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Cryptocurrencies in a Changing Financial Landscape: A Systematic Review

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Abstract. *2024 marks a significant milestone in integrating digital finance into the global financial landscape. The U.S. Securities and Exchange Commission's approval of Bitcoin and Ethereum ETFs signaled wider mainstream adoption. Shortly thereafter, Donald Trump's return to the presidency drove Bitcoin prices beyond $100,000. In light of these developments, we observe the rapid changes in cryptocurrency market prices, trends, and regulatory policies, which drive us to conduct a comprehensive review of cryptocurrencies asset's literature and examine its robustness.*

Our study covers several themes: how cryptocurrencies fit into broader asset allocation strategies, techniques to create crypto-based indexes, current debates over speculative bubbles, and the evolution of valuation models to highlight the dual aspects of market opportunities and risks.

Throughout our review, we compare previous studies with the latest data, seeking to determine which arguments continue to hold up and which require adjustment. Although digital assets have experienced multiple crashes, they often rebound more strongly than expected, making them a topic of intense debate among academics, regulators, and investors. We aim to assemble an organized summary of research findings, providing a comprehensive framework that unites historical evolution with recent shifts and future perspectives.

Keywords: Cryptocurrencies, Asset Allocation, Speculative Bubbles, Valuation Models, Index Construction, Digital Finance, Systematic Review.

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Introduction

Since the concept of Bitcoin was proposed by Nakamoto (2008), cryptocurrencies (CCs) have gradually become one of the most prominent emerging assets in the global financial markets. Built upon blockchain technology, Bitcoin emphasizes decentralization, immutability, and verifiability, sparking a wave of financial innovation. After years of development, Bitcoin and other alternative tokens have evolved from "virtual payment instruments" into a new form of investment assets.

The rapid emergence of CCs can be attributed not only to the innovations brought by blockchain technology but also to the critical role played by the global financial crisis in 2008 (Poskart, 2022). At that time, the traditional financial system was experiencing a severe trust crisis, and decentralized systems offered a transaction and bookkeeping model that did not require third-party endorsements (Zetzsche et al., 2020). Although the early use cases and user groups of CCs were relatively limited, as technology continued to evolve, exchanges and related infrastructure became more mature. The prices of many CCs, including Bitcoin, have experienced multiple significant fluctuations, bubble crushes, and bull-bear cycles, creating a market with multiple functions such as investment, speculation, risk hedging, and even payment methods.

In recent years, CCs have not only for a small group of speculators and have gradually gained acceptance from major investment institutions and market participants. Especially between 2020 and 2021, the COVID-19 pandemic increased the global demand for digital financial services. International financial institutions such as PayPal and MasterCard announced support for cryptocurrency payments. Furthermore, Elon Musk, the founder of Tesla, publicly endorsed Bitcoin and Dogecoin multiple times through social media, instantly boosting market sentiment. In 2024, the U.S. Securities and Exchange Commission (SEC) approved Bitcoin and Ethereum ETFs, symbolizing the deeper integration of CCs into the traditional financial system. Investors can allocate cryptocurrency assets through compliant and familiar financial product channels. This move not only signifies the further institutionalization and regulation of the cryptocurrency market but also makes it an unavoidable significant issue in the global financial market. At the end of 2024, Donald Trump was elected the 47th President of the United States. His policies, such as replacing part of the gold reserves with virtual currencies, appointing crypto-friendly regulators, and supporting legislation to ease licensing and compliance requirements for crypto firms, underscored a positive development for the CC industry. For instance, Bitcoin surged by 45% following Trump's election, with its price surpassing $100,000.

Since the advent of Bitcoin, its price has experienced multiple instances of skyrocketing by several times or even hundreds of times within a short period, as well as significant crashes and substantial declines. Such extreme and rapid volatility is a field that requires in-depth exploration for investors and researchers alike. Return analysis encompasses a wide range of areas, including but not limited to:

Asset Allocation and Portfolio Management: As CCs have increasingly gained attention in the mainstream financial market, more and more investors have started to incorporate them into their asset allocation strategies. What is the correlation between CCs and traditional assets such as stocks, bonds, and gold? How should their allocation weights in investment portfolios be determined? Can they achieve significant risk diversification and return enhancement? These questions have been widely studied in recent years, with various methodologies proposed. Considering factors such as rapidly changing markets, evolving regulatory measures, and trading structures, this paper aims to combine the latest market data to reassess the findings of existing literature to verify their robustness.

Index Construction: Index construction plays a pivotal role in capturing the dynamic behavior, overall performance, and inherent risk characteristics of the CC market. Over time, several indices, such as the CRIX (Trimborn and Härdle, 2018), VCIRX (Kim et al., 2021), and CRRIX (Ni et al., 2020), have been developed to serve as benchmarks for monitoring market trends and for use in portfolio management. In addition, well-designed indices help regulators and market participants assess shifts in investor sentiment and the impact of policy changes on market stability.

