Learning from Prices in Models of Higher Order Beliefs

by

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Abstract

This experiment examines forecasting behavior under varying information conditions to assess the extent to which traders in asset markets incorporate information in prices to resolve fundamental certainty *and* to resolve higher-order uncertainty. Fundamental uncertainty refers to a trader's uncertainty about fundamental value of the asset while higher-order uncertainty refers to uncertainty about the beliefs of other traders about fundamental value of the asset. Such higher-order uncertainty is at the core of a large stream of more recent theoretical literature looking at information and price anomalies in asset markets. I find strong evidence that in an experimental asset market where higher-order beliefs play a role, subjects do not *fully* impound the information contained in prices to resolve either of the two uncertainties. However, in so far as resolving the higher-order uncertainty is concerned, they seem to *bette*r impound the information contained in other publicly available pieces of information.

Keywords. Higher-order Beliefs, Learning from Prices, Single-period Security Market, Belief Elicitation

1. Introduction

This experiment examines forecasting behavior under varying information conditions to assess the extent to which traders in asset markets incorporate information in prices to update their own beliefs about asset value and to resolve higher-order uncertainty. Higher-order uncertainty refers to a decision maker's uncertainty regarding the uncertainty of other decision makers (Morris, 1995; Shin, 1996; Feinberg and Skrzypacz, 2005; Kondor, 2012).

My experiment uses elicited forecasts before and after trading to examine if decision makers use prices to update their expectation of dividend value and their beliefs about the beliefs of others. In my experiment participants are endowed with cash and an asset paying an uncertain amount at the end of the experimental round. In each round participants begin with a common prior and each receives a private signal, which consists of an independent draw from a commonly known distribution. Each participant then privately submits two personal estimates, an estimate of the expected dividend, and an estimate of the group average estimate. Participants then engage in trade using a double auction. After the auction participants again submit estimates of the expected dividend distribution and the average group estimate. After this the dividend is announced. Upon announcement of the dividend, participants receive feedback on their forecast errors for each estimate they submitted. Participant accounts are updated for trading cash flow, dividends, and a tax based on their forecast errors.[1]

The first-round forecast of the dividend should be the expected dividend, conditional on the individual's private signal. The first-round forecast of the average opinion should be based on the forecaster's revised signal distribution, conditional on her private signal. A comparison of these first-round forecasts with the second-round forecasts allows one to see whether participants use the information contained in prices to update their own beliefs about the asset value and / or to resolve higher-order uncertainty. Note that the trading price is the only statistic available between the first-round and second-round forecast.

[1] Imposing an explicit tax on forecast error is meant to sharpen the incentive to forecast and to truthfully announce one's forecasts prior to trading. In the RE models (Allen, et. al. 2006; Gao, 2008, and Banerjee et. al. 2009), the forecast accuracy incentive is inherent, but the forecast reporting incentive is not.

In the first set of experiments, I find that while subjects use the information contained in prices to update their priors, the posteriors for both the expected dividend and for the forecast of average opinion do not coincide with the price. That is, information contained in prices is not fully impounded in forming posterior expectations. This raises the question whether information contained in *any* public statistic is not fully impounded in forming posterior expectations. To answer this, I ran another set of experiments and this time an additional piece of public information was made available to the participants before trading commenced. The pre-trading expected dividend estimate of each participant was averaged and publicly announced. I find that the information contained in this additional statistic is better impounded in forming posterior expectations.

The theoretical literature on higher-order uncertainty comes mostly from two sources: Rational Expectations model (RE) and Differences of Opinion model (DO). In the market setting, RE predicts that price information will be utilized by traders to coordinate expectations, establishing a publicly known common opinion on expected payout. The DO model depicts trading where participants form their fundamental expectations based on their private information and do not update their expectations using market price. The root of this behavior is in a participant's refusing to accept the credibility of the private information of others, yet trusting the credibility of their own private information. A trader who believes that other traders are using price, however mistakenly, to form their dividend expectation might personally believe price does not reflect dividend value; but price would still fairly reflect the average opinion of dividend value. Under RE, the second-round forecasts of the expected dividend and of the average opinion should coincide with the market price. Under DO, the second-round forecast of the expected dividend should coincide with the first-round forecast while the second-round forecast of the average opinion should coincide with price.

Early noisy rational expectations models of the aggregation of private information in asset prices come from Grossman (1976, 1980), Hellwig (1980), and Diamond and Verrecchia (1981). Experimental evidence on information aggregation in asset prices provided by Plott and Sunder (1982, 1988) and Forsythe et al (1982) is mixed. Rational Expectations theory tends to receive stronger support when there is perfect private information or a subset of perfectly informed traders.

Plott and Sunder (1982) create a setting where traders have a common prior on the underlying state, and some traders are privately informed of the true state. The state determines how much the asset will pay to each trader. But traders have diverse preferences in that dividend payoffs also depend on trader type. The authors posit two potential models. The Rational Expectations (RE) model predicts full information aggregation; all private information is revealed in price. The Prior Information (PI) model predicts no information aggregation. Asset price should reflect the highest prior valuation. The RE prediction of price and asset allocation is strongly supported in their study.

Forsythe et al (1982) examine a two-period security paying traders different amounts in each period. Traders in this experiment also have diverse preferences; the periodic dividend of each security was different for different trader types. Each trader knows only his or her own valuation, not that of others. They also find support for RE, but while second-period price strongly supports RE predictions, first period prices do not immediately converge to the RE prediction. Individual trades occur at prices that do not consistently reflect the reservation prices of traders, and ignore arbitrage opportunities. There is evidence that replication of both periods of trade is necessary and sufficient for period A price to converge to the RE prediction.

Plott and Sunder (1988) introduce a setting where traders have diverse state-contingent valuations, and no trader is certain of the underlying state. On an aggregate basis, there is no state uncertainty; knowledge of the state depends on the aggregation of diverse information in trading. In this setting a single security market fails to achieve the RE predicted price or allocation, but a market with a complete set of state-contingent securities does support the prediction.

Guarnaschelli, Kwasnica, and Plott (Guarnaschelli et al. 2002) examine information aggregation in a double auction setting with symmetrical state-contingent valuations. Their information structure does contain aggregate state uncertainty; full information aggregation does not reveal the true fundamental value. This structure has previously given rise to winner's curse when the trading institution is a sealed-bid auction (Kagel and Levin, 1986). In a double auction setting a winner's curse should arise under the PI model but not under the RE model. The results do not absolutely support either model, but the price appears to show some information aggregation and is closer to the RE prediction than the PI prediction.

In the above experiments, where the PI model is invoked, it is not provided an explicit rationale. But the PI prediction is consistent with the formation of beliefs under the Difference of Opinion (DO) model. The DO model, as characterized by Harrison and Kreps (1978) and later by Harris and Raviv (1993), has been used to explain speculative premia and empirically observed phenomena, such as serial correlation in price changes and trading volume (e.g., Harrison and Kreps (1978), Harris and Raviv (1993), Kandel and Pearson (1995), Scheinkman and Xiong (2003), Banerjee and Kremer (2010)). In these models, traders are aware that other traders' expectations of the fundamental value of the asset differ from their own beliefs, but they agree to disagree about that value. In other words, all traders agree that the valuations of others, which are assumed to be common knowledge, are erroneous. Thus, each trader relies on her own information, ignoring information in price. More recently, DO models have incorporated learning from prices. In the DO model of Banerjee and Green (2015), investors may exhibit differences of opinion, but uninformed investors still condition on prices to update their beliefs about fundamentals. In the DO model of Banerjee et al. (2009), investors agree to disagree but depending upon the level of disagreement, they may use the price to update their beliefs about higher order expectations. The behavioral finance models (e.g. Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999)) do not explicitly invoke higher-order beliefs but rely on investor over-confidence in their own private signals to explain investors' undermining of publicly available information including the information contained in prices.

The literature on higher order beliefs invokes the "beauty contest effect" to describe deviation of asset prices from expected dividend value in a double auction. The beauty contest idea of price formation states that market traders are not making bids and offers based on their expectation of the assets fundamental value, but rather on their expectation of the beliefs of other traders. The beauty contest effect requires a higher order of uncertainty than traditionally invoked in the difference of opinion model. It applies to settings where traders do not know the average belief of other traders. The effect is similar, however; price strays from fundamental dividend value when traders assess that others do not take price to reflect fundamental dividend value. Forsythe et al

(1982) invoke the beauty contest effect as an alternative to RE pricing. But the impact of the beauty contest effect on asset prices is driven by the way beliefs are modeled. The beauty contest effect has been modelled in a RE setting by Allen et al (2006), Banerjee et al (2009), and Gao (2009) as the result of a public information announcement. These models begin by imposing uncertainty about the uncertainty of other traders. These models show a rift between asset value and price due to the incorporation of public information into higher order beliefs.

Early theory on the emergence of common knowledge in private information settings comes from Jordan (1982) and McKelvey and Page (1986). These models describe an inference process, where decision makers facing state uncertainty, endowed with private information, privately report their posterior probabilities on the state. They receive a publicly announced summary statistic on the reports in each round and use the statistic to update their expectation. Over repeated reports, the private information is revealed and a consensus posterior probability emerges. McKelvey and Page (1990) present experimental evidence examining the inference process. Their experiment is designed to reach consensus within a few periods. They find considerable variation in their data. They report participants tended to underweight the evidence provided by the signal, so their predictions tended toward the prior probability. Strikingly this tendency continued even when all private information was explicitly revealed. This provides early evidence either of an inability to update using the public statistic or an unwillingness to lend it credibility.

My experiment also contributes to the body of knowledge on speculative trading in laboratory markets by focusing on participants' use of private information and subsequent use of price information. Breakdowns of RE are a common occurrence in laboratory markets. Smith et al (1988) document price bubbles and crashes that they attribute to speculative trading based on traders' belief that other traders are irrational. This is consistent with the observation of Forsythe et al (1982), described above. Lei et al (2001) examine a similar market where opportunity for price speculation is removed and they still find bubbles and crashes, leading to the conclusion that traders simply are irrational. I explicitly break down the process of expectations formation that is supposed to occur simultaneously in the laboratory markets. I make explicit the incentives for correctly updating beliefs that are implicit but perhaps weak in laboratory markets. If participants do behave irrationally, I should be able to observe where the breakdown starts. Anctil, Lunawat and O'Brien (2014) examines the effect of the forecasting exercise per se on trading itself.

The next section of this paper provides the basic theoretical framework for the experiment.

2. Hypothesis Development

The experiment groups *I* risk-neutral traders. Each trader *i* is endowed at the beginning of each experimental round with cash C^i, and K^i shares of a risky security. The security's liquidation value $\tilde{v}$ is a random variable, normally distributed with mean θ and precision $\frac{1}{\sigma}$. That is, $\tilde{v}\sim N(\theta,\sigma)$. Each trader receives a different private signal $\tilde{x}_i$, where $\tilde{x}_i = \tilde{v} + \tilde{\epsilon}_i$, and $\tilde{\epsilon}_i$ is independently and normally distributed with mean 0 and precision $\frac{1}{\eta}$. Note that $\tilde{x}_i|v \sim N(v,\eta)$. One experimental round consists of the timeline showed in Figure 1. The participants make pre-trading forecasts of both the expected dividend and the average opinion of the market participants about the expected dividend. Then, they trade in double auction. After the trade, they make post-trading forecasts of both the expected dividend and the average opinion of the market participants about the expected dividend. Finally, the dividend is realized and the payoffs are distributed. The pre-trading and post-trading forecast stages are described in greater detail next.

Pre-trading forecast stage: Each subject reports to the experimenter her prediction of $\tilde{v}$, denoted by $E^i_{F1}(\tilde{v})$ and her prediction of the average value of $\tilde{v}$ that everyone else will report, denoted by $\bar{E}^i_{F1}(\tilde{v})$. Note that $E^i_{F1}(\tilde{v}) = E_i(\tilde{v}|x_i)$ and $\bar{E}^i_{F1}(\tilde{v}) = E_i\bar{E}(\tilde{v})|x_i$.

Observing signal $\tilde{x}_i$, a Bayesian trader *i* assesses the expected liquidating dividend as $E_i(\tilde{v}|x_i) = \frac{\frac{\theta}{\sigma}+\frac{x_i}{\eta}}{\frac{1}{\sigma}+\frac{1}{\eta}} = \frac{\eta\theta+\sigma x_i}{\eta+\sigma}$.

