Overconfidence and Market Performance

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Abstract

How does trader overconfidence (judgemental or self-enhancement) affect individual performance in asset markets, and overall market quality? Conversely, how does market participation affect traders' overconfidence? To address such questions, we build a laboratory asset market in which human participants receive private information of varying precision and then trade an asset that pays a single state-contingent dividend. Among other results, we find that greater trader overconfidence can improve price efficiency in some environments, but not in the most realistic environment with experienced traders and ambiguous mixed information precision. In that environment, overconfidence reduces trader profits. We detect no substantial impact of market exposure on trader overconfidence.

Key Words: Overconfidence; Information Aggregation; Market Efficiency; Laboratory Asset Market.

JEL Classifications: C92, D83, D91, G14, G41.

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1 Introduction

There is a widespread impression that professional traders tend to be overconfident about their own relative ability and the accuracy of their beliefs. If so, how would such overconfidence affect their personal performance in asset markets? How would it affect the overall performance of financial markets? But perhaps traders are not actually so overconfident. At least since Alchian (1950), some economists have argued that participants who deviate from rationality will suffer from lower payoffs, and they either will learn to act more rationally or else will be displaced by more rational agents. Other economists, such as De Long et al. (1990), Kyle and Wang (1997), and Benos (1998) have argued the opposite, suggesting that overconfidence can thrive in financial markets. To what extent do markets discipline traders and reduce their overconfidence?

To investigate such questions, we build a new laboratory asset market in which key variables can be directly controlled and observed. Human participants in our laboratory sessions receive private information and then trade an asset that pays a single state-contingent dividend. We construct different information environments in which the private information has homogeneous precision, either high or low, and also consider heterogeneous environments in which the precision distribution either is explicitly announced or remains ambiguous. To assess overconfidence (or underconfidence), we elicit traders' beliefs about the state, the asset value, and their relative profitability. We do so right after traders receive their private information prior to trade, and again right after the asset market closes.

We find that overconfidence measurement via belief elicitation is highly correlated with measurement via value elicitation, but not with measurement via anticipated profit rank. We find that the markets do a good job of disseminating private information, and that price efficiency is enhanced by trader experience and by unambiguous precision distribution. Overconfidence reduces price efficiency in some environments, but (perhaps surprisingly) tends to increase it in other environments. Also, we find considerable persistence in traders' overconfidence, and little evidence that it is mitigated by market participation.

Our experiment draws on and contributes to several strands of literature. Various existing studies investigate the impact of overconfidence on market performance. Overconfidence can affect asset prices and bubbles (e.g., Aragón and Roulund (2020), Michailova and Schmidt (2016)), price volatility (e.g., Benos (1998), Odean (1998)), portfolio choices (e.g., Chen et al. (2024), Cueva et al. (2019), Merkle (2017)), and trading volume (e.g., Yang and Zhu (2016), Glaser and Weber (2007), Statman et al. (2006), Caballé and Sákovics (2003), Odean (1998)). Laboratory as well as field experiments found increased trading volume arising from calibration-based overconfidence (Deaves et al. (2009), Biais et al. (2005)), the better-than-average effect (Glaser and Weber (2007)), and misperceived signal reliability (Fellner-Röhling and Krügel (2014)). Evidence is mixed on how overconfidence affects trading profits. Reduced profits are reported in Barber et al. (2020), Odean (1998), Biais et al. (2005), but increased profits are suggested in Inghelbrecht and Tedde (2024), Benos (1998), Kyle and Wang (1997). A few recent papers (e.g., Bregu (2020), Meier and De Mello (2020), Ida and Okui (2020)) find that overconfidence declines when participants are given feedback, but other papers (e.g., Banerjee et al. (2023), Huffman et al. (2022), Murad and Starmer (2021), Banerjee et al. (2020), Hoffman and Burks (2017)) find more persistent overconfidence.

Most existing literature on the topic neglects heterogeneous signal precision, although such heterogeneity would seem to offer greater scope for overconfidence. Partial exceptions include Lunawat (2021), who publicly announces the average of subjects' pre-trading dividend forecast. Kirchler and Maciejovsky (2002) vary the precision of the public signals and find that participants are not generally prone to overconfidence. Barron and Qu (2014) include a high asymmetry treatment in which only half of the traders receive private signals. Our experiment seems to be the first to systematically examine the market impact of over- and underconfidence given varying and possibly heterogeneous signal precision.

One of our market environments features an ambiguous signal precision distribution. The most closely related previous literature includes Epstein and Schneider (2008), Bao et al. (2020), and Bao et al. (2021), who examine *individual* belief-updating processes in ambiguous environments and find that bad signals that indicate the realized asset value is lower than the prior will be treated as if they are more accurate (have smaller variance) than good signals that indicate the opposite. At the aggregate level, some works find asset prices tend to be lower when the fundamental value is ambiguous than when it is risky (e.g., Sarin and Weber (1993), Corgnet et al. (2020)), and price volatility is significantly larger under ambiguous signals (e.g., Bao et al. (2020)); however, Corgnet et al. (2013) find no significant differences in the control versus ambiguity treatments regarding prices, price volatility and trading volume for experienced subjects. Yang and Zhu (2016) report that traders who think they have better than average trading ability tend to trade more in the ambiguity treatment. Our paper contributes to this growing literature by incorporating overconfidence in an ambiguous market environment. Note that, unlike other treatments of ambiguity, the ambiguity in our environment concerns the precision distribution; traders still know the precision of their own private signal. This treatment of ambiguity has two advantages. First, knowing their own signal's precision allows traders to form posterior beliefs with a clearly measurable degree of overconfidence (see below). Second, we are able to hold constant across market environments the actual information distribution and thus to avoid potential confounds.

A separate strand of literature is concerned with the measurement of overconfidence. Moore and Healy (2008), Hilton et al. (2011), and Glaser et al. (2013) recognize four sorts of overconfidence. (i) Judgmental overconfidence refers to overestimating the precision of one's judgment. (ii) Self-enhancement bias, also known as the better-than-average effect, refers to an unrealistically high estimate of one's own rank or relative position. (iii) Overestimating the quality of one's absolute performance. (iv) Over-optimism regarding societal risks. The discussion on connections and differences between different overconfidence is still ongoing. While Glaser et al.

(2013) finds stable individual differences in the degree of overconfidence in interval estimates. Moore and Healy (2008) points out that task difficulties can impact agents' overconfidence level, and judgmental overconfidence appears to be more persistent than Self-enhancement and Overestimating one's absolute performance. One of our findings is consistent with Hilton et al. (2011), who find that "better-than-average" does not correlate with judgmental overconfidence.

Among these different sorts of overconfidence, judgemental overconfidence (i) is most commonly examined in the economics and finance literature. Typically (e.g., in Meier and De Mello (2020), Glaser et al. (2013), Biais et al. (2005)), the measurement task is to elicit a 90% confidence interval for each of several numerical general knowledge questions (e.g., how long is the Nile river?); the subject is deemed overconfident if significantly more than 10% of correct answers lie outside those confidence intervals. However, there are disadvantages to this interval measure. According to Cueva et al. (2019), this measure is difficult to incentivize, noisy at the individual level, and sensitive to responders' numeracy, general knowledge, and ability to conceptualize 90% confidence intervals. In addition, Teigen and JØrgensen (2005) and Langnickel and Zeisberger (2016) find the decision makers' stated intervals and perceived confidence are unaffected by the requested confidence level.

Therefore, instead of an interval measure, we shall use a direct measure of judgemental overconfidence, and deem a subject to be overconfident (resp. underconfident) to the extent that her elicited probabilities or valuations reflect greater (resp. lesser) precision than her private information actually has. Such direct measures have been used in relevant psychology literature at least since Brehmer and Lindberg (1970), Ganzach (1993), Czaczkes and Ganzach (1996), and Ganzach (1994), but are underutilized in the economics and finance literature (e.g., Grežo (2021), Meier and De Mello (2020), Fellner-Röhling and Krügel (2014), Fellner and Krügel (2012)). We prefer such measures because they capture what behaviorally inspired economic models refer to as overconfidence (e.g., Kyle and Wang (1997), Odean (1998), Benos (1998)), i.e., overestimating the precision of the signal. Also, such measures connect directly to the asset market in which the subjects perform. We will also employ a measure of self-enhancement bias that connects directly to our asset market.

A companion paper (Friedman and Wang (2024)[1]) uses similar procedures to elicit traders' beliefs and assess their market impact. The present paper deals with homegrown overconfidence, while the companion paper is concerned with induced polarized motivated beliefs.

The present paper unfolds as follows. Section 2 collects relevant standard theoretical material. Section 3 lays out the laboratory procedures and experiment design, and lists the specific hypotheses that we will test. Section 4 presents data summaries and hypothesis test results. Section 5 concludes. Appendix A offers supplementary figures and tables and Appendix B is a copy of instructions to laboratory subjects.

[1]This paper, titled "Motivated Beliefs Meet in the Marketplace", is currently under review at SSRN, and thus is not yet available to be cited.

2 Theoretical Considerations

Consider a world with two equally likely states, {G, B}, and imperfect signals about the true state. Low precision signals s_L are independent Bernoulli trials that indicate the true state with probability $q_L \in (0.5, 1)$, and high precision signals are similar but with probability $q_H \in (q_L, 1)$. Bayes' Theorem tells us that, after observing N_L low precision signals of which L indicate state G and N_H signals of which H indicate G, the posterior probability that the true state is G is

$$P = \frac{q_L^L \cdot (1-q_L)^{N_L-L} \cdot q_H^H \cdot (1-q_H)^{N_H-H}}{q_L^L \cdot (1-q_L)^{N_L-L} \cdot q_H^H \cdot (1-q_H)^{N_H-H} + (1-q_L)^L \cdot q_L^{N_L-L} \cdot (1-q_H)^H \cdot q_H^{N_H-H}}. \quad (1)$$

Figure 1 illustrates with an example used in the experiment. The left side presents s_L in terms of two bags that each contain 5 balls. If the true state is G (resp. B) then the decision maker sees only balls drawn randomly (with replacement) from the "Good bag" that contains 3 black balls and 2 white balls (resp. from the "Bad bag" with 2 black balls and 3 white balls). The decision maker does not see the bag, only the balls drawn from it. Thus $q_L = \frac{3}{3+2} = 0.6$ is the low precision signal accuracy, i.e., the probability that a black (resp. white) ball correctly indicates state G (resp B). The right side of Figure 1 similarly illustrates that the high precision signal s_H has accuracy $q_H = 0.8$. For example, consider two low precision signals, so $N_L = 2, N_H = 0$ in equation 1. The equation tells us that the posterior probability of state G in this example is $\frac{0.6^2 \cdot 1 \cdot 1 \cdot 1}{0.6^2 + 0.4^2} \approx .692 \approx 70\%$ if both balls are black (so $L = 2$), versus about 30% if both balls are white or exactly 50% if one ball is black and the other is white.

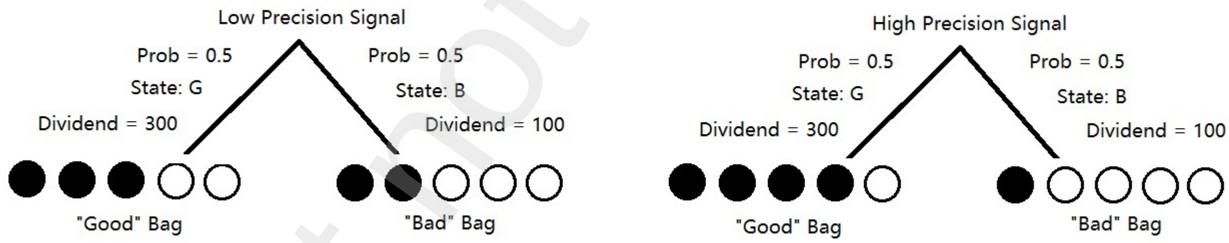

Figure 1: Private Signals

Of course, human subjects can't be expected to always implement equation (1) exactly. Recall the first notion of overconfidence in the literature is that private information is treated as if it were more precise than it actually is. To formalize that notion in our setting, note that increasing a uniform signal precision q in (1) pushes the posterior probability further away from the prior probability 0.5. Also, recall the signum function $sgn(y) = +1$ if $y > 0$, =0 if $y = 0$, and =-1 if $y < 0$. Suppose that a subject reports subjective probability p of state G when, according to equation (1), the true probability is P. Our *index of overconfidence* is then defined as

$$x = (p - P)sgn(P - 0.5). \quad (2)$$

That is, the report p is overconfident ($x > 0$) to the extent that it is further away than P from the prior probability 0.5 of state G, and it is underconfident ($x < 0$) to the extent that it lies closer to 0.5 than does the Bayesian posterior probability P. We often drop observations where $P = 0.5$ (e.g., the signal realization is one black ball and one white ball) but when we retain them we refer to any deviation from P as overconfident, and set $x = |p - P|$. When p and P lie on opposite sides of 0.5, we redefine the report as "confused" rather than underconfident.

We would like to measure subjects' overconfidence x for both pre- and post-trading but, unfortunately, it is impractical to do so. It turns out that in the vast majority of realizations, the fully-aggregated probability P given all private signals is very close to one of the two end points (as in Figure 6), and so leaves almost no room to observe overconfidence in post-trade elicited beliefs. Therefore, our analysis focuses on traders' *pre-trade* beliefs and over (or under) confidence x. In that case, P in equation (2) is the Bayesian posterior, given an individual trader's private signal.

2.1 Information Aggregation

An asset market is informationally efficient to the extent that it aggregates private information into the asset price. For example, suppose that each unit of an asset pays $d_G = 300$ in state G and $d_B = 100$ in state B. Suppose also that the state is revealed only after the market closes, but that each trader receives private information before the market opens. Then the market is informationally efficient to the extent that actual transactions prices converge to the fully-aggregated or rational expectations price

$$V^* = Pd_G + (1 - P)d_B = 100 + 200P, \tag{3}$$

where P = the Bayesian posterior probability from equation (1) conditional on all private signals, with N_L = the total number of balls from low precision bags seen by any market participant, L = the number of such balls that are black, and with N_H and H similarly defined for high precision signals.

For example, suppose that (as in period 13 of Figure 6 below) there are four participants who each receive two low precision ($q_L = 0.6$) signals and 5 of those 8 signals indicate state G, and four other participants who each receive two high precision signals ($q_H = 0.8$), of which 2 indicate G. Then $P = \frac{0.6^5 \cdot 0.4^3 \cdot 0.8^2 \cdot 0.2^6}{0.6^5 \cdot 0.4^3 \cdot 0.8^2 \cdot 0.2^6 + 0.4^5 \cdot 0.6^3 \cdot 0.2^2 \cdot 0.8^6} \approx 0.0087 \approx 1\%$ and $V^* \approx 102$. Although low precision participants have mostly misleading information, in this example at least two of the high precision participants see two white balls and so have pre-trade posterior probability of G of $\frac{0.2^2}{0.8^2 + 0.2^2} \approx 0.0588 \approx 6\%$. With full aggregation, those two (or possibly three) pieces of high-quality private information far outweigh the misleading low precision information.

It is difficult to model the actual process by which self-interested asset market traders might aggregate their private information (see Copeland and Friedman (1991) for an early attempt), but the general idea is that offer prices and trade prices may reveal some of the market participants' private information to the other participants. As a practical matter, aggregation will typically be less than complete, so it is useful to have measures of incomplete aggregation, or informational inefficiency. Perhaps the most direct measures are in terms of deviations of actual prices ν from the true value V^* given in equation (3). The mean absolute deviation (or, alternatively, the root mean squared deviation) of ν from V^* is a natural inefficiency metric that we will use in empirical work. We will also use an alternative metric proposed by Page and Siemroth (2021). Their idea is to find the fraction $\lambda \in [0, 1]$ of the actual number of private signals (e.g., balls drawn from a bag) that would account for the observed precision of actual prices; see Appendix A.11 for details on our implementation of λ.

Signed deviations from V^* can also be used as an index of overconfidence when traders' asset valuations v are elicited instead of probabilities:

$$x = (v - V^*)sgn(V^* - 200). \tag{4}$$

Similar to equation (2), the report v is over(under-)confident when $x > 0$ ($x < 0$). The fully-aggregated price is again usually very close to one of the two end points, so again we only compute x for pre-trade elicited valuations, where V^* in equation (4) is the true value conditional on an individual trader's private signal.

2.2 Trading strategies and overconfidence

A *market format* defines how market participants (traders) can make offers to trade and how those offers are processed to create actual trades (transactions). Our experiment will use the format known as the continuous double auction (CDA), variants of which are used in most modern financial markets; see e.g., Friedman and Rust (1993).

In a CDA, there is a known time interval (3 minutes in our experiment) in which the market is open. During this time, each trader is free to submit (or cancel or replace) a publicly observable limit order to buy (a bid) and to sell (an ask). In our experiment, a bid at limit price y is an offer to buy a single asset unit at the lowest ask price currently in the order book, but if all such prices exceed y, then the bid is placed in the order book. Likewise, an ask at limit price z will execute immediately at the highest bid price in the current order book if it is at least z, but if no such bids are present then the new ask enters the order book. The trader who places a new order that executes immediately is called the (price) "taker" and the counterparty (whose order was resting in the orderbook) is called the (market) "maker."

For our asset market under any format, we can write trading profits as $\pi = nd + R - C$, where n is the number of asset units held when trading closes, d is the dividend for the realized true state, R is the revenue from selling asset units, and C is the cost of all the units purchased by a given trader. For the CDA format we can take a deeper look at the sources of trading profits. Makers earn larger profits (via increasing $R - C$) to the extent that they (a) have a larger positive spread, where spread = ask price minus bid price, and (b) attract greater trading volume. Takers earn larger profits (via increasing the expected value of $d - C$ for asset purchases and of $R - d$ for asset sales) to the extent that they buy at prices below V^* and sell at prices above V^*, and have larger such trading volume.

We will address several open questions concerning the connection between trader profit and overconfidence. The highest volume takers might be those who are most confident about their estimates of P and V^*. But if excessive, such confidence might lead them to trade at less favorable prices. Moreover, both makers and takers might be more active (and perhaps less profitable) when they are more overconfident about their innate trading ability. Before formulating testable hypotheses on these and other matters, we lay out the structure of our laboratory experiment.

3 Experimental Design

3.1 Procedures

Each session follows the same timeline, illustrated in Figure 2. First the human subjects receive instructions. Then they play the game for several periods, receive their payments, and the session ends. Key details follow.

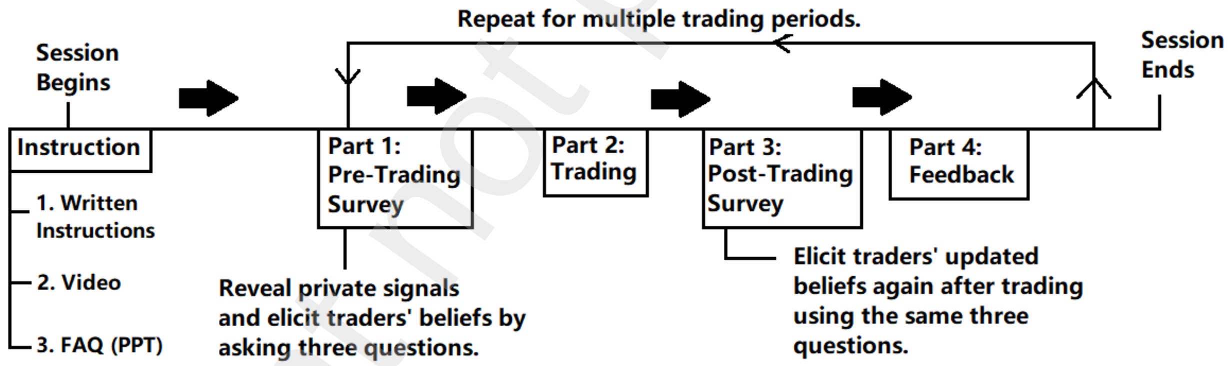

Figure 2: Session Timeline

Instructions. Each session begins with all subjects reading two instruction documents, one that explains the game, and another that explains why truthtelling is a dominant strategy in responding to the survey questions that they will answer. Appendices B.2, B.3, and B.4 include copies of these documents. Next, subjects watch a video that features animations of the user interface. The experimenter then presents PowerPoint slides with answers to questions frequently asked in pilot sessions, and subjects are encouraged to ask their own clarifying questions. In post-experiment surveys, all subjects reported that they understood all tasks.

After instruction, subjects complete two unpaid practice periods and 14 paid periods. As the timeline indicates, each period has the following four parts.

Part 1: Pre-Trading Survey. Subjects see two balls drawn with replacement from an unseen bag related to the true state, as detailed in Section 3.2 below. Then a three question survey elicits traders' beliefs about the probability of state G (Question 1, using the Karni (2009) mechanism), about their willingness to accept an asset unit (Q2, using the BDM mechanism, cf. Becker et al. (1964)), and about their relative trading profit in the current period (Q3, using the Barron and Qu (2014) mechanism). The exact payment formulas for Q1-Q3 appear in Appendix B.4, along with proof sketches that truth-telling is dominant.

Part 2: Trading. Each trader is endowed each period with two units of an asset that pays the per-unit liquidating dividend of $d_G = 300$ in state G and $d_B = 100$ in equally likely state B. There is no cash budget constraint. In each period, 8 human subjects trade for 3 minutes in a continuous double auction (CDA) market for this common value asset; see Figure 3 for a screenshot of the trading user interface (UI). No short sales are allowed, and traders are not allowed to hold more than 8 asset units, i.e., half of market supply. As illustrated in Figure 3, current bids and asks, and transaction price history, are public information seen by all market participants. Traders' own offers and transactions are colored green for buying and blue for selling. Transaction prices so far are shown in chronological order with the most recent trades on top. The UI shows traders' current holding of cash (including receipts from asset units sold minus cost of units bought) and the asset. The right-hand side of the UI reminds the traders of the state-contingent dividends, and their private signals. There is a large "Error Message" box at the bottom of the screen; it alerts subjects when an order is rejected, e.g., an ask by a trader currently holding zero units.[2] Asset units expire each period after paying a state-dependent liquidating dividend d; they do not carry over into the next period.

Part 3: Post-Trading Survey. To learn how traders update their beliefs from their trading experience, we conduct a post-trading survey. The same three questions — Q1, Q2 and Q3 as in Part 1— are asked again, but this time while the subject sees the transaction history. To help them improve their trading strategies, subjects also see the color-coded transaction prices sorted from highest to lowest, making transparent their success (or lack thereof) in buying low and selling high.

