PROGRAMMING AN EXPERTIZED TRADING AGENT: FROM A PERSPECTIVE OF MARKET MICROSTRUCTURE

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This paper investigates market microstructure in an experimental artificial futures market using the data generated by the submitted trading agents in two laboratory experiments. Since our previous analyses reveal that the price series successfully replicate so-called "stylized facts" in some regards, the aim of this study is to check whether such phenomena are also observed at micro-level. Our empirical results confirm that although there are locally mispricing effects of several trading agents, in most cases the market liquidity improves over the rounds. Future perspectives of agent-based computational finance and experimental economics are also discussed.

Keywords: Strategy experiment; Artificial market; Market microstructure.

1. Introduction

"UnReal Market as an Artificial Research Test bed" (hereafter U-Mart) is an artificial futures market in which human subjects and trading agents take part in together [a] and lots of contributions have been made in economic and engineering literature. For instance, Sato et al. have clarified the differences between the behavior of human subjects that of trading agents or profitability of simple technical trading rules [24]. It has been also widely used in educational program for teaching computational economics.

However, there seems few researches which report quantitative analytical results of laboratory and computational experiments. A possible reason is that the data are limited in terms of quantity of quality, even there are plenty of micro-level data available, because total trading days or experiments are small in order to avoid that the human subjects become bored. Or futures trading itself is not so popular for human subjects. Therefore, it appears difficult to judge what and how U-Mart has accomplished and what is required. So far, we have implemented some strategy experiments in U-Mart with human subjects in order to investigate market dynamics created by submitted strategy files and have confirmed that the time series data support so-called stylized facts in some regards and that experiments of human subjects seem to make the prices be closer to a theoretical value [29]. But the detailed investigation such as market impact of each participant or market microstructure has not been examined yet[b]. In other words, it is unclear whether those results are aleatory or from the expertization of human subjects.

There are several researches on laboratory market with human subjects and trading agents. Das et al. have implemented a co-existence trading market, extending the flamework by Smith et al. [8]. But the market is not a double-auction one unlike U-Mart. Glossklags and Schmidt have observed how the existence of trading agents affects the behavior of human subjects and thereby the market dynamics [10]. The most apparent difference from our framework is that human subjects also created their trading agents, not we offered simple ones. On the other hand, Hommes et al. or Sonnemans have conducted strategy experiments in a simple asset pricing model in order to test whether the asset price converges to a theoretical value and

[a]For more information, see official website [28] or the book [25].

[b]Biais et al. [3] and Madhavan [11] have independently provided great reviews and Sunder has briefly summarized the results of market microstructure in experimental economic literature.

how each strategy file evolve over the round [13,26]. However, since their experiments have assumed a particular utility function in the economy, the excess demand of each strategy file is determined automatically, namely they were not designed so as to investigate market microstructure.

In recent years there have been several collaborations between experimental/cognitive economics and agent-based computational economics. One of the attempts is to incorporate the findings of experiments into the frameworks of agent modelling and vice versa [9]. Therefore, this paper tries to clarify whether our earlier results would be observed at the level of market microstructure and considers what U-Mart should be required in agent-based computational finance and experimental economics.

The rest of this paper is organized as follows: The next section explains experimental design. Section 3 shows some computational results focusing on market microstructure and discusses future perspectives of U-Mart. Section 4 gives some concluding remarks.

2. Experimental Design

The experiment was implemented as a part of a course “System Modeling,” an engineering introduction to computational intelligence and systems science in the graduate school of science and engineering program at Tokyo Institute of Technology. Participation was a course requirement for master’s course students in this department. Almost all the students had no prior knowledge about financial markets, but several students had some skills in computer programming. Note that this course does not intend to teach how to make more money in financial markets.

2.1. *Tutorial*

The objectives of this tutorial were to provide the students with some experiences with operating U-Mart and to give lectures about computer programming. After installing U-Mart for each personal computer, three introductory sessions were held as follows: In the first session, a trading pre-contest was implemented. In this session, only human subjects took part in the artificial market in order to grasp how a futures market ran. In the second and the third sessions, computer programming lectures were given. While the students were taught elementary JAVA programming in the first half of the classes, they learned how to create a machine agent using a template file distributed in the second half of the lecture.

A trading agent in the template file monitors past 120 spot prices and 60 futures ones. It knows its current position, if the position is long (short) then the value is positive (negative), cash, and the number of today’s remaining bid/ask matching on a board. The decision rule is how many assets it is going to buy or sell at a certain price, namely limit order. But since the behavior is arbitrary, a trading agent in this file is considered as a zero-intelligent trader or a random agent. More concretely, it thinks that the futures price follows a random walk with the previous price as mean and a pre-determined value as standard deviation. The next position of this agent is also determined randomly, but if both the current and the expected position are over (under) a threshold value then the agent does nothing.

2.2. *Strategy experiment and computational run*

The experiments lasted two weeks, each of which had one round. In each round, subjects had to submit a strategy file in JAVA. Students could submit their own strategy anytime before the previous day of the contest. In the first round subjects had about two weeks to create agents, while in the second round they had only one week to revise their strategy. In other words, they could make machine agents after taking all the introductory lectures. The number of submissions were 87 and 89 of 89 registrations respectively. The instructors and two teaching assistants checked these strategies for not having any bug or error. As a result, two strategies were excluded in the round one, and three were in the round two.

