Short run dynamics in an artificial futures market with human subjects

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Abstract. This paper presents the computational results obtained in the strategy experiments in an artificial futures market with human subjects. Participants submit their own strategy files and they receive the performances of all the market participants in order to improve for the next round. After two-round experiments, simulations with only machine agents are run. We find 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.

1 Introduction

The advent and development of computer technology have improved the methodology of experimental and cognitive economics. Before computer era researchers implemented so-called "pencil-and-paper" experiments and thus the amounts of results obtained had to be somewhat limited. In the present era, on the other hand, higher computer abilities enable us to implement iterated experiments by changing setup conditions and thereby to collect accurate data for proper analyses (a good review is made by Duffy [2] and an example of computer-oriented cognitive economics is by Ueda et al. [12]).

Such an improvement has led to create a bland-new economics: agent-based computational economics (e.g. Tesfatsion and Judd [11]). This approach has been able to explain micro-macro relations in economic dynamics and to cover the fields of which experimental economics with human subjects is difficult to implement such as long run or extensive simulation.

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 (also Duffy presents a good explanation [2]). The other is to develop a methodology or toolkit in order to make use of teaching computational economics (e.g. Kendrick et al. [6]). At the same time, practitioners have made use of computer abilities in order to trade in the markets, analyze financial data, and train traders (e.g. Ueda et al. [12]). The same can be said to personal investors. For instance, they try to experience and understand market mechanisms through trading artificial economies (e.g. LIVE by Simplex Institute, Inc. [8] and SimStockExchange by Hoffman et al. [9]). Or, hasty investors may take advantage of trading agent services as program trading, namely such market participants need to write some programs to express their own trading strategies. Hence the diffusion of computer technology and changes in trading environments lead both investors and financial institutes to take into account utilization of information technology for investing service. In other words, agent-based computational finance is also considered as a kind of service so long as program trader exists in the markets.

"UnReal Market as an Artificial Research Testbed" (hereafter U-Mart) is one of the common used toolkits in experimental and agent-based economic studies [13]. This is an artificial futures market in which human subjects and trading agents take part in at the same time. By using this testbed, researchers try to clarify the market dynamics/mechanism, to make use of this tool for engineering and economic studies, and to do a campaign for enlightenment. This paper explores what U-Mart can contribute to computer oriented economics and what it should be required for the future through the simulation results with and without human subjects.

The rest of this paper is organized as follows: The next section describes the experimental setup. Section 3 presents the results of time series analyses using sample paths generated. Section 4 discusses future perspectives of computational economics and its usage for service sciences. And finally, Section 5 concludes this paper.

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. Almost all the students had no prior knowledge about financial markets, but several students had some skills in computer programming. Note that the procedure employed in this study happened to be similar to that in Hommes et al. and Sonnemans et al. [4, 10] and 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 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.

2.2 Strategy experiment

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 first round, and three were in the second.

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).

Problems often addressed by many researchers are motivations of subjects and attempts to obfuscate the market. The former problems 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 prohibited them from making a destabilizing machine agent since we knew that such an attempt would be quite hard to succeed due to the existence of nearly 200 market participants plus originally installed machine agents [1] as Hommes et al. have pointed out [4].

[1] They are 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.

Table 1. Experimental setups

Item	Memo
Initial wealth	One-billion
Initial holdings	No
Ordering for human subjects	Limit order and market order
Ordering for machine agents	Limit order only
Cancellation of orders	Allowed only for human subjects
Risk free rate	0.1
Trading unit	1000-fold
Commission	300-thousand per unit
Credit taking	Up to 30-million

Table 2. Characteristics of submitted strategies (Some strategies have more than two characteristics.)

	First round	Second Round
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

Fortunately, all the strategies submitted which will be explained in the sequel were ordinal.

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.

3.2 Stylized facts

Financial market data contain many statistical properties called "stylized facts" for which traditional economics is difficult to explain. Some of them are about price movements per se and others are the relations between trading volumes, and price movements or volatility. We will focus on the following four properties which seem to be the most popular and significant facts and have been reproduced by several agent-based simulation models (e.g. Hommes, and Lux and Marchesi [3, 7] for example) [2]:

