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Correlative Relationships Between Cryptoassets and Price Bubbles: Risk and Contagion Dynamics of Digital Markets

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Abstract

The development of cryptographic digital markets and the growing number of investors have generated concerns about the formation of price bubbles. We can describe the formation of a price bubble as a manifestation of the pricing paradox, characterised by an increase in an asset's value beyond its intrinsic worth. Investor sensitivity and emotional responses, disequilibrium in supply and demand, speculation and irrational investor behaviour, excessive volatility, and uncertainty nourish this paradoxical tendency. Examining balloon formations in these markets offers valuable insights for educating investors about market cycles and risk management, which can aid policymakers in preserving market stability and protecting financial systems. The objective of this study, which examines the phenomenon of price bubbles in digital asset markets, is to ascertain whether these bubbles are unique to the digital asset market or whether they have a broader economic origin. The objective is to identify, establish the stability of, and facilitate the prediction of price developments, with a particular focus on the potential for market crashes. The GSADF methodology examined 18 digital assets in total, including CCC, NFT, and DeFI, for price bubble formation in this context. The digital assets analysed in this study were selected based on their market representativeness, as evidenced by 200 weeks of observation data covering the period from October 5, 2020, to July 29, 2024. The analysis yielded two key findings: the existence of asset-specific and market-induced bubbles and the observation that different markets exhibit common risk sensitivity. Additionally, the movements of highly liquid digital assets (BTC, etc.) may serve as an indicator of impending market crashes due to their high correlation with other markets. The current body of research on cryptoassets tends to focus on traditional assets and relationships between binary or restricted asset groups, leaving this study poised to make a significant and comprehensive contribution to the existing literature on this subject.

Keywords Cryptocurrencies · NFT · DeFI · Price Bubbles · GSADF

JEL Classification G12 · G15 · C58

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The pioneer in cryptographic digital assets (CDA) is cryptocurrencies, specifically Bitcoin. The term cryptocurrency was founded on the idea of digital cash in an article published by American Cryptologist David Lee Chaum in 1983. It took its place in the literature with the cryptographic digital currency called "DigiCash", which he invented in 1989 by using cryptography for transaction security and accuracy (Akıntola et al., 2019). Although decentralised digital currency formations were built on this foundation, the first successful application was in 1998 by Computer Engineer Wei Dai (Dai, 1998), The concept of an anonymous distributed electronic money system was introduced by "b-money" and "Bit Gold" applications, in which Nick Szabo, one of the pioneers of blockchain, introduced the operating system in 1998 (Szabo, 2005). These unofficial forms of cryptocurrency have managed to inspire the search for alternatives to the traditional financial system that developed after the 2008 global financial crisis. The dynamism of today's cryptographic digital financial system was created with the article titled "Bitcoin: A Peer-to-Peer Electronic Cash System" (Nakamoto; 2008), published under the pseudonym "Satoshi Nakamoto". Since the first transaction was made in 2009; the momentum that these assets have gained in terms of value, diversity, transaction volume, distribution, etc. is interesting. Bitcoin, which started its journey at a price of $ 2, has become the financial instrument with the most unattainable trend in financial history with the correction equal to $ 1 in February 2011, today's price of $ 63,841.19, a market value of $ 1.262 Trillion and a daily trading volume of $ 27.865 Billion.

In addition to all traditional cryptocurrencies (CCC) that have emerged in the world created by Bitcoin, the NFT and DeFi industry, which are developing more and more each passing day in terms of both diversity and market value as an important member of the same technological system network, exhibit a course far above the development of the digital economy. In terms of their characteristic features; they do not have an intrinsic value, nor do they have a final payment or a specific return presentation. In addition, they are not considered an official exchange element, as they are not a legal means of payment. Despite this, due to the high trends in the development process and the permanent market volatility they have experienced in the past, bubble formations are observed in price developments. Inspired by these reasons, the main purpose of this research, which analyzes price bubbles in cryptographic digital assets in the DeFI, NFT and CCC variety, are:

- To reveal whether the possible price bubbles are asset-specific or general market-related;
- To determine the stability structures of price developments among asset groups;
- To provide a perspective to facilitate the prediction of market crashes through the perspective gained from the behaviour of asset price bubbles.

The aim is to provide important information that may be useful for investors, portfolio managers, current and potential users, and policy makers seeking diversification alternatives within the framework of market structure, internal dynamics, and price movements.

The general perspective of the research carried out in line with this purpose and objective was created to reflect the instrument diversity in the cryptographic digital financial asset markets (CDAM). In addition, asset group members were selected according to the market sizes that can represent the asset group they belong to, market internal dynamics and operating procedures, adhering to the relevant literature. This care regarding the formation of dataset components will make the research results relatively more generalisable. The main motivation of the research is the limited number of studies evaluating all asset groups in CDAs in terms of price bubbles based on the market development course and the lack of a comprehensive independent study presenting bubble formations. The existing literature is intensively examined specifically for cryptocurrencies or is based on binary asset group comparison or limited asset group representation. The study will make significant and comprehensive contributions to the literature with both this motivation and the academic sensitivity and analysis process starting from the data selection of the research. In addition, the research, which will contribute to the recognition of the internal dynamics of CDAs with theoretical evaluations and definitions appropriate to the nature of crypto markets and the general characteristics of market instruments, strives to fill the gap in the existing literature. The roadmap of the research is shaped by this potential and belief; the first part is about the presentation of the theoretical and conceptual framework, the second part is about the summary of detailed literature research on the research topic and the existence of price bubbles. It was created from the perspective of the third section, where the relevant empirical analysis findings are presented.

Theoretical and Conceptual Framework

The main components of CDAs in the current market structure are cryptocurrencies (CCC), non-fungible digital assets (NFT), and decentralised finance (DeFi) assets. Cryptocurrencies consist of digital currencies with similar properties and no fundamental value, which do not require a third party for verification of ownership and transaction certification purposes, are secured by cryptographic software, allow value transfers between peers, and can be traced back to their first creation (Giudici et al., 2020; Baur et al., 2018). NFTs are members of the blockchain system that imply ownership records of assets such as collectibles, game elements, and digital art, music, videos, and virtual property (Liao, 2024). Market transactions related to NFTs, whose uniqueness, verifiability, and traceability are provided by smart contracts created by developers, are generally based on the Ethereum network and occur over a cryptocurrency value it has adopted (Dowling, 2022). DeFi, which is used as an umbrella term, is a protocol that characterises digital financial services that have emerged in the field of modern finance, developed to perform transactions such as lending, borrowing, spot and margin trading, and digital wallet management between peers without a central authority (Corbet et al., 2023). Within this scope, the basic features of CDAs that reveal their internal dynamism are shown in Table 1.

According to the general inference of the characteristic features of the market assets shown in Table 1, CDAM generally exhibits high volatility and price movements based on investor sentiment. Increasing demand due to investor sentiment is the main driver of the upward movement in asset prices. This situation is in a paradoxical trend as irrational purchases cause prices to constantly move upwards regardless of the intrinsic value of the assets. We define this situation as **the pricing paradox in the cryptoasset markets.** This paradox arises from the interaction of several factors within the internal dynamics of the market. These factors, which we evaluate as the Dynamics of the Pricing Paradox, are Naeem et al. (2021), Cheung et al. (2015), Benedetti & Kostovetsky (2021), Blau (2018), Cheah & Fry (2015), Baur & Dimpfl (2021), Katsiampa (2017), Hayes (2017), Baur et al. (2018), Foley et al. (2019), Zohar (2015), Cong et al. (2021) and Scharfman (2021) references; investor sentiment and emotional reactions, demand fluctuations and supply-demand balance, speculative behaviour and irrational investments, volatility and market imbalance, supply constraints and deflationary structure, technology innovation expectations and regulatory uncertainties.

