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Asset Prices and Informed Traders' Abilities: Evidence from Experimental Asset Markets

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Abstract: This study reports the results of fifteen experimental asset markets designed to investigate the effects of forecasts on market prices, traders' abilities to assess asset value, and the link between the two. Across the fifteen markets, the authors investigate alternative forecast-generating processes. In some markets the process produces an unbiased estimate of asset value and in others a biased estimate. The processes generating the biased forecasts, though, are less variable than the process generating the unbiased forecast. The authors find that, in general, period-end asset price reflects private forecasts, regardless of the forecast-generating process. Subsequently, they investigate whether traders' abilities to use forecasts differ across the forecast-generating processes. The authors find that most are able to properly use unbiased forecasts. They refer to them as smart traders. By comparison, a significant proportion is unable to properly use biased forecasts (typically traders' adjustments for bias are insufficient). Linking market outcomes and traders' abilities, the authors find that asset price appears to properly reflect unbiased forecasts as long as the market includes at least two smart informed traders who have sufficient ability to influence market outcomes. To obtain a comparable result in markets with the biased forecast, at least three smart informed traders with sufficient ability to influence market outcomes are necessary.

JEL classification: D82

Key words: forecast bias, experimental markets, smart traders

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Asset Prices and Informed Traders' Abilities:

Evidence From Experimental Asset Markets

1. Introduction

This study reports the results of 15 experimental asset markets designed to investigate the effects of forecasts on market prices, traders' abilities to assess asset value, and the link between the two. Each market consists of a series of trading periods in which traders can purchase a forecast of period-end asset value. Across the 15 markets, we investigate alternative forecast-generating processes: one that produces an unbiased estimate of asset value, one that produces an optimistic biased estimate, and one that produces a pessimistic biased estimate. The processes generating the biased forecasts, though, are less variable than the process generating the unbiased forecast. After the trading periods are completed, each market includes a series of prediction periods in which forecasts are publicly announced and participants predict asset value.

We investigate whether the alternative forecast-generating processes affect the convergence of asset price over time: specifically, whether asset prices are similar, regardless of forecast bias and variability. Next, we examine individual traders' abilities to properly use the forecasts. By examining market outcomes *and* individual abilities, we link the two. An important contribution of this study is that we investigate the number of smart, informed traders (i.e., those able to properly use forecasts) necessary to produce an outcome that approaches a rational price.

An understanding of the link between market outcomes and traders' abilities is critical to assess theoretical models of market behavior. Traditional models contend that asset prices are not affected by traders' abilities and information is fully reflected in market outcomes in accordance with the laws of statistics and probability. Recent models, on the other hand, suggest that market prices may deviate from rational outcomes, primarily because market participants have limited abilities and are susceptible to judgment biases and heuristics (Barberis, Shleifer, & Vishny, 1998; Daniel, Hirshleifer, & Subrahmanyam, 1998). Bossaerts (2002) underscores the importance of properly modeling traders' beliefs in order to appropriately characterize market outcomes.

Experimental evidence on market pricing is mixed. Ganguly, Kagel, & Moser (1994; 2000) and Tuttle, Coller, & Burton (1997) report that individual biases persist in market pricing, whereas Knez, Smith, & Williams (1985), Forsythe, Nelson, Neumann, & Wright (1992), and Forsythe, Reitz, & Ross (1999) find otherwise. More recently, Ackert & Church (2001) and Kluger & Wyatt (2002) suggest that the mix of traders who are susceptible to judgment biases affects whether rational market outcomes are achieved. They encourage research in this area to provide insight into market behavior. Our study directly examines the association between market participants' abilities to properly use private forecasts and resulting market prices. A model of how individuals form beliefs about market valuations is a significant missing chapter in current asset pricing theory (Hirshleifer, 2001). Our work provides direction for future theoretical modeling of the link between individual behavior and market outcomes.

A notable feature of our design is that we include optimistic as well as pessimistic forecasts. Prior studies have focused on optimistic forecasts (e.g., Ackert, Church, & Shehata, 1996; 1997a; Ackert, Church, & Zhang, 2002). Yet research documents that individual analysts are persistently optimistic *or* pessimistic (Butler & Lang, 1991). Notably, adjustments for bias may differ depending on the direction of the bias. Prior research suggests that sophisticated users may overreact to positive information and underreact to negative information (Amir & Ganzach, 1998; Easterwood & Nutt, 1999). In our setting, we investigate whether traders' adjustments for optimistic forecasts are less pronounced than their adjustments for pessimistic forecasts. We then examine whether market outcomes differ depending on the direction of the bias. An understanding of market participants' abilities to adjust for optimistic *and* pessimistic bias, which determines their revised beliefs, is critical to evaluate market outcomes (Bossaerts, 2002).

Lastly, we investigate traders' preference for information produced by the alternative forecast-generating processes. Recall that in our experimental markets unbiased forecasts contain more variability than biased (optimistic or pessimistic) forecasts. If traders are able to adjust for bias, then biased forecasts are preferable because the information provides a superior estimate of asset value. But adjustment for bias is not an easy task. Biased forecasts include systematic and random error components and disentangling the two can be quite daunting (Klayman, 1988). We examine the frequency with which traders acquire unbiased versus biased forecasts when both are available. An understanding of traders' forecast acquisition decisions is necessary to provide insight into the financial analyst's role as a vital source of information in the marketplace. The examination is particularly relevant because analysts have incentives to release biased forecasts and such forecasts can be optimal (Gu and Wu, 2000; Lim, 2001).

Our findings indicate that closing price typically approaches a rational price. Further inspection of the data indicates heterogeneity in traders' abilities to properly use forecasts. We refer to traders who make unbiased predictions of asset value as smart traders. The vast majority of traders who make predictions using the unbiased forecast are smart traders. By comparison, the proportion of smart traders is much less in markets with biased forecasts: 56 percent with an optimistic bias and 70 percent with a pessimistic bias. Further inspection of the data indicates that in markets with the unbiased forecast, the closing price approaches a rational outcome as long as the market includes two smart informed traders who have sufficient ability to influence market outcomes. In markets with the biased forecast, three smart informed traders, with sufficient ability to influence market outcomes, are necessary to produce a comparable result. Lastly, our data indicate that traders do not have a preference for the biased forecast over the unbiased forecast, even though the former contains less variability. This result appears to arise because many traders (30-45 percent) have difficulty adjusting for systematic bias.

We describe the experimental asset markets in section 2 and then develop experimental predictions in section 3. Subsequently, we present the experimental results. We offer concluding remarks and discuss the findings in the final section.

2. Experimental asset markets

Overview and design

We conduct 15 experimental asset markets, each of which consists of a series of trading periods. Each period participants trade an asset having a one-period life. Before trading begins, participants may acquire a forecast of asset value. At period end, the asset pays a liquidating dividend, which determines asset value. In addition, each market includes a series of prediction periods, which take place after the trading periods are completed. In prediction periods, forecasts are publicly announced and participants individually predict asset value.

Across the 15 markets, we vary the forecast-generating process and the availability of forecasts. One forecast is available in the first nine markets. In markets 1-3, the forecast-generating process produces an unbiased estimate of asset value. The forecast is computed as the period-end dividend plus a mean zero, random error term, determined by drawing from a normal distribution with a standard deviation of $100 (denoted NOBIAS). In markets 4-6, the forecast-generating process produces an optimistic biased estimate of asset value. The optimistic forecast is computed as the period-end dividend plus a constant (bias) of $200 plus a mean zero, random error term, determined by drawing from a normal distribution with a standard deviation of $50 (denoted UPBIAS). In markets 7-9, the forecast-generating process produces a pessimistic biased forecast. The forecast is determined similar to the optimistic forecast, except that the constant is !$200 (denoted DOWNBIAS).

In the final six markets, two forecasts are available and traders may acquire one, both, or neither. In markets 10-12, the NOBIAS and UPBIAS forecasts are available (denoted NOUP markets). In markets 13-15, the NOBIAS and DOWNBIAS forecasts are available (denoted NODOWN markets). The forecasts are identical to those used in markets 1-9. The experimental design is summarized in Table 1.

[insert Table 1 here]

Experimental procedures

At the beginning of each market, participants receive a set of instructions and follow along as an experimenter reads aloud.[1] Participants are third- and fourth-year undergraduate and fifth-year post baccalaureate students in business and economics at a medium-sized university. All participants are inexperienced in that none took part in more than one market. Eleven markets include eight participants and four include seven participants. The average compensation across the 116 participants was $26.36, with a range of $16.41 - $33.67.

