International Review of Financial Analysis 64 (2019) 13–21

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Stock index pegging and extreme markets

Xinyue Dong, Rong Ma, Honggang Li*

School of Systems Science, Beijing Normal University, China, No. 19, XinJieKouWai St., HaiDian District, Beijing 100875, PR China

ARTICLE INFO

Keywords:
Stock index
Market stress
Extreme market
Synchronize
Positive feedback

ABSTRACT

In this paper, we design a multi-agent model to explore endogenous mechanisms that create extremes in stock markets. This study will show that when making trading decisions, if the changing trends of a stock index are taken into consideration, several stylized facts, including synchronized behavior, increased downside correlations and the leverage effect, are reproducible in the model. If reversed, these facts prove the reliability of our assumption of the microscopic mechanism in the model. We finally conclude that a market drop causes synchronized behavior and further market drops. In other words, the stock index not only represents and describes a general market assessment but can also affect market sentiment and change future market trends.

1. Introduction

An extreme market is not an uncommon phenomenon in the world's stock market history. The “Black Monday” event that occurred on October 19, 1987 (Carlson, 2006) and the “Flash Crash” event on May 6, 2010 (CFTC and SEC, 2010) are two typical examples. Obviously, an extreme market has a very large impact on a stock market and may result in substantial losses to investors. Therefore, exploring ways to prevent, or at least reduce, such market collapses is crucial for financial risk management; a good starting point is studying extreme market mechanisms.

Traditional economic and financial theories provide insufficient explanations for the sudden and systematic collapse of a financial system. The efficient market hypothesis holds that price collapses are caused by specific exogenous shocks, but previous studies have shown that stock price crashes are not usually explained by negative shocks or changes in market fundamentals. For example, Cutler, Poterba, and Summers (1989) tried to analyze the effect of macroeconomic data and major news events on market returns after the stock market crash in 1987 and found that neither could explain the change in returns. They finally concluded that extreme price changes were not caused by fundamental shocks. Siegel (1992) attempted to use standard valuation models to explain the 1987 market crash but they found that predictions of corporate value could not explain the phenomenon of stock prices suffering a sharp drop after rising steeply in 1987. Because external factors cannot satisfactorily explain these extreme financial market events, many researchers abandoned exogenous explanations and turned to endogenous causes (Jacklin, Kleidon, & Pfeiderer, 1992; Madhavan, 2012; Roll, 1988).

Some scholars believe that certain trading strategies or mechanisms are responsible for extreme markets. Shiller (1988) thought that portfolio insurance strategies were an important factor leading to the 1987 stock market disaster. Ben-David, Franzoni, and Moussawi (2014) found that ETF arbitrage strategies could increase market volatility and make asset prices deviate significantly from their fundamental values when price shocks occurred. Torii, Izumi, and Yamada (2015) constructed a multi-asset artificial stock market and found that arbitrage traders could make market shocks pass between different assets, and some regulatory rules, such as circuit breakers, could exacerbate market volatility in some cases.

Other scholars have explained extreme markets from a behavioral finance perspective. Lee, Jiang, and Indro (2002) found that excess returns were contemporaneously positively correlated with shifts in sentiment. Moreover, the magnitude of bullish changes in sentiment led to downward revisions in volatility and higher future returns. Lux (1995) applied the nonlinear dynamic method to study the impact of herd behavior, which indicated that herd behavior could lead to market bubbles and market crashes. Bikhchandani and Sharma (2000) also pointed out that herd behavior could lead to a decline in stability and an increase in the vulnerability of financial markets, resulting in excessive market volatility.

In the process of studying the causes of extreme markets, some scholars uncovered some of the common characteristics of crashes. First, heterogeneous trading behavior tended to converge, and ask orders were overwhelming (Blume, MacKinlay, & Terker, 1989). This behavioral consensus causes a stock price to drop or even creates “liquidity black holes” (Morris & Shin, 2004). In fact, a severe mismatch in liquidity is regarded as the source of crashes (Borkovec, Domowitz,

* Corresponding author.
E-mail address: hli@bnu.edu.cn (H. Li).

https://doi.org/10.1016/j.irfa.2019.04.012
Received 1 February 2019; Received in revised form 4 April 2019; Accepted 30 April 2019
Available online 03 May 2019

Serbin, & Yegerman, 2010; Brunnermeier, Gorton, & Krishnamurthy, 2013). Second, individual stocks have stronger correlations in a downside market when compared to those in normal conditions (Campbell, Koedijk, & Kofman, 2002; Estrada, 2000; Solnik, Boucrelle, & Le Fur, 1996). Lastly, negative returns further increase future volatility, which is called the leverage effect (Bouchaud, Matacz, & Potters, 2001; Figlewski & Wang, 2000; Yook, 2003).

From our point of view, an extreme market is just a self-organizing phenomenon of a multi-agent system. In the market, traders make trading decisions based on the market quotation index (In fact, many intraday technical traders, even some fundamental traders, keep an eye on stock quotations especially when the prices drop considerably.). Traders' behaviors are coupled with this "index pegging", leading to a self-organized market pattern of collective behavior (Ma, Zhang, & Li, 2017). Indeed, Shiller created questionnaire surveys to study investors' behavior during the 1987 crash and found that investors reacted to the market drop itself rather than any other specific news (Shiller, 1989).

In this paper, we explore the endogenous mechanisms of an extreme market (Giardina & Bouchaud, 2003) by using agent-based modeling, which is an effective method for studying financial market phenomena and exploring micro-market structures (Amman, Tesfatsion, Kendrick, Judd, & Rust, 1996; LeBaron, 2006; Tesfatsion, 2002). In previous studies, we found that when traders depend strongly on the stock index, the behavioral consensus of traders is higher, the consistency of stock movements is higher, the market's volatility is higher, and the market's liquidity is weaker (Ma et al., 2017). We not only tried to reproduce conditions of the crash but also explored extreme market related mechanism stylized facts such as synchronized behavior, increased downside correlations and the leverage effect. We designed the decision-making mechanism that traders would consider with index fluctuations and the degree that traders refer to the index. Trader's reliance on the index strengthened in a highly volatile market. With this mechanism, the traders' behavior was expected to synchronize spontaneously when the market falls sharply. In our model, the order price is affected by expectations, and the effect is more severe in a downside market.

This paper is organized as follows: We present the model in Section 2. In Section 3, we put forward measurement indexes for expressing stylized facts. Section 4 presents the simulation results of our model. Section 5 supplements a sensitivity analysis with some important parameters. Section 6 performs the empirical analysis and Section 7 concludes.

