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The effects of behavioral and structural assumptions in artificial stock market

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Abstract

Recent literature has developed the conjecture that important statistical features of stock price series, such as the fat tails phenomenon, may depend mainly on the market microstructure. This conjecture motivated us to investigate the roles of both the market microstructure and agent behavior with respect to high-frequency returns and daily returns. We developed two simple models to investigate this issue. The first one is a stochastic model with a clearing house microstructure and a population of zero-intelligence agents. The second one has more behavioral assumptions based on Minority Game and also has a clearing house microstructure. With the first model we found that a characteristic of the clearing house microstructure, namely the clearing frequency, can explain fat tail, excess volatility and autocorrelation phenomena of high-frequency returns. However, this feature does not cause the same phenomena in daily returns. So the Stylized Facts of daily returns depend mainly on the agents' behavior. With the second model we investigated the effects of behavioral assumptions on daily returns. Our study implicates that the aspects which are responsible for generating the stylized facts of high-frequency returns and daily returns are different.

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Keywords: Stylized facts; Artificial stock market; Behavioral and structural assumptions; Minority game; Market clearing frequency

1. Introduction

Agent-based models of complex adaptive systems are attracting significant interest in many disciplines. An important area receiving much attention is agent-based computational finance (ACF), which gives a new approach providing deep insights into the dynamics of security markets [1]. Researchers in agent-based computational finance have built artificial stock markets (ASM) that reproduce characteristic behavior (stylized facts) of regular markets, such as heavy tails of the (unconditional) distribution of daily and hourly returns, excess volatility, volatility clustering, and volume/volatility correlation.

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However, Ghoulmie et al. [2] and Raberto et al. [3] have argued that most artificial stock markets are formulated in a complex manner and, due to their complexity, it is often not clear which aspect of the model is responsible for generating the observed stylized facts and whether all the ingredients of the model are indeed required for explaining empirical observations. Further, Raberto et al. [3] pointed out that no artificial stock market is yet able to explain all the known stylized facts of real-life markets.

Thus, further work is required to determine which aspects of the artificial markets are responsible for the stylized facts that emerge.

Recent literature [3–6] has led to the conjecture that the emergence of some stylized facts is mostly due to their microstructure. The dynamics of a stock market depends on the interaction between the trading mechanism and the behavior of the participants. The trading mechanism defines the rules of the market, which specify how orders are placed and filled and how the price changes. The behavior of the participants is the outcome of their trading strategies, which include how they form expectations or interpret signals. Li Calzi and Pellizzari [4] believe that the first generation of agent-based simulations of stock markets has explored a very rich set of behavioral assumptions, but has paid comparatively little attention to structural assumptions.

Cincotti, Focardi, Marchesi and Raberto [5–7] developed the Genoa artificial stock market (GASM, which has a detailed microstructure similar to the real stock market. They found that both cleaning house and continuous double auction structures can produce heavy-tailed distribution of returns even with a market populated by zero-intelligence agents. LiCalzi and Pellizzari [4] presented a structurally detailed model with a minimal set of behavioral assumptions that also produced a heavy-tailed distribution. Their results supported the conjecture that heavy-tailed distribution is mostly due to the microstructure.

However, more research with ASMs, including the pioneering work done at the Santa Fe Institute [8,9] and our previous work [10,11] reproduced the stylized facts of markets without consideration of their detailed microstructures.

So, we believe that it is desirable to pay attention to investigate the effects of behavioral and structural assumptions in artificial stock markets.

In this paper, we present two artificial stock markets and use them to explore how both the behavior and microstructure features impact the stylized facts of market performance.

The paper is organized as follows. Section 2 presents a simple model with zero-intelligence agents and a clearing house mechanism, which is used to study the effects of the microstructure on high-frequency fluctuations of intraday trading. Section 3 presents an artificial stock market based on Minority Game, by which we study the effects of behaviors on daily returns; Section 4 describes the conclusions from these studies.

2. The effects of microstructure mechanisms

Researchers [4–6] have developed models with detailed microstructures and shown that with a minimal set of behavioral assumptions even zero-intelligence agents suffice to generate leptokurtosis. A possible conclusion could be that the fat tails phenomenon may depend mainly on the market microstructure. Does the market microstructure play a so important role? And how does microstructure generate this phenomenon? We will build a simple zero-intelligence agents model to answer these questions.

2.1. The model

Economic environment: there is only one virtual asset (stock) where the fundamental value is unknown, because we are nor concerned with whether the price converges to or diverges from the fundamental value. Each day, each agent decides to buy or sell a share of stock randomly. He issues an order with limit price based on exogenous information. Each trading day is subdivided into T elementary time steps with the market clearing at each time step.

Behaviors of agents: there are N agents with zero intelligence. At a given time step t, agent i issues an order. The order is either a bid or an ask, each with probability 50%. The limit price of the bid or ask is based on $\varepsilon_i \sim \mu(0, \sigma^2)$, where ε_i is a random draw by agent i from a Gaussian distribution with constant mean $\mu = 0$ and standard deviation σ. We assume that the limit price associated with the buy order is given by $p_i^B = \varepsilon_i$, and the limit price associated with the sell order is given by $p_i^A = \varepsilon_i$. The price p_i^A or p_i^B is logarithmic return.

