Overconfidence and (Over)Trading: The Effect of Feedback on Trading Behavior

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Abstract

The existing literature argues that people overestimate the accuracy of their information, which then leads to higher trading volume and lower profits in financial markets. This paper reports a laboratory experiment designed to confirm this conjecture and to identify how feedback about the accuracy of information can limit the negative impact of overconfidence. An experiment, similar to Deaves et al. (2008), is designed to study trading behavior when signals depend on the performance on an overconfidence task. In this experiment, overconfidence leads to higher trading volume in the absence of feedback, but this effect disappears when participants are given feedback. Contrary to previous research, there is only weak evidence of overconfidence negatively affecting trading profits. Markets with heterogeneous accuracy of information, due to the performance on the overconfidence task, aggregate information at similar levels to markets where the accuracy is homogenous and the distribution of information is common knowledge. Lastly, no gender differences are found on the level of overconfidence, on trading volume, and on profits.

JEL Classification: C90, C92, G12

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1 Introduction

Recently financial models have been modified to account for a variety of behavioral biases, one of the most researched being overconfidence. Theoretical models conclude that overconfidence about one's accuracy of information leads to higher trading volume and lower utility (Odean, 1998), and this finding is supported by empirical research(i.e., Biais et al., 2005; Glaser and Weber, 2007; Deaves et al., 2008). While there has been extensive research on the effects of overconfidence on trading behavior, researchers have not explored how one can mitigate these negative effects.

This paper fills a void in the literature by offering experimental evidence of the role feedback can play in mitigating the overtrading and lower profits caused by overconfidence in asset markets. Feedback has been shown to play a very important role in improving one's calibration and lowering overconfidence (Arkes et al., 1987; Hoch and Loewenstein, 1989; Remus et al., 1996; Pulford and Colman, 1997; Eberlin et al., 2011). This suggests that feedback may be used to improve outcomes in financial markets. Hence, feedback that eliminates one's overestimation of the accuracy of information may also mitigate the negative effects of overconfidence on trading. To examine this, a baseline experiment where traders can be overconfident about the accuracy of their information is designed. Feedback is provided in two additional conditions to shed light on its role in asset markets.

The experiment builds on the work of Deaves et al. (2008), who use the performance on the task used to elicit overconfidence to determine the accuracy of the signals traders receive. In Deaves et al. (2008) the accuracy of the signal is determined before trading starts, and it is the same through all trading periods. In the current experiment, participants complete a task before each trading period, and the signal they receive depends on their performance on this task. This same task is used in the first stage of the experiment to elicit two different measures of overconfidence: overestimation and overplacement. Overestimation occurs when one overestimates her ability, while overplacement occurs when one overplaces her relative ability (Moore and Healy, 2007). Another difference between the current experiment and Deaves et al. (2008) is the market structure. In Deaves et al. (2008) the dividends are chosen from a uniform distribution with values between one and 99, in the current paper the asset value is either zero or 100. Hence, the market structure used in this paper is similar with market structures that are used to study information aggregation properties of prices. Lastly, the current experiment extends the work of Deaves et al. (2008) by providing individuals with feedback about the accuracy of their signals and the accuracy of signals of the other traders in their group.

In the current experimental design both overestimation and overplacement can affect trading. First, overestimation can lead a trader to believe her signal is more accurate than it is. Second, she can falsely think that the accuracy of her own signal is better than that of the other traders in the group, causing her to overplace her relative standing. Previous research predicts that both of these manifestations of overconfidence may lead to more trading and lower profits in the baseline. Feedback provided in two additional conditions is designed to dampen the effect of overestimation and overplacement incrementally. In one of the conditions participants receive feedback about their own accuracy, and in the next condition participants also receive feedback about the accuracy of the signals of the other traders.

The results confirm the findings in Deaves et al. (2008) that overconfidence, specifically overestimation, leads to higher trading volume. In the baseline, an increase in overestimation by one standard deviation leads to 20.95 percent more traded assets, than the average participant in the baseline. When traders receive feedback about the accuracy of their information, overestimation does not have a significant effect in trading volume. This is the first experimental evidence which shows that feedback can help limit the effects of overconfidence in trading volume. Although overconfidence leads to higher trading volume, the experiment provides only weak evidence that overconfidence about one's accuracy of information leads to lower profits.

The overconfidence literature often finds men to be more overconfident than women, but not always. Regarding any gender differences in the overconfidence level or trading behavior there are two main findings from this experiment. First, there are no significant differences on the level of overconfidence between men and women. Second, there is no difference in the trading volume and on profits between men and women.

Lastly, the paper also contributes to the literature on information aggregation. This strand of research has concentrated on studying markets where the accuracy of information is common knowledge and exogenous (Plott and Sunder, 1988; Oprea et al., 2007; and Deck et al., 2013). While this can be informative, it is important to recognize that in naturally occurring markets the accuracy of the signals depends on one's ability to gather and interpret information. In other words the accuracy of information in naturally occurring markets is endogenous and heterogeneous. The data from this experiment show that, perhaps unsurprisingly, the market does not aggregate information well when traders do not explicitly know the accuracy of their information. However, information aggregation improves when traders are given feedback about the accuracy of their signal, and is reasonably good when traders know their own accuracy and that of others.

The rest of the paper is organized as follows. Related literature is presented in Section 2 and experimental design in Section 3. Results are presented in Section 4 followed by a discussion of the main results and suggestions for future research in Section 5.

2 Related Literature Review

An extensive body of research has explored the effects of overconfidence on asset trading. There are several theoretical models that support the link between overconfidence and high trading volume and low profits. Odean (1998) models trading behavior with agents who are overconfident about the accuracy of their information. The author concludes that overconfidence increases expected trading volume and lowers expected utility. Gervais and Odean (2001) develop a model in which agents become overconfident by taking too much credit for their successes and blaming losses on bad luck. The authors report that overconfident people trade too aggressively, which leads to increased expected trading volume and lower expected profits (see also Daniel et al., 2001). Kelly and Tetlock (2013) develop a model with informed rational investors and uninformed investors. Uninformed investors trade for two reasons, either for hedging or because they are overconfident about the information they have. They find that the model matches the market activity well and that nearly all uninformed trading can be explained by overconfidence. Lastly, Daniel and Hirshleifer (2015) also argue that overconfidence is a plausible way to explain excessive trading patterns.

The evidence that links overconfidence with excessive asset trading extends to empirical research. Barber and Odean (2000) find that households that trade the most, the top 20 percent based on trading volume, earn 5.5 percent less annually than a value-weighted market index. Since the overconfidence literature has found overconfident people to trade more, Barber and Odean (2000) argue that the lower profits for the top 20 percent can be attributed, at least in part, to overconfidence. Glaser and Weber (2007) find that individuals who are overconfident about their investment skills or past performance trade more. In another paper, Glaser and Weber (2009) report that past market and portfolio returns are positively correlated with trading volume. They argue this is caused by self-attribution bias which makes investors overconfident after high performances of their portfolio or the market (see also Statman et al., 2006). Using survey data to create a measure of overconfidence, Grinblatt and Keloharju (2009) conclude that overconfident investors trade more frequently and have lower returns.

The effects of overconfidence on trading performance have been studied using laboratory experiments as well. Deaves et al. (2008) find that overconfidence leads to more trading and lower profits. Deaves et al. (2008) use a series of confidence interval questions with specific numeric answers to calculate a measure of overconfidence (known as calibration-based overconfidence). The performance on these questions is used to determine the accuracy of the signal a participant receives in the trading portion of the experiment. The trading was done in a computerized double auction market environment where participants could post bids and asks or accept existing bids and asks. Assets traded in this experiment earned some dividend drawn from a uniform distribution.

In the current experiment participants also complete a task, which is used to calculate overconfidence, before trading. This same task is later used to determine the accuracy of the signal in a given trading period. In this regard the current experiment is similar to Deaves et al. (2008) since both use task-specific measures of overconfidence. That is to say, both experiments use overconfidence measures that are designed to influence market behavior. Yet, the studies differ in three important ways. First, there is no feedback provided in Deaves at al. (2008) at the end of the trading periods, while in the current experiment traders, in all conditions, receive performance feedback at the end of each trading period. In two of the conditions subjects receive additional feedback about the accuracy of their signal at the beginning of each trading period. Second, the two studies have different market structures. In Deaves et al. (2008) assets with dividends drawn from a uniform distribution are traded. In the current experiment assets are either worth zero or 100. This market structure is often used in information aggregation experiments and has shown to be a reliable market structure to use in asset markets (see below for a detailed discussion of the literature on the market structure). Third, in Deaves at al. (2008) the accuracy of the signal is based on the subjects' performance in trivia quiz and remains the same for all trading periods. In the current experiment traders complete a task before each trading period and the accuracy of the signals depends on their performance on this task. Other experimental evidence comes from Biais et al. (2005) who use the same environment as Market 7, Series C, in Plott and Sunder (1988), find that overconfidence lowers trading performance. Lastly, Kirchler and Maciejovsky (2002) also present experimental evidence of the negative effects overconfidence has on trading performance.

The literature on overconfidence has also reported gender differences when it comes to overconfidence and trading behavior. Research has found that men tend to be more affected by overconfidence (Lundeberg et al., 1994; Deaux et al., 1977; Estes and Hosseini, 1988). Men are especially found to be overconfident in those tasks that are perceived to be in the masculine domain (Deaux and Emswiller, 1974; Lenney, 1977; and Beyer and Bowden, 1997). Motivated by this research Barber and Odean (2001) find that men tend to trade 45 percent more than women. As a consequence, men earn 2.65 percentage points less per year than if they had held the portfolio they had at the beginning of the year while women earn 1.72 percentage points less. However, in more recent experimental papers there is some evidence that gender does not play a role in trading behavior. Both Deaves et al. (2008) and Biais et al. (2005) find no evidence of a gender effect on trading behavior. The current paper adds to the existing literature by providing further experimental evidence of a lack of gender effect in trading behavior.

Given the findings of research to date on the effects of overconfidence on asset markets, it is important to examine potential solutions. Some indirect evidence suggests that feedback can limit the adverse effects of overconfidence in asset markets. Past research has shown that people are well calibrated (their estimates do not experience overconfidence) in tasks with high predictability and clear, fast feedback. For instance, expert bridge players (Keren, 1987), race-track bettors (Dowie, 1976; Hausch et al., 1981) and meteorologists (Murphy and Winkler, 1984) tend to be well calibrated. Feedback has been found to improve decision making (Balzer et al., 1989). Research has also shown that feedback can improve one's calibration and lower overconfidence (Pulford and Colman, 1997; Arkes et al., 1987; Hoch and Loewenstein, 1989; Remus et al., 1996; Eberlin et al., 2011). Further, Odean (1998) argues that learning is fastest when feedback is quick and clear, but he points out that in the asset markets feedback is often slow and noisy, which can partly explain why people are not well calibrated. Motivated by this evidence an experiment is designed to answer the following question: Does feedback aimed at eliminating one's overconfidence about the accuracy of information improve asset trading outcomes? To answer this question the current experiment extends the work of Deaves et al. (2008) by providing traders with feedback about the accuracy of their information. The feedback provided to traders in the current experiment is both clear and quick. The feedback is clear because it provides the exact accuracy, and it is quick because it is given to traders at the beginning of each trading period.

