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Forecasting Bubble Bursts Assessing the Ex-ante Usability of the Log-Periodic Power Law Singularity Model

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ABSTRACT

Speculative bubbles have throughout the times foiled various scholars; many have tried to accurately predict their ends, but few have succeeded. In this study, we examine the robustness and ex-ante usability of the log-periodic power-law model in predicting end dates of speculative bubbles on one mature and two emerging financial markets. We have found that the predicted end dates are somewhat dependent on at which point in time the prediction is conducted, especially in regards to at which point in the oscillatory cycle the prediction is conducted. This is mostly due to that predictions are sensitive to their most recent price movements, especially when data is limited and a clear oscillatory pattern is not yet established. We conclude that observing one particular estimation without further context can be misleading. To achieve a sound understanding of and reasonable expectations on how prices might develop it is necessary to follow a bubble as it develops. This study is, to our knowledge, first to examine to what extent the predictions of the model are dependent on at which point in time the predictions are conducted.

KEYWORDS: bubble forecasting, financial crisis, stock market crash, log-periodic power law singularity model (LPPLS-model), asset price dynamics.

1. Introduction

Speculative bubbles can be traced far back in history, and have throughout the time's foiled various scholars. Experts have suggested that this time is different, but history has proved that heavy debt-accumulation and speculative behavior strikes back. Technology has improved in society, as has the height of human capital, but the ability of governments, banks, and investors to delude themselves seems to remain constant (Reinhart and Rogoff 2009). Thus, the phenomenon of speculative bubbles applies to both mature and emerging markets. Minsky (1986) and Shiller (2005) are two out of many economists who have made attempts to explain the underlying causes of and the structural imbalances which precede financial bubbles. Shiller successfully predicted the crash of the dot-com bubble in 2000 and that of the housing bubble in 2007 (Shiller 2005), while Minsky's financial instability hypothesis could explain the subprime crisis which accompanied the housing bubble of 2007.

Feigenbaum and Freund (1996), as well as Sornette et al. (1996), express a different view of the formation of financial bubbles where they analogize previous work on earthquakes and view the peak of a bubble as a complex exponent in a hierarchical system with discrete scaling. The asset price dynamics during a speculative bubble is quantified in this log-

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periodic power-law singularity model, the LPPLS-model, where speculative bubbles are assumed to arise as a result of the endogenous market dynamics where asset prices increase as a power law decorated with log-periodic oscillations. The price development during a speculative bubble is assumed to be driven by two main characteristics; faster-than-exponential growth and accelerating oscillatory movements. The faster-than-exponential growth is explained by the concept of positive feedback (Sornette et al. 2013); when prices go up, investors tend to buy because they are expecting further price increases (Shiller 2005). This concept, in turn, is derived from the psychological phenomenon known as herding behavior as discussed by Shiller (1984) and Nofsinger and Sias (1999). Johansen et al. (2000) describe the presence of noise traders as the cause for this self-reinforcing loop, driving the market out of equilibrium. The loop continues until the bubble reaches its critical point, which is when a change in regime, i.e. a change in the growth rate of prices, occurs. Sornette et al. (1996) propose that the oscillations during a speculative bubble decrease in amplitude as the bubble approaches its regime shift. When the amplitude of oscillations reaches zero, the asset prices will change the regime. The reasoning behind the oscillations are mainly based on empirical observations, but also bear resemblance to the Elliott wave principle (Elliott 1938/2012), which is recurring in technical analysis.

The LPPLS-model has proven useful in predicting the end of speculative bubbles both ex-post and ex-ante such as the 2006-2008 oil bubble (Sornette et al. 2009), historical bubbles on the Dow Jones Industrial Average (Vandewalle et al. 1999), the gold price peak of 2009 (Geraskin and Fantazzini 2011), the Chinese index bubble in 2009 (Jiang et al. 2010), the U.K. real estate bubble (Zhou and Sornette 2003), the U.S. real estate bubble (Zhou and Sornette 2006), the Polish stock market bubble (Gnaciński and Makowiec 2004), and the South African stock market bubble (Zhou and Sornette 2009). In other studies, the test of the LPPLS-model indicates limitations about the prediction of financial crashes (Brée and Joseph, 2013). The authors conclude that the use of stock price alone is unlikely to be the only input for predicting the burst of stock market bubbles. Besides, two previous studies (Gustavsson and Levén 2015 and Gustavsson et al. 2016) found that the bursting of speculative bubbles seems to be influenced by both endogenous speculative growth and exogenous factors.

The many successful predictions of the model suggest that it can be utilized to detect speculative bubbles and foresee their ends. However, for the model to be truly useful and reliable ex-ante continuously performed ex-ante predictions must present a consistent view regarding when the bubble will burst. Through this study we are, to our knowledge, first to assess the robustness and thus the ex-ante usability of the model. We do this by monitoring and comparing a larger number of ex-ante estimations than what has been done before. We aim to assess to what extent the results are dependent on at which point in time the prediction is conducted.

In the next section, the model and estimation procedure are presented, followed by a presentation of the analyzed bubbles and data. Then follow the empirical tests and a comparative analysis of the selected bubbles, before the results are summarized.

2. Model and estimation

Before being implemented on financial markets, the LPPLS-model was studied in research focused on the prediction of earthquakes (see for example Johansen et al. 1996). The earthquake-financial market analogy stems from the idea that financial markets, like earthquakes, are self-organizing cooperative systems characterized by discrete scale invariance. The equation underlying the LPPLS-model was, in a financial context, first presented by Sornette et al. (1996) and Feigenbaum and Freund (1996) in independent articles. In a later study by Filimonov and Sornette (2013) the equation is modified as

$$p(t) = A + B(t_c - t)^z + C_1(t_c - t)^z \cos\big(\omega \, log(t_c - t)\big) + C_2(t_c - t)^z \sin\big(\omega \, log(t_c - t)\big)$$

Where,
$C_1 = C \cos \varphi,$
$C_2 = C \sin \varphi$

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In the above equation asset price, p, is a function of time, t, and tc expresses the critical point, the most probable time of a change in regime. The parameter z controls the strength of the feedback mechanism as well as the amplitude of oscillations while ω denotes the frequency of oscillations. ϕ signifies the direction of the oscillations.

The estimation procedure is based on a nonlinear least-squares estimation to solve the minimization problem of the above equation using a Gauss-Newton algorithm. The nonlinear least-squares estimation is conducted over a great number of iterations, using a rolling window technique, where the start and end date of the analyzed period are changed between iterations. This is consistent with the recommendations of Sornette et al. (2013) to make the predictions more statistically robust, as well as an approach to circumvent the difficulties in distinguishing the beginning of a bubble as discussed by Brée & Joseph (2013). The estimation procedure returns the fit with the lowest sum of squared errors for each window of estimation. In each iteration we use all available data up until the date when the ex-ante prediction is assumed to be performed, henceforth called the last observed date. Since no subsequent data is being used, the estimation is the equivalent of performing an ex-ante prediction on the last observed date. The procedure yields thousands of fits, both good and bad. The fits of no explanatory significance are filtered out through enforcing constraints on the parameters of the equation. Regarding the parameter ω, we follow the guidelines proposed by Filimonov and Sornette (2013) in allowing for values between 3 and 15. We constrain the parameter z to take on values between 0 and 1 while B is constrained to only take on negative values. Also, we introduce constraints on the augmented Dickey-Fuller and Phillips-Perron values of the fits to filter out stationary fits which have no explanatory power in predicting the critical points. Only fits that are non-stationary at a 1 percent significance level are accepted.

The end date of each fit signifies the predicted critical point of the bubble, i.e. the point in time at which the asset prices are expected to change regime. These end dates are the objects of analysis, where they comprise confidence intervals of critical points, indicating where it is most likely for the analyzed bubble to change regime.

3. Bubble selection and data

In the empirical study, we focus on the bubbles preceding three well-known crashes; the Black Monday crash of 1987, the burst of the emerging markets bubble in 1997 and the Chinese stock market crash in 2015.

Black Monday refers to 19 October 1987, when stock markets around the world crashed, shedding a huge value in a very short time. The contagion spread from Hong Kong to Western Europe and then hit the United States, where the Dow Jones Industrial Average fell by nearly 23 percent. The crash has been attributed to a range of factors, such as international disputes about foreign exchange and interest rates, fears about inflation, overvaluation and market psychology, but also the introduction of program trading. The idea of using computer systems to engage in large-scale trading strategies was still relatively new and the consequences of a system capable of placing thousands of orders during a crash were unknown. These computer programs automatically began to liquidate stocks as certain loss targets were hit, pushing prices lower. To the dismay of the exchanges, program trading led to a domino effect as the falling markets triggered more stop-loss orders (Shiller 1990). There were some warning signals of excesses: the stock market and economy were diverging for the first time in the bull market, and as a result, valuations climbed to excessive levels. Besides, economic growth had slowed while inflation was rearing its head and the strong dollar was putting pressure on U.S. exports (Sobel 1988). Market participants were aware of these issues, but another innovation-led many to shrug off the warning signals, as portfolio insurance gave a false sense of confidence to institutions and brokerages. The Black Monday crash of 1987 is one of the most examined crashes using the LPPLS-model. However, no previous study has examined the ex-ante usability of the model as thoroughly as we do in this article.

