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Overall fluctuations and fat tails in an artificial financial market: The two-sided impact of leveraged trading

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ABSTRACT

Recent years have seen leveraged trading playing an increasingly important role in financial markets. However, the effect of leverage on the markets is still an open question. Here, we introduce a framework to investigate leveraged trading through both agent-based simulations and controlled human experiments on a one-stock artificial market. It shows that leverage increases the market risks, and at the same time decreases the outbreak probabilities of financial bubbles or crises. This work helps to understand the impact of leverage on financial markets appropriately.

1. Introduction

In recent years, leverage has played an increasingly important role in financial markets all over the world [1–3]. Usually, leveraged trading means purchasing more of an asset by borrowing funds. And an important concept related to leverage is leverage ratio, which is defined as the ratio of an investor's total assets (his/her own wealth plus borrowed funds) to his/her own wealth. The use of leverage offers investors an opportunity to amplify their profits if the asset price changes in the way as they predict. However, greater risks come along at the same time. When the asset price moves against these investors, their loss will also be magnified. This two-sided nature of leverage has attracted enormous discussion around its influence on investors and firms [4–7], as well as on the whole financial markets [8–12].

Coricelli et al. [4] confirmed with a sample from Central and Eastern European countries that the total factor productivity growth of a firm increases with the rise of leverage ratio until leverage ratio reaches a critical level above which leverage lowers the productivity growth instead. Besides, Lang et al. in their paper [5] found that leverage ratio is negatively related to the growth of firms who either have poor growth opportunities or have good investment opportunities but not being recognized by capital markets. So we can see that although leverage can help firms to gain excess profits, the excessive use of leverage is to the obvious disadvantage of firm growth. But Jin and Zhou [6] pointed out one fact through a behavioral portfolio choice model that a sufficiently greedy behavioral agent is still willing to gamble on potential gains by using leverage despite the risk of catastrophic losses. From the aspect of financial markets, Thurner et al. [8] built a simple model of leveraged asset purchases with margin calls and found that leverage can cause fat tails and clustered volatility in the markets. And Feldman [9] showed that regulating leverage using margin calls can lead to less frequent financial crises, however, it creates harder hit of each crisis than without regulation. Furthermore, the excessive use of leverage is considered to be one of the main factors that created the latest global financial crisis [10,11]. By reviewing literatures on leverage, it can be seen that studying the effect of leverage is also of great practical application. It can either help investors and firms to make right investment decisions [4,7] or help economic policy makers to draft proper regulations [9,13,14].

In our paper, we design a one-stock artificial market in which the effect of leverage is tested. In our agent-based model on this market, there are two types of virtual agents, i.e., the intelligent agents and the quasi-random agents. The intelligent agents mainly represent institutional investors who can gain access to the use of leverage. When making trading decisions, these intelligent agents use heterogenous strategies which take the form modified from the famous minority game [15–19]. The quasi-random agents stand for small investors who cannot use leverage and only trade stocks in a

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small amount. When simulating the model, we only alter the value of leverage ratio of the intelligent agents, while the other market conditions and parameters including trading regulations are fixed. Through this controlled manner, we try to directly reveal the causation between the change of leverage ratio and the variations of statistical properties of the market. In addition, we also combine our agent-based simulations with controlled human experiments [20] to further show the reliability of our model design and to validate our simulated results.

Agent-based models [21–28] and controlled human experiments [20,29–33] have been regarded as two very promising new methods to explore economic systems. And the combination of these two methods to examine the same phenomenon is also shown to be a successful approach [34–42]. Thanks to these preceding researches by both economists and econophysicists mentioned above, we are able to raise the inspirations and ideas in combining the two methods to give a new point of view on the effect of leverage. This is where our work would stand out: to build a one-stock artificial market where leverage is available, combine the methods of agent-based simulations and controlled human experiments, and focus on the pure effect of leverage by fixing all the other parameters or conditions in the market. This work is of value for investors and firms as well as regulators of financial markets to understand and utilize leverage appropriately.

2. Methods

In this section, we adopt the essential ideas from both financial markets and leverage regulations to design a one-stock artificial market. In this market, both agent-based simulations and controlled human experiments are conducted.

