Opening call auction designs and price manipulation for price discovery: An experimental study

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Abstract

This study conducts laboratory experiments under three opening call auction designs to improve the price discovery process. The first design resembles the opening session of major stock exchanges, where traders can place and cancel their orders before the opening price is announced. We alternatively investigate two call auction designs in which traders are not allowed to cancel orders during the session, while the call auction time is divided into sub-periods and orders are executed every sub-period before the opening price is announced. We first demonstrate price manipulations in an economy with cancellations. However, we can mitigate manipulative behavior when we prohibit order cancellations or execute orders periodically before the end of a call auction. Second, we find a gradual price discovery process in economies with and without cancellations. However, price discovery can be quickly achieved in periodic clearings. These results indicate that price manipulations and longer non-trading minutes result in slower price discoveries. Third, we demonstrate that reinforcement learning, by which traders attempt to find profitable strategies from past performances, explains the order choices of our lab participants, and thus, price manipulations and price discovery. We contribute to the literature by emphasizing the important role of reinforcement learning on price manipulations and the price discovery process under different opening call auction designs. Our study has important policy implications regarding which call auction design is better for the opening call market.

Keywords: Laboratory experiment; call auction design; price manipulation; price discovery; reinforcement learning

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1. Introduction

Major stock exchanges adopt a call auction mechanism for setting the opening price. This trading protocol is designed to allow overnight news to be suitably reflected in prices, thereby enhancing price discovery.[1] Opening price discovery, measured by the difference between opening and fundamental prices, should be achieved to stabilize transaction prices during normal trading hours (Pegano, Peng, and Schwartz, 2013). However, previous studies have presented mixed conclusions regarding the preopening price discovery.[2] For example, Biais et al. (1999) show that the preopening price discovery process is noisy because of price manipulations,[3] and that the fundamental price is gradually discovered toward the end of the call auction. The empirical results imply that stock exchanges need to revise their current trading protocols for the efficient functioning of stock markets.

This study conducts laboratory experiments using three call auction designs to improve the price discovery process. In our benchmark call market, which resembles the opening session of major stock exchanges, traders place limit orders and cancel them before the market simultaneously clears all the placed orders at the end of a fixed clearing time. Alternatively, we conduct two experiments on call mechanisms without cancellations and

[1] Overnight news is often made at major stock exchanges. For example, in the Tokyo Stock Exchange, over 75% of earnings announcements are made after the market closes between September 2013 and August 2014 (Xiao and Yamamoto, 2024).

[2] On the one hand, preopening orders reflect fundamental information about the asset values (e.g., Cao et al. (2000) for NASDAQ and Davies (2003) for the Toronto Stock Exchange). On the other hand, Barclay and Hendershott (2003) and Ibikunle (2015) indicate only most actively traded stocks gain price efficiency.

[3] Manipulation is the strategy, which is intended to misalign the price. Consequently, it slows down the speed of price discovery (Kyle & Viswanathan, 2008).

with periodic clearings before the end of the call session. The periodic clearing rule divides the call auction time into sub-periods and clears the markets in every sub-period before the opening price is decided.

We first demonstrate price manipulations by our laboratory participants under a call market design in which cancellations are allowed during the call session. Conversely, price manipulations are less likely but are still observed in markets without cancellations and with periodic clearings. We find that the price manipulation strategy intensifies as traders repeatedly experience call transactions. We show that as the experiments are repeated, traders' profits increase when they place limit orders to deviate the price from the fundamental value during the call auction and capture the arbitrage chance at the end of the auction. The first result implies that our laboratory participants learn profitable strategies over time from past trading performances and attempt to manipulate prices to improve their trading performance.

Second, we find a gradual price discovery process in economies with and without cancellations.[4] However, price discovery is quickly achieved in periodic clearings associated with high trading volumes. Trades before the end of the call session disseminate information, and traders can quickly learn the fundamental value, resulting in faster convergence to price efficiency. The first two results indicate that price manipulations and longer non-trading minutes result in slower price discovery. Consequently, we derive an important policy

[4] The result on the gradual price discovery is consistent with that of Biais et al. (1999).

implication: major stock exchanges should adopt the call auction design, which executes orders a few times before the market opens, to improve the price discovery process and stabilize prices during normal trading hours. Third, we demonstrate that reinforcement learning, by which traders attempt to find profitable strategies based on past performance, significantly explains the order choices of our laboratory participants under all three call market setups. Thus, reinforcement learning explains the sources of price manipulations and discovery.

This is the first experimental study to address how reinforcement learning impacts price manipulations and the price discovery process under different opening call auction designs. The previous literature emphasizes the importance of certain forms of learning in analyzing the impact of call auction designs. Empirical studies, such as Biais et al. (1999), suggest that competitive and strategic investors learn the equilibrium price from order flows toward the end of the preopening period. He and Lin (2022) show that learning can be the key to understanding the information channel for order choice and market outcomes.[5] Furthermore, learning by uninformed traders plays an important role in supplying liquidity to informed traders (O'Hara, 2001 and He and Lin, 2022) and, therefore, the market outcomes. However, no experimental studies have demonstrated causality from reinforcement learning

[5] Furthermore, Pouget (2007) experimentally shows a higher gain from trade through a Walrasian tatonnement due to adaptive learning. Meanwhile, in recent limit order markets, machine learning has been increasingly popular in stock trading (Easley et al., 2019).

to price manipulations and call mechanism designs. We contribute to the literature by experimentally addressing the important but unsolved question in market microstructure literature for the efficient functioning of an opening call market.

Our contribution enhances the knowledge in the finance literature on market manipulations, price discovery, and call auction designs. First, the current study broadens our knowledge of the important role of learning in price manipulations and evaluating different opening call auction designs, which are missing in previous studies.[6] Second, our contribution provides a possible explanation for previous empirical studies, for not only why the fundamental price is not discovered at the opening session in some studies but also for why price discovery is a noisy or gradual process, which has been raised but unaddressed by past research.[7]

Our testing trading protocols are motivated by real market structures and/or past research as follows. Our first call auction design resembles that of major stock exchanges, in which traders place and cancel their orders during the call auction. The second rule imposes a

[6] The price manipulations in other mechanisms than an opening call auction are widely studied in previous studies, such as 1) spoofing in continuous double auction (Kong & Wang, 2014; Lee, Eom, & Park, 2013); 2) closing price manipulation (Comerton-Forde & Putniņš, 2011; Comerton-Forde & Putniņš, 2014; Cumming et al., 2020; Park et al., 2022); 3) IPO manipulation (Neupane et al., 2017, Duong et al 2021); and 4) insider trading (Allen and Gale, 1992; Allen and Gorton, 1992; Agrawal and Cooper, 2015; Aitken et al., 2015). Meanwhile, the manipulations in a call market are studied by Liu et al (2022), Kelly (2008), and Hauser et al. (2022) by empirical approaches and Biais et al. (2014) by the experimental approach. Market designs are evaluated by Park et al., 2022 for closing auctions and Biais et al. (2014) for opening sessions.

[7] Certain studies, which discuss that market manipulations worsen the price efficiency, are those by, for example, Biais et al. (1999), Comerton-Forde & Putniņš, 2011; Cong, Li, Tang, & Yang, 2020; Li, Shin, & Wang, 2020; Aggarwal & Wu, 2006; Allen & Gale, 1992.

restriction on the cancellation of preopening orders. Biais et al. (1999) show noisy opening prices due to manipulative orders. They explain that preopening orders can be cancelled; therefore, the indicative prices do not reflect informative orders, which is empirically supported by Kuk et al. (2011) for the Australian Stock Exchange. Order manipulations would be prevented by imposing no cancellation rules in call auctions, which motivates our second call auction design; some stock exchanges, such as the Tel Aviv Stock Exchange and NASDAQ, set no cancellation rule in call auctions (Kalay et al. 2004, Hauser et al. 2009, and NASDAQ Stock Market 2007). The third experimental rule is a periodic clearing mechanism before the end of the call auction period. A periodic clearing rule may also encourage informed traders to place orders and take advantage of their information before the end of the time interval, possibly contributing to removing significant noisy trading, and thus faster price discovery. The periodic clearing rule was suggested by Budish et al. (2015) as an alternative to the continuous trading and was used in real markets such as the stock exchange in Taiwan; however, it has never been tested for whether or not the periodic clearing rule facilitates price discovery at the opening call auction.

The experimental work by Biais, Bisière, and Pouget (2014) tests preopening mechanisms for facilitating high liquidity and gains from trade. They found that a call auction that prohibits cancellation and thus manipulative orders, outperforms those with random

clearing times and cancellations.[8] Our work is closely related to that of Biais, Bisière, and Pouget (2014), but differs in that 1) we examine price discovery while they examine liquidity and gains from trades; 2) we investigate how reinforcement learning by traders is interrelated to the impact of regulation on the call market, which is not examined in Biais, Bisière, and Pouget (2014); and 3) we investigate a periodic clearing call auction, which is not examined in their laboratory experiments.

Previous experimental work on call markets focuses on allocative and/or informational efficiency (Smith et al., 1982; Cason and Friedman, 1997; Davis and Williams, 1997; Plott and Pogorelskiy, 2017; Schnitzlein, 1996). Brunner and Levinsky (2023), Pouget (2007), and Liu (1996) show that insider information determines the call market price efficiency. However, they do not relate the issue of learning to call auction designs. A growing number of studies compare call auction mechanisms with continuous trading mechanisms. For example, Friedman (1993), Theissen (2000), and Palan, Huber, and Senninger (2020) compare the informational efficiencies in laboratory call and continuous markets.[9] However, this study is neither a work on strategic choice nor the informational efficiency or market quality between call and continuous double auctions. Additionally, because we study call auction designs, we do not discuss the role of high-frequency traders.[10]

[8] See Comerton-Forde and Rydge (2006) and Madhavan and Panchapagesan (2000) for the empirical examples of the call auction designs.
[9] For the empirical studies, see, for example, Pagano and Schwartz (2003).
[10] Among several past studies, see, for example, Boehmer, Fong, and Wu (2014), Kirilenko, Kyle, Samadi, and Tuzun (2017), Brogaard (2010), and Easley, Lopez de Prado, and O'Hara (2012).