Table 1
Cryptographic Digital Assets and Their Comparative Basic Features

Comparison Criteria	Traditional Cryptocurrencies	NFTs	DeFi Assets
Time of Emergence	• BTC: 2009 • ETH: 2015	• CryptoKitties:2017	• Using the Smart contract infrastructure of the ETH platform: 2017 • With the creation of his first project, MakerDAO, in 2018
Areas of Use	• Digital Money • Transfer • Store of Value • Platform operations	• Digital Art • Collection • Virtual Property • Entertainment and Media	• Credit and Insurance services. • Borrowing, Spot and Margin trading • Interest yield based on liquidity, yield farming and staking • Decentralised Exchange Transactions
Purpose of Use	• Payment, Transfer, Investment	• Collection-Investment	• Access to finance at low cost • Liquidity provision and trading
Distinctive Basic Features	• Monetary functions • Investment	• Uniqueness	• Decentralisation • Low-cost financial services
Financial Function	• Monetary functions • Investment	• Uniqueness • Immutability • Investment	• Financial services • Investment aimed at generating interest income
Opportunity to Provide Liquidity	• None	• None	• Liquidity Pools • Staking
Liquidity Level	• High (BNB)	• Low and Project-specific Limited Liquidity	• Very High (24/7 operation possible)
Technological Infrastructure	• Blockchain • PoW/PoS	• Blockchain • Smart Contracts	• Blockchain (ETH in general) • Smart Contracts
Investor Base	• Individual investors • Institutional Investors (Reserve Asset)	• Collectors • Digital Art Lovers • Individual Investors	• Enterprising investors • Institutional investors (Limited) • Tech-savvy individual investors
Risk Level	• Medium–high	• Very high	• High
Risks	• Volatility • Regulatory Risk • Technology Risk	• Volatility • Liquidity Risk • Regulatory Risk • Sustainability or Project Risk	• Volatility • Smart Contract Risk • Regulatory Risk • Liquidity Risk • Governance Risk
Price Volatility	• High	• Very high	• High

Comparison Criteria	Traditional Cryptocurrencies	NFTs	DeFi Assets
Price Dynamics	• Supply and demand	• Rarity and Demand	• Platform Usage and Liquidity
	• Halfway	• Auction Strategies	• Liquidity
	• Limited Supply	• Collection Value	• Liquidity and Usage
Pricing Strategies	• Request Status	• Community and Hype	• Returns and Incentives
	• Macroeconomic Impacts		• Smart Contract Performance and Security
General market trends	• High Trend	• Very High Trend	• High Trend
	• Request Status	• Request Status	• Request Status
Market Trend Measures	• Critical Incidents	• Investor Features	• TVL
	• Investor Sentiment	• Investor Sentiment	• Investor Sentiment
	• Macroeconomic Factors	• Critical Incidents	• Critical Incidents

Source: Created by the authors

The biggest negative aspect of the pricing paradox in CDAMs is the formation of price bubbles. Price bubbles have a historical background that begins with exchange transactions based on the economic identities of assets and have been the subject of study in almost every market. However, there is no general definition of a bubble that is agreed upon. According to some researchers such as Kindleberger (1987) and Brunnermeier (2008), price bubbles have been evaluated within the scope that requires the existence of market crashes for their comprehensibility and have been defined as “dramatic increases in asset prices followed by market crashes”. The second school of thought, formed by researchers such as Garber (2000) and Kindleberger & Aliber (2005) in the field of traditional finance, evaluates bubbles as a market phenomenon characterised by significant differences between the market price of the asset and its fundamental value. Since cryptographic assets do not have fundamental values, this definition is neither inclusive nor appropriate for cryptoasset markets. Instead of these definitions that are not compatible with market dynamism, we define digital asset bubbles as "**cross-sectional speculative price movements that feed market demand and have the ability to manipulate the market based on it"** in the light of the information we have gained from the accumulation of academic literature on the existence of bubbles.

There are famous bubbles in CDAMs, some of which have reached a level that has caused collapses and are known throughout the financial world. These have been studied in detail in various academic studies, reports, articles and news and have taken their place in market history. These bubbles are shown in Table 2 with their relevant reference sources and basic information.

Table 2

Large-Scale Cryptographic Asset Market Bubbles

Ordinary	Explanation	Comprehensive Analysis Resource	Reference Source
Bitcoin Bubble of 2011	It was one of the first cryptobubbles. It was featured in the work of Eric Posner and Glen Weyl and in various media reports.	Forbes The Economist	Posner & Weyl, (2011)
Bitcoin Bubble of 2013	It increased the popularity of BTC with two big price increases. It resulted in a crash. Mt. Gox is attributed to the stock market crash.	Coindesk, Bloomberg	McMillan, (2014)
2017-2018 ICO Bubble	It is the biggest cryptobubble. The market crash has been studied in academic platforms such as	Gerard (2017)	Gerard (2017) Catalini & Gans, (2018)

Ordinary	Explanation	Comprehensive Analysis Resource	Reference Source
	Harvard Business Review and *MIT Technology Review*		
Crypto Bubble of 2021	The abundance of liquidity and the interest of institutional investors created cryptobubble. It resulted in a collapse.	Forbes, CNBC, The Wall St. journal	Popper (2021)
2022 Terra/Luna and the Stablecoin Bubble	It has been associated with the collapse of Terra/Luna. It has caused discussions about the sustainability of stablecoins. It has highlighted the issues of regulation and risk management in the crypto ecosystem.	CoinDesk, The Financial Times Bloomberg	Helms (2022)
2022 FTX Crisis	It emerged due to the bankruptcy of the FTX exchange. It took place as the biggest financial scandal. It resulted in a collapse.	The New York Times, Reuters, and The Guardian Media	Vigna (2022)

Source: Created by the authors

The theoretical background of price bubbles can be explained using various approaches within the framework of traditional finance and economic theories. In general, these approaches, which are developed depending on many factors such as investor psychology, market dynamics and macroeconomic elements, present an important reality for cryptographic asset markets. Considering that the irrational behaviours of investors in cryptoasset markets are shaped by cognitive biases and emotional decisions, the relationship between bubble formations and these emotionally based approaches will be more easily understood. In this context, the theoretical equivalents of the reasons that give the market a speculative structure and direct investors to irrational transactions are explained below:

Speculative/Rational Bubble Theory: This theory, which constitutes the most basic theoretical framework for bubble formation, argues that bubbles occur when market prices increase excessively due to investors' irrational optimism and speculation. It refers to prices reaching unsustainable levels based on market participants' excessive purchases in the expectation that they can sell an asset at a higher price (Tirole, 1985; Diba and Grossman, 1988). The Rational Bubble Theory explains speculative periods in which rational investors continue to invest despite the excessive increases in asset prices based on available information. According to this theory, investors continue to participate in this process because they believe that they can sell this asset at a higher price in the future, despite being aware that the value of an asset deviates from basic economic indicators. Increases in demand cause market prices to increase excessively and gain a speculative norm, shaping the formation of price bubbles .

Behavioural Finance Theory: Explaining how irrational behaviours of investors can lead to unsustainable price increases, this theory suggests that investors make decisions under psychological influences such as herd mentality, excessive self-confidence, misleading thinking errors and FOMO (fear of missing out). FOMO refers to investors with high future expectations investing in an asset by taking excessive risks due to the fear of missing out. The background of FOMO is excessive self-confidence and social approval. Overconfidence is seen as investors showing a high level of optimism that prices will continue to rise and making purchases based on excessive confidence in their ideas. Social approval, on the other hand, suggests that demand concentrations created by investing in the same asset based on the tendency to follow the investments made by others will give a positive trend to asset prices (Barberis & Thaler, 2003; Shiller, 2000).

The Greater Fool Theory: This theory, which explains the motivation behind investors buying assets at irrationally high prices, is related to investors' beliefs that an asset can be bought and sold at a higher price than its real value. It is based on the principle of adapting the motivation that Harrison & Kreps (1978) put forward for stock markets with heterogeneous expectations to the cryptoasset markets. According to the theory, investors continue to buy even if they know that the asset is overvalued because they believe that they can sell it to a greater fool at a higher price in the future, or they continue to hold their assets in the hope of greater profit opportunities (Harrison & Kreps, 1978; Shiller, 2000).

Minsky/Financial Instability Hypothesis: According to this theory, which explains the mechanisms behind speculative bubbles and financial crises, financial bubbles are generally associated with debt and excessive leverage. This theory, which is shaped within the framework of the idea of debt-based investment driven by overly optimistic future expectations, was put forward by Hyman Minsky (1986). Initially balanced markets cause investors to take more risks and borrow as economic growth continues. This process, fed by overly optimistic future expectations, leads to high leverage in the markets. Minsky argues that this process will create fragility in the financial system over time and will eventually result in a collapse or financial crisis. In other words, even in a market that initially appears balanced, instability becomes inevitable because of the development of these processes. Therefore, the theory states that excessive debt and risk-taking behaviours can create a financial bubble and its bursting can lead to a financial crisis (Minsky, 1986).

