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A Case Study on the Bucharest Stock Exchange

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Herding Behaviour, Bubbles and Log Periodic Power Laws in Illiquid Stock Markets. A Case Study on the Bucharest Stock Exchange

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Abstract

In this paper we investigate the herding behaviour of the Bucharest Stock Exchange (BSE), using log periodic power laws models.

By analysing the behaviour of the most speculative index from the Bucharest Stock Exchange, the BET-FI, we are able to demonstrate that Log-Periodic Power Law (LPPL) models are a useful tool for recognizing the behaviour of a stock market bubble, and have good abilities for predicting the critical point of a bubble. From our statistical investigation, it turns out that an iterative calibration of the model for the BET-FI regime leads ex post to a rather accurate forecast of the stock market crash in January 2008. Next, by using the same methodology, the anti-bubble regime from 2008 is used for a statistical fit. We then find an accurate "prediction" of the local point of phase transition on 27 October 2008.

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Keywords: Log-periodic Power Law, Stock Market Bubble, Crash

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1. Introduction

1.1. Context

At this moment, the researchers and practitioners involved in the study of economic phenomena are facing a critical time, when the very foundations of economics are in question; the economy is a complex system and understanding the dynamics of such a system cannot be made without using a set of tools, methods and techniques combining mathematical rigour, empirical observation and a methodological approach coming from physics. This combined approach, also known as 'econophysics', has proved to be extremely useful in understanding the dynamics of complex phenomena regarding the financial markets as a whole and especially the stock markets.

The history of stock markets may be regarded as a succession of stationary regimes, upwards and downwards trends, and also severe crashes. Large financial crashes, such as the Tulip Mania (17th century, in the Netherlands) and the South Sea Bubble (18th century, in Great Britain) had an influential effect on the economic environment of their time. In more recent times, the 20th century had plenty of such catastrophic events, including the Great Depression in the 1930s, Black Monday in 1987, 'dot.com' bubble in the late 1990s in the US and the stock markets crash in 2007.

In the context of the financial and economic crisis, it is essential to establish a general framework in order to identify the bubble behaviour of a stock price, and to estimate the most probable time of a crash. The detection of a speculative stock market bubble and the estimation of the critical point, i.e. the moment when the transaction price drops dramatically, are topics which are extensively discussed by both researchers in academia and practitioners.

In order to understand the origin and the evolution of stock market bubbles, which in most of the cases end in a severe crash, we need to address several fundamental questions, as the entire process of building a model for a stock market crash depends on the responses to these questions. Synthetically, these questions can be stated in the following manner (Sornette, 2003): What is a stock market crash? What is the mechanism of appearance and evolution of a stock market crash? What is the cause of a stock market crash? Can the moment of appearance, as well as its magnitude be predicted?

The answers to these questions can be found after the careful examination of the theoretical models of stock market crashes, as well as after applying appropriate quantitative methods on the stock prices time series, as well as after testing some fundamental hypotheses related to the predictability regime of these data series. There is an extensive literature on this subject, but most of the research deals with the modelling of stock market bubbles in the case of very mature markets, while small, illiquid markets seems to be neglected.

In this paper we investigate the behaviour of such a market, the Bucharest Stock Exchange, and we test some of the fundamental hypothesis related to herding and stock market bubbles.

1.2. The Bucharest Stock Exchange: From exchange of goods to a modern institution of the capital market

Against the background of a more than 70 years-old tradition- which actually dates from the first years of the 18th century according to the Western countries model, Romanian history records the establishment of the first stock exchange in 1881, when, after adopting the *Law on exchanges, exchange and commodities brokers*, this institution characteristic of a market economy started to become visible within the Romanian economic environment. Based on the French model, this law stipulated, by Royal Decree, the establishment of commodities and stock exchanges, the Bucharest Stock Exchange (BSE) was inaugurated on the 1 December 1882, in the Trade Chamber building, while the quotation lists of the first Romanian traded corporations were published in December 1882 in the Official Journal of Romania. The 1989 Revolution, which marked an important turning point in the national history, has imposed, through the resulting reform programme, the necessity to revive the capital market and its related institutions, including the BSE. A group of specialists in various economic sectors benefitted from the chance, sometimes asserted as unique in a lifetime, to revive this market, beginning in 1992, the starting point of this process The recovery process was not easy. Starting with the legislative area it took two years before the adoption of the law on transferable securities and stock exchanges, accompanied by measures of educating the general public with regard to some concepts, long forgotten or never known in the past. This process is still going on.

1.3. The Bucharest Stock Exchange in a regional context

Currently, the Bucharest Stock Exchange calculates and publishes a few indices: BET, BET-C, BET-FI, ROTX, BEX-XT, BET-NG, RASDAQ-C, RAQ-I, RAQ-II. Here we will only refer to BET and BET-FI as these indices will be the ones most used in our study.

