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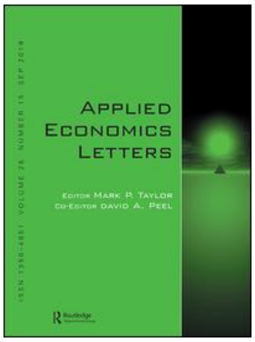

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ARTICLE

How well the log periodic power law works in an emerging stock market?

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ABSTRACT

A growing body of research work on Log Periodic Power Law (LPPL) tries to predict market bubbles and crashes. Mostly, the fitment parameters remain confined within certain specific ranges. This paper examines these claims and the robustness of the reformulated LPPL model of Filimonov & Sornette (2013) for capturing large falls in the S&P BSE Sensex, an Indian heavyweight index over the period 2000–2019. Thirty-five mid to large-sized crashes are identified during this period, forming a clear LPPL signature. This confirms the possibility to predict the embedded risk of future uncertain events in the Indian stock market with the LPPL approach.

KEYWORDS
Financial bubbles; crashes; log-periodic power law; fit method

JEL CLASSIFICATION
C13; C53; G01

I. Introduction

Crash predictor model development has been in demand for many decades now. Extensive work from three researchers back in 1996 introduced a critical observation, which could probably unearth the reasons for endogenous crashes (Sornette, Johansen, and Bouchaud 1996). They've observed that bourses (during a speculative bubble) move in line with a clear power law signature having an embedded log-periodic oscillation (LPPL) and the climax of such oscillation results in the inevitable crash. Various studies on LPPL provide certain fundamental assumptions: (1) Traders of financial markets tend to influence each other mutually, a behaviour that gives birth to bubble followed closely by a crash (Johansen, Ledoit, and Sornette 2000); (2) Crashes tend to be preceded by 'uncanny' bubbles, however, both the bubble as well as the crash could be identified by LPPL in specific situations and for specific bounds (Geraskin and Fantazzini 2013); (3) More often than not, parameters are found to be sufficient to identify between LPPL fits which precede a crash from those fits which do not (Johansen and Sornette 2001).

LPPL model not only help in predicting bubble and anti-bubble, but also can work to detect the crash points (climax of the bubble). It has been observed that the large drawdown or large cumulative losses follow a completely different probability density distribution compared to the smaller and more regular tinier drawdowns (Geraskin and Fantazzini 2013). The smaller drawdowns are more regular and indicate normal market regime. Interestingly, it has been noted that for almost two-third of the large drawdowns, the prices or log returns do follow a power law behaviour; this means they go up exponentially higher bounds in virtually no time immediately before the eventual crash.

A number of empirical studies on developed countries' stock returns (Zhou and Sornette 2003; Kurz-Kim 2012; Bree and Joseph 2013) applied the basic LLPL model and proved the existence of log-periodic structures. In this paper, we differentiate and test the robustness of the LPPL following the reformulated version of LPPL calibrations proposed by Filimonov and Sornette (2013). The aim is to capture large falls in the S&P Bombay Stock Exchange (BSE) Sensex index over 18-year period, which includes the 2007–2009 global financial crisis.[1] There is only one relevant study on this emerging market following the LPPL (Sarda et al. 2010). However, it has certain shortcomings. Firstly, its parameters were fixed; secondly, the authors followed the basic JLS model; thirdly, they followed parameters suggested by Bree and Joseph (2013) which ideally contradicts JLS construct. That

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[1]The BSE lists close to 6,000 companies and is one of the largest exchanges in the world, while Sensex measures the performance of the 30 largest, most liquid and financially sound companies across key sectors of the Indian economy.

could possibly be the reason of their poor fitment of LPPL signature, since they found 6/14 (43% LPPL signature) crashes from 1997 to 2009 in the Indian stock market. Instead, we find a profound LPPL signature in 35 mid- to large-sized crashes, suggesting a 100% LPPL signature.

The remainder of the paper is organized as follows: The data and methodology are presented in section II. Section III presents and discusses the results. Section IV concludes.