Part 4: Feedback and Profit Calculation. After the post-trading survey page, traders go to the feedback page, which shows the true state realized in the current period, and also reminds traders of their final asset and cash holdings. The page then computes trading profit as well as payments for responses to all the survey questions. As noted in the previous section, trading profit is $\pi = nd + R - C$. Payments for survey question are scaled to roughly equalize maximal payments across questions and so that their average over the $2 \cdot 3 = 6$ questions is about half of average trading profit. Let τ be a subject's average questionnaire payment in a given period. Then their total payoff for that period is $\pi + \tau$. Payoffs are summed over all 14 paid periods, and paid to the subject at the end of the session.[3]

[2]Error messages are also triggered by trying to accept one's own offer and by trying to acquire more than 8 asset units.

[3]We adopt the common convention from market experiments of paying for all periods, and not just one

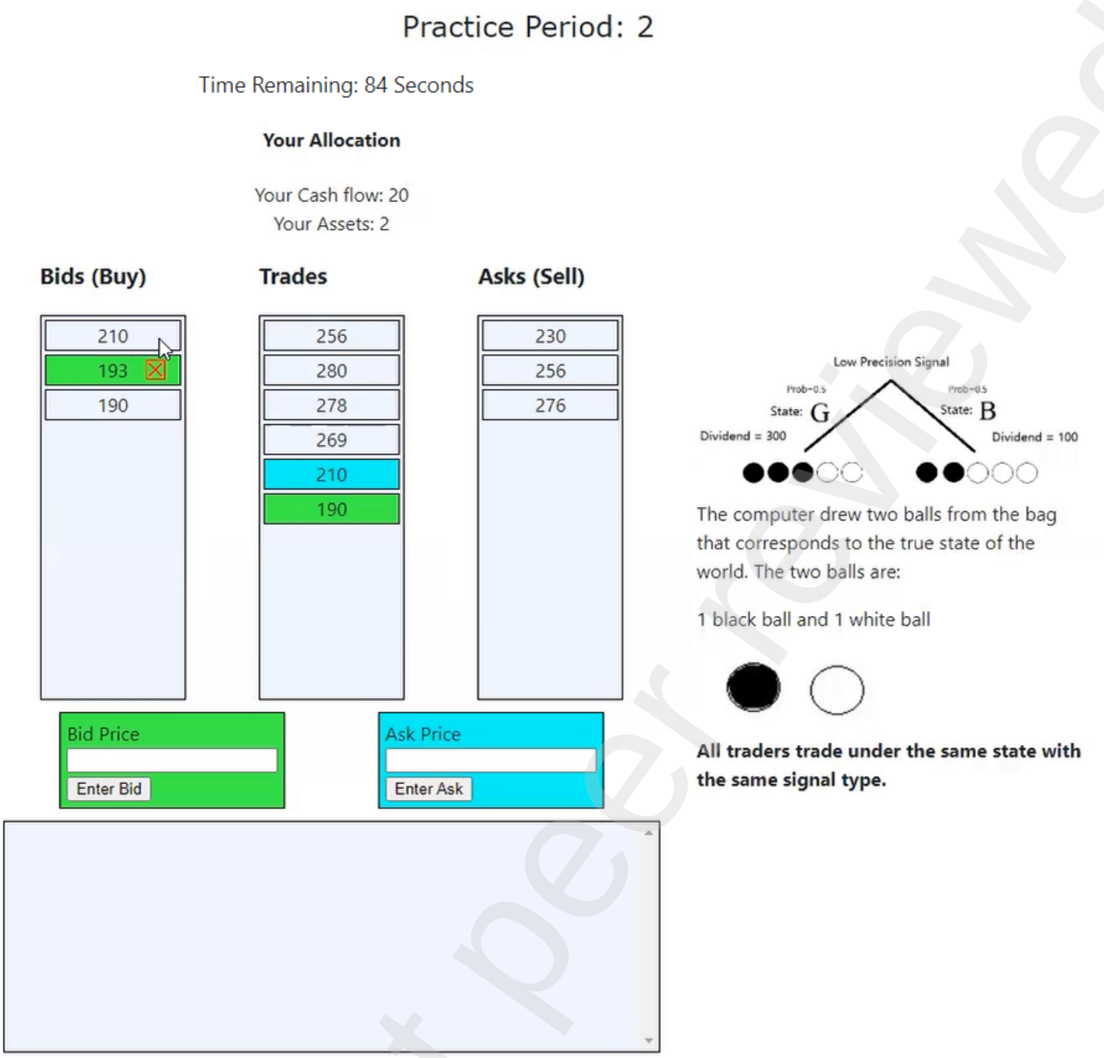

Figure 3: User Interface for Trading in Environment aL

3.2 Information Environments

Traders all face the same unknown state each period, but their private information is generated differently in different environments. In Environment aL, all traders receive independent low precision signals and are so informed, as in Figure 3. Environment aH is the same except that all signals are high precision, as in the right panel of Figure 1. Among the 14 periods in Environment a sessions, half of the periods are randomly selected to be Environment aL, and the other half to be Environment aH.

In each of 14 periods in Environment b, half the traders are randomly selected to receive high precision signals while the other half receive low precision signals; each trader gets H precision signals in 7 periods on average. The UI reminds them of that heterogeneity, and tells them their own signal type, H or L.

Environment c is exactly the same as b, except that the UI tells the trader nothing about

period selected randomly. That convention harmonizes with our risk-neutral theoretical predictions.

the precision of other traders' private information other than that it may differ from their own. Traders' private signals are not labelled L or H, and therefore relative precision is unknown or ambiguous in Environment c. Traders may tend to be more (less) overconfident if they know that their own signal is more (less) precise than some other traders'; if so, that effect may disappear when traders know nothing about the relative precision of their own signal.

3.3 Implementation Details

Twenty sessions were conducted online from May 2021 to June 2022. Using ORSEE (Greiner (2015)), 112 human subjects were recruited from the LEEPS lab subject pool; they are predominantly University of California, Santa Cruz undergraduates pursuing a variety of majors. Each session had 8 of these subjects facing a single information environment (a, b or c). Subjects in "inexperienced" sessions had no prior experience with any of these environments nor with analogous environments featured in the companion paper (Friedman and Wang (2024)). Subjects with above average performance in such a session were invited to participate in a subsequent "experienced" session. Table 1 summarizes the entire set of sessions.

Table 1: Sessions Implementation

Environment	Number of Inexperienced Sessions	Number of Experienced Sessions
a	5	2
b	5	2
c	4	2

The software for running the sessions was built at LEEPS lab using the oTree platform (Chen et al. (2016)). The sum of earnings (in points) in the 14 paid trading periods is converted to US dollars at a pre-announced rate and paid to each participant, together with a $7 guaranteed show-up fee (increased to $10 in the last few sessions, as the available subject pool shrank due to a Covid upsurge.) Average payments were approximately $30 per subject for a two-hour session.

3.4 Hypotheses to Test

Those laboratory procedures allow us to crystallize our general research questions into testable hypotheses. We begin with preliminary hypotheses PH1 - PH2, which set the stage for our main hypotheses MH1 - MH3.

PH1. Overconfidence is a consistent individual trait: the overconfidence indexes for each subject's pre-trade responses to Q1, Q2 and Q3 will be highly correlated, and the market environments do not have significant impact on the correlations.

Existing literature casts doubt on this hypothesis.[4] To test PH1, we will compute Pearson

[4] For example, Fan et al. (2021) finds a major gap between asset valuation (as in Q2) and elicitation of

correlations across individual subjects for their x values obtained from Q1 responses via equation (2) and for those obtained from Q2 responses via equation (4). The overconfidence index obtained from Q3 responses is $x =$ actual rank - elicited expected rank. We hypothesize there is no significant difference across market environments because the overconfidence indexes are measured before subjects enter the markets. The results of testing PH1 will inform how we implement and interpret tests of our main hypotheses regarding overconfidence and market behavior.

PH2. The post-trade deviations of traders' elicited beliefs and valuations from their fully-aggregated values P and V^* will be substantially smaller than their pre-trade deviations, especially in environments where signals are more precise and precision is more homogeneous. Post-trade deviations will generally be smaller among experienced subjects.

This hypothesis deals with another important preliminary issue — whether market participation disseminates dispersed private information in different market environments – that will affect the implementation and interpretation of the main hypotheses.[5] As suggested by the discussion in Section 2.1, we expect dissemination to be better when traders know more about other traders' precision (which is clearest with homogeneous precision, as in Environment a) and when they believe that other traders' information is high precision. It is natural to conjecture that experienced traders will be better at extracting information from market participation. Testing this hypothesis will involve regressing the metrics introduced in Section 2.1 (absolute deviation of asset price from V^*, and Page and Siemroth (2021)'s λ) on environment dummy variables.

MH1. The more overconfidence among traders, the greater will be the price overreaction to aggregated information, especially in market environments with higher signal precision and unambiguous precision distributions.

Our first main hypothesis concerns the impact of aggregate overconfidence on market price in different environments. The idea is that more overconfident traders will tend more to overplay their hands, and that will lead to price overreaction; see, for example, Aragón and Roulund (2020) and Michailova and Schmidt (2016). We hypothesize there will be more overreaction in unambiguous environments, which is consistent with previous literature (e.g., Sarin and Weber (1993), Corgnet et al. (2020)). To test MH1, we will define price overreaction in a manner parallel to equation (4), and regress it on mean overconfidence among market participants. That regression will allow us to see which environments (and experience levels) best support the hypothesis.

MH2. Overconfidence and underconfidence will both impair traders' overall profits in all

the underlying probabilities (as in Q1). We noted earlier that the standard literature distinguishes between judgemental overconfidence (as in Q1 and Q2) and self-enhancement (as in Q3).

[5] Barron and Qu (2014) suggests the distribution of private signal precision affects market efficiency. While traders in their market have perfect information about signal precision distribution, traders in one of our market environments do not.

environments. More specifically, (a) overconfidence will enhance trading volume of both makers and takers but (b) will impair their price favorability. (c) Takers on average will trade at less favorable prices than makers.

MH2 is concerned with the impact of individual traders' overconfidence on their own profitability. The general statement reflects the Alchian (1950) tradition that markets punish deviations from full rationality, while the specifics reflect the distinctions mentioned in Section 2.2 concerning the CDA market format. We will test this hypothesis by regressing $|x|$, the absolute value of our overconfidence index, on traders' realized profits and profit components such as trading volume.

MH3. Trading experience attenuates traders' self-enhancement overconfidence (measured by question 3) in all market environments.

Our final hypothesis pertains to reciprocal effect of trading experience on overconfidence, and it reflects the other aspect of the Alchian tradition, that rationality is enhanced by market-level punishment of irrationality. We would like to use subjects' responses to all three questions but, as explained in previous section, it is infeasible to obtain post-trade overconfidence indexes for Q1 and Q2. Therefore, we shall test MH3 only on the Q3 overconfidence index.

4 Results

We begin with descriptive statistics and tests of the preliminary hypotheses (PH1 - PH3) in Section 4.1. Tests of main hypotheses MH1 and MH2 are presented in Section 4.2. Section 4.3 looks at MH3, the reciprocal impact of market experience on overconfidence.

4.1 Preliminaries

Using pre-trade survey responses in sessions with inexperienced subjects, Figure 4 plots the cumulative distribution function (CDF) of the overconfidence index x for question 1. Neither panel shows much difference across environments. It is reassuring to see that pre-trade beliefs seem largely unaffected by the market environment that subjects will face later in the period (and that they faced in earlier trading periods). This impression is reinforced by Wilcoxon Signed-Rank (WSR) test results presented in Table A4.

The right panel shows that traders with high precision signal are, roughly speaking, as likely to be under- as over-confident. By contrast, the left panel shows rather little underconfidence among traders receiving a low precision signal. Again, that is reassuring, since there is less room for underconfidence when the Bayesian posterior P is closer to 0.5. Similar CDFs lead to similar conclusions for questions 2 and 3, and for experienced sessions, as can be seen in Appendix A.2.

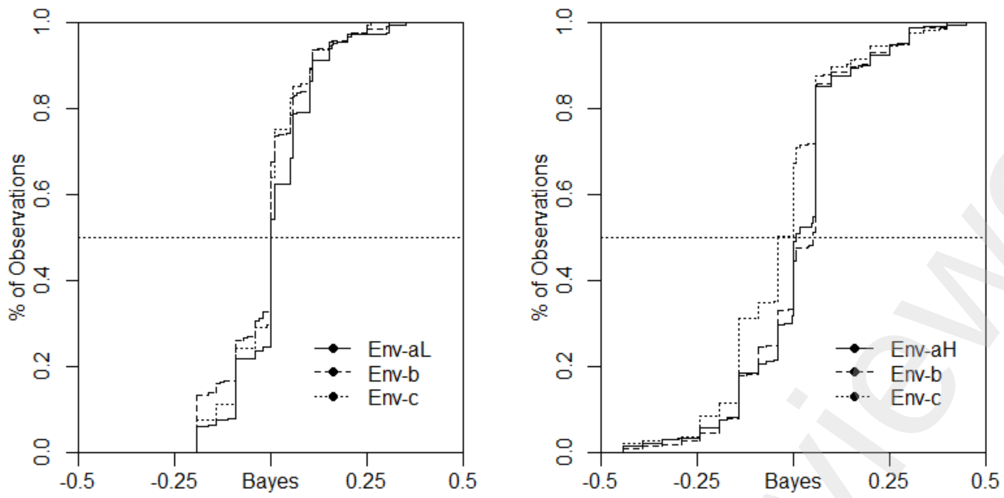

Figure 4: Q1 Pretrade Over-/Under-confidence.

Note: Cumulative distribution functions of overconfidence index x for Survey Question 1 prior to trading. Left panel is for subjects with low precision (L) signals, and right panel is for high precision (H) signals.

Table 2 shows correlations between overconfidence measured in different survey questions. It supports PH1 for Q1 and Q2; those correlations are often above 0.5 and are all highly significant. This is reassuring since the underlying variables are linearly related and both deal with judgemental overconfidence.[6] On the other hand, correlations with the self-enhancement question Q3 responses are all lower; the highest ρ_{13} or ρ_{23} is less than the lowest ρ_{12}, and most of the ρ_{13} and ρ_{23} are insignificant.

Table 2: Overconfidence Correlations

Inexperienced Sessions					
	All Envs	Env-aL	Env-aH	Env-b	Env-c
Corr(Q1,Q2)	0.52***	0.42***	0.54***	0.55***	0.51***
Corr(Q2,Q3)	0.00	-0.08	0.09	-0.05	0.04
Corr(Q1,Q3)	0.05*	-0.04	0.11*	-0.01	0.10**
(Obs.)	(1427)	(247)	(256)	(509)	(415)
Experienced Sessions					
	All Envs	Env-aL	Env-aH	Env-b	Env-c
Corr(Q1,Q2)	0.36***	0.37***	0.43***	0.27***	0.46***
Corr(Q2,Q3)	0.09**	-0.11	0.15	0.06	0.21***
Corr(Q1,Q3)	0.07*	0.14	0.21**	-0.01	0.04
(Obs.)	(625)	(103)	(105)	(203)	(214)

Note: Corr(Qi,Qj) refers to the Pearson correlation between overconfidence index x for pre-trade question i responses and that for the same subject's pre-trade question j responses, $i, j = 1, 2, 3$. The number of observations is shown in parentheses for each environment and subject experience level. For Q1 and Q2, some responses are $< 0.5 (> 0.5)$ when the private signal is two black (white) balls. We dropped those observations in this correlation analysis since the overconfidence index x is not defined in these cases. Asterisks $^{***}, ^{**}, ^{*}$ respectively indicate p-values 0.01, 0.05, and 0.10.

[6] This finding does not directly contradict Fan et al. (2021), since their finding of a gap between probability judgements and valuation judgements is based on overconfidence levels rather than overconfidence correlations. Appendices A.5 and A.6 show that our L-precision data exhibit a gap in overconfidence levels similar to theirs.

Result 1 (PH1) *Across different market environments, pre-trade over- and under-confidence revealed in Q1 (beliefs about the state) is highly correlated with that revealed in Q2 (asset valuation), but neither is well correlated with that revealed in Q3 (rank in trading profit).*

We now turn to post-trade beliefs, and examine whether trading experience attenuates signed deviations $p - P$ of elicited probabilities p from fully-aggregated Bayesian posterior probabilities P. The black solid (and dashed) lines in Figure 5 show the CDFs of such deviations in inexperienced sessions for pre- (and post)-trade elicitation p. For comparative purposes, the red dashed line shows deviations from P of individual traders' pre-trade true Bayesian posteriors (i.e., given only their personal pre-trade private signals). One gets the impression that trading experience has little impact in the low precision environment aL, but that it does indeed attenuate both positive and negative belief errors in the other environments. Appendix A.13 includes graphs for the other two questions and for experienced sessions, and they exhibit similar patterns.

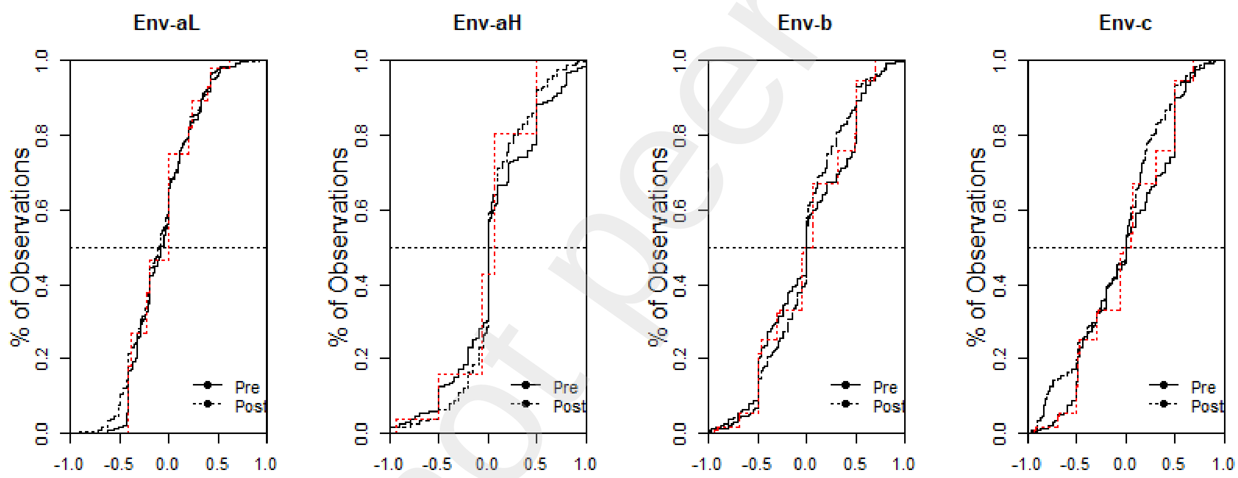

Figure 5: Deviations of elicited beliefs (Q1) from fully-aggregated Bayes posteriors.

Table 3 provides more formal support for these impressions from Q1 as well as parallel results for Q2 and Q3. It reports p-values for the Wilcoxon signed rank test comparing absolute deviations of pre- and post-trade elicited beliefs from P. Except for env-aL, we can clearly reject the null hypothesis that post-trade deviations are no smaller than pre-trade deviations. Rejection is especially emphatic for Q1 and Q2 for experienced subjects in the mixed environments b and c.

Result 2 (PH2) *Deviations from fully-aggregated Bayesian beliefs and valuations are significantly reduced after market participation when at least half the participants have high precision signals, especially in environments b and c with experienced subjects. On the other hand, market participation has little or no impact when all participants have low precision signals.*

Table 3: WSR p-values for Pre- vs Post-Trade Absolute Belief Deviations

	Inexperienced Sessions				Experienced Sessions			
	Env-aL	Env-aH	Env-b	Env-c	Env-aL	Env-aH	Env-b	Env-c
Q1	0.143	0.002	<0.001	0.011	0.274	0.273	<0.001	<0.001
Q2	0.721	<0.001	<0.001	0.005	0.420	0.037	<0.001	<0.001
Q3	0.343	0.261	0.010	0.039	0.180	0.023	0.044	<0.001

The next several hypotheses deal, one way or another, with market prices. To provide perspective, Figure 6 illustrates price dynamics. In most periods for the particular session shown, transaction prices tend to move away from the prior expectation of 200 towards the fully-aggregated expected asset value (the red dashed horizontal line, usually near 300 or 100). Convergence failed in period 10, where the high precision signals were least informative (5 of 8 balls were black). Similar tendencies can be observed to a greater or (more often) lesser extent in the other 19 sessions; see appendices A.7, A.8, A.9, and A.10.

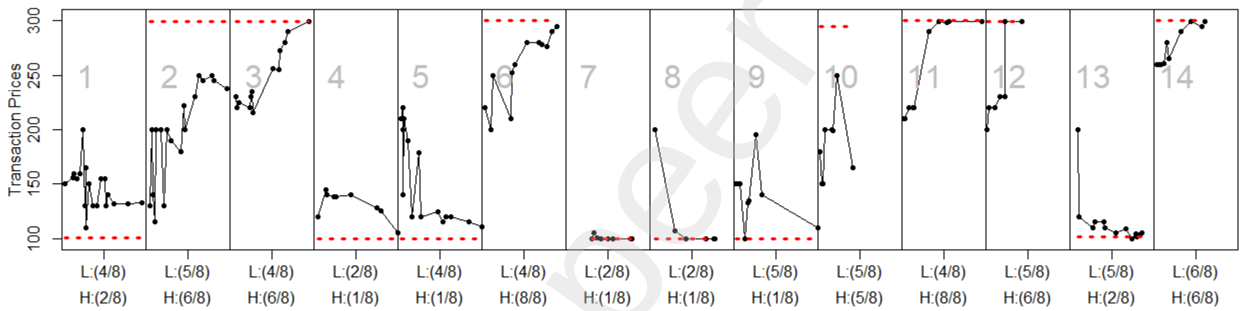

Figure 6: Transaction Prices in Env-b Inexperienced Session 2

Note: Connected black dots show sequences of transacted prices in each of the 14 periods of one session. Horizontal axis labels show aggregate private information, e.g., L(4/8) H(2/8) means that 4 of the 8 balls seen by Low precision traders were black, and 2 of 8 balls seen by high precision traders. Fully aggregated Bayes expected asset values are plotted as red dashed lines.

