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PREDICTION OF CRASHES IN MOEX RUSSIAN INDEX USING LOG-PERIODICITY

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ABSTRACT

Financial crises in emerging nations pose significant dangers to economic stability yet predicting them remains difficult. This study tests whether speculative bubbles and subsequent crashes can be predicted by using the Log-Periodic Power Law (LPPL) model to the MOEX Russian Index using daily data from 1997–2024. We estimate that with little lag, LPPL can predict crash dates and detect important moments of instability in MOEX. The results demonstrate that log-transformed data produce smaller error margins, indicating trade-offs between variance capture and forecasting precision, even if raw price data frequently anticipate crashes more accurately in terms of timing. Although LPPL's ability to predict smaller collapses and lower false positives is still limited, these findings imply that it can give regulators and policymakers early warning signs of systemic risk.

Keywords: *LPPL model, Financial Market, Speculative Bubbles, MOEX Russian Index, Market Crashes*

1. INTRODUCTION

Financial crashes and the accompanying bubbles have sparked much scientific interest, especially in recent years. Because bubble prices appear to move away from the basic worth of stocks, financial bubbles are sometimes linked to investors' irrational excitement. If historical earnings are high and investors use them to predict future earnings, prices will likely have a long memory, resulting in stock price bubbles. However, the evidence for long memory in financial pricing is largely ambiguous. (1). Similarly, financial bubbles appear considerably larger than expected. When prices are unsustainable, price decreases and volatility occur, resulting in prices below intrinsic value. Such dramatic price changes significantly affect risk management and financial security value. Not unexpectedly, there is ongoing debate in academic and business circles over the extent to which financial regulation can prevent such dramatic price fluctuations. (2).

Forecasting stock price variations has long been a key issue in financial economics. Classical theories, such as the Efficient Market Hypothesis (EMH), hold that asset prices fully represent all available information, rendering future movements unforeseeable. (3). According to the Random Walk Theory, price fluctuations follow a stochastic process driven by new information arrivals, meaning that

historical prices do not accurately forecast future prices (4). Real-world market behavior often deviates from rational expectations, with speculative bubbles leading to unexpected, large-scale crashes. This highlights the shortcomings of completely efficient market models.

Behavioural finance incorporates cognitive biases, herd behavior, and emotion-driven decisions into asset pricing models. (5,6). Various forecasting methodologies have been presented in this paradigm, including sentiment analysis of news and social media, agent-based simulations of heterogeneous investors, and herding models based on statistical physics. (7,8). While these methods provide valuable qualitative insights into market psychology, many lack the mathematical framework or parametric form required to predict the timing of a market crash.

While the mechanics of speculative bubbles and crashes have been extensively researched, the practical question remains: why do such events attract continual attention? Historically, financial collapses have caused significant macroeconomic disruptions, especially in developing nations like Russia where volatility is exacerbated by reliance on commodity cycles and geopolitical considerations. Examples of how abrupt downturns affect both domestic markets and international financial flows include the 2020 oil-COVID catastrophe and the 1998 Russian default.(9)

The Log-Periodic Power Law (LPPL) model, developed by Sornette, Johansen, Ledoit, and collaborators, aims to identify and forecast financial bubbles and their demise. (10–12). LPPL, based on critical events in physics, describes bubble dynamics as accelerating super-exponential expansion with log-periodic oscillations, leading to a finite-time singularity (the crash) (10,11). By fitting this nonlinear, parameterized model to observable price series, one can predict not only the existence of a bubble but also the most likely time window for its burst. (12).

Feigenbaum et al. (13), and Sornette et al. (11) We were the first to use the LPPL variation to predict financial market speculative bubble collapses. They each found LPPL signals before the October 1987 S&P 500 crisis. (14). Since then, there have been five primary avenues of research into LPPL structures in financial time series. (14):

- Detection: Finding LPPL patterns both ex ante and ex post crises (e.g., in equity indices and commodity-price time series).
- Herding Dynamics: Empirical evidence that investor imitation causes "anti-bubbles" to slow down and bubbles to accelerate.
- Forecasting: Predicting bubble and anti-bubble end dates by integrating LPPL into pattern-recognition algorithms.
- Assessing whether log-periodic patterns originate from random fluctuations in synthetic data or from actual imitation behavior is known as statistical validity.
- Theoretical underpinnings: Agent-based and spin-model derivations of LPPL, such as the Ising-type, can be generically generated by inertia, nonlinear momentum, and mean-reversion, as well as the strong calibration improvements by Filimonov & Sornette (14).

Empirical applications of LPPL include major events such as the 1987 Black Monday catastrophe. (10), the 2000 dot-com bubble (11), the 2007-2008 housing market collapse (12), and recent crypto-asset bubbles (11). These experiments indicate LPPL's capacity to uncover precursory signals from noisy financial data, which are often obscured in classic time-series or sentiment-based models. (8). LPPL's closed-form structure allows for rigorous statistical testing and out-of-sample validation, distinguishing it from diagnostic ratios like CAPE and simulation-based methods.

Despite significant empirical applications of the LPPL model to U.S., European, and Asian markets, few researchers have applied it to the Russian MOEX Index over such a long period. This leaves a question of whether LPPL is resilient in high-volatility, resource-driven economies. We postulate that the LPPL model may correctly predict large crashes in MOEX with a short lag between predicted and actual crash dates. However, we also recognize its limits. LPPL may not reliably predict modest downturns or account for exogenous shocks.(15)

This study uses a quantitative, time-series design with nonlinear optimization techniques using MOEX data. By comparing raw and log-transformed fits, we assess LPPL's predictive validity and contribute to the continuing debate over the trustworthiness of crash forecasting models.

2. LITERATURE REVIEW

2.1 Log-Periodic Oscillations and Market Crashes

Cvijović et al. (16) Offer insight into financial market behavior by considering stock market crashes and optimization techniques. Their study indicates that markets display patterns exhibiting critical points like physical systems and that log-periodic oscillations may be precursors to crashes. However, the predictive power of these models remains uncertain, as their accuracy has not been statistically proven across multiple crashes.

Sornette et al. (11) analyzed stock market collapses through the lens of critical phenomena, suggesting that financial markets exhibit cooperative behavior akin to self-organizing systems in physics. They found that log-periodic oscillations before and after crashes indicate that markets approach critical points comparable to phase transitions in physical systems. While these findings offer a compelling perspective on market dynamics, the predictive power of log-periodic models remains unconfirmed.