Regulatory Uncertainty and Institutional Intervention Theory: This theory is used to explain the pressure that regulatory risk, which is a significant risk factor for cryptographic asset markets, creates on market prices. This theory, based on the research conducted by Akerlof & Shiller (2015), claims that a lack of regulation and regulatory uncertainty can accelerate bubble formation. It is also based on the principle that speculative behaviour can spread rapidly and that regulatory pressures can accelerate market crashes when regulatory arrangements are limited or uncertain.

Herd Behaviour Theory: Also known as the bandwagon effect, this theory explains the intensity of demand resulting from individuals' tendency to act based on majority preferences. The scope of the theory is examined within the framework of group dynamics, social interactions, and social norms. Herd psychology is based on individuals losing their identities within a group and exhibiting irrational and emotional behaviours. The theory provides an important framework for understanding the behaviour of individuals in many areas such as social events, crowds, and social media. The cognitive biases created by individuals' trust in group decisions form the basis of herd psychology. In finance literature, this psychology refers to investment decisions being based on general trends in the market rather than individual independent decisions.

Banerjee (1992) discussed the role of this theory based on following and imitation behavior in financial markets. The concept of information flow (information cascade) explained the process of accessing and adopting market information on the basis of following behaviour and was detailed by Banerjee et al. (2000). Imitation behavior is inspired by the "Social Learning Theory" proposed by Albert Bandura (1977). The potential of herd behaviour to create bubbles in financial markets stems from market clusters and the pressure on demand. In particular, cryptocurrency markets are an area where the effect of herd behaviour is felt intensely due to high volatility, uncertainty and rapidly changing dynamics.

Technology Bubbles and Innovation Theories: These are important theoretical frameworks that explain how the effects of technological innovations on financial markets can lead to large bubbles. This theory argues that the rapid adoption of new technologies and the excessive optimism of investors in innovative technologies can cause excessive inflation in the markets and the formation of speculative bubbles. Like Schumpeter's Innovation Theory, it states that technological innovations can create major changes in markets through creative destruction processes. Cryptocurrency markets have frequently been examined in the context of this theory, and many studies have shown that cryptocurrencies create bubbles based on innovative technologies.

Media and Social Network Effects: The proliferation and diversification of communication tools along with technological developments have greatly increased the power of media tools to create, manage and direct mass psychology, as well as increasing the speed of information dissemination. This power has significant potential in cryptoasset markets where investor sentiment is dominant. In particular, social media platforms (such as X, Reddit) and news portals can rapidly influence investor behaviour. According to the theory of King & Wadhwani (1990), investors enter the market as a result of "hype" and speculation spread through media and social networks, creating mass agglomerations, increasing market volatility and preparing a suitable ground for bubble formations. Intense media interest around cryptoasset projects and marketing via social networks can lead to speculative price movements based on demand concentration in markets with limited supply structures.

This theoretical framework, which forms the theoretical background of investor sentiment, which is considered an important risk element in the general market structure, provides valuable information in terms of understanding the formation and dynamics of bubbles that are a result of the pricing paradox. In addition, understanding the internal dynamics of market assets is also of great importance in terms of preventing the negative effects of the pricing paradox. Although the asset components of the crypto markets, the CCC, NFT and DeFi supergroups, have different functions and characteristics, the markets in which they are traded tend to respond to the same economic shocks and investor sentiments. The benefits of all these explanations include investors, policy makers, and potential users.

Literature Research

The literature examining bubble formation in the cryptocurrency and digital asset markets (CDAM) can be categorized into two main domains: theoretical frameworks and econometric analyses. While theoretical studies emphasize overarching market dynamics, speculative structures, and the potential for bubble formation, econometric approaches focus on detecting bubbles within specific temporal contexts. This section synthesizes key contributions within the theoretical framework.

Behavioral finance theory has been pivotal in explaining speculative bubbles in the cryptocurrency markets. For instance, Baek and Elbeck (2015) analysed bubble dynamics through behavioural finance principles, highlighting the role of cognitive biases. Corbet et al. (2018) further advanced this perspective, demonstrating how speculative bubbles in Bitcoin (BTC) and Ethereum (ETH) are influenced by overconfidence, excessive optimism, and herd psychology. Their findings suggest that these biases compel investors to continue investing irrationally, fostering bubble formation. Similarly, Shahzad et al. (2019) and Liu and Tsyvinski (2021) observed herd behaviour among cryptocurrency investors, attributing price volatility to collective irrationality.

In a related vein, Mai et al. (2018) explored the influence of investor sentiment, as captured through social media metrics, on bubble development. Complementing this, Fang et al. (2022) analysed the role of mainstream media, showing that both positive and negative news trigger irrational investor responses, leading to price bubbles. Their findings emphasise the impact of behavioural finance factors such as panic and euphoria in driving significant market volatility.

Rational Bubbles Theory also provides critical insights into cryptocurrency markets. Cheah and Fry (2015) and Bauri et al. (2017) argued that speculative bubbles emerge from rational investor behaviour, where expectations of continued price increases sustain investment momentum despite significant price surges. Kristoufek (2015), employing a wavelet coherence analysis, demonstrated that Bitcoin's price movements are decoupled from underlying economic fundamentals, driven instead by rational investor dynamics. Philip et al. (2018) reinforced this perspective by linking the significant volatility of cryptocurrency markets to rational expectations of future price changes, which amplify speculative activity and bubble formation.

The disruptive nature of blockchain technology is another cornerstone of bubble formation theories. Research by Glaser et al. (2014), Böhme et al. (2015), Catalini and Gans (2016), Harwick (2016), Fry and Cheah (2016), and Yermack (2017) highlighted blockchain's role as an innovative and transformative force in financial markets. These studies argue that investor enthusiasm for technological breakthroughs and confidence in their long-term potential inflate asset prices, contributing to speculative bubbles.

In summary, the theoretical literature underscores the multifaceted drivers of bubble formation in the cryptocurrency markets. Investor psychology, speculative behaviour, media influence, technological advancements, and excessive leverage collectively shape these dynamics. The substantial volatility and speculative nature of cryptoassets make them a fertile ground for applying behavioural finance, rational bubbles, and disruptive innovation theories.

The presence of bubbles in CDAM has been extensively evidenced through econometric and statistical methodologies. Early studies, such as Garcia et al. (2014), highlighted the role of social interaction in bubble formation. Their research demonstrated that socio-economic signals, including online stock market prices, exchange rates, social media communication volumes, and search trends, significantly contribute to the development of price bubbles.

Cheung et al. (2015) conducted the first econometric analysis specifically focused on Bitcoin (BTC) using the Generalised Supremum Augmented Dickey-Fuller (GSADF) test. Their findings identified three distinct bubble episodes between 2011 and 2013, each lasting 66–106 days. Cheah and Fry (2015) corroborated these results, emphasising Bitcoin's susceptibility to speculative bubbles and its intrinsic value being effectively zero. Further analysis by Baek and Elbeck (2015) reinforced these conclusions, demonstrating speculative behaviour through relative volatility measures in the cryptocurrency markets. Market efficiency in CDAM was first evaluated by Urquhart (2016), who revealed significant inefficiencies in these markets. Subsequent studies expanded the scope to encompass various cryptocurrency asset classes, highlighting the interconnections and contagion effects within the broader ecosystem.

Table 3 categorises the extensive body of literature on bubbles and bubble dynamics in CDAM, delineating studies by scope, methodology, significance, and key findings. Among these, Cheah and Fry (2015) and Aharon and Demir (2022) stand out for their pioneering analyses of bubble formation in cryptocurrencies and non-fungible tokens (NFTs). Corbet et al. (2020) extended this understanding to stablecoins, identifying their potential as a safety net against market volatility while also revealing their vulnerability to bubble risks.

The empirical literature on bubble dynamics in the cryptocurrency and digital asset markets reveals the speculative and volatile nature of these ecosystems. Traditional cryptocurrencies, such as Bitcoin, are particularly susceptible to speculative bubbles due to their inherent volatility and high-risk profiles. Studies have demonstrated that the interactions between cryptocurrencies and conventional asset classes can amplify bubble dynamics. Moreover, the formation of bubbles in cryptocurrency markets often extends into adjacent sectors, including non-fungible tokens (NFTs) and decentralised finance (DeFi), highlighting the interconnected nature of these markets.

