

Title

"Bubbles and Crashes in Cryptocurrencies: Detecting Market Anomalies and Future Trends"

Author 1**Twinkle Jaiswal**

Doctoral Fellow, Institute of Management Studies, Banaras Hindu University, Varanasi, India

E-mail ID- *twinklejaiswal@fmsbhu.ac.in*

Mailing Address- Institute of Management Studies, Banaras Hindu University, Varanasi, 221005, Uttar Pradesh, India

Mobile number- +91 9919362088

ORCID- 0000-0002-3578-8892

Author 2**Vishal Roy**

Doctoral Fellow, Institute of Management Studies, Banaras Hindu University, Varanasi, India

E-mail ID- *vishalroy@fmsbhu.ac.in*

Mailing Address- Institute of Management Studies, Banaras Hindu University, Varanasi, 221005, Uttar Pradesh, India

Mobile number- +91 8954544295

Author 3**Dr. Amit Gautam**

Professor, Institute of Management Studies, Banaras Hindu University, Varanasi, India

E-mail ID- *amitgautam@fmsbhu.ac.in*

Mailing Address- Institute of Management Studies, Banaras Hindu University, Varanasi, 221005, Uttar Pradesh, India

Mobile number- +91 9839248497

ORCID- 0000-0002-9672-7217

Title

Bubbles and Crashes in Cryptocurrencies: Detecting Market Anomalies and Future Trends

Abstract

The market capitalisation of cryptocurrencies has surged significantly from 2019 to 2024, making them a critical asset class prone to speculative bubbles. Unlike traditional assets, cryptocurrencies lack conventional valuation metrics, leading to extreme volatility driven by investor sentiment, behavioural biases, and market inefficiencies. This study employs the Log-Periodic Power Law Singularity (LPPLS) model to detect bubbles and anti-bubbles (crashes) additionally wavelet coherence analysis is employed to explain detected anomalies in five major cryptocurrencies - Bitcoin, Ethereum, XRP, BNB, and Dogecoin. The LPPLS model captures price acceleration and oscillatory behaviour before a critical point, signalling market instability. Our findings confirm speculative bubbles across all selected cryptocurrencies. The estimated critical times suggest potential corrections in early 2025. Furthermore, wavelet coherence analysis reveals that investor sentiment and external factors significantly influenced price dynamics, reinforcing the presence of non-fundamental anomalies in cryptocurrency markets. The study contributes to risk management strategies by developing a predictive framework for cryptocurrency market crashes, aiding investors and policymakers.

Keywords

Bubble, Crash, Cryptocurrency, LPPLS, Wavelet Coherence

Words

5558 (excluding tables and references)

1. Introduction

Cryptocurrencies are digital currencies that utilise cryptography to safeguard and validate transactions, as well as to regulate the creation of new units. They are decentralised and operate on a peer-to-peer network, whereby transactions are authenticated and documented on a public ledger referred to as the blockchain, which is upheld by a community of users. Bitcoin, the earliest and most renowned cryptocurrency, was launched in 2009. Since that time, other cryptocurrencies have been developed, including Ethereum, Ripple, and Dogecoin. Every cryptocurrency possesses unique attributes and traits; yet, they all adhere to fundamental principles of cryptography, decentralisation, and blockchain technology. The market capitalisation of cryptocurrencies has surged by over 75 percent from 2019 to 2024, increasing from \$1.92 trillion to \$3.39 trillion, a rise more than the GDP of nations like Turkey and Indonesia (www.coinmarketcap.com). The valuation of cryptocurrencies is linked to their capacity to function as a store of value and medium of exchange, security factors, and the anticipations of investors regarding future demand for these assets. However, they have no intrinsic value of their own and hence, cannot be priced using conventional asset valuation methods. Often their return and volatility are high compared to other assets. For example, Bitcoin shows an annualised return of 62% and an annualised standard deviation of 54% from November 19, 2019 to January 20, 2025. This "high return/high volatility" trait may indicate an enduring speculative bubble.

Bubbles are defined as phases of swift price escalation followed by a collapse (Kindleberger, 1996). In practice they are perceived as substantial divergences from intrinsic values. Conventional economic theory posits that investors act rationally. They contend that markets are efficient and that asset prices include all available information. When asset prices deviate from their intrinsic value, the arbitrage mechanism will realign them with their underlying values (Fama 1970). However, in practice, the activities of arbitrageurs are incapable of realigning prices with underlying values due to constraints on arbitrage (Shleifer & Summers 1990). Minsky (2008) tried to explain the formation of bubbles in financial market by arguing that the period of stability foster overconfidence, resulting in excessive investment and the formation of asset price bubbles. In essence, stability is inherently destabilising, rendering financial bubbles intrinsic to capitalism. Although this theory is plausible, it fails to elucidate why bubbles manifest in certain assets and countries while absent in others.

The bubbles are driven by speculation and behavioural biases of the investors. Behavioural economic research indicate that investors lack complete rationality, resulting in asset prices being influenced by their sentiments, emotions, and beliefs. Baker & Wurgler (2006) observed that market players exhibit emotional and reactive tendencies, leading them to make excessively optimistic or gloomy assessments and decisions. More sentiment-induced crashes and bubbles are result from the fact that most participants in the market are amateur investors who behave impulsively, emotionally, and irrationally (Fruehwirt et al., 2021).

But to consider majority of investors as irrational is not fair. According to the Rational Bubble Theory, bubbles can survive in efficient markets if investors rationally anticipate price appreciation, sustaining overvaluation despite fundamental mispricing (Blanchard & Watson, 1982; Froot & Obstfeld, 1991). Informed investors may acquire an asset recognised as overvalued, anticipating that the market surge may persist in the short term, allowing them to subsequently sell the asset to a less discerning buyer for a financial gain (O'Hara, 2008). This technique, known as 'riding the bubble', may be a logical reaction to the uncertainty over the timing of a share price correction (Xiong & Yu, 2011). Direct evidence exists of investors capitalising on the dot-com bubbles (Griffin et al., 2011). Dhar & Goetzmann (2005) discovered that more than fifty percent of respondents regarding their trading behaviour during the dot-com bubble had purchased stocks they perceived as expensive, anticipating further price escalations. Then there is Greater Fool Theory, where investors purchase overpriced assets with the intention of selling them to a "greater fool" for a higher price (Zou, 2018). This increases prices until market sentiment changes, causing a crash (Barlevy, 2015).

Further, herding behaviour has been widely used in literature to understand the bubble formation. Investors follow collective sentiment instead of individual analysis and thus amplify the price distortions (Barberis & Thaler, 2003; Daniel et al., 1998). In addition to behavioural explanations, structural factors also cause bubbles. Demand and supply mismatch play a crucial role, as speculative demand and liquidity constraints can drive prices away from intrinsic values (Brunnermeier & Oehmke, 2012; Porter & Smith, 2003). A separate segment of the literature has examined the relationship between bubbles and emerging technology. Perez (2009) contends that bubbles, such as the dot-com boom, arise when enthusiasm for a novel technology, often coupled with early adopters reaping substantial gains, leads to asset values exceeding their intrinsic value. The spark of a bubble is often a technological innovation or government policy. (Quinn & Turner, 2023).

Monitoring bubbles can be advantageous for investors, since significant fluctuations in cryptocurrencies values may negatively impact returns or present investment opportunities. Moreover, for market stability as well as risk management, identification of bubbles and their subsequent reversals (anti-bubbles) is necessary. Our research is driven by the theoretical framework of cryptocurrency pricing and bubble formation, along with the advantages that crypto bubble analysis offers investors to evade the illusion of wealth and excessive excitement. Moreover, figuring

out the bubble development is a vital step that helps us to go beyond just identifying bubbles to fully replicate their whole cycle. The log-periodic oscillations of the financial bubble pattern define a power law that leads to the development of the log-periodic power law (LPPL) model (Johansen, 2003). LPPLS has the ability to detect future bubbles (both positive and negative), hence we have substituted LPPLS model over models based on ADF. It is needless to say that LPPLS is an advance variation of LPPL model. Using LPPLS model, we aim to identify bubbles and anti-bubbles (crashes) in cryptocurrencies; subsequently, we have explained the found anomalies using wavelet coherence analysis of cryptocurrencies with investor sentiment.