2. Model design

We use a multi-agent model with a multi-asset continuous double auction market to simulate stock transactions. The following are some of the basic assumptions:

(1) There exist M kinds of stocks in the market, and we define a stock index weighted by the market value of the stocks.
(2) There are N traders in the market, and each of them trades only one kind of stock. To simplify the simulation, we exclude the influence of asset portfolios. In fact, our model does not involve the heterogeneous risk-return characteristics of various stocks, so even considering the portfolio of assets as equally weighted does not have a qualitative impact on the conclusion of our model. Therefore, we randomly choose one kind of stock for each agent to trade during the model's initialization period and it remains fixed throughout the simulation process.
(3) Margin-buying or short-selling is not permitted. Although short-selling and margin-buying does have a significant impact on market volatility, this effect can be isolated to be studied in another particular model (Zhang & Li, 2013; Zhou & Li, 2017). Therefore, for simplicity, our model does not consider short-selling or margin-buying.
(4) Each agent has only one chance to submit a limit order in each trading day. This simplification is also for modeling convenience. In fact, our trading "day" here does not necessarily correspond to a real trading day. If we map this model's trading day to a more realistic shorter time interval, this assumption more closely aligns to the actual market. Unsettled orders are canceled when the trading day is closed. However, emptying orders at the end of a trading day does not mean that traders must close their position on the same day.

Some assumptions in our model seem to be inconsistent with the real stock market, but these assumptions are intended to simplify the design of the model (Chiarella, He, & Pellizzari, 2012) and have little impact on the qualitative conclusions.

On a typical trading day t (t = 1, 2, …, T), the transaction system would randomly determine the trading sequence. Agents submit orders in turns according to a determined sequence. The trade direction of agent i *is* chosen by the following function:

$$z_i(\tau;t) = bv(\tau;t) + (1-b)v_i(\tau;t) \tag{1}$$

where a positive $z_i(\tau;t)$ results in a bid order, and a negative $z_i(\tau;t)$ corresponds to a ask order. If $z_i(\tau;t)=0$, agent i does not submit any order on day t. The variable $v(\tau;t) \in \{-1,0,1\}$ represents the short-term ups and downs of the stock index (market quotation) within a trading day, and the variable $v_i(\tau;t) \in \{-1,0,1\}$ is determined by random factors, which are associated with all the other information except the index and is heterogeneous for different agents. The parameter b denotes the index-dependent strength; that is, how much the traders refer to index changing trends when making trading decisions.

Note that we record both tick data and isochronous data. Tick data is only updated when a new transaction happens, whereas isochronous data is recorded at regular time intervals, similar to the high frequency data recorded at 1 min intervals in a real stock market. Each agent takes turns to submit an order, and if a deal is reached, the trading system outputs new tick data that contains the deal price, transaction volume and the latest index. We produce a new isochronous data record after a fixed number of traders λ have made a trading decision. The data includes the latest price of each stock, the latest stock index and the total transaction volume during the period. In fact, if there is only one stock, we do not need to distinguish between these two data time horizons. However, in a multi-asset model, it is easier for us to handle the index pegging process.

We use isochronous data to judge market trends. Similar to the real market, we simply know that the tick data is only recorded by the transaction system but is unknown to the traders. $v(\tau;t)$ is calculated as follows:

$$v(\tau;t) = \mathrm{sgn}(L(\tau;t) - L(\tau-1;t)) \tag{2}$$

where $L(\tau;t)$ denotes the τth stock index of day t, $L(\tau-1;t)$ denotes the $(\tau-1)$th stock index of day t, and sgn denotes the sign function. If the market was up in the last time interval, then $v(\tau;t)=1$; if the market was down in the last time interval, then $v(\tau;t)=-1$; if the market was at a fixed state in the last time period, then $v(\tau;t)=0$. Furthermore, $v_i(\tau;t)$ gets its value by a random sampling from the set $\{-1,0,1\}$. The parameter b is assumed to be valued as follows:

$$b = \left|\tanh\left[h * \frac{L(\tau;t) - L(\tau-1;t)}{L(\tau-1;t)}\right]\right| \tag{3}$$

where h denotes an adjustment parameter. The hyperbolic tangent function can limit b to the range [0, 1]. As compared to the previous study (Ma et al., 2017) in which parameter b is fixed in the simulation, the traders in this model will adjust parameter b according to the latest market information in the transaction process. In fact, the formula (3) is based on three simple ideas; first, a greater (weaker) index change rate leads to a larger (smaller) b, which means if the market quotation changes substantially, then traders will care about the index more; second, if the index return rate is large enough, then b is approximate to 1, that is to say the traders totally depend on the index when making decisions; lastly, if the index return rate is close to 0, then b is approximate to 0, meaning that traders make decisions according to other information. The submitted limit price is determined as follows:

$$p_b^i(t) = p(\tau;t)(1 + \delta\eta_1 + h_1 z_i(\tau;t)) \quad (4)$$

$$p_a^i(t) = p(\tau;t)(1 + \delta\eta_2 + h_2 z_i(\tau;t)) \quad (5)$$

where $p_b{}^i(t)$ denotes the submitted limit price of agent i on day t if it is a bid order, $p_a{}^i(t)$ denotes the submitted limit price of agent i on day t if it is an ask order. The parameter δ represents the standard deviation of the price adjustment. $p(\tau;t)$ is the latest price (based on the isochronous data) that stock agent i trades on day t. $\eta_1 \sim N(0,1)$, $\eta_2 \sim N(0,1)$, denote the stochastic fluctuations of the price adjustment. Moreover, h_1 and h_2 represent the adjustment parameters associated with the expectation. The quantity of the submitted order is determined as follows:

$$Q_b^i(t) \in \{1, 2, ..., \lceil C^i(t)/p_b^i(t) \rceil\} \quad (6)$$

$$Q_a^i(t) \in \{1, 2, ..., Q^i(t)\} \quad (7)$$

where $Q_b{}^i(t)$ denotes the quantity submitted by agent i on day t if it is a bid order; $Q_a{}^i(t)$ denotes the submitted limit price of agent i on day t if it is an ask order. $Q^i(t)$ denotes the quantity of stocks agent i owns on day t; $C^i(t)$ denotes the quantity of cash agent i owns on day t.

If an agent submits an order, the order will be sorted by a price and time priority principle. Next, the trading system will match the orders instantly using double auction rules until the orders on the order book cannot be traded anymore, and the latest transaction price, index and agents' asset accounts will be updated. Then, the next agent will submit an order, and the transactions continue as previously processed.

3. Measurements and stylized facts

As we discussed in the Introduction, we focused on reproducing some stylized facts from the financial market, including synchronized behavior, increased downside correlations and the leverage effect. We required some initial measurements so we used a normalized index return to measure market quotations. The indicator was calculated as follows:

$$L(k) = L_0 \frac{\sum_{j=1}^{M} Q_j p_j(k)}{\sum_{j=1}^{M} Q_j p_{j0}} \quad (8)$$

where $L(k)$ denotes the kth sample of the isochronous stock index, which was calculated using the current market capitalization and an initial market capitalization. Q_j and p_{j0} denote the total quantity and initial price of stock j, respectively. $p_j(k)$ denotes the kth observation price of stock j, and L_0 denotes the initial stock index.

$$r_L(k, \Delta k) = \ln(L(k + \Delta k)) - \ln(L(k)) \quad (9)$$

$$\sigma_L(\Delta k) = \sqrt{\frac{1}{K - \Delta k}\sum_{k=1}^{K-\Delta k} r_L(k, \Delta k)^2 - \left[\frac{1}{K - \Delta k}\sum_{k=1}^{K-\Delta k} r_L(k, \Delta k)\right]^2} \quad (10)$$

$$R(k, \Delta k) = \frac{r_L(k, \Delta k) - \frac{1}{K-\Delta k}\sum_{k=1}^{K-\Delta k} r_L(k, \Delta k)}{\sigma_L(\Delta k)} \quad (11)$$

$r_L(k,\Delta k)$ denotes the log of the index return in a Δk period from the kth sample of isochronous observations to the $(k+\Delta k)$th observation (see in Table 1). $\sigma_L(\Delta k)$ denotes the standard deviation of the index return. K denotes the total number of isochronous data in all trading days. Therefore, k is not only a concept of number sequences but also a concept of time. $R(k,\Delta k)$ denotes the normalized index return in a Δk period from the kth sample of an isochronous observation to the $(k+\Delta k)$th observation.