Price formation: every order will be stored in the book if it is not traded. At the end of the trading day, the book will be emptied. The principles of clearing are: 1. the clearing price must generate the maximum trading volume; 2.

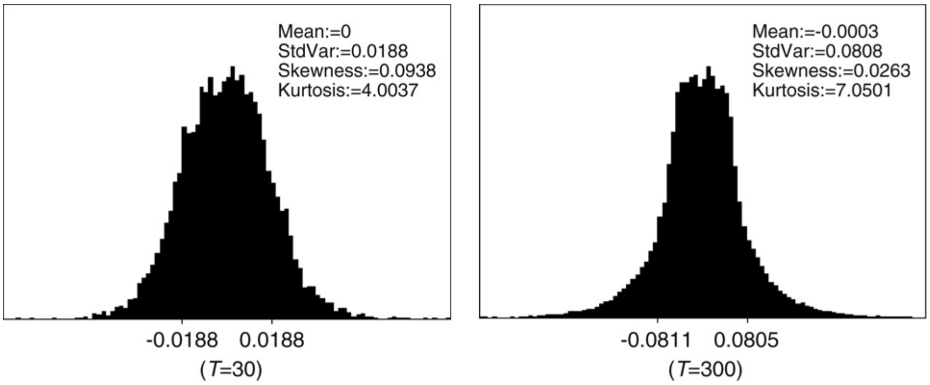

Fig. 1. The distributions of high-frequency fluctuations. (Note: The run has 400 days.)

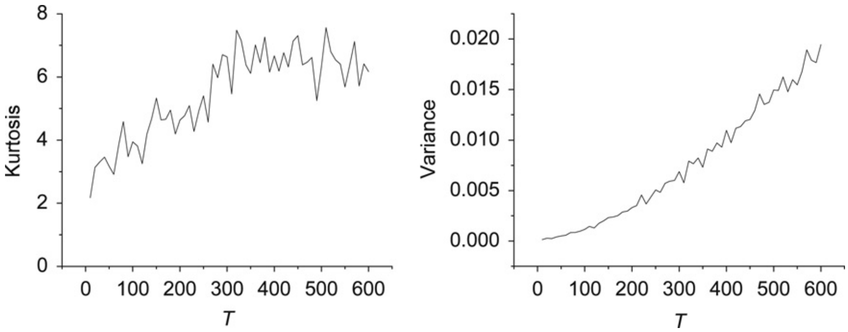

Fig. 2. The kurtosis and variance of the distribution of high-frequency returns *vs*. T. Each curve is an average of 10 independent runs, each run has 400 days.

all the bid orders with limit prices above or equal to the clearing price and all ask orders with limit prices under or equal to the clearing price must be traded; 3. if there are two prices that satisfied the two requirements, chose one of them randomly.

2.2. *Computational experiments*

2.2.1. *Effects on high-frequency fluctuations*

The number of agents $N = 5000$, with information $\varepsilon_i \sim \mu(0, \sigma^2)$, where $\sigma = 0.25$. The number of time steps in each trading day is T.

2.2.1.1. Effects on the kurtosis and variance of the distribution of high-frequency returns. Fig. 1 shows the distributions of high-frequency returns for different T. As in the literature [4,6], our model also generates excess kurtosis (>3). We know the agents' decisions are based on random information, so this means that the microstructure of clearing house can convert the normal distributed limit prices into a leptokurtosis distribution.

Fig. 1 also shows that the kurtosis and standard deviation (represented by StdVar in Fig. 1) are all bigger when $T = 300$ than when $T = 30$. Does T influence kurtosis and standard deviation? Fig. 2 shows further tests relating to kurtosis and variance as T changes.

Fig. 2 shows that the kurtosis as well as the variance tends to be bigger as T increases. A conclusion could be that the clearing frequency T is the key parameter impacting on the excess kurtosis. With higher kurtosis, variance is bigger, so we can also conclude that the excess kurtosis mainly originates from the more observations in the tails of the distribution. Why does higher T lead to more observations in the tails?

We can divide the clearing process into three sub-processes: sub-process 1, the new orders are imported into the book; sub-process 2, the orders are cleared to form the price and volume; and sub-process 3, the traded orders are

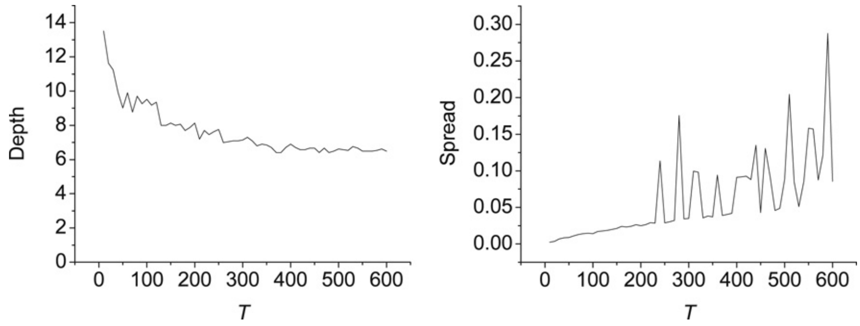

Fig. 3. Depth and spread *vs*. T. Each curve is an average of 10 independent runs, each run has 400 days.

removed from the book (the others are still in the book until the end of the trading day). When T increases, there are fewer new orders entering sub-process 1 of every clearing period. So the density of the orders, especially close to the best bid and best ask in the book will decrease. The best bid is the buy order with highest limit price; the best ask is the sell order with lowest limit price. The book with decreased order density will give more chances for orders with larger fluctuations in limit prices to be traded off, and thus brings more observations into the tails of the distribution (leading to excess kurtosis). Meanwhile, the bigger-fluctuation prices in sub-process 2 leads to wider average spreads in sub-process 3.

