic	msl	Subject	Mean	Test statistic	msl
sg1	0.023	0.094	.925	su1	0.017	−0.282	.778	sp1	0.030	0.470	.638
sg2	−0.003	−1.410	.158	su2	−0.005	−1.504	.133	sp2	0.065	2.444	.015
sg3	0.022	0	1	su3	0.022	0	1	sp3	0.035	0.771	.441
sg4	0.025	0.188	.851	su4	0.023	0.094	.925	sp4	0.025	0.188	.851
sg5	0.025	0.188	.851	su5	0.023	0.075	.940	sp5	0.040	1.053	.292
sg6	0.007	−0.846	.397	su6	0.017	−0.244	.807	sp6	0.028	0.376	.707
sg7	0.035	0.771	.441	su7	0.013	−0.470	.638	sp7	0.022	0.000	1.000
sg8	0.022	0	1	su8	0.015	−0.376	.707	sp8	0.035	0.752	.452
sg9	−0.005	−1.504	.133	su9	0.002	−1.128	.259	sp9	0.013	−0.470	.638
				su10	0.035	0.733	.463	sp10	0.031	0.508	.612
								sp11	0.023	0.056	.955
								sp12	0.020	−0.075	.940
								sp13	0.010	−0.658	.510
								sp14	0.060	2.162	.031
								sp15	0.034	0.715	.475
								sp16	−0.008	−1.673	.094
								sp17	0.023	0.056	.955
								sp18	0.020	−0.094	.925
								sp19	0.017	−0.282	.778
								sp20	0.002	−1.128	.259

The mean of the rational-expectation (exact random walk) forecast errors is 0.022. The test statistics (denoted "test statistic") are approximately normally distributed. The "msl" is the marginal significance level for a two-tailed test.

Table 7
Tests of Equality of Overall Means
One-step-ahead Forecast Errors

Group	Overall mean	Participants' means to each other			Overall mean to rational expectation	
		Test statistic	df	msl	Test statistic	msl
Graduate participants	0.017	0.554	8.261	.815	−0.875	.382
Intermediate participants	0.016	0.305	9.290	.973	−0.979	.328
Inexperienced participants first group	0.032	0.465	9.290	.907	1.927	.054
Inexperienced participants second group	0.020	0.876	9.290	.547	−0.303	.762

The mean of the rational-expectation (exact random walk) forecast errors is 0.022. The test statistic for testing the hypothesis that the means are equal have F-distributions under the null hypothesis. The test statistics for testing the hypothesis that the mean equals the rational-expectation mean are approximately normally distributed. The "df" is the degrees of freedom for the F-statistic. "msl" is the marginal significance level.

Table 8
Test Statistics for Restrictions on Estimated Error Correction Mechanisms

Subject	Simplify regression F-ratio msl	Rational expectations t-ratio msl	Rational expectations estimated coefficients	Adaptive expectations t-ratio msl	Adaptive expectations estimated coefficient standard error
			Graduate students		
sg1	0.541	0.000	1.000	0.000	1.000
	.707	1.000	0.000	1.000	.017
sg2	1.287	2.172	0.737	2.492	1.119
	.307	.039	0.432	.019	.082
sg3	0	0		0	1
sg4	0.957	0.700	1.018	-0.181	0.983
	.451	.490	-0.036	.858	.024
sg5	1.762	0.723	0.427	2.847	0.803
	.174	.476	0.500	.008	.102
sg6	1.218	1.548	0.917	1.242	1.117
	.333	.134	0.261	.224	.105
sg7	0.876	2.393	0.474	4.138	1.019
	.495	.024	0.719	.0004	.086
sg8	0	0		0	1
sg9	0.810	1.110	0.434	2.587	0.795
	.533	.277	0.449	.015	.109
			Intermediate subjects		
su1	0.244	2.912	0.677	3.860	1.080
	.910	.007	0.554	.001	.085
su2	3.442	1.999	1.079	0.839	1.191
	.026	.056	0.153	.409	.105
su3	0	0		0	1
su4	0.354	1.778	1.141	-0.081	1.127
	.818	.087	-0.017	.936	.061
su5	0.419	2.151	.781	0.232	0.826
	.793	.041	.048	.818	.077
su6	2.240	2.592	.842	2.324	1.137
	.099	.005	.428	.028	.093
su7	0.151	0.904	.951	0.562	1.058
	.960	.374	.143	.579	.081
su8	0.754	0.660	.833	0.956	1.012
	.433	.515	.234	.348	.084
su9	1.329	1.159	.950	0.782	1.083
	.292	.257	.162	.441	.088
su10	1.007	0.100	1.400	-2.760	1.098
	.426	.921	-0.407	.001	.061

Table 8 (continued)