In each round we implemented an experimental asset market with human subjects and submitted strategies only one time and a computer simulation with only machine agents 10 times. The reason why we could not conduct iterated experiments in case of the market with students is human subjects surely learn from the past events. The two kinds of time series spot data, the one is NIKKEI225 and the other is USD/JPY, were converted such that the mean and the variance were all equal to those of originally installed data, J30. Since each simulation run had 20 days each of which had eight bid/offer matching done on a board, one matching could be considered as one-hour long. Moreover, the human subjects had about 20 seconds in each matching for their decision makings. Market participants were allowed to do infinitely short-selling so long as their budget permitted, but the ones who had gone bankrupt could not take part in the market anymore (other setups are described in Table 1). At the end of each round, the subjects received open information about all the source codes, order information, historical data (price and volume), and the rankings of the strategies and human subjects by final wealth. After experiment students revised their strategy based on the results and submitted for the next competition (even if the third round did not take place).

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Table 1 is here.

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Problems often addressed by many researchers are motivations of subjects and attempts to obfuscate the market. The former problem would be overcome by letting the participants be financially motivated, namely instructors announced that the most profitable human subject and the student who created the winner agent could receive sweet treats for the amount of 10 dollar. On the other hand, with respect to the latter obstacle we did not prohibit them from making a destabilizing machine agent because we knew that such an attempt would be quite hard to succeed due to the existence of nearly 100 market participants including originally installed machine agents [c] as Hommes et al. have pointed out [13]. Fortunately, the strategies submitted which will be explained in the next section were ordinal.

[c]They were as follows: one trend follower, one contrarian, two random walkers, two RSI traders, two moving average strategies, one arbitrager (he/she focuses on the spread between spot price and futures price), and one stop loss trader. For more details, see the textbook [25].

3. Results

3.1. *How are agents created?*

In agent-based computational finance models, the characters of agents are mostly bounded rational, namely the characters of agents are usually fundamentalists, chartists, deterministic, or ones using evolutionary algorithm. Before presenting the results of market dynamics, we will briefly review general distinctions of submitted strategies.

Table 2 shows main characteristics of the strategy files. About one-thirds are arbitragers, namely they think that the futures price will eventually converges to the spot price. The rest strategies are something like Markov-property or moving average ones. That is to say, the former strategies can be considered as ones with characters of fundamentalists and the latter ones are chartists. Around 10 strategies employ stop loss orders, which is because the U-Mart allows market participants to do more than two orders at a time. Finally, around 10 other strategies are more complex ones, namely they consist of neural-network program, classifier systems, or reinforcement learning.

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Table 2 is here.

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3.2. *Market dynamics*

Figure 1 shows a snapshot of generated sample paths. Panel a contains time series of spot and futures price, and panel b has trading volumes in each session. Unlike the laboratory experiments with human subjects, there were no price jumps in the economy because market order was not allowed for trading agents.

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Figure 1 is here.

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In order to check if the market with only trading agents successfully led the dynamics observed in actual financial markets, namely "stylized facts" [12,17], we conducted the following time series analyses [29]:

- Exchange rates and stock prices have almost unit roots.
- Returns have fat-tailed distributions.

- Returns per se cannot be predicted, namely they have almost zero autocorrelations.
- Return distribution shows long memory, namely absolute or squared returns are significantly positive and decrease slowly as a function of the lags.

We observed that the time series supported the unit root property and fat-tailed distributions but did not replicate long memory properties. This is because the number of observations is too scarce to be analyzed. Instead, we also confirmed that some trading experiments and knowledge of computer programming seemed to make the prices be closer to a theoretical value.

3.3. *Market microstructure and expertization*

The time series reviewed in the preceding part appears to lead the dynamics observed in real financial markets in some regards. However, that does not always mean the expertization of human subjects. Therefore, in this part of the section, we need to investigate market microstructure of each sample path in order to check whether the trading agents become more sophisticated or their behavior is not redundant employing the following four measures:

- Bid-Ask spread
  Bid-Ask spread is usually the difference between the lowest ask available and the highest bid available calculated as

$$\text{raw spread}_t = P_{ask,t} - P_{bid,t} \tag{1}$$

  where $P_{ask,t}$ and $P_{bid,t}$ is the ask price and bid one at time t respectively. While the measure above represents raw differences between the two quotes, other measures take into consideration the ratio of mid-point, effectiveness [16], or all the unsettled and new orders in the market [6] as

$$\text{mid-point spread}_t = \frac{2(P_{ask,t} - P_{bid,t})}{P_{ask,t} + P_{bid,t}} \,, \tag{2}$$

$$\begin{aligned} \text{effective spread}_t &= \frac{2\sum_{i=1}^{N} |P_t - (P_{ask,t} + P_{bid,t})2/|Q_{t,i}}{\sum_{i=1}^{N} Q_{t,i}} \text{ (per day)} \,, \\ &= |P_t - \frac{P_{ask,t} + P_{bid,t}}{2}| \text{ (per session)} \,, \end{aligned} \tag{3}$$

$$\text{weighted spread}_t = \frac{\sum_{i=1}^{M} P_{ask,t,i} \cdot D_{ask,t,i}}{\sum_{i=1}^{M} D_{ask,t,i}} - \frac{\sum_{i=1}^{M} P_{bid,t,i} \cdot D_{bid,t,i}}{\sum_{i=1}^{M} D_{bid,t,i}} \,, \tag{4}$$

where N is the number of sessions in a day, M is the number of prices offered and $Q_{t,i}$ is the trading volume traded in the i's session at day t, and $D_{t,i}$ is the orders submitted to the market in the i's session at day t.

- Market depth
  Market depth is the quantity of an order which is required to change the prices calculated as follows:

$$\text{depth}_t = D_{ask,t} + D_{bid,t} \tag{5}$$

  where $D_{\cdot,t}$ is the quantity of bid or ask order at $P_{\cdot,t}$. That the market depth is larger means that the market is liquid, namely a large order is necessary to move the market.

