Testing for the burst of bubbles in dry bulk shipping market using log periodic power law model

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Abstract

Purpose – The occurrence and unpredictability of speculative bubbles on financial markets, and their accompanying crashes, have confounded economists and economic historians worldwide. The purpose of this paper is to diagnose and detect the bursting of shipping bubbles *ex ante*, and to qualify the patterns of shipping price dynamics and the bubble mechanics, so that appropriate counter measures can be taken in advance to reduce side effects arising from bubbles.

Design/methodology/approach – Log periodic power law (LPPL) model, developed in the past decade, is used to detect large market falls or "crashes" through modeling of the shipping price dynamics on a selection of three historical shipping bubbles over the period of 1985 to 2016. The method is based on a nonlinear least squares estimation that yields predictions of the most probable time of the regime switching.

Findings – It could be concluded that predictions by the LPPL model are quite dependent on the time at which they are conducted. Interestingly, the LPPL model could have predicted the substantial fall in the Baltic Dry Index during the recent global downturn, but not all crashes in the past. It is also found that the key ingredient that sets off an unsustainable growth process for shipping prices is the positive feedback. When the positive feedback starts, the burst of bubbles in shipping would be influenced by both endogenous and exogenous factors, which are crucial for the advanced warning of the market conversion.

Originality/value – The LPPL model has been first applied into the dry bulk shipping market to test a couple of shipping bubbles. The authors not only assess the predictability and robustness of the LPPL model but also expand the understanding of the model and explain patterns of shipping price dynamics and bubble mechanics.

Keywords Bubble modelling, LPPL model, Positive feedback, Shipping crisis

Paper type Research paper

1. Introduction

Financial bubbles have gained substantial attention of academic researchers and industry over centuries. What characterizes a bubble is a rise in valuations of some types of assets, and the collapse of these valuations always cripples the economy and leads to subsequent pain (Filimonov and Sornette, 2013). Thus, many economists make attempts to diagnose the formation of bubbles and to detect the bursting of bubbles *ex ante*, so that appropriate counter measures can be taken in advance to reduce side effects arising from bubbles. The problem is however extremely difficult.

Superficially, financial bubbles are easily defined as transient upward acceleration of the observed price above a fundamental value, see Suzuki (1993), Shiller (2000), Kindleberger (2000), Sornette (2003, 2009), Shi (2005), Galbraith (1997), among others. The paradox is that the determination of a bubble requires a precise determination of what is the fundamental value. But the fundamental value is in general poorly constrained, so that it is not possible to distinguish bubbles from time-varying fundamentals. This drawback is however circumvented in studies of Johansen and Sornette (1999), Johansen et al. (1999), Johansen et al. (2000) and Sornette (2003), who propose the Log Periodic Power Law (LPPL) model, where a quantification is presented of the asset price dynamics leading up to a crash. The authors propose that a bubble is defined as a faster-than-exponential increase explained by the concept of positive feedback, see Sornette et al. (2013). When the positive feedback becomes dominant, the result is a self-reinforcing loop driving the market out of equilibrium. This loop continues until the bubble reaches its critical point. Based on this description, it seems possible to predict the bursting of speculative bubbles.

As regards the prediction of bubbles, Shiller (2000) is one among the few who have successfully predicted the bursting of bubbles ex ante, e.g. the crash of the dot-com bubble in 2000 and that of the housing bubble in 2007. However, Shiller and many others face the same fundamental drawback: using their methods they are unable to consistently and accurately predict the end date of a bubble (Gustavsson et al., 2016). The LPPL model provides a framework to detect bubbles and forecast their most probable end, reported by Sornette (2003). This approach has been applied to make a series of real-life tests and has been proven useful in predicting bubbles both ex post and ex ante in various markets, see Sornette and Zhou (2006), Sornette et al. (2009) and Zhou and Sornette (2003, 2005, 2008, 2009).

However, most previous studies present results that reinforce the theory, and only a few have highlighted both the potential and the limitations of the LPPL-model. The LPPL model is empirically appealing, as it provides a forecast of the date by which a financial crash might occur (Laloux et al., 1999). This is an important attribute relative to other methods of financial risk assessment. Furthermore, the LPPL model contains a component that captures the market's excessive volatility prior to a crash. This feature is consistent with several theoretical models of financial crashes as well as with empirical results, see for instance Levy(2008) and Choudhry(1996). Gustavsson et al. (2016), who apply the model to time series of eight bubbles, chosen based on their historical context, argue as well that the predictions of the LPPL-model in most cases are quite accurate. The robustness, however, can be questioned, as the precision seems to be dependent on when they are conducted.

Furthermore, several critical considerations merit our attention associated with fitting an LPPL model to financial data. First, Johansen et al. (2000) show that the parameter estimates of the LPPL model are confined within certain ranges and that it is these ranges that are the indicators of market crashes. This approach considerably restricts the number of classes of permissible LPPL fits to just those fits with parameters that fall within the specified ranges rather than to LPPLs with any values for their parameters. Second, the mechanism underlying the LPPL model is such that prices must be expected to increase throughout the bubble, which is largely in line with the rational bubbles literature, instead of what has been found in early empirical fits of the LPPL model.

When it comes to the international dry bulk shipping market, it is widely accepted that this market, as the major component of the world shipping industry, has been recognized as highly risky and volatile, as it is subject to a number of uncertainties, ranging from geopolitical shocks and the ever-changing world economy to fleet changes and the sensitive market sentiment (Chen et al., 2014). During highly risky and volatile shipping market,

topics like the investment timing and market entry/exit decisions have attracted much attention of researchers, as the asset prices may vary enormously, see for instance, Alizadeh and Nomikos (2007), Bulut *et al*. (2013), Goulielmos *et al*. (2012) and Merikas *et al*. (2008). In particular, the exit before the burst of a bubble would be of vital importance for investors, as the burst of a shipping bubble will erode net worth and cause businesses to fail, touching off a devastating effect for both individual investors and the whole industry. Against this backdrop, the study on shipping bubbles counts for much.

