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Identifying Systemic Risks and Policy-Induced Shocks in Stock Markets by Relative Entropy

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Abstract: Systemic risks have to be vigilantly guided against at all times in order to prevent their contagion across stock markets. New policies also may not work as desired, instead even induce shocks to market, especially those emerging ones. Therefore, timely detection of systemic risks and policy-induced shocks is crucial to safeguard the health of stock markets. In this paper, we show that the relative entropy or Kullback-Liebler divergence can be used to identify systemic risks and policy-induced shocks in stock markets. Concretely, we analyzed the minutely data of two stock indices, the Dow Jones Industrial Average (DJIA) and the Shanghai Stock Exchange (SSE) Composite Index, and examined the temporal variation of relative entropy for them. We show that clustered peaks in relative entropy curves can accurately identify the timing of the 2007–2008 global financial crisis and its precursors, and the 2015 stock crashes in China. Moreover, a sharpest needle-like peak in relative entropy curves, especially for SSE market, always served as a precursor of an unusual market, a strong bull market or a bubble, thus possessing a certain ability of forewarning.

1. Introduction

Systemic risks have to be vigilantly guided against at all times in order to prevent the collapse of a financial system or the entire market. Many empirical studies on systemic risks exist, especially after the 2008 global financial crisis. They include study of bank contagion [18,22], contagion of systemic risks spreading across markets [4], bank capital ratios and bank liabilities [3,10], contagion, spillover effects and co-movement in financial markets [9,15,25], and identification of financial crises [8,16]. Existing research also thoroughly examines the measurement of systemic risk and the prediction of financial crises. In [1], the authors proposed measuring an institutions systemic risk as its Systemic Expected Shortfall (SES). They then showed that SES could predict the 2007-2008 financial crisis. Systemic risk could also be measured using the price of insurance against financial distress [11–13]. In [4], a new Early Warning System (EWS) model was developed for predicting financial crises based on a multinomial logit model. Among above studies, large and various data about financial institutions, especially banks, or other sectors are involved, when different objectives were concerned. Since systemic risks and financial crises are related to the entire stock market, it is still unknown whether systemic risks can be measured by mainly focusing on the most closely monitored data, the stock index data.

In troubled economic times, special policies often are applied to stabilize and stimulate the economy. However, sometimes the new policies do not work as desired; instead, they even induce

shocks to the market. This is especially so in emerging markets, including China. The issue has recently been tackled through the study of the relationship between policy and stock prices [14,21,24]. However, these results are mainly of theoretical significance, as they do not shed light on how to timely forewarn or detect the shocks a specific policy could induce in a market.

In studying the fluctuations of stock prices or stock index, a problem of enormous practical and theoretical interest is the distribution of stock returns and its dynamical evolution. Extensive literature exists on the former issue. Representative ones include Gaussian [2], Lévy [7,19], leptokurtic [5,6], truncated Lévy [20], and Tsallis distribution [23]. Unfortunately, such studies cannot help much with the identification of systemic risks and policy-induced shocks, since the long-term distribution of stock returns of a market is an average behavior.

In this paper, we show that an important concept in information theory, the relative entropy (also called Kullback-Liebler divergence) [17], can be used to effectively identify systemic risks and policy-induced shocks in stock markets. The only assumption we made here is that systemic risks and policy-induced shocks only occur occasionally. We show that this approach can accurately identify the timing of the $2007 - 2008$ global financial crisis and its precursors, and the 2015 stock crashes in China.

2. Data and Methods

2.1. Data

We analyzed the minutely data of two stock indices, the Dow Jones Industrial Average (DJIA) from January 2005 to December 2014, and the Shanghai Stock Exchange (SSE) Composite Index from January 2005 to April 2016. We mainly work with the index returns $R(t)$,

$$R(t) = \beta * [\ln P(t + \Delta t) - \ln P(t)] \tag{1}$$

where $P(t)$ is the closing price of the index at time t, Δt is the time interval, set to be 1 minute here, and β is a magnification factor set to be 100 following the usual practice.