2.1. The one-stock artificial market

In our artificial market, there is one stock that can be traded. And the market time is discrete which is denoted as t. Participants in the market can buy or sell the stock at any tick of the time. It is known that when trading in financial markets, investors should give their willing buy or sell prices and also the sizes of the orders for transactions, such like limited orders or market orders. However, for simplicity, participants in our market only need to decide whether they like to buy or sell the stock and their order sizes. Transaction price for all the orders at each time is generated through the market, which will be described later. After all the participants send their orders at a certain time t, the total demand (labeled as $O_d(t)$, which is the total amount of buy orders) and the total supply (labeled as $O_s(t)$, which is the total amount of sell orders) can be obtained in the market. It is a common sense that the stock price movement from $P(t)$ to $P(t+1)$ is determined by the excess demand at time t: the price will rise up if the total demand $O_d(t)$ is over the total supply $O_s(t)$, while the price will fall if the total supply $O_s(t)$ is larger. To quantitatively rule the price movements, we resort to [25,43] and get

$$\ln P(t+1) - \ln P(t) = \lambda\{\ln O_d(t) - \ln O_s(t)\}, \tag{1}$$

where λ is positive and called the market depth which represents the sensitivity of stock prices to excess demands. It can be seen from Eq. (1) that if λ is high, the market will fluctuate heavily when facing a large imbalance between the total demand and total supply; however, a deep market with a small λ can still be stable when in the same situation. Eq. (1) can also be written as

$$P(t+1) = P(t)\{O_d(t)/O_s(t)\}^{\lambda}. \tag{2}$$

Due to our discrete market time, we make another assumption that all the orders sent at time t are executed at the same transaction price which is the weighted average of $P(t)$ and $P(t+1)$:

$$P_{trans}(t) = (1-\beta)P(t) + \beta P(t+1), \tag{3}$$

where $\beta \in [0, 1]$. Now to sum up, the order transaction and price generating process is: all the buy orders $O_d(t)$ and sell orders $O_s(t)$ coming at time t will be executed at price $P_{trans}(t)$ defined in Eq. (3), and a new price $P(t+1)$ is generated from Eq. (2) when time flows discretely from t to $t+1$.

Next, we turn to the rules of leverage. In financial markets, the use of leverage involves many detailed and even complicated regulations that also usually vary from country to country. Here we only pick up the most general and essential rules of leverage to put into our artificial market: leverage qualification, leverage ratio, and margin call. Note that in this paper we mainly focus on the influence of different leverage ratios over statistical properties of the market, hence we control carefully over the other variables and conditions related to the participants and the market. And because the quasi-random agents (whose behaviors will be defined later) in the market get no access to leverage, the participants mentioned below refer only to the intelligent agents in our simulations or the human subjects in our controlled experiments.

- Leverage qualification: To begin trading in the market at $t = 0$, we give every participant the same initial portfolio: 10,000 cash, 1000 shares of the stock with an initial stock price $P(0)$ at 10, and zero debt. And by trading the stock along the time, wealth distributions of the participants will become diversified due to their heterogenous investment skills. Let $D(t)$ and $E(t)$ stand for the money and the equity (stock shares) a participant holds respectively at time t, then his/her total wealth $W(t)$ can be calculated by

  $$W(t) = D(t) + E(t)P(t). \tag{4}$$

  So the total initial (own) wealth held by every participant is $W(0) = 20{,}000$. In our market, we rule that only the participants whose total wealth reaches a qualification level W_L can have the right to borrow funds from a lending institution and then trade with leverage. This is a reasonable simplification for leverage qualification because those participants with total wealth satisfying the required qualification level must be the ones who have better investment abilities. We set $W_L = 125\%W(0) = 25{,}000$, which means that an accumulated 25% return from the total initial (own) wealth is needed for a participant to meet leverage qualification.
- Leverage ratio (denoted as L_r): L_r is defined as the ratio of an investor's total assets (his/her own wealth plus borrowed money) to his/her own wealth. Note that L_r can be decided by another quantity called initial margin requirement (denoted as M_I). M_I is the least proportion of margin (which can be earnest money or equity) required when an investor opens a position with borrowed money. It can be seen that if an investor uses up the entire margin buying power, his/her leverage ratio is $L_r = 1/M_I$ accordingly. In our market, we regulate that a participant will use up all the margin buying power when his/her total wealth just reaches $W_L = 25{,}000$ at time t'. Therefore, with a margin of W_L, the participant borrows $B_r = (L_r - 1)W_L$ and his/her total wealth (his/her own wealth plus borrowed money) now becomes $W(t') = L_r W_L$. By setting this regulation, we guarantee that all the participants qualified for leveraged trading use the same leverage ratio so that we can study the pure impact on the market when a change occurs in the value of L_r.
- Margin call: In financial markets, another important quantity named maintenance margin requirement (denoted as M_M) is also regulated by lending institutions. M_M is usually lower than M_I in order to allow some fluctuations in stock prices. When an investor's margin falls below M_M after a great loss,

