Price and Volume Reactions to Public Information Releases: An Experimental Approach Incorporating Traders’ Subjective Beliefs*

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Abstract
This paper examines how market prices, volume, and traders’ dividend expectations respond to public information releases in laboratory markets for a long-lived financial asset. The objective is to study deviations from the symmetric information risk-neutral rational expectations (RE) benchmark, which predicts no trade in such settings. The results of a series of double-auction and call markets are reported in which traders manage a portfolio of cash and asset shares over 15 rounds of trading. A public signal regarding the value of the liquidating dividend is released every third round, and traders’ subjective expectations of the liquidating dividend are elicited each round as cash-motivated forecasts. We find that, despite the public dividend signal, traders’ dividend forecasts are heterogeneous. Forecasts and prices both underreact to the public signals, with prices underreacting more than forecasts. In general, price changes are not closely associated with public signals, and there is greater excess price volatility in double auctions than in call markets. Forty-three percent of trades are inconsistent with the trader’s forecasts, and inconsistent trades occur more frequently in the double-auction markets. On average, approximately 10 percent of the outstanding shares are traded in each round, and trading

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volume is increasing in the mean absolute forecast revision and decreasing in the contemporaneous dispersion in forecasts. These results suggest that differential processing of the public signal and speculative trading for short-term gain may help to explain why not all public information releases improve market efficiency and experimental settings. They also suggest that market reactions to public information releases may be influenced by market microstructure.

Condensé
L'un des sujets qui attire le plus l'attention des chercheurs qui s'interessent à l'aspect comptable des marchés financiers est l'utilisation que font de l'information comptable par les marchés pour valuer les actions. Les participants au marché qui voient être interprété ou corriger leurs propres prévisions et revoir leurs positions. Les auteurs contribuent à l'avancement de ces recherches en examinant les différences dans les comportements des marchés, les volumes d'opérations et les prévisions de dividendes des négociateurs réagissant à la publication d'information dans des marchés de laboratoire, relativement à un actif financier de longue durée. En pareil contexte, les modèles prévisionnels rationalisent la valeur intrinsèque des actions après la publication d'information, les cours s'ajustent immédiatement et les prévisions des négociateurs et les cours du marché ne confirment pas cette corrélation (par exemple, Kandel et Pearson, 1995 ; Smith, Suchak et Williams, 1988). L'objectif premier des auteurs consiste à étudier l'ampleur et la nature des écarts en matière de comportement par rapport à l'indice repère des prévisions rationnelles en situation de symétrie de l'information, dans le contexte d'un marché à un seul élément d'information. Deux caractéristiques des marchés qui distinguent la présente recherche des études de laboratoire américaines dont les résultats sont répétés dans la littérature en comptabilité. Premièrement, la durée de l'information d'événements longue pour permettre que les prévisions déviées en cas de dividendes soient une motivation potentielle à la négociation et deuxièmement que les prévisions subjectives des négociateurs concernant la valeur du dividende et de l'actif sont mises à jour à intervalles réguliers à l'aide d'une structure de distribution monocorriente.

Les auteurs de l'expérience sont des étudiants de premier cycle en comptabilité et en économie de l'Indiana University. Chaque sujet a participé à un maximum de trois séances expérimentales, en trois jours différents. La première séance consistait dans un exercice prévisionnel non lié au marché dans lequel les sujets soumettaient des prévisions motivées par une estimation monétaire relative aux résultats d'un événement incertain. Dans la deuxième séance, les sujets qui avaient participé à l'expérience de la première séance négocient les actions d'un actif portant un dividende de liquidation après l'événement incertain. Les négociateurs recevaient à toutes les trois rondes un indice public connu quant à la valeur du dividende de liquidation de deux processus stochastiques identiques à celui qui avait servi à déterminer la valeur de l'événement incertain au cours de la première séance. Au début de chaque ronde, les sujets formulaient, au surplus, des prévisions motivées par une estimation monétaire quant à la valeur du dividende de liquidation. Au cours de la troisième séance, les sujets étaient placés dans le même contexte de marché que celui dont ils avaient fait l'expérience à la deuxième séance. Au total, 101 sujets ont participé à huit séances de prévisions, non liées au marché. L'expérience a donné lieu à la tenue de treize marchés d'actifs : huit séances (deuxième séance) comptant au total 96 négociateurs « inexperimentés » et cinq marchés (troisième séance) comptant au total 55 négociateurs « expérimentés ». Les huit marchés de la deuxième séance faisaient intervenir en moyenne 12 négociateurs et les cinq marchés de la troisième séance faisaient intervenir en moyenne 11 négociateurs. Les auteurs ont opté pour deux systèmes de négociation différents : le marché où le prix du dividende entre des parties (marché à prix moyen) et celui où le prix est unique pour toutes les parties (marché à prix unique). Cinq marchés à prix moyen ont été tenus : trois avec des négociateurs inexperimentés et deux avec des négociateurs expérimentés. Huit marchés à prix unique ont été tenus : cinq avec des négociateurs inexperimentés et trois avec des négociateurs expérimentés. À toutes les séances, les sujets recevaient la somme de trois dollars pour se présenter au laboratoire à l'heure dite, additionnée de rétributions supplémentaires basées sur leur performance. Les sujets étaient payés en espèces au terme de chaque séance.

Les résultats de l'expérience révèlent que, malgré les indices publics communs, les prévisions des négociateurs quant aux dividendes sont hétérogènes. En outre, la réaction des prévisions aux indices publics est atténuée (c'est-à-dire qu'elle reste au-dessous de la valeur intrinsèque après la diffusion d'un indice positif et au-dessus de la valeur intrinsèque après la publication d'un indice négatif) de l'environ 23 pour cent environ. En revanche, la réaction des cours est atténuée encore davantage que celle des prévisions, ce qui indique que les motivations à négocier s'étendent au-delà des prévisions relatives au dividende de liquidation. Cette observation fondamentale se vérifie tant pour le marché à prix unique que pour le marché à prix unique, bien que les cours de clôture du marché à prix unique affichent davantage de « volatilité excessive » que pour le marché à prix unique. L'analyse des opérations effectuées sur les marchés révèle que 43 pour cent d'entre elles ne correspondent pas à la dernière prévision des négociateurs, que les négociateurs qui les prévisions sont moins rationnelles sont plus susceptibles d'effectuer ces opérations « non conformes » et que les négociateurs, en moyenne, recollent moins d'argent. Quelques 10 pour cent des actions en circulation, de moyenne, se négocient à chaque ronde. La révision de la prévision affiche un lien positif avec le volume d'opérations observé et un lien négatif avec la dispersion des prévisions. Ces résultats inspirent au moins deux raisons pouvant expliquer pourquoi les prévisions des modèles prévisionnels rationnels où l'information est symétrique ne sont généralement pas conformées par la recherche empirique et expérimentale. Premièrement, la différence entre les prévisions des négociateurs et les cours du marché dans les situations menées donnée à penser que certains négociateurs (peut-être ceux) ne croient pas à l'information rationnelle des autres (conformément à l'hypothèse « sous-juste » des modèles prévisionnels rationnels où l'information est symétrique). Cette incertitude entraîne une hétérogénéité des prévisions relatives aux cours qui, en retour, peut mener à une négociation spéculative visant les gains à court terme. Deuxièmement, les prévisions de dividendes produites par les négociateurs dévoilent des convictions hétérogènes qui se manifestent dans le traitement différent d'information identique sur les dividendes. Ce traitement diffère peut équivaloir, sur le plan fonctionnel, à un marché où l'information est asymétrique et où la négociation spéculative est possible à l'intérieur du cadre des modèles prévisionnels rationnels. Le résultat selon lequel 43 pour cent des opérations de négociation ne correspondent pas aux prévisions de dividendes des négociateurs donne à penser que l'hétérogénéité des prévisions de dividendes est, au mieux, une explication incomplète de la négociation dans les marchés étudiés. Les observations des auteurs peuvent contribuer à combler l'écart entre les théories du marché, qui suppose une information privée asymétrique, pour générer les opérations de négociation, et les constatations d'information publique, comme celui qui fait l'objet de l'expérience prévisionnelle.
1. Introduction

A primary focus of capital markets research in accounting has been understanding how market participants use publicly released accounting information to update their beliefs and allocate their resources across firms. This paper contributes to this literature by examining how price, volume, and traders' dividend forecasts respond to public information releases in laboratory markets for a long-lived financial asset. In such settings, risk-neutral rational expectations (RE) models with symmetric information predict that after an information release prices adjust immediately to the posterior expected value of the asset with essentially no trading volume. However, prior empirical and experimental evidence suggests that traders' expectations and market prices do not support this prediction (e.g., Kandel and Pearson 1995; Smith, Suchanek, and Williams 1988). The primary objective of this paper is to study the magnitude and nature of behavioral deviations from the symmetric information rational expectations benchmark in a simple asset market setting. Two features of the markets distinguish the research reported here from past laboratory studies in the accounting literature. First, the asset's life is sufficiently long to allow capital-gains expectations as a potential motivation for trade, and second, traders' subjective expectations regarding the terminal value of the asset are elicited at regular intervals using a cash reward structure.

The results of a series of double-continuous auction and call markets are reported in which traders manage a portfolio of cash and asset shares over 15 rounds of trading. Traders receive a common public signal about the value of the liquidating dividend every third round. Thus, uncertainty about the value of the liquidating dividend declines after each public information release. The results indicate that despite common public signals, traders' forecasts of the dividend are

pas conforme à leurs observations. Des réductions importantes du taux de rotation sont également associées à des négociateurs plus expérimentés, à des prélèvements restants relatifs aux dividendes qui sont moindres et aux marchés à prix unique. En général, il semble que les marchés à prix unique soient quelque peu moins "perturbés" que les marchés à prix convenus, affichant moins de volatilité excessive des cours, moins d'opérations de négociation non conformes aux prévisions et un taux plus faible de rotation des actions. Les estimations de paramètres pour le modèle d'ajustement partiel laissent croire que, bien que les marchés à prix unique et les marchés à prix convenus aient des taux d'ajustement similaires à l'égard du cours d'équilibre sous-jacent, les mouvements de l'équilibre sont plus étroitement liés à la prévision de dividendes moyenne dans les marchés à prix unique et les marchés où les négociateurs sont expérimentés.

Des réponses détaillées et finales à toutes les questions soulevées par les chercheurs dont les résultats sont exposés ici dépassent la portée des données recueillies dans le cadre de ces expériences et celle de l'état actuel des connaissances sur le comportement humain dans les marchés. Le jour viendra peut-être où des interactions inédites entre les théoriciens du marché, les empiristes qui utilisent les données d'archives et les experimentateurs en laboratoire pourront jeter davantage de lumière sur les facteurs qui influencent sur le processus d'élaboration des prévisions et sur l'interaction complexe des stratégies de marché individuelles qui déterminent cours du marché et le volume d'opérations.
heterogeneous. Further, forecasts underreact to the public signals by approximately 23 percent on average. Prices, however, underreact even more to the public signals than do the forecasts, strongly suggesting that motivations for trading extend beyond expectations about the liquidating dividend. Analysis of individual traders’ data reveals that 42 percent of the trades are inconsistent with the trader's latest forecast, that traders with less rational forecasts are more likely to make such "inconsistent" trades, and that these traders, on average, make less money. Approximately 10 percent of the outstanding shares, on average, are traded in each round. Observed trading volume is increasing in the mean absolute forecast revision and decreasing in the contemporaneous dispersion in forecasts.

