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A controllable laboratory stock market for modeling real stock markets

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Abstract. Based on the different research approaches, econophysics can be divided into three directions: *empirical econophysics*, *computational econophysics*, and *experimental econophysics*. Because *empirical econophysics* lacks controllability that is needed to study the impacts of different external conditions and *computational econophysics* has to adopt artificial decision-making processes that are often deviated from those of real humans, *experimental econophysics* tends to overcome these problems by offering controllability and using real humans in laboratory experiments. However, to our knowledge, the existing laboratory experiments have not convincingly reappeared the stylized facts (say, scaling) that have been revealed for real economic/financial markets by econophysicists. A most important reason is that in these experiments, discrete trading time makes these laboratory markets deviated from real markets where trading time is naturally continuous. Here we attempt to overcome this problem by designing a continuous double-auction stock-trading market and conducting several human experiments in laboratory. As an initial work, the present artificial financial market can reproduce some stylized facts related to clustering and scaling. Also, it predicts some other scaling in human behavior dynamics that is hard to achieve in real markets due to the difficulty in getting the data. Thus, it becomes possible to study real stock markets by conducting controlled experiments on such laboratory stock markets producing high frequency data.

1 Introduction

As a typical complex adaptive system, economic/financial markets have received much attention from physicists, which have thus yielded a new discipline – "econophysics" since the 1990s [1,2]. According to the different research approaches, econophysics can be generally divided into three directions, namely, empirical econophysics, computational econophysics, and experimental econophysics.

(1) Empirical econophysics

Inspired by Stanley and his coauthors' pioneering work, physicists began studying the statistical properties of financial markets with methods widely used in statistical physics [1,2]. As a result, many universal rules, say, scaling laws and clustering behaviors were found in the markets of different countries [1–8]. This direction is based on the existing data in financial/economic markets.

(2) Computational econophysics

Clearly, because it is illegal or immoral to control real markets, researches in empirical econophysics lack controllability that, however, is very important to know the impact of a specific condition. To overcome this problem, computational econophysics comes to appear by building models to simulate the human behaviors and then try to understand the underlying rules in economic-social events. Starting from the research on the El Farol Bar problem to the minority game and many other models, physicists had many new ideas on the collective behavior of the crowd [9–18]. Among the two research directions of empirical econophysics and computational econophysics, the empirical way gives more persuading results because their researches are based on real data from the market. However, these findings may be challenged in some developing markets and also it is not that flexible to find data in a specific need. Even putting political, moral and legal issues aside, it is impossible to gather a great amount of resources (money, human resources, etc.) to conduct researches in real markets. On the other hand, the modeling way in computational econophysics is a much easier approach to check for a specific problem. With the booming computer capability, this methodology can put many factors into account and use many advanced algorithms like the genetic algorithm [19]. But it is very hard to keep the models simple and elegant, and on the other hand, robust and convincing. For completeness, many econophysicists now tend to use the joint method originating from both empirical econophysics and computational econophysics in their work.

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(3) Experimental econophysics