Table 1
The data used to calculate return (within the thick border).

	……	Sample k	……	Sample k + Δk	……
Stock 1	…	$p_1(k)$	…	$p_1(k + \Delta k)$	…
Stock 2	…	$p_2(k)$	…	$p_2(k + \Delta k)$	…
…	…	…	…	…	…
Stock M-1	…	$p_{M-1}(k)$	…	$p_{M-1}(k + \Delta k)$	…
Stock M	…	$p_M(k)$	…	$p_M(k + \Delta k)$	…

In the following section, we provide specific explanations for the stylized facts.

3.1. Synchronized behavior

Synchronization is mostly used to describe the stock market comovements (contagion) among different countries or markets, especially during a financial crisis (Lehkonen, 2015; Yang, 2005). In this paper, we use synchronized behavior to describe synchronizing on the same side of the limit order book (Amihud, Mendelson, & Wood, 1990). That is, heterogeneous trading behavior tends to be homogeneous and most traders submit sell orders during a crash. In this study, we want to prove that synchronous behavior is the origin of a market crash, and synchronous behavior is a result of increased concern about the index in a downside market.

In our model, we design an indicator to describe the synchronization of the types of agents' orders from period k to $k+\Delta k$, that is the degree of behavioral consensus, $D(k,\Delta k)$. The calculation is as follows:

$$\tilde{D}(k, \Delta k) = \frac{N_+ - N_-}{N_+ + N_-} \quad (12)$$

$$D(k, \Delta k) = |\tilde{D}(k, \Delta k)| \quad (13)$$

where $N_+(N_-)$ denotes the number of traders submitting buy (sell) orders in the time interval k to $k+\Delta k$. If the number of traders submitting sell and buy orders are the same in the interval, then $D(k,\Delta k)$ equals 0; If the number of traders submitting one kind of order is greater than the number of traders submitting another kind of order, then $D(k,\Delta k)$ is > 0; if all traders submit the same kind of order in the period, then $D(k,\Delta k)$ equals to 1. In addition, if we want to figure out the precise side of the synchronized behavior, we can keep track of $\tilde{D}(k, \Delta k)$. If sell side orders are dominant, then $\tilde{D}(k, \Delta k) < 0$; If buy side orders are dominant, then $\tilde{D}(k, \Delta k) > 0$.

3.2. Increased downside correlation

An increased downside correlation means the stock correlation is state-dependent, which means a larger market quotation change rate would cause an increased stock correlation and this would be more significant in a downside market. Preis, Kenett, Stanley, et al. (2012) conclude that the average correlation among stocks scales linearly with market stress as reflected by normalized index returns on various time scales. The indicator we use to describe this is the correlation of stock returns. Based on the hypothesis that the agent's trades are equally spaced we obtain isochronous data. We serialize the different intraday data and calculate the stock correlation matrix at different time intervals. We can then get the average correlation ρ. The formula is as follows:

$$\rho(k; \Delta k) = \frac{1}{M(M-1)} \sum_{i \neq j = 1}^{M} \rho_{ij} \quad (14)$$

where ρ_{ij} denotes the Pearson correlation coefficient of the returns of stock i and stock j in the time interval. The stock return is a log-return, calculated as follows:

$$r_k = \ln p_k - \ln p_{k-1} \quad (15)$$

where r_k denotes the return and p_k denotes the kth sample value of the stock price or the stock index.

3.3. Leverage effect

A leverage effect means there is a negative correlation between past returns and future volatility. Empirical studies have revealed that this negative correlation decreases over time and can be described by an exponential function (Christie, 1982). We describe it using this general indicator:

$$R(k) = \ln(L(k+1)) - \ln(L(k)) \quad (16)$$

$$\iota(\Delta k) = \frac{1}{\langle R(k)^2 \rangle^2} \langle [R(k+\Delta k)]^2 R(k) \rangle \quad (17)$$

where $\langle R(k)^2 \rangle^2$ is a normalization and $[R(k+\Delta k)]^2$ denotes future volatility.

4. Simulation results

In the simulation model, we will go a step further to explore the stylized facts in the downside market. To be specific, we will explore the formation mechanism of the stylized facts in the downside market, including synchronized behavior, varying correlations and the leverage effect. Our ultimate goal is to reproduce a market crash, which means synchronizing continuous market drops in a short time period.

4.1. Parameter setting

The parameter setting of the simulation is shown in Table 2.

4.2. Synchronized behavior

In this section, we examine the relationship between a normalized index return and behavioral synchronization. Because high frequency order data is hard to get, it is understandable that the empirical results are limited. Some scholars used questionnaires to obtain estimates after a crash event. However, in an agent-based model, we can easily get the simulated data and we can efficiently study the synchronized behavior.

As shown in Fig. 1, the synchronized behavior has a positive correlation with the absolute indexes rate of change. Specifically, positive index returns lead to more bid orders while negative index returns lead to more ask orders. What's more, this tendency becomes more obvious when the index makes numerous changes. If the market is relatively stable, which means the index return is close to zero, then the trading behavior is mostly heterogeneous and the buyers and sellers are roughly balanced. This phenomenon happens at different time scales and the positive and negative extremes are asymmetric. As we can see, the negative extreme returns are severer than positive extreme returns.

Table 2
Parameter setting in the simulation.

Parameter	Value	Description
L_0	1000	The Initial stock index
N	4000	The number of agents
M	5	The number of kinds of stock
T	500	Total trading day
λ	40	The number of agents making trading decisions in an interval for isochronous data
p_{j0}	100	The initial price of stock j
$C^i(0)$	100*{1,2…,10}	The initial cash endowment of agent i
$Q^i(0)$	{1,2…,10}	The initial stock endowment of agent i
δ	0.03	The standard deviation of the price adjustment
h	20	The adjustment parameter of the index coupling strength
h_1	0.02	The price adjustment parameter (associated with the expectation) for the bid order
h_2	0.03	The price adjustment parameter (associated with the expectation) for ask order

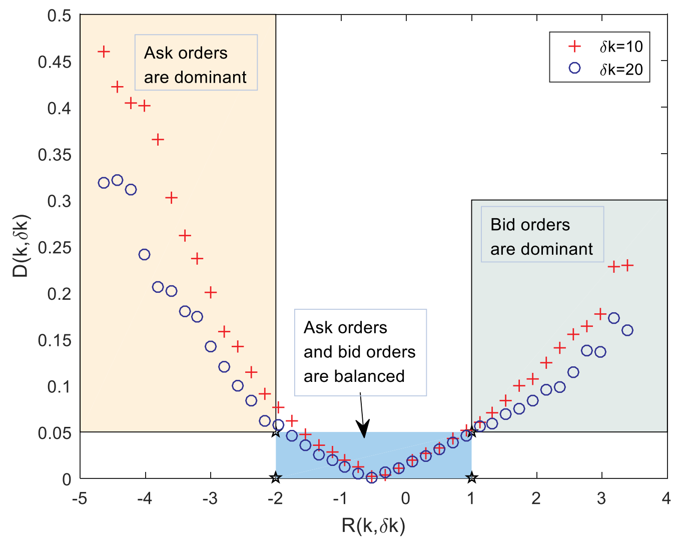


Fig. 1. Synchronized behavior. The relationship between the isochronous normalized index return rate and the degree of behavioral consensus.

