The University of Queensland
Australia
CREATE CHANGE

Discussion Paper Series
UQ School of Economics

Paper Name: An Experimental Analysis of Dynamic Informed Trading
Date: November 2023
Junqian Li, Yuqing Liu, Nhan Buu Phan and Shino Takayama

Discussion Paper No. 665

An Experimental Analysis of Dynamic Informed Trading*

Junqian Li† Yuqing Liu‡

Nhan Buu Phan§ Shino Takayama¶

November 12, 2023

Abstract

In this paper, we study the trading strategies of informed traders in a simulated asset market. There is a risky asset with two possible values, and participants receive private information about the value of the asset. Market maker's quotes are computationally simulated. We study whether the trading behavior of informed traders—specifically, the frequency of manipulative trading versus honest trading—is influenced by various conditions, including the bid–ask spread, retrading possibilities, and the risk attitude of traders. Our findings suggest that manipulation occurs in both long (e.g., 15 periods) and short (e.g., five periods) trading rounds. Furthermore, there is a significant increase in the number of manipulators when the bid–ask spread is narrow rather than wide. Our results also indicate that risk-seeking participants engage in manipulation more frequently than other participants.

*We would like to thank Andrew McLennan and Zachary Breig for useful comments. We are particularly grateful to the team at the UQ BESC Laboratory for their support. We acknowledge the UQ BEL LNR committee for the ethics approval of our project (Project Number: 2022/HE001023)

†Li: School of Economics, Shandong University; email: junqianli@sdu.edu.cn

‡Liu; School of Economics, University of Queensland; email: yuqing.liu@uq.edu.au

§Phan; School of Economics, University of Queensland, St Lucia, QLD 4072, Australia; email: b.phan@uq.edu.au.

¶Takayama (corresponding author); School of Economics, University of Queensland, St Lucia, QLD 4072, Australia; email: s.takayama1@uq.edu.au; tel: +61-7-3346-7379; fax: +61-7-3365-7299.

1 Introduction

Theoretical and empirical studies have analyzed the informational efficiency of market prices and how uninformed traders behave in the presence of informed traders and state uncertainty (see Chakraborty and Yılmaz, 2004; Back and Baruch, 2004; Ozsoylev and Takayama, 2010; Takayama, 2021). Following these strands of research, we study the trading strategies of informed traders under different market conditions in a laboratory setting using a simulated dealer asset market. Informed traders in this market are price takers who hold private information. We focus on how these traders change their trading strategies in response to a larger bid–ask spread and longer trading duration. In addition, we explore the impact of informed traders' risk attitudes on a trading strategy.

We adopt the framework proposed by Chakraborty and Yılmaz (2004), who examine the potential profitability of informed traders engaging in *manipulative* trades within the context of the Glosten and Milgrom (1985) framework. The *manipulative* strategy is *trade-based manipulation*, whereby informed traders exploit their informational advantage by intentionally inflating (deflating) asset prices via misleading trade orders, which enables them to sell (buy) their positions at high (low) prices. Such strategies induce price movements that favor their trading positions, thereby allowing them consistently to outperform the market.

In Chakraborty and Yılmaz (2004), before all traders enter the market, a trader—either an informed or a liquidity trader—is selected to trade with the market maker and, once chosen, trades in every period. Chakraborty and Yılmaz (2004) find that provided there is a sufficient number of remaining periods and assuming the existence of informed traders, manipulation within the equilibrium is inevitable. This occurs because informed traders will only engage in unprofitable trades if they expect that sufficient time periods remain to allow them to recover their initial losses incurred by trading against their information.

Early studies in experimental asset markets are largely driven by developments in theory. For instance, Kyle (1985) and Glosten and Milgrom (1985) focus on the interactions between market makers and an informed trader in the presence of uninformed traders.[1]

Canonical theoretical works including Glosten and Milgrom (1985) have motivated subsequent empirical and experimental studies, such as Schnitzlein (1996) and Bloomfield et al. (2009). The experimental literature on informed trading in asset markets is vast. For example, Bhattacharya (2014), Nuzzo and Morone (2017), and Merl (2022) provide recent and comprehensive surveys. Bhattacharya (2014) examines the advantages and disadvantages of informed trading, whereas Nuzzo and Morone (2017) reviews the impact of information release and dissemination on market performance.[2]

Our work is original in the sense that a notable simplification of our analysis is the sole focus on the trading behavior of a dynamic informed trader under the possibility of manipulation. We study how the trading process of an informed trader is affected by the condition of the market using an experimental asset market. Price manipulation is detrimental to a stable financial market.[3] The approach used in this study provides a better understanding of informed trading and price manipulation, which contributes to policy making in this area.

The challenges in studying trade-based manipulation arise from the difficulties in detecting and monitoring such behaviors (Putniņš and Comerton-Forde, 2014). Legal and ethical regulations in financial markets prohibit manipulative activities, and the private information held by informed traders is not publicly available. However, these challenges can be mitigated in a simulated experimental asset market. Here, the quantity and quality of private information can be carefully controlled, and strategic trading behaviors can be easily observed without legal repercussions.

In our experiments, participants take on the role of informed traders who know the value of the asset at the beginning of the game. Market makers' price quotes are

[1]Manipulation by informed traders is also studied in Allen and Gale (1992), Jarrow (1992), and Allen and Gorton (1992).

[2]For the most recent survey, see Merl (2022). See Palan (2013) for a review of the experimental literature on the formation and crashes of asset bubbles. Duxbury (2015a,b) focuses on behavioral finance.

[3]For example, European Parliament and Council of the European Union (2014) states that market integrity is fundamental for an efficient and transparent financial market. Price manipulation, as a form of market abuse, undermines this integrity and creates an environment that is unfavorable for investments. Without stringent regulatory measures, increased regulatory arbitrage would lead to financial instability and reduce economic growth.

simulated by adopting the computational method proposed in Takayama (2021). We assume that the market maker knows the probability of an informed trader being chosen to trade with them but does not know whether their trading partner is informed. In each period, the informed trader decides whether to buy or sell an asset after observing the bid and ask prices during that period. In this way, we investigate the dynamic trading strategies of informed traders.

The first question that we ask is whether smaller bid–ask spreads incentivize manipulative trading by informed traders. In an ideal, efficient market, the bid–ask spread should only reflect transaction costs but in real markets, spreads also compensate for inventory and information risks. To protect against asymmetric information, market makers often set a larger bid–ask spread as a form of insurance against potential losses when the presence of informed traders is certain.[4] The bid–ask spread can significantly influence the strategies of informed traders. A wider spread allows informed traders to trade in a way that maximizes the impact of their information on market prices, but it also discourages trading activity due to higher transaction costs. A sufficiently high spread may discourage even the most informed traders from entering the market unless their information is extremely valuable. Our first hypothesis is that manipulation is less frequently observed with larger bid–ask spreads than with smaller spreads.

In the experiment, the market maker quotes bid and ask prices from two simulated equilibrium pricing spreads: a larger spread with greater uncertainty about the presence of informed traders, and a smaller spread with less uncertainty. Our experimental result shows that manipulation occurs under both pricing regimes, but it is more frequent in sessions with a narrow spread.

The second question explores the impact of trading period length on informed traders' behavior. A longer trading time gives informed traders more opportunities to recoup losses from manipulation. Takayama (2010) shows that manipulation can lead market makers to misperceive an asset's value, thereby affecting future payoffs for informed traders through "continuation value" when a sufficient number of trading periods remains. Therefore, our second hypothesis is that, as the trading period becomes

[4]Studies that emphasize the role of asymmetric information costs include Copeland and Galai (1983), Glosten and Milgrom (1985), and Huang and Stoll (1997).

larger, it encourages more manipulative trading during the early stages. Our findings are consistent with this hypothesis.

The remainder of the paper is structured as follows. Section 2 describes the theoretical model. Section 3 discusses the experimental design. Section 4 presents the experimental results. Finally, Section 5 provides concluding remarks. The step-by-step instructions for the laboratory setting are also provided in Appendix A. The computational methodology for generating bid–ask pricing is detailed in Appendix B.

2 The Model

In this section, we describe the basic model and present the main theoretical analysis, which delivers hypotheses that are directly testable with data from our experiment.

We adopt the setting proposed by Chakraborty and Yılmaz (2004). There is a risky asset and a numeraire in terms of which the asset price is quoted. The true value of the risky asset is a random variable v, which can take the values 0 or 1. There are three types of risk-neutral market participants: a competitive market maker, an informed trader, and a liquidity trader. The game structure and the parameters of the joint distribution of the state variables are common knowledge. The private information or type of the trader is denoted by $\theta \in \Theta = \{0, 1, N\}$. When $\theta = 0$, the trader is informed and knows that the value of the asset is low, $v = 0$. When $\theta = 1$, the trader is informed and knows that the value of the asset is high, $v = 1$. When $\theta = N$, the trader is a liquidity trader, whose trading is driven by exogenous liquidity needs.