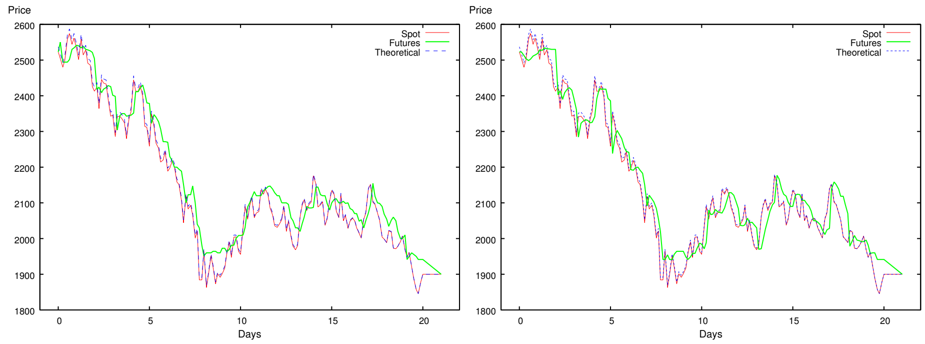
- Exchange rates and stock prices have almost unit roots.
  To check if a time series has a unit root, one often employs three unit root test, Dickey and Fuller test, Augmented Dickey Fuller test or Phillips-Perron test. If the p-value is less than a threshold value, 0.05 for instance, then the series has a unit root.
- Returns have fat-tailed distributions.
  Fat-tailed distribution is whose density function decreases in a power-law fashion. But according to Lux and Marchesi [7], the fact is seen for returns at weekly or shorter time scale.
- 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.

3.3 Market dynamics

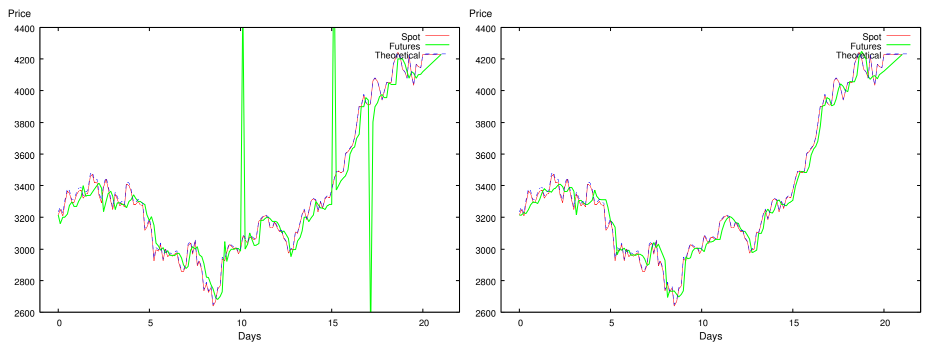
This part of the section reports the results of time series analyses using one laboratory experiments and one of 10 simulation runs for each round. Each time series plot is presented in Figure 1. The realized futures prices seemed to trace the spot prices, but sometimes large jumps are observed because human subjects did large amount of market order. In other words, the differences between simulated prices and spot ones with only machine agents are smaller than those in strategy experiments.

First, Table 3 depicts the p-values of three unit root tests, DF test, ADF test, and PP test for generated price series. Those tests prove that no simulation model or setup except one rejected the null hypothesis of the presence of a unit root. One possible explanation for non-rejected property is there were some jump processes in the second laboratory experiment (Figure 1b).

[2] With respect to the relations between price changes and trading volumes, there is a good and classical review by Karpoff [5], and Chen and Liao have clarified the mechanism by agent-based approach focusing on Granger's causality [1]. But this item will be omitted due to the smaller number of observations.



a. First round



b. Second round

Fig. 1. Time series plot (left panel: experiments with human subjects and machine agents, right panel: with machine agents only, horizontal axis: term, and vertical axis: price)

Second, Figure 2 presents normal probability plots of simulated return series. Due to the smallest observations for daily data, only hourly data are shown. The reason why the curves indicate fat-tailed distribution is when one takes up time series data at shorter time scale, a jump process is likely to take place. Therefore in this regard trading strategies with little experiments led market dynamics to the ones similar to real markets.

Third, Figure 3 reports auto-correlation functions which test for long memory distinctions of time series data. Clearly the generated returns do not show such a distinction, namely there is unrealistic pattern. Though we did not conduct deeper analyses, the possible reason may be that the time horizons of moving average strategies were similar to each other. But this is still an open question.