The NFT market exemplifies the rapid escalation of speculative bubbles, driven by extraordinary financial demand and intense media hype. Social media platforms and advancements in economic and commercial technologies play significant roles in catalysing these bubbles. Analytical tools, such as machine learning and sentiment analysis, have emerged as effective methods for detecting and predicting the formation of NFT bubbles, offering valuable insights into their dynamics. Similarly, the DeFi ecosystem faces unique exposure to bubble risks, primarily fuelled by the extensive use of liquidity pools, yield farming, and complex financial instruments. Factors such as regulatory enforcement, the proliferation of social media, and the concentration of individual investors further contributed to the creation and collapse of the DeFi bubbles, underscoring the system's vulnerability to speculative activity.

Cryptocurrency markets also exhibit strong interconnections, where bubbles in one asset class, such as cryptocurrencies, can proliferate into others, including NFTs and DeFi. This cross-bubble contagion effect emphasises the intricate and interdependent nature of these ecosystems, requiring comprehensive strategies to effectively address and mitigate bubble risks. Methodologically, the analysis of the bubble dynamics benefits from considerable diversity. While traditional econometric models remain foundational, contemporary approaches such as machine learning algorithms, sentiment analysis, and behavioural economics frameworks have significantly enriched the understanding of bubble formation and propagation. This methodological variety enhances the robustness of the insights into the speculative behaviour driving market dynamics.

In conclusion, the speculative nature of CDAM is shaped by both external factors, such as regulatory developments, technological innovation, and social media influence, and internal dynamics within asset classes. These forces collectively drive the creation and propagation of bubbles across interconnected markets. The complexity of these ecosystems necessitates a multidimensional approach to effectively understand, predict, and manage bubble risks.

Table 3

Bubbles and Bubble Dynamics in the CDAM

Study	Asset Type	Methodology	Importance	Key Findings
Cheah and Fry (2015)	Bitcoin (CCC)	SADF, GSADF	This is one of the first bubble analyses in cryptocurrencies.	Many bubbles have been observed in Bitcoin.
Aharon and Demir (2022)	NFT	RADF, GSADF	It is one of the first studies to detect bubbles in the NFT market.	Large speculative bubbles have been detected in the NFTs.
Katsiampa et al. (2019)	CCCs	GARCH, Copula	Examines the volatility relationships of cryptocurrencies.	Bitcoin has a high volatility correlation with other cryptocurrencies.
Corbet et al. (2020)	CCCs, Stablecoin	Copula, Volatility analysis	Examines the role of stablecoins in balancing volatility.	Although stablecoins reduce volatility, the risk of a bubble in the liquidity flow is high.
Wang and Kogan (2022)	NFT	Random Forest, SVM	Provides automated methods for bubble detection in the NFT market.	Machine learning models can detect NFT bubbles with high accuracy.
Zhang and Wen (2023)	DeFi	Event Study and Time Series Regressions	Examines the impact of regulatory announcements on DeFi bubbles.	Regulatory announcements cause bubbles to burst; uncertainty increases the risk of speculative bubbles.
Li and Jiang (2023)	CCC, NFT, DeFi	Co-integration, Granger Causality, Network Analysis	Examines the bubble contagion between different cryptoasset markets.	There is a bubble contagion effect between the CCC, NFT, and DeFi markets; CCC bubbles can spread to others.
Fernandez and Garcia (2023)	DeFi	Sentiment Analysis and Panel Data Analysis	Investigates the impact of social media sentiment on DeFi bubbles.	Positive social media sentiment fuels DeFi bubbles; negative sentiment accelerates the burst.
Garcia and Lee (2023)	NFT	Sentiment Analysis and Regression Models	Explores the impact of market sentiment on NFT bubble formations.	Positive social media sentiment spikes fuel NFT bubbles; negative sentiment accelerates bubble bursts.
Muller and Schmidt (2024)	CCC, NFT, DeFi	Multivariate GARCH Models and Machine Learning	Examines the interaction and bubble dynamics of different cryptoasset classes.	Interdependent bubbles form in the CCC, NFT, and DeFi markets; volatility increases in the CCC markets affect others.
Chen and Wang (2024)	CCC, NFT, DeFi	Regression Section, Panel Data Analysis	Analyzes the role of regulations on the bubble dynamics in crypto markets.	Regulatory uncertainty and negative news prevent or burst bubbles; positive news boosts confidence and supports bubbles.

Study	Asset Type	Methodology	Importance	Key Findings
Ozturk and Demir (2024)	NFT, DeFi	Survey Studies, Behavioural Economics Models	Examines the contribution of individual investor behaviour to bubble dynamics.	Factors such as overconfidence, herd behaviour, and loss aversion drive the NFT and DeFi bubbles.
Barbon and Ranaldo (2023)	NFT	Cross-Sectional Regression	Aims to determine the existence of bolons and bubble dynamics	It has been determined that mediating variables such as investor sentiment, heterogeneity and wash trading have a significant predictive ability of bubble formation and price crashes with aggregate variables such as volatility, price momentum and turnover.
Assaf et al. (2024)	CCC, DeFi	TVP-VAR, Volatility Spread	Examines the role of shock transmission across markets and global risk factors in shock transmission	CCCs transmitted significantly larger shocks and are therefore the primary driver of changes in DeFi returns.
Maouchi et al. (2022)	DeFi, CCC, NFT	GSADF, Correlation Analysis	Examines the effects of Crisis, Trading Volume and TVL on bubble formations	It has been determined that there are more frequent and large bubbles in CCCs and less frequent bubbles in NFTs and DeFis, and that TVL is a good market monitoring tool.
Guo et al. (2023)	NFT, CCC	GSADF, TVP-VAR	It also examines the existence of bolons and bubble dynamics, as well as the effects of sentiment trends, volatility and macroeconomic uncertainties on price formations.	Strong correlations were found across many NFTs and CCCs, and variable effects of investor sentiment across asset groups were noted.
Corbet et al. (2023)	CCC, DeFi	GSADF, DCC GARCH,	Examines the stability of asset price developments and the driving forces that distinguish asset groups from each other.	Although significant bubbles have been identified in both asset groups, despite the strong correlation between CCCs and DeFis, they do not contribute to the formation of bubbles between asset groups.

Source: Created by the authors

Methodology and Dataset

Dataset Components and Selection Criteria

The dataset of the research consists of 18 cryptoasset group components in 6 CCC, 6 NFT and 6 DeFi varieties. In the study where weekly (200 weeks) data was used between 05.10.2020 and 29.07.2024, the index values of the variables were obtained from coinmarketcap.com and coingecko.com. The dataset components and selection criteria are shown in Table 4 –5-6 within the framework of the asset groups.

Table 4

CCC Entity Group Members and Selection Criteria

CCC	Market Value (Billion $)	Market share (%)	Selection Criteria Explanations
BTC	1,257.40	51.65	It is a mainstream currency and represents 51.65% of the market. It is a financial asset with price behaviour that is disconnected from economic fundamentals and exhibits the fastest growth potential.
ETH	315.18	35034	It is ranked second in terms of market value. It enables the creation and exchange of thousands of DeFi and NFT applications. It is a high-tech platform with open access to data-friendly services.
USDT	119.08	32599	It is the largest cryptoasset known as a stablecoin. It is intended to protect against market fluctuations.
BNB	88.99	24167	It has its own blockchain and can support more than 1.5 million transactions per second. It is highly popular in the DeFi and NFT platforms. It is aimed at efficiency on transaction costs.
XRP	33.23	13516	It can make cross-border payments and money transfers cheap and secure.
ADA	13.62	0.56	It is the largest currency that uses the energy-efficient proof-of-stake blockchain. It can facilitate peer-to-peer transactions.

CCC	Market Value (Billion $)	Market share (%)	Selection Criteria Explanations

Note: Market value information was obtained from coinmarketcap on 30.09.2024.

CCCs, which constitute the largest share of cryptographic digital financial assets with a market value of $ 2,434,404,749,673 as of September 30, 2024, participated in the research under the representation of Bitcoin (BTC), Ethereum (ETH), BinanceCoin (BNB), Tether (USDT, XRP) and Cordano (ADA). CCC group members were created with a sensitivity that could reflect the general market structure with their functional features in the asset group, apart from their market values and market shares.

Table 5

NFT Representatives and Selection Criteria

NFT	NFT Market's Market Share	Selection Criteria Explanations
THETA	0,01	It focuses on Video and Media content. It can compete with the BTC and ETH platforms.
MANA	0,03	It enables the acquisition and development of NFT-based virtual properties.
XTZ	0,02	Low cost eco-friendly asset. Popular for art and digital content coverage
ENJ	1.5%	It is the most important entity representing the in-game entity group.
LINK	0.5%	It offers Oracle technology. NFTs play an important role in interacting with external factors.
SAND	0.25%	It plays a role in creative content such as games and digital property management in the Metaverse space. Although it is in the NFT world, it also has a DeFi function.