Market Efficiency and Speculative Bubbles in the CCs Market: The volatility of the cryptocurrency market is several times that of traditional finance (Ankenbrand and Bieri, 2018). Cryptocurrency prices are influenced not only by global economic conditions and market sentiment but also are easily affected by social media, celebrity endorsements (ZUO et al., 2024), or political factors such as regulatory laws and geopolitical conflicts (Ullah et al., 2024), making the market extremely sensitive to information. Additionally, many past studies have discussed the "bubble" phenomenon in CCs, arguing that they do not possess sufficient intrinsic value support, and investors mainly engage in speculation driven by heightened market sentiment (Haykir and Yagli, 2022; Enoksen et al., 2020; Wang and Vergne, 2017).

Impact of Regulatory Issues on CC Returns: There is a very close linkage between the price trends of CCs and regulatory policies. Financial regulatory authorities in the United States (SEC), the European Union, China, and other major countries have continuously introduced regulations or guidance regarding the cryptocurrency market (Frediani, 2024). These policies, such as anti-money laundering measures, security tokens, licensing, and compliance management, often affect investors' confidence in the market (Chokor and Alfieri, 2021). Additionally, news events or legislative changes can instantly cause severe market fluctuations, leading to significant swings in cryptocurrency returns within short periods. Therefore, the uncertainty brought by regulatory issues is also one of the important factors affecting cryptocurrency returns.

Overall, our systematic review provides a comprehensive framework that connects the historical evolution of CC returns with recent market trends. The remainder of the paper is organized as follows: Section 2 reviews the literature, Section 3 examines asset allocation with CCs, Section 4 discusses index construction of CCs, Section 5 analyzes speculative bubbles, and Section 6 concludes the study. Data, code, and regular updates for this paper are available at Quantlet ; the Quantinar platform offers further media content for this research.

Literature review

Recent advancements in cryptocurrency research have aimed to address pressing challenges and reveal complex market behaviors. In the domain of market bubble prediction, one study leverages the Log-Periodic Power Law Singularity (LPPLS) model to enhance accuracy in forecasting Bitcoin bubbles and crashes. Traditional approaches using daily price data often fail during periods of rapid price fluctuation, particularly in detecting short-term positive bubbles. To address these limitations, researchers introduced an adaptive multilevel time series detection methodology employing finer time intervals, such as one hour and 30 minutes, which significantly improves sensitivity to short-term volatility while preserving long-term stability. The study demonstrated that the LPPLS model effectively diagnoses bubbles and predicts crashes in real time, capturing the volatile dynamics of Bitcoin. This dual-scale analysis provides actionable insights into the cryptocurrency market and has broader implications for financial sectors facing similar instability (Shu and Zhu, 2020).

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Complementing this, another investigation explores speculative tendencies in cryptocurrency markets by examining the phenomenon of lottery-like demand, a behavior previously identified in equity markets. Using weekly data from 20 CCs between 2016 and 2019, the study adapts the MAX-effect framework to sort assets based on extreme daily returns and evaluate their subsequent performance. Results show a significant and economically substantial negative relationship between maximum returns and subsequent weekly returns, with high-MAX CCs underperforming their low-MAX counterparts by 1.54% per week. These findings confirm the presence of speculative patterns in digital asset markets, analogous to those observed in equity markets, offering critical insights into portfolio strategies and cross-sectional asset pricing (Grobys and Junttila, 2021).

The impact of financial crises, particularly the COVID-19 pandemic, on cryptocurrency and traditional safe-haven assets has been another focal point of recent research. A study investigates the shifting roles of assets like gold, Bitcoin, forex currencies, and commodities during this period of unprecedented market turmoil. Employing sequential monitoring procedures and cross-quantilogram analysis, the researchers assessed changes in asset return behaviors before and during the pandemic. The findings reveal that while Bitcoin and crude oil lost their effectiveness as safe havens, gold and soybean commodity futures maintained their robustness, underscoring the dynamic nature of safe-haven assets and their dependence on market-specific factors during crises (Ji et al., 2020).

Parallel to this, the structural complexity of cryptocurrency markets has been studied in relation to traditional systems like Forex. Advanced statistical physics methods, such as multifractal cross-correlation analysis and q-dependent detrended coefficients, were applied to analyze high-frequency data from 100 CCs. Findings indicate that while cryptocurrency markets exhibit complexity characteristics similar to Forex at the individual time-series level, they differ significantly in cross-correlations, showing slower information flow and more frequent arbitrage opportunities. The COVID-19 pandemic further highlighted a phase transition, where CCs shifted from acting as hedging assets to integrating with traditional financial instruments, signaling their growing maturity as an investment class (Watoreka et al., 2021).

The stability of algorithmic stablecoins has come under scrutiny, particularly in the wake of the Terra-Luna collapse in May 2022. A detailed analysis of this event highlighted its reliance on the Anchor protocol and the cascading effects of its failure on the broader cryptocurrency market. Using systematic reviews of news, hourly price data, and network science techniques, researchers identified speculative selling pressures, a liquidity pool attack, and the unsustainable high-interest mechanism of the Anchor protocol as key contributors to the collapse. Despite interventions like reserve deployments, the erosion of community trust and the interconnected dynamics between Terra and Luna tokens accelerated the market downturn. These findings emphasize the fragility of algorithmic stablecoins and the systemic risks they pose, underscoring the need for robust regulatory frameworks and intrinsic asset value to safeguard against similar failures in the future (Briola et al., 2023).