Finally, Figure 4 and Table 4 show whether generated sample paths converged to a theoretical value which is derived from

$$F_t = S_t \cdot (1 + r_t \cdot \tau_t/365) - d_t$$

where F_t, S_t, d_t, r_t, and τ_t are futures price, spot price, dividend, risk free rate, and days to maturity respectively. Since we postulated that there was no

Table 3. Unit root tests (p-value)

			DF	ADF	PP
First round	(w. human subjects)	Daily	0.677	0.382	0.795
		Hourly	0.742	0.785	0.817
	(w/o human subjects)	Daily	0.710	0.448	0.833
		Hourly	0.687	0.635	0.748
Second round	(w. human subjects)	Daily	0.934	0.911	0.965
		Hourly	0.010	0.046	0.010
	(w/o human subjects)	Daily	0.927	0.909	0.963
		Hourly	0.969	0.950	0.973

DF: Dickey and Fuller test
ADF: Advanced Dickey and Fuller test
PP: Phillips and Perron test
If the p-value is less than 0.05, then a series has a unit root.

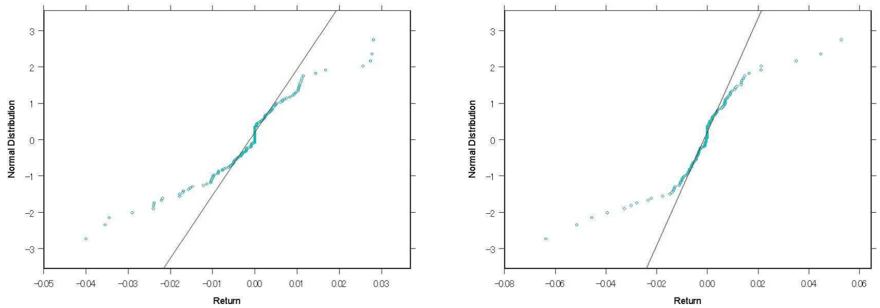
dividends paid to shareholders, the second term of the equation above is set to zero. Both the exhibits reveal that even though the sample paths in the first round had no jump processes the time series were hard to converge to the fundamental value. This fact is also supported by a positive Lyapunov exponent. Besides, this distinction is observed for all the 10 sample paths in the U-Mart with only machine agents. For one thing, the subjects did not get accustomed to JAVA programming and the mechanism of financial markets. Consequently, the prices formed in the market with simple but random-like traders became to be more chaotic. On the other hand, time series data with a negative Lyapunov exponent in the second round appeared to be more stable in spite that the laboratory experiment had a few large jump.

4 Discussion

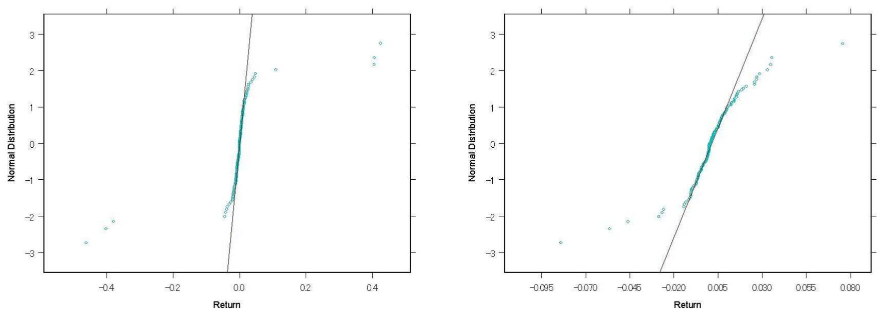
4.1 What is done, what is not?

On the one hand, one preferable result is that the prices would be closer to the theoretical value when subjects had some knowledge of the market and experiments in spite that the market is not the same as that in Hommes et al. [4]. Moreover, unit root property and fat-tailed distribution are observed when one takes up hourly time scale. This supports the fact that the market participants are boundedly rational and heterogeneous.

On the other hand, long run dynamics could not be analyzed in this setup at all because of time restrictions or computer/network problems. Therefore auto-correlation functions, BDS statistics, and relations between price changes and trading volumes were omitted. Besides we did not compare the results with/without human subjects and examine what if we add procedures of risk management, order cancellation, or market order to the template file.