We use further numerical simulations to test this analysis. A high density of limit orders per price results in high liquidity for market orders [12], so we can see the density of limit orders as the market depth. We know that the density of limit orders at the ends of the best bid and best ask in the book will mostly impact the liquidity. If we let Δp be the absolute value of the difference between the limit prices of the highest bid order and the second highest one, we can simply define the average depth in sub-process 1 as:

$$\text{Depth} = \frac{1}{\langle \Delta p \rangle}. \tag{1}$$

We consider only the depth of the bid side, and $\langle\cdot\rangle$ means average over all clearing periods.

The spread in sub-process 3 is:

$$\text{Spread} = \langle p_{S\,\min} - p_{B\,\max} \rangle, \tag{2}$$

where $p_{S\,\min}$ is the lowest sell limit price after clearing, $p_{B\,\max}$ is the highest buy limit price. The numerical results are shown in Fig. 3.

Fig. 3 shows that as T increases, the average depth of the market decreases and the average spread of the market increases. This result leads to more observations in the tails of the distribution of prices. Thus, we have explained why microstructure can produce excess kurtosis.

2.2.1.2. Impact on autocorrelation of high-frequency returns. Fig. 4 shows the autocorrelation function (ACF) of high-frequency returns with different clearing frequency T:

In Fig. 4, we find that clearing house can produce positive autocorrelation. But as T increases the phenomenon disappears. This new phenomenon means that microstructure mechanisms affect not only the heavy-tailed distributions but also the autocorrelation of returns series. As with excess kurtosis, the autocorrelation function is also related to clearing frequency T. Thus, we conclude that T is the key to discovering the dynamics of the microstructure that influences high-frequency returns.

We have now reached the conclusion that excess kurtosis may depend mainly on the frequency of clearing in a clearing house market microstructure. How does this microstructure feature impact on the fluctuations of daily returns? We will now consider this question.

2.2.2. Effects on the fluctuations of daily returns

Raberto and Cincotti [6] found that daily close returns are normally distributed despite high-frequency returns having a leptokurtic distribution. However, they did not explicitly discuss this phenomenon in their paper.

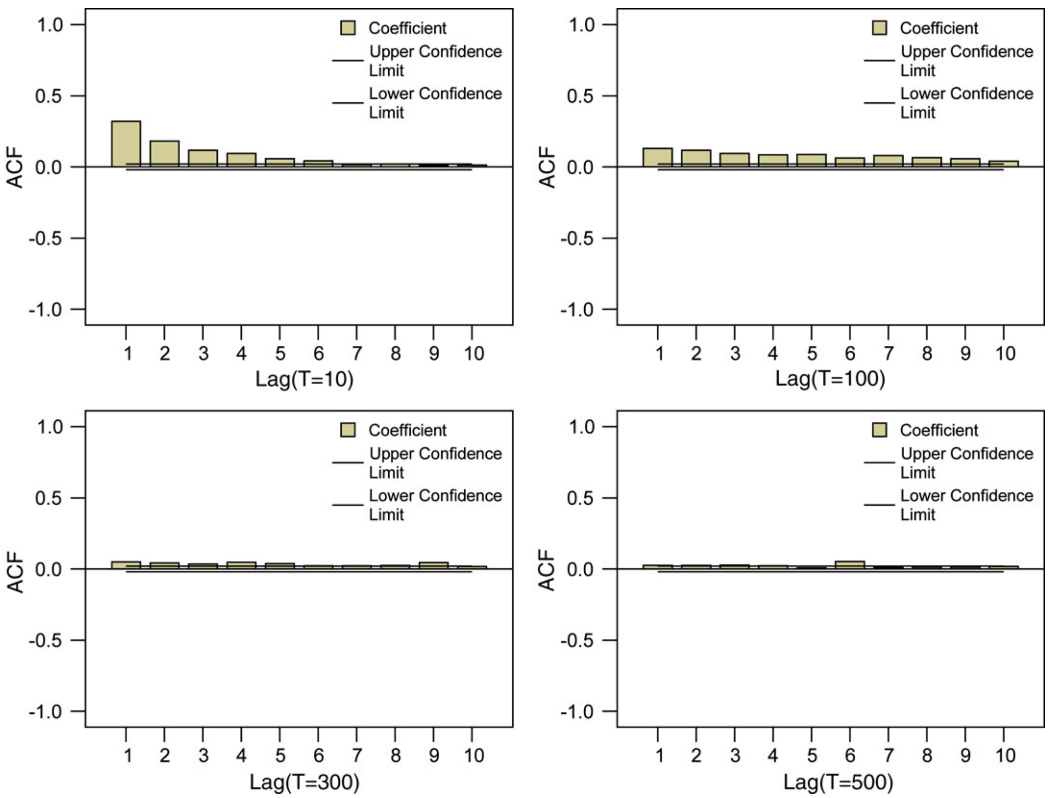

Fig. 4. Autocorrelation function (ACF) of high-frequency returns.