2. Literature Review

Given the tremendous volatility and irrational investor behaviour displayed in the digital currency markets, research of bubbles in these markets has become important. According to literature, structural inefficiencies, investor mood, and speculative activity generate bubbles in the cryptocurrency market (Gandal et al., 2018). Barnes (2019) observes that the absence of intrinsic value in cryptocurrencies leads to difficulties in valuation and exacerbates speculative bubbles stemming from the herding effects. Further, the founders and developers of cryptocurrencies have a tendency to engage in price manipulation due to minimal accountability and disclosure requirements. Liquidity and volatility are key factors that influence market efficiency in cryptocurrencies. Research indicates that higher liquidity and lower volatility enhance market efficiency, while illiquidity and high volatility, especially during events like the COVID-19 pandemic, increase price delays and reduce arbitrage opportunities (Tanos & Badr, 2024). The 2017 cryptocurrency bubble also highlighted the impact of investor sentiment, during periods of technological hype and availability of limited fundamental valuation metrics. Sentiment-driven trading led to prolonged price increases, followed by reversals once the bubble burst (Chen et al., 2019).

Several researches have been conducted to identify bubbles and crashes in cryptocurrencies. Fry and Cheah (2016) have used econophysics model to detect negative bubbles in Bitcoin and Ripple during 2011 to 2015. Chowdhury et al. (2022) have detected periods of bubbles and crashes in top cryptocurrencies from 2016 to 2021 using the Backward Sup Augmented Dickey-Fuller statistics (BSADF) method based on recursive regression developed by Philips et al. (2011). Likewise, Corbet et al. (2018) have applied the similar method (GSADF) to detect bubbles in Bitcoin and Ethereum from 2009 to 2017 and found Bitcoin to be in the bubble phase. Further, techniques like the Log-Periodic Power Law (LPPL) have been employed to detect such bubbles by identifying super-exponential growth patterns preceding crashes (Wheatley et al., 2019). The LPPL model assumes that financial bubble pattern is a power law with log-periodic oscillations. (Johansen, 2003). Geraskin & Fantazzini (2013) thoroughly explained the LPPL model, encompassing its theoretical framework and empirical estimations, which is used for identifying bubbles in financial markets. Multiple variations of the LPPL model have been formulated to address increased market volatility and more pronounced fluctuations over shorter durations (Lin et al., 2014; Zhang et al., 2016; Demos & Sornette, 2017; Demirer et al., 2019; Shu & Zhu, 2020; Ghosh et al., 2021; Gonçalves et al., 2022). Papastamatiou & Karakasidis (2022) developed the LPPLS model, which identifies both positive and negative bubbles. The utilisation of LPPL and LPPLS models in the crypto market is constrained. Zhang et al. (2024) had applied LPPL to identify bubbles in various cryptocurrencies from 2018 to 2022. Yao and Li (2021) have used GSADF along with LPPLS model to identify the bubbles in bitcoin and found two periods of bubble between 2015 and 2020.

Numerous researchers have studied the inefficiency in the crypto markets (Urquhart 2016; Nadarajah & Chu 2017). Palamalai et al. (2021) examined the random walk hypothesis in the cryptocurrency market and determined it to be weak-form inefficient. They found that the value of Bitcoin was

determined to be positively skewed, suggesting that the market responds more favourably to positive news than to negative news. Cheah & Fry (2015) determined that Bitcoin's valuation is driven by its speculative aspect, rendering its intrinsic value null. Urquhart (2016) additionally discovered indications of inefficiencies inside the Bitcoin market. They contend that Bitcoin is a relatively novel investment asset, and the cryptocurrency market resembles an emerging market. Kristoufek (2013) assessed Bitcoin sentiment through Google and Wikipedia search queries, discovering a substantial bidirectional correlation between Bitcoin prices and sentiment. They also record that speculation and trend-following predominate in Bitcoin valuations. Rajput et al. (2022) constructed a Bitcoin Sentiment Index (BSI) and found a substantial positive correlation between BSI and Bitcoin returns and volume. Anamika et al. (2021) concluded that sentiments significantly impact bitcoin prices. Karalevicius et al. (2018) examined the relationship between media sentiment and Bitcoin prices, concluding that investors exhibit an overreaction to news events. Ahn & Kim (2020) quantified emotions through postings from a cryptocurrency blog and discovered substantial evidence that emotions influence Bitcoin values. All the above studies suggest that the crypto market is influenced by investors sentiment. We have tried to build to further the research by analysing the role of positive and negative sentiments i.e., fear and greed in causing the bubbles and crashes in the crypto market by employing wavelet analysis.

While existing literature has substantially examined the development of speculative bubbles in cryptocurrency markets emphasising the roles of irrational investor behaviour, sentiment-driven trading, structural inefficiencies, and liquidity constraints, there remains a methodological gap in accurately detecting and validating such bubbles. Numerous studies have focused on behavioural explanations and macroeconomic triggers (Cai et al., 2019; Mokni et al., 2021; Wanidwaranan & Termprasertsakul, 2023), whereas the deployment of quantitative methodologies, such as the LPPLS model, is still comparatively underexploited in the context of cryptocurrencies.

Further, despite the LPPL and its extensions (Johansen, 2003; Geraskin & Fantazzini, 2013; Papastamatiou & Karakasidis, 2022) providing a solid theoretical framework for identifying super-exponential growth patterns preceding crashes, their incorporation with supplementary methodologies such as wavelet analysis has been limited. Moreover, despite the high-frequency, volatile, and sentiment-sensitive characteristics of cryptocurrency markets, limited research has examined the performance of LPPLS models under excessive volatility and systemic stress times (COVID-19). Thus, there is a critical need for further empirical investigations that integrate LPPLS models with time-frequency techniques like wavelet analysis to enhance the detection, prediction and interpretation of bubbles in crypto markets.

3. Data and Methodology

We have selected five cryptocurrencies- Bitcoin, Ethereum, XRP, BNB and DOGE, on the basis of market capitalization (as on January 30, 2025). We have excluded stablecoins such as tether due to less volatility in their prices. Also, only those cryptocurrencies were selected whose data was available for the whole time period. We have also taken Crypto Fear and Greed Index (FNG, hereafter) provided by alternative.me to account for investor's sentiment in the cryptocurrency market. The daily data of closing prices of selected cryptocurrencies from November 19, 2019 to January 20, 2025 have been extracted from investing.com. The aforementioned start date was chosen because on November 17, 2019, the first Covid-19 case was discovered in China. The FNG index was also extracted for the same period.

The LPPLS model is a quantitative approach used to detect financial bubbles and crashes. This model based on the principle, asset prices exhibit accelerating growth with log-periodic oscillations before a critical point, signalling a bubble's peak. The model captures the collective behaviour of

investors, integrating nonlinear dynamics and herding effects, by estimating parameters such as the critical time, amplitude, and frequency of oscillations, the LPPLS model information about market instability. In this study, LPPLS is employed to identify existing cryptocurrency bubbles and anti-bubbles as well as predict the potential crash.

LPPLS mathematically expressed as:

$$p(t) = A + B(t_c - t)^m + C(t_c - t)^m \cos(\omega \ln(t_c - t) + \phi)$$

Where, $p(t)$ represents the asset price at time, while A denotes the fundamental price component. The coefficients B and C determine the amplitude of the power-law and log-periodic oscillations. The parameter t_c signifies the critical time, which estimates the point at which the bubble is likely to burst. The exponent m , constrained within the range of 0 and 1, governs the power-law behaviour of price movements. ω is the log-periodic angular frequency and ϕ is the phase parameter that adjusts the oscillatory pattern of price fluctuations.

Further we have used wavelet coherence analysis to explain the bubbles detected in cryptocurrencies through their co-movement with investor's sentiment. The co-movement of each cryptocurrency with the FNG index will clarify if the bubbles are driven by investors sentiment.