Subject	Simplify regression F-ratio msl	Rational expectations t-ratio msl	Rational expectations estimated coefficients	Adaptive expectations t-ratio msl	Adaptive expectations estimated coefficient standard error
		Inexperienced subjects			
sp1	0.701	2.283	1.195	0.420	1.255
	.600	.031	0.095	.678	.095
sp2	0.847	4.204	.186	3.974	0.460
	.511	.0004	.481	.0004	.074
sp3	0.699	0.477	.440	3.027	0.935
	.601	.637	.588	.005	.058
sp4	0.691	0.431	.605	2.401	0.983
	.605	.670	.434	.024	.095
sp5	0.651	0.195	.975	0.238	1.009
	.633	.847	.058	.814	.133
sp6	0.544	4.041	.640	3.568	1.144
	.705	.0004	.679	.001	.074
sp7	0.056	0.446	1.292	-1.271	1.068
	.994	.659	-0.260	.215	.068
sp8	1.380	1.788	0.626	0.382	0.675
	.275	.085	0.076	.705	.149
sp9	0.812	2.447	1.084	0.574	1.173
	.532	.021	0.104	.571	.072
sp10	6.094	3.116	0.704	3.323	1.140
	.002	.004	0.586	.003	.095
sp11	1.755	0.498	0.719	1.458	0.978
	.176	.623	0.320	.156	.067
sp12	0.450	0.664	1.205	-0.780	1.068
	.771	.512	-0.158	.442	.064
sp13	0.549	0.454	1.020	0.306	1.078
	.702	.653	0.059	.762	.171
sp14	5.712	1.949	0.562	2.948	1.005
	.003	.062	0.636	.007	.088
sp15	0.350	1.504	0.632	1.385	0.853
	.841	.144	0.252	.177	.075
sp16	0.529	0.465	0.453	3.264	0.946
	.713	.646	0.593	.003	.110
sp17	0.700	0.093	0.777	0.917	0.959
	.601	.927	0.215	.367	.072
sp18	0.553	2.251	1.030	0.729	1.154
	.699	.033	0.160	.472	.068
sp19	0.879	3.583	0.536	4.418	1.098
	.493	.001	0.774	.0001	.093
sp20	0.741	4.235	0.628	4.537	1.167
	.575	.0002	0.772	.0001	.103

Table 9
Tests of Equality of Two-step-ahead Forecasts and One-step-ahead Forecasts

Graduate students			Intermediate participants			Inexperienced participants		
Subject	Mean standard deviation	Test statistic msl	Subject	Mean standard deviation	Test statistic msl	Subject	Mean standard deviation	Test statistic msl
sg1	.012	0.745	su1	−.038	−2.214	sp1	.009	0.448
	.087	.462		.092	.039		.104	.657
sg2	−.054	−3.598	su2	.012	−0.587	sp2	−.031	−3.415
	.081	.001		.111	.562		.049	.002
sg3	0	na	su3	0	na	sp3	−.002	−0.259
	0			0			.036	.798
sg4	.002	0.571	su4	.059	2.423	sp4	.005	0.474
	.016	.573		.130	0.22		.059	.639
sg5	−.052	−3.183	su5	.021	1.925	sp5	.062	3.455
	.088	.003		.060	.064		.096	.002
sg6	.000	9.4×10^{-7}	su6	−.015	−0.845	sp6	−.017	−1.355
	.094	1.000		.097	.405		.068	.186
sg7	.057	3.766	su7	−.024	−0.625	sp7	−.034	−3.099
	.082	.001		.205	.537		.060	.044
sg8	0	na	su8	.005	0.474	sp8	−.007	−0.379
	0			.059	.639		.098	.707
sg9	−.017	0.115	su9	−.021	−1.326	sp9	−.005	−0.828
	.081	.909		.084	.195		.034	.415
			su10	.007	0.420	sp10	−.015	−1.289
				.084	.678		.063	.208
						sp11	−.070	−3.663
							.102	.001
						sp12	−.014	−1.480
							.051	.150
						sp13	.009	0.578
							.080	.567
						sp14	−.043	−7.992
							.029	.000
						sp15	.014	2.221
							.034	.034
						sp16	.004	0.434
							.051	.667
						sp17	.016	1.729
							.049	.094
						sp18	−.017	−1.625
							.057	.115
						sp19	.016	1.361
							.061	.184
						sp20	.003	0.297
							.063	.769

The test statistics are distributed Student's t with 29 degrees of freedom. The "msl" is the marginal significance level for a two-tailed test.