This experiment has a similar information environment to that in Anderson and Holt (1997) and Hung and Plott (2001). In both of these papers subjects guessed which of two urns was used based on a ball that was drawn from one. Each of the urns contained three balls: Urn A contained two white balls and one black ball while Urn B contained two black balls and one white. Thus, if the only information one has is the color of a single draw and each urn is equally likely to be used, then there is a 2/3 chance the urn containing two balls of the drawn color was used. This information environment has subsequently been used to study the aggregative properties of market prices. For example, in Oprea et al. (2007) and Deck et al. (2013) participants trade assets that can either have a value of zero or a value of 100. Each participant is given a signal drawn from {0, 0, 100} if the true value of the asset was zero and {0, 100, 100} if the value of the asset was 100. In these designs each trader has the same accuracy of information, that is 2/3 of the time the signal is correct. In the current design a similar asset market structure is used. Participants trade assets that can have a value of zero or 100 and receive signals about the value of the assets they own. The difference in the current paper is that the accuracy of the signals for each participant depends on the performance on the task that is completed before each trading period. This means that different participants will have different levels of accuracy for their signals, which is different from Oprea et al. (2007) and Deck et al. (2013). Hence, the current experimental design allows one to explore how markets aggregate information when the accuracy of information is endogenous and heterogeneous. The first to examine how markets aggregate information in a laboratory setting was Plott and Sunder (1988). Their main finding was that the markets were able to identify the state of the world. More recent research finds that prices correlate with the Bayesian predictions, even though they do not fully aggregate information (Oprea et al., 2007, and Deck et al., 2013). The current experiment adds to the existing literature by providing experimental evidence on the aggregative properties of prices when the accuracy of information depends on one's ability and is thus heterogeneous.

3 Experimental Design

The study is composed of three conditions, designed to first establish the link between overconfidence and trading behavior and explore how feedback can mitigate the effects of overconfidence on asset markets. Each condition is structured in the same general format with three stages. The three stages are: I. Overconfidence Elicitation, II. Trading, III. Second Overconfidence Elicitation. The only difference between conditions is in Stage II of the experiment. The first subsection describes the task used to elicit overconfidence and how the overconfidence measures are calculated. The second subsection explains the market structure in Stage II and each condition. The third subsection is a summary of the procedures followed in the experiment, and the last subsection lays out the hypothesis that will be tested.

3.1 Measures of Overconfidence

Participants' overconfidence is elicited in two different stages, I and III, each composed of 10 paid periods. Both overestimation and overplacement are elicited in both stages. The second elicitation in Stage III is done to investigate if participants' overconfidence changes after they receive feedback in Stage II. The overconfidence elicitation is based on Bregu and Forbes (2015). Participants are shown a matrix with 100 rectangles with six different colors. Each participant is given seven seconds to count the number of red rectangles before they move to a new screen.[1] On the next screen, participants enter their guess of the number of red rectangles. After this, two follow up questions are asked to capture the two different forms of overconfidence: overestimation and overplacement.

The first question is: "How close were you to the true number of red rectangles?" There are several options, shown in Table 1, from which a subject can choose. This question is used to elicit one's level of overestimation. In any given period a participant can overestimate, underestimate or answer correctly. Overestimation occurs when one states that she is closer to the true number of red rectangles than she actually is. Underestimation occurs when one states that she is further away from the true number of red rectangles than what she actually is. Lastly, if a participant states the correct distance from the true number of rectangles than she neither overestimates nor underestimates her performance. To calculate the overestimation measure the number of periods a participant underestimated her ability is subtracted from the number of periods the participant overestimated her ability. This measure ranges from -10 to 10. A positive overestimation value means the participant is overconfident, a negative value means the participant is underconfident, and a value of zero means the participant is well calibrated (neither overconfident nor underconfident). I refer to overestimation elicited in Stage I as *Overestimation-1*, and to overestimation elicited in Stage III as *Overestimation-3*.

Table 1: Question one Options

Options	Payoff
Exact	\$33
Within 1	\$30
Within 2	\$27
Within 3	\$24
Within 4	\$21
Within 5	\$18
Within 6	\$15
Within 7	\$12
Within 8	\$9
Within 9	\$6
Guaranteed	\$3

To elicit overplacement, participants are asked: "How many of the other four people in your group were closer to the true number of red rectangles than you?" If a participant answers this question correctly she receives two dollars. A participant overplaces her ability when she states that the number of people who are closer than her is lower than the actual

[1]The time was determined based on a pilot. The goal was to create uncertainty on the part of participants. Seven seconds was found not to provide enough time for the participants to count every red rectangle, but was enough time to form an educated guess.

number of people who are closer. A participant underplaces her performance if the number of participants who are reported to be closer is greater than the true number of participants who are closer. There are two measures of overplacement: *Overplacement-1*, which is calculated based on the data from Stage I and *Overplacement-3* is calculated based on the data from Stage III. The overplacement measures are calculated in the same way as overestimation. Hence, overplacement ranges from -10 to 10, and a measure of zero indicates that the answers of the participant are not biased.

There is no feedback given at the end of each period of Stage I and Stage III, so participants cannot learn about their performance or the performance of others. Yet, the feedback that is provided in Stage II may affect the level of overconfidence in Stage III. For this reason the measures of overconfidence from Stage I are used in the analysis.

3.2 Market Structure and Trading Information

At the beginning of each period in Stage II, participants complete a counting task as in Stage I, but are not asked to rate their accuracy or the accuracy of others. Instead, after guessing the number of red rectangles participants trade in a double auction market for 120 seconds. Each participant is given three assets and 300 tokens at the beginning of each of the 10 trading sessions, and they are told that the value of each asset is either zero or 100 tokens with equal chance. Participants are also informed that the value of the asset is the same for everyone in the group and that tokens are converted to dollars at a ratio of one dollar for 20 tokens.

The true value of the asset is not known by participants while they trade, but each participant receives a signal about the value of the asset, which is referred to as "news" in the experiment. The signal about the value of the asset appears on the top left corner of the trading screen for the entire duration of each trading period (see Appendix A). Participants know that the accuracy of the signal depends on their performance on the counting task completed at the beginning of that period. Table 2 shows the level of accuracy of the signal based on the difference between the true number of red rectangles and a participant's guess. A similar table is provided to each participant. Part of the negative effect of overconfidence on profits has been attributed to transaction costs. To allow transaction costs to play a role in trading performance a three-token fee for each asset bought or sold is implemented.[2]

Table 2: Accuracy of the signal

Difference Between Guess and True Number of Red Rectangles	Accuracy
3 or less	95%
4, 5, 6	80%
7, 8, 9	65%
more than 9	50%

[2]Barber and Odean (2001) report that the average trade in excess of $1,000 incurs a round-trip cost of 2.4%. The transaction cost in the experiment is scaled up to account for the big difference between the true value of the assets and transaction prices that have been found in similar experiments (see Oprea et al., 2007, and Deck et al., 2013).

The experiment is composed of three conditions. The Baseline condition is designed to test the effect of overconfidence on trading behavior. The next two conditions are designed to assess the role feedback can play in limiting the negative consequences of overconfidence on asset markets. The difference among conditions is in what feedback, about the performance in the counting task in a given period of Stage II, is provided to participants. In the Baseline a participant only receives the signal about the value of the asset at the beginning of each trading period. Because the accuracy of the signal depends on the performance on the counting task a participant who is overconfident about her performance in the counting task will also be overconfident about the accuracy of her signal. In the current experimental design overconfidence can affect trading behavior in two ways: through an overestimation of one's accuracy of information and through an overplacement of one's accuracy of information.

To eliminate the possibility for one to overestimate the accuracy of information, in the second condition participants are given the accuracy with which their own signal is generated in addition to the signal itself. Both the signal and the accuracy of the signal are provided to participants at the beginning of each trading period. Since participants in this condition know only their own accuracy, this condition is referred to as the Own Accuracy Treatment. Participants in this condition know exactly what their signal accuracy is, so they cannot overestimate the accuracy of their information. Yet, in this condition one can still overplace the relative accuracy of her signal.

The last condition is designed to eliminate both overestimation and overplacement of one's signal accuracy. To achieve this, participants are shown their own accuracy and the accuracies of the other four group members in addition to their signal. It should be noted that participants do not know the signals of the other four people; they know only the accuracy with which each of these signals are generated. This condition is referred to as the Full Accuracy Treatment since participants receive full feedback with regard to the accuracy of the information in their group. In this condition both overestimation and overplacement are eliminated and neither should have any effect on trading behavior. Thus the difference between Baseline and the Own Accuracy Treatment can be attributed to overestimation while the difference between the Own Accuracy Treatment and Full Accuracy Treatment can be attributed to overplacement.

At the end of each trading period participants received feedback about their performance in that period. In all conditions participants see: the true value of the asset, their signal about the value of the asset, the number of assets held at the end of trading, the number of tokens held at the end of trading, and the total value of the assets and tokens converted to dollars (see Appendix A). In addition to these, in the conditions where feedback is provided participants see the accuracy of their signal.

Lastly, under this setup and before receiving any information, a participant's expected value for the asset is equal to 50. After receiving a signal, the participant can estimate the expected value based on her belief about how accurate the signal is. For example, if a participant receives a signal that the value of the asset is zero and she thinks this signal is 65% accurate, then the expected value, before trading starts, is equal to 35 tokens.

If markets perfectly aggregate information then one would expect the price of the asset to be equal to the Bayesian expected value, which is calculated based on the signals and accuracies of the five participants in the market. For instance, if four participants receive signals that the value of the asset is 100 with accuracies 50%, 65%, 80%, and 95% and one receives a signal of zero with 95% accuracy the Bayesian price would be 88.14 tokens. In other words, this would be the value of the asset if one saw all five signals and the accuracy with which each signal was generated.

3.3 Procedures

The experiment was conducted at the Behavioral Business Research Lab (BBRL) at the University of Arkansas. The experiment was coded and conducted using z-Tree (Fischbacher, 2007). Participants were informed in the instructions that they would get paid for one randomly selected period completed in Stage I, II or III. Participants earned a show-up fee of $7.50 and were paid an additional $13.93 on average. Participants were separated into fixed groups of five, which only interacted during the trading activity.

A total of 95 participants were recruited for the 90-minute study run across nine sessions. Eight of these sessions were composed of 10 participants, and one was composed of 15 participants. A group of five participants is dropped from the analysis because one of the participants showed complete lack of understanding of the instructions. The participant consistently bought at higher prices and sold at lower prices.[3] A set of written instructions was given to each participant, and after participants were seated the experimenter read the instructions for Stage I aloud. The experimenter answered any questions participants had during the reading of the instructions. Before starting with the experiment participants were informed that they would first answer two comprehension questions and complete a practice period before starting with the 10 paid periods of Stage I.