The next event to be surveyed is the emerging market bubble of the 1990s, which led to the financial crisis in East Asia commencing in July 1997. During the middle of the 1990s institutional investors, mainly in Europe and North America, found particular interest in emerging markets around the world. Their wishes to diversify their portfolios were met by the desire from developing borrowers to increase investments and growth rates. By 1997, the large inflow of capital into several Asian economies had led to dramatic rises in asset prices, fueled by deregulation of the financial market and a herd of euphoric investors. The situation was also marked by crony capitalism in Indonesia, a weak government in Thailand, enormous

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conglomerates in South Korea and a strong increase in bank debt accumulation in the region. Another factor behind the boom-and-bust-cycle was the expansion of Japanese direct investment into lower-wage areas, as the Japanese bank loans contributed to the increases in the current account deficits in these countries. The currencies of the countries were overvalued and these countries had been extremely vulnerable to any external shock leading to a decline in money inflows. The bubble burst when the instability in the Thai economy eventually led to increased perceived risks, which brought about a drop in asset prices in the emerging markets (Kindleberger and Aliber 1978/2011).

Finally, we will survey the stock market crash in China in 2015. The crash began with the popping of the stock market bubble on 12 June 2015. Within one month, a third of the value of A-shares on the Shanghai Stock Exchange was gone and half of the listed firms filed for a trading halt in an attempt to prevent further losses. Despite efforts by the government to reduce the fall, values of Chinese stock markets continued to drop. After three stable weeks, the Shanghai Composite Index fell by 8.5 percent on 24 August wiping out hundreds of billions of dollars in market capitalization. This event marked the largest one-day fall since 2007. Commodity prices fell into territory not seen since 1999, and the contagion infected Western markets (The Economist 2015a). One reason for the bubble was a herding behavior among domestic investors. The Chinese economy was expansive and enthusiastic individual investors, encouraged by state-owned media, invested in stocks, often using borrowed money. Since the prospects were high, the value of the stocks often exceeded the rate of growth and profits of the very companies. The inflated prices also reflected a long history of high market volatility in China, typical for emerging markets in transition economies. The bumpy prices and the burst of the bubble revealed structural imbalances in the Chinese economy (The Economist 2015b).

The datasets used in the estimation consist of daily closing prices of well-known stock price indices; for the bubble preceding Black Monday we use data from Dow Jones Industrial Average; for the emerging markets bubble, we use data from the Hang Seng Index of Hong Kong; for the Chinese stock market crash we use data from the Shanghai Stock Exchange Composite Index. The data for the two Asian bubbles is retrieved from Thomson Reuters DataStream while data for the Black Monday bubble is retrieved from www.measuringworth.com.

4. Results

In this section, we present the results of the conducted estimations. The section is divided into three subsections covering one historical bubble respectively. In each subsection, we present the results of twelve estimations, all with different last observed dates. Highlighted in dark grey in each figure (see Appendix A) is an 80 percent confidence interval of critical points, tc, that are the results of the fitting procedure. In lighter grey within this interval is a 50 percent confidence interval of critical points. These intervals thus represent the most probable time for a change in regime. The median date of critical points is marked by the (red) vertical line within the confidence interval and gives guidance to where it is more likely for the regime shift to occur. For the sake of visibility, only a dozen of the resulting LPPLS-fits are plotted in each graph, regardless of how many fits are produced. The total number of fitted curves is given in the upper left corner of each figure. The bold black line in each figure illustrates the last observed date, which is when the ex-ante prediction is assumed to be conducted. Only price data up until this date is used in the estimation. Due to the considerable amount of fitted curves we, instead of presenting the parameter values for each fit, present the parameter medians based on all fits for each estimation. These parameter medians along with confidence intervals of fits are presented in tables 1 to 3 (see Appendix B).

4.1 Black Monday of 1987

Figures 1a to 1l present the results from the twelve estimations conducted on this 1980s bubble, all with different last observed dates. The last observed dates range from 60 weeks to 2 weeks prior to the peak date of 25 August 1987. From observing the figures we can see that the model in all cases find the characteristic pattern leading up to the last observed date and beyond, although the predicted regime shift of figure 1a and 1b are way off the actual peak date.

The results are promising since all estimations except those of figure 1a and 1b, the two earliest estimations, exhibit median dates of critical points around mid or late mid-1987. It is evident that estimations conducted closer to the peak, in general, have narrower confidence intervals compared to earlier predictions. This is in line with what is expected, as uncertainty should decrease when more data is available as the bubble approaches its peak. It is also apparent that the results of

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later estimations are quite robust since the median date and confidence intervals are more or less static in between different estimations. These median dates are, in the estimations of figure 1e onwards never more than approximately six weeks off the actual peak date, although the prediction of figure 1l, conducted two weeks prior to the peak, is affected by the filtering out of fits occurring before the last observed date. In the estimation procedure, we only allow for fits with end dates after the last observed date since we know that the regime shift has not occurred before this date. The reasoning is quite intuitive but it results in the filtering out of fits which, if included, would have yielded an earlier occurring median date. If these fits would have been included, the median date would not simply have been shifted in between the estimations of figures 1k and 1l by the number of days in between the two estimations. This occurrence will be further discussed in the next section.

The number of fitted curves varies between different estimations where figure 1b stands out with by far the least amount of fits. For all figures except 1a and 1b, the actual peak date is encapsulated by the 80 percent confidence interval. On a 50 percent confidence level, the peak date is encapsulated in all estimations except those for figures 1a, 1b, 1d, and 1l.

The two earliest estimations, in figures 1a and 1b, both exhibit narrow confidence intervals with the median date close to the last observed date. These results are deceptive and indicate the impending regime shift much earlier than what turned out to be the case. The reasons behind these occurrences are similar for the two estimations. The erroneous estimation of figure 1a, conducted 60 weeks before the peak, is simply due to the bubble not being sufficiently far gone when the estimation is conducted. The estimation mistakenly regards the most recent oscillation as complete prior to the last observed date resulting in a sharp upturn for the fitted curves. The inaccurate estimation of figure 1b, conducted 52 weeks prior to the peak date, also has to do with misinterpreted oscillations. As in figure 1a, the predicted prices shoot upward closely following the peak resulting in narrow confidence intervals and in this case only 210 fits. To understand why this is, we have to look closer at the price movements preceding the last observed date. After a strong beginning of 1986 prices took a downturn in mid-1986 before a rapid recovery in august the same year. Shortly after the last observed date of 26 August 1986 prices fell over 8.5 percent in only six days and were thus back on the long term trend. When this estimation is conducted, data is only available up until the last observed date and the return to the trend of early September is unknown. Hence the estimation regards the recent price incline as oscillation and expects forthcoming oscillations to be decreasing in amplitude faster than what is actually the case. Thus the earlier predicted peak date. When more data is available as in figure 1c the above-mentioned price movements are considered nothing but an anomaly, not affecting the long term trend. How to spot and work around problematic results like the one in figure 1b will be discussed in the next section.

In the estimation of figure 1d, conducted 36 weeks before the peak, the 50 percent confidence interval misses the actual peak date with less than one month. The median date of 22 May 1987 is about five months after the last observed date. This makes the erroneous prediction quite unproblematic since the bubble observer still has plenty of time, through performing subsequent predictions, to figure out where the prices are going. Also, the wide confidence intervals indicate great uncertainty in the prediction. Narrower intervals as in figures 1a and 1b are more problematic since they indicate certainty where there should be uncertainty.

4.2 The emerging markets bubble of the 1990s

Figures 2a to 2l present the results of the twelve estimations conducted on the Hang Seng index for the time period of this emerging markets bubble. It is apparent that the model finds the characteristic pattern in all cases, although the estimation of figure 2b considerably misses the actual peak date of 7August 1997. This erroneous estimation is due to the model accrediting recent price movements more explanatory significance than what is justified. This estimation is conducted just after a relatively sharp downturn in late 1996 leading to a misinterpretation of the oscillatory movements and a sharp upturn in predicted results. When we move on to figure 2c we see that when further price data is available the model instead disregards these sharp movements as short term anomalies and finds the long-run pattern. These results are reminiscent of those of figures 1a and 1b in the previous subsection. Also in the sense that this estimation yields the fewest amount of fitted curves, it is in line with the unsatisfactory results of figures 1a and 1b.

As expected, the confidence intervals are generally narrower when the estimation is conducted closer to the peak. For figures 2a and 2c, we observe quite imprecise results where, although the 80 percent confidence intervals do encapsulate the

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actual peak date, the median dates are several months too early. Even if one were to observe these results without context, one would be remiss to give them much credit since the intervals of predictions are much too broad and the median dates are months away from the last observed date. Consequently, these results are quite unproblematic.

In the cases of figures 2e and 2g however, the confidence intervals are narrower than what is the case for figures 2a and 2c, and thus indicate a higher degree of certainty in regards to when the regime shift will occur. In figure 2e the 80 percent confidence interval just captures the actual peak while the same interval in figure 2g just misses the actual peak with the median date appearing too early. If one were to observe only one of these results without any further context, this could be regarded as misleading since a potential investor following the model's patterns could draw faulty conclusions.

