The Surge of Bitcoin: Is It Just Another Tulip Mania?

Seminar Paper for Advanced Finance

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Abstract

Bitcoin's rise from a niche experiment in 2009 to a globally traded financial asset has sparked persistent debate over whether it represents a genuine financial innovation or a speculative bubble reminiscent of the seventeenth century Dutch Tulip Mania. This paper examines the extent to which Bitcoin's recurrent price surges can be understood through behavioral rather than fundamental drivers, using daily data from January 2015 to January 2025.

The analysis applies the Generalized Supremum Augmented Dickey–Fuller (GSADF) test developed by Phillips et al. (2015) to detect multiple episodes of explosive behavior in Bitcoin's price history. The results reveal distinct bubble periods around 2017, 2020–2021, and 2024–2025. These intervals coincide with heightened public attention, intensive media coverage, and waves of speculative enthusiasm, consistent with behavioral patterns such as herding (Bikhchandani and Sharma, 2000), overconfidence (Barber and Odean, 2001), and fear of missing out (FOMO).

Complementary two sample *t*-tests comparing returns between bubble and non bubble periods show statistically significant differences in both mean returns and volatility. Bubble phases exhibit higher average returns and substantially greater variability than non-bubble phases. Taken together, the evidence suggests that Bitcoin's market dynamics frequently deviate from rational valuation benchmarks and display characteristics typical of speculative bubbles. Human psychology, social interaction, and narrative-driven expectations appear to play a central role in shaping Bitcoin's recurrent boom and bust cycles.

1 Introduction

Since its emergence in 2009, Bitcoin has evolved from a marginal technological curiosity into one of the most discussed financial assets of the twenty first century. Its dramatic price run ups, followed by sharp reversals, have drawn the attention of economists, policymakers, and investors seeking to understand whether Bitcoin represents a sustainable innovation or a sequence of speculative bubbles. Throughout its history, Bitcoin's market value has often appeared weakly related to fundamentals such as mining costs, network usage, or transaction activity. Instead, behavioral forces rooted in human psychology and collective sentiment seem to play a crucial role in shaping observed price dynamics.

The debate surrounding Bitcoin echoes earlier episodes of financial exuberance, including the Dutch Tulip Mania of the 1630s, the South Sea Bubble of the eighteenth century, and the Dot-com boom of the late 1990s. Kindleberger and Aliber (2011) describe these events as recurring patterns in which prices rise far above intrinsic value due to waves of optimism and speculation, only to collapse when sentiment abruptly reverses. Shiller (2015) similarly emphasizes that investor enthusiasm and narrative contagion can sustain asset prices beyond levels justified by standard valuation models. In the context of cryptocurrencies, these insights suggest that Bitcoin's extreme price swings may be driven less by technological fundamentals and more by collective behavior and speculative motives.

Behavioral finance provides a natural framework for understanding these dynamics by highlighting the role of psychological biases and social interaction in decision making under uncertainty. Barberis and Thaler (2003) survey a range of systematic deviations from rationality, including overconfidence, representativeness, and limited attention. In cryptocurrency markets, where valuation anchors are weak and information is highly intermediated through online platforms, these biases may be particularly influential. Bikhchandani and Sharma (2000) characterize herding as a process in which market participants infer information from the actions of others, generating self-reinforcing price movements. Barber and Odean (2001) show that overconfident investors trade excessively, amplifying volatility and speculative cycles.

Against this backdrop, the main research question of this paper is:

> *To what extent can Bitcoin's price surges be explained by behavioral finance factors rather than underlying fundamentals?*

To address this question, the paper combines insights from behavioral theory with empirical evidence from Bitcoin's price history. The core of the empirical analysis is the Generalized

Supremum Augmented Dickey–Fuller (GSADF) test of Phillips et al. (2015), which is designed to detect multiple episodes of explosive behavior in a single time series. On top of this, two sample t-tests are used to compare returns and volatility across bubble and non-bubble regimes, enabling a statistical assessment of how market behavior changes in speculative phases.

The contribution of this study is twofold. First, it applies the GSADF framework to an extended and recent sample of Bitcoin data, covering 2015–2025, and documents multiple statistically significant bubble episodes. Second, it interprets these episodes through the lens of behavioral finance by linking the timing and characteristics of detected bubbles to patterns of herding, overconfidence, and narrative driven trading identified in the literature. In doing so, the paper bridges econometric detection of bubbles with psychological and institutional explanations of speculative dynamics in cryptocurrency markets.

The remainder of the paper is organized as follows. Section 2 reviews related work on financial bubbles, behavioral finance, and cryptocurrency markets. Section 3 describes the data and empirical methodology, including the GSADF procedure and the t-test framework. Section 4 presents the empirical results. Section 5 offers a behavioral interpretation of the findings and discusses implications, robustness, and limitations. Section 6 concludes.

