Financial Innovation

RESEARCH

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Bitcoin as a financial asset: a survey

Daeyun Kang[1], Doojin Ryu[1*] and Robert I. Webb[2*]

*Correspondence:
sharpjin@skku.edu;
riw4j@virginia.edu

[1] Department of Economics, Sungkyunkwan University, Seoul, Korea
[2] McIntire School of Commerce, University of Virginia, Charlottesville, VA, USA

Abstract

Since its introduction as a decentralized digital currency for peer-to-peer transactions, Bitcoin's role in financial markets has undergone significant evolution. We employ bibliometric analysis to explore research trends in Bitcoin, identifying two primary perspectives in the recent financial economic literature: Bitcoin as a *speculative* asset and as a *safe-haven* asset. The speculative nature of Bitcoin is evident through its high volatility and frequent price jumps, largely influenced by rapid shifts in investor sentiment and attention, which create both risks and opportunities for traders. Conversely, Bitcoin exhibits characteristics of a safe-haven asset due to its asymmetric tail dependence and negative correlation within certain asset classes.

Keywords: Bibliometrics, Bitcoin, Safe haven, Speculation, Survey

JEL Classification: D84, G11, G15

Introduction

Satoshi Nakamoto introduced Bitcoin, a new virtual currency (or cryptocurrency), in the whitepaper, "Bitcoin: A peer-to-peer electronic cash system." One of the key purposes is to facilitate "peer-to-peer" transactions without the need for either financial intermediaries or government sponsorship (Böhme et al. 2015; Son et al. 2022). This goal is achieved through blockchain technology (Lee and Ryu 2025; Son and Ryu 2024), prioritizing strong security and decentralization at the expense of scalability. For instance, the cryptocurrency market does not require a bank account or credit card to execute transactions, thereby minimizing both the need for financial intermediation and reducing transaction costs (Härdle et al. 2020; Son et al. 2023). Despite these benefits, Bitcoin has struggled to fulfill the traditional currency functions as a medium of exchange, a store of value, and a unit of account (Yermack 2015). Because of its emphasis on decentralization and the reduction of scalability, Bitcoin suffers from the disadvantage of slower processing speed compared to credit cards (Bonneau et al. 2015; Shahriar Hazari and Mahmoud 2020). As a result, it has mainly been classified as a financial asset rather than a currency or financial security (Kim et al. 2021a, b, c; Kwon 2021; Song et al. 2023; White et al. 2020; Zhu et al. 2017).

We examine the trends in Bitcoin research in finance by conducting a bibliometric analysis. Given the extensive research on Bitcoin and other virtual currencies, a comprehensive *qualitative* review of all studies is impractical. Therefore, using bibliometrics to analyze Bitcoin-related research in finance and economics *quantitatively* is useful for identifying key papers and keywords while reducing bias in the analysis (Firdaus et al. 2019; Guo et al. 2021). We summarize the asset characteristics of Bitcoin using key variables (volatility and high-frequency trading; long-range dependence; investor attention and sentiment; negative correlations with other assets; asymmetric tail dependence) and demonstrate how Bitcoin can be defined as a unique asset class, different from traditional asset groups like stocks, bonds, gold, and commodities.

We make several contributions. First, this study serves as a survey paper on Bitcoin in the field of finance, incorporating the latest data and employing bibliometric analysis. Given that Bitcoin has been studied across diverse domains such as engineering, economics, and finance, it is challenging to comprehensively review this vast body of research. Bibliometric analysis identifies trends and keywords systematically, addressing these challenges. While relying solely on bibliometric analysis for a survey paper can provide quantitative insights, it may have limitations in terms of accuracy and depth. To address this, we supplement bibliometric analysis by directly reviewing and organizing key studies, thereby addressing the existing research gap. Second, we provide a comprehensive summary of the scattered literature on the asset characteristics of Bitcoin. According to the literature, Bitcoin exhibits paradoxical features, simultaneously displaying traits of both speculative and safe-haven assets. Our findings can aid market practitioners and policymakers in making more informed decisions. For investors, the analysis highlights Bitcoin's potential as an asset for portfolio diversification and risk management. For policymakers, our results offer insights into the risks associated with Bitcoin, supporting deliberations on regulation or support measures. Third, our survey underscores Bitcoin's leading role in the cryptocurrency market, serving as a critical benchmark for studying and discussing other cryptocurrencies. Examining Bitcoin's characteristics lays the foundation for understanding other cryptocurrencies as a valuable reference. Fourth, we synthesize a wide range of analyses, models, timeframes, frequencies, and results from existing research to comprehensively understand Bitcoin's asset characteristics.

The rest of this study is organized as follows. The study begins with a section that discusses the "Research Background". This is followed by a section that describes the "Data and Methodology" employed in this study. The "Results" section that immediately follows presents the results of the bibliometric analysis, and the "Discussion" section explores the financial asset characteristics of Bitcoin based on the keywords identified. Finally, the implications for financial theory, financial management and regulatory policy from the study as well as the limitations and opportunities for future research are presented in the "Conclusions" section.