As mentioned above, researches in empirical econophysics lack controllability. Moreover, agents adopted in computational econophysics are often far from genuine human beings because assumed/simplified artificial decision making processes are different from real decision making processes that are used by real humans to invest in financial markets. To overcome these problems, controlled human experiments in laboratory have been developed, which give birth to experimental econophysics. By controlled human experiments in laboratory, researchers could simplify the market environment and in the meantime retain the most important part of the market, the humans. All the results are produced by the human brains and the collective behaviors, and the external factors can also be carefully controlled. For example, Wang et al. did a series of controlled human experiments based on the minority game and explained the mechanism of the "invisible hand" in markets [14]. Zhao et al. [15] and Liang et al. [20] respectively added herd traders and contrarian traders into the human experiments and explained the roles of herding and contrarianism in a resource-allocation economic system. In fact, economists have already done a lot of great work in laboratory human stock markets [21,22]. In 1990s, Friedman wrote a paper to show his series of experiments; these experiments gave laboratory evidence of the efficiency of two different trading institutions [23]. Later, Porter and Smith designed a laboratory market with dividends, and also with several other extensions including short sells, limited price changing rules, associated future markets, etc.; they confirmed the existence of price bubbles in this market and examined the extensions' roles in the bubbles [24]. Hirota and Sunder published a paper based on a similar market structure; by studying the trading horizons, they suggested that the investors' short horizons and consequent difficulties of backward inductions are important contributors to the emergence of price bubbles [25]. These experiments offered good insights into the associated research problems. However, to our knowledge, all the experiments mentioned above have not convincingly reappeared the stylized facts (say, scaling) that have been revealed for real economic/financial markets by econophysicists. A most important reason is that in these experiments, time is divided into trading cycles, say 5 min. Hence the participators have to make decisions on the cycles [14,15,19–21,23–25]. In other words, discrete time steps make these laboratory markets deviated from real markets where trading time is naturally continuous. In this work, we attempt to overcome this problem by designing a continuous double-auction stock-trading market and carry out several human experiments in laboratory. As an initial work, the present artificial financial market can produce some stylized facts (clustering effects and scaling behaviors) that are in agreement with those of real markets. Also, it predicts some other scaling in human behavior dynamics that is difficult to achieve in real markets due to the difficulty in getting the data.

The remainder of this work is organized as follows. Sections 2 and 3 will describe the laboratory market structure and the design of our laboratory human experiments. Section 4 shows some results obtained from the experiments. This paper ends with a summary in Section 5.

2 Market structure

2.1 Basic framework

Consider a market with N traders, indexed by i. Trading time is indicated by t. To simplify the problem, traders only decide how to manage their portfolios consisting of one stock and risk-free asset. The risk-free asset in our market is simply bank savings (cash). There are Q shares of stocks issued in the market. The price of the stock is determined by the traders' trading activities and it will be updated every time when a deal is made.

2.2 Double-auction order book

The double auction has been the most widely used system in equity markets for more than 140 years [19]. In our market, a computer-aided double-auction order book is introduced to help dealing with the traders' orders. Traders could have limit orders. Compared to a market order that only contains a desired amount of the stock to buy or to sell and will be executed on the current price, a limit order in addition has a request of specific limit of price. For example, a limit sell order with a bid price p and amount q means this trader is willing to sell q shares of the stock in any price no less than p. A limit buy order with an ask price p and amount q means this trader is willing to buy q shares of stock in any price no more than p. Traders could have unlimited numbers of orders, but neither borrowing nor short selling is allowed. Our order book works in the following ways:

1. at first the order book is empty;
2. when an order, for example, a buy order, is posted, the maximum amount of cash that may be needed is frozen;
3. the system will check if there are sell orders with lower prices. If there is no such order, store the order in the order book and the process is done; if there exist such orders, the system will pick out the ones with lowest prices, sort them by time to find the oldest one;
4. the system will exchange cash and stock between the owners of this order and the chosen orders in step 3; these cash and stock will be unfrozen and delivered to the account of the traders. If the order is fully digested, the process is done; if not, the rest part will be treated as a new order and repeat step 2 and 3;
5. when the order is aborted, the frozen cash or stock will be released to the traders' account. An example of our double-auction order system can be found in Figure 1.

Fig. 1. An example of how our order book updates.

2.3 Exogenous rewards

It is known that real stock markets are always full of various kinds of information, but such information has only two roles: tending to increase or decrease the stock price. Because the stock in our laboratory market has no underlying value, our solution is to add exogenous rewards to the system. For this purpose, we resort to dividends (that are used to potentially increase the stock price; see below) and interests (that are utilized to potentially decrease the stock price; see below) to give traders information about the macro environment and the stock. In detail, there will be stochastic rewards for holding stock or cash every a few minutes. The rewards for stock are a random amount of cash d directly added to traders' account; they are like the dividends in real markets. As a result, this may increase the stock price. The rewards for cash mean increasing the traders' cash by a random percent f, which represents the interest. So, this may decrease the stock price. The rewards also cover the stock and cash frozen in the order book. To let the traders have time to evaluate their strategies, all the rewards are forecasted with partial information by the coordinator 2 minutes before they are distributed. For example, if the coordinator is going to pay a dividend of "2 cash per share" at 10:00 am, he broadcasts to the traders that there will be a dividend of "1 to 3 cash per share" at 9:58 am.