Table 10
Tests of Equality of Overall Means
Two-step-ahead Minus One-step-ahead Forecasts

Group	Overall mean	Participants' mean to each other			Overall mean to zero		
		Test statistic	df	msl	Test statistic	df	msl
Graduate participants	-0.004	6.539	8.261	.000	-0.856	259	.392
Intermediate participants	-0.002	1.970	9.280	.043	-0.826	289	.776
Inexperienced participants first group	-0.003	4.200	9.280	.000	-0.829	289	.408
Inexperienced participants second group	-0.008	6.273	9.280	.000	-2.117	289	.036

The mean of the rational-expectation (exact random walk) difference between the forecasts is identically zero. The test statistics for testing the hypothesis that the means are equal have F-distributions under the null hypothesis. The test statistics for testing the hypothesis that the mean equals zero are approximately distributed student's t. The "df" is the degrees of freedom for the test statistics, and "msl" is the marginal significance level.

Table 11
Summary of Earnings in Second Interval and Test Statistics

Participant	Earnings: One-step-ahead forecast	Earnings: Two-step-ahead forecast	One-step-ahead forecast errors: Mean	One-step-ahead forecast errors: Standard deviation	Error correction mechanism: Sum of coefficients	Mean difference two-step-ahead and one-step-ahead forecasts
re	5.25	4.10	.022	.097	1	0
sg1	5.20	4.15	.023	.098	1.000	.012
sg2	5.00	4.05	-.003	.101	1.169*	-.054*
sg3	5.25	4.10	.022	.097	1	0
sg4	5.25	3.69	.025	.099	0.982	.002
sg5	5.35+	4.44+	.025	.107	0.927	-.052
sg6	4.90	4.30+	.007	.109	1.178	.000
sg7	4.99	3.73	.035	.111	1.293*	.057*
sg8	5.25	4.10	.022	.097	1	0
sg9	5.05	5.35+	-.005	.102	0.883	-.017
su1	4.80	4.20+	.017	.114	1.231*	-.038*
su2	4.85	3.40	-.005	.108	1.232	.012
su3	5.25	4.10	.022	.097	1	0
su4	5.00	3.75	.023	.108	1.124	.059
su5	4.99	4.32+	.023	.101	0.829*	.021
su6	4.67	4.00	.017	.121	1.270*	-.015
su7	4.65	3.65	.013	.125*	1.094	-.024
su8	4.95	4.10	.015	.118	1.067	.005
su9	4.85	4.20+	.002	.107	1.112	-.021
su10	4.65	3.39	.035	.115	0.993	.007
sp1	5.35+	4.65+	.030	.126*	1.280*	.009
sp2	4.45	3.10	.065*	.117	.667*	-.031*
sp3	4.97	4.13	.035	.108	1.028	-.002
sp4	5.30+	3.85	.025	.096	1.039	.005
sp5	4.49	3.60	.040	.118	1.033	.062*
sp6	4.80	4.25+	.028	.119	1.319*	-.017
sp7	5.05	3.90	.022	.105	1.032	-.034*
sp8	5.40+	4.60+	.035	.097	0.692	-.007
sp9	5.10	4.40+	.013	.104	1.184*	-.005
sp10	4.97	4.11	.031	.109	1.290*	-.015
sp11	4.72	3.15	.023	.113	1.039	-.070*
sp12	4.99	4.16	.020	.106	1.057	-.014
sp13	6.10+	5.65+	.010	.074	1.079	.009
sp14	4.80	3.25	.060*	.111	1.198	-.043*
sp15	5.24	4.25	.034	.097	0.884	.014*
sp16	4.96	4.43	-.008	.106	1.046	.004
sp17	5.04	4.03	.023	.108	0.992	.016
sp18	4.80	3.95	.020	.116	1.190*	-.017
sp19	4.60	4.30	.017	.118	1.310*	.016
sp20	4.75	3.00	.002	.121	1.400*	.003

Table 12
Regressions of Earnings per Forecast on Statistics Characterizing Forecasts

	One-step-ahead forecast errors		Change in forecasts one and two steps ahead				
Constant	Absolute value of mean minus r.e.	Standard deviation	Absolute value	Standard deviation	Sum of coeffs. in r.e. e.c.m.	R^2 Se	F
			Average earnings from each one-step-ahead forecast				
.257 (23.30)	-.222 (-2.40)	-.841 (-7.58)	-.078 (-1.52)	.036 (1.26)	.012 (1.26)	.715 .006	16.55
.257 (23.57)	-.235 (-2.52)	-.830 (-7.91)			.014 (1.42)	.690 .006	25.90
.252 (23.28)		-.793 (-7.94)				.630 .006	62.97
			Average earnings from each two-step-ahead forecast				
.245 (9.56)	-.418 (-1.94)	-1.020 (-3.95)	-.244 (-2.02)	.114 (1.72)	.033 (1.50)	.446 .014	5.31
.232 (9.44)	-.309 (-1.50)	-.870 (-3.58)	-.258 (-2.11)	.122 (1.82)		.408 .014	5.86
.223 (8.97)	-.316 (-1.48)	-.720 (-3.06)	-.185 (-1.55)			.351 .014	6.30
.230 (9.01)		-.851 (-3.61)				.260 .015	13.00

The sum of coefficients is the estimated sum of the two coefficients in the error-correction mechanism consistent with rational expectations. The t-statistics for each coefficient are in parentheses. The R^2 is the fraction of variation explained; Se is the standard error of the residuals; and F is the F-statistic for the regression.