The remainder of this paper is organized as follows. Section 2 describes our experimental design. Section 3 introduces our empirical methodologies for analyzing the experimental data and presents the results. Section 4 summarizes the findings and presents the conclusions.

2. Experimental design

We denote t, which corresponds to a period of a call auction, which we call trading round t. Our call auction markets allow traders to place limit orders at any time during the preopening period to trade a single, risky asset. At the end of the call auction period, all transactions are made simultaneously at a single clearing price p_t, which maximizes the trading volume, given the orders placed during the time interval. The usual price priority rules are applied to simultaneous transactions, meaning that orders with lower selling prices and higher buying prices have higher priorities for execution. Orders placed at the same price are randomly ranked for the execution order.[11] One call auction lasts 120 seconds, dividing it into four sections, each of which lasts for 30 seconds, with indicative quotes being announced at the end of every section.[12] Figure 1 shows the time sequence of a call auction. All orders

[11] In a call auction, orders are simultaneously executed at a single price at the end of the time frame, which means that the usual time priority are not applied in a call auction. In the call auction at the Tokyo market, if multiple investors place orders at the same price, the investor with the largest order quantity has the high priority to be executed. If multiple investors place the same order quantity at the same limit price, the same number of shares are executed for the investors. In our experiment, the order quantity is one share. Therefore, when multiple investors place limit orders at the same price, but the total amounts are greater than the number of shares to be executed, we assume that we randomly select the orders to be executed.

[12] We assume the setups, which the indicative quotes are announced every 30 seconds, due to a technical

are cleared after a trading round and a new round begins with an empty order book. The call auction is repeated 10 times (rounds) for an experiment.

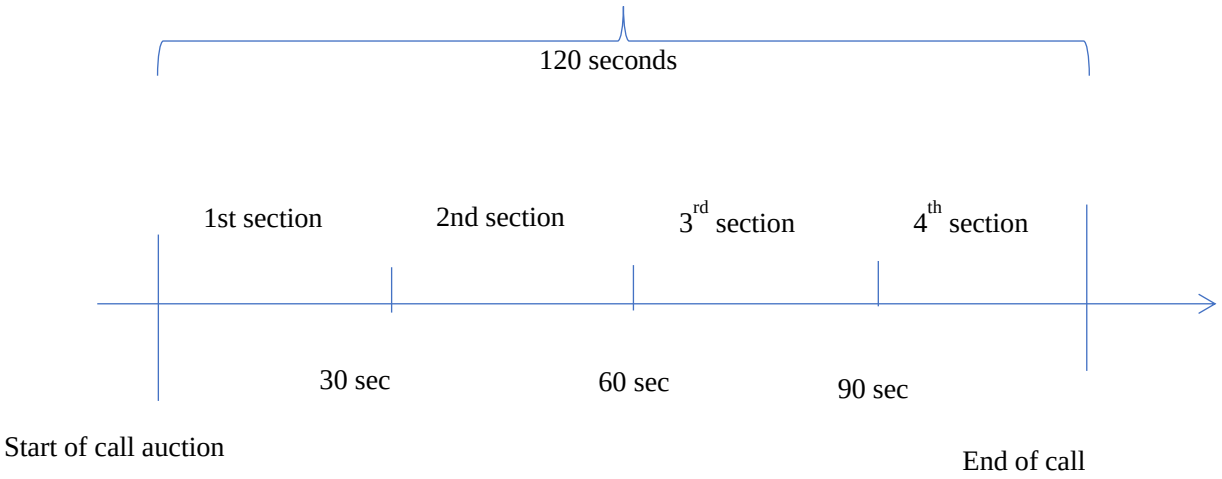


Figure 1. A call auction time frame

The fundamental price of the asset v_t increases or decreases by one Japanese yen with equal probabilities once per round with the initial value v_0, but the value is constant over a round. With the recent timing of fundamental news release in the major stock exchanges such as earning announcements in the Tokyo Stock Exchange, the fundamental price changes before a call session starts. There are informed and uninformed traders, where informed traders know the current fundamental price when they enter the market, and uninformed traders observe the value of a previous round.[13] We assume that traders do not

reason for not causing a delay for proceeding the experiments. The indicative quotes can be computed in real markets anytime by the order-book information.

[13] We set the initial fundamental value v_0 to 1000 Japanese yen, and the indicative quote at the first section at the first round is assumed to be 1000 yen, and the previous fundamental value at the first round is 999 yen. The indicative quotes at the first section at the following rounds are the trade prices at the previous round.

know the number of informed and uninformed traders or the types of other participants and that the types do not change during an experiment.

An experiment consists of 30 human subjects, each of whom is initially endowed with 10 shares of securities and 20000 Japanese yen. The remaining endowment is cleared when a trading round ends and a new trading round starts with the initial endowment. As traders can place up to 10 orders, endowments are sufficient for traders to place 10 sell or 10 buy orders. We divide the 30 participants into three independent markets, each of which consists of randomly assigned informed and uninformed traders; we set three for informed traders and seven for uninformed traders in an economy.[14] However, this information is not revealed to the participants. During the call session, all investors can observe 1) the aggregated amounts of buy and sell limit orders submitted to the market, 2) the fundamental price information and the most recent indicative and trade prices, and 3) the current section number.[15] The indicative quote is the hypothetical market price calculated using the orders submitted until the end of each section. The participants select the type of limit order (buy or sell) and limit price at one yen above the most recent indicative quote, at the most recent indicative quote, or at one yen below the indicative quote; thus, they have six possible order choices.[16] They are allowed to submit up to 10 orders anytime and possibly several times

[14] We set 30% of the traders as informed to resemble the fraction of the mutuals in the real stock market in Japan, who actually made profits (Financial Services Agency, 2020).
[15] The observed fundamental values are the current value for the informed trader and the previous fundamental price for the uninformed traders.
[16] The limited set of order choice is important for laboratory participants, in order to decide their order

during a call auction period, although they are allowed to place one share of an order at a time. They are also allowed to simultaneously submit buy and sell orders. However, the price of buy orders must be lower than that of sell orders to avoid self-trading.

The current experimental study is designed to answer whether and why traders manipulate prices in laboratory experiments, whether this manipulation affects price discovery, and what call auction designs improve price discovery. To answer these questions, we conduct laboratory call market experiments using three call auction designs: with cancellation, without cancellation, and with periodic clearing. In the cancellation design, traders are allowed to cancel orders submitted in the previous section and resubmit their orders during the call auction period, which is our benchmark call design. In the without cancellation design, the order submitted in the previous section can no longer be cancelled. In the periodic clearing design, cancellations are allowed, but orders are cleared in every section (periodic clearing) instead of every round. Therefore, our experiments have three treatments. From 2023 to 2024, two experiments are conducted for each call auction design; therefore, we collect a sample from six experiments for our analyses.[17] The experiments are conducted using z-tree toolbox provided by Fischbacher (2007).

The subjects comprised undergraduate students at Waseda University who had never

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choices within a limited amount of time in an experiment.

[17] The experiments for the market with cancellation were conducted on June 22, 2023 and October 19, 2023. the dates of the experiments for the market without cancellation were December 7, 2023 and April 22, 2024, while those for the periodic clearings were January 29, 2024 and May 30, 2024.

participated in this study. We recruited participants using the recruitment system at Waseda University. The subjects were randomly assigned to either the informed or uninformed type. Each participant had a cubicle seat with a computer platform that made their order choice. The subjects could not see the other participants' screens because of the partition of the cubicle and were not allowed to communicate with each other. After the written instructions were distributed to the participants, a pre-recorded instruction video was played. After the instructions, all subjects were asked to answer comprehensive questions to show their understanding of the experiment rules. After all subjects obtained correct answers to the comprehensive questions, one test round was implemented for them to get accustomed to the call auction trading system. After the test round, the payoffs, endowments, and orders in the test round were cleared and the experiment began with new initial values, such as the fundamental price. After all ten rounds, the subjects were asked to answer a questionnaire and receive payments.

The participants were paid compensation composed of a participation fee, additional pay 1, and additional pay 2. The participation fee was 2300 yen for informed traders and 2500 yen for uninformed traders.[18] Additional pay 1 was 50 times the trading profit. Buyers earned positive profits when their orders were executed at a transaction price less than the

[18] When the experiments lasted longer or the total profits are smaller than scheduled, we adjusted the participation fee by increasing certain yen to all participants for the total compensation to be 2200-3700 yen.

fundamental value. Sellers' profits were positive when their orders were executed at prices higher than the fundamental value. Additional payment 1 could be negative; if negative, it was deducted from the show-up fee. The additional pay 2 was designed to provide an incentive for uninformed traders to trade, which paid 10 yen times the number of executed orders, and zero for informed traders. We randomly selected five rounds to compute the additional pays 1 and 2. Each experiment lasted approximately 120 minutes, including 25 minutes of instructions and 45 minutes of comprehensive questions and test rounds. The average compensation was 2500 yen.

3. Results

3.1. A hunch for price manipulations and learning

First, we present the results for the transaction prices, volume, and profits. The results indicate a possibility of traders' learning for profitable order choices and price manipulations. In the subsequent subsections, we present the detailed statistical results for learning and price manipulations and their relationship with the price discovery process.

Figure 2 shows the differences between the opening prices and fundamental prices under the three call auction designs over the trading rounds, which indicates the possibility of upward price manipulation in a market with cancellation. As we divided the laboratory participants into three groups in each experiment and conducted the experiment twice for

each call auction design, we accumulated the differences between the three groups and two experiments. A positive value indicates that the opening price is higher than the fundamental price. The figure shows opening prices higher than the fundamental price for the last five trading rounds in a market with cancellations.[19] A possible interpretation of this result is that traders attempt to raise indicative and opening prices by placing limit orders at a higher price than the indicative quotes during the call session. This feature is less likely in markets without cancellations or with periodic clearings. Therefore, we summarize our first prediction as follows.

Prediction 1: Traders engage in upward price manipulations during the opening session. These manipulations are strikingly observed when traders are allowed to cancel orders.