Note: Market value information was obtained from coinmarketcap on 30.09.2024.

Table 5 shows detailed explanations regarding the NFT asset representatives and selection criteria. In the research, THETA, MANA, XTZ, ENJ, LINK and SAND were used to represent the NFT asset group. While NFT market sizes are the criteria for creating asset group members, functional group dynamics that reflect NFT asset diversity are decisive.

Table 6

DeFi Asset Representatives and Selection Criteria

DeFi	DeFi Market's Market Share	Growth Rate	Selection Criteria Explanations
MKR	4.3%	35-40%	Leader in DeFi lending and stablecoin production. Potential for growth
RUNE	6.8%	50%+	Liquidity pools and cross-chain asset swaps enable and grow potential
STX	2.4%	30-35%	It is a platform that offers smart contracts on BTC.
OM	1.7%	25-30%	It has a DAO and staking-focused platform
EGLD	8.5%	40-45%	It has a high market share and scalable blockchain structure
AAVE	0.5%	35-40%	Leading platform in DeFi lending and borrowing

Notes: Market value information was obtained from coinmarketcap on 30.09.2024.

Table 6 shows detailed explanations of the DeFi asset representatives and selection criteria. In the research, MKR, RUNE, STX, OM, EGLD, and AAVE were used to represent the DeFi asset group. While DeFi market shares and growth rates are criteria for the formation of asset group members, functional group dynamics that reflect DeFi asset diversity were considered. Descriptive statistics based on the market trends of cryptoasset group components are given in Table 7.

Table 7

Data and Descriptive Statistics

Asset	Average	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	JB(Probe)	Observation
BTC	37487.23	35334.19	71333.48	10676.53	15877.57	0.4462	2.1385	0.0016	200
ETH	2224.795	1936.159	4627.091	352.7368	977.1863	0.3714	2.4584	0.0296	200

Asset	Average	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	JB(Probe)	Observation
USDT	1.0003	1.0002	1.0074	0.9983	0.0008	3.5502	30.3505	0.0000	200
XRP	0.5991	0.5241	1.5625	0.2260	0.2649	1.4062	4.9194	0.0000	200
BNB	331.8784	310.5066	673.3354	27.621	154.7573	0.1091	2.8009	0.6951	200
ISLAND	0.7382	0.4660	2.9120	0.0960	0.6044	1.5321	4.8001	0.0000	200
THETA	2.7623	1.3020	12.9250	0.5970	2.7827	1.6838	5.1976	0.0000	200
MEANING	0.8770	0.6005	5.1500	0.0640	0.8849	2.1524	7.4184	0.0000	200
XTZ	2.2870	1.4460	8.7200	0.6510	1.7438	1.2969	3.9375	0.0000	200
ENJ	0.8432	0.4420	4.4930	0.1180	0.8377	1.5126	4.7528	0.0000	200
LINK	15.1065	13.5185	52.2480	5.1610	8.8152	1.0943	4.0185	0.0000	200
SANDA	1.0035	0.5705	7.5300	0.0360	1.2915	2.6633	10.186	0.0000	200
MKR	1731.896	1480.743	5280.562	513.0529	1003.058	0.7385	3.0650	0.0001	200
RUNE	4.5419	3.8048	19.4676	0.3942	3.6924	1.2875	4.7010	0.0000	200
STX	1.0677	0.8538	3.4629	0.0028	0.7992	0.7689	2.8049	0.0000	200
OM	0.1802	0.0752	1.3910	0.0186	0.2451	2.3225	8.3627	0.0000	200
EGLD	86.5999	52.7013	427.9319	7.5833	78.1517	1.7443	6.0317	0.0000	200
AAVE	151.5692	93.9394	527.2645	30.6573	116.0882	1.3205	3.5311	0.0000	200

In Table 7, general characteristics among asset group members can be examined depending on the price trends during the review period. Descriptive statistics of the variables are summarised as follows, specific to the upper groups.

DeFi assets generally include a component of assets with high values within the average price framework. MKR and AAVE are the most valuable assets of the group members. Price fluctuations are high among DeFi assets. MKR and AAVE are among the assets with the highest price volatility. The standard deviation values indicate that the prices of these assets show large fluctuations and may pose high risks for investors. A right-skewed distribution is observed in most DeFi assets, especially MKR and EGLD. This indicates that prices are concentrated at the high ends and are prone to large value increases. In terms of kurtosis (kurtosis) values, it is seen that especially MKR and AAVE are subject to more frequent price changes at the extreme ends and that these assets are more sensitive to large price shocks.

NFT assets are generally lower in terms of average price compared to DeFi assets. For example, the average prices of MANA and SAND are 0.0877 and 0.1003, respectively. This indicates that NFT assets appeal to a wider range of investors and are considered lower-priced assets. In terms of volatility, high volatility is observed in NFT assets. In particular, the standard deviation values of assets such as MANA and SAND indicate that these assets are exposed to high volatility risk. Therefore, investors should be prepared for high price fluctuations in NFTs. The fact that prices are largely skewed to the right among NFT assets means that large price increases can occur in extreme market conditions. High kurtosis values indicate that price movements occur more frequently at extreme price extremes, which means that large price shocks can occur frequently in NFT markets.

There are large differences between the average prices of CCCs. While major cryptoassets such as BTC and ETH have very high price levels, stablecoins such as USDT have a fixed average price of $ 1). Altcoins such as BNB and ADA are at medium price levels. The volatility of BTC and ETH is higher than that of other assets, while the volatility of the stablecoin USDT is found to be very low (standard deviation 0.00008), as expected. Stablecoins are safer in terms of volatility because they have a fixed value. CCCs, especially major cryptocurrencies, show high kurtosis values, which indicates that price movements can occur frequently at extreme price extremes. This means that investors should be prepared for sudden and large price changes, especially during volatile periods.

The correlation matrix between the variables is given in Appendix A. Accordingly, the presence of a very strong correlation (0.84) between BTC and ETH shows that the price movements between the two major cryptoassets are highly interconnected. BTC also has strong correlations with assets such as the STX and MKR. This can be interpreted as BTC affecting the price movements of smaller (in terms of density) assets in the market. ETH also exhibits high correlations with many assets similar to BTC, which is an expected situation for these two cryptoassets to have similar effects. It is observed that assets such as ADA, EGLD, RUNE, THETA, LINK and XTZ have high correlations with each other. This shows that altcoins markets tend to move parallel to each other. In the correlation matrix, it is seen that OM and USDT differ from other assets. OM has low correlations with other assets and even has a negative relationship with some of them. OM shows a different price dynamic than other assets or appears to react independently to speculative movements. In USDT, there is almost no correlation with other assets. In this respect, it can be interpreted that the USDT is seen more as a store of value and is very little exposed to market fluctuations.

Research Methodology

Econometric tests used to measure bubble formation in markets are referred to as right-tail ADF tests. In this context, the studies conducted by Phillips et al. (2011) and Phillips et al. (2015) are considered pioneers. The authors tested the formation of bubbles in markets and the start and end dates of bubbles using the SADF (Supremium ADF) and GSADF (Generalised Supremium ADF) tests. The important feature of these tests is that they have a recursive and expanding window structure (Güler & Gökçe, 2020)

The estimation process of the SADF and GSADF tests begins with estimating the standard ADF regression using the least squares method (Sharma & Escobari, 2018):

$$x_t = \mu_{r_1,r_2} + \delta_{r_1,r_2} x_{t-1} + \sum_{j=1}^{J} \varphi^{j}_{r_1,r_2} \Delta x_{t-j} + \varepsilon_{x,t}, \varepsilon_{x,t} \sim (0, \sigma^2) \tag{1}$$

In Equation 1 x_t, the asset price given, $\Delta x_t$the lagged value of the asset price, $j$the lag length, $\mu,\ \delta,\ \varphi$the estimation parameters and $\varepsilon_{x,t}$the error term assumed to have a normal distribution. However, in the right-tail ADF tests, parameter estimation is made for the entire sample as well as for the subsamples. In this context, $r_1\ ve\ r_2$the terms shown in the estimated parameter values represent the starting and ending points of the subsample (Mandacı & Çağlı, 2018). In right-tail ADF tests calculated using multiple iterations, each subsample starts with the first observation value, while the last observation value is allowed to change. The representative sample is shown with a window $r_w = r_2 - r_1$and it allows testing from a small sample to the entire sample (Elike & Anoruo, 2017).