Figure 1

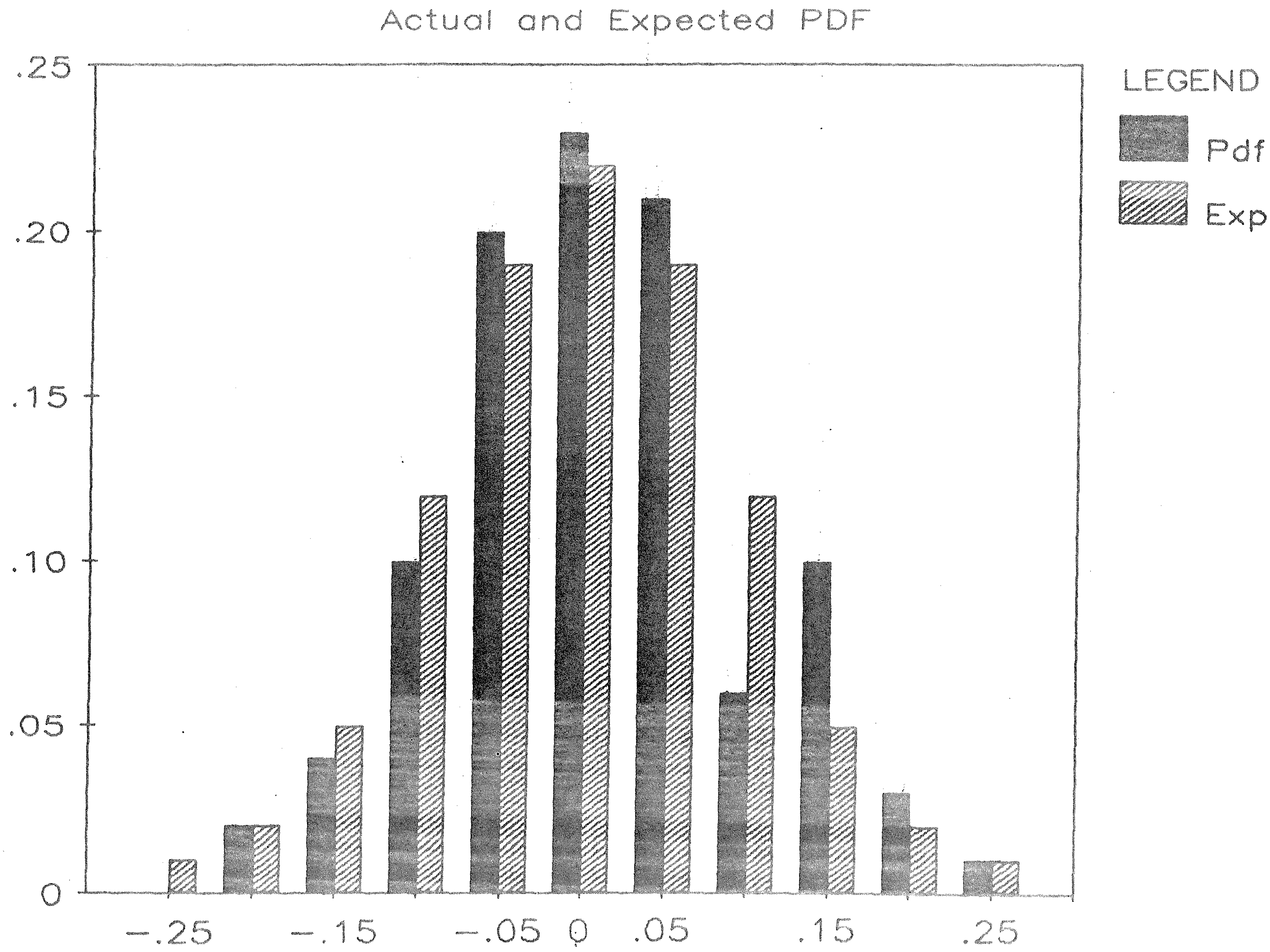
Actual and Expected PDF
LEGEND
Pdf
Exp
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Figure 2
The Events