Each market consists of 12 trading periods, and participants are not informed beforehand of the number of periods. Participants are instructed that the period-end dividend is determined by drawing from a normal distribution with a mean of $1,200 and a standard deviation of $400.[2] The instructions include a diagram of the density function and state that "the dividend is between $800 and $1,600 with a probability of 0.6826, between $600 and $1,800 with a probability of 0.8664, and between $400 and $2,000 with a probability of 0.9544." Further, the instructions state that "(p)ractically speaking, the dividend is always nonnegative." Prior to conducting the markets, the dividend draws are determined for periods 1-12 and the pre-selected values are used in all markets.[3]

Each trading period, participants are endowed with two certificates and $50,000. Participants are informed that they may be required to pay a tax on their dividend earnings: personal tax rates are either zero or 40 percent. The instructions indicate that the tax rates differ across traders and periods. At the beginning of each trading period, half of the participants are assigned each tax rate, and across the 12 periods, each participant is assigned each rate the same number of times.[4] The different tax rates introduce different preferences for dividend earnings and create incentives to trade. Certificates are worth more to participants with a zero tax rate on dividend earnings than those with a 40 percent tax rate. Hence, participants with a zero tax rate have incentives to buy certificates, whereas those with a 40 percent tax rate have incentives to sell. Importantly, capital gains are *not* taxed.

Before trading, participants are allowed to purchase a forecast of the period-end dividend at a fixed price of $150 per forecast. To allow them to assess the usefulness of the forecast, participants are provided with a forecast history collected over 12 practice periods. The history details the forecast error per period (forecast minus the period-end dividend) and the mean and standard deviation of the forecast error. We include the forecast history because historical data are typically available in naturally occurring markets. As mentioned earlier, two forecasts are available in markets 10-15, referred to as forecast A and forecast B. For each forecast, a history is provided. Across all markets, participants are informed that the process generating each forecast is unique and constant across periods.

At the beginning of each trading period, participants make a forecast acquisition decision. Those acquiring the forecast are provided with an updated forecast history (i.e., the forecast and asset value realizations for all prior periods) and the current period's forecast. The specific identity and total number of traders acquiring the forecast per period is not revealed. In markets 1-9, participants may spend $150 to acquire a forecast. In markets 10-15, they may spend $150 to acquire one forecast and $300 to acquire both. As discussed earlier, forecasts are unbiased in some markets, optimistic biased in other markets, and pessimistic biased in still other markets.[5]

In markets 10-15, we allowed participants to acquire both forecasts because the two forecasts represent independent estimates of asset value. As discussed in the next section, we posit that traders should acquire the biased forecast because it provides a superior estimate of asset value. But the biased forecast only provides a more precise estimate if traders are able to sufficiently adjust for bias. If traders have difficulty adjusting for bias (e.g., some amount of bias is presumed to represent noise), they may believe that both forecasts are useful. Accordingly, we provide them with the opportunity to acquire the unbiased, biased, or both forecasts.

All markets are organized as double oral auctions. The double auction institution has been examined extensively in the literature and has robust equilibrating properties when small numbers of traders possess private information (Smith, 1994). In our markets, traders are free to make verbal offers to buy or sell one certificate at a designated price at any time, and all offers are publicly announced and recorded. Outstanding offers stand until accepted or replaced by a better bid or ask price. Traders are allowed to short sell up to two certificates per period, but they are required to pay the dividend on all certificates sold short. The trading certificates are not carried across periods.

At the end of each trading period, the dividend is publicly announced and the same dividend is received for all certificates held by a participant. Period-end cash balances are computed as follows. The number of certificates on hand is multiplied by the dividend per certificate to determine dividend earnings. This amount is converted to an after-tax figure by multiplying by one minus the tax rate. Participants add the after-tax dividend earnings to their cash balance, subtract the cost of acquiring forecasted information, and then subtract the initial endowment of $50,000. The net amount represents participants' profits for the period. The instructions indicate that participants will be paid 0.1 percent of their total after-tax profit in cash.

After the 12 trading periods are completed, a second set of instructions is distributed. This phase is intended to gather information on participants' predictive abilities. We conduct additional, non-market periods in which a forecast is publicly announced and participants are given 30 seconds to predict the period-end dividend. The prior history, including the updated mean and standard deviation of the forecast error, is publicly displayed. Participants are instructed that the forecast is determined based on the same process used throughout the experiment. Participants receive $0.25 for each prediction that is within "$100 of the period-end dividend.[6] For markets 1-9, participants make predictions over six additional periods. For markets 10-15, participants make predictions over 12 additional periods. Over six periods the unbiased forecast (referred to as forecast A) is provided, and over six additional periods the biased forecast is provided (referred to as forecast B).

At the conclusion of each market session, participants compute the amount of cash to be received and complete a post-experiment questionnaire. The questionnaire is designed to collect general information about the participants and how they view the experiment.

3. Experimental predictions

Market outcomes

We adopt a noisy rational expectations framework to develop predictions of market outcomes. According to the NRE framework, private information is disseminated, though not immediately, and fully reflected in period-end prices (e.g., Hellwig, 1982; Grundy & McNichols, 1989). Asset prices adjust away from the uninformed or prior price, which reflects only publicly available information, toward the informed price, which reflects public as well as private information (e.g., Sunder, 1992).

Foster & Viswanathan's (1996) theoretical analysis is applicable to our experimental setting. They examine the informativeness of price when a subset of traders is endowed with an unbiased estimate of asset value. Their results suggest that when a sufficient number of informed traders possess identical information, asset price converges to the informed price after only a few trades.[7] We investigate whether this result occurs in markets with unbiased forecasts (i.e., the NOBIAS markets). Using a Bayesian updating process, the informed price is computed as $(F_A{}^2 F_u + F_{Fu}{}^2 \mu_A)/(F_A{}^2 + F_{Fu}{}^2)$, where F_A is the standard deviation of the asset value, F_u is the unbiased forecast, F_{Fu} is the standard deviation of the unbiased forecast, and μ_A is the mean asset value.

We also investigate whether the informed price is achieved in markets with biased forecasts (UPBIAS and DOWNBIAS). Prior experimental research indicates that individuals can adjust for optimistic bias forecasts, but that differences in abilities are apparent (Ackert et al., 1997a). Archival findings suggest that, in general, sophisticated users overreact to positive/optimistic information and underreact to negative/pessimistic information (Amir & Ganzach, 1998; Easterwood & Nutt, 1999). We investigate whether asset price approaches an informed price that adjusts for forecast bias, regardless of individuals' abilities (this issue is discussed further in the next subsection). The informed price is computed as $(F_A{}^2 F_b^{adj} + F_{Fb}{}^2 \mu_A)/(F_A{}^2 + F_{Fb}{}^2)$, where F_b^{adj} is the biased forecast adjusted for the systematic bias, F_{Fb} is the standard deviation of the biased forecast, and the other terms are as defined previously.

The unbiased forecast and informed price for trading periods 1-12 are shown in Table 2. We test whether the closing price per period differs between markets with unbiased or biased forecasts (NOBIAS, UPBIAS, and DOWNBIAS) and, for each market set, whether it differs from the informed price. We also explore the speed of the price adjustment process. As mentioned earlier, Foster & Viswanathan's (1996) analysis suggests that when the informed traders possess identical information, the informed price is achieved quickly in markets with unbiased forecasts. We investigate the speed of the price adjustment process and assess whether differences arise between market sets (NOBIAS, UPBIAS, and DOWNBIAS).

[insert Table 2 here]

Additionally, we investigate whether the informed price is achieved in markets with unbiased *and* biased forecasts (NOUP and NODOWN). Foster & Viswanathan (1996) analyze a second case in which informed traders possess diverse, imperfectly correlated estimates of asset value. They demonstrate that, as long as a sufficient number of traders possess private information, asset price converges to the informed price. Price convergence, however, is slower than in markets with identical private information. If informed traders collectively possess two forecasts, the informed price is computed as $(F_A^2 F_{Fb}^2 F_u + F_A^2 F_{Fu}^2 F_b^{adj} + F_{Fu}^2 F_{Fb}^2 \mu_A)/(F_A^2 F_{Fu}^2 + F_A^2 F_{Fb}^2 + F_{Fu}^2 F_{Fb}^2)$, where the terms are as defined previously.[8] We test whether the closing price per period differs between the NOUP and NODOWN markets and, for each market set, whether it differs from the informed price. We also explore whether the price formation process is slower in markets with two forecasts as compared to one as suggested by Foster & Viswanathan (1996).

Smart informed traders and market outcomes

Market outcomes are likely conditioned on informed traders' abilities to use forecasts. Experimental research suggests that such abilities differ across traders (e.g., Peterson, 1993; Ackert & Church, 2001, Kluger & Wyatt, 2002). Theoretical models have long recognized the importance of heterogeneity among agents in explaining economic behavior (e.g., Figlewski, 1978; Haltiwanger & Waldman, 1985; Chiarella &

He, 2002). We examine the association between the mix of market participants and market outcomes.

Market outcomes can be rational even though traders, on average, are not.[9] Becker (1962) argues that it is the behavior of the marginal investor, rather than the average investor, that determines market prices. Likewise, Camerer (1987; 1992) suggests that asset prices converge to a rational outcome as long as a subset of rational traders drives market prices. We are interested in the *number* of smart traders (i.e., those who can properly use forecasts) necessary to produce a rational outcome.