Nature chooses the state of the asset value: *high* or *low*. Independent of the asset value, with probability μ the informed trader is chosen to trade at the beginning of the game.[5]

In each period, the market maker posts bid and ask prices that, in equilibrium, are equal to the expected value of the asset, conditional on the observed history of trades, including the trade submitted in the current period. The trader trades at those prices. Suppose that trading occurs for $T < \infty$ successive periods, after which all private

[5]This setting differs from the model settings described in Glosten and Milgrom (1985) and Kyle (1985), where multiple types of traders are in the market simultaneously, and one type is selected in each period. We have chosen the current setting because our focus is on informed trading strategies.

information is revealed. Each informed trader's action space is $R = \{B, S\}$, where S denotes Sell and B Buy.

We focus on the equilibrium in which the informed trader's strategy is a function of the market maker's belief and the informed trader's strategy in the remaining trading periods.

We solve the equilibrium using backward induction so that the solution becomes a function of the market maker's belief about the asset value and the number of remaining periods. Here, let σ be the market maker's belief on asset value being high ($V = 1$). The market maker's ask (α) and bid (β) prices are functions of the market maker's beliefs. The market maker's posterior belief after observing an order is updated using Bayes's rule. Because the value of the asset is either 0 or 1, the market maker's prior belief σ is equal to the expected value of the asset conditional on their information.

Let x be the probability that the high-type informed trader buys and let y be the probability that the low-type sells. The equilibrium condition for the market maker is to set ask and bid prices equal to the posterior expected value of the asset. We can define the ask and bid price functions as:

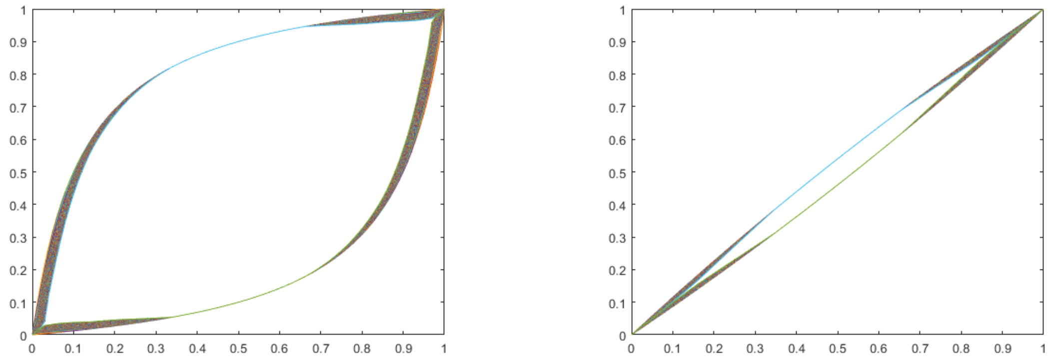
$$\alpha = \frac{[\frac{1}{2}(1-\mu) + \mu x]\sigma}{\frac{1}{2}(1-\mu) + \mu\sigma x + \mu(1-\sigma)(1-y)} \tag{1}$$

and

$$\beta = \frac{[\frac{1}{2}(1-\mu) + \mu(1-x)]\sigma}{\frac{1}{2}(1-\mu) + \mu\sigma(1-x) + \mu(1-\sigma)y} \tag{2}$$

To obtain bid–ask prices, we adopt the computational procedure presented in Takayama (2021). In Appendix B, we provide a detailed explanation of how we solve for equilibrium and generate the pricing tables. The key intuition behind our approach lies in changing the market maker's perception about the fraction of informed traders in the market μ. The market maker posts a bid–ask spread to hedge against the risk of dealing with informed traders. In Figure 1, we present the bid and ask prices corresponding to different values of μ. We can observe in panel (a) that when $\mu = 0.8$, the bid–ask spread is larger than the one presented in panel (b).

From the informed traders' perspective, it is easier to manipulate the market when



(a) $\mu = 0.8$ (b) $\mu = 0.08$

Figure 1: Bid–ask spread

the bid–ask spread is smaller. To understand this intuitively, we can compare two different systems for posting bid–ask prices. Suppose that for the current belief b, the low type buys a unit in period 0. Based on Bayes's rule, let us assume that the ask price is $b(1 + d_0)$ in a smaller bid–ask spread system and $b(1 + 2d_0)$ in a larger system. In period 1, the liquidity buy arises and the belief goes up to $b(1 + d_0)(1 + d_1)$ in a smaller system and $b(1 + 2d_0)(1 + 2d_1)$ in a larger system. In period 2, the low type can sell the unit he or she has bought at $b(1 + d_0)(1 + d_1)(1 - d_2)$ in a smaller system and $b(1 + 2d_0)(1 + 2d_1)(1 - 2d_2)$ in a larger system. Then, the low type can make profits from the round-trip trade when $(1 + d_1)(1 - d_2) > 1$ in a smaller system, and $(1 + 2d_1)(1 - 2d_2) > 1$ in a larger system, implying $d_1 - d_2 - d_1 d_2 > 0$ in a smaller system and $d_1 - d_2 - 2d_1 d_2 > 0$ in a larger system. Comparing the two conditions, we can see that the informed trader makes profits more easily in a smaller system.

3 Experimental Design

3.1 General setup

In each session of our experiment, there is a transferable asset with a fixed value, v, that can be either 0 or 100. For each market, there is one *market maker* and one *informed trader*.

The market maker. The market maker only presents simulated bid–ask prices. In our experiment, the market maker role is performed by a pre-generated program on a computer. Essentially, the market maker does not know the value of the asset but instead holds an initial belief about the value, $P(v = 100) = \rho = 0.5$, and updates this belief in each period according to trade history. In equilibrium, the market maker's pricing aligns with her belief about the value of the asset and, therefore, the more probable it is that the market maker believes the asset value is high, the higher is the trading prices that he or she offers. We can consider this setting as one in which the rational market maker behaves as if they were an uninformed trader who trades cautiously by taking every trade history into account to update her beliefs about the value of the asset.

As well as not knowing the value of the asset, the market maker is uninformed about whether the trader with whom the market maker is paired knows the asset's value. Therefore, the market maker holds another belief about the probability that her paired trader knows the true value of the asset, which we denote by μ. For simplicity, we assume that μ is fixed throughout each experimental session.[6]

The informed trader. The informed trader is played by the participants in the experiment. The informed trader learns the value of the asset at the start of each session and decides whether to buy or sell an asset in each period. He or she is aware that the market maker does not know either the asset's value or whether the informed trader is actually informed. We summarize the differences between the market maker and informed trader in the table below.

Table 1: Two types of trader

	Played by	Knows the value of the asset	Knows the other trader's information
Market Maker	Pre-generated Program	No	No
Informed Trader	Participants in Experiment	Yes	Yes

As the above theoretical analysis demonstrates, the information advantages of the informed trader provide room for price manipulation. The informed trader can simply

[6] Because μ is fixed, for the remainder of the paper, "belief" refers to the conditional probability for the high state after observing a history of trades.

trade against her private information about the value of the asset, mislead the market maker concerning her belief about the asset, and then exploit the market maker's "mistake" by trading the asset at its true value.

The market. We focus on the trading strategies of the informed trader. More specifically, we restrict our attention to the informed trader's manipulative trading strategy, without considering the strategic interaction among traders or the aggregate market outcome. Therefore, for each market, there is only one informed trader and one market maker. Following the theoretical literature, one unit of the asset is traded in each trading period. In each trading period, the market maker quotes her bid–ask prices, and the informed trader decides whether to buy or sell one asset from the market maker. Because there is only one informed trader in each market, waiting is not an option, and the informed trader must choose to either buy or sell in each period.

In each session, there are six trading rounds. Each trading round contains either 5 or 15 trading periods to simulate either a short or long trading round, respectively. At the start of a short (long) trading round, each participant is endowed with 500 $(1,500)$ experimental currency units (ECUs) and 5 (15) assets. This endowment distribution allows each participant to have sufficient assets and ECUs to trade in every period. Short selling and bank loans are not applicable in our setup.

The timeline within a trading period is as follows:

1. **Pricing:** The market maker quotes the bid–ask prices.
2. **Trading:** Given the price quotes, the informed trader decides whether to buy (sell) an asset from (to) the market maker.
3. **Belief update:** The market maker updates her belief based on the trading decision of the informed trader. The informed trader learns the updated belief.

The market maker moves first in each period by quoting the bid and ask prices from the pre-generated pricing tables.

On observing the market prices, the informed trader decides whether to buy or sell an asset with the market maker. As the informed trader learns the value of the asset, he or she may either trade in an "honest" way, that is, buying the asset when $v = 100$

and selling when $v = 0$, or in a "manipulative" way, which involves buying when $v = 0$ and selling when $v = 100$.