he/she should bring the margin back to M_I immediately, otherwise he/she will be forced to liquid his/her stocks to return the borrowed money. This process of forced liquidation is also known as a margin call. Since the qualified participants in our market use up all the margin buying power, they will have no more extra money to add their margins when they suffer great losses. Therefore, these participants will face margin calls directly and be forced to sell their stock immediately to return the debts when they fail to meet the maintenance margin requirement. Since $L_r = 1/M_I$ and M_M is positively correlated to M_I, an increase in the value of L_r will lower the value of M_M. This means that if we use M_M as the quantity to control the trigger of a margin call, we have to set different values of M_M when changing L_r. So here we adopt another quantity, i.e., the critical percentage loss l_c of the margin from W_L which triggers a margin call on a participant. We call $(1 - l_c)W_L$ the critical margin level. It is easy to get the following equation for M_M:

$$M_M = \frac{1 - l_c}{L_r - l_c}. \tag{5}$$

In Eq. (5), we can see that with a fixed value of l_c, a value increase of L_r will directly lower the value of M_M. In the market, we set $l_c = 40\%$, so the critical margin level is $(1 - l_c)W_L = 15{,}000$. Therefore, in our market, if one participant's margin falls below the critical margin level of 15,000, he/she will be disqualified for leveraged trading and be forced to sell the stock to return his/her borrowed funds immediately. If after some time this participant gains great profits and his/her total (own) wealth comes above $W_L = 25{,}000$, he/she will be re-qualified and then be able to use leverage again.

Next, we will introduce the agent-based simulations and controlled human experiments conducted in this artificial market accordingly.

2.2. Agent-based simulations

In the simulations, we bring two types of artificial agents into our market, i.e., the intelligent agents and the quasi-random agents. The intelligent agents mainly represent institutional investors who can gain access to the use of leverage and trade in a huge amount of money and stock shares. The quasi-random agents are with almost zero intelligence and they mainly stand for small investors who get no access to leverage due to their small amount of wealth in the market.

The "intelligence" of the intelligent agents means that they can decide on their own whether they would like to buy or sell the stock at a certain time as well as their order sizes under organized market information. In this work, we adopt the design of strategy tables used in the paper of Yeung et al. [15] which was modified on the famous minority game [18]. One particular strategy table is shown in Table 1 which has two columns. The left column of the strategy shows all the possible history price binary series in which 1 is represented for stock price rising or staying the same while 0 for price falling. The history length that an intelligent agent considers when making his/her decision is denoted as m. We assume that the value of m is the same for all the intelligent agents and also fixed during the simulations, so there are in total 2^m different market history situations. Under every history situation, the right column is filled with $+1$, -1 or 0 which represents a decision of buying, selling, or holding the position respectively. Before entering into the market, every intelligent agent creates S strategies (which will be fixed during the whole trading period) by randomly filling $+1$, -1 or 0 into the right column of each strategy table. The

Table 1
A particular strategy table used by the intelligent agents (when $m = 3$).

History	Choice
000	1
001	−1
010	0
011	0
100	1
101	−1
110	1
111	−1

success of a strategy is evaluated by virtual profits that the strategy would have gained if it were used from the very beginning. At every time step, an intelligent agent will select his/her most successful strategy to guide his/her real actions under the associated market history situation. For example, at time t, suppose that the history situation is "011" (which means that stock price dropped from $t - 3$ to $t - 2$, and then went up or stayed unchanged both from $t - 2$ to $t - 1$ and from $t - 1$ to t) and Table 1 is the current strategy with the highest virtual profits for intelligent agent i. Then agent i will choose to hold the position from t to $t + 1$ accordingly, since choice 0 is related to history "011" in Table 1.

