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ORIGINAL RESEARCH

Magnificent 7: unsustainable growth and systemic risk

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Abstract

Faster-than-exponential growth is unsustainable, culminating in what physicists term a "finite-time singularity," marked by abrupt regime changes. This study shifts focus from traditional systemic risks to hypothesize that the massive market capitalization of the "Magnificent 7" companies poses a systemic risk under two conditions: (a) their stocks exhibit super-exponential growth, and (b) finite-time singularities occur simultaneously. Applying the log-periodic power law (LPPLS) model to daily log-price data from May 13, 2016, to January 17, 2025, this research identifies strong evidence of bubble formations in four of the seven stocks. The LPPLS model forecasts regime changes between February and June 2025. Given the unparalleled market capitalization of these companies, their concurrent collapse could destabilize the broader financial ecosystem. We note, however, that policy interventions, particularly those effective during the Trump administration, can influence or disrupt the endogenous stock price dynamics uncovered in this analysis. In this study, such policy interventions are regarded as exogenous shocks and are not formally modeled within the LPPLS framework.

Keywords Bubble · Finite-time singularity · Log-periodic power laws · Magnificent 7 · Singularity

JEL classification C22 · G12 · G13 · G14 · O10

1 Introduction

The terminology "Magnificent 7" refers to seven leading technology-driven companies that wield significant influence over global markets and innovation. These companies are: Apple (AAPL), Microsoft (MSFT), Amazon (AMZN), Alphabet (GOOGL) (parent company

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of Google), Meta Platforms (META) (formerly Facebook), Tesla (TSLA), and NVIDIA (NVDA). The Magnificent 7 operate across diverse yet interconnected industries. For instance, Apple, Microsoft, and NVIDIA are considered leading companies in technology and hardware/software development, with NVIDIA specializing in advanced semiconductors and artificial intelligence (AI) hardware. On the other hand, Amazon is considered a pioneer in e-commerce and exerts its market dominance in cloud computing through Amazon Web Services (AWS). Alphabet excels in digital advertising, search engine technology, and AI, whereas Meta Platforms focuses on social media, virtual reality, and the metaverse. Finally, Tesla innovates in electric vehicles (EVs) and renewable energy solutions.

Interestingly, the Magnificent 7 companies share several defining characteristics; that is, they drive transformative innovations in fields such as AI, cloud computing, and sustainable technologies, and by this, set industry benchmarks. Their market leadership secures dominant positions in their respective sectors, while their global influence shapes consumer behavior and business practices worldwide. Collectively, they exert substantial economic impact by representing a significant share of market capitalization in major indices, serving as key drivers of financial markets and economic progress. For the public, these companies are instrumental in introducing cutting-edge technologies designed to improve daily life, enhance productivity, or provide seamless connectivity. For financial economists, the Magnificent 7 are critical for understanding market dynamics. Their enormous market capitalization influences stock market performance, portfolio allocation, risk assessments, and macroeconomic predictions.

However, their dominance may pose a potential systemic risk to the global economy. The Magnificent 7 collectively represent a substantial share of major stock indices. For example, as of January 15, 2025, the cumulative market capitalization of the Magnificent 7 was 17.8 trillion USD or 34.25% of the total market capitalization of the S&P 500. Severe downturns in their valuations could trigger widespread financial instability. Their interconnectedness with various industries amplifies this risk, as disruptions in their operations (e.g., supply chain issues or regulatory challenges) can cascade through the economy. Furthermore, their influence over critical technologies, such as cloud computing and AI, concentrates economic and technological power, raising concerns about vulnerabilities in these essential systems.

This paper is the first to examine whether the Magnificent 7 companies pose a systemic risk to the financial ecosystem by focusing on the modeling of endogenous market dynamics that lead to bubble formation, as captured by the LPPLS framework.[1] We hypothesize that these companies present such a risk if they (a) exhibit unsustainable growth rates in their stock prices, and (b) experience regime changes as a consequence of these unsustainable growth rates occurring simultaneously. For instance, Table 1 illustrates that the Magnificent 7 accounted for only 12.16% of the S&P 500's market capitalization in January 2015, which underscores that their stock prices must have grown at an accelerated rate relative to the S&P 500. It is widely recognized that growth rates exceeding exponential trends are unsustainable and eventually lead to what physicists term a "finite-time singularity"—an abrupt transition to a new regime (Sornette 2017). Historical examples, such as the early 2000 s dot-com bubble burst, highlight how regime changes can manifest, with the prices of numerous telecom and technology stocks collapsing nearly simultaneously. To determine whether the stocks of the Magnificent 7 exhibit unsustainable super-exponential growth rates, we calibrated

[1] Policy interventions are considered exogenous shocks relative to the endogenous dynamics modeled by the LPPLS framework.

Table 1 Change of market capitalizations of the magnificent 7 over the 2015 to 2025 decade

Company	Market capitalization January 15, 2015	Market capitalization January 15, 2025
Alphabet	$534.1 billion	$2.4 trillion
Amazon	$323.0 billion	$2.3 trillion
Apple	$598.3 billion	$3.6 trillion
Meta	$287.1 billion	$1.5 trillion
Microsoft	$439.7 billion	$3.2 trillion
NVIDIA	$12.3 billion	$3.4 trillion
Tesla	$25.0 billion	$1.4 trillion
S&P 500	$18.3 trillion	$51.9 trillion

This table shows the market capitalization of the Magnificent 7, on January 15, 2015 versus January 15, 2025 in US dollar

log-periodic power-law singularity (LPPLS) models to the log-prices of these stocks over the period from May 13, 2016, to January 17, 2025. The LPPLS model was selected for its superior performance in predicting bubble formations in financial assets (e.g., Grobys 2025; Shu and Zhu 2020; Wheatley et al. 2019; Zhou and Sornette 2006, 2009). As emphasized by Sornette (2017), the LPPLS model effectively captures universal features of bubble formations, including price processes characterized by transient, faster-than-exponential growth driven by positive feedback mechanisms such as herding. Moreover, the model accounts for accelerating log-periodic volatility fluctuations, reflecting competing expectations of higher returns (bullish sentiment) and impending crashes (bearish sentiment). These log-periodic fluctuations, as argued by Sornette (2017), are a universal phenomenon in complex systems.

To test whether the LPPLS signatures exhibit statistical significance, we employ augmented Dickey–Fuller (ADF) tests to assess whether the residuals of calibrated LPPLS models exhibit stationarity (Lin et al. 2014). Furthermore, we evaluate the reliability of the parameters obtained from LPPLS models by iteratively reducing the sample size. Specifically, we progressively exclude observations from the beginning of the sample and re-estimate LPPLS models. This approach enables us to generate a cohort of estimated parameters and provides estimates of parameter uncertainty. For each iteratively calibrated LPPLS model, we also implement ADF tests to evaluate whether residuals derived from calibrated LPPLS models exhibit stationarity. Using this research design, we test the following research hypotheses (RH):

RH 1: The Magnificent 7 exhibit unsustainable faster-than-exponential growth.
RH 2: The Magnificent 7 will experience a finite-time singularity condition manifested in a regime change constituting the end of log-periodic oscillations.

This study makes significant contributions to the existing body of literature in several key areas. In the domain of financial economics, systemic risk is broadly understood as the potential collapse of the entire financial system resulting from the failure of interconnected institutions or markets. Such a collapse often leads to widespread economic disruption. Systemic risk is characterized by interconnectedness, where the failure of one entity can trigger cascading failures; contagion, which refers to the spread of financial distress across institutions; amplification mechanisms, such as leverage and fire sales, which exacerbate initial shocks; and non-linear effects, where small shocks escalate into major crises. Systemically important institutions play a pivotal role in this context, as their failure can have significant repercussions for the entire financial system. Events such as the 2008 Global Financial Crisis exemplify how systemic risk can destabilize economies on a global scale. The existing literature has primarily focused on systemic risk arising from the collective fragility of financial institutions. Numerous alternative measures have been proposed to quantify systemic risk levels within financial institutions (e.g., Acharya et al. 2012; Billio et al. 2012; Adrian and Brunnermeier 2016; Brownlees and Engle 2017; Van Oordt and Zhou 2019; Jasova et al. 2024). These studies underscore the importance of understanding systemic risk dynamics within the financial sector. The present study adds to this literature by adopting a novel perspective. Specifically, we argue that systemic risk is not confined to financial institutions alone but can also emerge from other sectors. This phenomenon occurs when (a) companies constituting a significant proportion of the overall market capitalization exhibit unsustainable super-exponential growth, and (b) these companies collectively experience a finite-time singularity. To our knowledge, this is the first study to investigate this issue with a focus on the "Magnificent 7" companies. By examining the systemic risk implications of these entities, this research provides a fresh lens through which to understand potential vulnerabilities in the broader market. Overall, this study not only builds upon the foundational work in systemic risk analysis but also extends the scope of inquiry to encompass sectors beyond traditional financial institutions. The findings have important implications for policymakers, regulators, and stakeholders aiming to mitigate systemic vulnerabilities across the economy.

Furthermore, this study contributes to the expanding body of literature that investigates LPPLS signatures in financial assets. The LPPLS framework characterizes the emergence of what physicists term a "finite-time singularity," a phenomenon marked by the abrupt cessation of periodic oscillations, signaling a regime shift. Johansen and Sornette (2001) pioneered this line of inquiry, exploring the potential occurrence of finite-time singularities in the dynamics of global population growth and prominent financial indices. Their analysis projected a significant regime shift around the year 2050. Building upon this foundation, Grobys (2023) revisited Johansen and Sornette's (2001) findings, employing an extended dataset, a refined estimation methodology, and monthly data on the S&P 500 instead of the DJ 30 data used in the original study. Notably, Grobys' (2023) analysis corroborated the earlier findings and reaffirmed the projection of a regime shift in 2050. Expanding this field of research, Grobys (2024) documented that Bitcoin undergoes a long-lasting bubble formation that culminates in a finite-time singularity, pinpointing the year 2140, coinciding with the anticipated completion of Bitcoin mining. Furthermore, Grobys (2025) examined the potential formation of a bubble in gold prices during the aftermath of the global financial crisis. Using daily gold futures data spanning December 2, 2015, to June 11, 2024, Grobys (2025) provided robust evidence for the occurrence of a finite-time singularity projected for October 6, 2029. Shu and Song (2024) also contributed to this growing body of work by offering a comprehensive review of the LPPLS literature, highlighting its theoretical and empirical advancements. This paper extends the LPPLS literature by shifting the focus from broad equity indices—explored extensively by Johansen and Sornette (2001), Sornette (2017), and Grobys (2023)—to individual stocks of large-cap companies. These companies, which dominate major stock market indices like the S&P 500, provide a novel lens through which to analyze regime shifts and finite-time singularities.[2]

[2] Recent research demonstrates the versatility of the log-periodic power law model across multiple disciplines. In the Earth sciences, it has been employed to capture oscillatory accelerations before catastrophic landslides (Lei and Sornette 2025) and to refine assessments of seismic criticality in earthquake clustering (Li et al. 2025). In engineering, it has been adapted for predictive maintenance, where sensor time series

Finally, the majority of studies employing the LPPLS model are primarily retrospective in nature, often described as "postdiction" (Grobys 2025). Also, this model has been subject to critique for its sensitivity to changes in time series input data, which can lead to substantial fluctuations in the estimated timing of critical events (Brée et al. 2013). Furthermore, Sornette (2017) highlights the stochastic nature of the critical time point estimates, emphasizing that the LPPLS model generally forecasts these critical times later than the actual occurrences. This study seeks to address gaps in the limited body of literature on real-time applications of the LPPLS model to predict potentially significant events, particularly finite-time singularities in financial markets (Johansen and Sornette 2001; Grobys 2023, 2024, 2025). A key contribution of this research lies in its detailed examination of the robustness of LPPLS parameter estimates. By iteratively calibrating the model across constrained sample sizes, the study assesses the reliability and stability of the derived parameters, offering a nuanced perspective on the applicability of the LPPLS model for predictive analysis.

By calibrating the LPPLS models using log-prices of the Magnificent 7 companies over the period from May 13, 2016, to January 17, 2025, our findings reveal strong evidence that four of these companies—namely, Alphabet, Amazon, Apple, and Microsoft—exhibit statistically significant LPPLS signatures. These results are validated through stationary residuals derived from the LPPLS model calibrations. Consequently, as of January 17, 2025, it is estimated that 65% of the total market capitalization of the Magnificent 7 companies is subject to finite-time singularities. Further analysis indicates that the critical time for three of the four identified companies (Amazon, Apple, and Microsoft) is expected to occur within a one-month window, specifically between May 15 and June 9, 2025. Iteratively estimated parameters derived from LPPLS models calibrated with constrained sample sizes reveal variability in parameter estimates for the critical time, which is consistent with the stochastic nature of these parameters. Despite this variability, the mean critical time estimates remain statistically significant, enabling the computation of robust confidence intervals. While the present study focuses on diagnosing endogenous bubble dynamics in key firms using the LPPLS framework, it does not explicitly model systemic transmission mechanisms such as volatility spillovers or contagion effects.[3]

The rest of the paper is organized as follows: The next section presents the data and the third section presents the methodology. The fourth section presents the results and the fifth section discusses the findings. The last section concludes.