II. Data and methodology

In this analysis, we'll consider as many crashes as possible from daily closing prices of the S&P BSE Sensex for which the decrease in the value of the index is greater than 7% of the value of the index on the previous local minimum of the crash.[2] The S&P 500 index on which most LPPL tests were conducted is structurally similar to the S&P BSE Sensex, as a free-float capitalization method is followed for both of them. However, the S&P500 is based on 500 global companies, whereas Sensex on top 30 firms in India. By selecting a time period from 3 January 2000 to 18 September 2019, which includes various economic and political events occurred not only in India but also worldwide, we follow the reformulated version of LPPL calibrations proposed by Filimonov and Sornette (2013). The classical JLS expression of the Log-Periodic Power Law quantified as a function of time, t is given by:

$$y_t = A + B(t_c - t)^{\beta} + C(t_c - t)^{\beta} \cos(\omega \, log(t_c - t)) + \phi \tag{1}$$

where t_c denotes the most probable time of the crash, β is the exponential growth, ω controls the amplitude of the oscillations and A, B, C and Φ are simply units and carry no structural information. y_t is the price index; y_t >0. A expected log price at the peak when the end of the bubble is reached at t_c; A >0. B is the increase in y_t over the time unit before the crash (amplitude of the power law acceleration); B < 0. Here, C is the proportional magnitude of the fluctuations around the exponential growth; |C| < 1. Again, t_c is the critical time; t_c>0; t is any time into the bubble preceding t_c; t < t_c.

Fitting the equation to financial data, the log-periodic oscillation captures the characteristic behaviour of a speculative bubble and follows the financial index to the critical time of a crash. The hallmark of the equation is the fast-accelerating price of the asset or index, and when t approaches t_c the oscillations occur more frequently with a decreasing amplitude. The most probable time of the event of a crash is when t = t_c, and for t ≥ t_c, the equation transcends to complex numbers. This precursory pattern makes it possible to identify the clear signatures of near-critical behaviour before the crash. Filimonov & Sornette (2013) proposed a major revision in the formulation of a classic JLS LPPL construct. This transforms the model from a function of 3 linear and 4 nonlinear parameters into a representation with 4 linear and 3 nonlinear parameters (Filimonov and Sornette, 2013). This amendment was crucial as it decreased both the fitting procedure and the complexity of the construct. The fundamental idea was to get rid of some nonlinear parameters and to end the uncanny interdependence between angular log-frequency ω and the phase ∅. A reconstructed version of reformulation of the log-periodic power law (LPPL) equation of the JLS model of financial bubbles have been introduced by Filimonov and Sornette (2013) as follows:

$$y_t = A + B(t_c - t)^{\beta} + C_1(t_c - t)^{\beta} \cos(\omega \, log(t_c - t)) + C_2(t_c - t)^{\beta} \sin(\omega \, log(t_c - t)) \tag{2}$$

where, $C_1 = CCos\emptyset$ and $C_2 = CSin\emptyset$

After required amendment suggested by Filimonov & Sornette (2013), LPPL function has now only three nonlinear (t_c, ω, β) and four linear parameters such as A, B, C_1, C_2. Now with the revised parameters, C_1 and C_2contain formerly the phase ∅. These make the model partially linear and partially 'quasi-periodic with multiple local minima'. These would help in investigating the bubble and predicting the crash in a rare event of significant regime change. 'Standard slaving principle' has been used for the four linear parameters (A, B, C1 and C2) from empirical test. The non-linear parameters (β, ω) were generated through subordination procedure that captures both of them.

[2]The data that support the findings of this study are available from the corresponding author upon reasonable request.

III. Empirical results

Table 1 presents the restrictions on LPPL parameters, as appeared in the relevant literature. We've to check whether all the crashes in the Indian stock market fit in at the same set of values declared in Table 1 or not. Fundamental models built such as JLS showcased model for β = 0.33+-0.18, ω = 6.36+-1.56 and ϕ = 0 to 2π. Drawdowns have been calculated using Sornette's method 'price coarse graining' algorithm with $\varepsilon = 0$.[3]

Table 1. Stylized facts of LPPL.

Parameter	Constraint	Literature
A	(>0)	Kuropka and Korzeniowski (2013)
B	(< 0)	Lin, Ren, and Sornette (2014)
C_1	(Cos function)	Filimonov & Sornette (2013)
C_2	(Sine function)	Filimonov & Sornette (2013)
t_c	(t to ∞)	Kuropka and Korzeniowski (2013)
β	(0.1 to 0.9)	Lin, Ren, and Sornette (2014)
ω	(4.8 to13)	Johansen (2003)

This table presents the constraints on the LPPL parameters of Equation (2) used in our empirical analysis.