The drivers of cryptocurrency valuation and market dynamics have been another area of significant exploration. A comprehensive empirical analysis identifies key factors influencing returns, including user adoption metrics such as wallet users and transaction volumes, while minimizing the role of production costs like electricity and hardware. Findings reveal strong time-series momentum and the predictive power of investor attention, with higher attention correlating with increased returns. Additionally, CCs show minimal correlation with traditional asset classes, emphasizing their distinct investment behaviors and suggesting that network and behavioral factors play a more significant role in shaping their valuation than production or external market forces (Liu and Tsyvinski, 2021).

Similarly, inefficiencies in arbitrage within cryptocurrency markets have been highlighted. By analyzing tick-level data from 34 exchanges between January 2017 and February 2018, a study documented significant price discrepancies across regions, particularly between countries with tighter financial restrictions like Korea and Japan, compared to regions like the US and Europe. These arbitrage inefficiencies were quantified, revealing potential profits exceeding 1 billion dollars during periods of high trading volume. The findings underscore the structural barriers to arbitrage mechanisms in cryptocurrency markets, emphasizing their complexity and inherent price inefficiencies (Makarov and Schoar, 2020).

Advances in trading technologies have also been pivotal in understanding cryptocurrency market dynamics. A study comparing Zero/Minimal Intelligence (ZI/MI) and Computational Intelligence (CI) trading agents highlighted the superior performance of CI agents during volatile periods. The introduction of GGSMZ, a neuro-fuzzy trading agent, demonstrated the ability to adapt to market dynamics effectively, outperforming existing models in various conditions. These findings provide valuable tools for investors and trading systems to navigate financial bubbles in cryptocurrency markets (Guarino et al., 2022).

Cryptocurrency pricing mechanisms have been further explored through a general equilibrium framework that integrates fundamental transactional benefits with extrinsic volatility driven by speculative behaviour. Analyzing Bitcoin prices and transaction data, researchers found that equilibrium prices are influenced by intrinsic and extrinsic factors, with speculative coordination accounting for the majority of market volatility. This dual influence underscores the complex interplay between speculative behavior and fundamental value in shaping cryptocurrency prices (Biais et al., 2023).

Finally, the emerging DeFi market has been analyzed for its distinct behavior and role as a separate asset class. Using econometric tools, a study identified distinct bubbles in DeFi tokens, such as Maker and Chainlink, and their limited influence from Bitcoin and Ethereum. These findings emphasize the importance of including DeFi tokens in diversification strategies and highlight their unique dynamics within the cryptocurrency ecosystem (Corbet et al., 2023).

To further understand cryptocurrency market dynamics, the cusp catastrophe model has been employed to integrate fundamental drivers like on-chain activity and macroeconomic factors with speculative elements such as investor attention and off-chain activities. Analyzing data from Bitcoin, Ethereum, Litecoin, XRP, and Dogecoin, the study revealed that all CCs except Dogecoin exhibit complex price dynamics shaped by these interactions. These findings highlight the interconnectedness of cryptocurrency and traditional financial markets and emphasize the necessity of incorporating both intrinsic and extrinsic factors in forecasting and risk management strategies (Kukacka and Kristoufek, 2023).

Asset Allocation with Cryptocurrencies

Before integrating CCs into asset allocation strategies, it is essential to verify whether these digital assets are statistically distinct from classical assets. In other words, one must first test the hypothesis that CCs represent an alternative asset class. Pele et al. (2023) adopt an empirical approach that begins with reducing the dimensionality of a comprehensive dataset of risk indicators derived from daily log returns. In their study, a total of 24 risk indicators are introduced, which include standard measures such as variance, skewness, and kurtosis, as well as additional parameters obtained via advanced methods like FIGARCH that capture long-memory effects and volatility clustering. (Mensi et al., 2019) Subsequently, Factor Analysis is applied to the high-dimensional dataset, based on eigenvalue criteria, three factors are selected that account for approximately 88% of the total variance, corresponding to the tail, memory, and moment dimension. Figure 1 illustrates the scree plot of the factor analysis, highlighting the dominance of the first three factors, while Figure 2 demonstrates the factor loadings of these 24 risk indicators.