Research background

Bitcoin is widely perceived as a speculative asset due to its volatile price fluctuations even in the absence of new fundamental information. Indeed, Bitcoin's strong correlation with changes in investor sentiment often prompts sharp increases and decreases in its prices, leading to a self-reinforcing cycle. However, since the introduction of Bitcoin futures contracts on the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange Group (CME) in December 2017, some researchers argue that market efficiency and volatility have stabilized (Akyildirim et al. 2020; Aleti and Mizrach 2021;

Entrop et al. 2020; Fassas et al. 2020; Hu et al. 2020). Some market observers believe that Bitcoin can hedge price risks associated with other assets (Zulfiqar and Gulzar 2021) and is sometimes called 'Digital gold' because of this perceived attribute. This belief persists even though there is often little or no economic intuition for a stable relationship between changes in the price of Bitcoin and other speculative assets. From this perspective, Bitcoin could be regarded as a safe-haven asset that is advantageous for diversification and risk hedging in portfolio composition (Kajtazi and Moro 2019; Platanakis and Urquhart 2020). Beyond its similarities to gold, Bitcoin's long-term negative correlations with certain assets help diversify risks, its asymmetric tail dependence ensures stable returns in extreme market conditions, and the growing number of trading options for Bitcoin and other cryptocurrencies further enhances its appeal. The U.S. Securities and Exchange Commission (SEC) has recently approved 11 Bitcoin spot ETF applications after losing a court case. This development suggests that Bitcoin has evolved from being viewed merely as a speculative asset to being recognized as a legitimate financial instrument for many market participants. Therefore, by exploring the role of Bitcoin in the financial market and its potential for future development, this study aims to organize and present the perspectives put forward by various research studies.

Data and methodology

We use the Web of Science (WoS) database of Clarivate. Over the period from 2014 to 2024, we collect 2,349 papers with journal categories limited to "Business, Finance" OR "Business & Economics" OR "Economics," and the topic specified as "Bitcoin," to focus solely on Bitcoin research in the field of finance. Studies before this period are excluded due to the insufficient number of relevant papers. Using the R package bibliometrix 4.2.1, we extract data from the WoS dataset including the number of articles published per year, the number of articles per topic over the years, and the most frequently cited studies and employ Word Cloud analysis to identify key topics (Aria and Cuccurullo 2017). Co-occurrence, co-authorship, and co-citation analyses are conducted using VOSviewer software 1.6.20 (Almeida and Gonçalves 2023; Van Eck and Waltman 2010).

The bibliometric analysis uses quantitative methodologies to study bibliographic data, involving techniques such as data coupling and mapping for co-authorship, keyword co-occurrence, co-citation, etc., to visualize relationships among studies (Price 1965; Broadus 1987). By considering factors such as the journal, citation number, and impact factor of each study, it's also possible to identify key studies in a particular topic. Bibliometrics allows researchers to assess current research trends and predict potential research directions through quantitative analysis. It is predominantly used in engineering, computer science, and business economics, and recently, there has been active research in bibliometrics related to virtual currencies, closely associated with each field (Khan et al. 2022; Merediz-Solà and Bariviera 2019; Miau and Yang 2018). While bibliometric analysis may face challenges such as the exclusion of the most recent literature, potential biases in citation practices, and data errors (Wallin 2005), given the vast amount of research being conducted across numerous fields on Bitcoin and virtual currencies, it is impossible to review all the studies comprehensively. Therefore, using bibliometrics to quantitatively analyze Bitcoin-related research in the fields of finance and economics is essential. This methodology not only identifies key papers and major keywords but also analyzes the foundational framework and key ideas within a particular field (Donthu et al. 2021).

Results

Figure 1 shows a notable upward trend in the number of articles over time, especially from 2018 onwards, with a significant increase each year. This trend could indicate increased interest or activity in the topic or publication. As shown, all topics have experienced growth over the years, with the topics of "volatility," "gold," and "hedge" showing particularly steep increases. This suggests rising interest and relevance in these subjects over the given period.