Having observed her own signal $\tilde{x}_i$, a trader should revise her beliefs about the signal received by others as follows:

$E_j(\tilde{v}|x_j) = \frac{\frac{\theta}{\sigma}+\frac{x_j}{\eta}}{\frac{1}{\sigma}+\frac{1}{\eta}} = \frac{\eta\theta+\sigma x_j}{\eta+\sigma}$

And $\tilde{x}_j|x_i \sim N(E_i(\tilde{v}|x_i), Var(\tilde{v}|x_i) + Var(\tilde{\epsilon}_i))$

That is, $\tilde{x}_j|x_i \sim N(\frac{\eta\theta+\sigma x_i}{\eta+\sigma}, \frac{\eta\sigma}{\eta+\sigma} + \eta)$

Therefore, $E_iE_j(\tilde{v}|x_j)|x_i = E_i(\frac{\eta\theta+\sigma\tilde{x}_j}{\eta+\sigma}|x_i) = \frac{\eta\theta+\sigma E(\tilde{x}_j|x_i)}{\eta+\sigma} \quad = \frac{\eta\theta}{\eta+\sigma} + \frac{\sigma}{\eta+\sigma}.\frac{\eta\theta+\sigma x_i}{\eta+\sigma}$

The trader assesses the expected average opinion based on her revised signal distribution, conditional on her private signal.

$E_i\bar{E}(\tilde{v})|x_i = \frac{1}{n}E_i(\tilde{v}|x_i) + \frac{1}{n}E_i\sum_{j\neq i}E_j(\tilde{v}|x_j)|\,x_i$, where n denotes the number of traders.

$= \frac{1}{n}.\frac{\eta\theta+\sigma x_i}{\eta+\sigma} + \frac{1}{n}E_i\sum_{j\neq i}E_j(\tilde{v}|x_j)|x_i = = \frac{1}{n}.\frac{\eta\theta+\sigma x_i}{\eta+\sigma} + \frac{n-1}{n}E_iE_j(\tilde{v}|x_j)|x_i$

$= \frac{1}{n}.\frac{\eta\theta+\sigma x_i}{\eta+\sigma} + \frac{n-1}{n}\left(\frac{\eta\theta}{\eta+\sigma} + \frac{\sigma}{\eta+\sigma}.\frac{\eta\theta+\sigma x_i}{\eta+\sigma}\right).$

The following hypothesis summarizes the above discussion about pre-trading stage.

Hypothesis 1A. The pre-trading dividend forecast is given by $E_i(\tilde{v}|x_i) = \frac{\eta\theta+\sigma x_i}{\eta+\sigma}$.

Hypothesis 1B. The pre-trading forecast of average opinion is given by $E_i\bar{E}(\tilde{v})|x_i = \frac{1}{n}.\frac{\eta\theta+\sigma x_i}{\eta+\sigma} + \frac{n-1}{n}\left(\frac{\eta\theta}{\eta+\sigma} + \frac{\sigma}{\eta+\sigma}.\frac{\eta\theta+\sigma x_i}{\eta+\sigma}\right).$

Post-trading forecast stage: Each subject reports to the experimenter her prediction of $\tilde{v}$, denoted $E^i_{F2}(\tilde{v})$ and her prediction of the average value of $\tilde{v}$ that everyone else will report, denoted $\bar{E}^i_{F2}(\tilde{v})$. A comparison of the pre-trading and post-trading forecasts will allow me to assess whether price plays a role in forecasting behavior.

I will first develop the hypotheses for the first set of experiments (referred to as the "No Information" condition hereinafter) where the trading price is the only statistic available to the participants between the pre-trading and post-trading forecasts.

Hypothesis 2. Individuals revise their dividend forecast in the direction of price. Note that this is consistent with RE.

$E^i_{F2}(\tilde{v}) = P$

Alternative Hypothesis: Individuals do not revise their dividend forecast. Note that this is consistent with DO.

$E^i_{F2}(\tilde{v}) = E^i_{F1}(\tilde{v})$

Hypothesis 3. Individuals revise their forecast of the average opinion in the direction of price. Note that this is consistent with both RE and DO.

$\bar{E}^i_{F2}(\tilde{v}) = \bar{E}^i_{F1}(\tilde{v}) = \mathrm{P}$

Alternative Hypothesis: It is possible that individuals completely ignore the information contained in prices. That is, they do not revise their forecast of the average opinion given price.

$\bar{E}^i_{F2}(\tilde{v}) = \bar{E}^i_{F1}(\tilde{v})$

I will now develop the hypotheses for the second set of experiments (referred to as the "Information" condition hereinafter) where an additional piece of public information was made available to the participants before trading commenced. The pre-trading expected dividend estimate of each participant was averaged and publicly announced. This publicly announced statistic is sometimes hereinafter referred to as the "aggregate disclosure".

Hypothesis 4. Individuals revise their dividend forecast in the direction of price. Note that this is consistent with RE.

$E^i_{F2}(\tilde{v}) = P$

Alternative Hypothesis: Individuals ignore the information contained in prices but revise their dividend forecast in the direction of the aggregate disclosure that is publicly announced. Such revision implies that they set their post-trading dividend forecast equal to the expected dividend given their private signal and the aggregate disclosure.

$E^i_{F2}(\tilde{v}) = E_i\left(\tilde{v} | x_i, \pi\right)$, where π denotes the aggregate disclosure

Another Alternative Hypothesis: It is possible that individuals completely ignore the information contained in prices *and* in the publicly announced aggregate disclosure. That is, they do not revise their dividend forecast. Note that this is consistent with DO.

$E^i_{F2}(\tilde{v}) = E^i_{F1}(\tilde{v})$

Hypothesis 5. Individuals revise their forecast of the average opinion in the direction of price. Note that this is consistent with both RE and DO.

$\bar{E}^{i}_{F2}(\tilde{v}) = P$

Alternative Hypothesis: Individuals ignore the information contained in price but revise their forecast of the average opinion in the direction of the aggregate disclosure that is publicly announced. . Such revision implies that they set their post-trading forecast of average opinion equal to the aggregate disclosure.

$\bar{E}^{i}_{F2}(\tilde{v}) = \pi$, where π denotes the aggregate disclosure

Another Alternative Hypothesis: It is possible that individuals completely ignore the information contained in prices *and* in the publicly announced average dividend forecast. That is, they do not revise their forecast of the average opinion.

$\bar{E}^{i}_{F2}(\tilde{v}) = \bar{E}^{i}_{F1}(\tilde{v})$

Hypothesis 4 uses the term $E_i\left(\tilde{v}|x_i,\pi\right)$. I will formulate this term next.

Average pre-trading dividend forecast = $\pi = \frac{1}{n}\sum_i E_i(\tilde{v}|x_i) = \frac{1}{n}\sum_i \frac{\eta\theta+\sigma x_i}{\eta+\sigma} = \frac{1}{n}\left[\frac{\eta\theta}{\eta+\sigma} + \frac{\sigma\sum_i x_i}{\eta+\sigma}\right]$

$Var(\pi) = \left(\frac{\sigma}{\eta+\sigma}\right)^2 \sum_i Var(x_i) = n\left(\frac{\sigma}{\eta+\sigma}\right)^2 \eta.$

$Precision(\pi) = \frac{(\eta+\sigma)^2}{n\eta\sigma^2}.$

Expected dividend, conditional on the individual's private signal and the aggregate disclosure =

$$E_i(\tilde{v}|x_i,\pi) = \frac{\frac{\theta}{\sigma}+\frac{x_i}{\eta}+\frac{(\eta+\sigma)^2}{n\eta\sigma^2}\pi}{\frac{1}{\sigma}+\frac{1}{\eta}+\frac{(\eta+\sigma)^2}{n\eta\sigma^2}}$$

3. Experiment Design

I had groups of 8 subjects, that is, I set $I = 8$. I had two between-subject treatments / conditions – the No Information condition and the Information condition. The subjects were recruited from the subject pool at the Experimental Social Sciences Laboratory at University of California, Irvine. The subject pool comprises of those undergraduate students at the university that have volunteered to participate in experiments. All subjects, including those that were turned away due to over-show, were paid a show-up fee of $7. After the subjects signed in, they were given a hard copy of the Instructions (a copy is included in the Appendix). They followed along on their copies as the experimenter read the Instructions aloud. Any questions from the subjects were answered privately, after which the computerized experiment began. The experiment was coded using *z-tree* (Fischbacher 2007).

There were twenty rounds of the experiment, of which the first four were practice rounds. In each round, the subjects had to make some forecasts and trade in the shares of *a* security. The security was liquidated at the end of the round. The liquidating dividend realizations were independent within the set of twenty securities (one security for each of the twenty rounds). For each security, I generated a dividend from a normal distribution with mean 500 and standard deviation 50. That is, I set $\frac{1}{\sigma} = \frac{1}{50^2}$ and $\theta = 500$.

Then, for each security, I generated eight private signals that had independent noise terms which were distributed with mean 0 and standard deviation 50. Each of the eight traders received one private signal. Since the standard deviation of the noise term for each signal is 50, the precision of each trader's private information was $\frac{1}{\eta} = \frac{1}{50^2}$.

I generated one set of twenty securities with dividend and private signals and used this set for all sessions of the No Information condition and all sessions of the Information condition. That way, all my sessions (even across treatments) were informationally identical. The last sixteen of the set of twenty securities with dividend and private signals is shown in Table 1.

After the subjects received their private signals, they were asked to make the following two forecasts:

1. A forecast of the dividend.
2. A forecast of the average of all traders' pre-trading forecast of the dividend.

Given the parameters selected earlier, I have:

[2]Expected dividend given a trader's private signal = $E_i(\tilde{v}|x_i) = \frac{\frac{1}{50^2}.500+\frac{1}{50^2}.x_i}{\frac{1}{50^2}+\frac{1}{50^2}} = \frac{500+x_i}{2}$

Therefore, $E_iE_j\left(\tilde{v}\middle|x_j\right)|x_i = \frac{50^2.500}{50^2+50^2} + \frac{50^2}{50^2+50^2}.\frac{50^2.500+50^2x_i}{50^2+50^2} = 250 + \frac{1}{2}.\frac{.500+x_i}{2} = \frac{1500+x_i}{4}$

[3]Forecast of the average opinion = $E_i\bar{E}(\tilde{v})|x_i = \frac{1}{8}.\frac{500+x_i}{2} + \frac{7}{8}.\frac{1500+x_i}{4}$

After the subjects input their forecasts, in the Information condition, the average of the eight subjects' dividend forecasts was announced.

[4]Average pre-trading dividend forecast = $\pi = \frac{1}{n}\sum_i E_i(\tilde{v}|x_i) = \frac{500}{2} + \frac{1}{8}.\frac{1}{2}\sum_i x_i = 250 + \frac{\sum_i x_i}{16}$

In both conditions, subjects were then endowed with 500 shares and 100,000 experimental dollars. That is, I set C^i = 100000 and K^i = 500. The cash endowment was a zero interest loan, which was subtracted from their final earnings. Subjects could trade in the shares of the security for two minutes. Trading was organized as a continuous double auction. The cash and stock holdings did not carry over from one round to another. At the beginning of trading in each round, the subjects received fresh endowments of shares and cash. The subjects could not sell more shares than they owned at a given point and they could not bid more shares than their cash holding allowed.

After trading, subjects were again asked to make the following two forecasts:

1. A forecast of the dividend.
2. A forecast of the average of all traders' post-trading forecast of the dividend.

In the Information condition, [5]expected dividend, conditional on the individual's private signal and the aggregate disclosure = $E_i(\tilde{v}|x_i,\pi) = \frac{\frac{500}{50^2}+\frac{x_i}{50^2}+\frac{\left(50^2+50^2\right)^2}{8.50^2.(50^2)^2}\pi}{\frac{1}{50^2}+\frac{1}{50^2}+\frac{\left(50^2+50^2\right)^2}{8.50^2.(50^2)^2}} = \frac{2(500+x_i)+\pi}{5}$

Subjects were paid for their forecast accuracy and for the trading profits they made (e.g. Barron and Qu (2014) and Eliot, Hobson and White (2015)). For each of the pre-trading forecasts and each of the

[2] This derivation is needed for Hypothesis 1A.
[3] This derivation is needed for Hypothesis 1B.
[4] This derivation is needed for Hypothesis 4.
[5] This derivation is needed for Hypothesis 4.

post-trading forecasts, subjects were paid as follows. The absolute value of their forecast error was computed. Then, forecasting profit was calculated as $250 – 7.50× the absolute value of the forecast error. If absolute forecast error times 7.5 was more than $250, they received 0 for their forecast. Trading Profit was calculated as $100,000 ± cash earned during the round from buying and selling shares + the realized dividend from any shares owned at the end of the round – $100,000. At the end of all twenty rounds, subjects' earnings for the non-trial periods were converted to U.S. Dollars using a pre-announced exchange rate of 5 cents for every 10,000 experimental dollars. These USD denominated earnings were paid out to them in cash.

Given the parameter selections and the formulas derived earlier, I can arrive at the hypothesized forecasts. For example, Table 2 shows the average hypothesized pre-trading forecast of dividend, the average hypothesized pre-trading forecast of average opinion, and the average of the dividend forecast conditional on the private signal *and* on the aggregate disclosure (note that this last metric is relevant for the Information Condition only).