Theoretical results suggest that asset price more readily converges to a rational equilibrium as the number of smart informed traders increases (Rustichini, Satterthwaite, & Williams, 1994). The competition to buy and sell certificates intensifies as this subset of traders increases, thereby moving price toward the informed price. The issue remains, however, as to *how many* smart informed traders are sufficient to produce a rational outcome. Foster & Viswanathan (1996) perform a numerical analysis and show that, in their setting, *three* smart informed traders are sufficient. Based on the theory of perfect competition, however, *two* smart informed traders are enough to produce an asset price that approaches the informed price. We empirically examine the association between number of smart informed traders and the closing price period and determine whether the results are comparable across market sets. As Kluger & Wyatt (2002) argue, an understanding of this issue is critical to link individual and market outcomes.

In addition to identifying the number of smart informed traders, we investigate other traders' abilities. We examine whether other traders' predictions of asset value fail to sufficiently adjust for forecast bias: i.e., predictions exceed asset value with UPBIAS forecasts and fall below it with DOWNBIAS forecasts. Simply put, we investigate whether other traders have systematic biases in their predictions of asset value. We assess whether the magnitude of adjustment for forecast bias differs between those who receive UPBIAS versus DOWNBIAS forecasts. The archival findings of Ganzach & Amir (1998) and Easterwood & Nutt (1999) suggest that the adjustment for optimistic bias may be less than that for pessimistic bias.

Forecast acquisition decisions

In a noisy rational expectations framework, traders may prosper by acquiring forecasts of asset value because private information is not reflected immediately in asset prices. Jackson (1991) demonstrates that the acquisition of costly information arises in equilibria and that, over time, the information is fully revealed in asset prices. Experimental evidence indicates that private imperfect information has value (Copeland & Friedman, 1991; Ackert, Church, & Shehata, 1997b). In markets with one forecast, a subset of traders is likely to acquire the forecast because it provides them with a useful estimate of asset value (Jackson, 1991). This result is expected, regardless of the forecast-generating process.

In markets with two forecasts, we investigate whether traders have a preference for information produced by a particular process. In all cases, the forecast-generating process includes a random error term; however, for the process generating the unbiased forecast, the standard deviation of the error term is twice as large as that for the processes generating the biased forecasts.[10] We know that, other things being equal, traders prefer unbiased to biased forecasts because the former do not have to be adjusted or processed further (Ackert et al., 1996). At the same time, we know that traders prefer less variability in a forecast because a less variable forecast reflects less uncertainty.

Moreover, traders have difficulty dealing with variability in general, which may have a deleterious effect on their abilities to properly use forecasts (Lopes & Oden, 1987).

For the NOUP and NODOWN markets, we test whether the frequency of forecast acquisitions differs between the process generating the unbiased, more variable forecast and that generating the biased, less variable forecast. If traders are able to adjust for systematic bias, they may acquire the biased forecast more frequently because it allows them to make a more precise estimate of asset value. Ackert et al. (1997a) provide evidence that participants can adjust for small amounts of optimistic forecast bias in an individual setting. Prior studies, however, have not examined participants' abilities to adjust for pessimistic forecast bias. Further, evidence suggests that adjustments for bias need not be symmetric (e.g., Amir and Ganzach, 1998). We investigate whether traders' abilities to adjust for systematic bias affect the frequency with which they acquire the biased forecast when the unbiased forecast also is available.

4. Results

Market outcomes

We investigate price behavior over the course of the experiment. We examine whether the closing price per period approaches the informed price and, further, test for differences between the market sets. We also investigate the price formation process. We assess whether the process differs between markets with one forecast as compared to markets with two.

Closing price. Figures 1-5 plot the time series of the closing and informed prices per period for each set of markets. Each figure includes prices for the three sessions conducted under the same experimental condition. In the NOBIAS markets, the closing price per period very closely tracks the informed price, particularly over the later periods. In the other markets, deviations from the informed price are more apparent, though the closing price per period generally is not far from the informed price.

[insert Figures 1-5 here]

We examine the nearness of closing price per period to the informed price. For each market set, we compute the absolute difference between the closing price and the informed price, normalized by the informed price. We refer to this measure as the normalized, absolute price deviation (NAPD). We perform a repeated measures analysis of variance (ANOVA) to test for differences between the market sets. The dependent measure is the NAPD per period and the independent variables include market set, period, and the interaction term. We find that period is significant at $p = 0.002$ ($F = 7.10$). The data indicate that the NAPD exhibits a downward trend over the course of the experiment. The other two independent variables (market set and the interaction term) are not statistically significant. The descriptive data suggest that the mean NAPD varies somewhat across the market sets (refer to Panel A of Table 3); however, pairwise tests indicate that none of the differences are statistically significantly.[11]

[insert Table 3 here]

Next, we assess whether the closing price per period approaches the informed price. For each market set, we perform a repeated measures ANOVA. The dependent measure is the signed difference between the closing price and the informed price, normalized by the informed price (referred to as the NSPD). The independent variable is period. We test whether the intercept is significantly different from zero. For each market set, we find that the intercept is not statistically significant.[12] Hence, we are unable to reject the null hypothesis that the NSPD equals zero. This result suggests that the closing price per period approaches the informed price across the market sets. Overall, market outcomes do not appear to be affected by the forecast-generating process.

Price formation. In addition to closing price per period, we examine the price formation process. According to the noisy rational expectations framework, price moves away from uninformed price toward the informed price as information is disseminated. Our earlier discussion suggests that asset price may approach the informed price faster in markets with one forecast as compared to two forecasts. We examine several measures of price behavior to gain insight into the speed of price convergence.

Descriptive data for various measures of price formation are shown in Table 3. The data are presented separately for periods 1-6, 7-12, and 1-12. As discussed previously, price behavior (measured by the NAPD) improves over the course of the experiment. Panel A shows the nearness of the closing price per period to the informed price, and Panel B shows the nearness of the opening price to the informed price. The normalized, absolute difference is greater using the opening price, which may be expected. That is, price moves *toward* the informed price within a period.

Panel C shows the proportion of transactions per period that produce an NAPD (based on the transaction price) equal to or less than 5, 10, 15, and 20 percent. The majority of transactions generally fall in the 10 percent or less category and the finding holds across market sets.

Panel D shows the number of transactions per period necessary to reach the minimum NAPD for the period (based on the transaction prices within a period). The data suggest that roughly three to five transactions are necessary. The total number of transactions per period is, on average, eight to nine so that the minimum NAPD is typically achieved over the first one-third to one-half of the trading period.[13] Further inspection of the data indicates that asset price often remains around that which produces the minimum NAPD. In a few instances, it moves away from the minimum, but typically it hovers around this price. The average increase in the NAPD, computed using the closing price per period, is roughly 3 percent across the different market sets.[14]

We perform several repeated measures ANOVAs with each measure of price formation as the dependent measure and test for differences over periods and across markets sets. Generally, period is statistically significant at $p < 0.05$. The deviation between the opening price and the informed price shows a downward trend over the course of the experiment and the proportion of transactions that produces an NAPD equal to or less than 5, 10, 15, and 20 percent shows an upward trend.

We do not find significant differences between market sets, with one exception. We find some evidence that the number of transactions to achieve the minimum NAPD is smaller in markets with two versus one forecast. Pairwise tests indicate that the mean of the NODOWN market is less than that of the UPBIAS and DOWNBIAS markets ($p < 0.07$). Likewise, the mean of the NOUP market is less than that of the DOWNBIAS market ($p = 0.087$).[15] This result is contrary to the experimental prediction; however, it may arise because several participants in the NOUP and NODOWN markets acquire *both* forecasts. Our prediction, based on Foster & Viswanathan's (1996) analysis, presumes that some traders acquire the unbiased forecast and others acquire the biased forecast – but traders do not acquire both forecasts. We investigate this possibility later in the results section.

The transaction price data provide evidence that asset price moves toward the informed price within a trading period. However, the price adjustment process is not necessarily smooth. Looking transaction by transaction, we observe that asset price may move toward the informed price, then away from it, then toward it, and so on. The data indicate that the pattern is sometimes quite erratic. We also observe that the distance between asset price and the informed price is often minimized over the first one-third to one-half of a trading period. Inspection of the data indicates that subsequent transactions are typically around the minimum, though in some cases the NAPD increases noticeably. Overall, asset price typically shows a trend toward the informed price within a trading period, though price adjustment is not necessarily smooth. Even in well-behaved markets, traders can make mistakes or incorrect inferences, particularly in deciphering the bid-ask behavior of other market participants. Bossaerts (2001) contends that even *good* Bayesian learners are subject to error, which affects price formation (see also Bossaerts & Hillion, 2001). Finally, we note that price behavior also appears to improve as traders gain experience with the experimental market (i.e., over periods 1-12).