3 Design of the experiments

3.1 Platform and participants

We designed and conducted a series of computer-aided human experiments. The experiments were held in a big computer laboratory of Fudan University; each participant had a computer to work with. All the computers were linked to an internal local area network and we deployed a web server to handle all the requests. We recruited 63 participants to act as traders, all of whom were students of Fudan University. Our trading platform provided the following information to the traders: 1-minute close prices, 1-minute trading volumes, five highest buy orders' prices and amounts, five lowest sell orders' prices and amounts, the trader's own cash and stock available, the trader's trading/ordering history and the trader's rewards-getting history (see Fig. 2). According to our server's performance, the close price and volume were shown in a chart which was automatically updated every 1 min, the order book information was updated every 15 s, and the traders could look at their histories at any time during the experiments.

3.2 Experiments settings

Before the experiments, 10 min for trade training is arranged to help the participants to get used to the trading interface and market rules. Then we had two rounds of experiments. Every round of experiment lasted for 30–40 min, but the traders did not know when the experiment would end, thus there would be less ending boundary effect. At the beginning of a new round, the stock price is set to 10. In the first round of experiment, all the traders started with 10 000 cash and 1000 shares of stock, while in the second round of experiment, the traders started with a random amount of cash and stock. In the second round, the traders' initial stock were randomly distributed between 200 and 1800, and to make the total amount of stock and cash comparable with the first round, every trader's initial cash is 10 times of his/her stock in number. In the first round of experiment, we initiated 63 000 shares of

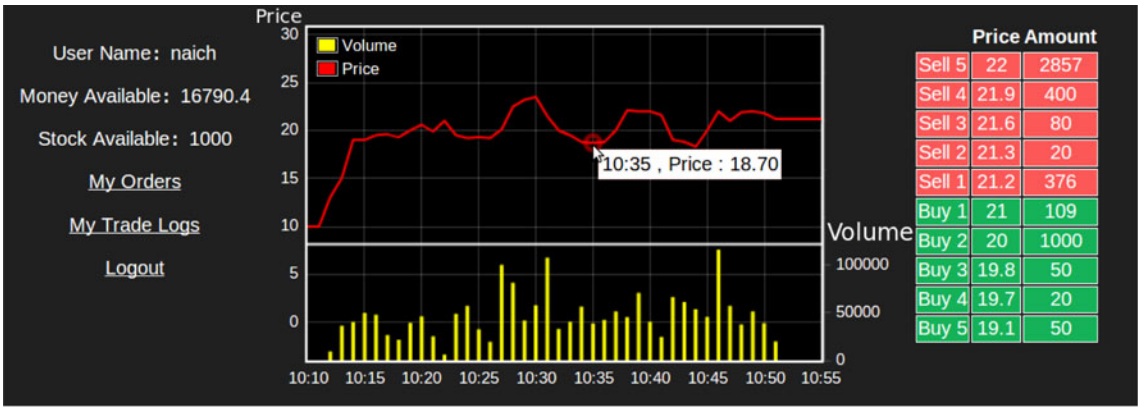

Fig. 2. A screenshot of the trading platform: the left part shows the trader's nickname, usable cash and stock (the number of shares); the middle chart demonstrates the stock price and trading volume as a function of time; the right table gives the five highest bid prices and five lowest ask prices. The middle chart refreshes per minute; when the mouse pointer (denoted by the white arrow) hovers above the stock price, it shows detailed information about time and the price of that time, say, "10:35, Price: 18.70" as shown in the chart.

stock and 630 000 cash; in the second round of experiment, we initiated 63 478 shares of stock and 634 780 cash.

