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The impact of margin trading on share price evolution: A cascading failure model investigation

Ya-Chun Gao [a,d], Huai-Lin Tang [b], Shi-Min Cai [c,d,*], Jing-Jing Gao [e], H. Eugene Stanley [d]

[a] School of Physics, University of Electronic Science and Technology of China, Cheng Du 610054, PR China
[b] School of Management and Economics, University of Electronic Science and Technology of China, Cheng Du 610054, PR China
[c] Web Sciences Center & Big Data Research Center, University of Electronic Science and Technology of China, Cheng Du 610054, PR China
[d] Center for Polymer Studies and Department of Physics, Boston University, Boston, MA 02215, USA
[e] School of information and communication engineer, University of Electronic Science and Technology of China, Cheng Du 610054, PR China

HIGHLIGHTS

- A cascading failure model is proposed to investigate the margin trading.
- The model is performed based a bipartite graph with trader and share nodes.
- The stock market evolves from the stable state to vulnerable state with an external shock.
- The share prices undergo a cascading failure process in the vulnerable stock market.
- The cascading failure of share prices is strongly affected by four key factors of margin trading.

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ABSTRACT

Margin trading in which investors purchase shares with money borrowed from brokers is blamed to be a major cause of the 2015 Chinese stock market crash. We propose a cascading failure model and examine how an increase in margin trading increases share price vulnerability. The model is based on a bipartite graph of investors and shares that includes four margin trading factors, (i) initial margin k, (ii) minimum maintenance r, (iii) volatility v, and (iv) diversity s. We use our model to simulate margin trading and observe how the share prices are affected by these four factors. The experimental results indicate that a stock market can be either vulnerable or stable. A stock market is vulnerable when an external shock can cause a cascading failure of its share prices. It is stable when its share prices are resilient to external shocks. Furthermore, we investigate how the cascading failure of share price is affected by these four factors, and find that by increasing v and r or decreasing k we increase the probability that the stock market will experience a phase transition from stable to vulnerable. It is also found that increasing s decreases resilience and increases systematic risk. These findings could be useful to regulators supervising margin trading activities.

* Corresponding author at: Web Sciences Center & Big Data Research Center, University of Electronic Science and Technology of China, Cheng Du 610054, PR China.
E-mail address: shimin.cai81@gmail.com (S.-M. Cai).

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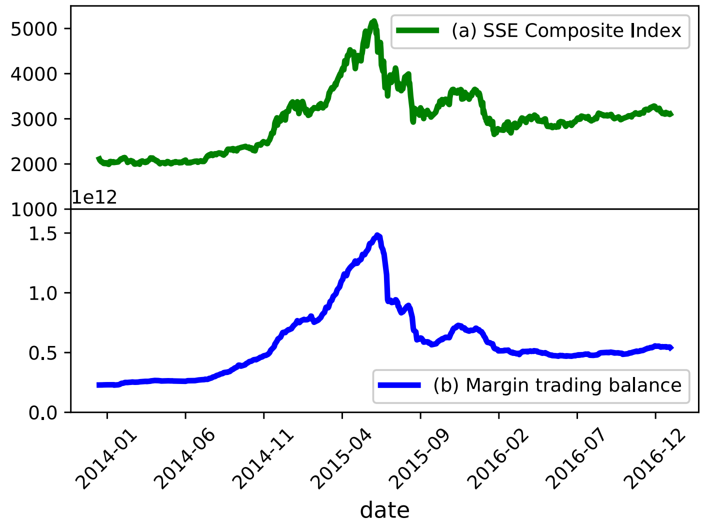


Fig. 1. (Color Online) (a) SSE Composite Index and (b) margin balance changed with time from the beginning of 2014 to the end of 2016.

1. Introduction

During the 2014–2015 period the Chinese stock market experienced extreme volatility and ruinous boom–bust behavior. The important Shanghai Stock Exchange (SSE) Composite Index rose approximately 33% in one month and then fell 29% in seven trading days. Fig. 1(a) shows that the extreme bull market began in July 2014, that the SSE index reached a seven-year high on 12 June 2015, but that within a short period of a few weeks the same index dropped sharply in what came to be known as the mid-2015 Chinese stock market crash.