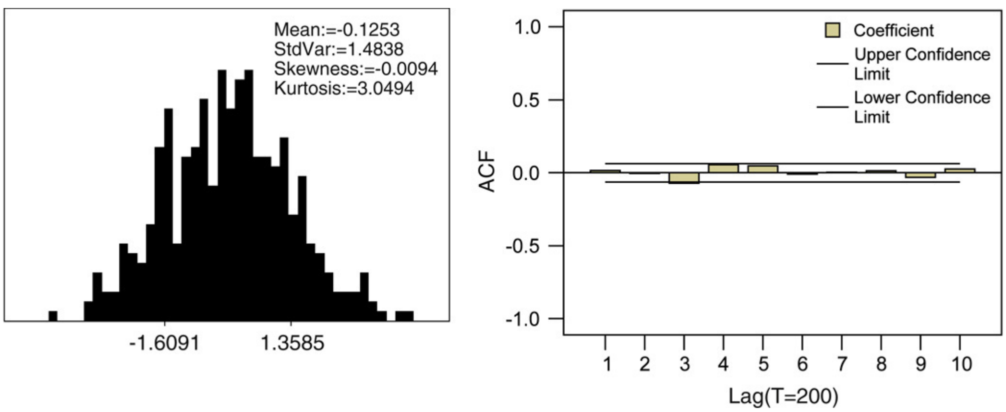

Fig. 5. The distribution and autocorrelation of daily returns. The run has 1000 days, $T = 200$.

We assumed that the prices are the logarithmic returns, so the simple additions of the prices of every clearing period in a trading day are the daily returns. In order to compare the variances of daily returns for different clearing frequency T s, we let the information the agent gets in every clearing period be $\varepsilon_i' \sim \mu(0, \sigma^2/T)$. So, if the market microstructure handles the information linearly, the variances of daily returns must be equal despite the value of T. Fig. 5 shows the distribution and autocorrelation of daily returns.

Fig. 5 shows that the excess kurtosis and autocorrelation present with high-frequency returns do not exist in daily returns. We test the phenomenon by changing T. The results are shown in Fig. 6.

Fig. 6 explicitly shows that daily returns are normally distributed (kurtosis $= 3$). The explanation is that the limit order book is emptied at the end of every trading day (as in the real market), so daily returns are independently and

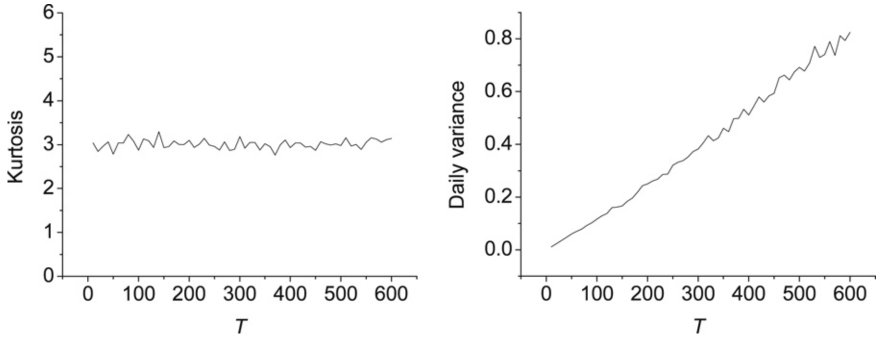

Fig. 6. The kurtosis and variance of daily returns *vs*. T. Each curve is an average of 10 independent runs, each run has 400 days.

identically distributed, and the distribution must converge to the normal distribution (according to the Levy–Lindberg theorem). For the same reason, the phenomenon of autocorrelation must disappear.

Thus, we reach the conclusion that leptokurtosis and heavy-tailed distributions in daily or longer returns is not produced by market microstructure, which is the key factor in producing the same phenomena in high-frequency returns. This conclusion differs from the literature [4–6].

However, we find in Fig. 6 that the variances tend to be bigger as T increases, similar to the high-frequency returns (Fig. 2). As mentioned previously, if the market microstructure handles the information linearly, the variances of daily returns must be equal regardless of the value of T. It follows from Fig. 6 that the clearing frequency in the market microstructure is responsible for the excess volatility, which is another stylized fact.

The simple zero-intelligence agent model shows that the clearing frequency in the market microstructure is the key factor in producing leptokurtosis and heavy-tailed distribution, autocorrelation and excess volatility in high-frequency returns, but it is only responsible to the excess volatility in daily returns. We have also given numerical explanations that support these findings.

Since our results suggest that the market microstructure is not responsible for the leptokurtic distribution of daily returns, we return to modeling the behaviors of agents. Most researchers believe that the behaviors of investors play the most important role in producing stylized facts.

3. Effects of the trading agent behavior

The behavior of agents is an outcome of the rules by which agents make decisions, the principles by which agents issue their orders and the mechanism by which agents learn or evolve.

The Minority Game (MG) [13] model is a very simple decision-making system of multi-agents with bounded rationality, inductive reasoning, diversified decisions and efficient learning mechanisms. The MG has the potential to modeling short-term dynamics of the stock market, although it is a decision-making system not a complete artificial stock market. It is necessary to modify it and then integrate it with other necessary ingredients to build an artificial stock market that is suitable for studying the short-term dynamics of stock market.