Volumes and profits per participant are plotted over the trading rounds for the three call auction designs in Figures 3 and 4, respectively. We divide the time series into informed and uninformed traders. Additionally, we divide the sample into the first and last five trading rounds, which are summarized in Tables 1 and 2, respectively.

[19] The positive values are magnified and thus the prices are manipulated upwards with a greater degree when the fundamental price goes down. The result indicates that the traders are strongly encouraged to involve the upward manipulations when the fundamental price decreases, to receive larger profits. The full dynamics of trade and fundamental prices are presented at the Appendix 1.

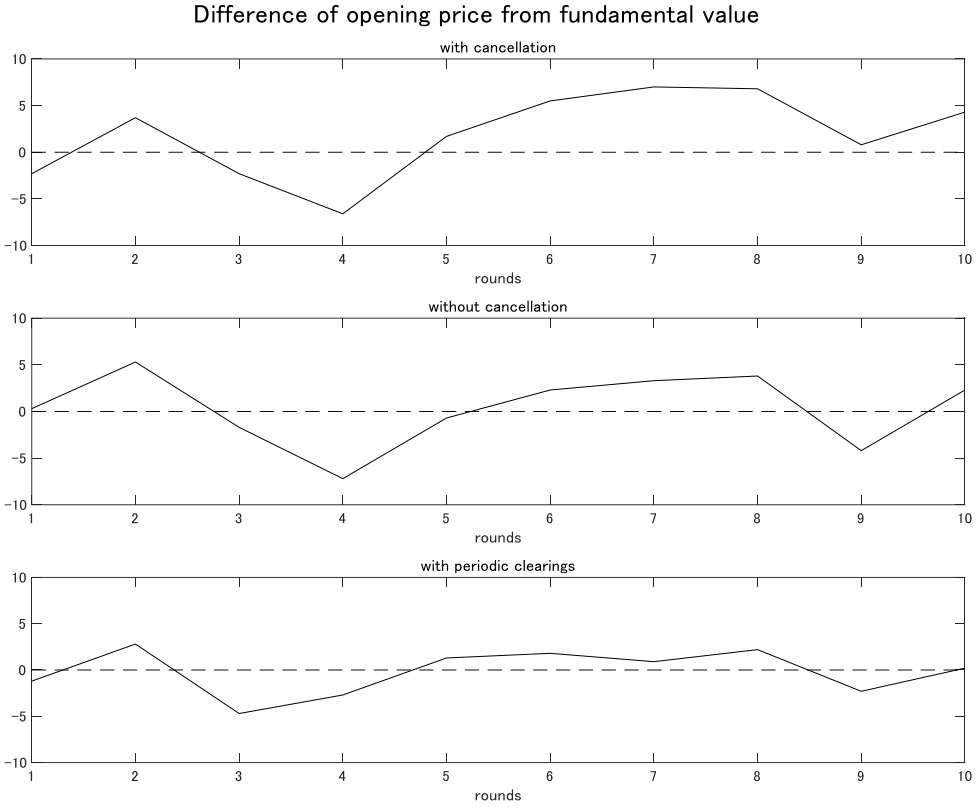


Figure 2: Difference between the opening price and fundamental price under three call auction designs. We accumulate the differences over the three groups in a market and the two experiments at each trading round. The positive value indicates the higher value of the opening price than the fundamental price.

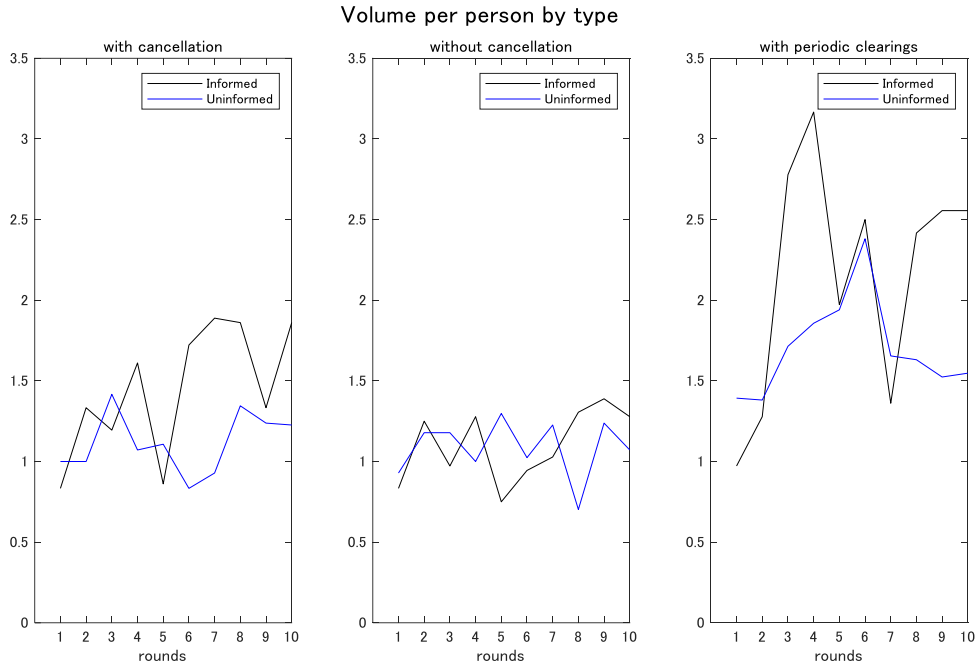


Figure 3: Volume per trader over trading rounds under three call auction designs.



Figure 4: Profit per trader over trading rounds under three call auction designs.

Table 1 (Panel A): Volume per trader in the first and last five rounds under the three call auction designs.

	With cancellation		Without cancellation		With periodic clearings	
	First 5 rounds	Last 5 rounds	First 5 rounds	Last 5 rounds	First 5 rounds	Last 5 rounds
Informed	5.83	8.67**	5.08	5.94	10.17	11.39*
Uninformed	5.60	5.57	5.58	5.26	8.29	8.74

Table 1 (Panel B): Profit per trader in the first and last five rounds under the three call auction designs.

	With cancellation		Without cancellation		With periodic clearings	
	First 5 rounds	Last 5 rounds	First 5 rounds	Last 5 rounds	First 5 rounds	Last 5 rounds
Informed	7.31	11.70**	4.93	6.53	14.01	13.14
Uninformed	-3.13	-5.01	-2.11	-2.80	-6.00	-5.63

The results suggest that traders are involved in certain forms of learning and select strategies that will produce higher profits. For example, in markets with and without cancellations, the volume is positively correlated with profits from the first five rounds to the last five trading rounds, particularly for informed traders. In Panels A and B of Table 1, the informed trader's volume is 5.83 and profit 7.31 in the first five rounds of a market with cancellation. However, they increase to 8.67 and 11.70, respectively, meaning that informed traders seek to find and successfully found profitable strategies over time. In a market without cancellations, they are 5.08 and 4.93 in the first five rounds, but rise to 5.94 and 6.53, respectively. In a market with periodic clearings, the volumes are higher for informed and uninformed traders, even in the early stages of the trading rounds, than in markets with and without cancellations, as shown in Figure 3.[20] The volume for informed and uninformed trader is 10.17 and 8.29, respectively in the first five rounds. The profits of informed traders are also higher (14.01) in the early trading rounds than under the other market designs (7.31 and 4.93 in markets with and without cancellation, respectively). These results imply that informed traders learn that they will lose money if they manipulate prices. For example, when they manipulate the price upward but the orders are executed in the early sections, they lose money because they buy shares at a price above the fundamental price. This indicates that informed traders compete with each other and place orders around the fundamental price, not

[20] There are four trade chances in the periodic clearings. However, the setup does not necessarily increase volume when the traders place conservative limit orders.

the orders that deviate from the fundamental price. Therefore, they would quickly learn that they can raise profits if they execute their order around the fundamental price from early sections and early trading rounds (i.e., high volume and profits) to take advantage of information. Order executions by informed traders would contribute to spreading the information to the market and, therefore, quickly help uninformed traders learn that they may raise profits if they do not attempt price manipulations but rather take other actions. Therefore, our second prediction, which is formally tested in the next subsection, is as follows.

Prediction 2: Both informed and uninformed traders use certain forms of learning to select their strategies.

The actions of informed traders lead to faster convergence to full-price discovery in periodic clearings. Conversely, in markets with and without cancellations, the volume of informed traders is higher in the last five trading rounds than in the first five rounds, indicating slower information dissemination to the market and thus a slower convergence to price discovery than the periodic clearing rule. Therefore, we statistically test the following prediction in the subsequent section.

Prediction 3: Periodic clearings enhance opening price discovery the most. The

opening price is better discovered in a market without cancellation than in one with cancellation.

3.2. Order choice for price manipulation

This subsection presents the results of our traders' order choices and price-manipulative behavior under three call auction designs. Given that the indicative quote is updated at the end of every section, our participants can choose to buy or sell limit orders 1) at one tick above the most recent indicative quote, 2) at the indicative quote, or 3) at one tick below the indicative quote at every section. We denote a buy limit order as "Buy" and a sell limit order as "Sell." We further denote the order with one tick above the indicative quote, at the quote, and one tick below the quote as "+1," "0," and "-1'," respectively.

Price manipulation is not a feature of one-time order placement but the sequence of actions over sections. Therefore, we use the following five classifications of order choice sequences over sections to statistically identify price manipulations: the first two strategies are those for upward price pressures; the third and fourth are for downward price pressures; and the fifth is a group of strategies unrelated to upward and downward price pressures. We classify the order sequences based on the difference between the fundamental price and observed indicative quotes. Detailed information on one-time order choices is presented in Appendix 2, which is sorted by informed and uninformed at the 1–3 and 4–th sections under

the three call auction designs.

The first strategy classification of the order sequence is the upward price manipulation strategy with profit intention, where a trader places a buy or sell order one tick above the indicative price during the first three sections and a sell limit order in the 4th section when the fundamental price is lower than the observed indicative quotes. We call this manipulation with profit intention because traders can sell at the fourth section at a price higher than the fundamental price. The sequence is denoted as 1) Buy+1 or Sell+1 at the 1st–3rd sections and Sell+1, Sell0, or Sell-1 at the 4th section.