4.3. Increased downside correlation

This study successfully reproduces the increased downside correlation at different time scales. As shown in Fig. 2, the average correlation among individual stocks increases during highly volatile periods. In addition, in a downside market, this correlation increases much more than in an upside market. This is because of the model's design. First, the traders' behavior tends to be affected more by the index return in a highly volatile market according to our hypothesis, and this would lead to highly homogenous orders and increase the stock correlation when the index changes considerably. Second, in our model, the agents tend to submit orders at lower prices when they have a negative expectation

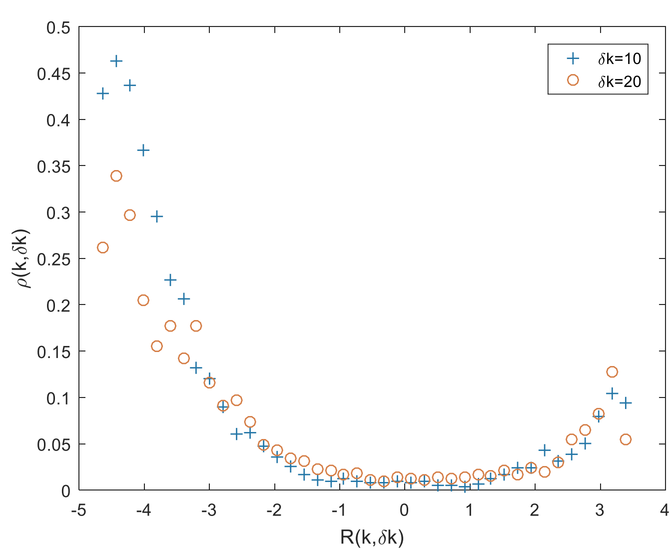


Fig. 2. Increased downside correlation. The relationship between the isochronous normalized index return rate and the average correlation among individual stocks.

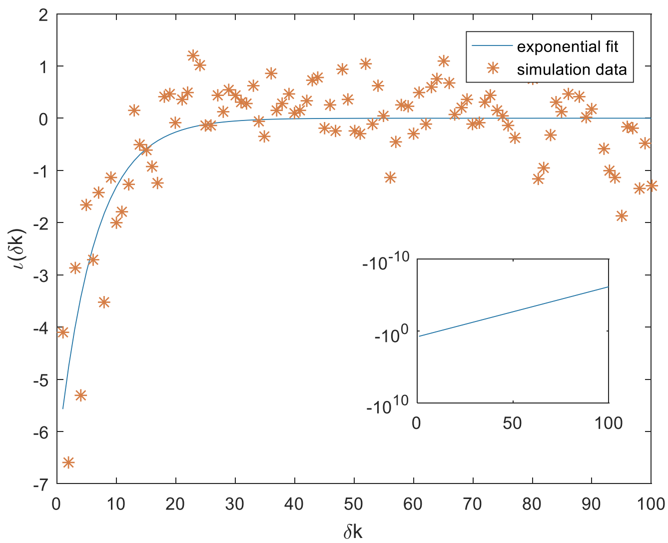


Fig. 3. Leverage effect. The return-volatility relationship can be described by an exponential function $\iota(\Delta k) = -6.54e^{-0.1603\Delta k}$. In addition, the sub graph is the semi-log result of the fitted exponential function.

compared to a positive expectation. These two factors lead to the result together.

4.4. Leverage effect

Our model also successfully reproduces the leverage effect. As shown in Fig. 3, the current index return and future volatility have a negative correlation and this correlation decreases over time. The negative correlation lasts until the lag is approximately 20. The points can be fitted with the exponential function $\iota(\Delta k) = -6.54e^{-0.1603\Delta k}$.

In fact, we have to say that the leverage effect mainly results from a downside quotation. To test this, we simply show the relationship between the current return and volatility in the next period (see in Fig. 4). As you can see, if the current return is negative, then the current return and future volatility have a negative correlation. However, if the current return is positive, then the current return and future volatility have a positive correlation. Moreover, it results in an asymmetry in the downside and upside situations, if we consider correlations in all ranges

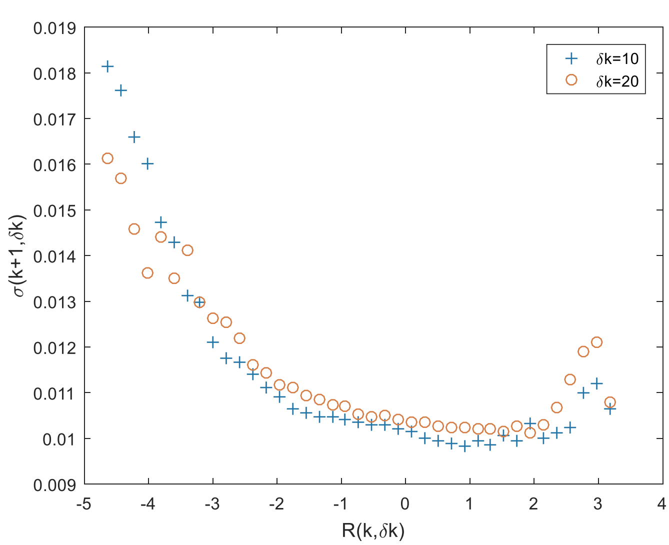


Fig. 4. The relationship between the current index return rate and the volatility in the next time period. $\sigma(k+1, \Delta k)$ denotes the standard deviation in the Δk period from $k+1$ time node.

of the stock index returns, we still come to the conclusion that current returns have negative correlations with future volatility. If we can gain insight into these phenomena, then it would be easier to understand the leverage effect.

4.5. Market crash

We display a typical crash day (see Fig. 5), which is the day containing the largest negative isochronous index changing rate. (a)–(e) are the price trends of individual stocks, while (f) is the quotation of the stock index. Although the largest negative isochronous index changing rate happens at the beginning of the day, both the stock index and the individual stocks experience synchronized big drops (almost 40%) following this day. This proves our reasoning for the causes of crashes is plausible; a market drop itself can cause a market crash.

The conduct mechanism is as follows: first, the market experiences a relatively big drop for some reasons or from just random factors; second, the traders panic and they start to depend more on the stock index when making decisions; third, their expectations are then more likely to be negative, so they submit sell orders (that is to say, synchronized behavior is enhanced) with lower prices; individual stock prices fall at the same time (so the correlation among individual stocks is greater) and causes a further market drop (leverage effect). In a word, the stylized facts are highly related to the crash conduct mechanism. We can understand the stylized facts within the same framework.