As mentioned above, the intelligent agents should also be able to decide their order sizes. Let $W_i(t)$, $D_i(t)$, and $E_i(t)$ be intelligent agent i's total wealth (his/her own wealth plus borrowed money), total money, and total shares of the stock held at time t. Then we define an investment ratio $r_i(t)$ with which agent i controls the shares of the stock to buy or sell at time t:

$$r_i(t) = 1 - \exp\{-cW_i(t)\}, \tag{6}$$

where c is assumed to be a positive constant for all the intelligent agents, and it is obvious that $r_i(t) \in [0, 1)$ and $r_i(t)$ is positively related to $W_i(t)$. At time t with a stock price $P(t)$, based on whether to buy or to sell, agent i's order size is defined accordingly as

$$\text{shares to buy} = \lfloor r_i(t)D_i(t)/P(t) \rfloor, \tag{7}$$

$$\text{shares to sell} = \lfloor r_i(t)E_i(t) \rfloor, \tag{8}$$

where $\lfloor X \rfloor$ gives the largest integer no greater than X. From Eqs. (6)–(8), we can see that the intelligent agents with more total wealth are more likely to give large orders.

The quasi-random agents mainly represent small investors who normally have the following typical trading behaviors: 1) trading almost randomly compared to institutional investors; 2) usually with herd behaviors; 3) with no access to leverage; 4) contributing a small proportion of the market volume. Therefore, we consider behaviors of the quasi-random agents as a whole. Suppose the total buy orders and total sell orders sent by the intelligent agents at time t are $O_d^{int}(t)$ and $O_s^{int}(t)$ respectively, then the total buy orders from the quasi-random agents are set as $R_d\{O_d^{int}(t) + O_s^{int}(t)\}$, and their total sell orders are $R_s\{O_d^{int}(t) + O_s^{int}(t)\}$. R_d and R_s are two uncorrelated random numbers whose values are drawn randomly from a uniform distribution in the scale of $[0.1, 0.3]$. It is shown that these quasi-random agents can contribute a percentage from 0.167 to 0.375 of the total market volume. And if the intelligent agents begin to trade actively in one period and increase market volume greatly, these quasi-random agents (with herd behaviors) are also more likely to become active and send more orders into the market. Therefore, we call this type of agents the "quasi-random" agents and it is assumed that these quasi-random agents cannot use leverage in our market.

Now let us discuss the values of the model parameters set in our simulations. For the intelligent agents, the history length that an agent considers is $m = 3$ and each agent has $S = 4$ strategies.

In Eq. (3), the weight β is set to 0.5 so that $P_{trans}(t)$ is a simple average of $P(t)$ and $P(t+1)$. It can be seen in Eqs. (1) and (2) that the market depth λ only affects the amplitude of market price fluctuations at every time step. Therefore, the exact value of λ has no impact on the intelligent agents' decisions of whether to buy or to sell (since the agents only check the directions of price movements when using their strategies). Due to this reason, we only need to consider the following two aspects when choosing a proper value for λ: first, if the value of λ is too small, the market will barely see large fluctuations and it may take a very long time for an agent to gain enough profits to meet leverage qualification; second, when λ is large, a huge unbalance between the total demand and total supply (which is not a very rare event in simulations) will drive the stock price directly to an extremely high level or to almost zero. Hence, we keep $\lambda = 0.005$ in simulations so that the market is stable and the well-performing agents are also able to use leverage in the finite simulation steps. Since the intelligent agents represent institutional investors, we expect them to behave rationally in the market according to the following two rules: first, when with zero leverage, the agents should trade neither too aggressively (varying their stock positions heavily) nor too conservatively (always keeping a very low level of stock positions); second, when trading with leverage, the agents should make full use of their borrowed money when they decide to add their stock positions and also they need to control their risks actively (i.e., clearing their positions quickly when the stock price is expected to fall). And it can be seen from Eqs. (6)–(8) that the value of c actually controls the agents' position changing behaviors. Therefore, in simulations we set $c = 5 \times 10^{-5}$, and according to Eq. (6), the investment ratio $r_i(t) = 1 - \exp(-1) \approx 0.632$ for the agents with initial (own) wealth $W(0) = 20{,}000$, $r_i(t) \approx 0.713$ when their total (own) wealth just reaches the qualification level $W_L = 25{,}000$, and after they trade under total wealth $W(t) = 50{,}000$ for $L_r = 2$, $r_i(t) \approx 0.918$, which well satisfies the two rules mentioned above.

