Real-time prediction and post-mortem analysis of the Shanghai 2015 stock market bubble and crash

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Abstract

The authors assess the performance of the real-time diagnostic, openly presented to the public on the website of the Financial Crisis Observatory (FCO) at ETH Zurich, of the bubble regime that developed in Chinese stock markets since mid-2014 and that started to burst in June 2015. The analysis is based on (i) the economic theory of rational expectation bubbles, (ii) behavioural mechanisms of imitation and herding of investors and traders and (iii) the mathematical formulation of the Log-Periodic Power Law Singularity (LPPLS) that describes the critical approach towards a tipping point in complex systems. The authors document how the real-time predictions were presented in the automated analysis of the FCO, as well as in our monthly FCO Cockpit report of June 2015. A complementary post-mortem analysis on the nature and value of the LPPLS methodology to diagnose the SSEC bubble and its termination is also given.

JEL classification: F37, G01, G17

Keywords: Financial bubbles, Crashes, Probabilistic forecast, Johansen-Ledoit-Sornette model, Log-periodic power law singularity (LPPLS), Advanced warning, Chinese bubbles, Financial crisis observatory

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1. Introduction

Mainly as a result of massive investments in real-estate and infrastructures over the past three decades, China's economy has moved from being largely closed to becoming a major global player. China's average annual GDP growth was 13% between 2000 and 2008, but has been slowing down to 7.8% in 2009 and to the estimate of 7% in 2015.

Accompanying this stellar growth, Chinese stock markets have experienced a roller coaster dynamics, with two large bubbles bursting respectively from May 2005 to Oct. 2007 and from Nov. 2008 to Aug. 2009 (Jiang et al., 2010). The latest bubble started around mid-2014 (see the analysis below for a qualification) and has recently started crashing in mid-June 2015. This last bubble corresponded to an approximate 150% growth in just one year. This growth of Chinese stocks was all the more remarkable as it occurred at the time when the Chinese real estate market along with the overall economy was cooling significantly. This bubble can be seen as a result of a strong leverage that is disconnected from the realities of economic activity and corporate earnings. About 7% of China's population has been active in this stock market frenzy, profiting from the easy access to credit to invest in the stock markets. An interesting specificity of Chinese stock markets is that insurance firms and pension funds that are traditionally stabilising investors by their buy-and-hold strategies are essentially absent in the Chinese investing universe. As a consequence, about 90 millions of small and medium size Chinese investors constitute the main drivers of the stock markets, making it much more susceptible to rumours, imitation, speculations and crowd effects. In fact, there are many indications that the Chinese government has encouraged small retail investors to join in investing in the stock market, driving it up for a while but also catalysing its fragility. One should however temper this negative view by noting that Chinese households have most of their wealth in real-estate so that a crash cannot have the impact it would have in Western markets. Moreover, the spillover effect on Western markets should be minimal as most foreign investors cannot participate, removing their well-known unstable strategies of investing late and withdrawing at the time the crash to enhance the severity of corrections.

Since its peak on June 12, 2015, the SSEC (Shanghai composite index) has lost 32% to its bottom reached on July 8, 2015 and has since moved sideway with a large volatility. The smaller Shenzhen stock market has lost 41% over the same period. The Chinese government has taken unprecedented measures aimed at stopping the descent. Particularly, the benchmark lending and deposit rates have been cut several times by the People's Bank of China (PBoC) and are now at record lows, margin lending rules have been relaxed, a de-facto suspension of new IPOs has been declared, and "malicious short-selling" has been announced to be probed, and so on. Wild swings have continued to develop. On Monday July 27, 2015, Shanghai stocks lost 8.5%, thus suffering its worst one-day loss since 2007.

Fig. 1 compares visually the bubble that ended in 2007 to the present 2015 bubble, both on the Shanghai stock market (top panel). One can observe very similar price trajectories. In contrast, a similar comparison for the Hong Kong market (bottom panel) shows that the market development in the last year has not followed the same type of bubble behaviour as occurred before and until 2007. This is notwithstanding the fact that, on Nov. 10, 2014, the China Securities Regulatory Commission jointly with the Hong Kong Securities Regulatory Commission announced that a connection between the two stock markets would officially start on Nov.17 2014, which grants foreign investors unprecedented access to China's tightly controlled capital market. This is likely due to the fact that, in fact, mainland Chinese investors were the main traders in the Shanghai stock market while the Hong Kong market is much more open to foreign investors. The difference can thus be traced to the divergence on the views of China's prospects between domestic and foreign investors as well as the hope for quick gains fuelling speculation among retail Chinese investors. The decline in July 2015 suffered by the Hong Kong stock market demonstrates the spillover effect from the Shanghai market to the Hong Kong market, mainly via the so-called "Shanghai-Hong Kong stock connect" programme launched on Nov.17 2014.