The combination of value estimation and trading in laboratory asset markets used here draws from Eliot, Hobson and White (2015) and Gillette, Stevens, Watts and Williams (1999). However, they use a multi-period asset as used by Smith, Suhanek and Williams (1988) and the extant literature on bubbles. Since my goal is to examine the extent to which market participants discern information from prices in contexts where higher-order beliefs are important, I restrict myself to a single-period asset.

It is possible to separate the predictors / forecasters from the traders / investors (e.g. Deck, Lin and Porter (2013), Hirota and Sunder (2007). However, to give the subjects a maximum shot at learning the information contained in prices and incorporating it into their trading, this paper allows the traders to double up as forecasters, too. Note that this approach gives the best possible chance to RE and biases against DO.

4. Results

I ran 4 sessions of the No Information Condition and 4 sessions of the Information Condition. 4 sessions of the No Information Condition with 8 subjects in each session and 16 paid rounds in each sessions implies I have 512 observations for the No Information Condition. Similarly, 4 sessions of the Information Condition with 8 subjects in each session and 16 paid rounds in each sessions implies I have 512 observations for the Information Condition. Note that I have repeated measures in my data for both conditions and I control for this in my data analysis reported below.

Dividend Forecasts in the No Information Condition – I first look at whether the actual pre-trading dividend forecasts are consistent with the hypothesized ones (as stated in Hypothesis 1A). As stated earlier, the hypothesized pre-trading dividend forecast is given by $E_i(\tilde{v}|x_i) = \frac{500+x_i}{2}$. Of the 512 observations, there was not a single observation where the actual pre-trading dividend forecast was equal to the hypothesized pre-trading dividend forecast (Table 3A). However, it may still be that subjects get close to the hypothesized pre-trading dividend forecast, thereby, making the hypothesized pre-trading dividend forecast a good predictor of the actual pre-trading dividend forecast. Accordingly, I tested the following regression model:

Actual Pre-Trading Forecast of Dividend = $\alpha + \beta_1$ Hypothesized Pre-Trading Forecast of Dividend + β_2 Subject + β_3 Period

The results from the regression model show that the hypothesized pre-trading dividend forecast is a good predictor of the actual pre-trading dividend forecast (Table 4, Panel A).

Next I look at whether the post-trading dividend forecasts are consistent with the price or with the pre-trading dividend forecasts (Hypothesis 2). I use volume-weighted average price as an ex-post measure of market price. Of the 512 observations, there were 124 observations where the post-trading dividend forecast was exactly equal to the pre-trading dividend forecast (Table 3A). However, there was not a single observation where the post-trading dividend forecast was equal to the price (Table 3A). A question arises as to which of the two (namely, pre-trading dividend forecast and price) is better correlated with post-trading dividend forecast and is thereby, a better predictor of the post-trading dividend forecast. Accordingly, Figure 2, Panels A – B plot the actual and hypothesized dividend forecasts in the No Information Condition. Panel A shows that the actual pre-trading and post-trading forecasts of dividend are fairly close together. Panel B shows that the actual post-trading forecast of dividend diverges from the volume-weighted average price.

To more directly compare the actual post-trading forecast of dividend with the hypothesized post-trading forecasts, I estimate the following regression model:

Actual Post-Trading Forecast of Dividend = $\alpha + \beta_1$ Actual Pre-Trading Forecast of Dividend + β_2 Volume-Weighted Average Price + β_3 Subject + β_4 Period

The results from the regression model re-iterate that pre-trading dividend forecast is a better predictor of post-trading dividend forecast (Table 4, Panel B). Note that the results are consistent with this even when I look at only the first eight periods, only the last eight periods, only those cases where the private signal / clue is greater than or equal to the mean of the signal distribution and only those cases where the private signal / clue is less than the mean of the signal distribution.

Given that there are 388 (of the 512) observations where the subjects update their pre-trading dividend forecasts (Table 3A), it seems very plausible that the information contained in prices is impounded in the post-trading forecasts. However, the divergence between the post-trading forecast and the price (Figure 2, Panel B) along with the results from the regression model (Table 4, Panel B) make it very clear that this information is not *fully* impounded in the post-trading forecast so much so that pre-trading dividend forecast remains a very good predictor of post-trading dividend forecast (Figure 2, Panel A and Table 4, Panel B). Note that the subject behavior reported here resembles the DO model and provides evidence (at least, partial evidence) against the RE model.

Forecasts of Average Opinion in the No Information Condition – I first look at whether the actual pre-trading forecasts of average opinion are consistent with the hypothesized ones (as stated in Hypothesis 1B). As stated earlier, the hypothesized pre-trading forecast of average opinion is given by $E_i\bar{E}(\tilde{v})|x_i = \frac{1}{8}.\frac{500+x_i}{2} + \frac{7}{8}.\frac{1500+x_i}{4}$. Of the 512 observations, there was not a single observation where the actual pre-trading forecast of average opinion was equal to the hypothesized pre-trading forecast of average opinion (Table 3A). However, it may still be that subjects get close to the hypothesized pre-trading forecast of average opinion, thereby, making the hypothesized pre-trading forecast of average opinion a good predictor of the actual pre-trading forecast of average opinion. Accordingly, I tested the following regression model:

Actual Pre-Trading Forecast of Average Opinion = $\alpha + \beta_1$ Hypothesized Pre-Trading Forecast of Average Opinion + β_2 Subject + β_3 Period

The results from the regression model show that the hypothesized pre-trading forecast of average opinion is a good predictor of the actual pre-trading forecast of average opinion (Table 5, Panel A).

Next I look at whether the post-trading forecasts of average opinion are consistent with the price or with the pre-trading forecasts of average opinion (Hypothesis 3). I use volume-weighted average price as an ex-post measure of market price. Of the 512 observations, there were 91 observations where the post-trading forecast of average opinion was exactly equal to the pre-trading forecast of average opinion (Table 3A). However, there was not a single observation where the post-trading forecast of average opinion was equal to the price (Table 3A). A question arises as to which of the two (namely, pre-trading forecast of average opinion and price) is better correlated with post-trading forecast of average opinion and is thereby, a better predictor of the post-trading forecast of average opinion. Accordingly, Figure 3, Panels A – B plot the actual and hypothesized forecasts of average opinion in the No Information Condition. Panel A shows that the actual pre-trading and post-trading forecasts of average opinion are fairly close together. Panel B shows that the actual post-trading forecast of average opinion diverges from the volume-weighted average price. To more directly compare the actual post-trading forecast of average opinion with hypothesized the post-trading forecasts, I estimate the following regression model:

Actual Post-Trading Forecast of Average Opinion = $\alpha + \beta_1$ Actual Pre-Trading Forecast of Average Opinion + β_2 Volume-Weighted Average Price + β_3 Subject + β_4 Period

The results from the regression model re-iterate that pre-trading forecast of average opinion is a better predictor of post-trading forecast of average opinion (Table 5, Panel B). Note that the results are consistent with this even when I look at only the first eight periods, only the last eight periods and only those cases where the private signal / clue is greater than or equal to the mean of the signal distribution. However, when I look at only those cases where the private signal / clue is less than the mean of the signal distribution, then the significance on β_1 disappears, suggesting that the support for the result in this case is driven purely by the cases where the private signal / clue is greater than or equal to the mean of the signal distribution.

Given that there are 421 (of the 512) observations where the subjects update their pre-trading forecasts of average opinion (Table 3A), it seems very plausible that the information contained in prices is impounded in the post-trading forecasts. However, the divergence between the post-trading forecast and the price (Figure 3, Panel B) along with the results from the regression model (Table 5, Panel B) make it very clear that this information is not *fully* impounded in the post-trading forecast so much so that pre-trading forecast of average opinion remains a very good predictor of post-trading forecast of average opinion (Figure 3, Panel A and Table 5, Panel B). Note that the subject behavior reported here provides evidence (at least, partial evidence) against both the RE and DO models.

Dividend Forecasts in the Information Condition – As before, I first look at whether the actual pre-trading dividend forecasts are consistent with the hypothesized ones (as stated in Hypothesis 1A). As stated earlier, the hypothesized pre-trading dividend forecast is given by $E_i(\tilde{v}|x_i) = \frac{500+x_i}{2}$. Of the 512 observations, there was not a single observation where the actual pre-trading dividend forecast was equal to the hypothesized pre-trading dividend forecast (Table 3B). However, it may still be that subjects get close to the hypothesized pre-trading dividend forecast, thereby, making the hypothesized pre-trading dividend forecast a good predictor of the actual pre-trading dividend forecast. Accordingly, I tested the following regression model:

Actual Pre-Trading Forecast of Dividend = $\alpha + \beta_1$ Hypothesized Pre-Trading Forecast of Dividend + β_2 Subject + β_3 Period

The results from the regression model show that the hypothesized pre-trading dividend forecast is a good predictor of the actual pre-trading dividend forecast (Table 6, Panel A).

Next I look at whether the post-trading dividend forecasts are consistent with the price, or with the pre-trading dividend forecasts, or with the expected dividend given the private signal and the aggregate disclosure (Hypothesis 4). As before, I use volume-weighted average price as an ex-post measure of market price. Of the 512 observations, there were 147 observations where the post-trading dividend forecast was exactly equal to the pre-trading dividend forecast (Table 3B). However, there was not a single observation where the post-trading dividend forecast was equal to the price (Table 3B) and there was not a single observation where the post-trading dividend forecast was equal to the expected dividend given the private signal and the aggregate disclosure (Table 3B). A question arises as to which of the three (namely, pre-trading dividend forecast, price, and expected dividend given the private signal and the aggregate disclosure) is better correlated with post-trading dividend forecast and is thereby, a better predictor of the post-trading dividend forecast. Accordingly, Figure 4, Panels A – C plot the actual and hypothesized dividend forecasts in the Information Condition. Panel A shows that the actual post-trading dividend forecast diverges from the expected dividend given private signal and the aggregate disclosure. Panel B shows that the actual post-trading forecast of dividend diverges from the volume-weighted average price. Panel C shows that the actual pre-trading and post-trading forecasts of dividend are fairly close together. To more directly compare the actual post-trading forecast of dividend with the hypothesized post-trading forecasts, I estimate the following regression model:

Actual Post-Trading Forecast of Dividend = $\alpha + \beta_1$ Actual Pre-Trading Forecast of Dividend + β_2 Volume-Weighted Average Price + β_3 Expected Dividend Given Private Signal and the Aggregate Disclosure + β_4 Subject + β_5 Period

The results from the regression model show that pre-trading dividend forecast is the best predictor of post-trading dividend forecast (Table 6, Panel B). Neither the co-efficient on price nor the co-efficient on expected dividend given private signal and aggregate disclosure is statistically significant (Table 6, Panel B). Note that the results are consistent with this even when I look at only the first eight periods or I look at only those cases where the private signal / clue is greater than or equal to the mean of the signal distribution or I look at only those cases where the private signal / clue is less than the mean of the signal distribution. However, when I look at the last eight periods, then the co-efficient on price becomes significant.

Given that there are 365 (of the 512) observations where the subjects update their pre-trading dividend forecasts (Table 3B), it seems very plausible that the information contained in prices and in the aggregate disclosure is impounded in the post-trading forecasts. However, the divergence between the post-trading forecast and the price (Figure 4, Panel B) along with the results from the regression model (Table 6, Panel B) make it very clear that the information contained in prices is not *fully* impounded in the post-trading forecast. Similarly, the divergence between the post-trading forecast and the expected dividend given private signal and aggregate disclosure (Figure 4, Panel A) along with the results from the regression model (Table 6, Panel B) make it very clear that the information contained in aggregate disclosure is not *fully* impounded in the post-trading forecast. The natural consequence is that pre-trading dividend forecast remains a very good predictor of post-trading dividend forecast (Figure 4, Panel C and Table 6, Panel B). Note that the subject behavior reported here resembles the DO model and provides evidence against the RE model.

It is very interesting that price becomes a significant predictor of post-trading dividend forecast in the last eight periods (Table 6, Panel B). Putting this result together with those for dividend forecasts in the No Information Conditions suggests that the presence of an additional piece of public information (namely, the aggregate disclosure) enables *better* impounding of the information contained in prices in the latter periods.