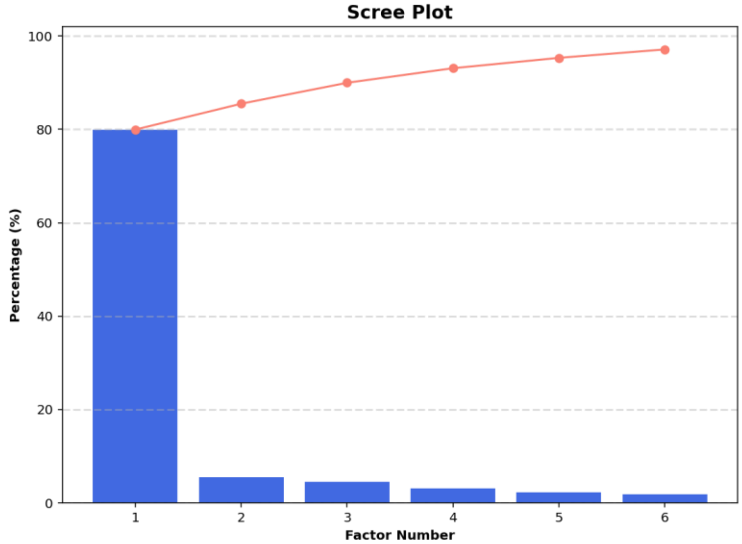

Figure 1. Scree Plot

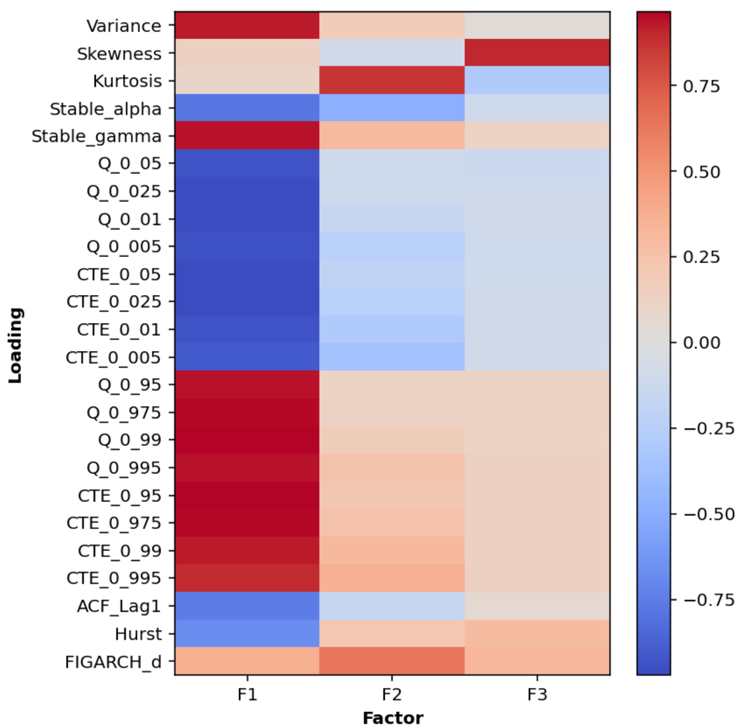

Figure 2. Loadings of the three factors

Our results, obtained by replicating the methodology with an updated dataset spanning from June 2017 to January 2025, reveal that the selected three factors account for 90% of the total variance, each factor accounts for 74.2%, 10.2%, and 5.6% of the total variance, respectively. This clearly indicates that the tail factor is overwhelmingly dominant, capturing the heavy-tailed behavior of CC returns, while the memory and moment factors add supplementary explanatory power. In addition, a dynamic analysis using an expanding window approach further reinforces the robustness of these findings. Figure 3 illustrates how the evolving asset universe projects the evolving asset universe onto the extracted factor space over successive time intervals. The analysis demonstrates that CCs consistently converge toward a distinct region. This synchronic evolution is indicative of their persistent heavy-tailed behavior and overall stability in classification. The empirical evidence from our replication establishes a robust statistical foundation for classifying CCs as an alternative asset class.