3.1. Extended Minority Game (EMG)

The Minority Game model was first presented in 1997 by Challet and Zhang [13]. The MG was motivated by the *El Farol* bar problem of Arthur [14]. At a given time, N agents have two choices, buy a share of a stock or sell a share; they take their decisions simultaneously, without any kind of communication between them; those who happen to be in the minority win.

Agents have available two main types of information:

Public information: for instance, the "state of the world". The most basic global information about the system is which choices were successful in the past. Global information is encoded by a string of M bits (bounded rational agents can only remember the last M bits). For example, 0 stands for "sell was winning" and 1 for "buy was winning". So there are 2^M possibilities.

Private information: adaptive agents are able to trace how well they perform and to modify their behavior when needed.

Adaptive agents have global information processing devices (called strategies) that transform the global information into a decision: 1 or 0, meaning buy or sell. A single strategy maps each of the possible "histories" to a prediction. Thus there are 2^{2^M} different possible binary strategies. Each agent randomly draws S strategies. After each time step, the agent adds a point to the score (virtual score) of each of its strategies that have correctly predicted a win, and subtracts one point from the others. At each time step, the agent uses the strategy with the maximum score to guide its decision.

Algorithm (*See Challet [15]*). The MG is a closed dynamic system. N agents play at each time step t and base their decision on the common pieces of information $\mu(t) \in \xi$, where ξ is the set of all possible pieces of information. Each agent has S strategies (behavior rules) $a_{i,s}$, $i = 1, \ldots, N$, $s = 1, \ldots S$, which is a function from the set ξ into the set of possible actions; here, the possible actions are -1 and $+1$, hence $a^{\mu}_{i,s} = -1$ or $+1$. Each strategy $a_{i,s}$ is given a score $U_{i,s}(t)$ which aims at reflecting the strategy's success rate. At time t, the agent uses the strategy $s_i(t)$ according to

$$s_i(t) = \arg \max_{s=1,\ldots,S} U_{i,s}(t). \tag{3}$$

That is, the strategy with the highest score and the agent takes the decision given by this strategy. The agent's decision is indicated by:

$$a_i(t) = a^{\mu(t)}_{i,s_i(t)}. \tag{4}$$

The decisions of all agents are aggregated into the global quantity

$$A(t) = \sum_i a_i(t). \tag{5}$$

The agent updates the score of its strategies according to the formula:

$$U_{i,s}(t+1) = U_{i,s}(t) - a^{\mu(t)}_{i,s} \operatorname{sgn}[A(t)]. \tag{6}$$

Eqs. (3)–(6) define the basic Minority Game.

Our previous work extended the basic MG [10,11]. For the basic MG, the agent's memory size M is limited, but the score $U_{i,s}(t)$ accumulates each strategy's virtual points from the beginning of the game process. We know that $U_{i,s}(t)$ is the key impetus for the agent's evolution and adaptability. A horizon that is too long will result in $U_{i,s}(t)$ containing too much historical information and will weaken the ability of an agent to adapt and keep up with the evolution of the whole system. So, we extended the basic MG by adding a parameter H into the model. H represents the horizon for which a score for each strategy is recorded: that is, only the virtual points for the last H steps can be added to $U_{i,s}(t)$. So Eq. (6) can be updated to

$$U_{i,s}(t+1) = U_{i,s}(t) - a^{\mu(t)}_{i,s} \operatorname{sgn}[A(t)] - U_{i,s}(t-H). \tag{7}$$

Our previous works [10] showed that this extension leads to a more efficient learning mechanism suitable for modeling the short-term dynamics of the stock market. When H is in the range of about 3–10, the agents are more intelligent and the system is more like the real market.

In this paper, we also change the payoff used by the agents to update their $U_{i,s}(t)$ at every step. In the basic MG, the agents add a point to the score of each strategy that has predicted a correct outcome. However we argue that if the fluctuation of the price was large in the last H steps, then the payoff for the strategy should have a discount. If the strategy has not predicted the correct outcome, the payoff subtracted from its score must have some compensation. So we further change Eq. (7) to (8):

$$U_{i,s}(t+1) = U_{i,s}(t) - a^{\mu(t)}_{i,s} \operatorname{sgn}[A(t)][1 - k\sigma(p_t)] - U_{i,s}(t-H) \tag{8}$$

where $\sigma(p_t)$ is the standard variance of the price within H steps and k is the coefficient (in our work we used $k = 1$).

Eqs. (3)–(5) and (8) define the Extended Minority Game (EMG) which we will use to model our artificial stock market below.

3.2. The artificial stock markets

3.2.1. Economic environment

There is also only one virtual asset (stock) and its fundamental value is not stated.

Every day, each agent decides to buy or sell a share of the stock following the decision-making principles of the Extended Minority Game (EMG). Each agent issues an order with a limit price based on its confidence coefficient.

Prices and volumes are formed by a clearing house mechanism, which in the interest of simplicity clears the order book once a trading day.

3.2.2. Agent behavior

There are two parts of the agents' behavior that is of interest: making predictions and submitting limit orders.