The reason for the informed trader electing to trade in a manipulative way is that he or she can mislead the market maker and, by influencing the market maker's beliefs, thus influence market prices in such a way that the informed trader can profit in later trading periods.[7]

The total payoffs for each participant in a trading round are calculated by aggregating the payoffs that the participants earn in each period. The payoff is the difference between the asset value and the transaction price in each period. When a trader places a buy (sell) order, her asset holding increases (decreases), and her ECUs decrease (increase) by the buying (selling) price. When a trading round finishes, participants are ranked according to their total payoffs in that round. At the end of each experimental session, one trading round is randomly selected, and participants are paid according to their rankings in that selected round.

3.2 Treatments

We adopt a 2×2 experimental design, which means that there are four treatments in total. For each treatment, we run two experimental sessions. It is widely acknowledged in the experimental literature that the duration of the preceding match has significant effects on actions in subsequent matches.[8] Therefore, for each treatment, we vary the length of the first trading round in the two sessions. The first session starts with a 5-period trading round followed by a 15-period round. Then, the session repeats this round rotation two more times. Therefore, the order of round lengths for the participants in the first session is $5, 15, 5, 15, 5, 15$. Similarly, for the second session, the order of rounds for the participants is $15, 5, 15, 5, 15, 5$. Participants have the same total number of periods in each session. The only difference between the two sessions is the

[7]In the experiment instructions, we emphasize the correlation among trades, beliefs, and prices. It is crucial that participants in the experiment understand how trade affects price movements through beliefs because this is a prerequisite for informed traders to conduct any price manipulation.

[8]For example, Engle-Warnick and Slonim (2006) find that cooperation is less likely to happen after a short match than a long one. Recently, Mengel et al. (2022) find that the realised length of the first match in an infinitely repeated experiment has a significant effect on participants' behaviors in later matches.

sequence of trading rounds.[9]

Treatments differ in terms of the bid–ask spread and the value of the asset. Below, we introduce and discuss each treatment in detail.

Bid–ask spread. We vary the market maker's bid–ask price spread by adjusting her prior belief that the paired trader is informed, μ. The higher μ is, the more likely it is that the market maker thinks her paired trader actually knows the value of the asset. When μ is high, the market maker thinks it is likely that the paired trader is informed and puts a high weight on the trade order submitted by the paired trader when setting bid–ask prices. This is because the market maker considers that the trade order has a high probability of containing information on the true value of the asset when μ is high. This leads to a wide spread in the market maker's bid–ask prices. Conversely, when μ is low, trade orders submitted to the market maker are likely to be noisy and less informative to the market maker in setting prices, which results in a narrow bid–ask price spread.

In our experiment, there are two values of μ. In the control group, W (for "wide"), we set $\mu = 0.8$ to simulate a market with a market maker who is sensitive to trade orders and thus there is a wider bid–ask price spread. In the treatment group, N (for "narrow"), $\mu = 0.08$ and the market maker puts a low weight on trade orders when adjusting prices.

Value of the asset. We are interested in the relationship between the value of the asset and price manipulation. In our control group, L (for "low"), $v = 0$, so the asset has no value in L. In the treatment group, H (for "high"), $v = 100$. As mentioned previously, price manipulation in L means buying the asset, whereas H denotes selling the asset. The table below summarizes the parameters for our treatments.

3.3 Experimental procedures

The experiment sessions were conducted at the Behavioral and Economic Science Cluster laboratory at the University of Queensland between September 2022 and March

[9]We compare the results of the two types of sessions in Appendix A. Sessions starting with 15-period trading rounds have slightly more manipulations than those starting with 5 rounds.

Table 2: Treatment parameters

	μ	v
N/L	0.08	0
N/H	0.08	100
W/L	0.8	0
W/H	0.8	100

2023. Participants were recruited through the online recruitment system ORSEE (Greiner, 2015). A total of 80 participants, who were undergraduate or postgraduate students at the University of Queensland, took part in the experiment. A non-prescreening approach was adopted, ensuring a diverse registration pool. The experiment was programmed in ZTree (Fischbacher, 2007). A total of eight sessions were conducted, with 10 participants in each session. We ensured that all participants participated in the experiment only once. In other words, we adopted a *between-subjects* design. In each period, participants were informed about the current bid–ask prices set by the market maker and her belief about the value of the asset. Then, the participants chose to either buy or sell one unit of the asset at the given bid–ask prices. When all rounds were finished, one trading round was chosen randomly and participants were paid according to their earnings in that round. Each session lasted around 90 minutes, and the average payment for a participant was $30 AUD.

Before commencing the experiment, participants were given time to read the instructions carefully. Next, the instructions were read aloud by the experimenter. Participants were given ample time to review the instructions and to ask questions privately. To familiarize participants with the software interface and experimental process, a 20-period practice round was conducted. The experiment did not begin until all participants had completed the practice round. Upon completion of the experiment, participants were asked to complete a brief demographic questionnaire and to respond to a few questions that measured their risk attitude. A sample of the instructions can be found in Appendix A.

3.4 Hypotheses

Before discussing our hypotheses, we provide definitions of manipulation, completed manipulation, and completed manipulation length.

Manipulation. In the experiment, we count a period of trade as manipulation when the informed trader trades against her information. That is, manipulation occurs when the informed trader buys the asset when $v = 0$ and sells the asset when $v = 100$.[10] The theoretical literature proposes a definition that provides an operational measure—a strategy is considered as *manipulative* if the dynamic informed trader trades against their information (see Chakraborty and Yılmaz, 2004; Takayama, 2021). Huberman and Stanzl (2004) define price manipulation as a round-trip trade. In the setting that we consider, manipulation occurs as a round-trip trade in equilibrium.

Completed Manipulation. To complete a manipulation, the informed trader must make a round-trip trade (that is, buy and then sell after a certain period, or the other way around) within a certain period. Thus, we count a round-trip trade as one observation of *completed manipulation*. Notice that this definition rules out the case where the informed trader keeps trading against their information but never trades the asset following their information, which would result in a negative payoff. If the informed trader commences a new manipulation after completing the previous manipulation, then the same definition applies.

Completed Manipulation Length. We define the completed manipulation length as the number of periods during which the informed trader trades against their information before he or she trades following their information. According to this definition, if the informed trader never completes her manipulation, then the completed manipulation length is null. For example, when there are three periods, $v = 0$, and the order submitted by the informed trader in each period is BUY, BUY, and BUY, then the completed manipulation length is null. Using the same example, if the order submitted in each period is BUY, BUY, and SELL, then the completed manipulation length is 2.

Following Takayama (2010), manipulation can affect future payoffs by misleading the

[10] In the legal literature, Fischel and Ross (1991) argue that an effective definition of manipulation must focus on a trader's "bad" intention to distort market prices for personal gain.

market maker and influencing their belief regarding the asset's value. Despite incurring short-term losses, manipulation yields a considerable "continuation value" when the remaining trading round is sufficiently long, and the informed trader earns a higher profit overall from manipulation than from trading honestly from the start.

Therefore, the requirement for manipulation to succeed is that there are sufficient periods in the current trading round. With our parameter setup, one would expect to see price manipulation in trading rounds with 15 periods and no manipulation in trading rounds with 5 periods. We propose the following hypothesis with regard to the trading round duration and price manipulation.

Hypothesis 1. *Manipulation occurs only in trading rounds with* 15 *periods.*

From the theoretical discussion at the end of Section 2, we can see that trade manipulation by the informed trader makes trading the asset against her information in earlier periods more likely. In our setup, this indicates that it is more likely that the informed trader sells the asset when $v = 100$ and buys the asset when $v = 0$ in earlier periods. The only reason for the informed trader to do this is to mislead the market maker and influence their belief about the asset. The market maker has a high ρ when $v = 0$ and a low ρ when $v = 100$. Once the market maker's belief is sufficiently "distorted," the informed trader trades the asset following their information in later periods because he or she can sell the asset at a high price when $v = 0$ and buy the asset at a low price when $v = 100$. Although the information about the asset's value is revealed to the market maker, this does not concern the informed trader greatly because the trading round ends soon afterward.

As illustrated by the intuitive example in Section 2, it is easier for the informed trader to manipulate with a narrow bid–ask spread than with a wide bid–ask spread. Thus, we expect to see more price manipulation by the informed trader in N than in W.

Hypothesis 2. *There is more price manipulation in* N *than in* W*.*

In our setup, the market maker's prior on the value of the asset is $\rho = P(v = 100) = \frac{1}{2} = P(v = 0)$. Because of the symmetry of this prior belief, the informed trader should manipulate at the same rate regardless of whether the asset is of high or low value. In other words, manipulative behavior should not be affected by the asset's value at all.

Hypothesis 3. *Manipulations are similar in* L *and* H*.*

Because the manipulative trading in our setup involves early losses to distort the market maker's belief, we expect to observe less price manipulation from more risk-averse traders.