I want to check for the possibility that subjects were not able to accurately update their posterior expectations of the dividend to the expected dividend given their private signal and the aggregate disclosure and instead ended up simply setting their posterior expectations of the dividend to the aggregate disclosure. Accordingly, as an additional analysis, I estimated the following regression model:

Actual Post-Trading Forecast of Dividend = $\alpha + \beta_1$ Actual Pre-Trading Forecast of Dividend + β_2 Volume-Weighted Average Price + β_3 Aggregate Disclosure + β_4 Subject + β_5 Period

The results from the regression model once again confirm that pre-trading dividend forecast is the best predictor of post-trading dividend forecast (Table 6, Panel C). The co-efficient on price and on aggregate disclosure are statistically insignificant. However, the co-efficient on aggregate disclosure has a much larger economic magnitude than the co-efficient on price. As a matter of fact, when I restrict myself to only those cases where the private signal / clue is greater than or equal to the mean of the signal distribution or only those cases where the private signal / clue is less than the mean of the signal distribution, then the co-efficient on aggregate disclosure becomes significant. Overall, this suggests that if one allows for the possibility of inaccurate updating of posteriors, then the information contained in aggregate disclosure is impounded much better than the information contained in prices.

Forecasts of Average Opinion in the Information Condition – I first look at whether the actual pre-trading forecasts of average opinion are consistent with the hypothesized ones (as stated in Hypothesis 1B). As stated earlier, the hypothesized pre-trading forecast of average opinion is given by $E_i\bar{E}(\tilde{v})|x_i = \frac{1}{8}.\frac{500+x_i}{2} + \frac{7}{8}.\frac{1500+x_i}{4}$. Of the 512 observations, there was not a single observation where the actual pre-trading forecast of average opinion was equal to the hypothesized pre-trading forecast of average opinion (Table 3B). However, it may still be that subjects get close to the hypothesized pre-trading forecast of average opinion, thereby, making the hypothesized pre-trading forecast of average opinion a good predictor of the actual pre-trading forecast of average opinion. Accordingly, I tested the following regression model:

Actual Pre-Trading Forecast of Average Opinion = $\alpha + \beta_1$ Hypothesized Pre-Trading Forecast of Average Opinion + β_2 Subject + β_3 Period

The results from the regression model show that the hypothesized pre-trading forecast of average opinion is a good predictor of the actual pre-trading forecast of average opinion (Table 7, Panel A).

Next I look at whether the post-trading forecasts of average opinion are consistent with the price or with the aggregate disclosure or with the pre-trading forecasts of average opinion (Hypothesis 5). I use volume-weighted average price as an ex-post measure of market price. Of the 512 observations, there were 87 observations where the post-trading forecast of average opinion was exactly equal to the pre-trading forecast of average opinion (Table 3B). However, there was not a single observation where the post-trading forecast of average opinion was equal to the price (Table 3A) and there were only 6 observations where the post-trading forecast of average opinion was exactly equal to the aggregate disclosure. A question arises as to which of the three (namely, pre-trading forecast of average opinion, aggregate disclosure and price) is better correlated with post-trading forecast of average opinion and is thereby, a better predictor of the post-trading forecast of average opinion. Accordingly, Figure 5, Panels A – C plot the actual and hypothesized forecasts of average opinion in the Information Condition. Panel A shows that the actual post-trading forecasts of average opinion and aggregate disclosure are fairly close together. Panel B shows that the actual post-trading forecasts of average opinion diverge from the volume-weighted average price. Panel C shows that the actual pre-trading and post-trading forecasts of average opinion are fairly close together. To more directly compare the actual post-trading forecast of average opinion with hypothesized the post-trading forecasts, I estimate the following regression model:

Actual Post-Trading Forecast of Average Opinion = $\alpha + \beta_1$ Actual Pre-Trading Forecast of Average Opinion + β_2 Volume-Weighted Average Price + β_3 Aggregate Disclosure + β_4 Subject $+ \beta_5$ Period

The results from the regression model show that both pre-trading forecast of average opinion and aggregate disclosure are very good predictors of post-trading forecast of average opinion (Table 7, Panel B). Note that the results are consistent with this even when I look at only the first eight periods, only the last eight periods, only those cases where the private signal / clue is greater than or equal to the mean of the signal distribution and only those cases where the private signal / clue is less than the mean of the signal distribution.

Given that there are 425 (of the 512) observations where the subjects update their pre-trading forecasts of average opinion (Table 3B), it seems very plausible that the information contained in prices and in aggregate disclosure is impounded in the post-trading forecasts. However, the divergence between the post-trading forecast and the price (Figure 5, Panel B) along with the results from the regression model (Table 7, Panel B) make it very clear that this information is not *fully* impounded in the post-trading forecast. On the other hand, the convergence between the post-trading forecast and the aggregate disclosure (Figure 5, Panel A) along with the results from the regression model (Table 7, Panel B) make it clear that the information contained in aggregate disclosure is impounded very well in the post-trading forecast. Note that the subject behavior reported here provides evidence against both the RE and DO models.

5. Discussion and Conclusion

This paper examines whether subjects in the role of traders use the information contained in prices to resolve their uncertainty about the fundamental value of the asset *and* to resolve their uncertainty about the average opinion of the market participants about the fundamental value. The former is referred to as first-order or fundamental uncertainty and the latter is referred to as second-order / higher-order uncertainty. A trader may use the information contained in prices in the following three ways:

1. If a trader is fully rational, s/he would use the information contained in prices to resolve both first-order and higher-order uncertainties. This is consistent with the Rational Expectations model.
2. A trader believes that price does not reflect the true fundamental value but that it still reflects the average opinion of the market participants about the fundamental value.

Accordingly, the trader uses price to resolve second-order uncertainty but not first-order uncertainty. This is consistent with the Differences of Opinion model.

3. A trader believes that price reflects neither the fundamental value nor the average opinion about the fundamental value. Accordingly, the trader does not use price to resolve either first-order or second-order uncertainty.

The experiment reported in this paper allowed the subjects to trade in a single-period security market. Additionally, both before and after trading, the subjects were to submit their forecasts of the dividend value and of the average opinion. A comparison of the pre and post-trading dividend forecasts allowed examination of whether subjects use the information contained in prices to resolve fundamental uncertainty. Analogously, a comparison of the pre and post-trading forecasts of average opinion allowed examination of whether subjects use the information contained in prices to resolve higher-order uncertainty.

When price is the only piece of information available between pre-trading and post-trading forecasts, then the information contained in prices is impounded in both the post-trading forecast of dividend and the post-trading forecast of average opinion but it is not fully impounded into these so much so that the respective pre-trading forecasts remain strong predictors of the post-trading forecasts. When an additional piece of public information (namely, the average of the traders' pre-trading dividend forecasts) is made available, then the following happens with the post-trading forecasts. The information contained in neither of the two pieces of public information is fully impounded in post-trading dividend forecast. However, if one allows for the possibility of inaccurate updating of posteriors, then the information contained in aggregate disclosure is impounded much better than the information contained in prices. Further, the presence of an additional piece of public information allows for post-trading dividend forecasts to much better impound the information contained in prices in the latter periods as compared to the case where price was the only piece of public information. With post-trading forecasts of average opinion, the information contained in aggregate disclosure is impounded much better than the information contained in prices.

This experiment explicitly asked subjects for their forecasts of average opinion. It is possible to use alternative experiment designs which instead allow for higher-order beliefs to emerge more naturally. An over-lapping generations setting is one example of such an experiment design. The research question here might be sensitive to the trading mechanism used. This experiment uses continuous double auction. An alternative trading mechanism that might be worth looking into in this context is call auction. While there are several profitable ways in which this research can be extended by future work, the experiment reported in this paper contributes to our understanding of the extent to which traders incorporate the information contained in prices in asset market settings where higher-order uncertainty is important.

References

Allen, F., S. Morris, and H. S. Shin. 2006. Beauty contests, bubbles and iterated expectations in asset markets. *Review of Financial Studies* 19:719–52.

Anctil, R., R. Lunawat and J. O'Brien. 2014. Information and beliefs formation in asset markets. *Working paper.* University of St Thomas, University of California – Irvine and Carnegie Mellon University.

Banerjee, S., & Green, B. 2015. Signal or noise? Uncertainty and learning about whether other traders are informed. *Journal of Financial Economics*, Vol. 117, Issue 2, pp. 398-423.

Banerjee, S., R. Kaniel, and I. Kremer. 2009. Price drift as an outcome of differences in higher-order beliefs. *Review of Financial Studies* 22: 3707-3734.

Banerjee, S. and Kremer, I. 2010. Disagreement and learning: Dynamic patterns of trade. *Journal of Finance*, Vol. 65, Issue 4, Aug 2010, pp. 1269-1302.

Barberis, N., Shleifer, A. and Vishny R.W. 1998. A model of investor sentiment. *Journal of Financial Economics* 49: 307-343.

Barron, O., and Qu, H. 2014. Information asymmetry and the ex ante impact of public disclosure quality on price efficiency and the cost of capital: Evidence from a laboratory market. *The Accounting Review* 89.4 (2014): 1269-1297.

Daniel, K., Hirshleifer, D. and Subrahmanyam, A. 1998. Investor psychology and security market under- and over-reactions. *Journal of Finance* 53: 1839 – 1886.

Deck, C., Lin, S. and Porter, D. 2013. Affecting policy by manipulating prediction markets: Experimental evidence. *Journal of Economic Behavior and Organization* 85: 48-62.

Diamond, D. W. and R. E. Verrecchia. 1981. Information aggregation in a noisy rational expectations economy. *Journal of Financial Economics* 9: 221-235.

Eliot, W. B., Hobson, J. L., and White, B. J. 2015. Earnings metrics, information processing, and price efficiency in laboratory markets. *Journal of Accounting Research* 53.3 (2015): 555-592.

Feinberg, Y. and A. Skrzypacz. 2005. Uncertainty about uncertainty and delay in bargaining. *Econometrica* 73: 69-91.

Fischbacher. U., 2007. Z-tree: Zurich toolbox for readymade economic experiments. *Experimental Economics* 10: 171-178.

Forsythe, R., T. R. Palfrey, and C. R. Plott. 1982. Asset valuation in an experimental market. *Econometrica* 50: 537-567.

Gao, P. 2008. Keynesian beauty contest, accounting disclosure, and market efficiency. *Journal of Accounting Research* 46: 785-807.

Gillette, A. B., Stevens, D. E., Watts, S. G., & Williams, A. W. 1999. Price and volume reactions to public information releases: an experimental approach incorporating traders' subjective beliefs. *Contemporary Accounting Research*, *16*(3), 437-479.

Grossman, S. 1976. On the efficiency of competitive stock markets where traders have diverse information. *Journal of Finance* 31: 573-85.

Grossman, S. J. and J. E. Stiglitz. 1980. On the impossibility of informationally efficient markets. The American Economic Review. 70: 393-408.

Guarnaschelli, S., A. M. Kwasnica, and C. R. Plott. 2002. Information aggregation in double auctions: rational expectations and the winner’s curse. California Institute of Technology Social Science Working Paper.

Harris, M. and A. Raviv. 1993. Differences of opinion make a horse race. *The Review of Financial Studies* 6: 473-506.

Harrison, J. M. and D. M. Kreps. 1978. Speculative investor behavior in a stock market with heterogeneous expectations. *The Quarterly Journal of Economics* 2: 323-336.

Hellwig, M. F. 1980. On the aggregation of information in competitive markets. *Journal of Economic Theory* 22: 477-498.

Hirota, S. and Sunder, S. 2007. Price bubbles sans dividend anchors: Evidence from laboratory stock markets. *Journal of Economic Dynamics and Control* 31, 1875-1909.

Hong, H. and Stein, J. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54: 2143-84.

Jordan, J. S. 1982. A dynamic model of expectations equilibrium. *Journal of Economic Theory* 28: 235-254.

Kagel, J. H. and D. Levin. 1986. The winner’s curse and public information in common value auctions. *American Economic Review* 76: 894-920.

Kandel, E., & Pearson, N. D. 1995. Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy*, 831-872.

Kondor, P. 2012. The more we know about the fundamental, the less we agree on the price. *Review of Economic Studie*s 79: 1175-1207.

Lei, V., C. N. Noussair, and C. R. Plott. 2001. Nonspeculative bubbles in experimental asset markets: lack of common knowledge of rationality vs. actual irrationality. *Econometrica* 69: 831-859

McKelvey, R. D., and T. Page. 1986. Common knowledge, consensus, and aggregate information. *Econometrica* 54: 109-127.

McKelvey, R. D. and T. Page. 1990. Public and private information: experimental study of information pooling. *Econometrica* 58: 1321-1339.

Morris, S. 1995. The common prior assumption in economic theory. *Economics and Philosophy* 11: 227-253.

O'Brien, J. and S. Strivastava. 1991. Dynamic stock markets with multiple assets: an experimental analysis. *The Journal of Finance* 46: 1811-1838.

Plott, C. R. and S. Sunder. 1982. Efficiency of experimental security markets with insider information: an application of rational-expectations models. *Journal of Political Economy* 90: 663-698.

Plott, C. R. and S. Sunder. 1988. Rational expectations and the aggregation of diverse information in laboratory security markets. *Econometrica* 56: 1085-1118.