Once participants finished with Stage I of the experiment the experimenter read the rest of the instructions. Before participants started the trading stage they answered two comprehension questions and completed three practice periods to familiarize themselves with the trading platform. Participants completed 10 paid trading periods; then they started with Stage III of the experiment. In Stage III participants, in all conditions, completed another 10 periods identical to those in Stage I.

Recent experimental evidence shows that being able to infer others' information based on asset prices requires high cognitive reflection skills (see Corgnet et al., 2015). Hence, market outcomes in the current experiment may be affected by one's level of cognitive reflection. After Stage III an incentivized cognitive reflection test (CRT) composed of seven questions developed by Toplak et al. (2014) is used to elicit participants' cognitive reflection. Participants received one dollar for each correct question and the payoff from these questions is added to the random payoff chosen from Stage I, II, or III. Lastly, subjects answered a short survey, designed to collect demographic information and information about the use of the feedback in Stage II of the experiment, at the end of the experiment (see Appendix B).

[3]The results with these five participants included are shown in Appendix E.

3.4 Hypotheses

This section summarizes the hypotheses that will be tested. First, the literature on overconfidence argues that overconfidence leads to higher trading volume. Hence, one would expect the two measures of overconfidence to be positively correlated with the number of assets traded in the Baseline. Second, overconfidence has been linked to lower profits. If this is the case, both overconfidence measures should be negatively correlated with profits in the Baseline.

Hypothesis 1: Overestimation and overplacement lead to higher trading volume in the Baseline.

Hypothesis 2: Overestimation and overplacement lead to lower profits in the Baseline.

The feedback provided to participants in the Own Accuracy Treatment eliminates the possibility that they to overestimate their accuracy of information. Hence, one would expect overestimation to play no role in the trading volume or profits for this condition. In the Full Accuracy Treatment participants can neither overestimate nor overplace the accuracy of their information, which means neither overconfidence measure can have an effect on trading volume or profits.

Hypothesis 1a: Feedback eliminates the effect of overestimation on higher trading volume in the Own Accuracy Treatment.

Hypothesis 1b: Feedback eliminates the effect of overestimation and overplacement on trading volume in the Full Accuracy Treatment.

Hypothesis 2a: Feedback eliminates the negative effect of overestimation on profits in the Own Accuracy Treatment.

Hypothesis 2b: Feedback eliminates the negative effect of overestimation and overplacement on profits in the Full Accuracy Treatment.

4 Results

4.1 Summary Statistics and Measures of Overconfidence

The data consist of the choices of 90 participants, 30 in each condition. Table 3 presents summary statistics for the CRT and demographic survey. The variable Math & Stat. Classes is the number of math and statistics classes a participant has taken. Trading Experience is based on the data from the survey where each participant stated her trading experience ranging from no trading experience (1) to professional trader (5). The last three columns in Table 3 report the p-value resulting from t-tests for the differences of the means between conditions. As can be seen from Table 3, the only statistical difference, at the 5% level, is the one on age between the Own Accuracy Treatment and the Full Accuracy Treatment.

Table 4 presents summary statistics for the overconfidence measures and trading activity. The only statistical difference between conditions regarding overconfidence measure is that between the Own Accuracy Treatment and Full Accuracy Treatment for *Overestimation-1*. All the other t-tests yield a p-value greater than 10 percent. In terms of the number of assets traded, participants in the Own Accuracy Treatment traded significantly less than participants in the other two conditions. The variable Signal Accuracy in Table 4 shows the accuracy level (50%, 65%, 80%, or 90%) for each condition. As is apparent from the last three columns Signal Accuracy does not statistically differ for any condition pair. This shows that participants in each condition had similar counting abilities.

Table 3: Summary Statistics

Summary statistics for each condition.
The p-values reported in the last three columns come from t-tests on the differences between conditions.

Variables	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**	***p*-value Col. 1 vs. Col. 2**	***p*-value Col. 1 vs. Col. 3**	***p*-value Col. 2 vs. Col. 3**
Men	43.33%	63.33%	56.67%	0.119	0.304	0.600
Age	21.87	20.60	21.90	0.069	0.963	0.006
Math & Stat Classes	3.63	3.47	3.17	0.824	0.345	0.666
Trading Experience	1.40	1.47	1.63	0.681	0.244	0.431
CRT	1.77	1.90	1.50	0.739	0.513	0.377

Table 4: Overconfidence Measures and Trading

Summary statistics of the main overconfidence measures and trading activity.
The p-values reported in the last three columns come from t-tests on the differences between conditions.

Stage	**Variables**	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**	***p*-value Col. 1 vs. Col. 2**	***p*-value Col. 1 vs. Col. 3**	***p*-value Col. 2 vs. Col. 3**
Stage I	Overestimation-1	0.10 [5.54]	-2.03 [4.63]	0.70 [4.96]	0.112	0.660	0.032
	Max	8	8	9			
	Min	-10	-10	-10			
	Overplacement-1	0.77 [4.33]	0.80 [3.63]	0.47 [5.24]	0.977	0.810	0.778
	Max	9	10	10			
	Min	-9	-4	-10			
Stage II	Assets Traded	4.51 [2.08]	2.90 [1.21]	3.84 [1.62]	0.001	0.169	0.014
	Max	8.6	5.5	9			
	Min	0.3	0	1.9			
	Signal Accuracy	79% [17%]	81% [16%]	78% [18%]	0.641	0.826	0.498
Stage III	Overestimation-3	0.40 [5.42]	-2.13 [4.56]	-0.53 [5.82]	0.055	0.524	0.241
	Max	10	7	10			
	Min	-10	-10	-10			
	Overplacement-3	0.73 [3.81]	1.17 [4.48]	-0.20 [5.68]	0.684	0.459	0.304
	Max	7	10	10			
	Min	-8	-7	-8			

Standard deviations shown in brackets.

A t-test reveals that *Overestimation-1* is not different from zero for the Baseline and Full Accuracy Treatment (p-value=0.922 and p-value=0.446 respectively). This shows that taken as a whole participants neither overestimated nor underestimated their performance in Stage I in these two conditions. *Overestimation-1* is significantly different from zero for the Own Accuracy Treatment (p-value=0.023). Hence, participants in the Own Accuracy Treatment underestimate their abilities. While the conditions overall do not appear overconfident 42 out of the total of 90 participants have a positive *Overestimation-1* measure, which indicates they are overconfident. *Overplacement-1* is not significantly different from zero for any of the conditions, yet 45 out of 90 participants overplaced their ability. Hence while the average participant in each condition is not overconfident there are individuals in all conditions that are overconfident. If overconfidence affects trading one would expect these individuals to behave differently. Based on existing literature, one would expect overconfident participants to trade more and earn lower profits.

4.2 Overconfidence and Trading Volume

Past research argues that overconfidence about one's accuracy of information leads to high trading volume in asset markets. If this is true one would expect to find a positive effect of overconfidence on the trading volume for the Baseline. Table 5 presents regression results for each condition. Standard errors are clustered at the individual level and include group dummies. Column one and four in Table 5 show that *Overestimation-1* leads to more trading in the Baseline. This confirms previous findings which link overestimation with high trading volume. On the other side, it is apparent from the regression results that *Overplacement-1* does not lead to more trading in the Baseline, suggesting that overplacing one's level of accuracy does not lead to more trading.

Result 1: Overestimation leads to higher trading volume in the Baseline, while overplacement has no significant effect.

The main purpose of this paper is to show the role feedback can play in limiting the effects overconfidence has on asset markets. If feedback is successful in eliminating the effect of overestimation on trading volume, then one would expect to find no significant effect of *Overestimation-1* in these two conditions. *Overestimation-1* does not have a significant effect for any of the specifications in the Own Accuracy Treatment and Full Accuracy Treatment, which shows that feedback was successful in eliminating the effects of overestimation on trading volume. *Overplacement-1* does not have an effect on trading volume in the Baseline, but it is marginally significant in the Own Accuracy Treatment (p-value=0.095 and p-value=0.055 for column two and five in Table 5, respectively). This is an interesting finding and suggests that when both overestimation and overplacement can play a role, overestimation is the stronger measure, but once people cannot overestimate, they seem to be affected by overplacement. When participants are offered feedback about the accuracy of their group members *Overplacement-1* is no longer significant. This shows that feedback successfully eliminates any effect of *Overplacement-1* on trading.

Result 1a: Feedback eliminates the effect of overestimation on higher trading volume in the Own Accuracy Treatment.

Result 1b: Feedback eliminates the effect of overestimation and overplacement on trading volume in the Full Accuracy Treatment.

Table 5: Overconfidence and Trading Volume

The dependent variable is the number of trades a participant completed in one period. OLS regressions, standard errors clustered by participant.

Variables	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**
Overestimation-1	0.175***	-0.008	-0.052	0.160***	0.037	-0.014
	[0.055]	[0.044]	[0.053]	[0.050]	[0.055]	[0.040]
Overplacement-1	-0.022	0.077*	0.027	0.040	0.099*	0.049
	[0.058]	[0.045]	[0.059]	[0.066]	[0.049]	[0.037]
Age				0.056	-0.640**	-0.500***
				[0.087]	[0.250]	[0.171]
Male				-0.803	-0.965**	0.663
				[0.649]	[0.408]	[0.443]
Math & Stat Classes				0.202	0.134	0.540**
				[0.144]	[0.100]	[0.242]
Trading Experience				-0.193	0.228	-0.197
				[0.550]	[0.351]	[0.190]
CRT				0.193	0.060	0.364*
				[0.215]	[0.121]	[0.192]
Signal Accuracy				0.536	-0.657	-0.596
				[1.092]	[1.208]	[0.649]
Group Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.622***	2.870***	3.200***	-0.623	16.755***	12.049***
	[0.409]	[0.405]	[0.234]	[2.056]	[5.519]	[2.966]
R-squared	0.310	0.074	0.145	0.344	0.133	0.224
Observations	300	300	300	300	300	300

Standard errors given in brackets. *p<0.10, ** p<0.05, ***p<0.01

Note: Math & Stat Classes is the number of math and statistics classes a participant has taken. Trading Experience is the reported trading experience by subjects on a scale of one to five with one being no experience and five being professional trader. CRT is the number of correct CRT questions. Signal Accuracy is how accurate the signal was for a given participant in that period (50%, 65%, 80% or 95%).