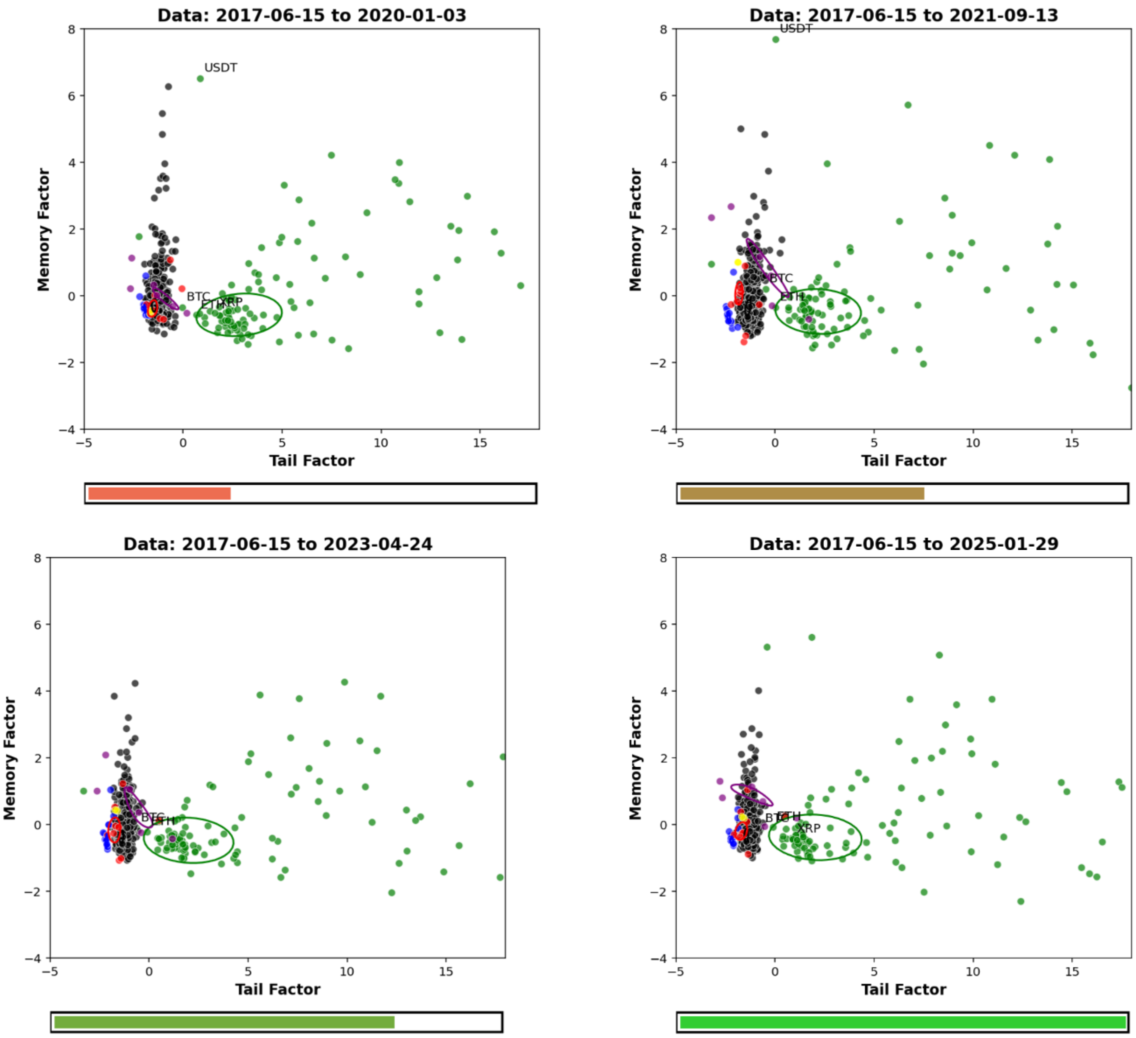

Figure 3. The dynamics of the asset universe with CCs, stocks, commodities, foreign exchange, bonds, real estate

Building upon this framework, we revisit the asset allocation potential of CCs by updating and reproducing the seminal analysis of Ankenbrand and Bieri (2018). In this research, the authors evaluated CCs as an individual assets class by analyzing their risk/return characteristics. The original study covered a sample period from April 2013 to mid-August 2018 and used proxies for various asset classes including CCs, stocks, commodities, bonds, and foreign exchange (FX). The researchers

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constructed a Laspeyres-type index, $CCI(t)$ to represent the overall CC market and applied portfolio optimization methods to assess diversification benefits and risk-adjusted performance.

The cryptocurrency index at time t is defined as:

$$CCI(t) = K(T) \cdot \frac{\sum_{i=1}^{n} p(i,t) \cdot q(i,T)}{\sum_{i=1}^{n} p(i,0) \cdot q(i,0)} \cdot 100$$

where $K(T)$ is the chain factor at the date of the last index adjustment T, $p(i,t)$ is the price of CC i at time t, $q(i,T)$ is the index weight of CC i at the last adjustment date T, $p(i,0)$ and $q(i,0)$ are the price and index weight of CC i at the base date, respectively, and n is the total number of CCs included in the index.

The index is calculated on a weekly basis. Whenever the index composition changes, the weights are rebalanced and a new chain factor, K(T), is computed as:

$$K(T) = \frac{K(T_{old}) \cdot \dfrac{\sum_{i=1}^{n} p(i,T-1) \cdot q(i,T_{old})}{\sum_{i=1}^{n} p(i,0) \cdot q(i,0) \cdot 100} \cdot 100}{\dfrac{\sum_{i=1}^{n} p(i_{new},T-1) \cdot q(i_{new},T)}{\sum_{i=1}^{n} p(i_{new},0) \cdot q(i_{new},0)} \cdot 100}$$

where T_{old} denote the dates of the previous index adjustment and i_{new} represents the newly included component in the index at date T.

In our updated analysis, we replicate the methodology of the original study while extending the sample from April 2013 to January 2025. Table 1 presents the comparison between the original and updated annual risk/return profiles for the asset classes. In contrast, CC market continues to show higher average returns and volatility.

Table 1. Annual risk/return profiles of established asset classes and CCs

Asset Class	Average Return	St. Dev.	Sharpe Ratio	Max. Drawdown	Weeks to Recovery
Apr. 2013 to mid-Aug. 2018					
Cryptocurrencies	130.81%	89.43%	1.45	-79.17%	96
Stocks	10.72%	11.30%	0.86	-12.31%	21
Commodities	-9.88%	11.57%	-0.94	-46.77%	Not yet recovered
Bonds	2.17%	3.34%	0.36	-4.52%	35
Foreign Exchange	4.21%	4.72%	0.69	-7.16%	Not yet recovered
Apr. 2013 to Jan. 2025					
Cryptocurrencies	72.82%	76.99%	0.93	-83.84%	105
Stocks	11.95%	15.50%	0.67	-33.04%	21
Commodities	-1.94%	13.26%	-0.26	-56.65%	Not yet recovered
Bonds	1.40%	4.27%	-0.04	-18.30%	Not yet recovered
Foreign Exchange	2.79%	5.08%	0.24	-12.58%	68

Source: Authors' own research.