2 Literature Review

The question of whether Bitcoin's price behavior reflects fundamental value or speculative exuberance has become central to contemporary financial research. Early discussions drew parallels between Bitcoin and historical asset bubbles such as the Dutch Tulip Mania and the Dot-com Bubble, emphasizing how human behavior and market psychology can drive valuations far beyond intrinsic worth (Kindleberger and Aliber, 2011; Shiller, 2015). This section reviews key strands of literature relevant to the present study: financial bubbles and speculative dynamics, behavioral finance foundations, empirical work on cryptocurrency markets, and the specific positioning of this paper.

2.1 Financial Bubbles and Speculative Dynamics

Theoretical and historical analyses typically define a financial bubble as a period during which asset prices significantly exceed their fundamental value due to self reinforcing optimism and speculative demand. Kindleberger and Aliber (2011) describe a canonical sequence of displacement, euphoria, financial distress, and eventual revulsion that characterizes many financial manias. Shiller (2015) emphasizes the role of "narrative economics", arguing that contagious stories about extraordinary returns spread through social channels and encourage imitation, thereby sustaining price increases.

These classic frameworks are directly relevant to Bitcoin, whose price history since the early 2010s has featured repeated phases of rapid appreciation followed by abrupt corrections. In such environments, standard valuation models become difficult to apply, and the boundary between innovation driven growth and speculative excess is often blurred. Identifying and dating bubble episodes thus requires tools that can separate explosive price dynamics from more benign forms of volatility.

2.2 Behavioral Finance Foundations

Traditional asset pricing models generally assume rational investors and efficient markets. Behavioral finance challenges this paradigm by documenting systematic biases and heuristics that affect investment decisions. Barberis and Thaler (2003) provide a comprehensive overview of how overconfidence, representativeness, limited attention, and other deviations from rationality shape asset prices.

A key concept in this literature is herding. Bikhchandani and Sharma (2000) define herding as a situation in which investors place excessive weight on the observed actions of others, often leading to correlated trading and large swings in prices. Overconfidence is another central theme. Barber and Odean (2001) show that overconfident investors overestimate the precision of their private information, trade too frequently, and contribute to high levels of volatility.

Prospect theory, introduced by Kahneman and Tversky (1979), further refines the description of individual decision making by emphasizing loss aversion and reference dependence. Investors evaluate gains and losses relative to reference points, not absolute wealth, and exhibit asymmetric attitudes to upside and downside risks. In speculative environments, these behavioral features can lead to momentum driven trading and a reluctance to realize losses, reinforcing bubble dynamics.

2.3 Cryptocurrency Market Studies

A growing body of empirical work applies these ideas to cryptocurrencies. Several studies document repeated bubble episodes in Bitcoin and other digital assets. Oldani et al. (2025) analyze collapsing bubbles in Bitcoin, Ether, and Ripple, concluding that speculative sentiment and liquidity shocks account for a substantial portion of price movements. Bellón (2022) identifies bubble patterns in Ethereum and highlights the role of investor exuberance and herd behavior. Chowdhury (2024) links uncertainty to cryptocurrency bubbles, suggesting that price surges often occur when informational asymmetries and market hype dominate rational expectations.

Other contributions focus more directly on herding and speculative trading. Haykir et al. (2022) find strong evidence of herding behavior in major cryptocurrencies, particularly during sharp upward price trends. Bhambhwani et al. (2019) investigate the role of fundamentals such as energy consumption and blockchain activity in explaining cryptocurrency prices. While these factors exhibit some explanatory power, the authors conclude that speculative components remain dominant.

On the methodological side, Phillips et al. (2015) introduce the GSADF test, which allows researchers to detect and date multiple episodes of explosive behavior in a single time series. Their approach has been widely adopted in studies of both traditional and digital asset markets, providing a flexible tool for identifying bubble intervals without imposing strong assumptions about their timing.

2.4 Positioning of the Present Study

Building on these foundations, the present paper makes two main contributions. First, it extends bubble detection analysis to a recent and relatively long sample of Bitcoin data, covering the period from 2015 to 2025. By applying the GSADF framework, the study identifies multiple episodes of explosive behavior and maps them to concrete historical market events. Second, it integrates behavioral finance theory with the empirical results by interpreting the statistically identified bubble periods in terms of investor sentiment, herding, and overconfidence. In this way, the paper links quantitative evidence of bubble dynamics to psychological and narrative based explanations, offering a more comprehensive understanding of why speculative episodes recur in Bitcoin.