BET, the first index developed by the BSE, is the reference index for the BSE market. BET is a free-float weighted capitalization index of the most liquid 10 companies listed on the BSE regulated market.

As the first sectorial index launched by BSE, BET-FI reflects the price movements of the investment funds (SIFs) traded on the BSE regulated market. BET-FI is a free float weighted capitalization index. The index methodology allows BET-FI to become an underlying support for derivatives and structured products. The year 2007 branded BSE’s first year as a market operator in the integrated EU financial market and the stock exchange’s 125th anniversary.

The evolution of BSE in 2007 was mainly determined by the change of foreign investors’ perception of the Romanian economy and its growth perspectives. In an international environment favourable for investments, Romania’s integration in the EU and the related change of perspective have rapidly been reflected, even at the beginning of 2007, by the various segments of the local financial market. At the beginning of that year, the national currency continued its upward trend, the interest rate went down and the capital market indices registered new historical records.

In order to position the Bucharest Stock Exchange in the Central and East European (CEE) countries we will use stock market capitalization as an indication of the size and performance of stock markets, and therefore the importance of private investor capital in the economy. In the following graph (Figure 1) we plotted the figures which are aggregations of the market capitalization of the most representative stock exchanges of each Member State from the CEE countries.

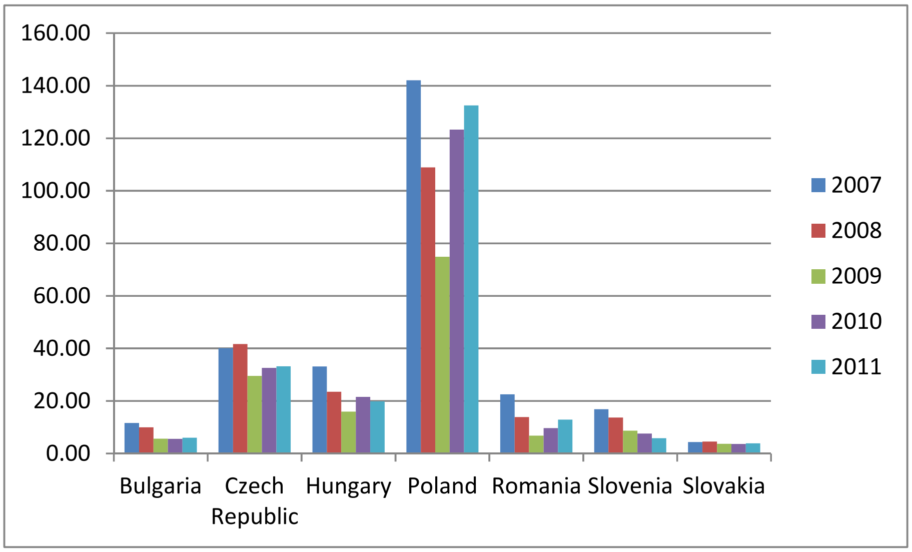

Figure 1. Market capitalization (in billions of euros).

According to the most recent available data, Romania occupies the fourth place, after Poland, the Czech Republic and Hungary.

In recent years, the number of active investors in the stock market has dramatically decreased, and reached its lowest level in September 2011, since 2005, the year when the BSE first began publishing statistical data on the number of active accounts on the market. The number of accounts through which the investors had bought shares in September 2011 was only 2800, an absolute minimum in the last six years, although the 2011 corrections were not nearly as steep as those suffered by the stock market in 2008 when the index fell by over 75 per cent.

In 2007, when all markets reached a peak, BSE had 20000 active accounts. A great many investors left when Lehman Brothers collapsed. When the market began to recover in 2009, the investors gradually reappeared. In 2010 two decisions were taken but they did not please the investors: the requirement to report to NAFA four times a year and another year-end reporting, and also the introduction of a 16 per cent tax on profits compared to just 1 per cent previously. The increase in VAT from 19 to 25 per cent, while public servants revenues fell by 25 per cent were other aggravating factors affecting the BSE.

News of Greece's near default, the nationalization of some European banks, and the predicament of the credit institutions have all scared investors even more and stopped them from trading.

The decreasing trend has however been reversed in the first semester of 2012, mainly due to the dividends distribution period, as the big players have not yet returned to trade on the Romanian market.

The new trend can be gleaned from the evolution presented in the following graph (Figure 2).

Figure 2. Evolution of the BET and the BET-FI indexes: 2011-2012

2. Literature Review And Hypotheses

2.1. The origin and evolution of stock market bubbles

Building a theoretical model for stock market bubbles has proved to be extremely difficult, especially due to the lack of agreement among economists regarding a coherent definition of stock market bubbles.