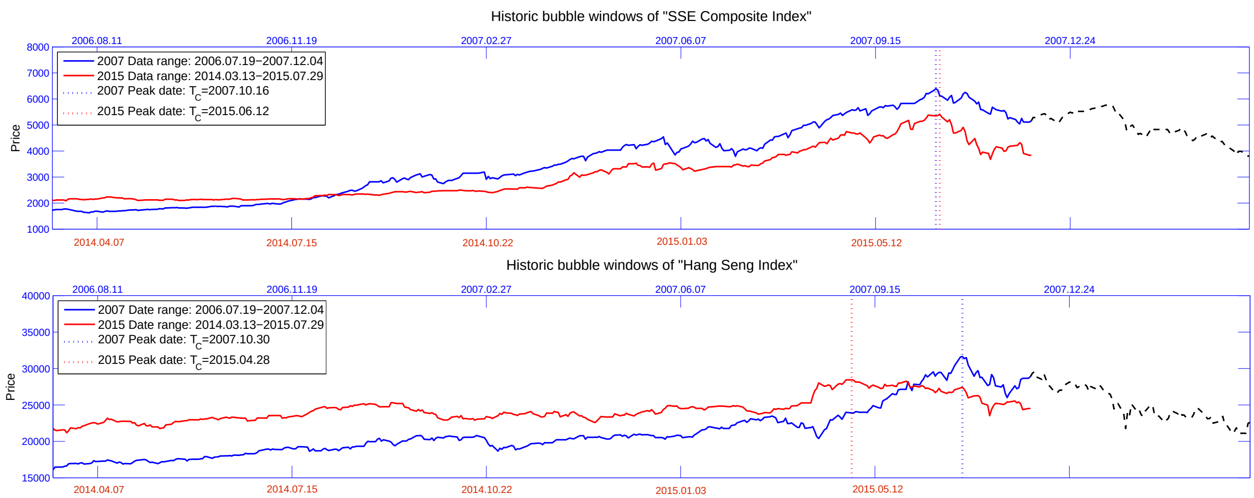


Figure 1: **top panel**: For the Shanghai stock market, comparison between the bubble that ended in October 2007 and the present one ending in June 2015. **bottom panel**: Same as top panel for the Hong Kong stock market. The blue line extended by dotted black line is the price time series within the window of [2006.07.19, 2008.03.25]. The red line corresponds to the window of [2014.03.13, 2015.07.29]. The blue dotted vertical lines T_c = 2007.10.16 (for Shanghai market) and T_c = 2007.10.30 (for Hong Kong market) represent the peak dates in 2007. The red dotted vertical lines T_c = 2015.06.12 (for Shanghai market) and T_c = 2015.04.28 (for Hong Kong market) represent the peak dates in 2015.

In this article, we describe the remarkable success of the real-time diagnostic of the bubble regime that was obtained in our Financial Crisis Observatory (FCO: available at: `tasmania.ethz.ch/pubfco/fco.html`) that we are currently running at ETH Zürich. The analysis is based on the Johansen-Ledoit-Sornette (JLS) (Johansen et al., 2000) model, which is built on (i) the economic theory of rational expectation bubbles, (ii) behavioral mechanisms of imitation and herding of investors and traders and (iii) the mathematical formulation of the Log-Periodic Power Law Singularity (LPPLS) that describes the critical approach towards a tipping point in complex systems. The early warning signals that were reported in real time ex-ante provide strong additional supportive evidence for the relevance of the LPPLS-based methodology in the diagnostic of bubbles. We here document how the real-time predictions were presented in the automated analysis of the FCO, as well as in our monthly FCO Cockpit report of June 2015, where we have warned that Chinese equities were in bubble territory with the highest possible readings, that the price path followed was not sustainable and a correction was due. These results add to previous accounts of similar ex-ante advanced warning and predictions performed for the two previous financial bubbles in two most important Chinese stock indexes, Shanghai (US ticker symbol SSEC) and Shenzhen (SZSC), (i) from mid-2005, bursting in October 2007 and (ii) from November 2008, bursting in the beginning of August

2009 (Jiang et al., 2010).

The article is organised as follows. Section 2 presents the methodology, recalling briefly the JLS model, then explaining how the calibration is performed and introducing the DS LPPLS Confidence and DS LPPLS Trust indicators, as well as the functioning of the FCO. Section 3 describes how the real-time diagnostic of the SSEC bubble was performed and communicated to the public and offers a summary of the evidence. Section 4 gives a complementary post-mortem analysis on the nature and value of the LPPLS methodology to diagnose the SSEC bubble and its termination. Section 5 concludes.

2. Methodology

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

In a bubble regime, we assume that the observed price trajectory of a given asset decouples from its intrinsic fundamental value (Kindleberger, 1978; Sornette, 2003). We use the Johansen-Ledoit-Sornette (JLS) model (Johansen et al., 2000) that assumes the logarithm of the observable asset price $p(t)$ to follow

$$\frac{dp}{p} = \mu(t)dt + \sigma(t)dW - kdj \ , \tag{1}$$

where $\sigma(t)$ is the volatility, dW is the infinitesimal increment of a standard Wiener process and dj represents a discontinuous jump such as $j = 0$ before and $j = 1$ after the crash occurs. The parameter k quantifies the amplitude of a possible crash. The crash hazard rate $h(t)$ is defined as proportional to the expectation of dj: $h(t) := \mathrm{E}[dj]/dt$. By the rational expectation condition (Blanchard and Watson, 1982), one obtains

$$\mu(t) = kh(t) \ , \tag{2}$$

thus determining the return μ to be proportional to the crash risk $h(t)$ and vice-versa. In the JLS formulation, it is $h(t)$ that is the driver of the bubble: the existence of noise traders with herding behaviour leads to a progressively growing crash hazard, which translates mechanically via the no-arbitrage condition to an instantaneous return (2) that grows together with $h(t)$ in order to remunerate investors for their willingness to be invested in a risky asset. Johansen et al. (2000) propose that, as a consequence of the destabilising herding behaviour of imitative agents who are organised in a hierarchy of clusters together with the competing influence of value investors, $h(t)$ takes the following explicit deterministic dependence during the course of a bubble:

$$h(t) = \alpha(t_c - t)^{m-1}\big(1 + \beta \ \cos(\omega \ \ln(t_c - t) - \phi'\big), \tag{3}$$

where $\alpha, \beta, \phi', m, \omega$ and t_c are parameters. Eq. (3) writes that the herding behaviour of the noise traders leads to a power law singularity $\alpha(t_c - t)^{m-1}$, combined with large scale amplitude oscillations that are periodic in the logarithm of the time to the singularity (or critical time) t_c. The power law singularity embodies the positive feedback mechanism at the origin of the formation of bubbles. The log-periodicity focuses on the tension and competition between the two types of investors that create large scale volatility structures accelerating towards t_c. Combining (3) with (2) and integrating the expectation of (1) conditional on no crash occurring yields

$$\mathrm{E}[\ln p(t)] = A + B(t_c - t)^m + C(t_c - t)^m \cos\big(\omega \ln(t_c - t) - \phi\big) , \tag{4}$$

with $B = -k\alpha/m$ and $C = -k\alpha\beta/\sqrt{m^2 + \omega^2}$. Bubble regimes are in general characterised by $0 < m < 1$ and $B < 0$. The first condition $m < 1$ writes that a singularity exists (the momentum of the expected log-price diverges at t_c), while $m > 0$ ensures that the price remains finite at the critical time t_c. The second condition together with $0 < m < 1$ expresses that the price is indeed growing super-exponentially towards t_c. For more information on the model and its estimation, we refer to (Sornette et al., 2013).