Table 2 presents the coefficients of LPPL parameters in equation (2). DD or drawdown is the gap between the local minima to the next local maxima and is $\geq 7\%$. Table 3 presents the identified events behind some of the double-digit crashes. A profound LPPL signature is observed in all 35 occasions (100% LPPL signature) in S&P BSE Sensex from 2000 to 2019 (no false positives were found). Extremely lower levels of Root Mean Square Errors (RMSE) in all 35 cases support the accuracy of our fitment. It has been found empirically that all 35 past crash instances occurred with the following three stylized facts:

(1) $\beta = 0.52 \pm 0.38$
(2) $\omega = 9.29 \pm 3.39$
(3) Drawdown (%) as 7%

Table 2. Coefficients of LPPL parameters.

Critical Time	t_c	β	ω	A	B	C_1	C_2	DD (%)	RMSE
17–07-2000	41.1	0.7	8.2	8.5	0.0	0	0	−14%	0.01
11–09-2000	23.1	0.2	8.1	8.5	0.0	0	0	−23%	0.01
20–02-2001	86.9	0.4	11.8	8.8	−0.2	0	0	−25%	0.01
17–05-2001	25.1	0.7	8.8	8.2	0.0	0	0	−31%	0.02
07–02-2002	100.1	0.4	10.0	8.2	0.0	0	0	−23%	0.02
27–12-2002	46.3	0.2	7.0	8.2	0.0	0	0	−12%	0.01
09–12-2003	150.9	0.8	6.8	8.9	0.0	0	0	−27%	0.02
07–03-2005	208.5	0.3	12.4	8.9	0.0	0	0	−10%	0.02
19–09-2005	100.9	0.2	9.3	9.1	0.0	0	0	−13%	0.01
19–04-2006	115.0	0.8	10.9	9.5	0.0	0	0	−29%	0.02
07–03-2007	186.3	0.6	6.7	8.0	$4.6*10^5$	$-4.6*10^5$	-977	-15%	0.02
10–07-2007	80.0	0.6	7.2	8.7	396.2	7	−8	−11%	0.02
03–01-2008	93.3	0.7	8.5	9.9	0.0	0	0	−29%	0.02
16–10-2009	30.4	0.7	7.9	9.8	0.0	0	0	−11%	0.01
05–01-2010	43.5	0.8	6.6	9.8	0.0	0	0	−11%	0.01
29–03-2010	33.3	0.7	12.3	9.8	0.0	0	0	−11%	0.01
09–11-2010	124.6	0.8	9.9	9.4	14.9	0	−1	−9%	0.01
31–12-2010	27.9	0.8	10.2	9.9	0.0	0	0	−15%	0.01
21–04-2011	50.2	0.2	9.2	9.8	$1.57*10^4$	-5331	-2845	-10%	0.02
07–07-2011	13.8	0.2	9.4	9.8	0.0	0	0	−17%	0.00
19–09-2011	15.3	0.3	7.1	9.7	0.0	0	0	−7%	0.01
28–10-2011	16.7	0.6	12.4	9.8	0.0	0	0	−15%	0.01
06–02-2012	34.6	0.9	7.2	9.8	0.0	0	0	−12%	0.01
28–01-2013	158.6	0.4	10.9	9.9	0.0	0	0	−9%	0.01
30–05-2013	36.5	0.8	9.6	9.9	0.0	0	0	−8%	0.01
16–07-2013	17.9	0.3	7.7	9.9	0.0	0	0	−12%	0.01
29–01-2015	348.8	0.9	12.2	10.3	0.0	0	0	−7%	0.02
13–04-2015	11.0	0.6	7.9	10.3	0.0	0	0	−9%	0.00
21–07-2015	53.1	0.2	6.6	10.3	0.0	0	0	−13%	0.01
23–10-2015	32.8	0.5	9.1	10.2	0.0	0	0	−7%	0.01
02–12-2015	23.6	0.3	9.9	9.7	0.0	0	0	−12%	0.01
07–09-2016	152.4	0.3	12.7	10.3	0.0	0	0	−11%	0.01
29–01-2018	298.9	0.6	8.9	10.5	0.0	0	0	−12%	0.01
20–08-2018	102.6	0.5	10.9	10.6	0.0	0	0	−14%	0.01
03–06-2019	147.3	0.1	11.2	10.4	225.8	−15	−34	−9%	0.01

This table presents the estimates of all the parameters of equation (2) in the text. DD or drawdown is the gap between the local minima to the next local maxima and is ≥7%. RMSE is the Root Mean Square Error. All estimates have been generated by the authors using Python language in Anaconda program with project Jupyter notebook.

