Journal of Organizational and End User Computing
Volume 35 • Issue 1

Research on Monitoring Method of Stock Market Systematic Crash Based on Market Transaction Data

Yan Li, Dongguan University of Technology, China*
Zhan Li, Dongguan University of Technology, China

ABSTRACT

Sharp rises and falls in stock prices have become increasingly frequent in recent years. Stock market crashes bring great risks to the stability of the securities markets. Using recurrence plot theory and a heuristic segmentation algorithm for detecting abrupt changes in nonlinear time series, this study investigates the problem of detecting abrupt endogenous structural changes before a stock market crash. Based on an analysis of crash events in 12 developed and 10 emerging countries and regions, the authors find the following: (1) The market laminar flow (LAM) value will fall greatly before a stock market crash; (2) the LAM sequence of the US stock market during the 2008 financial crisis presents a fractal-like self-similar structure, and blank bands appears in the recurrence plot, indicating a phase transition in the LAM sequence before the crash; and. (3) using a heuristic segmentation algorithm to detect abrupt changes in nonlinear time series, this study finds that before a crash, the endogenous structure of the market continuously experiences abnormal abrupt changes, and abnormal abrupt change time.

KEYWORDS

financial crisis, nonlinear dynamics, stock market crash

INTRODUCTION

A crash is an extreme event in which the stock price of a listed company or a market index suddenly drops sharply without warning. Although theoretical research on stock price crashes began in the 1970s (Christie, 1982; Romer, 1993), the topic did not attract significant research attention for some time. In 2008, however, when the subprime mortgage crisis in the US triggered the global financial crisis, causing global markets to fall sharply, stock price crashes aroused widespread interest among academics and practitioners. In recent years, sharp fluctuations in stock market indexes (or prices) have become increasingly frequent, with stock market slumps posing great risks to the stability of securities markets. Stock market crashes can destroy confidence in the financial market, cause panic

DOI: 10.4018/JOEUC.324062
*Corresponding Author

among investors and the public, and reduce the resource allocation efficiency of the securities market. Classical financial analysis methods cannot effectively explain stock market crashes. Therefore, stock market crash risk stands out as a ubiquitous and highly influential risk factor. At the same time, crash risk is one of the risks that market participants focus on when making investment decisions. When the stock market crashes, multiple markets and stocks often crash simultaneously. As a result, investors cannot diversify investment risks through diversified investment portfolios; a stock market crash is thus an extreme systemic risk.

LITERATURE REVIEW

Hong and Stein (2003) define stock market crashes using the following three criteria: (1) the stock market index (or price) drops sharply and suddenly without warning, (2) stock market index (or price) changes are negative and asymmetric, and (3) stock market index (or price) crashes are contagious. At present, research on stock market crashes mainly focuses on the following aspects. First, the factors affecting stock price crashes are studied from perspectives such as corporate governance (Xu, 2014; Andreou, 2017; Liang et al., 2016; Peng et al., 2018), corporate social responsibility (Yongtae et al., 2014; Quan et al., 2016; Song, 2017), dividend policy (Zhu, 2017), company information quality (Li et al., 2011; Zhou et al., 2016; Meng et al., 2017; Xiao et al., 2017), institution and environment (Li & Cai, 2016; Chu et al., 2016, 2017), and investors (An & Zhang, 2013; Hong et al., 2013; Cao et al., 2015; Wang et al., 2015; Kong et al., 2016; Shen et al., 2017; Hua et al., 2018).

The second aspect is the measurement of the risk of securities market collapse. Chen et al. (2001) propose negative conditional skewness and the down-to-up volatility (DUVOL) ratio. If the values of these two indicators are large, the skewness coefficient of stock returns is negative, and the degree of left skewness is large, indicating that the risk of stock price crash is also greater. However, Jin and Myers (2006) find that DUVOL can only capture some effects of extreme values. Thus, the abovementioned methods were not widely used until Kim et al. (2011) improved upon them. In their approach, the daily return of stocks within six months is no longer used; rather, the method that Hutton et al. (2009) introduce defines the weekly returns of listed companies. In subsequent research, most measures of stock crash risk draw on this method (Chu & Fang, 2016; Song, 2017; Hua & Sun, 2018). Naik et al. (2021) construct a stock market crash prediction model using the hybrid feature selection method. Mahata et al. (2021) analyze the risk of stock market collapse during the COVID-19 pandemic using Hilbert–Huang transformation and structural break analysis. Using the change-point detection approach, Boubaker et al. (2021) investigate the relationship between news diversity and financial market crashes. Ho et al. (2021) investigate the effect of modern pandemics on the risk of stock price crashes. Zhu et al. (2023) use recurrence plots, recurrence quantification, and cross-recurrence plot methods to investigate stock markets' potential nonlinear dynamic characteristics. Ashe et al. (2023) use a recurrence plot to study the level of convergence and synchronicity between the real and financial economy in the 2008 crisis.

While many studies focus on the risk measurement and influencing factors of stock market crashes at the individual stock level, relatively few consider the market level. Nevertheless, the harmful effects of stock market crashes extend beyond the crash of individual stocks. In recent years, the time-point detection of the systematic collapse of securities markets has become a challenging problem. Such detection has practical significance for decision-making by investors and for risk-management activities by market managers. For example, the systematic collapse of the securities market during the 2008 financial crisis and the "1,000 shares limit down" crash in the Chinese market in 2015 highlights the practical significance of studying the timing of crashes. Sornette et al. (2004) propose that stock market price bubble formation, proliferation, and crash have evolutionary laws similar to physical phenomena, such as earthquakes and material fractures. Johansen et al. (2000) use the log-periodic power law model (LPPL) equation to describe the herd effect of investors and the inflation and bursting of stock market bubbles caused by positive feedback. Sornette (2004) characterizes the stock market as a complex system. Interaction between individuals in a complex system can lead to large-scale collective behavior, and extreme events may result from individuals' interaction, self-organization, and dynamic evolution within the system. Other studies, meanwhile, find similarities between a stock market crash and endogenous structural phase transitions in the market (Vandewalle, 1998; Guhathakurta, 2010; Yalamova, 2011).

Other approaches have been used in comparative studies. For example, Eckmann et al. (1987) propose recursive graph theory based on reconstructed phase space, and Zbilut and Webber (1992) propose recurrence quantification analysis (RQA). RQA methods have been widely applied in biomedicine, atmospheric science, water conservancy science, physical signal analysis, and network traffic analysis. They have also been used to study financial markets (Guhathakurta, 2010; Niu, 2016; Addo, 2013; Bastos, 2013). RP and RQA are highly suitable for handling nonstationary and noisy data and detecting changes, such as phase transitions. Thus, RP and RQA techniques can detect critical states before the endogenous collapse, seen as phase transitions, which can provide an initial bubble time estimate. Strozzi et al. (2002, 2007) use RP and RQA techniques to measure financial data volatility, while Fabretti and Ausloos (2005) use them to detect and estimate the time of bubbles in financial markets. Meanwhile, Piskun et al. (2008) propose that laminar flow (LAM) is suitable for measuring extreme events in financial markets. LAM is the ratio of the sum of recursive graph points on the lines of the vertical structure in the recursive graph to the points in the recursive graph (Marwan et al., 2007). The inverse of LAM reflects the liquidity level of the market (Strozzi, 2007). However, using the LPPL equation to estimate crash time points has several problems. For example, there are seven parameters to be estimated in the model. While fitting such a highly nonlinear function with many parameters, during the optimization process, the objective function may find multiple local minima with small values; thus, it is not guaranteed that the optimization algorithm can directly obtain a reliable result. Fabretti and Ausloos (2005) and Piskun et al. (2008) use RP and RQA to study financial market bubbles and estimate when they started. The disadvantage, however, is that the start time of a bubble can only be estimated by subjective observation, and there is no strict mathematical method for determining it. Thus, this method cannot be used to determine the time point of an abrupt endogenous structural change before a crash.