These results suggest at least two potential explanations for why symmetric information RE model predictions are generally not supported by empirical and experimental research. First, the difference in trader forecasts and market prices in our experiments suggests that some (perhaps all) traders do not believe that others will react in a rational manner (as assumed in symmetric information RE models). This creates heterogeneity in price expectations that, in turn, may lead to speculative trading for short-term gain. Second, the dividend forecasts submitted by traders reveal heterogeneous beliefs rooted in differential processing of identical dividend information. This differential processing may have created the functional equivalent of a market with informational asymmetries, where speculative trading is possible within the framework provided by RE models. The result that 43 percent of trades are inconsistent with the trader's latest dividend forecast suggests that heterogeneity of dividend expectations is, at best, an incomplete explanation of trade in the markets reported here.

2. Research motivations and placement in the literature

The motivations for our experiments arise from prior theoretical, empirical, and laboratory experimental research in the accounting, economics, and finance literatures.

Theory

The appropriate theoretical underpinnings for the experiments reported in this study are rational expectations models with symmetrically informed traders (e.g., Milgrom and Stokey 1982; Geanakoplos 1992; and Neeman 1996). These papers all prove variants of the "no-trade theorem." Intuitively, this theorem states that if traders begin with Pareto optimal allocations prior to the release of information, then upon the release of that information, price adjusts to the new expected value and no trade takes place. Geanakoplos (1992) and Neeman (1996) show that the result depends on the assumption of common knowledge and that such models exhibit trade when there is "almost" common knowledge. Intuitively, dropping the assumption of common knowledge allows traders to believe that other traders may not act rationally. This creates a potential motivation for speculative trading.

An alternative explanation for speculative trading arises from heterogeneous beliefs of traders. Generally, theoretical models produce heterogeneous beliefs by introducing differential information while retaining the common knowledge assumption. Kim and Verrecchia (1991a, b, and 1994), Demski and Feltham (1994), and McNichols and Trueman (1994) provide models in which this perspective is present. While there are only public information releases in our experiments, subjects reported heterogeneous beliefs about the liquidating value of the asset being traded. This result suggests that, in the presence of differential processing of public information, the trading implications of asymmetric information RE models may be more broadly relevant than the formal structure suggests.

By comparing traders' contemporaneous dividend forecasts with market price and volume outcomes, this study addresses the nature of the breakdown of the no-trade theorem in a laboratory environment devoid of informational asymmetries.

Empirical and laboratory studies

Empirical accounting research has established that prices adjust swiftly after a public earnings announcement (e.g., Patell and Wolfson 1984); however, there is some question about whether this initial reaction is too large or too small. A growing number of papers (e.g., Bernard and Thomas 1989, 1990; Abarbanell and Bernard 1992) have shown that prices initially underreact to earnings news and then slowly adjust to reflect the new information over a period of weeks. De Bondt and Thaler (1985, 1987) present evidence that they interpret as an overreaction of stock prices to information. In particular, they show that stock returns of extreme winners and losers tend to reverse over three- to five-year holding periods. This empirical evidence suggests that prices in naturally occurring markets do not behave in a manner consistent with RE models, but as noted in Boll 1992 and Bernard 1993, such evidence does not indicate why deviations from fundamental value are observed. Again, by eliciting traders' contemporaneous dividend forecasts in conjunction with their observed market behavior, the research reported here may provide insights into why prices overreact or underreact to public information releases.

Laboratory research in economics and accounting has provided mixed support for the empirical result that market prices do not always reflect intrinsic dividend value and may not adjust in an unbiased fashion to public information releases. While early experimental economics studies (e.g., Plott and Sunder 1982) demonstrated that the results of short-lived asset markets are generally consistent with risk-neutral RE predictions, Smith et al. (1988) observed frequent price bubbles and crashes in laboratory markets where a long-lived asset was traded. Their results indicate that when traders have longer time horizons, capital-gains expectations may result in prices that initially stray far from intrinsic value. The price bubble-crash phenomenon does not rely on informational asymmetries or injections of new public information into the market. An important implication of this early research with a long-lived asset is that common dividend information is not a sufficient condition for creating common price expectations.

Experimental research in accounting has extended this literature and contributed to the empirical under- and overreaction literature by exploring the way in which subjects in short-lived asset markets update beliefs and trade on
stochastic process used to determine the value of the uncertain event in the first session. In the third session, subjects participated in the same market environment they experienced in session 2.

A total of 101 subjects participated in eight non-market forecasting sessions. From this group, 13 asset markets were conducted: eight (second session) markets with a total of 96 "inexperienced" traders, and five (third session) markets with a total of 55 "experienced" traders. The eight second-session markets used an average of 12 traders, and the five third-session markets used an average of 11 traders. Two distinct exchange involvements were utilized: double-continguous auctions and call markets. Five double-auction markets were conducted, three with inexperienced traders and two with experienced traders. Eight call markets were conducted, five with inexperienced traders and three with experienced traders.

In all sessions, subjects received $3 for arriving at the lab on time plus additional rewards based on their performance. Subjects were paid in cash at the end of each session.

The forecasting objective (called the uncertain event in the non-market forecasting sessions and the terminal dividend in the market sessions) was determined by the sum of five random components. A component could take on the values of $0.00, $0.20, $0.40, $0.60, or $0.80 with probabilities of 1/9, 2/9, 2/9, 2/9, and 1/9 respectively. Component values were publicly determined by having a subject draw one poker chip from a bucket of 90 chips. The color of the chip drawn determined the component value. The expected value of each component was $0.40, and the expected value of the sum of five components, prior to any being drawn, was $2.00. In expected value terms, a draw could cause a positive shift ($0.60 or $0.80 draw), a negative shift ($0.20 or $0.20 draw), or no shift in expected value ($0.40 draw).

Procedures for non-market forecasting sessions

The primary purpose of the non-market forecasting sessions was to give the subjects experience with the probability distribution and the draw process used to determine the value of the liquidating dividend in the asset-market sessions. The forecasting task required each individual to predict the value of the "uncertain event." Subjects participated in four sequences (A, B, C, D) of five decision rounds (r = 1, 2, 3, 4, 5) for a total of 20 forecasts.

During Round 1 of each forecasting sequence, none of the actual values of the five components was known to the forecasters. Thus, the statistically rational forecast of the event was the expected value of 5 x $0.40 = $2.00. Note that the instructions (Appendix 1) were very explicit regarding the calculation of the expected value of the uncertain event. After all forecasts were collected for Round 1, a subject was randomly chosen to draw a chip from the bucket. Chip draws were performed publicly and recorded on an overhead projector at the front of the room (see Appendix 2). Subjects then made their Round 2 forecasts of the uncertain event with an expected value equal to the actual value of the first component plus 4 x $0.40. This process continued until Round 5, after which the fifth and final component was determined. At this point, the actual value of the
forecasting objective (the uncertain event) was fully determined, and the magnitude of the subjects’ forecast errors could be calculated.

After completing forecasting sequence D, subjects’ final earnings from all 20 forecasts were calculated by the experimenters using a spreadsheet. For each forecast, each subject earned $1.00 minus the absolute value of his or her forecast error, or zero if this difference was negative. Next, the subjects were given the same handout shown in Appendix 3, which presented an overview of the stock market for the following session. Each subject was then logged into the following session’s computerized market to work through the instructional module at his or her own pace. However, no trading rounds were conducted. The forecasting sessions lasted approximately 2.5 hours, and the average pay received by the subjects was $16.08.

**Procedures for asset-market sessions**

Upon arriving at the lab for the asset-market sessions, subjects were given and read aloud the instructional handout shown in Appendix 4. The instructions stressed that: (1) the market would include a sequence of 15 two-minute trading rounds; (2) at the end of Round 15, each asset share would earn a dividend equal to the sum of five dividend components, with the component values and associated probabilities being identical to the non-market forecasting session; (3) one component was determined after trading rounds 3, 6, 9, 12, and 15; and (4) a cash-motivated forecast of the terminal per share dividend would be submitted by each trader prior to the beginning of each round. The subjects again worked through the computerized asset-market instructions. When all traders had completed the instructions and submitted a Round 1 forecast of the terminal dividend, the first trading round began.

All traders were endowed at the beginning of Round 1 with $8.00 in cash and four asset shares. They could add to their share holdings (reduce their cash holdings) by purchasing shares in the market, or reduce their share holdings (add to their cash holdings) by selling shares in the market. Margin buying and short selling were prohibited. Cash and share holdings were carried over from round to round. After the final dividend component was drawn at the conclusion of Round 15, subjects were paid privately in cash their final “working capital” (initial cash endowment + net capital gains + dividend earnings), the $3.00 show-up payment, and their market forecast earnings. The market forecast earnings were determined by taking one-third of their forecast earnings over the 15 forecasts. Thus, the expected earnings were identical to a five-round non-market forecasting sequence ($3.49). The asset markets typically lasted just over two hours, and the average earnings per subject, including the $3.00 show-up payment, was $22.33. (The range was $14.83 to $30.16.)

**Trading institutions**

This study used computerized versions of the double-continuous auction and call market trading institutions. The trader interfaces were similar in appearance and used identical record-keeping procedures. Trading rounds in both institutions ended after 120 seconds of elapsed time or when traders unanimously agreed to move on to the next round. The display of the market price and volume history provided to traders between rounds was identical across institutions. The differences between the two trading institutions are highlighted below.

**The double-continuous auction**

In the double-continuous auction market institution, the highest bid (buy) and lowest offer to sell an asset share are publicly displayed as the standing bid-ask spread. Contracts are made when a trader accepts the bid or offer submitted by another trader. The contract is immediately recorded in the relevant subjects’ display screens. All bids, offers, and transactions in the continuous auction are for single shares. A bid-ask spread improvement rule was used in the markets reported here as a “queue,” where bids and offers that are away from the standing bid-ask spread are ordered by price priority. After a contract is made, the highest queued bid and lowest queued offer are automatically entered as the new bid-ask spread.

**The call market**

In the call market institution, all trades occur at a uniform clearing price rather than at the submitted bid or offer prices. All bids to buy and offers to sell are really “limit orders” specifying the highest acceptable purchase price or lowest acceptable sale price. During each call market round, a trader may submit up to six price-quantity orders to buy and/or sell asset shares. Traders are permitted to both buy and sell orders in any round (subject to cash and share constraints), but they are not permitted to “churn” shares and create false volume by trading with themselves. For each individual, the highest bid price must be less than the lowest offer price.

At the end of each trading round, the computer sorts the set of all bids to buy from high price to low price and sorts the set of all offers to sell from low price to high price. The two arrays are then crossed, and the intersection of the downward-sloping array of bids and upward-sloping array of offers determines the clearing price and trading volume at that price. If the intersection of the bid and ask arrays is a range of prices, the midpoint of this range (rounded down to the nearest integer cent) is used as the market price. Further, if there is an excess of buy or sell orders at the market price, a random selection of the excess orders are excluded from trade. Note that it is possible for the array of buy orders to lie entirely below the array of sell orders. In this case trading volume is zero, and each trader is informed of the highest bid to buy and the lowest offer to sell.