The second strategy classification of order sequence is the upward trend-following strategy, in which a trader attempts to push up the indicative quotes during the 1st–3rd sections but does not place the profitable order at the fourth section. Specifically, we define the second-order strategy as 2) Buy+1 or Sell+1 at the 1st–3rd sections but Buy+1, Buy0, Buy-1, or no order is placed at the 4th section, when the fundamental price is lower than the observed indicative quotes.[21] We do not call the second sequence as a price manipulation because traders do not sell at a price higher than the fundamental price in the fourth section, although they attempt to push up the price in the earlier sections. The traders would take the strategy, when they have uncertainty about the clearing price at the end of the fourth section

[21] We also include the upward trend-following strategy for the second strategy sequence, which are Buy+1 or Sell+1 at the 1st–3rd sections when the fundamental price is lower than the observed indicative quotes at the first three sections but Buy+1, Buy0, or Buy-1 at the 4th section when the indicative quote becomes greater than the fundamental price at the section.

or when they try to push up the price but the price does not reach to the level they expected. Thus, they do not sell at the fourth section.

The third strategy classification is the downward trend-following strategy where 3) a trader places Buy-1 or Sell-1 during the first three sections but Sell+1, Sell0, or Sell-1 or no order is placed at the 4th section, when $v_t > p_\tau$.[22] We do not call the third classification as a price manipulation, because they do not buy to make money, although they attempt to lower the transaction price than the fundamental price in earlier sections. The fourth one is the downward price manipulations with profit intention, and therefore, 4) Buy-1 or Sell-1 at the 1st–3rd sections but Buy+1, Buy0, or Buy-1 at the 4th section, when $v_t > p_\tau$. The fifth strategy classification is a sequence of rules other than the four classifications, which are not related to strategies for upward or downward price pressures.[23]

It is possible and the case that laboratory participants took multiple strategies. When a trader uses multiple order sequences during a trading round, we determine the "representative strategy" on which he/she assigns more orders on the strategy than the others. For example, suppose that the trader engages in upward manipulation with profit intention and downward trend-following strategy, where the final trade state is "sell." We select the

[22] We add the sequence for the downward trend-following strategy, which are Buy-1 or Sell-1 at the first three sections when $v_t > p_\tau$ but Sell+1, Sell0, or Sell-1 at the 4th section when $v_t < p_\tau$.

[23] Specifically, the fifth category includes 5) non-manipulative strategies or no orders at the first three sections and 5-1) non-manipulative strategies, 5-2) buy order at any price when $v_t > p_\tau$, or 5-3) sell order at any price when $v_t < p_\tau$. The non manipulative strategies include 1) Buy+1 or Sell+1 when the fundamental price is not lower than the observed indicative quotes, 2) Buy-1 or Sell-1 when the fundamental price is not higher than the observed indicative quotes, or 3) Buy0 or Sell0 for any conditions on v_t and p_τ.

downward trend-following strategy as a representative strategy when the trader places more orders at Buy-1 or Sell-1 during the first three sections for downward price movements than at Buy+1 or Sell+1 for upward manipulations.

Panels A and B in Table 2 present the frequencies of the five strategies being selected as the representative strategies and those of the executed representative strategies over the two experiments under each call auction design, respectively. Because a trader selects a representative strategy in each round, the numbers illustrate the frequencies of traders, who select the representative strategy and successfully execute the orders by the strategy. Panel C in Table 2 summarizes the average profits of executed representative strategies. We sort the information by type. The numbers to the left of the arrows are those in the first five trading rounds, whereas those to the right represent the last five rounds. We also add the information on the relative frequencies among selected strategies. For example, the fourth column from the right shows the relative frequencies between upward and downward price manipulations. We conduct the Wilcoxon signed-rank test for the upward price manipulation and upward trend-following strategies to determine whether traders are more likely to use the strategies in the last five trading rounds than in the first five rounds. We also repeat the test for the downward trend-following and downward price manipulation strategies to test whether the strategies are used less in the last five rounds than in the first five rounds. For the other strategy, we test the hypothesis that there is no change from the first to the last five rounds.

***, **, and * indicate 1%, 5%, and 10% significance. We explain the following three main results.

First, informed and uninformed traders clearly involve upward price manipulations with profit intention in a call market with cancellation, which supports Prediction 1. For example, in Panel A of Table 2, the frequency of taking the upward price manipulation is 39 for informed traders and 31 for uninformed traders in the last five rounds, which is significantly greater than those in markets without cancellation and with periodic clearings. The relative frequencies of taking the upward price manipulation to the other strategies such as the downward price manipulation is high in the same market in the last five rounds. For example, in the fourth column from the right in Panel A in Table 2, the relative frequencies of taking the upward price manipulation to the downward price manipulation in the last five rounds are 0.95 and 0.86 for the informed and uninformed traders, respectively.

Table 2 (Panel A). The frequencies of taking representative strategies by type, which are accumulated over the two experiments under each of the call auction design. We count the numbers of the unexecuted and executed representative strategies. The numbers left to the arrows are those in the first five trading rounds, while those right to the arrows are for the last five rounds. ***, **, and * indicate 1%, 5%, and 10% significance.

Frequencies (accumulated)		**Upward manipulation**	**Upward trend-following**	**Downward trend-following**	**Downward manipulation**	**Others**	**Upward manipulation /(Upward+Downward manipulations)**	**Upward trend-following /(Upward+Downward trend-following)**	**Upward manipulation /(Upward manipulation +trend-following)**	**Downward manipulation /(Downward trend-following + manipulation)**
With cancellation	Informed	4→39***	1→3	2→1	13→2**	64→41***	0.24→0.95	0.33→0.75	0.80→0.93	0.87→0.67
	Uninformed	12→31***	15→31***	14→4**	9→5	140→112**	0.57→0.86	0.52→0.89	0.44→0.50	0.39→0.56
Without cancellation	Informed	3→11**	1→4	3→0	6→7	63→55	0.33→0.61	0.25→1	0.75→0.73	0.67→1
	Uninformed	16→11	10→7	8→6	15→9	140→139	0.52→0.55	0.56→0.54	0.62→0.61	0.65→0.60
Periodic clearings	Informed	1→1	2→0	2→0	2→0	77→85*	0.33→1	0.50→0	0.33→1	0.50→0
	Uninformed	2→8**	7→4	1→5	5→10	182→160***	0.29→0.44	0.88→0.44	0.22→0.67	0.83→0.67

Table 2 (Panel B). The frequencies of executed representative strategies by type, which are accumulated over the two experiments under each of the call auction design. The numbers left to the arrows are those in the first five trading rounds, while those right to the arrows are for the last five rounds. ***, **, and * indicate 1%, 5%, and 10% significance.

Frequencies (accumulated)		**Upward manipulation**	**Upward trend-following**	**Downward trend-following**	**Downward manipulation**	**Others**	**Upward manipulation /(Upward+Downward manipulations)**	**Upward trend-following /(Upward+Downward trend-following)**	**Upward manipulation /(Upward manipulation +trend-following)**	**Downward manipulation /(Downward trend-following + manipulation)**
With cancellation	Informed	4→25***	1→0	1→1	8→2*	42→31	0.33→0.93	0.50→0	0.80→1	0.89→0.67
	Uninformed	7→4	13→32***	11→3**	5→4	91→69*	0.58→0.50	0.54→0.91	0.35→0.11	0.31→0.57
Without cancellation	Informed	1→6*	1→3	3→0	6→4	36→41	0.14→0.60	0.25→1	0.50→0.67	0.67→1
	Uninformed	7→4	8→4	7→5	7→6	94→81	0.50→0.40	0.53→0.44	0.47→0.50	0.50→0.55
Periodic clearings	Informed	0→0	0→0	0→0	1→0	46→47	0→0	0→0	0→0	1→0.75
	Uninformed	0→3	2→1	1→0	3→1	106→88*	0→0.75	0.67→1	0→0.75	0.75→1

Table 2 (Panel C). Average profits of executed representative strategies by type over the two experiments under each of the call auction design. The average profits measure those per executed strategy. The numbers left to the arrows are those in the first five trading rounds, while those right to the arrows are for the last five rounds. ***, **, and * indicate 1%, 5%, and 10% significance.

Profits (accumulated)		**Upward manipulation**	**Upward trend-following**	**Downward trend-following**	**Downward manipulation**	**Others**
With cancellation	Informed	2.08→4.52***	-1.00→0	0→-8.00	4.51→2.75	2.07→3.22
	Uninformed	-1.20→3.13***	0.08→-2.98	-2.19→-1.50	1.52→-0.90**	-0.88→-1.77*
Without cancellation	Informed	1.00→2.85*	-9.00→-2.20	0.40→0	3.27→1.63	1.28→1.95
	Uninformed	0.13→-0.25	0.09→0.93	-2.23→0.60	-2.01→-0.77	-0.49→-0.95
Periodic clearings	Informed	0→0	0→0	0→0	0.4→0	4.00→2.70
	Uninformed	0→-2.97	0.75→0	0→0	-0.27→0.60	-1.47→-1.61

Second, the upward price manipulation strategy is more likely to be used by the informed and uninformed traders in the last five rounds than in the first five rounds in a market with cancellations and by informed traders in markets without cancellations and with periodic clearings. For example, in Panel A of Table 2, the frequencies of taking the upward price manipulation strategy are 4 for informed traders and 12 for uninformed traders in a market with cancellations. However, these values increased significantly to 39 and 31, respectively. The tendency is also observed in a comparison with the downward price manipulations. In the fourth column from the right in Panel A in Table 2, the relative frequencies on using upward price manipulations against downward price manipulations increase from 0.24 to 0.95 for the informed traders and from 0.57 to 0.86 for the uninformed traders in a market with cancellation. The increased tendency of upward price manipulations with profit intention arises because of the increased chance of profit, as shown in Panel C of Table 2. The average profits from the strategy increase to 4.52 from 2.08 for informed traders and to 3.13 from -1.20 for uninformed traders. Meanwhile, the other strategy, which is the one unrelated to upward or downward price pressure, is more likely to be used by the informed traders in a market with periodic clearings than the other strategies even during the first five rounds because of relatively high average profits. For example, in Panel A in Table 2, in a market with periodic clearings, informed traders use the other strategy a total of 77 times in the first five rounds and 85 times in the last five rounds, while the other strategies are used

less than 10 times, because the average profits from the other strategy are 4.00 in the first five rounds and 2.70 in the last five rounds. Although the frequencies of taking strategies and their average profits are not correlated in some strategies, our results seem to suggest that traders would attempt to learn and use the profitable strategy as they experience call auctions under our three market designs, which supports Prediction 2. Section 3.4 will provide evidence that both informed and uninformed traders engage in reinforcement learning for their order choices.