Although the research on shipping bubbles remains one of hot topics for both researchers and practitioners, only a handful of studies qualify shipping bubbles when discussing investment timing or decisions [Barberis *et al*. (1998), Duru (2013) and Greenwood and Hanson (2014) among others], largely as a result of the difficulties in detecting, defining and quantifying bubbles in shipping market.

Barberis *et al*. (1998) explain shipping bubbles as the over-extrapolation of current profit levels. Merikas *et al*. (2008) introduce the relative price ratio between second-hand/newbuilding values as an investment indicator and the indictor of detecting shipping bubbles as well. Greenwood and Hanson (2014) analyze the value of Panamax second-hand vessels from 1976 to 2011 with their own intrinsic value measure, and bubbles arise when firms over invest during good times.

All of these studies center on qualifying and explaining bubbles, instead of quantifying them. It is the first time, to our knowledge, the LPPL model has been first applied into the dry bulk shipping market to test a couple of shipping bubbles. We not only assess the predictability and robustness of the LPPL model but also expand the understanding of the model and explain patterns of shipping price dynamics and bubble mechanics. The examination of shipping asset bubbles' mechanics and the prediction of possible market regime switching, as a warning sign relating to market entry/exit, therefore, are of vital importance to both researchers and practitioners.

The remaining sections of this paper are as follows. Section 2 presents the model, the fitting procedure and the data. The empirical analysis of three bubbles in the dry bulk shipping market will be demonstrated in Section 3, and the final one summarizes the results.

2. Methodology
The LPPL model was developed to describe the dynamics of financial markets during bubbles and crashes. It is assumed that there are rational traders and noise traders who exhibit herding behavior that can destabilize the asset price (Filimonov and Sornette, 2013). In a bubble, the price undergoes certain oscillations that can reflect human grouping patterns (Sornette and Cauwels, 2015), and these social hierarchies manifest themselves in log periodic oscillations of the price with decreasing amplitudes, argued by Zhou *et al*. (2005).

These oscillations are superposed onto the super-exponential growth in a bubble. Super-exponential growth is however not sustainable and is bound to undergo a regime change before the singularity in finite time as an infinitely large price is not sensible in reality (Kaizoji and Sornette, 2010). The regime of unsustainable growth due to social imitation is described by the LPPL model.

2.1 The log periodic power law model
This model is first presented by Sornette *et al*. (1996) and the equation is defined as:

$$p(t) = A + B(t_c - t)^\alpha + C(t_c - t)^\alpha \cos(\omega \log(t_c - t) + \phi) \qquad (1)$$

where $p(t)$ is the logarithmic price at time t, A is the value that $p(t)$ would have if the bubble was to last until the critical time t_c; B is the decrease in $p(t)$ over the time unit before the crash if C is close to zero, and controls the growth rate of the magnitude. C is the magnitude of the fluctuations around the exponential growth as a proportion; t_c is the critical time; $t < t_c$ is any time into the bubble preceding t_c; α is the exponent of the power law growth; ω is the frequency of the fluctuations during the bubble; ϕ is a shift parameter.

Filimonov and Sornette (2013) present a modification of the equation where they expand the cosine term of the original equation and rewrite the equation (1) as follows:

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

$$(2)$$

where

$$C_1 = C \cos\varphi \qquad (3)$$

$$C_2 = C \sin\varphi \qquad (4)$$

The modification leads to two important implications, as explained by Filimonov and Sornette (2013).

First, the dimensionality of the nonlinear optimization problem is reduced from a four-dimensional space to a three-dimentional space. This significantly decreases the complexity of the problem.

Second, the cost function to be minimized now contains a single minimum instead of multiple minima, as long as the model is appropriate for the empirical data. The stability of the model is thereby significantly improved. Due to this transformation the need for complex search algorithms such as a taboo search is eliminated, and more simple algorithms, e.g. a Gauss–Newton algorithm, can be used without any reduction in the robustness of the estimation.

Taking into account all of these reasons, the methods in this article are based on equation (2) to investigate shipping bubbles.

2.2 Fitting procedure
Based on equation (2), there are four linear parameters (A, B, C_1, C_2) and three non-linear parameters (t_c, α, ω). To reduce the fitting parameters, equation (2) should be rewritten simply as:

$$\begin{cases} f(t) = (t_c - t)^\alpha \\ g(t) = (t_c - t)^\alpha \cos(\omega \ln(t_c - t)) \\ h(t) = (t_c - t)^\alpha \sin(\omega \ln(t_c - t)) \\ p(t) = A + Bf(t) + C_1 g(t) + C_2 h(t) \end{cases} \qquad (5)$$

By using an estimate of the non-linear parameters, these four linear parameters can be solved via:

$$
\begin{bmatrix}
N & \sum f_i & \sum g_i & \sum h_i \\
\sum f_i & \sum f_i^2 & \sum g_i f_i & \sum h_i f_i \\
\sum g_i & \sum g_i f_i & \sum g_i^2 & \sum g_i h_i \\
\sum h_i & \sum f_i h_i & \sum g_i h_i & \sum h_i^2
\end{bmatrix}
\begin{bmatrix}
\hat{A} \\
\hat{B} \\
\hat{C}_1 \\
\hat{C}_2
\end{bmatrix}
=
\begin{bmatrix}
\sum y_i \\
\sum y_i f_i \\
\sum y_i g_i \\
\sum y_i h_i
\end{bmatrix}
\tag{6}
$$

where $y_i = p(t_i)$, $f_i = (t_c - t_i)^\alpha$, $g_i = (t_c - t_i)^\alpha \cos(\omega \ln(t_c - t_i))$ and $h_i = (t_c - t_i)^\alpha \sin(\omega \ln(t_c - t_i))$.