Immediately after a crossing of orders, each trader receives feedback on the clearing price, market volume, and status of his or her submitted orders. At this point, traders can press a key to see a graphical display of the bid and offer arrays and the exact determination of the clearing price and trading volume for the trading round just completed. All of the call markets reported here are “closed book” markets. That is, at no time do subjects receive real-time information on the market bid or offer arrays determining the tentative clearing price and trading volume for the round currently in progress.
4. Experimental results
This section presents the results of the experimental sessions described in Section 3. First, the forecasting data are analyzed. This analysis documents the subjects' understanding of the forecasting task and provides insights into the formation of their subjective beliefs. Next, market price data are analyzed, followed by individual trading data and market volume data.

Forecasting data
The subjects in the eight non-market forecasting sessions generated a total of 2,020 forecasts of the ending value of the uncertain event (20 forecasts per subject per session), and the subjects in the 13 asset-market sessions generated a total of 2,265 forecasts of the per share value of the terminal dividend (15 forecasts per trader per market). Figure 1 presents the relative frequency histograms of the deviations of forecasts from the expected value of the forecasting objective. This figure suggests that, while forecasts tracked expected value very well overall, some heterogeneity in forecasts is caused by differential processing of the public signals. 14

FIGURE 1
Relative frequency of forecast deviations (Forecast – Expected value)

![Histogram of forecast deviations](image)

The subjects' forecasting behavior was strikingly similar across the non-market sessions and the market sessions. In the non-market sessions, 58.6 percent of the forecasts are exactly equal to the expected value of the uncertain event, and an additional 32.5 percent are within $0.20 of expected value (with most of these occurring at $0.20, since expected value could only change in integer multiples of $0.20). In the market sessions, 58.2 percent of the forecasts are exactly equal to the expected value of the dividend, and an additional 33.3 percent are within $0.20 of expected value. Thus, in both the non-market and market sessions, approximately 91 percent of the individual forecasts are within one change unit of the statistically rational forecast. The analysis presented below focuses on the dividend forecasts from the asset-market sessions.

Across all forecasts in the asset-market sessions, the mean forecast is $1.97, and the mean expected value of the terminal dividend is $1.95. 17 While the magnitude of this difference in sample means is very small, a matched-pairs t-test rejects the null hypothesis of no population difference (N = 2,265, p < 0.01) assuming independence of the paired differences. However, the average earnings from forecasting in the markets of $3.46 is not statistically different from the $3.49 expected earnings of a statistically rational forecaster (N = 101, p > 0.10).

Figure 2 displays a scatter plot of mean forecasts (\( \bar{F} \)) on the expected dividend (\( ED_t \)) in each round and the ordinary least squares (OLS) fit of this data.

FIGURE 2
Scatter plot of mean forecasts vs. expected dividend (all market rounds, \( N = 195 \))

![Scatter plot of mean forecasts vs. expected dividend](image)

OLS fit: \( \bar{F} = 0.342 + 0.8326 ED_t \)

RE benchmark: \( \bar{F} = ED_t \)
Also included is a 45-degree reference line reflecting the risk-neutral rational expectations benchmark, with an intercept coefficient of zero and a slope coefficient of 1. A comparison of these two lines reveals a tendency for subjects to submit forecasts that are somewhat below $E_D$ when it is above $2.00$ and somewhat above $E_D$ when it is below $2.00$. Given that all markets began with an expected dividend of $2.00$ in Round 1, Figure 2 provides evidence of a small but systematic underreaction of forecasts to changes in the expected dividend.

Table 1 presents the OLS estimates for four regressions relating four forecast measures ($F_I$, $F$, $\Delta F$, $\Delta E_D$) to their corresponding expected dividend measure ($E_D$). These regressions reveal a strong positive correlation between forecasts and the expected dividend; however, the 95% confidence intervals show that the slope coefficient is significantly less than 1 in each regression. These results provide further evidence that subjects were not perfectly rational forecasters, and that their forecasts tended to underreact to changes in the expected dividend. 

It is difficult to derive an economic explanation for the forecast underreaction documented here. Subjects were given extensive training and experience with the probability distribution, and the economic incentive for the forecasts motivated subjects to set their forecasts at the expected dividend. However, this underreaction is consistent with heuristics and biases found in prior studies of probabilistic judgments in the behavioral literature. For example, forecast underreaction is consistent with the “anchoring and adjustment” heuristic (Tversky and Kahneman 1974), which reflects the tendency for human subjects to only partially adjust away from an initial estimate. This behavior is also consistent with the well-known “gambler’s fallacy” (Kahneman and Tversky 1972), where chance occurrences are viewed as a self-correcting process in which a deviation in one direction induces a deviation in the opposite direction to restore equilibrium (reversion to the mean).

### Table 1

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Intercept $a$</th>
<th>Independent variable $b$ (95% conf. interval)</th>
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</tr>
<tr>
<td>$\Delta \bar{F}$</td>
<td>-0.0028</td>
<td>$\Delta E_D$</td>
<td>182</td>
<td>0.819</td>
</tr>
</tbody>
</table>

Notes: * Reject $H_0: a = 0$, $p < 0.05$, 2-tailed test

---

**Market-price data**

The 13 markets reported here generated 185 market-price observations. In any given round, the market price ($P_I$) is measured as the closing price for the double-auction market and the uniform clearing price for the call market. Figure 3 displays a scatter plot of $P_I$ on the expected dividend ($E_D$), the OLS fit of this data, and a 45-degree reference line reflecting the rational expectations benchmark ($a = 0$ and $b = 1$). This figure illustrates that prices underreact to changes in the expected dividend, and the magnitude of this price underreaction is greater than the underreaction exhibited by mean forecasts (Figure 2).

Table 2 presents the OLS estimates for two simple regressions relating two price measures ($P_I$ and $\Delta P_I = P_I - P_{I-1}$) to measures of the expected dividend ($E_D$ and $\Delta E_D$). In both regressions the slope coefficients are significantly less than 1.

### Figure 3

Scatter plot of market price vs. expected dividend (all market rounds, $N = 183$)
TABLE 2
Regressions relating market prices to the expected dividend

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Intercept</th>
<th>Independent variable</th>
<th>Slope coefficient b (95% conf. interval)</th>
<th>N</th>
<th>Adj. R² (DW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P_i</td>
<td>1.1001*</td>
<td>ED_i</td>
<td>0.4410</td>
<td>185</td>
<td>0.347</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.3535 to 0.5285)</td>
<td></td>
<td>(1.14)</td>
</tr>
<tr>
<td>ΔP_i</td>
<td>-0.0132</td>
<td>ΔED_i</td>
<td>0.1310</td>
<td>164</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-0.0190 to 0.2720)</td>
<td></td>
<td>(1.97)</td>
</tr>
</tbody>
</table>

Notes:
* Reject H_o: a = 0, p < 0.05, 2-tailed test
P_i = market price in round i (double auctions = closing price)
ΔP_i = change in market price from around t - 1 to round t

1. Confirming the substantial underreaction of prices to dividend signals revealed in Figure 3, the conclusion that prices underreact more than forecasts is supported by the fact that there is no overlap in the 95 percent confidence bands of the slope coefficients when comparing regressions of ΔP_i (Table 2) and ΔF_i (Table 1) as a function of ΔED_i. These results are consistent with Abarbanel and Bernard's (1992) finding that stock market prices underreact to earnings announcements more than forecasts from Value Line analysts. In contrast to their capital market study, however, the forecasts in these experimental markets were gathered directly from the market traders.

To further investigate the differential reactions of market prices and traders' forecasts to dividend signals, we compare the magnitudes of price changes and mean forecast changes after non-zero signals. Of the 52 trading rounds immediately following dividend signals (13 markets × 4 rounds), 14 rounds are associated with positive dividend signals (ΔED_i > $0), and 20 rounds are associated with negative dividend signals (ΔED_i < $0). For the 14 rounds where ΔED_i > $0, the mean ΔED_i = $0.257, the mean ΔF_i = $0.177, and the mean ΔP_i = $0.011. Both matched-pairs t-tests and matched-pairs Wilcoxon tests reject the null hypothesis of a zero difference between ΔP_i and ΔED_i, between ΔF_i and ΔED_i, and between ΔP_i and ΔE_i at the 0.05 level (N = 14). For the 20 rounds where ΔED_i < $0, the mean ΔED_i = -$0.224, the mean ΔF_i = -$0.206, and the mean ΔP_i = -$0.035 (with a sample size of 18 due to two rounds with no trades). The specific null hypotheses referred to above are all rejected at the 0.05 level. This analysis supports the conclusion that |ΔED_i| > |ΔF_i| > |ΔP_i| for both positive and negative dividend signals.

Figure 4 displays the closing price (P_i), expected dividend (ED_i), mean forecast (F_i), and market volume (Q_i = shares traded/shares outstanding) from four double-auction continuous auctions. The top two graphs are from markets with inexperienced traders (session 2 markets), and the bottom two graphs are from markets with experienced traders (session 3 markets). Figure 5 displays similar time series for four call markets, except that P_i represents the uniform market-clearing price. These figures present the conclusions of the previous analyses in graphical form. While mean trader forecasts track the expected dividend quite well, market prices exhibit sustained deviations from expected dividend value. To a much greater extent than forecasts, prices tend to underreact to changes in the expected dividend induced by public information releases, lying below ED_i after upward shifts and above ED_i after downward shifts.

In addition to comparing the price data with the risk-neutral rational expectations benchmark, we investigate the effects of market institution and trader experience on price dynamics. The following OLS equation is estimated:
The variable \textit{CALLMKT} is an institutional dummy variable (\textit{CALLMKT} = 0 for double-auction markets and 1 for call markets), and the variable \textit{EXPERIENCE} is a market experience dummy variable (\textit{EXPERIENCE} = 0 for Session 2 traders and 1 for Session 3 traders). Two interaction terms are also included to capture differential price reactions to changes in the expected dividend across trading institution and market experience. There is insufficient empirical or theoretical research to derive expectations regarding the sign or significance of the dummies or interaction terms in equation (1).

The results from OLS estimation of equation (1) appear in Table 3. The \textit{CALLMKT} coefficient is significantly positive ($p < 0.05$), but the coefficients for the other two main effects and the two interaction terms are not significantly different from zero ($p > 0.10$). To further investigate the existence of a significant trading institution effect, separate regressions of $\Delta P_t$ on $\Delta ED_t$ were run for each institution. The results appear in Table 4. An $F$-test comparing the residual sum of squares from the separate regressions (Table 4) with the residual sum of squares from the pooled regression (Table 2) rejects the null hypothesis of regression homogeneity across the two institutional subsamples ($p < 0.05$).