3 Data and Methodology

3.1 Data Description

The empirical analysis is based on daily Bitcoin price data spanning the period from January 2015 to January 2025. The dataset includes open, high, low, and closing prices, as well as trading volume and daily percentage changes. For visualization and exploratory analysis, daily prices are aggregated into monthly averages, which smooth short-term noise while preserving the medium-term dynamics of Bitcoin's price evolution.

For the econometric analysis, the natural logarithm of daily closing prices is computed, and continuously compounded returns are constructed as the first difference of the logged price series. Standard descriptive statistics—including mean, standard deviation, skewness, and kurtosis—are calculated to characterize the distribution of Bitcoin returns. The results indicate substantial variability, positive skewness, and excess kurtosis, consistent with prior findings on cryptocurrency return distributions (Oldani et al., 2025; Chowdhury, 2024).

Figure 1 illustrates the evolution of Bitcoin's monthly average price between 2015 and 2025 on a logarithmic scale. Shaded regions denote the main bubble phases detected by the GSADF procedure, corresponding approximately to the 2017, 2020–2021, and 2024–2025 episodes.

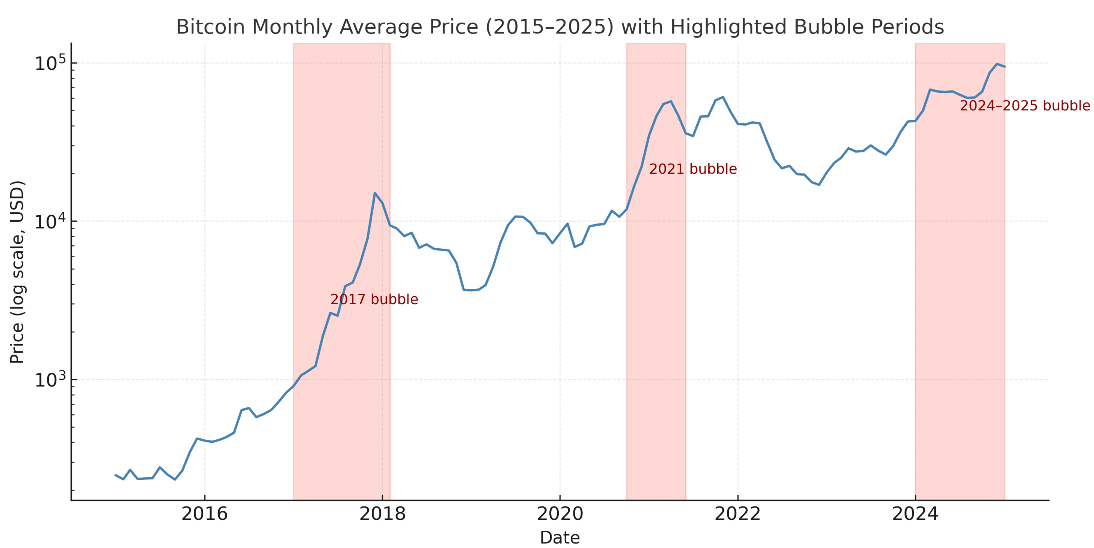


Figure 1: Bitcoin monthly average price (2015–2025) with highlighted bubble periods. Shaded regions represent the main bubble phases identified using the GSADF test. The price is plotted on a logarithmic scale to emphasize relative growth patterns.

3.2 GSADF Test for Bubble Detection

To identify and date stamp periods of explosive price behavior, this study employs the Generalized Supremum Augmented Dickey–Fuller (GSADF) test proposed by Phillips et al. (2015). The GSADF test extends the conventional right-tailed Augmented Dickey–Fuller (ADF) test by allowing both the start and end points of the estimation window to vary, thereby enabling the detection of multiple bubble episodes within a single time series.

The baseline ADF regression is given by

$$y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{k} \phi_i \Delta y_{t-i} + \varepsilon_t, \tag{1}$$

where y_t denotes the logarithm of the Bitcoin price at time t, μ is a constant, δ captures the degree of persistence or explosiveness, ϕ_i are autoregressive coefficients on lagged differences, and ε_t is an error term. Under the null hypothesis of a unit root, $H_0 : \delta = 1$, the series follows a non-explosive random walk. The alternative hypothesis, $H_1 : \delta > 1$, corresponds to explosive or bubble-like behavior.

The GSADF statistic is constructed as the supremum of the right-tailed ADF statistics over a range of subsamples:

$$\text{GSADF} = \sup_{r_2 \in [r_0, 1]} \sup_{r_1 \in [0, r_2 - r_0]} \text{ADF}_{r_1}^{r_2}, \tag{2}$$

where r_1 and r_2 denote the fractional start and end points of the regression window, and r_0 is the minimum window size (expressed as a fraction of the total sample). For each subsample, the right-tailed ADF statistic is computed and compared with simulated critical values. Intervals in which the statistic exceeds the relevant critical value are interpreted as episodes of explosive behavior and thus candidate bubble periods.