Table 2 shows the updated correlation matrix among the asset classes for the extended period. The matrix indicates that the correlation between CCs and other traditional asset classes remains very low, underscoring the diversification benefits that CCs may provide in a multi-asset portfolio, thereby reaffirming their role as an individual asset class.

Table 2. Correlation matrix of asset classes

Asset Class	Stocks	Bonds	Commodities	Foreign Exchange	Cryptocurrencies
Apr. 2013 to mid-Aug. 2018					
Stocks	1.00	-	-	-	-
Bonds	-0.17	1.00	-	-	-
Commodities	0.26	-0.05	1.00	-	-
Foreign Exchange	-0.19	-0.38	-0.44	1.00	-
Cryptocurrencies	0.05	-0.02	0.00	0.02	1.00
Apr. 2013 to Jan. 2025					
Stocks	1.00	-	-	-	-
Bonds	0.18	1.00	-	-	-
Commodities	0.33	-0.03	1.00	-	-
Foreign Exchange	-0.47	-0.39	-0.40	1.00	-
Cryptocurrencies	0.17	0.02	0.13	-0.08	1.00

Source: Authors' own research.

Figure 4 illustrate the comparison of efficient frontiers and portfolio performance for two periods. The results indicate that although the portfolio including CCs is accompanied by higher volatility, its excess returns are more significant after risk adjustment, thus demonstrating a higher Sharpe ratio. This indicates that the portfolio has achieved a better balance between risk and return.

Index Construction of Cryptocurrencies

The construction of CC indices is essential for capturing the dynamic behavior, risk characteristics, and overall market evolution of the crypto ecosystem. These indices serve not only as benchmarks for performance evaluation and investment strategies but also as tools for risk management and regulatory analysis.

Among the various methodologies developed in the literature, the CRIX and VCRIX series are one of the earliest comprehensive indices developed to represent the CC market. The CRIX index, introduced by (Trimborn and Härdle, 2018), represents the overall CC market through a dynamic selection of constituents. Its construction relies on model selection criteria such as the Akaike Information Criterion (AIC), which is minimized as,

$$\mathrm{AIC} = 2k - 2\log\left(\hat{L}\right)$$

where k is the number of parameters and $\hat{L}$ is the maximized likelihood of the model. This approach ensures that only CCs contributing significant informational value are included.

Building upon CRIX, Kim et al. (2021) extend this framework to construct VCRIX, a volatility index similar to the VIX in equity markets. VCRIX employs the Heterogeneous Auto-Regressive (HAR) model to forecast future volatility. Let RV_t^d be the daily realized volatility at time t,

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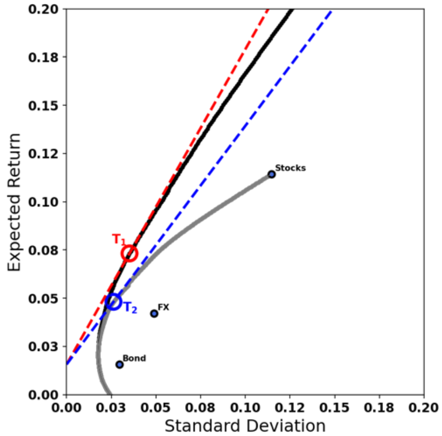
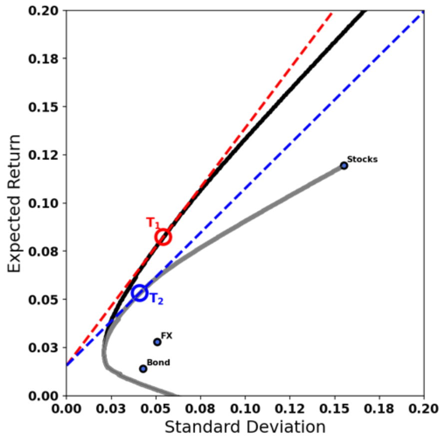
Apr. 2013 to mid-Aug. 2018



	Including CC	Excluding CC
Expected Return	0.069	0.043
Standard Deviation	0.028	0.021
Sharpe Ratio	2.10	1.58
Asset Allocation		
Crypto	0.021	-
Stock	0.149	0.158
Commodity	0.000	0.000
FX	0.379	0.392
Bond	0.451	0.450

Apr. 2013 to Jan. 2025



	Including CC	Excluding CC
Expected Return	0.082	0.053
Standard Deviation	0.054	0.041
Sharpe Ratio	1.233	0.919
Asset Allocation		
Crypto	0.047	-
Stock	0.242	0.288
Commodity	0.000	0.000
FX	0.633	0.645
Bond	0.077	0.067

* The average 3-month treasury bill rate has been utilized as a proxy for the risk-free rate.