Then there are only three non-linear parameters needed to fit. As the chosen values of these parameters should be the ones that minimize the root mean squared error between the data and the predicted value of the model, the optimal function is:

$$
F = \sum \left[A + Bf(t_i) + C_1 g(t_i) + C_2 h(t_i) - p(t_i) \right]^2
\tag{7}
$$

The generic algorithm is then adopted to fitting equation (7). The generic algorithm is a search heuristic that mimics the biological evolution process of natural selection and is routinely used to solve both constrained and unconstrained optimization problems. This algorithm is allowed to optimize parameters after encoding them into chromosomes without the limit constrains, and the search space starts at a set of problem solutions rather than a single individual with a characteristic of the parallel search. The solution with the best fitness, i.e. minimal optimal function, is taken as the solution.

The optimization procedure operates on the parameter space of the variables α and ω, using a rolling window technique, as explained by Filimonov and Sornette (2013). In this article, we use a moving window $[t_1, t_2]$ with a length of 10 months, scanning the whole range of dates. The start and end date of the analyzed period is changed in between iterations, consistent with the recommendations of Sornette *et al.* (2013) to make the predictions more statistically robust.

The ranges of values given for both α and ω are based on the observed parameters of crashes for many stock markets (Johansen, 2003). α must lie between 0 to 1, else we are dealing with some other types of process and not a power law characterized by the faster-than-exponential growth; ω empirically takes on values between 3 and 15, see Johansen and Sornette (2010). Researchers tend to rely on established ranges for α and ω, rather than any goodness-of-fit test, to identify the bubbles that precede crashes.

We constrain B to only take on negative values as well. In addition, we introduce constraints on the augmented Dickey–Fuller and Phillips–Perron values to filter out stationary fits which have no explanatory power in predicting the critical points, and only the non-stationary fits are accepted at a 1 per cent significance level (Gustavsson *et al.*, 2016).

3. Empirical analysis

Shipping markets can be treated as a complex network of interacting traders. Under this theory, the aggregate behavior of all traders and investors can be modeled as a complex physical network. This network of traders transitions between the state of idiosyncratic behavior and herd behavior. During the state of irrational herd behavior, the shipping prices may demonstrate an exponential growth. When the market displays exponential growth, they may not always display signs of periodic oscillations of increasing frequency. These increasing periodic patterns only occur shortly before the rupture, or market crash.

In the dry bulk shipping market, there are three boom-burst cycles since 1980s, as proposed by Chen *et al.* (2014). Thus, the LPPL model is used to investigate the exponential growth of prices and the possible periodic oscillations of increasing frequency. In addition,

we examine as well the predictive ability of the LPPL model to forecast the burst of bubbles through modeling of price dynamics on a selection of historical bubbles. This paper fits parameters for daily logarithmic Baltic Dry Index (BDI) by making use of the LPPL model, based on a rolling window with a length of 10 months, as explained in the Section 2, Methodology.

The daily BDI is the weighted average of voyage rates and time charter rates on major trading routes by four major ship types of dry bulk carriers carrying a range of commodities including coal, iron ore and grain. It is the aggregate index and provides an assessment of the price of moving the major raw materials by sea. It can be served as an indicator of dry bulk shipping market and the world economy as well.

Since this index was first published on January 4, 1985, we check the time series of BDI and make an attempt to identify bubbles in the dry bulk shipping market over the period of January 1985 to November 2016. The trend of BDI can be observed in Figure 1. All the data were retrieved from Baltic Exchange. Descriptive statistics, shown in Table I, reveal that the mean values of logarithmic changes of the BDI are significantly different from zero. Both skewness and excess kurtosis are significant such that the Jarque–Bera test rejects the null of normality at a 1 per cent level.

We identify a peak as one initiating a crash based on the criterion proposed by Johansen *et al.* (2000). First, there exists a peak for which there is no value higher than the peak during the previous one trading year (262 weekdays); second, the price trend continues to increase in general for at least six months; third, the drop in price, a drop in price of 25 per cent, i.e. down to 0.75 of the peak price, needs to occur over a period of 60 weekdays.
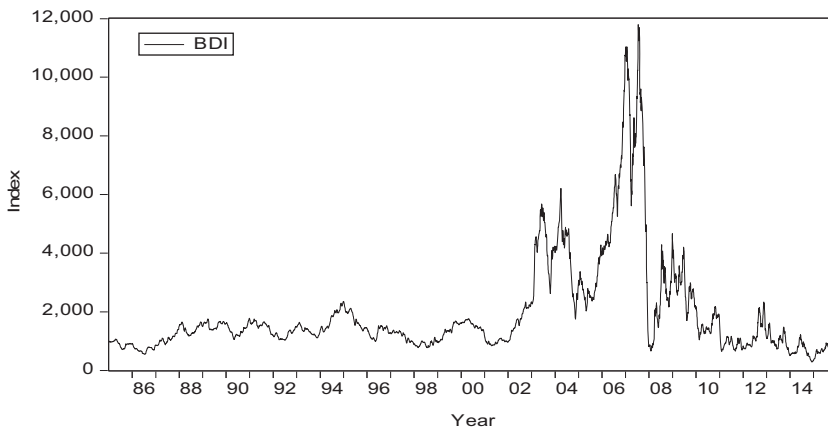

Figure 1.
Trends of BDI over
the period of January
4 1985 to November
20 2016

	N	Mean	Std. Dev.	Skewness	Kurtosis	J-B
BDI returns	8000	0.000027	0.015	0.113464	12.3773	29343.07

Notes: • All series are measured in logarithmic first differences; • N is the number of observations; • Figures in square brackets [.] indicate exact significance levels; • Skew and Kurt are the estimated centralized third and fourth moments of the data; their asymptotic distributions under the null are $T\hat{\alpha}_3' \hat{\alpha}_3/6 \sim \chi^2(1)$ and $T(\hat{\alpha}_4 - 3)' (\hat{\alpha}_4 - 3)/24 \sim \chi^2(1)$, respectively

Table I.
Descriptive statistics
of logarithmic first
differences of BDI
over the period of
January 1985 to
November 2016

Based on this selection criterion, and due to the lack of previous thorough empirical examination, we select three bubbles to base our analysis upon: the bubble in 1995, when the shipping market was negatively affected by severe overcapacity; the bubble of 2004, when the market was heavily hit by the influx of massive fleet capacity growth and heavy deliveries, as well as the crash of 2007-2008, one of the most spectacular and speculative bubbles since 1970s.