Furthermore, we recruit 1000 intelligent agents into the market for simulations. The value of L_r varies in our simulations from 1 to 9 by an interval of 0.2. Note that $L_r = 1$ represents the market with zero leverage. Under each value of L_r, an ensemble of 100 simulation rounds are run and each round has a period of 10,000 time steps.

2.3. Controlled human experiments

In our controlled human experiments [20], we replace the intelligent artificial agents in simulations with students from Fudan University. Therefore, now the students represent institutional investors who can use leverage in the market. At each time, the students can decide on their own whether to buy or to sell as well as their order sizes. And except for these different decision-making processes between the intelligent artificial agents and the human subjects, all the other settings (such as the behaviors of the quasi-random artificial agents, the properties of the market, and the regulations of leverage mentioned above) are the same in both our simulations and experiments.

In order to make our experimental results more general, we have done two series of experiments at different time with different groups of students but under the same experimental settings. Our first experiments were conducted on Jul. 8th, 2013, in which we recruited 22 students and studied the market with L_r being 1 and 5 accordingly. And the second experiments were conducted on Sep. 27th, 2013, in which we recruited 46 students and investigated the cases with L_r being 2, 3, and 4, respectively. For each value of L_r, we conducted 60 time steps. Due to the different number of participants and different length of time steps conducted between our simulations and experiments, we set the market depth $\lambda = 0.16$ in Eqs. (1) and (2) to guarantee that the market was stable and the well-performing students were also able to use leverage in the finite experimental steps. One round of pre-game with $\lambda = 0.16$ was also conducted right before the formal experiments to let the students become accustomed to the stock price fluctuations under $\lambda = 0.16$ accordingly. Besides, the weight β in Eq. (3) was still kept as 0.5 in our experiments.

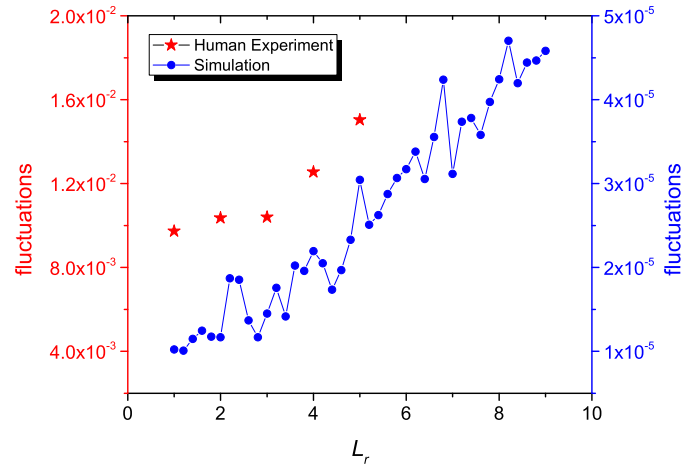

Fig. 1. (Color online.) The influence of different leverage ratios on overall market fluctuations for both simulations (shown in blue dots and measured with the right vertical scale) and human experiments (shown in red stars and measured with the left vertical scale) respectively. For simulations, the value of overall fluctuations under each leverage ratio is calculated as the ensemble average of 100 simulation rounds with each round having 10,000 time steps. And for experiments, it is calculated from the data of a single experimental round with 60 time steps.

3. Results

In Fig. 1, it can be seen that for both simulations and experiments, a higher value of L_r generally leads to larger overall fluctuations of the market (defined as the variance of the market log-return series). This is a negative effect of leverage on the market, since the level of overall fluctuations is usually the measure of market risks. There are mainly two reasons behind this positive relationship between leverage ratio and market risks. First, there will be a great amount of money flowing into the market from time to time to buy the stock when L_r is high, which pushes the stock price up with great fluctuations. Second, Fig. 2 shows the relation between L_r and the total margin calls per intelligent agent (denoted as N_{mc}/N_{agents}) or per subject (denoted as $N_{mc}/N_{subjects}$) happening in the simulated or the experimental market. It can be seen that when L_r increases, margin calls are more likely to occur in both simulations and experiments. Therefore, in the market with a high value of L_r, a moderate crash of the stock price can trigger margin calls on many participants and force them to liquid their stock shares. With these large sell orders coming from the participants whose original trading strategies are mostly violated due to margin calls, the stock price will go down further and even more margin calls will be triggered. And due to this nonlinear feedback on stock prices that is created by leveraged trading with margin calls, one can also see in Fig. 1 that when increasing L_r from 1, overall fluctuations of the market rise slowly at first and then climb up much heavily.