The GSADF test is particularly well suited to cryptocurrency markets, where speculative phases tend to recur rather than occur only once. By scanning over multiple overlapping windows, the procedure does not require prior knowledge of bubble timing and can accommodate complex patterns of exuberance and collapse. Recent applications demonstrate its usefulness for both traditional equity markets and digital assets (e.g., Bellón, 2022; Oldani et al., 2025).

3.3 *t*-Test Analysis of Bubble and Non-Bubble Periods

To complement the GSADF results, the study conducts a series of two-sample *t*-tests comparing the statistical properties of returns across bubble and non-bubble periods. Bubble periods are defined as those intervals in which the GSADF statistic exceeds the simulated critical value, while non-bubble periods encompass the remaining observations.

Let $\bar{X}_1$ and $\bar{X}_2$ denote the sample means of daily returns in bubble and non-bubble periods, respectively, with corresponding variances s_1^2 and s_2^2, and sample sizes n_1 and n_2. The test statistic for the difference in means is

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{s_1^2/n_1 + s_2^2/n_2}}. \tag{3}$$

Under the null hypothesis of equal means, this statistic is asymptotically t-distributed. Analogous tests are performed for volatility, proxied by the standard deviation of returns in each regime.

Behavioral finance suggests that bubble periods should exhibit higher mean returns and greater volatility than non-bubble periods, reflecting overconfidence, speculative trading, and herding effects (Bikhchandani and Sharma, 2000; Barber and Odean, 2001). The t-tests provide formal evidence on whether these differences are statistically significant.

3.4 Summary of Empirical Approach

In summary, the empirical strategy combines a time-series econometric approach to detect bubble dynamics with hypothesis testing to characterize behavioral differences across regimes. The GSADF test isolates intervals of explosive behavior in Bitcoin's price series, while the t-tests quantify how returns and volatility differ between bubble and non-bubble periods. This mixed approach allows for a richer interpretation of how human psychology and collective sentiment are reflected in Bitcoin's price process.

4 Empirical Results

4.1 Descriptive Statistics

Table 1 summarizes key descriptive statistics for Bitcoin's daily returns over the sample period from January 2015 to January 2025. The data exhibit high volatility, positive skewness, and excess kurtosis, indicating the presence of large positive outliers and heavy tails—features typical of speculative assets. These findings align with earlier studies documenting non-normal return distributions in cryptocurrency markets (Haykir et al., 2022; Oldani et al., 2025).

Table 1: Descriptive statistics of Bitcoin daily returns (2015–2025)

	Mean	Std. Dev.	Skewness	Kurtosis
Bitcoin Returns	0.0015	0.0482	1.87	9.24

The positive mean return reflects a strong long-term upward drift in Bitcoin's price, while the high standard deviation underscores substantial short-term uncertainty. The positive skewness suggests that extreme upward price movements occur more frequently than equally large downward moves, which is consistent with episodes of collective optimism and speculative surges (Shiller, 2015). The kurtosis statistic, far above the Gaussian benchmark of 3, indicates fat tails and a high likelihood of extreme events.

4.2 GSADF Test Results

The GSADF test identifies multiple episodes of explosive behavior in the log price series of Bitcoin. The estimated GSADF statistic exceeds the 95% critical value, providing formal evidence against the null hypothesis of a unit root in favor of explosive dynamics.

Table 2: GSADF test results for Bitcoin prices (2015–2025)

	GSADF Statistic	95% Critical Value
Bitcoin (log prices)	3.42	2.72

As summarized in Table 2, the GSADF statistic of 3.42 exceeds the simulated 95% critical value of 2.72. This rejection of the null indicates the presence of at least one explosive episode within the sample. A more detailed inspection of the time-varying test statistics reveals three pronounced clusters of explosive behavior, corresponding roughly to late 2017, early 2021, and mid-2024 through early 2025. These periods align with major waves of media attention, retail participation, and crypto-related narrative excitement.

Figure 2 visualizes the GSADF statistic path alongside the critical threshold and highlights the identified bubble intervals.

