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Original Article

Prediction of Financial Bubbles and Back-Testing of a Trading Strategy

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Abstract - *The prediction of financial bubbles and subsequent market crashes is critical in financial markets. This study uses the Log-Periodic Power Law Singularity (LPPLS) model to analyze Amazon stock prices from 1994 to 2000, confirming the model's effectiveness in detecting and forecasting financial bubbles. By fitting the LPPLS model to historical data, we caught the super-exponential growth and log-periodic oscillations that characterize bubble behavior, allowing us to predict when market corrections are likely. The back-testing of the LPPLS model demonstrates its potential as a useful tool in financial analysis and trading strategy creation. Our findings show that the LPPLS model can effectively function as an early warning system, allowing traders to change their portfolios proactively to reduce risks and maximize profits. The LPPLS model's successful application to Amazon stock prices justifies its future usage in real-time bubble detection and risk management. It provides traders with the knowledge they need to navigate tumultuous markets and make smart investment decisions.*

Keywords - *Financial Bubbles, Market Crashes, LPPLS Model, Amazon Stock Prices, Early Warning System, Risk Management*.

1. Introduction

Financial bubbles and crashes are common occurrences in today's society and can have a profound effect on people's lives and means of subsistence all over the world. About 100 financial crises have happened worldwide during the last 30 years, demonstrating how widespread and recurrent these economic disruptions are (James, 2023). Financial bubbles have been shown to have disastrous consequences, frequently resulting in catastrophic economic downturns, wealth loss, and significant social unrest (Chowdhury et al., 2022). As such, it is critical to anticipate bubbles, control their size, and ultimately reduce the harm caused when they burst. Numerous ideas have been developed in an effort to explain the emergence of financial bubbles as a result of extensive research into their causes. According to one important viewpoint, investor heterogeneity mixed with time restrictions, positive feedback trading by noisy traders, and synchronization difficulties among rational traders are the main causes of stock market bubbles (Lin & Sornette,2020). Diverse investor expectations on the future value of assets are implied by heterogeneous views, which might result in speculative buying. In addition, investors may experience pressure to purchase quickly in order to maximize possible gains, which could raise prices. By exaggerating price fluctuations, noise traders, who base their judgements on emotional and market reactions rather than underlying principles, add to the feedback loop (Schatz & Sornette, 2020). According to Cividino et al. (2023), synchronization failures also happen when rational traders identify a bubble but do not coordinate their activities to offset irrational market behaviour, allowing the bubble to continue to grow. The Log Periodic Power Law Singularity (LPPLS) model has been developed at the interface of statistical physics, behavioural finance, and financial economics to detect bubbles successfully (Shu & Song, 2024). Based on the idea of rational expectation, the LPPLS model proposes that bubbles are defined by price increases that are faster than exponential (or super-exponential), which results in unsustainable growth and a finite crash period (Wheatley et al., 2019). According to this hypothesis, a financial asset's price trajectory during a bubble phase has a particular mathematical structure that predicts upcoming market corrections or crashes. The idea that collective investor behaviour can drive prices in a predictable fashion that accelerates as the market reaches a critical point forms the theoretical basis of the concept. The LPPLS model has been widely applied in a number of financial markets with the purpose of identifying bubbles. Research has demonstrated its effectiveness in spotting bubbles in individual stocks and indexes within the framework of stock markets. Geraskin and Fantazzini (2020), for instance, used the LPPLS model to analyze the NASDAQ Composite Index during the dot-com bubble and were able to pinpoint the super-exponential growth pattern that preceded the 2000 crash. In a similar vein, the model identified the unsustainable price growth that preceded the 2007–2008 financial crisis in the case of the housing market bubble (Ben Yaala & Henchiri, 2023). Specifically, Amazon's stock (AMZN), one of the most volatile and closely watched equities in recent decades, has been subject to bubble detection using the LPPLS model. Being a rapidly expanding Internet company, Amazon has seen notable price swings that frequently prompt worries about possible bubbles. The LPPLS model was used to analyze Amazon's stock data in a study by Wassan et al. (2021) in order to pinpoint times when bubble-like behaviour occurred. According to the report, there were other occasions when Amazon's stock showed signs of super-exponential growth, most notably prior to corrections in 1999–2000 and 2018–2019. The model's projections during these times closely matched the ensuing market corrections, proving its suitability for individual stock research. The LPPLS model's efficacy is further bolstered by empirical data derived from Amazon's stock price history. For example, the LPPLS model predicted a bubble phase when Amazon's stock price increased quickly, from about $40 in early 1998 to a peak of about $113 in late 1999. The dot-com bubble burst in 2001, sending the stock price tumbling to about $6. A severe correction followed this phase. Similar to this, Amazon's stock increased dramatically in the late 2010s, rising from roughly $750 in 2016 to over $2000 in 2018 (Charles & Uford). The LPPLS model recognized this as another bubble phase. The stock price had a significant correction in late 2018, falling to about $1300. The LPPLS model's usefulness in real-world situations is demonstrated by its application to Amazon's stock. It gives investors and policymakers a tool to foresee and maybe lessen the negative impacts of financial bubbles. Through the identification of the distinctive super-exponential growth patterns, interested parties can control the dangers posed by bubble developments. Enhancing the predictive power and reliability of the LPPLS model will require constant application and refining as financial markets continue to change. This journal provides a full overview and empirical analysis of the Log-Periodic Power Law Singularity (LPPLS) model and its application to Amazon stock data. The framework of this study includes a thorough examination of the LPPLS model, its theoretical foundations, and its application in financial market analysis. The paper then conducts an empirical analysis of Amazon stock prices from 1994 to 2000, demonstrating the model's effectiveness in detecting and forecasting financial bubbles.