Scheinkman, J. A., & Xiong, W. 2003. Overconfidence and speculative bubbles. *Journal of political Economy*, *111*(6), 1183-1220.

Shin, H. S. 1996. Comparing the robustness of trading systems to higher-order uncertainty. *Review of Economic Studies* 63: 39-59.

Smith, V. L., G. L. Suchanek, and A. W. Williams. 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica* 56: 1119-1151.

Appendix

Experimental Instructions
(No Information Condition)

Overview

Welcome. You are about to participate in an experiment on decision making under uncertainty. If you follow the instructions and make careful decisions, you may earn a considerable amount of money. Your earnings will be paid in cash at the end of the experiment.

Your earnings in the experiment are measured by experimental dollars. At the end of the experiment, your total experimental dollar earnings will be converted to U.S. dollars at the rate of 5 cents for every 10,000 experimental dollars. Every dollar you earn will increase your cash payment. Losses will decrease your cash payment, down to a minimum of $7, U. S. (show-up fee). From this point forward all units of account will be in experimental dollars.

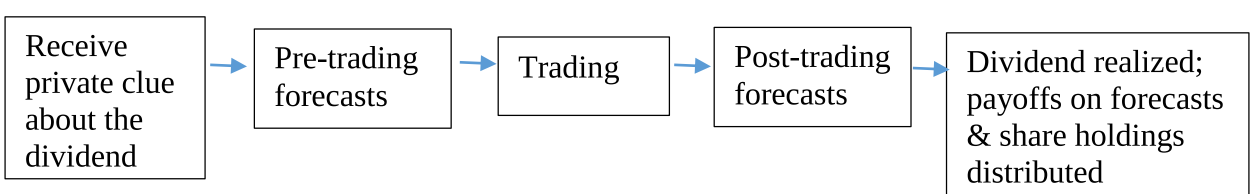
If you have any questions during the experiment, please raise your hand and wait for an experimenter to come to you. Please do not talk, exclaim, or try to communicate with other participants during the experiment.

Your task

During this session, you will have the opportunity to trade shares of stock in a sequence of market trials. In each trial, you trade shares of a single stock. The stock pays a dividend for each share held at the end of the trial, and then expires. You will not know the amount of the dividend until after the market trial, but you will receive a private clue about the dividend before trading in the market commences. Your goal is to earn as much trading profit as you can over all the trials.

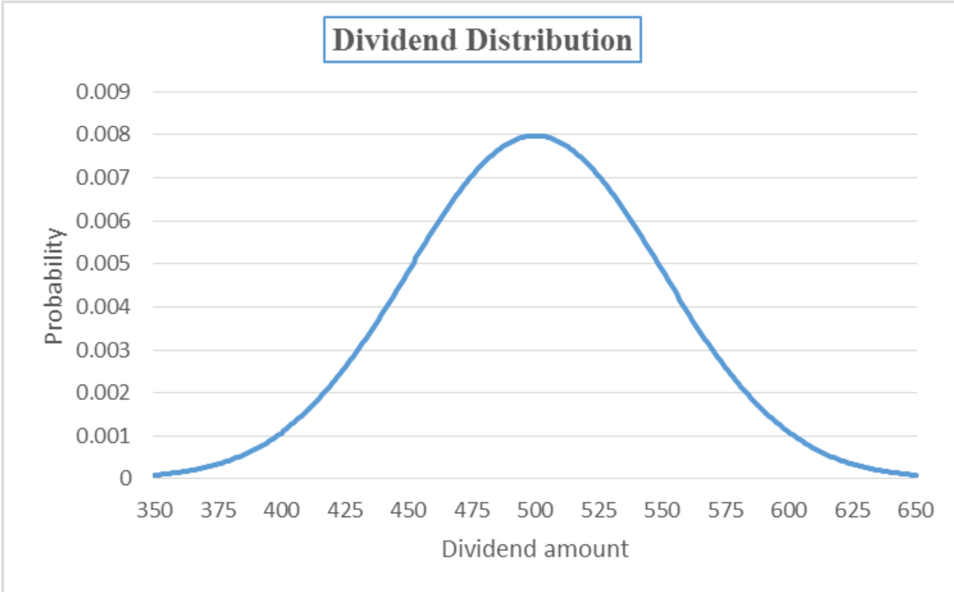
After you have received your private clue about the dividend you will be asked to make forecasts of the dividend amount and the forecasts of your fellow participants. These forecasts will take place before and after trading in the market. At the end of each trial, you will be rewarded in experimental dollars for each of your forecasts. The more accurate your forecasts, the higher your reward will be. Your goal will be to forecast as accurately as you can.

A timeline of the sequence of events in each trial is as follows.



Dividend

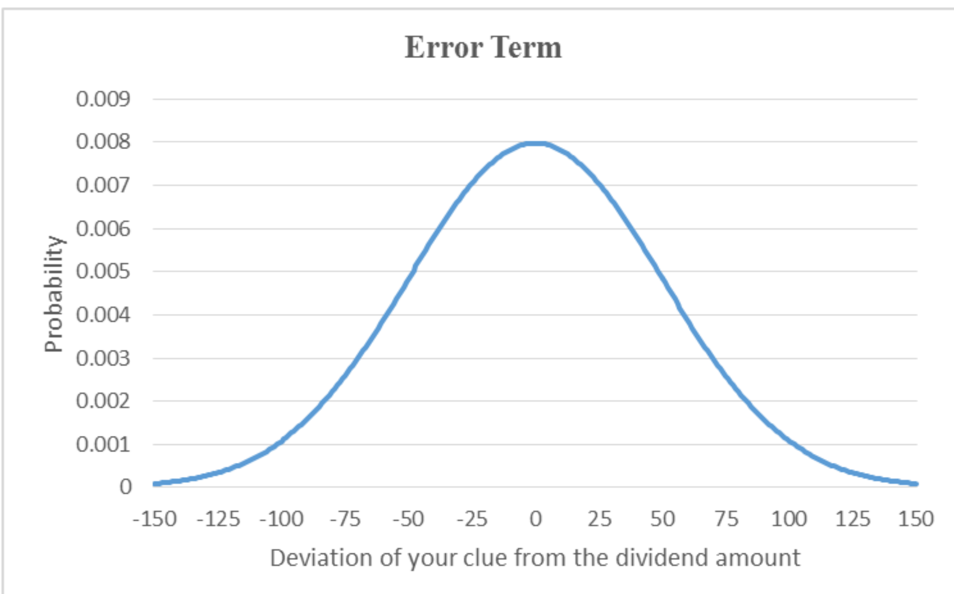
The dividend for each share of the stock is a random number drawn from a normal distribution. The average of the distribution is 500 and the dispersion of the distribution is 50. Two-thirds of the time, the dividend is within the range between the average minus and plus 50. In 95% of times, the dividend is within the range between the average minus and plus 100. In 99.7% of times, the dividend is within the range between the average minus and plus 150. Graphically, the distribution will look as follows.



In each trial, the computer randomly draws the dividend per share amount from the distribution. The dividend drawn for a trial is independent of the dividend drawn for every other trial. At the beginning of each trial, you start with a fresh stock and a fresh dividend per share amount is drawn.

Private clues about dividends

In each trial, you will receive a private clue about the dividend of the stock you are trading. Your clue will not be equal to the clues received by other participants. Each clue is equal to the dividend per share amount plus a random error term. The error term is drawn from a normal distribution. The average of the error term is 0 and the dispersion of the error term is 50. In two-thirds of the time, the clues are within the range between the dividend minus and plus 50. In 95% of times, the clues are within the range between the dividend minus and plus 100. In 99.7% of times, the clues are within the range between the dividend minus and plus 150. Graphically, the distribution will look as follows.



For example, suppose the dividend is 400, the clues may be 365, 340, 440, 449, 469...In two- thirds of the times the clues are between 400±50, that is, in the interval [350, 450]. In 95% of times, the clues are between 400±100, that is, in the interval [300, 500]. In 99.7% of times, the clues are between 400±150, that is, in the interval [250, 550].

Dividend Forecasts
In each market, I ask you to make a total of four forecasts.

Pre-trading Forecast – After each trader receives his or her private clue but before trading, I ask each participant to make the following two forecasts.

3. Forecast the dividend.
4. Forecast the average of all traders' pre-trading forecast of the dividend.

Post-trading Forecast – After trading concludes, I ask each trader to again make the following two forecasts.
1. Forecast the dividend.
2. Forecast the average of all traders' post-trading forecast of the dividend.

At the end of the trial, the experimenters will compare each of your forecasts to the actual realization and you will be rewarded for *each* forecast as follows.

The absolute value of your forecast error is computed.
Absolute value of forecast error = |Your forecast – actual realization|

Forecasting profit = $250 – 7.50× |Your forecast – actual realization|
If your absolute forecast error times 7.5 is more than $250, you receive 0 for your forecast.

For example, suppose the dividend is $300. If you forecast that the dividend is 300, you receive $250. Suppose you forecast that dividend is $320. Your absolute forecast error is $20. You receive $250-7.50×20=$100 for this forecast.

Trading instructions
Your endowment – At the beginning of each trial, you are endowed with 500 shares of the stock and initial cash of 100,000 experimental dollars. During trading in the trial, you may buy and sell stocks. Your trading profit is determined as follows.

Trading Profit = $100,000 ± Cash earned during the trial from buying and selling shares + The realized dividend from any shares you own at the end of the trial – $100,000

Note that your cash and stock holdings will not carry over from one market to another. At the beginning of each trial, you receive fresh endowments of shares and cash.

Example 1
Suppose you have initial endowment of 2 shares and you buy 1 share at the price of $p. The realized dividend of the stock is $400 per share. How much is your trading profit?

Answer: You hold 3 shares at the end of trading, so your dividend earnings are 3×400, which is $1200. Cash you paid for the share is $p and you do not receive any cash for selling stocks. Therefore you total earning is 1200 – $p.

Example 2

Suppose you have initial endowment of 2 shares and you sell 1 share at the price of $q. The realized dividend of the stock is $400 per share. How much is your trading profit?

Answer: Your hold 1 share at the end of trading, and your dividend earnings are 1×400. Cash receipt from selling 1 share is $q. Therefore, your total earning is $q+400.

Trading details

How can you buy and sell shares? In the market, you can both make offers and accept offers. Making offers is referred to as "Market Making." Accepting existing offers is referred to as "Market Taking."

Market Making

You can "**ask to sell"** if you want to sell; "**bid to buy"** if you want to buy. You have to specify both the price and quantity for your offer. All offers are stored in a central order book and you can view the offers. The lowest ask price is listed at the top and the highest bid price is listed at the top. Observe that an "ask to sell" or "bid to buy" does not guarantee that you will sell or buy the stock. For this to happen someone else in the market must be prepared to buy from your ask or sell to your bid as described next.

Market Taking

If there are ask or bid offers available from other traders in the market, you can accept the offer, that is buy from the ask offer or sell to the bid offer. This is referred to as a market order and will be executed immediately at the best offers available. If you submit a buy order, you will buy from the lowest ask price. If you submit a sell order, you will sell to the highest bid. Operational details will be explained in a moment.

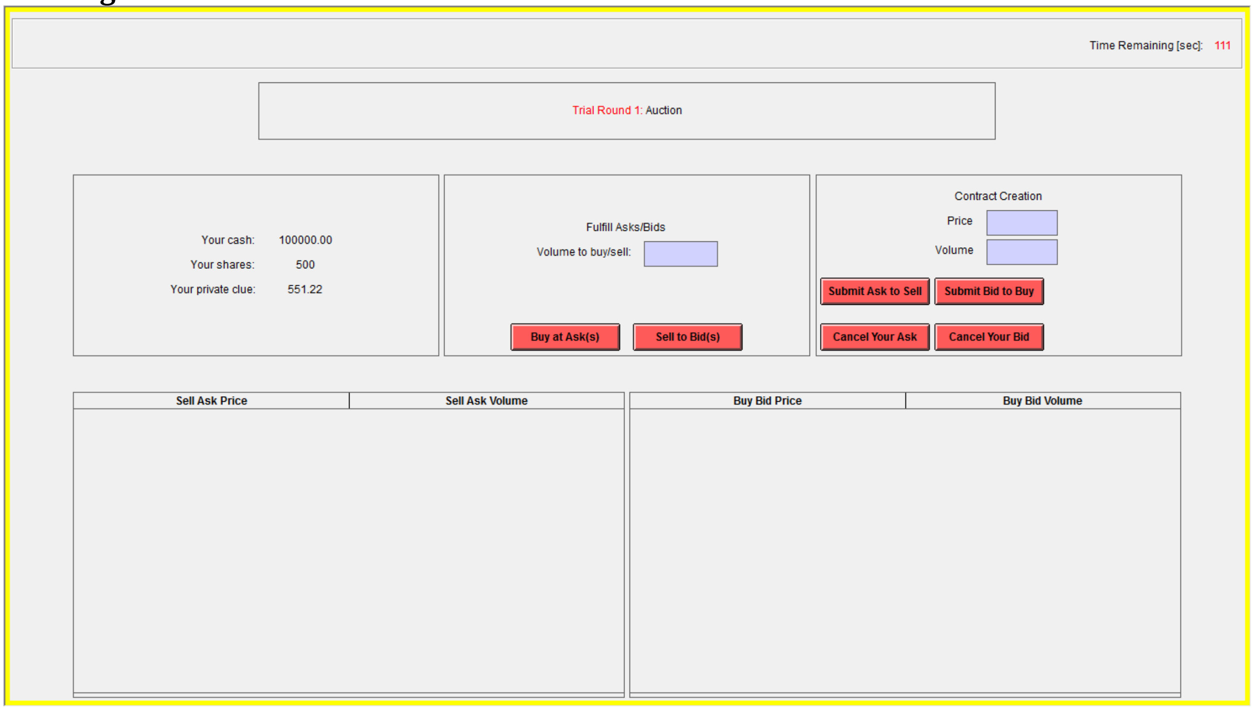
You cannot sell more shares than you currently own and you cannot bid more shares than your current cash holding allows.