The existing literature argues that gender plays an important role in trading behavior. In fact, Barber and Odean (2001) split the data in two groups based on gender and find that men trade more than women, which they attribute in part to the higher level of overconfidence that men have been found to have in fields similar to trading. In the current experiment there is no evidence that men are more overconfident than women based on *Overestimation-1* (p-value=0.972) or *Overplacement-1* (p-value=0.298). More importantly, contrary to the findings of Barber and Odean (2001) men do not trade more than women in any of the conditions. On the contrary, there is some evidence that men trade less when they know the accuracy of their own information (column 5 in Table 5). Age also does not have a significant effect on trading volume in the Baseline, but it has a significant negative effect on the two conditions where feedback is provided. Older participants traded fewer assets in the Own Accuracy Treatment and the Full Accuracy Treatment. The number of math and statistics classes one has taken has a significant and positive effect on trading volume for the Full Accuracy Treatment, but not for the other two conditions. Cognitive reflection skills have been shown to play a role on the ability to infer others' information based on prices (Corgnet et al., 2015). In this experiment CRT only plays a marginally significant role in the Full Accuracy Treatment.

4.3 Overconfidence and Profits

Researchers have argued that people who are overconfident tend to trade more and as a consequence earn lower profits. The lower profits are attributed to the transaction costs (Barber and Odean, 2000) and the disposition effect (Chen et al., 2007).[4] Table 6 presents regression results of the effect of *Overestimation-1* and *Overplacement-1* on profits. The dependent variable in Table 6 is the Bayesian net profit. The profits one earns in this experiment may be affected by the realization of the asset value. The different markets across conditions have different levels of accuracies, which translates to different realizations of asset values. Hence it is possible that one properly infers the value of the asset based on her signal and the prices, but the realization of the asset value is not what is expected. To control for this, the profits are calculated using the value of the asset based on the Bayesian expected value. Bayesian net profits are calculated by multiplying the Bayesian expected value by the number of assets one has at the end of the period plus tokens at the end of the period. The total is divided by 20 to convert the value to dollars.[5]

If overconfidence leads to lower profits, then one would expect *Overestimation-1*, *Overplacement-1* or both to be negatively correlated with profits for the Baseline. If overconfidence leads to lower trading profits and feedback is successful in eliminating this effect, one would expect no significant effect of *Overestimation-1* in the Own Accuracy Treatment and no effect of either overconfidence measure in the Full Accuracy Treatment. Note, the Bayesian net profits account for any transaction costs a trader incurred during that period since traders pay the transaction cost each time they buy or sell, and this is reflected in the amount of tokens one has at the end of the period. The regression results, in Table 6, show that there exists a negative relationship between the measures of overconfidence, but this relationship is not significant for any of the conditions. This result shows that Hypothesis 2 is not supported by the data in this experiment. Because there is no significant effect of either overconfidence measure in the Baseline one cannot evaluate the role feedback plays in limiting the effect of overconfidence on profits. Hence, there is no support from this experiment for Hypotheses 2a and 2b.

[4] The disposition effect refers to the tendency for people to hold stocks that have depreciated and sell stocks that have appreciated.

[5] The results remain qualitatively the same when profits are calculated with the actual value of the asset instead of the Bayesian expected value.

Result 2: Neither overestimation nor overplacement lead to significantly lower profits in the Baseline.

Result 2a: The effect of feedback on limiting the role of overestimation on trading profits cannot be evaluated using the data from this experiment.

Result 2b: The effect of feedback on limiting the role of overestimation or overplacement on trading profits cannot be evaluated using the data from this experiment.

Table 6: Overconfidence and Bayesian Net Profits

The dependent variable is the net profit (in dollars) in a period when the value of the asset is the Bayesian expected value. OLS regressions, standard errors clustered by participant.

Variables	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**
Overestimation-1	-0.110	-0.079	-0.110	-0.161	-0.147	-0.060
	[0.119]	[0.126]	[0.083]	[0.120]	[0.143]	[0.093]
Overplacement-1	-0.126	-0.106	0.047	-0.044	-0.002	-0.002
	[0.149]	[0.106]	[0.068]	[0.164]	[0.106]	[0.073]
Age				0.288	0.063	0.269
				[0.214]	[0.618]	[0.206]
Male				2.759**	-0.251	-0.466
				[1.300]	[1.677]	[0.691]
Math & Stat Classes				-0.465**	0.072	-0.817**
				[0.182]	[0.246]	[0.328]
Trading Experience				-1.100	0.049	-0.194
				[1.434]	[0.836]	[0.7582]
CRT				0.165	0.326	0.065
				[0.437]	[0.410]	[0.292]
Signal Accuracy				2.521	7.733*	1.065
				[2.527]	[4.316]	[3.912]
Signal Value				3.471**	1.401	1.950*
				[1.302]	[1.555]	[1.067]
Group Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	23.349***	24.325***	20.623***	14.932***	14.348	15.293**
	[1.108]	[1.354]	[0.795]	[4.566]	[12.134]	[5.994]
R-squared	0.072	0.052	0.141	0.122	0.088	0.166
Observations	300	300	300	300	300	300

Standard errors given in brackets. *p<0.10, ** p<0.05, ***p<0.01

Note: Math & Stat Classes is the number of math and statistics classes a participant has taken. Trading Experience is the reported trading experience by subjects on a scale of one to five with one being no experience and five being professional trader. CRT is the number of correct CRT questions. Signal Accuracy is how accurate the signal was for a given participant in that period (50%, 65%, 80% or 95%). True Signal is one if a participant saw the true value of the asset and zero otherwise.

Lastly, there is disagreement in previous research about the effect of gender on trading profits. Barber and Odean (2001) find that men trade more and have lower returns than women. But experimental studies have found no effect of gender on profits (Biais et al., 2005 and Deaves at al., 2008). The results from Table 6 show that men earn significantly higher profits in the Baseline. This finding appears contrary to previous findings that find men earn lower or similar profits with women. To examine the effect of gender on profits a new set of regressions with gender and interaction terms of gender and each overconfidence measure for all three conditions are conducted and show that gender has no significant effect for any of the conditions (see Appendix C). Hence, the data from this experiment, in line with other experimental results on gender, show that there is no significant effect of gender on profits.

4.4 The Effect of Feedback on Overconfidence

Because Stage III replicated Stage I, in addition to exploring the effect of feedback on trading behavior, one can examine the effect of feedback on the level of overconfidence as well. The data in Table 4 show that overall, participants are not overconfident in fact in the Own Accuracy Treatment participants are slightly underconfident. Yet, there are individuals who are either overconfident or underconfident, and if feedback helps one learn about her ability, one would expect to find a lower variance of overconfidence in Stage III than in Stage I of the experiment. In other words, participants will become better calibrated if they learn about their ability from the feedback given. To examine if participants became better calibrated in Stage III an F-test for differences in variances is conducted. The F-test shows that there is no statistical difference in the variance between Stage I and Stage III for overestimation or overplacement in any of the conditions. This finding is contrary to previous research that finds feedback to be useful in helping people be better calibrated (Pulford and Colman, 1997; Arkes et al., 1987; Hoch and Loewenstein, 1989; Remus et al., 1996; Eberlein et al., 2011).

4.5 Information Aggregation

The current experimental design also provides the opportunity to investigate information aggregation when the accuracy of information is endogenous and heterogeneous. In Figures 1-3 the average observed price (the average price of all trades in a period) is plotted against the Bayesian expected value. If the market aggregates information well, one would expect to find the data concentrated on the 45-degree line. The first observation from the graphs shows that traders do not aggregate information well. Yet, moving from the Baseline to the Full Accuracy Treatment it becomes clear that the graphs get closer to what one would expect them to be if information is perfectly aggregated. Table 7 shows that the market in the Baseline fails to distinguish between the two states of the world. The price is close to 50 tokens regardless of the true state of the world. However, as participants gain information about the signal accuracy the average observed prices move closer to the true state of the world.

Table 7: Summary statistics for each condition.

	Baseline		Own Accuracy Treatment		Full Accuracy Treatment	
True Asset Value	0	100	0	100	0	100
Bayesian Expected Value	6.2 [17.3]	92.8 [19.6]	5.3 [16.6]	92.5 [20.8]	8.5 [25.0]	96.2 [7.6]
Average Observed Price	49.6 [16.7]	50.5 [19.3]	41.9 [18.6]	53.2 [18.0]	36.0[19.8]	60.0 [15.0]

Standard deviations in brackets.