It is speculated that this erratic Chinese market behavior was caused in part by a huge increase in margin trading [1]. Generally speaking, margin trading uses financial leverage. When investors feel bullish toward an investment opportunity they borrow capital from brokers or other resources, e.g., shadow banks, to purchase shares. To minimize losses, brokers require investors to pay a portion of the share price as a margin and to use the purchased shares as collateral for the loan. There is also a requirement that there be a minimum maintenance margin, above which the total amount of equity must be maintained in the margin account [2].

Margin trading is high risk and can yield huge profits or total losses. Because China's securities market was immature and approximately 90% of its traders were retail investors, margin finance and short-selling services were not made available prior to 2010 [3,4]. In that year the China Securities Regulatory Commission (CSRC) conducted a pilot project and allowed shares of a few dozen companies to be bought on margin or sold short. In September 2014, the approved list of stocks was expanded to include more than 900 companies. Fig. 1(b) shows that margin trading rapidly increased and nearly doubled in the four months from September to December 2014. A huge amount of credit was injected into the securities market and the SSE Composite Index rapidly increased. Fig. 1 shows that the time series of the SSE Composite Index and of margin loans were strongly correlated and fluctuated following the same trends. During this bull market period, share prices and margin financing activities promoted each other, and a huge market bubble was created.

Margin financing is a high-risk double-edged sword. Although some propose that stock price behavior indicates [5–7] that margin eligibility can raise liquidity [8] and stabilize the market [9], others argue that margin trading produces excess volatility and destabilizes the market [10,11]. We conjecture that margin trading activities are a strong factor in the drop in stock prices during a crash and can accelerate the decline. Fig. 1 shows that immediately following the sharp drop in share prices, margin lending also dropped sharply, which in turn accelerated the devaluation of the market index. This behavior was described previously [12,13], but the obtained results were based on observations and regression results and did not explain the mechanism driving the behavior.

Here we propose a cascading failure model [14–18] to identify the mechanism that allows margin trading to amplify the vulnerability of share price and that caused the 2015 Chinese stock market crash. The basic idea is that margin-covering resulting from the minimum maintenance margin requirement rapidly decreases share price, which further triggers more margin-covering and results in a cascading failure of share prices.

2. Model

A bipartite graph is used to show the cascading failure model of margin trading [19–21]. Nodes are divided into two non-overlapping sets of $N = 20000$ margin investors and $M = 1000$ shares. We abstract the margin trading market on this bipartite graph and simplify the model by assigning M shares the same market capitalization and price impact factor. Each investor initially purchase s shares on margin, with one unit of trading volume, namely, each node from the investors set is linked with s nodes from the shares set. Here s is a constant and $s_i = s, (i = 1, 2, \dots, N)$ for investor i. Thus the property in each margin account is the total value of s shares, and all the purchased shares serve as collateral for the loan.

Suppose the *initial margin* or the *leverage ratio* is $k \in [0, 1)$, i.e., the deposit of the investor is a k fraction of the whole property in the margin account, or the investor borrows $1 - k$ of the value of all purchased shares. In the stock market, share prices constantly fluctuate. During a bull market, investing on margin is a leverage technique that can boost profits. When the market suddenly drops, those investing on margin may find their margin account equity insufficient to cover their restriction of maintenance fee. If the equity in the margin account falls below a certain level, the investor must deposit more cash to the account to cover the difference. This is referred to as a *margin call*. If the investor does not add money quickly enough, the broker can sell the securities without notice and liquidate the account to cover the loan. We here denote r the *minimum maintenance margin*. If the ratio between the market value of the collateral and the margin loan is less than r, the broker can issue a margin call.

