Dissecting the 2015 Chinese Stock Market Crash

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Abstract
In this study, we perform a novel analysis of the 2015 financial bubble in the Chinese stock market by calibrating the Log Periodic Power Law Singularity (LPPLS) model to two important Chinese stock indices, SSEC and SZSC, from early 2014 to June 2015. The back tests of the 2015 Chinese stock market bubbles indicate that the LPPLS model can readily detect the bubble behavior of the faster-than-exponential increase corrected by the accelerating logarithm-periodic oscillations in the 2015 Chinese Stock market.

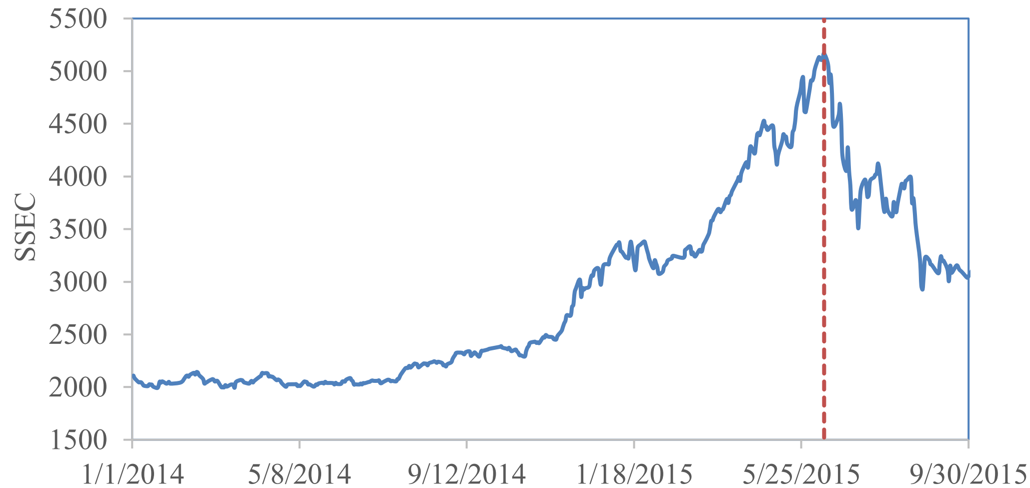
Key Words: Chinese Stock Market, Covariance matrix adaptation evolution strategy, Financial bubble, Log-periodic power law singularity model (LPPLS), Market crash

1. Introduction

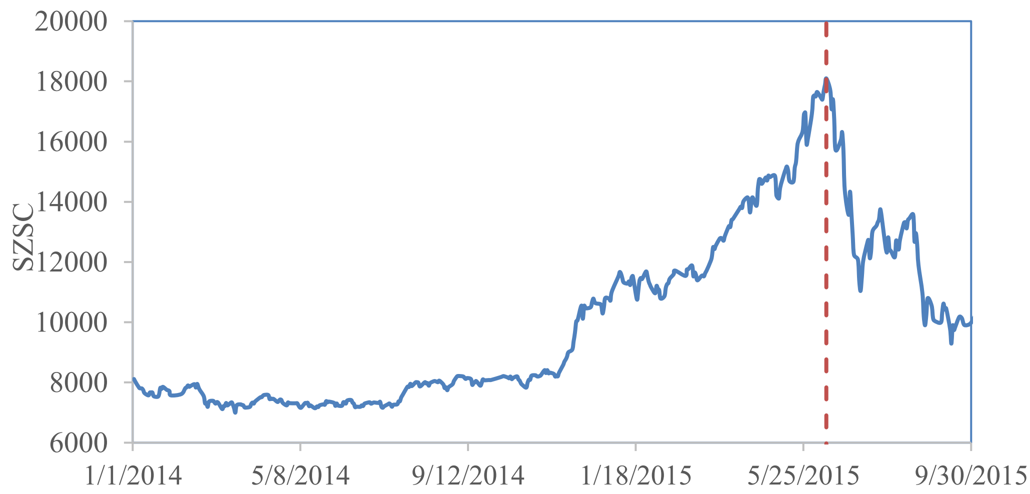
In the past three decades, the Chinese economy has experienced a tremendous growth accompanied by a roller coaster ride of the Chinese stock markets, with three large bubbles bursting respectively from May 2005 to October 2007, from November 2008 to August 2009 and from mid-2014 to June 2015. In mainland China, the organized stock market consists of two stock exchanges: Shanghai stock exchange (SHSE) and Shenzhen stock exchange (SZSE), the third and the ninth largest stock exchanges in the world by market capitalization as of July 2021. The Shanghai stock exchange composite index (SSEC) and the Shenzhen stock exchange component index (SZSC) are the most important indices for A-shares in SHSE and SZSE. Due to the easy access to credit to invest in the stock markets, about 7% of China's population has been active in stock market. From December 31, 2014 to June 12, 2015, the SSEC and SZSC indices soared by 60% and 122% in nearly five and a half months, respectively, while the Chinese overall economy had significantly cooled down during that time. The 2015 Chinese Stock Market bubble can be seen as a result of a strong leverage that the reality of economic activity is disconnected from the corporate earnings.