Figure 1: Baseline

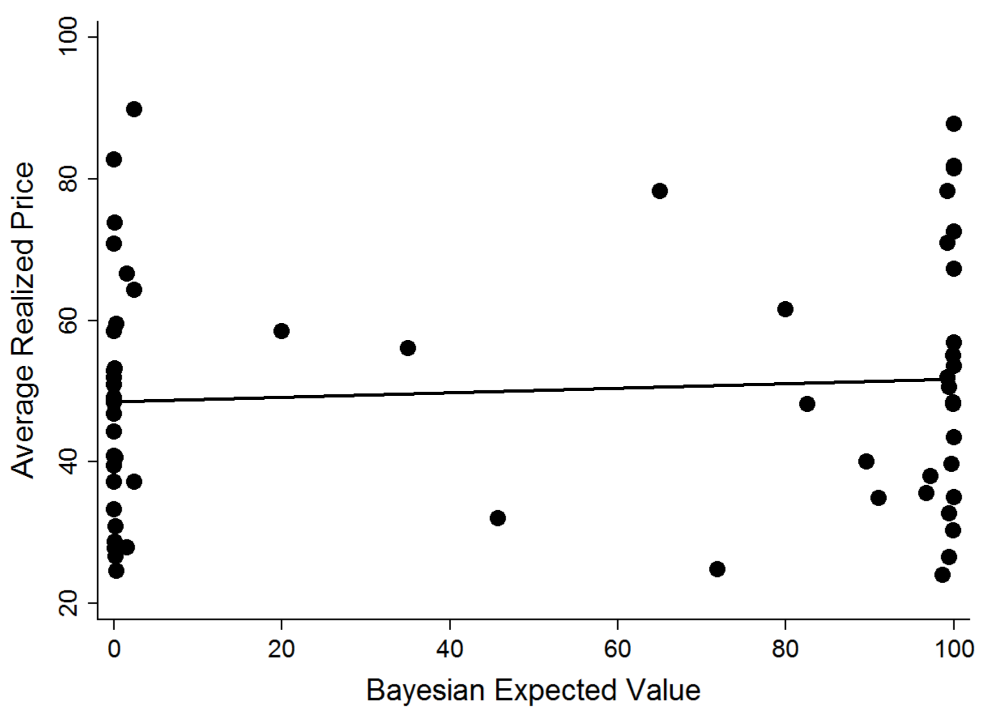


Figure 2: Own Accuracy Treatment

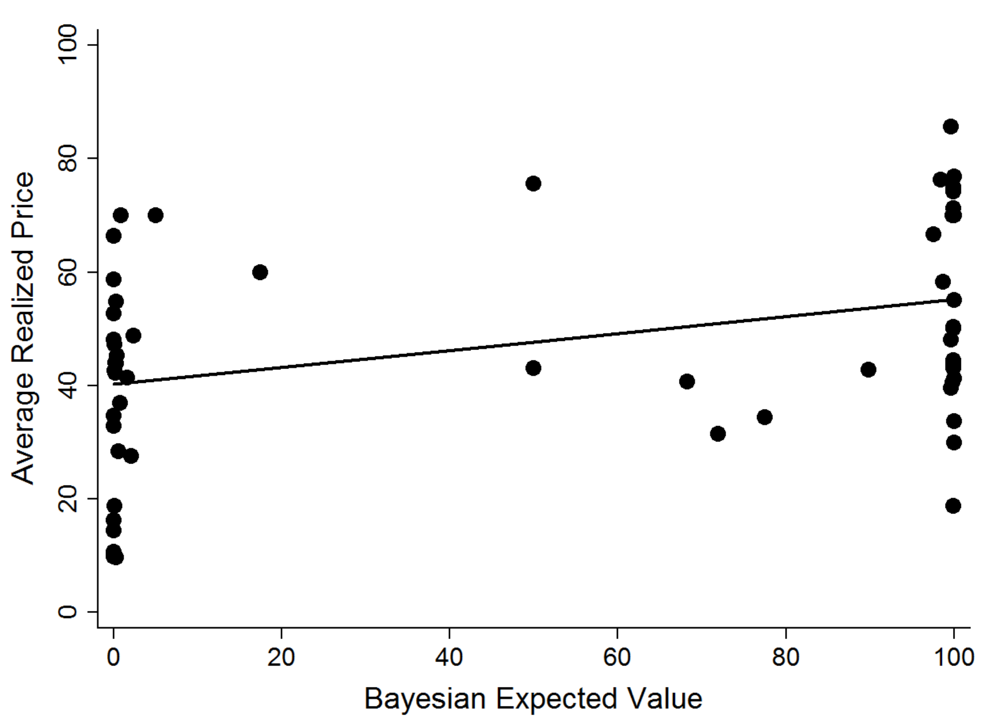
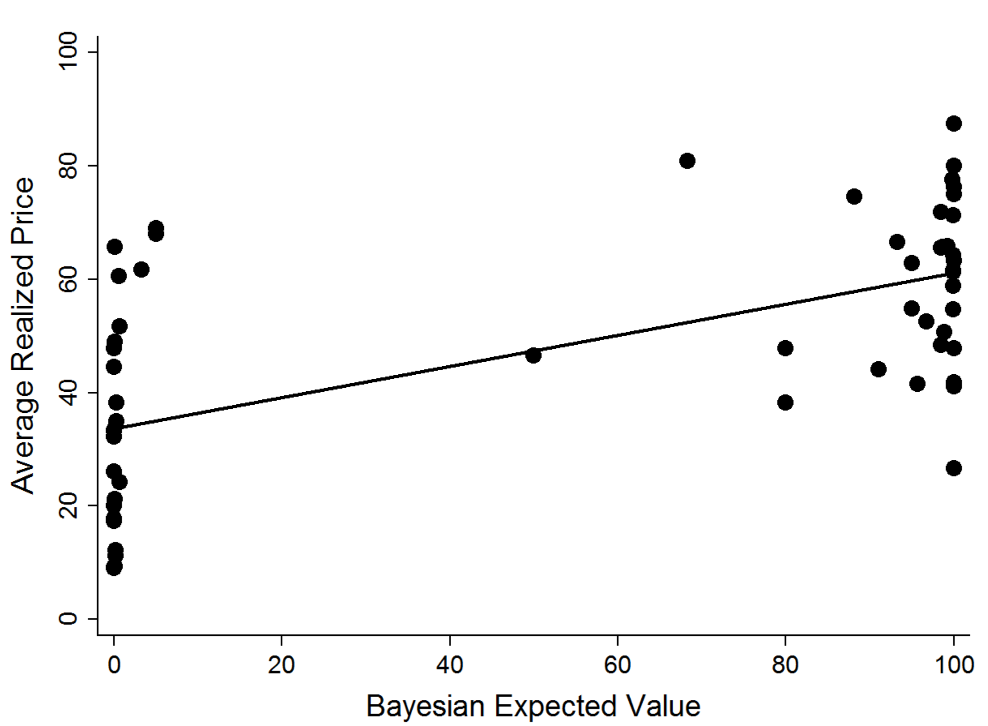


Figure 3: Full Accuracy Treatment



To explore information aggregation in more detail a set of regressions, is conducted with the variable Bayesian expected value as the dependent value and the Average observed prices as the independent variable is conducted. These regression results are shown in Table 8 for each condition separately. As can be seen, the Average observed price only has explanatory power in the Own Accuracy Treatment and the Full Accuracy Treatment. The results from the Own Accuracy Treatment and the Full Accuracy Treatment are qualitatively similar to previous studies which use a similar market structure (see Oprea et al., 2007, and Deck et al., 2013).

Previous research has found that information aggregation is in part explained by excess bids (Deck et al., 2013). Excess bids are the number of bids minus the number of asks at the end of a period. As a robustness check, the last three columns in Table 8 report regression results controlling for excess bids. There are no qualitative changes in the effect of average prices on the Bayesian expected value in this set of regressions. Average observed prices are still positively correlated with Bayesian expected values and significant for both the Own Accuracy Treatment and the Full Accuracy Treatment. Excess bids are significant and positive for the Baseline and the Own Accuracy Treatment but not for the Full Accuracy Treatment. This shows that in the Baseline and Own Accuracy Treatment excess bids carry information regarding the value of the asset, but not in the Full Accuracy Treatment. The positive coefficient on excess bids indicates the value of the asset is high when there are more standing bids than standing asks.[6]

Table 8: Information Aggregation

The dependent variable is the Bayesian expected value in a given period.
OLS regressions, standard errors clustered by group.

Variables	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**
Average observed price	0.219	0.949**	1.403***	0.047	0.385*	1.360***
	[0.381]	[0.334]	[0.116]	[0.332]	[0.173]	[0.164]
Excess bids				2.818***	2.355**	0.433
				[0.412]	[0.791]	[0.459]
Constant	37.048*	3.780	-14.975**	66.706***	50.232***	-11.790
	[18.275]	[19.003]	[5.650]	[14.325]	[10.557]	[9.772]
R-squared	0.007	0.143	0.385	0.149	0.278	0.390
Observations	60[a]	60	60	60	60	60

Standard errors given in brackets. *p<0.10, ** p<0.05, ***p<0.01
a. There are 10 observations for each group of five and for each condition there are six groups

5 Discussion

A lab experiment is used to explore the role of feedback in eliminating the effect of overconfidence in asset markets. Overconfidence in this experiment affects trading by leading

[6] The results presented here remain qualitatively the same when closing price is used instead of average price. The only exception is that prices are not significantly correlated with Bayesian expected value for the Own Accuracy Treatment when closing price is used as the independent variable (see Appendix D).

to higher trading volume. Specifically, of the two measures of overconfidence only overestimation affects trading volume, while overplacement does not have a significant effect in the Baseline. These findings support previous theoretical and experimental research which claims that it is through an overestimation of one's knowledge that overconfidence affects trading behavior (Odean, 1998 and Deaves et al., 2008). There is also some evidence that overplacement leads to overtrading when the effect of overestimation is blocked. This finding is in line with previous research that finds that people who think they have better investment skills than others trade more (Glaser and Weber, 2007).

Feedback is successful in eliminating the effect of overconfidence on trading volume. Overestimation has a positive and significant effect on trading volume in the Baseline, but the significance disappears when people are provided with feedback. This shows that feedback can be used to remedy the overtrading effect that overconfidence has on asset markets. There is some evidence that feedback is also successful in eliminating the effect of overplacement. While overplacement is not significant in the Baseline it does have a marginally significant effect in trading volume in the Own Accuracy Treatment. When traders are informed of the accuracy of the other group members in the Full Accuracy Treatment overplacement no longer significantly affects trading volume. This suggests that feedback was successful in eliminating the effect of overplacement in trading volume.

Several studies (Deaux et al., 1977; Estes and Hosseini, 1988; and Lundeberg et al., 1994) have shown that men tend to be more overconfident than women, but more recent studies report no gender differences on the level of overconfidence (Biais et al., 2005, and Deaves et al., 2008). In this experiment there are no gender differences for either measure of overconfidence. One possible explanation for this could be that gender differences highly depend on the type of the task (Deaux et al., 1977 and Lundeberg et al., 1994). Other research has shown that men tend to be more overconfident when the tasks are in the masculine domain (Deaux and Emswiller 1974; Lenney, 1977; and Bowden 1997). In this experiment traders faced a counting task which can be considered gender-neutral. Hence, the lack of gender difference in the level of overconfidence can be attributed, at least in part, to the task employed here.

Information aggregation when the accuracy of the signals is heterogeneous and endogenous was also explored in this experiment. While in previous experiments on information aggregation signals have had exogenous accuracy, in naturally occurring markets this is not the case. In naturally occurring markets the quality of information depends on the ability of individuals to gather and interpret information. In this aspect the current experiment is more similar to the naturally occurring markets than are previous experiments. The modest success of the markets to aggregate information in the Own Accuracy Treatment and Full Accuracy Treatment, similar to previous lab experiments, shows that this phenomena is more robust than previously thought. However, the lack of information aggregation in the Baseline shows that prices may not always aggregate information well when the accuracy of information is not known. The results from the Baseline indicate that policy makers who use prediction markets to make decisions should consider that these markets may fail to aggregate information well.

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Appendix

A Sample Instructions - Full Accuracy Treatment

Welcome, and thank you for participating in this experiment.

Just for participating, you are guaranteed a $7.5 payment. You can earn additional money based on your decisions, so it is important that you read the directions carefully. If you have any questions during the experiment, please raise your hand and wait for the experimenter to come to you. Please do not talk or communicate with other participants over the duration of the experiment.

This study is composed of five parts. The first three parts consist of 10 periods each, in the fourth part you will answer 7 short questions, and the last part is a short survey. You will be placed in a group with four other people. The people in the group will be **the same** during the whole experiment.

Part I

In the first part, each period you are shown 100 rectangles of various colors (red, yellow, purple, black, green and blue), and your task is to count the number of red rectangles shown. You have 7 seconds to finish this task, once time runs out you are asked to enter your best guess about the number of red rectangles. Then you will be asked two follow-up questions.

Question 1

Table 9: Question one Options

Options	Payoff
Exact	$33
Within 1	$30
Within 2	$27
Within 3	$24
Within 4	$21
Within 5	$18
Within 6	$15
Within 7	$12
Within 8	$9
Within 9	$6
Guaranteed	$3

The first question asks you how close your guess was to the true number of red rectangles. Your payoff in that period will depend on the accuracy of your answer. You have several options and the wider the interval you select, the less you are paid if you are correct.

If you state that your guess was the **exact** number of red rectangles and you were right, you will get paid 3, but if you are wrong you will earn $0.
If you state that your guess was **within +/- 1** and you are right, you are paid $30, but if you are wrong you will be paid $0.
If you state that your guess was **within +/- 2** and you are right, you are paid $27, but if you are wrong you will be paid $0.
Each consecutive row has a wider interval and a lower payment. The next to last option is:
If you state that your guess was **within +/- 9** and you are right, you are paid $6, but if you are wrong you will be paid $0.
The last option is a **guaranteed** payment of $3 which you get regardless of how accurate your guess is.