The basic idea of system dynamics is that every system has a structure, which determines its function. Different system structures have different dynamic behaviors and exhibit different dynamic characteristics. Studying the geometric structure of the stable manifolds of complex systems is a central issue in the theory of nonlinear complex systems. The stable manifolds of systems play an important role in understanding systems' global structure and evolution. Based on the reconstructed phase space theory, the recursive graph method is an effective analytical method for studying the internal structure and dynamic feature extraction of complex systems. This method can study the phase space manifolds of complex systems intuitively. For example, when the dynamic process of the evolution of the stock market's operating state is not fully known, by calculating the recursive behavior of the state phase points on different state trajectories during the steady flow of phase space, we can obtain the structural information and change trend of the stable manifold around the attractor. To some extent, this reflects the state evolution behavior of the dynamic complex system. In the evolution process of a dynamic system, the evolution trend of the system state and the 'graphical' characteristics of the path can suitably characterize the evolution behavior of the system.

Considering the above, this study makes the following contributions: (1) Previous stock market crashes all presented sudden and catastrophic extreme events that seemed to occur without warning. Is it true that those crashes occurred without warning? If not, what happened before the crashes, and how can we detect such changes? Investigating these three issues has theoretical and practical significance for understanding stock market crashes and reducing catastrophic collapses. (2) We reconstruct the phase space to embed the stock market index (or price) serial data in the phase space. Then, we analyze the state vector's trajectory in the phase space with invariant topological properties to investigate the stock market's dynamic evolution behavior. By studying endogenous structural changes in the market, we can discover "abnormal" behavior before a crash, providing a new perspective and technology for "observing" the history of stock price time series in studying the systematic collapse of stock markets. (3) Based on the decline of the LAM value of the US stock market during the 2008 financial crisis, we conduct a recursive analysis of the LAM of the market and find that the LAM sequence presents a fractal-like self-similar structure. Further, blank bands appear in the recurrence plot, showing a phase transition in the LAM sequence before the crash. (4) We analyze crash events in the financial markets of 12 developed countries/regions (Australia, Austria, Switzerland, New Zealand, France, Germany, Hong Kong, Japan, Netherlands, Singapore, the UK, and the US) and ten emerging countries (Argentina, Brazil, Egypt, India, Indonesia, Israel, South Korea, Malaysia, Mexico, and Taiwan). We find that before a market crash, the endogenous structure of the market continuously presents abnormal abrupt changes, and the time point of the abnormal abrupt change occurs two to eight months before the market crash.

HEURISTIC SEGMENTATION ALGORITHM FOR THE RECURSIVE GRAPH AND THE DETECTION OF ABRUPT CHANGES IN NONLINEAR TIME SERIES

Recursive Graph Method

The recursive graph method developed by Eckmann et al. (1987) can analyze state-trajectory characteristics in the reconstructed phase space by determining the delay time parameter and the embedding dimension parameter and reconstructing a one-dimensional chaotic time series into a reconstructed phase space. Then, the nonlinear dynamic characteristics and evolution behavior of chaotic time series can be analyzed. Traditional methods for analyzing time series usually have certain assumptions about the length and stationarity of the time series. The recursive graph method, however, does not require strict assumptions about the length and stationarity of the time series; thus, it has become an effective short-term nonstationary tool for time series analysis. The recurrence plot method is based on the delay embedding theorem (Takens, 1981).

According to the time delay embedding theorem, reconstructed phase space technology can be used for a one-dimensional market index (or price) time series $\left\{x_i \middle| i = 1,2,\cdots,n\right\}$. By determining the delay time τ and embedding dimension m, the chaotic time series of the market index (or price) can be embedded into m-dimensional state phase space. Then, a state vector set, $R^m = \left\{\vec{X}_i\right\}$, is constructed, $\vec{X}_i = \left(x_i, x_{i+\tau}, \cdots, x_{i+(m-1)\tau}\right), i = 1,2,\cdots,n'$ and $n' = n - \left(m-1\right)\tau$. The state vector set $\{\vec{X}_i \left| i = 1,2,\cdots,n' \right.\}$ represents the state trajectory of the market index (or price) time series $x_i\left(i = 1,2,\cdots,n\right)$ in reconstructed phase space. However, in reconstructing the state phase space, m and τ need to be determined, and there is currently no unified method for determining these two parameters. In this study, we use the C-C method (Kim et al., 1999) to determine parameter τ and use the false nearest-neighbors method (Abarbanel et al., 1993) to determine parameter m. After phase space reconstruction is completed, we must consider how to determine whether the two-state vectors are recursive in phase space. The critical value ε is an important parameter, which is usually taken as the time-series standard where the difference is 5%–10%, or the limited recursion rate is 10%–30%. In this study, the limited recursion rate is 10%. If the distance between two state vectors in the reconstructed phase space is greater than the critical value ε, the two states do not exhibit recursive behavior. $R_{i,j} = \Theta\left(\varepsilon - \vec{X}_i - \vec{X}_j\right), \vec{X}_i, \vec{X}_j \in R^m, i,j \in \left(1,2,\cdots,n'\right)$ and $\Theta\left(\bullet\right)$ are the Heaviside function, where $\Theta\left(x\right) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$, and the value of $R_{i,j}$ expresses the recurrence relationship between state vectors $\vec{X}_i$ and $\vec{X}_j$ in reconstructed phase space. By using a recurrence plot, the dynamic behavior characteristics of system-state trajectories in high-dimensional phase space in two-dimensional graphs can be intuitively analyzed.

The recurrence plot can be used to intuitively analyze the dynamic characteristics of the system-state trajectory in the high-dimensional reconstructed phase space in a two-dimensional graph. The recurrence plot mainly includes the following geometric structures: dispersion points, diagonal lines, vertical lines, and horizontal lines. RQA quantifies the features of these geometric structures in the recurrence plot (Eckmann et al., 1987). The LAM index describes the ratio of recurrence points in the vertical structure to all recurrence points, which represents the probability of a laminar state in a dynamic complex system.

$$LAM = \frac{\sum_{v=vmin}^{N} vP\left(v\right)}{\sum_{v=1}^{N} vP\left(v\right)},$$

where $P\left(v\right)$ represents the length of the line segments in the recursive graph. The LAM value reflects the dynamic characteristics of the complex system staying in a certain state. Marwan et al. (2002) note that this indicator can find the transition from chaos to chaos in a complex system.

Heuristic Segmentation Algorithm for Detecting Abrupt Changes in Nonlinear Time Series

Stock market index (or price) time series are usually nonlinear and nonstationary sequences. When external conditions change dramatically, the stock market index (or price) time series will undergo abrupt structural changes, and new dynamic behavior will appear. Understanding these abrupt structural changes can help us study the dynamic evolution of stock markets. Researchers generally recognize the nonlinearity of the stock market. The stock market is a highly dynamic evolutionary complex system, and financial time-series data present nonlinear characteristics. In addition, due to the complex and changeable external environment and investors' psychology, the structural characteristics of the stock market index (or price) time series show great dynamic changes, the series is nonlinear and nonstationary, and the sequences are nonlinear and nonstationary. Bernaola-Galván (2001) proposes the heuristic segmentation algorithm (BG algorithm) to detect the mean variation point in human heart-rate variation with nonlinear and nonstationary characteristics. The algorithm for detecting abrupt changes in a chaotic series is based on a sliding t-test, which divides a nonstationary time series into multiple stationary subsequences with different means. The obtained subsequences represent different physical backgrounds, effectively solving the problems of detecting abrupt changes in time series based on stationary and linear process assumptions. The algorithm is divided into two parts with multiple iterations in the segmentation, greatly reducing the detection calculation amount. This method is more practical, but white noise and peak noise have less influence on the abnormal point detection results. This study, therefore, combines RQA and the BG algorithm to detect the time points of abnormal abrupt changes in financial time series, thus proposing a new idea for such detection in stock market crashes.