- Kyle's measure [15]
  Kyle has developed an illiquidity measure, called λ, which measures how large changes in prices are while the volume of a fixed quantity is formed. In this study, we conduct a linear regression with zero interceptions as

$$\lambda_t = \frac{\sum_{i=1}^{N} |R_{t,i}| \cdot Q_{t,i}}{\sum_{i=1}^{N} Q_{t,i}} \tag{6}$$

  where $R_{t,i}$ and $Q_{t,i}$ is the session i's return of an asset price and trading volume at time t respectively, and N is the number of sessions/contracts in a trading day. A small λ means that the market has a high liquidity, i.e. larger orders are contracted in a small change in prices.

- Amihud's measure [2]
  Amihud has crated an illiquidity measure, called formally *ILLIQ*, which is the daily ratio of absolute return of a risky asset to its currency volume, averaged over some period as follows:

$$ILLIQ_t = \frac{1}{N} \sum_{i=1}^{N} \frac{|R_{t,i}|}{P_{t,i} \cdot Q_{t,i}} \tag{7}$$

  where N is the number of sessions per day. As well as Kyle's λ, a small $ILLIQ$ means that the market is more liquid.

Figure 2 and Tables 3, 4, 5, and 6 show fundamental statistics of four bid-ask spread of each sample path. With respect to mean values, those in Round 1 seem smaller than those in Round 2 except Table 6. In other words, Tables 3, 4, and 5 appear that the trading and programming skills of human subjects did not become expertized. Especially, the maximum values in Round 2 are much larger than those in Round 1. But this is due to some statistical outliers or because some trading agents mispriced the future prices. For instance, as in Table 7a, while the highest price of remaining bid orders became 3376 after the bid orders at the price of 3376 or higher were all contracted, 200 ask orders at the price of 4960 were still on the board. In this case, the bid-ask spread became much larger. Although we did not investigate each strategy file in greater detail, the highest ask was from the mispricing of a trading agent because the difference between the price and the second highest price is over 1500. Instead, the differences between weighted ask prices and those bid ones in Round 2 are much smaller than those in Round 1 (Table 6, Figure 5). These two exhibits explain the following two points; First, some orders in Round 1 were redundant but did not affect the bid-ask spread. Second, mispricing of a few strategy files worsened the bid-ask spread in the market, but the distributions of expected prices became more sophisticated in Round 2. Thus, in this regard, it can be said that the human subjects learned to write a more sophisticated trading agent.

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Figures 2 and 5 are here.

Tables 3, 4, 5, 6, and 7 are here.

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Second, Figure 3 and Table 8 summarize market depth of each round. The empirical findings are basically the same as the case of bid-ask spread, i.e. the market depth in Round 1 seems larger than that in Round 2. But, as Figure 3 precisely tells, there are several unrealistic figures observed in Round 1. This is because some trading agents submitted huge orders and as a result most of their orders were still unsettled (Table 7b). It is true that the similar situations are observed in Round 2, but the market microstructure in Round 2 sometimes seems normal when we take into consideration the fact that the maximum values of depth in sample paths 6, 9, and 10 are much smaller. Therefore, that the market depth, namely the market liquidity, is small does not mean that the behaviors of trading agents are not random or that the market is still thin.

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Figure 3 is here.

Table 8 is here.

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By the way, Table 9 presents the correlation between bid-ask spread and market depth. Usually those two measures are negatively related to each other, namely when a bid-ask spread is small (large), the corresponding market depth is likely to large (small). In most cases, the values are negative, but they are not significant level. Possible reasons are that the number of observations are not plenty enough or that there are sometimes huge, but meaningless orders in the market. In other words, even if the bid-ask spread is small, the large remaining orders weakens the correlation. Thus we need to implement long run simulations to obtain more data. This is one of the problems which agent-based computational finance and experimental economics should resolve.

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Table 9 is here.
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Third, Figure 4 and Tables 10 and 11 illustrate daily market illiquidity measures both of which are small if the market has more liquidity. Now, we easily confirm that the values in Round 2 are significantly smaller than those in Round 1. Besides, the fact that both the tables do not provide with any abnormal number implies that occasional mispricing did not affect the market liquidity. In summary, these two measures support our earlier results, i.e. the human subjects got accustomed to trading and programming. Interestingly, the correlation between Kyle's λ and Amihud's illiquidity measure becomes worse over the rounds unlike the report in Amihud 12. To our regret, since we did not find any reason from our past and present investigation, more efforts should be done in the near future.

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Figure 4 is here.
Tables 10, 11, and 12 are here.
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3.4. *Discussion*

It has been about a decade since the birth of U-Mart and lots of contributions have been made in economic and engineering literature. At the same time, it has been widely used in educational program for teaching computational economics. However, our computational results provide with some open questions. In this part of the section, we address what U-Mart is required for the future.

First, we guess that not allowing trading agents to cancel their past and unsettled orders may worsen some bid-ask spread and the market depth. We should implement another experiment taking into consideration this effect.

Second, as well as cancellation of orders, when implementing a laboratory experiment with human subjects and trading agents, U-Mart project members should make it possible to standardize the experimental designs such as market order or information availabilities. So far as we know, only human subjects are allow to cancel their mistaken/undesirable orders, submit market orders, or monitor the board in the market. This would hinder detailed investigation except the one on information asymmetry [23].

Third, since U-Mart is an artificial 'futures' market, it would be fine if the spot asset is tradable in the market. As some experimental economic researches, introducing futures market leads the prices in spot market to fundamental values and then diminishes the bubble trend [19]. If it becomes possible to trade not only futures but also spot asset in U-Mart, researchers will be able to re-confirm the market microstructure in another way [20].