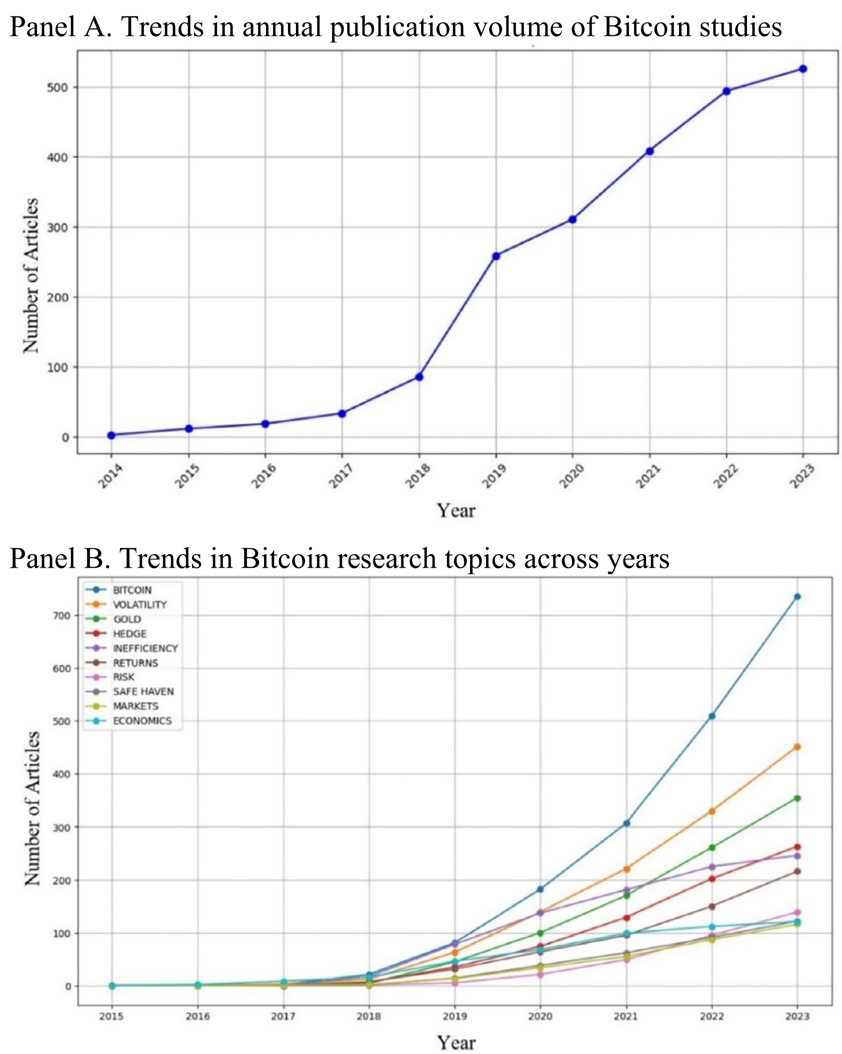

Fig. 1 Publication trends in Bitcoin and financial research. *Note:* This figure depicts annual publication trends in finance with Bitcoin as the topic. The *x*-axis represents the years, and the *y*-axis represents the number of articles. Panel **A** shows the number of articles published yearly from 2014 to 2023. Studies for 2024 have not yet been fully published, they have been excluded from the graph. Panel **B** shows the number of articles per topic over the years from 2015 to 2023. The main keywords are "volatility," "gold," "hedge," "inefficiency," "returns," "risk," "safe haven," "markets," and "economics." Research from the years 2014 and 2024 that included the keyword is insufficient, so it has been excluded from the graph

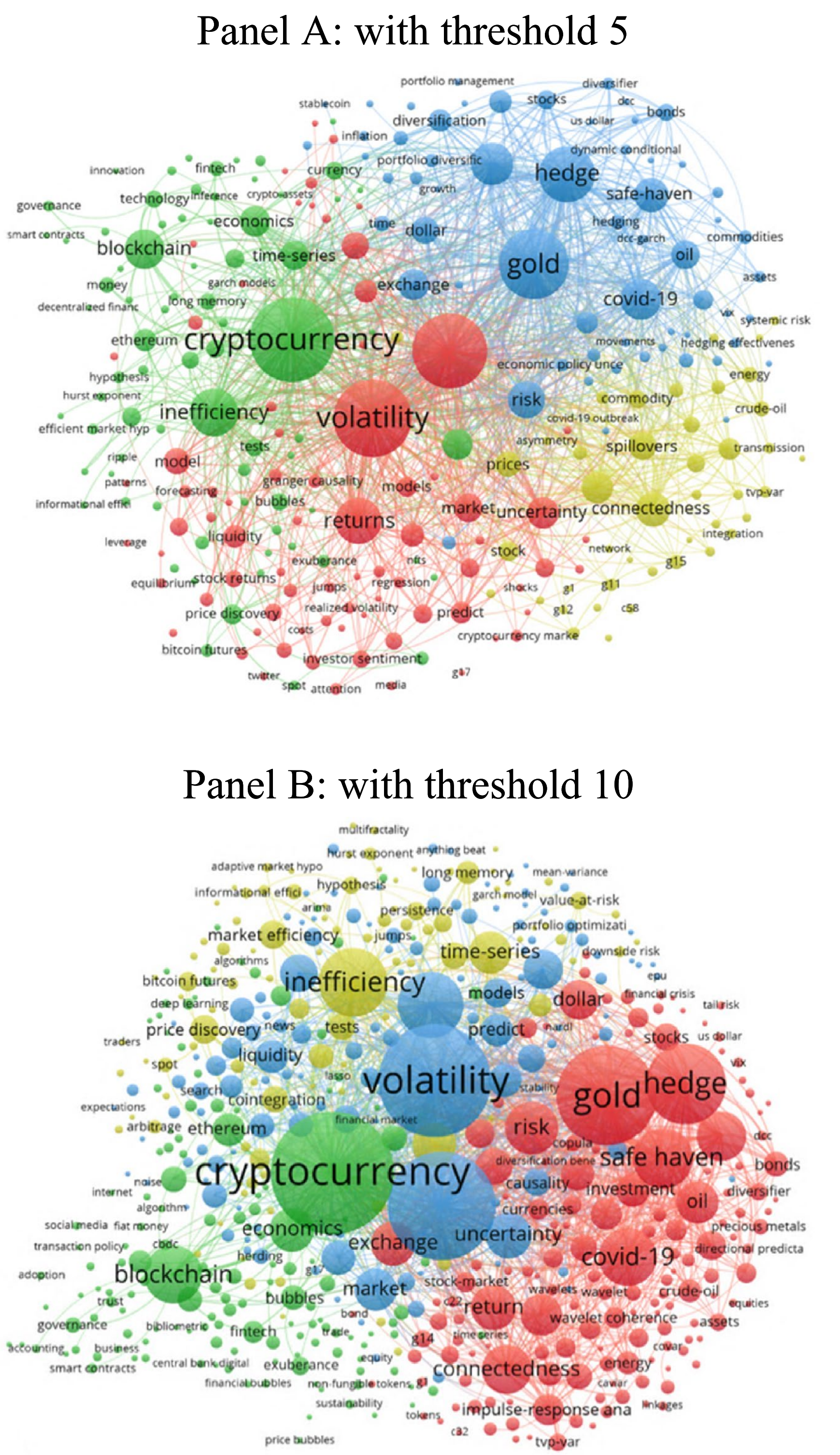

Fig. 2 Co-occurrence analysis. *Note:* This figure shows the results of co-occurrence analysis of the main keywords excluding Bitcoin in each study, with thresholds set at 5 and 10, respectively, out of 2,349 documents. Among 5,087 keywords, there are 527 with occurrences of 5 or more in Panel **A** and 259 with occurrences of 10 or more in Panel **B**. In the case of co-occurrence links, the strength of a link is calculated as the number of publications in which two terms occur together