3.3 Payoffs

Our experiments were carried out during the Econophysics course taught in Fudan University. The participants were students enrolled in this course. 47 of the 63 participants select the course and 16 students are auditors. The performance of the students who select the course took 10% of their final score of this course. They were required to trade at least 20 times to get a base score of 3.3%. And based on their final wealth rank, they could get another 3.3%–6.7% score: based on their scores, top 10% students will get all of the 6.7% score, top 10%–30% will get 6.0% of the final score, ..., and the last 10% will only get 3.3% score. Their final total scores are the calculated score rounded to the nearest whole number.

It is worth noting that the crucial role of markets is to let participants have chances to pursue profits. In different situations, "profits" could have different forms. For example, in real stock markets, investors pursue money ("profits") by exchanging stocks and money. In our laboratory market, 47 students who select the course pursue scores ("profits"), and the other 16 auditors voluntarily participated the experiments with an aim at learning how laboratory experiments are conducted for econophysics ("profits"). In this sense, our laboratory market can be equivalent to real stock markets, at least to some extent.

4 Results and discussion

4.1 Price, volume and return series

In this section we will show the data we get from the human experiments (Fig. 3). The first is the 1-minute close price series, $p(t)$. Here a 1-minute close price is the last transaction price that occurs at the end of a certain minute: if there is no order execution in this minute, the close price will stay the same with the price of last minute.

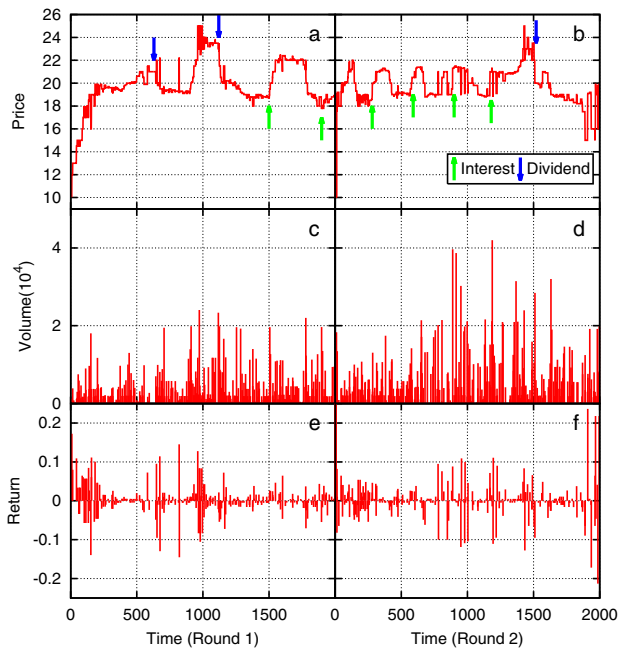

Fig. 3. Time series of (a, b) 1-minute closing prices, (c, d) volumes and (e, f) returns for the (a, c, e) first and (b, d, f) second round of the laboratory human experiment. In (a, b), up arrows demonstrate the time when there is an interest (reward for cash), and down arrows demonstrate the time when there is a dividend (reward for stock). In (a), from left to right, the four arrows denote rewarding "2 cash per share", "2.4 cash per share", "10% of the cash", and "6% of the cash", respectively. In (b), from left to right, the arrows mean rewarding "3%, 5%, 7%, and 9% of the cash" for the four up arrows, and "3.2 cash per share" for the down arrow. (c, d) show the trading activities lasting through the experiments. In (e, f), clustering behavior occurs.