For the comparison of our simulations and experiments, it has been seen in Figs. 1 and 2 that the changes of the market properties (the overall fluctuations or the margin call frequencies) in both simulations and experiments share the same trend when increasing L_r. However, their specific values are different for the same L_r in the two approaches. This is just because the number of participants (i.e., the intelligent agents in simulations and the human subjects in experiments) and the value of market depth λ

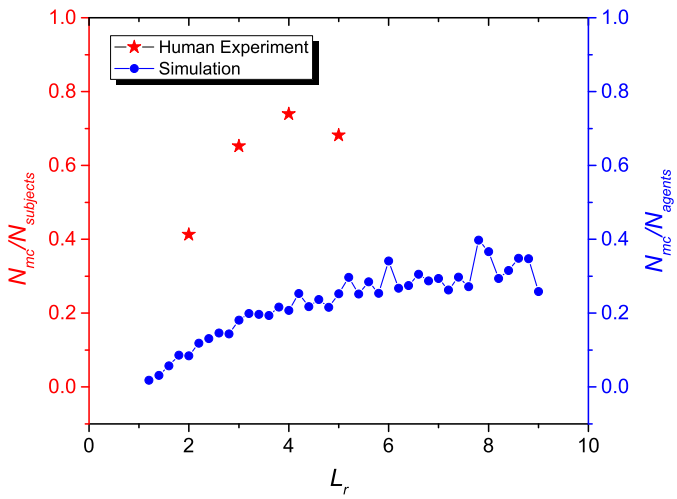

Fig. 2. (Color online.) The total number of margin calls occurring N_{mc} over the total number of the intelligent agents N_{agents} or the human subjects $N_{subjects}$ in the market under different values of leverage ratio. Each blue dot represents the simulated result which is the ensemble average of 100 simulation rounds with each round having 10,000 time steps. Each red star is calculated from the experimental data of a single round of human experiment with 60 time steps.

in Eqs. (1) and (2) are set differently between our simulations and experiments. Therefore, we can say that our agent-based model is a reasonable design to study the effect of leverage because of the resemblance between the statistical results from our simulations and experiments. Superior to controlled human experiments in which the length of experimental time is unavoidably limited, agent-based simulations can be run with evolutional time being as long as possible. Hence, we use simulations next to study another important market statistical property, i.e., the kurtosis, which demands a much larger data set to calculate.

It is known that tails of the probability density function (pdf) of market return series represent the occurring rates of extreme cases like financial bubbles or crises. Although these extreme cases are rare, once they take place, they will bring extraordinary severity into the market. Fat tails showing in the market return distributions mean that these extreme cases happen more frequently in financial markets than predicted by traditional economic theories where Gaussian distributions are adopted to describe price movements. Hence, studying the fat-tail effect is of great importance not only for fundamental researches but also for market predictions. The empirical studies have already shown that the price return distributions of various financial indices or stocks all possess fat tails [44]. Usually, the kurtosis is a measure of fat tails in pdf (a higher value of the kurtosis means fatter tails with a sharper peak), which is defined as,

$$\text{kurtosis} = \frac{\mu_4}{\sigma^4} - 3, \tag{9}$$

where μ_4 is the fourth central moment and σ is the standard deviation of the price return series. And the value of the kurtosis is 0 for Gaussian distributions. Fig. 3(a) shows that under different values of L_r, distributions of the market log-return series all reproduce the phenomenon of fat tails that is well known in real financial markets. Furthermore, the kurtosis falls down with the increase of L_r. This is surprising when comparing Fig. 3(a) with Fig. 1, because increasing L_r brings up the overall fluctuations (a negative effect) and shrinks down the fat tails (a positive effect) of the market at the same time.