Traders' predictive abilities and market outcomes

We investigate whether participants are able to predict asset value. At the conclusion of the 12 trading periods, forecasts are publicly announced and participants predict asset value for six or 12 additional periods. No trading takes place in the additional periods. Thus, the focus is strictly on predictive abilities.

Traders' predictive abilities. For markets with one forecast, we classify traders as making unbiased or biased predictions of asset value. To classify them, we examine the signs of their prediction errors and determine whether the signs are consistently positive or negative. If at least five of six prediction errors have the same sign, the trader is classified as a biased trader: upward if the sign is consistently positive and downward if it is consistently negative.[16] Otherwise, the trader is classified as an unbiased trader. For markets with two forecasts, we classify each trader twice: once based on their predictions using unbiased forecasts and once using biased forecasts.

Panel A of Table 4 shows the classification of traders conditioned on their use of unbiased forecasts. The vast majority of traders (81 percent) make unbiased predictions. A binomial test indicates that traders are more likely to be classified as unbiased than biased ($p < 0.001$). Notably, those making biased predictions typically exhibit a downward bias.

[insert Table 4 here]

Panel B of Table 4 shows the classification of traders conditioned on their use of optimistic bias forecasts. In this case, a smaller percentage of traders (56 percent) make unbiased predictions. A binomial test indicates that traders are no more likely to be classified as unbiased than biased ($p = 0.551$). We further note that traders making biased predictions tend to be biased upward. Hence, their adjustments for optimistic bias are insufficient.

Finally, Panel C of Table 4 shows the classification of traders conditioned on their use of pessimistic bias forecasts. A majority of traders (70 percent) are classified as unbiased. A binomial test indicates that traders are more likely to be classified as unbiased than biased ($p = 0.012$). Those making biased predictions always exhibit a downward bias, indicating that their adjustments for pessimistic bias are insufficient.

Informed smart traders and market outcomes. We refer to traders who make unbiased predictions of asset value as smart traders. For markets with one forecast, we examine the link between the number of smart informed traders and the NAPD. Table 5 shows the average NAPD, partitioned by the number of smart informed traders, for each market set. The table also shows the percentage of transactions per period that involve at least one smart informed trader.

[insert Table 5 here]

The data for the NOBIAS markets are shown in Panel A of Table 5. The NAPD decreases as the number of smart traders increases, with the exception of seven smart informed traders. The conspicuously high NAPD is the result of an extreme observation that occurs in the first period of market 2: the NAPD is 0.322. With the exception of this extreme observation, the NAPD is quite low as long as the market includes at least three smart informed traders. Interestingly, this result coincides with Foster & Viswanathan's (1996) numerical results. We also observe that the vast majority of transactions involve at least one smart informed trader.

The data for the UPBIAS markets, shown in Panel B of Table 5, indicate that the NAPD is relatively high with three or fewer smart informed traders. Notably, with three smart informed traders, 100 percent of the transactions involve at least one of them. Yet the activity of these traders is not sufficient to drive the NAPD below 17 percent. The NAPD improves markedly with five smart informed traders and even more with six – with at least one of these traders participating in the vast majority of transactions.

The data for the DOWNBIAS markets, shown in Panel C of Table 5, suggest that the NAPD generally decreases as the number of smart informed traders increases. With at least three smart informed traders, the vast majority of transactions involve at least one of these traders. But at least five smart informed traders are necessary to produce an NAPD less than 10 percent. Generally, the results are consistent with those in the UPBIAS markets. The findings for markets with biased forecasts are consistent with

Rustichini et al. (1994): asset price behavior improves as the number of smart informed traders increases.

Overall, our findings suggest that a larger number of smart informed traders are necessary to drive price toward the informed price in markets with UPBIAS and DOWNBIAS forecasts as compared to markets with NOBIAS forecasts. A drawback of the preceding analysis, however, is that smart traders' ability to influence market outcomes is potentially affected by their tax rate on dividends (zero or 40 percent). Traders who have a zero tax rate usually buy certificates, whereas those who have a 40 percent tax rate usually sell. In our markets, traders have a sufficient cash endowment such that they can buy as many certificates as others are willing to sell. By comparison, traders can only sell four certificates: their initial endowment of certificates plus two short sales. Consequently, smart informed traders likely have a greater impact on market outcomes if their tax rate is zero.[17]

We investigate the link between the number of smart informed traders with a zero tax rate and the NAPD. We refer to these as smart informed buyers. We also examine the percentage of transactions per period that involves at least one smart informed buyer. Our findings are shown in Table 6.

[insert Table 6 here]

In the NOBIAS markets, the NAPD is below ten percent with two or three smart informed buyers. The increase in the NAPD with four smart informed buyers is attributable to one extreme observation: as mentioned earlier, the NAPD is 0.322 in the first period of market 2. Excluding this observation, the average NAPD is 0.026. In the UPBIAS and DOWNBIAS markets, the NAPD decreases as the number of smart informed buyers increases. Three smart informed buyers are necessary to push the

NAPD below ten percent. Finally, we note that, across all markets, the percentage of transactions that involves at least one smart informed buyer increases as the number of smart informed buyers increases. Further, with at least two smart informed buyers, a majority of the transactions involves at least one of them.

Forecast acquisition decisions

In markets with one forecast, traders readily acquire the forecast, regardless of the forecast-generating process. The average number acquiring the forecast per period is 5.47, 4.94, and 5.56 in the NOBIAS, UPBIAS, and DOWNBIAS markets, respectively. A repeated measures ANOVA indicates that the number does not vary across markets sets (F = 0.83, p = 0.480) or over time (F = 1.41, p = 0.265).[18] This finding is consistent with that reported elsewhere (Ackert et al., 2002). The finding is also consistent with Jackson's (1991) theoretical analysis, which suggests that information is acquired over time, even though it is eventually revealed in asset price.

In markets with two forecasts, we investigate the frequency with which traders acquire the unbiased forecast, the biased forecast, and both forecasts. If traders are able to adjust for systematic bias, they may acquire the biased forecast more frequently than the unbiased forecast. The biased forecast contains less variability and, thus, may provide a more precise estimate of asset value.

[insert Table 7 here]

The average number of times that traders acquire each forecast is shown in Table 6. The data are partitioned by market set and presented for periods 1-6, 7-12, and 1-12. Traders do not appear to have a preference for the biased over the unbiased forecast. We also observe that a small subset of traders acquire both forecasts, particularly in the

NOUP markets. This finding, as suggested earlier, potentially impacts the speed of price formation.

For each market set, we perform a repeated measures ANOVA to formally test whether traders have a preference for a particular forecast. The dependent measure is the number of times that a forecast is acquired. The independent variables include the forecast (unbiased, biased, or both), time (periods 1-12), and the interaction term.[19]

For the NOUP markets, only forecast is significant at conventional levels ($F = 3.52$, $p = 0.098$). Pairwise comparisons indicate that traders acquire the unbiased forecast *more* frequently than the biased forecast ($p < 0.05$). For the NODOWN markets, again forecast is the only statistically significant independent variable ($F = 25.07$, $p = 0.001$). In this case, pairwise comparisons indicate that traders acquire unbiased and biased forecasts more frequently than both forecasts ($p < 0.01$). In markets with two forecasts, traders may not exhibit a preference for the biased forecast, even though it contains less variability, because many have difficulty adjusting sufficiently for the systematic bias. From our earlier analysis (refer to Table 4), 20 of 45 have difficulty adjusting for optimistic bias and 14 of 46 have difficulty adjusting for pessimistic bias.

5. Conclusions

This study reports the results of 15 experimental asset markets designed to investigate the effects of alternative forecast-generating processes on market prices, traders' abilities to assess asset value, and the link between the two. We manipulate the forecast-generating process between markets. In some markets the process produces an unbiased, but more variable estimate of asset value, and in others a biased, but less variable estimate. The bias is always systematic, though in some markets it is optimistic and in others pessimistic. In all markets, traders decide whether to acquire the forecast.

We find that, in general, period-end asset price reflects private information, regardless of the forecast-generating process. Within a trading period, asset price appears to move toward the informed price, as suggested by a noisy rational expectations framework. The price formation process, however, is not smooth. Looking at each transaction, we find that price sometimes moves toward the informed price and at other times away from it. But over the course of a trading period, the general trend is to move toward the informed price. Informed traders likely bid strategically in an effort to conceal their informational advantage. The bidding strategies, in turn, may affect uninformed traders' inferences of asset value. If the inferences are incorrect, asset price may temporarily wander away from the informed price, as suggested by Bossaerts (2001) and Bossaerts & Hillion (2001). The theoretical work of Rustichini et al. (1994) suggests that strategic bidding occurs, but they do not attempt to model the price formation process. Future theoretical research may investigate the price formation process, explicitly recognizing that price adjustment may occasionally move away from the informed price due to incorrect inferences.