Figure 4. Efficient frontiers and portfolio performance comparison including and excluding the cryptocurrency market.

Source: Authors' own research.

$$RV_t^w = \frac{1}{7}\sum_{j=1}^{6} RV_{t-j}^e$$

$$RV_t^m = \frac{1}{30}\sum_{j=0}^{29} RV_{t-j}^d$$

$$RV_{t+1}^d = \alpha + \beta^d RV_t^d + \beta^w RV_t^w + \beta^m RV_t^m + \varepsilon_{t+1}$$

where $\alpha, \beta^d, \beta^w, \beta^m$ are parameters to be estimated, and ε_{t+1} is the error term. Together, CRIX and VCRIX provide a robust framework for tracking market performance and risk in a highly volatile environment.

An alternative approach to constructing a cryptocurrency index is based on Principal Component Analysis (PCA), as proposed by y Shah et al. (2021). In this method, both the number of constituents and their weights are determined dynamically by extracting the dominant common

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factor—namely, the first principal component, PC_1, from the return matrix of selected CCs. Specifically, define the aggregator a_t as

$$a_t = \sum_{i=1}^{n_c} PC_{1,i} M_{t,i}$$

where $M_{t,i}$ is the market capitalization of the i-th CC on day t and n_c is the number of constituents. Let a_{base} denote the value of a_t in the base period. Then, the PCA-based index is constructed as

$$I_{\text{PCA},t} = \frac{a_t}{a_{\text{base}}} \times m$$

with m being a multiplier that sets the initial scale of the index and is updated periodically. By capturing the largest share of return variance, the PC_1-based index effectively reflects the dominant market dynamics and serves as a complementary alternative to traditional market cap-weighted or volatility-focused indices.

In addition, regulatory changes exert a profound influence on the cryptocurrency market. To quantify this impact, Ni et al. (2020) propose the Cryptocurrency Regulatory Risk Index (CRRIX) using advanced machine learning techniques. In their framework, policy-related news articles are systematically collected from leading online CC platforms. These articles are then classified into regulatory-relevant and non-regulatory categories by applying methods such as Latent Dirichlet Allocation (LDA) and support vector machines (SVM). The CRRIX is then computed as the ratio of the frequency of regulatory-related news to the total number of news items, thereby capturing the level of regulatory uncertainty affecting market dynamics.

$$\text{CRRIX}_t = \frac{N_{t,\text{reg}}}{N_{t,\text{all}}}$$

where $N_{t,\text{reg}}$ is the count of regulatory news at time t and $N_{t,\text{all}}$ is the total news count. Empirical analysis demonstrates that CRRIX effectively tracks major regulatory events and correlates significantly with market volatility, and peaks in CRRIX coincide with abrupt price changes in CCs. These findings underscore the utility of the index in risk management and regulatory assessment.

Speculative Bubbles in Cryptocurrencies

Speculative bubbles in CCs occur when prices increase very rapidly and exceed fundamental values, then crash. In Wheatley et al. (2019), the authors examine whether CCs behave like alternative assets, focusing on price and user activity. This study demonstrates that network effects driven by user behavior and trading sentiment can trigger significant price fluctuations. When market enthusiasm is high, prices may exceed fair value and form a bubble. Later, these bubbles often burst, leading to rapid price declines.

The authors establish a basic BTC value estimation model based on data from 17 July 2010 to 26 February 2018. We further replicated their study using daily data on BTC prices, market capitalization, and the number of unique active addresses from January 2010 to January 2025. This model is based on the generalized Metcalfe's Law and employs log-linear regression to quantify the relationship between BTC market capitalization and the number of unique active addresses.

$$p = e^{\alpha} u^{\beta}$$

where p and u denote the market capitalization and the number of unique active addresses, respectively; α and β are coefficients, with the original Metcalfe's Law suggesting that $\beta = 2$. As shown in Figure 5, we observe a strong log-linear relationship. The authors estimate the relevant parameters using a log-linear regression model based on the generalized Metcalfe's Law,

$$\log(p) = \alpha + \beta \log(u) + \varepsilon$$

where ε is the error term.