Then the LPPL model will be used and the fitting procedure is translated into a code working in MATLAB to accurately predict the end of speculative bubbles through modeling of asset price dynamics on these three bubbles (matlab coding for the fitting procedure can be acquired from authors). Highlighted in dark gray in each figure of the subsections below is the 50 per cent confidence interval of the critical points t_c, the results of the fitting procedure described above. The confidence intervals are plotted with the motivation that the date of the regime shift is a highly stochastic process and that the prediction of one specific crash date in fact might be misleading, and the 50 per cent confidence interval indicates the most probable period when bubbles are going to burst (Gustavsson *et al.*, 2016). The median date of the critical points is marked in the corner of each figure and gives guidance to where it is more likely for the regime shift to occur. In each figure, the last observed date is illustrated as well, which indicates where the *ex ante* prediction is assumed to be conducted.

In each graph, only a dozen of the resulting LPPL fits are plotted, regardless of how many resulting fits are produced. We do this for the sake of visibility, while the total number of fitted curves is given in the upper corner of each figure. Due to there, in most cases, being a lot of fitted curves we, instead of presenting the parameter values for each fit, present the parameter means based on all fits. These values are demonstrated for each estimation conducted one month prior to the peak.

3.1 Back test of the shipping bubble in 1995

The world economy moved into recession in 1992, but the dry bulk shipping market was not heavily influenced because it had not much burden from tonnage supply. After a brief dip freight rates recovered, reaching a peak in 1995. These years of relatively firm market had triggered heavy investment in dry bulk carriers leading to a huge orderbook, which went up to the peak in 1996. As deliveries were continuing up, the dry bulk market dropped since the second half of 1995 and moved into recession in 1996.

In this subsection, the time interval covers a moving window $[t_1, t_2]$ with a length of 10 months, as explained in the Methodology section. The initial starting date is $t_1 = 4$ March 1994, when the index was the lowest one year before the peak in 1995, while the end date t_2 runs form 13 January 1995 to 23 March 1995 in steps of five (trading) days. In these time intervals, the price of the index performed a faster-than-exponential increase. Means of parameters for LPPL equations can be found in Table II.

Figure 2 illustrates last three fitting results of a prediction conducted one month prior to the peak. The results are promising. The actual market peak date is 1 May 1995. The median is exactly the peak date, and the actual peak date is captured by the 50 per cent confidence

Table II.
Means of parameters for LPPL equations of predicting the bubble in 1995

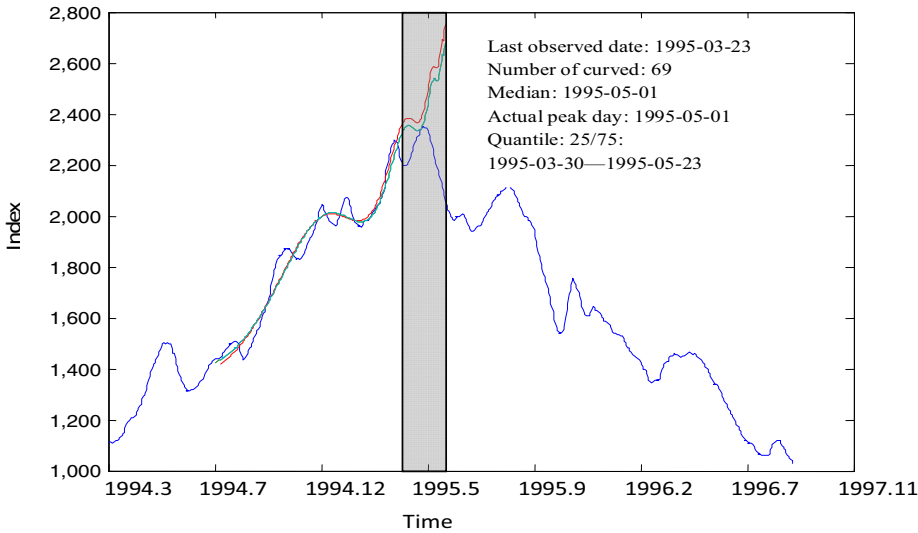| Period	A	B	C_1	C_2	α	ω
The bubble in 1995	7.9837	−0.0184	−0.00085	0.0021	0.6832	5.8664

Figure 2.
The LPPL model
fitted to the BDI prior
to the bubble in 1995

interval. The dark shadow box in the figure indicates a nearly two-month range of the actual market crash date. It can be observed that last three predicted crash dates t_c lie in the range using only data before the market crashes.

3.2 Back test of the negative bubble from 2004

Since 2002, the world economy recovered and continued to grow rapidly. Stimulated by the sound growth of the world economy, the seaborne trade gained a consecutive annual increase, especially for shipments of main bulk commodities. One-year time charter rate for a Panamax soared from an average of $7,499 per day in 2001 to a historic peak in 2004. The buoyant freight market brought a rocketing increase of orderbook, achieving 67.8 million dwt in 2004 from 33.5 million dwt in 2000 (Clarksons Shipping Intelligence Network, 2016). The tremendous construction of new buildings since 2002 also gave rise to large deliveries from 2004, which dragged down the dry bulk shipping market.
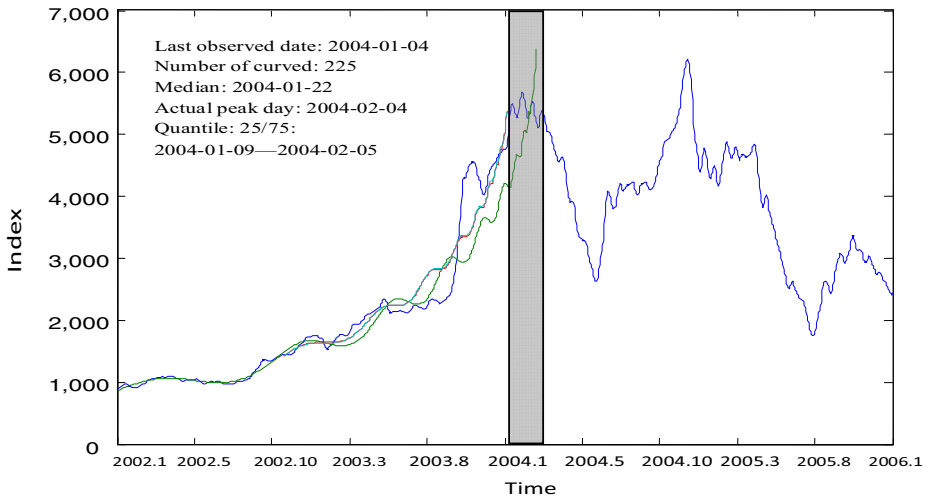
The time interval window is rolling with an initial start date t_1 = 2 January 2002 with the end date t_2 increasing from 13 November 2002 to 4 January 2004 in steps of five (trading) days. Excluding stationary time series, 225 curves are produced by the model. In these time intervals, the price of the BDI performed a faster-than exponential decrease. All the parameters can be seen in Table III.