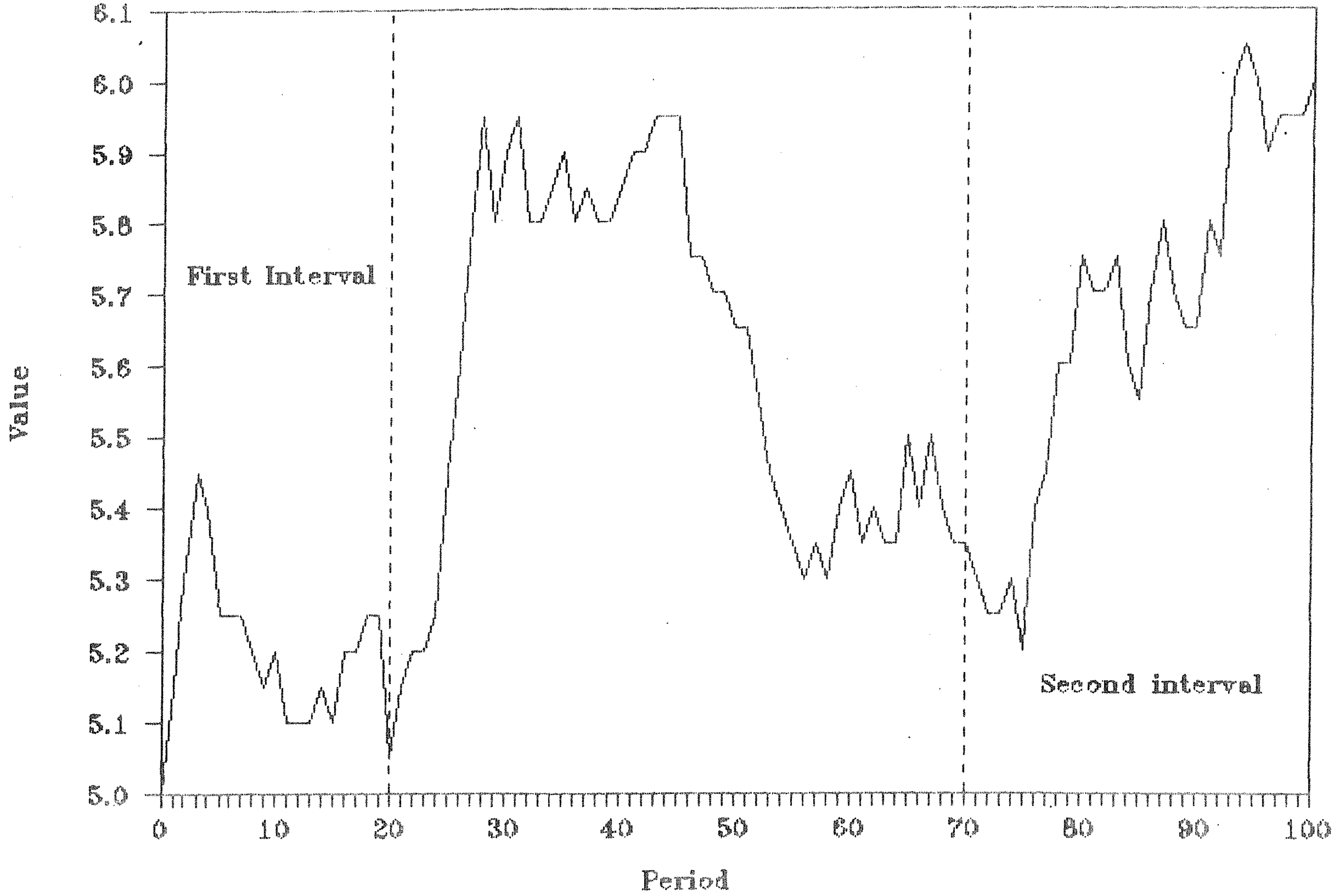


Figure 3
Estimated Slope Coefficients

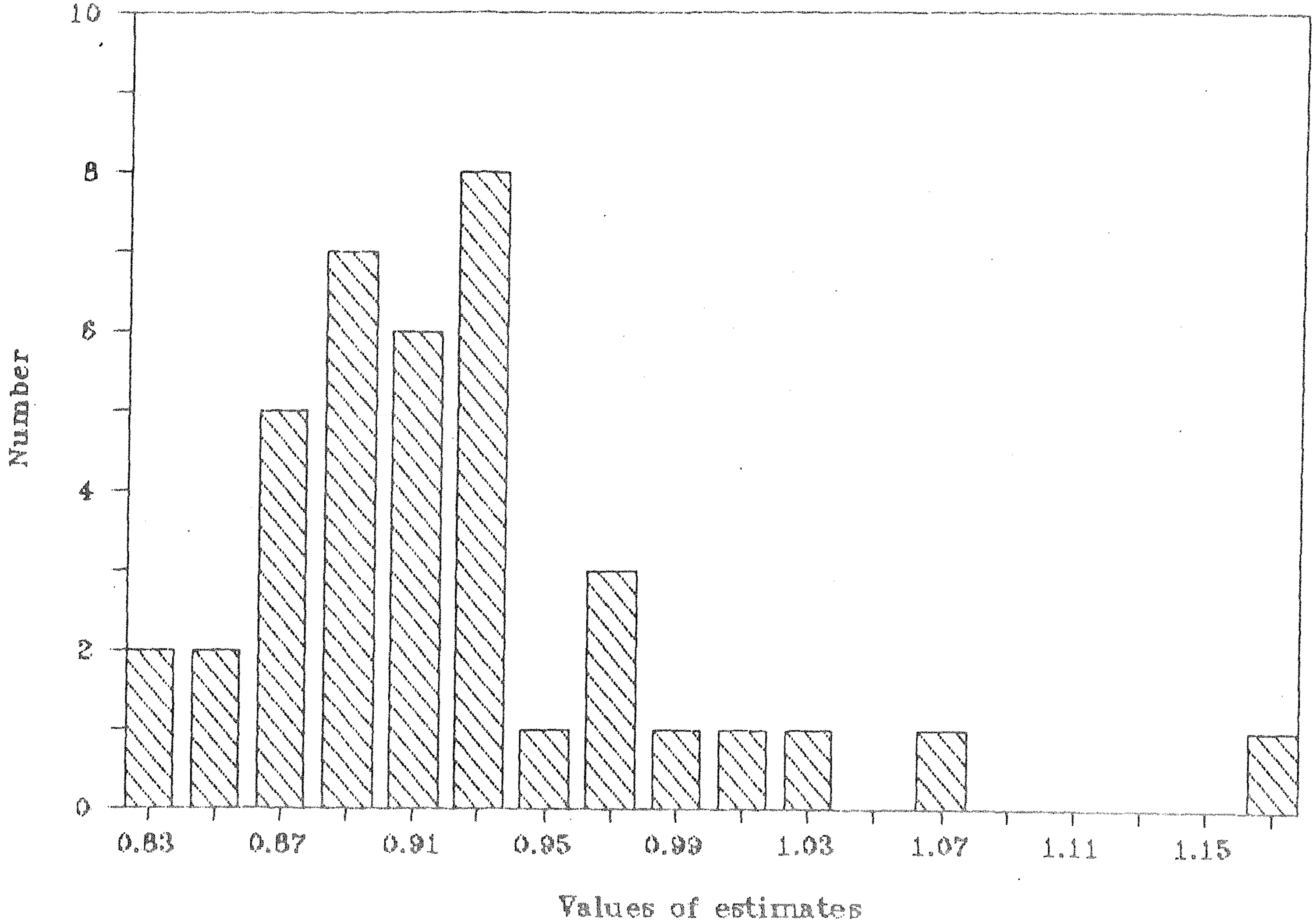