A possible reason for traders to select upward and not downward price manipulation is that our traders misunderstood our setup, where 10 shares and 20000 yen are initially given per round, and they could place 10 shares at most during a round. They may have felt that they only have limited amounts to sell but sufficient amounts to buy, which increases their tendency to buy rather than sell.[24] Meanwhile, the uninformed traders at the periodic clearings increase the attempt of downward price manipulations toward the end of the experiments because the profit from the strategy is slightly higher than that from the other strategies, although it is very small.

Third, informed traders earn greater profits from the other strategy in a market with periodic clearings than the other strategies even during the first five rounds. The result suggests that informed traders attempt to capture information advantage by trading at early

[24] The asymmetric price movements are demonstrated by the short-sale constraint, for example, by Jones and Lamont (2002) and the borrowing constraint, for example, by Yuan (2005).

stages of a call session. It implies that the fundamental information is disseminated throughout the market quicker in the market with periodic clearings than the other market designs, which, therefore, contributes to faster convergence to price discovery than the other market designs. Traders compete each other and eventually tend to place orders closer to the fundamental price for obtaining certain executions and thus profits, enhancing price discovery. Therefore, in a market with periodic clearings, traders are less likely to place orders for deviating the trade price from the fundamental price like the upward or downward price manipulation strategy, due to the reduced chance for making profits. The argument suggests that price discovery will be worsen in a market with cancellations than in other call auction designs due to the high tendency of the upward price manipulations. In the next subsection, we investigate price discovery under the three market designs in detail.

3.3. Price discovery

The results on volume and profits in Section 3.1 indicate that in a periodic clearing market, informed traders' executions in early trading rounds make the information spread throughout the market, which would lead to quick convergence to price discovery. Meanwhile, stronger correlations between volume and profit are observed in the last five trading rounds in the markets with and without cancellation, which would be linked to gradual price discoveries rather than periodic clearings. Furthermore, we find stronger price

manipulation in a market with cancellation than in other market designs, which leads to the slowest convergence to price discovery in the market with cancellation. Therefore, Prediction 3 is supported.

We empirically measure price discovery by 1) the mean absolute deviation of prices from the fundamental value (in percentage) at each section, and 2) the estimates of the unbiasedness regression model at each section (Biais et al., 1999). The unbiasedness regression equation is given as:

$$v_t - E(v_t|I_0) = \alpha_\tau + \beta_\tau[P_\tau - E(v_t|I_0)] + \varepsilon_\tau \quad (1)$$

where v_t is the fundamental value at a call auction trading round t, $E(v_t|I_0)$ is the expected value, and P_τ is the indicative price at τ-th section. $E(v_t|I_0)$ is the expected value of v_t, given the information I_0. In our case, all traders can observe the previous fundamental price v_{t-1} and know it changes by one yen at a time with equal probabilities. Therefore, $E(v_t|I_0)$ can be re-expressed as v_{t-1}. Equation (1) is expressed as follows:

$$v_t - v_{t-1} = \alpha_\tau + \beta_\tau(P_\tau - v_{t-1}) + \varepsilon_t \quad (2)$$

where:

$$\beta_\tau = \frac{Cov(v_t - v_{t-1}, P_\tau - v_{t-1})}{Var(P_\tau - v_{t-1})} \quad (3)$$

When information is reflected in the indicative price, the change between the indicative price and last fundamental price contains information about the fundamental value. Therefore, $\beta_\tau = 1$. If the indicative price is not entirely informative, the change between the

indicative price and last fundamental price is not predictive; therefore, the slope coefficient is zero. Equation (3) indicates that the indicative price underreacts (overreacts) to the efficient price when $\beta_\tau < (>)1$. Therefore, we can observe whether and how the indicative price approaches or diverges from the fundamental value over time. We estimate β_τ at each section and plot them in Figures 2–4 (in the figures on the right) with the mean absolute deviation of the prices from the fundamental values in percentage (in the figures on the left). The mean absolute price deviation is zero when the price is fully discovered.

Figures 5 and 6 illustrate that prices are gradually discovered in call auction designs with and without cancellation, which is consistent with the empirical findings of Biais et al. (1999). However, the estimates of β_τ and the mean difference between the trade price and the fundamental price start deviating from the full price discovery at the second and third sections in the market with cancellation. Therefore, price manipulation with a combination of cancellations triggers the price to deviate from its fundamental value, as suggested by Biais et al. (1999). However, this does not occur when cancellations are prohibited. However, the estimates of β_τ are lower and the mean absolute price deviation from the fundamental values are higher in a market with cancellation than that without cancellation, although both of the markets do not achieve the full price discovery. The result indicates that the call market without cancellation not only reduces price manipulation behavior but also enhances price discovery relative to that with cancellation.

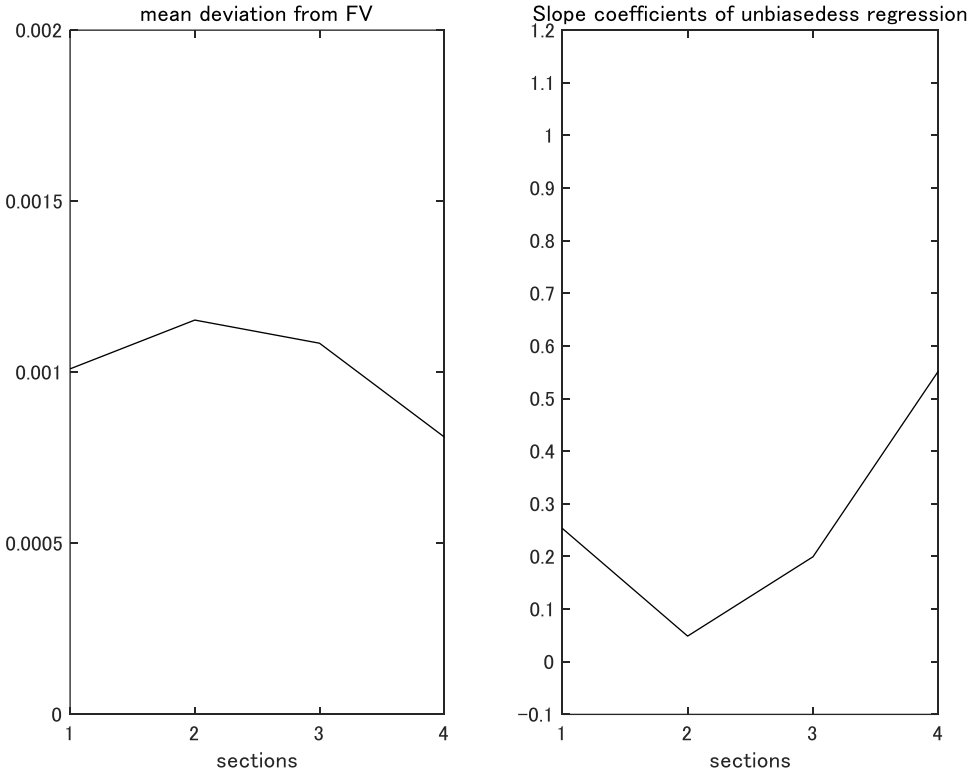


Figure 5: Price discovery in a call market with cancellation. The left figure plots the mean absolute price deviations from fundamental value over sections. The right figure is the plot of the estimates of the unbiasedness regression across sections.

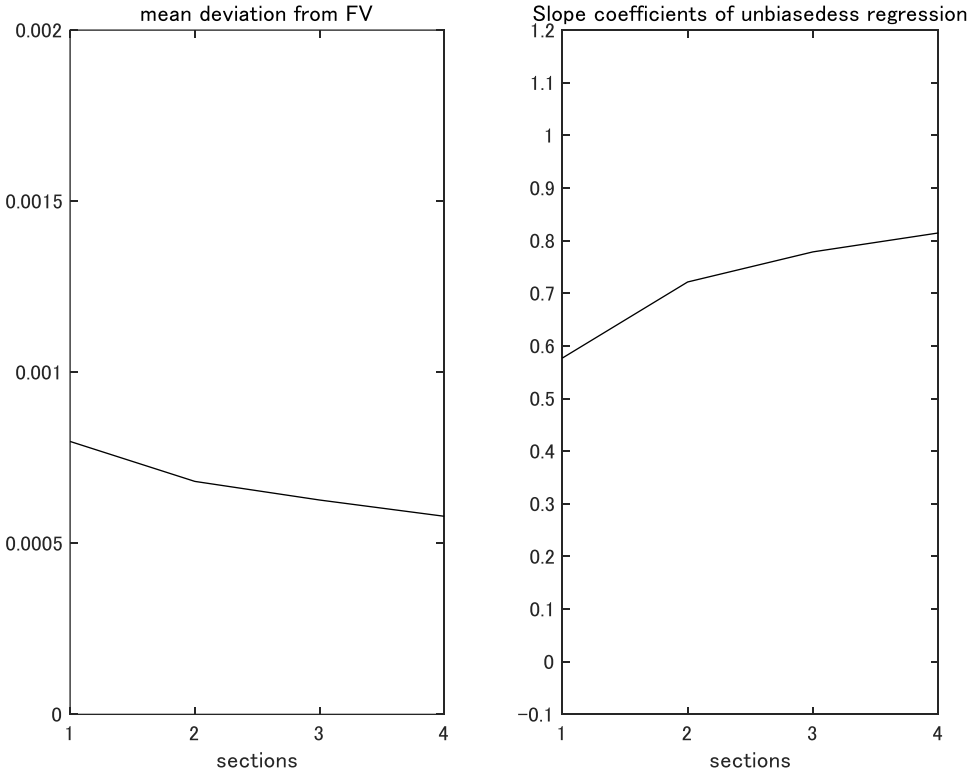


Figure 6: Price discovery in a call market without cancellation. The left figure plots the mean absolute price deviations from fundamental value over sections. The right figure is the plot of the estimates of the unbiasedness regression across sections.