From Figure 3, it is apparent that BDI prior to the slump in 2004 follows the characteristic pattern as proposed by the LPPL model; the prices seem to oscillate around a faster-than-exponential growth where the oscillations become smaller closer to the peak. These price movements act as they are expected to during a speculative bubble, according to

Table III.
Means of parameters
for LPPL equations
of predicting the
bubble in 2004

Period	A	B	C_1	C_2	α	ω
The bubble in 2004	8.6990	−0.0477	−0.00219	−0.00193	0.5993	12.9406

Last observed date: 2004-01-04
Number of curved: 225
Median: 2004-01-22
Actual peak day: 2004-02-04
Quantile: 25/75:
2004-01-09—2004-02-05

Figure 3.
The LPPL model
fitted to BDI prior to
the bubble in 2002

the LPPL framework. It can also be seen from Figure 3 that the actual first peak date of February 4, 2004 is encapsulated by the 50 per cent confidence interval, and the median appears only 9 days ahead of the actual peak day. It implies that an *ex ante* estimation conducted one month prior to the actual peak date would have accurately predicted the upcoming change in regime.

3.3 Back test of the negative bubble from 2007 to 2008
Starting in 2005, the strong and sustainable growth of China, India and other dynamic developing countries was increasingly becoming the main driver of the world economy. China's GDP growth remained above 10 per cent from 2003 and gained a record high of 11.5 per cent in 2007. The seaborne trade of dry bulk shipping slowed down significantly in the wake of a globally gloomy economy and a lack of demand for steel. On the supply side, ship owners have ordered massive tonnage during the shipping boom since 2004, and the market was seriously hit by massive deliveries. The total dry bulk fleet in 2012 was 615.5 million dwt, increased by about 130 per cent since 2000. Resulting from both sluggish demand and surplus of tonnage, charter rates of dry bulk vessels plummeted and so did ship values of both second-hand and newbuilding vessels. For example, one-year timecharter rate for a Panamax dripped from a record high level of $71,500 per day in 2007 to an average of $4,350 per day in 2012 (Clarksons Shipping Intelligence Network, 2016).

When fitting the LPPL equation to the time series preceding the peak we arrive at the results presented in Figure 4. The time interval window is rolling with an initial start date $t_1 = 25$ January 2006 with the end date t_2 increasing from 6 December 2006 to 10 October 2007 in steps of five (trading) days. In these time intervals, the price of the CSI300 index performed a faster-than exponential decrease.

It can be seen from the figure that the indices during this period follow the characteristics of LPPL. It can also be seen from Figure 4 that the 50 per cent confidence interval captures the actual peak date, or regime shift of 13 November 2007, while the median date is only six days later. This means that if an *ex ante* prediction would have been performed on the Baltic indices one month prior to the actual peak in 2007, it would have given us a good estimation of the upcoming date of the regime shift (Table IV).

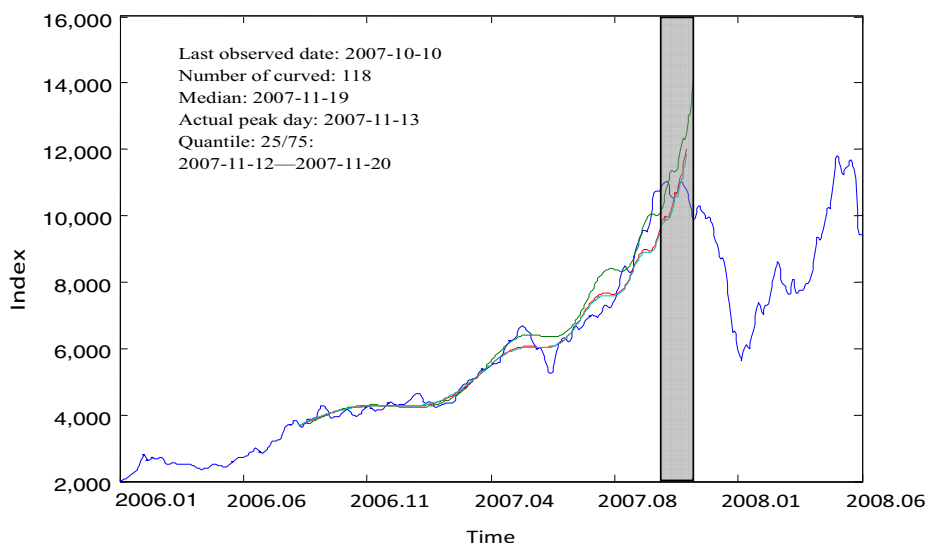Last observed date: 2007-10-10
Number of curved: 118
Median: 2007-11-19
Actual peak day: 2007-11-13
Quantile: 25/75:
2007-11-12—2007-11-20

Figure 4.
The LPPL model
fitted to BDI prior to
the bubble in 2007
with the last observed
date one month prior
to the peak day

Table IV.
Means of parameters
for LPPL equations
of predicting bubble
in 2007

Period	A	B	C_1	C_2	α	ω
The bubble in 2007	9.4575	−0.0436	−0.00263	0.00239	0.5923	9.3734

3.4 Testing the robustness of the model

In testing the robustness of the model, we proceed by changing several parameters or conditions and see whether there is any distinct difference in results. First, we test the influence of the last observed date on the robustness of the model by setting the last observed date two months and two weeks prior to the actual peak, respectively, and repeat the estimation process. Second, we change the length of the rolling window to be 15 months, increased from 10 months. Here, we only present results of making the comparative analysis conducted in the case of predicting the bubble in 2007, and results of the others can be acquired from authors.