We also document heterogeneity among traders in their abilities to use the forecast to make unbiased predictions of asset value (i.e., whether they are smart traders). We find that most traders are able to properly use the unbiased forecast. By comparison, a significant proportion is unable to properly use biased forecasts, with adjustments for bias typically being insufficient. Traders' adjustments for bias, though sometimes insufficient, do not appear to be affected by the direction of the bias.

Linking market outcomes and traders' abilities, we find that asset price appears to properly reflect unbiased forecasts as long as the market includes at least two smart informed traders who have sufficient ability to influence market outcomes. This result is consistent with the theory of perfect competition. We find that the result changes slightly when the forecast contains bias. With optimistic or pessimistic biased forecasts, at least three smart informed traders who have sufficient ability to influence market outcomes are necessary to produce a comparable result. This finding is consistent with Foster & Viswanathan's (1996) numerical results.

An important aspect of our findings is that the make-up of the market can dramatically affect asset price. Theoreticians need to consider this crucial feature in the development of models to explain price behavior. Incorporating heterogeneity, in terms of traders' cognitive processing abilities, and looking at the comparative statics of different trader compositions (i.e., the make-up of smart versus other traders) are fundamental to understanding price formation. We encourage theoretical research along these lines.

Lastly, our data indicate that traders do not have a preference for the biased forecast over the unbiased forecast, even though the former potentially provides a more precise estimate of asset value. The result likely arises because a significant proportion of traders have difficulty fully adjusting for systematic bias. An important question for future research is why traders are unable to completely adjust for optimistic or pessimistic bias. In our markets, some of the difficulty may arise from traders' inability to separate systematic and random error components. Future research may examine the relative magnitude of systematic to nonsystematic error components to determine when difficulties arise. It is unclear how much nonsystematic error is necessary to prevent traders from fully adjusting for systematic error.

Endnotes

[1] The instructions are available from the authors upon request.

[2] The dividend draw is rounded to the nearest dollar and all trading is in dollars.

[3] The use of a pre-selected sequence enhances comparability of markets conducted under similar as well as different experimental conditions. The pre-selected sequence also may be used in future research as a means to compare data from an earlier study (Cason & Friedman, 1996, note 4).

[4] Operationally, we numbered traders 1-8 and randomly selected four traders, who were assigned a zero tax rate for period 1, with the remainder assigned a tax rate of 40 percent. We followed the same procedure for periods 2-12; however, once a trader had been assigned a zero (40 percent) tax rate six times, the trader was removed from any further draws and assigned a 40 percent (zero) tax rate for the remaining periods. In markets with seven traders, each period three or four were assigned each tax rate. One trader number (always trader 8) was omitted across the 12 periods in these markets.

[5] The mean zero, random error term used to determine the forecast value is established prior to conducting the markets. For the unbiased forecasts, we randomly drew and used the same values across trading periods 1-12 in the NOBIAS, NOUP, and NODOWN markets. For the biased forecast, we randomly drew and used the values across trading periods 1-12 in the UPBIAS, DOWNBIAS, NOUP, and NODOWN markets.

[6] We administered this phase of the experiment after the 12 trading periods were completed so as not to influence participants' forecast acquisition decisions.

[7] Foster & Viswanathan (1996) examine the case in which informed traders possess diverse, but perfectly correlated estimates of asset value. A special case is when informed traders possess identical information, as in our markets with one forecast.

[8] The informed price also may be computed assuming that traders only possess the biased forecast (as it is computed in the UPBIAS and DOWNBIAS markets). Theoretically, this computation is appropriate if traders only acquire the biased forecast, even though unbiased *and* biased forecasts are available. As discussed subsequently, traders may prefer the biased forecast because it provides a more precise estimate of asset value, assuming that traders adjust for the systematic bias. Although not reported, both informed prices are used in the data analysis reported in the next section and inferences are unaffected.

[9] Experimental research indicates that traders' predictions of asset price, on average, are biased with prediction errors being correlated with observable variables (e.g., Peterson, 1993; Ackert & Church, 2001).

[10] Based on the parameter values used in the experimental markets, the absolute forecast error using the unbiased forecast is three times larger than that using the adjusted, biased forecast (i.e., assuming participants adjust for the systematic bias component). The absolute difference between the period-end dividend and the unbiased forecast ranges

from \$8 to \$150 with a mean of \$81.33. The absolute difference using the adjusted, biased forecast (i.e., adjusted for the systematic bias component) ranges from \$3 to \$65 with a mean of \$25.83. If participants fail to acquire the forecast and maintain an uninformed prior (i.e., the mean of the asset value distribution of \$1,200), the absolute forecast error ranges from \$65 to \$854 with a mean of \$285.83.

[11] As reported subsequently, neither the *number* of traders acquiring the forecast per period nor the *proportion* of informed traders per period differs across market sets or over periods.

[12] Specifically, $F = 0.09$, $p = 0.792$ for the NOBIAS markets, $F = 0.04$, $p = 0.868$ for the UPBIAS markets, $F = 2.28$, $p = 0.270$ for the DOWNBIAS markets, $F = 0.39$, $p = 0.596$ for the NOUP markets, and $F = 2.56$, $p = 0.251$ for the NODOWN markets.

[13] A repeated measures ANOVA indicates that the total number of transactions per period does not differ across market sets or over periods.

[14] A repeated measures ANOVA indicates that the increase in the NAPD does not differ across market sets. Further, the increase is zero in 75 of 180 periods and less than 5 percent in 145 of 180 periods.

[15] Inferences are unaffected using the proportion of transactions per period to achieve the minimum NAPD as the dependent measure. We also performed a repeated measures ANOVA in which we collapsed the data based on the number of forecasts available (one versus two). We find that the number of transactions to reach the minimum NAPD is smaller when two forecasts are available as opposed to one ($F = 6.38$, $p = 0.025$): the means are 3.53 and 4.86, respectively.

[16] We also classify traders using a Wilcoxon matched-pairs test. We determine whether traders' predictions are significantly different from asset value realizations. If we are able to reject the null hypothesis of no difference at the 10 percent significance level, the trader is classified as a biased trader. Otherwise, the trader is classified as a smart trader. Although not reported, inferences are unaffected using the alternative classification criterion.

[17] In Rustichini et al. (1994), buyers and sellers can each transact one certificate. Hence, individual traders do not have the ability to dramatically influence market outcomes.

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[18] We repeat the analysis using the proportion of traders acquiring the forecast per period as the dependent measure and inferences are unaffected.

[19] Inferences are unaffected using the proportion of traders acquiring each forecast per period as the dependent measure.

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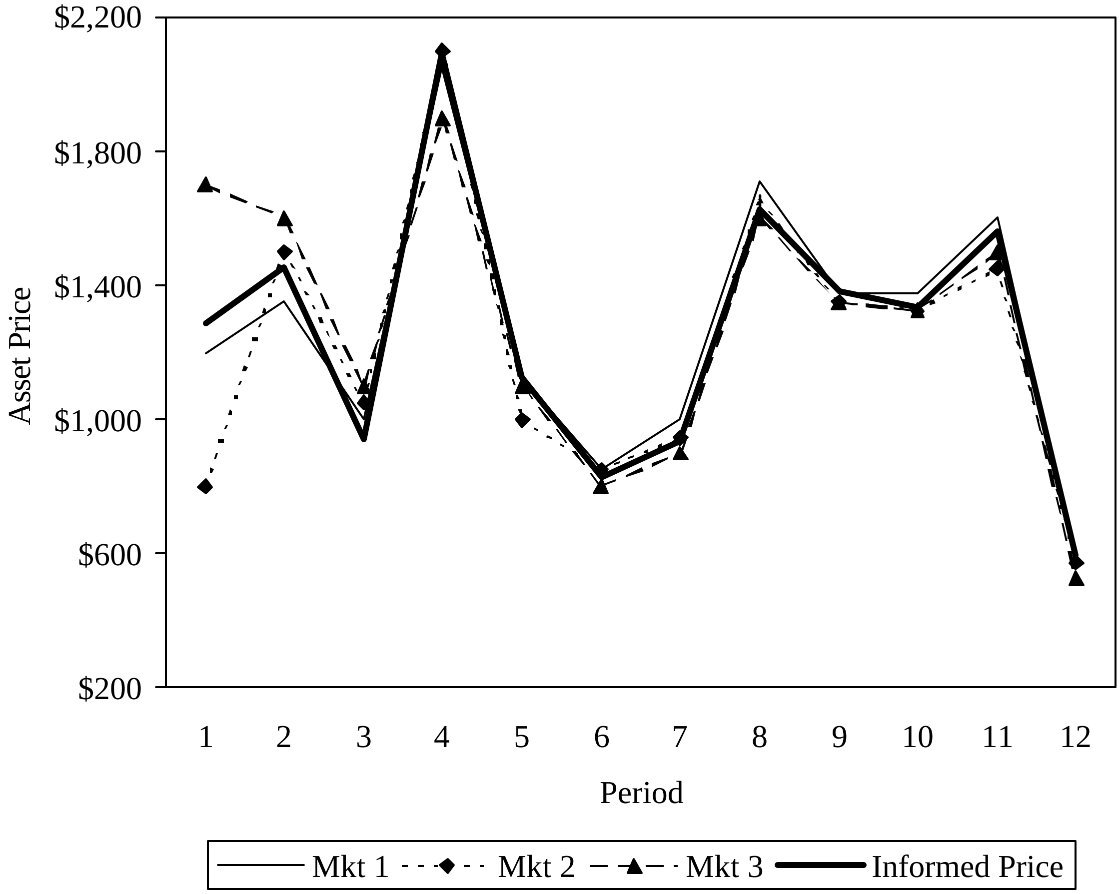

Figure 1 – The figure depicts the closing price per period in the NOBIAS markets (markets 1-3) as well as the informed price, which reflects the Bayesian updated price conditioned on the NOBIAS forecast.