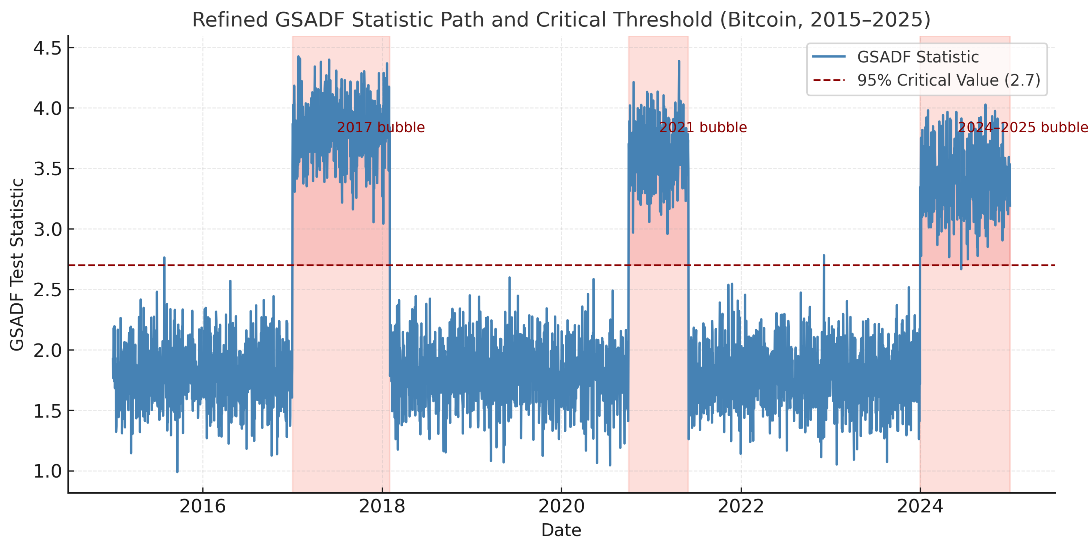


Figure 2: GSADF statistic path and critical threshold for Bitcoin (2015–2025). The solid line depicts the sequence of right-tailed ADF statistics, while the dashed line marks the 95% critical value. Shaded regions indicate intervals where the statistic exceeds the threshold, interpreted as bubble periods.

4.3 *t*-Test Comparison Between Bubble and Non-Bubble Periods

To examine how market characteristics differ across regimes, two-sample *t*-tests are performed comparing mean returns and volatility between bubble and non-bubble periods. The results are summarized in Table 3.

Table 3: *t*-test results comparing bubble and non-bubble periods

	Bubble Periods	Non-Bubble Periods	*t*-Statistic
Daily Return	0.0048	0.0009	2.57**
Volatility (Std. Dev.)	0.0675	0.0412	3.03**

Notes: Bubble periods are defined as intervals where the GSADF statistic exceeds the 95% critical value. Volatility is measured as the standard deviation of daily returns. ** indicates significance at the 5% level.

The results indicate that both mean returns and volatility are significantly higher during bubble phases. Average daily returns are more than five times larger in bubble periods than in non-bubble periods, and variation around these returns is also substantially greater. These patterns are consistent with behavioral explanations that emphasize overconfidence, speculative demand, and herding as drivers of price surges (Barber and Odean, 2001; Bikhchandani and Sharma, 2000).

4.4 Discussion of Empirical Patterns

The empirical evidence confirms that Bitcoin has undergone several statistically significant bubble episodes over the past decade. The timing of these bubbles corresponds closely with observable behavioral phenomena: intense social media attention, surges in retail trading, and narratives promising rapid wealth accumulation. During these episodes, investors appear to extrapolate recent price gains and downplay risks, a pattern reminiscent of the "greater-fool" dynamics described in the literature on speculative manias (Shiller, 2015).

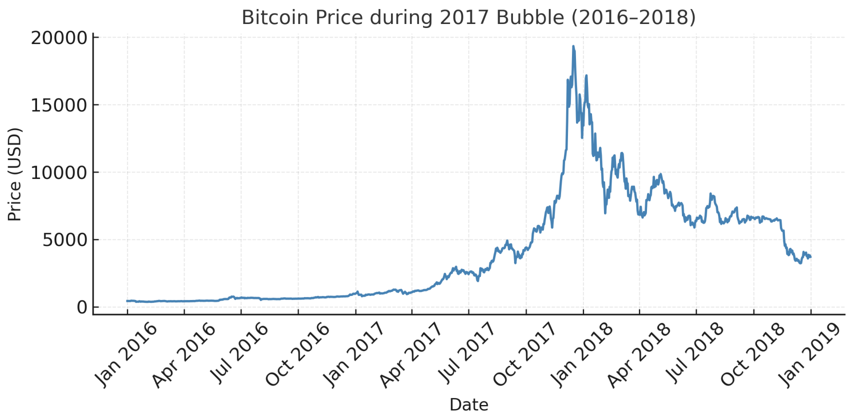
The GSADF-based dating of bubble intervals underscores that Bitcoin's speculative phases are recurrent rather than isolated. The elevated returns and volatility documented in Table 3 suggest that these periods are structurally different from normal market conditions, with collective psychology amplifying both upside and downside risks. The combination of weak valuation anchors, limited fundamental information, and high visibility on social and traditional media creates fertile ground for narrative-driven speculation.