On June 12, 2015, the Chinese Stock Market bubble started to crash. The SSEC index has suffered more than 43% drop from the peak on June 12, 2015 to the bottom on August 26, 2015, and SZSC index has lost 45% over the same period. Figure 1 shows the time evolution of the price trajectories of the SSEC index and the SZSC index in the 2015 Chinese Stock Market bubble.

In this study, we perform a novel analysis of the 2015 financial bubble in the Chinese stock market by calibrating the Log Periodic Power Law Singularity (LPPLS) model to two important Chinese stock indices, SSEC and SZSC, from early 2014 to June 2015. Originating from the interface of financial economics, behavioral finance and statistical physics, the LPPLS model defines a financial bubbles as a process of unsustainably super-exponential growth to achieve an infinite return in finite time, forcing a short-lived correction molded according to the symmetry of discrete scale invariance (Sornette, 1998). The LPPLS model combines (i) the economic theory of rational expectation bubbles, (ii) behavioral finance on imitation and herding of traders, and (iii) the mathematical and statistical physics of bifurcations and phase transitions. The LPPLS model takes into account the faster-than-exponential growth in asset prices as well as the accelerating logarithm-periodic oscillations to detect the bubbles. So far, the LPPLS model has been used to detect bubbles and crashes in many financial markets, such as the stock markets (Demirer et al., 2019; Shu, 2019; Shu et al., 2021; Shu & Zhu, 2020a; Song et al., 2021; Sornette et al., 2015) and the cryptocurrency market (Shu & Zhu, 2020b; Wheatley et al., 2019).



(a) SSEC index



(b) SZSC index

Figure 1: Evolution of the price trajectories of the SSEC index and the SZSC index before and after the 2015 Chinese stock market crash.

2. Methodology

2.1 The Log-Periodic Power Law Singularity (LPPLS) Model

The simple mathematical formula of the LPPLS can be described as (Filimonov & Sornette, 2013):

$$\mathrm{LPPLS}(t) \equiv E[\ln p(t)] = A + B(t_c - t)^m + C_1(t_c - t)^m \cos[\omega\, ln(t_c - t)] + C_2(t_c - t)^m \sin[\omega\, ln(t_c - t)] \quad (1)$$

where $p(t)$ is the observed asset price, t_c is the critical time, which is the most probable time for a regime change. Here m is the power parameter with a range between 0 and 1 to ensure that not only the price remains finite at the t_c, but also the expected logarithmic price diverges at the t_c. Furthermore, A, B, C_1 and C_2 are four linear parameters. Using the Ordinary Least Squares method, the seven parameters ($t_c, m, \omega, A, B, C_1, C_2$) can be estimated by calibrating the LPPLS model. In this study, we used the covariance matrix adaptation evolution strategy (CMA-ES) (Hansen et al., 1995) to search the best estimation of the three nonlinear parameters (t_c, m, ω) to minimize the sum of the squared residuals between the fitted LPPLS model and the observed price time series. The CMA-ES, rated among the most successful evolutionary algorithms for real-valued single-objective optimization, is typically applied to difficult nonlinear non-convex black-box optimization problems in continuous domain and search space dimensions between three and a hundred.