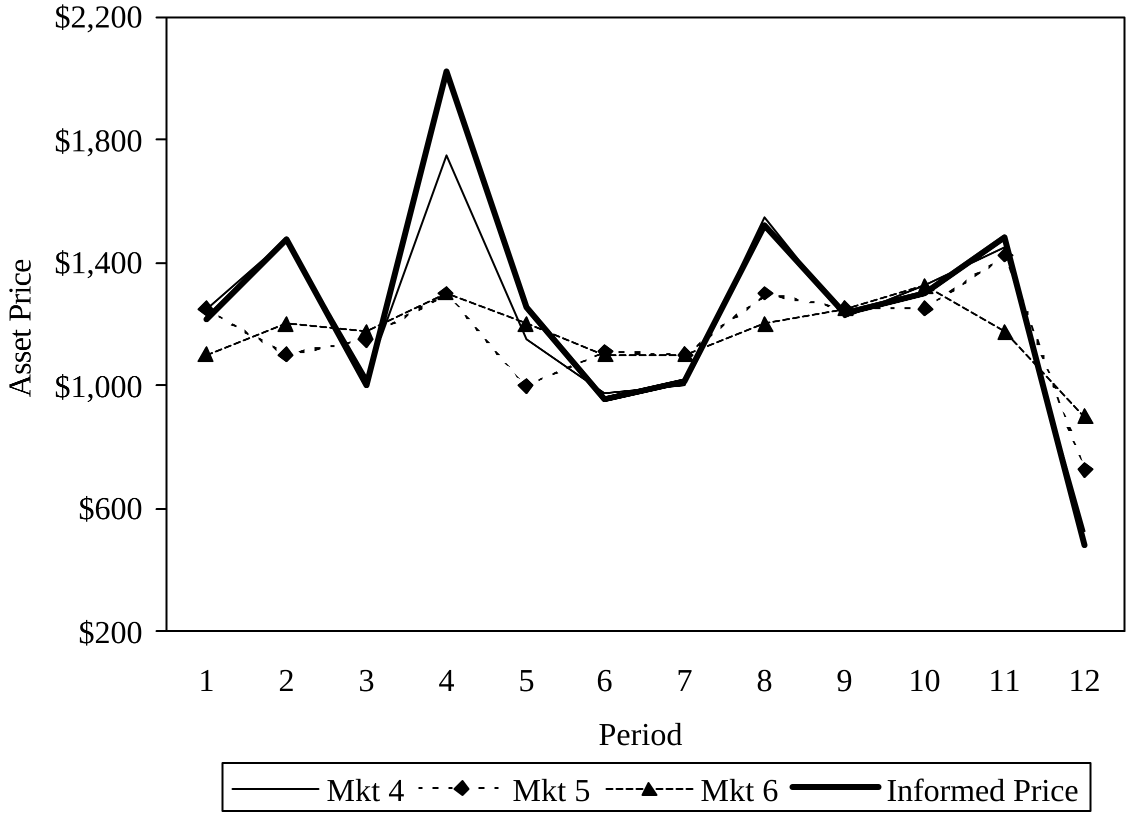

Figure 2 – The figure depicts the closing price per period in the UPBIAS markets (markets 4-6) as well as the informed price, which reflects the Bayesian updated price conditioned on the UPBIAS forecast.

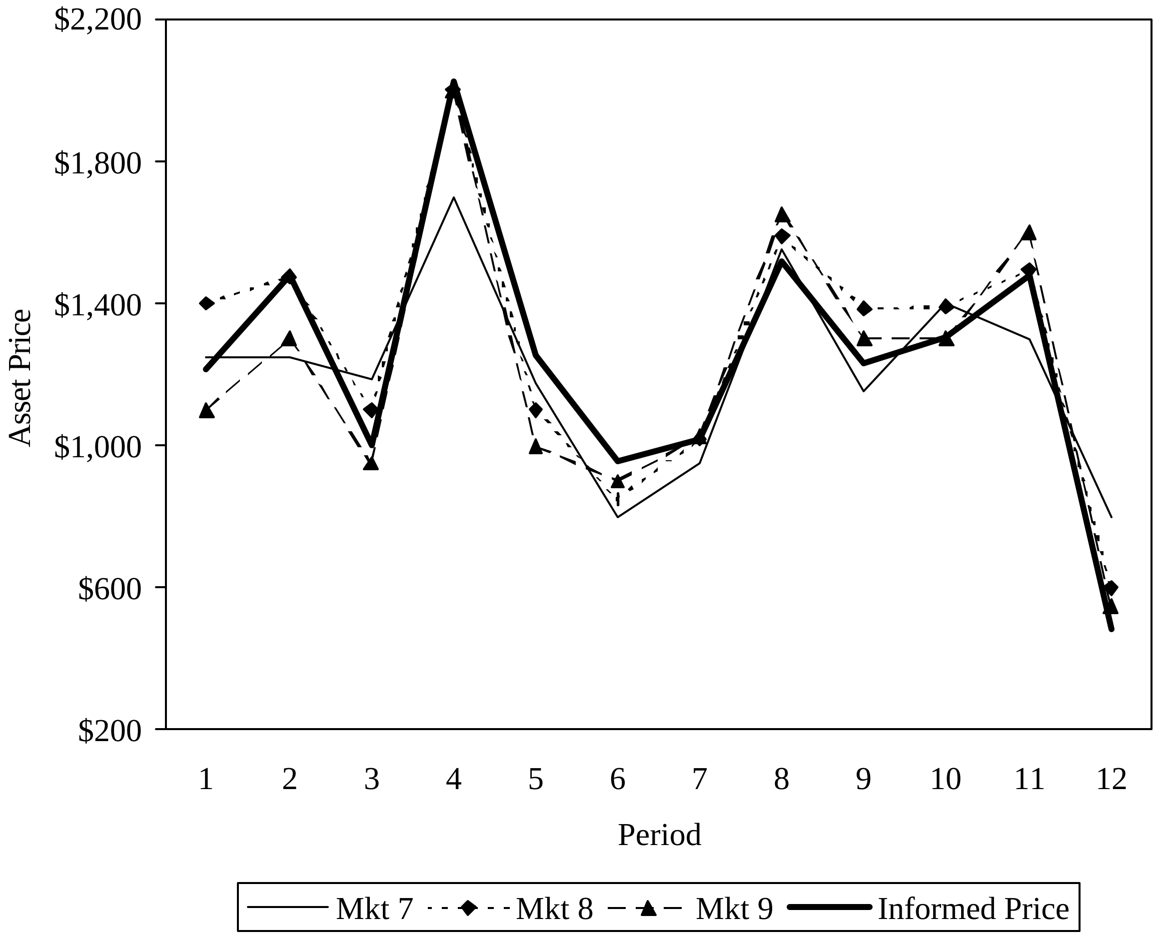

Figure 3 – The figure depicts the closing price per period in the DOWNBIAS markets (markets 7-9) as well as the informed price, which reflects the Bayesian updated price conditioned on the DOWNBIAS forecast.