Fourth, more comparison with other studies are also required; For instance, since the time series data used in the round one is NIKKEI 225, the comparisons of the computational results and the empirical findings (e.g. [14]) would be helpful to improve the design of laboratory experiment and computer simulation. Or, that the trading agent is allowed to do only limit orders means that it is possible to confirm what is different from the market microstructure in actual limit order books (e.g. [22]). On the other hand, in the experimental economic literature, Bloomfield and O'Hare [4] and Bloomfield et al. [5] have investigated the effects of information disclosure on market microstructure and welfare of market participants in an electronic limit order market. Besides, Raberto et al. [21], and Consiglio and Russino [7] have employed agent-based approach to investigate the relations between market liquidity and prices. Especially, since Genoa artificial stock market in Raberto et al. [21] enables the agents to do a market order, it is necessary to check whether the same computational results are obtained in the U-Mart and vice versa.

4. Concluding Remarks

This paper investigates market microstructure in an experimental artificial futures market using the data generated from the submitted trading agents in two laboratory experiments. Since our previous analyses reveal that the price series successfully replicate so-called "stylized facts" in some regards, the aim of this study is to check whether such phenomena are also observed at micro-level. Our extended analyses support that if the subjects had some knowledge and experiences of financial markets then the simulations seemed to lead similar dynamics observed in actual financial data. Especially, although some mispricing effects failed to replicate the bid-ask spread and the market depth properly in some regards, the appropriate weighted bid-ask spread and two market illiquidity measures, Kyle's λ and Amihud's illiquidity measure, are observed.

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Table 1. Experimental setup.

Item	Memo
Initial wealth	One-billion
Initial holdings	No
Ordering for machine agents	Limit order only
Cancellation of orders	Not allowed
Risk free rate	0.1
Trading unit	1000-fold
Commission	Nothing
Credit taking	Up to 30-million

Table 2. Characteristics of submitted strategies.

	Round 1	Round 2
Random	5	2
Stop loss	10	11
Trend follower	20	20
Contrarian	4	5
Moving average	22	20
Spot-futures spread	28	31
Others	8	10
Total strategies	87	89

Table 3. Bid-Ask spread (Raw value)

a. Round 1

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	2.94	13.67	0	1	1	2	167
2	3.15	12.46	0	1	1	2	154
3	2.09	3.04	0	1	1	2	24
4	2.90	13.25	0	1	1	2	167
5	1.92	2.62	0	1	1	2	24
6	3.48	13.85	0	1	1	2	167
7	3.26	12.63	0	1	1	2	150
8	1.94	2.74	0	1	1	2	17
9	3.93	14.78	0	1	1	2	167
10	1.88	2.79	0	1	1	2	26

b. Round 2

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	23.17	152.86	0	1	1	3	1584
2	15.63	150.01	0	1	1	3	1890
3	9.61	68.34	0	1	1	3	842
4	4.40	16.92	0	1	1	3	204
5	3.36	7.60	0	1	1	3	71
6	8.34	66.26	0	1	1	3	836
7	16.10	145.23	0	1	1	3	1828
8	4.65	18.39	0	1	1	3	205
9	3.90	9.81	0	1	1	3	74
10	4.10	17.18	0	1	1	3	207

Table 4. Bid-Ask spread (Mid value)

a. Round 1

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	1.35	6.30	0.00	0.42	0.48	0.95	77.58
2	1.47	5.81	0.00	0.43	0.49	0.94	71.76
3	0.99	1.51	0.00	0.42	0.49	0.97	12.28
4	1.35	6.15	0.00	0.43	0.48	0.98	77.58
5	0.90	1.28	0.00	0.43	0.49	0.97	12.28
6	1.62	6.41	0.00	0.43	0.49	0.97	77.58
7	1.50	5.84	0.00	0.44	0.49	0.89	69.96
8	0.91	1.29	0.00	0.41	0.48	0.95	8.72
9	1.82	6.80	0.00	0.43	0.48	0.97	77.58
10	0.88	1.33	0.00	0.41	0.48	0.94	12.79

b. Round 2

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	6.56	40.71	0.00	0.30	0.33	0.77	380.03
2	3.61	30.32	0.00	0.30	0.33	0.73	376.49
3	2.84	19.12	0.00	0.30	0.33	0.93	229.30
4	1.44	6.46	0.00	0.30	0.34	0.92	79.16
5	0.98	2.26	0.00	0.30	0.33	0.94	23.65
6	2.35	18.07	0.00	0.30	0.34	0.92	227.86
7	3.80	29.15	0.00	0.30	0.33	0.98	360.41
8	1.50	6.75	0.00	0.30	0.33	0.90	79.53
9	1.14	2.77	0.00	0.30	0.33	0.99	22.67
10	1.35	6.55	0.00	0.30	0.34	0.99	80.28

Table 5. Bid-Ask spread (Effective spread)

a. Round 1

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	11.49	17.14	0.00	1.50	7.00	14.13	134.50
2	12.46	17.98	0.00	1.50	8.25	16.63	143.00
3	11.40	16.93	0.00	1.50	7.00	14.13	142.50
4	11.57	16.75	0.00	1.50	7.50	14.50	146.50
5	12.60	20.10	0.00	0.88	8.00	16.75	162.00
6	12.13	16.41	0.00	1.50	6.75	16.50	125.00
7	11.38	17.04	0.00	1.50	7.25	14.50	144.00
8	12.14	18.01	0.00	1.50	8.00	13.50	132.50
9	12.77	18.02	0.00	1.50	9.00	15.50	141.50
10	11.72	19.35	0.00	1.00	7.00	13.50	162.00

b. Round 2

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	30.03	77.32	0.00	2.00	13.50	27.75	732.00
2	27.76	79.18	0.00	3.38	14.00	29.63	961.00
3	24.08	41.05	0.00	2.50	14.50	29.63	403.00
4	21.74	26.00	0.00	4.00	14.50	29.13	143.00
5	22.57	28.12	0.00	3.25	13.25	29.50	169.00
6	22.36	37.70	0.00	2.88	13.25	27.50	397.00
7	27.99	81.39	0.00	4.50	17.25	30.63	1008.00
8	21.32	29.00	0.00	2.38	12.50	26.00	173.00
9	20.70	23.54	0.00	4.50	13.50	25.50	108.50
10	21.73	25.81	0.00	2.88	14.50	29.50	137.00