The standard ADF test statistic is obtained by dividing the prediction coefficient of a lagged value of the asset price by the standard error of the same prediction parameter (İskenderoğlu & Akdağ, 2019).

$$ADF_{r_1,r_2} = \frac{\delta_{r_1,r_2}}{se\left(\delta_{r_1,r_2}\right)} \tag{2}$$

Given in Equation 2 $r_1$is equal to 0 or 1, the standard ADF test statistic is reached. Philips et al. (2011) r_1, r_2 stated that performing the ADF test by creating subsamples with different values can be used to detect bubble formation. Accordingly, the test, which is applied to different subsamples in order, determines the periods when the asset price becomes dominant. In this approach, which uses a window structure that expands to include all observations starting from the first observation, it is stated that the bubble formation in the asset price is between the date when the ADF test statistic value is greater than the critical value and the date when the value of the ADF test statistic is less than the critical value (Güler & Gökçe, 2020).

The SADF model is an ADF test that expands forward for each subsample. The feature of the model is that a fixed initial $r_0$value can be assigned that can expand up to 1 (Liu et al., 2016).

$$SADF(r_0) = \frac{\sup}{r_2 \in [r_0, 1]} ADF_0^{r_2} \tag{3}$$

Equation 3 shows the recursively estimated SADF regression. $[r_0, 1]$The ADF statistic values calculated for the range are estimated for each sub-period. The model includes the null hypothesis that no asset bubble has formed ($H_o : \delta = 1)$and the alternative hypothesis that the series has an explosive unit root; therefore, a bubble has formed in the asset price () $H_1 : \delta > 1)$. The test statistic being greater than the critical value causes the null hypothesis to be rejected and the formation of a bubble in the series to be statistically significant (Güler and Gökçe, 2020).

The SADF model has been found to be successful in the real-time detection of bubble formation and especially in revealing bubbles that may arise from various sources such as changes in preferences (Homm & Breitung, 2012). On the other hand, in the case of the formation of more than one asset bubble or in the presence of non-linear series and structural breaks, the SADF test cannot show sufficient performance (Phillips et al., 2015).

Phillips et al. (2015) proposed the GSADF test, which is a generalised version of the SADF test, to detect the formation of multiple bubbles. The GSADF model, which has a flexible estimation window, gives statistically consistent and accurate results by considering structural breaks in long-term series (Mandacı & Çağlı, 2018).

$$GSADF(r_0) = \frac{\sup}{\substack{r_1 \in [0, r_2 - r_0] \\ r_2 \in [r_0, 1]}} ADF_{r_1}^{r_2} \tag{4}$$

If the GSADF right tail test statistic value obtained from Equation 4 is greater than the critical value, the null hypothesis that there is no bubble in the asset price is rejected. The most important difference between the GSADF and SADF tests is that the starting point can be varied when creating a subsample. In addition, in the SADF and GSADF tests where Boostrap and Monte Carlo simulations are used, the critical values differ from the traditional ADF test critical values (Caspi, 2017). In this study, the GSADF test used in the detection of multiple asset bubbles was preferred.

Empirical Findings

GSADF Test Statistics Analysis and Results

In the analysis, the index values of 18 variables classified under the cryptographic digital assets CCC, DeFI and NFTs were used. While selecting the variables, those with high representation power of digital assets were preferred, and six variables were used for each asset type. The GSADF analysis conducted with weekly data was performed on 200 observations in the period between 05.10.2020 and 29.07.2024. As explained before, the GSADF test, which is one of the right-tail unit root tests, gives successful results in detecting the asset bubble in terms of the estimation process rather than standard unit root tests (Phillips et al., 2015). The null hypothesis to be used in the analysis(H_0) It has been established that there is no bubble formation in the relevant asset market. If the G SADF test statistics results are found to be greater than the critical values given in the studies of Phillips et al. (2011) and Phillips et al. (2015), the null hypothesis will be rejected and an asset bubble formation can be mentioned. The analysis results are given in Table 8.

Table 8
GSADF Test Findings

Variable	t-statistic	Critical Values		
		1%	5%	10%
BTC	1.4230 [b]	1.6968	1.2080	1.0000
ETH	2.0558 [a]	1.6968	1.2080	1.0000
USDT	−0.2535	1.6619	1.2288	1.0197
XRP	0.3695	1.6968	1.2080	1.0000
BNB	2.7140 [a]	1.6968	1.2080	1.0000
ISLAND	1.0931	1.6968	1.2080	1.0000
THETA	4.2472 [a]	1.6968	1.2080	1.0000
MEANING	1.2850 [b]	1.6968	1.2080	1.0000
XTZ	−0.3874	1.6968	1.2080	1.0000
ENJ	4.6561 [a]	1.6968	1.2080	1.0000
LINK	2.0362 [a]	1.6968	1.2080	1.0000
SANDA	8.4512 [a]	1.6968	1.2080	1.0000
MKR	2.1343 [a]	1.6619	1.2288	1.0197
RUNE	3.9516 [a]	1.6619	1.2288	1.0197
STX	2.9146 [a]	1.6968	1.2080	1.0000
OM	12.4601 [a]	1.6968	1.2080	1.0000
EGLD	1.1323	1.6968	1.2080	1.0000
AAVE	−0.7608	1.6619	1.2288	1.0197

Note: Symbols a and b represent 1% and 5% significance levels, respectively. GSADF tests were performed with 10% initial window size using 1000 iterations of Monte Carlo simulation. Considering the structure of the CDAMs, the fixed and trended model was preferred in the GSADF analysis.

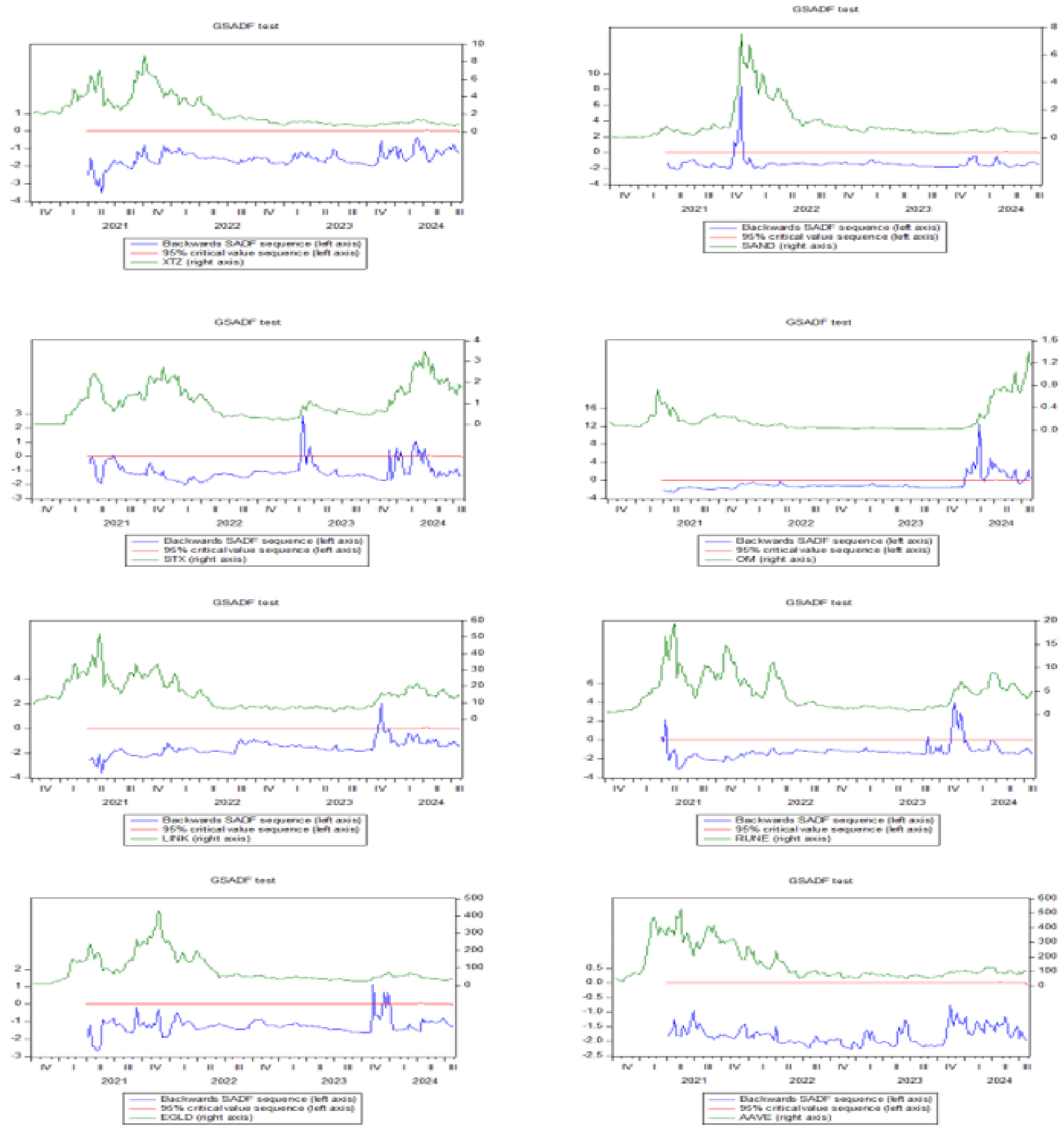
According to Table 8, since the GSADF test statistics of 12 variables are greater than the critical values in the 200-week period between 05.10.2020 and 29.07.2024, the basic hypothesis that there is no asset bubble is rejected. In other words, while bubble formation was found in 12 variables, no evidence of bubble formation was found in 6 variables. Of the variables where asset bubbles are not found, 3 belong to CCC, 1 to NFT and 2 to DeFi markets.