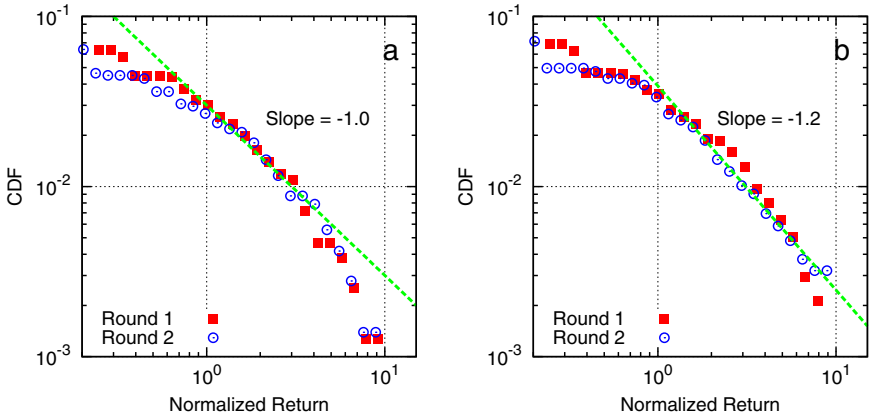

Fig. 4. Cumulative distribution functions (CDFs) of the normalized return: (a) the negative tails of the experiments and (b) the positive tails of the experiments. Symbols of squares and circles denote the results obtained from the first and second round of experiments, respectively. Here the negative tails in (a) denote the CDF (<0.064) of the absolute value of negative normalized returns, and the positive tails in (b) denote the CDF (<0.071) of the value of positive normalized returns. In (a) or (b), "Slope" denotes the slope of the corresponding green dashed line.

The (log) return $r(t)$ is defined as follows:

$$r(t) = \ln p(t) - \ln p(t-1), \tag{1}$$

where trading time t is denoted by the count seconds from the start of the experiment. Figures 3a and 3b give the price series of our experiments: during the first round of experiment, there are 2 interests (rewards for cash) and 2 dividends (rewards for stock), and during the second round of experiment, there are 5 dividends (rewards for stock) and 1 interest (rewards for cash). Because our rewards are forecasted 2 min in advance, there are notable price changes before the rewards' distribution. Specifically, before a reward for stock, the price goes up; before a reward for cash, the price goes down. This could be explained: when a signal of holding stock is sent to the traders, they tend to hold more units of stock. As a result, more buy orders will come to the order book and pull up the price. However, if one buy the stock in a price much higher than the present price, he will gain less profit in this turn of reward. Thus the price will not go up infinitely. The same theory works for the case of rewards for cash. Because traders have different strategies and prediction of the future event, plus our forecast is not accurate, different traders have different responses to the news. This mechanism provides liquidity to our markets. Figures 3c and 3d show the trading volume series. It is observed that there are trading constantly all the time.

Figures 3e and 3f show the return series of the two rounds of experiments. It is easy to recognize that there are clusters in the return series; this is distinctly different from Gaussian random series. So we analyze the return series' statistical properties. In order to compare the data from the two rounds clearly, the normalized return, $g(t)$, is used,

$$g(t) = \frac{r(t) - \langle r \rangle}{\sigma(r)}. \tag{2}$$

Here $\langle \cdots \rangle$ denotes the average of time series $\cdots$, and $\sigma(\cdots)$ means the standard deviation of $\cdots$. We calculate the cumulative distribution function (CDF) of the first and second round, respectively. Since the returns distribute symmetrically around zero, we respectively calculate the positive returns and negative returns and put them in Figure 4 for comparison. For the two rounds (Fig. 4), the negative and positive tails share almost the same CDF. Further, in the log-log plot all the four tails have a particular region that is approximated by a straight line. Clearly this behavior is an evidence of scaling, and meets the statistical analysis of many real stock markets [4].

The autocorrelation function is another important feature of the return series [5]. If $x(t)$ is a time series, the autocorrelation function, $C(\Delta T)$, is defined as

$$C(\Delta T) = \frac{\langle (X_{-\Delta T} - \langle X_{-\Delta T} \rangle)(X_{\Delta T} - \langle X_{\Delta T} \rangle) \rangle}{\sqrt{\sigma(X_{-\Delta T})\sigma(X_{\Delta T})}}, \tag{3}$$

where $X_{-\Delta T}$ is the series with the last elements removed and $X_{\Delta T}$ with the first elements removed. $\langle X \rangle$ denotes the average of X and $\sigma(X)$ the standard deviation. Our calculations of $g(t)$ confirm the existence of short negative correlation (less than 20 seconds or so) on both rounds of experiments (as indicated by the green dashed line in Fig. 5a), which shows our laboratory market is similar to the real developed stock markets [26]. The short time correlation also fits our orderbook information refreshing time (15 s). We also calculate the autocorrelation of absolute normalized return, $|g(t)|$, and find that the correlation lasts much longer than 20 seconds (see Fig. 5b). This result confirms the volatility clustering behavior in our market, and echoes with many other articles, for example, see references [7,26]. In addition, if we compare the two rounds, we can conclude that in the present market, the initial wealth distribution has little influence on the statistical properties of return.