2 Data

Daily price data for Apple (AAPL), Microsoft (MSFT), Amazon (AMZN), Alphabet (GOOGL), Meta Platforms (META), Tesla (TSLA), and NVIDIA (NVDA) are obtained from investing.com. The data are constrained to the period May 13, 2016 to January 17,

from industrial compressors reveal critical points signaling imminent failures (Łobodziński 2025). Within economics and finance, the model has been applied to stock market dynamics (Molero-González et al. 2025), crash contagion during the 2010 Flash Crash (Shi et al. 2025), speculative bubbles in NFT markets (Tewari and Pande 2025), early warnings of agricultural commodity bubbles (Xu et al. 2025), and nonlinear interdependencies between China's stock, housing, and foreign exchange markets (Zhang et al. 2025). Together, these studies illustrate the growing role of LPPL-based approaches in detecting critical transitions and bubble-like dynamics in both natural and socio-economic systems.

[3] A full analysis of how localized instabilities propagate through broader financial networks remains an important avenue for future research.

2025 because price quotations for NVIDIA exceeded USD 1.00 only in the ex-post May 13, 2016 period and calibrating the LPPLS model by means of logarithmic data requires price quotation in excess of USD 1.00.

3 Methodology

3.1 Implementing the LPPLS model based on the daily log-prices of the Magnificent 7 companies

A plain power law model for financial log-prices is given by the following:

$$\ln\left[p\left(t\right)\right] = A + B(t_c - t)^{\beta}\,, \tag{1}$$

where $\ln\left[p\left(t\right)\right]$ denotes the logarithm of some Magnificent 7 company's price at time t, t_c is the critical time, A is the expected value of the company's stock price when approaching t_c, B defines the exposure to faster-than-exponential growth, and β is the power law exponent controlling faster-than-exponential price growth (Sornette 2017). The critical time t_c indicates the end of the accelerating oscillations, resulting in a "finite-time singularity" manifested in a regime change (Zhang et al. 2016). Consistent with Sornette (2017), the simple power law model of Eq. (1) needs to be extended by accounting for periodic oscillations:

$$\ln\left[p\left(t\right)\right] = A + B(t_c - t)^{\beta}\left[1 + C\cos(\omega \ln\left(t_c - t\right) + \varphi\;)\right], \tag{2}$$

where C denotes the exposure of the log-periodic oscillations around the power law singular growth, ω denotes the angular log-frequency of oscillations during the formation of the bubble, φ is the phase parameter, and all other notations are as previously defined. Calibrating the LPPLS model requires imposing the following constraints:

$$\begin{aligned} &A > 0, \\ &B < 0, \\ &0 < \beta < 1, \\ &\omega > 0, \\ &|C| < 1. \end{aligned}$$

Furthermore, Sornette (2017) stressed that the parameter φ cannot be meaningfully restricted.

3.2 LPPLS model calibration and parameter constraints

In contrast, for the remaining parameters of the LPPLS model, it is standard practice to impose specific constraints to ensure the fitted dynamics accurately reflect the theoretical properties of speculative bubbles. The LPPLS model is calibrated to the observed price trajectories using a nonlinear least squares (NLLS) optimization procedure, minimizing the sum of squared residuals between the observed logarithmic prices and the LPPLS functional form. In this context, the terms *"calibration"* and *"estimation"* are used interchangeably, following standard practices in the LPPLS literature (e.g., Sornette and Zhou 2006; Filimonov and Sornette 2013). To ensure that the fitted solutions represent realistic bubble dynamics, we impose parameter constraints that are widely accepted in the literature: specifically, $A > 0,\ B < 0,\ 0 < \beta < 1,\ \omega > 0,\ |C| < 1$. These constraints reflect essential theoretical properties of the LPPLS model: for example, $0 < \beta < 1$ ensures a super-exponential price trajectory approaching the critical time, while $\omega > 0$ is necessary to produce the characteristic log-periodic oscillations, which have been historically observed during speculative bubble phases. Furthermore, following Sornette (2017), we recognize that parameter values approaching the boundaries (e.g., $\beta \to 0$ or $\beta \to 1$) can lead to pathological model behavior of the model, such as unphysical divergence or near-linear trends masquerading as bubbles. For this reason, we follow the literature in adopting reasonable contraints. After fitting the LPPLS model under these constraints, we assess the adequacy of the residuals by applying unit root testing procedures, as described below.

3.3 Statistical testing of the LPPLS signature

The estimated parameter vector $\widehat{\boldsymbol{\Phi}} = \left(\widehat{A} \quad \widehat{B} \quad \widehat{\beta} \quad \widehat{\omega} \quad \widehat{t}_c \quad \widehat{C} \right)$ gives us the estimated residuals defined as $\widehat{u}_t = \ln\left[p\left(t\right)\right] - \widehat{\ln\left[p\left(t\right)\right]}$, where $\widehat{\ln\left[p\left(t\right)\right]}$ is the predicted log-price of the some Magnificent 7 company's price at time *t*. To test the statistical significance of the LPPLS signature, we assess whether the residual process exhibits stationarity (Lin et al. 2014). Consistent with Grobys (2023, 2024, 2025) we employ the ADF test to test for stationarity. In line with earlier studies, calibrations with the 99% confidence level of stationarity of the residuals derived from $\widehat{\boldsymbol{\Phi}}$ are considered statistically significant (Jiang et al. 2010). The ADF test requires the implementation of the following regression model:

$$\Delta\widehat{u}_t = \delta_0 + \delta_1 u_{t-1} + \gamma_1 \Delta u_{t-1} + \ldots + \gamma_p \Delta u_{t-p} + \epsilon_t, \tag{3}$$

where ε_t is assumed to be an IID error term. Following earlier studies, the optimal lag-order *p* is selected in line with the Schwarz criterion (Grobys 2023, 2024, 2025).

3.4 Constraining the information set and iteratively estimated LPPLS models

After calibrating the LPPLS model under the imposed parameter constraints, we further investigate the robustness of the estimated critical times by examining the sensitivity of the results to variations in the information set. Brée et al. (2013) question the reliability of the LPPS model and stress that the estimated critical time exhibits considerable fluctuations as the time series input data are changed, and hence, refer to t_c as "sloppy parameter." On the other hand, Sornette (2017) emphasizes that the endogenous system becomes more unstable as we approach the critical time, and moreover, the point estimate of the critical time is stochastic: the LPPLS model predicts the critical time "systematically later than the real time of the crash: the critical time $\widehat{t}_c$ is included in the log-periodic power law structure of the bubble, whereas the crash is randomly triggered with a biased probability increasing strongly close to $\widehat{t}_c$." (Sornette 2017, p. 332). This latter effect might be more pronounced as we approach the peak of the bubble and uncertainty in the endogenous system increases.

As a consequence, to investigate the sensitivity of the $\widehat{t}_c$ with respect to changes in the information set $\boldsymbol{\Omega}$ used for calibrating the LPPLS model, we iteratively re-estimate the model defined by Eq. (2) and re-run the ADF test as defined by Eq. (3). Specifically, in each iteration j, we cutoff 20 observations from the beginning of each data set. Overall, we perform $j = 1, \dots, 20$ iteration; that is, in the first iteration the data set used for LPPLS model calibration contains $T - 20$ observations, whereas in the last iteration, the data set used contains only $T - 400$ observations. For each iteration, we store the corresponding parameter vector $\widehat{\boldsymbol{\Phi}}_j$ and ADF test statistic implemented for the residual vector $\Delta \widehat{\boldsymbol{u}}_{j,t}$. Having established the robustness of the LPPLS calibration and the stability of the predicted critical times across varying information sets, we now turn to the empirical results of the fitted models.

The empirical results from this iterative calibration exercise are summarized below. The results from the iterative re-estimation exercise indicate that the predicted critical times t_c remain relatively stable across different information sets. This finding suggests that the LPPLS signals detected in our study are not artifacts of a particular sample choice but instead reflect persistent endogenous market dynamics. Therefore, despite known concerns about the potential sloppiness of parameter estimation in LPPLS models, our iterative testing supports the robustness and reliability of the finite-time singularity patterns identified.

4 Results

4.1 Main results

This section presents the empirical findings of the LPPLS model calibrations applied to the Magnificent 7 firms, focusing on the detection of finite-time singularity patterns and the associated systemic risk implications. Figures 1, 2, 3, 4, 5, 6, and 7 illustrate the evolutions of the log-prices for the Magnificent 7 companies as well as the fitted LPPLS models, whereas Figs. 8, 9, 10, 11, 12, 13, 14, and 15 illustrate the corresponding model residuals. The overall sample period is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations. Visual inspection of Figs. 1, 2, 3, 4, 5, 6, and 7 shows that the fitted LPPLS models appear to provide a proper data fit. Also, the residual processes appear to exhibit stationarity even though exhibiting high levels of autocorrelation.

Table 2 reports the point estimates for the parameter vector $\widehat{\boldsymbol{\Phi}}$ estimated for each Magnificent 7 company. From Table 2 it becomes evident that the predicted stock price $\widehat{A}$ associated with the critical time $\widehat{t}_c$ vary between $\widehat{A} = 5.2622$ for Amazon and $\widehat{A} = 6.4314$ for Tesla, whereas Meta appears to exhibit a disproportionate estimate of $\widehat{A} = 5290.7670$. For example, whereas the closing stock price for Tesla on January 17, 2025 (viz., the end of the sample) was quoted at USD 426.50, the LPPLS model predicts that the stock price reaches USD 567.59 when approaching $\widehat{t}_c$. Furthermore, we observe from Table 2 that the point estimates for $\widehat{t}_c$ range between $\widehat{t}_c = 2200.1360$ for Meta and $\widehat{t}_c = 2284.0000$ for Amazon implying that the critical time is reached between $T + 17.1360$ and $T + 101.0000$. From Table 13 in the appendix, it becomes evident that because $T = 2183$ corresponds to January 17, 2025, $\widehat{t}_c$ corresponds to February 11, 2025 for Meta and June 9, 2025 for Amazon, whereas for the remaining Magnificent 7 companies, $\widehat{t}_c$ falls between the range of these two dates.

Next, in Table 3, we report the results from ADF tests implemented for the residuals plotted in Figs. 8, 9, 10, 11, 12, 13, 14, and 15. We observe from Table 3 that the residual

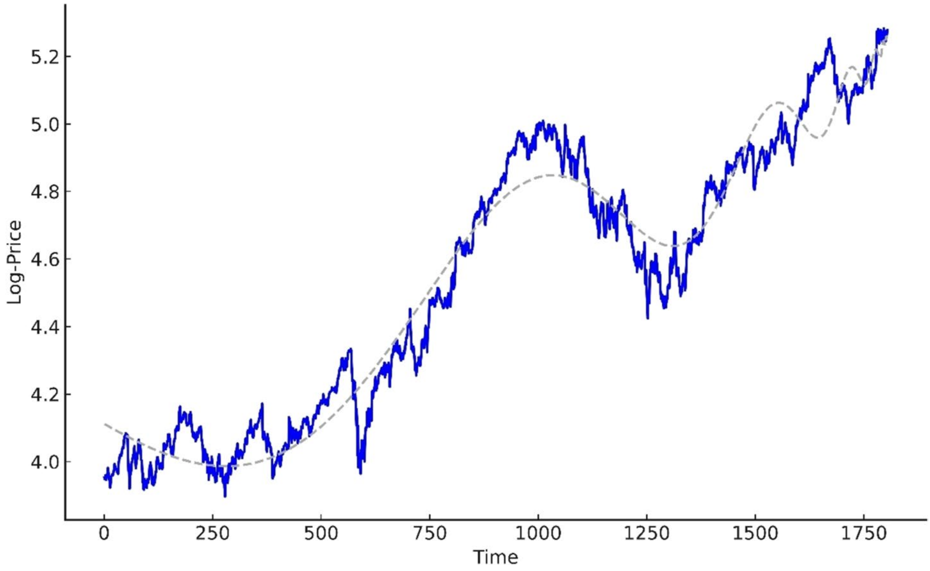

Fig. 1 Log-prices for Alphabet and fitted LPPLS model. This figure presents the daily log-prices (blue graph) for the stock of the company Alphabet and the fitted LPPLS model (dashed grey graph). The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