Questions 2

The second question regards the other four people in your group. For this question you will need to state how many of the other four people in your group were more accurate than you. More accurate means they were closer to the true number of red rectangles than you were. You will receive $2 if you answer this question correctly.

Example: if the true number of red rectangles is 48. You enter 44 and the other four people enter 45, 47, 54, 58 then two people were more accurate than you since you are 4 away and the other four are 3, 1, 6, and 10 away respectively. Thus the other two people who (3 away and 1 away) are closer than you.

After you answer these two questions, you will start with another counting task with a new display of 100 rectangles and go through the same questions for a total of 10 periods.

Payment

If a period is chosen from Part I of the experiment for your payoff you will be paid for both questions. That is, you will receive the payment from question one plus $2 if you answered question two correctly.

Part II

Part two of the experiment is composed of 10 periods. In each period you will complete a rectangle counting task as in Part I. You will only need to enter the number of red rectangles for this part. Then you will participate in a trading session lasting 120 seconds where you can buy and sell assets. At the beginning of each period, you and the four other people in your group are each given a capital balance of 300 tokens and 3 assets. The value of the three assets is the same and it is **either** 100 or 0 tokens each. **The value of the assets is the same for everyone in the group**. The value of the assets for your group will be determined randomly by the computer, with a 50% chance all assets will have a value of 100 tokens and a 50% chance all assets will have a value of 0 tokens. Tokens are converted at the end of the experiment for dollars. You receive $1 for every 20 tokens you have after trading. **This means that your assets are worth either $5=100 tokens/20 each or $0 = 0 tokens/20 each.**

You do not know the true value of the assets during the trading session, but you will receive some news about the value. The accuracy of the news depends on how close your guess was to the true number of red rectangles that period. The more accurate your guess, the more accurate your news is. The table below shows the different levels of accuracy for your news:

Difference Between Guess and True Number of Red Rectangles	Accuracy of the News
3 or less	95%
4, 5, 6	80%
7, 8, 9	65%
more than 9	50%

Accuracy means the **chance** that the news you receive is **correct**.

Example: If you are within six then the news you receive is correct 80% of the time. This means that you will see the correct value of the assets 80 times out of 100 (80% of the time) and the incorrect value of the assets 20 times out of 100 (20% of the time). So, if the value of the asset picked by the computer is 100 then 80% of the time you would receive news that the value is 100, and 20% of the time you would receive news that the value is 0. If instead the value of the asset picked by the computer is 0 then 80% of the time you would receive the news that the value is 0 and 20% of the time you would receive the news that the value is 100.

What does the accuracy of information mean?

Example 1

If you see a value of 100 tokens with 80% accuracy the expected value of each of the assets you hold until the end of the trading is 80 = (100*80%) + (0*20%). So, if you hold your 3 assets until the end of trading your expected value of the 3 assets is 240 tokens = 80 tokens * 3 assets.

Example 2

If you see a value of 0 tokens with 95% accuracy the expected value of each of the assets you hold until the end of the trading is 5 = (0*95%) + (100*5%). So, if you hold your 3 assets until the end of trading your expected value of the 3 assets is 15 tokens = 5 tokens *3 assets.

The same accuracy rules applies for everyone in the group. The more accurate someones guess of the number of red rectangles, the more likely it is that the news they receive is correct. Notice that if your guess is 10 or more away from the true number of red rectangles then your accuracy is 50% which means that the news is equally likely to be 0 and 100 regardless of what the value of the assets is. In this case the news does not actually contain any information.

Please turn your attention to the screen in front of you where we will go over each part of the trading platform.

For **each** asset you trade there is **a fee of three tokens**. So, if you sell three assets you pay a fee of nine tokens or if you buy two assets you pay a fee of six tokens.

At the end of each period you will receive feedback on your performance in the trading task. You will see:

1. The **true value** of the asset
2. The value of the asset **according to your news**
3. The **accuracy** with which you saw the **news**
4. The number of assets you have
5. The number of tokens you have
6. The total value of your assets and tokens in dollars

How is the total value of assets and tokens converted to dollars?

Example: if at the end of the experiment you have two assets and 384 tokens and the asset value for that period is 100 you will receive \$29.20 = (384 tokens + 2 assets x 100 tokens)/20. Once you receive this feedback you will start the next period with another counting task and go through all these steps again. Tokens and assets cannot be carried from one period to the next. You will start each period with 3 assets and 300 tokens.

Part III

You will complete 10 periods that are the same as the periods in Part I of the experiment.

Part IV

In this part you will answer 7 short questions. You will receive \$1 for each question answered correctly. You will have 45 seconds to answer each question.

Part V

In part five you will complete a short survey.

Payoff for the experiment

Your payoff will be determined by your performance in one of the tasks you complete from Part I, II, or III. First, the computer randomly chooses one of the 30 periods you completed. If the period chosen is from the first or the third part you will get paid for both questions you answered on that part of the experiment. If the period chosen for your payoff is from the second part of the experiment you will get paid based on your earnings from the trading task. The amount of money you make in **Part IV** will be added to the random payoff chosen. Please raise your hand if you have any questions and someone will approach you.

Script used for the Full Accuracy Treatment

You will see the news about the value of your assets on the top left of your screen. Below the news you will be able to see the accuracy with which your news was generated. To the right of this box you will see the accuracy with which the other four people in your group receive their news. The accuracy of the news for the other four people in your group is determined in the same way the accuracy of your news is determined. In the screen now you see: Your accuracy is 95% the accuracies of the other four people are 95%, 80%, 50%, and 50% respectively. Therefore, you and another person have the highest accuracy of the news.

Just below your signal is the number of tokens and assets you have. These numbers change when you start buying and selling assets. Below this information you can see the trading platform. The box in the middle allows you to enter the price and volume at which you want to sell or buy. When you buy, the number of tokens you have is reduced by the number of tokens you spent and the number of assets you buy is added to the assets you have. When you sell, the number of assets you have is reduced by the number of assets you sell and the amount of tokens you have is increased by the price multiplied by the number of assets you sell.

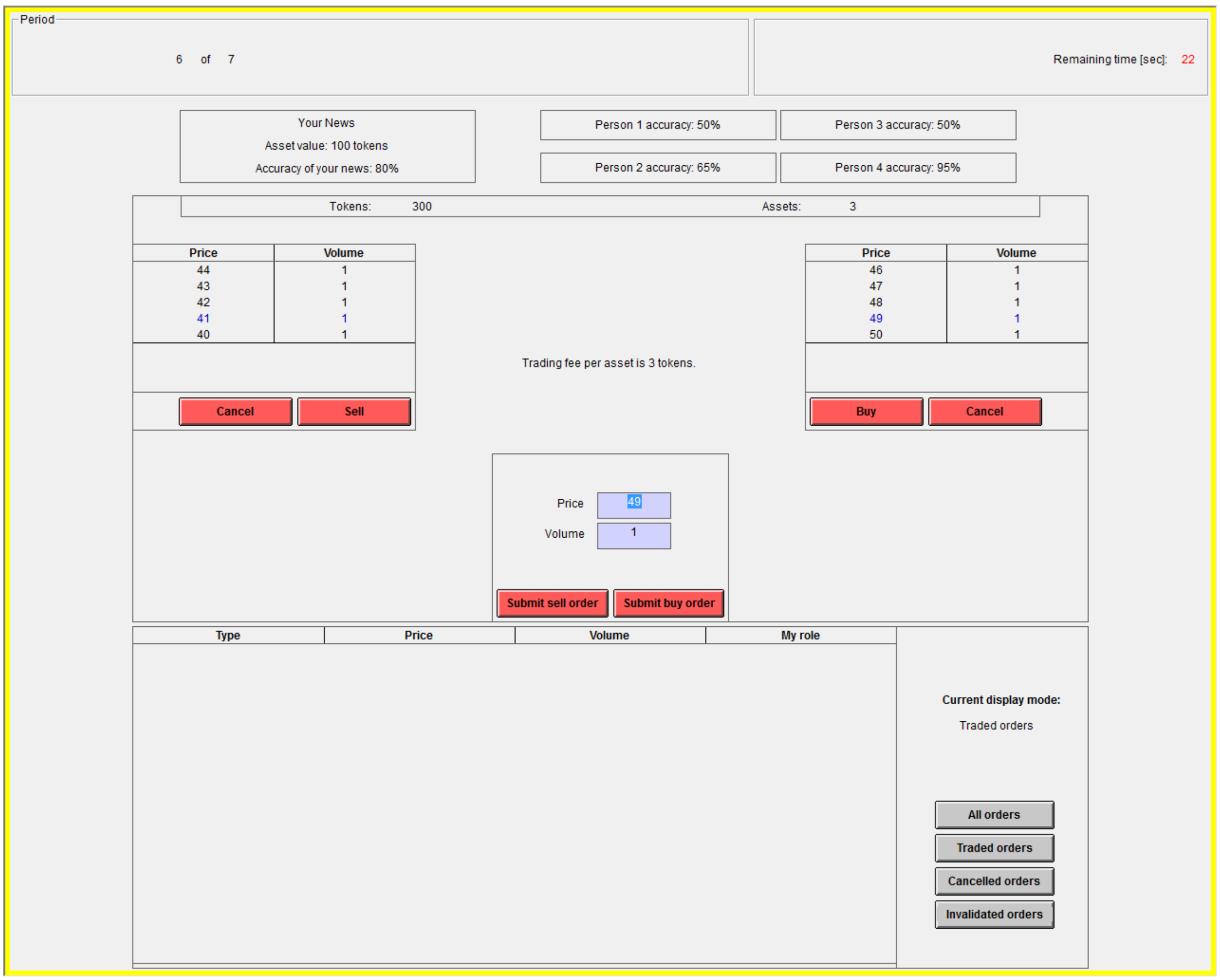
If you want to sell, you first enter the price and the number of assets you want to sell and then click the button "Submit sell order." If you want to buy you first enter the price and the number of assets you want to buy then click the button "Submit buy order." You can see your sell orders above and on the right of the box where you enter the price and volume and your buy orders on the box on the left. You can cancel an order at any time by selecting it and clicking cancel. You are not allowed to buy or sell the orders you yourself have placed. Your buy or sell orders are shown in blue while the orders of others in your group are shown in black. You are not allowed to place a sell order with more assets than you own or buy more assets than what you can afford with the cash you have.

Example: if you have three assets that is the maximum number you can sell. On the other side of the market, if you have 200 tokens you cannot buy three asset at 70 tokens each because this would require 210 tokens. The computer shows a message each time you enter an invalid order.