By examining the clustering in Fig. 2, we can explore the relationships between keywords more thoroughly. Cluster 1 pertains to the principal themes of "cryptocurrencies," "volatility," "returns," and "uncertainty," which are accentuated in red, scrutinizing the fluctuating nature and potential financial outcomes of digital currencies amidst prevalent uncertainties. Cluster 2 is associated with the keywords "cryptocurrency," "inefficiency," and "blockchain," highlighted in green, exploring the inefficiencies inherent in cryptocurrency systems and the underlying technology of blockchain. Cluster 3 relates to the themes "gold," "hedge," and "safe haven," marked in blue, examining gold's role as a defensive asset that potentially shields against economic and market volatilities. Cluster 4 engages with "connectedness," "spillovers," and "impulse-response analysis," denoted in yellow, focusing on the interconnectedness within financial markets and the analysis of how market variables respond to external economic shocks.

Figure 3 depicts the scholarly association among Bitcoin research in the finance field. The co-authorship analysis is utilized to comprehend and analyze collaboration relationships among authors, examining the relationships between authors who have participated in joint research or co-authored works. The co-citation analysis involves analyzing the frequency with which papers or documents are cited together, identifying the most important authors or papers within a specific topic or research area, thereby facilitating the understanding of scholarly trends and developments. Table 1 presents the key documents in Bitcoin research within the finance field.

Discussion

When examining Bitcoin-related finance research and identifying major keywords, it becomes evident that exploring Bitcoin's asset characteristics is a primary trend in the field. Research typically divides these characteristics into two categories: speculation, primarily based on volatility, and safe-haven status in risk situations. Focusing on this theme, the study reviews key research on the topic and applies bibliometric tools such as Co-occurrence analysis, Co-authorship analysis, and Co-citation analysis to quantitatively analyze a large volume of studies. However, to address potential errors in quantitative analysis, the paper directly reviews and organizes the research findings to qualitatively complement the results. Through this approach, this study initiates a discussion on Bitcoin's asset characteristics.

Speculative nature of Bitcoin

Bitcoin's high volatility enables traders to gain or lose substantial amounts rapidly. Market participants will trade Bitcoin or its derivatives in the hope that their position will profit if prices rise if they are long or fall if they are short. In this section, we examine the speculative nature of Bitcoin as an asset. Research shows that the Bitcoin market deviates from the efficient market hypothesis, providing evidence through the long-term memory dependencies in time series and the strong correlation with investor sentiment. This indicates that the presence of long-term dependencies, showing that prices do not quickly reflect information and exhibit weak predictability, suggests that some speculative strategies that exploit this relationship might be more profitable than one