From a theoretical perspective, the concept of a stock market bubble could be embedded in one of the following frameworks: the Efficient Market Hypothesis (EMH), the Rational Bubble View (RBV) or Log-periodic Power Laws (LPPL).

From the classical definition of Fama (1970), until the more recent developments of Timmerman and Granger (2004), the Efficient Market Hypothesis is inseparable from the concept of information and the mechanism of the incorporation of a certain set of information in the trading price of a financial asset. Under the EMH approach, all the relevant information is immediately reflected in the stock prices, so tomorrow's price change will reflect only the tomorrow's information, and will be independent of today's price change (Malkiel, 2003). As the information is unpredictable, the price changes must be unpredictable and purely random.

In this context, the concept of a bubble is questionable, since at any moment the prices reflect all the available information. From this point of view, a crash is only the effect of negative information which is incorporated in the trading price for a short period of time and it is virtually impossible to predict the magnitude or the time of a stock market crash.

The Rational Bubble View paradigm (Friedman and Abraham, 2007) assumes the existence of a fundamental value for a financial asset (intrinsic value), V_t, which is unobservable, and a directly observable transaction price P_t. The speculative bubble can be defined in this context as an abnormal deviation of the transaction price from the intrinsic value ($B_t = P_t - V_t >> 0$) and, consequently, the stock market crash can be seen as an event consisting of the sudden evolution of $B_t = P_t - V_t$, from a large, positive value, to zero, or even a negative value. The major challenge arising from this approach is how to define and estimate the intrinsic value of a financial asset.

Using the LPPL approach, Sornette and Johansen (1999) have analysed the stock market bubbles and crashes at the macroeconomic and microeconomic levels. From a macroeconomic point of view, the model assumes that we are dealing with rational markets which have incomplete information. In such a market, the trade price reflects not only the fundamental value but also the future expectations related to profitability and risk. From a microeconomic point of view, the Sornette–Johansen model assumes that investors (rational investors and noisy traders) are connected locally through certain networks that govern their anticipations regarding market earnings. Also, along with this imitative behaviour manifested on a horizontal level, each investor receives information on a vertical level from other public or private sources. Moreover, trading decisions depend on the decisions of other members of the network, but may also include external influences.

Following these interactions, investors develop imitative behaviour, pushing the market into a speculative bubble regime, which may end in a severe crash, or may exhibit a smooth evolution around a descending local trend.

In this approach, a stock market bubble is a market regime where trading prices exhibit a super-exponential behaviour, i.e. the price changes have an exponential evolution.

2.2. The Johansen-Ledoit–Sornette (JLS) model

At a microscopic level, JLS (2000) and Sornette (2003) assume that the *noise traders* are locally connected through a network, and every investor could be described by two trading positions: $s_i = 1(buy)$ or $s_i = -1(sell)$.

If, in addition, for every investor *i* there are *N(i)* investors in the local network, then the state of the investor *i* is a result of the following Markov process: $s_i = sign(K\sum_{k\leq N(i)} s_k + \sigma\epsilon_i)$, where $K>0$ controls for the herding behaviour: $\sigma>0$ controls for the idiosyncratic behaviour; and ϵ_i is a Gaussian white noise.

According to this model, at the origin of stock crashes is not a chaotic type of behaviour, but an ordered one, resulting from the herding effect among investors. Imitative behaviour of irrational agents leads to the development of a speculative bubble. When this trend reaches a critical point, most investors will take a short position, leading to a dramatic decrease in the transaction price. A crash is not yet a certain event, but is characterized by a certain probability distribution: therefore, to invest in the context of a speculative bubble is a rational choice, because the risk of a crash is compensated by the expected large returns, since the probability that a speculative bubble will collapse suddenly in a crash is negligible.

At the macroscopic level, according to the mean field theory, an imitative process could be described by the hazard rate *h(t)*, as the solution of a differential equation:

$$\frac{dh}{dt} = Ch^{\delta}, \tag{1}$$

where $C>0$ and $\delta+1>1$ is the average number of interactions among investors. The hazard rate *h(t)* is the probability per time-unit of having a crash, conditioned by the fact that the crash will not happen until the time *t*.

The solution of equation (1) is $h(t) = \left(\frac{h_0}{t_c - t}\right)^{\alpha}$, with $\alpha = \frac{1}{\delta-1}$, t_c being the critical time of the crash.

There are several restrictions in this formula:

- $\alpha > 0 (\delta > 1)$, meaning that the hazard rate increases before the critical time;
- $\alpha < 1 (\delta > 2)$, meaning every investor is connected via a local network with at least two other investors.