However, comparing the 95 percent confidence intervals for $b$ shown in Table 4, the null hypothesis of identical price reactions to public dividend signals across institutions cannot be rejected. Focusing on each regression separately yields the somewhat surprising result that $b$ is not significantly different from zero ($p > 0.10$) in the double-auction regression but is significantly positive ($p < 0.05$) in the call market regression. This analysis suggests that there may be subtle differences in market-price dynamics across the two trading institutions, but perhaps the most striking result is how poorly a model based on risk-neutral rational expectations organizes the price data in both institutions.

In an effort to more accurately describe price dynamics, and to further analyze the effects of the market institution and trader experience, the following partial adjustment model was estimated:

\begin{equation}
P_t = \alpha + \beta P_{t-1} + \gamma (P_{t-1} - P_{t-1}) + \epsilon_t.
\end{equation}

Equation (2) characterizes the underlying equilibrium price ($P_t^*$) as a linear increasing function ($\beta > 0$) of the mean dividend forecast ($\bar{F}_t$) that implicitly incorporates unobserved factors such as traders' risk preferences and expectations about other traders' behavior. Equation (3) implies that the current price ($P_t$) equals the lagged price ($P_{t-1}$) plus a fraction ($0 < \gamma < 1$) of the difference between the current equilibrium price and the lagged price. Substituting equation (2) into (3) and solving for the observed price yields

\begin{equation}
P_t = \gamma \alpha + \gamma \beta \bar{F}_t + (1 - \gamma) P_{t-1} + \epsilon_t.
\end{equation}

which is estimated as

\begin{equation}
P_t = a + b \bar{F}_t + c P_{t-1} + \epsilon_t.
\end{equation}

Note that the special case of risk-neutral rational expectations implies $\bar{F}_t = ED_t$, $a = 0$, and $\beta = \gamma = 1$; thus $P_t = ED_t + \epsilon_t$. 

\textbf{FIGURE 5}  
Time Series Data: Four Call Markets 

\begin{equation}
\Delta P_t = a + b \Delta ED_t + c \textit{CALLMKT} + d \textit{EXPERIENCE} + e \Delta ED_t \textit{CALLMKT} + f \Delta ED_t \textit{EXPERIENCE} + u_t
\end{equation}
TABLE 3
OLS estimates of price adjustment model (Dependent variable = price change \( \Delta P_t \))

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>t-value</th>
<th>p-value*</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta D_t )</td>
<td>0.0157</td>
<td>0.1299</td>
<td>0.121</td>
<td>0.904</td>
</tr>
<tr>
<td>CALLMKT</td>
<td>0.0404</td>
<td>0.0171</td>
<td>2.364</td>
<td>0.019</td>
</tr>
<tr>
<td>EXPERIENCE</td>
<td>-0.0037</td>
<td>0.0173</td>
<td>-0.596</td>
<td>0.552</td>
</tr>
<tr>
<td>( \Delta D_t \times \text{CALLMKT} )</td>
<td>0.1166</td>
<td>0.1487</td>
<td>0.787</td>
<td>0.432</td>
</tr>
<tr>
<td>( \Delta D_t \times \text{EXPERIENCE} )</td>
<td>0.0521</td>
<td>0.1473</td>
<td>0.354</td>
<td>0.724</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.0342</td>
<td>0.0146</td>
<td>-2.338</td>
<td>0.021</td>
</tr>
</tbody>
</table>

Notes:
Adjusted \( R^2 = 0.029; \text{DW} = 1.98; N = 164 \)
* \( H_0: \) Coefficient = 0; 2-tailed test

\( \Delta D_t \) = change in expected dividend from round \( t-1 \) to \( t \)

\( \text{CALLMKT} \) = market institution dummy variable (0 = double auction; 1 = call)

\( \text{EXPERIENCE} \) = trader experience dummy variable (0 = 1st market; 1 = 2nd market).

---

TABLE 4
Regressions analyzing price adjustment by market institution (\( \Delta P_t = a + b \Delta D_t \))

<table>
<thead>
<tr>
<th>Subsample</th>
<th>( a )</th>
<th>( b )</th>
<th>95% Confidence interval for ( b )</th>
<th>( N )</th>
<th>Adj. ( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Double auctions</td>
<td>-0.0381*</td>
<td>0.0389</td>
<td>-0.272 to 0.339</td>
<td>66</td>
<td>-0.015</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(2.04)</td>
</tr>
<tr>
<td>Call markets</td>
<td>0.0021</td>
<td>0.1548</td>
<td>0.0174 to 0.2923</td>
<td>98</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(1.91)</td>
</tr>
</tbody>
</table>

* \( H_0: a = 0; \) \( p < 0.05; \) 2-tailed test

Table 5 reports two OLS regression models based on equation (5). Panel A presents the "full model," which includes the \( \text{EXPERIENCE} \) and \( \text{CALLMKT} \) dummy variables and four interaction terms with \( \bar{F}_t \) and \( P_{t-1} \). Having \( P_{t-1} \) in the model substantially increases its ability to explain the price data relative to the \( P_t = f(\Delta D_t) \) specification reported in Table 2. Panel B presents a "condensed model" where the statistically insignificant \( \text{EXPERIENCE} \) dummy and one insignificant interaction term (\( P_{t-1} \times \text{CALLMKT} \)) are omitted in order to reduce the impact of multicollinearity on the standard errors of the remaining coefficient estimates. Panel C presents the point estimates of the \( \alpha, \beta, \) and \( y \) parameters in equations (2) and (3) using the full model. The \( y \) estimates indicate that the rate of adjustment to the underlying equilibrium price is not significantly different between double auctions and call markets, but is significantly higher with more experienced traders. The \( \beta \) estimates reveal that market institution and trader experience both have a significant impact on the relationship between \( P_{t}^* \) and \( \bar{F}_t \). For inexperienced double auctions in particular, the large deviations of the \( \alpha \) and

---

TABLE 5
OLS estimates of partial adjustment model (Dependent variable = \( P_t \))

<table>
<thead>
<tr>
<th>Panel A: Full model Independent Variable</th>
<th>Coefficient</th>
<th>Std Error</th>
<th>t-value</th>
<th>p-value*</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \bar{F}_t )</td>
<td>0.1948</td>
<td>0.0788</td>
<td>2.474</td>
<td>0.015</td>
</tr>
<tr>
<td>( P_{t-1} )</td>
<td>0.9277</td>
<td>0.0976</td>
<td>9.507</td>
<td>0.000</td>
</tr>
<tr>
<td>( \text{CALLMKT} )</td>
<td>0.2453</td>
<td>0.1501</td>
<td>1.634</td>
<td>0.104</td>
</tr>
<tr>
<td>( \text{EXPERIENCE} )</td>
<td>0.0869</td>
<td>0.1854</td>
<td>0.469</td>
<td>0.640</td>
</tr>
<tr>
<td>( \bar{F}_t \times \text{CALLMKT} )</td>
<td>-0.1281</td>
<td>0.0839</td>
<td>-1.431</td>
<td>0.154</td>
</tr>
<tr>
<td>( P_{t-1} \times \text{CALLMKT} )</td>
<td>0.0190</td>
<td>0.1017</td>
<td>0.187</td>
<td>0.852</td>
</tr>
<tr>
<td>( \bar{F}_t \times \text{EXPERIENCE} )</td>
<td>0.1965</td>
<td>0.1151</td>
<td>1.708</td>
<td>0.090</td>
</tr>
<tr>
<td>( P_{t-1} \times \text{EXPERIENCE} )</td>
<td>-0.2327</td>
<td>0.0956</td>
<td>-2.435</td>
<td>0.016</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.2840</td>
<td>0.1283</td>
<td>-2.213</td>
<td>0.028</td>
</tr>
</tbody>
</table>

Adjusted \( R^2 = 0.862; \) \( N = 164 \)

<table>
<thead>
<tr>
<th>Panel B: Condensed model Independent Variable</th>
<th>Coefficient</th>
<th>Std Error</th>
<th>t-value</th>
<th>p-value*</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \bar{F}_t )</td>
<td>0.1752</td>
<td>0.0553</td>
<td>3.166</td>
<td>0.002</td>
</tr>
<tr>
<td>( P_{t-1} )</td>
<td>0.9387</td>
<td>0.0473</td>
<td>19.849</td>
<td>0.000</td>
</tr>
<tr>
<td>( \text{CALLMKT} )</td>
<td>0.2238</td>
<td>0.1137</td>
<td>2.100</td>
<td>0.037</td>
</tr>
<tr>
<td>( \bar{F}_t \times \text{CALLMKT} )</td>
<td>-0.0989</td>
<td>0.0570</td>
<td>-1.733</td>
<td>0.085</td>
</tr>
<tr>
<td>( \bar{F}_t \times \text{EXPERIENCE} )</td>
<td>0.2346</td>
<td>0.0884</td>
<td>2.655</td>
<td>0.009</td>
</tr>
<tr>
<td>( P_{t-1} \times \text{EXPERIENCE} )</td>
<td>-0.2255</td>
<td>0.0860</td>
<td>-2.623</td>
<td>0.010</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.2648</td>
<td>0.0926</td>
<td>-2.858</td>
<td>0.005</td>
</tr>
</tbody>
</table>

Adjusted \( R^2 = 0.863; \) \( N = 164 \)

| Panel C: Equation (2) and (3) parameter estimates from the full model |
|-------------------------------------------------|----------------|----------------|----------------|----------------|
| \( P_t = \alpha + \beta \bar{F}_t + \gamma (P_{t-1} - P_{t-1}) \) |

<table>
<thead>
<tr>
<th>Model parameter</th>
<th>Double auction inexperienced</th>
<th>Double auction experienced</th>
<th>Call market inexperienced</th>
<th>Call market experienced</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>-3.9281</td>
<td>-0.6462</td>
<td>-0.7261</td>
<td>0.1685</td>
</tr>
<tr>
<td>( \beta )</td>
<td>2.6943</td>
<td>1.2830</td>
<td>1.4015</td>
<td>0.9483</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>0.0723</td>
<td>0.3050</td>
<td>0.0533</td>
<td>0.2860</td>
</tr>
</tbody>
</table>

Notes:
* \( H_0: \) Coefficient = 0, two-tailed test
\( \beta \) estimates from the risk-neutral RE benchmarks \((\alpha = 0, \beta = 1)\) suggest that equation (2) is, at best, a very crude specification of the true process generating the underlying equilibrium price. This analysis decomposes the total price effect of a change in market institution or trader experience into “price equilibrium adjustment effects” and “price equilibrium formation effects.” In summary: (1) double auctions and call markets have similar adjustment rates toward \( P^* \), but (2) the complex process that determines \( P^* \) is not homogeneous across the two institutions, and (3) trader experience affects both the adjustment to and the formation of \( P^* \).