Table 6. Bid-Ask spread (Weighted value)

a. Round 1

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	996.41	153.28	92.71	977.29	1032.43	1075.83	1135.19
2	852.21	184.37	104.27	732.63	884.07	1003.65	1123.06
3	842.80	228.08	81.69	711.79	901.97	1025.61	1128.91
4	999.18	143.13	101.65	972.27	1024.93	1073.52	1128.17
5	959.47	210.60	122.11	961.56	1035.83	1080.80	1132.25
6	966.05	195.89	123.52	960.72	1033.04	1076.68	1136.92
7	965.21	195.84	103.73	959.46	1026.08	1076.39	1132.75
8	937.22	256.90	81.74	962.63	1030.94	1072.30	1136.96
9	960.40	194.06	135.77	956.82	1014.17	1073.87	1131.65
10	818.26	218.78	90.73	631.41	866.71	1017.60	1115.42

b. Round 2

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	380.86	178.19	−30.45	255.71	345.24	497.42	958.81
2	396.50	188.27	70.56	266.82	357.75	496.56	1068.14
3	399.14	177.39	124.56	275.48	363.55	508.56	1033.15
4	398.39	174.59	22.42	269.81	354.71	527.09	909.45
5	393.74	170.38	−64.71	267.85	379.57	504.90	884.12
6	414.01	148.66	15.65	287.34	381.95	537.59	995.52
7	401.94	186.07	78.73	263.32	352.01	515.48	1000.53
8	402.37	190.72	31.02	259.24	370.34	521.62	988.30
9	417.67	188.68	−111.18	271.91	384.31	543.89	1025.32
10	412.42	177.27	97.52	281.76	367.50	543.55	984.92

Table 7. Examples of the limit order book

a. Wide bid-ask spread

Before contract			After contract		
Bid	Price	Ask	Bid	Price	Ask
7792	3386−	632	10	3376	0
0	3391	10	0	3391	0
50	3394	0	0	3394	0
38	3397	0	0	3397	0
57	3401	0	0	3401	0
116	3423	0	0	3423	0
27	3427	0	0	3427	0
354	3561	0	0	3561	0
0	4960	200	0	4960	200

b. Huge order unsettled

Bid	Price	Ask
1568	1940−	
14	1941	
49520	1942	
	1943	10
	1944	6
	1945+	52292

Table 8. Market depth

a. Round 1

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	13966.38	65825.92	0.00	61.75	157.00	344.25	411099.00
2	10304.28	56513.16	0.00	55.25	146.00	311.75	374437.00
3	16688.54	81688.71	0.00	54.00	152.00	312.75	727892.00
4	6577.53	36486.69	0.00	67.50	150.00	273.75	316611.00
5	18077.68	92702.55	0.00	83.50	168.00	354.50	730432.00
6	11784.24	58471.56	0.00	82.75	143.00	283.25	418633.00
7	15420.16	73022.77	0.00	77.00	152.50	323.25	473004.00
8	22463.97	99150.62	0.00	69.50	129.50	334.50	727292.00
9	9049.56	48289.38	0.00	56.75	117.50	236.25	408978.00
10	17221.81	92618.46	0.00	83.75	164.50	340.50	730482.00

b. Round 2

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	5488.78	37791.34	0.00	79.00	176.00	424.75	280749.00
2	3896.57	32185.41	0.00	77.00	184.50	396.00	290897.00
3	2096.69	22871.15	0.00	74.00	181.50	390.50	289560.00
4	2117.66	23026.47	0.00	68.50	142.00	394.25	291516.00
5	9360.79	60497.52	0.00	79.50	157.50	342.50	581124.00
6	242.23	276.08	0.00	71.50	145.00	353.25	1757.00
7	2094.49	22498.80	0.00	72.75	176.50	444.75	284874.00
8	8923.84	57576.04	0.00	67.75	133.50	343.00	553698.00
9	288.33	390.83	0.00	53.50	134.00	328.25	2192.00
10	270.17	295.07	0.00	69.00	173.50	367.00	1546.00

Table 9. Correlations between bid-ask spread and market depth

a. Round 1

Sample path	Raw	Effective	Mid-point	Weighted
1	−0.032	−0.154	−0.031	−0.183
2	−0.027	−0.068	−0.026	−0.153
3	−0.061	0.370	−0.024	−0.404
4	−0.023	−0.128	−0.023	−0.357
5	−0.096	0.688	−0.022	−0.336
6	−0.028	−0.139	−0.027	−0.111
7	−0.043	−0.152	−0.041	−0.096
8	−0.115	0.399	−0.071	−0.524
9	−0.018	−0.026	−0.019	−0.237
10	−0.114	0.723	−0.078	−0.211

b. Round 2

Sample path	Raw	Effective	Mid-point	Weighted
1	−0.023	−0.032	−0.024	−0.205
2	−0.013	−0.013	−0.014	−0.183
3	−0.011	0.010	−0.012	0.010
4	−0.016	0.024	−0.014	0.018
5	−0.066	0.250	−0.052	−0.263
6	−0.039	−0.068	−0.037	−0.242
7	−0.008	−0.022	−0.008	−0.034
8	−0.038	0.261	−0.028	−0.242
9	0.020	−0.155	0.017	0.020
10	0.234	0.089	0.240	−0.108