Initially, the prices of all shares are randomly assigned from a log-normal distribution, and the mean value of the prices is in the same magnitude of the SSE Composite Index. We designate the market index p to be the mean value of share prices, $p_{i,t}$ the price of share i, and $p_t = \Sigma_{i=1}^{i=M} p_{i,t}$ the market index at time step t. Although actual indices, e.g., the SSE Composite Index, are usually capitalization-weighted, we here measure the market index using the mean value of the share prices and assume an equal market capitalization for all companies. At the first time step, negative factors from external circumstances cause share prices to drop. The negative factors could be panic selling in response to bad news, or the prohibition of shadow margin loans enacted by Chinese regulators on 12 June 2015 that precipitated an increase in margin covering and reduced market liquidity. In our model we uniformly distribute the initial price decline $d_{i,1}$ for stock i across a range of $[0, \frac{v}{100}]$, where v denotes fluctuation volatility. If $v = 10$, then the price drop is between 0 and 10%. Thus following the initial shock the share price at the first time step is $p_{i,t=1} = p_{i,t=0}(1 - d_{i,1})$. A number of share prices drop slightly, and a few drop sharply. The ensuing cascading failure is then evolved as follows:

- In time step t, the maintenance margin $r_{i,t}$ of investor i is

$$r_{i,t} = \frac{\sum_{j \in \mathscr{M}_i} p_{j,t}}{\sum_{j \in \mathscr{M}_i} p_{j,0}(1 - k)} \tag{1}$$

  where $\mathscr{M}_i$ is the set of shares held by investor i. The numerator of the right-hand term is the property of each margin account, and the denominator is the margin loan. According to the minimum maintenance margin rule, when $r_{i,t} < r$, the broker liquidates the account and sells all the s shares belonging to $\mathscr{M}_i$ to pay off the margin loan.
- We then obtain the number of selling orders for each company, denoted $n_{i,t}^{\text{sell}}, (i = 1, 2, \dots, M)$. The current market price $p_{i,t}$ is then calculated to be

$$p_{i,t} = p_{i,t-1} - \eta_i n_{i,t}^{\text{sell}} \tag{2}$$

  Here η_i is the price impact factor that measures the price decline under one unit of selling order. We set $\eta_i = \eta = 5$, which means the prices of all shares are equally impacted and decline five units under one unit of selling order.

The margin covering thus increases the number of selling orders, and the growth of selling orders further depresses the share price, which in turn triggers the margin call to other margin accounts. This cascading failure continues until the price no longer cascades, i.e., until the range of price drop converges to a infinitesimal quantity. Here τ is the total number of cascading time steps. If margin covering does not cause cascading failure, $\tau = 1$. Otherwise, $\tau > 1$.

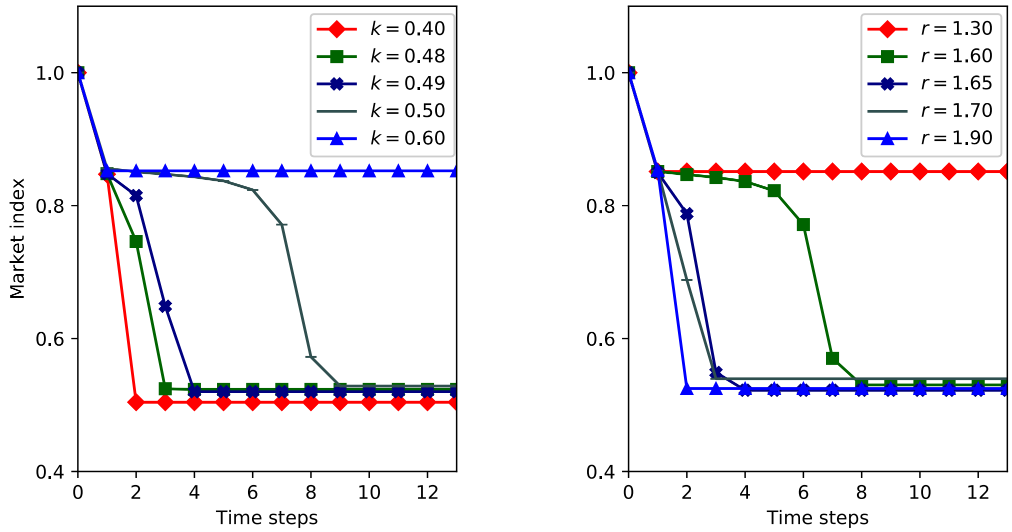
3. Results and discussion

The dynamic process is determined by Eqs. (1) and (2) and the minimum maintenance margin rule. We analyze this by applying the mean-field method and approximating the cascading process. Roughly speaking, a margin investor must liquidate their position and cover their margin when