The wavelet methodology converts signals into time and frequency components. A wavelet can be visualised as a wave-like oscillations with changing amplitudes. A mother wavelet of the time series represented by ψ , is transformed into continuous wavelet. It generates a family of wavelets. The equation of continuous wavelet transform is:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t) \psi^* \left(\frac{t - \tau}{s} \right) dt$$

Here, ψ^* represents the complex conjugate of ψ while s is the scale parameter of the series $x(t)$ and τ is the translation parameter. The cross-wavelet time series $x(t)$ and $y(t)$, with continuous wavelet $W_x(\tau, s)$ and $W_y(\tau, s)$ is calculated by:

$$W_{xy}(\tau, s) = W_x(\tau, s) W_y^*(\tau, s)$$

To analyse the co-movement of the two time-series, the wavelet coherence (WSC) is used and defined as follows:

$$WSC = R_{XY}^2(\tau, s) = \frac{\left| S \left(\frac{1}{s} W_{XY}(\tau, s) \right) \right|^2}{S \left(\frac{1}{s} |W_X(\tau, s)|^2 \right) S \left(\frac{1}{s} |W_Y(\tau, s)|^2 \right)}$$

Where S represents a smoothing operator used in both the time and frequency domain. In the wavelet coherence plot, the x axis shows time period and y axis shows frequency. The frequency scale is divided into short, medium and long term. The colours on the plot shows strength of co-movement. The red and blue colours represent strong and weak linkages respectively. The arrows show lead and lag relationship as well as the phase relationship. If the arrows are pointing towards right, the two series are moving in the same direction and if they are pointing towards left, the two series are moving in opposite direction.

4. Results and Discussion

Table 1: Descriptive Statistics of Cryptocurrencies

	BITCOIN	ETHEREUM	XRP	BNB	DOGECOIN
Mean	0.001256983	0.001504	0.001241	0.001856	0.002576
Standard Error	0.00078595	0.001017	0.001264	0.00107	0.00351
Median	0.000514999	0.00139	0.001042	0.00125	0
Standard Deviation	0.034312836	0.04442	0.055173	0.04672	0.15324
Sample Variance	0.001177371	0.001973	0.003044	0.002183	0.023483
Kurtosis	25.53996032	20.14752	20.07372	28.31252	569.5581
Skewness	-1.583009755	-1.36847	0.495898	-0.43628	0.529675
Range	0.674702052	0.820411	1.089128	1.111732	8.297679
Minimum	-0.497277989	-0.58964	-0.54101	-0.58116	-4.15589
Maximum	0.177424062	0.230772	0.548118	0.530574	4.141786
Sum	2.395809008	2.865982	2.365331	3.536873	4.909189
Count	1906	1906	1906	1906	1906

Source: Author's own work

The descriptive statistics of daily returns for the five selected cryptocurrencies (Table 1) show substantial differences in central tendency, standard deviation, and distributional features, which represent the return profiles of the cryptocurrencies during the observed period. Dogecoin has the highest average daily return (0.002576), followed by XRP (0.001241), Ethereum (0.001504), Bitcoin (0.001257), and BNB (0.001856). Although the relatively small magnitude highlights the short-term variability inherent in daily return series, these positive mean values point to an overall upward trend in prices over the sample period. The standard deviation, a proxy for return volatility, differs significantly across cryptocurrencies. Dogecoin stands out with a markedly high standard deviation of 0.15324, more than triple that of Ethereum (0.04442) and over four times that of Bitcoin (0.03431). This suggests that Dogecoin is considerably more volatile and prone to extreme price fluctuations compared to other cryptocurrencies because it is highly speculative currency influenced by social media trends and retail investor sentiment. With standard deviations of 0.05517 and 0.04672, respectively, XRP and BNB show moderate volatility. The shape of the return distributions, as captured by skewness and kurtosis, deviates significantly from the assumptions of normality. The negative skewness of Bitcoin (-1.58), Ethereum (-1.37), and BNB (-0.43) suggests a greater likelihood of extreme negative returns, or a longer left tail, which suggests downside risk. On the other hand, Dogecoin (0.53) and XRP (0.50) show positive skewness, indicating sporadic significant positive returns that are probably caused by media-driven demand spikes and speculative rallies. All cryptocurrencies show extreme leptokurtosis in terms of kurtosis, with values significantly higher than the Gaussian benchmark of 3. Dogecoin has a particularly noticeable excess kurtosis of 569.56, which indicates an exceptionally high frequency of extreme return observations, while Bitcoin (25.54), Ethereum (20.15), XRP (20.07), and BNB (28.31) all display heavy-tailed distributions. This statistical feature highlights Dogecoin's susceptibility to sudden price swings and validates the existence of "fat tails," making it noticeably riskier and less predictable than its competitors. These conclusions are further supported by the range of returns. The currencies with the largest return ranges are Dogecoin (8.30), BNB (1.11), XRP (1.09), Ethereum (0.82), and Bitcoin (0.67). With a minimum return of -4.16 and a maximum return of 4.14, this suggests that Dogecoin saw the most

extreme gains and losses over the sample period. These values are higher than other cryptocurrencies, whose minimum and maximum returns are confined to narrower bands.

Table 2: LPPLS model parameter.

CURRENCY		Estimate	Std. Error	t value	Pr(> t)	
BITCOIN	A	11.2000000	0.0296000	379.7270000	0.0000000	**
	B	-0.0061900	0.0012800	-4.8350000	0.0000014	**
	C	-0.0035400	0.0006710	-5.2800000	0.0000001	**
	tc	1910	5.6800000	336.5870000	0.0000000	**
	beta	0.7440000	0.0265000	28.0790000	0.0000000	**
	omega	6.0000000	0.0785000	76.4600000	0.0000000	**
	phi	29.7000000	0.5750000	51.5980000	0.0000000	**
ETHEREUM	A	8.1500000	0.0204000	400.4280000	0.0000000	**
	B	-0.0008440	0.0001690	-5.0050000	0.0000006	**
	C	-0.0008670	0.0001600	-5.4040000	0.0000001	**
	tc	1940	5.9000000	328.2290000	0.0000000	**
	beta	0.9900000	0.0251000	39.4010000	0.0000000	**
	omega	8.1100000	0.0715000	113.3620000	0.0000000	**
	phi	14.7000000	0.5460000	26.8820000	0.0000000	**
XRP	A	-0.4160000	0.0197000	-21.0880000	0.0000000	**
	B	-0.0002250	0.0001120	-2.0150000	0.0440000	*
	C	0.0005240	0.0002270	2.3090000	0.0211000	*
	tc	1910	11.0000000	173.0190000	0.0000000	**
	beta	0.9900000	0.0596000	16.6120000	0.0000000	**
	omega	8.1100000	0.1350000	60.0220000	0.0000000	**
	phi	11.7000000	1.0300000	11.3650000	0.0000000	**
BNB	A	6.5500000	0.0334000	196.0370000	0.0000000	**
	B	-0.0012900	0.0003110	-4.1530000	0.0000343	***
	C	0.0010000	0.0002270	4.4290000	0.0000100	**
	tc	1910	7.0900000	269.2010000	0.0000000	**
	beta	0.9900000	0.0307000	32.2240000	0.0000000	**
	omega	8.6600000	0.0899000	96.2850000	0.0000000	**
	phi	14.1000000	0.6890000	20.5150000	0.0000000	**
DOGECOIN	A	-1.5900000	0.0439000	-36.3350000	0.0000000	**
	B	-0.0013000	0.0003590	-3.6270000	0.0002940	**
	C	0.0015000	0.0003810	3.9460000	0.0000824	**
	tc	1910	6.8600000	278.1960000	0.0000000	**
	beta	0.9900000	0.0347000	28.4950000	0.0000000	**
	omega	8.6600000	0.0871000	99.4680000	0.0000000	**
	phi	7.8400000	0.6670000	11.7630000	0.0000000	**