When performing an estimation where the last observed date is two months prior to the peak, we reach similar results to those of Figure 4. It can be seen from Figure 5(a) that the median date is shifted four days to the left in the graph, while the confidence interval is slightly broadened compared to the first estimation of Figure 4. These results indicate that an *ex ante* prediction conducted two months prior to the peak would have yielded almost the exact same conclusions regarding the upcoming regime shift as those of the estimation performed one month prior to the peak. However, the broadened confidence interval indicates some additional uncertainty, which is expected when performing an earlier *ex ante* prediction.

From Figure 5(b), where the last observed date is set two weeks prior to the peak, it is evident that both the confidence interval as well as the median are shifted a couple of days later compared to the estimation of Figure 4. As the LPPL framework suggests that the

Last observed date: 2007-09-12
Number of curved: 81
Median: 2007-11-15
Actual peak day: 2007-11-13
Quantile: 25/75:
2007-11-02—2007-11-16

(a)

Last observed date: 2007-10-31
Number of curved: 102
Median: 2007-11-21
Actual peak day: 2007-11-13
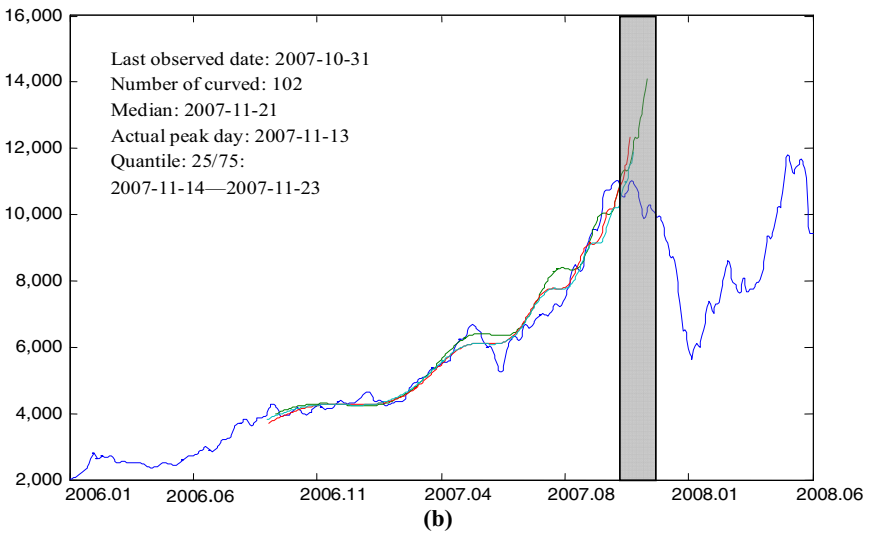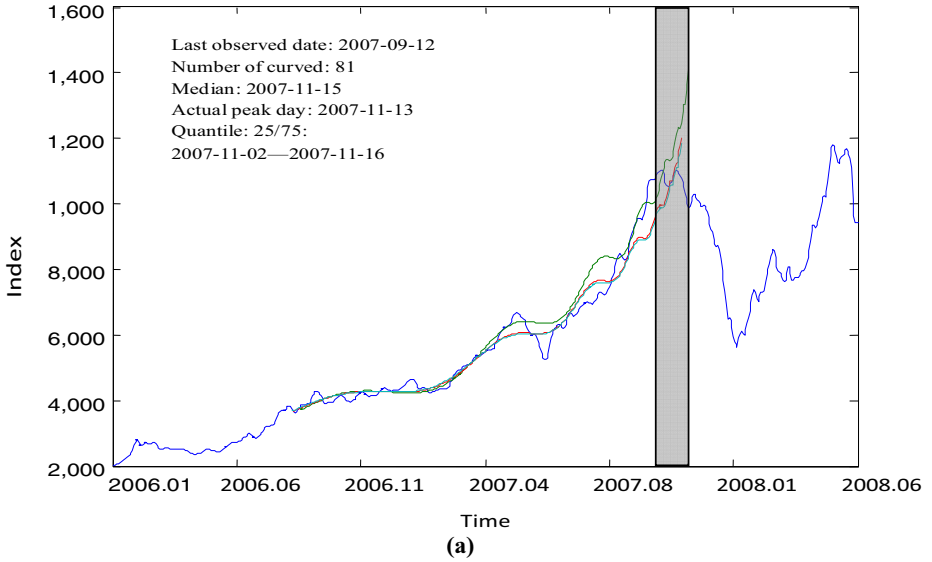Quantile: 25/75:
2007-11-14—2007-11-23

(b)

Figure 5.
(a). The LPPL model
fitted to BDI prior to
the bubble in 2007
with the last observed
date two months
prior to the peak day
(b). The LPPL model
fitted to BDI prior to
the bubble in 2007
with the last observed
date two weeks prior
to the peak day

regime shift should occur when the oscillations reach zero, one possible explanation for this behavior could be that the amplitude of oscillations is already quite low when the predictions are conducted. The confidence intervals will continue to move to the right in the graph when moving the last observed date to the right, as long as the oscillations soon after the last observed date are close to zero.

This means that estimations performed two months and two weeks prior to the actual peak day would have yielded similar conclusions regarding the upcoming change in regime.

Results that are largely unaffected by when the predictions are conducted are what one wishes to see when examining a bubble.