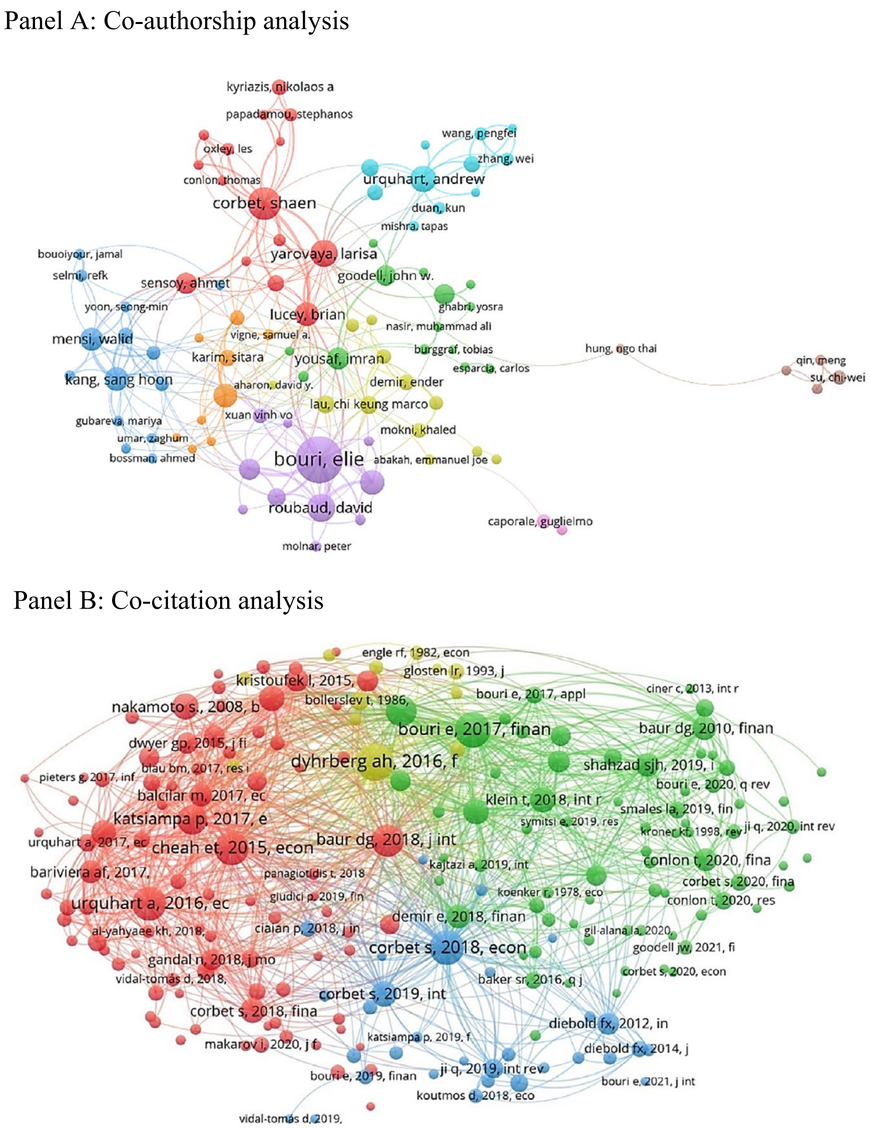

Fig. 3 Scholarly association. *Note:* This figure displays scholarly association. Panel **A** displays the results of the co-authorship analysis. It connects 144 authors who satisfy an author's minimum number of documents set to 5 out of a total of 4043 authors. The strength of the connections is determined by the number of publications two researchers have co-authored. Panel **B** visualizes the results of papers cited at least 50 times out of 44,506 references. Selected cited references comprise 201 documents, and the strength of the links is determined by the number of cited references the two publications have in common

would expect if the market were informationally efficient. Moreover, the close correlation between changes in sentiment indices and Bitcoin prices implies that Bitcoin can be influenced by changes in market participants' collective sentiment.

Volatility and high-frequency trading

Some studies warn that the extreme price movements of Bitcoin may contribute to *excessive speculation*. Bouoiyour and Selmi (2016) analyze Bitcoin volatility using extended Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) models across two periods, from December 1, 2010, to December 31, 2014, and from January 1, 2015,

Table 1 Key Bitcoin research in finance

References	Title	Journal	TC
Panel A. Most global cited documents: Total citations			
Dyhrberg (2016a)	Bitcoin, gold and the dollar—A GARCH volatility analysis	Finance Research Letters	770
Corbet et al. (2018)	Exploring the dynamic relationships between cryptocurrencies and other financial assets	Economics Letters	717
Urquhart (2016)	The inefficiency of Bitcoin	Economics Letters	698
Böhme et al. (2015)	Bitcoin: Economics, Technology, and Governance	Journal of Economic Perspectives	694
Bouri et al. (2017a, b)	Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions	Finance Research Letters	684
Cheah and Fry (2015)	Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin	Economics Letters	674
Baur et al. (2018)	Bitcoin: Medium of exchange or speculative assets?	Journal of International Financial Markets, Institutions and Money	603
Katsiampa (2017)	Volatility estimation for Bitcoin: A comparison of GARCH models	Economics Letters	552
Dyhrberg (2016b)	Hedging capabilities of bitcoin. Is it the virtual gold?	Finance Research Letters	510
Corbet et al. (2019)	Cryptocurrencies as a financial asset: A systematic analysis	International Review of Financial Analysis	503
References	**Title**	**Journal**	**NCS**
Panel B. Most local cited documents: Normalized citation score			
Corbet et al. (2019)	Cryptocurrencies as a financial asset: A systematic analysis	International Review of Financial Analysis	12.95
Fang et al. (2022)	Cryptocurrency trading: a comprehensive survey	Financial Innovation	9.80
Almeida and Gonçalves (2023)	A systematic literature review of investor behavior in the cryptocurrency markets	Journal of Behavioral and Experimental Finance	9.32
Urquhart and Zhang (2019)	Is Bitcoin a hedge or safe haven for currencies? An intraday analysis	International Review of Financial Analysis	9.09
Smales (2022)	Investor attention in cryptocurrency markets	International Review of Financial Analysis	6.09
Platanakis and Urquhart (2020)	Causality and dynamic spillovers among cryptocurrencies and currency markets	British Accounting Review	5.28
Elsayed et al. (2022)	Causality and dynamic spillovers among cryptocurrencies and currency markets	International Journal of Finance & Economics	4.77
Alexander and Dakos (2020)	A critical investigation of cryptocurrency data and analysis	Quantitative Finance	4.65
Kajtazi and Moro (2019)	The role of bitcoin in well diversified portfolios: A comparative global study	International Review of Financial Analysis	4.57
Sebastião and Godinho (2021)	Forecasting and trading cryptocurrencies with machine learning under changing market conditions	Financial Innovation	4.46

This table presents the most cited documents among financial research papers on Bitcoin. The table includes information on the researchers and publication years of the literature, along with the title, and journal name. Panel A shows the documents with the highest Total number of Citations (*TC*) globally, indicating the total number of citations each document has received worldwide. Panel B shows the most cited documents in order of high Normalized Citation Score (*NCS*). *NCS* is calculated locally by dividing the citation count of an individual document by the average citation count of documents published in the same field in the same year. Local cited documents refer to scoring based on only 2,349 papers to July 20, 2016. They find that Bitcoin's volatility is decreasing but still shows explosive tendencies like what is sometimes observed in some speculative asset markets. Gronwald (2019) notes it is striking that, despite the certainty in Bitcoin's short-term supply, the price fluctuations in the market are exceptionally severe. This suggests that the observed drastic price changes must be driven primarily by factors on the demand side. Scaillet et al. (2020) utilize the jump detection test of Lee and Mykland (2012) on high-frequency data to confirm the presence of jumps in the Bitcoin market. Through a probit regression model, they identify factors such as the order flow imbalance, the proportion of aggressive traders, and the bid-ask spread as determinants of price jumps. Their research demonstrates that the presence of aggressive investors may drive price jumps at the microsecond level, providing evidence for the speculative nature of the early Bitcoin market.