Hypothesis 4. *The manipulation rate decreases with participants' risk aversion.*

4 Experiment Results

We present our experimental results in this section. Section 4.1 discusses the results of manipulation. Section 4.2 provides the results of a completed manipulation. For each variable of interest, we present the results using all observations and those when *noisy observations* are excluded. The *noisy observations* are the observations of participants within a round when they manipulated trading in the last period. Manipulating in the last period of a round is a strictly dominated strategy and implies a certain level of confusion about the experiment (at least in that trading round).[11] Mann–Whitney U-tests are applied for all the pairwise comparisons unless otherwise mentioned.

4.1 Manipulation

We categorize the participants into two groups: *manipulators* and those who never manipulate. The variable *manipulator* measures the share of participants who manipulated at least once in a round.

The treatment N/L has a surprisingly high share of manipulators, which is 99.58%. The number decreases by only 0.02% without noisy observations. This indicates that when the bid–ask spread is narrow and the asset is of no value, almost every informed trader manipulates. Although significantly lower than N/L, the share of manipulators in N/H is high at 95% (decreasing by 1.38% without noisy observations). When the

[11] Among the 480 last-period observations, 75 involved manipulations, resulting in 15.63% of observations being noisy.

Table 3: *Share of manipulators*

	N/L	N/H	W/L	W/H
Manipulator	99.58%	95%	70%	67.08%
N/L		$>^{***}$	$>^{***}$	$>^{***}$
N/H			$>^{***}$	$>^{***}$
W/L				$\approx$
Manipulator clean	99.56%	93.62%	68.56%	53.53%
N/L		$>^{***}$	$>^{***}$	$>^{***}$
N/H			$>^{***}$	$>^{***}$
W/L				$>^{***}$

Note: *Manipulator* is the share of participants who manipulated at least once in a trading round. *Manipulator clean* is the share of participants who manipulated at least once in a trading round when the noisy observations are excluded. The differences between the treatments are tested using Mann–Whitney U-tests. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

bid–ask spread is low, the share of manipulators declines significantly to 70% when the asset is of no value and 67.08% when the asset is of high value. The numbers are even lower without noisy observations, decreasing to 68.56% and 53.53%, respectively. Overall, there are significantly more manipulators when the bid–ask price is narrow. Moreover, the share of manipulators significantly decreases with the asset value without noisy observations.

It is worth noting from Table 3 that most noisy observations are from W/H. It is almost impossible to manipulate when the spread is large. At the same time, we can imagine that in reality, even rational traders may exhibit reluctance to short sales (Shiller, 2003). We interpret the result as follows: these two factors (namely, a large bid–ask spread and reluctance for short sales) are important for the trading behavior of rational traders, whereas noisy traders may not be concerned about them, because we observe that they continue to trade against their information in the final period. This could make a difference in our observations for cases where spreads are wide and values are high.

We summarize the results for the manipulator share below:

Result 1. *There are significantly more manipulators in* N *than in* W*.* L *has signif-*

icantly more manipulators than H *when the bid–ask spread is narrow. Without noisy observations,* L *has significantly more manipulators when the bid–ask spread is wide.*

Table 4: *Manipulation rate*

	N/L	N/H	W/L	W/H
Manipulation 5	37.33%	37.66%	19.33%	27.33%
N/L		$\approx$	$>^{***}$	$>^{***}$
N/H			$>^{***}$	$>^{***}$
W/L				$<^{**}$
Manipulation 15	44.22%	42.11%	24.56%	31.56%
N/L		$\approx$	$>^{***}$	$>^{***}$
N/H			$>^{***}$	$>^{***}$
W/L				$<^{***}$
Manipulation 5 clean	36.84%	30.45%	17.82%	10%
N/L		$\approx$	$>^{***}$	$>^{***}$
N/H			$>^{***}$	$>^{***}$
W/L				$>^{**}$
Manipulation 15 clean	43.86%	39.86%	24.83%	16.03%
N/L		$\approx$	$>^{***}$	$>^{***}$
N/H			$>^{***}$	$>^{***}$
W/L				$>^{***}$

Note: *Manipulation 5* is the rate of manipulation in 5-period trading rounds. *Manipulation 15* is the rate of manipulation in 15-period trading rounds. *Manipulation 5 clean* is the rate of manipulation in 5-period trading rounds without noisy observations. *Manipulation 15 clean* is the rate of manipulation in 15-period trading rounds without noisy observations.

First, notice that participants manipulate in 5-period trading rounds, although the rate is lower than in 15-period trading rounds. The difference in the manipulation rate between the 5- and 15-period rounds is significant (the p values are less than 5%) in all four treatments without noisy observations.[12] Thus, we have to reject our Hypothesis 1, which states that participants only manipulate when the trading round has 15 periods.

Result 2. *Manipulation occurs in both 5-period rounds and 15-period rounds. The 15-period rounds involve significantly more manipulation without noisy observations.*

[12]With the noisy observations, the difference is only significant in the L treatments, but not in the H treatments.

Next, we examine how the bid–ask spread affects manipulation rates. When the value is zero, the manipulation rate is 37.33% (44.22%) with a narrow bid–ask spread in 5-period (15-period) rounds, and it drops to 19.33% (27.33%) with a wide spread. This implies a drop of 18% (16.89%) from N/L to W/L in 5-period (15-period) rounds. The drops are even larger when noisy observations are excluded. Without noisy observations, the drop of manipulation rates from N/L to W/L is 19.02% (19.03%) in 5-period (15-period) rounds. A similar pattern is observed when the asset has a high value. The drop in manipulation rates from N/H to W/H is 10.33% (10.55%) in 5-period (15-period) rounds. Without noisy observations, the drop almost (more than) doubles to 20.45% (23.83%).

To obtain a better sense of how manipulation rates in each treatment differ over time, we generate the average manipulation rate per period for each treatment, excluding the noisy data. The two figures below show the paths of the manipulation rates.

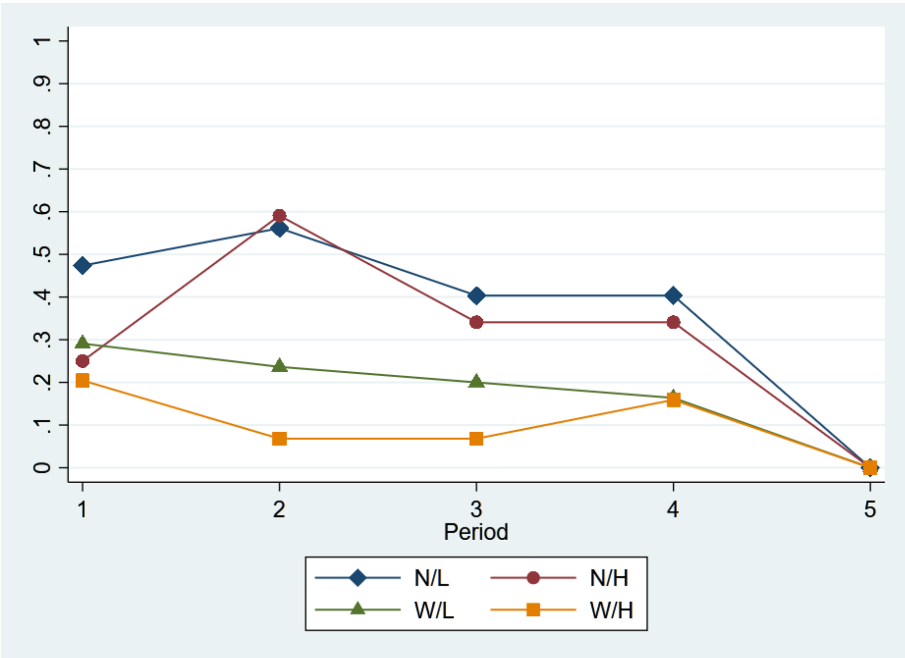


FIGURE 2: *Average manipulation rate in 5-period rounds*

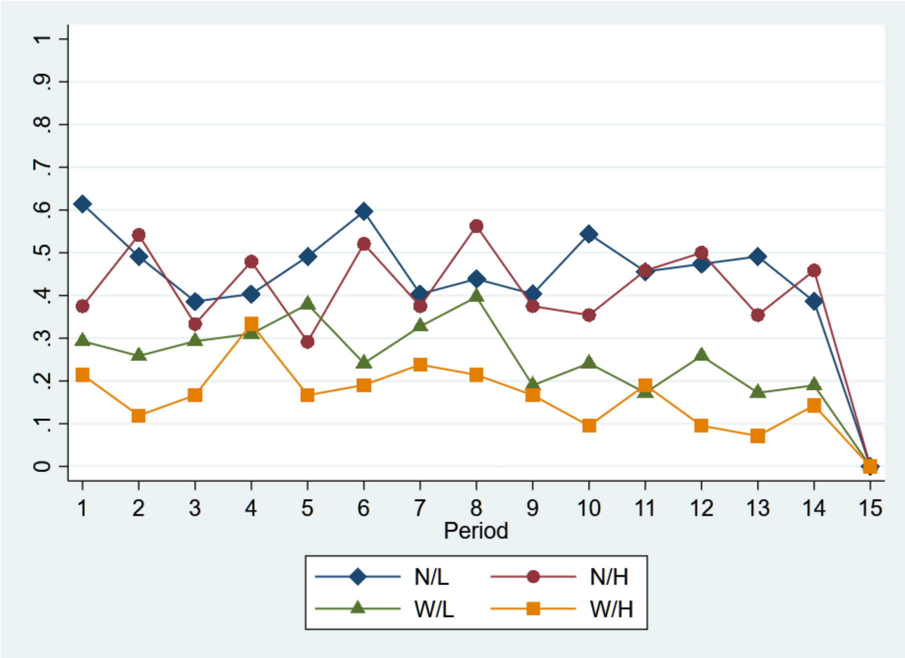


FIGURE 3: *Average manipulation rate in 15-period rounds*

We can see that after controlling for the asset value, the line for N is always above the line for W, except for the last period when manipulation becomes strictly dominated. Overall, our Hypothesis 2 is confirmed by the experimental data.