2.2. LPPLS calibration and indicators

The model is calibrated on the data using the Ordinary Least Squares method, providing estimations of all parameters t_c, ω, m, ϕ, A, B, C in a given time window of analysis. We use the robust procedure proposed by Filimonov and Sornette (2013), which reduces the estimation to just three nonlinear parameters m, ω and t_c. For each fixed data point t_2 (corresponding to a fictitious "present" up to which the data is recorded), we fit the price time series in shrinking windows (t_1, t_2) of length $dt := t_2 - t_1$ decreasing from 750 trading days to 125 trading days. We shift the start date t_1 in steps of 5 trading days, thus giving us 126 windows to analyse for each t_2. In order to minimise calibration problems and address the sloppiness of the model (4) with respect to some of its parameters (and in particular t_c) (Brée et al., 2013), we use a number of filters to condition the solutions, which are summarised in Table 1. These filters derive from the empirical evidence gathered in investigations of previous bubbles (Sornette and Johansen, 2001; Sornette and Zhou, 2006; Johansen and Sornette, 2010; Jiang et al., 2010; Yan et al., 2012; Forró et al., 2015). Only those calibrations that meet the conditions given in Table 1 are considered valid and the others are discarded.

Item	Notation	Search space	Filtering condition 1	Filtering condition 2
3 nonlinear parameters	m	[0, 2]	[0.01, 1.2]	[0.01, 0.99]
	ω	[1, 50]	[2, 25]	[2, 25]
	t_c	$[t_2 - 0.2dt,$ $t_2 + 0.2dt]$	$[t_2 - 0.05dt,$ $t_2 + 0.1dt]$	$[t_2 - 0.05dt,$ $t_2 + 0.1dt]$
Number of oscillations	$\frac{\omega}{2} \ln \lvert \frac{t_c - t_1}{t_2 - t_1} \rvert$	—	$[2.5, +\infty)$	$[2.5, +\infty)$
Damping	$\frac{m\lvert B\rvert}{\omega\lvert C\rvert}$	—	$[0.8, +\infty)$	$[1, +\infty)$
Relative error	$\frac{p_t - \widehat{p}_t}{\widehat{p}_t}$	—	[0, 0.05]	[0, 0.2]

Table 1: Search space and filter conditions for the qualification of valid LPPLS fits. Within the JLS framework, the condition that the crash hazard rate $h(t)$ is non-negative by definition (van Bothmer and Meister, 2003) translates into a value of the Damping parameter $\frac{m|B|}{\omega|C|}$ larger than or equal to 1.

From the ensemble of qualified fits, we construct two DS bubble indicators (Sornette and Cauwels, 2015) as follows.

- **DS LPPLS Confidence:** It is the fraction of fitting windows for which the LPPLS calibrations satisfy the filtering condition 1 in Table 1. It measures the sensitivity of the observed bubble pattern to the time scale dt. A large value indicates that the LPPLS pattern is present at most scales and is thus more reliable. A small value signals a possible fragility of the signal since it is present only in a few time windows.

- **DS LPPLS Trust:** Because the calibration is an attempt to disentangle the LPPLS signal from an unknown realisation of the residuals, it is important to assess the sensitivity of the results to different instances of these residuals. We thus resample 100 times the residuals and add them to the calibrated LPPLS structure to generate 100 synthetic price time series that proxy for 100 supposed independent realisations of equivalent price patterns. The DS LPPLS Trust indicator is the median level over the 126 time windows of the fraction among the 100 synthetic time series that satisfy the filtering condition 2 in Table 1. It measures how closely the theoretical LPPLS model matches the empirical price time series, 0 being a bad and 1 being a perfect match. As a rule of thumb, a value of DS LPPLS Trust larger than 5% indicates that the price process is not sustainable and there is a substantial risk for a critical transition to occur.

2.3. Financial Crisis Observatory

These two indicators 'DS LPPLS Confidence' and 'DS LPPLS Trust' constitute the core measures provided in the analyses presented daily on the website of the Financial Crisis Observatory (FCO) at ETH Zurich (`tasmania.ethz.ch/pubfco/fco.html`). Started in August 2008 in reaction to the on-going financial crisis, the FCO has the ambition to test and quantify rigorously, in a systematic way and on a large scale, the hypothesis that bubbles can be diagnosed before they burst and their end can be predicted probabilistically ex-ante. Before the launch of the daily watch of bubble indicators, a number of experiments have been performed, such as the financial bubble experiments (Sornette et al., 2009, 2010; Woodard et al., 2010).

The FCO provides the real-time values of the 'DS LPPLS Confidence' and 'DS LPPLS Trust' indicators, which are updated daily on 21 world stock markets, commodities, US sectors and US firms (our intra-group version developed for research purposes monitors a much larger number, approximately 25'000 assets). Every morning, the FCO system automatically acquires asset prices of the previous day and generates the DS LPPLS Confidence and Trust indicators for the previous day as described above. These daily updates have been freely available to anyone since 2012 and enjoy a suite of followers among private and professional investors. The philosophy driving the FCO is that only advanced forecasts can be free of data-snooping and of other statistical biases of standard ex-post tests. And it is up to everyone to assess the quality and usefulness of the indicators.

3. Real-time diagnostic of the 2015 SSEC bubble

The 2015 Shanghai bubble has been tracked and diagnosed in real-time with two different versions of our methodology that we now summarise.

3.1. The real-time daily FCO 'DS LPPLS Confidence' and 'DS LPPLS Trust' indicators

Fig. 2 shows a screenshot of the FCO website interface taken on Aug. 4, 2015, showing all monitored assets available to the public since 2012. Whenever our method detects a bubbly signature in the underlying price time series, a red bar is displayed. Each day, the screen is shifted by one day to include the new information, in a real causal time setting. For the 2015 SSEC bubble, one can observe that red bars form two clusters. The first one is from Dec. 1, 2014 to Jan. 1, 2015 and announced correctly the correction that occurred in January 2015. The second cluster starts on Apr. 4, 2015 and culminates on Jun. 17, 2015 with the start of the crash. This second cluster is actually made of two sub-structures, as shown in Fig.3.