$$\frac{\overline{p}_0(1 - \overline{d})}{\overline{p}_0(1 - k)} = \frac{1 - \overline{d}}{1 - k} < r \tag{3}$$

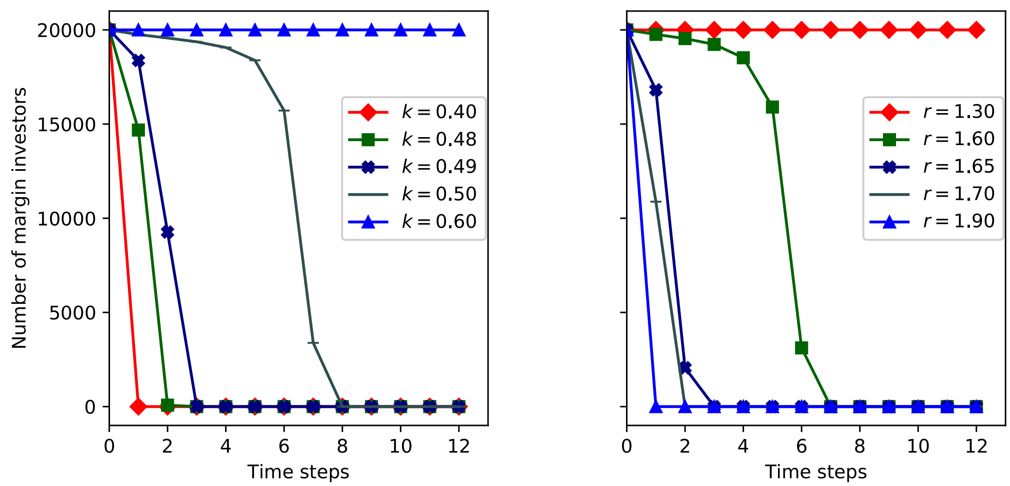
Here $\overline{d}$ is the averaged range of share price decline at the initial shock, and $\overline{p}_0$ is the average share price at the initial time. Thus margin covering is affected by minimum maintenance guarantee r, initial margin k, and d. According to Eq. (3), the growth of d and r or the reduction of k will cause a margin call to be issued and make the system more vulnerable to cascading failure. On the other hand d is related to v. Thus in our simulation r, k, and v all affect cascading failure.

Fig. 2 plots the cascading failure process and shows that the average price of all shares (the market index) evolves with time. In Fig. 2(a), the value $r = 1.6$ is set, and the simulation is carried on for a series of k value, while in Fig. 2(b), $k = 0.5$ is set, and cascading processes for different r values are simulated. In both plots $v = 30$. When $k = 0.6$ there is no cascading effect following the initial external shock, but when k decreases to a critical value, the initial attack will cause the forced



(a) $r = 1.6$. (b) $k = 0.5$.

Fig. 2. (Color Online) Dynamical process of cascading failure with a variety of (a) k and (b) r values. Here, market index is the mean value of share prices. After a number of time steps, the market index reaches a steady state. In (a), $r = 1.6$, and the cascading failure evolves differently for different k values, while in (b), various r values are investigated at $k = 0.5$. In both plots $s = 20$, $v = 30$.