Appendix A.12 reports formal tests of price convergence within period, adapting the methods of Noussair et al. (1995) and of Page and Siemroth (2021). Key conclusions are summarized in the following.

Result 3 *Prices generally tend to move towards their fully aggregated value V^* within each trading period. This tendency is enhanced by subject experience, especially in the ambiguous mixed environment c. It is impaired when all signals are low precision, as in environment aL.*

Subsequent analysis will therefore focus on the final transaction price in each period, denoted ν below.

4.2 Tests of Main Hypotheses

To assess the impact of the average overconfidence $\bar{x}$, as revealed in traders' pre-trade responses to Q1, on actual asset price, we form the dependent variable $\mathcal{R} = (\nu - V^*)sgn(V^* - 200)$ and run the regression

$$\mathcal{R} = \beta_0 + \beta_c \bar{x} + \beta_{aL} \bar{x} \mathbb{1}_{aL} + \beta_{aH} \bar{x} \mathbb{1}_{aH} + \beta_b \bar{x} \mathbb{1}_b. \tag{5}$$

The final price ν over- (under-) reacts relative to fully aggregated price V^* to the extent that $\mathcal{R}$ is positive (negative), and traders in a given period are on average over- (under-) confident to the extent that $\bar{x}$ is positive (negative). The symbols $\mathbb{1}_{aL}$, $\mathbb{1}_{aH}$, $\mathbb{1}_b$ are dummy variables for treatments other than environment c, which is the baseline. Therefore, β_c captures the impact of average over- (under-) confidence on actual asset price in environment c, while β_{aL}, β_{aH}, and β_b capture the relative differences in other environments.

Table 4: Coefficient Estimates for Equation (5)

	Inexperienced		Experienced	
VARIABLES	Q1	se	Q1	se
β_c	-100.9	(155.0)	-292.2*	(149.4)
β_{aL}	380.2	(305.2)	409.7	(462.0)
β_{aH}	50.14	(206.9)	-88.58	(199.5)
β_b	457.6**	(215.2)	957.7**	(410.0)
Constant	-52.19***	(16.05)	-30.65**	(13.89)
Observations	196		84	
R-squared	0.259		0.121	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Here ν is the last transaction price in a given period. Appendix A.15 reports similar using the average of the last two transaction prices.

Table 4 reports the results. The significantly negative constant coefficients suggest that we generally see under-reaction. The average level $\bar{x}$ of overconfidence across traders is typically small, and it has insignificant impact in the inexperienced sessions except in the unambiguous mixed environment b. In that environment, overconfidence tends to partially offset under-reaction, i.e., it pushes prices towards V^*, consistent with MH1. That directional impact is at least as large in experienced sessions with environment b. In experienced sessions with the ambiguous environment c, overconfidence may actually increase underreaction qualitatively. Appendix A.15 reports similar results for overconfidence in Q2 responses, albeit with lower significance levels. It also reports generally insignificant results for Q3 overconfidence.

Result 4 (MH1) *Asset prices generally underreact to aggregate information. In experienced sessions, trader overconfidence offsets that effect in mixed precision environment b, but not in ambiguous environment c.*

General underreaction is not surprising since the target V^* is so often very close to an endpoint, $V = 100$ or 300. The contrast between the unambiguous (b) and ambiguous (c) mixed precision environments may arise from low-precision traders' greater reliance on observed market prices in the unambiguous environment. We see that overconfidence in the experienced ambiguous environment pushes towards underreaction.

We now turn to the question of how overconfidence affects individual traders' market behavior. Here the most relevant elicitation is Q2, on subjective asset valuation, since it pertains most directly to trading strategies. We therefore use the overconfidence index $x = (v - V^*)sgn(V^* - 200)$ from equation (4). To estimate the different impact on individual overall trading profit ($\pi = nd + R - C$) from over- and underconfidence, we break the sample into overconfident ($x > 0$) vs underconfident ($x < 0$) trader-periods. To get consistent signs, we use the absolute value of x in the following regression.

$$\pi = \beta_0 + \beta_c|x| + \beta_{aL}|x|\mathbb{1}_{aL} + \beta_{aH}|x|\mathbb{1}_{aH} + \beta_b|x|\mathbb{1}_b \tag{6}$$

Table 5 reports the coefficient estimates (and robust standard errors). In the ambiguous precision baseline treatment c, being overconfident tends to impair profits, quite significantly so in experienced sessions. In that environment, being underconfident boosts profits significantly in inexperienced sessions, but the effect size shrinks considerably and significance disappears in experienced sessions. In homogeneous environment a, overconfidence boosts profits in low precision experienced periods, while underconfidence impairs profits in high precision inexperienced periods. In the unambiguous heterogeneous precision environment b, both under and over-confidence seem to boost experienced trader profits.

Table 5: Coefficient Estimates for Equation (6)

	Inexperienced				Experienced			
VARIABLES	Over	se	under	se	Over	se	under	se
β_c	-0.828	(1.053)	2.779***	(0.857)	-4.318***	(1.213)	0.772	(1.295)
β_{aL}	0.726	(1.278)	-0.329	(1.954)	4.015***	(1.492)	-1.096	(2.661)
β_{aH}	-1.691	(1.246)	-3.870***	(1.146)	0.872	(1.949)	-0.202	(2.072)
β_b	0.745	(1.240)	-0.156	(1.196)	4.983***	(1.482)	3.712**	(1.786)
Constant	472.8***	(45.91)	401.8***	(59.40)	445.6***	(43.56)	443.7***	(104.6)
Observations	714		523		310		195	
R-squared	0.020		0.065		0.084		0.076	

Note: Coefficient estimates for the restricted sample of overconfident (resp. underconfident) traders are reported in the columns labeled "Over" (resp. "Under"). Robust standard errors (se) are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Result 5 (MH2) *Overconfidence significantly impairs (resp. improves) experienced traders' profits in environment c (resp. b and aL) but elsewhere has little impact on overall trader profits.*

Underconfidence may boost experienced trader profits in environment b and inexperienced trader profits in environment c, but elsewhere has insignificant or negative impact.

These apparently diverse findings mostly seem to jibe with the previous result that prices under-react more in environment c than in b. Perhaps being overconfident is more profitable when prices are less inclined to underreact.

For a finer-grained analysis relevant to parts (a-c) of MH2, we now consider key observable elements of a trader's performance: their trading volume, their tendency to buy low and sell high, and their tendency to act as a market maker or taker. A contingency table sets the stage for that analysis. Table 6 shows that fairly often (in 300 of 1568 instances) a trader never buys and simply sells both her endowed shares. In about 20% of all instances the trader is an active market maker, selling at least 2 shares and buying at least 2 shares, and in about 5% of instances the trader does not trade at all. Appendix A.19 shows that the same general patterns are also seen in most environments separately.

Table 6: Instances of Buy and Sell Volume

	# of Sell: 0	# of Sell: 1	# of Sell: 2	# of Sell: More	Sum of Obs.
# of Buy: 0	79	112	300	0	491
# of Buy: 1	99	105	128	110	442
# of Buy: 2	77	57	42	80	256
# of Buy: More	129	43	48	159	379
Sum of Obs.	384	317	518	349	1568

Note: Entries report the overall number of instances (in all environments) in which a trader buys and sells specified numbers of units in a single period.

We shall now examine more carefully the 772 instances where a trader both buys and sells in a single period. For those data, we run regression (7) below to study whether overconfidence coincides with trade at less favorable prices. The dependent variable is G, the "Sell-Buy-Gap" defined as the average price at which a trader sold asset units in a given period minus the average purchase price, i.e., their success in "buying low and selling high." Explanatory variables are the pre-trade Q1 overconfidence index x together with the usual treatment dummies.

$$G = \beta_0 + \beta_c x + \beta_{aL} x \mathbb{1}_{aL} + \beta_{aH} x \mathbb{1}_{aH} + \beta_b x \mathbb{1}_b \tag{7}$$

Table 7 reports the regression results separately for makers (instances in which the trader had both an accepted bid and an accepted ask) and takers (where a trader accepted both a posted bid and a posted ask). The constant terms indicate that the effective bid/ask spread is about 20 in inexperienced sessions and is considerably wider (!) in experienced sessions. However, we find little evidence that overconfidence has an impact on traders' success in buy and sell strategies. Most of the estimated coefficients are insignificant, except one in low information environment aL, where overconfidence seems to significantly hurt inexperienced makers.[7] Parallel (but weaker) results are reported in Appendix A.18 for x computed using Q2 responses.

Table 7: Overconfidence on Sell-Buy-Gap

	Inexperienced				Experienced			
VARIABLES	Maker	se	Taker	se	Maker	se	Taker	se
β_c	55.09*	(29.05)	-11.39	(32.64)	9.739	(42.91)	-33.16	(51.16)
β_{aL}	-140.1***	(41.55)	-30.50	(53.56)	-63.25	(79.74)	-48.54	(190.6)
β_{aH}	-72.08*	(40.98)	-12.65	(59.58)	-94.02	(64.64)	105.6	(97.77)
β_b	-23.50	(36.16)	2.887	(37.67)	-44.61	(62.75)	-17.94	(64.46)
Constant	19.33***	(4.898)	-20.33***	(5.915)	44.28***	(13.74)	-78.87***	(24.81)
Observations	374		289		149		107	
R-squared	0.076		0.060		0.257		0.137	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Result 6 (MH2bc) *Takers tend to trade at less favorable prices than makers. Overconfidence does not significantly impact traders' buy-and-sell strategies. However, being more overconfident may worsen makers' transaction prices in an unambiguous environment with low signal precision.*

Of course, trading volume is the other component of profitability. To examine it, we run similar regressions with dependent variable $M =$ the number of a maker's offers accepted in a given period:

$$M = \beta_0 + \beta_c \cdot x + \beta_{aL} \cdot x \cdot \mathbb{1}_{aL} + \beta_{aH} \cdot x \cdot \mathbb{1}_{aH} + \beta_b \cdot x \cdot \mathbb{1}_b. \tag{8}$$

Table 8 reports the results. Appendix A.17 reports parallel results on taker volume. In general, the patterns of taker volume are not systematic and less significant.

Result 7 (MH2a) *In experienced sessions, overconfidence reduces maker volume in mixed precision environments b and c, but increases it in the homogeneous environments aL and aH. Patterns are generally not significant in inexperienced sessions.*

An interpretation is that the impact of overconfidence on the buy-sell gap noted in the previous result is offset by its impact on trading volume, resulting in a mixed overall impact on trader profits.

[7] Readers might wonder why the experienced maker and taker constant coefficients don't approximately offset each other. The discrepancy seems largely due to a single outlier, a trader with $x = -34$ and a sell-buy-gap = -159.

Table 8: Overconfidence on Maker Volume

	Inexperienced			Experienced		
VARIABLES	Q1	Q2	Q3	Q1	Q2	Q3
β_c	0.0909	0.00290	-0.00599	-2.342**	-0.00478	-0.0997**
	(0.698)	(0.00233)	(0.0297)	(0.973)	(0.00325)	(0.0438)
β_{aL}	-0.319	-0.00921***	-0.0588	4.198**	0.00667	0.0644
	(1.136)	(0.00350)	(0.0491)	(1.776)	(0.00497)	(0.0668)
β_{aH}	0.557	0.000404	-0.0981**	3.730**	0.00502	0.0805
	(1.116)	(0.00325)	(0.0484)	(1.486)	(0.00548)	(0.0745)
β_b	-0.440	-0.00428	-0.0250	0.144	0.00594	0.0954
	(0.965)	(0.00330)	(0.0442)	(1.540)	(0.00442)	(0.0646)
Constant	1.688***	1.761***	1.708***	0.969***	0.904***	0.942***
	(0.136)	(0.140)	(0.132)	(0.0968)	(0.109)	(0.0944)
Observations	1,526	1,464	1,568	663	631	672
R-squared	0.094	0.104	0.099	0.107	0.097	0.099

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Note: We run the regression for different survey questions. “Q1”, “Q2”, and “Q3” mean x is measured by question 1, question 2, and question 3, respectively.

4.3 Does Overconfidence Survive Market Experience?

Finally, we examine the reciprocal effect of market experience on traders' overconfidence. Recall that it is infeasible to properly measure post-trade overconfidence for Q1 and Q2. Therefore Figure 7 below, and the corresponding figure for experienced sessions in Appendix A.4, use only Q3 responses. These figures suggest, and the Wilcoxon summed-rank tests reported in Table A6

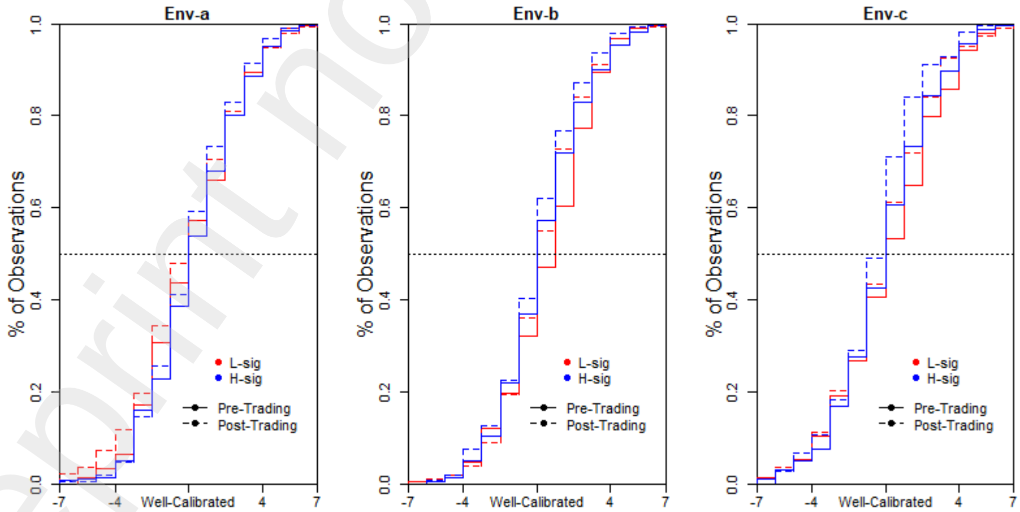

Figure 7: Pre vs Post-Trading Overconfidence (Question 3)

Note: More negative (resp. positive) entries in each panel indicate more under-(over-)confident traders.

confirm, that the distribution of overconfidence is largely unaffected by market participation.

Result 8 (MH3) *Trading experience does not substantially attenuate traders' overconfidence (measured by question 3) in any of the environments we examined.*

This finding is consistent with some previous literature, e.g., Huffman et al. (2022), Murad and Starmer (2021), Banerjee et al. (2020), Hoffman and Burks (2017).

5 Conclusion

Our results can be summarized briefly. First, correlations indicate no substantial gap between judgemental overconfidence in valuation (Q2) and in assessing probabilities (Q1). However, consistent with the standard distinction between judgemental and self-enhancing overconfidence, we find a substantial gap between our self-enhancement measure (Q3) and either sort of judgemental overconfidence.

We add a bit of nuance to previous research on information dissemination and aggregation in asset markets. When at least half our traders received high precision signals prior to trade, their post-trade beliefs better reflect aggregate information, despite the fact that the aggregate information is more precise in such cases and thus creates a harder target to hit. On the other hand, market participation has little or no impact on beliefs when only low precision pre-trade private information was available. Likewise for information aggregation: asset prices better reflect aggregate private information when at least half of it is high precision (especially in the ambiguous precision environment c), but not when it is all low precision.

Our main results concern the impact of overconfidence on market performance and the reciprocal impact of market experience on overconfidence. At the market level, we find that average trader overconfidence can sometimes improve price efficiency (i.e., information aggregation). This improvement arises mainly from mitigating the general under-reaction of asset price to aggregate information. Such improvement occurs in our unambiguously mixed precision environment, but not in the most challenging environment with ambiguous mixed precision.

At the individual level, we find that trader profitability and trading volume are also impacted by trader overconfidence. For example, more overconfident traders earn lower profits in the ambiguous precision environment when their peers are experienced.

A bit to our surprise, we are unable to detect any systematic impact of market exposure on traders' overconfidence. This supports skeptics, such as De Long et al. (1990), Kyle and Wang (1997), and Odean (1998) of the traditional Alchian (1950) argument. Of course, in our laboratory market, traders are not reliably punished for irrational over (or under) confidence. Given that, it is perhaps less surprising that market experience fails to eliminate over (or under) confidence.

Our experiment is exploratory, but we hope that it will encourage future research on interactions between trader overconfidence and asset market performance. Such work will help sharpen theoretical understanding, and may also help financial market regulators who seek to improve access and market performance.

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Appendix

A Supplementary Figures and Tables

A.1 Notes for Data Cleaning

- There are a few instances of misreported data. For example, there occasionally is no response to some survey questions, typically because the subject spent too much time thinking about their responses and didn't realize that time had run out for the current page. Another sort of misreport, also rare, is an out of range response, e.g., the subject accidentally reported a probability of 120% for Q1. In such cases we used the midpoint of the admissible range (e.g., p = 0.5) as the response for the pre-trade survey, and for the post-trade survey we used the answer from the pre-trade survey.
- 4.90% (1.20%) of the observations from inexperienced (experienced) sessions are corrected as above.
- We also considered simply omitting all such misreported observations. As one might expect, this does not substantially alter the results.
- We dropped data from three failed sessions:
  - One session was canceled because a subject lost internet connection after the session was underway.
  - In two other early sessions, a very confused subject had a major impact on the market. The exclusion criteria here are (a) trader profits (much) less than half the average, and (b) all transaction prices in the entire session below the prior expected value of 200. Specifically, in one session, one of the players, regardless of the private signal, sold all his/her assets at low prices at the beginning of the period and did nothing else. In the other excluded session, a subject's responses to question 1 and question 2 are negatively correlated, indicating a willingness to sell at lower prices when he/she believes the good state is more likely.

A.2 Overconfidence Across Environments

Here we collect analogues of Figure 4: empirical cumulative distribution functions of overconfidence indices x for all three questions, by experience level.

A.2.1 Inexperienced Sessions

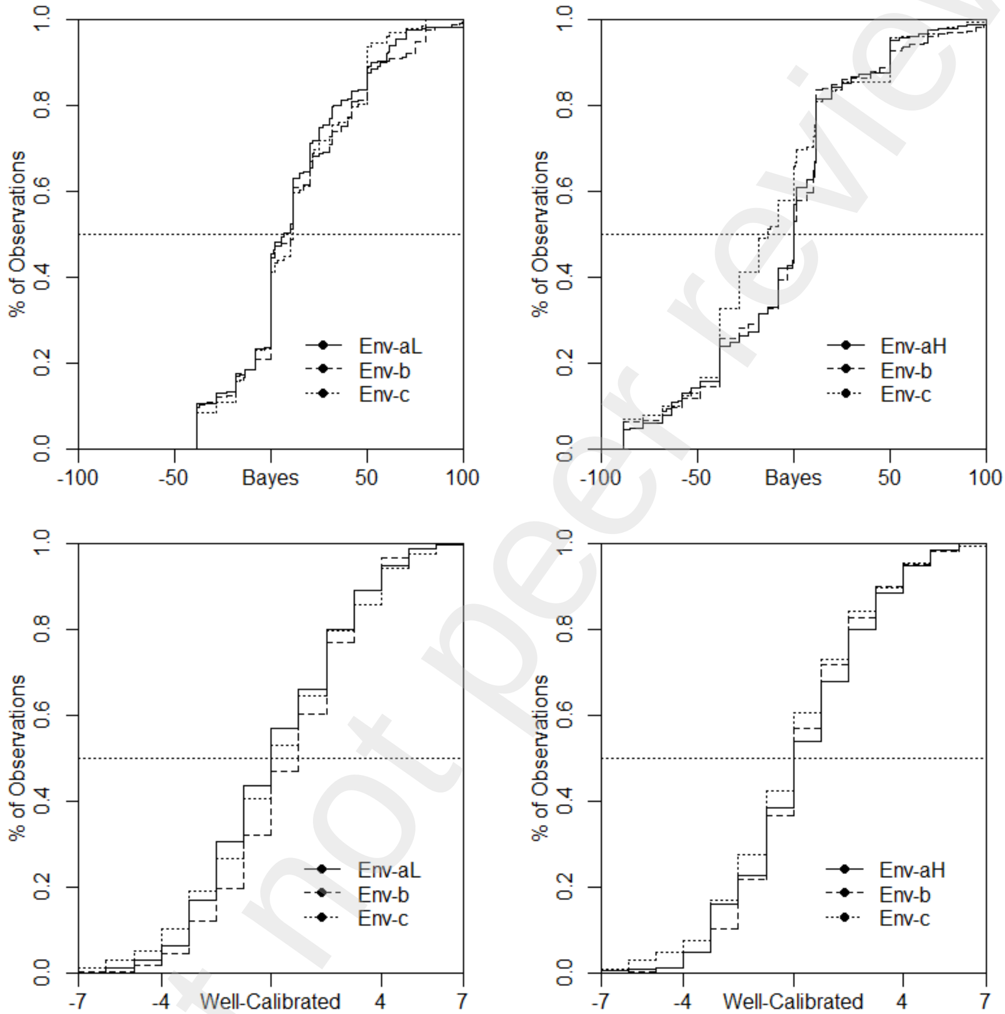


Figure A1: Q2 and Q3 Pretrade Over-/Under-confidence

Note: Figure A1 replicates figure 4 using elicited data of question 2 (top) and question 3 (bottom) from inexperienced sessions. Similar to figure 4, the left (right) panel is the L-(H-)prcn signal precision. Within each panel, the farther away to the left (right), the more under-(over-)confident the trader is.