In Figure 6, the LPPL equation is fitted to Baltic indices one month preceding the downturn of 2007 based on the rolling window of a length of 15 months. It is apparent that the indices follow the characteristics of LPPL. It is also evident that the predictions of the LPPL model in this case produce similar results as those obtained based on the first estimation of Figure 4. The confidence interval is slimmer, but the actual peak day on 13 November is still captured.

4. Further discussion

In our study, the actual peak date is not known when conducting *ex ante* predictions, and the date of the regime shift is a stochastic process; therefore, the prediction of the bursting of a speculative bubble at one critical point may be misleading. Instead of looking at estimation of one crash time, we make an attempt to estimate a period when the bubble will burst at certain confidence intervals. The timing of crash can happen in the middle of, immediately after or long after this estimated period, although our empirical results exhibit the capture of actual peak days within the 50 per cent confidence interval.

4.1 Findings relating to the model

The period of predicted end dates of a bubble, in this way, should be interpreted as the start of a period when the market becomes more sensitive to negative external events, which is consistent with the analysis by Gustavsson *et al.* (2016), who propose that the model's ability to predict the bursting of bubbles is not as strong as has been claimed in previous studies, and the results of all estimations have to be interpreted in a more careful manner.

Second, the theory of the model only applies to bubbles that are driven by the endogenous factors of the LPPL framework and does not claim that all bubbles follow this pattern, see Johansen and Sornette (2010). In reality, factors triggering a bubble are complex, which may be not only driven by endogenous super-exponential growth but also by other factors. In this case, we propose that the LPPL model may not be enough to explain and
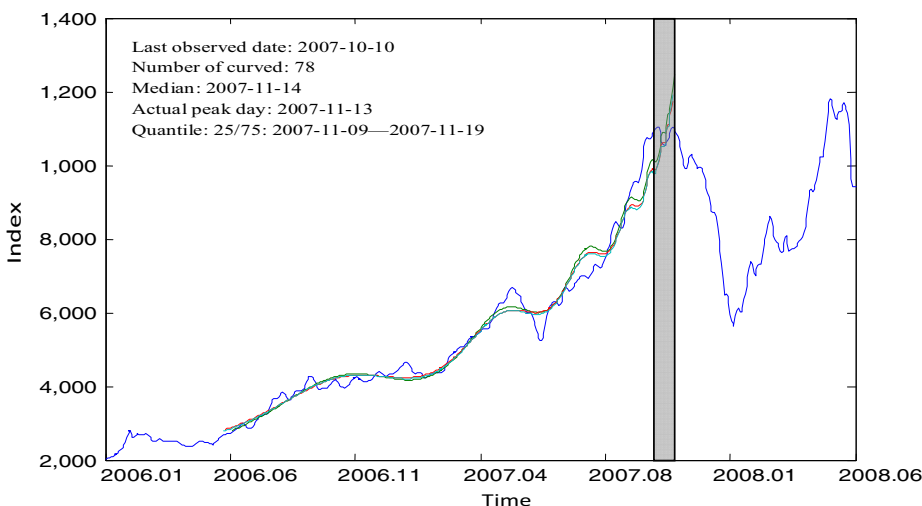
Last observed date: 2007-10-10
Number of curved: 78
Median: 2007-11-14
Actual peak day: 2007-11-13
Quantile: 25/75: 2007-11-09——2007-11-19

Figure 6.
The LPPL model
fitted to BDI prior to
the bubble in 2007
with the rolling
window of 15 months

predict the end of a speculative bubble in some cases, where exogenous shocks may have significant influence on the burst of a bubble.

For example, we can see two peaks during the period of 2007-2008. The burst of the bubble in November 2007 was followed soon by the outbreak of the financial crisis occurring in the USA, which can be deemed as a critical exogenous factor to the market. It is argued by Gustavsson *et al.* (2016) that if such an exogenous event occurs before the speculative behavior has reached maturity, the price will not fall drastically as they are not sufficiently overvalued to begin with. A dip in prices can be expected as they are affected by exogenous shocks, and the index quickly returns to the trend and thereafter continues to rise. The downturn in early 2008 was triggered by an unsustainable faster-than-exponential growth of a bubble and the negative credit crisis spread all over the world.

We have already observed that the 50 per cent confidence interval and the median are shifted as the last observed date is changed. It indicates that the time series is sensitive to a regime shift just following the last observed date, so that the regime could be influenced significantly by both exogenous and endogenous factors.

Third, it is evident from all figures that the oscillations decrease in amplitude as the bubble approaches its regime shift. The possible explanation for this could be the results of diverse investors' psychology and investment actions. When the market reached a record peak, it is argued that investors get more anxious, and they are less confident of the future movements of the market, while at the same time, some believe the market continues to increase and are afraid of missing out on further increases. Heterogeneous views of the market and investment strategies of market participants result in frequent trading actions of sell-outs and buy-ins over a short period, leading to more frequent oscillations with lower amplitude as the bubble gets older.

4.2 Economic explanations of bubbles

It is demonstrated by the empirical analysis that during three bubble phases, the price index follows a faster-than-exponential power law growth process, accompanied by log periodic oscillations. When resources are unlimited, exponential growth can go on indefinitely. This is different in systems of finite size, where there is competition for limited resources (Sornette and Cauwels, 2015). When the resources are not unlimited, prices will follow an unsustainable track, bringing the market to a critical state characterized by the existence of an intrinsic end-point.

The key ingredient that sets off an unsustainable growth process, which is a prerequisite for a financial bubble, is positive feedback. Positive feedback is often caused by imitation: when investors display herd behavior, a price increase triggers even greater demand due to the strengthening of the herd, and consequently, the equilibrium of supply and demand breaks down.