From figure 2h onwards, with the exception of figure 2l, the actual peak date is encapsulated within the 50 percent confidence interval with satisfactory precision and from figure 2f onwards we can see that the median date is relatively stable in the interval of July to august of 1997. Note that figure 2h is also the point at which we reach the completion of the second oscillation, which will be of interest in the discussion in the next section.

As in figure 1l, the estimation in figure 2l overestimates the peak date since many predicted end dates occur just before the last observed data and are filtered out in the filtration process. As a result, the median date is shifted towards later dates than what would have been the case otherwise.

4.3 The Chinese stock market crash in 2015

The estimations for our final bubble are presented in figures 3a through 3l where the actual peak date occurred on 12 June 2015. Once again the narrowest confidence intervals occurring in the later estimations while the widest appears in the earlier estimations. All estimations find the characteristic pattern leading up to the predicted end dates. We note that the estimations of figures 3b and 3i erroneously predict the regime shift to occur right after the last observed date. In figure 3b we, yet again, see the pattern of prematurely predicted intervals when the estimation is conducted just after a dip in prices and the oscillatory movements are not far gone. The consequence is that recent short term price movement is accredited more influence on the predicted end dates than what is justified. Figure 3i exhibits similar results where the predicted end dates are affected by misinterpreted oscillatory patterns. This prediction is conducted right on a local maximum causing the prediction to assume a steeper development and predicted end dates that appear earlier than the actual peak date. In this estimation, the narrow confidence intervals make the prediction a greater concern since they indicate an overstated certainty in regards to when the bubble will change the regime.

As in figures 3b and 3i both the 80 percent and the 50 percent confidence intervals of figure 3d miss the actual peak date. The confidence intervals are narrower than those of surrounding results, 3c and 3e, and thus indicate a higher degree of certainty in regards to when the bubble will change regime. However, note that the median date is quite far after the last observed date, and the results are therefore not as problematic as those of figures 3b and 3i. This occurrence, and how one should interpret the results, will be discussed further in the next section.

In figures 3g and 3h we observe median dates that overshoot the actual peak by several weeks. These results could be regarded as somewhat misleading since an investor looking at these predicted median dates would be at risk of being fully invested when the regime shift occurs. However, note that the confidence intervals are quite wide indicating uncertainty and that the 80 percent confidence intervals capture the actual peak. The 50 percent confidence intervals just barely miss the peak.

From figure 3j onwards we start to see consistently narrow prediction intervals with relatively stable median dates indicating more certainty in the results. These figures also, in this case, coincide roughly with the passing of the second large oscillation, a pattern that we have seen recurring for both previously examined bubbles.

As in figures 1l and 2l, the estimation of figure 3l overshoots the actual peak date due to the filtering out of fits just prior to the last observed date. These occurrences will be further discussed in the next section.

5. Comparative Analysis

Our empirical tests suggest that the LPPLS-model in all examined cases find the characteristic pattern leading up to the predicted end dates, while the confidence intervals, in general, tend to be narrower when the prediction is conducted closer to

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the peak as more information is available. The estimations on each time period investigated in most cases exhibit predictions that are somewhat robust. However, there are some irregularities and results that might mislead the bubble observer. In this section, we will shed light on these, more or less, problematic results and propose methods on how to circumvent them.

An observation that is recurring for all bubbles analyzed is that short term price movements in some cases are accredited more significance than what is justified. These results are somewhat worrisome since an observer of for example the estimation of figure 1b might draw the conclusion that the impending regime shift is much closer than what is actually the case and thus misses out on future earnings. The same goes for figures 1a, 2b, 3b, and 3i where the estimation results show faulty predictions with predicted end date much sooner than what turns out to be the case. With the exception of figure 3i, these estimations have in common that they are conducted when the amount of available data used in the estimation is limited or when a sudden price movement is erroneously regarded as an oscillation. The estimation of figure 3i stands apart somewhat since in this case the oscillatory pattern already is far gone and there is no apparent downturn in the most recent price data.

These results prove that the predictions, in fact, are not entirely independent of when they are conducted, although the different estimations in most cases exhibit similar results. Nevertheless, if one were to observe only the prediction of e.g. figure 1b one would arrive at faulty conclusions. To truly understand a forming bubble and draw reliable conclusions on when it might change regime, it is important to conduct several estimations over some period of time and follow how the prices and the predictions develop. To achieve trustworthy results it is necessary that the different estimations paint a consistent picture of expected price movements and predicted end dates. Consider for example figures 3a to 3c, where figures 3a and 3c show similar results. Looking solely at figure 3b would lead to faulty conclusions, but when studying the three estimations together one can easily determine that the results of figure 3b are deceptive and clearly a result of misinterpreted short term price movements. The same "wait and see" procedure could have been utilized to determine that the prediction of figure 3i was a result of insufficient information about the next coming oscillation. Observing the twelve estimations of figures 3a to 3l all together one can determine that they in general paint a uniform picture of anticipated price movements and thus can be regarded as reliable. The fact that the results of the three most recent estimations, figures 3j to 3l, are almost identical gives additional comfort in the decision making. This pattern can also be observed in the other two bubbles (see 2j to 2l and 1i to 1l), although the latest estimations for all bubbles are affected by the filtering out of fits with predicted end dates prior to the last observed date, why the median date is shifted forward.

It is important to note that several estimations painting a consistent picture of what one should expect of prices going forward does not necessarily mean that the confidence intervals and the median date have to be entirely static in between estimations. The different estimations utilize different sets of data and thus the results must vary somewhat in between estimations. It is apparent from going through the results of the previous section that the confidence intervals and the median dates are shifted back and forth to some extent. However, this is not of major importance as it is the bigger picture that the estimations paint all together that is important. It is also evident that later estimations tend to vary less amongst one another, which is natural as these estimations utilize more information and more similar sets of data.

As previously mentioned we have identified that in regards to later conducted estimations, the median date and to some extent the confidence intervals are simply shifted to later dates in between estimations. We have concluded that this is due to the filtering out of fits with end dates prior to the last observed date. For most estimation, the number of fits with end dates prior to the last observed dates is negligible. However, later estimations can have a significant number of end dates before the last observed date, and these fits can thus make up a large portion of the confidence interval before the filtration. These end dates are obviously incorrect since they occur before the last observed date, but they can nevertheless form a crucial part of the confidence intervals. The question of whether to include these predicted end dates or not falls outside of the scope of this study and we here simply encourage caution when analyzing results with a great number of end dates prior to the last observed date.

Another observable pattern is that trustworthy results generally start to appear after two completed oscillations. From this observation, we conclude that if one were to follow the development of a specific bubble using the LPPLS-model, one should be wary of drawing too many conclusions from results obtained roughly before the completion of the second large oscillatory movement.

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6. Conclusion

This study is, to our knowledge, first to examine the robustness and ex-ante usability of the log-periodic power-law model. We have found that the estimation results are somewhat dependent on at which point in time the prediction is conducted, especially in regards to at which point in the oscillatory cycle the prediction is conducted. This is mostly due to that predictions are sensitive to their most recent price movements, especially when data is limited and a clear oscillatory pattern is not yet established. We conclude that observing one particular estimation without further context can be misleading. With this newfound knowledge, it is possible to, through following a bubble as it develops, and achieves a broad understanding of and reasonable expectations on how prices might develop. It is only when one puts each prediction into perspective and relation to other predictions that one can draw significant conclusions. We conclude that the key to successful bubble prediction using the LPPLS-model is in following a bubble as it develops, being patient and listening carefully to the signals.

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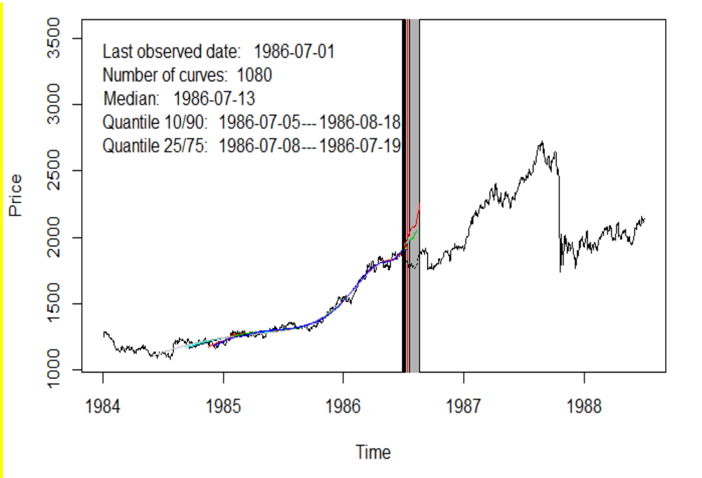
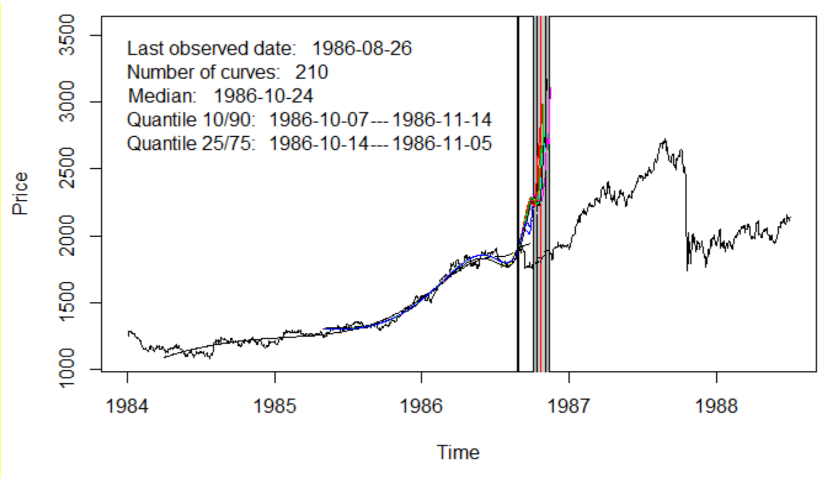
Appendix A