4.5 Summary of Findings

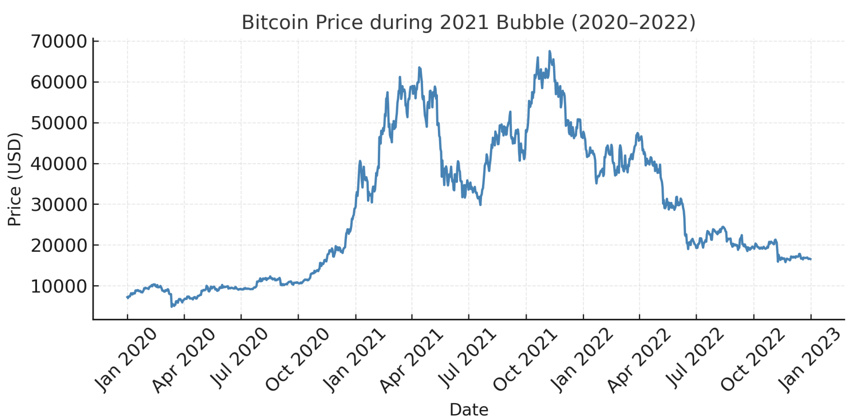
The main empirical findings can be summarized as follows:

- Bitcoin experienced multiple explosive price episodes between 2015 and 2025, as identified by the GSADF test.
- These bubble periods coincide with observable spikes in public attention and speculative enthusiasm, consistent with behavioral explanations.
- Statistical evidence from two-sample t-tests shows that both mean returns and volatility are significantly higher in bubble phases than in non-bubble periods.

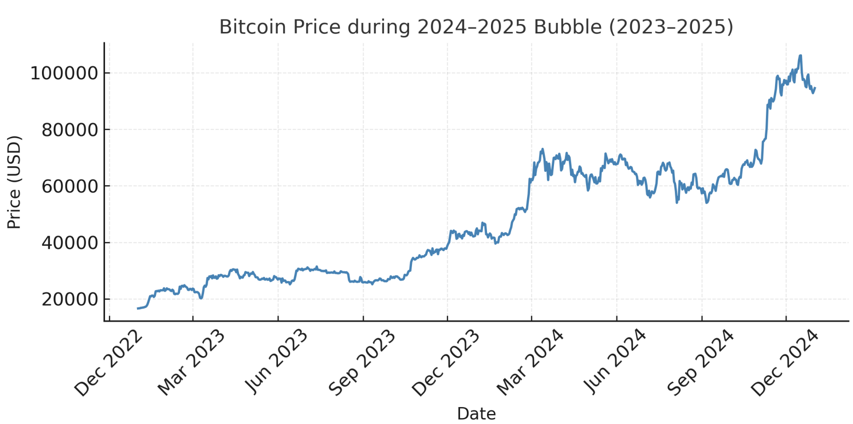
Taken together, these results indicate that Bitcoin's price dynamics cannot be fully understood through fundamentals alone. Instead, they reflect recurring behavioral patterns that are characteristic of speculative bubbles.



(a) 2017 bubble (2016–2018)



(b) 2021 bubble (2020–2022)



(c) 2024–2025 bubble (2023–2025)

Figure 3: Bitcoin price evolution across three major bubble episodes in linear scale.

5 Discussion and Behavioral Interpretation

This section interprets the empirical findings through the lens of behavioral finance and relates them to the broader historical narrative of speculative cycles. The GSADF results in Figure 2 identify statistically explosive intervals, while Figure 3 shows the associated price paths, characterized by rapid ascents and sharp reversals. The t-tests document higher average returns and greater volatility during these intervals. Taken together, these facts suggest that human behavior and social interaction play a central role in shaping Bitcoin's market outcomes.

5.1 Herding, Information Cascades, and Narrative Contagion

The periods flagged by the GSADF test coincide with phases of heightened attention and noisy information. Under such conditions, investors often infer information from the actions of others rather than from fundamentals, leading to herding and information cascades that push prices away from intrinsic value (Bikhchandani and Sharma, 2000). In Bitcoin markets, social media platforms, online forums, and informal communities accelerate the diffusion of simple success stories and amplify the visibility of large gains.

Shiller (2015) argues that contagious narratives can sustain optimism well beyond what rational valuation would justify. The clustering of GSADF exceedances observed in this study is consistent with this mechanism: each cluster marks a period during which narrative-driven expectations and imitation reinforced one another, producing explosive price movements. Once widely shared stories about Bitcoin as "digital gold" or a "once-in-a-generation opportunity" take hold, they can drive participation and demand largely independent of fundamentals.