Conversely, price discovery is achieved more quickly in periodic clearings than in markets with and without cancellations, as shown in Figure 7. The increased chances of execution during the auction disseminate fundamental information across the market, allowing uninformed traders to quickly learn the fundamental value. Therefore, periodic clearings accelerate price discovery faster than call auction designs, with and without cancellation. This implies that traders attempt to learn fundamental information and update their order choices to acquire positive profits. Therefore, we support Prediction 3.

We conduct the sign-ranked test and t-test to test the hypothesis that periodic clearings improve price discovery better than markets with or without cancellations at any section. We also test the hypothesis that prohibiting cancellations improves price discovery compared with the market with cancellations. We tested this using each of the two price discovery measures. As summarized in Tables 3 and 4, the *p*-values for all tests were less than 1%. Therefore, we draw the following two conclusions. First, price discovery is enhanced in a no-cancellation market compared to a market with cancellations. Second and most importantly, the periodic clearing market is the best market design for price discovery.

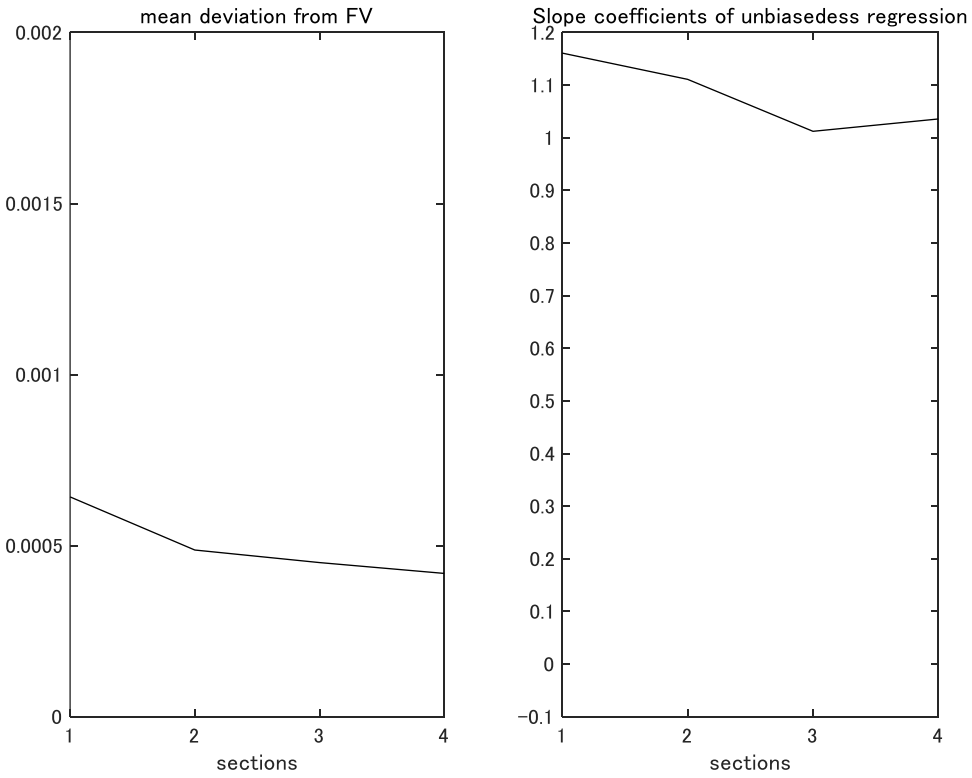


Figure 7: Price discovery in a call market with periodic clearing. The left figure plots the mean absolute price deviations from fundamental value over sections. The right figure is the

plot of the estimates of the unbiasedness regression across sections.

H1:	**Sec 1**	**Sec 2**	**Sec 3**	**Sec 4**
Periodic clearing > Cancellation	<0.01	<0.01	<0.01	<0.01
Periodic clearing > No cancellation	0.028	0.032	0.015	0.028
No cancellation > Cancellation	0.029	<0.01	<0.01	0.012

Table 3: p-values for sign-ranked test for whether the price discovery measure (mean absolute price deviation from the fundamental value) is better under periodic clearing than the market with or without cancellation.

H1:	**Sec 1**	**Sec 2**	**Sec 3**	**Sec 4**
Periodic clearing > Cancellation	<0.01	<0.01	<0.01	<0.01
Periodic clearing > No cancellation	<0.01	<0.01	0.015	0.014
No cancellation > Cancellation	0.020	<0.01	<0.01	0.024

Table 4: p-values for t-test for whether the price discovery measure (unbiasedness regression estimates) is better under periodic clearing than the market with or without cancellation.

3.4. Reinforcement learning for order choice

We present the characteristics of our traders' order choices, such as price manipulation and price discovery, under our three call auction setups. Price discovery and manipulation emerge from traders' order choices. This subsection demonstrates that traders involve reinforcement learning, which directly supports Prediction 2 and significantly explains the order choice. Therefore, we conclude that our previous results regarding order choice and price discovery arise because of reinforcement learning.

Reinforcement learning is more suitable for model parameter estimation than other learning models, such as genetic algorithm (GA) learning, and more sophisticated

belief-based learning, such as exponentially weighted attraction (Camerer and Ho, 1999) because of its simpler setup. Furthermore, GA learning or other sophisticated learning methods require more parameters to be set in experiments, and sophisticated belief-based learning requires observing the opponents' behavior to determine the action. Therefore, they will require not only great amounts of treatment in the experiments, but also many parameters to be estimated to determine the learning impact on the market, both of which are not feasible for experiments and statistical analyses.

We extend the models of past studies, such as that of Chen and Hsieh (2011), to test whether they adjust their strategies through reinforcement learning. To statistically identify the reinforcement learning effect on price manipulations, we classify the order choice sequences over sections into the five strategies introduced in Section 3.2, and define them as traders' action space A. We use the representative strategies, which are introduced in Section 3.2 for the action space, and test whether traders involve reinforcement learning on the five-order sequences in A.[25] As explained in Section 3.2, the representative strategy is selected on which a trader puts more orders on the strategy than the other strategies in a round. Therefore, each trader can select one representative strategy at each trading round. We denote action A_i where i is a strategy taken from the action space A.

The reinforcement learning model states that traders attempt to choose action A_i,

[25] Recall that the five strategies are the upward price manipulation, upward trend-following, downward trend-following, downward price manipulation, and the other strategies.

that generates higher trading profits in the past. The participants earn trade profits from the difference between the fundamental value v_t and transaction price p_t, which are $v_t - p_t$ for a buy order and $p_t - v_t$ for a sell order. We denote the order profit from action i chosen by trader k in trading round t as $O_{i,t}^k$. Since we had 30 traders in each call auction experiment and conducted each experiment twice, k = 1, …, 60.

The expected profit at call auction round t for an executed action A_i of k trader is calculated as follows:

$$q_{i,t}^k = (1-\phi)q_{i,t-1}^k + \phi O_{i,t-1}^k \quad (4)$$

For a submitted but non-executed action,

$$q_{i,t}^k = q_{i,t-1}^k \quad (5)$$

ϕ is the propensity of the last order profit known as the forgetting parameter, which measures the updating speed of the expected profit, which takes a value between 0 and 1.

We assume that action i is selected by trader k at t according to a probability distribution function using the Gibbs–Boltzmann distribution:

$$\pi_{i,t}^k = \frac{e^{\delta q_{i,t}^k}}{\sum_j e^{\delta q_{j,t}^k}}, \qquad A_i, A_j \in A \quad (6)$$

where δ measures the switching intensity to the propensity $q_{i,t}^k$.[26] When δ is higher, the tendency to switch to an action A_i is stronger; therefore, it is known as the speed of learning

[26] The probabilities by the original model by Roth and Erev (1995) is linear to the expected profit. However, the order profits are sometimes negative giving the negative probabilities.

(Roth and Erev, 1995).

Defining representative strategy $i*$ as a chosen strategy at time t from the distribution function, we set the likelihood function as:

$$L(\phi, \delta) = \prod_{t=1}^{t=T}\left(\pi_{i*,t}^{k}\right) \quad (7)$$

where $T = 10$ rounds in our experiments.[27]

We convert it into the log form as:

$$l(\phi, \delta) = \sum_{t=1}^{t=T} ln\pi_{i*,t}^{k} \quad (8)$$

We estimate the parameters ϕ and δ by the method of the maximum likelihood estimation by following Chen and Hsieh (2011) as:

$$\max_{\phi,\delta} l(\phi, \delta) = \max_{\phi,\delta} \sum_{t=1}^{t=T} ln\pi_{i*,t}^{k} \quad (9)$$

For investigating the significance of the reinforcement learning in the traders' behavior, we first conduct a test for whether the parameters ϕ and δ are significant or not, meaning whether the traders involve the reinforcement learning or make random order choices suggested by the model with zero-intelligent agents, which is discussed by Chen and Hsieh (2011). The zero-intelligence agent model was originally introduced by Gode and Sunder (1993), where agents are not intelligent enough and, therefore, have no ability to learn from past successes. Therefore, the parameters ϕ and δ should be both equal to zero, and thus, the log likelihood value is $l(0,0)$. Given that the estimators of ϕ and δ are denoted as

[27] Action $i*$ is the strategy, which is taken at t. The action includes the strategy, which is and is not executed. We test whether the strategy choice is made based on the past performance or randomly.