Sornette et al. (17) Further argue that self-organized critical behavior produces log-periodic patterns in market prices before major crashes, signifying underlying instability. By examining the 1929 and 1987 crashes, they identified striking parallels in key parameters, supporting the notion that crashes develop gradually due to growing market cooperation rather than occurring suddenly. This challenges the Efficient Market Hypothesis by proposing that market prices contain hidden information about impending crashes, which traders have not yet fully deciphered. Consequently, if traders can decode these indicators, crash risk may be reduced or avoided. Additionally, the study posits that external events often act as triggers but are not the primary cause of crashes; systemic instability due to prolonged price acceleration sets the stage for collapse.

Johansen et al. (18) Challenge the assumption that stock market crashes are merely extreme events within a fat-tailed distribution of price fluctuations. Their analysis suggests that major crashes are statistical outliers, driven by specific amplification processes rather than random market fluctuations. Detecting these crashes as outliers supports the hypothesis that detectable precursory signals can precede significant market downturns.

Drożdż et al. (19) demonstrated the existence of log-periodic components in financial dynamics, self-similarly appearing across multiple time scales. They caution, however, that the functional form of log-periodic modulation currently lacks a rigorous theoretical foundation, leaving room for mathematically unrigorous assignments of patterns.

Johansen (20) strengthened the evidence that outliers in financial markets provide an objective and quantitative way to describe market crashes. His analysis found that 13 of the 15 most significant drawdowns were preceded by an LPPL bubble, indicating a one-to-one correspondence between market crashes and LPPL bubbles or significant external events. Only one previously identified LPPL bubble was not categorized as an outlier, whereas the other two exceptions were linked to important historical events. This suggests that market instability can arise internally (through LPPL bubble dynamics) and externally (via major shocks).

Jacobsson (21) critiqued the characterization of crashes as outliers to a stretched exponential put forth by Johansen et al. (22), arguing that it ignored the actual market crashes. He defined a crash as a drop exceeding the 99.5% empirical quantile, ensuring consistency with historical events. Using this definition, he effectively fitted a three-parameter Weibull distribution. He employed LPPL signatures to identify multiple fits in the OMXS30 and DJIA markets, while also discovering LPPL patterns in the S&P 500 Index, which had not been previously studied.

Sornette et al. (15) evaluated the JLS financial bubble model (Johansen-Ledoitte-Sornette model) and found it to be a robust framework for understanding the dynamics of financial bubbles and crashes. They demonstrated the role of positive feedback mechanisms in driving asset prices to unsustainable levels, resulting in corrections or crashes. Despite criticism regarding theoretical assumptions, parameter constraints, and fitting methodologies, the JLS model has shown predictive capabilities in multiple markets. It contributes to the literature by providing a probabilistic framework for

evaluating bubble risks and emphasizing the importance of fitting methodology refinements.

2.2 Criticism of Log-Periodic Power Law (LPPL) Models

Laloux et al. (23) argued that predictions of crashes using log-periodicity or other critical-phenomena-based techniques remain unconvincing. While they observed some notable retrospective fits to past crashes, they criticized the absence of a solid theoretical foundation and statistically significant empirical data. They found that forecast failures and methodological issues with data fitting undermine the reliability of LPPL-based predictions.

Feigenbaum (24) conducted a rigorous statistical analysis of log-periodic precursors to financial crashes, emphasizing the need for thorough validation before attributing such oscillations to underlying economic structure. Using S&P 500 Index data before the October 1987 crash, he applied statistical tests to examine the significance of log-periodic patterns in mean and volatility functions. His results suggested that these patterns could be random artifacts rather than genuine market signals, highlighting the challenges of testing financial models given unmodeled disturbances and complex dependencies.

Chang et al.(25) applied Bayesian methods to assess the JLS model's log-periodic hypothesis. Their analysis of the 1987 crash found that although the model outperformed a null hypothesis in estimating crash timing, the estimated oscillatory parameters lacked statistical significance. This implies that log-periodic behavior may not be an inherent market characteristic. While broader investigation across multiple periods offered more substantial support for the JLS model, their analysis was limited to a single log-periodic spell. They also suggested alternative explanations, such as support and resistance oscillations arising from psychological barriers, which align with behavioural finance notions and contradict the Efficient Market Hypothesis.

Chang et al. (26) further studied whether log-periodic behavior could be detected in stock returns using a regime-switching model. They observed log-periodic signals before significant collapses (e.g., 1962 and 1987), but the estimated parameters did not consistently align with JLS model predictions. Additionally, their evidence for the 1998 crash was mixed, raising concerns about the universality of log-periodic patterns across different market events.

Brée et al. (27) highlighted the inaccuracy and "sloppiness" of LPPL models, especially the disconnect between the critical time parameter (tc) and the oscillatory structure. They proposed simplified estimators for LPPL parameters that preserve some predictive power, demonstrating via synthetic data with autoregressive noise that Levenberg–Marquardt–based fitting can be adequate. Nevertheless, they emphasized the substantial uncertainty in estimating tc, which undercuts the accuracy of real-world crash predictions. Even efforts to compute an 80% confidence interval for tc may underestimate genuine uncertainty, particularly since "sloppy" parameters can exhibit fluctuations that are not reflective of actual variance in a single noise realization.

Brée et al. (2) used the LPPL model to forecast crashes in the Hang Seng Index for 1971, 1973, 1978, 1980, 1981, 1987, 1989, 1994, 1997, 2000, and 2007. They identified multiple problems with LPPL implementations, notably the model's assumption that bubble trends strictly correspond to rising prices—an assumption contradicted by instances of price decline within purported bubbles. Many prior studies failed to meet LPPL's critical assumptions using raw data rather than log-transformed prices, leading to flawed results. They also noted challenges in identifying crash initiators and asserted that an LPPL fit is valid only if the exponent β is less than 1. Seven of the 11 bubbles they studied had LPPL parameters (β and ω) within acceptable ranges, yet the optimal fits frequently violated these ranges. Notably, crashes in 1973 and 2000 did not satisfy LPPL conditions, casting doubt on model validity. They also underscored that the root mean square error (RMSE) is sensitive to parameter variation and that acceptable parameter ranges should not be viewed in isolation. Despite these concerns, they suggested that LPPL might yield probabilistic crash forecasts if augmented with additional factors such as trading volume and log returns.