5. Sensitivity analysis

We apply a sensitivity analysis to important parameters in our model and show how these parameters influence our results. The variation in results mainly come from three aspects: the first is the adjustment parameter of the index coupling strength, h; the second is the price adjustment parameter (associated with the expectation) for the bid (ask) order, $h_1(h_2)$; the last is the standard deviation of the price adjustment, δ.

At $h = 10$, the leverage effect still exists, but the negative correlation between the current return and future volatility decreases much quicker than from the basic situation where $h = 20$. The increased downside correlation disappears, which means the correlation becomes quite weak. While at $h = 30$, the increased correlation becomes more symmetric no matter whether the market quotation is downside or upside, but the leverage effect shows regular oscillations at the first few steps (see Fig. 6). We find that the orders are highly homogenous when h is big enough and this makes the market liquidity temporarily decrease. According to our simulation, the leverage effect and increased downside correlation stays stable when h is in the range from 18 to 22 (synchronized behavior is more severe if h is larger, but the basic qualitative trends are the same under the adjustment mechanism of b, so we don't display it in this section).

In regard to h_1 and h_2, we just need to consider the relative values. Therefore, we fix h_2 and change the value of h_1. When $h_1 = 0.01$, the downside and upside increased correlation become more asymmetric (see in Fig. 7). This is because the difference in price adjustment between positive and negative expectations is widening. When the expected function is positive, the price is adjusted upward by a smaller amount than the negative situation. In other words, the positive feedback effect of price changes is stronger in the case of market declines. In addition, when $h_1 = h_2 = 0.03$, the downside and upside increased correlations become more symmetric. The leverage effect breaks down, that is to say, there is no significant negative correlation between return and future volatility. This proves the increased downside correlation and the leverage effect are both related to the asymmetric price adjustment mechanism.

Lastly, we explore the effect of δ. When $\delta = 0.04$, the downside and upside increased correlation become more symmetric (see in Fig. 8) for the reason that the asymmetry of the price adjustment of selling and

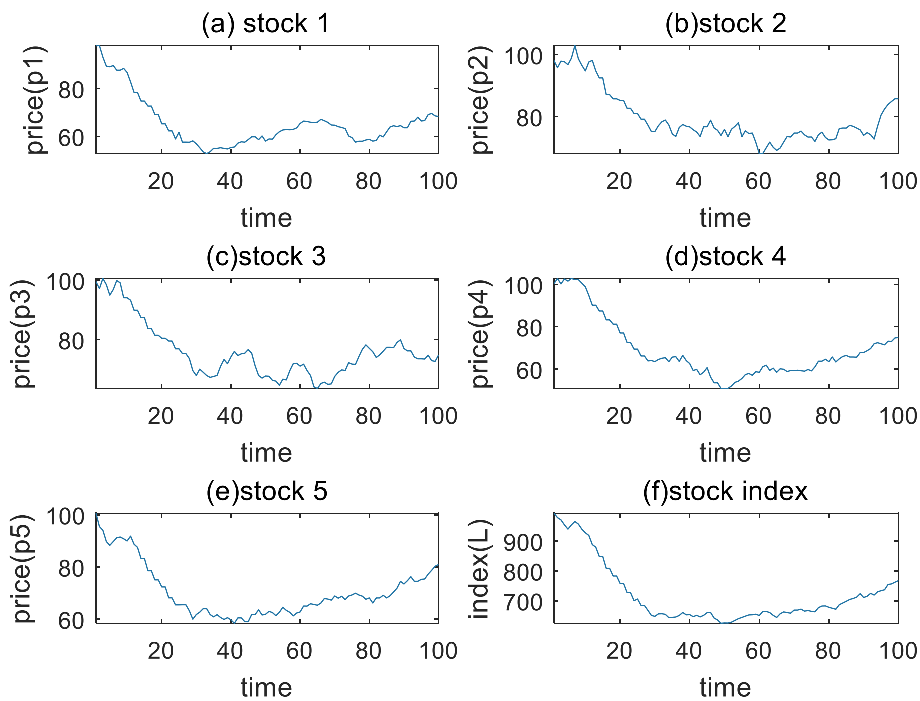


Fig. 5. The market quotation of the day containing the biggest negative isochronous normalized index return rate. (a)–(e) are price trends of individual stocks, and (f) is the quotation of the stock index.

buying orders is relatively weakened when δ is larger. When $\delta = 0.02$, the downside and upside increased correlation become more asymmetric, which is because the price adjustment factor associated with the expected effect is more effective when δ is smaller. The leverage effect decays more quickly.

To be precise, the most important mechanism is how we adjust b and get the order price. The leverage effect and increased downside correlation mainly result in the mechanism where traders care more about the market quotation in volatile conditions and traders tend to submit sell orders with lower prices when they encounter a negative index return.

6. Empirical analysis

In this part, we choose two samples of Chinese stock market to verify the stylized facts of increased downside correlation and leverage effect. All the data of this part comes from the China Stock Market and Accounting Research (CSMAR) database.

6.1. Increased downside correlation

Preis et al. (2012) analyzed the daily closing price of the 30 stocks forming the Dow Jones Industrial Average (DJIA) for 72 years. The result showed that the average correlation among individual stocks