Making predictions: every trading day, an agent must choose to buy or sell a share based on the prediction of which action will be on the minority side. Agents make the predictions by the principles of the EMG. These principles lead to the bounded rationality, inductive reasoning and evolution of the agents and the diversity of their predictions.

Submitting orders: each agent must transform the prediction of buy or sell into an order with a limit price. In order to do this the agent needs another variable: the confidence coefficient $C_i(t)$.

In a real market, traders are likely to wait on the sidelines until they are reasonably confident that they are able to make a profit with their next trade. They will observe the market passively, mentally updating their various strategies; until their confidence overcomes some threshold value then they will jump in and make a trade.

In order to endow agents with this ability, we use the confidence coefficient that was analyzed by Jefferies et al. [16].

The agents of the MG keep a tally of the virtual score $U_{i,s}$ of each of their strategies whether it is played or not. They may also keep a tally of their own personal prediction success, the score R_i which aims at reflecting the success rate of the whole strategies set. Asserting that agents are rational and risk averse implies that agents never really make a trade if R_i is too small. So there is a threshold $r_{\min,i}$. The value $r_{\min,i}$ has three features: 1, $r_{\min,i} > 0$ means the strategy won more than lost; 2, $\frac{dr_{\min,i}}{dR_i} < 0$ means that the agent will take fewer risks if the strategy lost more; 3, $\frac{dr_{\min,i}}{d\sigma[R_i]} > 0$ means that the agent will take fewer risks if the fluctuation of R_i increases. So $r_{\min,i}$ can be defined as:

$$r_{\min,i}(t) = \mathrm{Max}[0, -(R_i - \lambda\sigma[R_i])] \tag{9}$$

where, λ is coefficient of risk-aversion. $\sigma[\cdot]$ means standard variance. $r_{\min,i}$ exhibits the extent of the agent's risk-aversion.

The agent still uses the strategy with highest virtual score to predict. It computes the confidence coefficient $C_i(t)$:

$$C_i(t) = \frac{U_{i,s_i(t)}(t) - r_{\min,i}(t)}{H}. \tag{10}$$

Thus $-2 < C_i(t) < 1$, but the agent only plays if $C_i(t) > 0$.

In the mind of a risk-averse agent, the confidence coefficient reflects the performance of the strategies within the last H steps.

Agents choose to buy or sell based on the strategy with the highest virtual score, and then decide the limit prices based on the confidence coefficient. If the confidence coefficient is high, the agent has more confidence in its prediction system and it is inclined to submit an order with a more aggressive limit price to ensure that its order is traded in the competitive market. On the other hand, if the confidence coefficient is low, it is inclined to submit an order with a less aggressive limit price, or even submit an order with a reverse limit price. For example, there is a stock with present market price \$12. An investor predicts that the price will climb up to \$14 tomorrow. If she trusts her prediction, she may submit a bid order with limit price of \$13, else if she has not enough confidence, she may submit a bid with a limit price \$12.50, else if she has even less confidence she might submit a bid with a reverse limit price \$11.80. These are common behaviors in the real market. Of course, if the confidence is low enough, she will not submit orders at all.

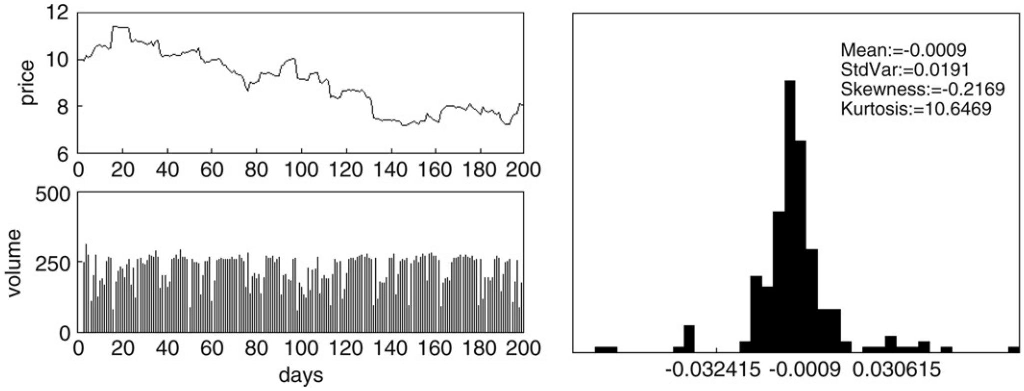

Fig. 7. Price, volume and the distribution of daily returns. $N = 1000$, $M = 4$, $S = 4$, $H = 5$, $\lambda = 0.1$, $C_{\min} = 0.15$, $\upsilon_{\min} = -0.01$, the run has 200 days.

Assume that the limit on fluctuations of returns in a day is $\pm 10\%$, the maximum reverse quoted price is $\upsilon_{\max}$, and the threshold value of the confidence coefficient is $C_{\min}$. Then quoted prices (logarithmic returns) are:

$$p_i^B(t) = -\upsilon_{\max} + (0.1 + \upsilon_{\max}) \times (C_i - C_{\min})/(1 - C_{\min}) \quad C_i \geq C_{\min} \tag{11}$$

$$p_i^A(t) = \upsilon_{\max} - (0.1 + \upsilon_{\max}) \times (C_i - C_{\min})/(1 - C_{\min}) \quad C_i \geq C_{\min} \tag{12}$$

where p_i^B is the limit price of a bid order, p_i^A is the limit price of an ask order. If $C_i < C_{\min}$, the agent does not submit an order.