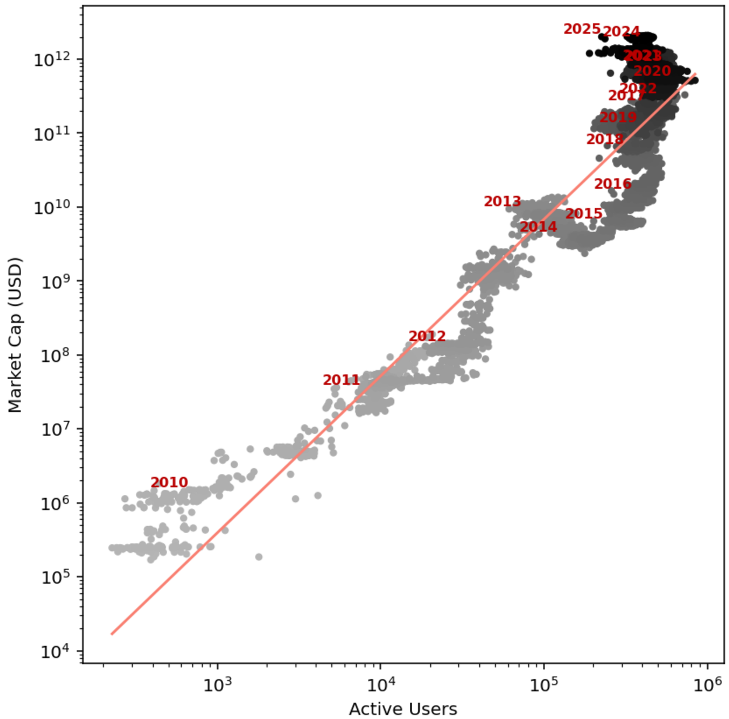

Figure 5. Relationship between Bitcoin's market capitalization and the number of unique active addresses. The red line is the fitted curve based on the generalized Metcalfe's Law

Source: Authors' own research.

In contrast to the original Metcalfe's Law, when applied to BTC market data, the authors obtain estimates of (α, β) as $(1.51, 1.69)$. In our extended dataset, we obtained updated estimates of (α, β) as $(-1.75, 2.12)$.

The authors further define the Market-to-Metcalfe value (MMV) ratio,

$$\mathrm{MMV}_i = \frac{p_i}{e^{\alpha} u_i^{\beta}}$$

which is the market capitalization at time i divided by the market capitalization predicted by the generalized Metcalfe's Law support level. Based on the MMV ratio, we have identified six major Bitcoin bubbles. Table 3 shows the start dates, durations, and associated market capitalization values of the bubbles, while Figure 6 depicts the dynamic evolution of the MMV ratio.

Our updated review confirms that CCs still experience speculative bubbles, as identified by the MMV ratio. By extending the dataset to January 2025, we observe that speculative cycles persist, which underscores the importance of understanding network effects and investor behavior.

Conclusion

This paper examines the evolution of CC market dynamics, focusing on their role in asset allocation, the development of crypto-based indices, and the impact of speculative bubbles. Our findings confirm that CCs maintain a low correlation with traditional assets, offering potential diversification benefits in portfolios. However, extreme price swings still occur, driven by factors such as user adoption, regulatory announcements, and market sentiment.

Table 3. Six major Bitcoin bubble periods

Index	Start	End	Days	M-Cap$_0$	M-Cap$_1$	Growth	Mean Return
1	2012-06-10	2014-01-15	584	5.10×10^7	1.00×10^{10}	202.938	0.009
2	2016-01-20	2018-03-10	780	5.70×10^9	1.60×10^{11}	28.222	0.004
3	2019-03-20	2019-08-20	153	7.00×10^{10}	1.81×10^{11}	2.581	0.006
4	2020-07-01	2021-06-27	361	1.68×10^{11}	6.48×10^{11}	3.865	0.004
5	2022-12-10	2023-05-20	161	3.29×10^{11}	5.19×10^{11}	1.579	0.003
6	2023-09-15	2025-02-02	506	5.17×10^{11}	2.01×10^{12}	3.887	0.003

Source: Authors’ own research.

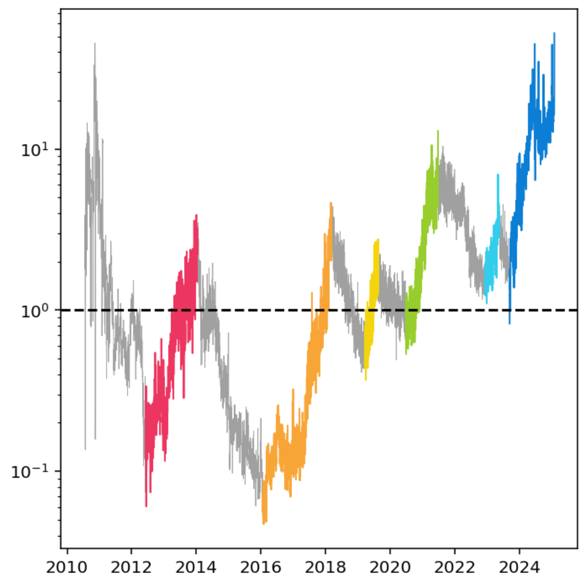

Figure 6. BTC MMV ratio over time. The bubbles are coloured and given in table 3

Source: Authors’ own research.

Extended data reveal that CCs, although highly volatile, continue to exhibit strong returns over time. This makes them attractive to investors willing to accept higher risk in exchange for potential gains. Crypto indices, such as CRIX, VCRIX and CRRIX, can capture different dimensions of the market, including overall performance, volatility, and policy risks. Speculative bubbles are still an important part of the CC landscape. The Market-to-Metcalfe value (MMV) ratio highlights how price surges often outpace fundamental network growth. When prices exceed these fundamental levels, investors face significant crash risk.

In summary, CCs remain a distinct and fast-evolving asset class. Their integration into mainstream finance will likely deepen in the coming years. Understanding both their opportunities, such as portfolio diversification, and their risks, like speculative bubbles, can help market participants make better decisions.

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