2.2. Relative Entropy

Given two sets of discrete probability distributions $\{P_i, i = 1, 2, \cdots, n\}$ and $\{Q_i, i = 1, 2, \cdots, n\}$, the relative entropy, denoted as $D_{KL}(P||Q)$, is defined as [17]:

$$D_{KL}(P||Q) = \sum_i^n P(i) \ln \frac{P(i)}{Q(i)} \tag{2}$$

$D_{KL}(P||Q)$ provides a good means of quantifying the similarity or dissimilarity between two distributions. Here, $\{P_i, i = 1, 2, \cdots, n\}$ is the distribution of the minutely returns of a stock index on a certain day. $\{Q_i, i = 1, 2, \cdots, n\}$ is the distribution of minutely returns of a stock index over a long period of time, such as a few years. We assume that as the time period covered is long enough, $\{Q_i, i = 1, 2, \cdots, n\}$ will be well defined and essentially no longer change when a longer period of time is used to compute it. This is indeed so, as is clearly shown by Figure 1a,b, where we observe that $\{Q_i, i = 1, 2, \cdots, n\}$ defined over a 4-year, 6-year, 8-year, and 10-year period are essentially the same.
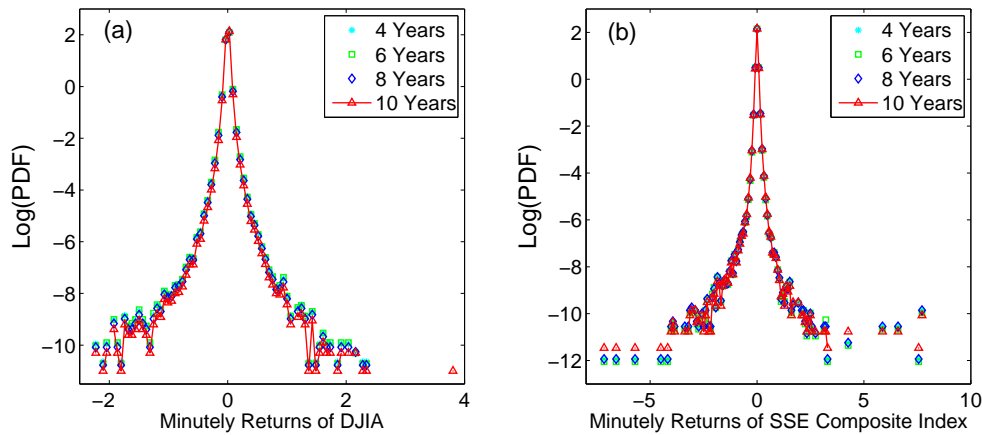
Figure 1. The distributions of minutely returns for (**a**) DJIA and (**b**) SSE Composite Index over long-term.

In this paper, for each stock index, $\{Q_i, i = 1, 2, \cdots, n\}$ is defined as the empirical distribution of its minutely returns over the entire study period (longer than 10 years). For each stock index, two trading days, a normal day and a crisis day, are selected to illustrate how the distributions of the minutely returns on these two days deviate from their references. As shown in Figure 2a,c, the distributions of the minutely returns on normal days are very close to their references (with small relative entropy), while the distributions of the minutely returns on crisis days are significantly different from their references (with big relative entropy) as shown in Figure 2b,d. Note that the Y-axis is log(PDF) rather than PDF.
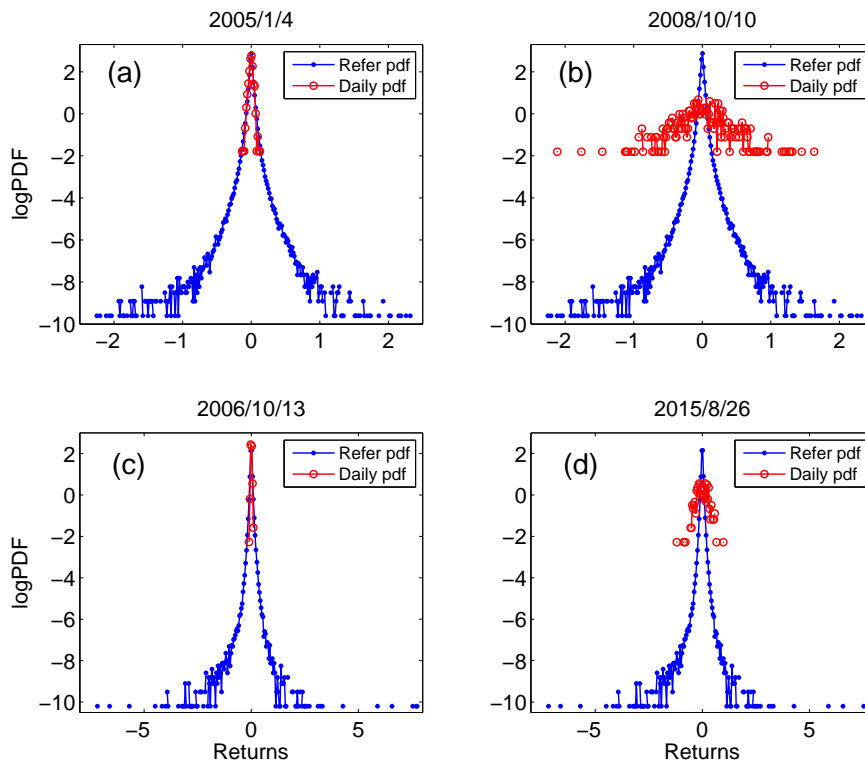

Figure 2. The deviations of the distributions of minutely returns from their references on two selected days for DJIA (**a**, **b**) and SSE Composite Index (**c**, **d**).