Table 10. Kyle's λ (Daily, $\times 10^{-4}$)

a. Round 1

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	4.04	0.95	2.46	3.23	4.10	4.83	5.64
2	4.01	0.95	2.45	3.05	4.10	4.69	5.54
3	4.06	1.13	2.47	3.05	4.09	4.69	6.99
4	3.99	0.98	2.47	3.24	3.94	4.59	6.45
5	4.01	1.00	2.46	2.99	4.23	4.64	6.13
6	4.01	1.00	2.46	3.31	4.18	4.56	6.45
7	4.00	0.90	2.47	3.30	4.08	4.61	5.70
8	4.05	0.92	2.44	3.11	4.14	4.75	5.69
9	4.07	0.96	2.46	3.22	4.16	4.72	5.75
10	4.04	1.14	2.46	3.02	4.04	4.62	6.80

b. Round 2

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	3.36	1.13	1.67	2.54	3.18	4.01	5.51
2	3.33	1.04	1.70	2.61	3.19	3.99	5.18
3	3.34	1.14	1.83	2.43	3.13	4.08	5.50
4	3.20	1.14	1.88	2.25	2.89	3.77	5.60
5	3.42	1.10	1.73	2.63	3.32	4.06	5.33
6	3.50	1.17	1.80	2.70	3.28	4.03	5.74
7	3.27	1.09	1.74	2.33	2.97	3.84	5.21
8	3.39	1.15	1.88	2.50	3.24	4.10	5.31
9	3.56	1.28	1.96	2.61	3.19	4.51	5.92
10	3.47	1.12	2.02	2.70	3.23	4.19	5.61

Table 11. Amihud's illiquidity (Daily, $\times 10^{-9}$)

a. Round 1

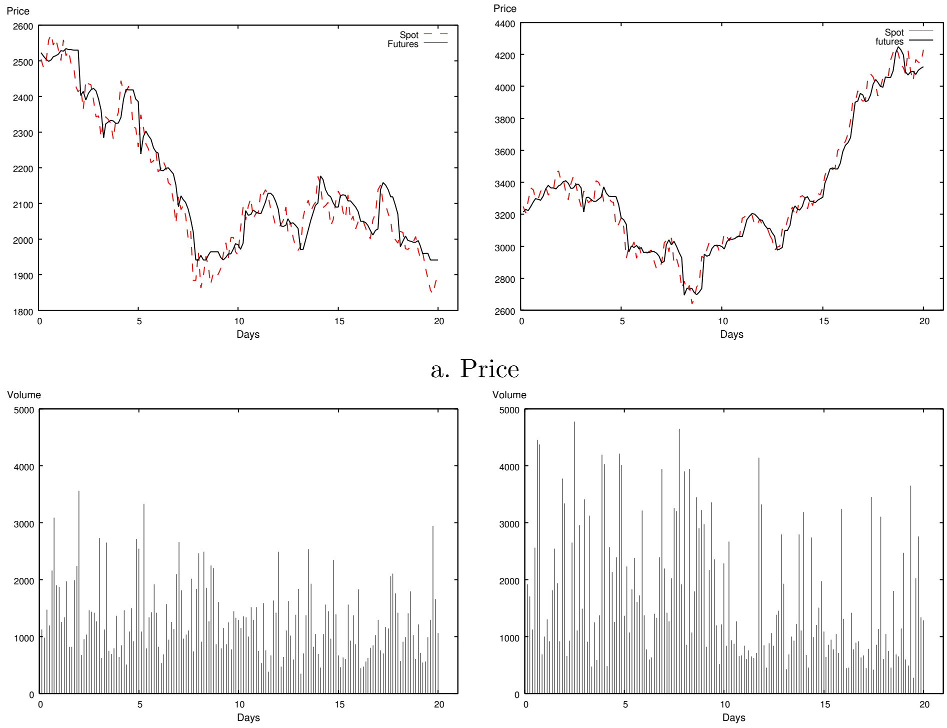
Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	6.83	1.90	2.88	5.72	7.21	7.70	10.55
2	6.83	2.20	2.83	5.68	6.60	7.95	10.65
3	6.82	2.39	2.58	5.49	6.69	8.27	12.00
4	6.44	1.55	2.87	5.93	6.63	7.37	9.26
5	6.44	1.93	2.83	5.30	7.01	7.76	10.14
6	6.83	1.87	2.89	5.96	6.99	8.24	9.50
7	6.39	1.75	2.87	5.36	6.53	7.55	9.67
8	6.62	1.92	2.80	5.79	6.94	7.55	9.77
9	6.52	1.71	2.81	5.42	6.88	7.70	9.31
10	6.75	2.49	2.83	5.78	6.21	7.50	13.94

b. Round 2

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	3.63	1.07	1.78	2.87	3.77	4.26	5.77
2	3.83	1.31	1.76	2.70	4.01	4.67	6.25
3	3.78	1.28	1.74	2.89	3.95	4.41	5.99
4	3.92	1.32	1.74	2.52	4.27	4.90	4.30
5	3.78	1.20	1.73	2.94	3.63	4.36	6.38
6	4.10	1.30	1.90	3.09	4.41	4.90	6.30
7	3.68	1.30	1.52	2.40	4.02	4.56	6.32
8	4.04	1.50	1.80	2.66	4.12	4.69	7.25
9	4.05	1.15	1.80	2.95	3.78	5.19	6.92
10	3.63	1.21	1.76	2.69	3.55	4.46	5.95

Table 12. Correlation between Kyle's λ and Amihud's illiquidity.