In order to minimize the fitting problems and address the sloppiness of the model with respect to some of its parameters, we applied the following filter conditions:

$$m \in [0.1,0.9], \omega \in [6,13], t_c \in [t_2, t_2 + (t_2 - t_1)/3], m|B|/(\omega\sqrt{C_1^2 + C_2^2}) \geq 1, (\omega/\pi)\, ln[(t_c - t_1)/(t_c - t_2)] \geq 2.5 \quad (2)$$

2.2 Stability of fits and probabilistic forecasts

In order to test the sensitivity of variable fitting intervals $[t_1, t_2]$, we adopted the strategy of fixing one endpoint and varying the other one. If t_2 is fixed, the time window shrinks in terms of t_1 moving towards t_2 with a step of dt_1. If t_1 is fixed, the time window expands in terms of t_2 moving away from t_1 with a step of dt_2. Due to the rough nonlinear parameter landscape in the LPPLS model and the stochastic nature of solving multiple dimensional nonlinear optimization problems, a different set of fitting parameters is expected for each implementation of fit process. To investigate an optimal region of solution space, the fitting procedure is repeatedly implemented three times per window interval. Since the theoretical distribution of t_c is unknown and the sample size may be insufficient for straightforward statistical inference, we used the bootstrap technique to resample the sample data and perform inference thereafter. Based on bootstrap resampling of many intervals, the probabilistic forecasts of the critical time t_c can be obtained.

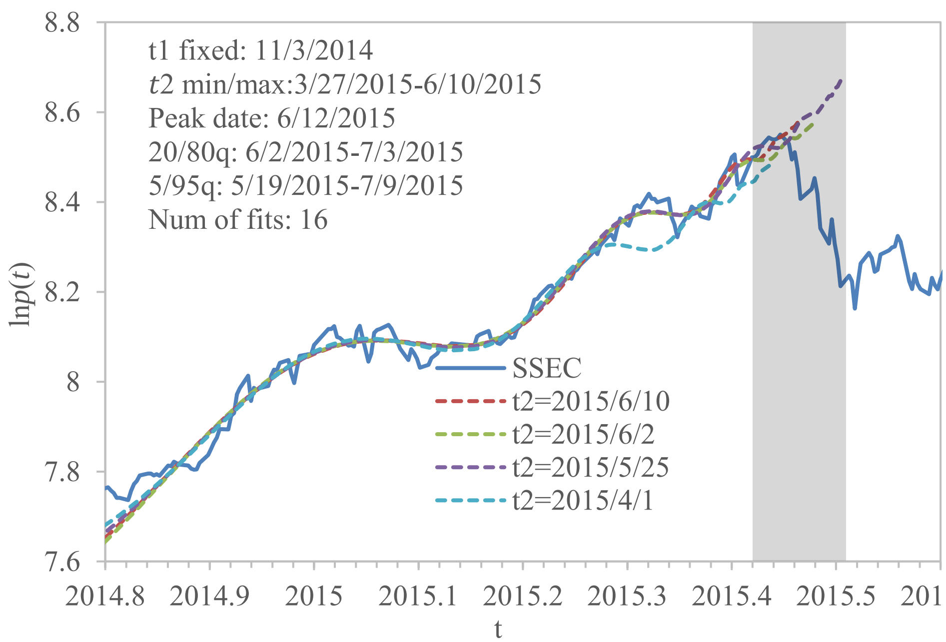
3. Bubble Identification

Sensitivity of parameter estimation for each major Chinese stock index, SSEC or SZSC, is tested by varying the size of the fit intervals. In the expanding windows, the start time t_1= November 3, 2014 is fixed with the end date t_2 increasing from March 27, 2015 to

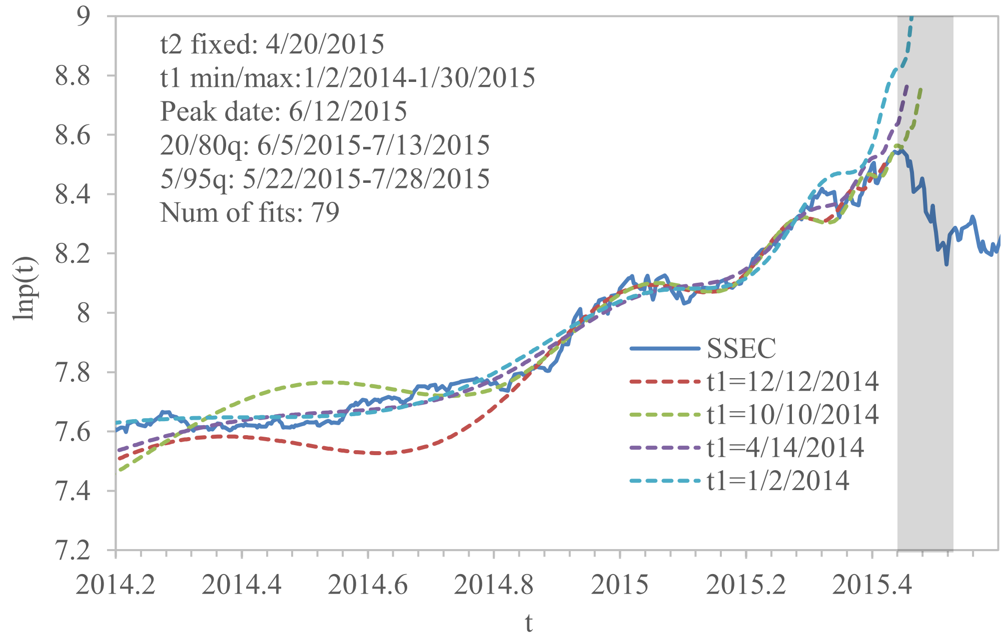
June 10, 2015 in steps of three trading days. In the shrinking windows, the end time t_2= April 20, 2015 is fixed with the start time t_1 increasing from January 2, 2014 to January 30, 2015 in steps of three trading days. In the expanding and shrinking fitting procedures, 18 times in expanding windows and 89 times in shrinking windows are fitted. Based on the LPPLS conditions, 16 (17) and 79 (75) results for SSEC (SZSC) are filtered in expanding and shrinking windows, respectively.