Significance level- ‘***’ 0.01 & ‘*’ 0.05

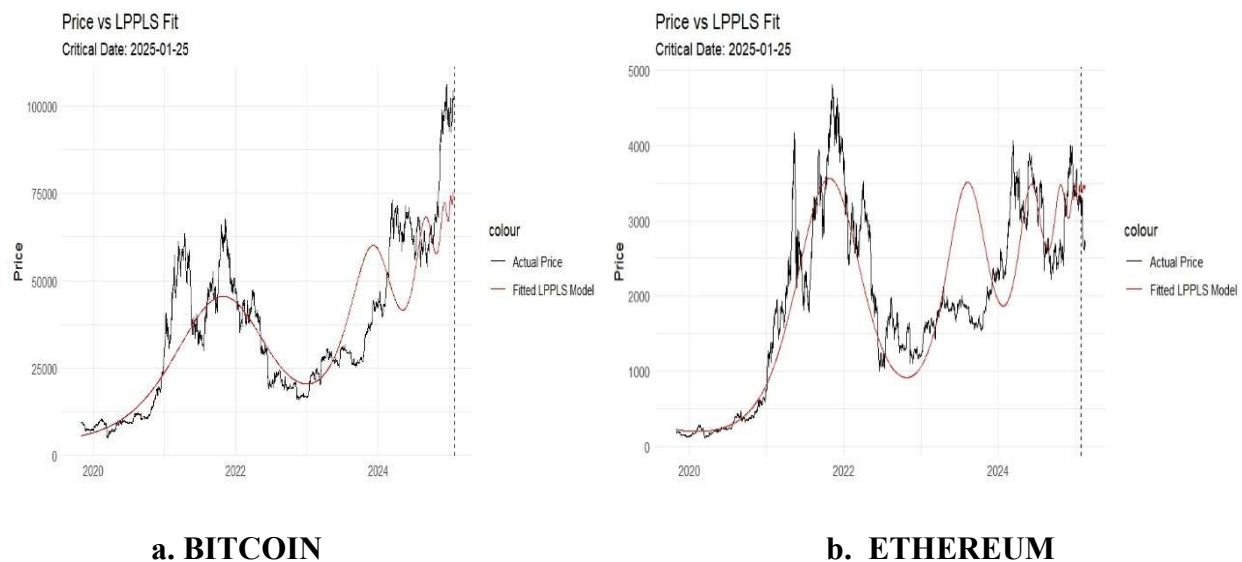
Source: Author’s own work

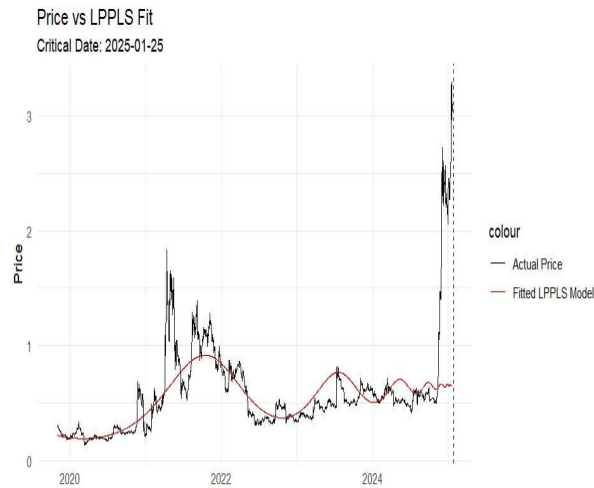
The results obtained from the LPPLS model (Table.2) provide strong evidence of bubble formation across multiple cryptocurrencies, including Bitcoin, Ethereum, XRP, Binance Coin (BNB), and Dogecoin. The LPPLS model estimates key parameters that indicate the presence of speculative bubbles and potential market corrections. Among these parameters, the coefficient B , which represents the price acceleration, is negative for all currencies, suggesting that they are currently in a bubble phase. Bitcoin exhibits a powerful bubble signal with $B = -0.00619$, a β value of 0.744, and a critical time (t_c) of approximately 1910 days i.e. January 2025, indicating that a price correction is imminent. Similarly, Ethereum demonstrates bubble characteristics, though its B coefficient (-0.000844) is weaker than Bitcoin's. However, its β value of 0.99, which is close to 1, suggests a strong tendency towards bubble formation. The critical time ($t_c = 1940$ i.e. February 2025) indicates that Ethereum may also be approaching a turning point.

For XRP, the bubble signal appears weaker than for Bitcoin and Ethereum, as its B coefficient (-0.000225) is only slightly negative. However, its β value of 0.99 and critical time ($t_c = 1910$ January 2025) still indicate the potential for a speculative bubble. BNB exhibits similar patterns to Bitcoin, with $B = -0.00129$, $\beta = 0.99$, and a critical time of 1910 i.e. January 2025, suggesting that its price is also in a highly speculative phase. Dogecoin follows the same trend, with $B = -0.00130$, $\beta = 0.99$, and a critical time of 1910 i.e. January 2025, reinforcing the presence of bubble-like behaviour.

The statistical significance of the estimated parameters across all cryptocurrencies is strong, with p -values well below 0.001 in most cases, indicating that the results are highly reliable. The critical time (t_c) values for Bitcoin, XRP, BNB, and Dogecoin cluster around 1910 i.e. January 2025, suggest a synchronized speculative phase that may lead to a broader market correction. Ethereum, with $t_c = 1940$, could experience a delayed correction compared to the other assets.

Figure 1: LPPLS Model Fitted to Cryptocurrencies

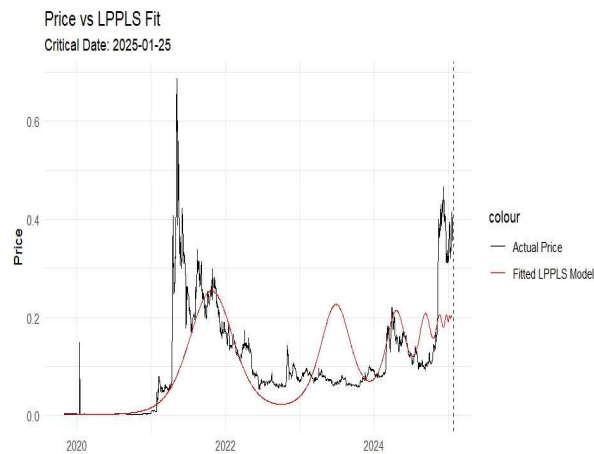




c. XRP



d. BNB



e. DOGECOIN

4.1 Bubble and Anti-Bubble Detection

The differentiation between bubble and anti-bubble phases is essential for comprehending price movements in currency markets. A bubble phase is characterised by positive confidence values, indicating accelerating growth with oscillatory behaviour, whereas negative confidence values signify anti-bubbles, which are marked by rapid price declines or prolonged stagnation.

Bitcoin's (fig. a) market cycles show bubble and anti-bubble phases, with price surges and corrections aligning with confidence score fluctuations. In 2021, Bitcoin peaked at \$66,000, coinciding with high confidence values above 1.5, followed by a sharp decline to \$16,000 in mid-2022, signalling an anti-bubble phase. A similar trend is expected in 2025, with projections indicating a peak at \$102,000 before a subsequent correction. The confidence score serves as a key market indicator, with values above 0.5 suggesting speculative momentum, such as in February 2021 (1.99 confidence) and March 2024 (0.81 confidence), preceding major rallies. As observed in mid-2022 (-0.72) and September 2023 (-0.75), negative confidence values indicate potential buying opportunities before market recoveries.

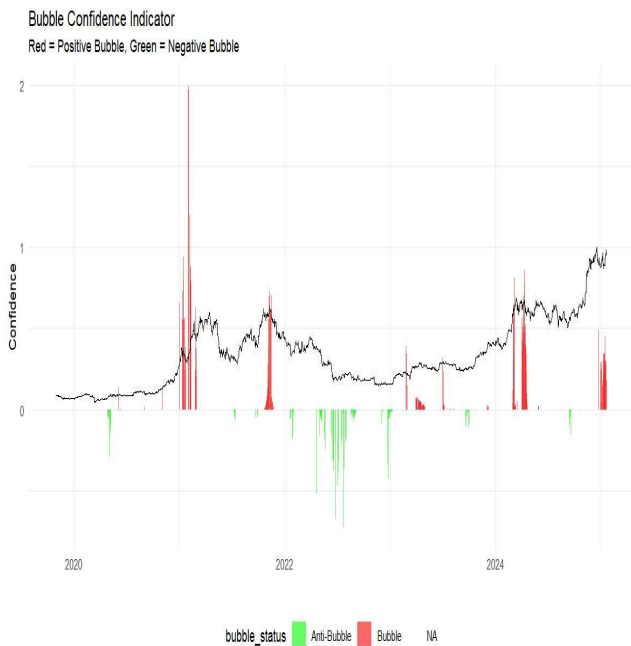
Ethereum (fig. b) also demonstrates periods of speculation and correction. The 2021 bull run exhibited strong bubble signals, with confidence peaking at 1.08 in September, coinciding with Ethereum's price surge to \$3,340 and its subsequent rise to an all-time high of \$4,800 in November 2021. The bear market of 2022–2023 saw a significant decline in confidence, reaching -0.75 in June 2022, aligning with Ethereum's price falling to the \$1,000–\$1,200 range. More recent confidence scores in 2024, such as 0.58 in March, suggest renewed bullish activity, with Ethereum trading between \$3,500 and \$4,065. However, mixed signals in late 2024 indicate potential market instability, despite Ethereum approaching the \$4,000 level.