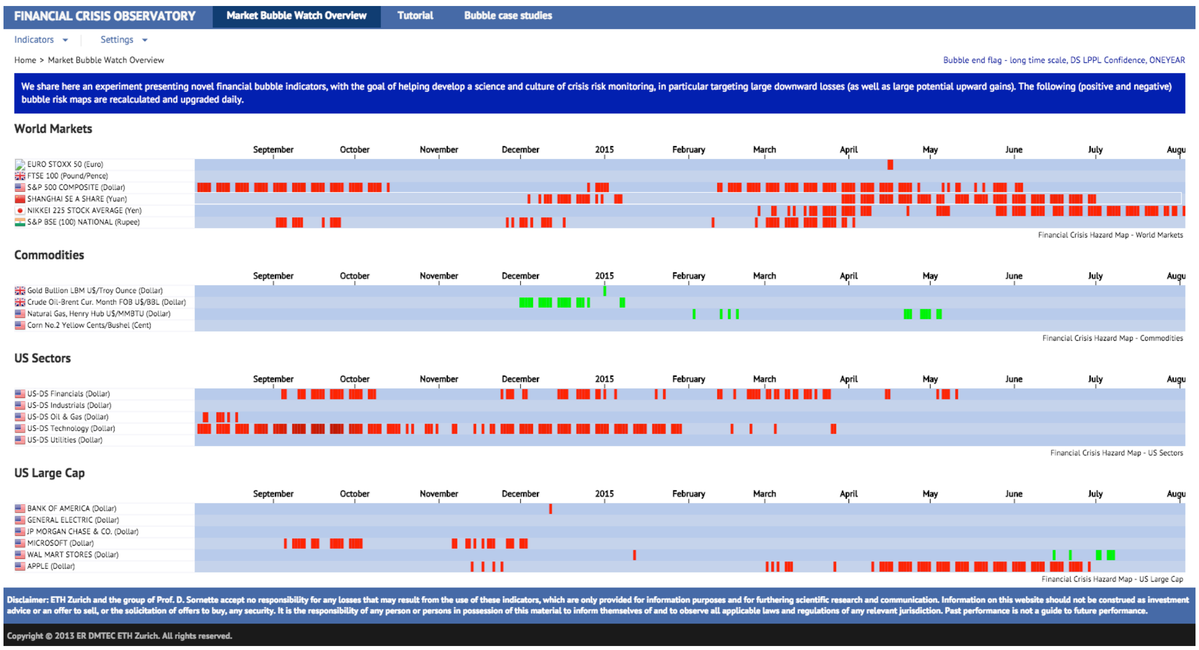


Figure 2: Snapshot of the FCO website (`tasmania.ethz.ch/pubfco/fco.html`) on Aug. 4, 2015. The SSEC index corresponds to the row emphasised by the rectangle with the white frame (fourth row in the 'World Markets' section), which covers the time interval from August 2014 to Aug. 4, 2015. Our first diagnostic of a "bubbly" SSEC Index occurred Dec. 2014 and persisted until Jan. 2015, when a change of regime indeed occurred (see Fig. 5). Afterwards, the signal re-appears even stronger on early April 2015 and persisted until the eventual burst of the bubble on June 16, 2015. Note the consistency of the bubble signal during this later period.

Fig. 3 shows the value of the 'DS LPPLS Confidence' indicator in red together with the SSEC index in blue from July 2013 to July 2015. This graph could be retrieved each day up to the time of the observation, providing a real-time diagnostic of the on-going bubble. The website allows one to travel back in time to visualise the signal as was available at any time in the past. Note that the three peaks of the indicator anticipate shortly each the following most significant corrections exhibited by the SSEC index.

3.2. FCO cockpit reports

From February 2014 (with a gap for May to September 2014), and with an uninterrupted monthly periodicity since October 2014, we release so-called 'FCO cockpit reports' that provide a global status of the major bubbles developing in the world in all asset classes. These reports are available at `www.er.ethz.ch/financial-crisis-observatory`. The methodology is similar to that developed for the 'DS LPPLS Confidence' and 'DS LPPLS Trust'