In order to see what exactly happens to the kurtosis in Fig. 3(a), we draw the distributions of the normalized log-return series under different values of L_r. As shown in Fig. 3(b), it is obvious

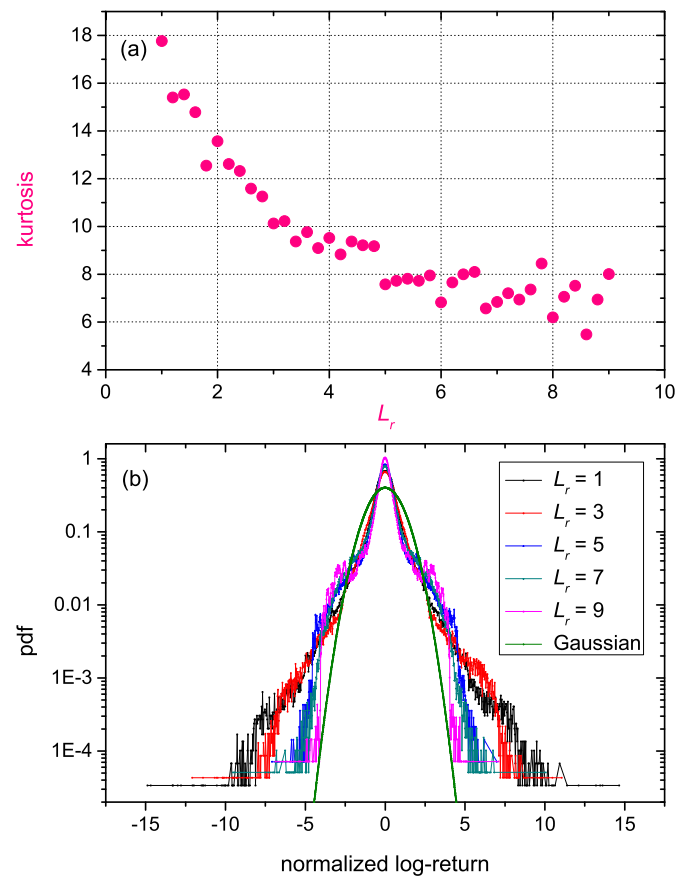

Fig. 3. (Color online.) Simulated results for the effect of leverage on fat tails of the market: (a) shows the kurtosis as a function of leverage ratio; (b) displays the pdf curves of the normalized log-return series of the market under different values of leverage ratio. Here the "normalized log-return" is defined as $(\log\text{return} - \bar{r})/\sigma$, where $\bar{r}$ is the average value and σ is the standard deviation of the log-return series. In (b), the standard Gaussian distribution (denoted as "Gaussian" in the subfigure label) is also included for comparison. Both (a) and (b) are the ensemble averaged results of 100 simulation rounds with each round having 10,000 time steps.

that by increasing L_r, the tails of the distributions are moving towards the standard Gaussian distribution, which means that the tails get thinner and thinner. The explanation on this negative correlation between the kurtosis of the market and L_r can be found in Fig. 4. Here, we use $N_{leverage}$ to denote the total number of times that participants gain the right to trade with leverage in the market. Then $N_{mc}/N_{leverage}$ represents the percentage by which participants trading with leverage end up with meeting margin calls. In Fig. 4, it can be seen that when L_r increases in our simulations, $N_{mc}/N_{leverage}$ at first rises up greatly and then increases with much slower paces. The highest value of $N_{mc}/N_{leverage}$ shown in our simulations is only 0.557 at $L_r = 9$ (which is the largest value of L_r run in simulations). This means that even under the heavy overall market fluctuations induced by large values of L_r (as shown in Fig. 1), there still exist a percentage of the intelligent agents who are never confronted with margin calls when trading with leverage. Therefore, leverage qualification and margin call can be seen as two filters which screen out the intelligent agents with best investment abilities. First, leverage qualification gives the well-performing intelligent agents extra funds to trade in the market, so these agents with great investment abilities now can have a great influence on the market. Then, through margin call, only the most skilled and rational agents who are able to handle market crashes properly can still trade with leverage in the market. When L_r increases, it is obvious that the filter of margin call on the