To further explore the nature of institutional differences in price dynamics, actual and expected price volatility are compared by calculating the variance of \( \Delta P \), divided by the variance of \( \Delta ED \), for each market. Since \( F_t \) and \( ED \) are highly correlated, the result that \( \beta > 1 \) in the partial adjustment model suggests that price changes are likely to exhibit “excess volatility” relative to expected dividend changes. In both double auctions and call markets, the mean ratio of actual to expected volatility is greater than unity: 2.24 for double auctions \((N = 8)\) and 1.116 for call markets \((N = 8)\). The small sample distributions of this volatility ratio are highly non-normal, so the nonparametric Mann-Whitney U-statistic is used to test the null hypothesis of identically distributed populations. The null can be rejected with a 0.05 probability of a type-I error \((U = 10, \alpha = 0.13)\). The data suggest that, after controlling for differentials in volatility of the asset’s intrinsic dividend value, call markets tend to have less volatility in closing prices than double auctions. A potential explanation may arise from the real-time flow of bids, asks, and contracts in double auctions that motivate some traders to attempt to extract intra-round capital gains based on small price movements. These traders may flip back and forth between buying mode and selling mode several times during a round. This search for very short-term capital gains adds an additional element of variance to the double-auction closing prices relative to the uniform call market prices. Such intra-round “noise trading” is clearly not motivated by changes in the asset’s fundamental value and might be mitigated in capital markets by transactions costs that are more substantial than those found in this laboratory market environment.

**Individual forecasting and trading behavior**

We now use traders’ dividend forecasts and market trading data to explore the behavioral roots of the discrepancies between observed prices and subjects’ forecasts of the terminal dividend value. In RE models with symmetrically informed risk-neutral traders and only public releases of information, traders’ price expectations equal their subjective dividend expectations, which equal the objective expected dividend of an asset share. This characterization of price and dividend expectations, however, relies on the critical supporting assumption of common knowledge: each trader believes that all other traders are risk-neutral and statistically rational. To the extent that this assumption is incorrect, individual beliefs about other traders, a divergence in price and dividend expectations may emerge (even if all traders actually are risk-neutral and statistically rational). With heterogeneous beliefs about others’ behavior (arising from the lack of common knowledge or for other reasons) and the perceived effects of this behavior on market prices, speculative trading motivated by capital-gains expectations becomes a potentially viable strategy. To directly address the magnitude of differences between traders’ price and dividend expectations in these markets, an explicit measure of price expectations would be required. Price forecasts, however, were not collected in conjunction with the markets conducted for this research. Previous experimental research suggests that price forecasting data are surprisingly consistent with a simple adaptive expectations model (Carliner 1992). This backward-looking price expectation dynamic, which resembles “anchoring and adjustment,” is consistent with the general price underreaction documented in the previous subsection. The following analysis presents indirect evidence, based on individual traders’ buying and selling decisions, that there is frequently a separation of price expectations from dividend expectations.

This individual analysis begins with the construction of a measure of the statistical rationality of dividend forecasts. As before, a rational forecast is equal to the expected dividend, \( \hat{F}_t = ED \). Our measure of forecast rationality is the per round average absolute forecast deviation from the expected dividend \((\Sigma|\hat{F}_t - ED|/15)\) labeled AAFDEV. Across all traders \((N = 151)\), AAFDEV ranges from $0.00 to $0.43, with a mean of $0.10 (s.d. = $0.09). Thirty-one traders (20.5 percent) exhibit zero AAFDEV, 92 traders (60.9 percent) exhibit AAFDEV values of $0.10 or less, and 58 traders (89.4 percent) exhibit AAFDEV values of $0.20 or less.

To analyze individual trading behavior and performance, we examine the relation between AAFDEV and two other variables defined at the individual level: (1) the number of trades inconsistent with the trader’s latest forecast of the liquidating dividend over 15 rounds, called ITTRADES; and (2) the percentage of average earnings extracted from the market \((100 \times \text{individual earnings/average earnings})\), called %MKTEARN. The first variable proxies for speculative capital-gains trading, and the second is a measure of relative earnings performance. The mean value of ITTRADES is 5.28 per trader (s.d. = 6.47). When compared with the mean total trades per trader of 12.20 (s.d. = 10.93), this suggests that, on average, just over 43 percent of all trades were inconsistent with the buyer’s and/or seller’s most recent dividend forecast. This evidence is consistent with the proposition that capital-gains trading, rooted in price expectations that deviate from subjective dividend expectations, played an important role in the market results reported here.

AAFDEV is found to be positively correlated with ITTRADES (Spearman’s rho = 0.220, \(p < 0.01\)) and negatively correlated with %MKTEARN (rho = -0.171, \(p < 0.05\)). Traders who exhibited fewer forecast deviations from the expected dividend traded more consistently with their forecasts and extracted more earnings from the market, on average. Similarly, ITTRADES is negatively correlated with %MKTEARN (rho = -0.302, \(p < 0.01\)), suggesting that those who traded less consistently with their forecasts extracted less earnings from the market on average.
To further explore individual trading in these markets, we compare average ITTRADES across market institution and subject experience. In the market institution comparison, the mean ITTRADES in double-auction markets \((N = 58)\) is 6.14 (s.d. = 6.09) with a median of 4.00, while the mean ITTRADES in call markets \((N = 93)\) is 4.74 (s.d. = 6.15) with a median of 3.00. A Wilcoxon test rejects the null hypothesis of no difference \((Z = -2.194, p < 0.05)\), suggesting that capital-gains trading was more prevalent in double-auction markets than in call markets.

In the subject experience comparison, the mean ITTRADES for traders in session 2 "inexperienced" markets \((N = 96)\) is 5.75 (s.d. = 5.57) with a median of 4.00, while the mean ITTRADES for traders in session 3 "experienced" markets \((N = 55)\) is 4.46 (s.d. = 7.01) with a median of 2.00. A Wilcoxon test again rejects the null hypothesis of no difference \((Z = -2.916, p < 0.05)\), suggesting that inexperienced traders engaged in more capital-gains trading than experienced traders.

Finally, we assess the effect of a time-trend variable on ITTRADES. We expect capital-gains trading to decline as (1) the time horizon shortens, and (2) the variance of the terminal dividend distribution declines. To investigate this relationship, we correlate the average ITTRADES in each market round \((N = 195)\) with the number of dividend draws left in the market, DRAWLEFT (which has values over the sequence of trading rounds of 5, 5, 4, 4, 4, 3, 1, 1, 1). ITTRADES (per round) is found to be positively correlated with DRAWLEFT (Spearman's rho = 0.204, p < 0.01), suggesting that capital-gains trading declined as dividend uncertainty in the market declined.

This analysis suggests that there was frequently a separation of price expectations from dividend expectations in these markets, since just over 43 percent of trades were inconsistent with the buyer's or seller's most recent dividend forecast. Such forecast-inconsistent behavior is interpreted as being indicative of speculative capital-gains trading based solely on expected price movements rather than terminal dividend earnings. This behavior was more frequent in double-auction markets, in markets with inexperienced traders, and in earlier trading rounds. On average, traders with more rational dividend forecasts engaged in less forecast-inconsistent speculative trading and had greater market earnings.

Market volume data

The measure of market volume used in this analysis is the share turnover rate, TURNOVER, defined as the number of shares traded in a given round divided by the total number of shares outstanding in the market. The share turnover results in Figures 4 and 5 do not reveal a consistent surge in volume in rounds 4, 7, 10, and 13 immediately after the release of a public signal. This is inconsistent with empirical capital market evidence that trading volume increases around earnings announcements (e.g., Bamber 1986 and 1987). The mean TURNOVER, of 0.109 in these rounds \((N = 52, \text{s.d.} = 0.065)\) is not significantly different from the mean TURNOVER, of 0.096 in the other rounds \((N = 143, \text{s.d.} = 0.059)\) using either a t-test or Wilcoxon test (one-tailed \(p = 0.10\) and \(p > 0.10\), respectively). However, the mean TURNOVER, of 0.116 in rounds immediately following a non-zero signal \((N = 34, \text{s.d.} = 0.065)\) is significantly higher than the mean TURNOVER, of 0.096 in the other rounds \((N = 161, \text{s.d.} = 0.059)\) using either a t-test or Wilcoxon test (one-tailed \(p < 0.05\)). Thus, share turnover immediately after a non-zero dividend signal is approximately 20 percent (0.02/0.096) greater than in other trading rounds.

Using the extant capital market and experimental market literature as a guide, we estimate a model of share turnover using forecast revisions, forecast dispersion, dividend uncertainty, market institution, and trading experience as independent variables. The full model, which includes six interaction terms to measure differential reactions due to institution and experience, is presented in panel A of Table 6. Panel B of Table 6 presents a condensed version of the model, where the statistically insignificant interaction terms in the full model are omitted.

Forecast revision is measured by \(\Delta F_{ij}\), the absolute value of the mean forecast change from round \(i - 1\) to \(i\). Ajinkya, Atiase, and Gift (1997) find this measure of surprise to be positively related to trading volume. The full forecast revision is measured by \(FDISP\), the contemporaneous standard deviation of forecasts in round \(i\). The expected sign on \(FDISP\) is uncertain. While the empirical work of Ajinkya et al. reveals a positive relation between this variable and trading volume, there is little theoretical guidance on what to expect in our symmetric-information market environment.\(^{35}\) Dividend uncertainty is measured by DRAWLEFT, the number of dividend draws remaining, and is expected to have a positive sign because capital-gains trading (as measured by forecast-inconsistent trades) declines as the time horizon becomes shorter and the variance of the terminal dividend distribution declines.

The share turnover model also includes dummy variables to measure the effects of market institution \((CALLMKT = 1\) for call markets) and subject experience \((EXPERIENCE = 1\) for experienced subjects) on trading volume. Previous experimental markets research (e.g., Friedman 1993; Van Boening, Williams, and LaMaster 1993) suggests that the expected sign for both the CALLMKT and the EXPERIENCE dummy variables is negative. Furthermore, the prior analysis of forecast-inconsistent trades indicated that capital-gains trading is less prevalent in call markets and with experienced traders. Finally, six interaction terms are included to capture the potential influence of CALLMKT and EXPERIENCE on the relationship between turnover and the three non-dummy independent variables.

The OLS results presented in panel A of Table 6 reveal that, consistent with capital market findings in Ajinkya et al. 1997, the \(\Delta F\) coefficient is significantly positive (one-tailed \(p = 0.072\)). However, inconsistent with Ajinkya et al., the \(FDISP\) coefficient is significantly negative (two-tailed \(p = 0.020\)).\(^{35}\) Consistent with our expectations, the DRAWLEFT coefficient is significantly positive, and the CALLMKT coefficient is significantly negative (two-tailed \(p < 0.01\)). The coefficient for EXPERIENCE, however, is positive and not significant. The only significant interaction coefficient is \(FDISP \times CALLMKT\) (two-tailed \(p < 0.01\)). The regression model's adjusted \(R^2\) of 0.200 is quite high compared with typical capital market studies of trading volume.\(^{36}\)
The significance of $FDISP \times CALLMKT$ suggests estimating the condensed turnover model using data partitioned by market institution (double auction versus call market). Consistent with Table 6, the $FDISP$ coefficient is negative and highly significant in the double-auction subsample ($b = -0.460$, $S_b = 0.113$, $p = 0.000, N = 70$). In the call market subsample, however, the $FDISP$ coefficient is positive and insignificant ($b = 0.020$, $S_b = 0.121$, $p = 0.869, N = 112$). We have no formal explanation for this result; higher forecast dispersion may be associated with lower forecast confidence, and hence more uncertainty regarding within-round price movements in double auctions. This uncertainty may reduce within-round capital-gains trading, which is possible only in the double-auction markets.