MONITORING ABNORMAL CHANGES IN HISTORICAL STOCK MARKET CRASHES

RQA of Stock Market Bubbles and Crashes

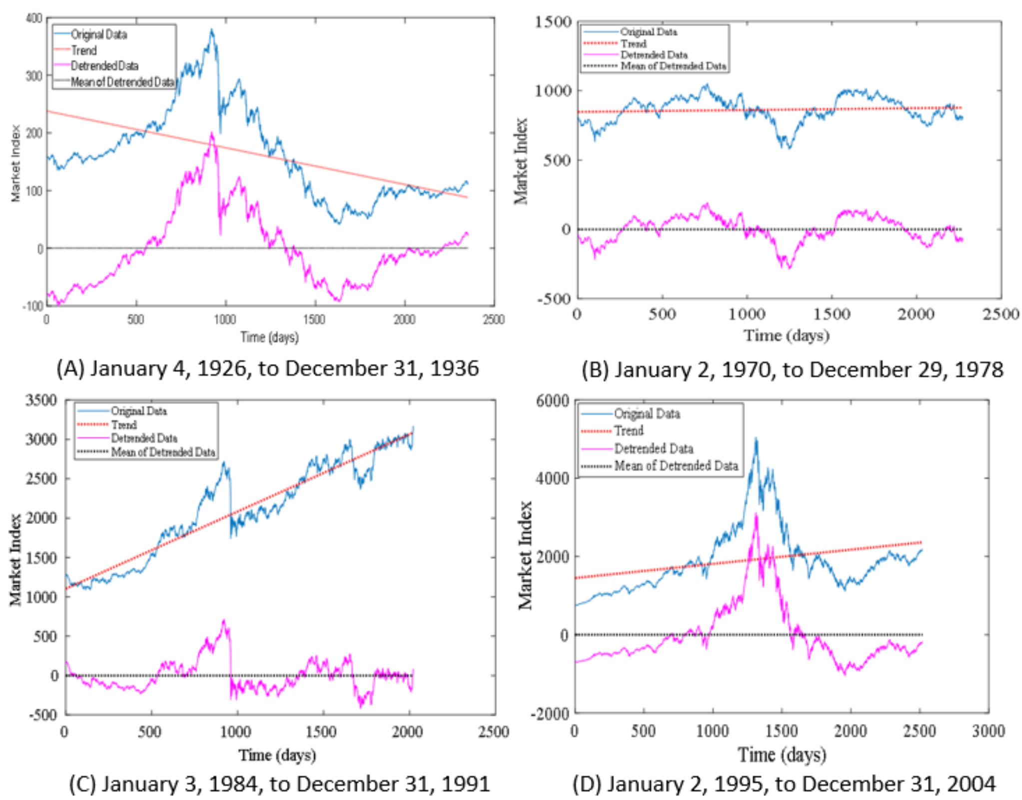
First, we analyze financial and economic crisis events affecting the world in the past 100 years. Given the long history of the Dow Jones Industrial Average, other stock markets had not been established when certain financial crisis events occurred; thus, no data is available to analyze those events.

Therefore, we first use the US Dow Jones Industrial Average to analyze the collapse behavior of the US stock market in previous financial crises. Specifically, we analyze four major crises: the Great Depression of 1929–1933, the economic crisis triggered by the oil crisis from 1973 to 1975, the "Black Monday" financial crisis of 1987–1988, and the speculative Internet bubble of 1999–2001. We collected daily closing prices from January 4, 1926, to December 31, 1936 (2351 data); January 2, 1970, to December 29, 1978 (2273 data); January 3, 1984, to December 31, 1991 (2022 data); and January 3, 1995, to December 31, 2004 (2519 data) (since the speculative Internet bubble was mainly related to small and medium-sized scientific and technological innovation enterprises, it is more appropriate to use the Nasdaq index than the Dow Jones Industrial Average). Since the stock price index shows a certain trend, and we want to analyze abrupt changes in the endogenous structure of the market before a crash, we first use the detrend function in MATLAB to remove the linear trend of the Dow Jones Industrial Average. Figure 1 shows the results.

Figure 1 shows that the US stock market crashed during the four investigated crises, and investors suffered huge losses. Therefore, understanding how to monitor changes in the endogenous structure of the market before a crash and the relationship between structural changes and market crashes have great practical significance for investors and market managers. Below, the LAM value in the RQA is used to analyze the start time of a market bubble to detect the time point of abrupt endogenous structural change before the stock market crash.

Figure 2 shows that the LAM value of the stock market will decline slightly during the bubble accumulation stage. When the market is unstable and is approaching the crash stage, the LAM value will decline sharply. This change process of the LAM value is very similar in all four crashes, and the

Figure 1. Detrending of stock market indices during various financial crises



(A) January 4, 1926, to December 31, 1936

(B) January 2, 1970, to December 29, 1978

(C) January 3, 1984, to December 31, 1991

(D) January 2, 1995, to December 31, 2004 changes in the LAM value are obvious. Regarding the time point, the abrupt endogenous structural change in the market comes long before the crash. Toward the final stage of the market crash, the LAM value continues to show a sharp downward trend or fluctuate after the downward trend. After a period of fluctuation, when the LAM value tends toward a new stable state or returns to the value before the decline, the market usually stops falling and stabilizes. Therefore, when the market is about to collapse, its endogenous structure will see abnormal changes.

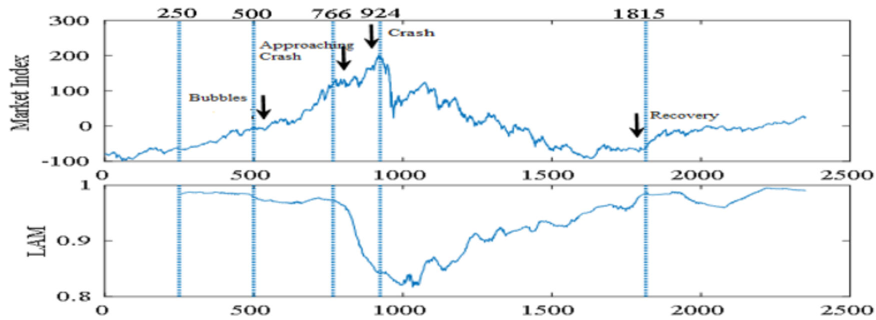
During the 1929–1933 crisis, the change in the LAM value reflects the complete fluctuation process experienced by the US stock market: bubble formation (a bubble began to form around January 1918, and the LAM value began to decline) → approaching collapse (around January 1929, the LAM value began to decline rapidly) → collapse (collapse began in September 1929, and the LAM value continued to decline; from the approach of the collapse to its occurrence, the structure of the LAM sequence changed abruptly eight months in advance) → stabilization and recovery (in April 1933, the stock market stopped falling and stabilized, and the LAM value returned to the level before the fall). Before the 1929–1933 crisis, the US Industrial Production Index had averaged only 67 in 1921 (100 during 1923–1925), but it rose to 110 by July 1928 and then increased to 126 in June 1929. People were so enthusiastic about the US stock market that Andrew Mellon, then secretary of the US Treasury, assured the public in September 1929, "There is no reason to worry now, and this boom will continue." However, on October 29, 1929, crowds gathered on Wall Street in New York, the day the stock market plummeted. According to the monitoring of the LAM value, in January 1929, the US stock market began to form a bubble, reaching the critical point of collapse in September 1929. Meanwhile, the Internet bubble crisis occurred around 2000. The changes in the LAM value reflected the fluctuations in the US stock market: bubble formation (the bubble began to form around November 1997, and the LAM value began to decline) → crash approaching (the LAM value began to decline rapidly as the collapse was approaching in March 1999) → crash (the collapse began in March 2000, and the LAM value continued to decline; from approaching the crash to the collapse, the structure of the LAM sequence changed suddenly 11 months ahead of schedule) → stable recovery (the stock market stabilized and recovered starting in February 2004, and the LAM value returned to the level before the decline).

In summary, although these crashes seemed to have occurred without warning, the endogenous structure of the market had already begun to change before the crash, providing a new perspective for understanding stock market crashes.