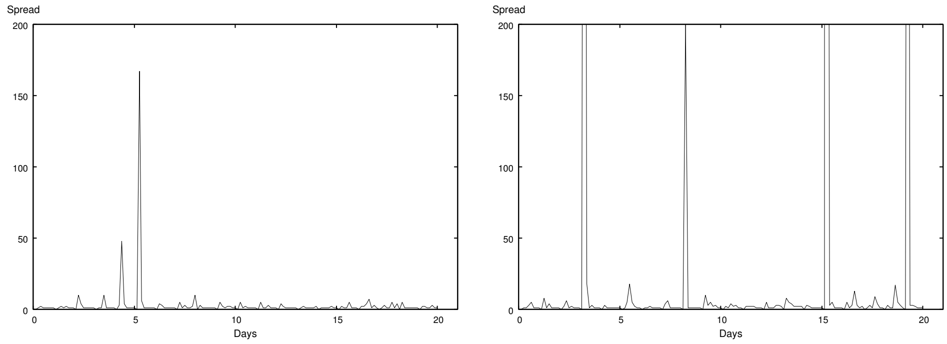
Round	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	0.764	0.075	0.614	0.724	0.761	0.808	0.862
2	0.633	0.132	0.408	0.513	0.691	0.734	0.785



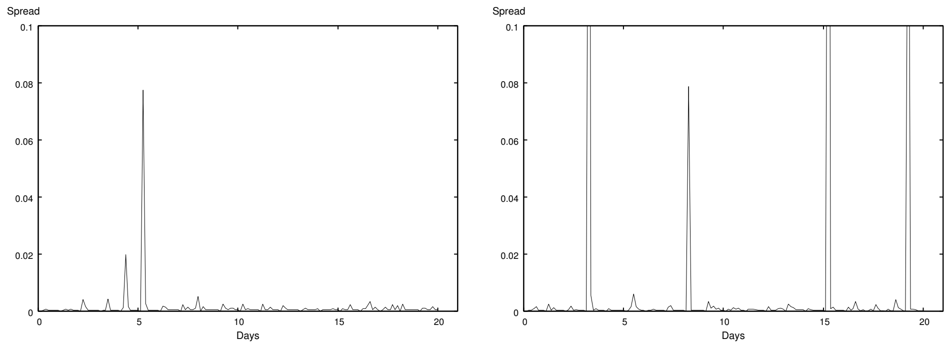
a. Price

b. Volume

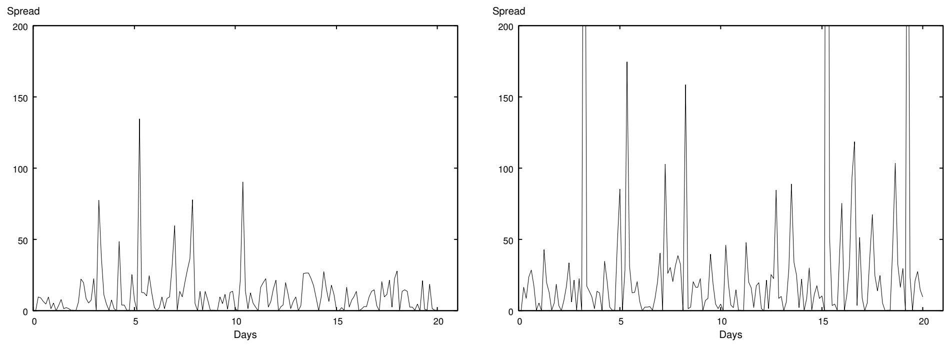
Fig. 1. Market dynamics (Left panel: Round 1, Right panel: Round 2)