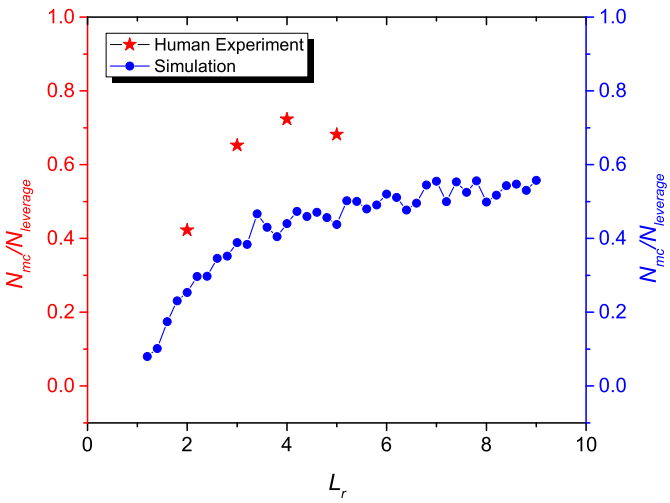

Fig. 4. (Color online.) The total number of margin calls triggered N_{mc} divided by the total number of times that participants gain the right to trade with leverage $N_{leverage}$ in the market under different values of leverage ratio. Each blue dot represents the simulated result which is the ensemble average of 100 simulation rounds with each round having 10,000 time steps. Each red star is calculated from the experimental data of a single round of human experiment with 60 time steps.

agents becomes harsher. Therefore, especially by increasing L_r, the market will be dominated by the most talented agents gradually. And the dominance of these most talented agents can in turn prevent the market from crashing irrationally. So increasing L_r brings down the fat tails in the distributions of the market log-return series. Fig. 4 also shows the same trend of $N_{mc}/N_{leverage}$ with the increase of L_r in both our simulations and experiments. This may imply that if our experiments were conducted for months to gather enough data for the statistics of the kurtosis, we could find the same phenomenon that increasing L_r shrinks down the fat tails in our experiments.

4. Discussion and conclusions

Note that Thurner et al. [8] showed in their agent-based simulations that increasing leverage ratio leads to heavier tails of the market log-return series, which is at odds with our findings. This is because the agents they designed in their model have very different behaviors from real-world traders. In their model, there are also two types of agents trading in a one-stock virtual market: the random traders and the value investors. They assumed that the stock has a constant fundamental value which is known to all the value investors (note that this is untrue in real financial markets); and the more greatly the stock price falls under the fundamental value, the more shares of stock the value investors will try to buy. This means that when the price falls lower and lower, no value investors have the intelligence to keep small positions to avoid margin calls. Therefore, there is no filtering effect of leverage qualification and margin call to screen out the best-performing agents who can handle market crashes properly in Thurner et al.'s model, and under a high leverage ratio even small price fluctuations can destroy their market. Since the behaviors of the intelligent agents in our model are much more reasonable, and our model can also reproduce the fat-tails shown in real financial markets as well as the phenomena occurring in our human experiments under all the values of L_r including $L_r = 1$ (note that in the model of Thurner et al. [8], when the value investors all trade with no leverage, the simulated price returns simply follow a Gaussian distribution), our findings are much more reliable.

Therefore, it is shown that agent-based simulations and controlled human experiments are two complementary methods. Agent-based simulations are usually confronted with exhausting questions on their model designs. One can doubt the correctness of a conclusion from simulations simply through criticizing the associated model designs. Hence, with the combination of agent-based simulations and controlled human experiments to examine the same phenomenon, researchers can easily show their model designs are proper by comparing the statistical results from the two approaches. For controlled human experiments, researchers always find in pain that their experiments are limited unavoidably with the funds, the experimental time length, the sample size and the representativeness of the human subjects recruited, etc. These limitations make it somehow difficult to generalize the conclusions obtained from controlled human experiments. Besides, researchers may also find from time to time that the small data sets obtained from experiments are not enough for the use of some important statistical analyses. Fortunately, with the help of agent-based simulations, researchers can do deeper analyses through a much larger simulated data base and further generalize the conclusions from controlled human experiments.

To sum up, in this work, we have designed a one-stock artificial market, and then used both agent-based simulations and controlled human experiments to study the pure effect of leverage on the market with the other market parameters and conditions being fixed. We have found that leveraged trading has a two-sided impact on the market: on one hand, leverage causes large overall fluctuations in the market, thus increasing the market risks; on the other hand, leverage shrinks down fat tails in the distribution of the market log-return series, thus decreasing the probabilities of outbreak of extreme market events such as financial bubbles or crises. Hence, by limiting leverage ratios into a proper region, regulators may confine both overall market fluctuations and occurring rates of extreme market events to a moderate level for creating healthy financial markets.

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