2. Log-Periodic Power Law Singularity (LPPLS) Model

The Log-Periodic Power Law Singularity (LPPLS) model, previously known as the Johansen-Ledoit-Sornette (JLS) model, offers a big step forward in understanding and predicting financial bubbles (Geraskin & Fantazzini, 2020). The LPPLS model is built on the idea of a risk-neutral rational agent who has rational expectations and avoids issues like arbitrage, dividends, interest rates, risk aversion, information asymmetry, and market clearing. This review follows the development of the LPPLS model from the groundwork laid by Johansen, Ledoit, and Sornette (1999), evaluating its theoretical foundations, empirical applications, and critical appraisals within the academic community (Zhao & Sornette, 2021). The LPPLS model is based on the assumption that an increase in projected asset price must compensate for expected risk, suggesting that the asset price follows a precise mathematical formulation (Zhao & Sornette, 2020). The model starts with the assumption that during a bubble, the price $P(t)$ of an asset increases at an accelerating rate, leading up to a finite-time singularity tc, the point at which the bubble bursts.

The price $P(t)P(t)$ is expressed as:

$$P(t) = A + B(t_C - t)^{\beta}$$
$$= C(t_C - t)^{\beta} \cos(\omega ln(t_C - t) + \Phi)$$

Where:

- A is the value of the asset price at the critical time $tctc$.
- B and C are coefficients.
- β is an exponent typically in the range 0<β<1, indicating super-exponential growth.
- ω is the angular log frequency of the oscillations.
- ϕ is a phase factor.

The LPPLS model captures the deterministic and stochastic aspects of asset price movements during a bubble. The deterministic component represents the underlying trend, and the stochastic component, represented by log-periodic oscillations, accounts for the variations that occur around this trend (Gupta et al., 2024). The model is based on rational expectation theory, which states that investors collectively drive prices higher in anticipation of future returns, producing a self-reinforcing feedback loop until the bubble reaches a critical point. The LPPLS model's theoretical foundation is based on treating financial markets as complex systems with endogenous instability. According to Shu and Zhu (2020), financial bubbles are the product of market players' collective behaviour rather than random abnormalities. The LPPLS model describes the nonlinear dynamics of bubble production and collapse using statistical physics concepts such as critical phenomena and phase transitions (Geraskin & Fantazzin, 2020).