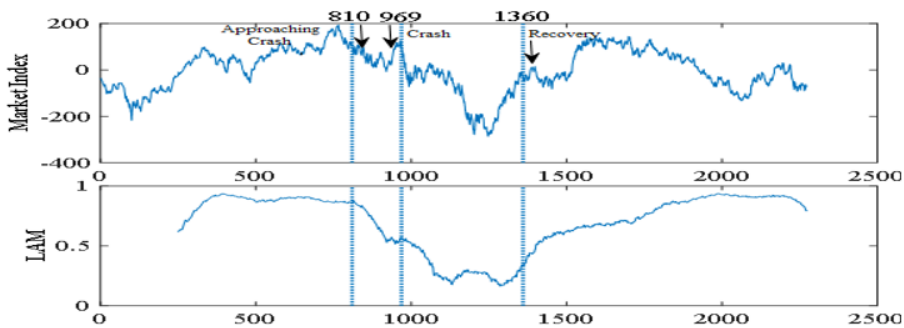
Time-Point Detection of Abrupt Endogenous Structural Changes Before the Stock Market Crashes Based on the BG Algorithm

Using the LAM value to detect sudden changes in the endogenous structure of the market before a crash has various shortcomings. Specifically, a sudden change in the market structure can only be obtained by direct visual observation, and the time point of the sudden change still cannot be detected. The stock market is a nonlinear, complex system with multilevel, nonstationary characteristics. Therefore, linear methods for detecting abrupt structural changes are not suitable. The BG algorithm, developed by Bernaola-Galván (2001), divides nonlinear and nonstationary time series into stationary subsequences at different scales based on the £ test. The algorithm has achieved good results in the time-point detection of abrupt structural changes in nonlinear and nonstationary time series (Gu et al., 2011; Qin et al., 2011; Hu et al., 2011; Huang et al., 2014). Therefore, to enhance empiricism and interpretability, we introduce the BG algorithm to detect the time point of abrupt change in the endogenous structure of the market before a stock market crash. The RQA method and the BG algorithm are used together to detect the time point of abrupt endogenous structural change. First, we analyze the recurrence plot of the LAM sequences of the US stock market during the four investigated financial crises. In Figure 3, we can see that the LAM sequences of the US stock market during each crisis show a fractal-like self-similar structure, and the sequences exhibit complexity. Blank bands appear in the recurrence plot, indicating the LAM sequence has phase transition behavior. During

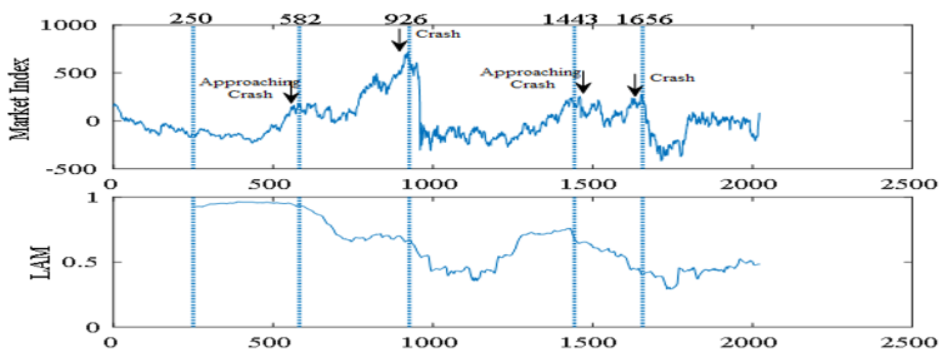
Figure 2. Market crash process and LAM value changes



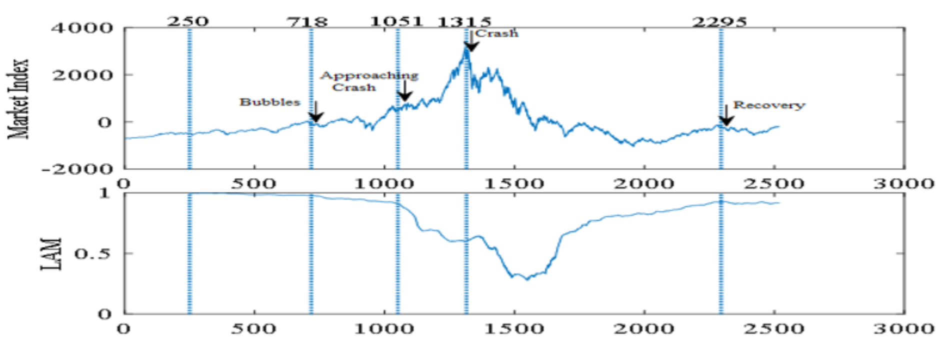
(A) January 4, 1926, to December 31, 1936



(B) January 2, 1970, to December 29, 1978



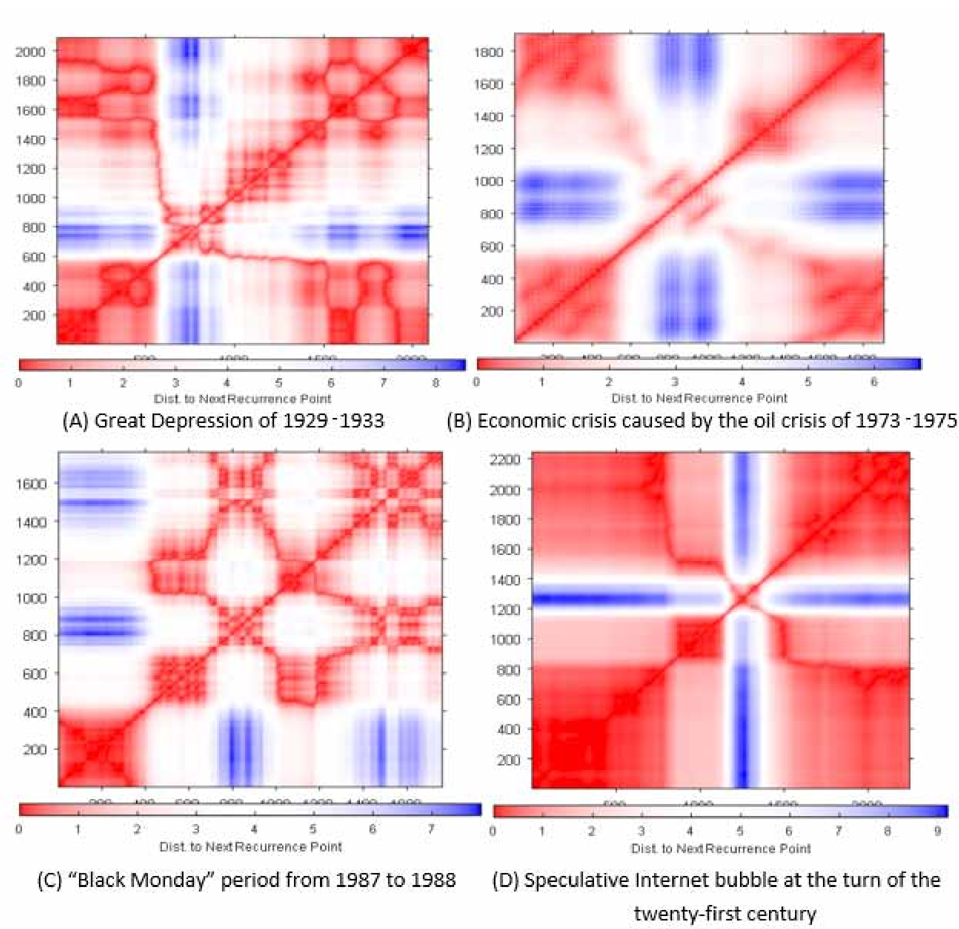
(C) January 3, 1984, to December 31, 1991



(D) January 2, 1995, to December 31, 2004 the phase transition, the LAM sequence has an abnormal mutation. These abrupt change points correspond to abnormal abrupt changes in the endogenous structure of the stock market. Below, the BG algorithm detects these abrupt change time points.