A.2.2 Experienced Sessions

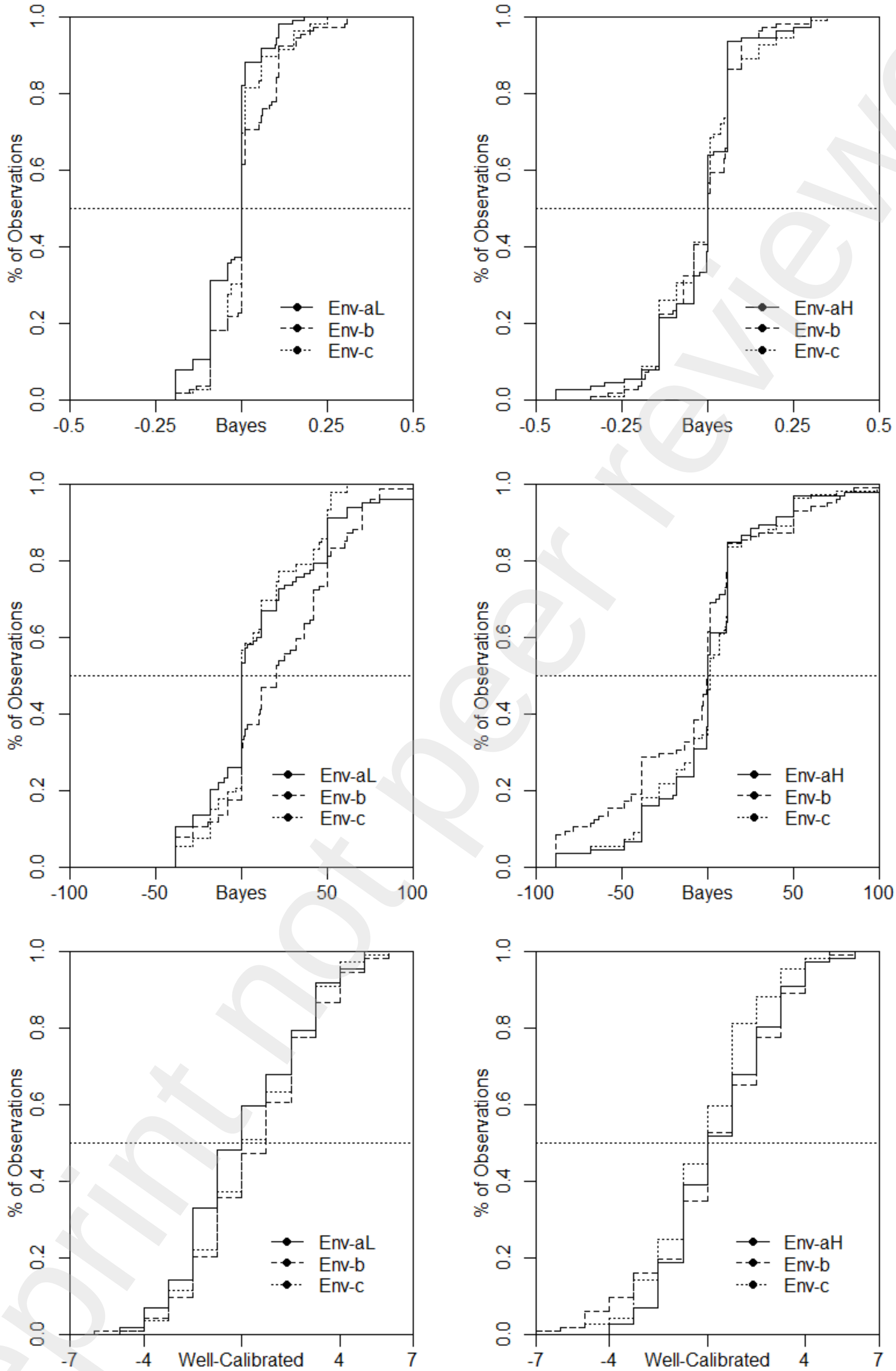


Figure A2: Pretrade Over-/Under-confidence

Note: Figure A2 replicates figure 4 using elicited data of question 1, question 2, and question 3 from experienced sessions.

A.3 Overconfidence Post-Trading (Question 3 Only)

The following two figures plot the CDF of traders' Over-/Under-confidence after trading using only elicited beliefs of question 3. Figure A3 and figure A4 plot graphs for inexperienced and experienced sessions, respectively. The patterns show that there is no significant difference in post-trading confidence level across environments (See hypothesis test results in table A4). The plot on the left (right) panel shows L-prcn (H-prcn).

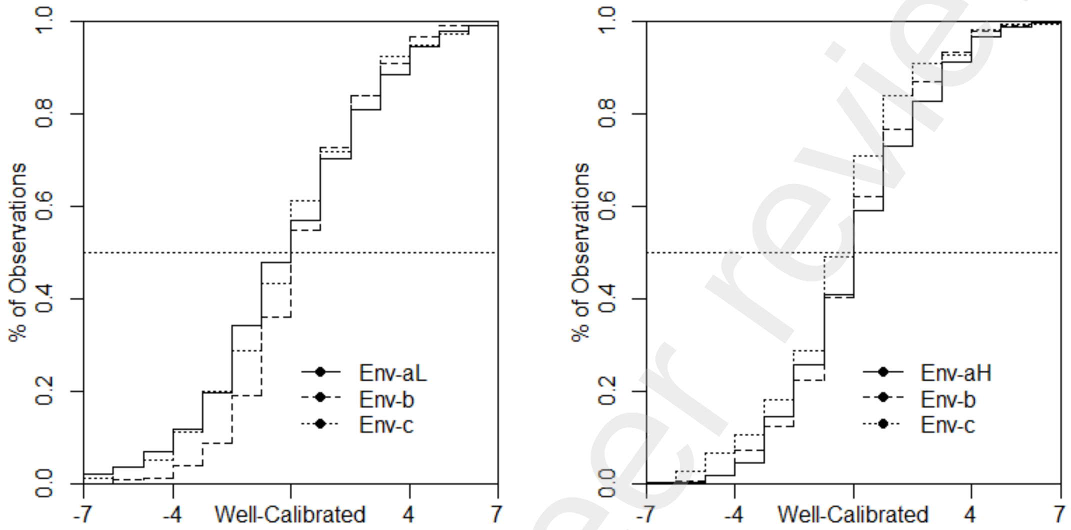


Figure A3: Posttrade Over-/Under-confidence (Inexperienced Sessions)

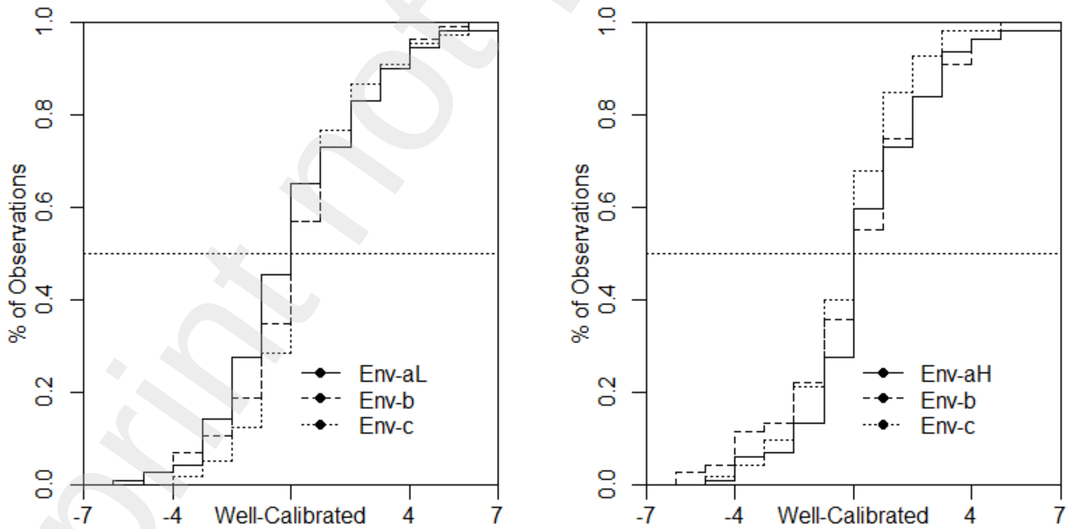


Figure A4: Posttrade Over-/Under-confidence (Experienced Sessions)

A.4 Overconfidence Pre and Post Trading (Experienced Sessions)

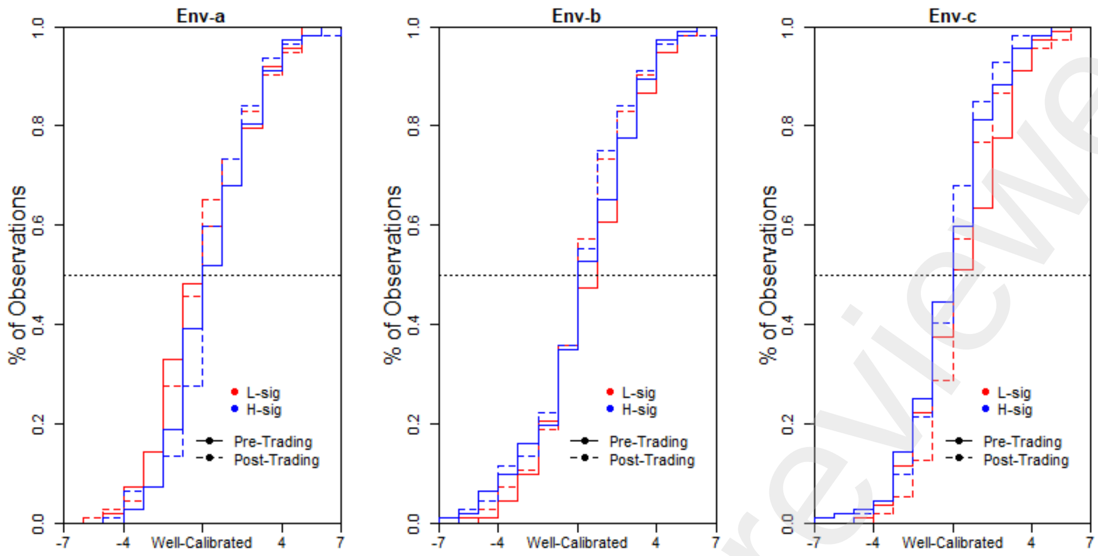


Figure A5: Pre vs Post-Trading Overconfidence (Question 3 in Experienced Sessions)

A.5 Level Of Confidence (Inexperienced Sessions)

The level of confidence is defined by the percentage deviations of traders' elicited beliefs from Bayesian P, from V^*, and from "actual rankings". For question 2 and question 3, we rescale the deviation by dividing their x by the possible range of the answers, i.e., $x/200$ for Q2 and $x/8$ for Q3. In this case, the levels of all three questions fall into the same interval of $[-0.5, 0.5]$. We compare the levels conditional on different signal precision. The following two figures illustrate the pattern of inexperienced sessions.

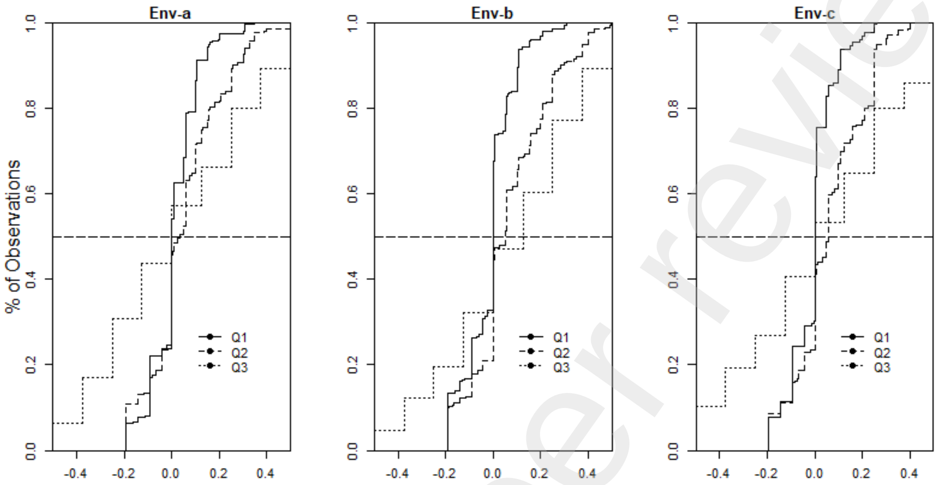


Figure A6: Level of Confidence (L-prcn)

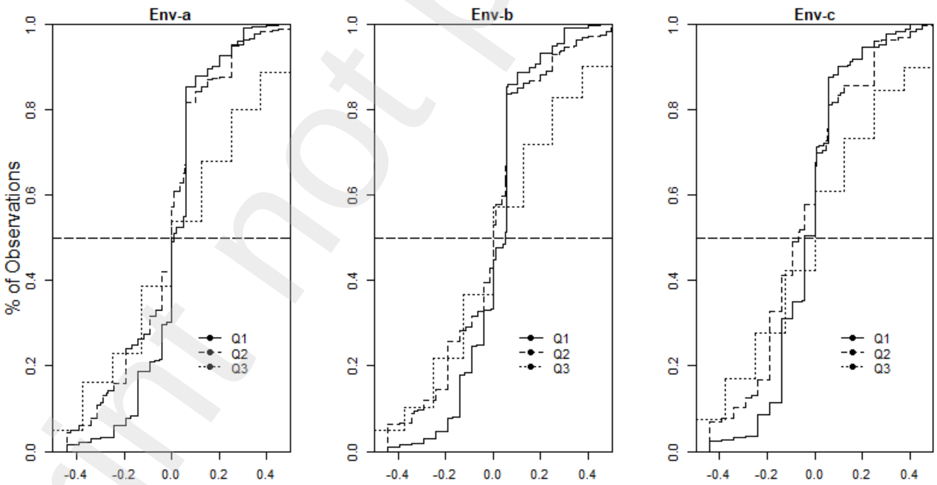


Figure A7: Level of Confidence (H-prcn)

Overall, the level of over and underconfidence are stronger in Q3 than the other two questions. When comparing Q1 and Q2 confidence levels, signal precision seems to have an effect. When traders hold L precision signals, traders are more overconfident in Q2 than Q1 (consistent with Fan et al. (2021)), but exhibit similar level of underconfidence. However, the patterns are reversed when they hold H precision signals. The patterns are similar in experienced sessions, which are shown in Appendix A.6.

A.6 Level Of Confidence (Experienced Sessions)

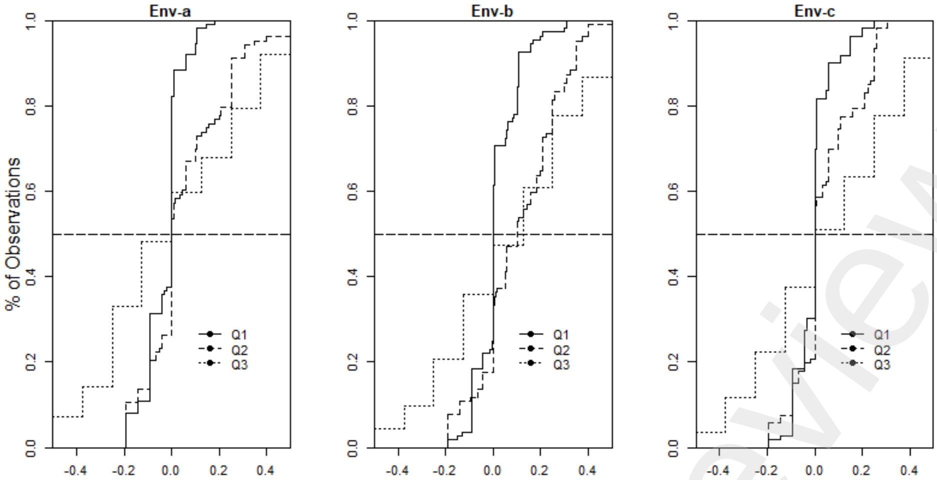


Figure A8: Level of Confidence (L-prcn)

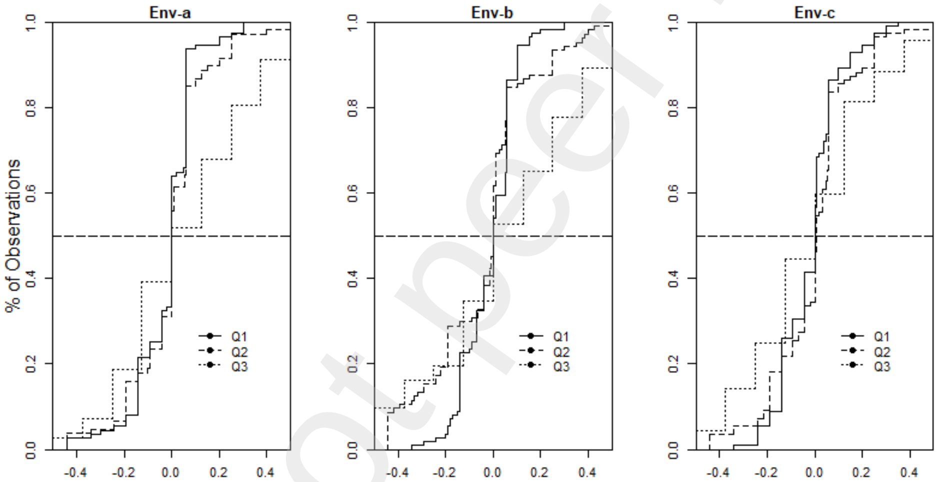


Figure A9: Level of Confidence (H-prcn)

A.7 Transaction Prices, Env-a

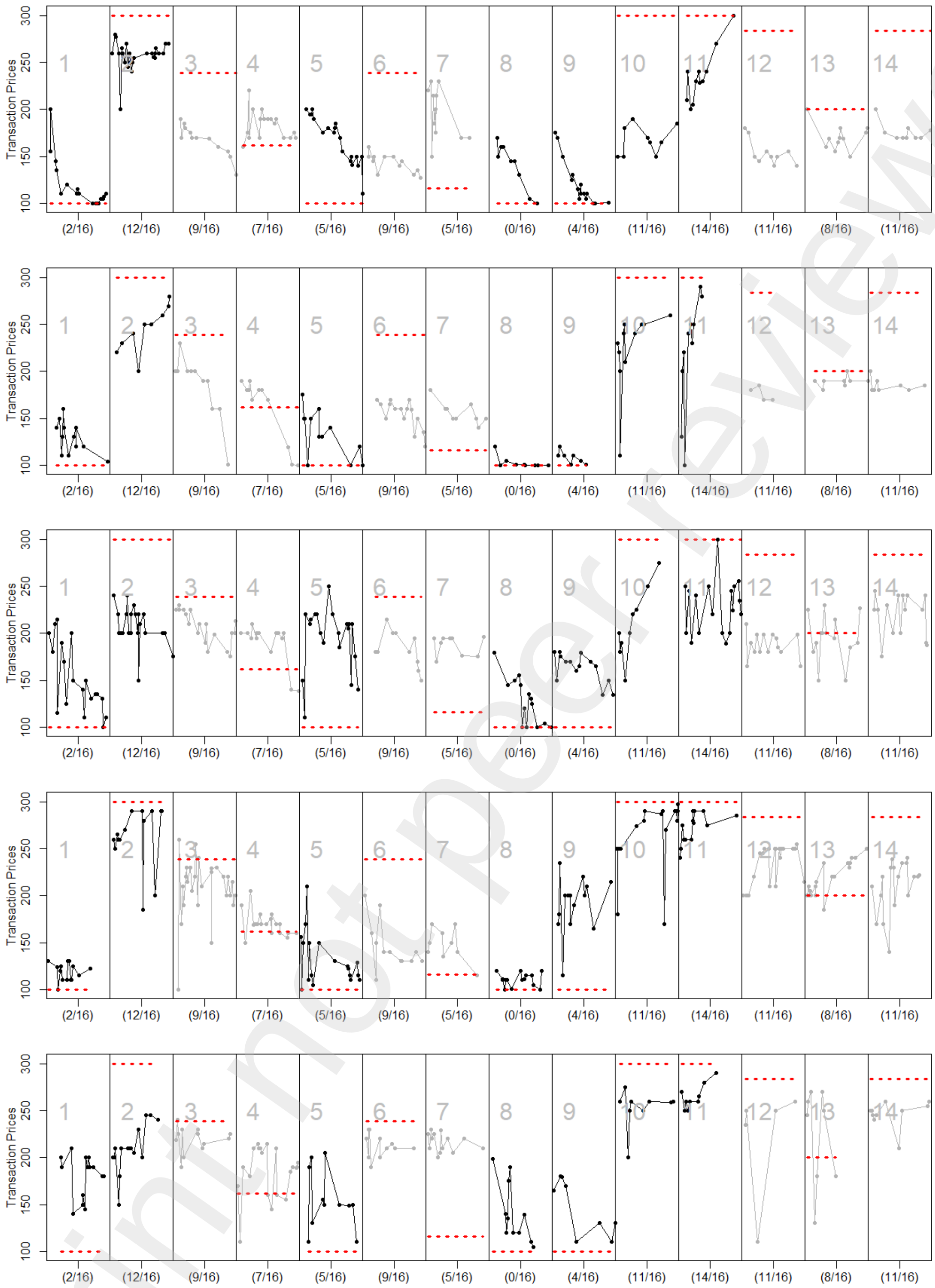


Figure A10: Transaction Prices Under Env-a (All 5 sessions)

Note: Transaction Prices in black (gray) means this period is in environment aL (aH).