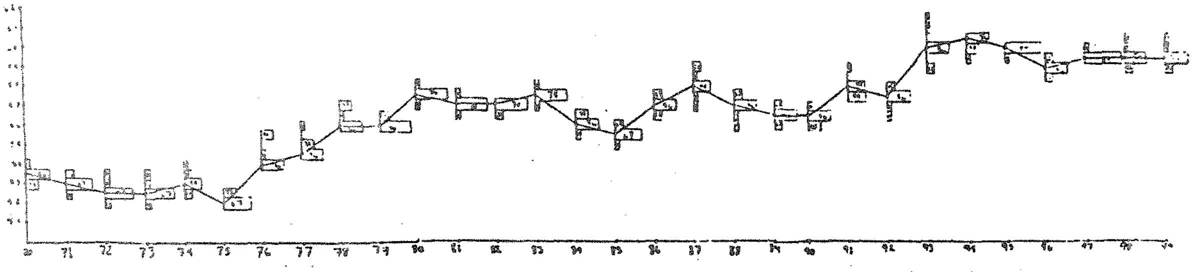
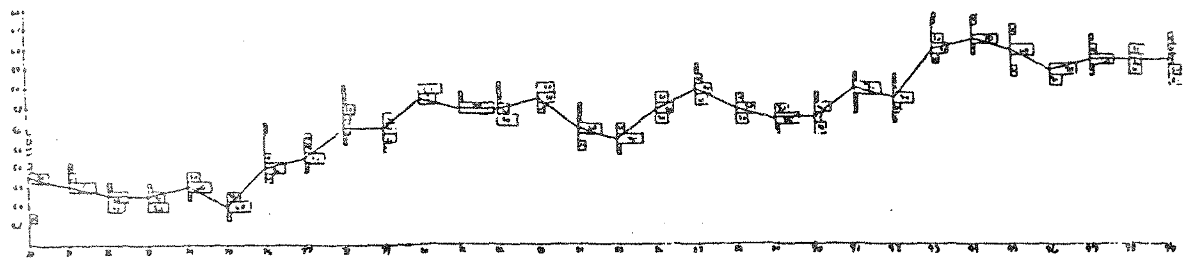