As shown in Figure 4, during the Great Depression (1929–1933), the BG algorithm detects abnormal changes in the LAM value of the Dow Jones Industrial Average on September 11, 1928, April 3, 1929, and May 17, 1929. This detection is accompanied by a continuous decline in the LAM value, indicating that the market bubble began to form on September 11, 1928, and the market had continuous abrupt abnormal phase changes for a short period from April 3, 1929, to May 17, 1929. Market instability increased, and the market entered a state of near collapse; an avalanche crash occurred in October 1929. Meanwhile, during the oil crisis of 1973–1975, the BG algorithm detected abnormal abrupt phase changes in the LAM values of the Dow Jones Industrial Average on June 13, 1973, January 6, 1974, March 29, 1974, and July 1, 1974, indicating that the market began to form bubbles on June 13, 1973. On January 6, 1974, March 29, 1974, and July 1, 1974, the market continuously experienced abnormal abrupt phase changes in a short period. Market instability intensified, and it entered a state of near collapse. The market collapsed in November 1974 and continued to decline. By 1974, 12 Dow Jones Industrial Average shares had fallen by 50%. Then, during the "Black Monday" financial crisis of 1987–1988, the BG algorithm detected

Figure 3. Recursion diagram of the LAM series of the US stock market during major worldwide financial crises



abnormal abrupt phase changes in the LAM value of the Dow Jones Industrial Average on June 3, 1985, October 2, 1985, September 12, 1986, and October 16, 1986, showing that the market formed a bubble on June 3, 1985. The market experienced abnormal abrupt phase changes on October 2, 1985, September 12, 1986, and October 16, 1986. Market instability intensified, and it entered a state of near collapse. Then, on October 19, 1987, the Dow Jones Industrial Average plummeted 508 points, a drop of 22%. This market crash produced a violent shock in the global stock market. Major stock markets such as London, Frankfurt, Tokyo, Hong Kong, and Singapore were strongly affected. Lastly, during the speculative Internet bubble crisis at the turn of the twenty-first century, the BG algorithm detected abnormal phase changes in the LAM value of the Nasdaq index on May 19, 1999, and February 14, 2000, showing that the market had entered a state of near collapse. The US Nasdaq index plummeted on March 13, 2000, from 5038 to 4879, a 4% drop. On June 5, 2000, July 25, 2000, and September 25, 2000, the LAM values of the Nasdaq index continuously showed abnormal phase changes. In fact, on March 10, 2000, the Nasdaq index reached its highest level at 5048.62 points. The stochastic Nasdaq fell continuously. The dot-com bubble collapsed from March 2000 to October 2002, wiping out $5 trillion of the market value of Internet technology companies. The BG algorithm is, therefore, effective for detecting abnormal abrupt changes in the endogenous structure of markets before crashes. Generally, the endogenous structure of the monthly market will experience sudden abnormal changes about three to eight months before a crash.

Abnormal Abrupt Changes in the Endogenous Market Structure in the 2008 Financial Crisis

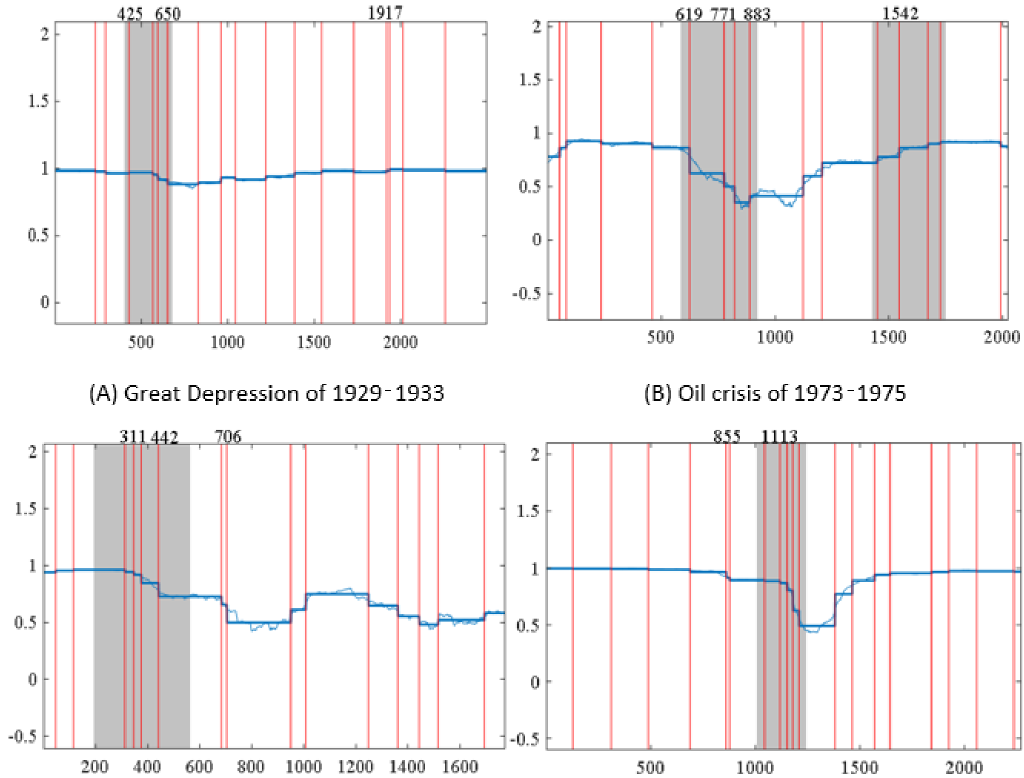
We use RQA and the BG algorithm to detect the time points of abnormal abrupt changes in the endogenous market structure before and during the 2008 financial crisis in 12 developed countries/regions (Australia, Austria, Switzerland, New Zealand, France, Germany, Hong Kong, Japan, Netherlands, Singapore, the UK, and the US) and ten emerging countries (Argentina, Brazil, Egypt, India, Indonesia, Israel, South Korea, Malaysia, Mexico, and Taiwan). Table 1 shows the results.

Table 1 shows that between July 2007 and October 2007, most stocks continuously experienced abrupt endogenous structural changes, and global stocks began to collapse after December 2017. While a stock market crash might seem to occur without warning, the stock market will experience continuous and abnormal changes before the crash, thus making the crash "traceable." This study's method for detecting abnormal abrupt endogenous changes embeds the stock market index time series in high-dimensional reconstructed phase space using reconstructed phase space theory, which can then be used in a topologically invariant high-dimensional reconstructed phase space. We study the evolution of the dynamic characteristics of stock markets by analyzing the trajectory of the state vector, and "abnormal" stock market behavior is identified by studying the endogenous structural changes before a market crash. The approach provides a fresh perspective and technology for monitoring stock market crashes.

Changes in the Structure of the A-Share Market in 2015 During the "1,000 Shares Limit Down" Crash

2015 China's A-share market experienced a rapid "1,000 shares limit down" crash. During the crash, market liquidity was almost completely lost. On June 19, 2015, the market index showed a weak performance and fell sharply in the afternoon, with a drop of more than 6% at one point, and nearly 1,000 stocks in Shanghai and Shenzhen markets fell by the limit. On June 26, 2015, the Shanghai–Shenzhen Index and the Growth Enterprise Index opened sharply lower across the board and showed a no rebound and sell-off pattern. The Shanghai Index kept hitting new intraday lows and hit the limit down for a while. The Growth Enterprise Index, meanwhile, fell more than 9%, and more than 2,000 individual stocks fell by the limit. On July 27, 2015, the Shanghai Index opened sharply lower, and all three major stock indexes took dives. The Shanghai Index fell below 3900, and 3800 points in succession, a drop of nearly 8%, and the Growth Enterprise Index fell below 2700 points,

Figure 4. Monitoring of abnormal abrupt change time points in the BG algorithm in the LAM sequence of the US stock market in the 2008 financial crisis



(A) Great Depression of 1929-1933

(B) Oil crisis of 1973-1975

(C) "Black Monday" period from 1987 to 1988

(D) Speculative Internet bubble at the turn of the twenty-first century

a drop of nearly 7%. On August 24, 2015, the Shanghai and Shenzhen stock markets opened sharply lower. After the opening, the stock index continued to fall sharply, and the market plummeted across the board. Only 15 stocks in the Shanghai and Shenzhen markets rose, and nearly 2,200 fell by the limit. We study this crash using the proposed method for detecting abnormally abrupt changes in the endogenous structure of the stock market. Figure 5 shows the results.

Figure 5(B) shows that on May 18, 2015, June 29, 2015, and August 17, 2015, the endogenous structure of the A-share market continuously experienced abnormal abrupt changes. However, the time point of the abnormal abrupt change was shorter than that of the market crash, which was only one month ahead of time. The main reason is that the 2015 crash was driven by the frantic rise of securities companies' stocks in the second half of 2014, which led to "frantic" speculation in the entire market. As a result, the amount of stock allocation (including off-site allocation) rose sharply, and the market generated a more serious bubble. This endogenous market factor led to a more unstable market structure. Meanwhile, in 2015, the exogenous conditions of the A-share market also experienced relatively abnormal changes, such as the rigorous investigation of illegal capital allocation, changes in monetary policy, and unconventional "malicious" short-selling behaviors in the market. These exogenous changes accelerated and exacerbated the market's decline.