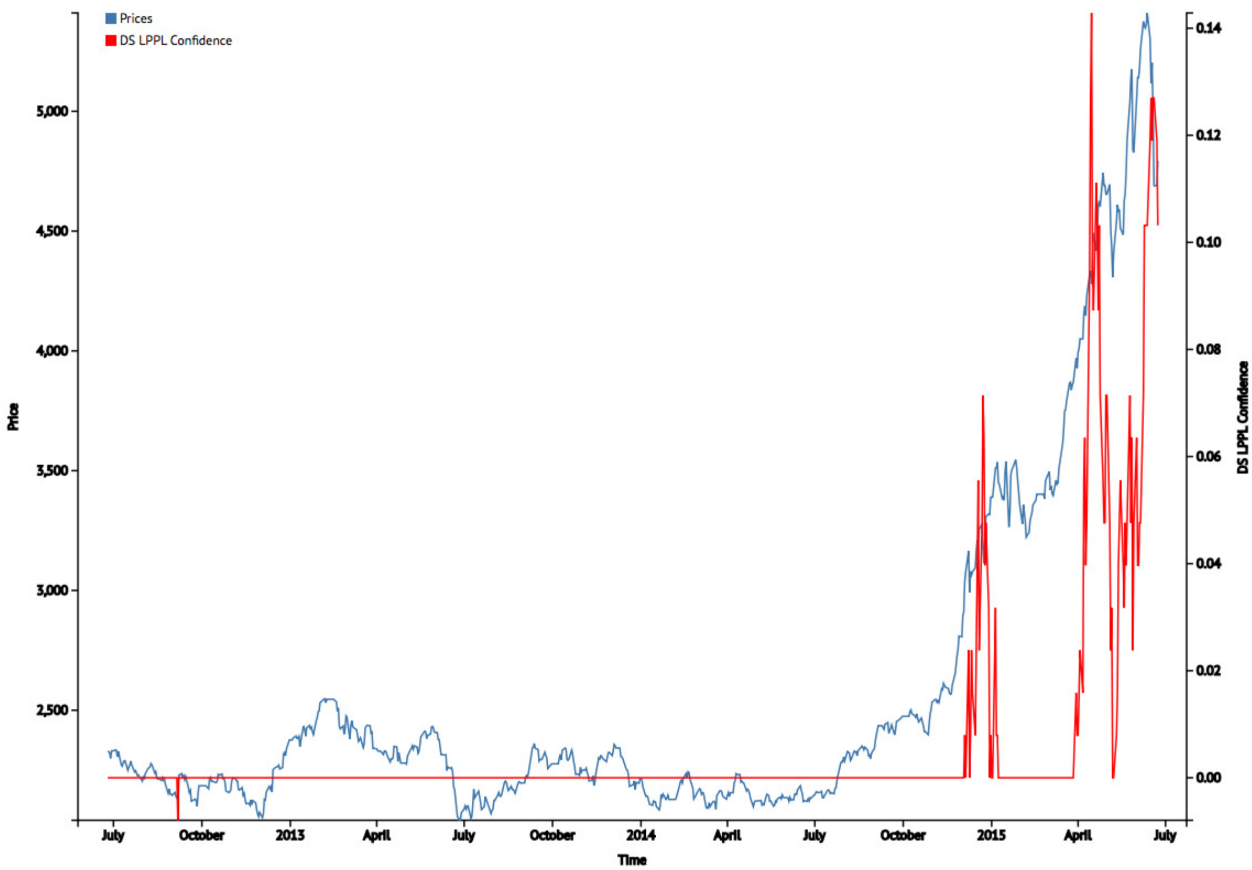


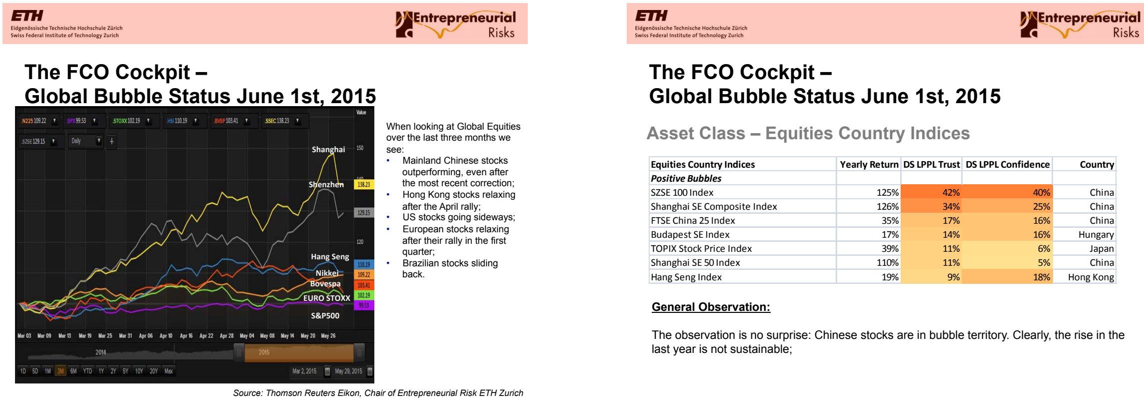
Figure 3: 'DS LPPLS Confidence' indicator in red (right scale) together with the SSEC index in blue (left scale) from July 2013 to July 2015, as could be retrieved each day up to the time of the observation, providing a real-time diagnostic of the on-going bubble. After correctly diagnosing a change of regime to occur on early 2015, the DS-Confidence Indicator signalled an even larger upcoming correction by late April and early June 2015. Retrieved from the FCO website on June 16, 2015.

indicators presented above but is more coarse-grained to shape a general view of the developing bubble risks.

As can be checked from `http://www.er.ethz.ch/content/dam/ethz/special-interest/mtec/chair-of-entrepreneurial-risks-dam/documents/FCO/FCO_Cockpit_June1st_2015.pdf` (see also (Cauwels and Sornette, 2015)), the Report of June 1^{st}, 2015 warned about the overheated Chinese market (Fig. 4): "*... The observation is no surprise: Chinese stocks are in bubble territory. Clearly, the rise in the last year is not sustainable*". The table on the right side of Fig. 4 shows that the 'DS LPPLS Confidence' and 'DS LPPLS Trust' indicators were the highest among all other signals for world equity indices.

3.3. Summary of the FCO early warnings

Fig. 5 shows the SSEC index from May 2014 to July 2015 and illustrates how a LPPLS analysis works. The coloured curves covering the rainbow-coloured spectrum represent the LPPLS fits of the SSEC index from Dec. 2014 to May 25, 2015 (indicated by the boundary with the grey domain), which illustrates how the LPPLS model could extract useful information on May 25, 2015 on the possible subsequent developments. Other earlier and later



Equities Country Indices	Yearly Return	DS LPPL Trust	DS LPPL Confidence	Country
Positive Bubbles				
SZSE 100 Index	125%	42%	40%	China
Shanghai SE Composite Index	126%	34%	25%	China
FTSE China 25 Index	35%	17%	16%	China
Budapest SE Index	17%	14%	16%	Hungary
TOPIX Stock Price Index	39%	11%	6%	Japan
Shanghai SE 50 Index	110%	11%	5%	China
Hang Seng Index	19%	9%	18%	Hong Kong

Figure 4: Reproduction of the diagnostic of the SSEC bubble in the FCO Cockpit report of June 1, 2015.

dates between May 2015 and June 2015 give similar results. The different coloured curves correspond to different weights given to the deviations from the pure LPPLS model, allowing us to assess the robustness of the calibration of the LPPLS model. They exemplify a quite remarkable match with the expected LPPLS structure. The smoothed double-humped curve filled with red represents the distribution of critical times t_c at which the bubble was anticipated on May 25, 2015 to burst. It turned out that the first peak of the estimated probability for the critical time coincides with the time when the SSEC peaks and then started to drop. The second high peak coincided with the time of fastest drop of the index. The bottom panel shows the returns of the SSEC index together with a robust estimation of the crash hazard rate (the probability that the crash will occur per unit time, conditional on not yet having occurred). The colors from green to red encode the strength of the crash hazard rate, and indicate an increasing danger for a crash to occur as the bubble was developing. The inset in the top panel shows the return time series as embodied by the deterministic component of the LPPLS fits and can be compared with the bottom panel.

4. Complementary post-mortem analysis

This section presents additional results that provide complementary insights on the nature and value of the LPPLS methodology to diagnose the SSEC bubble and its termination.