Figure 4
One-step-ahead Forecasts in Second Interval

Graduate Participants



Intermediate Participants



Inexperienced Participants

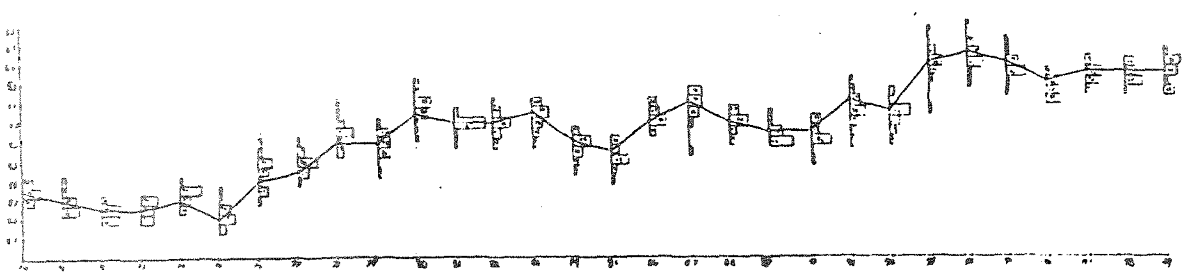


Figure 5

Forecasts and Rational-expectation Forecasts

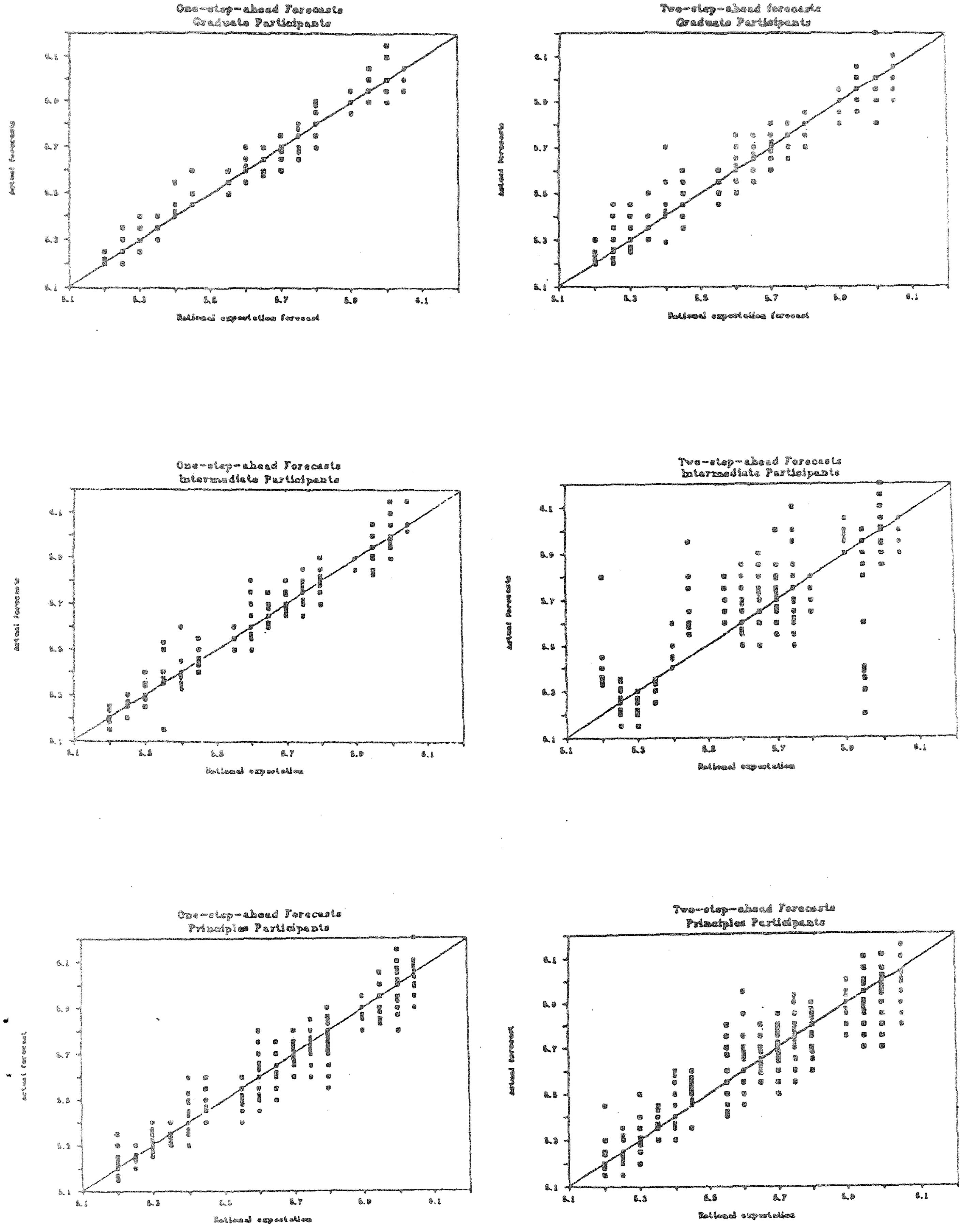


Figure 6

Distribution of First and Second Forecasts

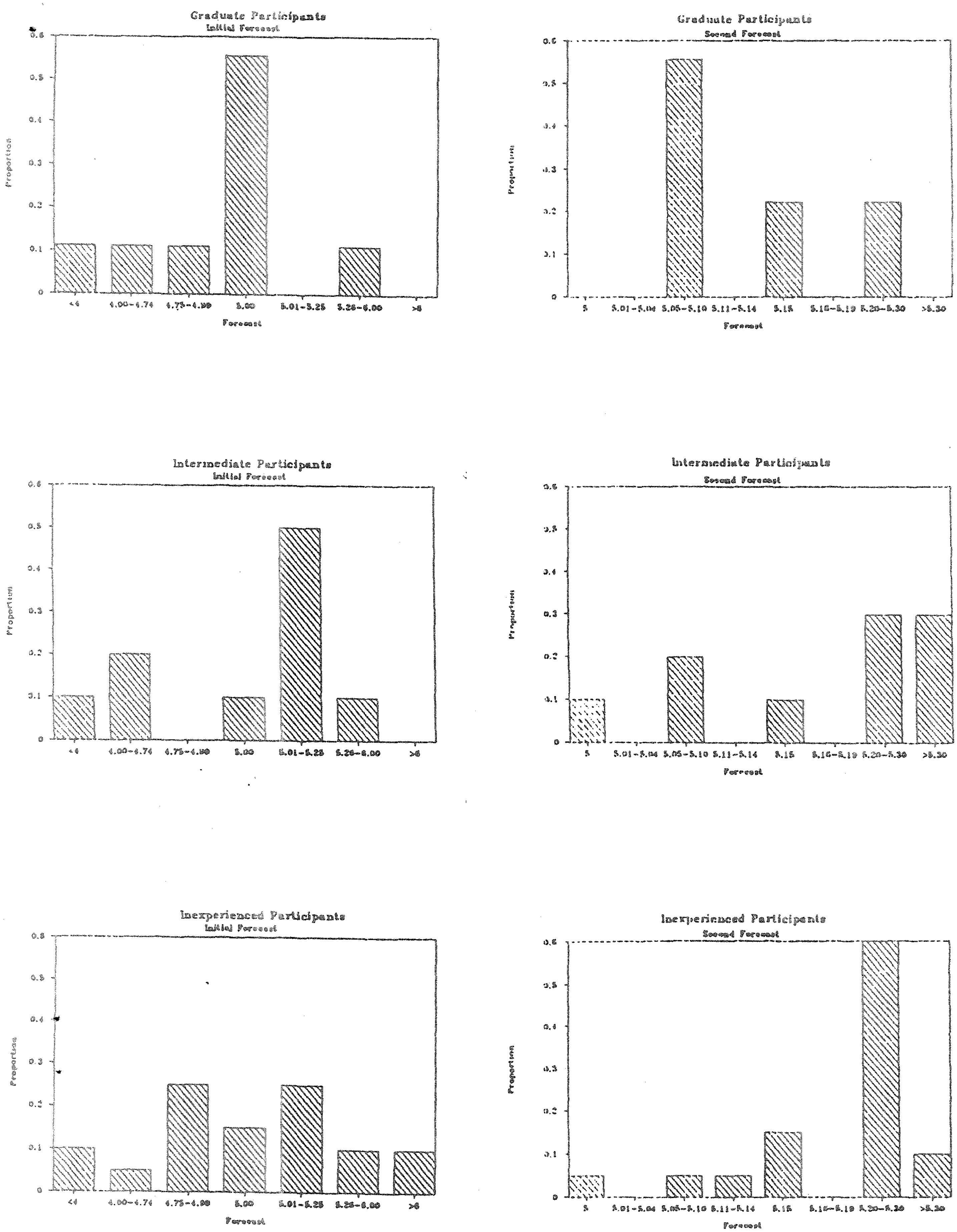


Figure 7
Standard Deviations of One-step-ahead Forecast Errors
Relative to Rational Expectation