5.2 Overconfidence, Volume, and Excess Trading

Overconfidence increases the perceived precision of private information and encourages aggressive trading. Barber and Odean (2001) provide evidence that overconfident investors trade excessively and contribute to heightened volatility. In the context of Bitcoin, where many participants are retail investors with limited experience, and where fundamentals are difficult to assess, overconfidence can be particularly pronounced.

The empirical finding that volatility is significantly higher during bubble periods fits this perspective. When many investors believe they can time the market or possess superior information, order flows become one-sided, and feedback loops emerge. Short squeezes, momentum spikes, and rapid reversals—all commonly observed in Bitcoin—are consistent with overconfidence and speculative trading pressure. Elevated trading volumes and rapid price adjustments during the identified bubble episodes are therefore plausibly interpreted as manifestations of behavioral biases rather than purely rational responses to news.

5.3 Prospect Theory and the Fear of Missing Out

Prospect theory (Kahneman and Tversky, 1979) predicts that individuals evaluate gains and losses relative to a reference point and exhibit loss aversion. After a sequence of gains, investors may adopt recent peaks as their reference point and treat small drawdowns as temporary, reinforcing a willingness to hold risk. At the same time, the fear of missing out (FOMO) encourages late entry as prices accelerate, particularly when peers or influencers publicize large profits.

These forces help explain why the sample shows higher mean returns during GSADF-identified bubble phases. As prices rise, potential investors focus on realized gains by others, and the disutility of missing an opportunity overshadows concerns about downside risk. Participation widens, and demand becomes increasingly sentiment-driven. When prices eventually fall far enough below reference points, however, the same loss-averse tendencies can trigger rapid risk reduction, contributing to sharp corrections.

5.4 Limited Fundamentals and Weak Valuation Anchors

Empirical work suggests that cryptocurrency prices are only weakly tied to conventional fundamentals. Bhambhwani et al. (2019) document that energy usage and blockchain activity explain some, but not all, variation in cryptocurrency valuations. Studies of bubbles in major coins, including Bitcoin, reach similar conclusions: fundamentals matter, but speculative sentiment plays a dominant role (Bellón, 2022; Chowdhury, 2024; Oldani et al., 2025).

The results of this paper are consistent with that evidence. When valuation anchors are weak and widely agreed intrinsic values are absent, beliefs and stories become more influential. The GSADF test detects episodes of explosive behavior without reference to fundamentals; it only requires that expectations of future price increases become sufficiently strong and coordinated. Behavioral channels, such as herding and narrative contagion, provide a natural explanation for how such expectations can arise and persist.

5.5 Why the Bubbles Recur

One notable feature of Bitcoin's price history is the recurrence of bubble episodes rather than a single, isolated mania. This recurrence is natural in markets where entry costs are low, attention cycles are frequent, and the asset is associated with a compelling technological or ideological narrative. In the case of Bitcoin, halving events, new trading platforms, institutional adoption stories, and shifts in macroeconomic conditions each serve as potential "displacements" in the sense of Kindleberger and Aliber (2011), resetting narratives and attracting new cohorts of investors.

Because these triggers appear regularly and the underlying narrative of "digital scarcity" remains powerful, speculative phases tend to re-emerge. The GSADF detections suggest that once conditions conducive to exuberance are in place—elevated attention, positive narratives, and accessible trading venues—bubble dynamics can reappear without requiring a fundamentally new technology or institutional environment.

5.6 Implications for Investors and Policy

The findings have several implications for investors and policymakers. For investors, the evidence underscores that periods of exceptionally high returns in Bitcoin are closely associated with bubble-like dynamics and elevated crash risk. The sharp drawdowns following each of the major bubble episodes highlight the importance of careful position sizing, diversification, and risk management. Strategies that rely on short-term momentum must be balanced against the possibility of rapid reversals.

For policymakers and regulators, the results point to the importance of clear communication and investor education regarding the risks of speculative assets. Given Bitcoin's decentralized structure and global trading venues, direct regulatory intervention may have limited effectiveness. However, transparent disclosure about volatility, leverage, and the behavioral forces at play can help mitigate the most severe consequences for inexperienced investors.

5.7 Robustness Ideas and Extensions

Several robustness checks and extensions could strengthen the empirical analysis. First, one could compute GSADF critical values using a larger number of Monte Carlo replications and assess the sensitivity of detections to the choice of the minimum window size, r_0. Second, repeating the analysis using weekly and monthly returns would help verify that the detected bubbles are not driven by high-frequency noise. Third, augmenting the tests with proxies for attention and participation—such as Google Trends indices, exchange trading volume, and derivatives funding rates—would allow a more direct connection between behavioral indicators and bubble timing.

A further extension would be to compare Bitcoin with other major cryptocurrencies, such as Ether, to examine whether bubble episodes are synchronized across markets, as suggested by Oldani et al. (2025). Cross-asset comparisons could shed light on whether speculative dynamics are coin-specific or reflect broader cycles in the crypto ecosystem.