Black Monday 1987

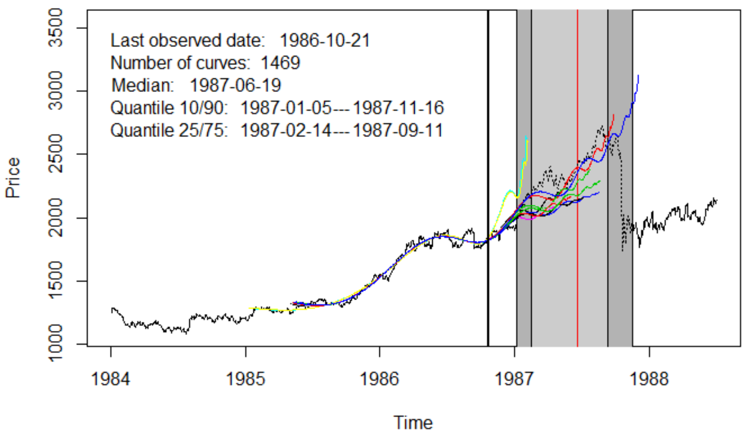
1a. 60 weeks



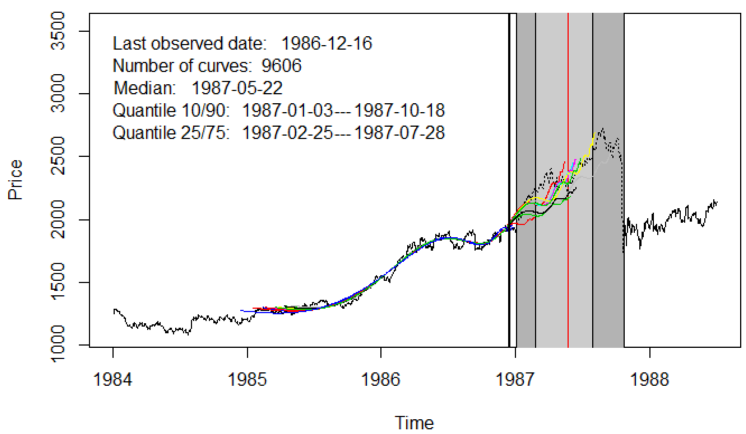
1b. 52 weeks



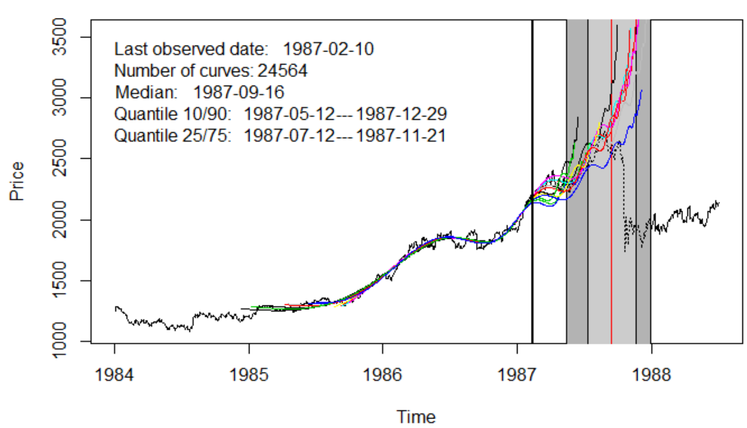
1c. 44 weeks



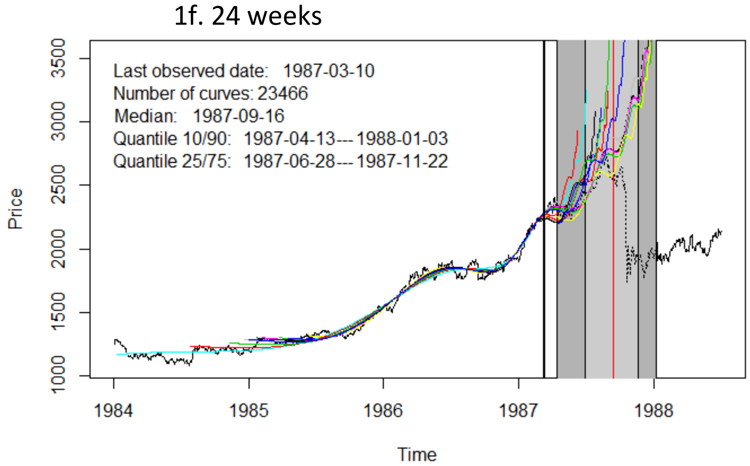
1d. 36 weeks



1e. 28 weeks



1f. 24 weeks



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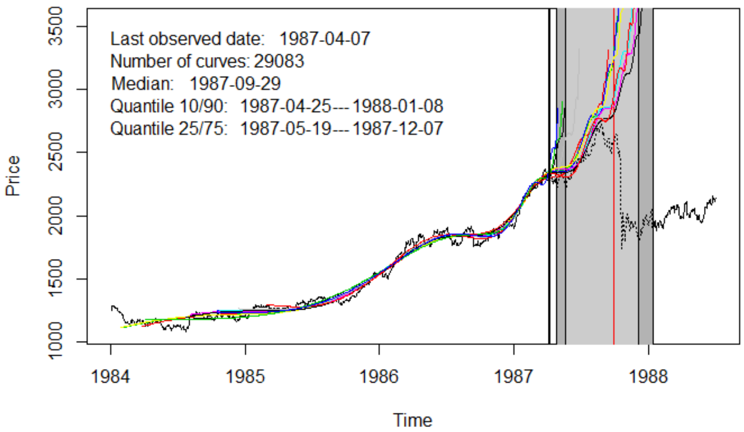
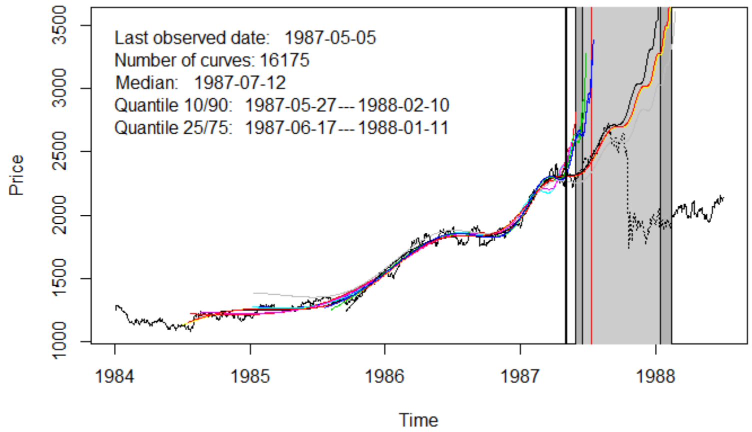
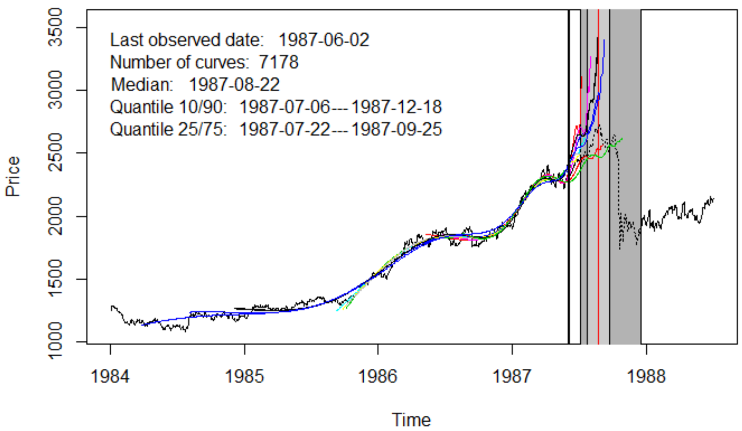
1g. 20 weeks