Result 3. *There is significantly more manipulation in* N *than in* W*. The difference becomes even more prominent without noisy observations.*

In terms of the relationship between manipulation and the value of the asset, we can observe from the first two columns in Table 4 that the manipulation rate does not change significantly with the value of the asset when the bid–ask spread is narrow. This holds with and without noisy observations. However, when the bid–ask spread is wide, the manipulation rate significantly decreases (increases) with the value of the asset without (with) noisy observations. Thus, it seems that the value of the asset only affects the manipulation rate when the bid–ask spread is wide, and our Hypothesis 3 is partially supported.

Result 4. *When the bid–ask spread is narrow,* L *and* H *have a similar manipulation rate. However, when the bid–ask spread is wide,* H *has a significantly higher (lower) manipulation rate with (without) noisy observations.*

4.2 Completed manipulation

In Section 4.1, we examined the frequency of manipulation in each treatment. However, it remains unclear how many completed manipulations there are, what are their average lengths, and whether there is any difference across treatments. We investigate this issue here. Tables 5 and 6 present the results for the completed manipulations and completed manipulation lengths in each treatment for the full sample and the subsample without noisy observations, respectively.

Table 5: *Completed manipulations*

	N/L	N/H	W/L	W/H
CManipulation 5	90	78	36	25
N/L		$\approx$	$>^{***}$	$>^{***}$
N/H			$>^{***}$	$>^{***}$
W/L				$\approx$
CManipulation 15	299	298	147	126
N/L		$\approx$	$>^{***}$	$>^{***}$
N/H			$>^{***}$	$>^{***}$
W/L				$\approx$
CManipulation 5 clean	87	60	35	15
N/L		$\approx$	$>^{***}$	$>^{***}$
N/H			$>^{***}$	$>^{***}$
W/L				$>^{**}$
CManipulation 15 clean	286	235	145	69
N/L		$\approx$	$>^{***}$	$>^{***}$
N/H			$>^{***}$	$>^{***}$
W/L				$>^{**}$

Note: *CManipulation 5* is the number of completed manipulations in 5-period trading rounds. *CManipulation 15* is the number of completed manipulations in 15-period trading rounds. *CManipulation 5 clean* is the number of completed manipulations in 5-period trading rounds without noisy observations. *CManipulation 15 clean* is the number of completed manipulations in 15-period trading rounds without noisy observations.

For completed manipulations, a very similar pattern appears as in the previous section on the manipulation rate: there are significantly more completed manipulations

Table 6: *Completed manipulation lengths*

	N/L	N/H	W/L	W/H
CManipulation length 5	1.2111	1.1026	1.4167	1.52
N/L		$\approx$	$<^{**}$	$<^{**}$
N/H			$<^{***}$	$<^{***}$
W/L				$\approx$
CManipulation length 15	1.3177	1.2114	1.4898	1.6587
N/L		$>^{*}$	$\approx$	$<^{***}$
N/H			$<^{***}$	$<^{***}$
W/L				$\approx$
CManipulation length 5 clean	1.2069	1.1167	1.4	1.4667
N/L		$\approx$	$<^{**}$	$<^{*}$
N/H			$<^{***}$	$<^{**}$
W/L				$\approx$
CManipulation length 15 clean	1.3111	1.2213	1.4897	1.4638
N/L		$\approx$	$\approx$	$\approx$
N/H			$<^{**}$	$\approx$
W/L				$\approx$

Note: *CManipulation length 5* is the average length of completed manipulations in 5-period trading rounds. *CManipulation length 15* is the average length of completed manipulations in 15-period trading rounds. *CManipulation length 5 clean* is the average length of completed manipulations in 5-period trading rounds without noisy observations. *CManipulation length 15 clean* is the average length of completed manipulations in 15-period trading rounds without noisy observations.

for N than for W. Without noisy observations, there are significantly more manipulations for L than for H only when the bid–ask spread is W. In terms of the lengths of completed manipulation, on average, N has a shorter length than W. This is expected because manipulation is easier to sustain in N than in W. The value of the asset does not have a significant impact on the completed manipulation length: there is no significant difference between H and L. Without noisy observations, we observe no changes in the pattern in 5-period trading rounds. However, in the 15-period rounds, we now observe that neither the asset value nor the spread affects the completed manipulation length.

However, this is still sufficient to infer that not only are there more manipulations in N but also shorter ones. Which scenario leads to more price distortion depends on the trade-off: on the one hand, manipulations are more likely to happen in N than in W; on the other hand, manipulations are longer-lasting and more severe in W than in N.

4.3 Regressions

We run regressions to test if there is any significant effect on the key variables as a result of participants' learning and risk preferences. For participants' risk preferences, we adopt the multi-price-list method. The variable *Risk* measures participants' risk preferences, with 5 denoting extremely risk-seeking and 1 denoting extremely risk-averse participants. Because the number of completed manipulations should be weakly increasing with PERIOD, it is not very revealing as a dependent variable. Instead, we use the binary variable CMANIPULATION INDICATOR, which equals 1 if participants completed a manipulation in that period, and 0 otherwise. Thus, a positive coefficient of PERIOD for CMANIPULATION INDICATOR implies that participants are more likely to complete their manipulation in later periods.

Table 7: *Round, period, and risk preference*

	Manipulation	*CManipulation Indicator*	*CManupulation length*
Period	−0.0375***	0.0542***	0.0008
Round	−0.0133	0.0081	−0.0196
Risk	0.1009***	0.0735***	0.0150
const	−0.8061***	−1.8101***	1.3351***

Notes: The table reports regressions of the main variables on period, round, risk preference, and a constant using only nonnoisy observations. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

From the regression table, we can see that participants who are risk-seeking are more likely to manipulate and complete their manipulations. Moreover, participants are less likely to attempt to manipulate but more likely to complete their ongoing manipulation in later periods. There is no evidence of learning because the coefficient of ROUND is insignificant for all key variables.

Result 5. *Risk-seeking participants manipulate and complete manipulation more frequently.*

5 Conclusion

In this paper, we have studied the manipulative behavior of informed traders in response to different market conditions within a simulated asset market. We defined trade-based manipulation in each period as a strategy where informed traders act against their information and generate negative returns. In addition, we defined a completed manipulation as a dynamic trading strategy where informed traders initially conduct trade-based manipulation and subsequently trade in line with their information.

We examined two market conditions, bid–ask spreads and re-trading possibilities. Our findings suggest that manipulation arises not only in longer trading rounds but also in shorter rounds, although at a lower rate in the latter case. In addition, we found that more manipulation occurs, and significantly more manipulations are completed in sessions with a narrow bid–ask spread than in those with a wide spread.

Regarding manipulation lengths, which we defined as the number of periods during which the informed trader engages in manipulation before trading the asset at its true value, narrower spreads lead to shorter manipulation lengths compared with wider spreads, which highlights the following trade-off: whereas manipulations in the case of narrower spreads are more frequent, those in sessions with wider spreads may persist for longer and potentially exert more severe impacts, thereby affecting the market's susceptibility to manipulation and price distortion in varied ways.

We find that risk attitude influences traders' strategies to a certain extent. Risk-seeking participants are more likely to conduct and complete manipulations than risk-averse participants. In this experiment, we find no evidence of learning effects.

Information manipulation is detrimental to the social welfare of traders in a financial market as well as to market capitalization. In this paper, we have determined how informed traders use their information to exploit the market. Our results include various important findings for policymakers. In particular, even when a bid–ask spread is wide, manipulation arises in longer periods. Policymakers should take both factors into consideration when assessing the market's vulnerability to manipulation and price distortion.