A.8 Transaction Prices, Env-b

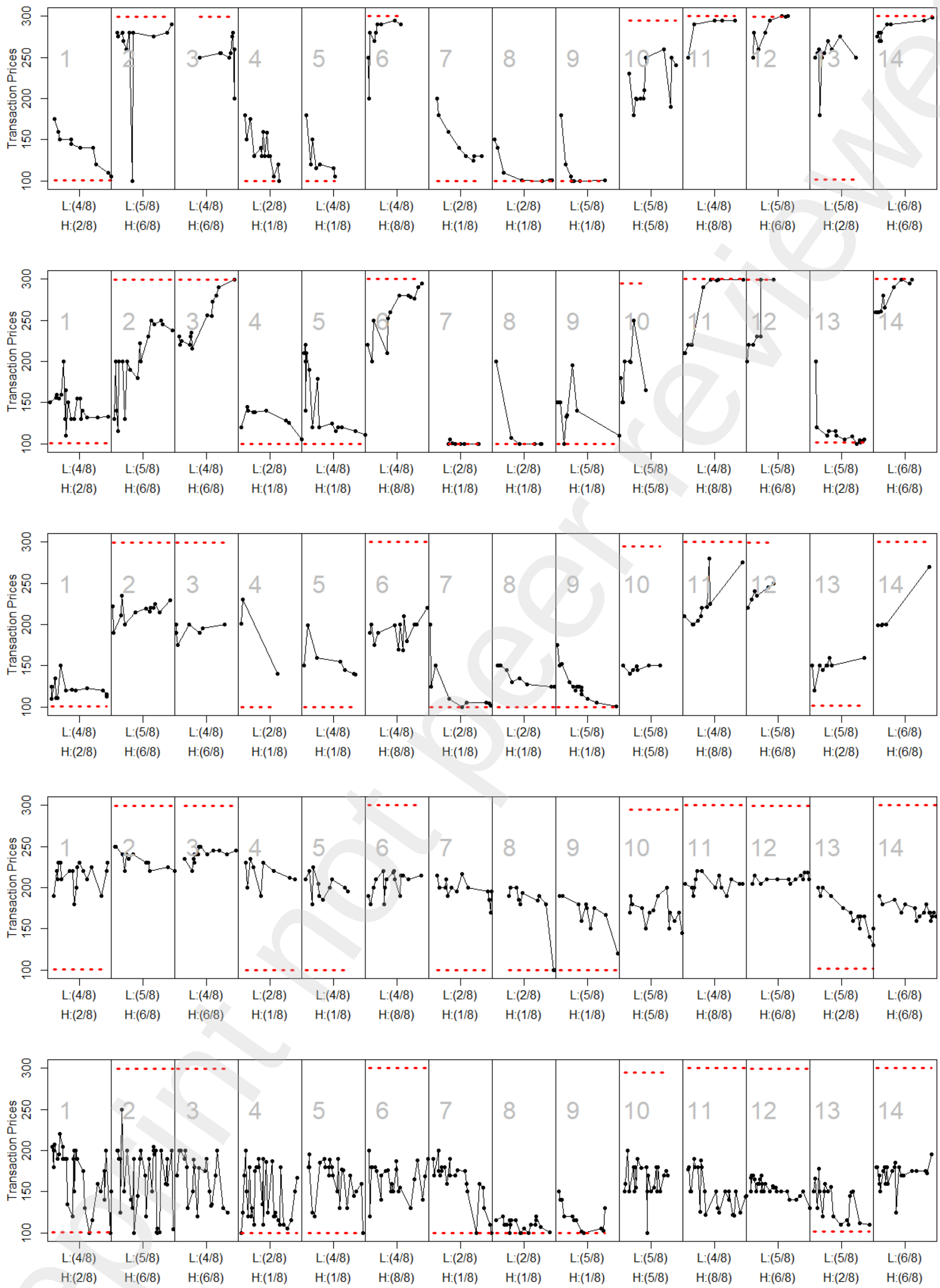


Figure A11: Transaction Prices Under Env-b (All 5 sessions)

A.9 Transaction Prices, Env-c

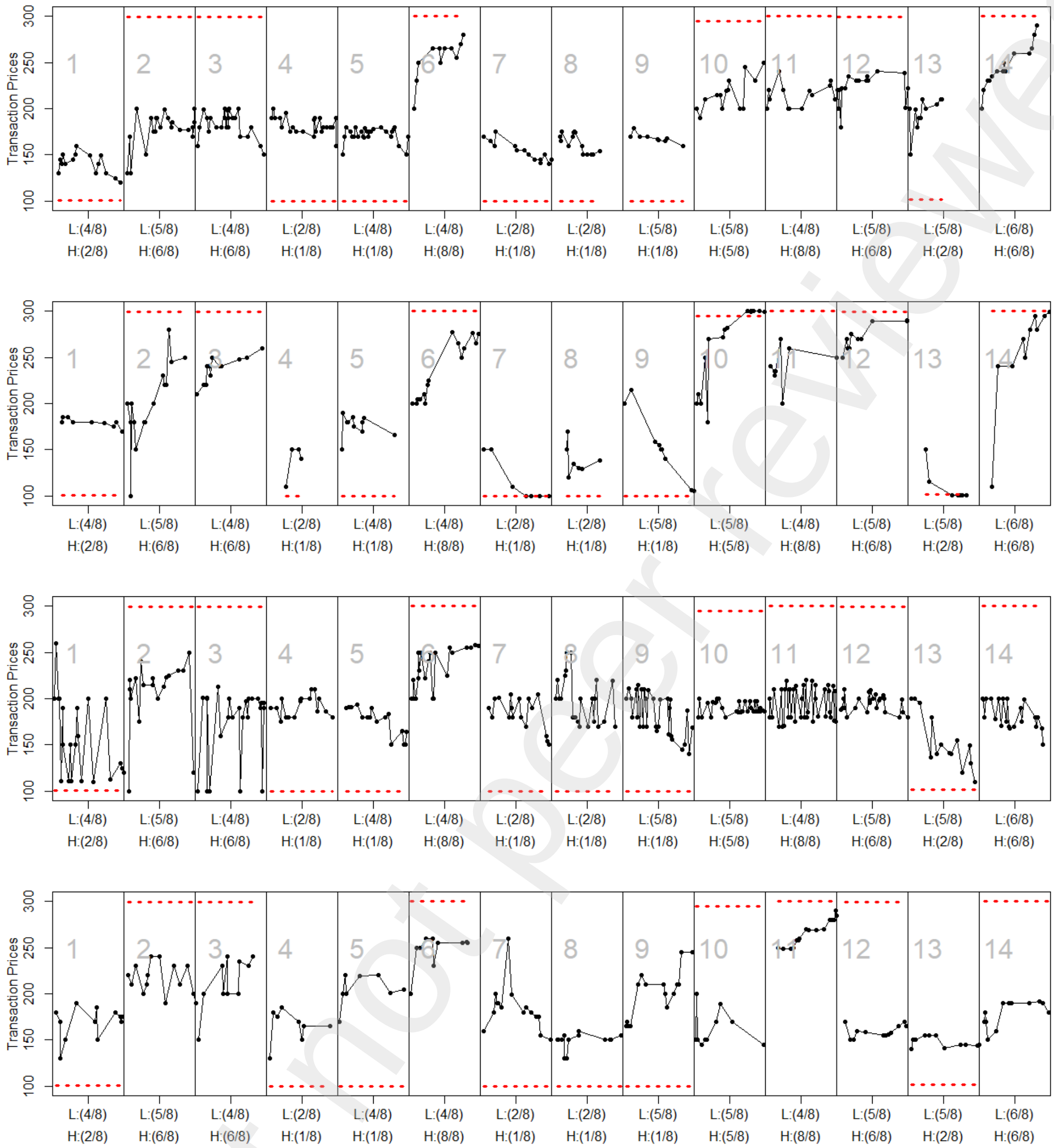


Figure A12: Transaction Prices Under Env-c (All 4 sessions)

A.10 Transaction Prices, Experienced Sessions

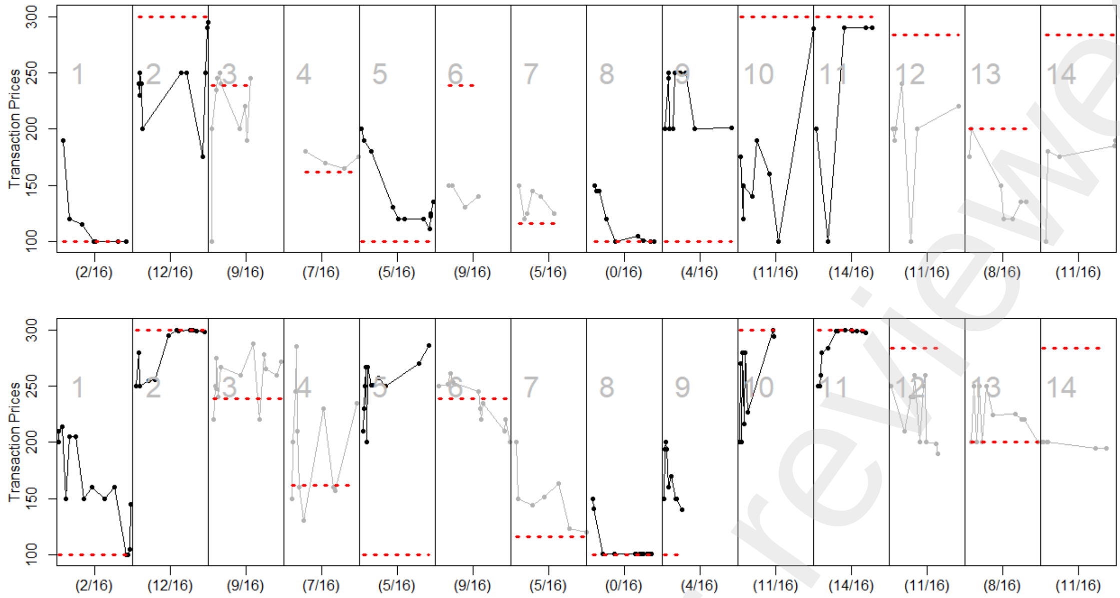


Figure A13: Transaction Prices Under Env-a (Two sessions)

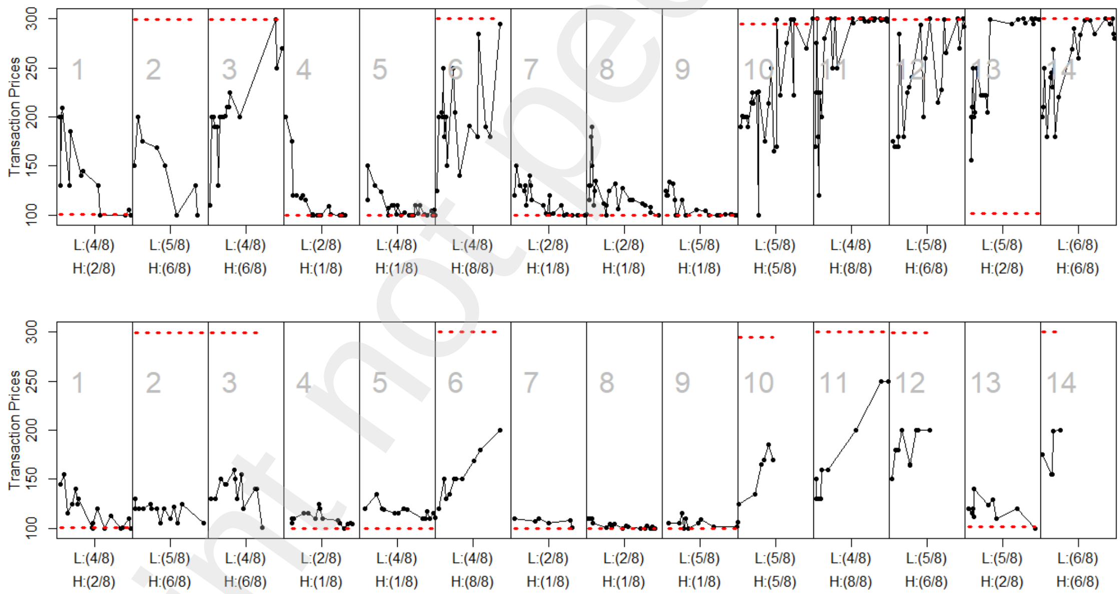


Figure A14: Transaction Prices Under Env-b (Two sessions)

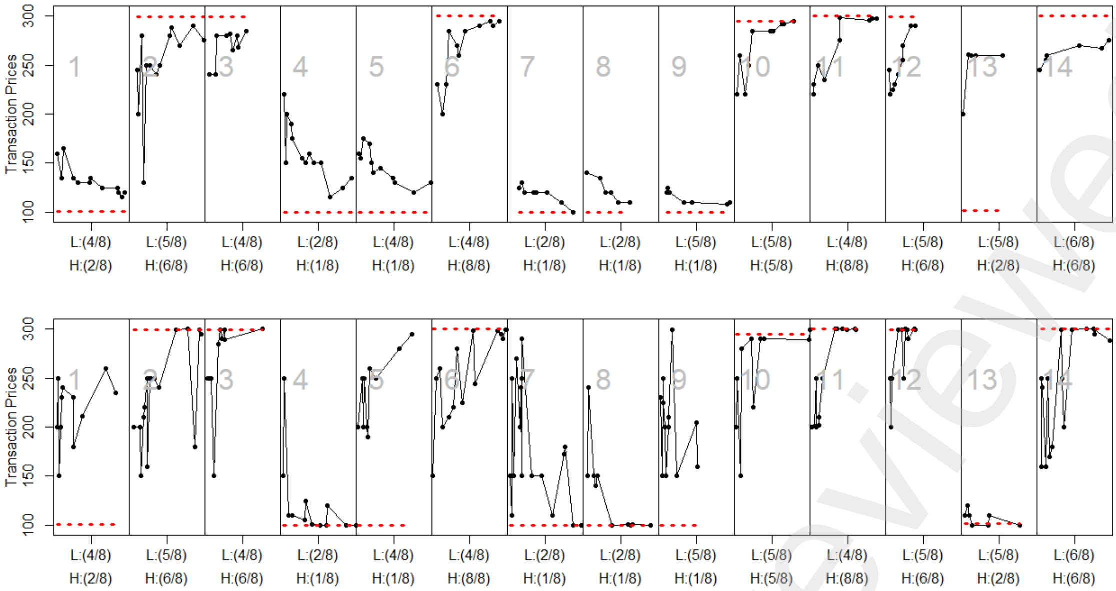


Figure A15: Transaction Prices Under Env-c (Two sessions)

A.11 Information Aggregation

A.11.1 Estimation in Environment-a

After rescaling the prices into the interval [0,1], the fully aggregated Bayes expected asset value is simply the Bayesian posterior (P) of state G given the realized draws for all 8 subjects:

$$P = Pr(G|S_N) = \frac{q^K \cdot (1-q)^{N-K}}{q^K \cdot (1-q)^{N-K} + q^{N-K} \cdot (1-q)^K}$$

where S_N is the set of all available signals, thus $N = 16$. $q = 0.6(0.8)$ if the period is L-prcn (H-prcn) period. K is the total number of realized black balls in each period.

The model from Page and Siemroth (2021), however, assumes the market can incorporate a subset of the available signals into the prices. The observed prices are set as if the market incorporates a randomly drawn (without replacement) subset $S_n \subseteq S_N$. Therefore, the observed prices only incorporate $n \leq N$ of all the signals and correspondingly $k \leq K$ number of black balls:

$$\hat{P} = Pr(G|S_n) = \frac{q^k \cdot (1-q)^{n-k}}{q^k \cdot (1-q)^{n-k} + q^{n-k} \cdot (1-q)^k},$$

where, $n = \lceil \lambda N \rceil$ and $\lambda \in [0, 1]$ is the proportion of all available signals used and it is the main parameter of interest. $\lceil x \rceil$ is the ceiling function. In order to estimate λ, the model assumes that the observed prices (denoted as P_m for trading periods $m = 1, 2, ..., M$) are generated by:

$$P_m = \hat{P}(\lambda, k) + \epsilon_m \iff \epsilon_m = P_m - \frac{q^k \cdot (1-q)^{\lceil \lambda N \rceil - k}}{q^k \cdot (1-q)^{\lceil \lambda N \rceil - k} + q^{\lceil \lambda N \rceil - k} \cdot (1-q)^k}, \tag{9}$$

where the stochastic deviation ϵ_m is assumed to be normal: $\epsilon_m \sim \mathcal{N}(0, \sigma^2)$, and σ is also a parameter to be estimated. Then the model assigns a probability of observing a specific market price P_m given (λ, k, σ):

$$Pr(P_m|\lambda, k, \sigma) = \phi\Big(\frac{\epsilon_m}{\sigma}\Big)/\sigma = \phi\Big(\frac{P_m - \hat{P}(\lambda, k)}{\sigma}\Big)/\sigma,$$

where $\phi(x)$ is the standard normal density. Also, the probability of drawing a specific k given λ is:

$$Pr(k|\lambda) = \frac{\binom{K_m}{k}\binom{N-K_m}{\lceil \lambda N \rceil - k}}{\binom{N}{\lceil \lambda N \rceil}}$$

Now, given all the above components, the likelihood of observing market price P_m given the model is the probability of drawing an information subset with k black balls and an error term ϵ_m such that $P_m = \hat{P}(\lambda, k) + \epsilon_m$. Thus,

$$\begin{aligned} Pr(P_m|\lambda, \sigma) &= \sum_{k=max\{0, \lceil \lambda N \rceil - N + K_m\}}^{k=min\{\lceil \lambda N \rceil, K_m\}} Pr(P_m|\lambda, k, \sigma) \cdot Pr(k|\lambda) \\ &= \sum_{k=max\{0, \lceil \lambda N \rceil - N + K_m\}}^{k=min\{\lceil \lambda N \rceil, K_m\}} \phi\left(\frac{P_m - \frac{q^k \cdot (1-q)^{\lceil \lambda N \rceil - k}}{q^k \cdot (1-q)^{\lceil \lambda N \rceil - k} + q^{\lceil \lambda N \rceil - k} \cdot (1-q)^k}}{\sigma}\right)/\sigma \cdot \frac{\binom{K_m}{k}\binom{N-K_m}{\lceil \lambda N \rceil - k}}{\binom{N}{\lceil \lambda N \rceil}} \end{aligned}$$

The objective of this estimation is to find $(\hat{\lambda}, \hat{\sigma})$ that maximize the overall log-likelihood of observing the prices $(p_1, p_2, ..., p_M)$ in M trading periods:

$$(\hat{\lambda}, \hat{\sigma}) = \underset{\lambda \in [0,1], \sigma > 0}{\arg\max} \sum_{m=1}^{M} lnPr(P_m|\lambda, \sigma)$$

Due to the ceiling function in $n = \lceil \lambda N \rceil$, λ and σ are not continuous, and therefore, λ and σ both take values in the interval of $[0, 1]$ in 0.01 steps, meaning that $\lambda \in [0, 1] \cap \{0 + 0.01 \cdot l\}_{l=0,1,...,100}$, and similarly for σ.

A.11.2 Estimation in Environment-b and Environment-c

The estimation of λ in the other two environments are different because we have two signal precision in the market. Bayesian posterior is the following:

$$P = Pr(G|S_N) = \frac{0.6^{K_L} \cdot 0.4^{N_L - K_L} \cdot 0.8^{K_H} \cdot 0.2^{N_H - K_H}}{0.6^{K_L} \cdot 0.4^{N_L - K_L} \cdot 0.8^{K_H} \cdot 0.2^{N_H - K_H} + 0.6^{N_L - K_L} \cdot 0.4^{K_L} \cdot 0.8^{N_H - K_H} \cdot 0.2^{K_H}}$$

In each market, the total number of private signals are $N = N_L + N_H = 16$. We have $N_L = N_H = 8$ means both L-prcn and H-prcn provide 8 balls and $K_L(K_H)$ refers to the number of black balls from L-prcn (H-prcn). Like the original model, $n = \lceil \lambda N \rceil$ indicates the number of the private signals incorporated into the price, which is a subset of N. But, in environment b and c, we need to figure out how many of n is L-prcn and how many is H-prcn. Since we have half traders receive L-prcn and the other half receive H-prcn, we assume n is splitted evenly between these two precisions. Therefore, we have $n = n_L + n_H$ and $n_L = n_H = \lceil \frac{\lambda}{2} N \rceil$. Therefore, we would have Bayes posterior given the subset of signals equal to:

$$\hat{P} = Pr(G|\lambda, k_L, k_H) = \frac{0.6^{k_L} \cdot 0.4^{n_L - k_L} \cdot 0.8^{k_H} \cdot 0.2^{n_H - k_H}}{0.6^{k_L} \cdot 0.4^{n_L - k_L} \cdot 0.8^{k_H} \cdot 0.2^{n_H - k_H} + 0.6^{n_L - k_L} \cdot 0.4^{k_L} \cdot 0.8^{n_H - k_H} \cdot 0.2^{k_H}}$$

and the probability of observing the market price P_m given the parameters is:

$$Pr(P_m|\lambda, k_L, k_H, \sigma) = \phi\Big(\frac{\epsilon_m}{\sigma}\Big)/\sigma = \phi\Big(\frac{P_m - \hat{P}(\lambda, k_L, k_H)}{\sigma}\Big)/\sigma$$

Similar to the original model, we can find the upper and lower bound for k_L and k_H:

$k_L \in [max\{0, n_L - 8 + K_{L,m}\}, min\{n_L, K_{L,m}\}]$, and $k_H \in [max\{0, n_H - 8 + K_{H,m}\}, min\{n_H, K_{H,m}\}]$

The probability of drawing a specific k_L and k_H given λ is:

$$Pr(k_L|\lambda) = \frac{\binom{K_{L,m}}{k_L}\binom{8-K_{L,m}}{\lceil \frac{\lambda}{2} N \rceil - k_L}}{\binom{8}{\lceil \frac{\lambda}{2} N \rceil}}, \text{ and } Pr(k_H|\lambda) = \frac{\binom{K_{H,m}}{k_H}\binom{8-K_{HH,m}}{\lceil \frac{\lambda}{2} N \rceil - k_H}}{\binom{8}{\lceil \frac{\lambda}{2} N \rceil}}$$

The modified version of the model looks like:

$$\begin{aligned} Pr(P_m|\lambda, \sigma) &= \sum_{k_H} \sum_{k_L} Pr(P_m|\lambda, k_L, k_H, \sigma) \cdot Pr(k_L|\lambda) \cdot Pr(k_H|\lambda) \\ &= \sum_{k_H} \sum_{k_L} \phi\left(\frac{P_m - \hat{P}_m(\lambda, k_L, k_H)}{\sigma}\right)/\sigma \cdot Pr(k_L|\lambda) \cdot Pr(k_H|\lambda) \end{aligned}$$

Again, the objective is to find $(\hat{\lambda}, \hat{\sigma})$ that maxmize the overall log-likelihood of observing the prices in M markets,

$$(\hat{\lambda}, \hat{\sigma}) = \underset{\lambda \in [0,1], \sigma > 0}{\arg\max} \sum_{m=1}^{M} lnPr(P_m | \lambda, \sigma)$$

Table A1: Estimated λ and ψ (Last Price)

Data	In-experienced λ	Experienced λ	Inexperienced ψ	Experienced ψ
Env_aL	0.06	0.37	0.02	0.25
	[0.00,0.25]	[0.00,0.50]	[-0.19,0.24]	[-0.15,0.54]
Env_aH	0.12	0.25	0.72	0.68
	[0.12,0.31]	[0.12,0.34]	[0.60,0.82]	[0.43,0.89]
Env_b	0.12	0.25	0.48	0.52
	[0.12,0.25]	[0.12,0.37]	[0.39,0.60]	[0.29,0.77]
Env_c	0.12	0.25	0.34	0.73
	[0.00,0.12]	[0.12,0.50]	[0.22,0.44]	[0.55,0.91]

Note: This table replicates Table A3 using the very last transaction price in each period.