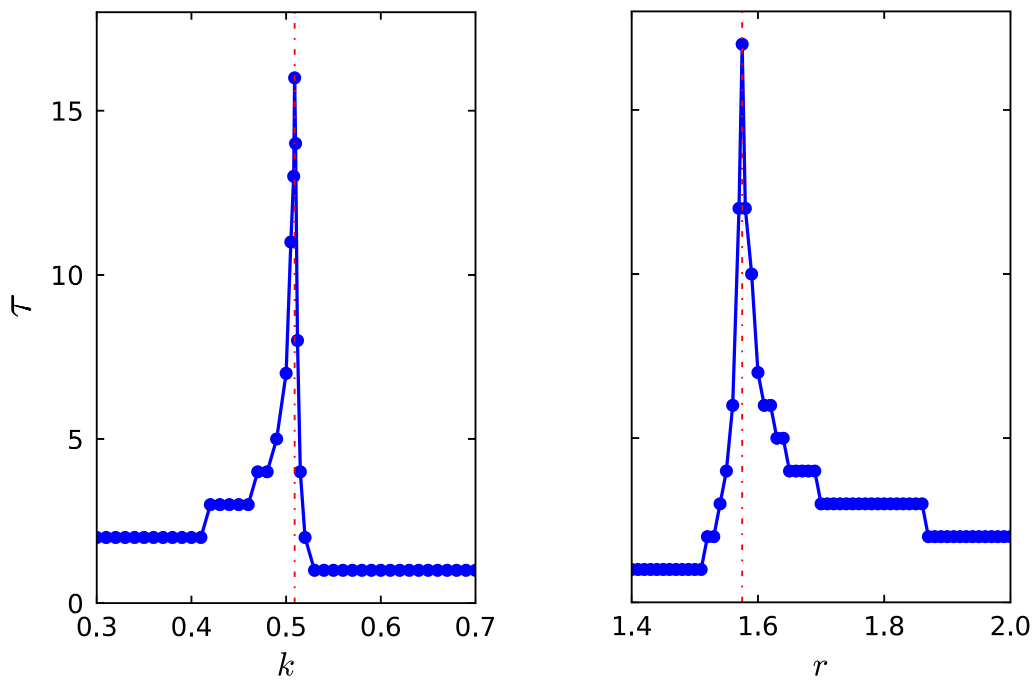


(a) $r = 1.6$. (b) $k = 0.5$.

Fig. 3. (Color Online) Number of margin investors evolves in process of cascading failure with a variety of (a) k values when $r = 1.6$ and (b) r values when $k = 0.5$. Other parameters are set as $s = 20$, and $v = 30$.

selling due to the margin call in some accounts, thus margin buying activities take places, pulling down the market index ulteriorly. After a small number of time steps the system converges to a steady state, all share prices remain approximately constant, and no more margin accounts are liquidated. This is the classic cascading failure process. The market index in the steady state is p_∞ and the number of active margin investors in the steady state N_∞. Fig. 2(a) shows that when $k < 0.6$ there is cascading failure. This indicates that the stock market experiences a phase transition from a stable state to a vulnerable state that is fragile to external shocks. Note that the minimum market index value p_∞ seldom changes when $k = 0.4 \sim 0.5$ because in the steady state all margin accounts have been liquidated and margin covering reaches its maximum (see Fig. 3).

When the p_∞ value is unchanging, the market index drops more rapidly when k is smaller and more slowly when k is large, slowing the cascading failure process and allowing market regulators more time to respond. Similar behavior for various r are also presented in Fig. 2(b). We then plot the total cascading time τ as a function of k and r, respectively, as shown in Fig. 4. Fig. 4(a) shows that when k is large there is no margin covering following an initial shock. Thus $\tau = 1$. This value of τ rapidly increases as k decreases and reaches its maximum where the value of k becomes k_c. When $k < k_c$



(a) Threshold k_c.

(b) Threshold r_c.

Fig. 4. (Color Online) Total cascading time τ as a function of (a) k values when $r = 1.6$, and (b) r values when $k = 0.5$, respectively. From the curve the threshold values of the phase transition k_c and r_c can be recognized from the peaks. The results are obtained by averaging over 20 simulation times. In both plots $s = 20$ and $v = 30$.