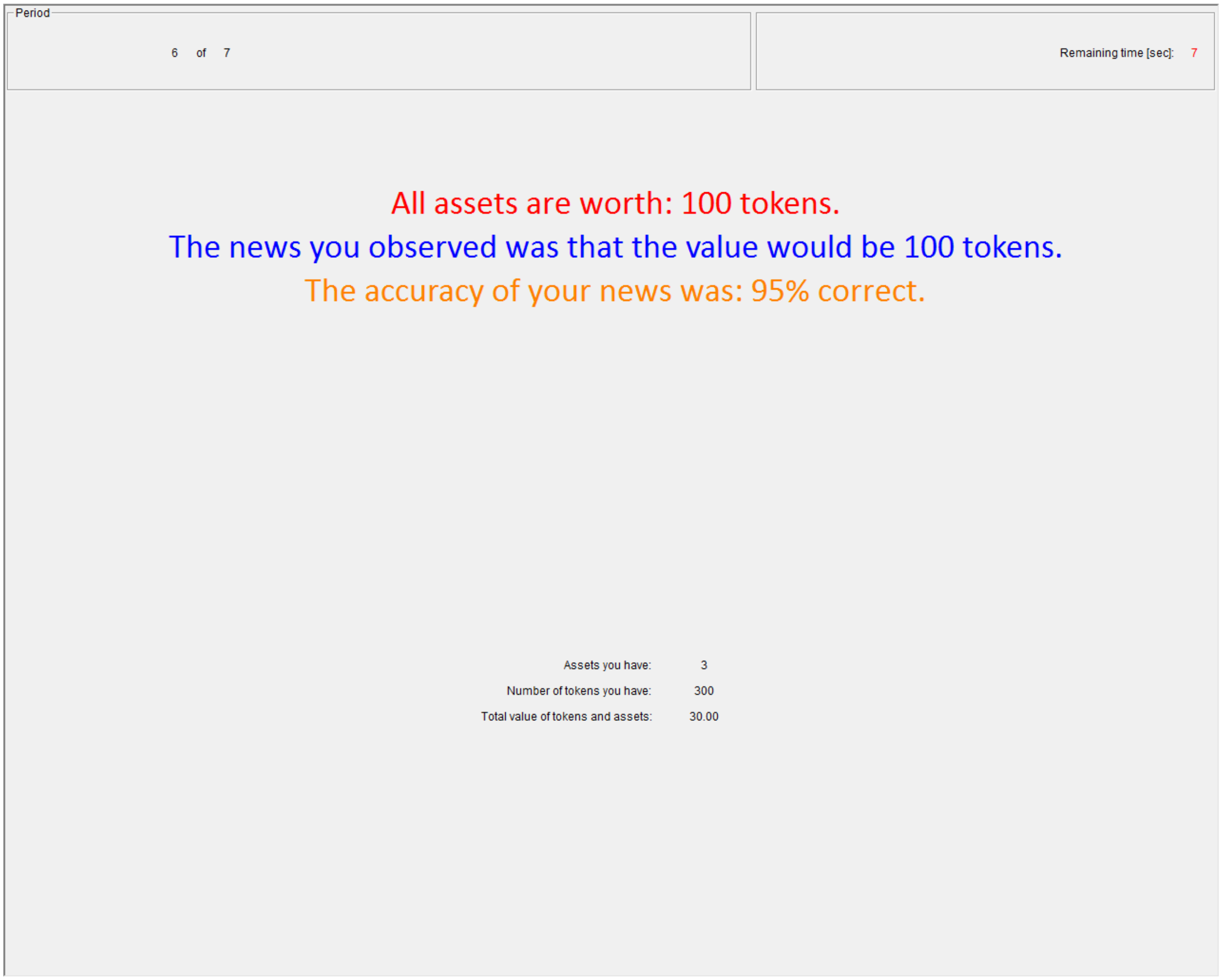
On the box above and to the right of the price and volume box you will also see the orders you can buy in addition to your order to sell. These orders will be ranked from the lowest price on the top to the highest price on the bottom. If you want to enter a new order to sell the price must be lower than the lowest price on the list. On the left above the price and volume box you will see orders you can sell in addition to your order to buy. These orders will be ranked from the highest on top of the list to the lowest on the bottom of the list. If you want to enter a new buy order your price must be higher than the highest price on the list. To buy or sell you need to select (by clicking on that row) the order which you are trying to buy or sell and then click either buy or sell.

Below the trading platform there is a table where you can see all of your previous actions. You can choose what you see in this table by clicking on the buttons on the right. If you want to see all orders you click on "All Orders" button, if you want to see only the orders you traded you click on "Traded Orders" button, if you want to see your canceled orders you click on "Canceled Orders", and if you want to see the orders that were invalid you click on "Invalidated Orders." You only see your orders here not the orders of the other four people in your group.

Screenshot for the Full Accuracy Treatment.



Feedback Screenshot for the Full Accuracy Treatment.



B CRT Questions and Survey

B.1 CRT Questions

1. A bat and a ball cost $1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost (in cents)?

2. It takes 5 machines 5 minutes to make 5 widgets. How many minutes would it take 100 machines to make 100 widgets (enter a numeric value)?

3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how many days would it take for the patch to cover half of the lake (enter a numeric value)?

4. If John can drink one barrel of water in 6 days, and Mary can drink one barrel of water in 12 days, how long would it take them to drink one barrel of water together?

5. Jerry received both the 15th highest and the 15th lowest mark in the class. How many students are in the class?

6. A man buys a pig for $60, sells it for $70, buys it back for $80, and sells it finally for $90. How much has he made?

7. Simon decided to invest $8,000 in the stock market one day early in 2008. Six months after he invested, on July 17, the stocks he had purchased were down 50%. Fortunately for Simon, from July 17 to October 17, the stocks he had purchased went up 75%. At this point, Simon has:

   (a) broken even in the stock market

   (b) is ahead of where he began

   (c) has lost money

B.2 Survey

1. Gender

   (a) Male

   (b) Female

2. Age

3. How much trading experience do you have?

   (a) None

   (b) Some

   (c) Average

   (d) More than average

   (e) Professional

4. How many Math and Statistics classes have you taken?

5. On a scale 0-10 (with 0 being did not use it at all and 10 used it all the time) how much did you use the accuracy of your news?

6. On a scale 0-10 (with 0 being did not find it useful at all and 10 very useful) how useful did you find the accuracy of your news?

7. On a scale 0-10 (with 0 being did not use it at all and 10 used it all the time) how much did you use the accuracy of the news of the other four group members?

8. On a scale 0-10 (with 0 being not useful at all and 10 very useful) how useful did you find the accuracy of the news of the other four group members?

C Robustness Check Analysis

C.1 Gender Effect on Profits

Table 10: Gender Effects on Bayesian Net Profits

The dependent variable is the average net profit a participant earned in Stage II. OLS regressions, standard errors clustered by group.

Variables	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**
Overestimation-1	0.037	-0.557*	-0.320
	[0.361]	[0.277]	[0.332]
Overplacement-1	0.231	-0.673	0.360
	[0.458]	[0.552]	[0.337]
Male	1.082	-4.493	0.169
	[1.856]	[2.981]	[2.481]
Male-Overestimation-1	0.040	-0.509	-0.011
	[0.461]	[0.560]	[0.358]
Male-Overplacement-1	-0.593	1.686	-0.192
	[0.593]	[1.229]	[0.360]
Constant	14.267***	28.619***	29.606***
	[3.032]	[5.238]	[3.455]
R-squared	0.765	0.668	0.673
Observations	30	30	30

Standard errors given in brackets. *p<0.10, ** p<0.05, ***p<0.01

C.2 Robustness Check - Information Aggregation

Table 11: Summary statistics for each condition.

	Baseline		**Own Accuracy Treatment**		**Full Accuracy Treatment**	
Asset Value	0	100	0	100	0	100
Bayesian Expected Value	6.2 [17.3]	92.8 [19.6]	5.3 [16.6]	92.5 [20.8]	8.5 [25.0]	96.2 [7.6]
Average Price	49.7 [16.7]	50.5 [19.3]	41.9 [18.6]	53.2 [18.0]	36.0[19.8]	60.0 [15.0]
Closing Price	46.7 [18.7]	49.3 [22.8]	35.7 [23.2]	56.2 [23.7]	34.5[22.5]	63.5 [19.1]

Standard deviations in brackets.