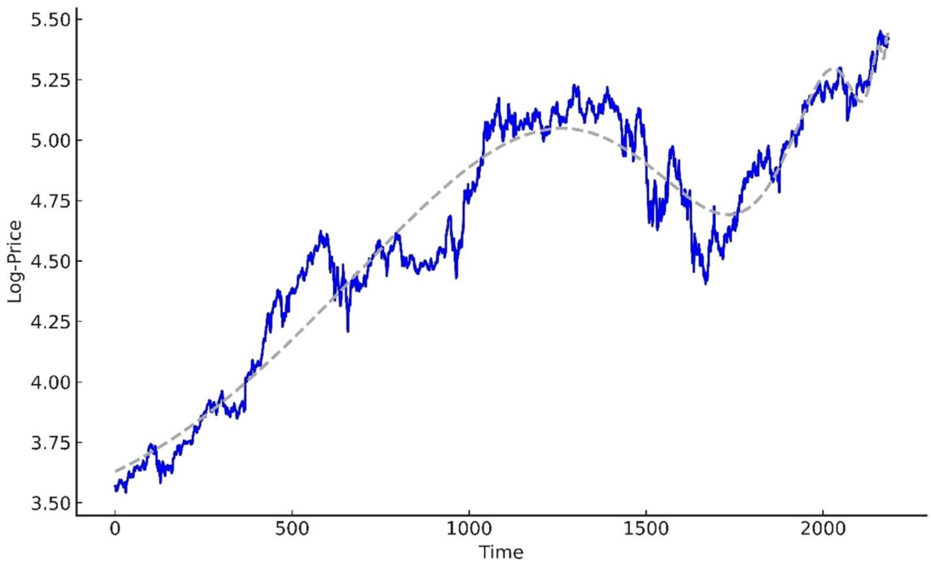

Fig. 2 Log-prices for Amazon and fitted LPPLS model. This figure presents the daily log-prices (blue graph) for the stock of the company Amazon and the fitted LPPLS model (dashed grey graph). The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

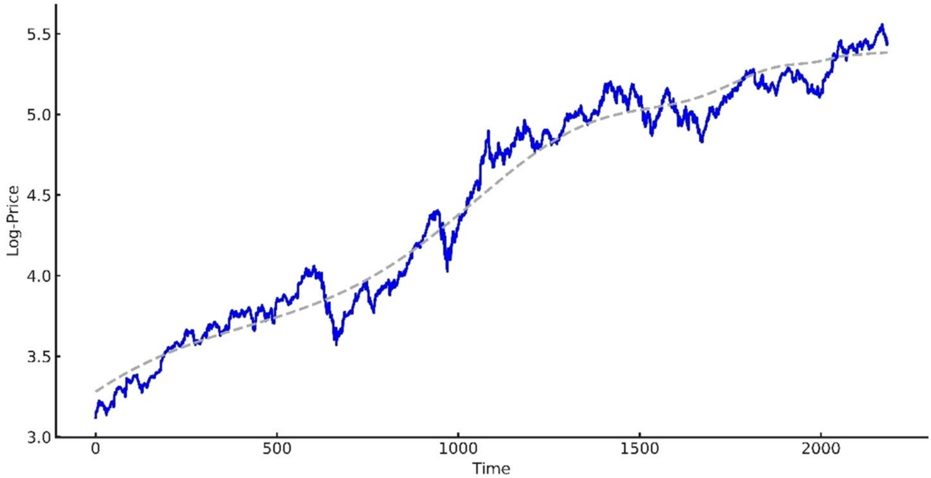

Fig. 3 Log-prices for Apple and fitted LPPLS model. This figure presents the daily log-prices (blue graph) for the stock of the company Apple and the fitted LPPLS model (dashed grey graph). The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

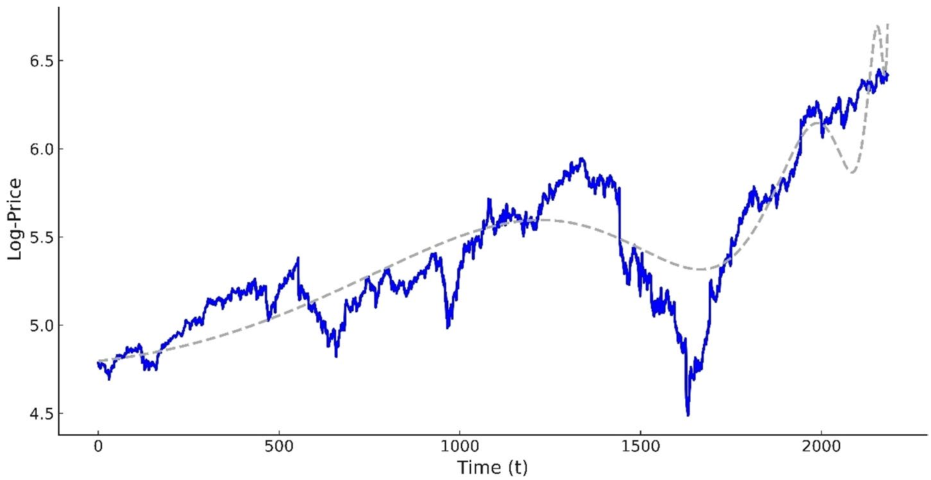

Fig. 4 Log-prices for Meta and fitted LPPLS model. This figure presents the daily log-prices (blue graph) for the stock of the company Meta and the fitted LPPLS model (dashed grey graph). The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

processes for Alphabet, Amazon, Apple, and Microsoft exhibit stationarity on at least a 1% significance level. Hence, the LPPLS signature is statistically significant for these four stock companies. This implies, in turn, that the super-exponential growth in the prices for these stocks, assessed via the LPPLS model, is statistically significant. From Table 1 we see that these four companies comprise 65% of the overall market capitalization of the Magnificent 7 companies as of January 17, 2025.

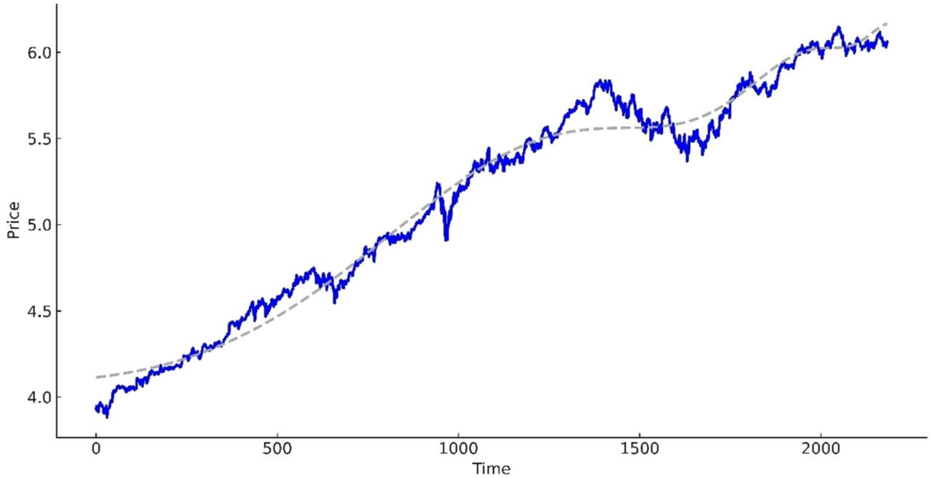

Fig. 5 Log-prices for Microsoft and fitted LPPLS model. This figure presents the daily log-prices (blue graph) for the stock of the company Microsoft and the fitted LPPLS model (dashed grey graph). The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

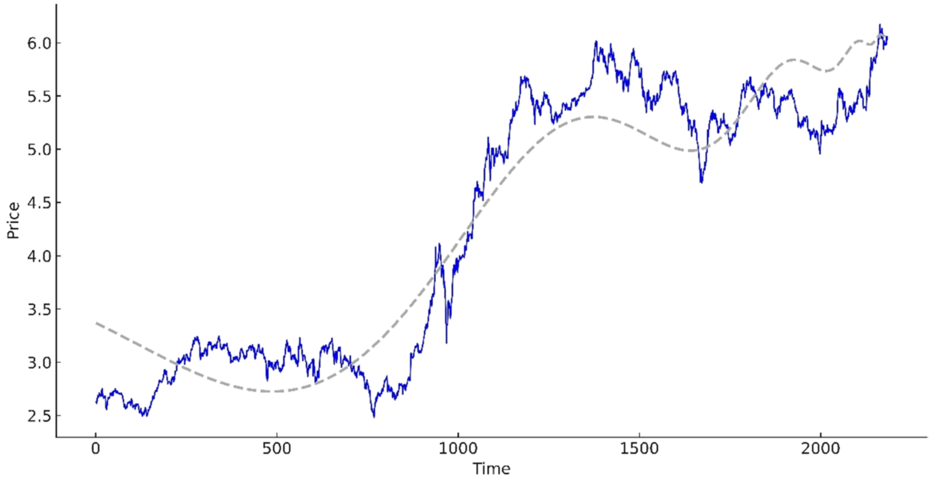

Fig. 6 Log-prices for Tesla and fitted LPPLS model. This figure presents the daily log-prices (blue graph) for the stock of the company Tesla and the fitted LPPLS model (dashed grey graph). The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

4.2 Robustness checks

Furthermore, we iteratively estimate the LPPLS model for each company by reducing the sample size used for calibrating the LPPLS model. The estimation results are reported in Tables 4, 5, 6, 7, 8, 9, and 10. For example, we observe from Table 4 that for Alphabet's stock price, $\widehat{A}$ ranges between $\widehat{A} = 5.2457$ and $\widehat{A} = 5.4829$ resulting in a mean value of $\bar{\widehat{A}} = 5.39$ with a standard deviation of $\widehat{\sigma}_{\widehat{A}} = 0.08$. The estimated critical time

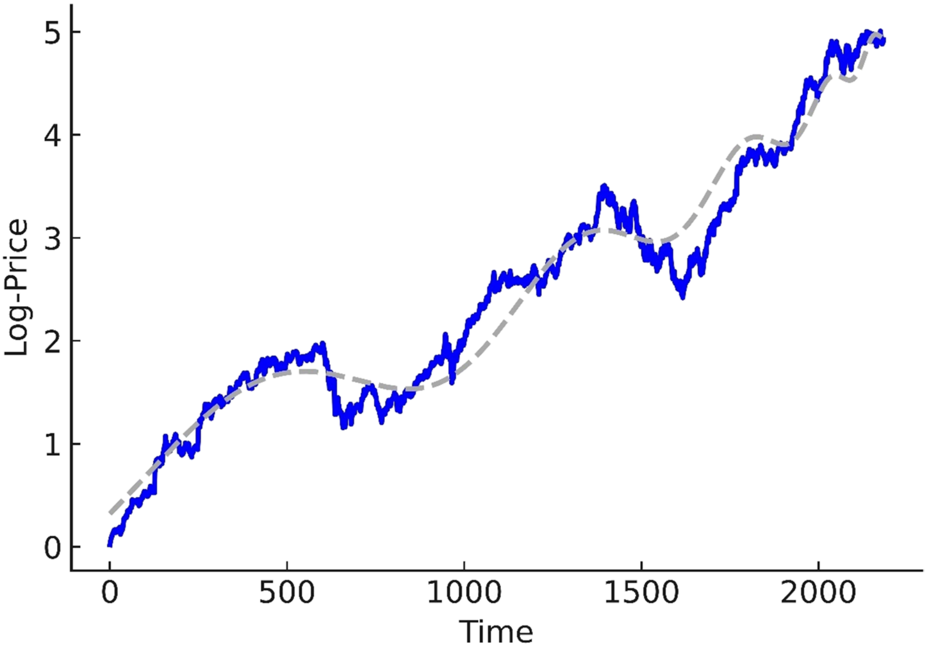

Fig. 7 Log-prices for NVIDIA and fitted LPPLS model. This figure presents the daily log-prices (blue graph) for the stock of the company NVIDIA and the fitted LPPLS model (dashed grey graph). The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

Table 2 Estimated parameters for the LPPLS models

Parameter	Company						
	Alphabet	Amazon	Apple	Meta	Microsoft	NVIDIA	Tesla
A	5.4091	5.2622	5.6774	5290.7670	6.2362	5.7504	6.4314
B	−0.0200	−0.0008	−0.0011	−5282.9500	−0.0008	−0.0429	−0.0032
t_c	2202.7920	2284.0000	2268.4070	2200.1360	2283.0000	2282.0000	2282.595
β	0.5563	0.9196	0.9840	0.0001	0.9999	0.6210	0.9168
C	−0.2153	−0.0004	0.0002	0.2626	0.1759	−0.0044	−0.0009
ω	4.1346	5.3669	5.9179	4.1041	5.4118	0.9435	6.3933
φ	−2.5969	3.1416	3.1389	15.3919	3.1416	−23.8790	3.1323
SSR	30.0141	64.3159	27.2834	87.1402	17.7529	121.0234	406.5169

This table reports the estimated parameters for the calibrated LPPLS models for the Magnificent 7 companies (viz., Alphabet, Amazon, Apple, Meta, Microsoft, NVIDIA, and Tesla). The LPPLS model is defined as:

$$\ln\left[p\left(t\right)\right] = A + B(t_c - t)^{\beta}\left[1 + C\cos(\omega\ln\left(t_c - t\right) + \varphi\ )\right],$$

where $\ln\left[p\left(t\right)\right]$ denotes the logarithm an asset price at time t, t_c is the critical time, A is the expected value of the asset when approaching t_c, B defines the exposure to faster-than-exponential growth, and β is the power-law exponent controlling faster-than-exponential price growth. Furthermore, C denotes the exposure the log-periodic oscillations around the power-law singular growth, ω denotes the angular log-frequency of oscillations during the formation of the bubble, φ is the phase parameter. The estimated model accounts for the constraints $A > 0$, $B < 0$, $\omega > 0$, and $0 \leq \beta \leq 1$. For every model, the sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