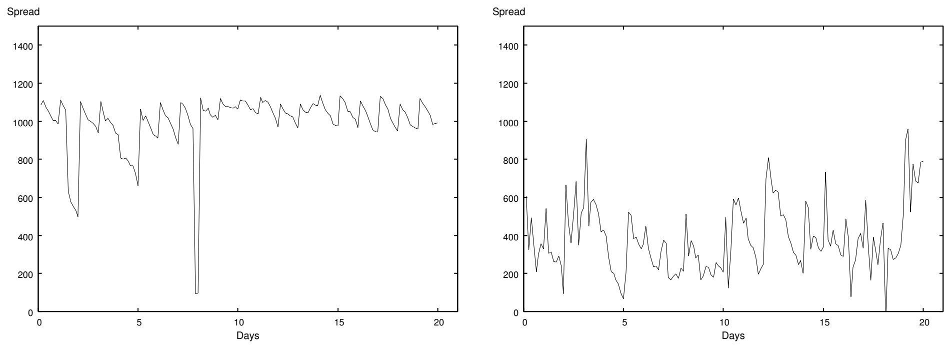
a. Raw spread



b. Mid-point spread

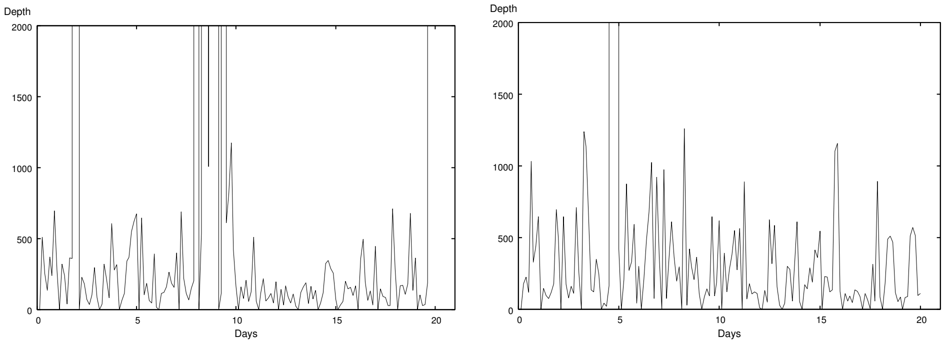


c. Effective spread



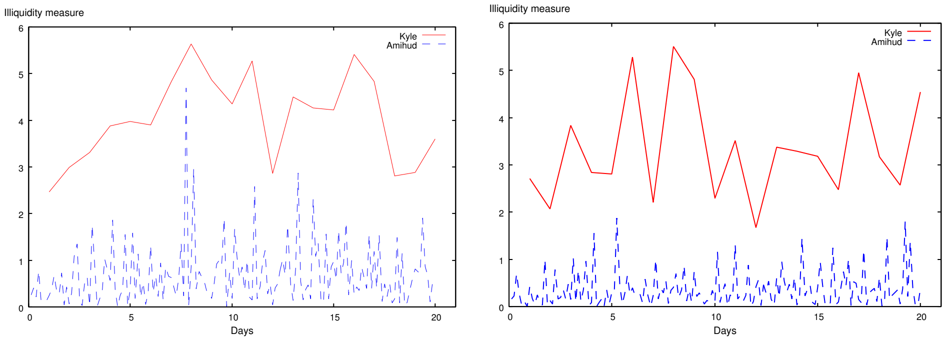
d. Weighted spread

Fig. 2. Time series of bid-ask spread



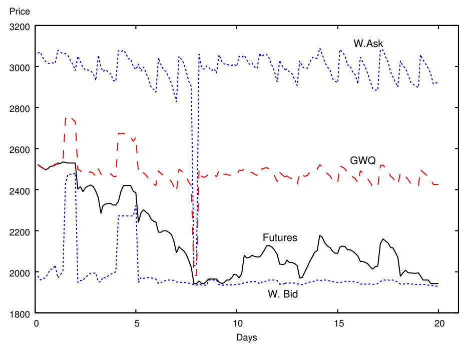
a. Round 1 b. Round 2

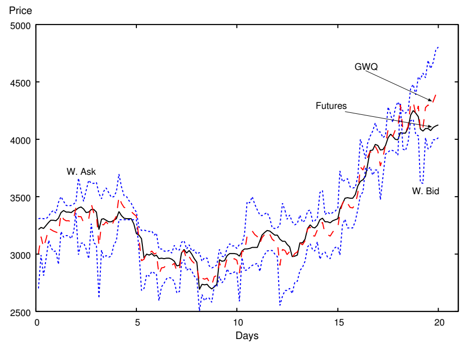
Fig. 3. Time series of market depth



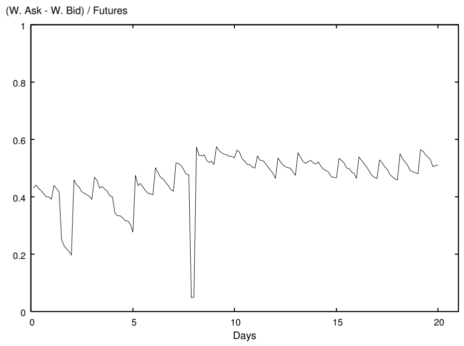
a. Round 1 b. Round 2

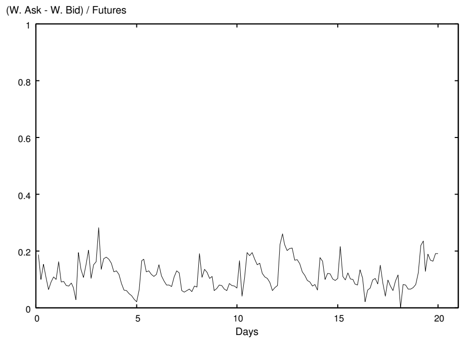
Fig. 4. Time series of two market illiquidity measures (Kyle: $\times 10^{-4}$, Amihud: $\times 10^{-9}$)



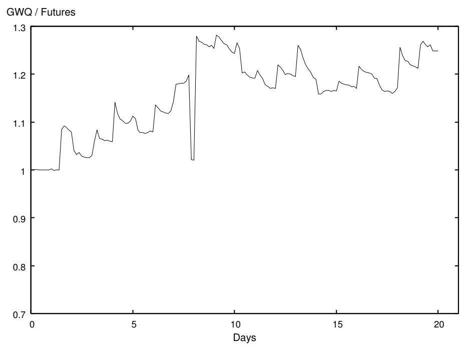


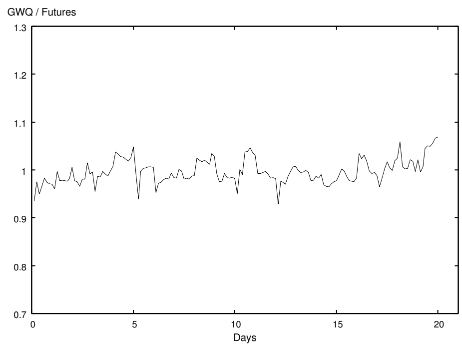
a. Weighted forecast prices (GWQ is the mid-point price between weighted ask and weighted bid.)





b. Ratio of the differences between weighted ask and weighted bid to the futures prices





c. Ratio of the mid-point weighted prices to the futures prices

Fig. 5. Time series plot of weighted forecast prices (Left panel: Round 1, Right panel: Round 2).