There is the potential for generating returns through high-frequency trading. Chu et al. (2019) use the consistent and integrated test (Domínguez and Lobato 2003; Khuntia and Pattanayak 2018) to demonstrate that the two major markets of Bitcoin and Ethereum follow the adaptive market hypothesis (Lo 2004) due to the varying linear and non-linear dependencies observed in high-frequency situations. This implies that the efficiency of the cryptocurrency market is not fixed but can change significantly based on the adaptation and learning of market participants. Chu et al. (2020) conduct a study exploring the feasibility of attaining surplus profits in seven prominent cryptocurrency markets (Bitcoin, Ethereum, Dash, Litecoin, MaidSafeCoin, Monero, and Ripple) through high-frequency momentum trading strategies. They employ two different approaches for momentum trading: a time series method and a cross-sectional method. The outcomes of their investigation demonstrate cumulative returns across all periods. However, considering that the study period coincides with a time when the prices of most cryptocurrencies were experiencing significant surges, there may be a bias related to the study period. Future research could address this issue by examining various periods. Bouri et al. (2021) forecast Bitcoin's cumulative intraday return curves using functional autoregressive models and functional principal component analysis. Their findings indicate that the curves of Bitcoin exhibit conditional heteroscedasticity, suggesting that opportunities for investment profits through intraday trading strategies can exist. Table 2 presents notable research papers concerning Bitcoin's volatility and high-frequency trading.

Long-range dependence

Many studies suggest that the early Bitcoin market, characterized by high long-range dependence, exhibited lower efficiency, but this inefficiency was expected to decrease over time. Urquhart (2016) conducts various tests to examine the efficiency of the Bitcoin market, including the Ljung–Box test (Ljung and Box 1978), Runs test (Wald and Wolfowitz 1940), Bartels test (Bartels 1982), Variance ratio test (Lo and MacKinlay 1988), Automatic variance test (AVR) proposed by Choi (1999), Wild-bootstrapped AVR test introduced by Kim (2009), BDS test (Broock et al. 1996), and Rescaled Hurst exponent (Hurst 1956). The sample is divided into two periods: 1st August 2010 to 31st July 2013, and 1st August 2013 to 31st July 2016. In the first period, they find that the Bitcoin market is inefficient, while in the second period, they discover that the market becomes efficient. Therefore, this study suggests that the Bitcoin market is gradually evolving towards

Table 2 Volatility and high-frequency trading

References	Method	Period	Frequency	Source
Yermack (2015)	Statistical analysis: Comparing volatility and correlation	Jul 2010 to Feb 2014	Daily	Bitcoincharts.com
Bouoiyour and Selmi (2016)	GARCH-M, C-GARCH, I-GARCH, T-GARCH, E-GARCH, P-GARCH, A-PARCH, CMT-GARCH	Dec 2010 to Jul 2016	Daily	Blockchain.info
Gronwald (2019)	GARCH, I-GARCH, E-GARCH, T-GARCH	Jul 2011 to Jan 2019	Daily	Mtgox.com Bitstamp.net
Scaillet et al. (2020)	Jump detection test Probit regression	Jun 2011 to Nov 2013	Intraday (5-min)	Mtgox.com
Chu et al. (2019)	MDH test proposed (Domínguez and Lobato 2003; Khuntia and Pattanayak 2018)	Jul 2017 to Sep 2018	Intraday (1-h)	Cryptocompare.com
Chu et al. (2020)	Momentum trading strategies	Feb 2017 to Aug 2017	Intraday (5-min)	Cryptocompare.com
Bouri et al. (2021)	Forecasting CIDR curves Functional autoregressive-typed models Functional principal component analysis	Jan 2014 to Aug 2019	Intraday (5-min)	Kaggle.com

This table presents key studies related to volatility and high-frequency trading in Bitcoin. The table includes information on the researchers (*Author*) and publication year (*Year*) of the literature, along with methodological details (*Method*), study periods (*Period*), and data frequencies (*Frequency*). *Source* refers to the origin of the data used in the research

efficiency. Bariviera (2017) examines the long-range dependence of Bitcoin returns and volatility. They argue that it is difficult to consider the efficient market, especially considering that daily volatility exhibits long-range memory throughout the entire period despite the daily returns time series becoming more efficient over time. Nadarajah and Chu (2017) extend the analysis conducted in Urquhart (2016) by employing three additional tests—the Robustified portmanteau test (Escanciano and Lobato 2009), Spectral shape tests (Choi 1999; Durlauf 1991), and the Generalized spectral test (Escanciano and Velasco 2006)—to the five tests used in the previous study. Through this extended analysis and utilizing a power transformation of Bitcoin returns as a variable, they demonstrate the market's efficiency. Kristoufek (2018) discovers strong evidence indicating that the Bitcoin markets are largely inefficient from 2010 to 2017, with efficiency observed only during cooling-downs following bubble-like price surges. Tiwari et al. (2018) analyze the issue of Bitcoin's informational efficiency using a range of computationally efficient long-range dependence estimators spanning the period from July 18, 2010, to June 16, 2017, and find that the market demonstrates informational efficiency.