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3. Results

Figure 3 and Figure 4 show respectively as blue curves the temporal variation of the relative entropy for two stock indices, DJIA and SSE Composite Index, and as red curves the re-scaled daily closing prices for two stock indices. We observe that while most of the time, the values for the relative entropy are small, there exist time points or short periods that they exhibit sharp peaks with quite significant values. Those time points relative entropy peaks occurring are labeled in Figure 3 and Figure 4 respectively. Relative entropy peaks embody timing information about financial crises and stock crashes, as detailed below. Note that relative entropy peaks not necessarily happened on just the day when stock crash occurred (there might be a couple of days' delay), they may even happen on the day with positive daily returns. However, sharp relative entropy peaks often imply more peaks following in short period if systemic risks stand behind, further forming clusters of peaks.
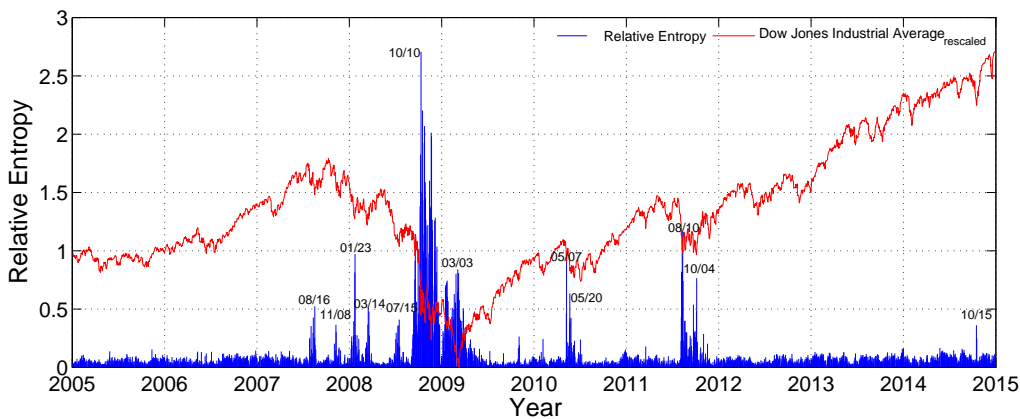

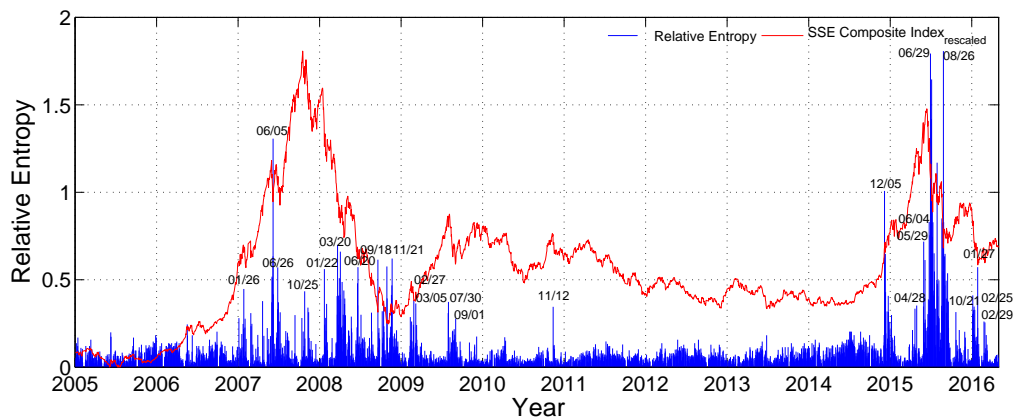**Figure 3.** Relative entropy (blue) vs re-scaled DJIA (red).

Figure 4. Relative entropy (blue) vs re-scaled SSE Composite Index (red).