Table 1. Abnormal abrupt change timing and crashes in major global stock markets during the 2008 financial crisis

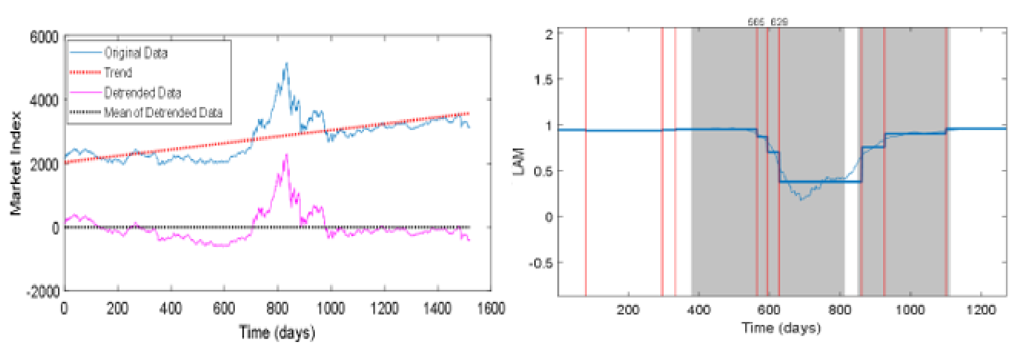
Market Index	Time Points of Abnormal Abrupt Changes	Market Crash Time and Crash Event Description
Australian As30 Index (AS30)	October 18, 2007; November 21, 2007; February 29, 2008; May 1, 2008	On November 1, 2007, the AS30 index reached its highest point of 6,897.2, and the market continued declining. From January 7, 2008, to January 17, 2008, it fell for nine consecutive trading days. As a result, the market index fell from 6,385.4 points to 5,730.9 points, down 654.5 points. From June 3, 2008, to January 20, 2008, the market fell continuously, from 5,703 points to 3,332 points, down 2,371 points.
Austrian ATX Index (ATX)	September 20, 2007; November 7, 2007; March 31, 2008; July 18, 2008	From November 9, 2007, to November 19, 2007, the market fell continuously for seven consecutive trading days, from 45,87.42 points to 4,267.32 points, down 320.1 points; from June 4, 2008, to November 21, 2008, from 4,310 points, it fell to 1,516 points, down 2,794 points.
Swiss Market Index (SMI)	February 1, 2007; June 20, 2007; July 28, 2008; October 31, 2008	From March 20, 2008, to August 11, 2009, the market index fell from 7,009.86 points to 5,949.98 points, down 1,059.88 points.
New Zealand 50 Index (NZSE50FG)	November 5, 2007; February 15, 2008; September 10, 2008	From January 3, 2008, to January 22, 2008, the market fell for 14 consecutive days, from 4,033.93 to 3,607.13, down 426.8; from June 5, 2008, to June 20, 2008, the market fell for 11 consecutive days, from 3,555.97 points to 3283.43 points, down 272.54 points; from October 3, 2008, to October 24, 2008, the market fell for 25 days, from 3,151.54 points to 2,575.48 points, down 576.06 points.
French CAC40 Index (FCHI)	September 5, 2007; November 19, 2007; January 15, 2008	From January 2, 2008, to March 17, 2008, the market fell for 34 days, from 5,550.36 points to 4,431.04 points, down 1,119.32 points; from June 6, 2008, to July 4, 2008, the market index fell from 4,795.32 points to 4,266 points, down 529.32 points.
German DAX Index (GDAXI)	September 5, 2007; November 19, 2007; January 29, 2008; May 29, 2008	From January 2, 2008, to January 25, 2008, it fell from 8,067.32 points to 6,816.74 points, a decrease of 1,250.58 points; from September 3, 2008, to October 24, 2008, it fell from 6,467.49 points to 4,295.67 points, a decrease of 2,171.82 points.
Hang Seng Index (HSI)	August 13, 2007; September 27, 2007; January 10, 2008; March 12, 2008	From October 31, 2007, to January 22, 2008, it fell from 31,352.58 points to 21,757.63 points, down 9,594.63 points; from May 7, 2008, to October 27, 2008, it fell from 26,262.13 points to 11,015.84 points, down 15,246.29 points.
Nikkei 225 (N225)	December 27, 2007; May 5, 2008	From June 19, 2008, to July 27, 2008, the market index fell from 14,452.82 points to 71,62.9 points, down 7,289.92 points.
Dutch AEX Index (AEX)	August 29, 2007; March 10, 2008	From November 1, 2007, to January 24, 2008, it fell from 547.85 points to 444.23 points, down 106.62 points; from June 4, 2008, to July 5, 2008, it fell from 483.9 points to 383.66 points, down 100.24 points; from June 4, 2008, to July 5, 2008, it fell from 483.9 points to 383.66 points, a decrease of 100.24 points; from June 4, 2008, to July 5, 2008, it fell from 483.9 points to 383.66 points, down 100.24 points.
FTSE Singapore Straits Times Index (STI)	July 26, 2007; September 14, 2007; February 29, 2008	From November 1, 2007, to November 22, 2007, it fell from 3,805.7 points to 3,312.88 points, down 492.82 points; from May 20, 2008, to October 24, 2008, it fell from 3,241.49 points to 1,590.36 points, down 1,651.13 points.
UK FTSE 100 Index (FTSE)	October 10, 2007; December 4, 2007; March 27, 2008	From December 28, 2007, to January 21, 2008, it fell from 6,497.8 points to 5,578.2 points, a decrease of 919.6 points; from May 22, 2008, to June 20, 2008, it fell from 6,198.1 points to 5,620.8 points, a decrease of 577.3 points; from July 24, 2008, to October 10, 2008, it fell from 5,362.3 points to 3,932.1 points, down 1,430.2 points.
US Dow Jones Industrial Average (DJI)	October 18, 2007; December 13, 2007	From May 19, 2008, to October 22, 2008, the market index fell from 13,028.16 points to 8,519.21 points, down 4,508.95 points.
US NASDAQ Index (IXIC)	August 30, 2007; January 24, 2008; April 18, 2008	From December 27, 2007, to January 22, 2008, the market index fell from 2,724.41 points to 2,292.27 points, down 432.14 points; from July 31, 2008, to November 20, 2008, the market index fell from 2,329.72 points to 1,316.12 points, down 1,013.6 points.
Argentina Merval Index (MERVAL)	September 21, 2007; February 5, 2008; May 5, 2008	From July 1, 2008, to October 27, 2008, it fell from 2,094.99 points to 836.23 points, down 1,258.76 points.
Brazil BOVESPA Index (IBOV)	September 28, 2007; December 21, 2007; March 20, 2008; May 23, 2008	From June 2, 2008, to October 27, 2008, it fell from 71,766.3 points to 29,435.11 points, down 42,331.19 points.