Figure 2 (a) illustrates four selected fitting results of the expanding windows for SSEC, and (b) illustrates four chosen fitting examples of the shrinking windows for SSEC. The 20%/80% and 5%/95% quantile range of values of the crash dates t_c are from June 2, 2015 to July 3, 2015 and from May 19, 2015 to July 9, 2015 for the expanding windows. In the figures, the dark shadow box indicates the 20%/80% quantile range of the values of the fitted crash date. For the shrinking windows, the 20%/80% and 5%/95% quantile range of values of the predicted crash dates t_c are from June 5, 2015 to July 13, 2015 and from May 22, 2015 to July 28, 2015, respectively. The observed market peak date for the SSEC is June 12, 2015, which lies in the quantile ranges of the predicted crash dates t_c fitted based on data before the actual stock market crash.

Figure 3 shows the daily trajectory of the logarithmic SZSC index and the sample fits using the LPPLS formula in the expanding (a) and shrinking (b) windows, respectively. The 20%/80% and 5%/95% quantile range of values of the crash dates t_c are from June 9, 2015 to June 24, 2015 and from May 27, 2015 to July 30, 2015 for the expanding windows. For the shrinking windows, the 20%/80% and 5%/95% quantile range of values of the fitted crash dates t_c are from June 5, 2015 to July 16, 2015 and from May 27, 2015 to July 27, 2015, respectively. We see that it is feasible to predict the crash date t_c in the stock market, in advance.

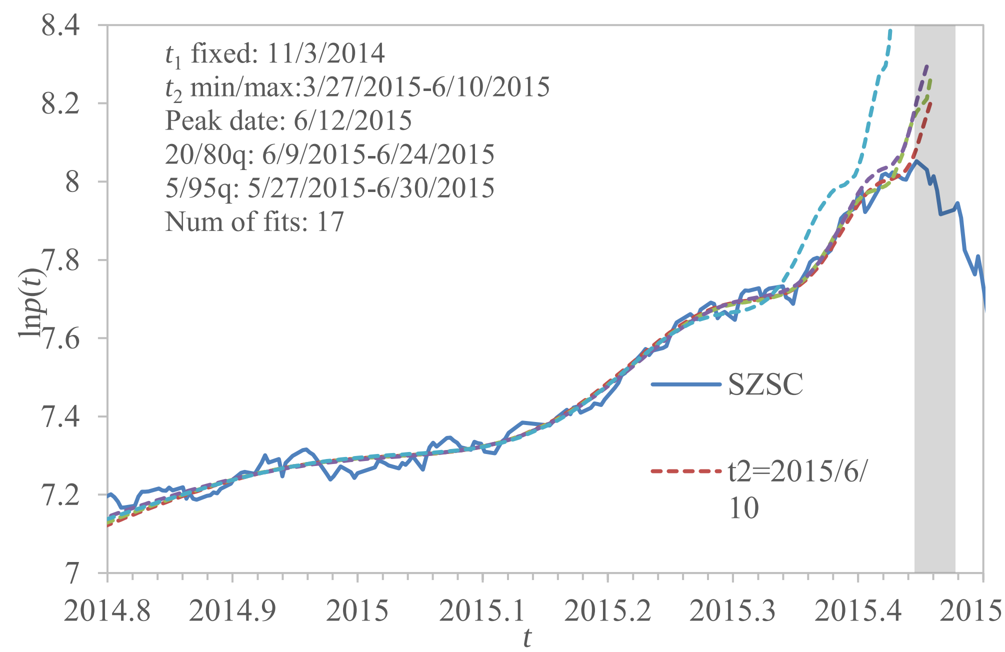


(a) Examples of fitting to the expanding windows with the t_1 fixed at November 3, 2014 and varied t_2 for SSEC. The four fitting examples are corresponding to t_2= 10 June 2015, 2 June 2015, 25 May 2015, and 1 April 2015.