[3]Drawdown is the cumulative loss from one local maximum to the immediate next minimum; a size that is above the threshold 'ε'.

Table 3. Certain large crashes with LPPL signature.

Critical Time	Drawdown %	Events
19–04-2006	−29%	Increase in risk weightage by 60bps to cost banks Rs 800 cr. The slowdown of the Chinese economy and the consequent devaluation of its currency has had a ripple effect on emerging market currencies.
07–03-2007	−15%	Bearish sentiment arises as new issue investors hit hard as most. IPOs fall up to 50%. Personal loan rates hiked by 0.75%. Over two dozen MNCs consider to sell off India units. Hike in cash reserve ratio and repo rate.
10–07-2007	−11%	Financial Crisis 2007–2008. Expectation of big hike in the ceiling for investments by foreign institutional investors (FIIs) in the Indian debt market to boost infrastructure. The cap was at $4.7 billion.
03–01-2008	−29%	Black Monday – FIIs sell off, Fears of US going into recession and a cut in US interest rates Petrol prices likely to rise by Rs. 4 Budget Anticipation. PSU alliance failed to deliver results. Finance Minister (FM) asks banks to meet credit targets.
16–10-2009	−11%	Expectation of rate hike as inflation touches 7.3%. Crude prices at record high, rupee fall, US and China trade sanctions and ballooning Current Account Deficit.
05–01-2010	−11%	Auction of 5400 crores of state loans, Rs. 8500 crores of T – Bills and 10,000 crore bond sale.
31–12-2010	−15%	Cost of capital is going up globally, yields are starting to go up internationally and the oil prices are going up. India imports capital as well as oil, so the cost of all this is going to go up for India. Additionally, lot of corporate scams coming to light.
21–04-2011	−10%	Markets slump on inflationary pressures and global cues like increased rate hike in US.
07–07-2011	−17%	Deep correction expectation from global cues and crude oil price rise.
28–10-2011	−15%	Shirking cash volumes and increased interest rates reduced Q2 earnings performances of companies.
06–02-2012	−12%	Budget anticipation by market participants.
16–07-2013	−12%	Reserve Bank of India's Liquidity tightening measures suddenly.
21–07-2015	−13%	FIIs sell-off of 9700 crores in overpriced blue-chip stocks.
02–12-2015	−12%	Indian Markets have lost its beta – Morgan Stanley Reports.
07–09-2016	−11%	Uri attack followed by Surgical Strike. Non-performing assets (NPas) of Indian banks, global weaknesses and global factors crack down on black money by the Indian government; Demonetization and US presidential Election as well.
29–01-2018	−12%	Economic slowdown, corporate governance concerns, asset quality concerns, liquidity crisis and weak earnings FM's proposal to introduce 10% long term capital tax (LTCG) on equity.
20–08-2018	−14%	Trump Accuses China, Europe of manipulating Currencies as dollar dips. Oil and Gold prices rises in worries of Sino-US trade dispute Bank refuses to lend to Pvt Power Companies.

This table shows certain events which are identified behind some of the double-digit crashes in the Indian stock market, consisting a clear LPPL signature; however all other crashes identified have also LPPL footprint, while there is no drawdown that is high without crash (no false positives were identified). A crore denotes ten million in the Indian numbering system.

Hence, these stylized facts can be used to predict exact time of crashes in Indian context. Most of the pointers as per Table 3 hint mostly towards five cardinal events: economic/financial crises, commodity and currency crises, geo-political issues (cross-border transactions) and Central Bank's decision about liquidity management. These set of information are largely qualified as shocks, thus ending the so-called 'wobbling bubbles' (as formed in phases and upward trending cyclical movements) and forming a clear LPPL signature. We provide evidence that 'drawdown outlier' is nothing but the end of a speculative unsustainable wobbling bubble which has been generated endogenously (Johansen and Sornette 2001). Therefore, our empirical analysis clearly shows that the price function of S&P BSE Sensex as an individual entity is characterized by a power law.