Table 3 Results for ADF tests for the residuals of the LPPLS models

Company	ADF test statistic	Lags	*p*-value
Alphabet	−3.78***	0	0.0032
Amazon	−4.05***	1	0.0010
Apple	−3.44***	9	0.0097
Meta	−2.72*	0	0.0704
Microsoft	−4.13***	9	0.0009
NVIDIA	−3.02**	9	0.0330
Tesla	−2.55	0	0.1029

This table reports the estimated test statistics for ADF tests implemented for residuals of the estimated LPPLS models for the Magnificent 7 companies (viz., Alphabet, Amazon, Apple, Meta, Microsoft, NVIDIA, and Tesla), the *p*-values and the number of lags used for the test regressions. The critical values for the 1%, 5% and 10% significance levels are −3.43, −2.86, −2.57. The Schwarz-Criterion (SC) is used for the selection of the optimal lag length in the test regressions. The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

***, **, * Statistically significant on 1%, 5%, 10% levels

ranges between $\widehat{t}_c = 21.0000$ and $\widehat{t}_c = 71.0000$ while exhibiting a mean value corresponding to $\bar{\widehat{t}}_c = 55.7599$ trading days ahead of $T = 2183$, with a standard deviation of $\widehat{\sigma}_{\widehat{t}_c} = 20.7977$ trading days.[4] Also, $\widehat{\beta}$ ranges between $\widehat{\beta} = 0.5250$ and $\widehat{\beta} = 0.8247$ with mean value $\bar{\widehat{\beta}} = 0.5800$ with a standard deviation of $\widehat{\sigma}_{\widehat{\beta}} = 0.0716$. That is, the range and mean value of the parameter capturing super-exponential growth rate of the asset price are consistent with $0 < \beta < 1$.

From Table 5, we observe that for Amazon's stock price, $\widehat{A}$ ranges between $\widehat{A} = 5.2622$ and $\widehat{A} = 5.4507$ resulting in a mean value of $\bar{\widehat{A}} = 5.40$ with a standard deviation of $\widehat{\sigma}_{\widehat{A}} = 0.07$. These figures a surprisingly similar as the ones reported for Alphabet. Next, the estimated critical time ranges between $\widehat{t}_c = 109.9984$ and $\widehat{t}_c = 121.0000$ while exhibiting a mean value corresponding to $\bar{\widehat{t}}_c = 120.1722$ trading days ahead of $T = 2183$, with a standard deviation of $\widehat{\sigma}_{\widehat{t}_c} = 2.6968$ trading days. Furthermore, $\widehat{\beta}$ ranges between $\widehat{\beta} = 0.3897$ and $\widehat{\beta} = 0.9196$ with mean value $\bar{\widehat{\beta}} = 0.5928$ with a standard deviation of $\widehat{\sigma}_{\widehat{\beta}} = 0.1672$. Again, the range and mean value of the parameter capturing super-exponential growth rate of the asset price are consistent with $0 < \beta < 1$.

From Table 6, we observe that for Apple's stock price, $\widehat{A}$ ranges between $\widehat{A} = 5.4773$ and $\widehat{A} = 5.5569$ resulting in a mean value of $\bar{\widehat{A}} = 5.53$ with a standard deviation of $\widehat{\sigma}_{\widehat{A}} = 0.03$. The estimated critical time ranges between $\widehat{t}_c = 21.0000$ and $\widehat{t}_c = 87.4469$ while exhibiting a mean value corresponding to $\bar{\widehat{t}}_c = 47.4122$ trading days ahead of $T = 2183$, with a standard deviation of $\widehat{\sigma}_{\widehat{t}_c} = 27.6747$ trading days. Moreover, $\widehat{\beta}$ ranges between $\widehat{\beta} = 0.9208$ and $\widehat{\beta} = 1.0000$ with mean value $\bar{\widehat{\beta}} = 0.9889$ with a standard devia-

[4] Note that $\widehat{t}_c = 21.0000$ and $\widehat{t}_c = 71.0000$ are calculated from Table 4 as $\widehat{t}_c = 1824 - 1803$ and $\widehat{t}_c = 2134 - 2063$, for instance.

Table 4 Results for iteratively estimated LPPLS models for alphabet

Iteration	A	B	C	t_c	β	ω	φ	T
1	5.3760	−0.0212	−0.0045	2184.0032	0.5457	3.3259	0.0000	2163
2	5.4237	−0.0213	−0.0046	2188.4159	0.5488	4.2116	0.0011	2143
3	5.2457	−0.0025	−0.0005	2179.9153	0.8247	5.1135	6.2819	2123
4	5.4487	−0.0232	−0.0050	2159.4415	0.5385	4.4261	4.7794	2103
5	5.4615	−0.0242	−0.0052	2144.8342	0.5338	4.5105	4.1797	2083
6	5.4789	−0.0249	0.0053	2134.0000	0.5315	4.6550	6.2832	2063
7	5.4829	−0.0261	0.0056	2114.0000	0.5250	4.6792	6.1348	2043
8	5.4079	−0.0145	−0.0033	2094.0000	0.5972	5.1092	6.2832	2023
9	5.4184	−0.0164	−0.0038	2074.0000	0.5806	5.1132	6.2832	2003
10	5.3408	−0.0074	0.0017	2054.0000	0.6818	5.5643	6.2832	1983
11	5.4342	−0.0200	−0.0048	2034.0000	0.5540	5.1210	6.2832	1963
12	5.4401	−0.0217	−0.0054	2014.0000	0.5429	5.1249	6.2832	1943
13	5.4451	−0.0234	−0.0059	1994.0000	0.5323	5.1291	6.2832	1923
14	5.4405	−0.0231	−0.0059	1974.0000	0.5332	5.1715	6.0035	1903
15	5.4347	−0.0225	−0.0059	1954.0000	0.5359	5.2173	5.6976	1883
16	5.4268	−0.0216	−0.0058	1934.0000	0.5398	5.2773	5.2965	1863
17	5.3147	−0.0134	−0.0041	1872.5876	0.5921	5.2452	5.7597	1843
18	5.2840	−0.0111	−0.0036	1844.0001	0.6136	5.3550	5.0616	1823
19	5.2767	−0.0104	−0.0035	1824.0000	0.6218	5.4775	4.2271	1803
20	5.2715	−0.0099	−0.0034	1804.0000	0.6276	5.5775	3.5465	1783

This table reports the estimated parameters for the calibrated LPPLS models for Alphabet. The LPPLS model is defined as:

$$\ln[p(t)] = A + B(t_c - t)^{\beta}\left[1 + C\cos(\omega\ln(t_c - t) + \varphi)\right],$$

where $\ln[p(t)]$ denotes the logarithm price of Alphabet at time t, t_c is the critical time, A is the expected value of Alphabet when approaching t_c, B defines the exposure to faster-than-exponential growth, and β is the power-law exponent controlling faster-than-exponential price growth. Furthermore, C denotes the exposure the log-periodic oscillations around the power-law singular growth, ω denotes the angular log-frequency of oscillations during the formation of the bubble, φ is the phase parameter. The estimated model accounts for the constraints $A > 0$, $B < 0$, $\omega > 0$, and $0 \leq \beta \leq 1$. In every iteration, the sample is reduced by cutting off 20 sample observations from the beginning of the sample. That is, the first iteration uses $T = 2163$ observations, whereas the last iteration uses $T = 1783$ observations

tion of $\widehat{\sigma}_{\widehat{\beta}} = 0.0235$. Notably, the range and mean value of the parameter capturing super-exponential growth rate of the asset price are close to the upper limit for $0 < \beta < 1$.

Furthermore, from Table 8, we observe that for Microsoft's stock price, $\widehat{A}$ ranges between $\widehat{A} = 6.1467$ and $\widehat{A} = 6.1475$ resulting in a mean value of $\overline{\widehat{A}} = 6.15$ with a standard deviation of $\widehat{\sigma}_{\widehat{A}} = 0.00$. The estimated critical time ranges between $\widehat{t}_c = 30.9888$ and $\widehat{t}_c = 121.0000$ while exhibiting a mean value corresponding to $\overline{\widehat{t}_c} = 80.5877$ trading days ahead of $T = 2183$, with a standard deviation of $\widehat{\sigma}_{\widehat{t}_c} = 38.7580$ trading days. Furthermore, $\widehat{\beta}$ ranges between $\widehat{\beta} = 0.8599$ and $\widehat{\beta} = 1.0000$ with mean value $\overline{\widehat{\beta}} = 0.9741$ with a standard deviation of $\widehat{\sigma}_{\widehat{\beta}} = 0.0377$. Like for Apple, the range and mean value of the parameter capturing super-exponential growth rate of the asset price are close to the upper limit for $0 < \beta < 1$.

Whereas the overall results for Alphabet, Amazon, Apple and Microsoft indicate that the LPPLS model estimates exhibit a high level of reliability, we observe from Tables 7, 9, and

Table 5 Results for iteratively estimated LPPLS models for Amazon

Iteration	A	B	C	t_c	β	ω	φ	T
1	5.2622	−0.0008	−0.0004	2284.0000	0.9196	5.3669	3.1416	2163
2	5.2778	−0.0012	−0.0006	2264.0000	0.8728	5.3713	3.1416	2143
3	5.2947	−0.0017	−0.0009	2244.0000	0.8260	5.3759	3.1416	2123
4	5.3110	−0.0024	−0.0012	2224.0000	0.7844	5.3803	3.1416	2103
5	5.3277	−0.0032	−0.0016	2204.0000	0.7450	5.3847	3.1416	2083
6	5.3441	−0.0042	−0.0022	2184.0000	0.7092	5.3889	3.1416	2063
7	5.3603	−0.0054	−0.0027	2164.0000	0.6763	5.3930	3.1416	2043
8	5.3841	−0.0077	−0.0038	2144.0000	0.6321	5.3986	3.1416	2023
9	5.4107	−0.0109	−0.0052	2124.0000	0.5877	5.4046	3.1416	2003
10	5.4368	−0.0148	−0.0069	2104.0000	0.5485	5.4103	3.1416	1983
11	5.4507	−0.0182	−0.0083	2084.0000	0.5217	5.4157	3.1416	1963
12	5.4507	−0.0202	−0.0093	2064.0000	0.5054	5.4212	3.1416	1943
13	5.4507	−0.0223	−0.0103	2044.0000	0.4905	5.4263	3.1416	1923
14	5.4507	−0.0243	−0.0112	2024.0000	0.4774	5.4308	3.1416	1903
15	5.4507	−0.0262	−0.0122	2004.0000	0.4654	5.4350	3.1416	1883
16	5.4507	−0.0285	−0.0132	1984.0000	0.4526	5.4394	3.1416	1863
17	5.4507	−0.0311	−0.0144	1964.0000	0.4388	5.4443	3.1416	1843
18	5.4507	−0.0345	−0.0160	1944.0000	0.4229	5.4499	3.1416	1823
19	5.4507	−0.0402	−0.0186	1918.4459	0.3998	5.4610	3.1416	1803
20	5.4507	−0.0458	−0.0213	1892.9984	0.3797	5.4714	3.1416	1783

This table reports the estimated parameters for the calibrated LPPLS models for Amazon. The LPPLS model is defined as:

$$\ln\left[p\left(t\right)\right] = A + B(t_c - t)^{\beta}\left[1 + C\cos(\omega\ln\left(t_c - t\right) + \varphi\ )\right],$$

where $\ln\left[p\left(t\right)\right]$ denotes the logarithm price of Amazon at time t, t_c is the critical time, A is the expected value of Amazon when approaching t_c, B defines the exposure to faster-than-exponential growth, and β is the power-law exponent controlling faster-than-exponential price growth. Furthermore, C denotes the exposure the log-periodic oscillations around the power-law singular growth, ω denotes the angular log-frequency of oscillations during the formation of the bubble, φ is the phase parameter. The estimated model accounts for the constraints $A > 0$, $B < 0$, $\omega > 0$, and $0 \leq \beta \leq 1$. In every iteration, the sample is reduced by cutting off 20 sample observations from the beginning of the sample. That is, the first iteration uses $T = 2163$observations, whereas the last iteration uses $T = 1783$ observations

10 that iteratively calibrated LPPLS models for Meta, NVIDIA, and Tesla do not exhibit consistent estimates. For example, considering Meta, the estimates for $\widehat{t_c}$ vary substantially and range between $\widehat{t_c} = 37.1845$ and $\widehat{t_c} = 1558.3058$. A similar pathology in iteratively estimated LPPLS models can be observed for NVIDIA. For example, from Table 9 we observe that estimates for $\widehat{t_c}$ not only vary between $\widehat{t_c} = 120.0000$ and $\widehat{t_c} = 416.1209$, but they do so in a monotonic increasing fashion as we cut off more observation from the sample. Despite iteratively estimated LPPLS models do not provide similar pathologies for Tesla, the results derived from iteratively estimated ADF tests, reported in Table 11 confirm earlier results: Specifically, we observe from Table 11 that for Alphabet, Amazon, Apple and Microsoft, the vast majority of iteratively estimated ADF tests indicates that the residuals of the LPPLS models are statistically significant on at least a 1% level.[5] On the other hand, none of the residual processes for iteratively calibrated LPPLS models for Meta reaches statistical significance on 1% level, whereas for NVIDIA and Tesla only one LPPLS model

[5] The optimal lag-orders for the iteratively estimated ADF tests are reported in Table A.2 in the appendix.