A.12 Price Convergence and information aggregation

We adapt the methods of Noussair et al. (1995), and estimate equation (10) below. The dependent variable y is the pricing error $|\nu - V^*|$, the absolute value of the deviation of actual price ν from rational expectations price (or Bayesian posterior expected asset value given all realized private information) V^* in equation 3. The explanatory variables include session-dependent transitory terms $D_i(1/t)$,[8] which vanish asymptotically as the number of periods t gets large, and a session-independent permanent term $(t-1)/t$ that converges to 1.0. Those terms are interacted with treatment dummies ($\mathbb{1}_{aL}$, $\mathbb{1}_{aH}$, $\mathbb{1}_b$, and $\mathbb{1}_c$), with Environment c taken as the baseline.

$$\begin{aligned} y_{it} = &\sum_{i=1}^{5} \beta_{aLi} D_i \mathbb{1}_{aL}(\frac{1}{t}) + \sum_{i=1}^{5} \beta_{aHi} D_i \mathbb{1}_{aH}(\frac{1}{t}) + \sum_{i=1}^{5} \beta_{bi} D_i \mathbb{1}_b(\frac{1}{t}) + \sum_{i=1}^{4} \beta_{ci} D_i \mathbb{1}_c(\frac{1}{t}) + \\ &+ \beta_c(\frac{t-1}{t}) + \beta_{aL}\mathbb{1}_{aL}(\frac{t-1}{t}) + \beta_{aH}\mathbb{1}_{aH}(\frac{t-1}{t}) + \beta_b \mathbb{1}_b(\frac{t-1}{t}) + u \end{aligned} \tag{10}$$

Table A2 shows our estimates for the permanent terms in equation (10), which are intended to pick up what would happen when the empirical convergence process is complete. The "actual price" ν in the first column in the Table is the last transaction price each period, while in the second column ν is the average of the last two transaction prices. The third column replaces the dependent variable pricing error by "Spread," the difference between the last best ask and the last best bid.

The results may seem a bit surprising. In inexperienced sessions, the baseline environment c is not at all conducive to convergence to the fully aggregated asset value (typically near 100 or 300); the estimated price error is over 80 and highly significant, and the estimated spread of almost 28 is also quite large and significant. Price errors on average are considerably less (by around 40 or 50, i.e., about half as large) in the high precision treatment aH, but there is so much variability across sessions that

[8] Here D_i is a session dummy variable. Equation 10 assumes 5 sessions for most treatments, as in the inexperienced data, but of course in the experienced data the sums are just $i = 1$ to 2.

Table A2: Regressions of Convergence

	Inexperienced			Experienced		
VAR	P-Error (Last Price)	P-Error (Last Two Prices)	Spread	P-Error (Last Price)	P-Error (Last Two Prices)	Spread
β_c	86.07***	83.89***	27.93***	4.826	4.009	24.22**
	(17.74)	(17.04)	(6.377)	(17.17)	(17.67)	(10.39)
β_{aL}	-14.10	-7.945	2.451	69.73***	76.93***	33.81*
	(28.50)	(27.52)	(11.86)	(24.76)	(25.12)	(20.14)
β_{aH}	-50.33*	-38.46	-16.92	38.59	60.12**	15.79
	(28.51)	(28.03)	(12.07)	(27.14)	(29.95)	(18.54)
β_b	-5.693	2.435	-3.184	55.92*	56.65**	10.02
	(31.37)	(29.89)	(10.54)	(28.72)	(28.02)	(14.55)
Obs.	196	196	195	84	84	84
R^2	0.702	0.728	0.663	0.395	0.424	0.620

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

the reduction is at best marginally significant. The other environments seem to have somewhat better convergence than baseline but not significantly so. By contrast, convergence in experienced sessions is remarkably good for baseline environment c: price errors are typically only about 5. Spread in env-c decreases only slightly, however, relative to inexperienced sessions. Not surprisingly, price errors are considerably larger in the other experienced treatments, and the difference is highly significant for aL, the environment with least precise private information.

To check the robustness of these results, we examine alternative measures of information aggregation. Recall the discussion in Section 2.1 of Page and Siemroth (2021)'s λ. The same paper also defines "price accuracy" as $\psi = min\{1, (p - 0.5)/(P - 0.5)\}$, where (only in the current paragraph) p and P are the actual price ν and fully aggregated value V^* rescaled from their natural range [100, 300] to the unit interval [0,1]. Thus this notion of price accuracy is in some ways reminiscent of our overconfidence index x, but the minimum operator ensures that ψ cannot exceed 1, thereby treating prices that overreact to information as if they reacted correctly. To estimate average accuracy ψ of the (average of the last two rescaled) observed prices p_m in reaching fully aggregated rescaled prices P_m in period $m = 1, ..., M$, one reports the fitted coefficient in the regression

$$Y_m = \psi(P_m - 0.5) + \epsilon_m \tag{11}$$

where

$$Y_m = \begin{cases} min\{p_m - 0.5, P_m - 0.5\}, & \text{if } P_m > 0.5, \\ max\{p_m - 0.5, P_m - 0.5\}, & \text{if } P_m < 0.5. \end{cases}$$

Table A3 collects the results. Consistent with the previous table, it indicates that markets aggregate information best in experienced sessions in environment c, and also quite well in aH, even in inexperienced sessions. The λ measure indicates that experienced sessions do better than inexperienced sessions in all environments, and agrees that aggregation is worst in inexperienced aL sessions.

Table A3: Estimated λ and ψ (Last Two Prices)

Data	Inexperienced λ	Experienced λ	Inexperienced ψ	Experienced ψ
Env_aL	0.06	0.25	0.05	0.24
	[0.00,0.31]	[0.00,0.50]	[-0.16,0.22]	[0.03,0.59]
Env_aH	0.12	0.25	0.69	0.64
	[0.12,0.31]	[0.12,0.37]	[0.59,0.78]	[0.34,0.88]
Env_b	0.12	0.12	0.47	0.5
	[0.12,0.25]	[0.12,0.37]	[0.34,0.57]	[0.30,0.69]
Env_c	0.12	0.25	0.35	0.72
	[0.00,0.12]	[0.18,0.50]	[0.26,0.43]	[0.52,0.88]

Note: The 95% confidence intervals below the estimated λ and ψ are calculated via the non-parametric percentile bootstrap method, which resamples (with replacement) the market periods within each environment 100 times to determine the final confidence intervals. We also estimate λ and ψ using the last transaction price in each period, the results are similar, please see table A1.

A.13 Belief Errors Biases

A.13.1 Inexperienced Sessions

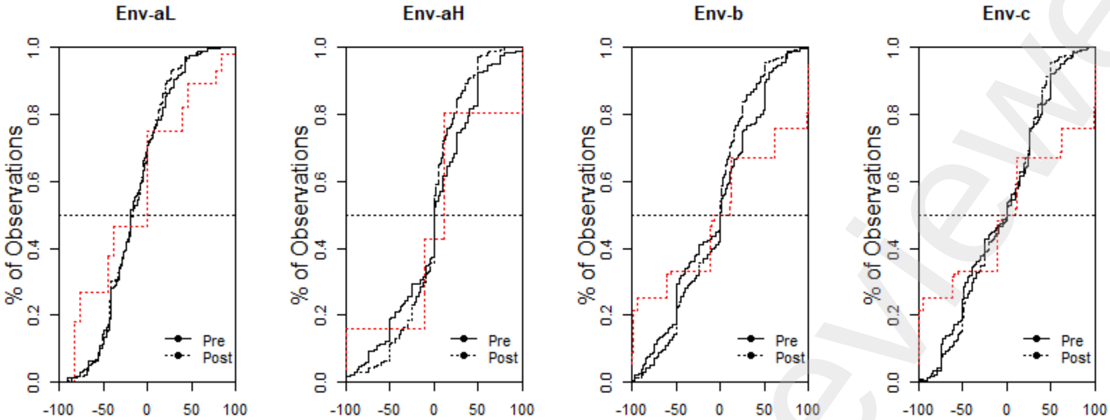


Figure A16: Belief Errors (Question 2)

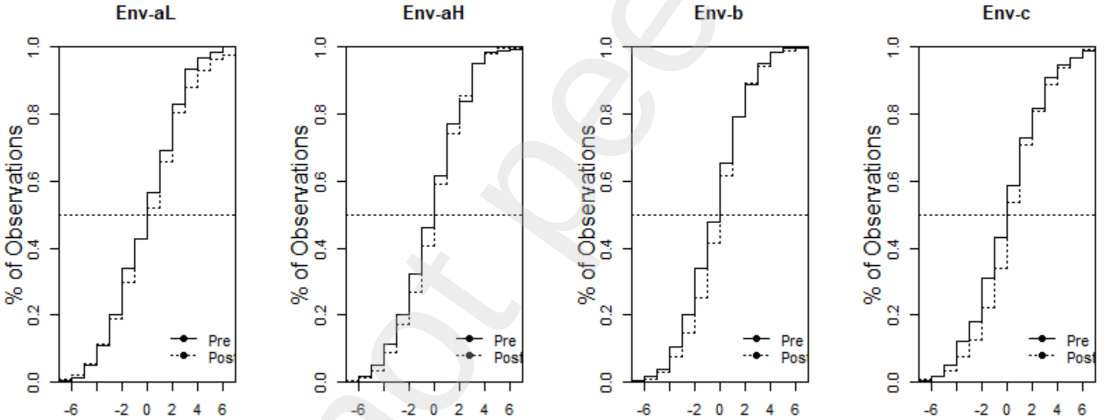


Figure A17: Belief Errors (Question 3)

A.13.2 Experienced Sessions

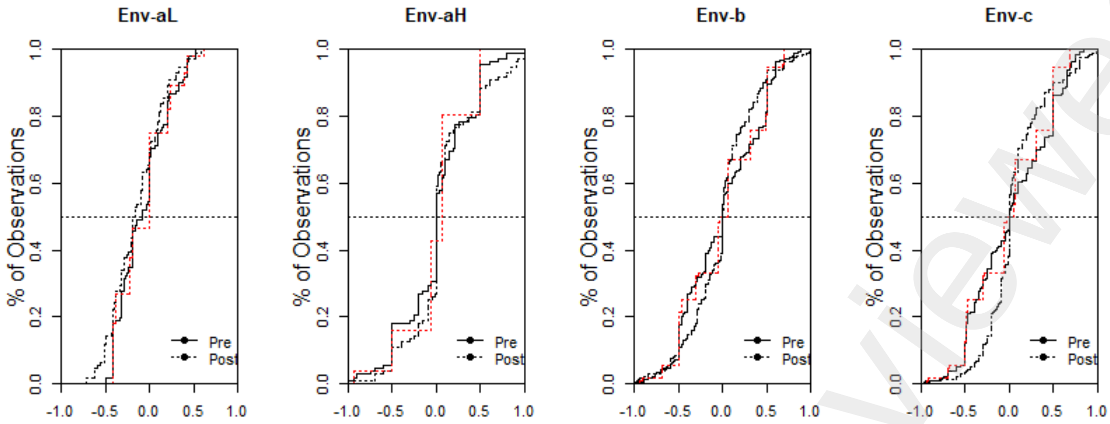


Figure A18: Belief Errors (Question 1)

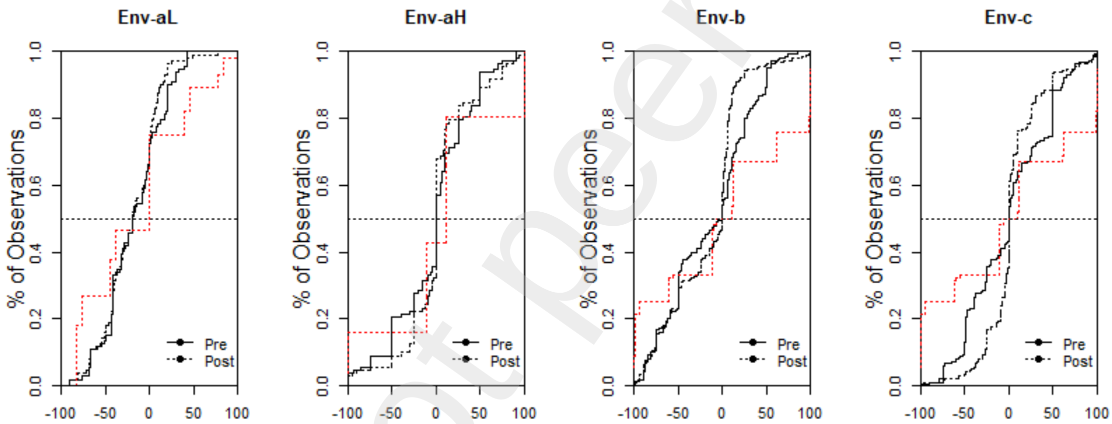


Figure A19: Belief Errors (Question 2)

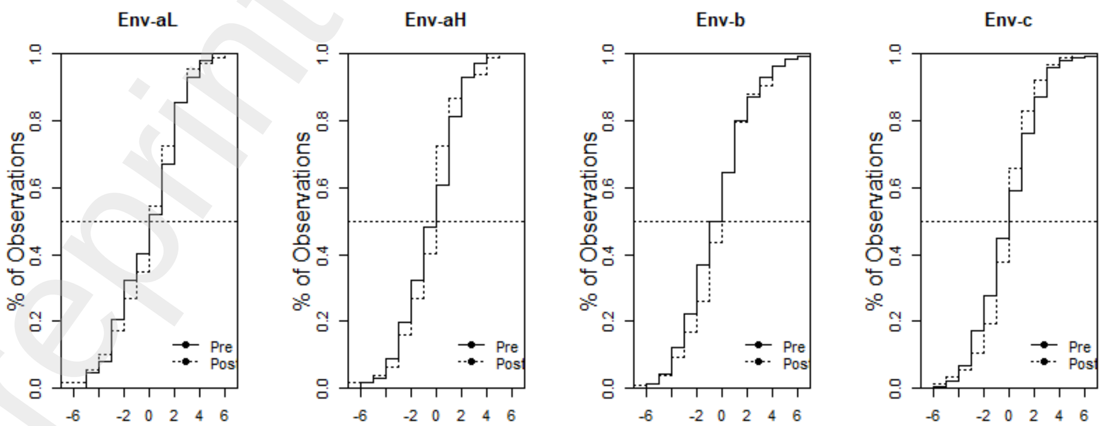


Figure A20: Belief Errors (Question 3)

A.14 Wilcoxon Signed-Rank (WSR) Test

Table A4: WSR Test on Confidence Levels

	Inexperienced Sessions							
	Question 1		Question 2		Question 3		Question 3 (Posttrade)	
	L-sig	H-sig	L-sig	H-sig	L-sig	H-sig	L-sig	H-sig
H_0 : Env-a = Env-b	0.0024	0.7746	0.3708	0.8372	0.0172	0.8431	0.0444	0.7162
H_0 : Env-b = Env-c	0.4668	0.0000	0.9722	0.0102	0.1019	0.1744	0.0615	0.0149
H_0 : Env-a = Env-c	0.0208	0.0001	0.4447	0.0142	0.6280	0.1456	0.9447	0.0087
	Experienced Sessions							
	Question 1		Question 2		Question 3		Question 3 (Posttrade)	
	L-sig	H-sig	L-sig	H-sig	L-sig	H-sig	L-sig	H-sig
H_0 : Env-a = Env-b	0.0003	0.7284	0.0056	0.0746	0.0603	0.9503	0.2217	0.5423
H_0 : Env-b = Env-c	0.1451	0.5232	0.0014	0.0487	0.6064	0.0813	0.6334	0.1847
H_0 : Env-a = Env-c	0.0165	0.8146	0.9740	0.8001	0.1593	0.0678	0.0593	0.0289

Note: This is the WSR test for figure 4 and figures in Appendix A1, Appendix A2, and Appendix A.3. Numbers in the table are the p-values.

Table A5: WSR Test on Belief Errors Biases

	Inexperienced Sessions			
	Env-aL	Env-aH	Env-b	Env-c
Question 1	0.3115	0.7009	0.4794	0.0036
Question 2	0.5846	0.3143	0.4132	0.7749
Question 3	0.3272	0.2747	0.0270	0.0202
	Experienced Sessions			
	Env-aL	Env-aH	Env-b	Env-c
Question 1	0.0909	0.6234	0.9802	0.3022
Question 2	0.6002	0.9655	0.0903	0.4093
Question 3	0.9735	0.9734	0.1975	0.8672

Note: This is the WSR test for figure 5 and figures in Appendix A.13. Numbers in the table are the p-values.

Table A6: WSR Test on Confidence Levels Pre and Post Trading (Question 3 Only)

	In-experienced Sessions					
	Env-a		Env-b		Env-c	
	L-sig	H-sig	L-sig	H-sig	L-sig	H-sig
H_0 : Pre = Post	0.3272	0.2747	0.0714	0.1744	0.1858	0.0489
	Experienced Sessions					
	Env-a		Env-b		Env-c	
	L-sig	H-sig	L-sig	H-sig	L-sig	H-sig
H_0 : Pre = Post	0.9735	0.9734	0.2834	0.4662	0.8972	0.8722

Note: This is the WSR test for figure 7 and figures in Appendix A.4. The null hypothesis (Pre=Post) is that traders' overconfidence does not change significantly after trading in the market. Numbers in the table are the p-values.

A.15 Overconfidence on Market Prices

Table A7 replicates Table 4. The column titled "Last One" ("Last Two") refers to the regression using the very last price (the average of the last two prices). Table A8 and Table A9 replicate Table 4 using x measured by Q2 and Q3.

Table A7: Coefficient Estimates for Equation (5), Question 1

	Inexperienced				Experienced			
	Last One		Last Two		Last One		Last Two	
VARIABLES	Q1	se	Q1	se	Q1	se	Q1	se
β_c	-100.9	(155.0)	-75.77	(148.3)	-292.2*	(149.4)	-344.3**	(158.8)
β_{aL}	380.2	(305.2)	301.6	(279.2)	409.7	(462.0)	304.2	(449.8)
β_{aH}	50.14	(206.9)	34.09	(195.1)	-88.58	(199.5)	38.11	(231.6)
β_b	457.6**	(215.2)	376.4*	(211.3)	957.7**	(410.0)	1,035***	(370.6)
Constant	-52.19***	(16.05)	-53.48***	(15.14)	-30.65**	(13.89)	-40.67***	(15.29)
Observations	196		196		84		84	
R-squared	0.259		0.262		0.121		0.121	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A8: Coefficient Estimates for Equation (5), Question 2

	Inexperienced				Experienced			
	Last One		Last Two		Last One		Last Two	
VARIABLES	Q2	se	Q2	se	Q2	se	Q2	se
β_c	0.196	(0.491)	0.0583	(0.442)	-0.521	(0.714)	-0.731	(0.747)
β_{aL}	-0.589	(0.892)	-0.425	(0.810)	1.401	(1.209)	1.569	(1.304)
β_{aH}	-0.857	(0.602)	-0.693	(0.527)	-0.850	(0.889)	-0.802	(0.918)
β_b	0.376	(0.768)	0.607	(0.711)	2.638**	(1.207)	2.870**	(1.148)
Constant	-48.35***	(15.65)	-50.45***	(14.63)	-38.18***	(12.05)	-48.01***	(14.06)
Observations	196		196		84		84	
R-squared	0.247		0.259		0.169		0.177	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A9: Coefficient Estimates for Equation (5), Question 3

	Inexperienced				Experienced			
	Last One		Last Two		Last One		Last Two	
VARIABLES	Q3	se	Q3	se	Q3	se	Q3	se
β_c	-10.81	(10.65)	-8.367	(9.812)	10.07	(17.45)	10.58	(17.35)
β_{aL}	20.95	(21.76)	20.91	(20.31)	-60.72	(71.24)	-48.00	(65.72)
β_{aH}	22.79	(16.43)	16.89	(15.16)	17.27	(29.07)	22.70	(28.88)
β_b	18.76	(15.27)	15.97	(14.63)	-16.76	(41.40)	-20.18	(39.92)
Constant	-52.16***	(16.33)	-53.70***	(15.63)	-25.21*	(13.01)	-36.83**	(14.40)
Observations	196		196		84		84	
R-squared	0.236		0.244		0.065		0.062	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.16 Overconfidence on Trading Profit

Table A10: Overconfidence on Trading Profit (x measured by Question 1)

	Inexperienced				Experienced			
VARIABLES	Over	(se)	Under	(se)	Over	(se)	Under	(se)
β_c	-404.2	(275.4)	61.18	(329.4)	-1,064**	(466.0)	-113.3	(646.1)
β_{aL}	340.3	(429.8)	196.5	(569.8)	-462.1	(821.3)	26.13	(915.1)
β_{aH}	-206.8	(332.3)	-332.1	(420.1)	-352.5	(738.6)	-5.203	(731.9)
β_b	-276.0	(337.8)	347.0	(457.4)	3.711	(601.8)	184.9	(899.9)
Constant	477.0***	(64.48)	409.8***	(53.73)	520.3***	(62.35)	423.1***	(93.82)
Observations	498		390		167		173	
R-squared	0.060		0.039		0.102		0.003	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table replicates table 5 with x measured by survey question 1.

