Physica A xx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Physica A

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

Log-periodic view on critical dates of the Chinese stock market bubbles

Chong Li

School of Business, China University of Political Science and Law, Beijing 102249, China

HIGHLIGHTS

- A log-periodic power law singularity model for the CSI300 index is supported.
- Two market crashes in 2007 and 2015 are detected well.
- A market reverse in 2008 is predicted effectively.
- The gap can be used for advanced warning of the market conversion.

ARTICLE INFO

Article history:
Received 13 January 2016
Received in revised form 5 July 2016
Available online xxxx

Keywords:
Market crash
Market rebound
Financial bubbles
Chinese stock markets
Log-periodic power law singularity

ABSTRACT

We present an analysis of critical dates of three historical Chinese stock market bubbles (July 2006–Oct. 2007, Dec. 2007–Oct. 2008, Oct. 2014–June 2015) based on the Shanghai Shenzhen CSI 300 index (CSI300). This supports that the log-periodic power law singularity (LPPLS) model can describe well the behavior of super-exponential (power law with finite-time singularity) increase or decrease of the CSI300 index, suggesting that the LPPLS is available to predict the critical date. We also attempt to analyze the fitting parameter α of the LPPLS and the forecast gap which is between the last observed date and the expected critical date, proposing that the forecast gap is an alternative way for advanced warning of the market conversion.

1. Introduction

The researches of financial crash and bubbles began in the last decade in different directions. On the definition of bubbles, Suzuki considered that bubble is a sustained sharp price increasing or dropping, which is unable to explain by fundamentals of an asset [1]. Shiller defined the bubble as increasing prices which completely divorced from the real value driven by investor sentiment [2]. Shi raised that bubble is a non-stationary deviation relative to the basic value, caused by the expected return of investors [3]. Yan presented the concept of negatives bubble as downward price spirals which were influenced by the positive feedbacks, which can also fuel positive bubbles [4,5]. In order to predict financial crashes, Kumar has developed a logit model to analyze microeconomic and financial market, and found out that money market can be effectively predicted [6]. Markwat has predicted financial crashes by ordered logit regression, and indicated that it was generally caused by crashes of small-scale local area markets that the international market crash [7].

In order to predicting these crashes more effectively, Sornette, Johansen, Zhou and the FCO group at ETH Zurich have developed a series of models and techniques based on financial economics and statistical physics, and found that the behavior of the market bubble had a lot of similarities with earthquakes, material rupture and other physical phenomena, which is self-organized critical behavior of complex systems [8]. By the log-periodic (super-exponential) power law

E-mail address: auloren@yahoo.com.

http://dx.doi.org/10.1016/j.physa.2016.08.050
0378-4371/

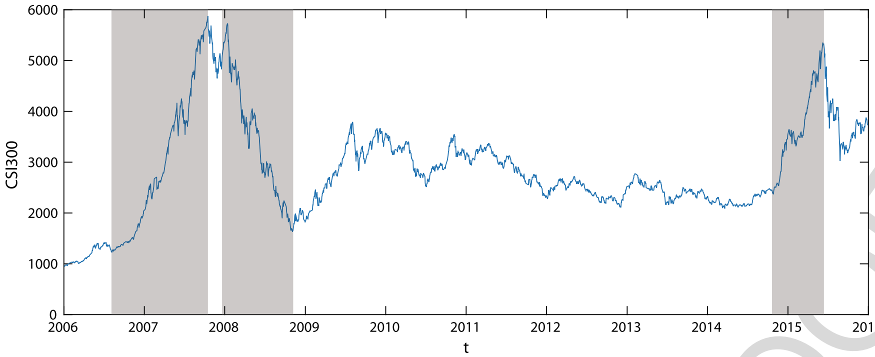

Fig. 1. Evolution of the price trajectories of the CSI300 index over the time interval of this analysis, from January 2006 to December 2015. Three bubbles indicated by dark shadow, are a market crash from July 2006 to October 2007, a market rebound from December 2007 to October 2008 and a market crash from October 2014 to June 2015.