Table 6 Results for iteratively estimated LPPLS models for Apple

Iteration	A	B	C	t_c	β	ω	φ	T
1	5.5569	−0.0009	−0.0002	2233.2149	1.0000	5.4978	3.1416	2163
2	5.5569	−0.0014	−0.0002	2176.0013	0.9506	5.7227	1.6559	2143
3	5.5569	−0.0009	−0.0002	2203.5396	1.0000	5.5039	3.1416	2123
4	5.5569	−0.0009	−0.0002	2186.9442	1.0000	5.5078	3.1416	2103
5	5.5569	−0.0017	−0.0003	2116.0404	0.9208	5.7803	1.3391	2083
6	5.5569	−0.0009	−0.0002	2150.1585	1.0000	5.5161	3.1416	2063
7	5.5569	−0.0009	−0.0002	2130.4469	1.0000	5.5206	3.1416	2043
8	5.5569	−0.0009	−0.0002	2109.7857	1.0000	5.5270	3.1416	2023
9	5.5569	−0.0009	−0.0002	2088.0783	1.0000	5.5338	3.1416	2003
10	5.5335	−0.0009	−0.0002	2027.7948	1.0000	5.5619	3.1416	1983
11	5.5228	−0.0009	−0.0002	2000.0220	1.0000	5.5700	3.1416	1963
12	5.5154	−0.0009	−0.0002	1976.0051	1.0000	5.5755	3.1416	1943
13	5.5379	−0.0014	−0.0004	1948.9300	0.9372	5.5853	3.0952	1923
14	5.5091	−0.0009	−0.0003	1929.1072	0.9886	5.6163	2.9140	1903
15	5.5021	−0.0009	−0.0003	1905.9482	0.9896	5.6245	2.8910	1883
16	5.4985	−0.0009	−0.0003	1890.2266	0.9912	5.5911	3.1405	1863
17	5.4865	−0.0008	−0.0003	1864.0000	1.0000	5.5981	3.1416	1843
18	5.4833	−0.0008	−0.0003	1844.0000	1.0000	5.6006	3.1416	1823
19	5.4791	−0.0008	−0.0003	1824.0000	1.0000	5.6041	3.1416	1803
20	5.4773	−0.0008	−0.0003	1804.0000	1.0000	5.6375	2.9194	1783

This table reports the estimated parameters for the calibrated LPPLS models for Apple. The LPPLS model is defined as:

$$\ln[p(t)] = A + B(t_c - t)^{\beta}\left[1 + C\cos(\omega \ln(t_c - t) + \varphi)\right],$$

where $\ln[p(t)]$denotes the logarithm price of Apple at time t, t_c is the critical time, A is the expected value of Apple when approaching t_c, B defines the exposure to faster-than-exponential growth, and β is the power-law exponent controlling faster-than-exponential price growth. Furthermore, C denotes the exposure the log-periodic oscillations around the power-law singular growth, ω denotes the angular log-frequency of oscillations during the formation of the bubble, φ is the phase parameter. The estimated model accounts for the constraints $A > 0$, $B < 0$, $\omega > 0$, and $0 \leq \beta \leq 1$. In every iteration, the sample is reduced by cutting off 20 sample observations from the beginning of the sample. That is, the first iteration uses $T = 2163$ observations, whereas the last iteration uses $T = 1783$ observations

produces residuals reaching statistical significance on 1% level which may be regarded matters of chance.

5 Discussion

5.1 Alignment with earlier literature

5.1.1 Comparison with recent relevant studies using the LPPLS model

Recent studies on real-time LPPLS (Log-Periodic Power Law Singularity) predictions have provided substantial evidence for regime switches in broad equity indices (Johansen and Sornette 2001; Sornette 2017; Grobys 2023) by identifying statistically significant LPPLS signatures. Specifically, the findings of Johansen and Sornette (2001) and Grobys (2023) suggest that the DJ 30 and S&P 500 indices are likely to undergo an abrupt regime change

Table 7 Results for iteratively estimated LPPLS models for meta

Iteration	A	B	C	t_c	β	ω	φ	T
1	4801.5679	−4793.7519	0.2619	2200.1845	0.0001	4.1102	15.3529	2163
2	5222.5655	−5214.7583	0.2602	2200.3098	0.0001	4.1259	15.2527	2143
3	2442.0948	−2434.5365	0.2546	2189.2757	0.0001	4.3585	13.8432	2123
4	2288.2700	−2280.7184	0.2537	2189.3399	0.0001	4.3801	13.7048	2103
5	4722.0565	−4714.2463	0.2608	2200.2831	0.0001	4.1219	15.2779	2083
6	2766.9445	−2759.3982	0.2529	2189.3971	0.0001	4.3980	13.5900	2063
7	3954.1020	−3946.5753	0.2502	2189.6487	0.0001	4.4687	13.1370	2043
8	307.8140	−296.2645	0.3141	3399.1247	0.0026	12.8124	−54.6099	2023
9	372.4558	−360.3904	0.3214	3561.3058	0.0023	14.0584	−65.1809	2003
10	5110.5392	−5103.0890	0.2433	2191.9783	0.0001	4.9300	10.1596	1983
11	4277.0115	−4269.5705	0.2431	2192.6133	0.0001	5.0306	9.5064	1963
12	4620.3057	−4612.4923	0.2619	2200.3829	0.0001	4.1285	15.2348	1943
13	4361.2338	−4353.4101	0.2647	2200.4632	0.0001	4.1295	15.2276	1923
14	4158.8503	−4151.0162	0.2676	2200.5812	0.0001	4.1335	15.2002	1903
15	4481.0320	−4473.1865	0.2708	2200.7482	0.0001	4.1412	15.1493	1883
16	3948.1218	−3940.2596	0.2757	2201.0334	0.0001	4.1558	15.0534	1863
17	2308.0456	−2300.1667	0.2805	2201.3520	0.0002	4.1729	14.9409	1843
18	2150.2509	−2142.3551	0.2854	2201.6977	0.0002	4.1921	14.8148	1823
19	4570.1291	−4561.4214	0.3155	2253.7601	0.0001	4.0473	15.4234	1803
20	200.7858	−191.1980	0.3202	2443.0249	0.0031	5.0356	7.6514	1783

This table reports the estimated parameters for the calibrated LPPLS models for Meta. The LPPLS model is defined as:

$$\ln[p(t)] = A + B(t_c - t)^{\beta}\left[1 + C\cos(\omega \ln(t_c - t) + \varphi)\right],$$

where $\ln[p(t)]$ denotes the logarithm price of Meta at time t, t_c is the critical time, A is the expected value of Meta when approaching t_c, B defines the exposure to faster-than-exponential growth, and β is the power-law exponent controlling faster-than-exponential price growth. Furthermore, C denotes the exposure the log-periodic oscillations around the power-law singular growth, ω denotes the angular log-frequency of oscillations during the formation of the bubble, φ is the phase parameter. The estimated model accounts for the constraints $A > 0$, $B < 0$, $\omega > 0$, and $0 \leq \beta \leq 1$. In every iteration, the sample is reduced by cutting off 20 sample observations from the beginning of the sample. That is, the first iteration uses $T = 2163$ observations, whereas the last iteration uses $T = 1783$ observations

around the year 2050. In a related investigation, Grobys (2025) examined whether log-prices for gold futures exhibit signs of an ongoing bubble formation. Analyzing daily data on gold futures spanning the period from December 2, 2015, to June 11, 2024, this study uncovered robust evidence indicating the occurrence of a finite-time singularity projected for October 6, 2029. Moreover, critical times derived from various LPPLS model calibrations pointed to a notably narrow time window for the anticipated regime switch, specifically between October 6, 2029, and November 5, 2029. Aligned with the predominant literature employing the LPPLS model (e.g., Sornette 2017), the present study utilizes daily log-price data for LPPLS model calibration. However, in contrast to earlier works (e.g., Sornette 2017; Shu and Song 2024), this research extends the analysis to LPPLS signatures in individual stocks. While single stocks are inherently more "noisy" than broad market indices, statistically significant LPPLS signatures were identified in four out of seven stocks examined. Further, iterative re-calibrations of the LPPLS model using constrained (i.e., reduced) sample sizes demonstrated that, for these four stocks, the detected LPPLS signatures are both reliable and consistently identifiable across the majority of subsamples.

Table 8 Results for iteratively estimated LPPLS models for Microsoft

Iteration	A	B	C	t_c	β	ω	φ	T
1	6.1475	−0.0011	−0.0002	2197.2130	0.9652	5.7414	0.9864	2163
2	6.1475	−0.0011	−0.0002	2177.1274	0.9655	5.7473	0.9908	2143
3	6.1475	−0.0008	−0.0002	2244.0000	1.0000	5.4214	3.1416	2123
4	6.1475	−0.0008	−0.0002	2224.0000	1.0000	5.4256	3.1416	2103
5	6.1475	−0.0008	−0.0002	2204.0000	1.0000	5.4295	3.1416	2083
6	6.1469	−0.0014	−0.0003	2096.4424	0.9310	5.8333	0.5333	2063
7	6.1468	−0.0013	−0.0003	2077.0181	0.9404	5.8221	0.6631	2043
8	6.1475	−0.0008	−0.0002	2144.0000	1.0000	5.4431	3.1416	2023
9	6.1467	−0.0008	−0.0002	2051.0216	0.9999	5.5062	3.0113	2003
10	6.1472	−0.0014	−0.0003	2018.9913	0.9263	5.8460	0.6102	1983
11	6.1475	−0.0011	−0.0003	2005.2922	0.9524	5.5388	2.8623	1963
12	6.1469	−0.0008	−0.0002	2018.6138	1.0000	5.4875	3.1415	1943
13	6.1475	−0.0007	−0.0002	2043.3693	1.0000	5.4657	3.1416	1923
14	6.1475	−0.0007	−0.0002	2021.5626	1.0000	5.4712	3.1416	1903
15	6.1475	−0.0007	−0.0002	1999.7926	1.0000	5.4764	3.1416	1883
16	6.1468	−0.0008	−0.0002	1956.3924	1.0000	5.4965	3.1416	1863
17	6.1475	−0.0007	−0.0002	1955.6739	1.0000	5.4883	3.1416	1843
18	6.1475	−0.0008	−0.0002	1929.6188	0.9885	5.4971	3.1416	1823
19	6.1475	−0.0021	−0.0006	1833.9888	0.8599	5.9452	0.3422	1803
20	6.1475	−0.0010	−0.0003	1873.6349	0.9536	5.5164	3.1416	1783

This table reports the estimated parameters for the calibrated LPPLS models for Microsoft. The LPPLS model is defined as:

$$\ln\left[p\left(t\right)\right] = A + B(t_c - t)^{\beta}\left[1 + C\cos(\omega \ln\left(t_c - t\right) + \varphi\ )\right],$$

where $\ln\left[p\left(t\right)\right]$ denotes the logarithm price of Microsoft at time t, t_c is the critical time, A is the expected value of Microsoft when approaching t_c, B defines the exposure to faster-than-exponential growth, and β is the power-law exponent controlling faster-than-exponential price growth. Furthermore, C denotes the exposure the log-periodic oscillations around the power-law singular growth, ω denotes the angular log-frequency of oscillations during the formation of the bubble, φ is the phase parameter. The estimated model accounts for the constraints $A > 0$, $B < 0$, $\omega > 0$, $t_c > T$, and $0 \leq \beta \leq 1$. In every iteration, the sample is reduced by cutting off 20 sample observations from the beginning of the sample. That is, the first iteration uses $T = 2163$ observations, whereas the last iteration uses $T = 1783$ observations

5.1.2 Cross-asset empirical validation of LPPLS signatures

Beyond the present application to the Magnificent 7 firms, the LPPLS framework has been extensively validated across a variety of asset classes and historical episodes, reinforcing its robustness as a diagnostic tool for endogenous bubble dynamics. Johansen and Sornette (2010) provide a comprehensive review of financial bubbles and crashes, documenting the presence of LPPLS-type signatures preceding major market downturns, including equity, bond, and commodity markets. In the real estate sector, Zhou and Sornette (2006) apply the LPPLS model to the U.S. housing market and identify clear signatures of unsustainable price dynamics indicative of bubble behavior prior to the 2007–2008 financial crisis. LPPLS structures have also been identified in commodity markets: Sornette et al. (2009) analyze the 2006–2008 oil price bubble and provide evidence that speculative dynamics captured by LPPLS modeling contributed significantly to the observed price escalation and subsequent collapse. In equity markets outside the United States, Ji and Zhang (2024) employ the LPPL