Figure 4: Baeline

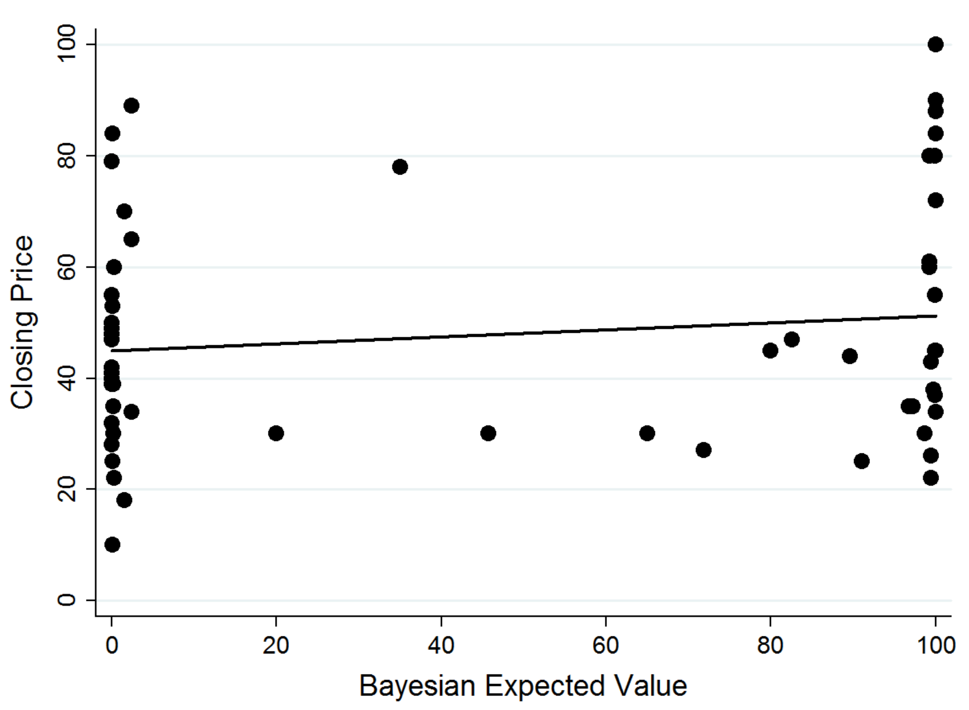


Figure 5: Own Accuracy Treatment

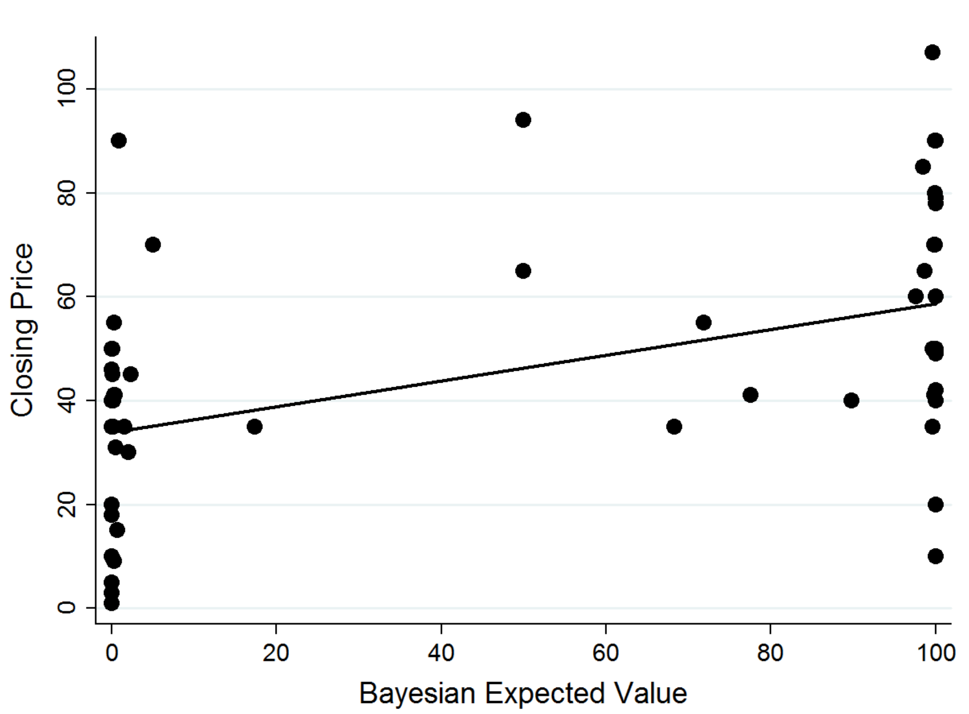
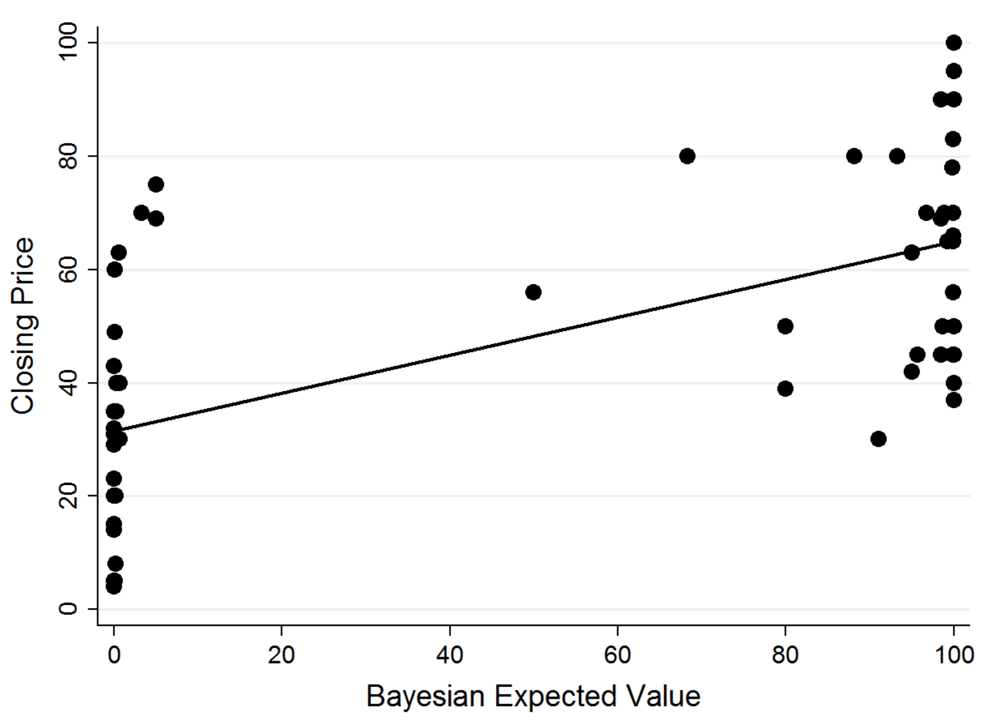


Figure 6: Full Accuracy Treatment



Information Aggregation Using Closing Price

The dependent variable is the Bayesian Expected Value in a given period.
OLS regressions, standard errors clustered by group.

Variables	Baseline	Own Accuracy Treatment	Full Accuracy Treatment	Baseline	Own Accuracy Treatment	Full Accuracy Treatment
Closing Price	0.32	0.85**	1.17***	0.08	0.44	1.14***
	[0.35]	[0.26]	[0.12]	[0.31]	[0.23]	[0.16]
Excess bids				2.77***	2.01*	0.35
				[0.50]	[0.89]	[0.46]
Constant	32.76*	9.64	-5.05	64.98***	45.24***	-2.63
	[15.69]	[16.45]	[7.62]	[14.16]	[16.26]	[10.77]
R-squared	0.020	0.211	0.391	0.150	0.297	0.394
Observations	60[a]	60	60	60	60	60

Standard errors given in brackets. *p<0.10, ** p<0.05, ***p<0.01
a. There are 10 observations for each group of five and for each condition there are six groups

D Analysis Including Dropped Group

The following tables differ from the tables in the paper only in Own Accuracy Treatment (and t-tests affected by this change) which now includes the group of five dropped from the main analysis.

Table 12: Summary Statistics

Summary statistics for each condition						
Variables	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**	***p*-value Col. 1 vs. Col. 2**	***p*-value Col. 1 vs. Col. 3**	***p*-value Col. 2 vs. Col. 3**
Men	43.33%	60.00%	56.67%	0.171	0.304	0.807
Age	21.87	20.66	21.90	0.064	0.963	0.007
Math & Stat Classes	3.63	3.45	3.17	0.800	0.345	0.657
Trading Experience	1.40	1.57	1.63	0.331	0.244	0.778
CRT	1.77	1.91	1.50	0.713	0.513	0.298

Table 13: Overconfidence Measures and Trading

Summary statistics of the main overconfidence measures and trading activity.							
Stage	**Variables**	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**	***p*-value Col. 1 vs. Col. 2**	***p*-value Col. 1 vs. Col. 3**	***p*-value Col. 2 vs. Col. 3**
Stage I	Overestimation-1	0.10 [5.54]	-1.83 [4.54]	0.70 [4.96]	0.128	0.660	0.036
	Max	8	8	9			
	Min	-10	-10	-10			
	Overplacement-1	0.77 [4.33]	0.71 [3.63]	0.47 [5.24]	0.952	0.810	0.829
	Max	9	10	10			
	Min	-9	-4	-10			
Stage II	Assets Traded	4.51 [2.08]	3.65 [3.38]	3.84 [1.62]	0.231	0.169	0.780
	Max	8.6	22	9			
	Min	0.3	0	1.9			
	Signal Accuracy	79% [17%]	80% [16%]	78% [18%]	0.808	0.826	0.637
Stage III	Overestimation-3	0.40 [5.42]	-2 [4.35]	-0.53 [5.82]	0.052	0.524	0.249
	Max	10	7	10			
	Min	-10	-10	-10			
	Overplacement-3	0.73 [3.81]	1.03 [4.17]	-0.20 [5.68]	0.765	0.459	0.319
	Max	7	10	10			
	Min	-8	-7	-8			

Standard deviations shown in brackets.

Table 14: Overconfidence and Trading Volume

The dependent variable is the number of trades a participant completed in one period. OLS regressions, standard errors clustered by participant.

Variables	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**
Overestimation-1	0.175***	0.159	-0.052	0.160***	0.152**	-0.014
	[0.055]	[0.125]	[0.053]	[0.050]	[0.071]	[0.040]
Overplacement-1	-0.022	-0.12	0.027	0.040	-0.167	0.049
	[0.058]	[0.146]	[0.059]	[0.066]	[0.135]	[0.037]
Age				0.056	0.519	-0.500***
				[0.087]	[0.527]	[0.171]
Male				-0.803	0.154	0.663
				[0.649]	[0.755]	[0.443]
Math & Stat Classes				0.202	-0.333	0.540**
				[0.144]	[0.221]	[0.242]
Trading Experience				-0.193	-0.371	-0.197
				[0.550]	[0.542]	[0.190]
CRT				0.193	-0.103	0.364
				[0.215]	[0.195]	[0.192]
Signal Accuracy				0.536	-0.801	-0.596
				[1.092]	[1.240]	[0.649]
Group Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.622***	3.575***	3.200***	-0.623	-5.124	12.049***
	[0.409]	[0.740]	[0.234]	[2.056]	[10.800]	[2.966]
R-squared	0.310	0.348	0.145	0.344	0.401	0.224
Observations	300	350	300	300	350	300

Standard errors given in brackets. *p<0.10, ** p<0.05, ***p<0.01

Note: Math & Stat Classes is the number of math and statistics classes a participant has taken. Trading Experience is the reported trading experience by subjects on a scale of one to five with one being no experience and five being professional trader. CRT is the number of correct CRT questions. Signal Accuracy is how accurate the signal was for a given participant in that period (50%, 65%, 80% or 95%).

Table 15: Overconfidence and Bayesian Net Profits

The dependent variable is the net profit (in dollars) in a period when the value of the asset is the Bayesian expected value. OLS regressions, standard errors clustered by participant.						
Variables	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**	**Baseline**	**Own Accuracy Treatment**	**Full Accuracy Treatment**
Overestimation-1	-0.110	-0.183	-0.110	-0.161	-0.209	-0.060
	[0.119]	[0.121]	[0.083]	[0.120]	[0.129]	[0.093]
Overplacement-1	-0.126	0.037	0.047	-0.044	0.098	-0.002
	[0.149]	[0.121]	[0.068]	[0.164]	[0.078]	[0.073]
Age				0.288	-0.325	0.269
				[0.214]	[0.421]	[0.206]
Gender (Male=1)				2.759**	-0.634	-0.466
				[1.300]	[1.047]	[0.691]
Math & Stat Classes				-0.465**	0.224	-0.817**
				[0.182]	[0.170]	[0.328]
Trading Experience				-1.100	0.407	-0.194
				[1.434]	[0.684]	[0.7582]
CRT				0.165	0.454	0.065
				[0.437]	[0.366]	[0.292]
Signal Accuracy				2.521	6.223	1.065
				[2.527]	[3.790]	[3.912]
Signal Value				3.471**	1.342	1.950*
				[1.302]	[1.386]	[1.067]
Group Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	23.349***	24.483***	20.623***	14.932***	23.299***	15.293**
	[1.108]	[0.995]	[0.795]	[4.566]	[8.322]	[5.994]
R-squared	0.072	0.059	0.141	0.122	0.091	0.166
Observations	300	350	300	300	350	300

Standard errors given in brackets. *p<0.10, ** p<0.05, ***p<0.01

Note: Math & Stat Classes is the number of math and statistics classes a participant has taken. Trading Experience is the reported trading experience by subjects on a scale of one to five with one being no experience and five being professional trader. CRT is the number of correct CRT questions. Signal Accuracy is how accurate the signal was for a given participant in that period (50%, 65%, 80% or 95%). True Signal is one if a participant saw the true value of the asset and zero otherwise.