Furthermore, this study points to interesting directions for future research. For example, as we pointed out, risk attitudes influence trading strategies, whereas in theory, traders are often assumed to be risk neutral (see Chakraborty and Yılmaz, 2004; Glosten and Milgrom, 1985). It would be interesting to add risk aversion to the model and determine whether equilibrium behavior is consistent with that observed in a laboratory. Moreover, we have observed asymmetric trading patterns between the high and low states when the trading patterns should be symmetric from a theoretical perspective. Thus, it would be interesting to develop a theoretical framework that includes aversion to short sales.

References

Allen, F. and Gale, D. (1992). Stock-price manipulation. *The Review of Financial Studies*, 5(3):503–529.

Allen, F. and Gorton, G. (1992). Stock price manipulation, market microstructure and asymmetric information. *European Economic Review*, 36(2-3):624–630.

Back, K. and Baruch, S. (2004). Information in securities markets: Kyle meets Glosten and Milgrom. *Econometrica*, 72:433–465.

Bhattacharya, U. (2014). Insider trading controversies: A literature review. *Annual Review of Financial Economics*, 6(1):385–403.

Bloomfield, R., O'Hara, M., and Saar, G. (2009). How Noise Trading Affects Markets: An Experimental Analysis. *The Review of Financial Studies*, 22(6):2275–2302.

Chakraborty, A. and Yılmaz, B. (2004). Informed manipulation. *Journal of Economic Theory*, 114(1):132–152.

Copeland, T. E. and Galai, D. (1983). Information effects on the bid-ask spread. *The Journal of Finance*, 38(5):1457–1469.

Duxbury, D. (2015a). Behavioral finance: insights from experiments i: theory and financial markets. *Review of Behavioral Finance*, 7(1):78–96.

Duxbury, D. (2015b). Behavioral finance: insights from experiments ii: Biases, moods and emotions. *Review of Behavioral Finance*, 7(2):151–175.

Engle-Warnick, J. and Slonim, R. L. (2006). Learning to trust in indefinitely repeated games. *Games and Economic Behavior*, 54(1):95–114.

European Parliament and Council of the European Union (2014). Regulation (eu) no 596/2014 on market abuse (market abuse regulation) and repealing directive 2003/6/ec of the european parliament and of the council and commission directives 2003/123/ec, 2003/125/ec, and 2004/72/ec.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, 10:171–178.

Fischel, D. R. and Ross, D. J. (1991). Should the law prohibit "manipulation" in financial markets? *Harvard Law Review*, 105(2):503–553.

Glosten, L. R. and Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1):71 – 100.

Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with orsee. *Journal of the Economic Science Association*, 1(1):114–125.

Huang, R. D. and Stoll, H. R. (1997). The components of the bid-ask spread: A general approach. *The Review of Financial Studies*, 10(4):995–1034.

Huberman, G. and Stanzl, W. (2004). Price manipulation and quasi-arbitrage. *Econometrica*, 72:1247–1275.

Jarrow, R. (1992). Market manipulation, bubbles, corners, and short squeezes. *Journal of Financial and Quantitative Analysis*, 27(03):311–336.

Kyle, A. S. (1985). Continuous auctions and insider trading. *The Econometric Society*, 53(6):1315–1335.

Mengel, F., Orlandi, L., and Weidenholzer, S. (2022). Match length realization and cooperation in indefinitely repeated games. *Journal of Economic Theory*, 200:105416.

Merl, R. (2022). Literature review of experimental asset markets with insiders. *Journal of Behavioral and Experimental Finance*, 33:100596.

Nuzzo, S. and Morone, A. (2017). Asset markets in the lab: A literature review. *Journal of Behavioral and Experimental Finance*, 13:42–50.

Ozsoylev, H. and Takayama, S. (2010). Price, trade size, and information revelation in multi-period securities markets. *Journal of Financial Markets*, 13:49–76.

Palan, S. (2013). A review of bubbles and crashes in experimental asset markets. *Journal of Economic Surveys*, 27(3):570–588.

Putniņš, T. J. and Comerton-Forde, C. (2014). Stock price manipulation: Prevalence and determinants. *Review of Finance*, 18(1):23–66.

Schnitzlein, C. R. (1996). Call and continuous trading mechanisms under asymmetric information: An experimental investigation. *Journal of Finance*, 51(2):613 – 636. Cited by: 59.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of economic perspectives*, 17(1):83–104.

Takayama, S. (2010). A dynamic strategy of the informed trader with market manipulation. *Annals of Finance*, 6:287–294.

Takayama, S. (2021). Price manipulation, dynamic informed trading, and the uniqueness of equilibrium in sequential trading. *Journal of Economic Dynamics and Control*, 125:Article 104086.

Appendix: Part A

Duration of first trading rounds

Table 8: Duration of the first trading rounds

	5		15
Manipulation	0.3279	$<^{**}$	0.3583
CManipulation	531	$\approx$	568
CManipulation length	1.3051	$<^{**}$	1.3627

Note: *Manipulation* is the average rate of manipulation. *CManipulation 15* is the number of completed manipulations in 15-period trading rounds. *CManipulation length* is the average length of completed manipulations.

Instructions

The instructions for all treatments are analogous. Here, we provide the instructions for the treatments with reverse order.

General instructions

Thanks for participating in this experiment. Please read the instructions carefully. A clear understanding of the instructions will help you make better decisions and thus increase your earnings. After reading the instructions, you will be given a 20-period practice round to help you become familiar with the experiment software and the experiment process. The earnings in the practice round do not affect your final payment. The main experiment consists of 6 rounds, which follow the same instruction.

The experiment money is expressed in Experimental Currency Unit (ECU). What you will be paid in the end of the whole session is determined by the amount of ECUs you earn during the experiment. The cash payment will be paid to you in private at the end of the experiment. If you decide to leave early, you will receive zero cash payment. We guarantee anonymity with respect to other participants, and we do not record any information connecting your name to your decisions.

If you have any questions during the experiment, please raise your hand and one of us will come to you. Please do not ask your questions out loud, or attempt to communicate with other participants, or look at other participants' computer screens at any time during the experiment. Please turn your mobile phone to silent mode and place on the floor.

Overall structure of the experiment

There will be 6 rounds of trading in this session, and each round consists of several periods of play. The number of periods in a round is predetermined as follows,

	PracticeRound	Round1	Round2	Round3	Round4	Round5	Round6
Periods	20	5	15	5	15	5	15

There are two different roles in this experiment, namely the "Market Maker" and the "Informed Trader". Your role in this experiment is an "Informed Trader", and you will be an Informed Trader throughout the whole experiment. An Informed Trader (You) can decide whether to BUY or SELL 1 unit of tradable good at the prices a Market Maker sets in each trading period. A Market Maker is a computer (i.e., program) that sets prices for buying and selling a tradable good.

Each round only differs in terms of total trading periods. Each round has the same market setting. In each round you will face the following situation:

1. There is a tradable good called Assets that have intrinsic value. At the beginning of each round, you will be informed of the asset value, while the Market Maker (hereafter MM) is not informed. The value can be either High (i.e., Value = 100) or Low (i.e., Value = 0), and this value remains Unchanged throughout the whole experiment.
2. In each trading period, the MM sets prices for buying and selling an asset, and you need to decide whether to buy or sell an asset. Your trading order (i.e., your BUY or SELL behaviour) will be processed immediately after you have made your decision. You want to maximize the total sum of your each-period payoff which is the difference between the value of asset and the price you pay/receive. More specifically,

- If you are informed that the asset value is “Value = 100 (High)” and
  - if you choose to BUY, then your payoff in this period is: 100 – Buying Price.
  - if you choose to SELL, then your payoff in this period is: Selling Price – 100.
- If you are informed that the asset value is “Value = 0 (Low)” and
  - if you choose to BUY, then your payoff in this period is: 0 – Buying Price.
  - if you choose to SELL, then your payoff in this period is: Selling Price – 0.

Please note this is the payoff for each period, and your total payoffs for each ROUND is the sum of the each-period payoff. A key point of this experiment is that: (1) the MM does not know the asset value and needs to guess the value based on the trading orders he receives from you (i.e., your BUY or SELL behaviour). He has an initial guess and will change his belief based on your trading strategies; (2) a BUY order from you will make the MM believe that the asset value is high, then in the next period, he will increase the price. A SELL order from you will make him believe that the asset value is low, then in the next period, he will decrease the price.

Timing of a period within each round

In each round, before the Market opens and before making any decisions, you will receive an initial endowment that consists of assets and ECUs. Depending on the number of periods in each round, the endowment consists of 5 assets and 500 ECUs in the 5 trading periods round and 15 assets and 1500 ECUs in the 15 trading periods round. You will need to use ECUs to trade assets. Within each period, there are three stages: (1) Pricing, (2) Decision making, and (3) Payoffs.