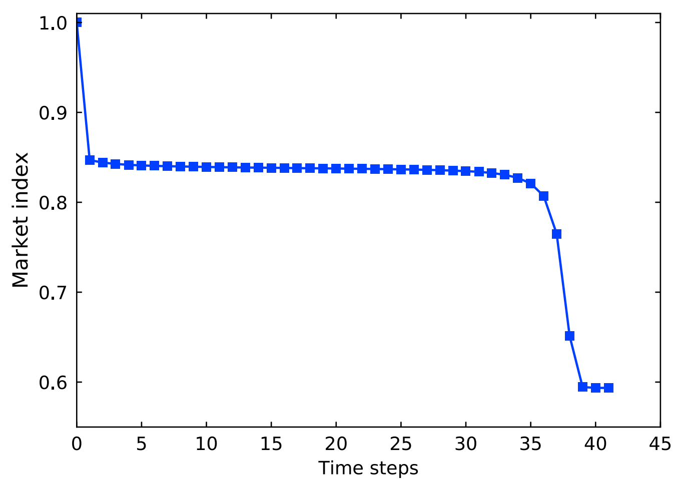


Fig. 5. (Color Online) The dynamic process of cascading failure at threshold of phase transition (i.e., $r = 1.6$, $k = 0.509$), in which a long-plateau regime is observed. Other parameters are set as $s = 20$, and $v = 30$.

the market damage is severe and after two time steps it reaches its minimum p_∞. Thus k_c is the critical point of the phase transition. The dynamical process of the cascading failure at k_c is presented in Fig. 5, and a long plateau stage is displayed, which is characterized by a random branching process.

Hence there are two attractors in the dynamic process of a bipartite stock market: the stable and vulnerable states. Fig. 6 plots a two-dimensional phase diagram to verify this. The colorbar displays different p_∞ values, and the phase diagram shows them as a function of both r and k, each of which is averaged over 20 simulation times. In all three subplots with various s values, the two market states are shown. The left region (dark color) is in the vulnerable state and is more susceptible to cascading failure under an external shock. The right region (light color) is in the stable state. We denote the critical values

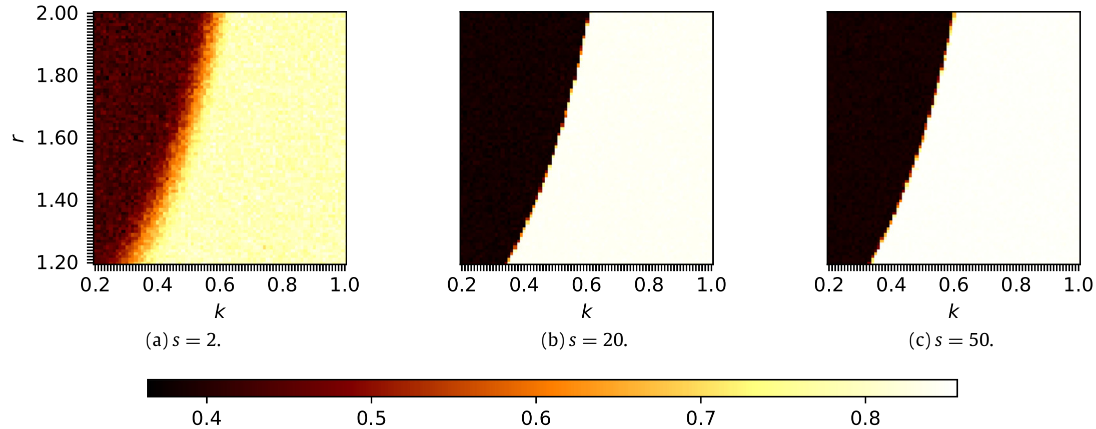


Fig. 6. (Color Online) Phase diagram of the **market index** as a function of maintenance guarantee r and initial margin k. The color represents averaged price of the stock market, analogous to market index. $v = 30$ for all plots.