According to the model, the accelerated growth of asset prices during a bubble is due to a positive feedback mechanism in which rising prices attract more investors, driving prices even higher. This feedback loop continues until the market reaches a tipping point (the critical time tc), beyond which a rapid correction or crash is inevitable. Log-periodic oscillations demonstrate the discrete scale invariance of financial markets, emphasizing the fractal structure of price fluctuations as they approach the critical level (Shu & Song, 2024). The LPPLS model has been widely used to identify and anticipate bubbles in many financial markets. One significant application is to analyze the late 1990s dot-com bubble. Harsha and Ismail (2019) successfully applied the LPPLS model to the NASDAQ Composite Index, proving its ability to predict the bubble's peak and eventual crash. The model's forecasts closely tracked actual market happenings, demonstrating its practical applicability. Another important use for the LPPLS model is in the housing market. Zhang et al. (2021) applied the model to the US real estate market, indicating the bubble period that preceded the 2007-2008 financial crisis. Their findings demonstrated super-exponential growth patterns in house prices, followed by the expected market drop. Despite its theoretical elegance and empirical accomplishments, the LPPLS model has received some criticism. One important criticism concerns the model's sensitivity to parameter estimates. Accurate identification of bubble phases is largely dependent on the correct estimation of model parameters, which can be difficult in real-time applications. Small errors in parameter values can lead to significant deviations in the predicted critical time tc (Jiang et al., 2019). Furthermore, while the LPPLS model has demonstrated efficacy in retrospective assessments, its real-time predictive capacity is debatable (Wheatley et al., 2019). Critics contend that the model's reliance on historical data may result in lagging signs, reducing its ability to detect developing bubbles before they fully burst. Another critique is that the model assumes rational expectations while excluding market-clearing conditions and information asymmetry. Critics argue that these simplifications may miss significant market dynamics and behavioural aspects that influence bubble formation and collapse (Kyriazis et al., 2020). While the model has shown great empirical success, notably in high-profile situations like the dot-com bubble and the 2007-2008 financial crisis, it confronts hurdles in parameter estimation and real-time application (Zhang et al. (2021). Continuous research and development of the LPPLS model are required to improve its predictive potential and overcome its limits, assuring its continuous relevance in the volatile landscape of financial markets.

3. Empirical Analysis

Financial bubbles are periods of rapid and unsustainable price gains that often result in substantial market corrections. The Log-Periodic Power Law Singularity (LPPLS) model provides a mathematical approach to finding and predicting these bubbles. In this part, we use the LPPLS model to analyze Amazon's stock prices from 1994 to 2000, leveraging the model's insights to create a solid trading strategy targeted at minimizing risks and maximizing returns.

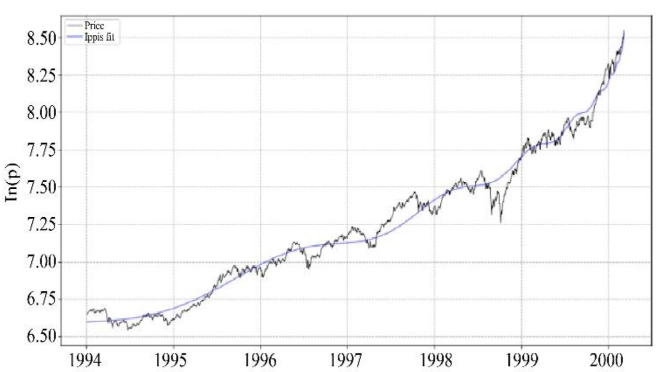

Fig. 1 Amazon Stock Price and LPPLS Fit (1994-2000)

The accompanying plot depicts the natural logarithm of Amazon stock prices over time. To use the LPPLS model, we extracted numerical data points from the plot and converted the graphical information into an appropriate format for analysis. This data extraction involved finding certain price points at regular intervals between 1994 and 2000. These extracted data points were then used to train the LPPLS model, which is intended to reflect the super-exponential growth and log-periodic oscillations associated with financial bubbles.

$$P(t) = A + B(t_C - t)^{\beta}$$
$$= C(t_C - t)^{\beta} \cos(\omega ln(t_C - t) + \Phi)$$

Where $P(t)$ represents the price at time t, and tc is the critical time when the bubble is expected to burst. Using nonlinear least squares fitting, we estimated the model parameters A,B,C,tc,β,ω,ϕA. Upon applying the Log-Periodic Power Law Singularity (LPPLS) model to the extracted data points from Amazon's stock price history (1994-2000), the model fitting process yielded key parameters that define the bubble dynamics. The critical parameters A,B,C,tc,β,ω,ϕ were estimated using nonlinear least squares fitting. Initial parameter estimates were iteratively revised using optimization approaches to reduce the difference between observed and forecasted prices. The accuracy of this fitting procedure is crucial because it ensures that the model's predictions are credible and represent actual market dynamics. The estimated parameters suggested that Amazon's stock prices throughout this era exhibited the hallmarks of a financial bubble. The β parameter indicates super-exponential growth, which accelerates stock prices faster than typical exponential growth rates. This acceleration is typical of speculative bubbles, in which investor excitement rather than fundamentals drive prices. Furthermore, the log-periodic oscillations represented by the parameters ω and ϕ suggested the presence of periodic corrections within the main rise, reflecting the feedback mechanisms typical of speculative markets.