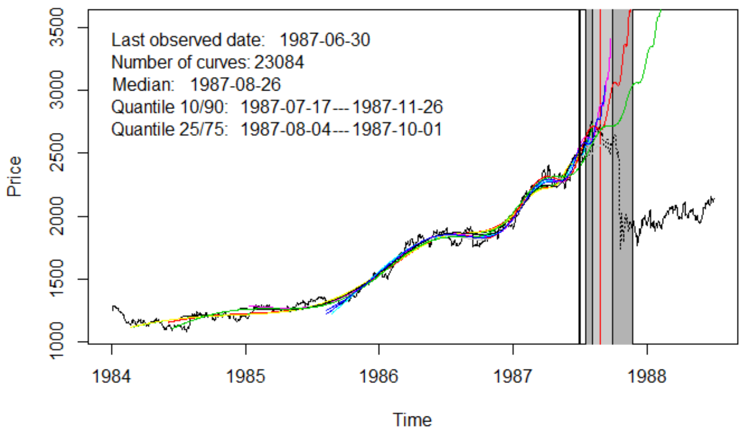
1h. 16 weeks



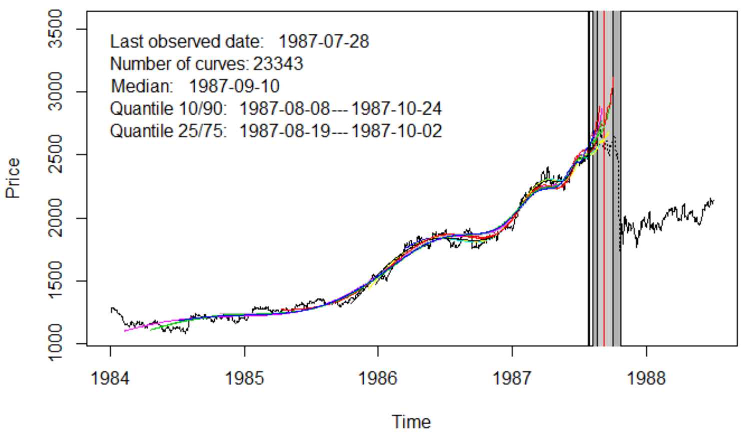
1i. 12 weeks



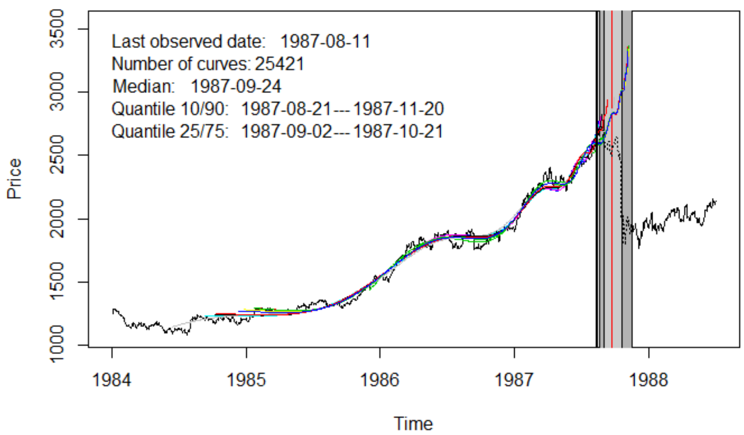
1j. 8 weeks



1k. 4 weeks



1l. 2 weeks



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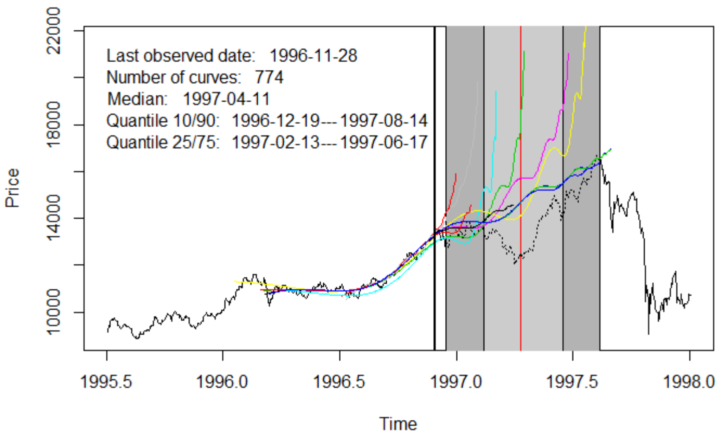
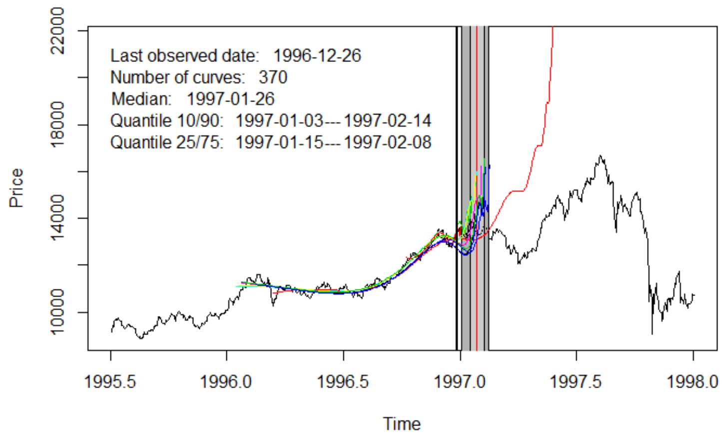
Hang Seng 1997