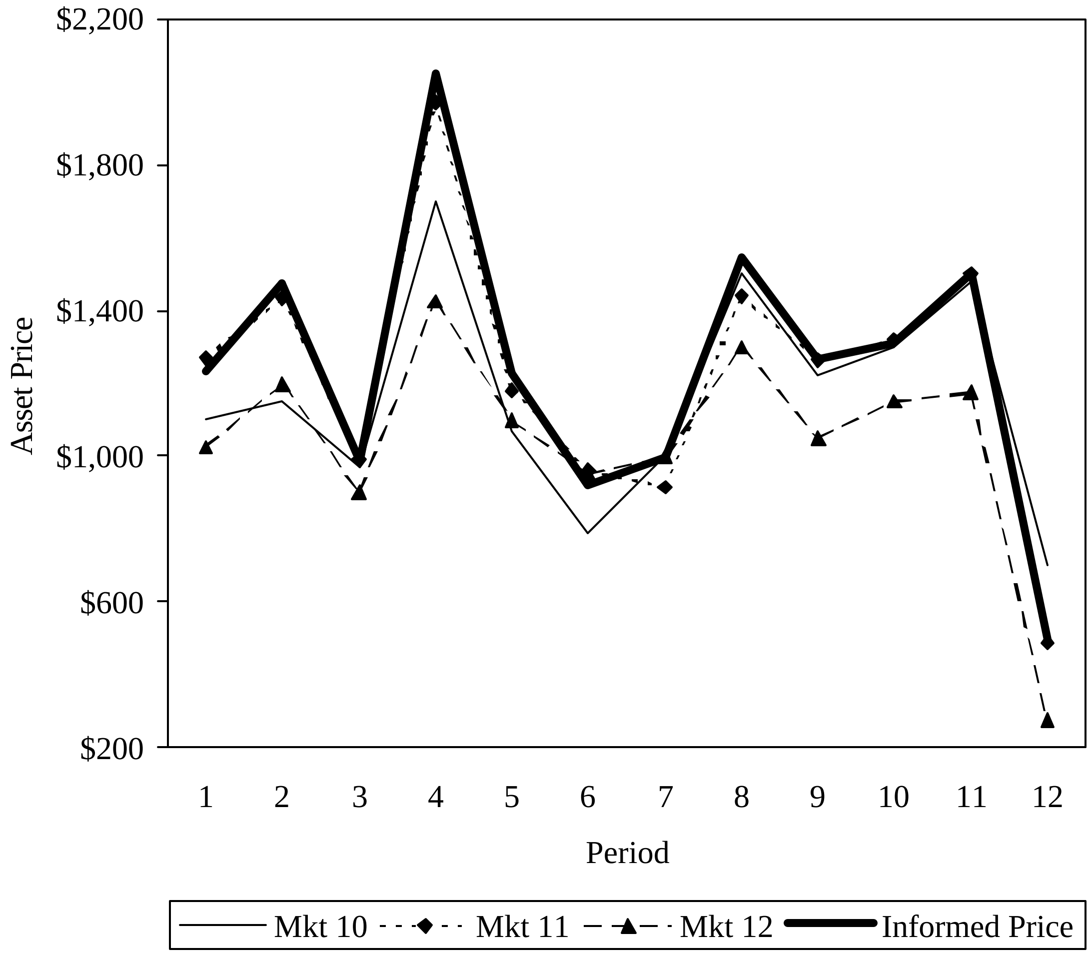

Figure 4 – The figure depicts the closing price per period in the NOUP markets (markets 10-12) as well as the informed price, which reflects the Bayesian updated price conditioned on the UPBIAS forecast.

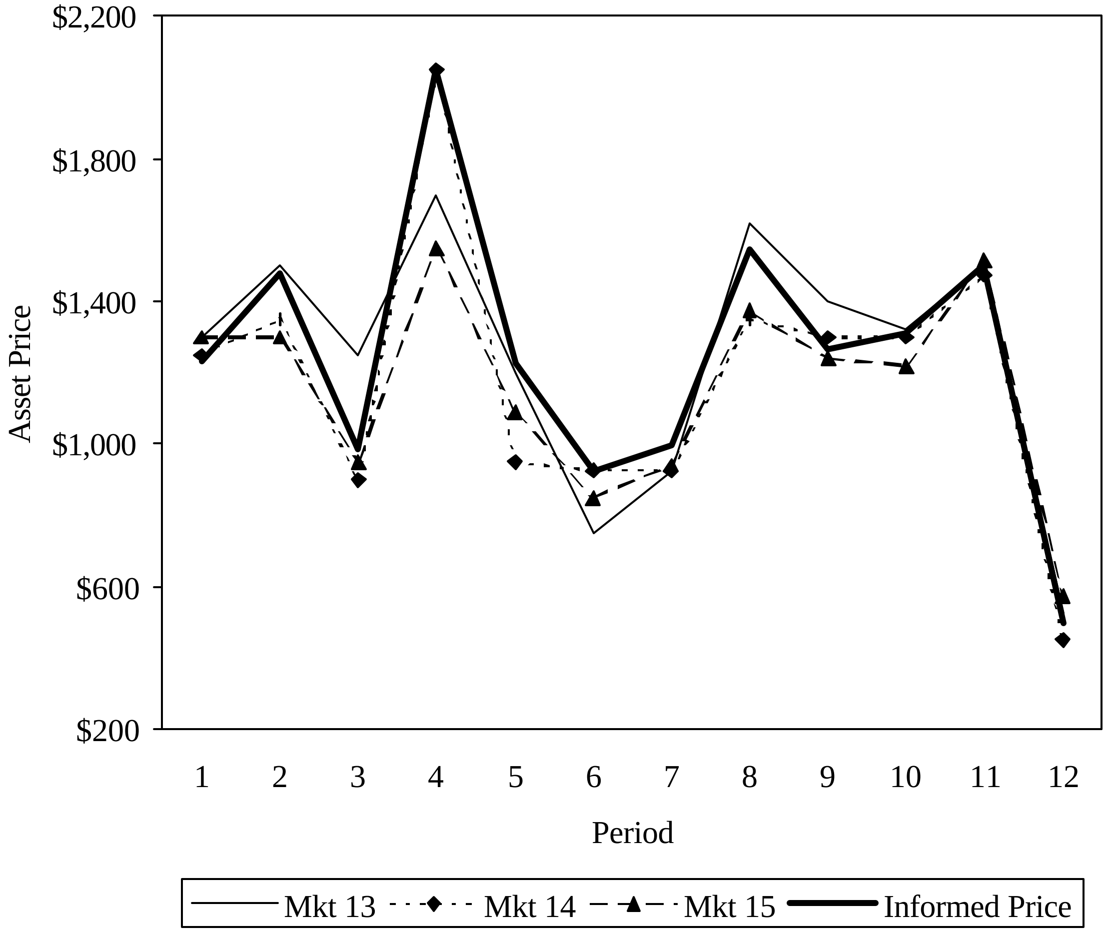

Figure 5 – The figure depicts the closing price per period in the NODOWN markets (markets 13-15) as well as the informed price, which reflects the Bayesian updated price conditioned on the DOWNBIAS forecast.

TABLE 1
Experimental design

Market	Referent	Forecast Available	Forecast Value[a]	Std Dev of Error
1-3	NOBIAS	Unbiased	Dividend + Error	100
4-6	UPBIAS	Upward Bias	Dividend + 200 + Error	50
7-9	DOWNBIAS	Downward Bias	Dividend - 200 + Error	50
10-12	NOUP	Unbiased	Dividend + Error	100
		Upward Bias	Dividend + 200 + Error	50
13-15	NODOWN	Unbiased	Dividend + Error	100
		Downward Bias	Dividend - 200 + Error	50

[a]The dividend is determined by drawing from a normal distribution with a mean of $1,200 and a standard deviation of $400. The forecast error term is determined by drawing from a normal distribution with a mean of zero and a standard deviation of $100 for the unbiased forecast and $50 for the biased forecasts.

TABLE 2
Forecast of asset value, the informed price, and realized asset value

Period	NOBIAS[a]		UPBIAS[a]		DOWNBIAS[a]		NOUP and NODOWN[a]	Realized Asset Value[e]
	Forecast	Inf. Price[b]	Forecast	Inf. Price[c]	Forecast	Inf. Price[c]	Inf. Price[d]	
1	1291	1286	1417	1217	1017	1217	1231	1265
2	1469	1453	1683	1479	1283	1479	1477	1461
3	928	944	1200	1003	800	1003	988	983
4	2148	2092	2237	2024	1837	2024	2049	2054
5	1124	1128	1456	1255	1056	1255	1229	1273
6	803	826	1149	953	749	953	923	953
7	922	938	1212	1015	812	1015	997	1020
8	1654	1627	1726	1521	1326	1521	1547	1529
9	1397	1385	1435	1234	1035	1234	1267	1300
10	1343	1335	1505	1303	1105	1303	1311	1276
11	1583	1560	1684	1480	1284	1480	1500	1531
12	558	596	670	596	270	481	496	503

[a]The NOBIAS forecast is an unbiased estimate of asset value. The UPBIAS and DOWNBIAS forecasts contain a constant bias of "200. For the UPBIAS and DOWNBIAS forecasts, the informed price is computed assuming that participants adjust for the bias. For the NOUP and NODOWN markets, the unbiased *and* biased forecasts are both available. The forecasts are the same as those made available in the NOBIAS, UPBIAS, and DOWNBIAS markets and, as such, are not repeated in the table. For the NOUP and NODOWN markets, the informed price is computed using both forecasts and assuming that participants adjust for the bias.

[b]In markets with the NOBIAS forecast, the informed price is a Bayesian updated price conditioned on the forecast. It is computed as $(F_A{}^2F_u + F_{Fu}{}^2\mu_A)/(F_A{}^2 + F_{Fu}{}^2)$, where F_A is the standard deviation of the asset value, F_u is the unbiased forecast, F_{Fu} is the standard deviation of the unbiased forecast, and μ_A is the mean asset value.