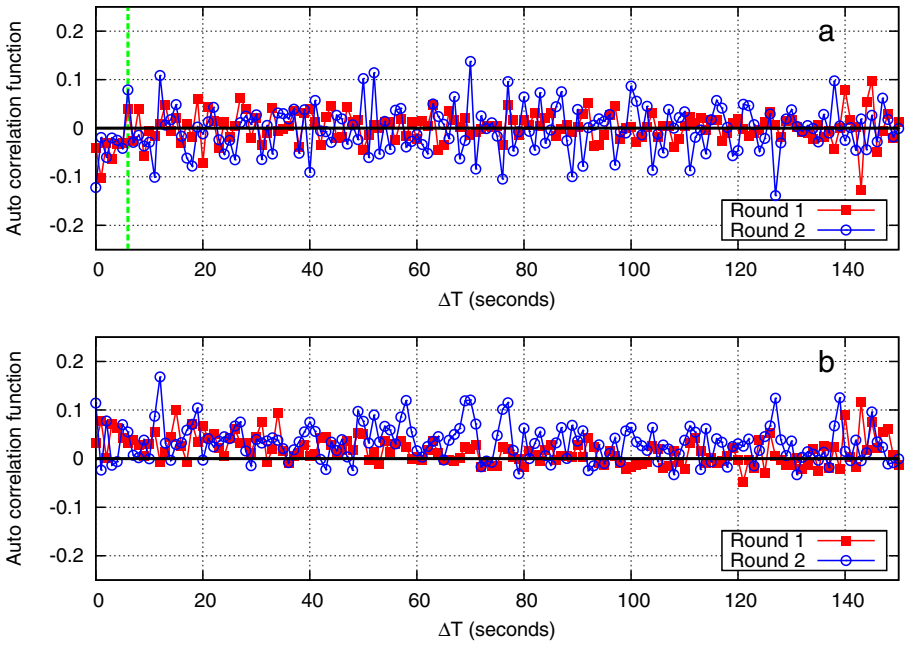

Fig. 5. Autocorrelation function of (a) normalized return series, $g(t)$, and (b) absolute normalized return series, $|g(t)|$, for round 1 and round 2. In (a), the green dashed line indicates the transition point. Details can be found in the text.

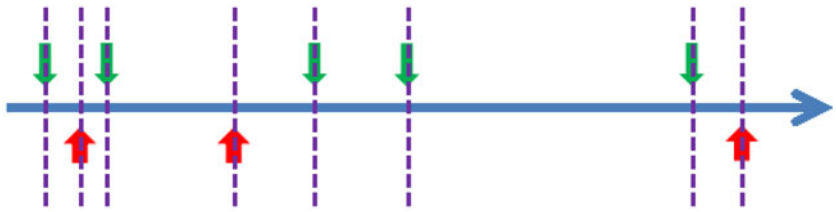

Fig. 6. Demonstration of the definition of waiting time. The axis represents the time. Assume our market has only two traders, the first trader's orders are marked with down arrows, and the second trader's orders are marked with up arrows. The stock waiting time is shown by the gaps between each pair of nearby slash lines, and the trader waiting time is indicated by the gaps between each pair of nearby down arrows and the gaps between each pair of nearby up arrows.

4.2 Human behavior dynamics

Our market experiments also give us an opportunity to study human behavior dynamics. In 2005, Barábasi and collaborators analyzed the letters of Darwin and Einstein; they found that both Darwin's/Einstein's patterns of correspondence and today's electronic exchanges follow the same scaling laws [27]. And they use an agent-based model to explain the origin of this scaling [28]. Here we turn our eyes to the waiting time of traders' actions. We define two kinds of waiting time, the stock waiting time and the trader waiting time. The stock waiting time describes the gaps between which two different orders are posted, see Figure 6. We put all the orders from all the traders together, sort them by time, and calculate the time gaps between two successive orders. While the stock waiting time is to focus on the collective behavior of a group, by defining the trader waiting time we try focusing on the decision-making processes of individuals. For the trader waiting time, we put orders from different traders in different piles, sort them respectively, and then calculate the gaps. This is because for any particular trader she/he only has tens of orders, this is insufficient for statistical analysis. Instead, if we are looking into the rules that work across the crowds, we could put all the gaps together, thus we get thousands of data. This method has been used in the literature on human behavior dynamics [29,30].