The behaviour of the hazard rate before the critical time could be expressed using a periodical-power law, following the Ising model, which originated from physics:

$$h(t) \approx A + B(t_c - t)^{\beta} + C(t_c - t)\cos[\omega \ln(t_c - t) + \phi]. \tag{2}$$

2.3. LPPL fit for stock market bubbles

Under risk neutrality and rational expectations hypothesis, JLS (2000) have deduced the price dynamics before the crash as:

$$\ln \frac{p(t)}{p(0)} = k \int_{t_0}^{t} h(u) du \ .$$

The reasoning behind this expression is that the crash probability should be compensated by larger price changes, prior to the stock market crash (Blanchard, 1979).

Sornette (2009) compares seismic activity to the evolution of speculative bubbles, and deduces the evolution law for stock prices before and during the crash, which is seen as a critical time. Thus, the trading price before the crash follows a log-periodic power law:

$$\ln p(t) \approx A + B(t_c - t)^{\beta}\{1 + Ccos[\omega \ln(t_c - t)^{\beta} + \phi]\}, \tag{3}$$

where *p(t)* is the price at moment *t*; t_c is the critical time (the most probable moment of the crash); and $\beta, B_0, B_1, \omega, \phi$ are the parameters of the model which give its log-periodic feature.

In order to have a proper specification of the model, several constraints are applied to the parameters:

- *A>0* - usually this is the price at the critical time t_c;
- *B<0 ;*
- $C \neq 0, |C| < 1$ – this parameter controls the magnitude of oscillations around the exponential trend;
- $0 < \beta < 1$ – this parameter controls the growth rate of the magnitude, and is the most important feature capturing the imminence of a regime switching, as this value is close to zero;
- $\omega \in (0, \infty)$ - controls for the amplitude of oscillations;
- $\phi \in [0,2\pi]$ – this is a phase parameter.

Although equation 3 above is written in terms of the logprice, there are many papers in which the raw trading price is used in order to estimate the critical time, and the literature is quite inconclusive whether the logprice or the raw price shoud be used. JLS (2000) have applied these models to successfully predict famous crashes like the one in October 1987, and, for the Brazilian market, Cajueiro et al. (2009) have applied these models to predict the catastrophic behaviour of the price series of 21 stocks. In recent years, the Financial Crisis Observatory (ETH – Zurich) has released predictions about the bubble behaviour of different assets and they have succeeded in predicting two famous events of this type: the Oil Bubble – 2008, and the Chinese Index Bubble – 2009.

Fantazzini and Geraskin (2011) provide an extensive review of theoretical background of the LPPL models, estimation methods, and various applications, pointing out that, although the literature on this subject is heterogeneous, the LPPL fit for asset bubbles could be a useful tool in predicting the catastrophic behaviour of capital markets as a whole.

Moreover, even using such a model, the prediction of the critical time is not very accurate, Kurz-Kim (2012) shows that LPPL models could be used as a early warning mechanism of regime switching in the case of a stock market.

2.4. Herding behaviour

Although these models have been applied on a large variety of markets and assets, there is one question that arises from the very foundation of the log-periodic power laws: Is the robustness of such models influenced by the market dimension, in terms of liquidity, capitalization, or number of investors?

The explicit form of the LPPL model, which fits the price dynamics before the crash, resides in the immitative behaviour of the investors, connected in local networks, and their actions are influenced by the behaviour of the members of the same network.

Yet, there is a difference between the very liquid and illiquid markets, between markets with large number of investors and markets with a relatively small population of investors.

The herding behaviour in small markets is not an issue on which a strong consensus has been reached in the literature.

Lee (2009) argues that herding in illiquid markets accompanies expansions in trading activity, whereas herding in liquid markets accompanies contractions in trading activity. In other words, a bubble signature is more likely to be detected in an illiquid stock market than in a well-established stock market.

Based on the expected pay-off function defined by Kim and Mangla (2012), we have deduced that the expected payoff of a trading strategy (such as buy or sell) is a decreasing function of the total number of investors in the stock market, when all the other investors adopt the same trading strategy. Therefore, the propensity for herding behaviour is larger in an illiquid than in a liquid market.

Borensztein and Gaston Gelos (2001), in a study about the herding behaviour in emergent markets, show that there is more herding in the largest stock markets than in the smallest ones, suggesting that illiquid markets may prevent the investors from imitating the behaviour of others in the smallest stock markets. Also, there is empirical evidence that small capitalization markets in general tend to experience a higher level of herding compared with markets with large capitalization levels (Lakonishok et al., 1992; Bikhchandani and Sharma, 2001; Sias, 2004). But, beyond the size of the market and capitalization, the informational context of the stock market is another factor that influences imitative behaviour; Fernández et al. (2011) argue that investors' herding behaviour in financial markets is driven by informational limitations: "investors feel particularly compelled to imitate others when they observe only a few previous transactions in the market". Thus, it would be more likely to observe herding behaviour in a very small market, with limited acces to information, where the liquidity level and the number of investors are at low levels.