The significance of $DRAWSLEFT$, in the turnover model, combined with the significant positive correlation between $DRAWSLEFT$, and forecast-inconsistent trades ($ITRADES$) reported in the previous subsection, helps explain why laboratory markets with short-lived assets tend to be more consistent with risk-neutral rational expectations predictions than long-lived asset markets. The short-time horizon mitigates or eliminates the motivation for speculative capital-gains trading. This implies that naturally occurring markets, with infinite time horizons, may be even more dominated by speculative trading than the simple finite-horizon markets reported here.

### 5. Summary and discussion

This study uses laboratory experimental methods to explore market price and volume reactions to public information releases regarding the asset's intrinsic dividend value. When all dividend information is publicly available, homogeneous traders with statistically rational dividend and price expectations should have identical reservation prices. Hence, the bid-ask spread should bracket the expected dividend value, and no trading should occur. The results of this research do not support these basic assumptions. Positive volume is observed in almost all trading rounds, and prices frequently deviate substantially from the expected dividend value.

The research reported here may help bridge the gap between market theories that rely on asymmetric private information to generate trade and pure public information environments like the one studied here. This bridge need not rely entirely on traders having heterogeneous "statistically irrational" dividend expectations, although the cash-motivated dividend forecasts collected as part of this research do reveal differential processing of the dividend signals. The market data suggest that traders do not uniformly believe that other traders will act in a risk-neutral, statistically rational manner when making buying and selling decisions. This creates heterogeneity in subjective price expectations that can lead to speculative trading strategies focusing on short-term price movements rather than the intrinsic dividend value.

The data reveal that traders' dividend forecasts and market prices both underreact to changes in intrinsic dividend value (i.e., linger below intrinsic value after a positive signal and above intrinsic value after a negative signal). The
magnitude of the underreaction is much larger for market prices than for traders' dividend forecasts. This basic result holds for both double auctions and call markets; however, double-auction closing prices exhibit more "excess volatility" (relative to intrinsic value) than call market prices. The forecast and price underreaction results are consistent with Barberanell and Bernard's (1992) finding that underreaction in analysts' forecasts were at most only about half as large as necessary to explain the magnitude of post-earnings-announcement drift. While a plausible explanation for their result is that investors are more biased than analysts, this explanation is not viable here. Finding laboratory support for their result, with forecasts gathered directly from traders, suggests that market price underreaction may be a fundamental characteristic of market behavior rather than an artifact of the limitations of archival data.

Why do prices in these markets deviate from the asset's intrinsic dividend value more than appears warranted by traders' dividend forecasts? Very general responses to this question emerge from analyses of price dynamics in a partial adjustment model and of individual trading behavior. Estimation of the partial adjustment model suggests that the link between traders' dividend forecasts and the unobserved equilibrium price is imperfect and far more complex than envisioned in RE models. The individual trading data reveal that 43 percent of all trades are at prices that are inconsistent with either the buyer's or the seller's most recent dividend forecast (i.e., a trader buys at a price that is above the trader's latest dividend forecast or sells at a price that is below the trader's latest forecast). We cannot dismiss the possibility that some of these forecast-inconsistent trades are simply errors by relatively unsophisticated subjects, however, another possibility is that traders often have price expectations that deviate from their dividend expectations and are attempting to extract gains from expected price movements.

The data further reveal that forecast-inconsistent trades are less prevalent incall markets (relative to double-auction markets), in markets with relatively experienced traders, and as the number of dividend draws remaining decreases.

An OLS regression model of trading volume (measured by the per round share turnover rate) indicates that turnover is directly related to the absolute value of the mean forecast revision and, in double auctions, inversely related to the standard deviation of traders' dividend forecasts. The former result is consistent with Ajinor et al.'s (1991) capital-market research. The latter result for double auctions is inconsistent with their findings. Significant decreases in turnover are also associated with more experienced traders, fewer dividend draws remaining, and call markets. In general, it appears that call markets are somewhat "noisy" than double auctions, exhibiting less excess volatility of prices, fewer forecast-inconsistent trades, and lower share turnover. The parameter estimates for the partial adjustment model suggest that, while call markets and double auctions have similar adjustment rates toward the underlying equilibrium price, movements of the equilibrium are more closely linked to the mean dividend forecast in call markets and markets with experienced traders.

Detailed, definitive answers to all of the questions raised by the research presented here are beyond the scope of the data collected in these experiments and

our current understanding of human behavior in markets. In the future, perhaps innovative interactions among market theorists, empiricists using archival data, and laboratory experimentalists will be able to shed additional light on the factors that affect expectation formation processes and the complex interaction of individual market strategies that determine market price and volume outcomes.

Appendix 1

Instructions for non-market forecasting sessions

General
Welcome. You are about to participate in the first of two experimental sessions. This is an experiment in the economics of individual decision making. If you understand the instructions and make careful decisions, you may earn a considerable amount of money. These earnings will be paid to you, in cash, at the end of each experimental session.

Specific
In today's experimental session you will be asked to forecast the dollar value of an uncertain event. Forecasts will be made over a sequence of five decision-making periods. The actual dollar value of the uncertain event will be known at the end of each sequence. Your earnings will be determined by the accuracy of your forecasts. The more accurate your forecasts, the more cash you will earn.

You will be forecasting the dollar value of an uncertain event that is determined by summing the dollar value of five components. The dollar value of each component is determined randomly, as discussed below. Each period consists of a forecasting phase and a component-determination phase. At the beginning of each period, you will forecast the dollar value of the uncertain event. Note that you are not forecasting that period's component dollar value but the dollar value of the sum of all five components. In the second phase of each period, the component value for that period is determined. Therefore, only after the dollar value of the fifth component is determined can the actual dollar value of the uncertain event be calculated (i.e., summing the five component values). Remember, it is the sum of the five component values that is the object of your forecasts.

The dollar value of each component will be determined by randomly drawing a poker chip from the stacks of poker chips at the front of the room. The heights of the stacks of colored poker chips represent the probabilities associated with the possible component values. After the forecasting phase in the first period, the poker chips will be dumped into an empty bucket. One of you will be randomly selected to draw a poker chip out of the bucket. The color of the drawn poker chip will determine the dollar value of that period's component. Given below are the dollar values assigned to each chip color and the number of chips of each color contained in the bucket.
<table>
<thead>
<tr>
<th>Color</th>
<th>Dollar value of chip</th>
<th>Number of chips</th>
<th>Chance of drawing chip</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green</td>
<td>$0.00</td>
<td>10</td>
<td>1/9</td>
</tr>
<tr>
<td>Red</td>
<td>$0.20</td>
<td>20</td>
<td>2/9</td>
</tr>
<tr>
<td>White</td>
<td>$0.40</td>
<td>30</td>
<td>3/9</td>
</tr>
<tr>
<td>Blue</td>
<td>$0.60</td>
<td>20</td>
<td>2/9</td>
</tr>
<tr>
<td>Yellow</td>
<td>$0.80</td>
<td>10</td>
<td>1/9</td>
</tr>
</tbody>
</table>

TOTAL

90

After a chip is drawn and the dollar value is recorded, the chip will be returned to the bucket. This same procedure will be followed in the component-determination phase of each period.

There are several important things you should understand about this probability distribution. A component’s value can range from $0.00 to $0.80. Notice that green chips (worth $0.00) and yellow chips (worth $0.80) have a relatively low chance of being drawn (1/9 = .111). The red chips (worth $0.20) and blue chips (worth $0.60) have twice the chance of being drawn (2/9 = .222). Finally, the chance of drawing a white chip (worth $0.40) is three times as great as drawing a green or yellow chip (3/9 = .333). The “expected value” of this distribution is: $(0.00)(1/9) + (0.20)(2/9) + (0.40)(3/9) + (0.60)(2/9) + (0.80)(1/9) = $0.40$. That is, if we drew many times from this distribution the average draw would be $0.40.

Since the actual value of the uncertain event is the sum of the five component values drawn, the value of the uncertain event can range from $0.00 (if all of the five component values drawn were $0.00) to $4.00 (if all of the five component values drawn were $0.80).

The procedure of drawing chips from the bucket will now be demonstrated. The frequency of each chip color drawn will be recorded on the board at the front of the room. You may use the space provided below to record this information.

[STOP — for demonstration of drawing chips from the bucket.]

Next, the specific procedures that will comprise the five-period decision-making sequence will be demonstrated.

Worksheet 1

The “expected value” of the uncertain event (the object of your forecasts), prior to any component draws, is the sum of the “expected value” of the five components:

$0.40 + 0.40 + 0.40 + 0.40 + 0.40 = 2.00$

Period 1

Forecast phase: You would make your Period 1 forecast of the uncertain event.

Reminder: The forecast is of the uncertain event, the sum of the five component dollar values, which will be determined in this sequence.

Component-determination phase: The first component will now be drawn.

[STOP — one person will be chosen to draw a chip from the bucket.]

You can now recalculate the “expected value” of the uncertain event given that you know the 1st component’s value. Notice that the “expected value” of the 2nd–5th components is still $0.40.

\[\_+_+_+_+_+$0.40+$0.40+$0.40+$0.40=_____.\]

Period 2

Forecast phase: You would make your Period 2 forecast of the uncertain event.

Component-determination phase: The second component will now be drawn.

[STOP — one person will be chosen to draw a chip from the bucket.]

You can now recalculate the “expected value” of the uncertain event given that you know the 1st and 2nd component values. Notice that the “expected value” of the 3rd–5th components is still $0.40.

\[\_+_+_+$0.40+$0.40+$0.40+$0.40=_____.\]

Period 3

Forecast phase: You would make your Period 3 forecast of the uncertain event.

Component-determination phase: The third component will now be drawn.

[STOP — one person will be chosen to draw a chip from the bucket.]

You can now recalculate the “expected value” of the uncertain event given that you know the 1st–3rd component values. Notice that the “expected value” of the 4th and 5th components is still $0.40.

\[\_+_+_+$0.40+$0.40+$0.40=_____.\]

Period 4

Forecast phase: You would make your Period 4 forecast of the uncertain event.

Component-determination phase: The fourth component will now be drawn.

[STOP — one person will be chosen to draw a chip from the bucket.]
You can now recalculate the "expected value" of the uncertain event given that you know the 1st–4th component values. Notice that the "expected value" of the 5th component is still $0.40.

\[ \text{Component 5 value} + \ldots + \text{Component 4 value} + \text{Component 3 value} + \text{Component 2 value} + \text{Component 1 value} = \text{Component 5 value} \]

Period 5
Forecast phase: You would make your Period 5 forecast of the uncertain event.

Component-determination phase: The fifth component will now be drawn.

[STOP — one person will be chosen to draw a chip from the bucket.]

Since all of the component values are known, the "expected value" and the actual value of the uncertain event are the same. Calculate this value.

\[ \text{Component 5 value} + \ldots + \text{Component 4 value} + \text{Component 3 value} + \text{Component 2 value} + \text{Component 1 value} = \text{Expected value} \]

Authors' note: Subjects then practiced more expected value calculations in Worksheet 2, which is not included here.