continued on following page

Table 1. Continued

Market Index	Time Points of Abnormal Abrupt Changes	Market Crash Time and Crash Event Description
Shanghai Composite Index	August 20, 2007; December 27, 2007	From October 15, 2007, to November 28, 2008, the market index dropped from 6,030.09 points to 4,803.39 points, down 1,226.7 points. From January 15, 2008, to October 27, 2008, the market index dropped from 5,443.79 points to 1,723.35 points, down 3,720.44 points.
Shenzhen Composite Index	July 27, 2007; September 13, 2007; January 9, 2008	From January 16, 2008, to October 24, 2008, the market index fell from 1,576.5 points to 505.82 points, a total decrease of 1,070.68 points.
Egypt Hermes Index (HERMES)	March 25, 2008; April 29, 2008	From May 5, 2008, to October 26, 2008, it fell from 1,023.72 points to 411.74 points, down 611.98 points.
Mumbai 30 Index (SENSEX)	September 11, 2007; October 19, 2007; November 20, 2007; June 12, 2008	From January 9, 2008, to February 12, 2008, it fell from 20,873.33 points to 16,608.01 points, a decrease of 4,265.32 points; from March 7, 2008, to November 3, 2008, it fell from 27,6314.71 points to 16,3278.75 points, a decrease of 6,435.41 points.
Jakarta Composite Index (JKSE)	September 3, 2007; November 2, 2007; February 18, 2008; May 5, 2008	From January 14, 2008, to January 22, 2008, it fell from 2,810.37 points to 2,294.52 points, a decrease of 515.85 points; from March 10, 2008, to April 3, 2008, it fell from 2,656.46 points to 2,237.97 points, a decrease of 418.49 points; from August 1, 2008, to October 28, 2008, it fell from 2,304.51 points to 1,111.39 points, down 1,193.12 points.
Israel ta-100 Index (TA100)	November 18, 2007; January 7, 2008; September 3, 2008	From January 15, 2008, to January 28, 2008, it fell from 1,106.4 points to 976.63 points, down 129.77 points. From January 15, 2008, to January 28, 2008, it fell from 1,106.4 points to 976.63 points, down 129.77 points. From August 25, 2008, to November 17, 2008, it fell from 943.39 points to 577.07 points, down 366.32 points.
Korea Kospi Index (KS11)	September 11, 2007; December 17, 2007; February 13, 2008; March 6, 2008	From November 11, 2007, to November 23, 2007, it fell from 2,063.14 points to 1,772.88 points, down 290.26 points; from November 11, 2007, to November 23, 2007, it fell from 2,063.14 points to 1,772.88 points, down 290.26 points; from December 28, 2007, to January 28, 2008, 1,908.62 points fell to 1,627.19 points, a decrease of 281.43 points; from June 9, 2008, to October 24, 2008, 1,832.31 points fell to 938.75 points, a decrease of 893.56 points.
Malaysia Kuala Lumpur Composite Index (KLSE)	July 10, 2007; August 17, 2007; October 26, 2007; April 10, 2008; May 20, 2008	From January 14, 2008, to March 17, 2008, 1,516.22 points fell to 1,177.53 points, down 338.69 points. From May 20, 2008, to October 29, 2008, 1,300.67 points fell to 829.41 points, down 471.26 points.
Mexico IPC Index (MEXBOL)	August 1, 2007; September 19, 2007; March 14, 2008	From June 2, 2008, to October 27, 2008, 31,594.89 points fell to 16,616.94 points, down 14,977.95 points.
Taiwan Weighted Index (TWII)	August 21, 2007; October 19, 2007; December 25, 2007; April 9, 2008	From May 20, 2008, to October 27, 2008, it fell from 9,068.89 points to 4,366.87 points, down 4,702.02 points.

Figure 5. Abnormal abrupt change in the LAM sequence of the Shanghai composite index in China's A-Share market, 2012–2018



(A) Detrending graph of the Shanghai Composite Index

(B) Time-point detection graph of the BG algorithm for abnormal abrupt changes

CONCLUSION

We show it is possible to detect the critical state before an endogenous market collapse, regarded as the stock market's endogenous structural phase transition using recursive graph and recursive quantification methods. Four major global economic crises—the Great Depression (1929–1933), the oil crisis of 1973–1975, the Black Monday financial crisis (1987–1988), and the speculative Internet bubble (1999–2001)—were analyzed. We find that when the stock market is in the stage of bubble accumulation, the LAM value declines slightly. When the market is unstable and approaching the crash stage, the LAM value declines sharply. This change process in the LAM value is very similar in the four investigated crashes, and the changes in the LAM value are obvious.

Regarding the time point, the time point of the market's abrupt endogenous structural change is much earlier than that of the market crash. Therefore, there seems to be no warning before a stock market crash. Our research shows, however, that the endogenous structure of the market changes before each crash. Our novel approach provides a new analytic tool and perspective for understanding stock market crashes.

We analyze the recursion graph of the LAM sequence of the US stock market during the financial crisis. The LAM sequences of the US stock market during the four crises all show a fractal-like self-similar structure, and the sequence has complex features. Blank bands appear in the recurrence plot, indicating that the LAM sequence has phase transition behavior, and abnormal abrupt changes in the LAM sequence occur at these phase transition points. The BG algorithm for the LAM sequence of the market index and the detection of abrupt changes in the nonlinear time series effectively detect abnormal abrupt changes in the endogenous market structure before a crash. Generally, the endogenous market structure will continuously experience abnormal changes two to eight months before the market crash.

We analyze the stock markets of 12 developed countries/regions (Australia, Austria, Switzerland, New Zealand, France, Germany, Hong Kong, China, Japan, Netherlands, Singapore, the UK, and the US) and 11 emerging countries (Argentina, Brazil, Egypt, India, Indonesia, Israel, China, South Korea, Malaysia, Mexico, and Taiwan) before and after the 2008 financial crisis, from January to December. We found sudden abnormal changes to have occurred continuously. From the end of 2007 to the end of 2008, the stock markets of various countries crashed. In the three to 12 months before the market collapse, the endogenous structures of the stock markets of various countries show continuous abnormal sudden changes.

When the exogenous conditions of the market change abnormally, the abnormal, sudden change in the endogenous structure of the stock market cannot be longer than the time point of the stock market crash. In 2015, the "1,000 shares limit down" crash of China's A-share market was primarily caused by exogenous factors.

Three main issues can be addressed by future research. First, future studies can improve the recursive graph method to build a more effective and accurate method for extracting the dynamic characteristics of the stock market. Second, such studies should examine the evolution of stock market dynamics over a longer period rather than only studying abrupt changes in stock market dynamics during four financial crises. Last, the stock markets of more countries should be included to gain a more comprehensive understanding of sudden changes in the stock market dynamics before crashes.

REFERENCES

Abarbanel, H. D. I., Brown, R., Sidorowich, J. J., & Tsimring, L. S. (1993). The analysis of observed data in physical systems. *Reviews of Modern Physics*, *65*(4), 1331–1392. doi:10.1103/RevModPhys.65.1331

Addo, P. M., Billio, M., & Guégan, D. (2013). Nonlinear dynamics and recurrence plots for detecting financial crisis. *The North American Journal of Economics and Finance*, *26*(4), 416–435. doi:10.1016/j.najef.2013.02.014

Andreou, P. C., Louca, C., & Petrou, A. P. (2017). CEO age and stock price crash risk. *Review of Finance*, *21*(8), 1287–1325. doi:10.1093/rof/rfw056

Bastos, J. A. (2013). Recurrence quantification analysis of financial markets. *Advances in Business Strategy and Competitive Advantage*, *57*(6), 857–862. doi:10.4018/978-1-4666-2509-9.ch003

Bernaola-Galván, P., Ivanov, P. Ch., Amaral, L. A. N., & Stanley, H. E. (2001). Scale invariance in the nonstationarity of human heart rate. *Physical Review Letters*, *87*(16), 1–4. doi:10.1103/PhysRevLett.87.168105 PMID:11690251

Boubaker, S., Liu, Z., & Zhai, L. (2021). Big data, news diversity and financial market crash. *Technological Forecasting and Social Change*, *168*, 120755. doi:10.1016/j.techfore.2021.120755

Cao, F., Lu, B., Li, Z., & Xu, K. (2015). Do institutional investors reduce the risk of stock price crash? *Accountability in Research*, *11*, 55–61.

Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns and conditional skewness in stock prices. *Journal of Financial Economics*, *61*(3), 345–381. doi:10.1016/S0304-405X(01)00066-6

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. doi:10.1016/0304-405X(82)90018-6

Chu, J., & Fang, J. (2016). Chinese-style margin financing and securities lending system and the deterioration of stock price crash risk. *Economic Research Journal*, *5*, 143–158.

Chu, J., Fang, J., & Zhang, W. (2017). Will corruption of regional officials worsen the risk of stock price crash? *Finance Quarterly*, *1*, 26–45.

Eckmann, J. P., Oliffson Kamphorst, S., & Ruelle, D. (1987). Recurrence plots of dynamical systems. *Europhysics Letters*, *4*(9), 973–977. doi:10.1209/0295-5075/4/9/004

Fabretti, A., & Ausloos, M. (2005). Recurrence plot and recurrence quantification analysis techniques for detecting a critical regime. Examples from financial market indices. *International Journal of Modern Physics C*, *16*(5), 671–706. doi:10.1142/S0129183105007492

Gu, C., Li, Z., & Xu, B. (2011). Research on the diagnosis method of concrete dam crack transformation based on sudden change of dynamic structure. *Science in China: Science and Technology*, *7*, 1000–1009.