Figure 1

GSADF Graphs

Figure 1

GSADF Graphs



[Figure 1](#) shows the graphs of the GSADF analysis results of the 18 digital assets. The graphs include both the raw data of the variables and the statistical results obtained from the sample (backwards SADF sequence). Bubble formation is observed in the weeks when the statistical results are higher than the critical values. The dates of the multi-asset bubbles formed according to the test results are given in Table 9.

Table 9

Asset Bubble Periods

Type of Asset	Presence	Number and Periods of Asset Bubbles Over 15 Days
	BTC	04.03.2024-25.03.2024 (28 days)
CCC	ETH	04.03.2024-18.03.2024 (21 days)
	USDT	There is not enough evidence for the existence of the bubble.

Type of Asset	Presence	Number and Periods of Asset Bubbles Over 15 Days
	XRP	There is not enough evidence for the existence of the bubble.
	BNB	04.03.2024-25.03.2024 (28 days)
	ISLAND	There is not enough evidence for the existence of the bubble.
NFT	THETA	04.03.2024-25.03.2024 (28 days)
	MEANING	There was no bubble formation over 15 days.
	XTZ	There is not enough evidence for the existence of the bubble.
	ENJ	05.04.2021-19.04.2021 (21 days)
	LINK	There was no bubble formation over 15 days.
	SANDA	08.11.2021-29.11.2021 (28 days)
DeFi	MKR	11.03.2024-25.03.2024 (21 days)
	RUNE	6.11.2023-27.11.2023 (28 days)
	STX	There was no bubble formation over 15 days.
	OM	01.01.2024-19.02.2024 (56 days) 04.03.2024-25.03.2024 (28 days) 22.04.2024-10.06.2024 (56 days)
	EGLD	There is not enough evidence for the existence of the bubble.
	AAVE	There is not enough evidence for the existence of the bubble.

Note: Asset bubble formation lasting 15 days or more is tabulated.

Table 9 summarises the bubble formations that lasted for more than 15 days. In addition, all bubble formation numbers and dates for the assets are given in Appendix B. As stated before, no bubble formation was observed in the USDT, XRP, ADA, XTZ, EGLD and AAVE digital assets during the review period. On the other hand, no bubble formation was observed in the MANA, LINK and STX variables for more than 15 days. Therefore, the interpretation of the findings will be made for the remaining nine digital assets.

A 28-day bubble has been detected in BTC and BNB , representing the crypto market , and a 21-day bubble has been detected in *ETH* . The history of bubbles is common for all three digital assets. In the NFT markets, a 28-day asset bubble formation was observed in THETA in March 2024, and a 21-day asset bubble formation was observed in ENJ and SAND in 2021. Among DeFIs, bubbles were encountered in the MKR, RUNE and OM assets. During the review period, an asset bubble of 21 and 28 days was observed in the MKR and RUNE variables, respectively, while there were three speculative bubbles in the OM variable. Moreover, the bubbles detected in the OM variable are the longest. A 56-day bubble formation was observed twice in 2024. The most interesting result obtained because of the analysis is that bubbles were detected in six variables in March 2024. The reason for the simultaneous multiple bubbles can be attributed to the following developments, depending on global macroeconomic and geopolitical developments and the internal dynamics of cryptoassets:

- In terms of macroeconomic factors, it can be attributed to the threats to global stability posed by high inflation in developing countries such as Argentina, Egypt and Turkey, and the decision of China, the second most important country in world trade, to slow down its economic development.
- The global problems regarding food supply and energy security experienced in early 2024 may be due to the Russia-Ukraine War and geopolitical tensions in the Middle East.

In terms of the internal dynamics of cryptoassets, multiple price bubbles can be associated with the four-year cycles of cryptocurrencies. This cycle, called Bitcoin Halving, is a process in which mining rewards are halved every four years. During the halving period, the market supply is reduced, causing price increases.

Increased liquidity, speculation, and investor interest in the post-halving markets may have had a strong impact, especially on smaller and volatile assets. These cyclical price movements and investor psychology, combined with the spillover effect among cryptoassets, contribute to the formation of multiple bubbles. Policymakers and investors should make more informed decisions by considering such cyclical events and develop strategies to manage potential bubble risks.

Conclusion and Evaluation

Cryptocurrency and digital asset markets (CDAMs) differ significantly from traditional financial markets in terms of their structure, operating principles, and the characteristics of their instruments. Understanding the market dynamics and the relationships between different asset classes is crucial for investors, market participants, and policymakers. The findings of this study provide several critical insights, which are evaluated below in the context of their implications for investors and policymakers.

The descriptive statistics and correlation analyses underscore the volatile and interconnected nature of CDAMs. All asset groups analysed in this study—cryptocurrencies (CCC), non-fungible tokens (NFTs), and decentralised finance (DeFi) assets—exhibit high volatility, with DeFi assets demonstrating particularly large price swings. NFTs also exhibit heightened volatility during extreme market conditions, while stablecoins, such as USDT, maintain much lower volatility, positioning them as relatively safer assets. These findings suggest that investors must carefully weigh the risks and opportunities associated with these assets, especially given their high skewness and kurtosis values, which indicate the potential for large price shocks and gains in extreme conditions.

From an investment perspective, diversification strategies should consider the distinct volatility profiles of DeFi and NFT assets. While these assets carry significant risk, they also offer substantial profit potential. Stablecoins, on the other hand, provide a stabilising influence within portfolios. Policymakers, however, should consider the implications of high volatility on financial stability. Strategies to regulate NFTs and DeFi assets, particularly during extreme market fluctuations, could mitigate systemic risks, while stablecoins offer a more manageable entry point for regulatory oversight.

Correlation analysis highlights the interconnectedness of CDAMs. Strong correlations were observed between major cryptocurrencies, such as BTC and ETH (0.84), as well as between BNB and ETH (0.89), suggesting that these assets respond similarly to overarching market trends. In the DeFi market, high correlations among tokens like AAVE and LINK (0.90) indicate synchronised responses to market conditions. In the NFT market, assets like MANA and SAND (0.96) exhibited almost identical price movements, reflecting similar investor sentiment and market drivers. These findings are critical for portfolio management, as assets with high correlations may expose investors to similar risks, reducing the benefits of diversification. Conversely, assets with lower correlations, such as USDT, can enhance risk management. Policymakers should also monitor these correlations, as synchronised movements among highly correlated assets may amplify systemic risks and necessitate tighter regulation.

Bubble dynamics analysis further revealed the speculative nature of CDAMs. Using the GSADF test, bubble formations were identified across various assets during the analysis period. Among the CCCs, bubble episodes were observed for BTC (28 days in March 2024), ETH (21 days in March 2024), and BNB (28 days in March 2024). These results highlight the susceptibility of major cryptocurrencies to speculative pressures. In the NFT market, bubbles were detected in assets such as THETA (28 days in March 2024), ENJ (21 days in April 2021), and SAND (28 days in November 2021), indicating a volatile and speculative market structure. For DeFi assets, bubbles were observed in MKR, RUNE, and OM across multiple periods, with OM experiencing prolonged bubble episodes of up to 56 days. These findings suggest that DeFi assets are particularly vulnerable to speculative activity, warranting closer monitoring and regulation.