2.3 Empirical Studies on Financial Bubbles and Market Crashes

Vandewalle et al. (28) analyzed the Dow Jones Industrial Average (DJIA) across three distinct periods and identified log-periodic patterns emerging

before market collapses. Using data up to August 1998, they successfully estimated a rupture point in late 1998, albeit with large error margins. Their results imply that log-periodicity has potential for forecasting crashes, but they emphasize the necessity of real-time testing across various time scales to enhance reliability.

Johansen et al. (12) compiled empirical evidence supporting log-periodic structures in financial bubbles across global markets. By examining eight notable crashes from 1929 to 1998 in the U.S., Hong Kong, Russia, and currency markets, they confirmed that bubbles are regularly preceded by power-law acceleration and log-periodic behavior. They also documented LPPL characteristics in "anti-bubbles," such as the Nikkei (since 1990) and gold (since 1980), demonstrating that log-periodicity applies to both gradual market decline and abrupt crashes.

Sarda (29) applied log-periodicity to 14 crashes in the Indian stock market (seven each on BSE Sensex and NSE Nifty 50). He concluded that the Indian market also exhibits log-periodic oscillations preceding crashes.

Yan et al. (30) investigated the real-time diagnostic and predictive potential of the LPPL model for financial bubbles and crashes. Case studies—namely, the 2008 oil price bubble and the 2009 Shanghai stock market crash—demonstrated the model's effectiveness, including its applicability to "negative bubbles." Their findings challenge that crashes are inherently unpredictable and underscore potential policy and regulatory implications. By gathering empirical data, they aimed to improve understanding of systemic risk and offer resources for policymakers, financial institutions, and central banks to enhance risk management and crisis avoidance.

Sarda et al. (31) examined three crashes in the Indian real estate market using Head and Shoulders chart patterns. They successfully predicted one of the three crashes with 100% predictive efficiency; the other two predictions failed.

Sarda et al. (32) continued their empirical work by applying Kagi charts to predict three real estate crashes. They accurately forecasted two of the three crashes (100% and 50% accuracy, respectively), while the third crash went undetected by the Kagi chart methodology.

Li (33) analyzed three financial bubbles in the CSI 300 index (Chinese stock market) from 2006 to 2015 using the LPPL model. He validated the model's ability to capture super-exponential growth by identifying bubbles exhibiting power-law behavior and log-periodic oscillations. Li introduced "t_c–t_2" as a novel indicator, which showed a sharp decline when a market collapse or recovery was imminent, thus providing an early warning system for financial bubbles. This indicator can assist investors and policymakers in risk management by offering actionable signals.

Demirer et al. (9) presented a methodology to detect positive and negative bubbles in various index markets using the LPPL model. They found that LPPL effectively captured major bubbles across different time scales and demonstrated that market liquidity and short-selling activity had significant predictive power for positive and negative bubbles, respectively. Their research underscored the importance of incorporating market microstructure variables (e.g., liquidity and short-selling) into LPPL-based bubble indicators for more accurate monitoring and simulation of bubble dynamics.

Sarda et al. (34) studied three crashes in the Indian real estate market between July 1997 and August 2011. Their findings showed that log-periodic structures were ineffective in predicting all crashes, indicating that LPPL may not reliably forecast real estate downturns in specific contexts.

Sarda et al. (35) extended their analysis to multiple crashes in the Indian financial market. They discovered that a crash is imminent when stock prices peak and cross the LPPL-projected curve. Their study confirmed that LPPL effectively predicted major crashes (over 25%) in the BSE Sensex but did not produce warnings for more minor crashes. This suggests that LPPL may be a valuable tool for anticipating substantial market downturns, although its sensitivity to the magnitude of the crash must be considered in practice.

Gonçalves et al. (36) presented the self-similar oscillatory finite-time theory in finance and applied it to predict crashes in the Portuguese stock market.

They analyzed the 1998, 2007, and 2015 crashes using LPPL and determined that the model performed well for Portugal—a relatively small market with liquidity constraints and a 20-stock index. Their findings suggest that LPPL methodology may help prevent significant losses in diversified portfolios by signalling when bubbles become unstable and are likely to burst. This bears important implications for policymakers and market regulators, as it provides a mechanism for implementing risk-reduction measures.

2.4 External vs. Internal Causes of Market Crashes

Johansen et al. (37) analyzed the Nasdaq Composite bubble (1997–2000), demonstrating power-law acceleration and log-periodic oscillations preceding the March–April 2000 crash. They argued that crashes often stem from internal market instability rather than external shocks. For instance, the August 1998 crash—commonly attributed to the Russian financial crisis—was seen as inevitable given prevailing market conditions. Likewise, legal pressures on Microsoft did not prevent the Nasdaq crash. The authors also discussed the difficulties in predicting crashes, noting three possible outcomes when warnings are issued: (1) the market ignores the warning and crashes, (2) panic triggered by the warning causes the crash, or (3) belief in the forecast deflates the bubble, making the forecast appear unreliable. This paradox highlights the ethical dilemma of scientific accountability in financial forecasting.

Johansen et al. (10) connected stock market crashes to critical behavior in complex systems. They showed that local imitation among traders can lead to large-scale coordination and market collapse, supported by empirical data from U.S. and Hong Kong markets. Their study found that extreme crashes (e.g., declines of 23.6% or more) are statistical outliers driven by cooperative phenomena rather than random fluctuations. They also demonstrated that standard models (e.g., GARCH) cannot replicate actual crashes, reinforcing the notion that conventional approaches fail to explain market downturns fully. Although log-periodic patterns were observed before major crashes (1929, 1987, 1997), the model tended to overestimate crash timing. Some predicted crashes did not materialize, indicating that bubble conditions do not guarantee collapse. Overall, their findings highlight the probabilistic nature of crashes and the limitations of forecasting exact timing.

Johansen and Sornette (38) classified financial market shocks, crashes, and bubbles into exogenous crashes (triggered by external events such as political upheavals, wars, or economic disruptions) and endogenous crashes (driven by speculative bubbles). They found that LPPL patterns often appear before endogenous crashes, reflecting self-organizing behavior in markets where speculative excess accumulates until collapse. However, exogenous shocks can precipitate crashes without endogenous buildup. Their framework provides valuable insights for risk management and early warning systems by distinguishing between different crash mechanisms.