If this hypothesis holds, then LPPL models should be able to detect the development of the herding behaviour, by properly fitting the dynamics of a stock market bubble, and by providing an accurate prediction of the regime switching.

According to the literature, we propose the following hypotheses:

H1: Herding behaviour could be detected in illiquid markets using log periodic power laws.

H2: The evolution of the BET-FI index of the Bucharest Stock Exchange had a bubble signature for the period 2001-2007.

H3: LPPL models have the ability to predict the critical time of a stock market bubble in the case of the BET-FI index.

To the best of our knowledge, this is the first study regarding the fitting of a bubble regime for the Romanian stock market, a market severely affected by excess illiquidity and incomplete information. The novelty of this research arises from the particularities of the BSE, as an illiquid market, where access to information is still limited and with few investors involved in the trading mechanism. If the proposed research hypothesis is validated, this is another argument for the universality potential of the log periodic power laws in detecting imitative behaviour in the stock markets.

3. Methodology

3.1. Research Goal

In this paper we aim to identify the bubble behaviour of the BET-FI index for the Romanian stock market, and to estimate the critical times using log-periodic power laws. Using daily data from the BSE, we apply Sornette's methodology, and we predict the moment of regime switching from January 2008, and also, applying LPPL for the anti-bubble developed during the year 2008, we obtain an accurate estimation of the critical point of 27 October 2008, which is a local minimum for the BET-FI index.

3.2. Data

We used daily data for the BET-FI index of the BSE, for the period 3.01.2001 – 23.12.2008 (1978 daily observations). Although the BSE reports the values of two other major indexes (BET, the index of the most liquid companies and BET-C, a composite index for the entire market), we choose the BET-FI index as a index of financial investment companies, because of its speculative potential.

The Romanian stock market, like all the emergent markets in the Eastern and Central Europe, did not react immediately to the critical event of 15 September 2007, when the collapse of Lehman Brothers was announced, triggering a severe financial crisis for markets all arround the world.

As can be seen from Figure 3, actually, from 2001 to 2007, the BET-FI index exhibits a near exponential behaviour, reaching its historical maximum on 25 July 2007, and for the rest of the year 2007 the evolution was quite stable.

As can be gleaned from Table 1, the moment of regime switching for the BET-FI index was a the very beginning of 2008, when during January the cumulated daily returns reached around -26 per cent.

Figure 3. Closing price of the BET-FI index

Table 1. Cumulated daily returns of the BET-FI index

Month	Cumulated Returns	Month	Cumulated Returns
Jun-07	19.46%	Mar-08	-13.85%
Jul-07	-1.24%	Apr-08	-0.42%
Aug-07	-2.16%	May-08	6.48%
Sep-07	-8.17%	Jun-08	-19.10%
Oct-07	2.95%	Jul-08	-29.12%
Nov-07	-12.32%	Aug-08	-9.21%
Dec-07	8.83%	Sep-08	-21.68%
Jan-08	**-25.40%**	Oct-08	-83.12%
Feb-08	-0.79%	Nov-08	28.13%

After this point, the evolution of the index followed a descending trend, until the turbulent period from October 2008, when the daily return was lower than -10 per cent for several days and the local mimimum value of the index was reached on 27.10.2008 (see Table 2).

Table 2. Large negative returns from October 2008

Date	BET-FI Index	Daily return
10/6/2008	24625.029	-11.09%
10/8/2008	19284.430	-15.83%
10/10/2008	15200.570	-16.08%
10/22/2008	13638.860	-14.53%
10/24/2008	11100.850	-13.72%
10/27/2008	10012.260	-10.32%

3.3. LPPL fit for the BET-FI index

The initial sample for fitting the LPPL model in the case of the BET-FI index for predicting the phase transition from January 2008 was 03.01.2001 – 31.06.2007 (1603 daily observations); starting from the last observation in the initial sample, we extended the sample using a rolling window with a fixed lower limit, so, at each step we estimated the LPPL model for $t \in [1, T+k]$, $k=1 \ldots 100$:

$$p(t) = A_k + B_k(t_c - t)^{\beta_k}\{1 + C_k cos[\omega_k \ln(t_c - t)^{\beta_k} + \phi_k]\}. \quad (4)$$

As initial parameters we used the values validated in the litterature (see, for example, Kurz-Kim (2012)): $A^{(0)} = p(\tau)$, $B^{(0)} = -|p(\tau) - p(\tau - 1)|$, $\tau = 1 \ldots k, C^{(0)} = 0, \beta^{(0)} = 0.33, \omega^{(0)} = 6.36, \phi^{(0)} = \pi$.