Fig. 6 summarises in its two panels the two ways of diagnosing bubbles using the LPPLS model. In the top panel, we show the distribution of predicted t_c's as well as estimated beginning of the bubble. This is obtained by scanning over several t_1's (grey shaded region) for different t_2's (black dashed vertical line). This allows us to determine that the SSEC bubble began as early as April 2014 (blue probability density function (*pdf*) in Fig 6) and that this unstable trajectory would be unlikely to persist past June 2015 (red *pdf* in Fig. 6).

In the lower panel of Fig. 6, the times at which the SSEC index is deemed to develop dangerously in a bubble are indicated by the DS LPPLS Confidence indicator shown as the black histogram together with the projections (coloured doted lines) of the LPPLS fits for different t_1's and for the t_2 indicated by the vertical dashed line. The "hazard zone" is a function of the DS LPPLS Confidence indicator: the darker the red, the higher is the probability for a significant change of regime to occur.

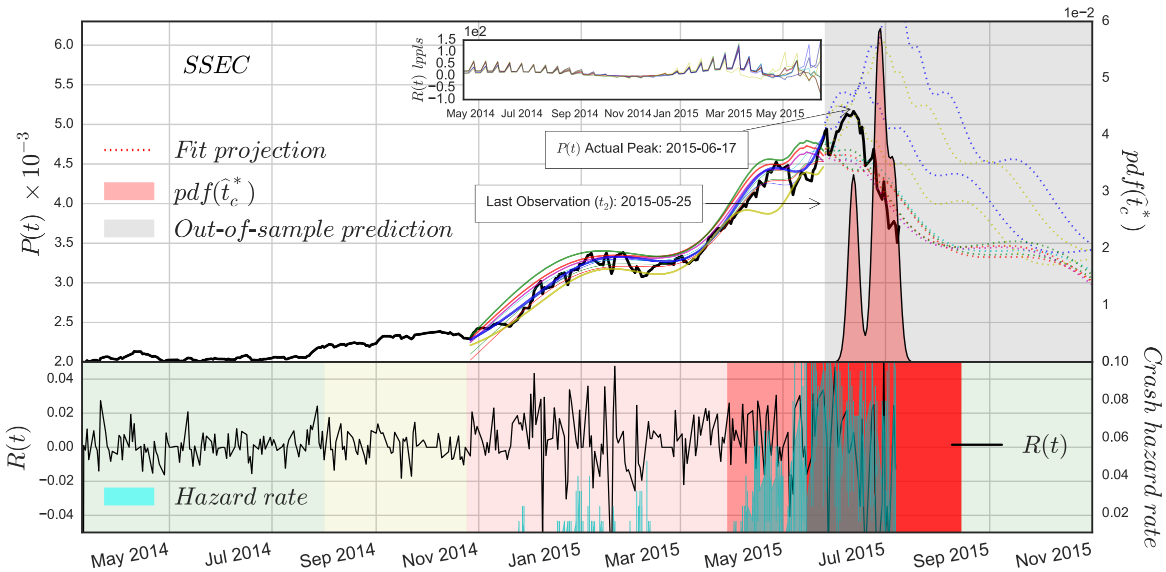


Figure 5: Summary of various indicators obtained by the LPPLS analysis performed at time t_2 = May 25, 2015 on the SSEC index that crashed in June 2015. See text for details. Note that the distribution of t_c's does not match exactly that shown in figure 6, which is obtained by averaging over a number of different t_2, thus showing some dependence of the results on the "present" time used for the analysis. This should be expected since different times are associated with different information. Even if details are different, the most striking point is however the overall robustness of the diagnostic and the quite remarkable convergence to the correct period for the predicted crash.

Fig. 7 provides additional information on the nature of the optimisation process via the two-dimensional cross-sections of its cost function in the space of the three nonlinear parameters m, ω and t_c of the LPPLS formula (4). This analysis allows us to provide an estimation of the typical confidence interval for t_c.

Fig. 8 suggests first a way to combine the 'DS LPPLS Confidence' and 'DS LPPLS Trust' indicators defined in section 2.2 to obtain perhaps a better diagnostic of the bubble development. This is performed by taking the product of DS LPPLS Confidence' indicator shown in the top panel and of the 'DS LPPLS Trust' indicator shown in the middle panel to form the confidence-trust product indicator shown in the bottom panel.

The bottom panel of Fig. 8 suggests a provoking interpretation. Here, the times when the People's Bank of China (PBoC) cut its benchmark lending rates are shown with the blue and green arrows. Notice how they coincide systematically with the end of plateaus or of the corrections that have punctuated the development of the bubble. Just looking at this data, one cannot escape the impression that the bubble may have been engineered, or at least catalysed, by the PBoC and its monetary policy. Given that the upbeat growth of the Chinese economy in the previous decades based on investment in real-estate and infrastructure has significantly abated, and given that the Chinese government is interested in diversifying the source of funding of both public, semi-public and private organisations, it is natural that the stock market would become both the witness as well as the engine of a transition towards a more capitalistic economy. Here, there is an analogy with the Western stock markets, which since 2008 have been supported and pushed up by the easy money policy of central banks (Sornette and Cauwels, 2014). The reasoning is that a booming stock