XRP (fig. c) reveal the strongest bubble signal on January 19, 2025, with a confidence score of 1.61 and a projected price of \$2.96, reflecting peak speculative interest. Historical data from 2021 similarly align with major price surges during the broader bull market. Multiple bubble signals in December 2024, with confidence values ranging between 0.95 and 1.15, suggest the potential for a sustained rally into 2025. Conversely, a major anti-bubble phase was observed on June 22, 2022, when the confidence score dropped to -0.87, coinciding with price of XRP decline to \$0.32. This trend was driven by broader macroeconomic conditions, including Federal Reserve policies that contributed to market downturns.

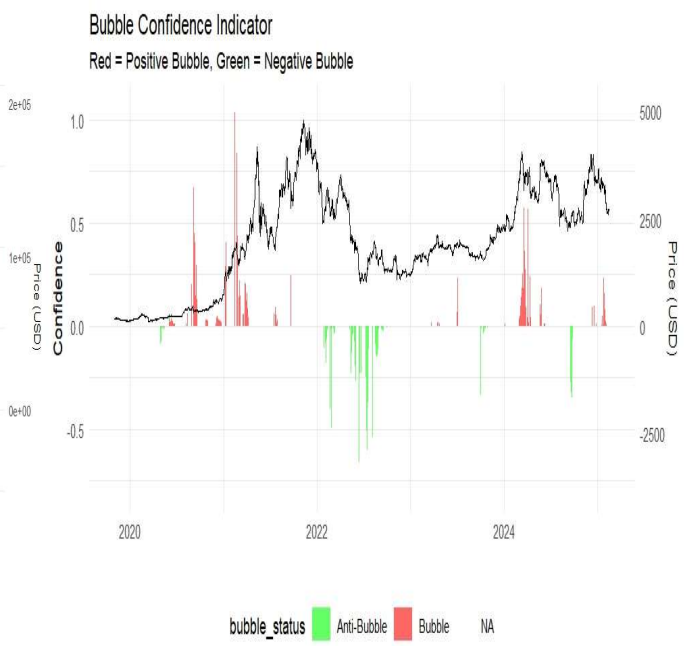
BNB (fig. d) show a strong bubble phase in November 2021, with confidence scores ranging between 2.78 and 2.93, as prices fluctuated between \$338 and \$454. Another notable speculative phase was observed in mid-2022, reaching a price peak of \$724. In late 2023 and early 2024, moderate bubbles (confidence scores between 0.68 and 0.85) resulted in price fluctuations between \$600 and \$650. The most pronounced anti-bubble phase occurred in June 2022, with a confidence score of -0.66, as BNB declined to \$258, mirroring the broader cryptocurrency market downturn. Additional anti-bubble signals in late 2023, with confidence values ranging from -0.24 to -0.36, were likely influenced by regulatory uncertainties surrounding Binance.

The initial bubble phase emerging in July-August 2020 show speculative behaviour of Dogecoin (fig. e), characterized by mild confidence values (0.05 - 0.15) and price increases from \$0.0032 to \$0.0047. The most significant speculative phase occurred between January and April 2021, with confidence scores peaking between 1.94 and 2.29, aligning with a price surge to \$0.365. A secondary bubble emerged in May 2021, with confidence values ranging between 1.23 and 1.40, resulting in price fluctuations between \$0.30 and \$0.65. In 2024, despite relatively lower absolute prices (\$0.15–\$0.20), confidence values between 1.31 and 1.55 indicate speculative interest, potentially influenced by external factors such as endorsements from Elon Musk. Prolonged anti-bubble phases were observed in mid-2020 and throughout late 2021-2022 (confidence $\leq$ -0.5), leading to an 80% decline in price. A further anti-bubble phase in mid-2023, with confidence values ranging from -0.21 to -0.87, reflected sustained bearish sentiment, which may set the stage for future price recoveries.

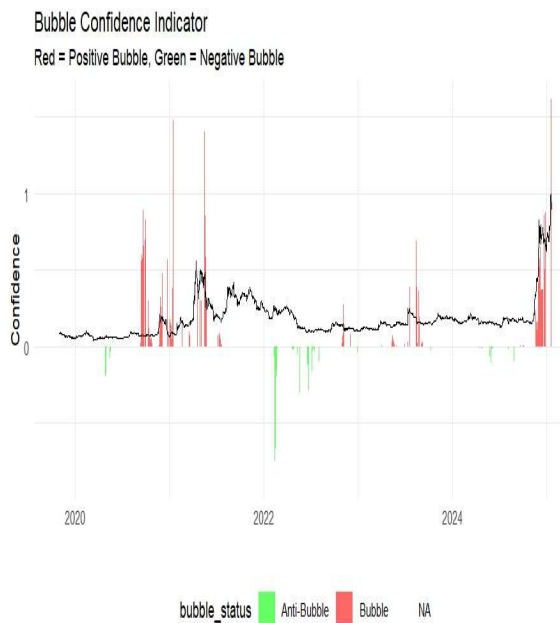
Figure 2: LPPLS confidence indicator for positive and negative bubbles in cryptocurrencies



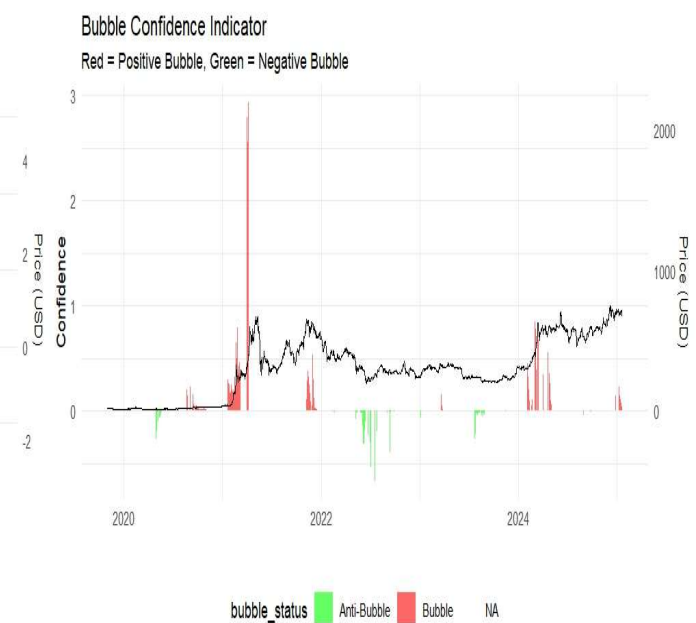
a. BITCOIN



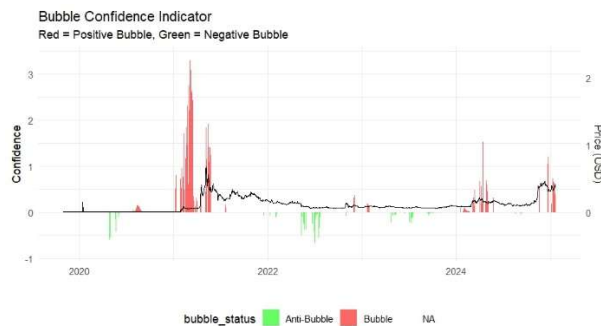
b. ETHEREUM



c. XRP



d. BNB



e. DOGECOIN

4.2 Wavelet Coherence

To understand the co-movement between cryptocurrencies and the fear index, we have applied wavelet coherence analysis (Figure 3). The WSC studies the two time series in the frequency domain.