Zhang et al. (39) applied the LPPL model to monthly S&P 500 data spanning 1814–2014, identifying two negative and eight positive bubbles, including the Wall Street Crash of 1929, Black Monday 1987, Dot-com bubble, and the 2007–08 Financial Crisis. They determined that 10 of 19 documented crashes were driven by internal bubble mechanisms with self-reinforcing feedback loops, whereas the remainder resulted from external economic or political events. The LPPLS model exhibited higher accuracy than EXCF(Exponential Curve Fitting) and GSADF(Generalized Supremum Augmented Dickey-Fuller) methods, which detected many bubbles but missed key ones (e.g., Black Monday 1987, Subprime Crisis 2007–08). Their results underscore that market regime shifts are standard, crises are frequently endogenous, and proactive risk management can mitigate economic losses using improved monitoring tools.

2.5 Role of Policy and Market Interventions in Preventing Crashes

Sornette et al. [30] examined the Chinese government's interventions during the 2015 market meltdown. They documented measures such as limiting large stakeholders' ability to sell shares and central bank interventions. They argued that China's stock market has become increasingly correlated with economic growth, driven by privatization of state-owned enterprises, reduced reliance on bank financing, and the goal of internationalizing the renminbi. Politically, a rising stock market legitimizes

China's elite and supports the country's capitalist ethos. Given these factors, they anticipate more frequent market bubbles, underscoring the need for timely interventions.

Westphal et al. (40) used an agent-based modelling approach to illustrate how proactive market interventions can avert financial bubbles and crashes. By simulating a policymaker who carefully counterbalances market exuberance, they found that intervention stabilizes markets, reduces volatility, and mitigates excessive price fluctuations without harming long-term growth. Their results suggest that well-designed policy actions can enhance market efficiency and improve investors' risk-adjusted returns. However, they note that central banks and regulators often hesitate to intervene pre-emptively; their findings underscore the potential benefits of such proactive measures.

3. RESEARCH METHODOLOGY

3.1 Data Collection

To study stock market crashes, we will use the log-periodic structure model as used by Bree and Joseph. (2). For this purpose, the MOEX index from the Russian stock market (Moscow Stock Exchange) is taken.

The MOEX Russian Index is a key benchmark for the Moscow stock exchange, reflecting the performance of the country's most liquid and capitalized companies. The data for the MOEX Russian index are taken weekly from 1997 to 2024. The data was collected from official MOEX sources and other sources.

3.2 Identification of Crash

We must first identify the crash to determine whether the LPPL can predict crashes. A stock market collapse is typically interpreted as a significant and atypical decline in value. A crash in our application may last for several days, and we also assume that the next bubble begins after the crash of the previous bubble.

There are two scenarios when we may mistakenly report that a crash has occurred. One instance is when the index rises in a bubble and suddenly falls sharply, but the decrease is just brief, and the bubble continues to rise. The other is when, during a crash, the index recovers on the way down, allowing us to see the start of a new bubble. However, this rebound is brief, and the anti-bubble remains in place. To avoid those situations, we select a peak as the one initiating a crash. (2) As follows:

- For 262 weekdays preceding the peak, no value is greater than the peak.
- A >25% decline in prices from the peak
- This decline should occur within <60 weekdays

3.3 Working Of the Algorithm

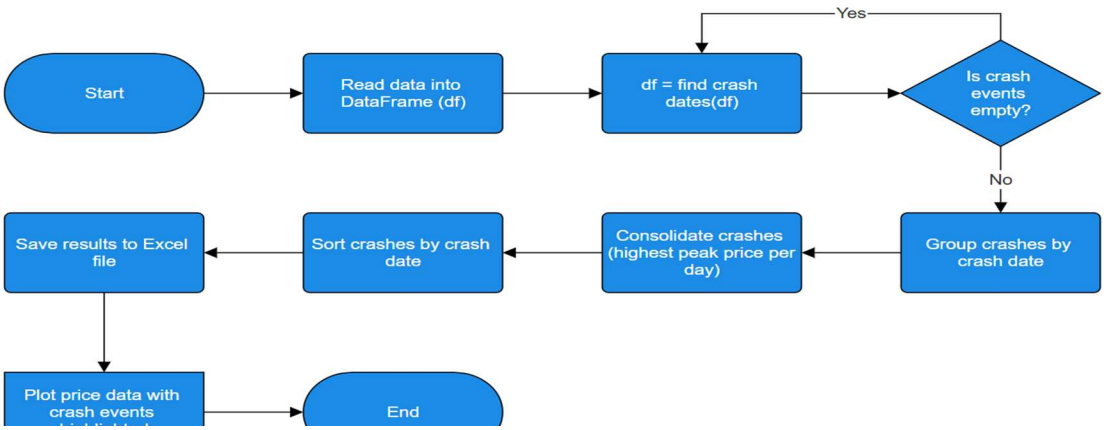

Figure 1. Flow of Crash Identification Algorithm

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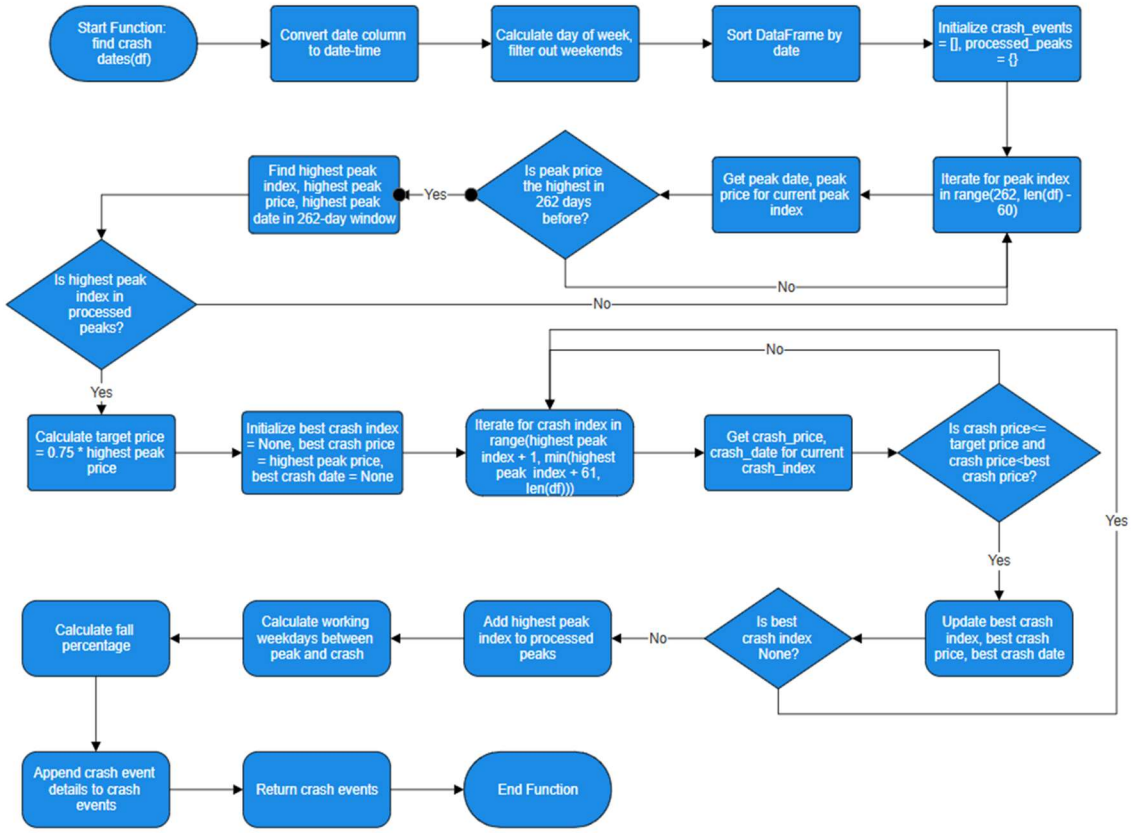