Earnings calculation
After the forecasting phase of each period a monitor will collect the forecast that you have recorded on your FORECASTING SLIP. In addition, you will record your forecast on your record sheet under the heading YOUR FORECAST.

The more accurate your forecasts, the more cash you will earn. When your forecast for a given period is within $1.00 of the actual value of the uncertain event, your earnings in that period will be positive. If, however, your forecast is off by more than $1.00, your period earnings will be zero.

Specifically, your earnings during any particular period are equal to $1.00 minus the absolute value of your forecast error. The forecast error is the difference between the actual event value and your forecast. Thus, the absolute forecast error is simply the numerical difference between the actual event value and your forecast, without the sign. That is, in calculating your earnings it is the magnitude of the difference that matters and not whether you "under" or "over" estimate the actual event value.

Your earnings for each period will be calculated as follows.

1. Absolute forecast error = |Actual event - Forecast|
2. If Absolute forecast error < 1.00, then Period earnings = $1.00 - Absolute forecast error
3. If Absolute forecast error ≥ 1.00, then Period earnings = $ 0.00.

At the end of the experiment you will be paid privately in cash your total earnings from participating in the experiment. The following examples will help to clarify how your earnings will be calculated during this experiment.

Example 1: Assume your forecast of the event in a given period is $2.50 and the actual event is $2.00. The absolute forecast error between the actual event and your forecast is thus 1.20 - 2.50 = $0.50, and your period earnings are $1.00 - $0.50 = $0.50.

Example 2: Assume your forecast of the event in a given period is $2.50 and the actual event is $4.00. The absolute forecast error between the actual event and your forecast is thus 14.00 - 2.50 = $1.50, and your period earnings are $0.00 (because $1.50 > $1.00).

Now, work this third example on your own to make sure you understand how to calculate your earnings. If you have any questions, please raise your hand and a monitor will come by to assist you.

Example 3: Assume your forecast of the event in a given period is $3.80 and the actual event is $3.60. The absolute forecast error between the actual event and your forecast is

\[ \text{Absolute forecast error} = |3.80 - 3.60| = 0.20, \text{ and your period earnings are } $0.00 \]

Record-keeping procedures
If you will now look at your record sheet you will see the following entries: YOUR FORECAST, ACTUAL EVENT VALUE, ABSOLUTE FORECAST ERROR, PERIOD EARNINGS, and CUMULATIVE EARNINGS. Each period you will record your forecast on the FORECASTING SLIP, and your record sheet under YOUR FORECAST. At the end of the fifth period, when the dollar value of the uncertain event has been determined, you will record it under the column ACTUAL EVENT VALUE. You will then calculate the absolute forecast error for each of the five forecasts made in that sequence, and record them in the column headed ABSOLUTE FORECAST ERROR. Next, you will calculate your earnings for each of the five forecasts, and record them in the column headed PERIOD EARNINGS. Finally, in the row labeled CUMULATIVE EARNINGS, you will record the summation of your earnings in all five periods. A monitor will come by to check your calculations.

Please keep accurate records throughout the experiment.

THIS IS THE END OF THE INSTRUCTIONS. IF YOU HAVE ANY QUESTIONS, PLEASE RAISE YOUR HAND AND ASK THEM AT THIS TIME. ONCE THE EXPERIMENT HAS STARTED, NO COMMUNICATION BETWEEN PARTICIPANTS WILL BE ALLOWED.

Authors' note: Subjects recorded their earnings on a Record Sheet, which is not included here.
Appendix 2

Overhead display of chip draws for non-market forecasting sessions

Distribution of poker chips in the bucket

<table>
<thead>
<tr>
<th>Color</th>
<th>Value (Value of each colored chip)</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>$0.40</td>
</tr>
<tr>
<td>Red</td>
<td>$0.20</td>
</tr>
<tr>
<td>Blue</td>
<td>$0.60</td>
</tr>
<tr>
<td>Green</td>
<td>$0.80</td>
</tr>
<tr>
<td>Yellow</td>
<td>$0.80</td>
</tr>
</tbody>
</table>

Actual component draws for sequence # ______________________

Component 1: ______________________
Component 2: ______________________
Component 3: ______________________
Component 4: ______________________
TOTAL: ______________________
(Object of forecasts)

Appendix 3

Post-experiment handout for the non-market forecasting sessions

In order to prepare for the next experimental session, you will need to read through the computerized instructions for this session. Read the instructions carefully, and ask questions if something is unclear. Everyone will receive the same instructions, and you will have an opportunity to work through these instructions again at the beginning of the next experimental session.

In the next experimental session, you will participate in a market in which shares of an asset are traded. You will begin the market with a certain number of shares of the asset and a certain amount of cash (so that you can buy additional shares if you wish). All market participants will be given the same initial amount of cash and number of shares.

The market will have 15 trading periods. At the end of the fifteenth trading period, a cash dividend will be paid to you for each share of the asset that you own. Your total earnings from participating in the market will equal your initial amount of cash plus revenues from selling shares in the market minus expenditures from buying shares in the market plus dividend earnings. Your dividend earnings will equal the number of shares that you own when trading period 15 ends, multiplied by the cash dividend.

The per share cash dividend paid at the end of the fifteenth period will be the sum of five components. One of the components will be determined after every three trading periods. That is, the first component will be determined after trading period 3; the second component will be determined after trading period 6; the third component will be determined after trading period 9; the fourth component will be determined after trading period 12; and the fifth and final component will be determined at the end of trading period 15. The per share cash dividend awarded after trading period 15 will be the sum of these five components.

The forecasting exercise that you participated in today gave you experience with the process that will be used to determine the per share dividend in the market. In the first part of this experimental session, you were asked to forecast an uncertain event that was the sum of five components. The components were determined by drawing a poker chip from a bucket containing poker chips with different values. In the market experiment, dividend component values will be determined after trading periods 3, 6, 9, 12, and 15 using this process of drawing a poker chip from a bucket.

Prior to each trading period in the market, you will enter a forecast of the per share cash dividend that you expect to be paid at the end of the fifteenth trading period. Note that this dividend forecasting exercise will be very similar to the task you performed today and will be in addition to your trading activities in the market. As in today's experiment, there will be cash rewards associated with the dividend forecasting exercise. The more accurate your dividend forecasts, the more cash you will earn in addition to your market earnings.

Read the instructions carefully and ask a question if something is unclear. The amount of cash that you earn in the next experimental session may suffer if you do not understand how the market works!

Appendix 4

Pre-experiment handout for the asset-market sessions

Welcome Back for the Second Experimental Session

Recall that in this experimental session you will participate in a market in which shares of an asset are traded. You will begin the market with an initial endowment of cash and asset shares. All market participants will start with the same amount of cash and asset shares.
The market will have 15 trading periods. At the end of the fifteenth trading period, a cash dividend will be paid to you for each share of the asset that you own. Your total earnings from participating in the market will equal your initial amount of cash plus revenues from selling shares in the market minus expenditures from buying shares in the market plus dividend earnings. Your dividend earnings will equal the number of shares that you own when trading period 15 ends, multiplied by the cash dividend.

The per share cash dividend paid at the end of the fifteenth period will be the sum of five components. A dividend component will be determined after trading periods 3, 6, 9, 12, and 15. The dividend awarded after trading period 15 will be the sum of these five components. Thus, the actual per share cash dividend will not be known with certainty until the end of trading period 15.

Each dividend component will be determined by randomly drawing a poker chip from a bucket containing the stacks of poker chips at the front of the room. The color of the drawn poker chip will determine the dollar value of that dividend component. After a chip is drawn and the dollar value is recorded, the chip will be returned to the bucket. Given below are the dollar values assigned to each chip color and the number of chips of each color contained in the bucket.

<table>
<thead>
<tr>
<th>Color</th>
<th>Dollar value of chip</th>
<th>Number of chips</th>
<th>Chance of drawing chip</th>
</tr>
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<tbody>
<tr>
<td>Green</td>
<td>$0.00</td>
<td>10</td>
<td>1/9</td>
</tr>
<tr>
<td>Red</td>
<td>$0.20</td>
<td>20</td>
<td>2/9</td>
</tr>
<tr>
<td>White</td>
<td>$0.40</td>
<td>30</td>
<td>3/9</td>
</tr>
<tr>
<td>Blue</td>
<td>$0.60</td>
<td>20</td>
<td>2/9</td>
</tr>
<tr>
<td>Yellow</td>
<td>$0.80</td>
<td>10</td>
<td>1/2</td>
</tr>
<tr>
<td>TOTAL</td>
<td>90</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

**Forecasting in the Market**

Prior to each trading period you will submit a forecast of the actual cash dividend. Each period you will record your forecast on a forecasting slip and the attached record sheet. The forecasting slips will be picked up by a monitor and recorded in a computer spreadsheet; the record sheet will be for your personal reference. Notice that the attached record sheet also provides lines for recording each of the five dividend component values (drawn after periods 3, 6, 9, 12, and 15).

As in the first experimental session, the more accurate your forecasts, the more cash you will earn. Your earnings for each period will be calculated as follows:

1. Absolute forecast error = |Actual Dividend - Forecast|
2. If Absolute forecast error < 1.00, then Period Earnings = $(1.00 - Absolute forecast error)
3. If Absolute forecast error ≥ 1.00, then Period Earnings = $0.00

You will be paid in cash one-third of the sum of the earnings from your 15 forecasts. These forecast earnings will be added to your market earnings. In order to save time at the conclusion of the experiment, the monitors’ computerized spreadsheet will perform the earnings calculations. Prior to being paid your total cash earnings, you will be given an opportunity to verify the forecast data recorded for you in the spreadsheet that performs the forecast earnings calculations. Feel free to ask the monitor for an explanation of anything that you do not understand.

Authors’ note: Subjects recorded their forecast earnings on a Record Sheet, which is not included here.

**Endnotes**

1. See, for example, Milgrim and Stokey 1982. As discussed in the next section, some recent theoretical work (Neeman 1996) suggests that in variants of the symmetric information RE model, speculative trading may be observed.
2. Bloomfield, Libby, and Nelson (1998b) observe that prices generated in relatively short-lived call markets (i.e., four periods) underreact to new public information more than do investors’ estimates of value elicited in a debriefing questionnaire.
3. A trade is inconsistent with the trader’s dividend forecast if the trade buys (sells) at a price above (below) the trader’s latest forecast.
4. If the condition of pre-announcement trading to share risk is not met, however, then some trading to share risk after the announcement is expected.
5. Intuitively, common knowledge means that each agent knows the structure of the model, knows that every other agent knows the structure of the model, knows that every agent knows that every other agent knows the structure of the model, etc. For a formal definition, see Greeko and Neeman 1992 or Neeman 1996.
6. See Neeman 1996 for a detailed discussion of these issues.
8. In a related paper, Bloomfield, Libby, and Nelson (1998b) show that over- and underreaction is also influenced by the portfolio-formation role (i.e., price-based or information-based) that the researcher employs. Further, Bloomfield (1996) concludes that reporting discretion may also play a role in underreaction.
9. Field implementations of continuous markets similar to the automated double auction used here include the Toronto Stock Exchange’s Computer Assisted Trading System (CATS) and the Tokyo Stock Exchange’s Computer Assisted Routing and Execution System. Field implementations of automated call markets include the Arizona Stock Exchange and the opening of trade on the New York and Tokyo Stock Exchanges. For a more detailed discussion of call versus double-auction markets in field environments and a laboratory comparison of their ability to track a nonstationary equilibrium, see Davis and Williams 1997.
10. The number of traders in the respective second session markets were 15, 10, 12, 11, 11, 11, 13, and 13, and in the third session markets 9, 12, 10, 12, and 12. Previous research with long-lived asset markets has shown that basic price performance characteristics appear to be insensitive to changes in market size of this magnitude. For example, see Smith, Suchanek, and Williams 1988 or Van Boven, Williams, and Laderman 1993.
The authors acknowledge the generosity of Miss Heather Stevens, whose beloved beach bucket served as the poke-it chip container vessel for the experiments reported in this paper.