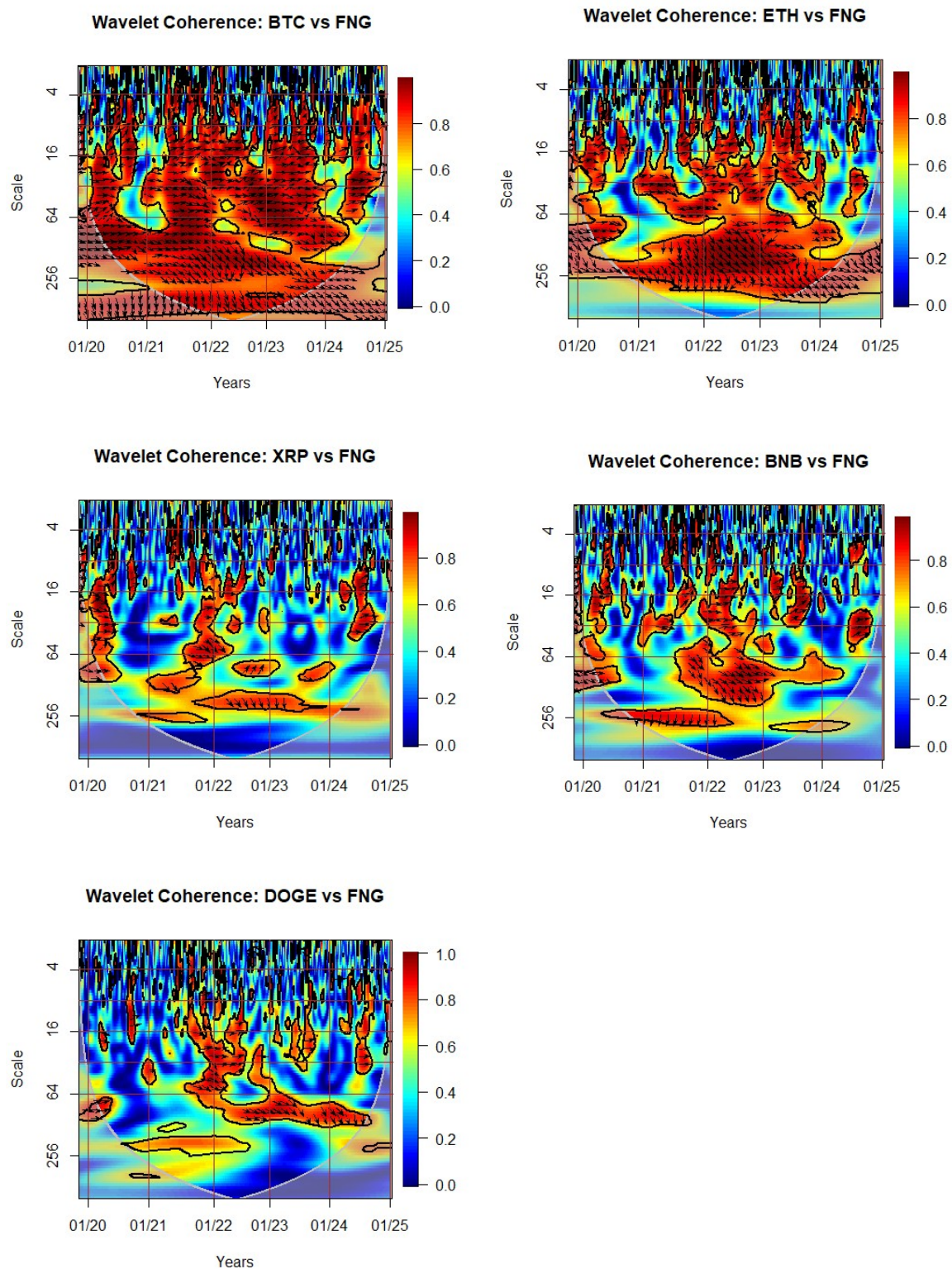
The wavelet coherence plot for BTC and the FNG shows strong co-movement. The presence of strong red regions, between 2021 and 2023 at medium to long scales (16-256 days), shows that BTC returns exhibited a significant degree of dependence on FNG index suggesting that market sentiment was a strong driver of BTC returns during the period, it is possibly influenced by macroeconomic factors and institutional adoption trends. Also, they both were in phase as represented by rightward arrows. After year 2024, coherence at lower frequencies (long-term) suggests continued influence of FNG, but with periodic shifts in correlation dynamics, possibly driven by evolving market structures and sentiment cycles.

ETH also shows strong dependencies on FNG across different frequency scales but the dependencies are lesser than BTC. The presence of extensive red regions in 2022 at medium-to-long scales (16-256 days), suggests a strong coherence between Ethereum returns and crypto market sentiment. This pattern indicates that the price movements of Ethereum were significantly influenced by investor sentiment during these periods. The co-movement between them is in phase as indicated by the rightward facing arrows. The post-2023 period shows pockets of strong coherence at longer time scales, suggesting that ETH's price remains sentiment-driven, though periodic shifts in correlation indicate evolving market dynamics.

The wavelet coherence plot for XRP versus FNG suggests a weaker and more intermittent relationship compared to BTC and ETH. While there are some red patches indicating strong coherence, they appear sporadic and mostly in specific time intervals. Notably, periods of high coherence occur mid-2021 till end of 2023 at medium-to-long scales (16-256 days), suggesting that market sentiment influenced XRP's price movements during those phases. Compared to BTC and ETH, XRP's coherence with FNG appears less persistent. The lower coherence in some periods suggests that factors other than sentiment, such as legal developments and institutional decisions, played a more dominant role in XRP's price dynamics. Nonetheless, pockets of high coherence indicate that sentiment still had an influence, particularly during major market trends.

The wavelet coherence plot for BNB versus FNG highlights periods of strong and moderate coherence, particularly at medium-to-long timescales (16-256 days) around 2021 and 2022. The presence of several red patches in these regions suggests that investor sentiment significantly influenced BNB's price movements during these periods. The directional arrows in these regions mostly point rightward and slightly upward, suggesting that BNB and FNG moved in phase, with some influence from long-term market trends.

Figure 3: Wavelet Coherence analysis between cryptocurrencies and fear and greed index



The wavelet coherence plot for DOGE versus FNG reveals notable periods of strong coherence, in mid-2021 and mid-2022 at medium-to-long timescales (16-256 days) and after that till long term coherence till 2025. One of the key observations is the strong coherence in mid-2021, aligning with the period when DOGE experienced massive price surges driven by social media influence, particularly Twitter activity and endorsements from high-profile figures. The arrows in this region

mostly point rightward, indicating that returns of Dogecoin were in phase with FNG, meaning shifts in investor sentiment were quickly reflected in DOGE's market trends. Compared to BTC and ETH, DOGE exhibits fewer coherence with FNG, reflecting its speculative nature and the influence of external factors such as social media trends and retail investor activity. This suggests that while sentiment is an important driver of DOGE's returns, it is not the sole determinant, as hype cycles and meme-driven dynamics play a substantial role.

4.3 Discussion

The findings from the LPPLS model and wavelet coherence analysis provide empirical support for the existence of speculative bubbles and subsequent anti-bubbles in major cryptocurrencies between 2019 and 2025. These results of the study have implications for understanding the price formation in cryptocurrency markets and the behavioural factors that influence them.

According to the LPPLS-based estimation, critical times for Bitcoin, XRP, BNB, and Dogecoin cluster synchronously around January 2025, with Ethereum trailing slightly into February 2025. This synchronization raises the possibility that systemic forces such as macroeconomic shifts, regulatory actions, or liquidity shocks, could all work together to fuel asset-specific speculative cycles. The negative values of coefficient B and the high values of β (close to 1) further validate that these cryptocurrencies are in advanced stages of speculative growth and consistent with LPPLS predictions of endogenous market instability.

