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Return volatility interval analysis of stock indexes during a financial crash

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HIGHLIGHTS

- Return volatility interval distribution has the largest power-law exponents in plummet stage.
- The developed markets show weak correlation to the volatility interval in soaring stage of a crash.
- Emerging markets have constant correlation behavior to the extreme volatility during the crash.

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ABSTRACT

We investigate the interval between return volatilities above a certain threshold q for 10 countries data sets during the 2008/2009 global financial crisis, and divide these data into several stages according to stock price tendencies: plunging stage (stage 1), fluctuating or rebounding stage (stage 2) and soaring stage (stage 3). For different thresholds q, the cumulative distribution function always satisfies a power law tail distribution. We find the absolute value of the power-law exponent is lowest in stage 1 for various types of markets, and increases monotonically from stage 1 to stage 3 in emerging markets.

The fractal dimension properties of the return volatility interval series provide some surprising results. We find that developed markets have strong persistence and transform to weaker correlation in the plunging and soaring stages. In contrast, emerging markets fail to exhibit such a transformation, but rather show a constant-correlation behavior with the recurrence of extreme return volatility in corresponding stages during a crash. We believe this long-memory property found in recurrence-interval series, especially for developed markets, plays an important role in volatility clustering.

1. Introduction

Recurrence interval analysis is widely used to study extreme events and has been applied extensively to various research areas including meteorology [1–4], seismology [5–8], ethology [9–11], and physiology [12,13]. Meanwhile, in recent years economists and physicists have paid greater attention to the study of recurrence intervals between higher return volatility events in the financial data, which is an issue for risk management and estimation [14–19]. Numerous studies have shown that return volatility interval series follow a stretched exponential distribution, or exhibit a multiscaled power-law tail distribution. Furthermore, other studies have used Detrended Fluctuation Analysis (DFA) to show that return volatility interval series have long-range persistence [20–31]. Researchers also maintain that the statistical distribution properties of the return volatility interval depend on financial factors including stock lifetime, market capitalization and trading

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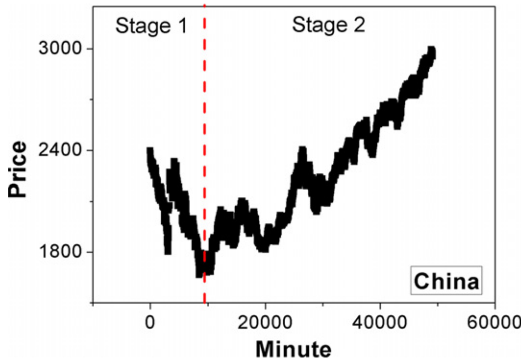

Fig. 1. (Color online): Run charts of China_SSEC can be separated into two stages according to their trends. Stock prices plunge in Stage 1 and rebound in Stage 2.

volume [32]. However, these studies mainly focus on long-range data sets taken in normal periods, and few studies have examined the statistical properties of return volatility interval series in a relatively short period during a crash. In addition, during a crash, stock prices plummet dramatically and then appear some crossovers. Such variation in stock price tendencies has a significant impact on trading behavior, but its effect on the return volatility interval series is still unknown. This paper seeks to fill this gap in the literature.

The remainder of the paper is organized as follows: Section 2 describes our data sets and methodology. Section 3 investigates the cumulative distribution function of the return volatility interval series. Section 4 uses DFA to analyze the persistence of return volatility interval series. Concluding remarks are provided in Section 5.

2. Methodology

2.1. Description of data

We analyze stock indexes at one minute intervals during the global financial crisis between Sep 2008 and Jun 2009. Ten stock markets from different countries are considered: Australia_AORD, Brazil_BVSP, China_SSEC, France_CAC40, Germany_XDAX, India_SENSEX, Japan_NIKKEI225, Portugal_PSI20, Taiwan_TAIEX, and USA_SP500. We compare the statistical and fractal properties of the stock indexes in different periods of the crash. The index series can be divided into two or three stages according to changes in stock price tendencies: a plunging stage (stage 1) in which the increment of daily stock prices is always a large negative value; a fluctuating or rebounding stage (stage 2) where the daily stock price increment is near zero or positive; and a soaring stage (stage 3) where the daily stock price increases continuously. We separate China_SSEC into two stages: plummet stage (stage 1) and rebounding stage (stage 2), whereas the other nine stock market indexes are appropriately separated into three stages representing a drastic plunge in the stock price (stage 1), fluctuation at low values (stage 2), and a strong rebound (stage 3). See Figs. 1 and 2.

2.2. Definition of normalized volatility

We define the logarithmic return volatility of a stock price series as follows:

$$V(t) = |LnP(t) - LnP(t-1)|\,, \tag{1}$$

where $p(t)$ denotes the stock price at time t. In most stock markets, the 1 min return volatility data follow specific intraday patterns shown in Eq. (2) [15,20]:

$$A(s) = \frac{\sum_{i=1}^{N} V_i(s)}{N}. \tag{2}$$

In Eq. (2), $A(s)$ represents the return volatility at a specific moment s of the day averaged over all N trading days, and $V_i(s)$ denotes the return volatility at time s in the ith day. To eliminate an artificial correlation induced by such intra-day patterns, we employ a new parameter $V'(t)$ [15,20]:

$$V'(t) = \frac{V(t)}{A(s)}. \tag{3}$$

The normalized volatility is established by dividing the standard deviation of $V'(t)$:

$$v(t) = \frac{V'(t)}{[\langle V'(t)^2\rangle - \langle V'(t)\rangle^2]^{1/2}}. \tag{4}$$