3.1. Temporal Variation of Relative Entropy for DJIA

The cluster of sharp peaks in Figure 3 can be readily connected to the $2007 - 2008$ global financial crisis. The first group of the peaks in this cluster was in mid 2007, indicating that the $2007 - 2008$ global financial crisis started in mid 2007. This is consistent with the analyses of in Gao et al. [8] and Zheng et al. [25]. The first group of peaks in the beginning of 2008 happened around January 23, 2008, with the sharpest needle-like peak reaching 1.0 on January 23. It turns out, two days ago, on January 21, 2008 global stock markets suffered their biggest falls since September 11, 2001, and on January 22, 2008 the US Fed cut rates to 3.5%, its biggest cuts in 25 years, to prevent the economy from slumping into recession. This caused an unusually strong bounce back of the market on January 23, 2008. The sharpest peak throughout the whole interval occurred on October 10, 2008, when the DJIA crashed

almost 700 points in the first few minutes of trading. The cluster of relative entropy peaks lasting about half and one year defined the $2007 - 2008$ global financial crisis in US market.

After the global financial crisis, two more relatively small groups of clustered peaks happened in May 2010 and August 2011. The former was related to the "2010 Flash Crash", which occurred on May 6, 2010 when the DJIA had its biggest intraday drop, plunging 998.5 points. The latter was known as "August 2011 stock markets fall" , which was due to fears of the spread of the European sovereign debt crisis to Spain and Italy, as well as downgrading of America's credit rating from AAA to $AA+$ by Standard & Poor on August 6, 2011 for the first time. However, a long bull market rather than a big stock crash followed the above clusters of relative entropy peaks. It reflects that systemic risks were not the root cause behind the short clusters of peaks. Therefore, the US market, a mature developed stock market, was high efficient in digesting market information and back to normal.

3.2. Temporal Variation of Relative Entropy for SSE Composite Index

There are two major groups of clustered peaks in Figure 4: one is from the beginning of 2007 till mid 2009, the other mainly about the 2015 stock crashes.

The first sharp peak in the first group, whose value close to 0.5, happened on January 26, 2007, a month earlier than the "Black Tuesday" on February 27, 2007, suggesting that the peak on this day served as a precursor of an unusual market ahead. On June 5, 2007, the market registered a sharpest peak, close to 1.5. Remarkably, stimulated by a series of policies including appreciation of the RMB, reform of non-tradable shares, and new batch of money injected into the market, the bubble survived the setback until October 2007, when the bubble finally fully broke up. This was much earlier than the impact of the 2007–2008 global financial crisis reaching to China's market. As a result, we do not observe many significant sharp peaks directly related to the 2007–2008 global financial crisis. The last salient subset of the peaks in the relative entropy curve happened in November 2008, when the Chinese government announced a $ 590 billion, two-year economic stimulus plan to curb the economy's slowdown. These policy-induced peaks also marked the ending of the 2007–2008 global financial crisis in China's market. After a few months, this stimulus successfully initiated another strong bull market, which occurred in the beginning of 2009, and lasted for about half year.

For the second group, the major events were the 2015 stock crashes, where the Chinese markets experienced a sharp rising phase and several serious crashes. The latter caused the relative entropy curve to behave very much like that of the US market during the 2007–2008 global financial crisis. The first sharp peak in this group appeared on December 5, 2014, signifying the initiation of the long-desired strong bull market. However, the major cluster of peaks was associated with a series of market crashes happened about half year later. The two sharpest peaks reached a large value close to 2, which were the largest not only in this whole episode, but also in the history of the Chinese market. The first of these two peaks occurred on June 29, 2015, when a day ago, in order to stimulate the economy, the government cut the interest rates and targeted RRR. The other sharpest peak occurred on August 26, 2015, when the government cut interest rates again. However, this new stimulus was not sufficient to prevent the market from keeping going down [26]. The saga of stock crashes continued in January 2016, especially related to the circuit-breaker mechanism hastily implemented by the China Securities Regulatory Commission, for the benign purpose of getting rid of stock crash like those in the summer of 2015.

4. Conclusion

In this paper, we show that systemic risks and policy-induced shocks in stock market can be readily identified by relative entropy. Concretely, we analyzed the minutely DJIA and SSE Composite Index data, and examined the temporal variation of relative entropy for them. Clustered peaks in relative entropy curves can accurately identify the timing of the 2007–2008 global financial crisis and its precursors, and the 2015 stock crashes in China. Moreover, a sharpest needle-like peak in relative

entropy curves, especially for SSE market, always served as a precursor of an unusual market, a strong bull market or a "bubble", thus possessing a certain ability of forewarning.

Conflicts of Interest: The authors declare no conflict of interest.

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