These synchronized turning points suggest interconnected bubble cycles across the crypto currency market, consistent with herding behaviour and contagion effects. This supports the view that crypto markets may not be fully segmented but respond collectively to both internal sentiment dynamics and external macro events, such as U.S. interest rate policy shifts or global regulatory announcements related to cryptocurrencies.

LPPLS confidence scores offer more in-depth behavioural insights. The Greater Fool and Noise Trader theories are supported by the fact that high confidence scores (>1.0) precede market peaks and sharp reversals in all five cryptocurrencies. These measures effectively quantify speculative exuberance, while negative values align with crash periods or extended drawdowns, capturing phases of pessimism and capitulation. These patterns illustrate the usefulness of LPPLS as a diagnostic tool for identifying not just bubbles but also transition phases within broader cryptocurrency market cycles. For example, prior to 2021 and anticipated 2025 corrections, LPPLS confidence of Bitcoin peaked above 1.5, whereas the 2022 bear market was captured by negative scores below -0.7. Similar trends were seen in Dogecoin and Ethereum, demonstrating the ability of LPPLS to map sentiment oscillations and speculative trends.

The wavelet coherence analysis further contextualizes these trends by illustrating the temporal linkage between price movements and investor sentiment as measured by the FNG index. Across all five assets, moderate-to-strong coherence is observed during key bubble period between 2021 and 2023, suggesting that sentiment was a significant explanatory variable for price movements. Particularly at medium-to-long scales (16–256 days), Bitcoin and Ethereum show the strongest and most consistent in-phase coherence with FNG, demonstrating that sentiment cycles drove both corrections and speculative surges. The sentiment-price linkage for Dogecoin during 2021 rally highlights sentiment-driven, non-fundamental price formation and supports credence to the notion that social media endorsements and meme-based speculation were important factors. Diverse market behaviors are also indicated by the different levels of coherence among cryptocurrencies. XRP and DOGE exhibit intermittent coherence, whereas BTC and ETH exhibit structurally persistent

sentiment dependence. This could be because of platform-specific developments or non-sentiment-based shocks like litigation (e.g., SEC vs. Ripple).

The findings reinforce and extend earlier research (Fry & Cheah, 2016; Corbet et al., 2018; Yao & Li, 2021) by applying an advanced bubble-detection model (LPPLS) across multiple cryptocurrencies and integrating it with sentiment analysis using wavelets. In contrast to earlier research that only employed BSADF or GSADF, this study provides a more thorough diagnostic of speculative behavior by capturing both the predictive structure of bubbles and their underlying mechanisms. Additionally, the co-dependence on investor sentiment highlights changes in sentiment dynamics over time and validates earlier wavelet-based studies (Phillips & Gorse, 2018; Qiao et al., 2020). This nuance is important for risk managers and institutional investors who seek forward-looking indicators rather than merely post-facto bubble identification.

5. Conclusion and Implications

This study contributes to the growing literature on speculative behaviour and investor sentiments in cryptocurrency markets by jointly applying the LPPLS model and wavelet coherence analysis. The identification of bubble and anti-bubble phases using LPPLS-derived confidence metrics reveals cyclical transitions in cryptocurrency market regimes. High confidence, price peaks, negative scores with market corrections provide a consistent diagnostic tool for predicting market reversals and grasping the ongoing speculative activity. The wavelet coherence analysis reveals significant and time-varying co-movements between the cryptocurrency returns and the FNG index. The findings indicate the importance of investor sentiment as a dynamic determinant of price movements, during speculative booms. The LPPLS model, through its ability to detect super-exponential growth and critical transition points, can serve as an early warning system for identifying speculative bubbles and anticipating sharp market corrections. By regularly calculating rapid growth coefficients and key turning points, investors can use LPPLS and sentiment measures to identify early bubble phases and set up automated alerts to adjust position size as well as employing hedging strategies when risk thresholds are crossing. Incorporating FNG Index values helps to refine buying and selling rules, strengthening risk management, and facilitating more informed decision-making during periods of extreme volatility in crypto market. This is beneficial for investors seeking to manage risk in highly volatile cryptocurrency markets. For regulators, the ability to detect bubbles and their associated sentiment drivers can help in designing more responsive policy tools to mitigate systemic risks arising from cryptocurrency speculation.

References

- Ahn, Y., & D. Kim. 2020. Emotional Trading in the Cryptocurrency Market. *Finance Research Letters*. <https://doi.org/10.1016/j.frl.2020.101912>
- Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of economic perspectives*, 21(2), 129-151. <https://doi.org/10.1257/jep.21.2.129>
- Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance*, 1, 1053–1128. [https://doi.org/10.1016/S1574-0102\(03\)01027-6](https://doi.org/10.1016/S1574-0102(03)01027-6)
- Barlevy, G. (2015). Bubbles and fools. *Economic Perspectives*, 39(2), 54–77.
- Barnes, P. (2019). Crypto currency and its susceptibility to speculative bubbles, manipulation, scams and fraud. *Journal of Advanced Studies in Finance*, 9(2), 60. [https://doi.org/10.14505/jasf.v9.2\(18\).03](https://doi.org/10.14505/jasf.v9.2(18).03)

Blanchard, O. J., & Watson, M. W. (1982). Bubbles, rational expectations and financial markets. *NBER Working Paper No. 945*.

Brunnermeier, M. K., & Oehmke, M. (2013). Bubbles, financial crises, and systemic risk. *Handbook of the Economics of Finance*, 2, 1221–1288. <https://doi.org/10.1016/B978-0-44-459406-8.00018-4>

Cai, Y., Chevapatrakul, T., & Mascia, D. (2021). How is price explosivity triggered in the cryptocurrency markets? *Annals of Operations Research*, 307(1-2), 37-51. <https://doi.org/10.1007/s10479-021-04298-4>

Chen, C. Y. H., & Hafner, C. M. (2019). Sentiment-induced bubbles in the cryptocurrency market. *Journal of Risk and Financial Management*, 12(2), 53. <https://doi.org/10.3390/jrfm12020053>

Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics letters*, 130, 32-36. <https://doi.org/10.1016/j.econlet.2015.02.029>

Chowdhury, M. S. R., Damianov, D. S., & Elsayed, A. H. (2022). Bubbles and crashes in cryptocurrencies: Interdependence, contagion, or asset rotation? *Finance Research Letters*, 46, 102494. <https://doi.org/10.1016/j.frl.2021.102494>

CoinMarketCap, “Cryptocurrency prices, charts and market capitalizations | CoinMarketCap,” CoinMarketCap. <https://www.coinmarketcap.com/>

Corbet, S., Lucey, B., & Yarovaya, L. (2018). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters*, 26, 81–88. <https://doi.org/10.1016/j.frl.2017.12.006>

Crypto Fear & Greed Index - Bitcoin Sentiment, *Alternative.me*. <https://alternative.me/crypto/fear-and-greed-index/>

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance*, 53(6), 1839–1885. <https://doi.org/10.1111/0022-1082.00077>

Demirer, R., Demos, G., Gupta, R., & Sornette, D. (2019). On the predictability of stock market bubbles: Evidence from LPPLS confidence multi-scale indicators. *Quantitative Finance*, 19(5), 843–858. <https://doi.org/10.1080/14697688.2018.1528491>

Demos, G., & Sornette, D. (2017). Birth or burst of financial bubbles: Which one is easier to diagnose? *Quantitative Finance*, 17(5), 657–675. <https://doi.org/10.1080/14697688.2016.1267539>

Dhar, R., & Goetzmann, W. N. (2006). Bubble investors: What were they thinking?

Fama, E. F. (1970). Efficient capital markets. *Journal of finance*, 25(2), 383-417.