Example 3

Suppose there are two traders: A and B. Each of them is endowed with 5 shares and 20 dollars. Trader A bids to buy 2 shares at 5 dollars per share. Trader B sells one share to trader A. How does this transaction affect traders A and B?

Answer: Trader A now has 6 shares and 15 dollars. Trader B now has 4 shares and 25 dollars.

Trading screen



Now please look at the trading screen and get yourself familiar with the following items on the screen.

The top right portion of the trading window has a timer. You will have a total of 120 seconds to trade in each trial. Currently you have 111 seconds left. The first row panel has the following information.

- **Cash** is your cash balance. Cash payment for share purchases reduce your cash balance and cash receipts for share sales increase your cash balance. Currently you have 100000 cash.
- **Shares** is the number of shares you have. Currently you have 500 shares.
- **Fulfill Asks / Bids** – You can buy or sell here. First type a quantity in the **Volume to buy / sell** box. Then click the corresponding button.
- **Contract Creation –** You submit your orders here. You can submit bid to buy or submit ask to sell. First you type a quantity in the **volume box** and type a price in the **price box**. Then click the corresponding button. Note that before your bid / ask is accepted, you have the opportunity to **Cancel Your Ask** or **Cancel Your Bid** by clicking on the corresponding button.

The second row panel lists the existing outstanding / unfulfilled bids and asks. Your bids and asks are listed in blue.

Figure 1 – Timeline of Stages in One Round of the Experiment

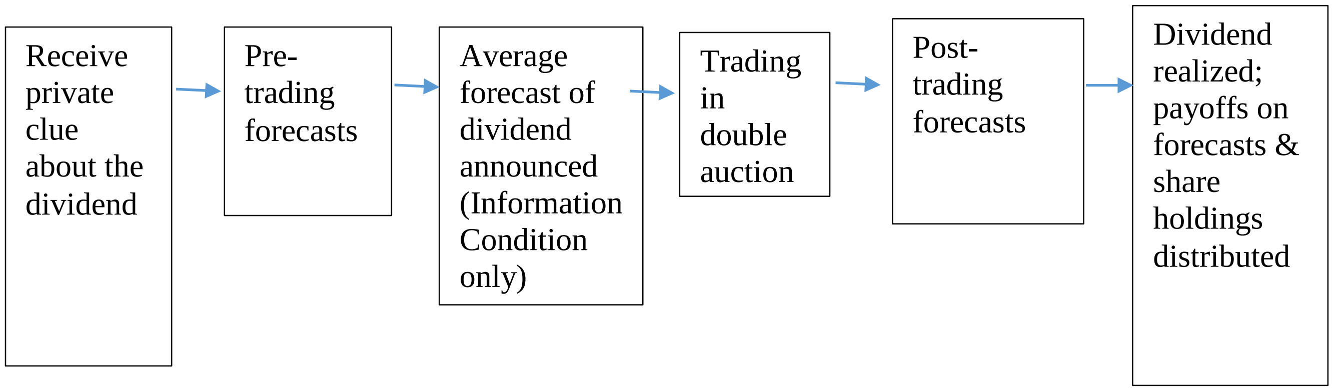
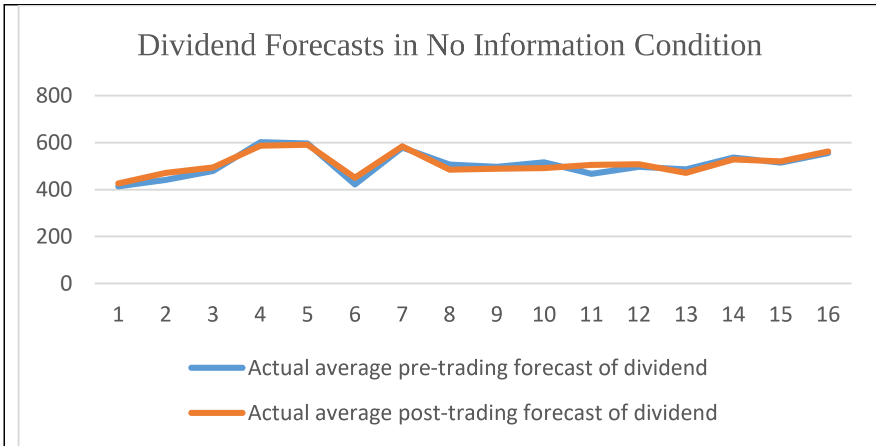
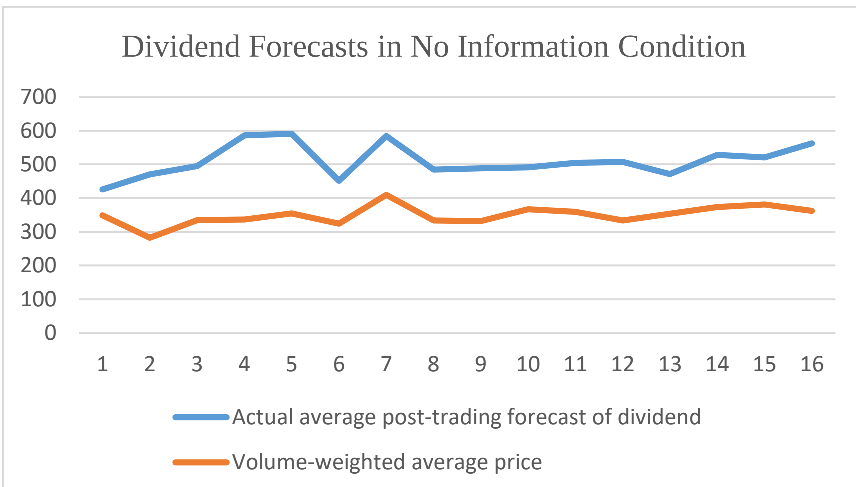


Figure 2 – Dividend Forecasts in the No Information Condition

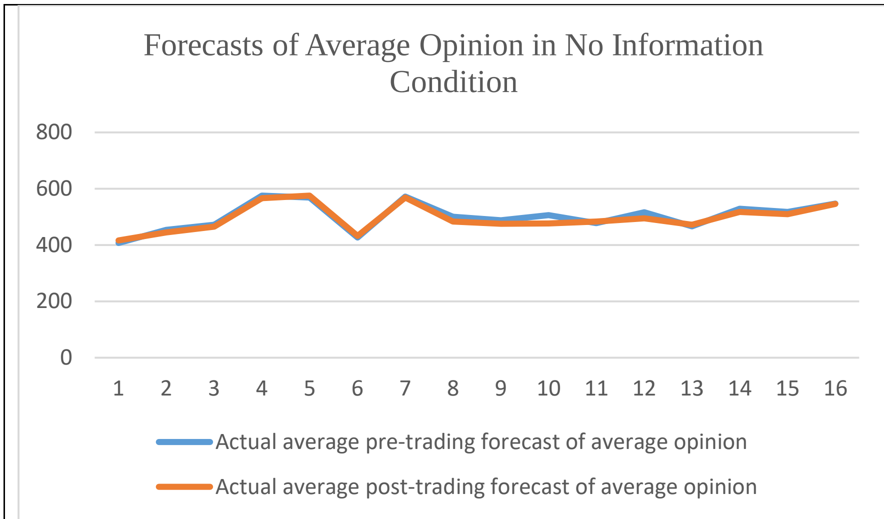


Panel A – Actual Average Pre-Trading and Post-Trading Forecasts of Dividend in the No Information Condition

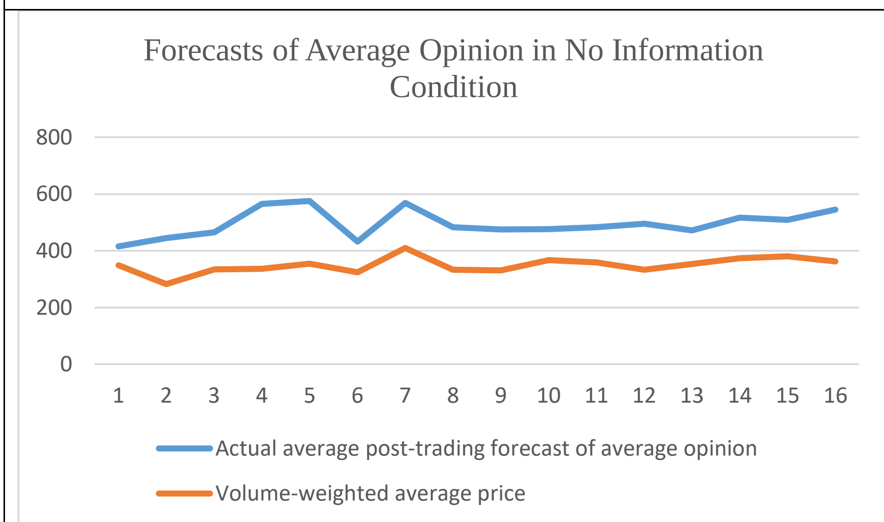


Panel B – Actual Average Post-Trading Forecast of Dividend and Volume-Weighted Average Price in the No Information Condition

Figure 3 – Forecasts of Average Opinion in the No Information Condition

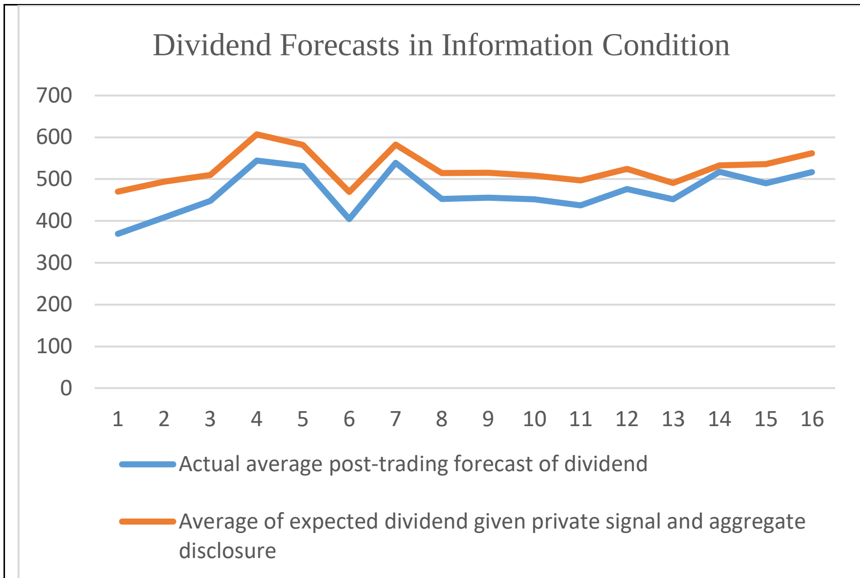


Panel A – Actual Average Pre-Trading and Post-Trading Forecasts of Average Opinion in the No Information Condition