Figure 2. Algorithm of Function (to find crash dates)

The main algorithm in Figure 1 works by first taking the data from the file and converting it into a data frame. Then it applies the find crash dates function with the data frame as the input and gets the crash dates back as an output, after which it checks whether the crash event variable is empty. If it is, it loops and runs the find crash dates function again. Then it groups all the crashes into one place and sorts them chronologically and outputs the results to Excel as a table, which contains the peak date, the crash date, as well as the peak close price and the crash close price, along with the fall percentage, which is calculated in the find crash dates function.

The find crash dates function algorithm in Figure 2 initially converts the input data from the date column into the date-time format, sorts it chronologically, and assigns each date a number in ascending order. After this, it enters the first loop, which considers a value. It scans the 262 days before it and ensures that the value selected exceeds all the values in the 262 days before. Then it checks to ensure that the selected peak value is the highest in the previous 262 days; once confirmed, the peak is added to the processed peak variable. After this, the algorithm checks whether the processed peak array is empty, and if it is, then it restarts the loop from finding a peak date. If the processed peak array is not empty, it calculates the target price, which is 25% lower than the peak price for the chosen peak date. The algorithm then scans the 60 days after the peak dates and checks whether the crash close price is 25% lower than the peak close price, and it does this for every single peak date in the processed peak array. After the lowest crash price is found for each peak date, the loop ends after we check if the best crash index array is not empty, after which we find the number of workdays between the peak date and crash date and also calculate the decline percentage and add all the information to the crash event array which is then given as the output of the function.

3.4 Stock Market Crashes in Russia

We analyzed the historical data for the study and identified nine market crashes, of which only five fit the criteria set. Four of the crashes were rejected since their peak dates were lying within the bubble period of another crash, and their peak was lower, which does not fulfill the criteria described by Bree and Joseph (1) in their definition of a crash. Thus, the crashes of 1998, 2000, 2004, 2006, and 2020 crashes are eligible for further analysis.

3.5 LPPL

A mathematical model called the Log-Periodic Power Law (LPPL) forecasts how financial markets will behave, especially during speculative bubbles and crashes. It combines power-law growth and oscillatory behavior to describe an asset's price as it approaches a catastrophic event, such as a crash.

This study uses the Log-Periodic Power Law (LPPL) model to detect and forecast significant events such as financial crashes in the MOEX Russian Index. The LPPL model is defined as:

$$\ln[p(t)] = A + B(t_c - t)^{\beta} * (1 + C(t_c - t)^{\beta} \cos(\omega \log(t_c - t) + \phi)) \quad -(1)$$

Where:

- p(t): Estimated Asset Price at time t
- A: Baseline price level
- B: Magnitude of Power Law growth/decay
- C: Amplitude 1of oscillatory behavior
- β: Exponent (typically 0 < m < 1, ensuring accelerating behavior)
- ω: Frequency of log-periodic oscillations
- ϕ: Phase Shift
- t_c: Estimated critical time (potential crash moment

3.5.1 LPPL model fitting using Non-Linear Least Squares (NLLS) and the trust region reflective (TRF) algorithm

This study uses a quantitative time-series research design in which the Log-Periodic Power Law (LPPL) model is applied to the MOEX Index to detect speculative bubbles and potential crash points. Traditional linear regression methods are ineffective on the LPPL function because of its extremely nonlinear nature, which includes both power-law growth and log-periodic oscillation components. Instead, we employ the Trust Region Reflective (TRF) technique to optimize Non-Linear Least Squares (NLLS). When used with noisy financial data, this approach ensures robust parameter estimate while lowering the probability of divergence.

The optimization problem minimizes the residual sum of squares (RSS) between observed and predicted prices:

$$\min_{\theta} RSS(\theta) = \sum_{i=1}^{n} [P_i - f(t_i; \theta)]^2 \quad (2)$$

Where:

- P_i : observed data at point i
- t_i : input value (like time) at point i
- $f(t_i;\theta)$: model prediction at point i given parameters θ
- θ : the parameter(s) of your model to optimize
- n : number of data points

The TRF approach works by defining a "trust region" around the current solution, which assumes that the residual function is well-approximated. At each iteration, the algorithm finds a step that minimizes the cost function while adhering to parameter limitations. If the step considerably lowers the cost, the trust region expands; otherwise, it contracts. This iterative procedure helps to stabilize convergence and prevent overfitting, making TRF ideal for the unstable parameter dynamics of LPPL fitting (8).

We chose the TRF method over unconstrained solvers like Levenberg-Marquardt because the latter frequently diverges in the LPPL's sensitive parameter space. TRF improves boundary conditions for β, ω, and tc, which are crucial for detecting speculative bubble dynamics. It's crucial to remember that TRF has drawbacks, including the possibility of local minima trapping the optimization process and convergence that is still susceptible to initial parameter assumptions. Brée & Joseph (2013) point out that these kinds of problems can impact the accuracy of predictions. Future research may investigate hybrid optimization approaches or Bayesian calibration frameworks to improve resilience.