3.2.3. *Price formation*

Prices and volumes are formed by a clearing house mechanism which clears the orders once a trading day.

The features of the behaviors of agents are bounded rationality, inductive reasoning, evolution and risk-aversion, and the diversity of the predictions. These exhibit the collective features of the behaviors of the investors. All agents in the model are of the same species; we do not divided agents into fundamentalists, chartists and noise investors. The model is suited for studying the short-term dynamics of stock market.

The features of the behaviors are rich, but the model is simple. The effects of the several parameters in the model can be investigated respectively.

3.3. *Computational experiments*

3.3.1. *Descriptive statistics of the daily fluctuations in the new model*

As mentioned previously, the clearing house microstructure has rich effects on high-frequency fluctuations in a stochastic model with zero-intelligence agents but does not lead to a leptokurtic distribution of daily returns. Our new artificial stock markets with both microstructure of clearing house and behavior assumptions can be used to investigate the effects of behavior assumptions on daily returns. The descriptive statistics are shown in Figs. 7 and 8:

Figs. 7 and 8 show that the new artificial stock markets can reproduce stylized facts in daily returns, such as absent autocorrelation, cross-correlation between returns and volume and leptokurtic distribution. It was shown previously that when the model is populated by zero-intelligence agents the distribution of daily returns does not exhibit excess kurtosis. Thus we reach the conclusion that the leptokurtic distribution of daily returns is mainly due to behaviors assumptions.

3.3.2. *The effect of the model's parameters on kurtosis in the distribution of daily returns*

There are several parameters involved in the model for the behavioral assumptions. These parameters are the agent's memory size M, the number of strategies held by agent S, the horizon for which the agent records its scores H, the risk-aversion coefficient λ, the threshold value of the confidence coefficient $C_{\min}$ and the maximum reverse quoted price $\upsilon_{\max}$. Admittedly, there are a little too many parameters for a simple model. But fortunately, we can make clear the effect of each parameter on the leptokurtosis in the distribution of daily returns.

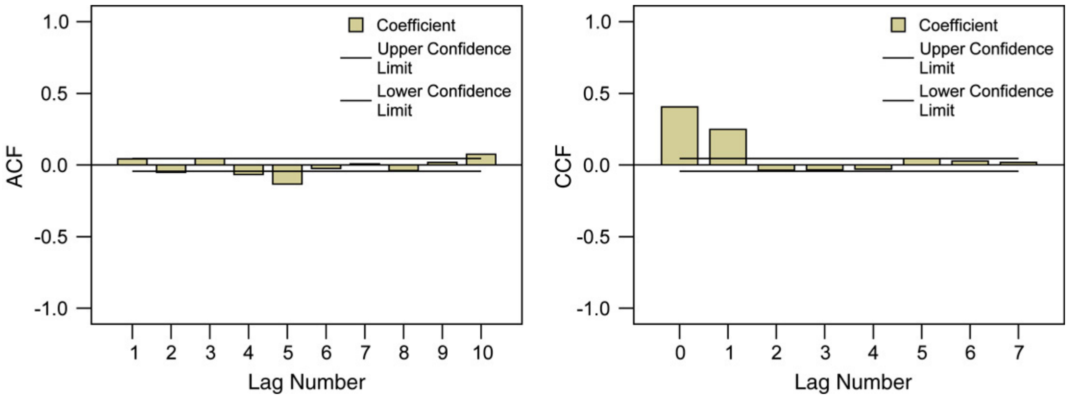

Fig. 8. Autocorrelation (ACF) of daily returns, cross-correlation (CCF) between absolute daily returns and absolute daily logarithmic variations of volume. $N = 1000$, $M = 4$, $S = 4$, $H = 5$, $\lambda = 0.1$, $C_{\min} = 0.15$, $v_{\min} = -0.01$, the run has 2000 days.

We investigated the kurtosis of the distribution of daily returns and the standard deviation of returns when parameters change. The results are shown in Fig. 9.

From the results shown in Fig. 9 we know that all of the 6 parameters (behavioral assumptions) influence kurtosis and standard deviation. In particular, they demonstrate the origins of the leptokurtic daily returns distributions.

We can see that when M, S and H have smaller values (4–7) the kurtosis is more similar to the kurtosis of the distribution of real daily returns (7–10). This means that our model grasps the main features of the short-term dynamics of stock market. We also find that kurtosis will decrease when the risk-aversion coefficient λ increases; that the reverse quoted price $v_{\max}$ causes higher kurtosis; but the influence of $C_{\min}$ is not monotonic.

From Fig. 9, we realize that the dynamics of these behavioral assumptions influencing kurtosis is different from the clearing house microstructure. For the behavioral factors, kurtosis increases mostly when the standard deviation decreases. This result means that the higher kurtosis is caused by the centralized distribution of daily returns. In comparison the clearing house microstructure makes more observations in the tails of the distribution to produce higher kurtosis. Only H is the exception.