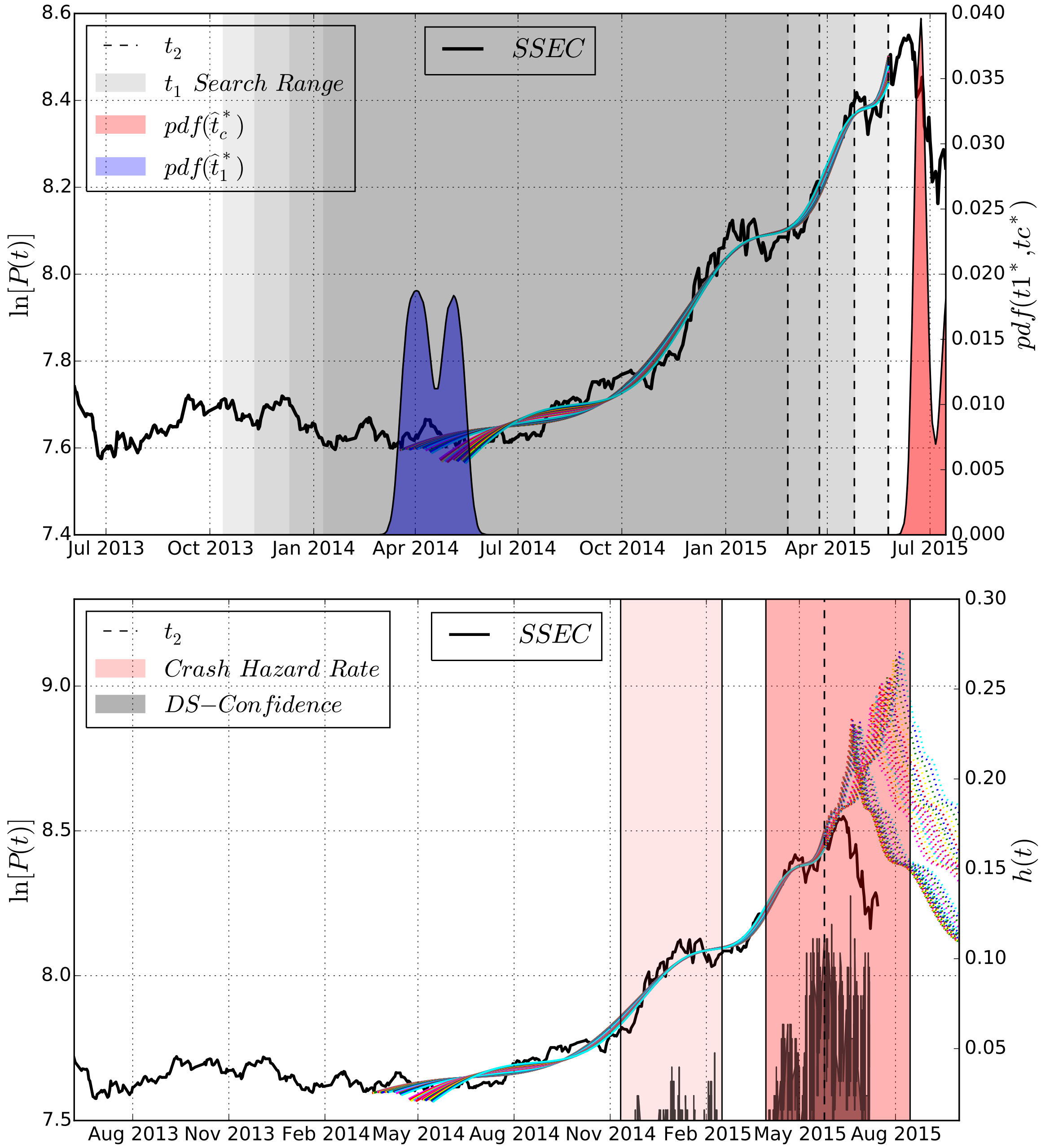


Figure 6: **top panel**: For each vertical dashed line t_2, we fit the LPPLS model for all windows of duration from 400 days to a minimum of 125 trading days prior to t_2, scanned daily. This search range for the beginning of the bubble t_1 is shown as the grey shaded regions. The optimal values for the bubble starting date t_1 are represented by the blue probability density distribution $pdf(\widehat{t_1^*})$. It is pleasant to observe that this pdf is concentrated in a time interval where, visually, the acceleration of the SSEC index is starting. The forecasted critical times depicted by the red $pdf(\widehat{t_c^*})$ present a strong probability measure at the time of the crash. The coloured lines illustrates the remarkable LPPLS characteristics of the SSEC index. **bottom panel**: The DS LPPLS Confidence (black *pdf*) successfully captures moments when the Index was bubbly. Values of the crash hazard rate $h(t)$ inform us about both the confidence and consistency of the critical time parameter t_c estimated over several windows (depicted here by coloured dashed lines). The darker the red shaded region, the higher is the probability of a change of regime to occur.