Figure 1 presents the graphical fitment of the reformulated LPPL model on various chosen drawdowns

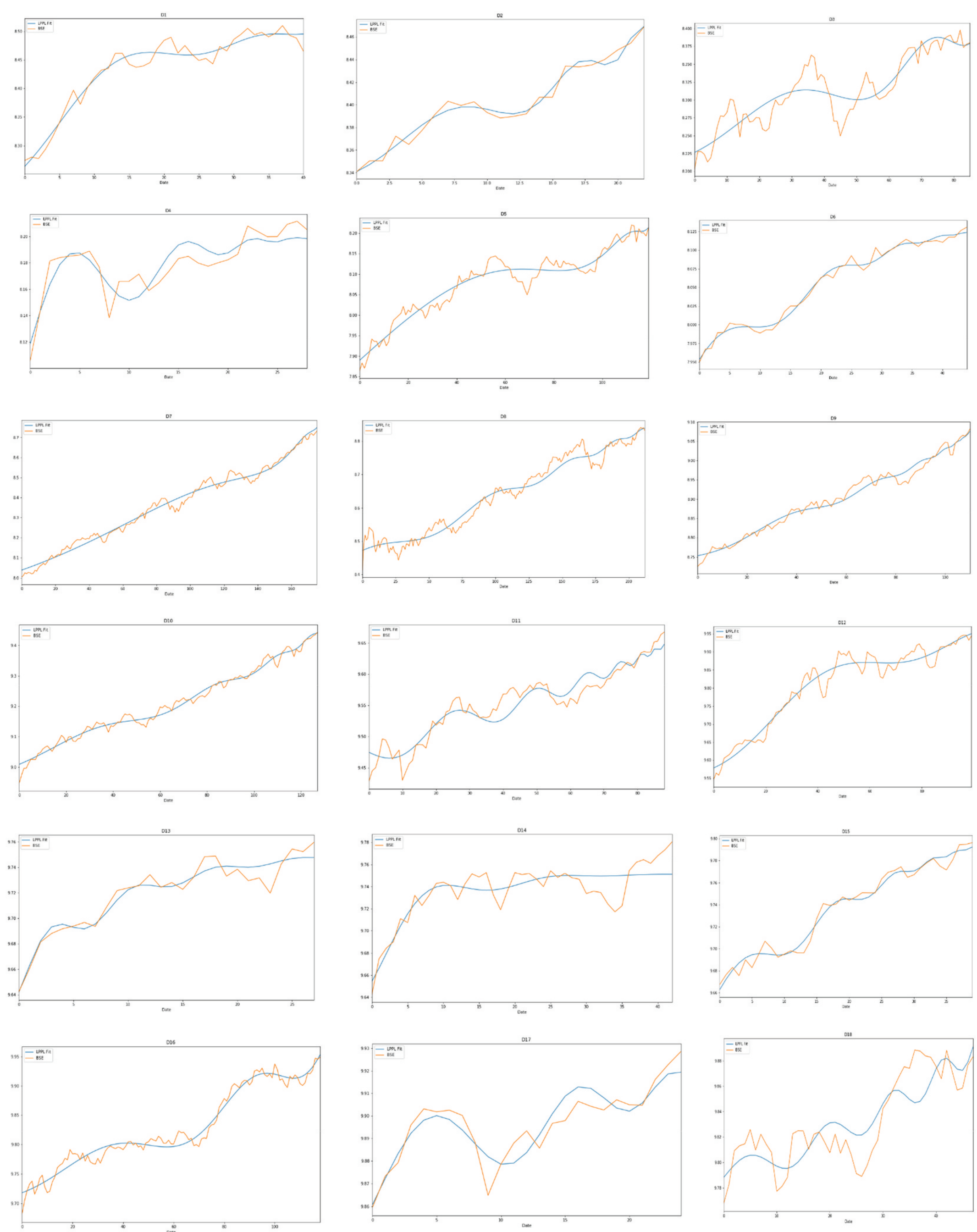

Figure 1. Fitment of reformulated LPPL model.