3.6 Model Validation

Several validation techniques were used to evaluate the LPPL model's predictive accuracy. The

Log of the data and the raw data have been used, and a fit is performed on both datasets. The difference between the actual close prices and the predicted prices is used through the Root Mean Square Error (RMSE) of the fit for the raw and log data, along with the Coefficient of Determination (R2) value, to find the accuracy of the fit. A visual analysis also evaluates how accurately the model captured the oscillatory behavior and price trend preceding a crash.

4. RESULTS

Using the method mentioned in the research methodology and the conditions, we identified the crashes shown in Table 1.

Table 1. Crashes Identified

Crash No.	Peak Date	Crash Date	Fall Percent
1	11-03-1998	01-06-1998	51.22%
2	22-06-1999	09-08-1999	26.87%
3	06-07-1999	21-09-1999	44.67%
4	24-03-2000	24-05-2000	29.10%
5	17-10-2003	19-11-2003	26.42%
6	12-04-2004	15-06-2004	25.55%
7	07-10-2004	10-12-2004	29.99%
8	05-05-2006	13-06-2006	30.73%
9	20-01-2020	18-03-2020	34.39%

Out of the crashes identified, we only consider Crashes no. 1, 4, 7, 8, and 9 since these crashes fulfil the three criteria for identifying a crash. Crashes 2, 3, 5, and 6 are not considered since their peaks come within the 262 days of the next crash and therefore are not considered. So, the further evaluation will be confined to crashes 1, 4, 7, 8, and 9.

Determining an LPPL model that aligns with a bubble preceding a crash relies on the values of the two critical parameters, β and ω. Therefore, it is essential to analyse the sensitivity of the RMSE of the fit to the changes in these parameters. We use all the bubbles in the MOEX Russian Index to examine the sensitivity of the LPPL fit to variations in each of the four search parameters (β, ω, ϕ, and t_c); the other three parameters (A, B, and C) are always set.

The quality of the model's curve fitting and the sensitivity of its main parameters (β, ω, ϕ, t_c) are assessed in the Log-Periodic Power Law (LPPL) model analysis for stock market collapse prediction. The curve fitting graph illustrates how well the model captures the escalating price dynamics that lead to a crash by displaying the LPPL fit and actual market prices.

4.1 Crash 1

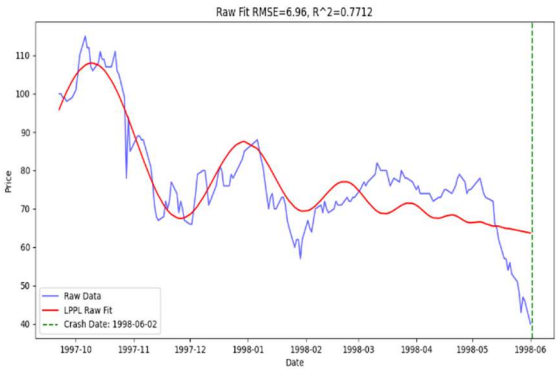

Figure 3. 1st Crash LPPL fit based on Raw Price Data

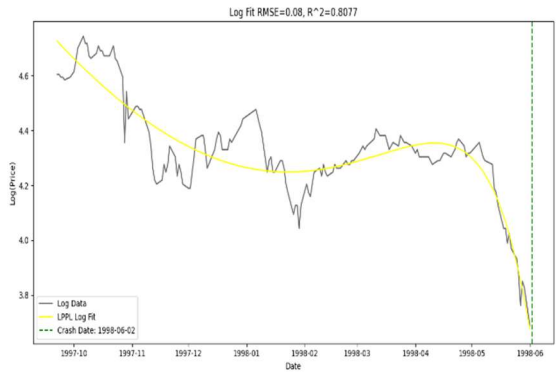

Figure 4. 1st Crash LPPL fit based on Log Price Data

Table 2. 1st Crash Parameters

Crash 1		
Type	**Raw**	**Log**
t_c	253.0000	253.2385
β	1.0000	0.5166
A	63.6332	3.5568
B	0.0959	0.1116
C	-0.0042	0.0403
ω	14.6461	1.4560
φ	-1.2462	2.3340

RMSE	6.9600	0.0800
R^2	0.7712	0.8077
Actual Crash Date	01-06-1998	
Predicted Crash Date	02-06-1998	02-06-1998
Days Between Predicted and Actual Crash Date	1	1

The first case under analysis involves the 1998 financial crisis in Russia. Multiple factors influenced the situation, such as the Asian economic crisis and falling oil prices, which resulted in the devaluation of the Russian Ruble. The timeline of this crash is from 22nd September 1997 to 1st June 1998. In the first crash, the raw data fit, and the log-transformed data predicted the same crash date of 2nd June 1998, only one day from the actual crash date of 1st June 1998.

The log-transformed data fit yielded a better fit than the raw data fit. As seen by a higher R^2 value and a lower RMSE, as shown in the

Table 2. The log-transformed data model can accurately capture the underlying trend, equating to a visually better portrayal of the trend preceding the crash.

Despite the differences in the goodness of fit, both the log-transformed and raw data used in the LPPL model accurately predicted the crash on 2nd Jun 1998, which is only 1 day of difference from the actual crash date of 1st Jun 1998. This shows that for this case, the critical time prediction is robust. However, comparing the estimated parameters uncovers significant differences between the two fits. These differences show that the log-transformed data influences the characteristics of the speculative bubble as captured by the LPPL model.

4.2 Crash 2

After the sharp decline of the index in 1998, the index recovered. The LPPL model was fitted to the timeline from 2nd June 1998 to 24th May 2000, trying to capture the speculative bubble leading to the subsequent bursting of the bubble on the 24th of May 2000.

The use of the LPPL model on the raw data for this timeline resulted in a better fit, as shown by the higher R2 value in Table 3. Notably, the predicted crash date is 25th May 2000, which is only 1 day off the actual crash date of 24th May 2000.

The LPPL model, when fitted using the log-transformed data, outputs a better visual fit with a lower RMSE. However, the predicted crash date is 22nd July 2000, 59 days after the actual crash date.