Table 9 Results for iteratively estimated LPPLS models for NVIDIA

Iteration	A	B	C	t_c	β	ω	φ	T
1	5.7984	−0.0476	−0.0047	2283.0000	0.6083	9.4200	−23.7796	2163
2	5.8607	−0.0542	−0.0051	2283.0000	0.5924	9.3947	−23.6082	2143
3	5.8986	−0.0597	−0.0055	2280.3026	0.5805	9.3406	−23.2088	2123
4	5.9238	−0.0648	−0.0058	2275.9591	0.5702	9.2643	−28.9229	2103
5	5.9520	−0.0716	−0.0063	2270.1195	0.5577	9.1530	−28.0996	2083
6	5.9808	−0.0799	−0.0068	2263.2020	0.5438	9.0050	−20.7354	2063
7	6.0013	−0.0868	−0.0072	2257.7347	0.5331	8.8731	−26.0644	2043
8	6.0160	−0.0924	−0.0076	2253.5602	0.5250	8.7621	−25.2691	2023
9	6.0334	−0.0999	−0.0081	2248.3820	0.5147	8.6125	−17.9199	2003
10	6.0607	−0.1121	−0.0091	2241.4233	0.4997	8.3877	−16.3318	1983
11	6.1318	−0.1439	−0.0118	2229.2481	0.4671	7.9271	−19.3939	1963
12	6.2387	−0.1886	−0.0162	2220.9112	0.4322	7.5594	−16.8434	1943
13	5.9947	−0.1655	−0.0164	2200.0902	0.4421	7.2450	−14.5190	1923
14	6.0247	−0.1772	−0.0181	2199.5089	0.4332	7.2206	−8.0680	1903
15	6.0509	−0.1877	−0.0198	2199.1796	0.4258	7.2136	−8.0179	1883
16	6.0716	−0.1962	−0.0212	2199.0342	0.4201	7.2180	−8.0457	1863
17	6.0906	−0.2042	−0.0226	2198.9816	0.4149	7.2299	−8.1234	1843
18	6.1046	−0.2102	−0.0237	2198.9966	0.4111	7.2443	−8.2185	1823
19	6.1132	−0.2140	−0.0244	2199.0377	0.4088	7.2563	−8.2981	1803
20	6.1219	−0.2176	−0.0251	2199.1209	0.4066	7.2716	−8.4002	1783

This table reports the estimated parameters for the calibrated LPPLS models for NVIDIA. The LPPLS model is defined as:

$$\ln\left[p\left(t\right)\right] = A + B(t_c - t)^{\beta}\left[1 + C\cos(\omega\ln\left(t_c - t\right) + \varphi\ )\right],$$

where $\ln\left[p\left(t\right)\right]$ denotes the logarithm price of NVIDIA at time t, t_c is the critical time, A is the expected value of NVIDIA when approaching t_c, B defines the exposure to faster-than-exponential growth, and β is the power-law exponent controlling faster-than-exponential price growth. Furthermore, C denotes the exposure the log-periodic oscillations around the power-law singular growth, ω denotes the angular log-frequency of oscillations during the formation of the bubble, φ is the phase parameter. The estimated model accounts for the constraints $A > 0$, $B < 0$, $\omega > 0$, $t_c > T$, and $0 \leq \beta \leq 1$. In every iteration, the sample is reduced by cutting off 20 sample observations from the beginning of the sample. That is, the first iteration uses $T = 2163$ observations, whereas the last iteration uses $T = 1783$ observations

model to detect and measure structural bubbles in the Chinese stock market, showing that LPPLS patterns preceded significant market corrections.

The LPPLS methodology has also been successfully extended to emerging asset classes. Huang and Wang (2024) analyze global carbon markets and identify LPPLS-consistent patterns during phases of explosive price growth, suggesting that bubble dynamics are not confined to traditional financial assets. Similarly, Kyriazis et al. (2020) systematically review the evidence of bubble behavior in cryptocurrency markets and report that many studies applying LPPLS techniques find strong support for speculative, unsustainable growth patterns across various digital assets.

Collectively, these studies demonstrate that LPPLS signatures recur across equities, real estate, commodities, carbon credits, and cryptocurrencies, reinforcing the framework's empirical relevance beyond any single market or asset class. Sornette (2017) further emphasizes that LPPLS structures exhibit remarkable universality across historical bubbles, characterized by specific log-periodic scaling behaviors, while Lin et al. (2014) show through extensive simulations that such signatures are highly unlikely to arise by chance under stan-

Table 10 Results for iteratively estimated LPPLS models for Tesla

Iteration	A	B	C	t_c	β	ω	φ	T
1	6.1471	−0.0014	−0.0006	2284.0000	1.0000	5.5234	3.1416	2163
2	6.1318	−0.0014	−0.0006	2264.0000	1.0000	5.5248	3.1416	2143
3	6.1150	−0.0014	−0.0006	2244.0000	1.0000	5.5265	3.1416	2123
4	6.0755	−0.0014	−0.0006	2177.6600	0.9999	5.5541	3.1390	2103
5	6.0820	−0.0013	−0.0007	2204.0000	1.0000	5.5303	3.1416	2083
6	6.0623	−0.0013	−0.0007	2184.0000	1.0000	5.5327	3.1416	2063
7	6.0116	−0.0014	−0.0008	2098.5085	0.9930	5.5710	3.1416	2043
8	6.0179	−0.0012	−0.0007	2144.0000	1.0000	5.5383	3.1416	2023
9	5.9931	−0.0012	−0.0008	2121.5252	1.0000	5.5426	3.1416	2003
10	5.9672	−0.0012	−0.0008	2092.0547	1.0000	5.5503	3.1416	1983
11	5.9322	−0.0013	−0.0009	2017.8797	0.9893	5.5831	3.1349	1963
12	5.9228	−0.0011	−0.0008	2038.0878	1.0000	5.5630	3.1416	1943
13	5.8884	−0.0011	−0.0009	1972.6668	1.0000	5.5907	3.1412	1923
14	5.8721	−0.0011	−0.0009	1947.3048	0.9995	5.5961	3.1414	1903
15	5.8597	−0.0011	−0.0009	1923.1200	0.9995	5.6003	3.1415	1883
16	5.8586	−0.0013	−0.0011	1897.0988	0.9803	5.6058	3.1400	1863
17	5.8352	−0.0011	−0.0010	1875.9572	1.0000	5.6087	3.1416	1843
18	5.8243	−0.0011	−0.0010	1852.5572	1.0000	5.6126	3.1416	1823
19	5.8190	−0.0011	−0.0010	1829.4414	0.9912	5.6168	3.1369	1803
20	5.8078	−0.0011	−0.0011	1804.1573	0.9884	5.6217	3.1414	1783

This table reports the estimated parameters for the calibrated LPPLS models for Tesla. The LPPLS model is defined as:

$$\ln\left[p\left(t\right)\right] = A + B(t_c - t)^{\beta}\left[1 + C\cos(\omega\ln\left(t_c - t\right) + \varphi\ )\right],$$

where $\ln\left[p\left(t\right)\right]$ denotes the logarithm price of Tesla at time t, t_c is the critical time, A is the expected value of Tesla when approaching t_c, B defines the exposure to faster-than-exponential growth, and β is the power-law exponent controlling faster-than-exponential price growth. Furthermore, C denotes the exposure the log-periodic oscillations around the power-law singular growth, ω denotes the angular log-frequency of oscillations during the formation of the bubble, φ is the phase parameter. The estimated model accounts for the constraints $A > 0$, $B < 0$, $\omega > 0$, $t_c > T$, and $0 \leq \beta \leq 1$. In every iteration, the sample is reduced by cutting off 20 sample observations from the beginning of the sample. That is, the first iteration uses $T = 2163$ observations, whereas the last iteration uses $T = 1783$ observations

dard financial models like GARCH(1,1). This extensive cross-asset validation strengthens the credibility of the LPPLS-based diagnostics applied to the current dynamics of the Magnificent 7 firms.

Taken together, these findings reinforce the interpretation that the LPPLS signatures identified in the Magnificent 7 firms are consistent with a well-established pattern of endogenous market fragility observed across a wide range of historical bubbles and asset classes.

5.2 Implications

5.2.1 Manifestations of finite-time singularities

Finite-time singularities in the log-prices of financial assets represent critical points at which the underlying dynamics of asset valuation become unsustainable, leading to extreme outcomes. According to Sornette (2017), these singularities manifest in three primary forms. The first is continued super-exponential growth, characterized by an accelerating increase in

Table 11 Results for iteratively estimated ADF tests for the residuals of the LPPLS models

Iteration	Alphabet	Amazon	Apple	Meta	Microsoft	NVIDIA	Tesla
1	−3.03	−2.84	−3.35	−2.72	−3.14	−2.99	−2.66
2	**−3.61**	−2.89	**−3.54**	−2.69	−3.42	−2.97	−2.65
3	−3.33	−2.90	**−3.84**	−2.88	**−3.73**	−2.97	−2.67
4	−3.39	−2.92	**−3.65**	−2.86	**−3.77**	−2.99	−2.66
5	**−3.44**	−2.96	−3.36	−2.65	**−3.92**	−3.04	−2.91
6	**−3.45**	−2.91	**−3.69**	−2.83	−3.31	−3.18	−2.96
7	**−3.65**	−3.13	**−4.16**	−2.82	−3.39	−2.97	−3.23
8	**−3.70**	−3.32	**−4.13**	−2.76	**−3.98**	−2.89	**−3.45**
9	**−3.78**	**−3.47**	**−4.26**	−2.62	**−3.78**	−2.87	−3.35
10	**−3.81**	−3.38	**−4.08**	−2.64	**−3.45**	−3.11	−3.22
11	**−3.92**	**−3.43**	**−4.10**	−2.63	**−3.92**	−3.17	−3.34
12	**−4.16**	**−3.51**	**−4.15**	−2.57	**−4.23**	**−3.52**	−3.26
13	**−3.87**	**−3.51**	**−3.93**	−2.57	**−4.28**	−3.09	−3.22
14	**−3.82**	**−3.43**	**−4.06**	−2.57	**−4.27**	−3.05	−3.22
15	**−4.00**	**−3.48**	**−4.34**	−2.61	**−4.54**	−2.99	−3.01
16	**−4.04**	**−3.51**	**−4.23**	−2.63	**−4.47**	−3.07	−3.10
17	**−4.19**	**−3.83**	**−4.22**	−2.66	**−4.57**	−2.94	−3.12
18	**−4.42**	**−3.97**	**−4.40**	−2.68	**−4.76**	−2.90	−3.02
19	**−4.40**	**−4.11**	**−4.31**	−2.69	**−4.10**	−2.85	−3.02
20	**−4.42**	**−3.94**	**−4.25**	−2.57	**−4.64**	−2.95	−3.14

This table reports the iteratively estimated ADF test statistics implemented for residuals of the estimated LPPLS models for the Magnificent 7 companies (viz., Alphabet, Amazon, Apple, Meta, Microsoft, NVIDIA, and Tesla). The critical values for the 1%, 5% and 10% significance levels are −3.43, −2.86, −2.57. Bold figures indicate statistical significance on a 1% level. The Schwarz-Criterion (SC) is used for the selection of the optimal lag length in the test regressions. The corresponding lag length is reported in Table 14 in the appendix.

log-prices, often associated with speculative bubbles. During such phases, prices are driven higher by self-reinforcing mechanisms such as herding behavior, irrational exuberance, and excessive leverage. According to West (2017), this scenario—marked by increased acceleration—would, however, necessitate innovation as the driving force. The second manifestation involves an abrupt discontinuity or crash, where the log-price undergoes a sudden, sharp decline. These events typically arise from systemic shocks, liquidity crises, or abrupt shifts in investor sentiment, resulting in rapid and destabilizing revaluations. Lastly, oscillatory divergence describes a scenario where log-prices exhibit increasingly volatile fluctuations as the singularity point approaches. This behavior is often observed in pre-crash conditions, as market dynamics oscillate between phases of optimism and fear, creating erratic yet intensifying price movements. These three scenarios represent potential manifestations of identified finite-time singularities for the majority of the Magnificent 7 companies.