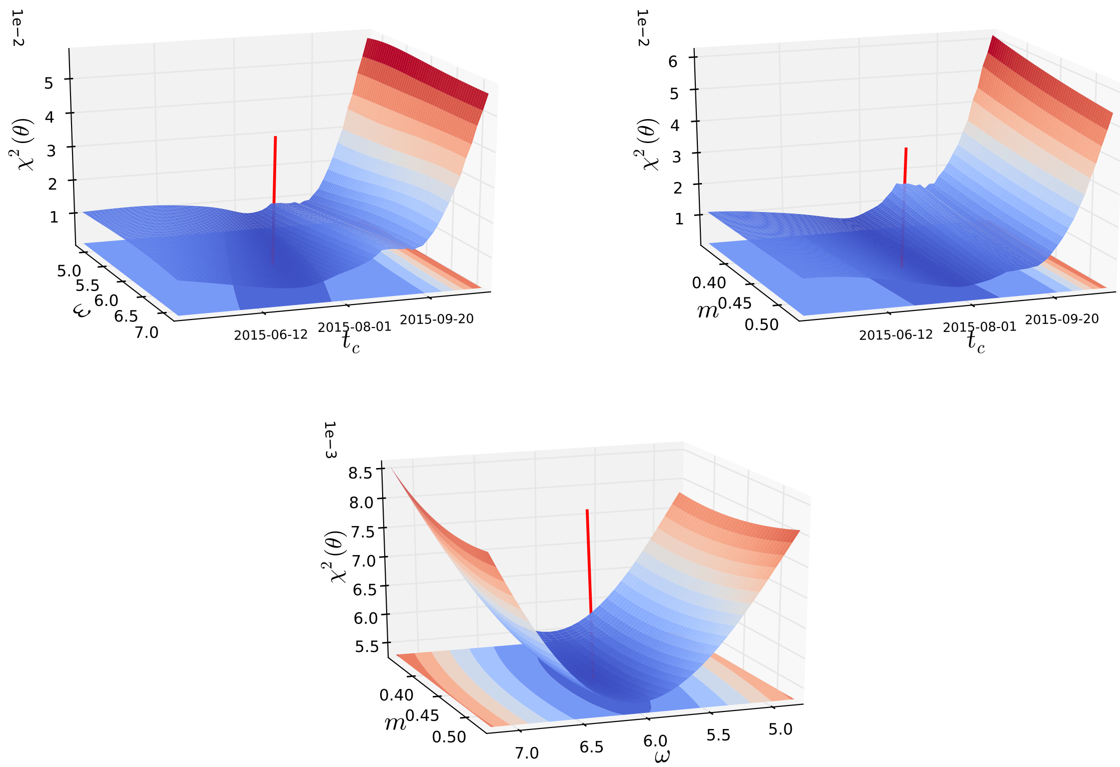


Figure 7: Three cross-sections of the cost function landscape as a function of pairs formed from the three nonlinear parameters m, ω and t_c of the LPPLS formula (4) obtained in the time window $w = [2014.06.20, 2015.05.12]$. The best-fit parameters are depicted by the red vertical lines. The cost function is convex in the space m, ω (bottom panel), showing a rather precise determination of the log-periodic angular frequency ω associated with the clear characteristic spells of log-price accelerations and corrections before the crash. In the two top panels, one can observe the existence of a secondary minimum for t_c, associated with the possibility of a scenario in which the crash of June-July 2015 would have been less severe and only an episode before a strong rebound followed by a latter even more severe crash. The shape of the cost function allows us to determine the following 90% confidence interval for the critical time t_c, namely $[2015.06.01,\ 2015.08.01]$, as could be determined on 2015.05.12.

market is good for investors, for firms and for consumers, via the wealth spillover and the confidence effect. Pursuing this line of reasoning would however seem to be in contradiction with the theory underlying our claim in this article that the bubble was diagnosable and was actually diagnosed in advance. It would seem to tell that the bubble was due to the exogenous influence of the PBoC and not to the endogenous self-organisation of the markets resulting from positive feedbacks between herding investors. Indeed, this exogenous story would be valid if we would consider central banks as impervious to the travails of mere mortals agitating themselves on the stock markets. In fact, as argued already with the Russian crisis and crash in August 1998 (Johansen and Sornette, 1999), central banks tend to be actually 'slaved' to the stock markets (Zhou and Sornette, 2004; Guo et al., 2011), so that their actions have to be considered as an endogenous component of the whole.

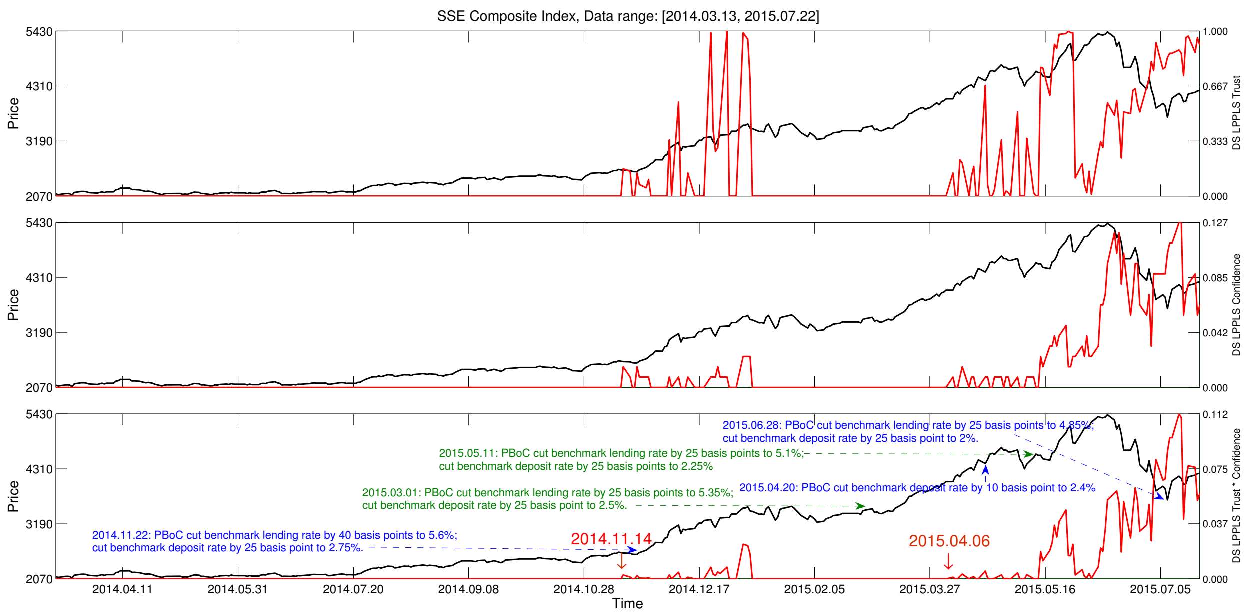


Figure 8: **top panel**: 'DS LPPLS Confidence' indicator (red) together with the SSEC index. **middle panel**: 'DS LPPLS Trust' indicator (red) together with the SSEC index. **bottom panel**: Product of the two above indicators and times when the People's Bank of China (PBoC) cut its benchmark lending rates (blue and green arrows).

5. Conclusion

Since the crash that started on June 17, 2015, the Chinese government has taken many unusual steps to stop it. For instance, on July 8, 2015, the central bank pledged to help maintain market stability, and Chinese stock regulators banned company officers and major shareholders from selling shares in listed companies. The following reasons can be invoked to understand the growing importance of stock markets for China, its economy, for the investors and people and for its government. First, the performance of the stock market will become increasingly correlated with economic growth, via the wealth effect mechanism and the use of stock markets by firms to fund their growth. The progressive trend towards privatisation of state-owned enterprises, the reduction of the reliance on bank lending, and the improvement of the pricing of capital relies on well-functioning and attractive stock markets. Moreover, in the medium term goal of the internationalisation of the renminbi, there is a need for the stock markets to rise in order to attract foreign investors. There are more political reasons also fostering the needs for a rising stock market, namely to reward China's elites for their support to the government's agenda by replacing previous sources of revenues associated with well-connected insider profits and booming property markets. The stock markets embody the "China dream" of successful entrepreneurship and the Chinese way towards capitalism, which can only succeed in the eyes of the Chinese public if the stock markets continue to grow in importance and in valuation.

For all these reasons, it is likely that the three large bubbles and crashes that have punctuated the ascent of the Chinese stock market in the last decade are just the vanguards of many more and larger bubbles to come. Hence, the FCO with its vision to provide advanced warnings is likely to become even more relevant and important in the future. We look forward to continuing improving the methodology and reporting our progress on the publicly accessible FCO website at ETH Zurich, as well as in specific publications.

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