a. First round

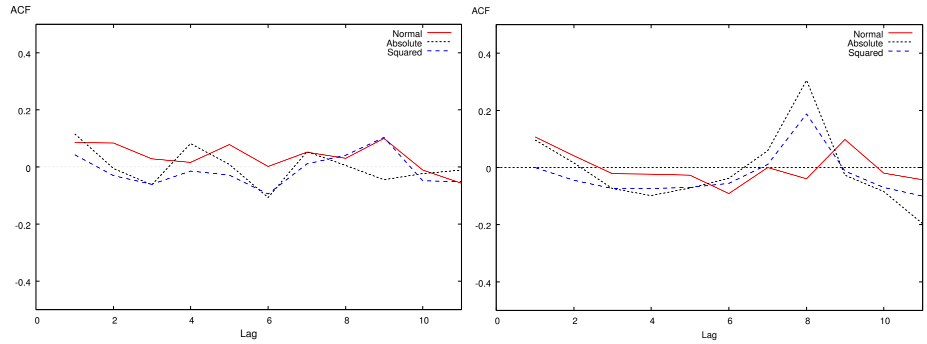


b. Second round

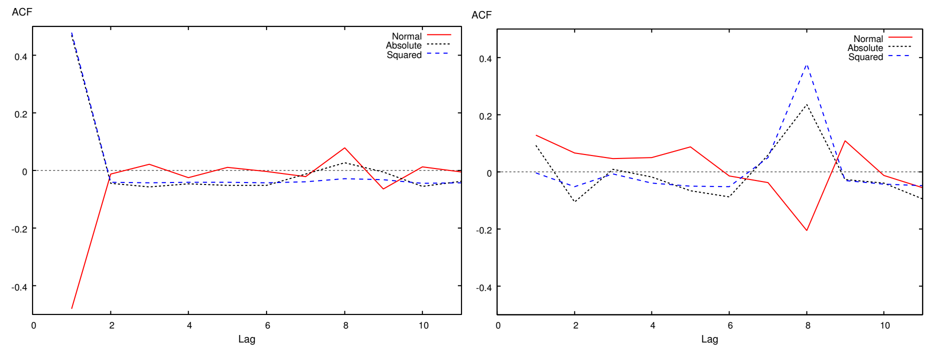
Fig. 2. Normal probability plots (left panel: with human subjects, right panel: machine agents only, horizontal axis: return, vertical axis: cumulative distribution)

4.2 Future of U-Mart as service sciences

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. In order to keep these trends, we believe that the following points should be grappled with in the near future: Firstly, more efforts to help researchers and practitioners understand the mechanism of markets and behaviors of market participants should be done. As far there are several studies about risk control abilities of human subjects, but no research about combining such findings into the behavioral economic theory is found. Secondly, for engineering program, instructors need to let students be interested in what social science is all about as well as writing a more complex/sophisticated machine agent. This is because being conversant with social science for engineering students as well as having skills in computer programming for economic students is required for understanding of computational economics.



a. First round



b. Second round

Fig. 3. Auto-correlation functions (left panel: with human subjects, right panel: machine agents only, horizontal axis: lag, vertical axis: ACF)

5 Conclusion

This paper reports the strategy experiments in an artificial futures market with human subjects in order to verify how current agent-based computational finance is useful for service sciences. Two rounds experiment and simulation results afterward reveal that an appropriate education program and some experiments of human subjects could make market dynamics the ones observed in real markets, namely more experienced machine agents and trading behaviors made a chaotic dynamics disappear even if the experiments were implemented under constrained environments. Instead, we also confirm that analyses of long run dynamics and the collaboration between establishment of course curriculum and experiments are required for future of computational economics and service sciences.

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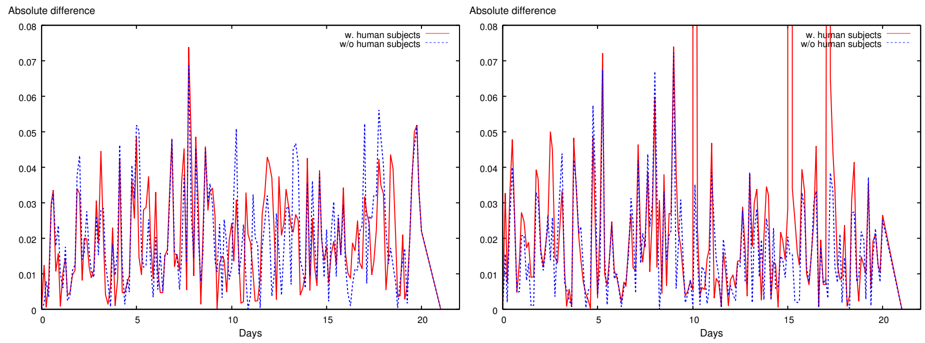

a. First round

b. Second round

Fig. 4. Absolute difference from the theoretical value (horizontal axis: term, vertical axis: difference between simulated futures price and theoretical one)

Table 4. Number of terms within a 0.01 range from a theoretical value

	Daily (20 obs.)	Hourly (160 obs.)
First round (w. human subjects)	3	46
First round (w/o human subjects)	1	43
Second round (w. human subjects)	5	52
First round (w/o human subjects)	6	64

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