Our focus on expected value in the instructions helped to ensure that subjects clearly understood the process that would determine asset value in the experiments. This understanding makes confusion about asset value determination a less likely explanation for our experimental results. One possible limitation of this design, however, is that subjects may focus on the calculation of the expected value of the whole series of chip draws rather than on the expected value of individual chip draws. We tried to mitigate this problem by presenting the expected value calculations in the instructions in a manner that emphasized that the expected value of each remaining draw was $0.40 (see Appendix A).

A computer simulation of 10,000 five-round sequences found that this reward structure yielded expected earnings of $3.49 per sequence for a statistically rational forecaster. For purposes of comparison, a simulation of 10,000 sequences from a constant $2.90 forecaster yielded expected earnings of $3.03 per sequence.

The procedures for submitting dividend forecasts and determining dividend components were identical to those used in the forecasting sessions.

Given an expected dividend of $2 per share and zero-sum capital gains, the expected final working capital was $16 per trader.

The small asymmetry (larger observed frequencies for positive forecast deviations) in the distributions shown in Figure 1 can be explained by the fact that, in both the non-market and market chip-draw samples, there were more negative draws than positive draws. As will be documented later in this section, forecasts tend to underreact to changes in the expected value of the forecast objective. This generates positive (negative) forecast deviations from expected value due to negative (positive) changes in expected value.

It is of some comfort to report that, for the 65 chips drawn in the 13 asset markets, a chi-square test cannot reject the null hypothesis that the sample of chips drawn came from our chip distribution ($p > 0.25$).

Given the time-series component of the data, serially correlated errors could result in an understatement of the variance of the reported OLS coefficients. This yields 95 percent confidence bands around the coefficient point estimates that are smaller than the true confidence bands. To address this, Durbin-Watson (DW) statistics are reported, where $DW = 2(1 − ρ)$ and $ρ$ is the first-order autoregression coefficient. Thus, $DW = 2$ when $ρ = 0$. For our pooled time-series data base, the DW computed by statistical analysis programs is incorrect if the program assumes that the data comprise a single time series. Our DW computations are based on "manual" OLS estimation of $ρ$ from the regression residuals: $u_i = u_{i-1} + ε_i$, for $t = 2 − 15$ in each market. In general, we can reject $ρ = 0$ in the forecast and price magnitude regressions, but not in the forecast and price change regressions. First-difference regressions appear to eliminate the autocorrelation problem. We also examined the robustness of our hypothesis tests across various time-subsample samples that completely eliminate the time-series element in the data. We are quite confident that autocorrelation does not affect the validity of our price and forecast underreaction finding.

This underreaction result does not appear to diminish as subjects' experience with the forecasting task increases. In the non-market sessions, a regression-based $F$-test indicates that the null hypothesis of homogeneous forecast reactions to changes in expected value across the four forecasting sequences (A, B, C, and D) cannot be rejected ($p > 0.10$). Surprisingly, additional regression analysis reveals that the magnitude of the mean forecast underreaction ($b−b$) is significantly larger in session 3 markets with experienced traders ($b=0.65$) than in session 2 markets with inexperienced traders ($b=0.84$). The latter coefficient is more consistent with the average underreaction in session 1 non-market forecasts ($b=0.82$). This unexpected result is further evidence of the influence of behavioral biases or heuristics on the subjects' forecasts.

Ten trading rounds in these markets had no price observation because there was no trading volume. Therefore the total number of price observations is (13 markets × 15 rounds) − 10 missing observations = 185.

Similar results were found when using the mean price in the round for the double-auction markets.

Using the technique of seemingly unrelated regression (SUR), a $t$-test rejects the null hypothesis of equal slopes in the $ΔP$ and $ΔE$ equations ($t = 8.44, p = 0.01$). The SUR technique applied to this data yields coefficient estimates that are identical to OLS, but the standard errors of the estimates are slightly different, because SUR accounts for the correlation among the residual errors in the two equations.

These statistical tests assume strict independence of the observations within each sample, which cannot be guaranteed since there are instances where multiple observations are drawn from a single market. However, the test statistics are well above the $p = 0.05$ critical values, and there is very little overlap across the rank-ordered samples. While determining an exact probability of type-one error is impossible, the data clearly imply meaningful separation of the underlying populations from which the samples are drawn.

A regression of $ΔP$ on $ΔE_0$ for each of the 13 markets reveals that the point estimates of the slope coefficients for $ΔE_0$ are positive but less than 1 in every market; however, the standard errors of the estimates tend to be quite large due to the small sample sizes ($N = 14$ if all rounds have non-zero volume). In 12 markets the 95 percent confidence interval of the slope coefficient includes zero, and in four markets the confidence interval includes $i$.

Not surprisingly, $ΔE_0$ is highly correlated with both $ΔE_0 × CALLMKT$ ($r = 0.79$) and $ΔE_0 × EXPERIENCE$ ($r = 0.61$). Multicollinearity makes disentangling their separate effects on the dependent variable problematic.

This result is robust for $t = 4, 7, 10, 13$, focusing only on trading rounds immediately after the revelation of public chip draws (dividend signals).

The Durbin "h" statistic was used to test for autocorrelation in the partial adjustment model. With a lagged dependent variable, the Durbin-Watson statistic is biased toward 2, and serially correlated residuals generate biased OLS coefficients. Estimation of equation (5) yields a first-order autocorrelation coefficient of $ρ = -0.010$ and $h = 0.325$, where $h = N(0, i)$. Thus, $H_0: ρ = 0$ cannot be rejected, $p > 0.10$.

In a very different decision-making environment, Schnitzelein (1996) obtains similar results.

Our use of the term speculative capital gains trading refers to trading based on expected gains from short-term price movements, in contrast to trading based on expected gains from trade-and-hold portfolios adjustments motivated by public information releases regarding the terminal dividend. Such speculative trading may
arise due to: (1) recognition and exploitation of a systematic price trend, such as lagged adjustment to the expected dividend; (2) attempts by the subjects to infer the behavior of others (possibly driven by a lack of common knowledge); or (3) simply guessing the direction of future price movements.

When planning this research project, the collection of both dividend and price expectations was explicitly discussed and rejected for two primary reasons: task complexity and the interdependency between trading behavior and price forecasting accuracy. Regarding task complexity, having traders submit both dividend and price forecasts, in addition to participating in the market, had too much potential for generating confusion. Regarding interdependency, since price forecasting accuracy is typically rewarded based on closeness to observed market prices, there was the very real possibility that traders would alter their market behavior in an attempt to influence the objective of the price forecasting game. Therefore, we did not gather price forecasts.

31. Traders inconsistent with the trader's forecast include those bought at a price above the forecast or sold at a price below the forecast. This variable required us to compare the price of each trade with the forecasts of the traders involved. For call markets, there was only one market price in each round, while double-auction markets had multiple prices in each round.

32. Because of non-normality, we report Spearman rank correlations. However, results are similar using Pearson correlations. The two correlation coefficients are always of similar sign and magnitude.

33. Speculative trading based on expected price changes can have either sophisticated or unsophisticated motivations. The former may be the result of recognition of a systematic price movement, presumably from information contained in the market history, while the latter may be the result of essentially guessing the direction of price movements. Unsophisticated trading is less likely to lead to trading profits and thus is more likely to lead to lower market earnings. The negative correlation between TRADESC and %MKTEARN suggests that unsophisticated motivations for speculative trading are an important component of the TRADESC measure.

34. This measure allows market volume to be compared across markets with different numbers of traders, and thereby different shares outstanding.

35. Surprisingly, there is no significant increase in the absolute magnitude of price changes in rounds immediately after non-zero signals. While understanding exactly what is driving this result is beyond the scope of this paper, it is consistent with the conjecture that many traders are motivated by factors other than a change in intrinsic dividend value.

36. Kim and Verrecchia (1991a) develop a model of trade with differentially informed traders and a commonly interpreted public signal that suggests an inverse relationship between trading volume and expectation dispersion. While the formal logic of this asymmetric information model does not apply directly to our symmetric information markets, we cannot dismiss the possibility that this inverse relationship may somehow generalize to our markets due to the differing expectations reflected in the forecasts.

37. Many capital market studies of trading volume since Ajinkya et al. have used prior forecast dispersion as an explanatory variable. Bamber, Barron, and Stoven (1997) find a significant positive relation between prior forecast dispersion and volume. In our markets, $FDISP_{t-1}$ is significantly correlated with $FDISP_t$ ($r = 0.64, p = 0.000$). When included in the full model in place of $FDISP_t$, the coefficient for $FDISP_{t-1}$ is significantly negative ($b = -0.281$, two-tailed $p = 0.080$). The interaction term $FDISP_{t-1} \times CALLMT$ is not significant (two-tailed $p = 0.144$), but the signs and significance levels of the other coefficients are unaffected. $FDISP_t$ is not significantly correlated with any of the other main effects (two-tailed $p > 0.10$), but $FDISP_{t-1}$ is significantly correlated with $\Delta F_t$ ($r = 0.138$, two-tailed $p = 0.062$).

38. Following Barron (1995), we computed the linear correlation between the $F_t$ and $\Delta F_t$ vectors of individual traders' forecasts for $t = 2, 3, \ldots, 15$ and used this variable as an explanatory variable for $TURNOVER$. Conceptually, this is an interesting measure of the "jumbling" of forecasts over time (with lower correlations implying more jumbling) and was expected to be inversely related to $TURNOVER$. In fact, the simple correlation between this jumbling variable and $TURNOVER$ is $r = -0.122$, which is significant using a one-tailed test ($p = 0.051$).

However, when added to the full or condensed model of $TURNOVER$ in Table 6, its coefficient is not significantly different from zero. This result can be attributed to the fact that the jumbling variable is highly correlated with $\Delta F_t$ ($r = -0.452$, $p = 0.000$).

39. The Durbin-Watson (DW) statistics presented in Table 6 suggest that autocorrelation is present in both the full and condensed turnover models. Given: (1) the model's complexity, (2) our lack of understanding of the source of the serially correlated errors (such as omitted autocorrelated variables), and (3) the econometric complexity of the solutions, our strategy for dealing with the significant DW statistics is simply to warn the reader that the coefficient standard errors reported in Table 6 may be smaller than the true standard errors.

References