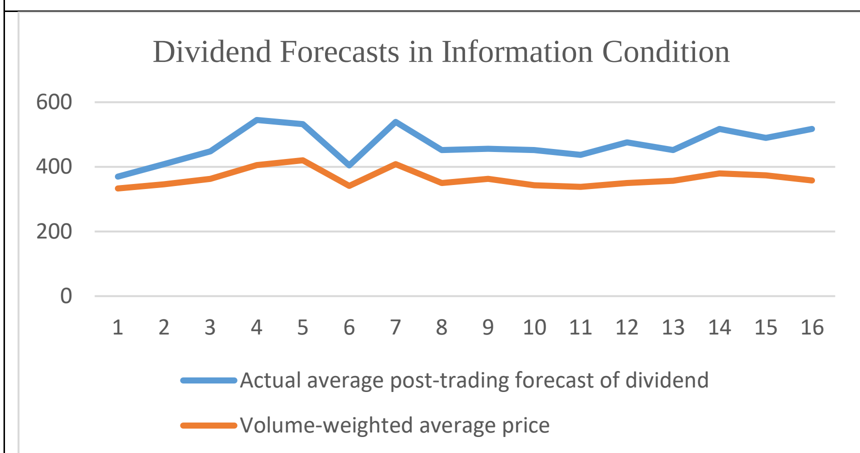


Panel B – Actual Average Post-Trading Forecast of Average Opinion and Volume-Weighted Average Price in the No Information Condition

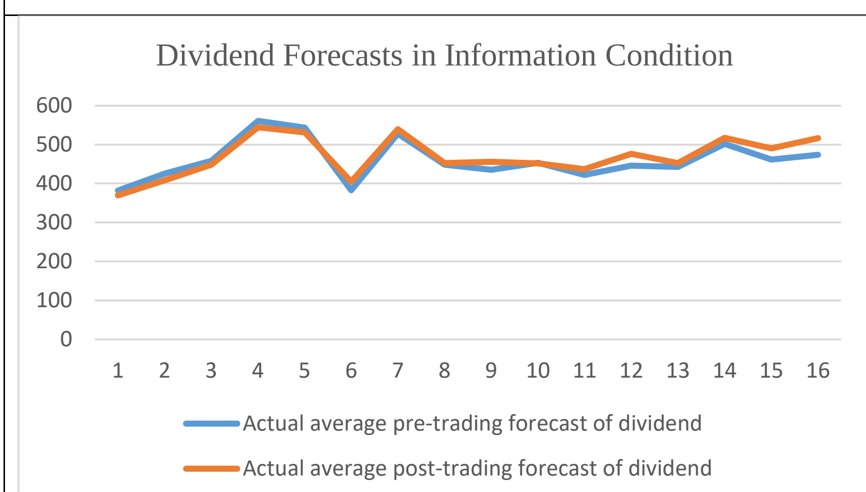
Figure 4 – Dividend Forecasts in the Information Condition



Panel A – Actual Average Post-Trading Forecast of Dividend and Average of Expected Dividend Given Private Signal and Aggregate Disclosure in the Information Condition

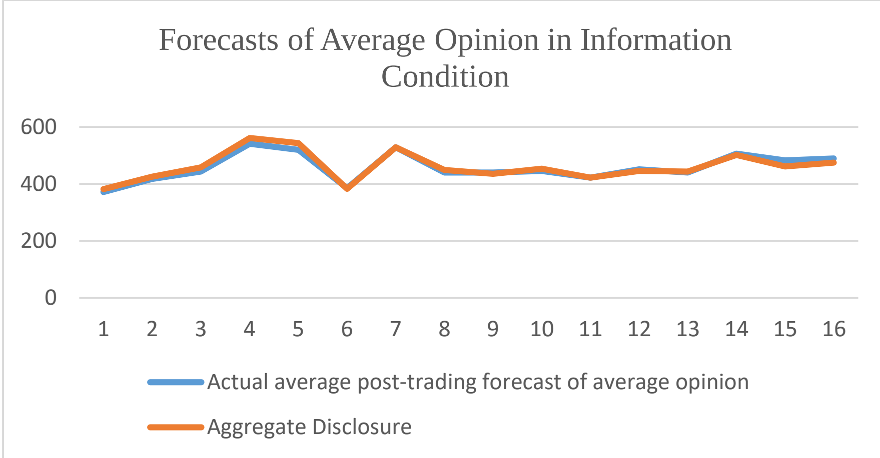


Panel B – Actual Average Post-Trading Forecast of Dividend and Volume-Weighted Average Price in the Information Condition

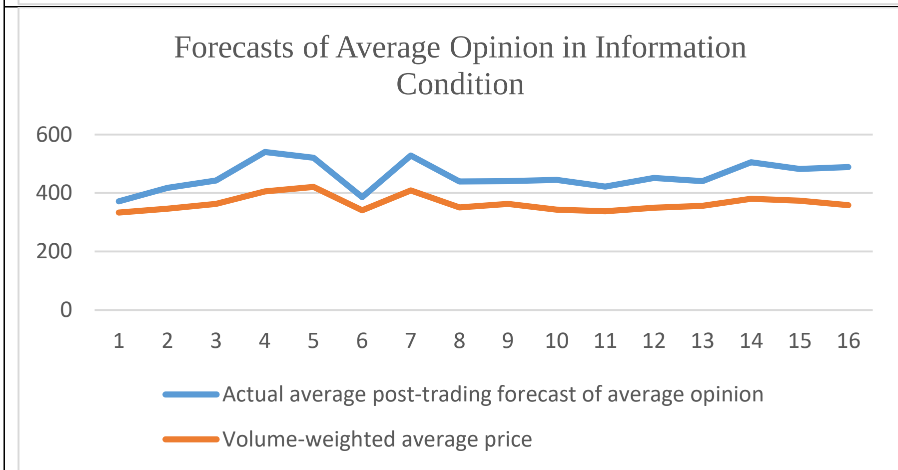


Panel C – Actual Average Pre-Trading Forecast of Dividend and Actual Average Post-Trading Forecast of Dividend in the Information Condition

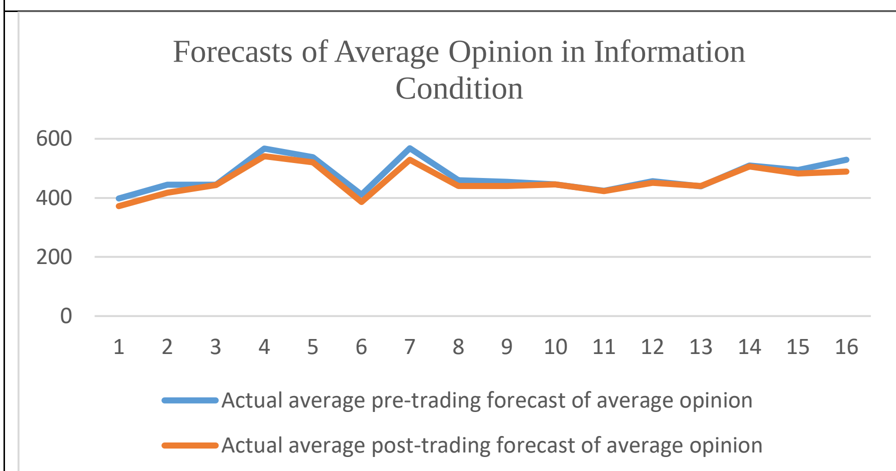
Figure 5 – Forecasts of Average Opinion in the Information Condition



Panel A – Actual Average Post-Trading Forecast of Average Opinion and Aggregate Disclosure in the Information Condition. Aggregate Disclosure refers to the publicly announced average of actual pre-trading dividend forecasts.



Panel B – Actual Average Post-Trading Forecast of Average Opinion and Volume-Weighted Average Price in the Information Condition



Panel C – Actual Average Pre-Trading Forecast of Average Opinion and Actual Average Post-Trading Forecast of Average Opinion in the Information Condition

Table 1 – Dividend / Liquidating Value and Private Signals / Clues

I generated one set of 16 securities and related signals. I used this set for all 4 groups in the Information treatment *and* for all 4 groups in the No Information treatment. For each security, I generated a dividend / liquidating value from a normal distribution with mean 500 and standard deviation 50. Then, for each security, I generated eight private signals that had independent noise terms which were distributed with mean 0 and standard deviation 50. The table and the figure below report the actual realizations. S1 – S8 is the set of eight private signals and 'Mean' is their mean.

		Private Signals / Clues								
Period	Value	S1	S2	S3	S4	S5	S6	S7	S8	Mean
1	434.62	396.88	378.95	552.14	469.45	390.22	336.58	460.01	482.83	433.38
2	478.32	546.83	477.98	447.54	520.07	483.32	468.44	492.41	504.32	492.61
3	517.13	431.56	593.76	554.53	504.95	489.91	456.74	518.8	516.13	508.3
4	678.92	673.81	640.44	669.3	689.7	694.09	824.32	612.24	677.19	685.14
5	638.47	626.4	657.03	682.9	580.18	608.46	679.73	694.84	598.57	641.01
6	432.51	448.47	421.24	394.27	375.12	456.94	501.45	450.01	483.44	441.37
7	651.75	667.39	707.61	581.64	656.99	688.71	598.85	636.8	645.09	647.89
8	536.27	493.03	481.82	465.16	572.38	621.86	512.84	537.41	500.55	523.13
9	496.85	495.35	498.47	521.25	626.12	487.15	483.23	483.76	564.41	519.97
10	535.74	527.5	563.36	526.88	502.4	428.83	590.66	448.23	524.51	514.05
11	489.75	521.13	544.78	479.95	499.11	447.78	475.86	475.47	460.3	488.05
12	493.79	548.45	571	564.75	489.67	561.51	528.86	452.23	479.11	524.45
13	493.79	518.23	508.48	440.35	488.68	450.55	548.45	433.08	455.31	480.39
14	574.48	626.21	535.12	534.01	562.41	572.98	629.94	518.8	593.05	571.57
15	570.86	607.2	615.28	423.65	586.82	562.62	527.68	570.52	559.58	556.67
16	581.51	565.81	524.16	653.43	597.15	612.9	585.38	658.14	637.39	604.3

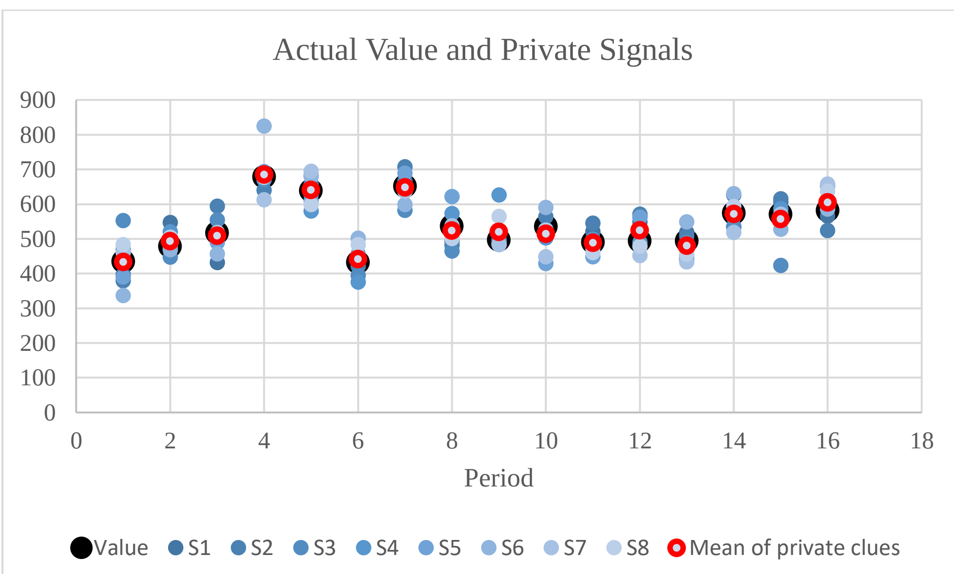


Table 2 – Predictions Using the Parameters Selected

Trader *i*'s hypothesized pre-trading dividend forecast is given by $\frac{1500+x_i}{4}$, where x_i denotes trader *i*'s private signal / clue. The hypothesized pre-trading dividend forecast is calculated for all the 8 traders in a group and the average across the 8 traders is reported in column (2) below. Trader *i*'s hypothesized pre-trading forecast of the average opinion is given by $\frac{1}{8}.\frac{500+x_i}{2}+\frac{7}{8}.\frac{1500+x_i}{4}$, where x_i denotes trader *i*'s private signal / clue. The hypothesized forecast of the average opinion is calculated for all the 8 traders in a group and the average across the 8 traders is reported in column (3) below. In the Information Condition, the dividend forecast conditional on the private signal *and* on the aggregate disclosure is given by $\frac{2(500+x_i)+\pi}{5}$, where x_i denotes trader *i*'s private signal / clue and π denotes the aggregate disclosure. Since aggregate disclosure is defined to be the average of *actual* pre-trading dividend forecasts across all traders in a group, it is different across the 4 groups in the Information treatment. The dividend forecast conditional on the private signal *and* on the aggregate disclosure is calculated for all 8 traders in each of the 4 groups and then the average across the 8 traders is calculated for each of the 4 groups. However, since this average is different for each of the groups, figures for only group 1 are reported in column (4) below.