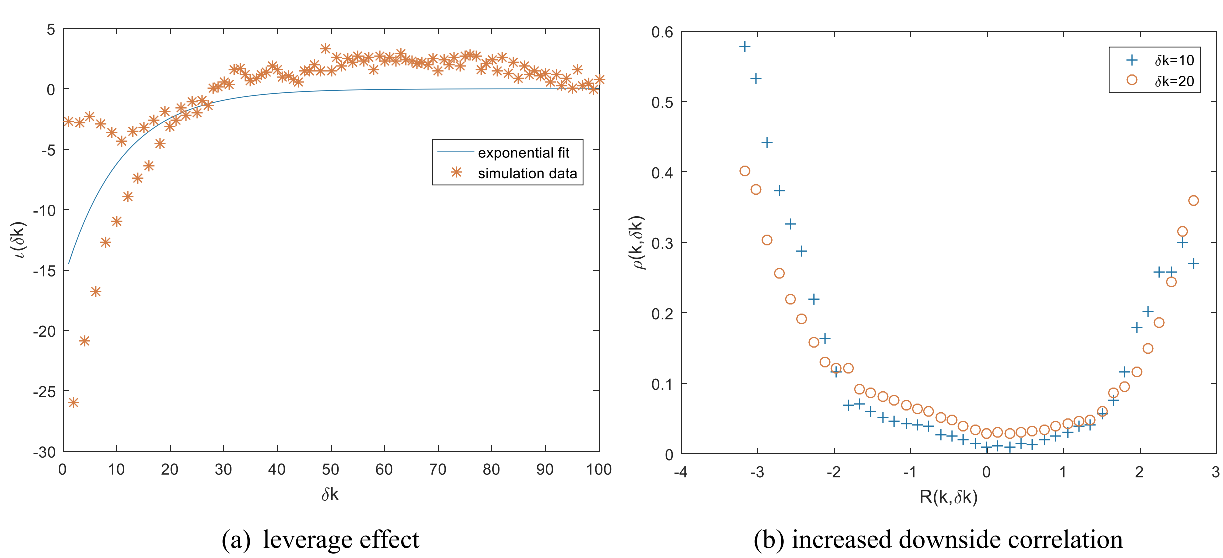
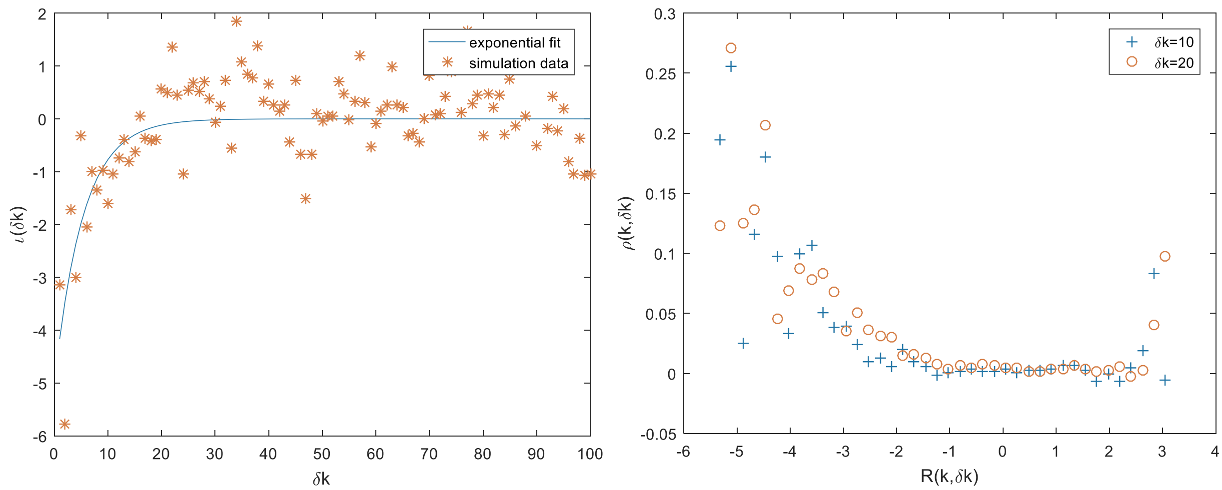
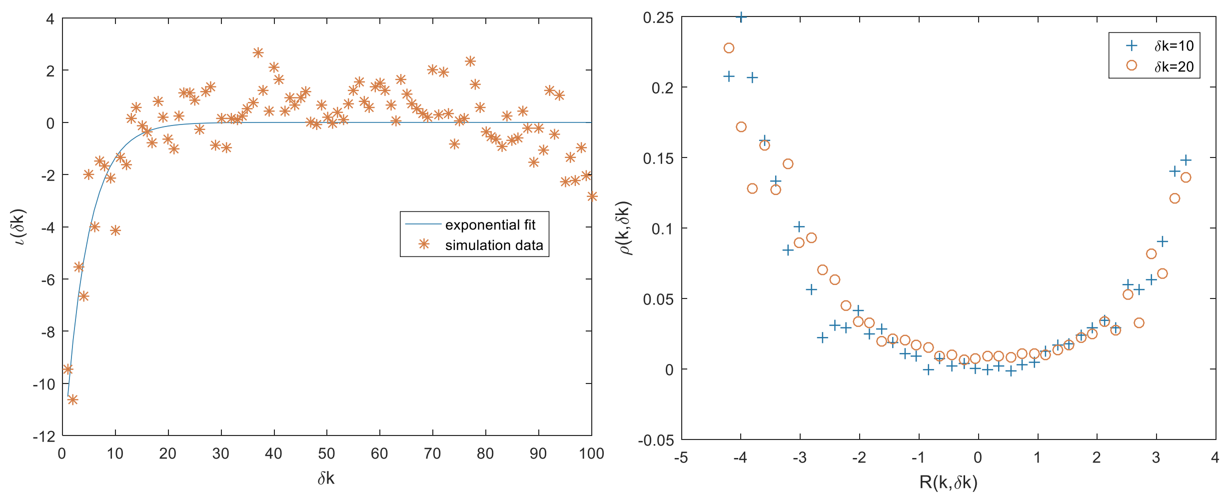


Fig. 6. The results when $h = 30$. (a) shows the result of the leverage effect, and (b) shows the result of increased downside correlation. The leverage effect shows a periodic oscillation in decay, while the increased correlation becomes more symmetric.



(a) leverage effect (b) increased downside correlation

Fig. 7. The results when $h_1 = 0.01$. (a) shows the result of the leverage effect, and (b) shows the result of increased downside correlation. The increased correlation becomes more asymmetric than $h_1 = 0.02$.



(a) leverage effect (b) increased downside correlation

Fig. 8. The results when $\delta = 0.04$. The increased correlation becomes more symmetric than $\delta = 0.03$. In addition, the leverage effect decays more slowly.

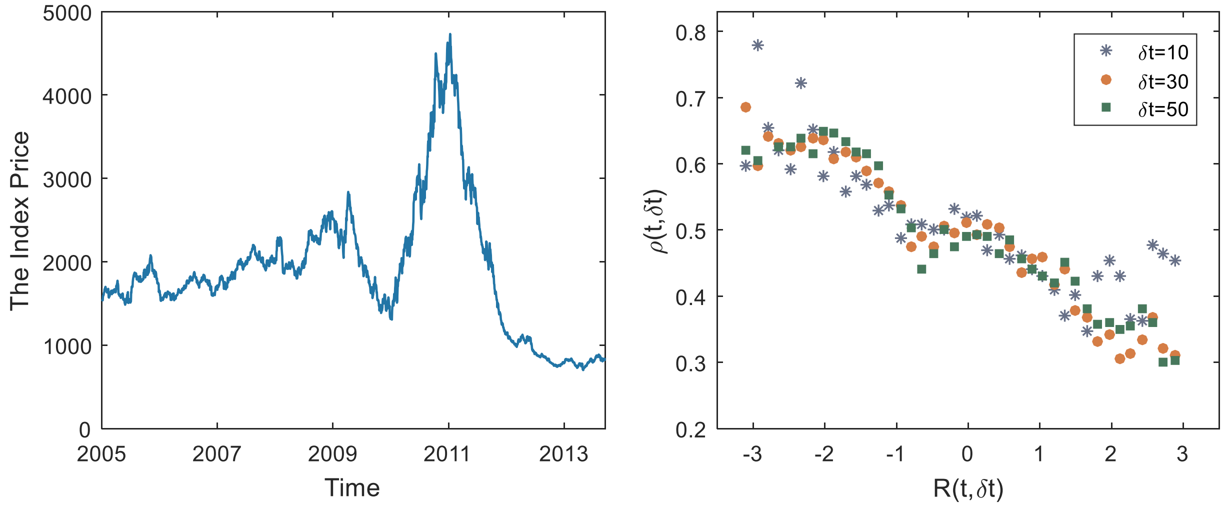
increased during highly volatile periods. In addition, in a downside market, this correlation increases much more than in an upside market.