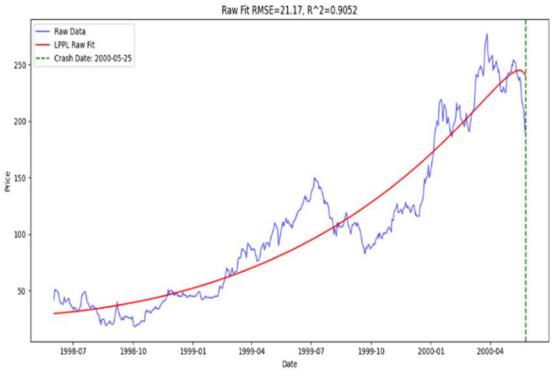

Figure 5. 2nd Crash LPPL fit based on Raw Price Data
Figure 6. 2nd Crash LPPL fit based on Log Price Data

Table 3. 2nd Crash Params

Crash 2		
Type	**Raw**	**Log**
t_c	723.0000	782.0000
β	0.4393	1.0000
A	238.7122	5.4491
B	1.0000	0.0000
C	1.0000	1.0000
ω	0.6654	0.8236
φ	-0.4416	-1.3056
RMSE	21.1700	0.2500
R^2	0.9052	0.8783
Actual Crash Date	24-05-2000	
Predicted Crash Date	25-05-2000	22-07-2000
Days Between Predicted and Actual Crash Date	1	59

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Comparing the two fits, the LPPL fit on raw data demonstrates a superior ability to understand the variance in price levels. However, it also has a larger average error in price predictions, shown by the higher RMSE. The most significant difference is in the prediction of the crash date; the raw data predicts a more accurate date, whereas the log-transformed data provides a better fit in terms of RMSE, but it overestimates the timing of the crash. This suggests that, for this case, the market trends were better predicted by the LPPL fit on the raw data.

4.3 Crash 3

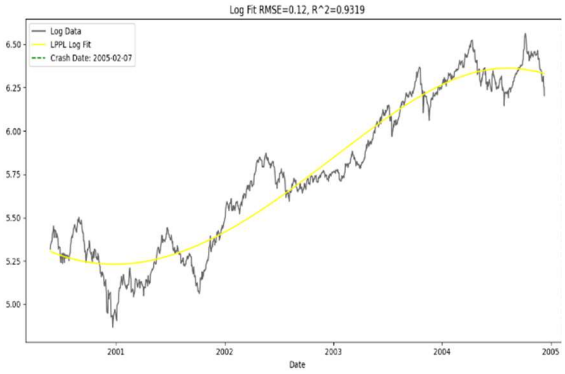

Figure 7. 3rd Crash LPPL fit based on Log Price Data

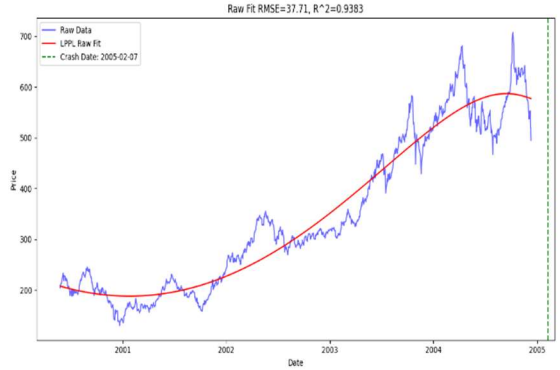

Figure 8. 3rd Crash LPPL fit based on Raw Price Data

Following the recovery from the crash in the second case, the index experienced a period of growth. The LPPL model was applied to a timeline from 25th May 2000 to 10th December 2004, with the crash date on 10th December 2004 as shown in Table 4.

The LPPL model fit on the raw data for this timeline is poor, with a low R^2 value and a high RMSE. The model fails to capture the changes in the market trends; it only broadly displays the upward market fluctuations and misses the fluctuations in between and the sharp decline. The predicted crash date is about 59 days after the actual crash date in this case, as shown in Table 4.

Table 4. 3rd Crash Params

Crash 3		
Type	**Raw**	**Log**
t_c	1720.0000	1720.0000
β	0.6974	1.0000
A	570.9040	6.3101
B	0.0210	0.0003
C	-1.0000	0.0039
ω	1.3574	1.1652
φ	-2.8243	1.8696
RMSE	37.7100	0.9383
R^2	0.1200	0.9319
Actual Crash Date	10-12-2004	
Predicted Crash Date	07-02-2005	07-02-2005
Days Between Predicted and Actual Crash Date	59	59

In contrast, the LPPL model fitted to the log-transformed data shows a better fit with a higher R^2 value and a lower RMSE. This demonstrates that the LPPL model could better capture the trend and the oscillations of the market. The predicted crash date is identical to the LPPL model fitted to the raw data.

The performance of the LPPL model on raw and log data for Crash 3 varies significantly. The log transformation enhances model fit, as seen by considerably larger R-squared and lower RMSE values. Visually, the log fit is substantially more accurate to the actual price activity. Interestingly, despite the significant difference in goodness of fit, both modifications produce the same anticipated crash date around two months later.

4.4 Crash 4

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Following the previous times of recovery and development, the MOEX index maintained its upward trend. The LPPL model was fitted to data in the timeline from 11th December 2004 to 13 June 2006, with the actual crash date of June 13th, 2006, as shown in Table 5.

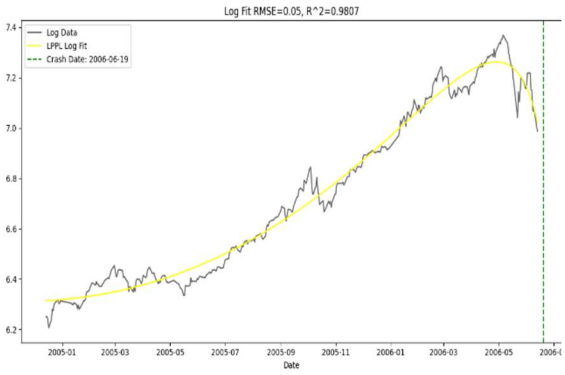

Figure 9. 4th Crash LPPL fit based on Raw Price Data

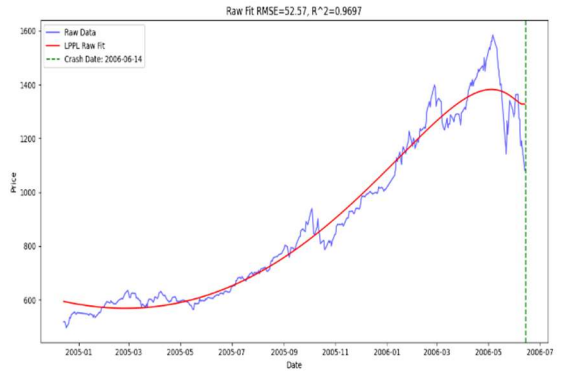

Figure 10. 4th Crash LPPL fit based on Log Price Data

The LPPL model applied to the raw price data for this period produces a good fit, with a high R-squared value and RMSE. The LPPL model on raw data accurately depicts the market's general trajectory, including the run-up to the crash. The predicted crash date based on this fit is 14th June 2006, which is exceptionally close, barely one day after the actual crash.