5.2.2 Empirical validation of predicted finite-time singularities

Following the submission of this manuscript on February 1, 2025, we monitored the stock prices of the companies analyzed. In line with the predictions made by the LPPLS model, significant drawdowns occurred for Alphabet, Amazon, Apple, and Microsoft between January 31, 2025 and April 13, 2025. Since February 1, 2025 fell on a weekend when markets were closed, we use the closing prices from January 31, 2025 as the reference point for calculating the maximum drawdowns. Table 12 presents the maximum drawdowns observed for each stock during this period, which range from −14.58% for Microsoft to −45.17% for Tesla, whereas Alphabet—the first stock predicted to reach a finite-time singularity—experienced a decline of −28.71%. These substantial price corrections provide supportive evidence for the predicted finite-time singularity dynamics. As evidenced by the substantial drawdowns reported in Table 12, the critical fragility predicted by the LPPLS model appears to have materialized across key stocks, lending further empirical support to the theoretical framework and enhancing the practical relevance of early warning indicators based on finite-time singularities. According to Sornette (2017), the critical time (t_c) estimated by the LPPLS model represents a phase of extreme market fragility rather than a deterministic crash date. As the system approaches t_c, the probability of a crash increases, but its precise timing remains stochastic and highly sensitive to small endogenous fluctuations or exogenous shocks. Therefore, it is entirely consistent with LPPLS theory that large drawdowns can occur before the predicted critical time.

The sharp declines observed in the Magnificent 7 stocks during this monitoring period may thus be interpreted as empirical manifestations of the systemic fragility diagnosed by the LPPLS model, supporting the validity and practical relevance of the finite-time singularity forecasts presented in this study. Taken together, these observations have important implications for financial risk management.

Overall, these findings highlight the practical utility of LPPLS-based diagnostics in identifying critical phases of market instability before major regime shifts occur. By capturing endogenous dynamics that lead to increasing systemic fragility, and by validating these patterns against observed price behavior, our results reinforce the value of finite-time singularity models as early warning tools for financial risk management.

5.2.3 Empirical indication of systemic spillovers

In addition to the substantial individual drawdowns observed among the M7 firms, broader market impacts were also clearly visible. Between January 31 and April 13, 2025, the Mag-

Table 12 Maximum drawdowns of the magnificent 7 stocks between February 1, 2025 and April 13, 2025

Company	Stock price in USD on day Jan 31, 2025	Minimum stock price in USD For the following period: Feb 1, 2025–Apr 13, 2025	Date of maximum drawdown	Maximum drawdown (in %)
Alphabet	205.60	146.58	Apr 8, 2025	−28.71
Amazon	237.86	170.66	Apr 8, 2025	−28.25
Apple	236.00	172.42	Apr 8, 2025	−26.94
Meta	689.18	504.73	Apr 4, 2025	−26.76
Microsoft	415.06	354.56	Apr 8, 2025	−14.58
NVIDIA	120.07	94.31	Apr 4, 2025	−21.45
Tesla	404.60	221.86	Apr 8, 2025	−45.17
S&P 500	6040.53	4982.77	Apr 8, 2025	−17.51

This table reports the maximum drawdowns of the Magnificent 7 stocks between January 31, 2025 (the last available trading day before the study's submission to the *Review of Quantitative Finance and Accounting*) and April 13, 2025 (the date when the first editorial decision was received). The maximum drawdown for each stock is defined as the largest observed percentage decline from the closing price on January 31, 2025, to the minimum closing price recorded during this period nificent 7 firms experienced an average maximum drawdown of −27.41%.[6] Given that these firms represented approximately 34.25% of the S&P 500 market capitalization at the time, a simple weighted average calculation suggests that, if the remainder of the index had remained unaffected, the S&P 500 should have experienced a maximum drawdown of approximately −9.39%. However, the actual maximum drawdown of the S&P 500 over the same period was substantially larger, at −17.51%. The fact that the observed index-level drawdown was almost twice as large as the expected value under a no-contagion assumption indicates that significant spillover effects were present. These results provide empirical support for the hypothesis that instability originating within a small group of highly influential firms can propagate beyond their own valuations, amplifying systemic risk across the broader market.

5.2.4 Treatment of policy interventions

The present study focuses on modeling endogenous bubble dynamics as captured by the LPPLS framework. We acknowledge that external factors, such as government policy interventions, may influence asset price trajectories by either amplifying, delaying, or mitigating the predicted regime shifts. However, such interventions are treated as exogenous shocks in our analysis and are not formally modeled within the LPPLS framework. Consequently, while policy shifts—such as those observed during the Trump administration—may disrupt the endogenous dynamics identified, assessing the timing or magnitude of such disruptions lies beyond the scope of this study. Moreover, the discussion of potential policy impacts in this paper remains conceptual and is not based on formal theoretical modeling or empirical validation. Future research could extend this analysis by integrating event studies, structural break analyses, or theoretical frameworks on policy-driven market interventions.

5.2.5 LPPLS signatures as diagnostics of systemic fragility

The LPPLS model, while capable of identifying endogenous bubble dynamics and forecasting critical phases of heightened market instability, should not be interpreted as providing deterministic crash predictions. Rather, the occurrence of a finite-time singularity as diagnosed by LPPLS signifies a regime where systemic fragility has escalated, and where the probability of an abrupt transition—such as a sharp correction or crash—substantially increases. This perspective aligns with the theoretical foundation articulated by Sornette (2017), who emphasizes that while the LPPLS model captures the buildup of unsustainable growth fueled by positive feedback mechanisms, the actual crash event is inherently stochastic and sensitive to small endogenous or exogenous perturbations. Consequently, LPPLS signals are best understood as early warning indicators of critical vulnerability, rather than precise predictors of market turning points.

5.3 Limitations

While the empirical and cross-asset validation presented above lends strong support to the applicability of the LPPLS framework, it is important to recognize the methodological and predictive limitations that remain. The presented analysis derived from calibrated

[6] See Table 12 for further details.

LPPLS models has its limitations. It is essential to note that the LPPLS model is specifically designed to model endogenous behaviors manifested in internal bubble mechanisms driven by positive (or negative) feedback loops (Sornette 2017). For instance, Grobys (2023) attempted to predict the U.S. stock market crash of October 15, 2008. Using daily data on the S&P 500 from October 9, 2002, to December 31, 2007, to calibrate the LPPLS model, Grobys (2023) identified evidence of a statistically significant LPPLS signature and projected the occurrence of a finite-time singularity on August 19, 2011, rather than the actual crash date of October 15, 2008.

Similarly, Grobys (2025) examined whether the LPPLS model could predict bubble formation in gold prices during the early 2000s. Employing a dataset spanning from July 19, 1999, to September 14, 2006, which included 1,745 daily observations for model calibration, his findings indicated a predicted crash in gold prices on March 21, 2007. However, the actual crash occurred ex-post on August 11, 2011. Grobys (2023, 2025) argued that the LPPLS model's inability to accurately predict these crashes was attributable to "external factors" interfering with the internal feedback mechanisms represented by the LPPLS dynamics. For example, Grobys (2025) emphasized that the model's "false positive" prediction for March 21, 2007, might reflect an external event: market participants observing early signs of the subprime mortgage crisis, which emerged in 2006, potentially redirected investments to gold. This capital influx could have artificially sustained the gold bubble, delaying its burst until 2011.

Furthermore, external factors such as government policies can also interfere with anticipated regime shifts. For instance, policy decisions under the Trump administration could influence stock prices and disrupt the predicted patterns documented in this study. This interference may occur through a combination of policy measures, strategic communication, and indirect economic mechanisms. Pro-growth policies, such as corporate tax cuts, deregulation, and stimulus initiatives, directly enhance corporate profitability and investor confidence, potentially driving stock prices upward. Moreover, trade negotiations, including announcements of favorable trade agreements or tariff reductions, could further bolster market sentiment by reducing economic uncertainty. Additionally, the Trump administration's pressure on the Federal Reserve (FED) to adopt dovish monetary policies—such as maintaining low interest rates or implementing quantitative easing—could stimulate investment by reducing borrowing costs. Infrastructure spending proposals, too, might generate optimism in specific industries while positively affecting the broader stock market. These external influences underscore the importance of considering exogenous factors when interpreting LPPLS model outcomes, as they may significantly alter the dynamics of bubble formation and regime transitions.

Although the LPPLS model may offer a powerful framework for diagnosing endogenous bubble dynamics, it is subject to several methodological limitations. In particular, concerns have been raised in the literature regarding the potential for overfitting and the sensitivity of parameter estimates to initial conditions (Brée et al. 2013). While our iterative re-estimation analysis suggests that the predicted critical times remain relatively stable across different information sets, indicating robustness, we acknowledge that the non-linear and non-convex nature of the LPPLS model can complicate precise parameter identification. Furthermore, while our study relies on nonlinear least squares (NLLS) optimization consistent with standard practice (e.g., Sornette and Zhou 2006; Filimonov and Sornette 2013), alternative estimation frameworks such as Bayesian methods or maximum likelihood approaches could offer complementary perspectives. Exploring these alternative methodologies remains an important direction for future research.

Finally, while the LPPLS model identifies endogenous dynamics indicative of growing systemic instability, its predictive power is inherently probabilistic rather than deterministic. Exogenous shocks, regulatory interventions, or unforeseen macroeconomic developments may alter market trajectories even when endogenous signals of fragility are present. Nevertheless, the universality of LPPLS signatures across historical bubbles—such as those preceding the 1987 stock market crash and the 2000 dot-com collapse—has been well-documented (Sornette 2017). Specifically, Sornette (2017, p. 232) derives the relationship $\lambda = \exp(2\pi/\omega)$ arguing that the value of $\lambda \cong 1.5 - 1.7$ "is remarkably universal and is found to be approximately the same for other crashes." Moreover, Monte Carlo simulations by Lin et al. (2014) show that such LPPLS structures are highly unlikely to emerge from standard financial models like GARCH(1,1), with a false positive rate below 0.2%. These findings reinforce the relevance of statistically significant LPPLS signatures as critical early warning signs, while recognizing the limits of forecasting precision in complex adaptive systems like financial markets.

6 Conclusion

The Magnificent 7 companies—Apple, Microsoft, Amazon, Alphabet (Google's parent), Meta Platforms, Tesla, and NVIDIA—revolutionize global markets and innovation. Operating across sectors like AI, cloud computing, and renewable energy, these firms epitomize industry leadership, shaping business practices and consumer behavior globally. They collectively hold immense economic sway, representing 34.25% of the S&P 500's market capitalization (17.8 trillion USD as of January 15, 2025). This study argues that although these technology-driven companies develop cutting-edge advancements, their market dominance could introduce systemic risks. For example, disruptions in their operations or valuations could trigger economic instability due to their industry interconnectedness and concentration of power in critical technologies like AI and cloud computing.

From the perspective of stock investors, this study hypothesizes that the Magnificent 7 companies pose a systemic risk if they (a) exhibit unsustainable growth rates in their stock prices, and (b) experience regime changes as a consequence of these unsustainable growth rates occurring simultaneously.

This study investigates the potential systemic risks associated with the stocks of the Magnificent 7 companies. By calibrating LPPLS models using the log-prices of these companies' stocks over the period from May 13, 2016, to January 17, 2025, the analysis reveals significant LPPLS signatures for Alphabet, Amazon, Apple, and Microsoft. The stationarity of residuals in four out of seven calibrated LPPLS models provides evidence that 65% of the total market capitalization—representing the majority of the Magnificent 7—is susceptible to finite-time singularities in the near future. This finding satisfies the first condition for positing systemic risk. Furthermore, the critical times for Amazon, Apple, and Microsoft are predicted to occur within a one-month window, specifically between May 15 and June 9, 2025. This supports the conclusion that the second condition for systemic risk is also met. While parameter estimates for critical times exhibit variability due to stochastic influences, the mean estimates remain statistically significant, yielding robust confidence intervals. These results underscore the potential systemic risks stemming from the market dominance of these companies. While this study highlights the critical role of endogenous bubble dynamics in systemic fragility, future research should extend this framework by explicitly modeling contagion pathways and cross-market transmission mechanisms.

However, government policies could significantly influence stock market dynamics by disrupting predicted regime changes. Pro-growth actions like tax cuts, deregulation, and stimulus initiatives could increase corporate profitability and investor confidence, potentially driving stock prices upward. Also, trade negotiations, dovish monetary policies, and infrastructure spending could further enhance market sentiment, underscoring the need to consider external factors in analyzing bubble formation and regime transitions.