Period (1)	Hypothesized average pre-trading forecast of dividend (2)	Hypothesized average pre-trading forecast of average opinion (3)	Average dividend forecast conditional on the private signal *and* on the aggregate disclosure (Information Condition – group 1 only) (4)
1	466.69	481.26	470.5
2	496.31	497.92	494.03
3	504.15	502.33	510.05
4	592.57	552.07	606.73
5	570.51	539.66	581.62
6	470.68	483.51	469.53
7	573.94	541.59	582.56
8	511.57	506.51	514.54
9	509.98	505.62	514.92
10	507.02	503.95	508.56
11	494.02	496.64	496.83
12	512.22	506.88	524.57
13	490.2	494.49	490.98
14	535.78	520.13	532.47
15	528.33	515.94	536.12
16	552.15	529.33	562.14

Table 3A – Forecast Errors in the No Information Condition

Forecast Errors	Number of zeros	Percentage of zeros
Actual Pre-Trading Dividend Forecast – Hypothesized Pre-Trading Dividend Forecast	0	0
Actual Pre-Trading Forecast of Average Opinion – Hypothesized Pre-Trading Forecast of Average Opinion	0	0
Actual Post-Trading Dividend Forecast – Actual Pre-Trading Dividend Forecast	124	24.2188%
Actual Post-Trading Forecast of Average Opinion – Actual Pre-Trading Forecast of Average Opinion	91	17.7734%
Actual Post-Trading Dividend Forecast – Volume Weighted Average Price	0	0
Actual Post-Trading Forecast of Average Opinion – Volume Weighted Average Price	0	0

Table 3B – Forecast Errors in the Information Condition

Forecast Errors	Number of zeros	Percentage of zeros
Actual Pre-Trading Dividend Forecast – Hypothesized Pre-Trading Dividend Forecast	0	0
Actual Pre-Trading Forecast of Average Opinion – Hypothesized Pre-Trading Forecast of Average Opinion	0	0
Actual Post-Trading Dividend Forecast – Actual Pre-Trading Dividend Forecast	147	28.7109%
Actual Post-Trading Forecast of Average Opinion – Actual Pre-Trading Forecast of Average Opinion	87	16.9922%
Actual Post-Trading Dividend Forecast – Volume Weighted Average Price	0	0
Actual Post-Trading Forecast of Average Opinion – Volume Weighted Average Price	0	0
Actual Post-Trading Dividend Forecast – Expected Dividend Given Private Signal and the Aggregate Disclosure	0	0.3906%
Actual Post-Trading Forecast of Average Opinion – Aggregate Disclosure	6	1.1719%

Table 4 – Dividend Forecasts in the No Information Condition

Panel A – Regression Summary Statistics from the Regression of Actual Pre-Trading Forecast of Dividend on Hypothesized Pre-Trading Forecast of Dividend, Subject and Period, Clustered by Subject (No Information Condition)

Actual Pre-Trading Forecast of Dividend	
Hypothesized Pre-Trading Forecast of Dividend	1.4451*** (11.27)
Subject	-.9306 (-1.13)
Period	1.6099 (1.02)
Constant	-242.7902*** (-3.71)
R-squared	0.2551
N	512

Panel B – Regression Summary Statistics from the Regression of Actual Post-Trading Forecast of Dividend on Actual Pre-Trading Forecast of Dividend, Volume-Weighted Average Price, Subject and Period, Clustered by Subject (No Information Condition)

Actual Post-Trading Forecast of Dividend	All 16 periods	First 8 periods	Last 8 periods	Private Signal Greater Than or Equal to Mean of Signal Distribution	Private Signal Less Than Mean of Signal Distribution
Actual Pre-Trading Forecast of Dividend	0.4857*** (3.28)	0.411** (2.16)	.5602*** (6.34)	.4950** (2.14)	.2833* (1.86)
Volume-Weighted Average Price	0.0245 (0.40)	-0.001 (-0.02)	.0404 (0.46)	-.0535 (-0.67)	.1142 (1.18)
Subject	-1.5713 (-1.53)	-1.9641* (-1.98)	-1.2098 (-0.98)	-2.0004 (-1.28)	-1.4724** (-2.27)
Period	0.6134 (0.72)	4.4904* (1.75)	4.052 (1.20)	-.3539 (-0.24)	1.0434 (0.64)
Constant	276.1411*** (3.38)	315.9606*** (3.66)	179.1893** (2.46)	328.1408** (2.55)	308.6241*** (3.64)
R-squared	0.3414	0.3611	0.3512	0.3469	0.1745
N	512	256	256	324	188

***, **, * indicate significantly different from 0 at $p < 0.01$, 0.05 and 0.10 levels, respectively. t-stats in parentheses.

Table 5 – Forecasts of Average Opinion in the No Information Condition

Panel A – Regression Summary Statistics from the Regression of Actual Pre-Trading Forecast of Average Opinion on Hypothesized Pre-Trading Forecast of Average Opinion, Subject and Period, Clustered by Subject (No Information Condition)

Actual Pre-Trading Forecast of Average Opinion	
Hypothesized Pre-Trading Forecast of Average Opinion	2.3788*** (9.35)
Subject	-.8193 (-0.98)
Period	2.0713 (1.32)
Constant	-718.6052*** (-5.64)
R-squared	0.2390
N	512

Panel B – Regression Summary Statistics from the Regression of Actual Post-Trading Forecast of Average Opinion on Actual Pre-Trading Forecast of Average Opinion, Volume-Weighted Average Price, Subject and Period, Clustered by Subject (No Information Condition)

Actual Post-Trading Forecast of Average Opinion	All 16 periods	First 8 periods	Last 8 periods	Private Signal Greater Than or Equal to Mean of Signal Distribution	Private Signal Less Than Mean of Signal Distribution
Actual Pre-Trading Forecast of Average Opinion	0.4507*** (2.96)	0.4006* (2.03)	0.4817*** (6.18)	.5121** (2.08)	.0639 (0.68)
Volume-Weighted Average Price	-0.0355 (-0.61)	0.0062 (0.10)	-0.1027 (-1.47)	-.0997 (-1.41)	-.0233 (-0.45)
Subject	-1.2063 (-1.32)	-1.1901 (-1.21)	-1.3874 (-1.31)	-2.0748 (-1.62)	-.6659 (-1.01)
Period	1.4224* (2.01)	6.6269** (2.37)	5.9493*** (4.19)	-.0846 (-0.07)	3.3355** (2.70)
Constant	289.5196*** (3.31)	282.6164*** (2.81)	238.2056*** (3.51)	322.6887** (2.24)	407.2357*** (11.13)
R-squared	0.3232	0.3065	0.3946	0.3768	0.0676
N	512	256	256	324	188

***, **, * indicate significantly different from 0 at *p* < 0.01, 0.05 and 0.10 levels, respectively. t-stats in parentheses.

Table 6 – Dividend Forecasts in the Information Condition

Panel A – Regression Summary Statistics from the Regression of Actual Pre-Trading Forecast of Dividend on Hypothesized Pre-Trading Forecast of Dividend, Subject and Period, Clustered by Subject (Information Condition)

Actual Pre-Trading Forecast of Dividend	
Hypothesized Pre-Trading Forecast of Dividend	1.3944*** (10.89)
Subject	-2.4166 (-1.04)
Period	-.5554 (-0.34)
Constant	-205.3171** (-2.43)
R-squared	0.1679
N	512

Panel B – Regression Summary Statistics from the Regression of Actual Post-Trading Forecast of Dividend on Actual Pre-Trading Forecast of Dividend, Volume-Weighted Average Price, Expected Dividend Given Private Signal and Aggregate Disclosure, Subject and Period, Clustered by Subject (Information Condition)

Actual Post-Trading Forecast of Dividend	All 16 periods	First 8 periods	Last 8 periods	Private Signal Greater Than or Equal to Mean of Signal Distribution	Private Signal Less Than Mean of Signal Distribution
Actual Pre-Trading Forecast of Dividend	.5379** (2.56)	.6757*** (3.28)	.3939* (1.82)	.4991** (2.45)	.6505** (2.64)
Volume-Weighted Average Price	.1247 (0.84)	.0396 (0.25)	.2422* (1.83)	.1352 (0.88)	.1054 (0.85)
Expected Dividend Given Private Signal and Aggregate Disclosure	.4136 (1.24)	.2522 (0.80)	.5547 (1.33)	.5719 (1.64)	.3219 (0.73)
Subject	-.0640	.3753	-.5622	-.1322	.3334

	(-0.06)	(0.35)	(-0.47)	(-0.10)	(0.46)
Period	3.1659** (2.62)	5.0052** (2.14)	3.0438 (1.46)	3.8770** (2.24)	2.6888*** (2.77)
Constant	-61.2491 (-0.78)	-25.4961 (-0.28)	-100.4799 (-0.89)	-137.6543 (-1.19)	-57.5246 (-0.47)
R-squared	0.5545	0.6661	0.4274	0.4952	0.5985
N	512	256	256	324	188

Panel C – Regression Summary Statistics from the Regression of Actual Post-Trading Forecast of Dividend on Actual Pre-Trading Forecast of Dividend, Volume-Weighted Average Price, Aggregate Disclosure, Subject and Period, Clustered by Subject (Information Condition)

Actual Post-Trading Forecast of Dividend	All 16 periods	First 8 periods	Last 8 periods	Private Signal Greater Than or Equal to Mean of Signal Distribution	Private Signal Less Than Mean of Signal Distribution
Actual Pre-Trading Forecast of Dividend	.5405** (2.67)	.6726*** (3.39)	.4044* (1.96)	.4995** (2.49)	.6512** (2.75)
Volume-Weighted Average Price	.1096 (0.73)	.0299 (0.18)	.2156 (1.50)	.1117 (0.70)	.1077 (0.86)
Aggregate Disclosure	.3308 (1.55)	.2207 (1.15)	.3168 (1.53)	.3806* (1.99)	.2621* (1.80)
Subject	.7837 (0.64)	.9966 (0.90)	.0351 (0.02)	.7941 (0.55)	.9567 (1.43)
Period	3.2960** (2.72)	4.9571* (1.92)	4.5644* (1.86)	3.9905** (2.35)	2.2198* (2.01)
Constant	-13.6147 (-0.40)	-3.8986 (-0.08)	11.8525 (0.22)	-23.9618 (-0.37)	-25.4665 (-0.46)
R-squared	0.5552	0.6679	0.4211	0.4953	0.6010
N	512	256	256	324	188

***, **, * indicate significantly different from 0 at $p < 0.01$, 0.05 and 0.10 levels, respectively. t-stats in parentheses.

Table 7 – Forecasts of Average Opinion in the Information Condition

Panel A – Regression Summary Statistics from the Regression of Actual Pre-Trading Forecast of Average Opinion on Hypothesized Pre-Trading Forecast of Average Opinion, Subject and Period, Clustered by Subject (Information Condition)

Actual Pre-Trading Forecast of Average Opinion	
Hypothesized Pre-Trading Forecast of Average Opinion	2.5363*** (15.18)
Subject	-2.8762*** (-3.03)
Period	.5853 (0.50)
Constant	-780.054*** (-10.59)
R-squared	0.3448
N	512

Panel B – Regression Summary Statistics from the Regression of Actual Post-Trading Forecast of Average Opinion on Publicly Announced Average of All Traders' Pre-Trading Forecast of Dividend (aka Aggregate Disclosure), Volume-Weighted Average Price, Actual Pre-Trading Forecast of Average Opinion, Subject and Period, Clustered by Subject (Information Condition)

Actual Post-Trading Forecast of Average Opinion	All 16 periods	First 8 periods	Last 8 periods	Private Signal Greater Than or Equal to Mean of Signal Distribution	Private Signal Less Than Mean of Signal Distribution
Actual Pre-Trading Forecast of Average Opinion	.6415*** (4.87)	.7016*** (4.22)	.5618*** (7.43)	.6304*** (5.37)	.7499*** (4.59)
Aggregate Disclosure	.3350** (2.75)	.3084** (2.18)	.5627*** (5.35)	.3763*** (3.80)	.5231*** (4.35)
Volume-Weighted Average Price	-.0227 (-0.29)	-.0923 (-0.96)	.0771 (1.11)	-.0320 (-0.38)	.0696 (0.84)
Subject	1.5041*** (3.00)	1.962652** (2.57)	1.6887*** (3.13)	1.9335*** (2.98)	1.8670** (2.68)
Period	1.2024* (1.88)	.0362298 (0.02)	-1.5334 (-1.29)	1.0320 (1.27)	1.5946* (1.78)
Constant	-27.211 (-1.25)	-22.01243 (-0.82)	-95.9344** (-2.25)	-47.6419 (-1.24)	-185.2372*** (-2.94)
R-squared	0.6676	0.7006	0.6320	0.6207	0.6843
N	512	256	256	324	188

***, **, * indicate significantly different from 0 at $p < 0.01$, 0.05 and 0.10 levels, respectively. t-stats in parentheses.