The LPPL model fitted to log-transformed pricing data also shows a firm fit, with an even higher R-squared value and a substantially lower RMSE than the raw data model. The LPPL fit line closely approximates the log-transformed data with slight variance. This analysis predicts a crash on 19th June 2006, near the actual date, with only a six-day discrepancy.

In this case, raw and log data transformations produce good model fits, as evidenced by the extremely high R-squared values. The log data fit offers a somewhat better statistical fit based on R-squared and significantly lower RMSE, implying a more accurate portrayal of the changed price movements. Regarding crash date prediction, the raw data fit yields a somewhat more precise prediction, being only one day off as opposed to the log data fit's six-day discrepancy.

Table 5. 4th Crash Params

Crash 4		
Type	**Raw**	**Log**
t_c	547.0000	552.7803
β	0.5650	0.4464
A	1327.5503	6.8536
B	1.0000	0.0610
C	-1.0000	0.1037
ω	1.2560	0.9801
φ	-0.7323	-2.5503
RMSE	52.5700	0.0500
R^2	0.9697	0.9807
Actual Crash Date	13-06-2006	
Predicted Crash Date	14-06-2006	19-06-2006
Days Between Predicted and Actual Crash Date	1	6

4.5 Crash 5

The fifth case looks at a long period of expansion in the MOEX index, followed by a collapse as the intermediate corrections do not qualify to be called a crash as per the definition used by Bree and Joseph (1). The LPPL model was fitted to the timeline covering 14th June 2006 to 18th March 2020, with the actual crash date on 18th March 2020, as shown in the

The LPPL model fitted to the log-transformed price data has a lower R-squared value, but a much lower RMSE than the raw data fit. The LPPL fit on

the log-transformed data captures the increasing trend while smoothing out short-term volatility. This analysis predicts that the crash will occur on 16th May 2020, approximately 59 days after the actual crash.

In this instance, the raw data fit has a bigger average error in price level prediction (higher RMSE), but it also explains a larger percentage of the variance (higher R-squared). On the other hand, the log data fit predicts the log-transformed prices with a substantially smaller average error but a lower R-squared. The accuracy of the crash date forecast shows the most significant difference. At the same time, the log data underestimates the crash's timing; the raw data fit yields an exact prediction.

Table 6.

The LPPL model fitted to the raw price data for this timeline produces a decent fit, with an R-squared value and a greater RMSE. The LPPL model roughly fits the raw data and follows the long increasing trend while missing many intermediate oscillations. Notably, it gives an exact forecast of the crash date, 19th March 2020, only one day after the event.

Figure 11. 5th Crash LPPL fit based on Log Price Data

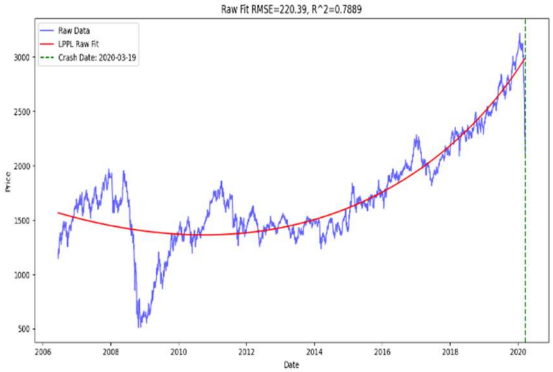

Figure 12. 5th Crash LPPL fit based on Raw Price Data

The LPPL model fitted to the log-transformed price data has a lower R-squared value, but a much lower RMSE than the raw data fit. The LPPL fit on the log-transformed data captures the increasing trend while smoothing out short-term volatility. This analysis predicts that the crash will occur on 16th May 2020, approximately 59 days after the actual crash.

In this instance, the raw data fit has a bigger average error in price level prediction (higher RMSE), but it also explains a larger percentage of the variance (higher R-squared). On the other hand, the log data fit predicts the log-transformed prices with a substantially smaller average error but a lower R-squared. The accuracy of the crash date forecast shows the most significant difference. At the same time, the log data underestimates the crash's timing; the raw data fit yields an exact prediction.

Table 6. 5th Crash Params

Crash 5		
Type	**Raw**	**Log**
t_c	5027.0000	5086.0000
β	0.5651	0.7768
A	2988.0248	7.9678
B	1.0000	0.0000
C	-1.0000	1.0000
ω	0.1924	0.0732

φ	-0.1708	-2.2195
RMSE	220.3900	0.1800
R^2	0.7889	0.6200
Actual Crash Date	18-03-2020	
Predicted Crash Date	19-03-2020	16-05-2020
Days Between Predicted and Actual Crash Date	1	59

Our findings support Johansen and Sornette's (1999, 2000) (12,37) claim that market crashes are statistical outliers rather than random fluctuations, as several MOEX disasters were predicted with a one-day lag. However, situations where predictions lag by 59 days are consistent with the complaints leveled by Brée and Joseph (2013) (2), who warn that LPPL's predictive accuracy is vulnerable to parameter instability.

Furthermore, our data confirm Demirer et al.'s (2019) (9) claim that combining liquidity and short-selling activity improves bubble detection. While our model accurately captures severe crashes, it ignores minor downturns, indicating that LPPL alone is insufficient for comprehensive risk monitoring. This duality emphasizes the probabilistic rather than deterministic nature of LPPL predictions.

5. CONCLUSION

This study indicates that the LPPL model can forecast numerous big MOEX crashes with near-perfect timing, but prediction performance differs depending on whether raw or log-transformed data is employed. The raw-data fits performed best in predicting specific crash dates, whereas log-transformed fits produced more statistically reliable results. These contrasts illustrate the sensitivity of LPPL forecasts to data scaling decisions.

Unanswered questions persist. Can LPPL consistently catch smaller crashes under 25%? How does integrating LPPL with market microstructure indicators like liquidity and trading volume impact forecasting accuracy? Finally, is the advantage of log transformation market-specific or a feature that can be applied across other economies? To answer these problems, we must expand LPPL analysis to additional emerging markets and try hybrid models.

By improving LPPL applications, this study helps regulators, investors, and policymakers create early warning systems to reduce systemic financial risks (36,40).

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