Based on each iterative estimation, we computed the Root Means Square Error (RMSE), and the best model was selected as the one that minimizes RMSE.

Also, in order to detect the local minima from 27.10.2008, we noticed that during the year 2008, the evolution of the BET-FI index could be described as an “anti-bubble”, meaning a super-exponential evolution of the price inverse.

In this case, the sample for fitting the LPPL model was 03.Jan.2008 – 13.10.2008 (129 daily observations); starting from the last observation in the initial sample, we extended the sample using a rolling window with a fixed lower limit, so, at every step we estimated the LPPL model for $t \in [1,T+k],\ k=1\ldots30$:

$$\frac{1}{\ln p(t)} = A_k + B_k(t_c - t)^{\beta_k}\{1 + C_k cos[\omega_k \ln(t_c - t)^{\beta_k} + \phi_k]\}. \quad (5)$$

Our initial values for the parameters were the following: $A^{(0)} = \frac{1}{\ln p(\tau)},\ B^{(0)} = -\left|\frac{1}{\ln p(\tau)} - \frac{1}{\ln p(\tau-1)}\right|,\ \tau = 1 \ldots k, C^{(0)} = 0, \beta^{(0)} = 0.33, \omega^{(0)} = 6.36, \phi^{(0)} = \pi$,

and the best model was selected as the one that minimizes RMSE.

In both cases, the model was estimated using a a dual quasi-Newton nonlinear fitting algorithm, implemented in SAS 9.2.

3.4. Results

3.4.1. The bubble regime

The best fit for the model which attempts to predict the regime switching from January 2008 was estimated for the n sample with the last observation on 6.07.2007 (5 months in advance of the switching).

Table 3. The best fit for model (4)

A	***B***	***C***	t_c	$\boldsymbol{\beta}$	$\boldsymbol{\omega}$	$\boldsymbol{\phi}$	***t***	***RMSE***	***AdjRSq***
1078545	-855721	-0.003	1730.603 **04.01.2008**	0.031	6.909	6.28	1608 06.07.2007	3808	0.97

As it can be seen from Table 3, the critical time estimated for the model with the minimum RMSE is the first trading day of 2008, 04.01.2008, which corresponds to the fact that January was the first month with a severe decline in the BET-FI index (see Figure 4).

The second best fitted model, based on the RMSE criterion, gave us 24.07.2007 as the critical point which was the trading day which corresponded to the historical maximum of the BET-FI index (see Figure 5).

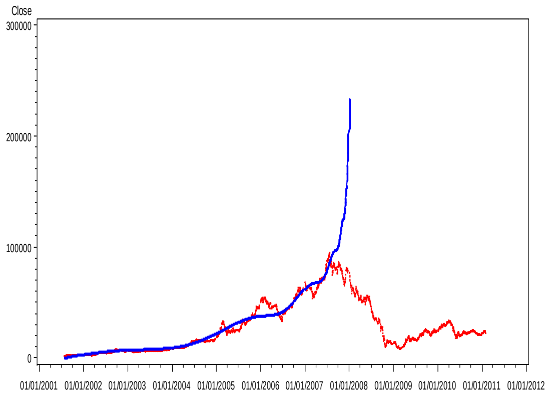

Figure 4. Log periodic power law (LPPL) and the BET-FI index

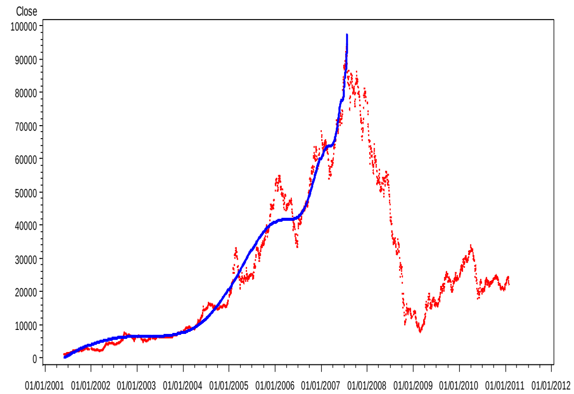

Figure 5. LPPL fit with the critical time of 24.07.2007

Based on these estimates, we can conclude that log periodic models could predict the bubble signature of the BET-FI index, and the critical time corresponds to the real evolution of the index.

This conclusion is strengthened even further by the evolution of the parameter β, the one controlling for magnitude of oscillations around the super-exponential trend before the critical time. Thus, small values of β and stationary behaviour around the critical time are a warning signal of an imminent phase transition (see Figure 6).