We use the daily closing price of the constituent stocks of the Shanghai Stock Exchange 50 Index (SSE 50 Index) from January 4, 2005 to December 25, 2013, a total of 2177 trading days. The SSE 50 Index is composed of 50 representative stocks with large scale and good liquidity in Shanghai stock market. We use the method of Section 3 to analyze the average correlation among individual stocks in Chinese stock market. We use Eq. (11) to calculate the normalized return $R(t, \Delta t)$ of the SSE 50 Index and Eq. (14) to calculate the average correlation $\rho(t, \Delta t)$ among constituent stocks. As shown in Fig. 9, the average correlation among constituent stocks is larger when the market is in a downward state. The maximum correlation is close to 0.8 when the interval is 10 trading days ($\Delta t = 10$).

6.2. Leverage effect

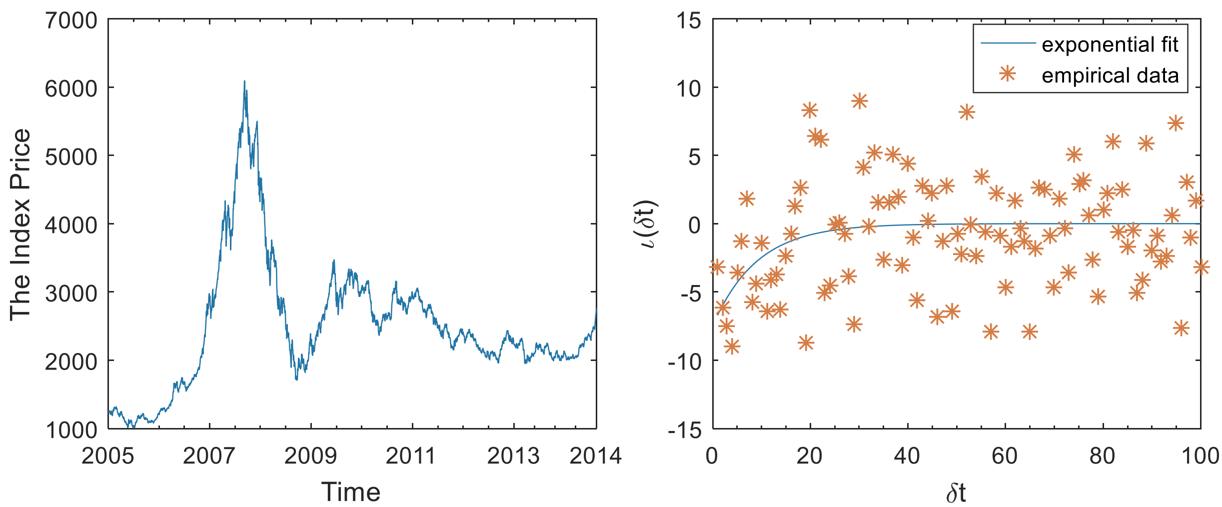
Bouchaud et al. (2001) analyzed the daily data of a set of 437 US stocks which were the constituent of S&P 500 index from January 1990 to May 2000 and a set of 7 major international stock indices from January 1990 to October 2000. They found that price drops increased the volatility (i.e. there was a negative correlation between past returns and future volatility). Li, Yang, Hsiao, and Chang (2005) examined the relationship between expected stock returns and volatility in the 12 largest international stock markets during January 1980 to December 2001, and the results showed that there was a significant negative relationship between expected returns and volatility in 6 out of the 12 markets. Bollerslev, Litvinova, and Tauchen (2006) found the correlations between absolute high-frequency returns and current and past high-frequency returns to be significantly negative for several days using the high-frequency S&P 500 futures data from January 4, 1988, through March 9, 1999. Yeh and Lee (2000) supported the evidence that the impact of negative unexpected return on future volatility is greater than the impact of positive unexpected return in Taiwan stock market and Hong Kong stock market from May 22, 1992 to August 27, 1996. All the above references supported the evidence of the negative correlation between past returns and future volatility.

We choose the daily trading data of the Shanghai Composite Index to analyze the leverage effect in Chinese stock market. The sample is the daily closing price of Shanghai Composite Index from January 4, 2005 to December 2, 2014, a total of 2406 trading days. We use Eq. (17) in Section 3.3 to calculate the correlation between past returns and future



(b) The price of the SSE 50 Index (b) increased downside correlation

Fig. 9. (a) The price of the SSE 50 Index from January 4, 2005 to December 25, 2013, a total of 2177 trading days. (b) Increased downside correlation. The relationship between the isochronous normalized index return rate and the average correlation among constituent stocks.



(a) The price of the Shanghai Composite Index (b) leverage effect

Fig. 10. (a) The price of the Shanghai Composite Index from January 4, 2005 to December 2, 2014, a total of 2406 trading days. (b) Leverage effect. The return-volatility relationship shows a negative correlation and it can be described by an exponential function.

volatility of the Shanghai Composite Index. As shown in Fig. 10, the current return and future volatility of the Shanghai Composite Index have a negative correlation and this correlation decreases over time. The negative correlation lasts until the lag is approximately 15. The points can be fitted with the exponential function $\iota(\Delta t) = -7.492e^{-0.1107\Delta t}$ (Fig. 10).

7. Conclusion

This paper focuses on the endogenous origins of extreme markets. We merge index coupling into investors' behavior and provide explanations of market collapses. In fact, we were inspired by the escape panic issue from the field of complexity science and feedback from questionnaire surveys about investors' behavior in the 1987 crash ("Black Monday"). We recall that the market crash was a result of the market itself dropping. Traders tend to panic under market stress, which leads to the self-reinforcement of a market drop. We designed a simple agent-based model with a double-auction multi-asset market, in which traders take the entire market quotation into consideration when making trading decisions. The simulation results show that when introducing such behavioral factors (panic when the market drops) into the trading process, the market may drop continuously in a short time. Moreover, some stylized facts in the market, such as synchronized behavior, the leverage effect and increased downside correlations can be reproduced in our model. In other words, we demonstrate that a market drop itself can cause an endogenous market crash and the stylized facts are related to this mechanism.

Acknowledgements

We thank the anonymous reviewers for their helpful comments and suggestions. They are not responsible for any of the errors in this paper. This work was supported by the National Natural Science Foundation of China under Grant No. 71671017.

Declarations of interest

None.

References

Amihud, Y., Mendelson, H., & Wood, R. A. (1990). Liquidity and the 1987 stock market crash. *Journal of Portfolio Management, 16*(3), 65–69.

Amman, H. M., Tesfatsion, L., Kendrick, D. A., Judd, K. L., & Rust, J. (Eds.). (1996). *Handbook of computational economics (Vol. 2)*. Elsevier.

Ben-David, I., Franzoni, F., & Moussawi, R. (2014). *Do ETFs increase volatility?* National Bureau of Economic Research (No. w20071).

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff Papers, 47*(3), 279–310. https://doi.org/10.2307/3867650.

Blume, M. E., MacKinlay, A. C., & Terker, B. (1989). Order imbalances and stock price movements on October 19 and 20, 1987. *The Journal of Finance, 44*(4), 827–848. https://doi.org/10.1111/j.1540-6261.1989.tb02626.x.

Bollerslev, T., Litvinova, J., & Tauchen, G. (2006). Leverage and volatility feedback effects in high-frequency data. *Journal of Financial Econometrics, 4*(3), 353–384. https://doi.org/10.1093/jjfinec/nbj014.