4. Conclusions

Pioneer research [4–6] has pointed out that important statistical features of stock price series, such as the fat tails phenomenon, may depend mainly on the market microstructure. This finding activated us to try to make clear the roles of microstructure and behavioral assumptions influencing both high-frequency returns and daily returns. We built two models to investigate these issues.

The first model we built is a stochastic model with a clearing house microstructure and a population of zero-intelligence agents. We found:

1. The microstructure of clearing house can convert the normal distributed limit prices into a leptokurtosis distribution, but does not cause the same phenomenon in daily returns;
2. With a clearing house microstructure, excess volatility is observed in both high-frequency returns and daily returns even agents are zero intelligent;
3. Both kurtosis and volatility tend to be larger as the clearing frequency T increases. T is the key variable determining the dynamics of microstructure;
4. Microstructure also can produce the autocorrelation of high-frequency returns.

We have also given numerical explanations of these phenomena. We found that a clearing house microstructure generates these phenomena by influencing market depth and spread.

The second model is based on Minority Game. The agents are given the behaviors of bounded rationality, inductive reasoning, evolution and risk-aversion, and the ability to make diverse predictions. We found:

1. The behavioral features can explain the leptokurtosis in daily returns;
2. The behavioral features explain the cross-correlation of daily returns and volume;

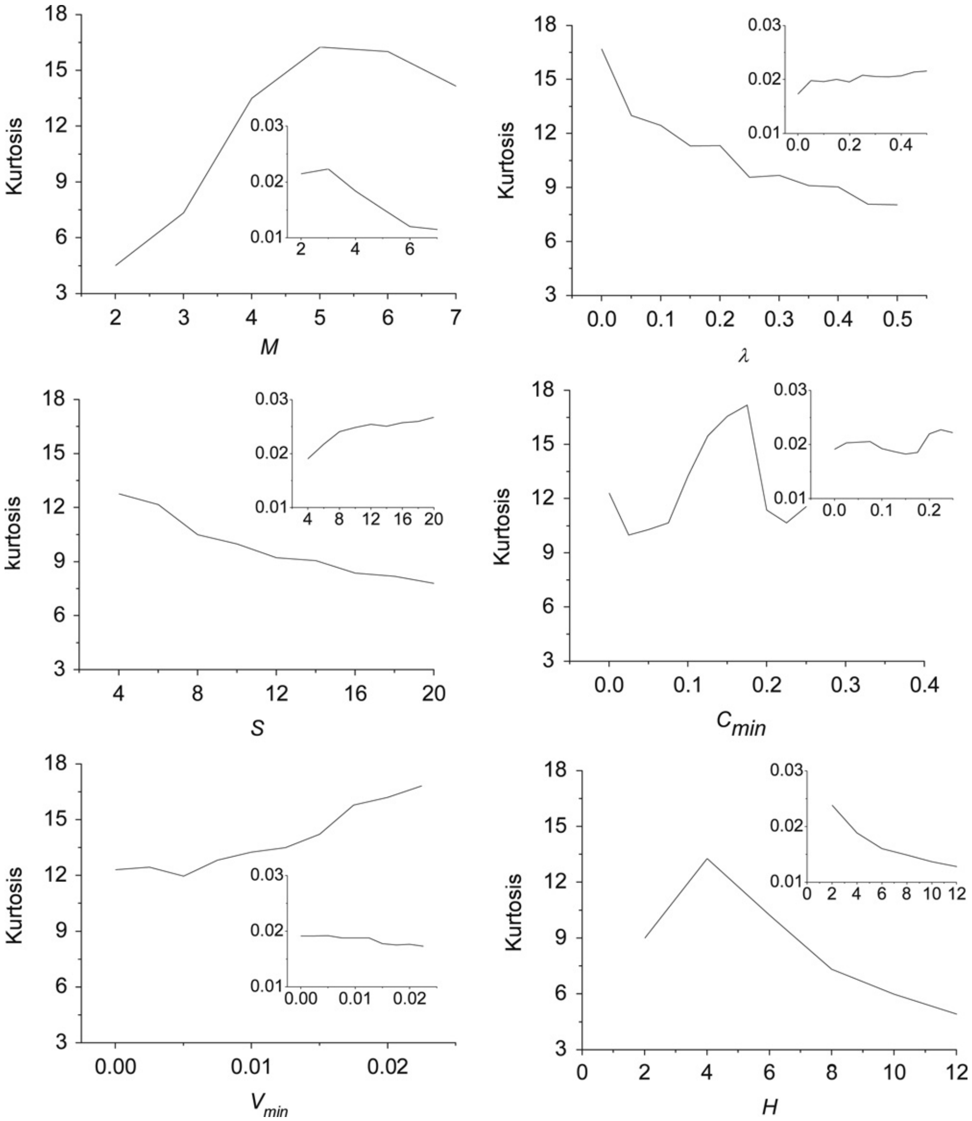

Fig. 9. Kurtosis and standard deviation *vs.* parameters. Inset figures show standard deviations. The value of parameters (if it is not the variable): $N = 1000$, $M = 4$, $S = 4$, $H = 5$, $\lambda = 0.1$, $C_{\min} = 0$, $v_{\min} = 0$. Each curve is an average of 10 independent runs, each run has 400 days.

3. The dynamics of the behavioral assumptions influencing the kurtosis of the daily returns distributions is different from that of microstructure influencing high-frequency returns.

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