1. Pricing Stage

At the beginning of each Period, the market maker sets market prices for trading an asset. The price may or may not be the same as the asset value because the market maker does not know what the value is. In the first period of each round, the market maker will have an initial belief, and this is his first guess on the chance that the asset value is High. This initial belief can be any number between 0 and 1, and for simplicity, it is set to be 0.5. Based on the belief, the market maker will set a Selling and a Buying price. You can buy the asset at the Buying Price and sell the asset at the Selling Price.

Both the Selling and Buying prices are extracted from a pricing table generated by our computer simulation results. In short, if the market maker receives a Buy Order from you in the current period, the market maker's belief on asset value being high will go up in the next period (but cannot exceed 1), and prices will go up (but cannot exceed 100); if the market maker receives a Sell Order from you in the current period, the market maker's belief on asset value being high will go down in the next period (but cannot be lower than 0), and prices will go down (but cannot be lower than 0). In this experiment, you do not need to calculate the belief by yourself, it is provided on the screen.

2.Trading Stage

For each trading period, the market will be open for exactly 60s, during which you need to make decisions as whether to buy or sell based on your information. You must decide whether to buy or sell 1 unit of asset at the given prices in each trading period. You cannot wait for the next period or do nothing.

Since you know the asset value, you have information advantage compared to the market maker. At this point, you can choose to trade honestly along with your information (i.e., honest trading) or trade against your information (i.e., strategic trading). For example, when you know the value is low, selling is honest trading, and buying is strategic trading. Your trade becomes signals about the true value to the market maker. Whenever a buy or sell order is received by the market maker, the transaction takes place immediately.

3. Payoff Stage

Your payoff in each period depends on your trading strategy. If you BUY, your assets in this period Increase by 1, and your ECUs in this period Decrease by the Buying Price. Your current period payoff will be the difference between the asset value and your buying price. If you sell, your assets in this period Decrease by 1, and your ECUs in this period Increase by the Selling Price. Your current period payoff will be the difference between your selling price and the asset value.

Your total payoffs in each Round are calculated as the sum of the payoff in each period in that round. At the end of each round, there will be a ranking of participants based on their final outstanding amounts in total payoffs. We will randomly choose one round as the paying round. Depending on your rank, the cash payments is as follows,

Rank	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Payments (AUD)	50	38	34	24	24	20	20	16	12	12

Examples

1. Suppose you are informed that the asset value is Low = 0, and you are informed the following message:

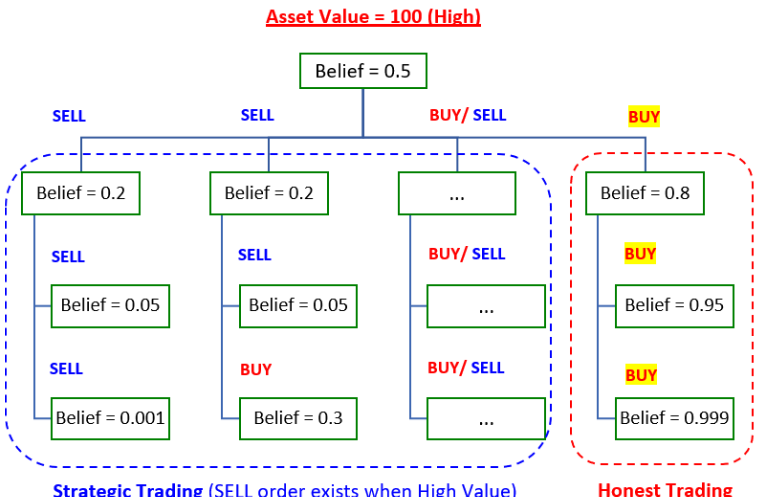
The market maker's belief is : 0.5
The market price for buying an asset is: 90
The market price for selling an asset is: 10

   In this case, the market maker's belief on asset value being high is 0.5. If you choose to Buy, you need to pay 90 ECUs and receive a 0-value asset, then your payoff in this period is $0 - 90 = -90$. But your buying behaviour will be a signal to the market maker that the asset value is High. In the next period, the market maker will increase his belief (but cannot exceed 1), and market prices for Selling will increase (but cannot exceed 100).

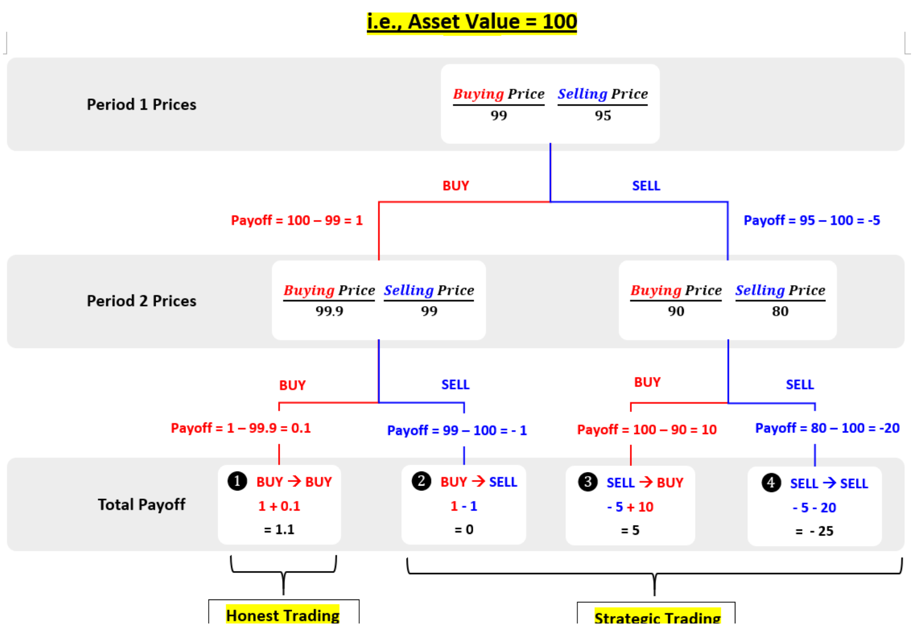
   If you choose to Sell, you can receive 10 ECUs and give a low value asset to the market maker, then your payoff in this period is $10 - 0 = 10$. But your selling behaviour will be a signal to the MM that the asset value is Low. In the next period, the market maker will decrease his belief (but cannot be lower than 0), and market prices for Selling will decrease (but cannot be lower than 0).

2. We provide a three-period example. Suppose you are informed that the asset value is High. For this case, only the strategy of buying always given High value can be

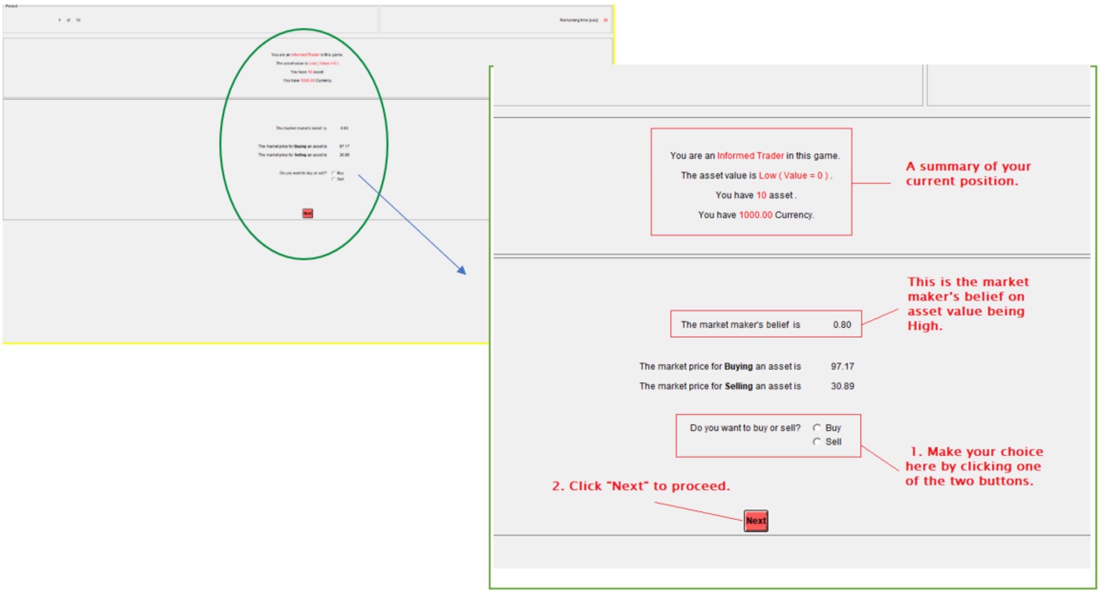
considered as honest trading. One buy and two sells, two buys and one sell, and selling always are considered strategic trading.