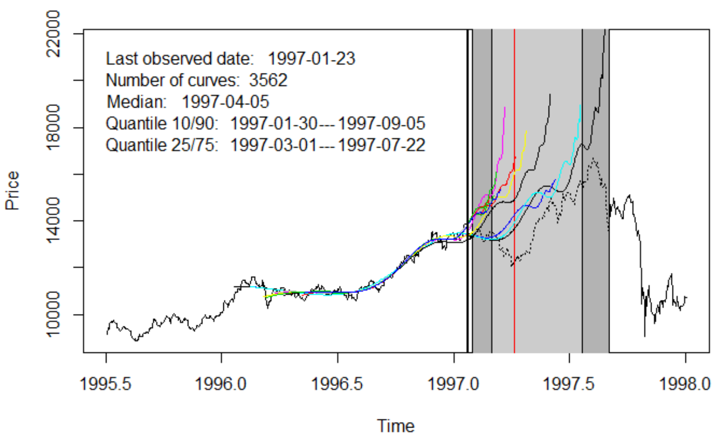
2a – 36w



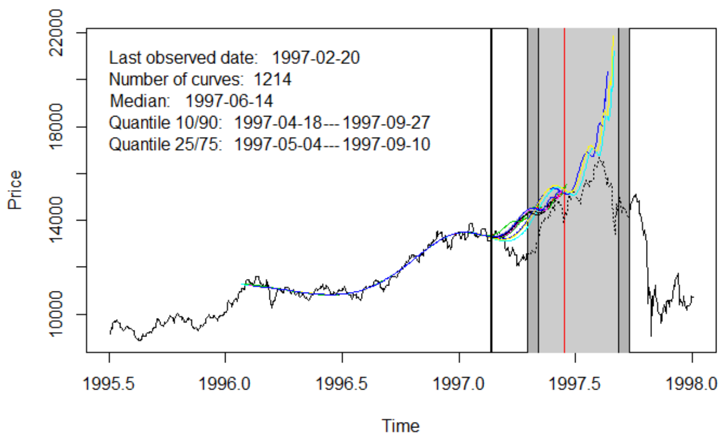
2b – 32w



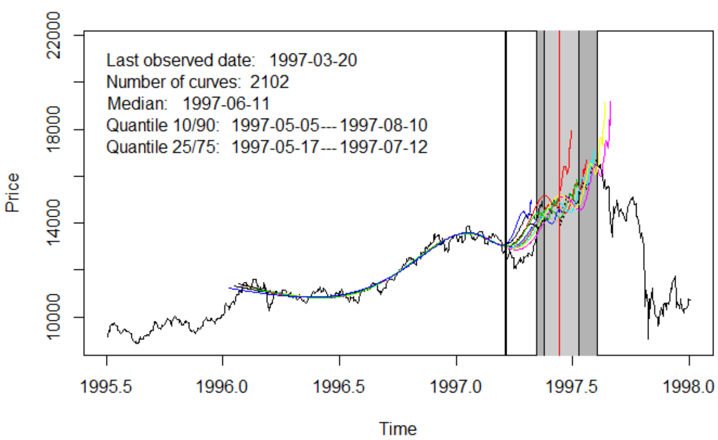
2c – 28w



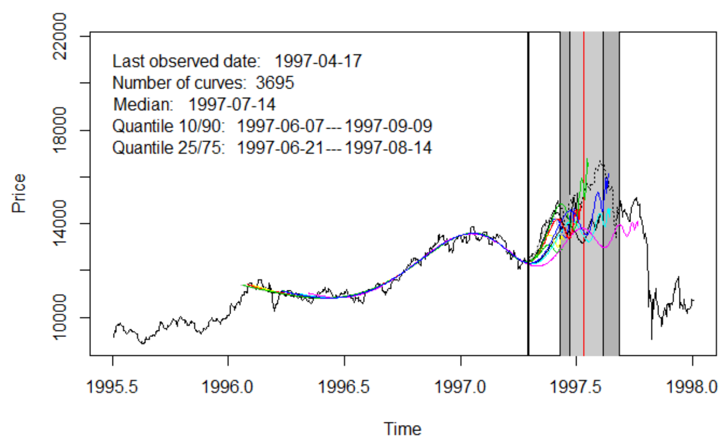
2d – 24w



2e – 20w



2f – 16w



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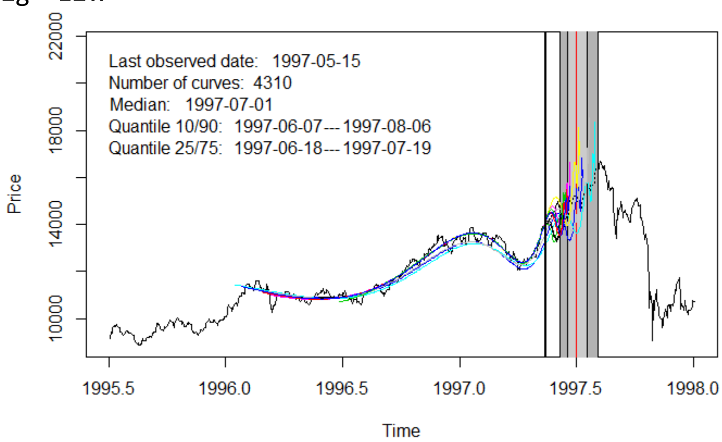
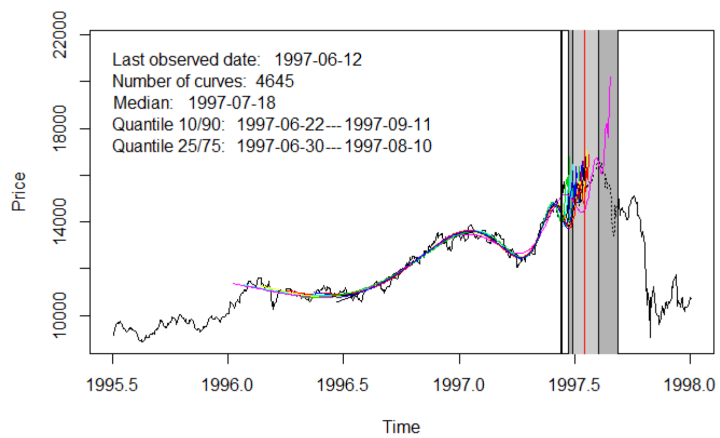
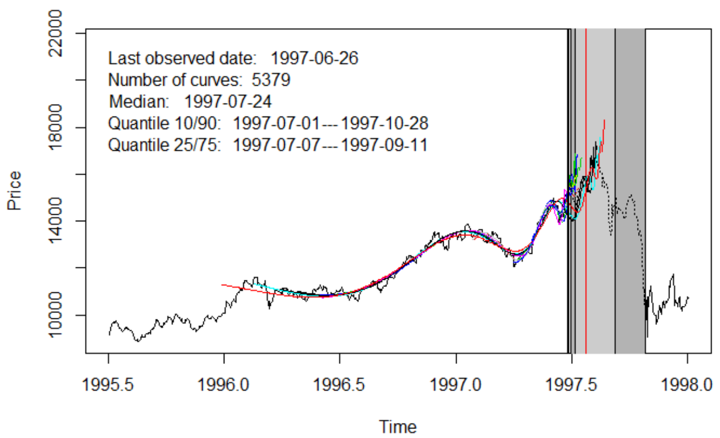
2g – 12w



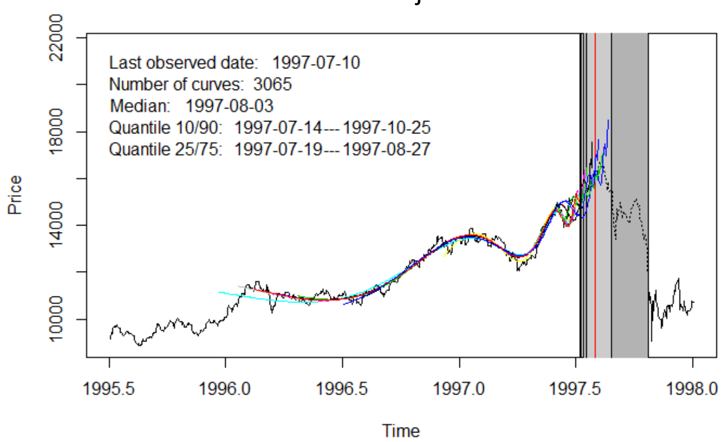
2h – 8w



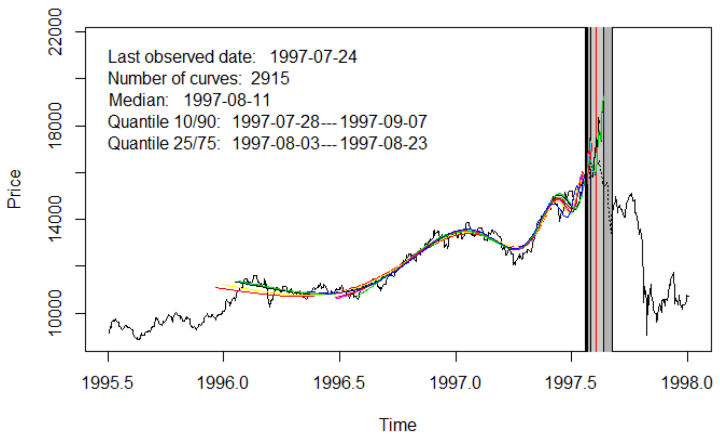
2i – 6w



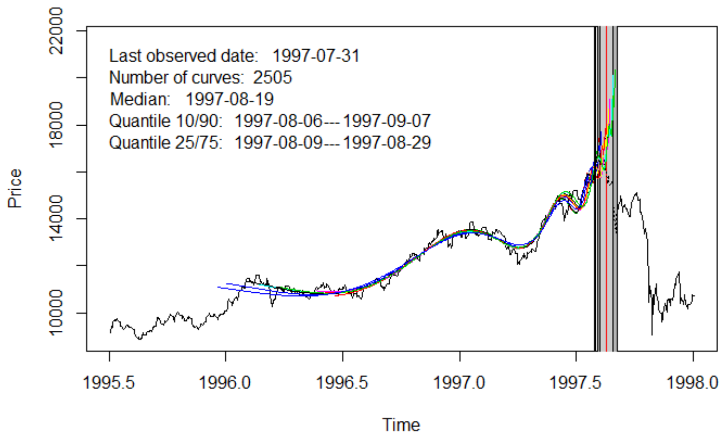
2j – 4w



2k – 2w



2l – 1w



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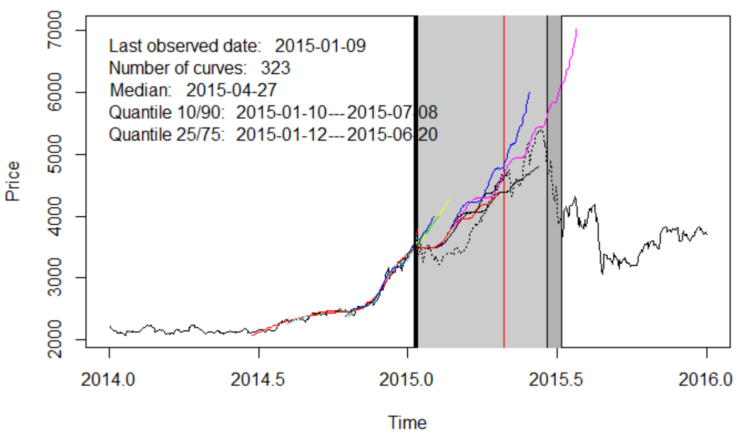
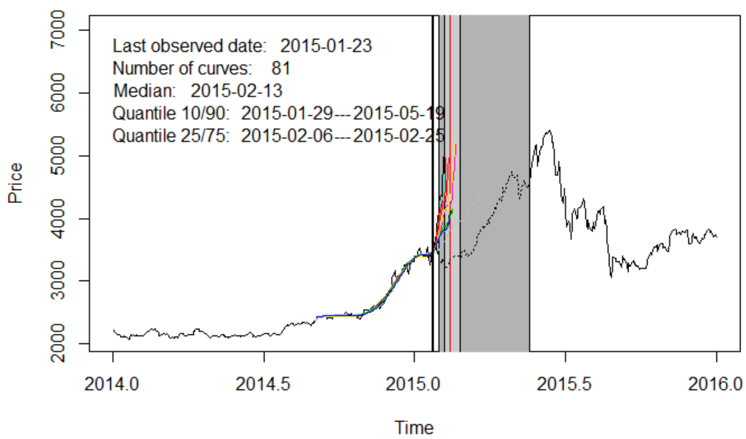
Shanghai 2015