Contrary to expectations of increasing market efficiency over time, most studies emphasize long-range dependence and market inefficiency in Bitcoin prices. Al-Yahyaee et al. (2018) employ the Multifractal Detrended Fluctuation Analysis (MF-DFA) to assess the efficiency of the Bitcoin market in comparison to gold, stock, and foreign exchange markets. Their findings indicate that the Bitcoin market is the most inefficient compared to the gold, stock, and currency markets, as the long-memory feature and multifractality of the Bitcoin market are stronger. Jiang et al. (2018) argue that the Bitcoin market is inefficient due to its Hurst exponent being above 0.5, indicating long-term memory. They also confirm a high degree of inefficiency ratio and note that the market does not become appreciably more efficient over time. El Alaoui et al. (2019) analyze the presence of nonlinear dependency and multifractality in the Bitcoin price–volume series. They provide empirical evidence indicating high correlations and anti-persistence in volume changes for both positive and negative values of moments. These findings suggest that the Bitcoin market demonstrates informational inefficiency. Chevapatrakul and Mascia (2019) demonstrate that investors tend to overreact under optimistic circumstances when weekly Bitcoin returns show positive values, leading to even stronger trends in positive returns. As a result, prices continue to rise, which supports the notion that the Bitcoin market is inefficient. Charfeddine and Maouchi (2019) confirm the inefficiency of all considered markets by analyzing returns and volatility in four crypto markets: Bitcoin, Ethereum, Ripple, and Litecoin. Zargar and Kumar (2019) utilize data at different frequencies, including 15, 30, 60, and 120 min, as well as daily data, to investigate the informational efficiency of the Bitcoin market in terms of daily returns. They found that while the Bitcoin market is efficient at the daily returns level, it becomes inefficient at higher frequencies. As a result, they identify the presence of a memory stochastic process in high-frequency analysis and argue that investors can exploit such inefficiencies to participate speculatively in the market.

During the COVID-19 pandemic period, industries experienced significant shocks across various sectors (Nuta et al. 2025), and the research trends during this time can be summarized as follows. According to Wu et al. (2022), Bitcoin shows efficiency levels like gold and displays less long memory and greater efficiency compared to Ethereum, Binance Coin, and the S&P 500 during the COVID-19 period. Sosa et al. (2023) examine Bitcoin and Ethereum returns volatility before and after the COVID-19 pandemic. Their findings suggest that the long memory in the Bitcoin market remains persistent and exhibits patterns unaffected by the pandemic crisis, thereby supporting the fractal market hypothesis. Assaf et al. (2023) analyze the long memory movements of hourly returns in the cryptocurrency market during the COVID-19 period using the methodology for testing long memory (Qu 2011; Sibbertsen et al. 2018), fractal connectivity matrix, and testing for change in persistence. The findings indicate that most cryptocurrencies exhibit long memory in high-frequency data, including Bitcoin. There is no research supporting the absence of long memory in Bitcoin during high-frequency situations during the pandemic period. Table 3 presents notable research papers concerning Bitcoin's long-range dependence.

Investor attention and sentiment in Bitcoin

Investor sentiment refers to a belief about future cash flows and investment risks that are not justified by the current facts and rationale (Baker and Wurgler 2007; Kim and Ryu 2022; Kim et al. 2014; Kim et al. 2021a, b, c; Lee and Ryu 2024; Ryu and Yu 2022; Seok et al. 2019a, 2019b, 2021, 2022, 2024a, 2024b). Changes in investor sentiment can create speculative overheating by causing investors to deviate from their focus on the intrinsic value of specific asset prices due to investor irrationality (Kim and Ryu 2021a, 2021b; Pan 2018; Ryu et al. 2023a, 2023b). The increased usage of search engines and social media platforms has provided behavioral economics researchers with opportunities to create proxies reflecting investor sentiment by utilizing daily occurrences of news, searches, and postings for research purposes (Bijl et al. 2016; Da et al. 2011; Smith 2012). Some researchers contend that most cryptocurrencies are heavily influenced by popularity

Table 3 Long-range dependence

References	Method	Period	Market Efficiency	Source
Urquhart (2016)	Ljung–Box test Runs test and Bartels test Variance ratio test AVR Test Wild-bootstrapped AVR test BDS test Rescaled Hurst exponent (R/S Hurst)	Aug 2010 to Jul 2016	Inefficiency (1st sample) Efficiency (2nd sample)	Bitcoinaverage.com
Bariviera (2017)	Rescaled Hurst exponent (R/S Hurst) Detrended Fluctuation Analysis (DFA)	Aug 2011 to Feb 2017	Efficiency	Bitcoincharts.com
Nadarajah and Chu (2017)	Ljung–Box test Runs test and Bartels test Variance ratio test AVR Test Wild-bootstrapped AVR test BDS test Rescaled Hurst exponent (R/S Hurst) Robustified portmanteau test Spectral shape tests Generalized spectral test	Aug 2010 to Jul 2016	Efficiency	Bitcoinaverage.com
Kristoufek (2018)	Capital market efficiency measure Long-range dependence and its estimators Fractal dimension Approximate entropy Statistical inference and moving window estimation	Feb 2014 to Jul 2017	Inefficiency	Coindesk.com
Tiwari et al. (2018)	CMA-1, CMA-2, DFA, GPH, MLE, Periodogram-LAD, Periodogram-LS	Jun 2010 to Jun 2017	Efficiency	Coindesk.com
Al-Yahyaee et al. (2018)	MF-DFA	Jul 2010 to Oct 2017	Inefficiency	Coinmarketcap.com
Jiang et al. (2018)	Generalized Hurst exponents Calculation of the standard errors	Dec 2010 to Nov 2017	Inefficiency	Bitcoinaverage.com
El Alaoui et al. (2019)	MF-DCCA	Jul 2010 to Ma 2018	Inefficiency	Cryptocompare.com
Chevapatrakul and Mascia (2019)	Quantile autoregressive (QAR)	Apr 2013 to Mar 2018	Inefficiency	Coinmarketcap.com
Charfeddine and Maouchi (2019)	Long-range dependence (LRD) test, BP test, ICSS algorithms test	Apr 2013 to Feb 2018	Inefficiency	Coinmarketcap.com
Zargar and Kumar (2019)	MVR, AVR and JVR statistics Non-overlapping and overlapping moving window analysis	Jan 2013 to Jan 2018	Inefficiency	Bitstamp.net