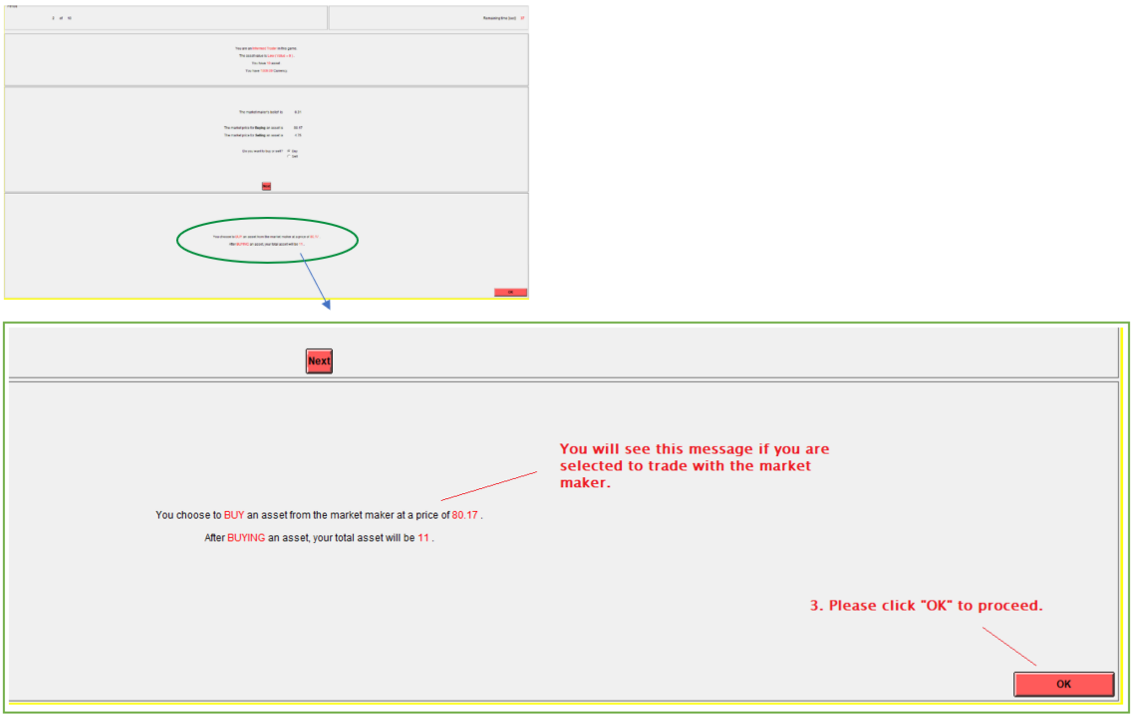
3. We provide a two-period example. In this example, suppose you are informed that the asset value is High. Your payoff in each period will depends on your trading strategies:

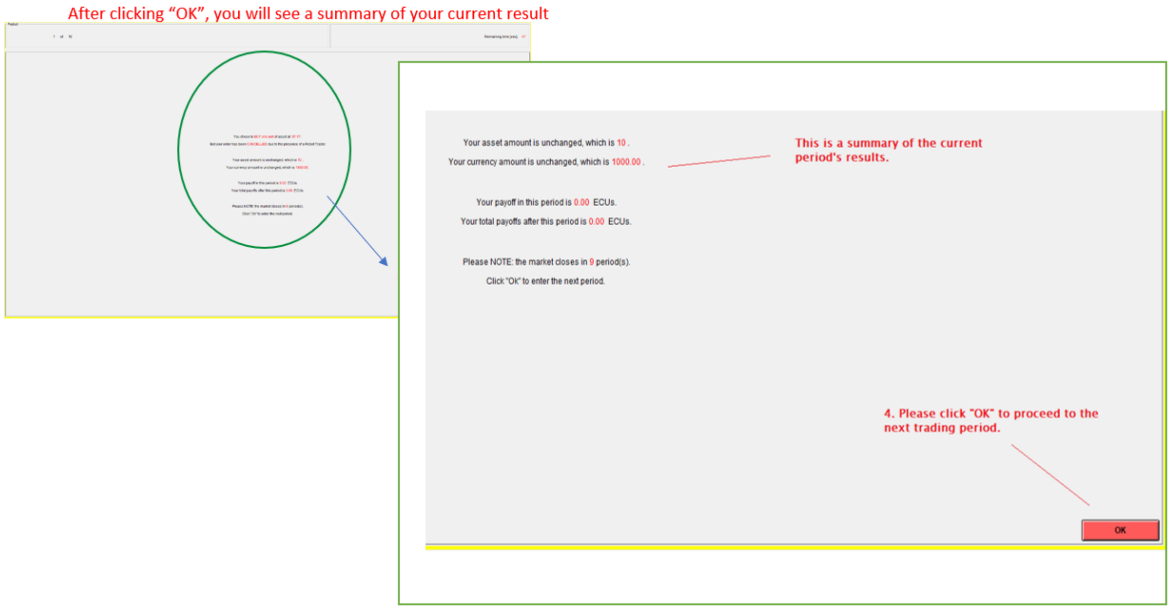


4. Instructions for traders: using the experiment software.



After making your choice, you will see the following message:





Appendix: Part B. Computation Procedures

The ask price is

$$A(b,x,y) = \frac{[\frac{1-\mu}{2} + \mu x]b}{\frac{1-\mu}{2} + \mu bx + \mu(1-b)(1-y)}. \tag{3}$$

The bid price is

$$B(b,x,y) = \frac{[\frac{1-\mu}{2} + \mu(1-x)]b}{\frac{1-\mu}{2} + \mu b(1-x) + \mu(1-b)y}. \tag{4}$$

We define the payoff when trading for the information as

$$\Pi_H(b,x,y) = 1 - A(b,x,y) + J_{t-1}(A(b,x,y)),$$

and

$$\Pi_L(b,x,y) = B(b,x,y) + V_{t-1}(B(b,x,y)).$$

where $J(b)$ and $V(b)$ specify the recursive computation of value functions such that

$$J_t(b) = \sigma_{Ht}(b)(1-\alpha_t(b) + \nu J_{t-1}(\alpha_t(b))) + (1-\sigma_{Ht}(b))(\beta_t(b) - 1 + \nu J_{t-1}(\beta_t(b))), \tag{5}$$

and

$$J_t(b) = \sigma_{Ht}(b)(1-\alpha_t(b) + \nu J_{t-1}(\alpha_t(b))) + (1-\sigma_{Ht}(b))(\beta_t(b) - 1 + \nu J_{t-1}(\beta_t(b))). \tag{6}$$

In equilibrium, $\sigma_{Ht}, \sigma_{H,t-1}, \ldots$ maximizes the expectation of the sum of current and future profits conditional on the value being high, and $\sigma_{Lt}, \sigma_{L,t-1}, \ldots$ maximizes the expectation of the sum of current and future profits conditional on the value being low. Implicitly we are assuming that the functions J_0 and V_0 are identically zero.

The payoffs when trading against the information for the high type and the low type are:

$$\pi_H(b, x, y) = B(b, x, y) - 1 + J_{t-1}(B(b, x, y)),$$

and

$$\pi_L(b, x, y) = -A(b, x, y) + V_{t-1}(A(b, x, y)).$$

Here we briefly explain how we solve for an equilibrium. The key to solving for an equilibrium is an indifference condition such that the profit from buying equals the profit from selling. Consider the low type at period t. Let α_t and β_t denote the bid and ask prices at period t. Using Bayes' rule, we can show that when the value function is monotone in terms of prior belief b, then $\alpha_t > b > \beta_t$, which indicates that there is no arbitrage opportunity. When the low type manipulates: $\Pi_L(b, x, y) = \pi_L(b, x, y)$, the following holds:

$$-\alpha_t + V_{t-1}(\alpha_t) = \beta_t + V_{t-1}(\beta_t).$$

When the high type manipulates: $\Pi_H(b, x, y) = \pi_H(b, x, y)$, the following holds:

$$1 - \alpha_t + J_{t-1}(\alpha_t) = \beta_t - 1 + J_{t-1}(\beta_t).$$

The following summarizes our procedure in detail. First, we segment [0,1] into a grid with N cells of equal sizes.

1. We start with the terminal period $t = 1$. In period 1, nobody manipulates; thus, we can compute the period 1 value functions using Bayes' rule. We linearly interpolate the period 1 value functions into N grid points.

2. Given linearly interpolated J_1 and V_1 for each grid point, we solve a system of equations such that each type of trader is indifferent between buying and selling by using Bayes' rule. We further check if the strategy we compute for each trader

satisfies optimality. In this way, we check which regime arises in each grid point belief.

3. We find a pair of equilibrium prices for each grid point belief.
4. We compute the period 2 value functions. Then we repeat the same procedure from step 2.

In the computational analysis, we assume that the liquidity buy arises with the probability γ, which is not necessarily $\frac{1}{2}$. Unless specifies, we use $N = 100$. To generate a pricing table with a smaller bid-ask spread, we set $\mu = 0.08$ in equation (1) and (2). For a larger spread, we set $\mu = 0.8$.