Appendix

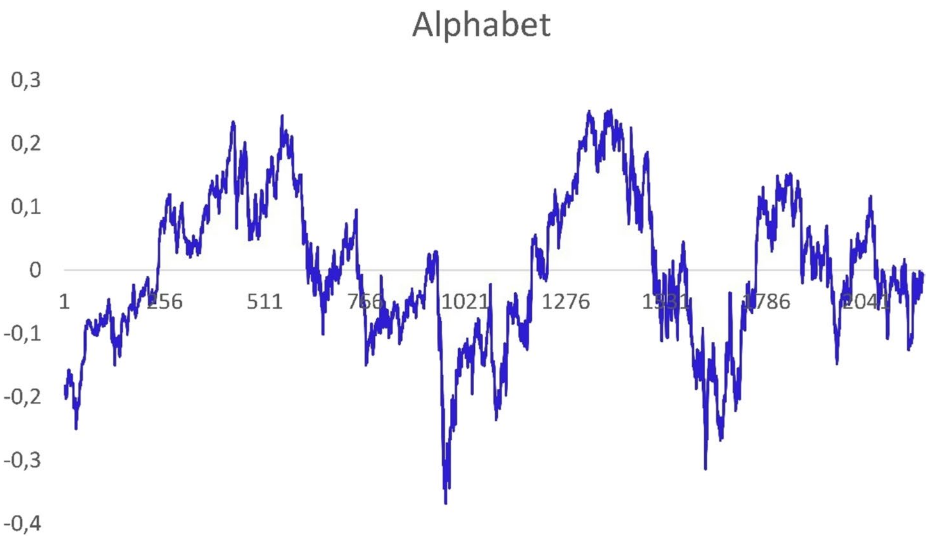

Fig. 8 Residuals of the calibrated LPPLS model implemented for Alphabet. This figure presents the time series evolution of the residuals of the LPPLS model implemented for daily log-prices for the company Alphabet The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

Fig. 9 Residuals of the calibrated LPPLS model implemented for Amazon. This figure presents the time series evolution of the residuals of the LPPLS model implemented for daily log-prices for the company Amazon. The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

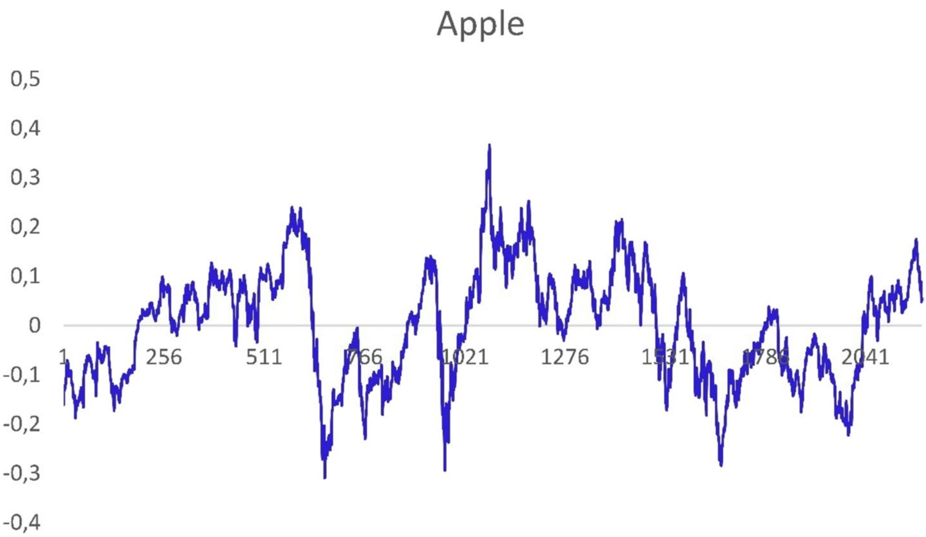

Fig. 10 Residuals of the calibrated LPPLS model implemented for Apple. This figure presents the time series evolution of the residuals of the LPPLS model implemented for daily log-prices for the company Apple. The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

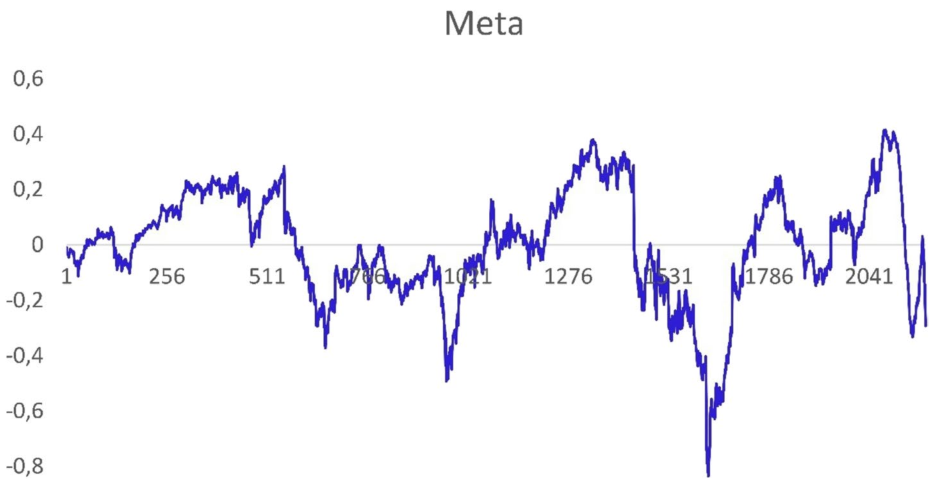

Fig. 11 Residuals of the calibrated LPPLS model implemented for Meta. This figure presents the time series evolution of the residuals of the LPPLS model implemented for daily log-prices for the company Meta. The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

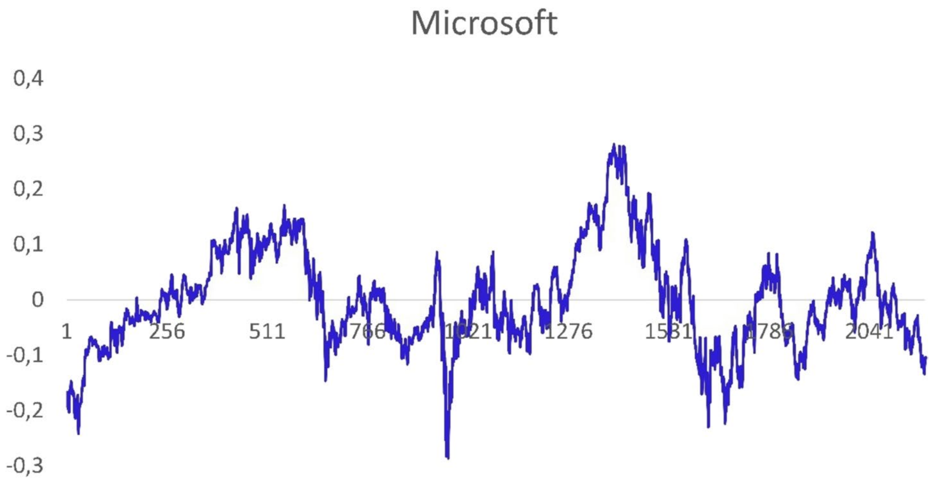

Fig. 12 Residuals of the calibrated LPPLS model implemented for Microsoft. This figure presents the time series evolution of the residuals of the LPPLS model implemented for daily log-prices for the company Microsoft. The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

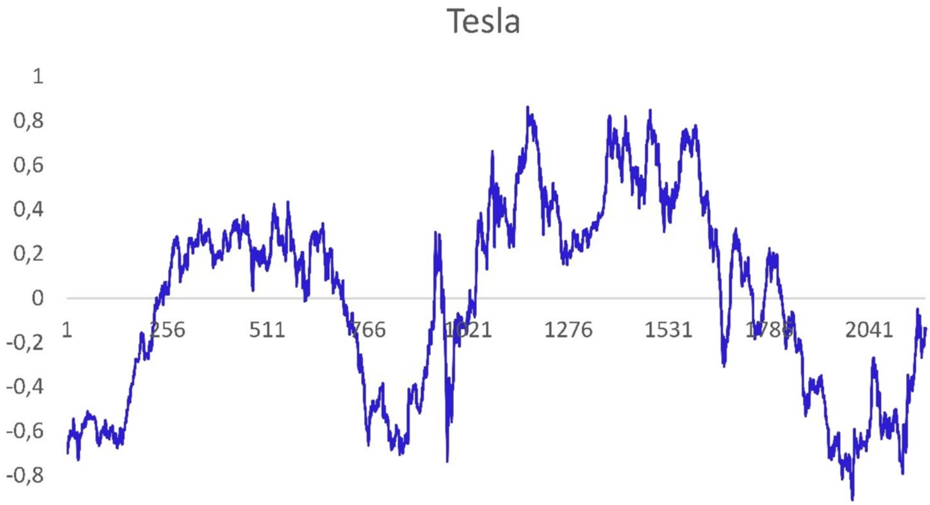

Fig. 13 Residuals of the calibrated LPPLS model implemented for Tesla. This figure presents the time series evolution of the residuals of the LPPLS model implemented for daily log-prices for the company Tesla. The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

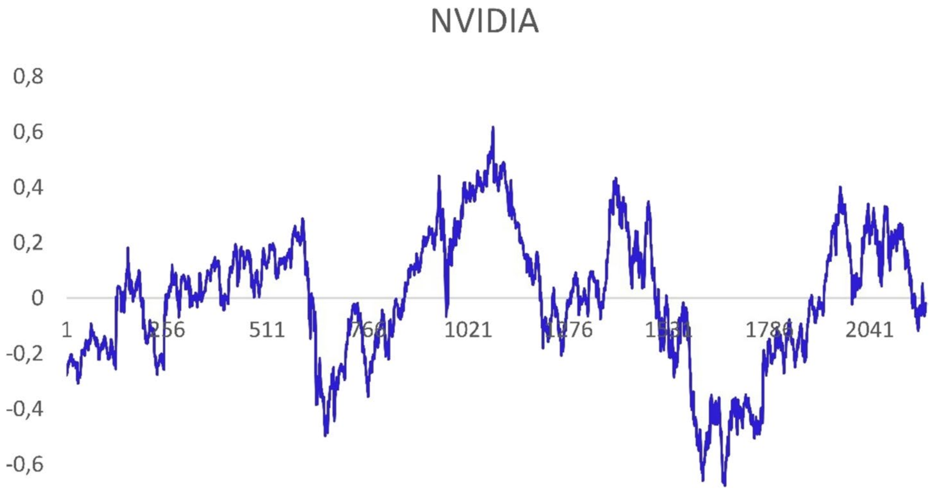

Fig. 14 Residuals of the calibrated LPPLS model implemented for NVIDIA. This figure presents the time series evolution of the residuals of the LPPLS model implemented for daily log-prices for the company NVIDIA. The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

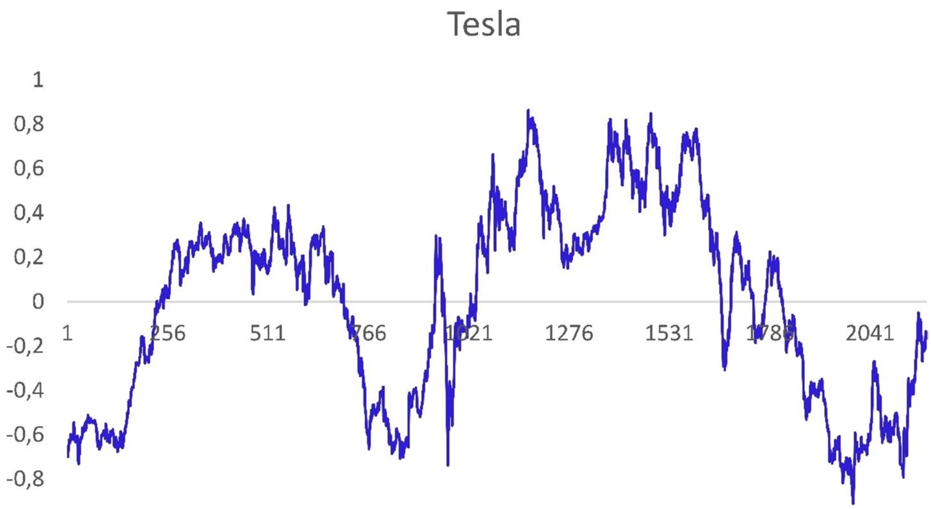

Fig. 15 Residuals of the calibrated LPPLS model implemented for Tesla. This figure presents the time series evolution of the residuals of the LPPLS model implemented for daily log-prices for the company Tesla. The sample is from May 13, 2016 to January 17, 2025 corresponding to $T = 2183$ sample observations

Table 13 Predicted critical times

Alphabet	February 14, 2025
Amazon	June 9, 2025
Apple	May 15, 2025
Meta	February 11, 2025
Microsoft	June 6, 2025
NVIDIA	June 5, 2025
Tesla	June 6, 2025

This table provides the critical times from Table 2 in dates

Table 14 Lag lengths for iteratively estimated ADF test statistics

Iteration	Alphabet	Amazon	Apple	Meta	Microsoft	NVIDIA	Tesla
1	9	0	9	0	9	1	0
2	9	0	9	0	9	1	0
3	9	0	9	2	9	1	0
4	9	0	9	2	9	1	0
5	9	0	9	0	9	1	0
6	9	0	9	2	9	1	0
7	9	0	9	2	9	1	0
8	9	0	9	1	9	1	0
9	9	0	9	1	9	1	0
10	9	0	9	0	9	1	0
11	9	0	9	0	9	1	0
12	9	0	9	0	9	1	0
13	9	0	9	0	9	1	0
14	9	0	9	0	9	1	0
15	9	0	9	0	9	1	0
16	9	0	9	0	9	1	0
17	9	0	9	0	9	1	0
18	9	0	9	0	9	1	0
19	9	0	9	0	9	1	0
20	9	0	9	1	9	1	0

This table reports the lag length for the lagged dependent variable in the implemented ADF test statistics reported in Table 11. The optimal lag length is selection using the Schwarz Criterion

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