The probability density function (PDF) is calculated; see Figure 7. Figure 7a demonstrates the PDF of stock waiting time in a log plot graph. The data points obviously locate in a straight line, which means the stock waiting time obey an exponential distribution [28]. This is because the traders have little interactions when submitting orders, their actions can be seen as independently decisions and overall exhibit a random-like behavior. However, in Figure 7b, we could find the trader waiting time is quite different. The PDF in a log-log plot forms a straight line for the gaps that are shorter than 100 s, and the tail of the PDF drops below the line when the gap is longer than 100 s. In the previous literature, Barabási showed that the power-low distribution of waiting time may come from a priority queuing system [28]. In our market, when traders

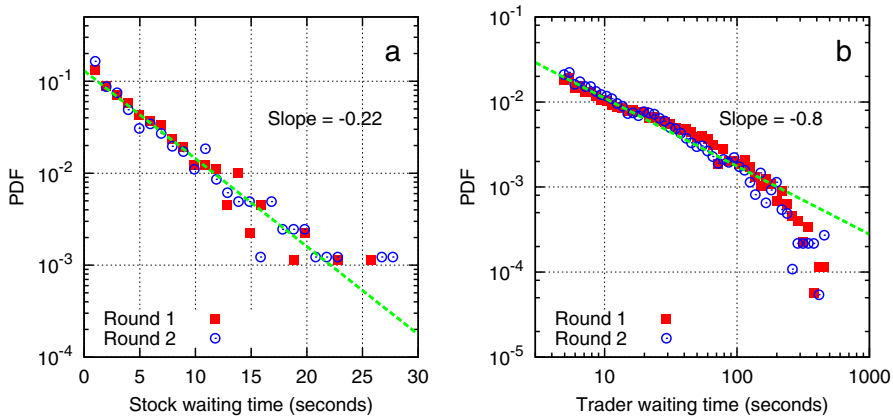

Fig. 7. Probability density functions (PDFs) of waiting times: (a) the stock waiting time and (b) the trader waiting time. Symbols of squares and circles denote the first and second round of experiments, respectively. In (a) or (b), "Slope" denotes the slope of the corresponding green dashed line.

make decisions on whether he/she should submit an order, there is no obvious use of a task queue. So the origin of power low in trader waiting time may contain some other mechanism. The turning point from which the PDF's tail drops from the straight line fits our rewarding time gaps in magnitude. We suspect that the tail of PDF may present the effect of our exogenous rewards. Those news break the traders original decision making process. For example, if there are no news in the market, a trader might trade every 20 min; however, if there are periodic news every few minutes, he/she is likely to respond according to the news. Therefore, the gap of 20 minutes will no longer exist. In a word, we believe the lack of long waiting time causes the fall of the tail in Figure 7b.

5 Summary

In contrast to the existing laboratory markets where trading time was set to be discrete [14,15,19–21,23–25], we have designed a double-auction stock-trading market where trading time is continuous. We have run two experiments in laboratory with human subjects and found that the initial outputs of the market fit some existing stylized facts (clustering effects and scaling behaviors). Besides, we have analyzed the orders and discovered some scaling in human behavior dynamics. Our laboratory market still has some weak points. For example, the traders of our experiments are all university students, and there might be different if we choose different groups of traders beyond university students. However, as a model market, it is easy for us to change different control parameters or add more extensions. Thus this market is expected to produce more results in future researches. The market and its output might also help modelers to mimic human behaviors in a more precise and realistic way. This work paves a way to study real stock markets by conducting controlled experiments on laboratory stock markets producing high frequency data.

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