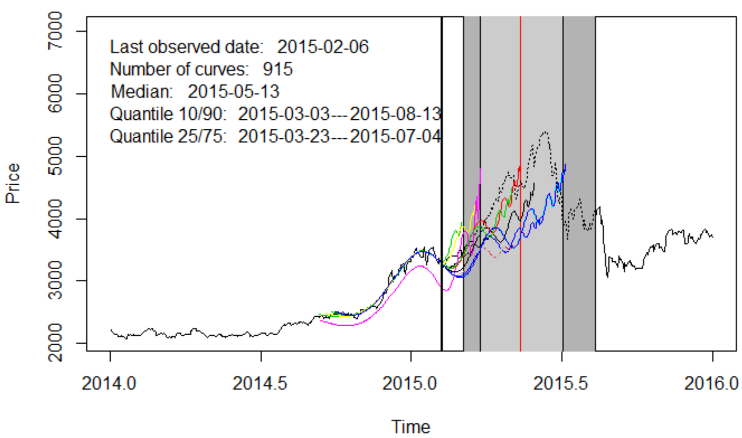
3a – 22w



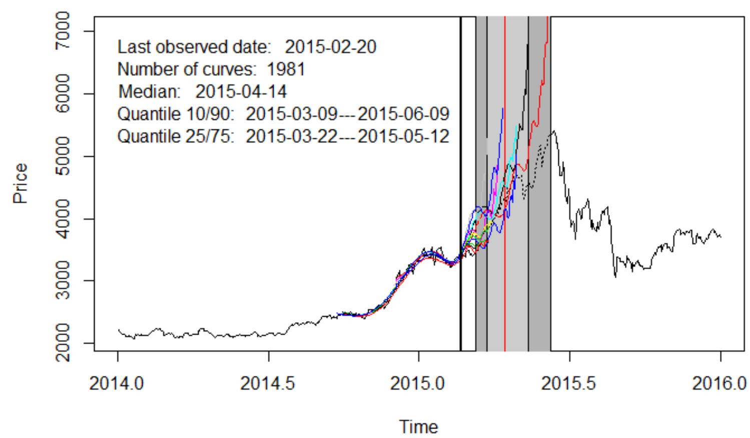
3b – 20w



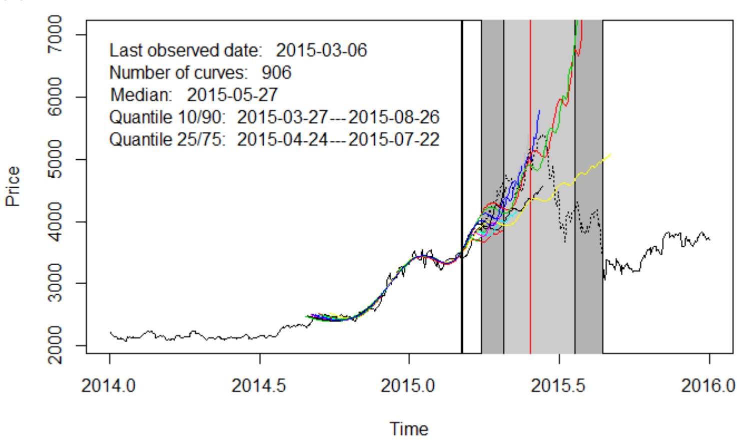
3c – 18w



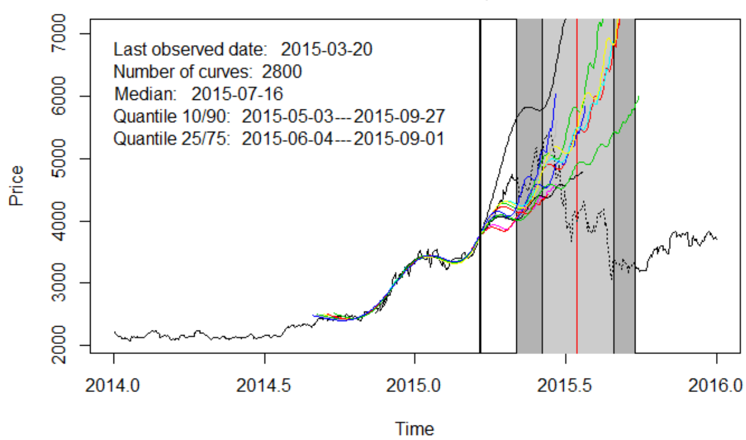
3d – 16w



3e – 14w



3f – 12w



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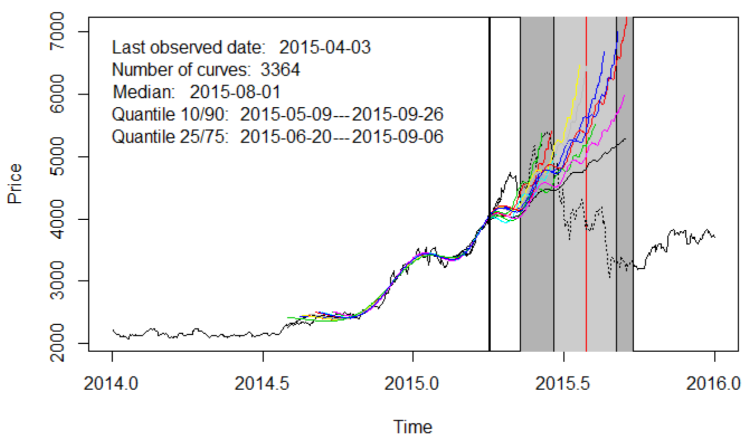
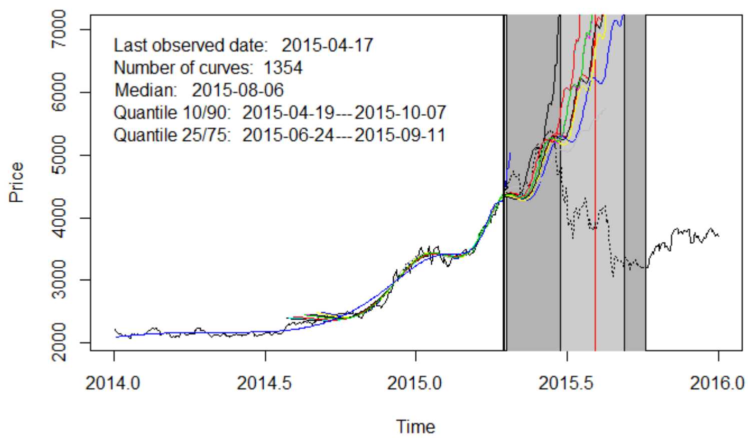
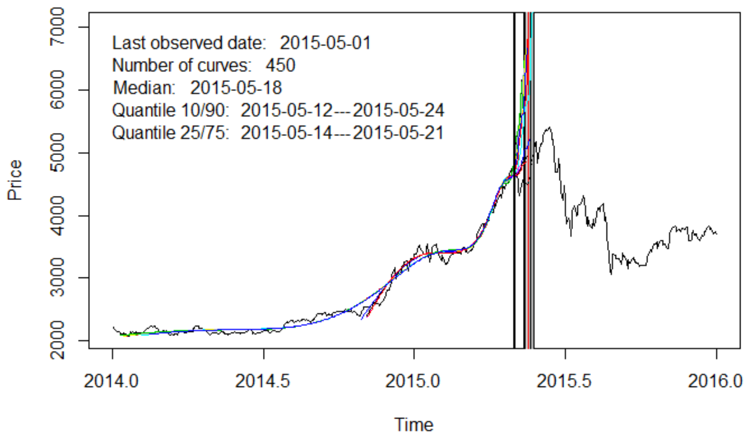
3g – 10w