[c]In markets with UPBIAS and DOWNBIAS forecasts, the informed price is a Bayesian updated price conditioned on the forecast. It is computed as $(F_A{}^2F_b{}^{adj} + F_{Fb}{}^2\mu_A)/(F_A{}^2 + F_{Fb}{}^2)$, where $F_b{}^{adj}$ is the biased forecast adjusted for the systematic bias, F_{Fb} is the standard deviation of the biased forecast, and the other terms are as defined in note c.

[d]In markets with two forecasts (NOUP and NODOWN markets), the informed price is a Bayesian updated price conditioned on both forecasts. It is computed as $(F_A{}^2F_{Fb}{}^2F_u + F_A{}^2F_{Fu}{}^2F_b{}^{adj} + F_{Fu}{}^2F_{Fb}{}^2\mu_A)/(F_A{}^2F_{Fu}{}^2 + F_A{}^2F_{Fb}{}^2 + F_{Fu}{}^2F_{Fb}{}^2)$, where the terms are as defined in notes b and c.

[e]The realized asset value is the period-end dividend, which does not vary across markets.

TABLE 3
Descriptive data on the price formation process

Panel A: Nearness of the closing price per period to the informed price

Market Condition	Periods[a]		
	1-6	7-12	1-12
NOBIAS	0.092	0.034	0.063
UPBIAS	0.137	0.134	0.135
DOWNBIAS	0.105	0.099	0.102
NOUP	0.093	0.093	0.093
NODOWN	0.099	0.059	0.079

Panel B: Nearness of the opening price per period to the informed price

Market Condition	Periods[b]		
	1-6	7-12	1-12
NOBIAS	0.216	0.047	0.131
UPBIAS	0.173	0.206	0.189
DOWNBIAS	0.204	0.119	0.161
NOUP	0.160	0.128	0.144
NODOWN	0.112	0.116	0.114

Panel C: Proportion of transactions per period near the informed price

Market Condition	Proportion of transactions per period within[c]			
	5 percent	10 percent	15 percent	20 percent
NOBIAS	0.560	0.725	0.840	0.862
UPBIAS	0.351	0.498	0.631	0.749
DOWNBIAS	0.376	0.515	0.664	0.760
NOUP	0.338	0.556	0.695	0.849
NODOWN	0.302	0.667	0.795	0.866

Panel D: Number of transactions per period to reach the minimum NAPD

Market Condition	Periods[e]		
	1-6	7-12	1-12
NOBIAS	4.56	4.11	4.33
UPBIAS	4.44	5.06	4.75
DOWNBIAS	5.61	5.39	5.50
NOUP	4.61	3.33	3.97
NODOWN	2.89	3.28	3.08

[a]The cell entries indicate the mean absolute difference between the closing price per period and the informed price, normalized by the informed price (NAPD).
[b]The cell entries indicate the mean absolute difference between the opening price per period and the informed price, normalized by the informed price (NAPD).
[c]The cell entries indicate the mean proportion of transactions per period that result in an NAPD (based on the transaction price) equal to or less than 5, 10, 15, and 20 percent. Although not reported, the means are similar using the proportion of transactions per period within $50, $100, $150, and $200 of the informed price.
[d]The cell entries indicate the mean number of transactions per period that occur to reach the minimum NAPD for a period. Although not reported, inferences are unaffected if the measure is normalized by the total number of transctions that occur in a period.

TABLE 4
Traders' predictive abilities

Panel A: Classification of traders' predictive abilities using unbiased forecasts[a]

Market Condition	Traders' Predictions Are		
	Unbiased	Biased Downward	Biased Upward
NOBIAS	20	3	1
NOUP	19	2	1
NODOWN	17	6	0
Total	56	11	2

$\chi^2 = 3.55$, $p = 0.470$

Panel B: Classification of traders' predictive abilities using optimistic bias forecasts[a]

Market Condition	Traders Predictions Are		
	Unbiased	Biased Downward	Biased Upward
UPBIAS	12	1	10
NOUP	13	0	9
Total	25	1	19

$\chi^2 = 1.07$, $p = 0.585$

Panel C: Classification of traders' predictive abilities using pessimistic bias forecasts[a]

Market Condition	Traders Predictions Are		
	Unbiased	Biased Downward	Biased Upward
DOWNBIAS	16	7	0
NODOWN	16	7	0
Total	32	14	0

$\chi^2 = 0.00$, $p = 1.00$

[a]Traders are classified as being able to make unbiased or biased predictions of asset value based on their performance in the prediction periods. For each trader, we determine whether the sign of the trader's prediction errors is consistently positive or negative. If five of six signs are the same, the trader is classified as biased: upward if the sign is consistently positive and downward if it is consistently negative. If the sign of the prediction errors is not consistently positive or negative, the trader is classified as unbiased. For markets with one forecast (NOBIAS, UPBIAS, and DOWNBIAS), each trader is classified as making unbiased or biased predictions of asset value conditioned on the trader's use of a unbiased or biased forecast. For markets with two forecasts (NOUP and NODOWN), each trader is classified twice: once based on the trader's use of the unbiased forecast and again based on the biased forecasts.
[b]The χ^2-statistic tests whether the mix of traders making unbiased and biased predictions of asset value differs across the relevant market sets, with the p-values being two-tailed.

TABLE 5
Association between the number of smart informed traders and the NAPD per period

Panel A: NOBIAS markets[a]

Smart Informed Traders[a]	Observations	Average NAPD[b]	Percent of Smart Informed Trades[c]
0	0	-	-
1	1	0.378	0.667
2	0	-	-
3	3	0.059	0.833
4	8	0.058	0.812
5	16	0.048	0.989
6	6	0.022	0.985
7	2	0.194	1.000

Panel B: UPBIAS markets[a]

Smart Informed Traders[a]	Observations	Average NAPD[b]	Percent of Smart Informed Trades[c]
0	2	0.252	0.000
1	11	0.196	0.295
2	10	0.157	0.541
3	1	0.171	1.000
4	0	-	-
5	2	0.093	0.967
6	8	0.032	0.990
7	2	0.015	1.000

Panel C: DOWNBIAS markets[a]

Smart Informed Traders[a]	Observations	Average NAPD[b]	Percent of Smart Informed Trades[c]
0	0	-	-
1	0	-	-
2	2	0.317	0.438
3	4	0.180	0.900
4	10	0.113	0.811
5	11	0.066	0.910
6	9	0.050	1.000
7	0	-	-

[a]Smart informed traders represents the number of informed traders who are classified as making unbiased predictions of asset value.
[b]The NAPD is the absolute difference between the closing price per period and the informed price, normalized by the informed price.
[c]The percent of smart informed trades represent the percentage of transactions per period that involve at least one smart informed trader.

TABLE 6
Association between the number of smart informed buyers and the NAPD per period

Panel A: NOBIAS markets[a]

Smart Informed Buyers[a]	Observations	Average NAPD[b]	Percent of Smart Informed Buyer Trades[c]
0	0	-	-
1	4	0.111	0.316
2	17	0.059	0.506
3	11	0.039	0.686
4	4	0.100	0.900

Panel B: UPBIAS markets[a]

Smart Informed Buyers[a]	Observations	Average NAPD[b]	Percent of Smart Informed Buyer Trades[c]
0	0	-	-
1	6	0.195	0.476
2	10	0.100	0.649
3	15	0.075	0.755
4	5	0.073	0.883

Panel C: DOWNBIAS markets[a]

Smart Informed Buyers[a]	Observations	Average NAPD[b]	Percent of Smart Informed Buyer Trades[c]
0	9	0.147	-
1	9	0.234	0.331
2	8	0.148	0.661
3	8	0.026	0.779
4	2	0.025	0.944

[a]Smart informed buyers represent the number of informed traders who are classified as making unbiased predictions of asset value *and* have a zero tax rate on dividends.
[b]The NAPD is the absolute difference between the closing price per period and the informed price, normalized by the informed price.
[c]The percent of smart informed buyer trades represents the percentage of transactions per period that involve at least one smart informed trader who has a zero tax rate on dividends.

TABLE 7
Forecast acquisition decisions per period when two forecasts are available

Market Condition	Forecast[a]	Periods[b]		
		1-6	7-12	1-12
NOUP	Unbiased	2.83	3.33	3.08
	Biased	1.17	1.39	1.28
	Both	2.06	1.56	1.81
NODOWN	Unbiased	2.89	2.83	2.86
	Biased	2.78	3.11	2.94
	Both	0.39	0.39	0.39

[a]Each period, traders could acquire an unbiased more variable forecast, a biased less variable forecast, or both forecasts.
[b]The cell entries indicate the average number of times that traders acquired unbiased, biased, and both forecasts per period.

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