Guhathakurta, K., Bhattacharya, B., & Chowdhury, A. R. (2010). Using recurrence plot analysis to distinguish between endogenous and exogenous stock market crashes. *Physica A*, *389*(9), 1874–1882. doi:10.1016/j.physa.2009.12.061

Ho, K.-C., Yao, C.-L., Zhao, C., & Pan, Z. (2022). Modern health pandemic crises and stock price crash risk. *Economic Analysis and Policy*, *74*, 448–463. doi:10.1016/j.eap.2022.03.010

Hong, H. A., Kim, J., & Welker, M. (2013). Divergence of cash flow and voting rights, opacity, and stock price crash risk: International evidence. *Journal of Accounting Research*, *55*(5), 1167–1212. doi:10.1111/1475-679X.12185

Hu, H., Dong, P., & Pan, J. (2011). Hail disaster risk zoning in Beijing based on disaster damage assessment. *Chinese Journal of Applied Meteorology*, *22*(05), 612–620.

Hua, M., & Sun, Q. (2018). Do foreign investors reduce the risk of stock price crash in emerging markets: Empirical evidence from "Shanghai-Hong Kong Stock Connect". *Contemporary Finance*, *1*, 57–67.

Huang, S., Huang, Q., Wang, Y., & Chen, Y. (2014). Variation diagnosis of runoff sequence based on heuristic segmentation and approximate entropy method. [Natural Science Edition]. *Journal of Sun Yat-Sen University*, *4*, 154–160.

Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R2 and crash risk. *Journal of Financial Economics*, *94*(4), 67–86. doi:10.1016/j.jfineco.2008.10.003

Jin, L., & Myers, S. C. (2006). R-squared the world: New theory and new tests. *Journal of Financial Economics*, *79*(2), 257–292. doi:10.1016/j.jfineco.2004.11.003

Johansen, A., & Sornette, D. (2001). Bubbles and anti-bubbles in Latin-American, Asian and Western stock markets: An empirical study. *International Journal of Theoretical and Applied Finance*, *4*(6), 853–920. doi:10.1142/S0219024901001218

Kim, H. S., Eykholt, R., & Salas, J. D. (1999). Nonlinear dynamics delay times and embedding windows. *Physica D. Nonlinear Phenomena*, *127*(1), 48–60. doi:10.1016/S0167-2789(98)00240-1

Kim, J., Li, Y., & Zhang, L. (2011). Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics*, *100*(3), 639–662. doi:10.1016/j.jfineco.2010.07.007

Kim, Y., Li, H., & Li, S. (2014). Corporate social responsibility and stock price crash risk. *Journal of Banking & Finance*, *2*, 1–13. doi:10.1016/j.jbankfin.2014.02.013

Kong, D., & Wang, J. (2016). Institutional investor information competition and stock price crash risk. *Nankai Management Review*, *5*, 127–138.

Li, W., & Cai, G. (2016). Religion and stock price crash risk: Evidence from China. *China Journal of Accounting Research*, *9*(3), 235–250. doi:10.1016/j.cjar.2016.04.003

Liang, Q., & Zeng, H. (2016). Reform of independent director system, independent director independence and stock price crash risk. *Management World*, *3*, 144–159.

Mahata, A., Rai, A., Nurujjaman, M., Prakash, O., & Prasad Bal, D. P. (2021). Characteristics of 2020 stock market crash: The COVID-19 induced extreme event. *Chaos: An Interdisciplinary Journal of Nonlinear Science, 31*(5), 053-115. 10.1063/5.0046704

Marwan, N., Romano, M. C., Thiel, M., & Kurths, J. (2007). Recurrence plots for the analysis of complex systems. *Physics Reports*, *438*(5-6), 237–329. doi:10.1016/j.physrep.2006.11.001

Meng, Q., Yang, J., & Lu, B. (2017). Information content and stock price crash risk disclosed in management discussion and analysis: A research based on text vectorization method. *China Industrial Economics*, *12*, 132–150.

Naik, N., & Mohan, B. R. (2021). Novel stock crisis prediction technique-A study on Indian stock market. *IEEE Access : Practical Innovations, Open Solutions*, *9*(07), 86230–86242. doi:10.1109/ACCESS.2021.3088999

Niu, B. V. W., Noorani, M. S. M., & Jaaman, S. H. (2016). Chaotic behavior in Malaysian stock market: A study with recurrence quantification analysis. *American Institute of Physics Conference Series, 1784*(1), 523-532. doi:10.1063/1.4966832

Peng, Q., & Zheng, Y. (2018). Does CFO concurrently serving as board secretary reduce the risk of stock price crash: From the perspective of information communication and risk aversion. *Journal of Shanxi University of Finance and Economics*, *4*, 49–61.

Piskun, S. O., Piskun, O. V., & Panteleeva, N. M. (2008). Recurrence quantification analysis of the stock markets in the light of the mortgage USA crisis. *Visnyk Universytetybankivskoi spravy Nacionalnogo banky Ukrainy, 3*, 212–217. https://doi.org/10.31812/0564/1135

Quan, X., & Xiao, H. (2016). Research on the impact of social responsibility disclosure on stock price crash risk: An intermediary mechanism based on accounting conservatism. *China Soft Science*, *6*, 80–97.

Romer, D. (1993). Rational asset-price movements without news. *The American Economic Review*, *83*(3), 1112–1130. doi:10.3386/w4121

Shen, H., Wu, X., & Wu, S. (2017). Controlling rights of controlling shareholders and the risk of stock price collapse: “Interest Synergy” or “Tunnel” Effect? *Economic Management*, *4*, 65–83.

Song, X., Hu, J., & Li, S. (2017). Social responsibility information disclosure and stock price crash risk: Path analysis based on information effect and reputation insurance effect. *Financial Research*, *4*, 161–175.

Sornette, D., & Cuypers, F. (2004). Why stock markets crash: Critical events in complex financial systems. *Physics Today*, *57*(3), 78–79. doi:10.1063/1.1712506

Strozzi, F., Zaldivar, J. M., & Zbilut, J. P. (2002). Application of non-linear time series analysis techniques to high-frequency currency exchange data. *Physica A*, *312*(3-4), 520–538. doi:10.1016/S0378-4371(02)00846-4

Strozzi, F., Zaldívar, J. M., & Zbilut, J. P. (2009). Recurrence quantification analysis and state space divergence reconstruction for financial time series analysis. *Physica A*, *376*, 487–499. doi:10.1016/j.physa.2006.10.020

Takens, F. (1981). Dynamical systems and turbulence. In D. Rand & L. S. Young (Eds.), *Lecture notes in mathematics* (Vol. 898, pp. 366–381). Springer-Verlag. doi:10.1007/BFb0091924

Vandewalle, N., Ausloos, M., Boveroux, P., & Minguet, A. (1998). How the financial crash of October 1997 could have been predicted. *The European Physical Journal B*, *4*(2), 139–141. doi:10.1007/s100510050361

Wang, H., Cao, F., & Ye, K. (2015). Hollowing or supervision: Major shareholders' shareholding ratio and stock price crash risk. *Guanli Shijie*, *2*, 76–88.

Xiao, T., Song, S., & Li, L. (2017). Information disclosure quality and stock price crash risk: The mediating role of analyst forecasts. *Financial Research*, *2*, 110–121.

Xu, N., Li, X., Yuan, Q., & Chan, K. C. (2014). Excess perks and stock price crash risk: Evidence from China. *Journal of Corporate Finance*, *25*(2), 419–434. doi:10.1016/j.jcorpfin.2014.01.006

Yalamova, R., & McKelvey, B. (2011). Explaining what leads up to stock market crashes: A phase transition model and scalability dynamics. *Journal of Behavioral Finance*, *12*(3), 169–182. doi:10.1080/15427560.2011.602484

Zhou, D., & Lai, S. (2016). Will the cash flow manipulation of listed companies aggravate the risk of stock price crash? *Journal of Shanxi University of Finance and Economics*, *2*, 100–111.

Zhu, H. (2017). Dividend payout ratio and stock price crash risk: An empirical study based on listed companies. *Journal of Jilin Business University*, *3*, 66–72.