$\hat{\phi}$ and $\hat{\delta}$, respectively, the log likelihood function $L(\hat{\phi}, \hat{\delta})$ will take a larger value than $l(0,0)$, when the reinforcement learning effect has a significant impact on improving the fitness of the likelihood function. Therefore, we test the following hypotheses on the randomness of trading behavior:

H_0: $l(\hat{\phi}, \hat{\delta}) - l(0,0) = 0$

H_1: $l(\hat{\phi}, \hat{\delta}) - l(0,0) > 0$

When five order sequences are made randomly, the log-likelihood function $l(0,0)$ takes the value of $\mathrm{T} \times ln\left(\frac{1}{5}\right)$ using the zero-intelligent model. We estimate a set of parameters for each trader, which provide 60 log-likelihood estimates, and conduct the Wilcoxon signed-rank tests to test our hypotheses.

Table 5: Parameter estimates of the reinforcement learning model where ϕ denotes forgetting parameter and δ is the choice intensity parameter.

Mean estimates	**With cancellation**		**No cancellation**		**Periodic clearings**	
	ϕ	δ	ϕ	δ	ϕ	δ
all	0.26	20.70	0.23	38.50	0.24	26.94
Informed	0.58	25.08	0.18	43.20	0.35	68.36
Uninformed	0.13	18.79	0.24	36.49	0.20	9.19

Table 6: Results of the Wilcoxon signed-rank test for reinforcement learning where the null hypothesis is no difference between the order choices by reinforcement learning and by random behavior. Averaged p-values over all traders, informed, and uninformed traders are presented for each market design.

	With cancellation	**No cancellation**	**Periodic clearings**
p-value: RL vs random			
all	<0.01	<0.01	<0.01
Informed	0.02	0.02	<0.01
Uninformed	<0.01	0.01	0.04

Table 5 presents the average estimates of ϕ and δ, and Table 6 summarizes the average p-values of the Wilcoxon signed-rank test over traders. We classify the results by trader type. Our results confirm the significant reinforcement learning effect in all three market designs, and are better suited to our laboratory participants' behavior than the model with zero-intelligent agents (Gode and Sunder, 1993). While the parameter estimates vary across call market designs, the average p-values are less than 5% for any trader type and market design, which supports the Prediction 2. The result indicates that traders do not randomly place their orders, but attempt to take strategies, which produce high performances in the past.

We have compared the model fitness of our reinforcement learning model and the random model in our previous test, and have confirmed that our reinforcement learning model better explains the behavior of our traders than the random model. Meanwhile, our reinforcement learning model assumes the distribution by equation (6), which determines the probabilities for the representative strategies to be selected. The model also assumes that the traders select the strategies based on the past profits, which is illustrated in equation (4). Therefore, we have not confirmed that our laboratory traders follow the probability distribution and refer to the past profits for the determination of their representative strategies. Consequently, we conduct an additional test for investigating whether the predicted strategy selections by the reinforcement learning model do not differ from the actual strategy choices

in our experiments.

We first compute the estimated probabilities of the reinforcement learning model by using the MLE estimates and the accumulated expected profits at the 10^{th} round. We pick up a strategy, which produces the highest estimated probabilities, for each trader at the last rounds, and compare them to the actual strategy choice at the last round in our laboratory experiments. We compare the model predictions and actual strategy choices at the last round, which allows the time for the learning to converge. We conduct the Wilcoxon signed-rank test under the null hypothesis where there is no difference between the strategies with the highest estimated probabilities and the actually selected strategy at the last round. Table 7 summarizes the p-values for the test. The results clearly show that we cannot distinguish the strategies selected by our reinforcement learning model and by the laboratory traders. The results indicate that our reinforcement learning model would not be a wrong model for explaining the strategy choices by our laboratory traders.

Table 7: p-values for the Wilcoxon signed-rank test for whether the highest estimated probabilities among strategies are consistent with the actual strategy selections at the last round.

With cancellation	0.24
No cancellation	0.26
Periodic clearings	0.27

Our test results imply that in a benchmark market with cancellation and a market

without cancellation, traders learn that profits increase by adopting an upward price manipulation strategy with profit intention. In markets with periodic clearings, traders quickly learn that strategies other than price manipulations earn profits. Traders' order choices cause emergent phenomena such as price manipulation and price discovery. Therefore, we conclude that reinforcement learning, which upgrades order choice to improve profitability, is a source of price discovery and price manipulations.

4. Conclusion

We used an experimental approach to evaluate traders' order choices and price discovery under three call auction designs: 1) with cancellation, 2) without cancellation, and 3) with periodic clearings. As a result of reinforcement learning, traders showed a distinct pattern of upward price manipulations in call markets with and without cancellations compared to those in markets with periodic clearings. Gradual price discovery processes were identified in markets with and without cancellations. However, the periodic clearings market showed quick price discovery owing to information release at an early stage in a call auction. The periodic clearings market also showed a larger trading volume than other designs. Therefore, we conclude that major stock exchanges should reconsider the current opening-call auction design and allow more executions than the current setup before the opening price is announced.

We tested whether traders' orders choices are consistent with a reinforcement learning model. It is the subject of our future work where we test it in an experiment with human subjects trading against a reinforcement learning algorithm. Furthermore, Experiments, which test the advantages and disadvantages of the recent change in extending trading hours at the closing auction at the Tokyo Stock Exchange implemented on November 5, 2024 and the role of high-frequency traders at the call action, are also important topics for our future research.

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Appendix 1: Full figures of opening and fundamental prices

Figures A1 and A2 summarize the time-series plot of the fundamental and opening transaction prices in the three groups under the three call auction designs over the trading rounds.

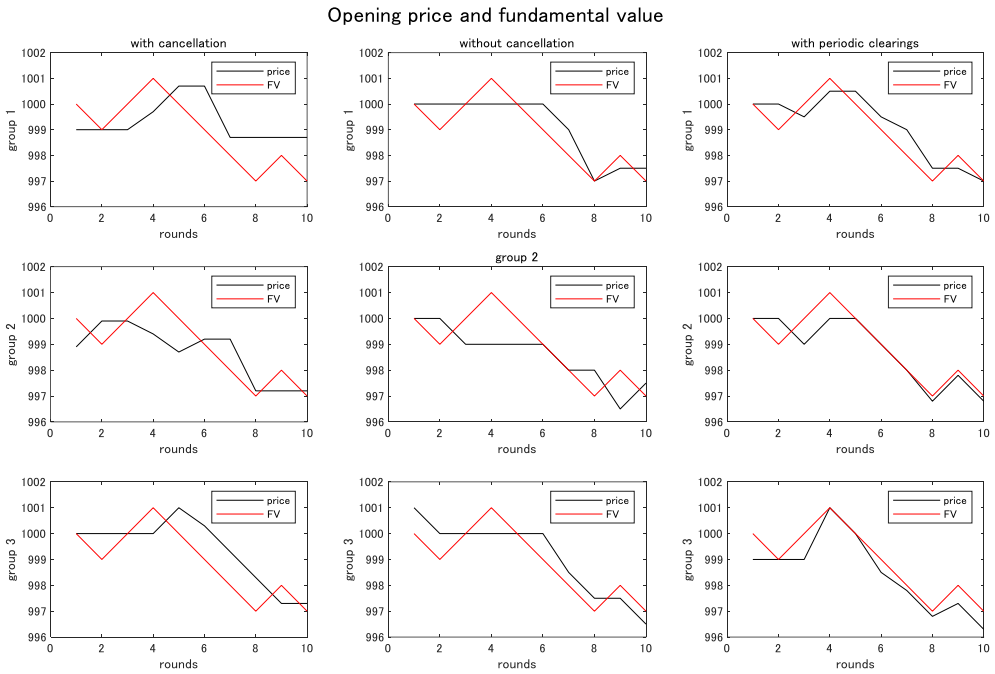


Figure A1: Opening and the fundamental prices in three groups under three call auction designs over trading rounds in the first experiments. The first column is the market with cancellation, the second is the market without cancellation, and the third is the market with periodic clearings.

The figures in the first, second, and third columns plot the fundamental and transaction prices at the end of each round over ten trading rounds in markets with cancellation, without cancellation, and with periodic clearings, respectively. In each column, the prices from the top represent the prices in the first, second, and third markets. Figure A1 is plots of the first and Figure A2 is the second one. Transaction prices are particularly higher than fundamental prices over the last five rounds in the market with cancellations, indicating that traders may place limit orders to increase prices. We observe a weaker tendency for

upward price manipulation in a no-cancellation market, but not in a periodic clearing market.

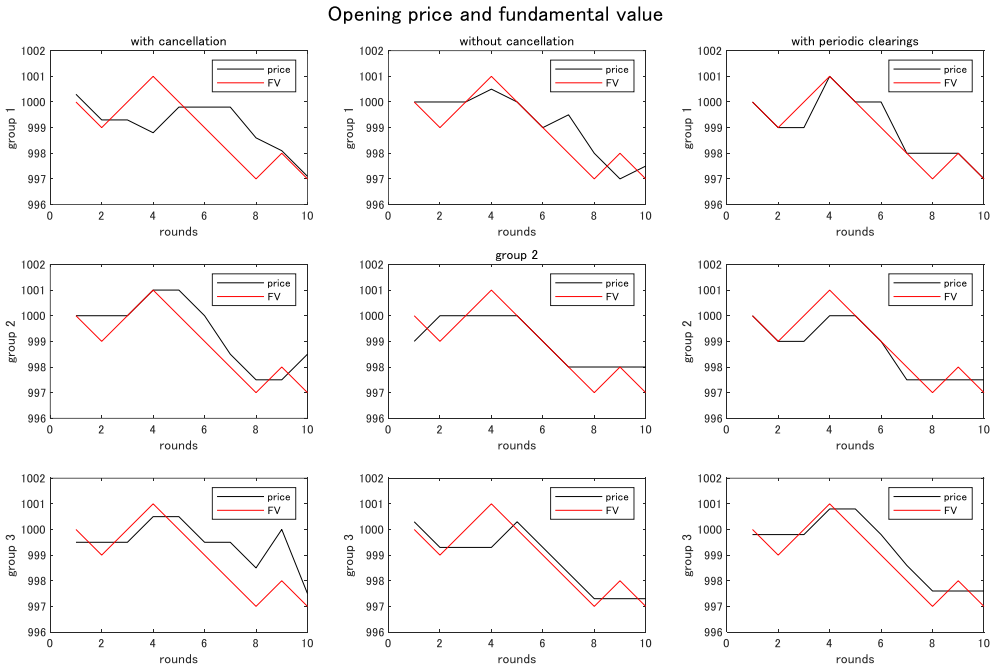


Figure A2: Opening and the fundamental prices in three groups under three call auction designs over trading rounds in the second experiments. The first column is the market with cancellation, the second is the market without cancellation, and the third is the market with periodic clearings.