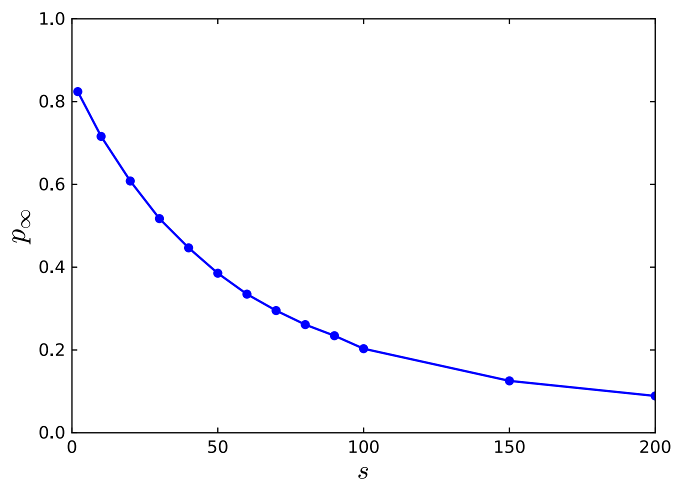


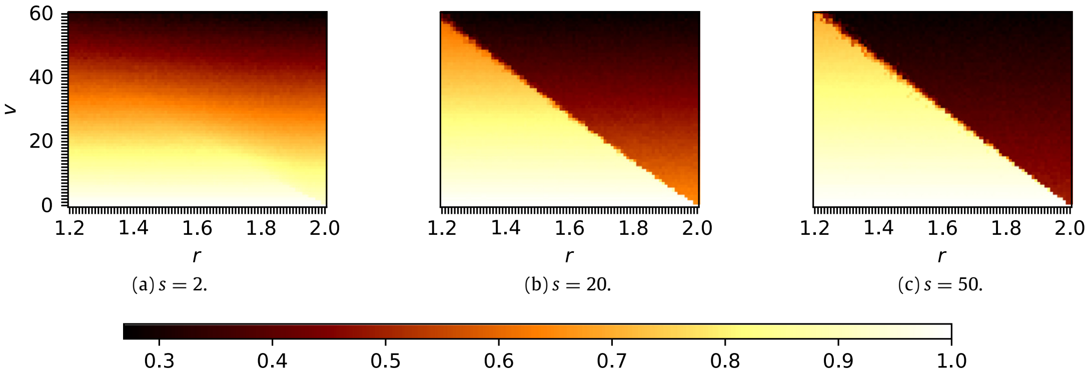
Fig. 7. (Color Online) p_∞ in the steady state vs diversification parameter s, other parameters are set $k = 0.4$, $r = 1.7$, $v = 30$. The results are obtained by averaging over 20 simulation times.

of r and k to be r_c and k_c, respectively, at which point the system changes from a stable state to a vulnerable state, and these values are associated with each other. Fig. 6 shows that as k increases r_c also increases, and vice versa. When k is sufficiently large there is no phase transition, and when it is small a cascading process occurs irrespective of the r value. The results are accord with Eq. (1).

In modern portfolio theory, diversification is considered the optimal investment strategy for lowering risk, but investor diversification may also increases systematic risk due to the interconnectness [22–27]. In the above simulations, $s = 20$. Here, in Fig. 6, for different s the phase configuration remains the same, which means s has little influence on r_c and k_c values. On the other hand, the average loss is greater when s is large because the p_∞ value in the vulnerable state is much lower when s is large. The reason is if more shares are purchased on margin by each investor, the initial shock of a proportion of share prices can give rise to the contagion of more other stocks.

To examine the impact of diversification, we calculate p_∞ using different s values (see Fig. 7). The market bench-march index in the steady state decreases monotonically with s, which indicates that diversification can lower the robustness and resilience of the securities system and result in higher systematic risk.

In recent years, the Chinese stock market has been highly volatile because of the high proportion of active retail investors [28–32]. From Eq. (1) we see that high volatility can amplify instability and give rise to cascading failure. Fig. 8 plots the phase diagram as a function of r and v to examine how volatility influence r_c. Note that when $s = 2$ there is no cascading failure in Fig. 8(a). This is because risk contagion is weakened when s is small, hence at some k value there is no further price decline after the initial shock, but r_c decreases when the volatility is high [see Fig. 8(b) and 8(c)] and a



(a) $s = 2$. (b) $s = 20$. (c) $s = 50$.