A.17 Overconfidence on Taker Volumes

Table A11: Overconfidence on Taker Volume

	In-experienced			Experienced		
VARIABLES	Q1	Q2	Q3	Q1	Q2	Q3
β_c	-0.655	0.00700*	0.129**	-0.0494	0.00685**	0.108**
	(0.896)	(0.00394)	(0.0638)	(0.956)	(0.00328)	(0.0530)
β_{aL}	0.310	-0.0112**	0.00140	2.806*	-0.00792*	0.0145
	(1.365)	(0.00529)	(0.0766)	(1.517)	(0.00459)	(0.0751)
β_{aH}	3.067***	-0.00255	-0.0248	1.171	-0.00411	0.152
	(1.130)	(0.00472)	(0.0791)	(1.527)	(0.00578)	(0.0967)
β_b	1.657	-0.00511	-0.159**	-1.682	-0.0135**	-0.112
	(1.232)	(0.00455)	(0.0732)	(2.008)	(0.00564)	(0.0934)
Constant	1.727***	1.779***	1.641***	0.972***	1.007***	0.900***
	(0.216)	(0.232)	(0.202)	(0.122)	(0.134)	(0.119)
Observations	1,526	1,464	1,568	663	631	672
R-squared	0.063	0.056	0.073	0.082	0.080	0.089

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.18 Overconfidence on Sell-Buy-Gap

Table A12: Overconfidence on Sell-Buy-Gap (Question 2)

	Inexperienced				Experienced			
VARIABLES	Maker	se	Taker	se	Maker	se	Taker	se
β_c	-0.0531	(0.0776)	-0.220**	(0.109)	-0.0115	(0.216)	-0.250	(0.545)
β_{aL}	0.296	(0.206)	-0.0252	(0.198)	0.0533	(0.279)	0.222	(0.719)
β_{aH}	-0.140	(0.173)	0.108	(0.188)	-0.482	(0.318)	0.234	(0.617)
β_b	0.0160	(0.104)	0.162	(0.130)	-0.121	(0.247)	0.146	(0.566)
Constant	15.98***	(5.299)	-19.99***	(6.289)	38.10**	(14.58)	-86.52**	(36.56)
Observations	362		266		144		105	
R-squared	0.084		0.097		0.254		0.127	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.19 Summary of Buys and Sells

A.19.1 Inexperienced Sessions

Table A13: Summary of Buys and Sells (Env-aL)

	# of Sell: 0	# of Sell: 1	# of Sell: 2	# of Sell: More	Sum of Obs.
# of Buy: 0	13	20	28	0	61
# of Buy: 1	27	32	34	21	114
# of Buy: 2	15	14	8	13	50
# of Buy: More	15	5	10	25	55
Sum of Obs.	70	71	80	59	

Table A14: Summary of Buys and Sells (Env-aH)

	# of Sell: 0	# of Sell: 1	# of Sell: 2	# of Sell: More	Sum of Obs.
# of Buy: 0	11	19	48	0	78
# of Buy: 1	14	19	25	32	90
# of Buy: 2	12	10	15	12	49
# of Buy: More	23	11	10	19	63
Sum of Obs.	60	59	98	63	

Table A15: Summary of Buys and Sells (Env-b)

	# of Sell: 0	# of Sell: 1	# of Sell: 2	# of Sell: More	Sum of Obs.
# of Buy: 0	31	35	124	0	190
# of Buy: 1	36	31	40	30	137
# of Buy: 2	34	18	12	38	102
# of Buy: More	52	13	13	53	131
Sum of Obs.	153	97	189	121	

Table A16: Summary of Buys and Sells (Env-c)

	# of Sell: 0	# of Sell: 1	# of Sell: 2	# of Sell: More	Sum of Obs.
# of Buy: 0	24	38	100	0	162
# of Buy: 1	22	23	29	27	101
# of Buy: 2	16	15	7	17	55
# of Buy: More	39	14	15	62	130
Sum of Obs.	101	90	151	106	

A.19.2 Experienced Sessions

Table A17: Summary of Buys and Sells (All Envs)

	# of Sell: 0	# of Sell: 1	# of Sell: 2	# of Sell: More	Sum of Obs.
# of Buy: 0	62	68	126	0	256
# of Buy: 1	63	48	36	38	185
# of Buy: 2	25	16	20	25	86
# of Buy: More	51	21	20	53	145
Sum of Obs.	201	153	202	116	

Table A18: Summary of Buys and Sells (Env-aL)

	# of Sell: 0	# of Sell: 1	# of Sell: 2	# of Sell: More	Sum of Obs
# of Buy: 0	18	16	13	0	47
# of Buy: 1	14	13	9	4	40
# of Buy: 2	8	2	1	4	15
# of Buy: More	5	3	0	2	10
Sum of Obs.	45	34	23	10	

Table A19: Summary of Buys and Sells (Env-aH)

	# of Sell: 0	# of Sell: 1	# of Sell: 2	# of Sell: More	Sum of Obs.
# of Buy: 0	14	7	23	0	44
# of Buy: 1	14	5	8	9	36
# of Buy: 2	6	2	2	3	13
# of Buy: More	5	6	5	3	19
Sum of Obs.	39	20	38	15	

Table A20: Summary of Buys and Sells (Env-b)

	# of Sell: 0	# of Sell: 1	# of Sell: 2	# of Sell: More	Sum of Obs.
# of Buy: 0	15	22	40	0	77
# of Buy: 1	13	15	7	14	49
# of Buy: 2	7	4	6	12	29
# of Buy: More	13	8	10	38	69
Sum of Obs.	48	49	63	64	

Table A21: Summary of Buys and Sells (Env-c)

	# of Sell: 0	# of Sell: 1	# of Sell: 2	# of Sell: More	Sum of Obs.
# of Buy: 0	15	23	50	0	88
# of Buy: 1	22	15	12	11	60
# of Buy: 2	4	8	11	6	29
# of Buy: More	28	4	5	10	47
Sum of Obs.	69	50	78	27	

A.20 Results Exclude Observations with Bayes Equal to 0.5.

Recall that our current definition of overconfidence says x is always categorized as overconfident and take a positive value when $P = 0.5$. One of the obvious shortcomings of this definition is that this does not allow underconfidence. This subsection presents relevant graphs and tables of x, excluding observations that have $P = 0.5$. We denote these the results as "EXC."

Figure A21 and A22 are measured x across environments excluding $P = 0.5$ cases. The systematic patterns are the following: 1. Overall in inexperienced sessions, elicited beliefs in environment c exhibit more underconfident bias when traders hold H-prcn signals. 2. In experienced sessions, however, traders who hold L-prcn in homogeneous environment (environment a) are relatively more underconfident.

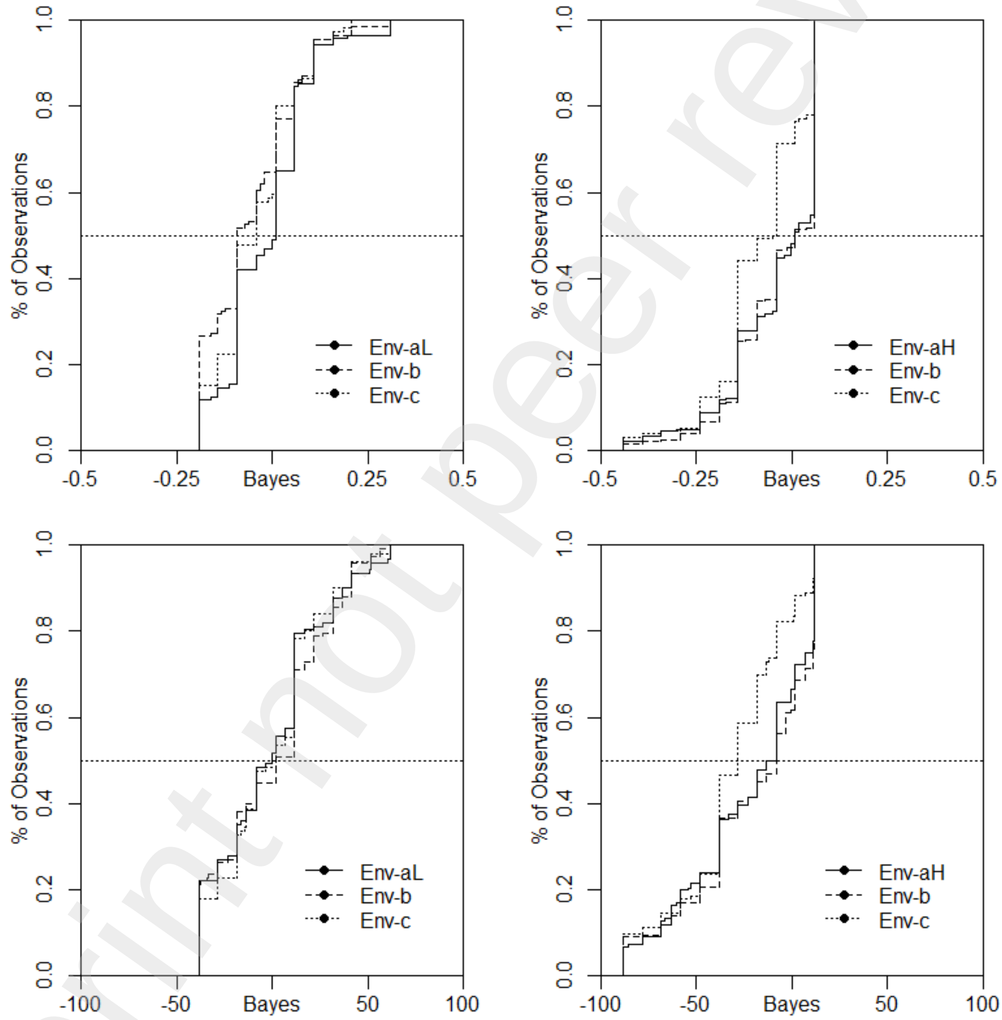


Figure A21: Q1 and Q2 Pretrade Over-/Under-confidence Inexperienced Sessions (EXC)

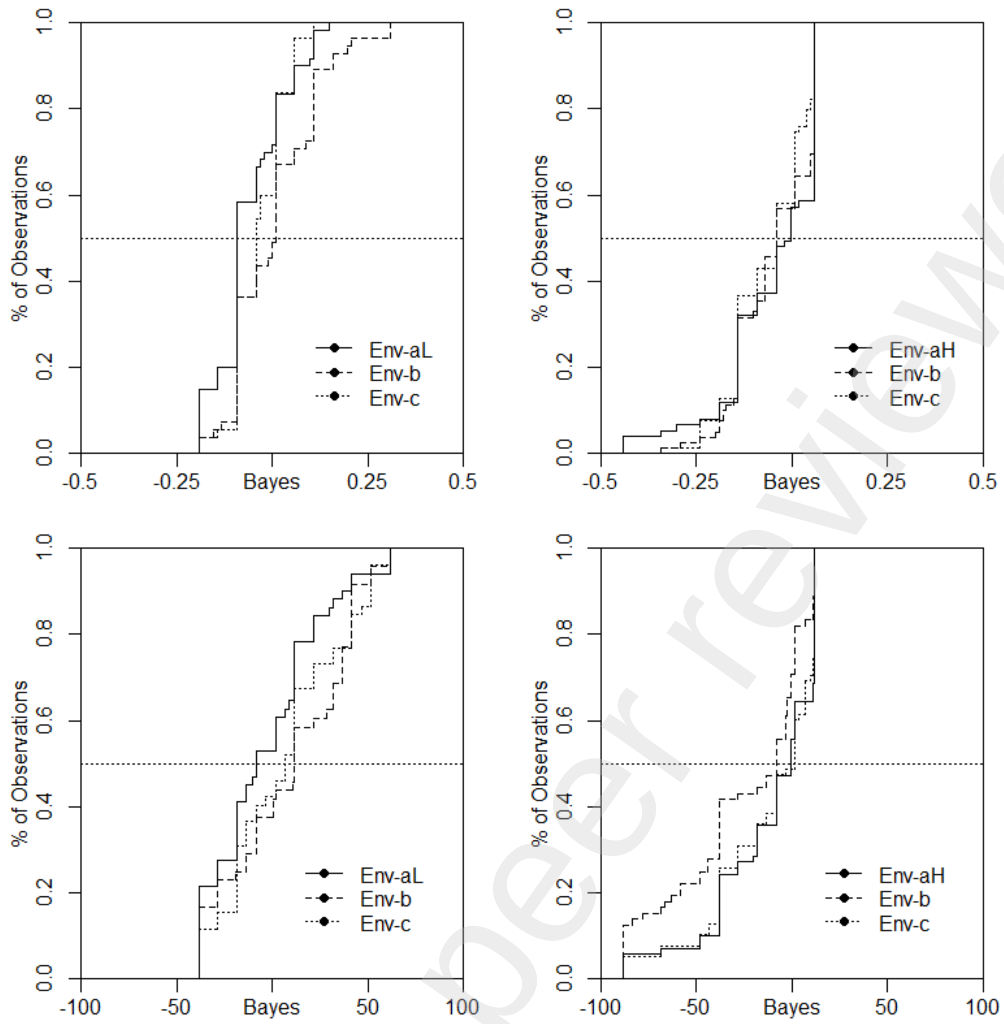


Figure A22: Q1 and Q2 Pretrade Over-/Under-confidence Experienced Sessions (EXC)

Table A22 has a similar pattern as Table 2, suggesting correlations of overconfidence are similar with and without the $P = 0.5$ cases.

Table A22: Overconfidence Correlations (EXC)

	Inexperienced Sessions				
	All Envs	Env-aL	Env-aH	Env-b	Env-c
Corr(Q1,Q2)	0.41***	0.44***	0.34***	0.47***	0.33***
Corr(Q2,Q3)	0.03	0.02	-0.09	0.04	0.02
Corr(Q1,Q3)	0.01	0.06	-0.07	0.01	0.03
(Obs.)	(820)	(117)	(166)	(294)	(243)
	Experienced Sessions				
	All Envs	Env-aL	Env-aH	Env-b	Env-c
Corr(Q1,Q2)	0.21***	0.40***	0.30**	0.13	0.28***
Corr(Q2,Q3)	0.10*	-0.21	-0.00	0.09	0.30***
Corr(Q1,Q3)	0.02	0.17	0.04	-0.04	-0.04
(Obs.)	(365)	(51)	(69)	(117)	(128)

A.20.1 Overconfidence on Trading Profit

Table A23 replicates equation 6 but exclude $P = 0.5$ cases. Note that, before, we categorize x only as overconfident when $P = 0.5$. Therefore, after dropping them, we only see changes in "Overconfident" columns. So the "underconfident" columns remain the same. The following table suggests that excluding $P = 0.5$ cases does not have a significant impact on result 5.

Table A23: Coefficient Estimates for Equation (6) (EXC)

	Inexperienced				Experienced			
VARIABLES	Over	se	under	se	Over	se	under	se
β_c	-3.547*	(1.823)	2.779***	(0.857)	-7.884***	(2.540)	0.772	(1.295)
β_{aL}	-0.886	(2.818)	-0.329	(1.954)	7.409**	(3.296)	-1.096	(2.661)
β_{aH}	0.0755	(6.049)	-3.870***	(1.146)	0.786	(6.670)	-0.202	(2.072)
β_b	0.226	(2.280)	-0.156	(1.196)	7.004**	(3.005)	3.712**	(1.786)
Constant	594.3***	(102.9)	401.8***	(59.40)	423.4***	(60.52)	443.7***	(104.6)
Observations	334		523		176		195	
R-squared	0.063		0.065		0.170		0.076	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Below, table A24 reports the same regression with x measured by Q1. The coefficients are mainly insignificant.

Table A24: Coefficient Estimates for Equation (6) (x measured by Q1, EXC)

	Inexperienced				Experienced			
VARIABLES	Over	se	Under	se	Over	se	Under	se
β_c	625.4	(661.3)	215.5	(265.1)	1,973	(1,242)	-141.3	(381.4)
β_{aL}	-314.5	(829.5)	328.1	(472.6)	-2,419	(1,508)	-8.492	(594.4)
β_{aH}	106.2	(1,160)	-379.2	(343.6)	-1,361	(1,768)	-62.30	(471.8)
β_b	-1,683**	(815.7)	-156.9	(392.9)	-2,271*	(1,280)	45.38	(613.4)
Constant	421.3***	(88.27)	382.3***	(48.63)	375.4***	(67.85)	452.2***	(62.93)
Observations	406		513		166		237	
R-squared	0.037		0.030		0.032		0.004	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.20.2 Overconfidence on Sell-Buy-Gap

The following table replicates regression 7. It turns out that, after dropping $P = 0.5$ observations, the result is slightly different from result 6, and it supports the following: Takers tend to trade at less favorable prices than do makers. Being more overconfident may improve (resp. worsen) traders' transaction prices in ambiguous environment c (resp. aL and b), but the effect may be partially reversed in environment aH.

Table A25: Overconfidence on Sell-Buy-Gap (EXC)

	Inexperienced				Experienced			
VARIABLES	Maker	se	Taker	se	Maker	se	Taker	se
β_c	92.13**	(43.53)	31.13	(58.05)	15.44	(48.65)	34.55	(106.7)
β_{aL}	-186.8***	(53.20)	-106.3	(77.05)	-113.2	(90.17)	-106.2	(227.0)
β_{aH}	-103.8	(70.02)	41.88	(84.16)	-103.1	(80.46)	4.139	(153.5)
β_b	-50.42	(52.06)	-48.88	(63.93)	-24.25	(68.17)	-108.3	(115.8)
Constant	17.62**	(7.433)	-15.15*	(7.868)	46.16**	(18.10)	-145.8***	(37.67)
Observations	236		161		92		75	
R-squared	0.113		0.119		0.304		0.184	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A26 shows regression with x measured by Q2. The patterns are in general not significant and not systematic.

Table A26: Overconfidence on Sell-Buy-Gap (Question 2) (EXC)

	Inexperienced				Experienced			
VARIABLES	Maker	se	Taker	se	Maker	se	Taker	se
β_c	-0.0597	(0.181)	-0.232	(0.233)	-0.141	(0.231)	0.234	(0.633)
β_{aL}	0.0307	(0.352)	-0.418	(0.375)	0.312	(0.704)	-0.148	(1.054)
β_{aH}	-0.170	(0.303)	0.496*	(0.293)	-0.530	(0.459)	-0.508	(0.736)
β_b	0.0268	(0.200)	0.0616	(0.285)	-0.00774	(0.309)	-0.382	(0.664)
Constant	12.39	(10.23)	-11.95	(9.240)	35.52	(26.07)	-164.0***	(6.858)
Observations	224		138		87		73	
R-squared	0.109		0.208		0.324		0.218	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.20.3 Overconfidence On Trading Volume

The following table replicates equation 8, but excluding $P = 0.5$. The result is largely the same as result 7.

Table A27: Overconfidence on Maker Volume (EXC)

	Inexperienced			Experienced		
VARIABLES	Q1	Q2	Q3	Q1	Q2	Q3
β_c	0.850	0.00503	-0.00599	-4.028***	-0.00575	-0.0997**
	(0.989)	(0.00315)	(0.0297)	(1.505)	(0.00406)	(0.0438)
β_{aL}	0.215	-0.0140**	-0.0588	5.835**	0.00236	0.0644
	(1.501)	(0.00545)	(0.0491)	(2.394)	(0.00621)	(0.0668)
β_{aH}	-0.0199	0.00125	-0.0981**	5.449***	0.0103	0.0805
	(1.379)	(0.00419)	(0.0484)	(2.087)	(0.00846)	(0.0745)
β_b	-0.103	-0.00199	-0.0250	1.727	0.0134**	0.0954
	(1.388)	(0.00531)	(0.0442)	(2.072)	(0.00611)	(0.0646)
Constant	1.793***	1.946***	1.708***	0.992***	0.958***	0.942***
	(0.207)	(0.210)	(0.132)	(0.142)	(0.137)	(0.0944)
Observations	919	857	1,568	403	371	672
R-squared	0.095	0.117	0.099	0.117	0.119	0.099

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A28 reports parallel results on taker volume. In general, the patterns are not systematic and less significant.

Table A28: Overconfidence on Taker Volume (EXC)

	In-experienced			Experienced		
VARIABLES	Q1	Q2	Q3	Q1	Q2	Q3
β_c	-0.344	-0.000615	0.129**	1.483	0.0137***	0.108**
	(1.496)	(0.00576)	(0.0638)	(1.466)	(0.00435)	(0.0530)
β_{aL}	-0.141	0.00277	0.00140	1.684	-0.0182***	0.0145
	(1.963)	(0.00899)	(0.0766)	(1.911)	(0.00650)	(0.0751)
β_{aH}	3.945**	0.00618	-0.0248	-1.755	-0.0201***	0.152
	(1.841)	(0.00671)	(0.0791)	(1.857)	(0.00663)	(0.0967)
β_b	2.325	0.00319	-0.159**	-4.119*	-0.0218***	-0.112
	(1.848)	(0.00667)	(0.0732)	(2.367)	(0.00741)	(0.0934)
Constant	1.968***	1.973***	1.641***	0.837***	0.807***	0.900***
	(0.340)	(0.358)	(0.202)	(0.124)	(0.151)	(0.119)
Observations	919	857	1,568	403	371	672
R-squared	0.066	0.044	0.073	0.133	0.130	0.089

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B Experiment Instructions and User Interface

B.1 User Interface

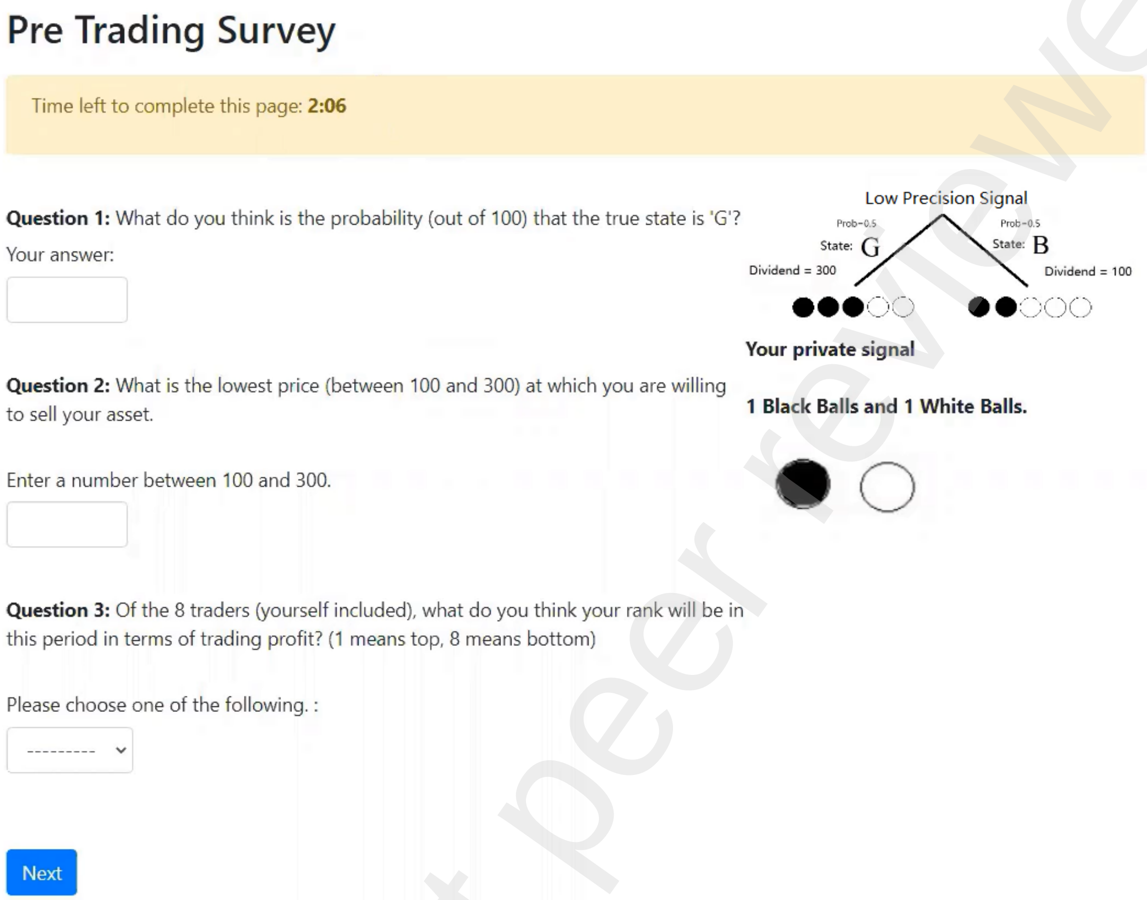


Figure A23: UI of Pre-Trading Survey

Note: In both environment-a and environment-b, we label each trader's signal precision to remind them if their signal precision is a "Low Precision Signal" or a "High Precision Signal" as in the above figure. However, in environment-c, to avoid traders get a sense of how precise their private signals are relative to other traders, we do not label their signal precision, all else stays the same on this UI.