Appendix 2

Tables A1-A6 summarizes the detailed information on order choices by informed and uninformed traders at the 1-3 and 4-th sections under the three call auction designs, conditioning on the difference between the fundamental price and observed indicative quotes. We further separate the information into those at the first and last five rounds, which are presented in Panels A and B, respectively. The numbers in the tables are the average units of

limit orders over five rounds for a trader placed in the first three sections or last section. In Panel B in Table A1, which is the order choice by informed traders for the last five rounds in a market with cancellation, they are more likely to place Buy+1 or Sell+1 at the first three section (6.91 units for Buy+1 and 4.46 units for Sell+1) and place Sell-1 at the fourth sections (4.63 units for Sell-1), when $v_t - p_\tau < 0$. The tendency is not observed for the first five round in Panel A, because only 0.54 units of Buy+1 and 1.28 units of Sell+1 are placed at the first three sections and 0.76 units of Sell-1 are placed at the last section. This result indicates that they learned that the strategy pushing up the indicative prices at the early stage of a trading round and selling at the last section results in higher returns than the other strategies as the trading rounds proceed. Upward price manipulation by uninformed traders is also observed in the last five rounds in the market with cancellations (Table A2), and by informed traders in the market without cancellations (Table A3).

Table A1 (Panel A): The order choice by the informed traders at the first five rounds in a market with cancellation. The averages of the order units per informed trader placed during the first three sections and at the last section over first five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	1.02	1.67	3.14	1.70	2.66	0.07	2.76	2.00
	=0	0.69	0.24	1.98	0.76	1.73	0.43	0.72	0.33
	<0	0.54	0.12	1.79	1.07	1.28	1.20	0.73	0.58
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.70	1.16	1.37	0.70	0.70	0.04	0.02	1.54
	=0	0.00	0.13	0.96	0.27	0.29	0.07	0.00	0.34
	<0	0.01	0.00	0.94	0.89	1.52	0.51	0.76	0.70

Table A1 (Panel B): The order choice by the informed traders at the last five rounds in a market with cancellation. The averages of the order units per informed trader placed during the first three sections and at the last section over last five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.57	0.24	0.62	0.27	0.40	0.11	0.64	0.46
	=0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	<0	6.91	0.81	2.31	3.61	4.46	2.57	3.11	2.78
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.31	0.10	0.16	0.18	0.10	0.00	0.00	0.12
	=0	0.00	0.00	0.02	0.03	0.29	0.00	0.00	0.02
	<0	0.11	0.00	0.67	3.04	1.88	1.38	4.63	2.30

Table A2 (Panel A): The order choice by the uninformed traders at the first five rounds in a market with cancellation. The averages of the order units per uninformed trader placed during the first three sections and at the last section over first five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.91	0.84	2.15	0.73	1.83	0.25	0.46	0.66
	=0	0.23	0.37	1.27	0.20	1.13	0.66	0.10	0.13
	<0	0.55	0.72	1.67	0.62	2.10	0.79	0.28	0.52
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.42	0.36	1.30	0.35	0.72	0.20	0.20	0.57
	=0	0.03	0.16	0.27	0.11	0.22	0.15	0.06	0.05
	<0	0.15	0.25	1.07	0.55	1.08	0.37	0.40	0.41

Table A2 (Panel B): The order choice by the uninformed traders at the last five rounds in a market with cancellation. The averages of the order units per uninformed trader placed during the first three sections and at the last section over last five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.59	0.41	0.73	0.32	0.68	0.08	0.33	0.36
	=0	0.07	0.00	0.03	0.10	0.14	0.00	0.00	0.09
	<0	1.25	1.07	3.00	1.10	5.50	2.08	1.42	1.49
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.07	0.16	0.38	0.28	0.25	0.13	0.09	0.13
	=0	0.00	0.00	0.07	0.03	0.06	0.00	0.04	0.07
	<0	0.28	0.40	1.35	0.99	2.80	0.79	0.65	0.94

Table A3 (Panel A): The order choice by the informed traders at the first five rounds in a market without cancellation. The averages of the order units per informed trader placed during the first three sections and at the last section over first five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.17	0.54	1.47	0.00	1.14	0.08	0.06	0.00
	=0	0.10	0.32	0.77	0.00	1.14	0.08	0.03	0.00
	<0	0.10	0.16	0.73	0.00	1.01	0.48	0.10	0.00
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.36	0.93	1.53	0.00	0.74	0.04	0.04	0.00
	=0	0.03	0.21	1.02	0.00	1.29	0.27	0.00	0.00
	<0	0.11	0.02	0.66	0.00	1.07	0.58	0.22	0.00

Table A3 (Panel B): The order choice by the informed traders at the last five rounds in a market without cancellation. The averages of the order units per informed trader placed during the first three sections and at the last section over last five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.02	0.09	0.62	0.00	0.22	0.02	0.01	0.00
	=0	0.00	0.00	0.17	0.00	0.22	0.08	0.00	0.00
	<0	0.14	0.02	1.34	0.00	1.96	1.58	0.71	0.00
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.24	0.43	0.97	0.00	0.18	0.00	0.01	0.00
	=0	0.00	0.06	0.40	0.00	1.16	0.11	0.10	0.00
	<0	0.06	0.04	1.34	0.00	1.96	1.48	0.92	0.00

Table A4 (Panel A): The order choice by the uninformed traders at the first five rounds in a market without cancellation. The averages of the order units per uninformed trader placed during the first three sections and at the last section over first five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.27	0.43	1.02	0.00	0.71	0.21	0.16	0.00
	=0	0.07	0.19	0.58	0.00	0.62	0.19	0.00	0.00
	<0	0.14	0.22	1.19	0.00	1.41	0.65	0.19	0.00
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.40	0.60	0.75	0.00	0.61	0.16	0.20	0.00
	=0	0.01	0.16	0.59	0.00	0.50	0.37	0.02	0.00
	<0	0.28	0.11	1.11	0.00	1.25	0.56	0.42	0.00

Table A4 (Panel B): The order choice by the uninformed traders at the last five rounds in a market without cancellation. The averages of the order units per uninformed trader placed during the first three sections and at the last section over last five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.10	0.25	0.73	0.00	0.85	0.06	0.16	0.00
	=0	0.09	0.12	0.70	0.00	0.55	0.20	0.10	0.00
	<0	0.04	0.11	0.60	0.00	0.99	0.80	0.15	0.00
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.40	0.38	1.53	0.00	1.23	0.10	0.20	0.00
	=0	0.03	0.21	0.83	0.00	0.51	0.24	0.17	0.00
	<0	0.10	0.19	0.49	0.00	0.96	0.29	0.18	0.00

Table A5 (Panel A): The order choice by the informed traders at the first five rounds in periodic clearings. The averages of the order units per informed trader placed during the first three sections and at the last section over first five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.68	4.33	1.91	1.27	1.10	0.14	0.00	0.42
	=0	0.09	0.41	2.71	0.89	2.66	0.53	0.06	0.80
	<0	0.01	0.07	1.83	0.49	1.51	2.94	0.03	1.04
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.07	1.53	0.66	0.57	0.82	0.07	0.00	0.29
	=0	0.02	0.31	1.18	0.59	1.22	0.27	0.00	0.61
	<0	0.00	0.04	0.44	0.12	0.27	0.64	0.09	0.26

Table A5 (Panel B): The order choice by the informed traders at the last five rounds in periodic clearings. The averages of the order units per informed trader placed during the first three sections and at the last section over last five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.23	2.76	0.36	0.76	1.07	0.04	0.00	0.27
	=0	0.00	0.51	1.20	0.57	1.54	0.07	0.02	0.90
	<0	0.00	0.00	4.69	0.82	2.54	10.38	1.19	3.83
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.02	1.39	0.21	0.24	0.86	0.08	0.00	0.44
	=0	0.00	0.22	0.72	0.31	0.87	0.28	0.04	0.42
	<0	0.00	0.00	1.57	0.97	0.36	2.50	0.00	0.90

Table A6 (Panel A): The order choice by the uninformed traders at the first five rounds in periodic clearings. The averages of the order units per uninformed trader placed during the first three sections and at the last section over first five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.16	1.10	1.59	0.56	1.02	0.51	0.05	0.33
	=0	0.32	0.75	2.21	1.30	1.90	1.37	0.27	1.42
	<0	0.06	0.55	1.24	0.68	1.30	1.38	0.15	0.72
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.10	0.49	0.51	0.32	0.48	0.21	0.01	0.47
	=0	0.04	0.47	0.58	0.38	0.70	0.31	0.08	0.49
	<0	0.03	0.32	0.52	0.44	0.50	0.59	0.05	0.43

Table A6 (Panel B): The order choice by the uninformed traders at the last five rounds in periodic clearings. The averages of the order units per uninformed trader placed during the first three sections and at the last section over last five rounds are computed.

1st-3rd sections		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.32	1.31	2.66	1.26	1.91	1.90	0.13	1.82
	=0	0.06	0.60	1.48	0.59	1.37	0.82	0.30	0.57
	<0	0.05	0.54	0.87	0.47	1.57	1.26	0.11	0.63
4th section		**Buy+1**	**Buy0**	**Buy-1**	**Buy cancel**	**Sell+1**	**Sell0**	**Sell-1**	**Sell cancel**
$v_t - p_\tau$	>0	0.18	1.23	1.24	0.90	0.88	0.76	0.14	1.13
	=0	0.02	0.11	0.33	0.16	0.30	0.18	0.09	0.14
	<0	0.00	0.35	0.20	0.20	0.38	0.24	0.04	0.40