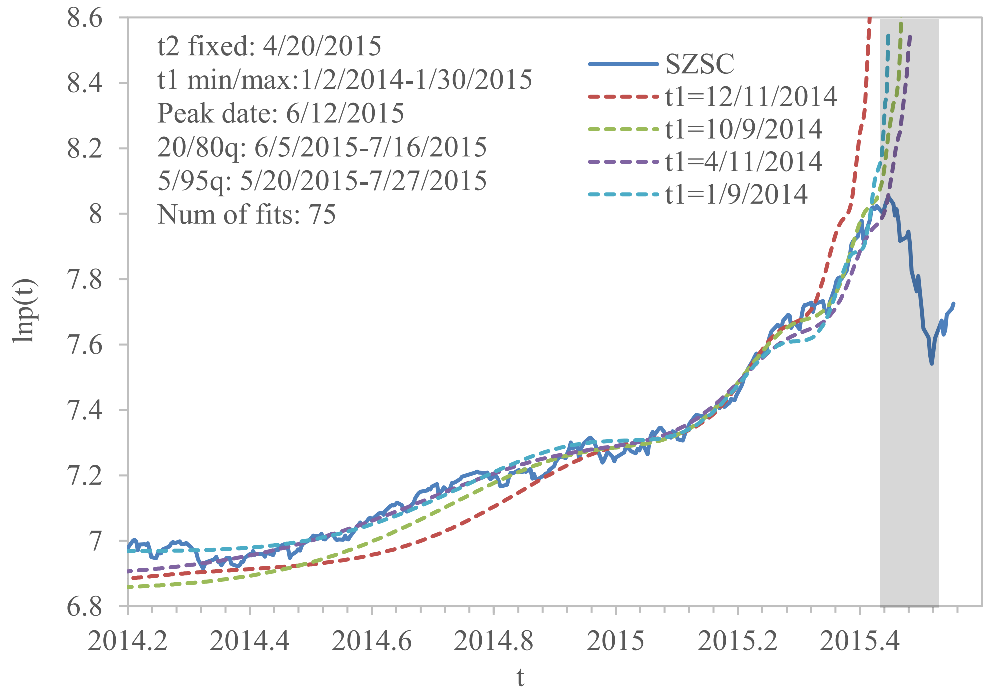


(b) Examples of fitting to the shrinking windows with the t_2 fixed at April 20, 2015 and varied t_2 for SSEC. The four fitting examples are corresponding to t_1= 12 December 2014, 10 October 2015, 14 April 2014, and 2 January 2014.

Figure 2: Daily trajectory of the logarithmic SSEC (a and b) index and the fits using the LPPLS formula. The dark shadow box indicates the 20%/80% quantile range of the fitted crash date.



(a) Examples of fitting to the expanding windows with the t_1 fixed at November 3, 2014 and varied t_2 for SZSC. The four fitting examples are corresponding to t_2= 10 June 2015, 2 June 2015, 25 May 2015, and 1 April 2015.



(b) Examples of fitting to the shrinking windows with the t_2 fixed at April 20, 2015 and varied t_2 for SZSC. The four fitting examples are corresponding to t_1= 11 December 2014, 9 October 2015, 11 April 2014, and 9 January 2014.

Figure 3: Daily trajectory of the logarithmic SZSC (a and b) index and the fits using the LPPLS formula. The dark shadow box indicates the 20%/80% quantile range of the fitted crash date.

4. Conclusions

In this study, the back tests indicate that the LPPLS model can well identify the bubble behavior of the faster-than-exponential increase corrected by the accelerating logarithm-periodic oscillations in the 2015 Chinese Stock market using both the SSEC and SZSC indices. While the post-mortem analysis of the 2015 Chinese stock market bubble is investigated in this study, the more important goal is to identify the bubbles and predict the critical time in advance of the demise of the bubble. According to our analysis, the LPPLS model may foretell the actual critical day two months before the actual bubble crash.

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