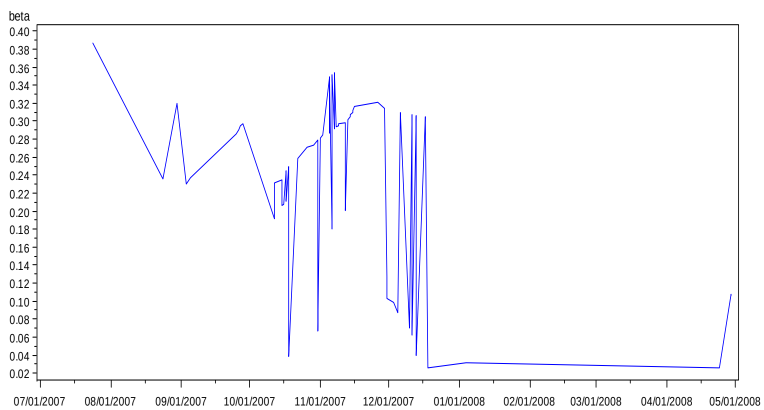

Figure 6. Estimates of β versus critical time

Plotting the values of parameter β for each value of the estimated critical time, we noticed that, starting from the beginning of January 2008, these values have a stationary dynamic, with values close to zero, clear evidence of a regime switching in the BET-FI index.

3.4.2. The "anti-bubble" regime

The best fit for the model which attempts to predict the local minimum of 27 October 2008 was estimated for the sample with the last observation on 15.10.2008 (12 days in advance (see Figures 7 and 8)).

Table 4. The best fit for model (5)

A	***B***	***C***	t_c	***β***	***ω***	***ϕ***	***t***	***RMSE***	***AdjRSq***
0	-8.996	0.007	208.06	0.039	6.875	0	201	0.049	0.93
			27.10.2008				15.10.2008		

The critical time estimated for the model with the minimum RMSE is 27.10.2008, which is the day of the local minimum for the BET-FI index (see Table 4 and Figure 7).

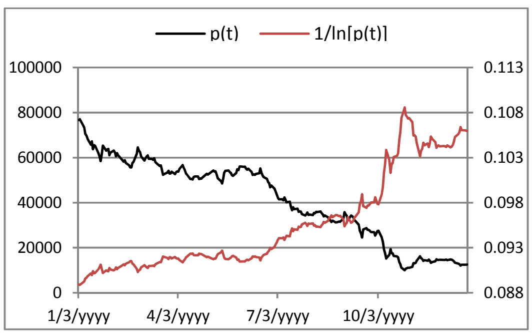

Figure 7. Bubble and anti-bubble behaviour for the BET-FI index during the year 2008

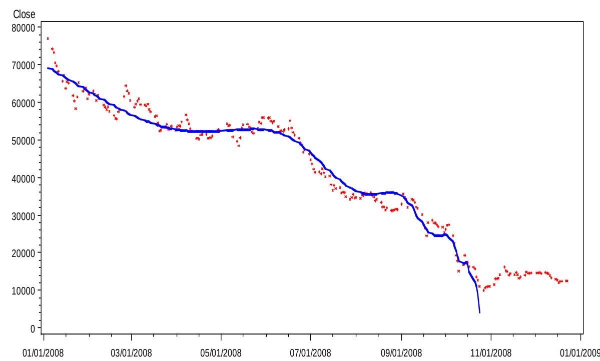

Figure 8. LPPL fit for the anti-bubble from 2008

This is a clear sign of the predictive ability of LPPL models for the detection of the herding phenomenon in the case of an anti-bubble regime, which leads ultimately to a recovery in the evolution of the trading price.

The Herding behaviour has a bivalent manifestation, either in the form of a positive informational cascade in the case of a bubble, or in the form a negative informational cascade in the case of an anti-bubble, yet the methodology is mainly the same. If the critical point is seen as a singularity, then reversing the time-arrow in the case of an anti-bubble allows us to apply the same methodology for fitting the bubble dynamics, and the results in the case of the BET-FI index are conclusive.

4. Conclusions

By analysing the behaviour of the most speculative index from the Bucharest Stock Exchange (BSE), BET-FI, we have proved that LPPL models can be a useful tool in recognizing the behaviour of a stock market bubble. Iterative calibration of the model for the BET-FI regime led to a reasonable estimate of the stock market crash in January 2008. Using the same approach, but in a reverse manner, we have estimated the critical time for the anti-bubble regime from 2008, and we have obtained an accurate prediction of the local point of phase transition from 27/10/2008. This is another validation of the predictive power of LPPL models in detecting the imitative behaviour of investors in an illiquid stock market, as until now, most of the research in this direction was focused on mature, highly liquid markets. The results are useful both from a theoretical point of view and from a business perspective.