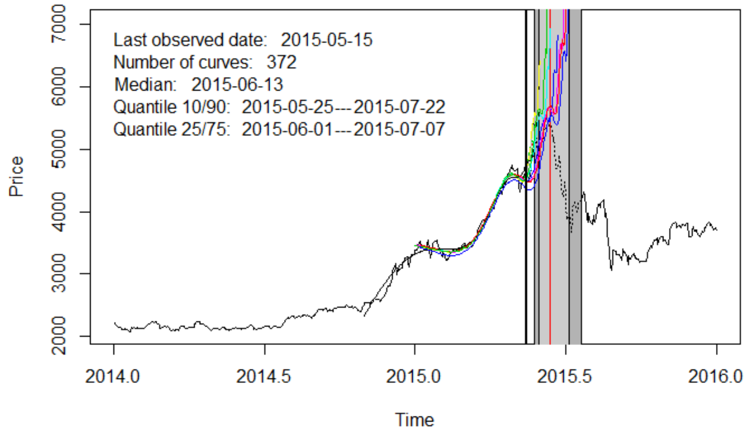
3h – 8w



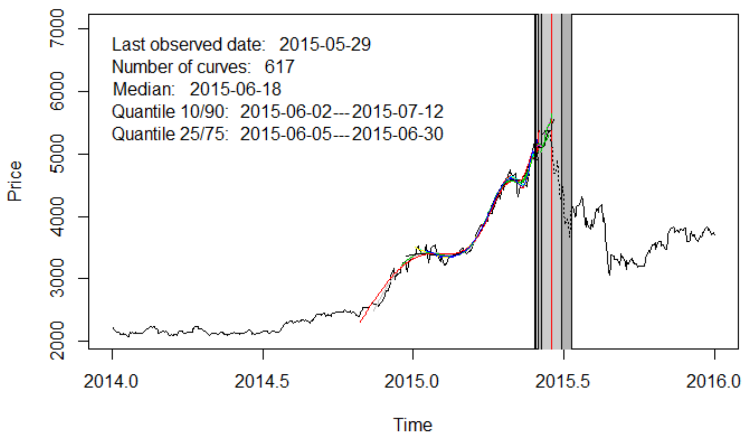
3i – 6w



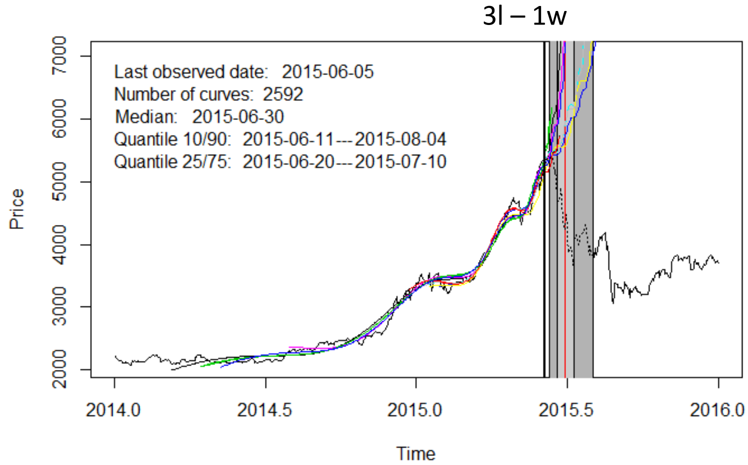
3j – 4w



3k – 2w



3l – 1w



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Black Monday 1987

Peak 1987-08-25

Figure	Last observed date	Median fit	80 % CI	80 % CI	50% CI	50% CI	A	B	C1	C2	Z	OMEGA
1a	1986-07-01	1986-07-13	1986-07-05	1986-08-18	1986-07-08	1986-07-19	1 928,03	-611,59	-10,22	139,81	0,91	3,22
1b	1986-08-26	1986-10-24	1986-10-07	1986-11-14	1986-10-14	1986-11-05	2 835,28	-1 365,14	-123,81	-51,51	0,22	3,55
1c	1986-10-21	1987-06-19	1987-01-05	1987-11-16	1987-02-14	1987-09-11	2 365,72	-581,49	-2,61	-25,31	0,66	6,50
1d	1986-12-16	1987-05-22	1987-01-03	1987-10-18	1987-02-25	1987-07-28	2 326,74	-548,80	23,42	-33,68	0,70	5,64
1e	1987-02-10	1987-09-16	1987-05-12	1987-12-29	1987-07-12	1987-11-21	3 226,21	-1 345,53	-9,97	29,43	0,37	7,04
1f	1987-03-10	1987-09-16	1987-04-13	1988-01-03	1987-06-28	1987-11-22	4 054,39	-2 185,30	5,80	20,93	0,25	6,65
1g	1987-04-07	1987-09-29	1987-04-25	1988-01-08	1987-05-19	1987-12-07	3 966,58	-2 175,33	-2,87	-16,82	0,22	6,67
1h	1987-05-05	1987-07-12	1987-05-27	1988-02-10	1987-06-17	1988-01-11	3 962,46	-2 123,83	80,62	16,60	0,26	5,48
1i	1987-06-02	1987-08-22	1987-07-06	1987-12-18	1987-07-22	1987-09-25	3 269,47	-1 391,94	-10,86	109,20	0,35	5,67
1j	1987-06-30	1987-08-26	1987-07-17	1987-11-26	1987-08-04	1987-10-01	2 870,82	-1 024,09	9,82	83,58	0,49	6,05
1k	1987-07-28	1987-09-10	1987-08-08	1987-10-24	1987-08-19	1987-10-02	2 886,64	-1 023,10	-9,97	80,78	0,49	6,39
1l	1987-08-11	1987-09-24	1987-08-21	1987-11-20	1987-09-02	1987-10-21	3 011,23	-1 115,89	-31,11	72,87	0,46	6,73

Hang Seng 1997

Peak 1997-08-07

Figure	Last observed date	Median fit	80 % CI	80 % CI	50% CI	50% CI	A	B	C1	C2	Z	OMEGA
2a	1996-11-28	1997-04-11	1996-12-19	1997-08-14	1997-02-13	1997-06-17	19 263,25	-8 953,12	-9,14	340,42	0,32	5,48
2b	1996-12-26	1997-01-26	1997-01-03	1997-02-14	1997-01-15	1997-02-08	24 912,90	-13 455,97	290,55	440,16	0,07	3,39
2c	1997-01-23	1997-04-05	1997-01-30	1997-09-05	1997-03-01	1997-07-22	17 133,28	-6 293,82	394,38	-50,16	0,42	5,52
2d	1997-02-20	1997-06-14	1997-04-18	1997-09-27	1997-05-04	1997-09-10	15 523,98	-4 118,01	-352,81	558,55	0,61	5,14
2e	1997-03-20	1997-06-11	1997-05-05	1997-08-10	1997-05-17	1997-07-12	15 417,87	-3 674,66	-904,92	390,88	0,42	4,08
2f	1997-04-17	1997-07-14	1997-06-07	1997-09-09	1997-06-21	1997-08-14	14 364,78	-2 206,28	-1 155,15	-198,79	0,36	4,11
2g	1997-05-15	1997-07-01	1997-06-07	1997-08-06	1997-06-18	1997-07-19	29 859,87	-18 103,42	-996,52	-121,77	0,06	3,99
2h	1997-06-12	1997-07-18	1997-06-22	1997-09-11	1997-06-30	1997-08-10	20 424,04	-8 490,16	-999,35	-248,48	0,14	4,53
2i	1997-06-26	1997-07-24	1997-07-01	1997-10-28	1997-07-07	1997-09-11	21 085,94	-9 179,64	-851,58	-385,91	0,17	5,03
2j	1997-07-10	1997-08-03	1997-07-14	1997-10-25	1997-07-19	1997-08-27	21 337,36	-9 452,45	-820,50	-351,90	0,17	4,82
2k	1997-07-24	1997-08-11	1997-07-28	1997-09-07	1997-08-03	1997-08-23	20 080,12	-8 237,89	-774,05	-431,95	0,19	5,12
2l	1997-07-31	1997-08-19	1997-08-06	1997-09-07	1997-08-09	1997-08-29	21 260,69	-9 370,46	-707,41	-462,82	0,17	5,32

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Shanghai 2015

Peak 2015-06-12

Figure	Last observed date	Median fit	80 % CI	80 % CI	50% CI	50% CI	A	B	C1	C2	Z	OMEGA
3a	2015-01-09	2015-04-27	2015-01-10	2015-07-08	2015-01-12	2015-06-20	4 489,05	-3 820,32	-249,77	-121,04	0,60	9,36
3b	2015-01-23	2015-02-13	2015-01-29	2015-05-19	2015-02-06	2015-02-25	5 216,15	-3 898,08	-162,78	-195,26	0,29	4,00
3c	2015-02-06	2015-05-13	2015-03-03	2015-08-13	2015-03-23	2015-07-04	4 755,18	-2 538,89	317,21	-294,74	0,36	6,81
3d	2015-02-20	2015-04-14	2015-03-09	2015-06-09	2015-03-22	2015-05-12	5 684,42	-3 683,32	-51,44	-292,45	0,30	6,24
3e	2015-03-06	2015-05-27	2015-03-27	2015-08-26	2015-04-24	2015-07-22	4 852,40	-2 776,95	230,00	-276,78	0,65	7,63
3f	2015-03-20	2015-07-16	2015-05-03	2015-09-27	2015-06-04	2015-09-01	5 642,76	-3 822,49	243,59	0,07	0,62	8,79
3g	2015-04-03	2015-08-01	2015-05-09	2015-09-26	2015-06-20	2015-09-06	5 702,69	-3 480,92	269,79	29,07	0,49	10,82
3h	2015-04-17	2015-08-06	2015-04-19	2015-10-07	2015-06-24	2015-09-11	16 315,02	-14 048,71	135,43	153,35	0,12	10,03
3i	2015-05-01	2015-05-18	2015-05-12	2015-05-24	2015-05-14	2015-05-21	13 962,75	-11 824,59	27,52	193,95	0,08	4,60
3j	2015-05-15	2015-06-13	2015-05-25	2015-07-22	2015-06-01	2015-07-07	12 484,74	-9 954,57	-293,32	-115,52	0,09	4,59
3k	2015-05-29	2015-06-18	2015-06-02	2015-07-12	2015-06-05	2015-06-30	5 626,14	-4 566,55	-294,25	369,54	0,58	5,52
3l	2015-06-05	2015-06-30	2015-06-11	2015-08-04	2015-06-20	2015-07-10	8 012,22	-6 023,62	108,29	189,57	0,28	6,95