The comparison of bubble periods across asset groups reveals important insights into the internal dynamics of CDAMs. Bubble synchronisation suggests the existence of central driving forces, with BTC and ETH acting as key influencers within the market. Additionally, the strong correlation between BTC and other CCCs, NFTs, and DeFi assets underscores the dominant role of Bitcoin in shaping market-wide liquidity and risk.

NFT markets, while distinct from cryptocurrencies and DeFi in their unique asset structure (e.g., art, games, digital assets), demonstrate sensitivity to Ethereum's ecosystem performance. Despite their divergence in liquidity and market behaviour, NFTs exhibit synchronisation with broader market trends, particularly during periods of heightened volatility. Similarly, DeFi assets, which provide decentralised financial services, are strongly linked to major cryptocurrencies like BTC and ETH in terms of liquidity and yield dynamics. These findings highlight the interdependence of CDAMs and the need for holistic risk management strategies.

This study provides a comprehensive analysis of the volatility, correlation, and bubble dynamics in CDAMs. The findings highlight the speculative nature of these markets and their susceptibility to systemic risks. For investors, careful portfolio diversification and a focus on low-correlation assets can help mitigate risks. Meanwhile, policymakers must address the challenges posed by high volatility and interconnectedness within these markets. Regulatory frameworks should focus on managing the risks associated with speculative bubbles and synchronised market movements while leveraging stablecoins as a foundation for greater stability. Future research could further explore the interplay between traditional financial markets and CDAMs, offering deeper insights into their evolving dynamics and potential for integration.

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Web Resources

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http://www.coinmarketcap.com

http://www.coingecko.com

http://www.coindesk.com

http://www.bloomberg.com

http://www.forbes.com

Appendix | Ek

Appendix 1

Correlation Matrix

VAR.	BTC	BNB	ADA	AAVE	EGLD	ENJ	ETH	LINK	MANA	MKR	OM	RUNE	SAND	STX	THETA	USDT	XRP	XTZ
BTC	1,00	0,77	0,49	0,49	0,48	0,28	0,84	0,67	0,29	0,82	0,77	0,71	0,19	0,89	0,52	0,03	0,54	0,39
BNB	0,77	1,00	0,5	0,31	0,52	0,47	0,89	0,42	0,5	0,71	0,63	0,67	0,41	0,81	0,45	−0,06	0,57	0,3
ADA	0,49	0,5	1,00	0,83	0,81	0,7	0,65	0,77	0,5	0,72	0,14	0,79	0,36	0,47	0,81	0,15	0,83	0,86
AAVE	0,49	0,31	0,83	1,00	0,68	0,56	0,44	0,9	0,31	0,73	0,2	0,75	0,16	0,38	0,88	0,23	0,72	0,83
EGLD	0,48	0,52	0,81	0,68	1,00	0,75	0,67	0,69	0,8	0,55	0,08	0,73	0,69	0,52	0,69	0,16	0,74	0,85
ENJ	0,28	0,47	0,7	0,56	0,75	1,00	0,55	0,54	0,77	0,54	−0,02	0,64	0,71	0,41	0,64	0,08	0,68	0,7
ETH	0,84	0,89	0,65	0,44	0,67	0,55	1,00	0,57	0,58	0,78	0,52	0,76	0,5	0,85	0,5	−0,01	0,68	0,46
LINK	0,67	0,42	0,77	0,9	0,69	0,54	0,57	1,00	0,34	0,82	0,36	0,85	0,18	0,58	0,85	0,19	0,77	0,82
MANA	0,29	0,5	0,5	0,31	0,8	0,77	0,58	0,34	1,00	0,33	−0,04	0,49	0,96	0,43	0,4	0,07	0,49	0,52
MKR	0,82	0,71	0,72	0,73	0,55	0,54	0,78	0,82	0,33	1,00	0,58	0,86	0,2	0,76	0,74	0,03	0,75	0,57
OM	0,77	0,63	0,14	0,2	0,08	−0,02	0,52	0,36	−0,04	0,58	1,00	0,37	−0,08	0,62	0,27	−0,04	0,17	0,08
RUNE	0,71	0,67	0,79	0,75	0,73	0,64	0,76	0,85	0,49	0,86	0,37	1,00	0,31	0,69	0,82	0,09	0,86	0,72
SAND	0,19	0,41	0,36	0,16	0,69	0,71	0,5	0,18	0,96	0,2	−0,08	0,31	1,00	0,36	0,22	0,04	0,32	0,38
STX	0,89	0,81	0,47	0,38	0,52	0,41	0,85	0,58	0,43	0,76	0,62	0,69	0,36	1,00	0,47	0,08	0,55	0,34
THETA	0,52	0,45	0,81	0,88	0,69	0,64	0,5	0,85	0,4	0,74	0,27	0,82	0,22	0,47	1,00	0,21	0,78	0,81
USDT	0,03	−0,06	0,15	0,23	0,16	0,08	−0,01	0,19	0,07	0,03	−0,04	0,09	0,04	0,08	0,21	1,00	0,1	0,21
XRP	0,54	0,57	0,83	0,72	0,74	0,68	0,68	0,77	0,49	0,75	0,17	0,86	0,32	0,55	0,78	0,1	1,00	0,75
XTZ	0,39	0,3	0,86	0,83	0,85	0,7	0,46	0,82	0,52	0,57	0,08	0,72	0,38	0,34	0,81	0,21	0,75	1,00

Appendix 2

Digital asset bubbles observed between 01.10.2020 and 29.07.2024

Number and Periods of Asset Bubbles										
		I	II	III	IV	V	VI	VII	VIII	IX
CCC	BTC	11.12.2023 (7 days)	04.03.2024-25.03.2024 (28 days)							
	ETH	10.05.2021 (7 days)	24.01.2022 (7 days)	11.12.2023 (7 days)	26.02.2024 (7 days)	04.03.2024-18.03.2024 (21 days)				
	USDT	There is not enough evidence for the existence of the bubble.								
	XRP	There is not enough evidence for the existence of the bubble.								
	BNB	1.01.2024 (7 days)	26.02.2024 (7 days)	04.03.2024-25.03.2024 (28 days)	22.04.2024-29.04.2024 (14 days)	6.05.2024 (7 days)	10.06.2024 (7 days)	8.07.2024 (7 days)		
	ADA	There is not enough evidence for the existence of the bubble.								
NFT	THETA	13.11.2023 (7 days)	11.12.2023 (7 days)	25.12.2023 (7 days)	04.03.2024-25.03.2024 (28 days)					

Number and Periods of Asset Bubbles										
		I	II	III	IV	V	VI	VII	VIII	IX
	MANA	29.11.2021 (7 days)								
	XTZ	There is not enough evidence for the existence of the bubble.								
	ENJ	05.04.2021-19.04.2021 (21 days)	03.05.2021-10.05.2021 (14 days)	27.12.2021 (7 days)	06.03.2023-13.03.2023 (14 days)	1.01.2024 (7 days)	4.03.2024 (7 days)			
	LİNK	13.11.2023- 20.13.2023 (14 days)								
	SAND	08.11.2021- 29.11.2021 (28 days)								
DeFi	MKR	11.03.2024-25.03.2024 (21 days)								
	RUNE	5.04.2021 (7 days)	19.04.2021 (7 days)	21.08.2023 (7 days)	6.11.2023-27.11.2023 (28 days)	04.12.2023-11.12.2023 (14 days)	18.03.2024 (7 days)			
	STX	21.06.2021 (7 days)	20.02.2023-27.02.2023 (14 days)	13.3.2023-20.3.2023 (14 days)	4.12.2023 (7 days)	25.12.2023 (7 days)	8.01.2024 (7 days)	19.02.2024-26.02.2024 (14 days)	11.03.2024 (7 days)	25.03.2024 (7 days)
	OM	01.01.2024-19.02.2024 (56 days)	04.03.2024-25.03.2024 (28 days)	22.04.2024-10.06.2024 (56 days)	15.07.2024-22.07.2024 (14 days)					
	EGLD	There is not enough evidence for the existence of the bubble.								
	AAVE	There is not enough evidence for the existence of the bubble.								