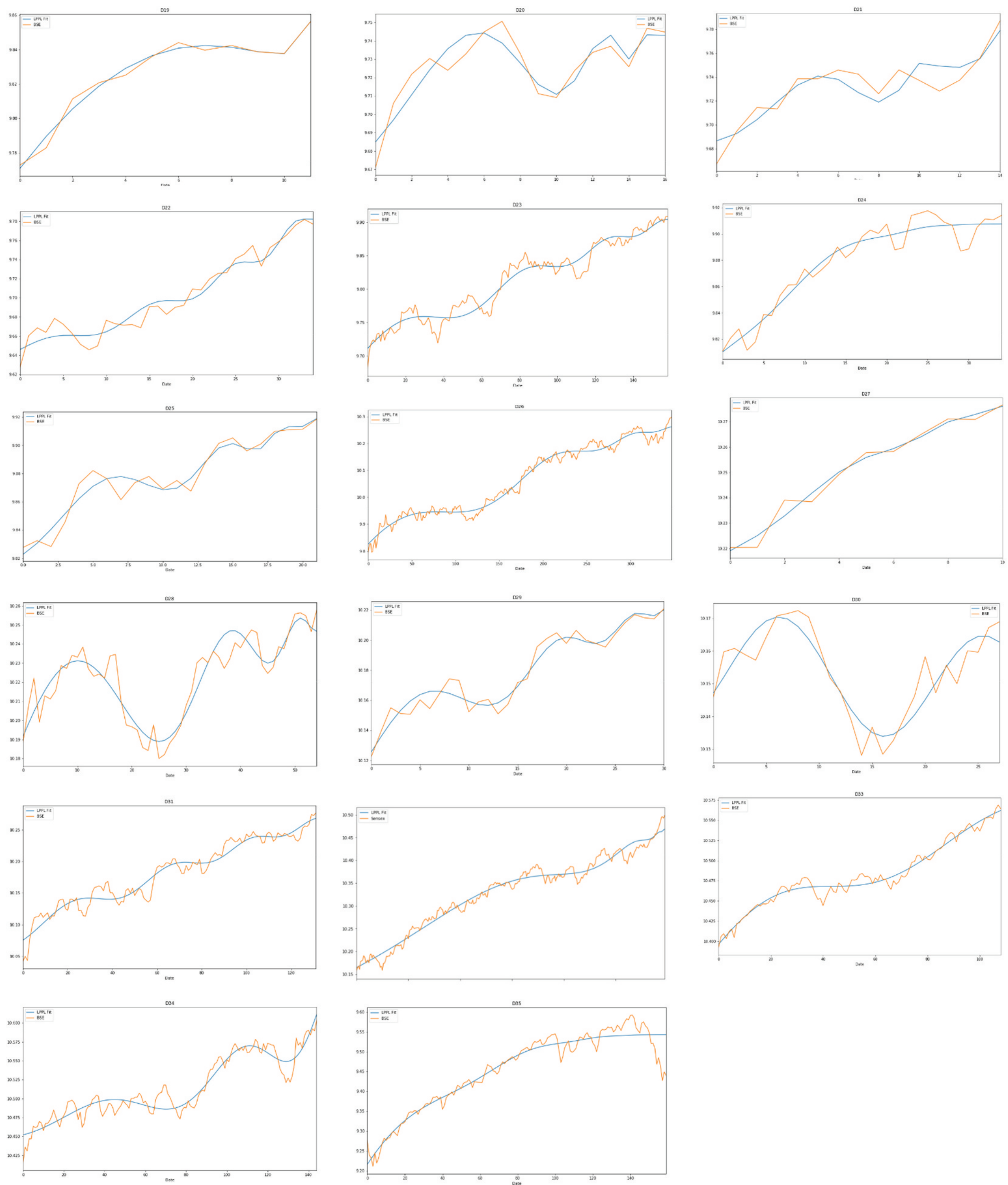

Figure 1. (Countinued).

≥7% as D1, D2, D3, etc. The LPPL fittment is in blue, while the actual BSE Sensex index movement in orange. This figure is an ensemble of all 35 crashes and respective LPPL fittment.

IV. Conclusion

Following the revised Log Periodic Power Law (LPPL) model of Filimonov & Sornette (2013), we've found profound LPPL signature in all 35 occasions (100% LPPL signature) in the Indian stock market from 2000 to 2019. It has been observed empirically that 'drawdown outlier' is nothing but the end of a speculative unsustainable wobbling bubble which has been generated endogenously (Johansen and Sornette 2001). Extremely lower levels of RMSE in all 35 cases proved the accuracy of our fitment. These findings imply that risk managers, foreign portfolio investors, foreign institutional investors, qualified institutional buyers all can predict the embedded risk of uncertain events in Indian stock markets with this LPPL signature.

Disclosure statement

No potential conflict of interest was reported by the authors.

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