Fruehwirt, W., Hochfilzer, L., Weydemann, L., & Roberts, S. (2021). Cumulation, crash, coherency: A cryptocurrency bubble wavelet analysis. *Finance Research Letters*, 40, 101668. <https://doi.org/10.1016/j.frl.2020.101668>

Froot, K. A., & Obstfeld, M. (1991). Intrinsic bubbles: The case of stock prices. *American Economic Review*, 81(5), 1189–1214. <https://www.jstor.org/stable/2006919>

Fry, J., & Cheah, E. T. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis*, 47, 343–352. <https://doi.org/10.1016/j.irfa.2016.02.008>

Gandal, N., Hamrick, J. T., Moore, T., & Oberman, T. (2018). Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics*, 95, 86-96. <https://doi.org/10.1016/j.jmoneco.2017.12.004>

Geraskin, P., & Fantazzini, D. (2013). Everything you always wanted to know about log-periodic power laws for bubble modeling but were afraid to ask. *The European Journal of Finance*, 19(5), 366–391. <https://doi.org/10.1080/1351847X.2011.601661>

Ghosh, B., Kenourgios, D., Francis, A., & Bhattacharyya, S. (2021). How well the log periodic power law works in an emerging stock market? *Applied Economics Letters*, 28(14), 1174–1180. <https://doi.org/10.1080/13504851.2020.1789044>

Gonçalves, T. C., Quiñones Borda, J. V., Vieira, P. R., & Matos, P. V. (2022). Log periodic power analysis of critical crashes: Evidence from the Portuguese stock market. *Economies*, 10(1), 14. <https://doi.org/10.3390/economies10010014>

Griffin, J. M., Harris, J. H., Shu, T., & Topaloglu, S. (2011). Who drove and burst the tech bubble? *The Journal of Finance*, 66(4), 1251-1290. <https://doi.org/10.1111/j.1540-6261.2011.01663.x>

Investing.com - stock market quotes & financial news, *Investing.com*. <https://www.investing.com/>

Johansen, A. (2003). Characterization of large price variations in financial markets. *Physica A: Statistical Mechanics and its Applications*, 324(1), 157–166. [https://doi.org/10.1016/S0378-4371\(02\)01882-9](https://doi.org/10.1016/S0378-4371(02)01882-9)

Karalevicius, V., Degrande, N., & De Weerd, J. (2018). Using sentiment analysis to predict interday Bitcoin price movements. *The Journal of Risk Finance*, 19(1), 56-75. <https://doi.org/10.1108/JRF-06-2017-0092>

Kindleberger, C. P. (1996). *Manias, panics and crashes: A history of financial crises (3rd ed.)*. Macmillan.

Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific reports*, 3(1), 3415. <https://doi.org/10.1038/srep03415>

Lin, L., Ren, R. E., & Sornette, D. (2014). The volatility-confined LPPL model: A consistent model of ‘explosive’ financial bubbles with mean-reverting residuals. *International Review of Financial Analysis*, 33, 210–225. <https://doi.org/10.1016/j.irfa.2014.02.013>

Minsky, H. P. (2008). *Stabilizing an unstable economy (2nd ed.)*. McGraw-Hill.

Mokni, K., El Montasser, G., Ajmi, A. N., & Bouri, E. (2024). On the efficiency and its drivers in the cryptocurrency market: the case of Bitcoin and Ethereum. *Financial Innovation*, 10(1), 39. <https://doi.org/10.1186/s40854-023-00566-3>

Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. *Economics Letters*, 150, 6-9. <https://doi.org/10.1016/j.econlet.2016.10.033>

O'Hara, M. (2008). Bubbles: Some perspectives (and loose talk) from history. *The Review of Financial Studies*, 21(1), 11-17. <https://doi.org/10.1093/rfs/hhn001>

Palamalai, S., Kumar, K. K., & Maity, B. (2021). Testing the random walk hypothesis for leading cryptocurrencies. *Borsa Istanbul Review*, 21(3), 256-268. <https://doi.org/10.1016/j.bir.2020.10.006>

Papastamatiou, K., & Karakasidis, T. (2022). Bubble detection in Greek stock market: A DS-LPPLS model approach. *Physica A: Statistical Mechanics and its Applications*, 587, 126533. <https://doi.org/10.1016/j.physa.2021.126533>

Perez, C. (2009). The double bubble at the turn of the century: Technological roots and structural implications. *Cambridge Journal of Economics*, 33(4), 779–805. <https://doi.org/10.1093/cje/bep028>

Phillips, P. C., Wu, Y., & Yu, J. (2011). Explosive behavior in the 1990s Nasdaq: When did exuberance escalate asset values? *International Economic Review*, 52(1), 201–226. <https://doi.org/10.1111/j.1468-2354.2010.00625.x>

Phillips, R. C., & Gorse, D. (2018). Cryptocurrency price drivers: Wavelet coherence analysis revisited. *PLOS ONE*, 13(4), e0195200. <https://doi.org/10.1371/journal.pone.0195200>

Porter, D. P., & Smith, V. L. (2003). Stock market bubbles in the laboratory. *The Journal of Behavioral Finance*, 4(1), 7–20. https://doi.org/10.1207/S15427579JPFM0401_03

Oad Rajput, S. K., Soomro, I. A., & Soomro, N. A. (2022). Bitcoin sentiment index, bitcoin performance and US dollar exchange rate. *Journal of Behavioral Finance*, 23(2), 150-165. <https://doi.org/10.1080/15427560.2020.1864735>

Qiao, X., Zhu, H., & Hau, L. (2020). Time-frequency co-movement of cryptocurrency return and volatility: Evidence from wavelet coherence analysis. *International Review of Financial Analysis*, 71, 101541. <https://doi.org/10.1016/j.irfa.2020.101541>

Quinn, W., & Turner, J. D. (2023). Bubbles in history. *Business History*, 65(4), 636-655. <https://doi.org/10.1080/00076791.2020.1844668>

Shleifer, A., & Summers, L. H. (1990). The noise trader approach to finance. *Journal of Economic perspectives*, 4(2), 19-33. <https://doi.org/10.1257/jep.4.2.19>

Shu, M., & Zhu, W. (2020). Real-time prediction of Bitcoin bubble crashes. *Physica A: Statistical Mechanics and Its Applications*, 548, 124477. <https://doi.org/10.1016/j.physa.2020.124477>

Tanos, B. and Badr, G. (2024). Price delay and market efficiency of cryptocurrencies: the impact of liquidity and volatility during the covid-19 pandemic. *Journal of Risk and Financial Management*, 17(5), 193. <https://doi.org/10.3390/jrfm17050193>

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, 148, 80-82. <https://doi.org/10.1016/j.econlet.2016.09.019>

Wanidwaranan, P. and Termprasertsakul, S. (2023). Herd behavior in cryptocurrency market: evidence of network effect. *Review of Behavioral Finance*, 16(3), 406-423. <https://doi.org/10.1108/rbf-03-2023-0079>

Wheatley, S., Sornette, D., Huber, T., Reppen, M., & Gantner, R. N. (2019). Are Bitcoin bubbles predictable? Combining a generalized Metcalfe's law and the log-periodic power law singularity model. *Royal Society Open Science*, 6(6), 180538. <https://doi.org/10.1098/rsos.180538>

Xiong, W., & Yu, J. (2011). The Chinese warrants bubble. *American Economic Review*, 101(6), 2723–2753. <https://doi.org/10.1257/aer.101.6.2723>

Xiong, J., Liu, Q., & Zhao, L. (2020). A new method to verify Bitcoin bubbles: Based on the production cost. *The North American Journal of Economics and Finance*, 51, 101095. <https://doi.org/10.1016/j.najef.2019.101095>

Yao, C. Z., & Li, H. Y. (2021). A study on the bursting point of Bitcoin based on the BSADF and LPPLS methods. *The North American Journal of Economics and Finance*, 55, 101280. <https://doi.org/10.1016/j.najef.2020.101280>

Zhang, J., Wang, H., Chen, J., & Liu, A. (2024). Cryptocurrency price bubble detection using log-periodic power law model and wavelet analysis. *IEEE Transactions on Engineering Management*. <https://doi.org/10.1109/TEM.2024.3427647>

Zhang, Q., Sornette, D., Balcilar, M., Gupta, R., Özdemir, Z. A., & Yetkiner, H. (2016). LPPLS bubble indicators over two centuries of the S&P 500 index. *Physica A: Statistical Mechanics and its Applications*, 458, 126–139. <https://doi.org/10.1016/j.physa.2016.03.089>

Zou, X. (2018). Can the greater fool theory explain bubbles? Evidence from China (No. 2018-04). *Working Paper*. <https://doi.org/10.2139/ssrn.3129355>