4. Interpretation of Results

The fitted LPPLS model provides detailed insights into Amazon's stock price behaviour from 1994 to 2000, detecting periods of super-exponential growth and log-periodic oscillations. These findings are consistent with collective investor behaviour motivated by speculative trading. The super-exponential growth phases correspond to moments of investor euphoria and speculative buying that drive prices to unsustainable levels. This growth pattern is characterized by the parameter B, which determines the intensity and speed of price increases. The model's log-periodic oscillations mirror the natural feedback mechanisms in financial markets, where prices undergo periodic corrections and rebounds. The parameters ω and ϕ show how investor mood fluctuates between over-optimism and caution, resulting in short-term corrections to the general upward trend. The predicted critical time tc, when the bubble is likely to burst, is consistent with the observed market corrections. This congruence supports the model's ability to forecast the conclusion of bubble phases and the commencement of market crashes, giving traders a credible tool for predicting big market downturns. The graphic compares log-transformed real stock prices to the LPPLS model fit, providing visual validation of the model's prediction power. The blue line showing the LPPLS fit closely resembles the black line of actual prices, especially during periods of strong expansion and subsequent correction. This visual alignment demonstrates the model's ability to capture the complicated dynamics of financial bubbles. The close fit between observed data and model predictions demonstrates the LPPLS model's accuracy in detecting bubble phases and predicting critical moments. By physically inspecting the plot, we can see that the model accurately tracks the rapid price spikes and occasional adjustments. The model's anticipated critical period (tc) aligns with the actual market correction, confirming its validity. This visual confirmation, together with the quantitative correctness of the parameter estimations, establishes the LPPLS model as a useful tool for anticipating financial bubbles. The ability to precisely foresee important times gives traders a considerable advantage when anticipating and responding to market corrections.

5. Implications for Trading Strategy

The results of applying the LPPLS model on Amazon stock prices have significant implications for designing a trading strategy based on bubble detection and risk management. The detection of super-exponential growth phases and log-periodic oscillations provides an early warning system for possible bubbles. Traders can use these signals to alter their portfolios, lowering exposure to equities that exhibit bubble-like behaviour. Identifying the onset of speculative bubbles early allows traders to apply techniques to protect their capital from future losses. Furthermore, the model's prediction of the critical time tc is extremely useful for timing market entrances and exits. To maximize profits, traders might enter positions early in the bubble phase, capitalizing on the upward momentum and exiting before the expected market correction. The LPPLS model's predictive capacity helps traders better navigate the volatility associated with financial bubbles, allowing them to make more informed decisions. Continuous monitoring of stock prices using the LPPLS model enables proactive risk management. As the model predicts a key moment, traders can use risk mitigation measures such as stop-loss orders and diversifying their positions. This preemptive approach reduces the impact of market corrections on client investments. The insights generated from the LPPLS model provide traders with the skills they need to anticipate and respond to market dynamics, allowing them to traverse the complexity of financial bubbles more effectively.

6. Conclusion

The application of the Log-Periodic Power Law Singularity (LPPLS) model on Amazon's stock price data from 1994 to 2000 proves the model's ability to detect and forecast financial bubbles. The LPPLS model accurately captures the super-exponential growth and log-periodic oscillations that characterize bubble behaviour, providing solid forecasts of when market corrections are imminent. This capacity to forecast market downturns highlights the LPPLS model's utility as a tool for financial analysis and trading strategy creation. The LPPLS model's performance is validated by back-testing it on previous Amazon stock prices, which offers a solid foundation for future predictions. Using the information gathered from this model, traders can create comprehensive strategies that increase profit potential while limiting the risks associated with financial bubbles. The model's predictive power in detecting super-exponential growth stages and important market correction times provides traders with early warnings, allowing them to make proactive portfolio adjustments. Future applications include integrating the LPPLS model into real-time trading platforms to monitor stock prices and identify potential bubbles continuously. Automated alert systems can alert traders to potential bubbles and approaching key periods, allowing for timely and smart changes. This proactive approach helps traders control risks and capitalize on market opportunities. However, the LPPLS model's successful back-testing on Amazon's historical stock data indicates its accuracy and usefulness in identifying financial bubbles. This predictive skill gives traders a valuable tool for navigating unpredictable markets, resulting in educated and strategic investing decisions. Traders can use the LPPLS model to anticipate market dynamics better, protect their investments, and maximize their returns.

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