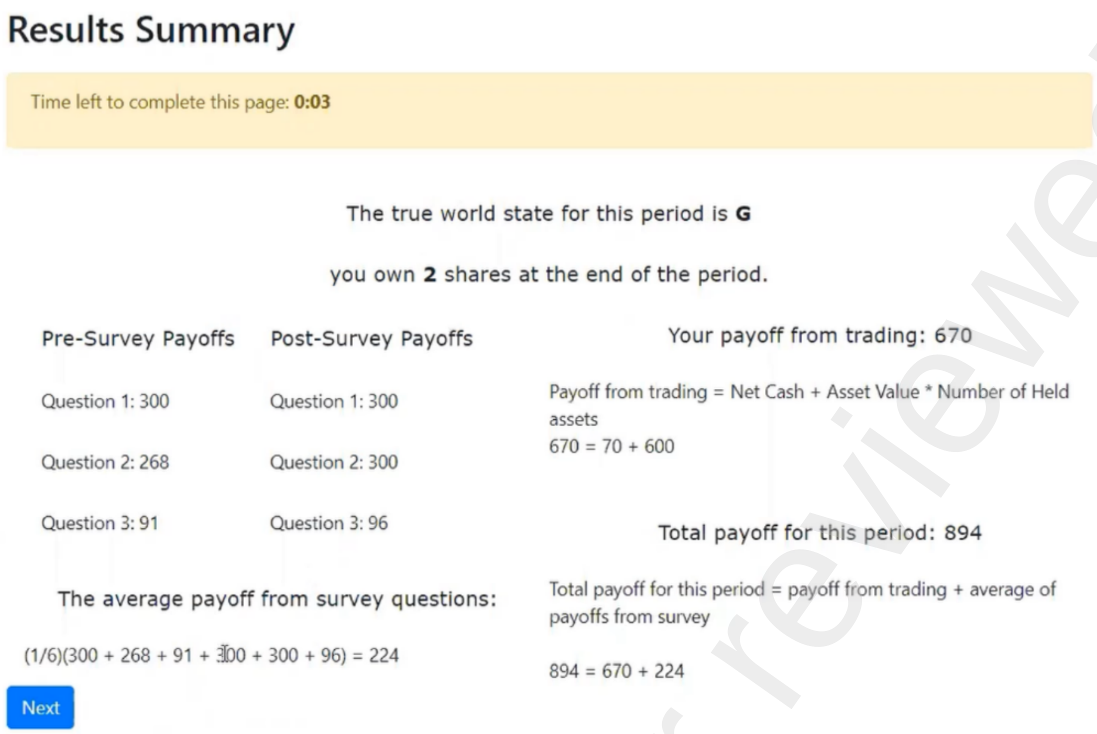


Figure A24: UI of Performance Summary

Note: This is the UI of the "Results Summary" page, which is the last feedback page that summarizes all the previous feedback pages.

The other feedback pages are the following. "Your Results" page shows the true state of this period and traders' final assets holdings. "Trading Result" shows traders their payoff from trading, "Survey Result" shows their payoffs from answering each question and the average of the payoffs. "Total Payoff" shows them the total experimental points they earned in this period. These individual feedback pages are all summarized in figure A24 and therefore we do not repeat them in the appendix.

B.2 Experiment Instructions

INSTRUCTIONS

Welcome! This is an experiment in the economics of decision-making. From now until the end of the experiment, please turn off your cell phone and do not communicate with other participants. If you pay close attention to the instructions and make good decisions, you can earn a significant sum of money which will be paid in cash at the end of the session. If you have any questions, please do not hesitate to let the experimenter know. We expect and appreciate your cooperation.

The Basic Idea.

You will trade an asset with other participants, using computerized trading screens. The value of the asset depends on the state of the world. If the state is good (G) then the asset pays 300 points to you, but it pays only 100 points if the state is bad (B). Before each trading period, the computer tosses a fair coin, and assigns state G if the coin comes up heads or B if tails. That is, at the beginning of each period there is a 50% likelihood for each state. **All traders trade under the same state of the world**.

You will not know what the true state is but, as explained below, you will get a useful hint from the computer in the form of a private signal. After receiving the private signal, you will be asked **how likely** you now think that the true state is G. Then you will be able to **trade with other participants**. Since they also get private signals that may differ from yours, the trading prices you see may also provide hints about the true state and the asset value. After the trading period is over you will be asked about your **final beliefs** about the true state in this period, based on both your private signal and on other traders' offers and trades. Then there will be feedback after the trading revealing the true state of the world, showing your payoff from trading, payoff for providing your beliefs, and the total payoff for this period.

Each trading period lasts approximately 3 minutes. There will be between 12 and 18 trading periods in today's experiment. The total of all points you earn in all periods will be converted into US dollars and paid to you in cash.

Private Signal

There are two types of private signals: Low precision signal (L-sig) and High precision signal (H-sig).

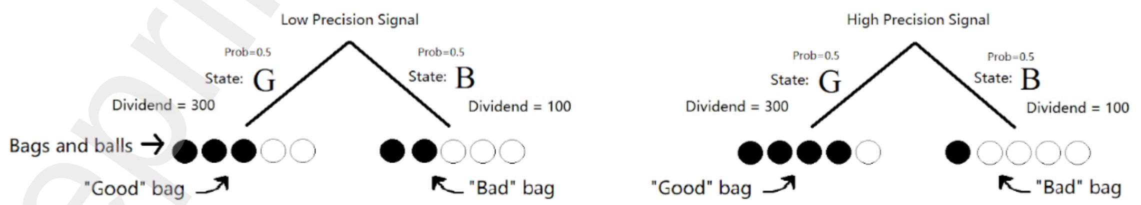


Figure 1

The left side of Figure 1 illustrates L-sig in terms of two bags that each contain 5 balls. If the true state is G then the computer draws balls **only** from a "Good bag" that contains 3 black balls and 2 white balls. Similarly, if the true state is "B", the computer will draw balls **only** from the "Bad bag" that contains only 2 black balls plus 3 white balls. The computer will randomly draw two balls with replacement from the bag corresponding to the true state and tell you the colors of those two balls. That is your private signal.

If your private signal is two black balls, then you should conclude that G is more likely than 50% because those two balls are more likely drawn from the "good bag", which contains more black balls. Likewise, if your private signal is 2 white balls then the true state is more likely to be "B". If your private signal is 1 black ball and 1 white ball, then the probability the true state is G might be a number in between the previous two cases.

What do "low precision" and "high precision" mean? As shown in figure 1, H-sig has a higher proportion of black balls in the "good bag" and a higher proportion of white balls in the "bad bag". This means the H-sig has higher precision. For example, two black balls from the H-sig are a stronger indication that the true state is G than are two black balls from the L-sig. In half the periods of today's experiment, all traders get an L-sig and in the other periods all traders get an H-sig. You will see each period whether L-sig or H-sig is used.

Pre-Trading Survey

Before each trading period, you will be asked three questions as shown in Figure 2. You will get extra payment from doing this survey and the payment amount depends on your answers. To increase your payment, you should think it over carefully and report accurately **given your private signal** which is shown on the right-hand side of the page.

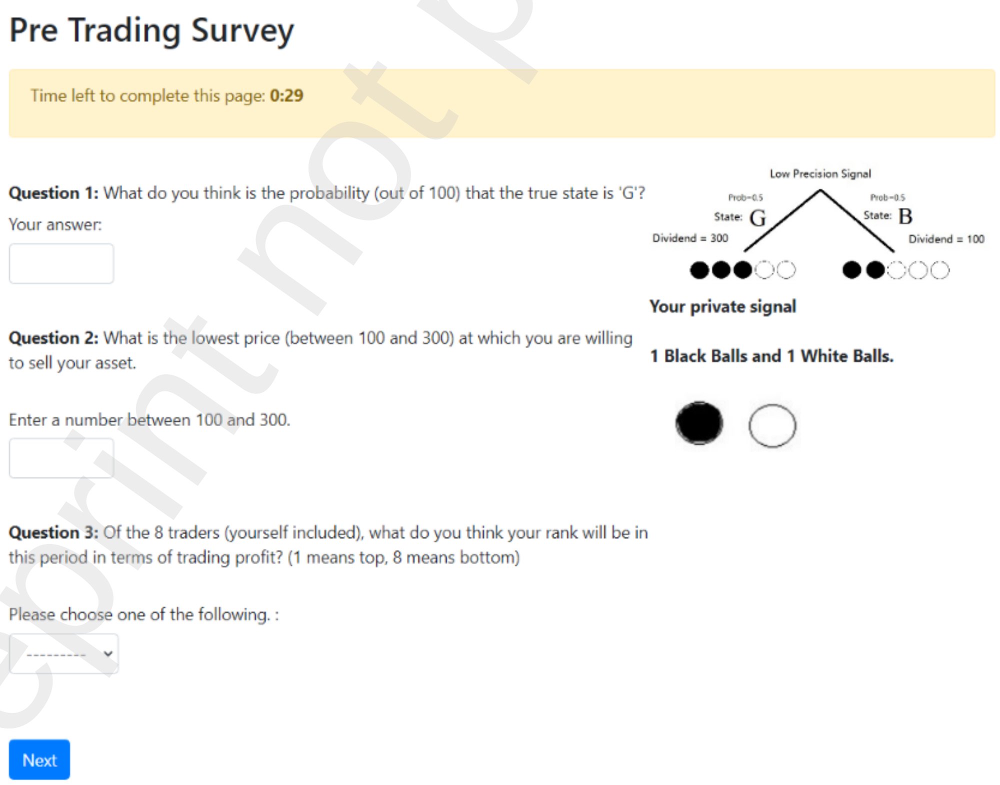


Figure 2

Question 1: What do you think is the probability (out of 100) that the true state is 'G'? Please enter a number that reflects your belief; if you think that, given your current private signal(s), it is 65% likely the true state is Good, then type 65 into the answer box.

Question 2: What is the lowest price (between 100 and 300) at which you are willing to sell your asset? You will soon have the opportunity to sell the asset and must decide on what price to accept for each unit, given your beliefs about whether it will eventually pay 100 (if B) or 300 (if G). Please type your lowest acceptable price into the answer box for this question.

Question 3: Of the 8 traders (yourself included), what do you think your rank will be in this period in terms of trading profit? (1 means top, 8 means bottom) The computer will rank all traders' payoffs earned in the current trading from the highest (1st) to the lowest (8th). Please guess how your own trading profits will compare to other participants'. For example, if you guess that your trading profits will be the 2nd highest among the 8 traders, then select the number 2 and click "Next".

The payment for the survey is made in such a way that it is in your best interest to think carefully and respond truthfully to each question. If you are curious about the details of the payment, please see <Survey Question Procedure>.

How to trade

Figure 3 shows the computer screen for trading. The right-hand side reminds you of your signal type and your private signal. There is a timer on the top counting down the time left. "Your Allocation" box tells you your current cash holding and number of asset units; it will update whenever you trade. You will start with two units of asset at the beginning of each trading period.

"Bids(Buy)" box shows the prices at which traders are offering to buy units of the asset and the "Asks(Sell)" box shows the prices at which sellers are offering to sell units. Bids are ordered from high to low since the highest bids are the most attractive offers to other traders. Likewise, asks are ordered from low to high since the lowest is the most attractive offer to other traders. If two bids/asks have the same price, the earlier offers will be displayed above the later ones. A bid/ask colored in green/blue indicates your own offer. "Trades" box in the middle shows the trading history in the market with the most recent trades on the top. Your own purchases/sales are colored in green/blue.

You submit a bid (buy offer) by typing in your price in the "Bid Price" box and clicking the Enter Bid button. Likewise, to offer to sell a unit, you type in the price in the "Ask Price" box and click Enter Ask. You can place at most 1 bid and 1 ask at the same time. If you enter a new bid or ask, it will replace your old offer. If your bid is higher than the best ask, then you will immediately buy a unit at that best ask. Similarly, entering an ask below the best bid held by someone else amounts to accepting that best bid. You can also directly accept someone else's bid or ask by double clicking on it, and then clicking Accept in the pop-up window. You can buy at most 8 shares of assets.

It is more profitable to buy low and sell high. Check the trading window and see whether your Green buy prices seem low, and your Blue sell prices seem high compared to the other prices (in white) this period. The large "Error Message" box at the bottom of the trading screen will tell you if you made some kinds of mistakes, such as trying to sell when you currently hold zero units of the asset.

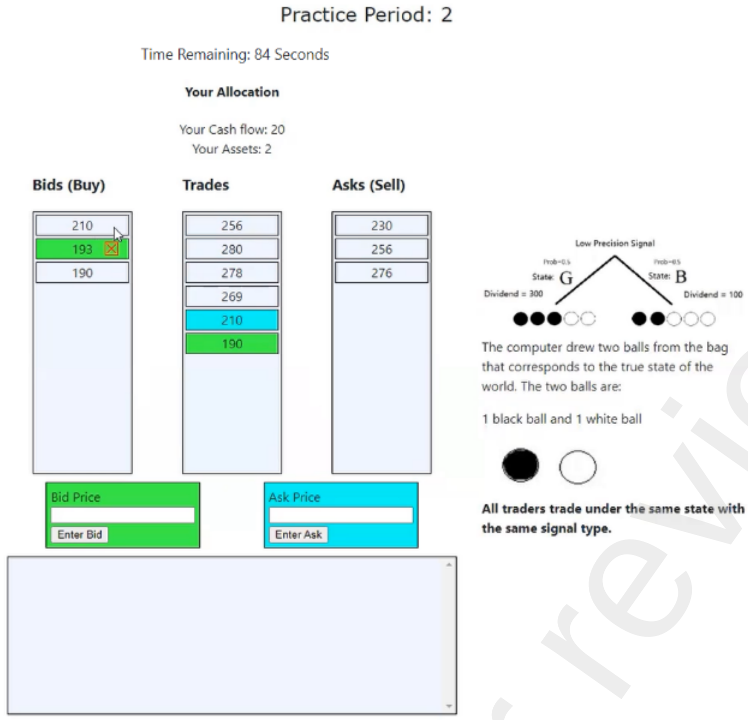


Figure 3

How do you get paid for trading in the market?

The payoff from trading in each period will be net cash flow (i.e., receipts from asset units sold minus cost of units bought), plus the payments on the assets you hold. For example, if you sold one unit for 280 and then you bought a unit for 260, your net cash flow would be 280 - 260 = 20. Moreover, since you started with 2 units of the asset, sold one unit and then bought one unit, your final asset holding is 2 units. Then your final payoff from trading in this period equals to 20+2*300=620 if the state turns out to be G, and 20+2*100=220 if the state is B.

Post-Trading Survey

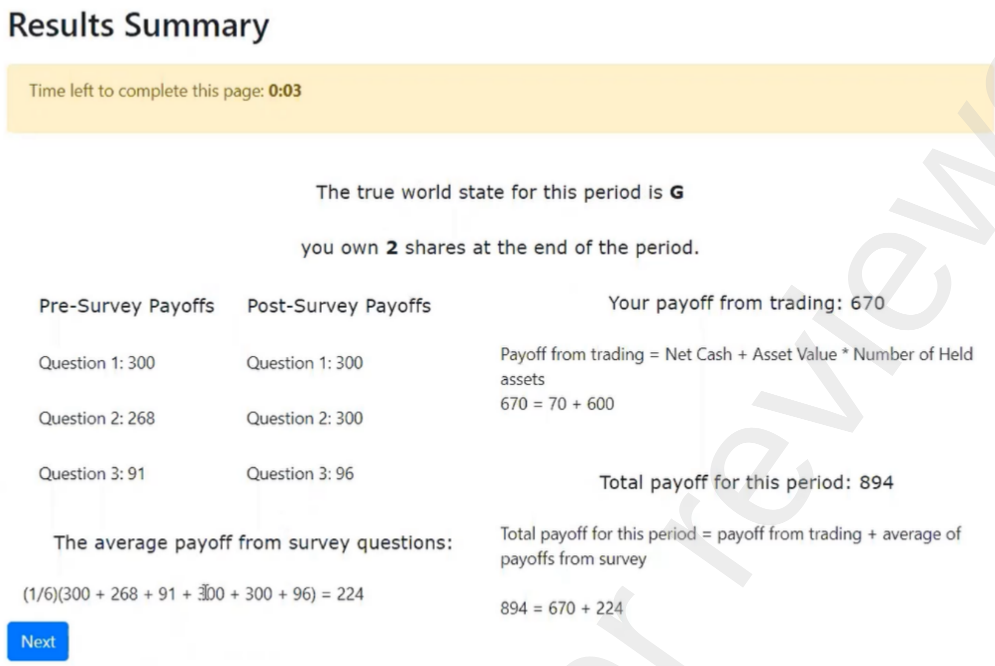
After each trading period, there will be another survey page that asks you the same three questions as in the pre-trading survey about your beliefs. The only difference between the post- and pre-trading survey is that the post-trading survey reminds you of the trading history from the current period, and that history might tell you something about what other traders' private signals are. So taking that history as well as your own private signal into account, you should **update your beliefs** before you answer the questions.

In addition, the trading history in this post-trading survey is ordered from high to low. The computer did this descending sorting for you to help you learn your trading strategy. If your buying prices (green) are, on average, lower than your selling prices (blue), then it means you are making profit. If it is the other way around, you need to adjust your trading strategy.

Feedback Page

After the post-trading survey page, you will see feedback pages similar to that shown below. These pages reveal the true state of the world and remind you of your final asset holding. They also show you the points you earned from answering survey questions and the payoff you earned from trading.

They also show the total payoff for this period, which is “payoff from trading” + “average payoff from survey questions”. After this feedback page, all traders go on together to the next period.



You will play 12 to 18 trading periods. Your final payoff for participating in today’s session equals the sum of the total payoffs from all periods. Your final payoff is converted from experimental points to cash (US Dollars) at a rate announced at the beginning of the session, e.g., 1,000 experimental points = $2.30 in cash.

B.3 Instructions for Other Treatments

All the instructions use the same format from the previous subsection and they only differ in the following points:

- At the end of the paragraph where we explain the difference between "low precision" and "high precision", we explain how the private signals are distributed among traders. This part distinguishes the treatments.
  - In the instructions of environment-a, we say "In half the periods of today's experiment, all traders get an L-sig and in the other periods all traders get an H-sig. You will see each period whether L-sig or H-sig is used."
  - In the instructions of environment-b, we say "In all the periods of today's experiment, half of the traders (by random) get an L-sig and the other half traders will get an H-sig. You will see each period whether you received a L-sig or a H-sig"
  - In environment-c, we say "In all the periods of today's experiment, you will know only your own signal and its precision. Other traders may have higher or lower precision than you, and their signals may differ — each trader gets fresh draws from either their own good bag or own bad bag, and those bags might have different numbers of black and white balls than your bags." We also explain that the two signal precisions explained in the instructions are two examples.
- In the instructions of environment-c, figure 2 and figure 3 do not label the signal precision. Also, figure 3 needs to change the reminder message of how the private signals are distributed among traders accordingly below the private signal.

B.4 Survey Questions Procedure

Survey Questions Procedure

Question 1 (in both the pre and post trading survey): "What do you think is the probability (out of 100) that the true state is 'G'?"

How you will get paid: When you answer this question, you will be offered one unit of the asset. You can earn the dividend from this asset or exchange it with another asset that will be described below.

- Enter what you believe the probability is that the true state of the trading asset is "G". Let us denote this probability as R.
- We will offer you another asset called the N-asset, which is worth 300 with probability P_N and 100 with probability (1-P_N). (The probability P_N is determined randomly between 0 to 99.)
- If $R > P_N$, you keep your trading asset and earn the dividend from the asset. (300 for G and 100 for B).
- If $R \leq P_N$, you exchange your trading asset with us, thus hold the N-asset, and earn the dividend from the N-asset.

Question 2 (in both the pre and post trading survey): "What is the lowest price (between 100 and 300) at which you are willing to sell your asset."

How you will get paid: When you answer this question, you will be offered one unit of the asset. You can either earn the dividend from this asset or sell it back to us.

- You decide on the lowest price at which you are willing to sell your asset and enter that price into the computer.
- We will offer you a price to buy the asset back from you. The price is a random number between 100 and 300.
- If the price you are willing to sell is higher than our purchase price, you will keep your asset and earn that asset's value.
- If the price you are willing to sell is lower than our purchase price, you will sell your asset to us at the price we offered.

Question 3 (in both pre post trading surveys): "Of the 8 traders (yourself included), what do you think your rank will be in this period in terms of trading profit? (1 means top, 8 means bottom)"

How you will get paid: Your payoff from answering this question is determined by the formula $100 - (C - R)^2$. Where, C refers to the correct ranking of your payoff among all traders. R refers to your guess, which you entered into the computer.

Your best strategy for answering the three questions is to truthfully report!
Here is why (we use question 2 as an example to explain):

▷ You think this asset is worth at least 200 to you, so 200 is the lowest price you would willing to sell. This is your true belief. But you enter 250 into the box. You overstate your true belief.

▷ Then the computer will offer a price to buy, and that price is a random number between 100 and 300. Suppose the computer randomly chooses 240 to offer you for the asset.

▷ The computer cannot purchase the asset from you because 240 is lower than the lowest price you would accept to sell (250). So you keep your asset.

▷ This means you only earn 200; however, if you truthfully report, 200 into the computer, then the computer would purchase that asset from you at the price of 240, so you would earn 240.
▷ Your earning is higher when you truthfully report.

The payment methods for question 1 and question 3 are designed in the same way, which means there is no circumstance in which offering a probability/price/ranking not equal to your true belief is to your advantage; it can only decrease your earnings.

After you finish reading the written instruction, we will show you a video to explain, visually, what this game is about.