Our findings support the argumentation of Lee (2009) that herding in an illiquid markets like Bucharest Stock Exchange accompanies expansions in trading activity, while herding in liquid markets accompanies contractions in trading activity.

In line with our first proposed hypothesis, the analysis provided strong evidences that herding behaviour could also be detected in illiquid markets, and this is a sign that LPPL models have a great potential for universal applications. From a business perspective, such an instrument could be used as a risk management tool, supporting the investment decisions in order to minimize risk, and to benefit from market evolutions.

These models could be used as an early warning tool for detecting the development of a bubble regime, and also to predict the critical time of the regime switching.

A recommendation for risk management arising from these results is to implement an iterative estimation method for LPPL models, which would allow the likelihood of a phase transition in the stock market to be assessed periodically. Yet, research in this direction needs to be improved, as this type of models has several weaknesses, like overparametrization or the absence of a standardized method to recognize a developing bubble. Another serious constraint of the LPPL model is the restriction that during a bubble the trading price cannot decrease, as this assumption is quite unrealistic.

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References

Bikhchandani, S. and Sharma, S. (2001). Herd Behavior in Financial Markets. *IMF Staff Papers*, 47(3):279-310.

Blanchard, O. J.(1979). Speculative bubbles: crashes and rational expectations, *Economics Letters*, 3: 387 - 9.

Borensztein, E. and Gaston Gelos, R. (2001). Are Foreign Investors in Emerging Market Economies a Panic-Prone Herd?, *Finance and Development,* International Monetary Fund, December 2001, Volume 38(4).

Cajueiro, D. O., B. M. Tabak, and F. K. Werneck (2009). Can We Predict Crashes? The Case of the Brazilian Stock Market, *Physica A,* 388(8), 1603-1609.

Fama, E. (1970). Efficient Capital Market: A Review Of Theory and Empirical Work, *Journal Of Finance*, 25, May 1970, Pp. 383 - 417.

Fantazzini, D., and Geraskin, P. (2011). Everything You Always Wanted to Know About Log Periodic Power Laws for Bubble Modelling But Were Afraid to Ask, *European Journal of Finance*, Forthcoming. Available at SSRN: http://ssrn.com/abstract=1752115.

Fernández, B., Garcia-Merino, T., Mayoral, R., Santos, V., Vallelado, E. (2011). Herding, information uncertainty and investors' cognitive profile, *Qualitative Research in Financial Markets*, Vol. 3 Iss: 1 pp. 7 – 33.

Friedman, D., Abraham, R.(2007). Bubbles and Crashes: Escape Dynamics in Financial Markets, *SCCIE WORKING PAPER*, 7.

Johansen, A., Ledoit, O., Sornette, D. (2000). Crashes as critical points, *International Journal of Theoretical and Applied Finance,* 3, 219-255.

Kim, T., Mangla, V. (2012) Investment Behavior under Uncertainty in Number of Competitors. Available at SSRN: http://ssrn.com/abstract=2043377 or http://dx.doi.org/10.2139/ssrn.2043377.

Kurz-Kim, J.R. (2012). Early warning indicator for financial crashes using the log periodic power law, *Applied Economics Letters*, 19:15, 1465-1469.

Lakonishok, J., Shleifer, A., and Vishny, R. W. (1992). The impact of institutional trading on stock prices, *Journal of Financial Economics*, 32:23-43.

Lee, S., (2009). Active Investment, Liquidity Externalities, and Markets for Information. Available at SSRN: http://ssrn.com/abstract=1300706 or http://dx.doi.org/10.2139/ssrn.1300706.

Malkiel, B.(2003). The Efficient Market Hypothesis and Its Critics, *Journal of Economic Perspectives*, Volume 17, Number 1, Winter 2003, pp. 59- 82.

Sias, R. W. (2004). Institutional Herding, *Review of Financial Studies*, 17(1):165-206.

Siklos, P., Bohl, M. and Klein, A. (2011). Short Selling Bans and Institutional Investors' Herding Behavior: Evidence from the Global Financial Crisis (30 July# 2011). Available at SSRN: http://ssrn.com/abstract=1744365 or http://dx.doi.org/10.2139/ssrn.1744365.

Sornette, D.(2003). *Why Stock Markets Crash*, Princeton University Press, Princeton, N.Y.

Sornette, D., Johansen, A. (2001). Significance of log-periodic precursors to financial crashes, *Quantitative Finance* 1, 452-471.

Sornette, D.(2009). Dragon-kings, black swans and the prediction of crises, *International Journal of Terraspace Science and Engineering*, 2(1):1–18 (http://arXiv.org/abs/0907.4290).

Timmermann, A. & Granger, C.(2004). Efficient market hypothesis and forecasting, *International Journal of Forecasting*, Volume 20, Issue 1 , January-March 2004, pp. 15-27.