Borkovec, M., Domowitz, I., Serbin, V., & Yegerman, H. (2010). Liquidity and price discovery in exchange-traded funds: One of several possible lessons from the flash crash. *The Journal of Index Investing, 1*(2), 24–42. https://doi.org/10.3905/jii.2010.1.2.024.

Bouchaud, J. P., Matacz, A., & Potters, M. (2001). Leverage effect in financial markets: The retarded volatility model. *Physical Review Letters, 87*(22), 228701. https://doi.org/10.1103/PhysRevLett.87.228701.

Brunnermeier, M., Gorton, G., & Krishnamurthy, A. (2013). Liquidity mismatch measurement. *Risk topography: Systemic risk and macro modeling* (pp. 99–112). University of Chicago Press.

Campbell, R., Koedijk, K., & Kofman, P. (2002). Increased correlation in bear markets. *Financial Analysts Journal, 58*(1), 87–94. https://doi.org/10.2469/faj.v58.n1.2512.

Carlson, M. (2006). A brief history of the 1987 stock market crash with a discussion of the Federal Reserve response. *Finance and economics discussion series no. 2007–13*Washington, DC: Divisions of Research & Statistics and Monetary Affairs, Federal Reserve Board. https://doi.org/10.2139/ssrn.982615 November 2006.

Chiarella, C., He, X. Z., & Pellizzari, P. (2012). A dynamic analysis of the microstructure of moving average rules in a double auction market. *Macroeconomic Dynamics, 16*(4), 556–575. https://doi.org/10.1017/S136510051000074X.

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics, 10*(4), 407–432. https://doi.org/10.1016/0304-405X(82)90018-6.

Cutler, D. M., Poterba, J. M., & Summers, L. H. (1989). What moves stock prices. *J. Portf. Manag. 15*(3), 4–12. https://doi.org/10.3386/w2538.

Estrada, J. (2000). The cost of equity in emerging markets: A downside risk approach. *Working paper*. IESE Business School.

Figlewski, S., & Wang, X. (2000). Is the 'Leverage Effect' a leverage effect? *Working paper*. New York University.

Giardina, I., & Bouchaud, J. P. (2003). Bubbles, crashes and intermittency in agent based market models. *European Physical Journal B: Condensed Matter and Complex Systems, 31*(3), 421–437. https://doi.org/10.1140/epjb/e2003-00050-6.

Jacklin, C. J., Kleidon, A. W., & Pfeiderer, P. (1992). Underestimation of portfolio insurance and the crash of October 1987. *The Review of Financial Studies, 5*(1), 35–63. https://doi.org/10.1093/rfs/5.1.35.

LeBaron, B. (2006). Agent-based computational finance. *Handbook of Computational Economics*. *Vol. 2*. *Handbook of Computational Economics* (pp. 1187–1233). . https://doi.org/10.1016/S1574-0021(05)02024-1.

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. *Journal of Banking & Finance, 26*(12), 2277–2299. https://doi.org/10.1016/S0378-4266(01)00202-3.

Lehkonen, H. (2015). Stock market integration and the global financial crisis. *Review of Finance, 19*(5), 2039–2094. https://doi.org/10.1093/rof/rfu039.

Li, Q., Yang, J., Hsiao, C., & Chang, Y. J. (2005). The relationship between stock returns and volatility in international stock markets. *Journal of Empirical Finance, 12*(5), 650–665. https://doi.org/10.1016/j.jempfin.2005.03.001.

Lux, T. (1995). Herd behaviour, bubbles and crashes. *The Economic Journal, 105*(431), 881–896. https://doi.org/10.2307/2235156.

Ma, R., Zhang, Y., & Li, H. (2017). Traders' behavioral coupling and market phase transition. *Physica A: Statistical Mechanics and its Applications, 486*, 618–627. https://doi.org/10.1016/j.physa.2017.05.072.

Madhavan, A. (2012). Exchange-traded funds, market structure, and the flash crash. *Financial Analysts Journal, 68*(4), 20–35. https://doi.org/10.2469/faj.v68.n4.6.

Morris, S., & Shin, H. S. (2004). Liquidity black holes. *Review of Finance, 8*(1), 1–18. https://doi.org/10.1023/B:EUFI.0000022155.98681.25.

Findings Regarding the Market Events of May 6, 2010, Report of the staffs of the CFTC and SEC to the Joint Advisory Committee on Emerging Regulatory Issues, September 30, 2010.

Preis, T. D., Kenett, Y., Stanley, H. E., et al. (2012). Quantifying the behavior of stock correlations under market stress. *Scientific Reports, 2*, 752. https://doi.org/10.1038/srep00752.

Roll, R. (1988). The international crash of October 1987. *Financial Analysts Journal, 44*(5), 19–35. http://www.jstor.org/stable/4479142.

Shiller, R. J. (1988). Portfolio insurance and other investor fashions as factors in the 1987 stock market crash. *NBER Macroeconomics Annual, 3*, 287–297. https://doi.org/10.1086/654091.

Shiller, R. J. (1989). Investor behavior in the October 1987 stock market crash: Survey evidence. *Market Volatility*MIT Presshttps://doi.org/10.3386/w2446.

Siegel, J. J. (1992). Equity risk premia, corporate profit forecasts, and investor sentiment around the stock crash of October 1987. *Journal of Business, 65*(4), 557–570. https://www.jstor.org/stable/2353197.

Solnik, B., Boucrelle, C., & Le Fur, Y. (1996). International market correlation and volatility. *Financial Analysts Journal, 52*(5), 17–34. https://doi.org/10.2469/faj.v52.n5.2021.

Tesfatsion, L. (2002). Agent-based computational economics: growing economies from the bottom up. *Artificial Life, 8*(1), 55–82. https://doi.org/10.1162/106454602753694765.

Torii, T., Izumi, K., & Yamada, K. (2015). Shock transfer by arbitrage trading: Analysis using multi-asset artificial market. *Evolutionary and Institutional Economics Review, 12*(2), 395–412. https://doi.org/10.1007/s40844-015-0024-z.

Yang, S. Y. (2005). A DCC analysis of international stock market correlations: The role of Japan on the Asian four tigers. *Applied Financial Economics Letters, 1*(2), 89–93. https://doi.org/10.1080/17446540500054250.

Yeh, Y. H., & Lee, T. S. (2000). The interaction and volatility asymmetry of unexpected returns in the greater China stock markets. *Global Finance Journal, 11*(1–2), 129–149. https://doi.org/10.1016/S1044-0283(00)00014-4.

Yook, K. C. (2003). Larger return to cash acquisitions: signaling effect or leverage effect? *The Journal of Business, 76*(3), 477–498. https://doi.org/10.1086/375255.

Zhang, T., & Li, H. (2013). Buying on margin, selling short in an agent-based market model. *Physica A, 392*(18), 4075–4082. https://doi.org/10.1016/j.physa.2013.04.052.

Zhou, X., & Li, H. (2017). Buying on margin and short selling in an artificial double auction market. *Computational Economics, 8*, 1–17. https://doi.org/10.1007/s10614-017-9722-4.