Fig. 8. (Color Online) Phase diagram of maintenance guarantee r and volatility v. The color represents averaged price of the stock market, analogous to market index. $k = 0.5$ for all plots, and the results are obtained by averaging over 20 simulation times.

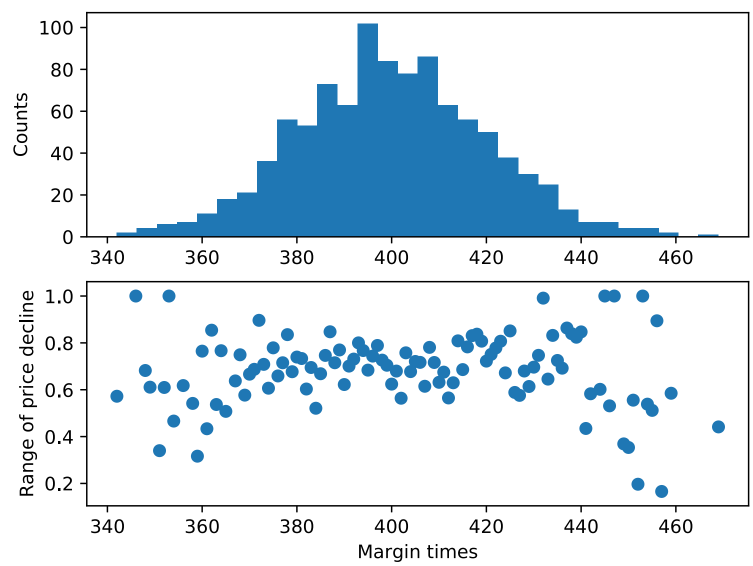


Fig. 9. (Color Online) The relationship between price decline and margin times. In this figure $k = 0.5$, $r = 1.8$, $s = 20$, and $v = 50$, but the results are valid for different values.

failure cascade can cause systemic failure even when the minimum maintenance r is low. Similar results are found in the $r - v$ phase diagram, and these are useful in shaping regulatory policy in China. To stabilize the securities market, the stock exchanges have imposed a daily price change limit of 10% on the trading of shares of listed companies. The influence of this price limitation remains unclear and is a topic of wide discussion [33]. Here we proposed that this price limitation can slow margin covering and is thus useful in stabilizing the market.

According to the margin trading rules set by the SSE, when a stock is bought on a margin with a proportion that is larger than 25% of its outstanding share capital, the securities exchange must stop the margin financing of this stock. This rule assumes that a share has a higher risk when the ratio of margin buying is high. To confirm this, Fig. 9(b) averages the price drop of stocks with the same margin times in order to link the price drop range with the margin times. The scatter plot takes the form of a butterfly, and the results are valid for numerous r and k values. Although the price drop changes very little in the middle range of margin times, the results fluctuate up and down wildly for stocks with small or large margin times. This can be explained from the distribution of the margin times shown in Fig. 9(a), in which stocks with small or large margin times are few in number, and this affects the accuracy of the results.

4. Conclusion

We have examined how margin trading affected the mid-2015 stock Chinese market crash. We use a cascading failure model – a bipartite graph of margin investors and a set of shares – that demonstrates how margin trading amplifies the systematic risk. After the initial external shock to the share price, the minimum maintenance margin required by brokers triggers a cascading margin that depresses the share price. This broker-induced cascading failure process can be rapid and can cause a systemic market crash.

To determine the factors influencing the cascading process, several parameters are investigated, including the initial margin k, the minimum maintenance r, the volatility v, and the diversity s. We find two market states, stable and vulnerable. In the stable state, an initial price decline affects the market but does not produce cascading failure, and the resilient system slowly recovers. In the vulnerable state, an initial price decline produces cascading failure. Both analytical and simulation results indicate that raising v and r or dropping k increases the probability that the state of the system will undergo a phase transition from stable to vulnerable. We also find that diversity, although a preferred investment strategy, can amplify systematic risk because higher s values increase stock market vulnerability.

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