In the dry bulk shipping market, smart money flows in at the early stage when the market is picking up, which leads to a first wave of price appreciation. Attracted by the prospect of extrapolated higher returns, more investors follow. At some point, demand goes up as the price increases, and the price goes up as the demand increases. This is a positive feedback mechanism, which fuels a spiralling growth away from equilibrium. The positive feedback before bubbles in the dry bulk shipping market could be revealed distinctly by Figures 7-9 (the dry bulk shipping market is generally divided into three sub-markets by ship size: the Capesize, the Panamax and the Handymax/Handy markets). Before crashes in the year of 1995, 2004 and 2007, the dry bulk shipping market was booming, witnessed by the sharp hike in the second-hand ship market. When second-hand ship prices go up, orders for new vessels pick up, together with the increasing volume of second-hand ship sales.
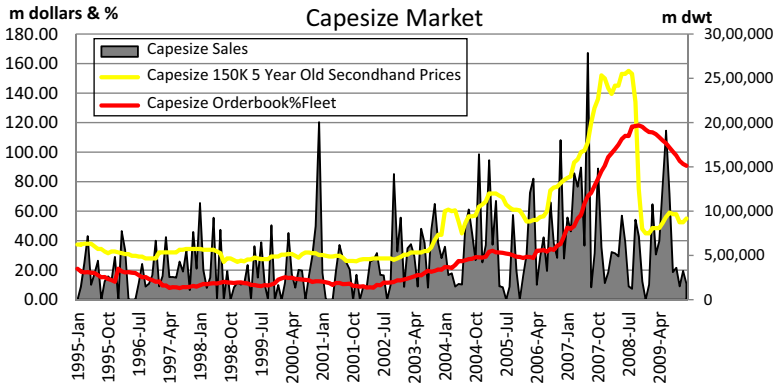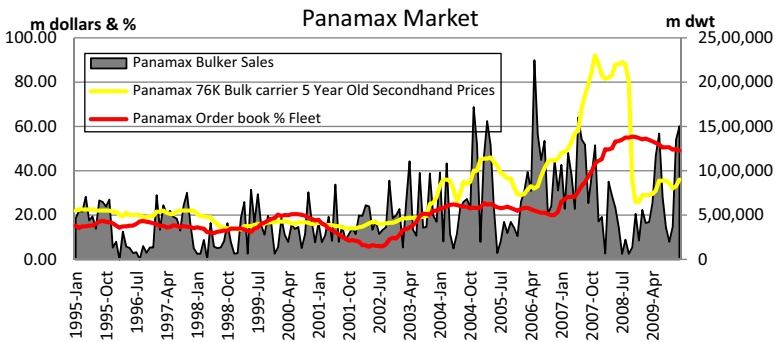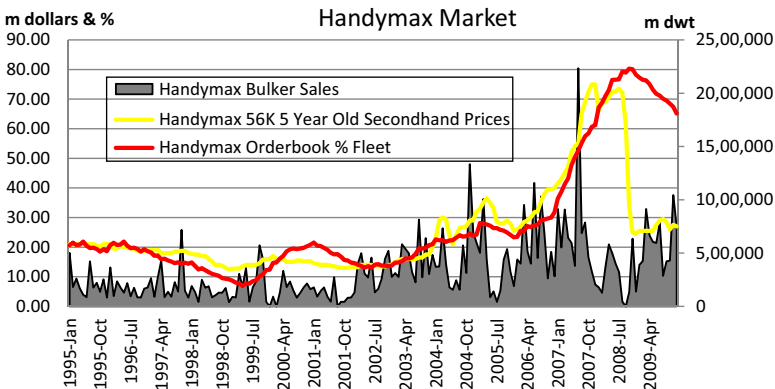
The process of positive feedback operates not only directly from past price increases but also from auxiliary psychological changes of investors that the past price increases helped generate. As prices continue to rise, the level of exuberance is enhanced by the price rise itself. Investors, their confidence and expectations buoyed by past price increases, bid up ship prices or freight rates further, thereby enticing more investors to do the same, so that the cycle repeats again and again.

Investors buy and sell ships in anticipation of future market prices, but those prices are contingent on the investors' expectations. Investors are striving to do the right thing, but they have limited abilities and certain natural modes of behavior that decide their actions when an unambiguous prescription for action is lacking. In the absence of knowledge and unlimited abilities, participants must introduce an element of judgment or bias into their decision-making. As a result, outcomes are liable to diverge from expectations.

5. Conclusions

The aim of this study is to analyze the predictive ability of log periodic functions which, according to some researchers (Sornette and Zhou, 2006; Sornette *et al.*, 2009) can be used to forecast accurately turbulent changes of certain phenomena, such as the changes observed on the financial markets.

The evaluation of this method's accuracy is based on three log periodic models constructed for the evaluation of Baltic index behavior over different periods. The objective is to predict the bursting time of shipping bubbles' occurrence. We find that all the bubbles analyzed (the bubble in 1995, the bubble in 2002 and the crash in 2007) behave in accordance with the expected characteristics of the LPPL model. The price movements leading up to the regime shift are characterized by faster-than-exponential growth and show clear oscillatory patterns where the oscillations decrease in amplitude leading up to the regime shift. In our analysis, actual peak dates are encapsulated by the confidence intervals of critical points, bolstering the argument that the model has the good predictive ability.

However, we also observe in some cases that the index continues to rise with small oscillatory patterns even after the predicted regime shifts. Furthermore, the comparative analysis by changing the last observed dates and the number of estimations for each bubble implies that the LPPL model may be sensitive to the time when the predictions are conducted and sensitive to the number of estimations for each prediction. In this way, to predict one crash date may be misleading when conducting the *ex ante* prediction, and to produce a period of critical points within some confidence intervals is more reliable.

It is worth nothing from this paper that fitting the model into historical data and using it to generate prediction in real time are two different things and the latter is much more difficult. The LPPL model is only applicable to the bubble driven by endogenous factors, while in reality, exogenous shocks could have significant influence on bubbles.

In considering the economic triggers for bubbles in the shipping market, to speak of supply and demand as if they are determined by forces that are independent of the market participants' expectations is quite misleading. Rising ship prices often attract buyers and vice versa, as evidenced by rising ship sales. The self-reinforcing trends cannot persist if supply and demand curves are independent of market prices. Hence, market investors' expectations could also behave as one of fundamentals when the positive feedback mechanism works.

Thus, it is not enough to just rely on this model to guide our investment decisions, more analyses are needed, such as the fundamental study, the exogenous factors/news influencing the dry bulk shipping market.

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