singularity (LPPLS) analysis, they concluded that bubbles would exhibit the property of critical behavior and log-periodic oscillations, when tending to burst. Many recently successful applications have been presented and published in the referred literature, which include the Nasdaq crash of April 2000 [9], the US 2000–2002 antibubble [10], the Chinese real-estate antibubble in 2003 [11], the UK real-estate bubble in mid-2004 [12], the US real-estate bubble in mid-2006 [13], the 2006–2008 oil bubble [14] and the Chinese SSEC (SSE Composite index) bubbles in 2007, 2009 [15] and 2015 [16]. In order to forecasting market crashes, they also built an alarm index based on an advanced pattern recognition method to detecting bubbles [17], and developed three indicators based on the LPPLS model, including the Bubble Status (DS LPPLS Bubble Status), the End-of-Bubble signal (DS LPPLS End-of-Bubble) [16], and the confidence (DS LPPLS Confidence) [18].

The one of the most important indexes for A-shares in mainland China is the Shanghai Shenzhen CSI 300 index (CSI300), which has been calculated since April 8, 2005, including 300 stocks traded in Shanghai Stock Exchange (SHSE) or Shenzhen Stock Exchange (SZSE). Fig. 1 shows the time evolution of the CSI 300 index. From January 2007 to July 2007 and from January 2015 to May 2015, the CSI300 index had been rising dramatically. From January 2008 to August 2008, the Chinese stock market value have suffered a huge drop. Here, this paper presents an ex-post analysis of two crashes and one rebound of Chinese stock markets, 2006–2007 bubble, 2007–2008 negative bubble and 2014–2015 bubble.

The remaining main sections of this paper are as follows. In Section 2, it introduces all the technical methods used in this paper, including the LPPLS model, the fitting technique, and the Lomb periodogram analysis. In Section 3, it presents the analysis of three bubbles in Chinese stock market. Two are the 2007 and 2015 bubbles, and one is the 2008 negative bubble. Section 4 concludes.

2. Methods

The main method for predicting the critical date t_c when the bubbles or negative bubbles will burst is by fitting observed financial index price time series to a log-periodic power law singularity (LPPLS) model [12,19,20]. The techniques used to fitting procedure is the Genetic algorithm, described below.

2.1. The log-periodic power law singularity (LPPLS) model

The simplest mathematical formulation of the LPPLS can be written as:

$$E\left[\ln\left[p\left(t\right)\right]\right] = A + B\left(t_c - t\right)^{\alpha} + C\left(t_c - t\right)^{\alpha}\cos\left[\omega\ln\left(t_c - t\right) + \phi\right] \tag{1}$$

where $p(t)$ is the price (index), at time t. $A > 0$ is the log of the value that $p(t)$ would have if the bubble were to last until the critical t_c. $B < 0$ ($B > 0$) is the decrease (increase) in $p(t)$ over the time unit before the crash (rebound) when C is close to zero. C is the proportion of the fluctuations around the exponential growth. t_c is the critical date. t is any date before t_c, during the bubble. $0 < \alpha < 1$ is the exponent of the power law growth. $2 < \omega < 15$ is the frequency of the fluctuations in the bubble. $-\pi < \phi < \pi$ is a shift parameter. The given ranges of value for both α and ω are based on the observed results of bubbles for other stock indexes [15].

In order to fit the LPPLS model to financial data, there are three presuppositions:

1. Investors are heterogeneous. Different investor has different investment strategies, different screening and judgments of the market information. They also have different transaction frequency and investment positions.
2. Investors are linked through a network. Investors in financial markets are one in which they influence each other's decisions within local neighborhoods through this network [21].

Please cite this article in press as: C. Li, Log-periodic view on critical dates of the Chinese stock market bubbles, Physica A (2016), http://dx.doi.org/10.1016/j.physa.2016.08.050