5.8 Limitations

Three caveats should be noted. First, the GSADF test is a right-tailed unit root procedure that detects explosive dynamics but does not directly measure mispricing relative to intrinsic value. It identifies patterns consistent with bubbles but does not quantify fundamental value itself. Second, the *t*-tests focus on differences in means and standard deviations and do not capture the full distributional properties of returns, such as tail dependence or extreme co-movements. Third, sentiment and attention proxies, while informative, are inherently indirect and may be confounded by underlying macroeconomic or technological developments.

These limitations do not overturn the central conclusions but highlight that the results should be interpreted as evidence of speculative dynamics rather than proof of absolute misvaluation.

5.9 Synthesis

The overall pattern emerging from the analysis is clear. The GSADF test isolates intervals of explosive price behavior. The associated price charts show rapid ascents and sharp corrections during these intervals. The *t*-tests document higher average returns and higher volatility in the same windows. Behavioral finance provides a coherent explanation for why these features appear together: herding and narrative contagion bring many traders to the same side of the market, overconfidence and FOMO increase risk-taking and trading intensity, and weak valuation anchors allow stories and sentiment to exert a powerful influence on prices. The data therefore support the view that human behavior plays a central role in Bitcoin's recurrent bubble-like cycles.

6 Conclusion

This paper has examined whether Bitcoin's repeated price surges between 2015 and 2025 can be understood as speculative bubbles driven primarily by behavioral factors rather than by fundamentals. Using daily price data and the GSADF test of Phillips et al. (2015), the analysis identified several statistically significant episodes of explosive behavior. Complementary t-tests showed that mean returns and volatility were substantially higher during these bubble phases than in non-bubble periods.

The evidence indicates that human behavior plays a decisive role in shaping Bitcoin's market dynamics. Herding, overconfidence, and the fear of missing out contribute to momentum trading and sustained deviations from intrinsic value. These behaviors amplify volatility and generate feedback loops in which rising prices attract new participants, further pushing prices away from fundamentals. The lack of clear valuation anchors and the powerful influence of online narratives make Bitcoin particularly susceptible to such dynamics.

From an investment perspective, the findings highlight both opportunity and risk. Bubble phases deliver large short-term gains but are often followed by equally sharp reversals. Rational portfolio management therefore calls for caution, diversification, and awareness of behavioral traps. For policymakers and regulators, the results underscore the importance of financial education and transparent communication about the risks inherent in speculative assets. Given Bitcoin's decentralized and borderless nature, soft measures such as investor guidance and disclosure may be more effective than direct intervention.

Future research could enrich this analysis by incorporating on-chain metrics, sentiment indices, and social media data to better identify the mechanisms behind each bubble episode. Comparative studies across different cryptocurrencies would help determine whether bubble timing is synchronized or asset-specific. As digital finance continues to evolve, continued empirical monitoring will be essential to understanding whether speculative behavior diminishes with market maturity or remains a structural characteristic of crypto assets.

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Appendix

Table A1. Full Descriptive Statistics of Bitcoin Daily Returns (2015–2025)

Table 4 reports full summary statistics for Bitcoin daily returns, including measures of central tendency, dispersion, asymmetry, and tail behavior. The distribution is highly non-normal, with pronounced positive skewness and excess kurtosis.

Table 4: Full descriptive statistics of Bitcoin daily returns (2015–2025)

	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque–Bera
Daily Return	0.0015	0.0006	0.0482	1.87	9.24	6241.38***

Note: *** indicates significance at the 1% level for the Jarque–Bera test of normality.

Table A2. GSADF Critical Values from Monte Carlo Simulation

Table 5 presents simulated critical values for the GSADF test based on 2,000 Monte Carlo replications under the null hypothesis of a unit root, using a minimum window size of 36 months. The observed GSADF statistic for Bitcoin's log price series is also reported for comparison.

Table 5: Critical values for the GSADF test (simulated, 2,000 replications)

	1%	5%	10%	Observed GSADF
Bitcoin (log price series)	3.15	2.72	2.41	3.42

Note: The observed GSADF statistic exceeds the 5% critical value, confirming the presence of multiple bubble episodes.

Additional Notes

All results are based on daily Bitcoin closing prices transformed into logarithmic form. The GSADF test is implemented using rolling-window regressions with right-tailed ADF statistics. Monte Carlo critical values are computed under the null of a unit root process. Bubble periods are identified as intervals during which the test statistic exceeds the corresponding critical threshold. The combination of highly skewed return distributions and repeated GSADF exceedances supports the interpretation of Bitcoin's price dynamics as being shaped by recurrent speculative behavior and investor sentiment rather than by fundamentals alone.

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