Table 3 (continued)

References	Method	Period	Market Efficiency	Source
Wu et al. (2022)	Hurst exponent estimation Tail index estimation	Jul 2019 to Oct 2020	Efficiency	Coinmarketcap.com
Assaf et al. (2023)	Testing for long memory Fractal connectivity matrix Testing for change in persistence	Jan 2019 to Feb 2021	Inefficiency	Bitfinex.com
Sosa et al. (2023)	ARFIMA-HYGARCH ARFIMA-FIGARCH	Sep 2014 to Nov 2021	Inefficiency	Yahoo.finance.com

This table presents key studies related to Bitcoin's long-range dependence. The table includes information on the researchers (*Author*) and the publication year (*Year*) of the literature, along with methodological details (*Method*), and study periods (*Period*). *Market Efficiency* refers to the presence or absence of long-term dependence, and if long-term dependence exists in the time-series data of Bitcoin, the market is considered inefficient. *Source* refers to the origin of the data used in the research

or investor sentiment indices (Aalborg et al. 2019; Zhang et al. 2018). One of the initial papers studying the relationship between Bitcoin and media sentiment is by Kristoufek (2013). The findings reveal a significant correlation between both Bitcoin prices and Bitcoin market liquidity and the search queries on Google SVI (Search Volume Index from Google Trends) and Wikipedia. Zhang et al. (2018) examine the cross-correlations between Google Trends and the Bitcoin market from June 1, 2011, to February 1, 2017. They identify a strong cross-correlation between changes in Google Trends and the Bitcoin market; however, this cross-correlation has weakened over time. Aalborg et al. (2019) find that none of the variables, including volatility, trading volume, transaction volume, change in the number of unique Bitcoin addresses, the Volatility Index (VIX), and Google searches for Bitcoin, are significant in forecasting Bitcoin returns during the period from March 1, 2012, to March 19, 2017. Only the SVI is significant in predicting trading volume. Eom et al. (2019) make predictions about Google SVI and the return and volatility of BTC/USD. They find that while the investor sentiment index does not help in forecasting returns and volatility for the dollar, changes in investor sentiment are useful in predicting Bitcoin volatility. This result is consistent with Bitcoin behaving more like a speculative asset than a currency. However, considering the highly nonlinear nature of Bitcoin price movements, simple AR models, which assume linear relationships, may fail to adequately capture the complex dynamics and sudden shifts in Bitcoin prices. This oversimplification can result in inaccurate predictions and an inability to fully explain the volatility patterns driven by speculative activities (Bouoiyour and Selmi 2016; Urquhart and Zhang 2019).

In analyses predating 2017, the correlation between changes in sentiment and key metrics such as returns and trading volume tends to be either partial or ambiguous. However, it becomes evident that over time, the relationships between returns, trading volume, and sentiment intensify and become more robust. Shen et al. (2019) indicate that tweet volume significantly influences next-day trading volume and realized volatility, a conclusion supported by both linear and nonlinear Granger causality tests. Philippas et al. (2019) introduce a dual-process diffusion model to investigate if Bitcoin prices exhibit jumps associated with informative signals from media attention. The empirical findings suggest that Bitcoin prices are partly influenced by momentum in sentiment on social networks, thereby justifying a sentimental demand for information. Choi (2021) utilizes high-frequency data to explore the immediate impact of tweets on Bitcoin liquidity. The findings indicate that a 1% rise in tweet volume results in a 7% enhancement in Bitcoin liquidity within the subsequent five to ten minutes. However, the positive impact of tweets on liquidity diminishes statistically after a 60-min interval. The real-time effects are more pronounced when tweets attract greater attention through retweets, likes, and replies. Telli and Chen (2021) investigate the correlation between Bitcoin, Ethereum, Litecoin, Ripple, and the platforms Reddit and Wikipedia, uncovering the multifractal relationship between public attention and the crypto markets. Cretarola and Figà-Talamanca (2021) apply the attention factor to the mathematical theory of financial bubbles (Protter 2013) and the economic theory of irrational bubbles (Shiller 2015) to ascertain the bubble effects on Bitcoin price dynamics. They demonstrate that the bubble is associated with the correlation between the market attention factor on Bitcoin and Bitcoin returns exceeding a threshold. In other words, heightened attention influences Bitcoin prices, and vice versa, creating a feedback loop. The research findings of Liu and Tsyvinski (2021) demonstrate that a strong time-series momentum effect and investor attention play a significant role in predicting the future returns of the major cryptocurrencies Bitcoin, Ethereum, and Ripple. Smales (2022) investigates the market dynamics among the top 20 cryptocurrencies, including Bitcoin. They confirm a positive relationship between cryptocurrency attention and returns, interpreting it as evidence that investors prefer to purchase attention-grabbing assets.

Unlike previous research, which primarily focused on examining the correlation between sentiment indices and Bitcoin prices and volumes, recent studies investigate whether sentiment can be effectively used as a feature in predicting Bitcoin movements through machine learning.[1] Wang et al. (2022) examine the influence of investor sentiment indices such as Tweets and Google SVI on Long Short-Term Memory (LSTM) models for predicting Bitcoin returns. They conclude that the attention variables could effectively enhance the LSTM's prediction accuracy, indicating that Google Trends and tweets contain more valuable information compared to traditional attention variables in terms of their impact on price or trading volume. Similarly, Critien et al. (2022) predict not only the direction of price movements but also the magnitude of increase/decrease. They demonstrate improved prediction performance when utilizing Twitter sentiment in Bitcoin price and volume forecasting using Convolutional Neural Network (CNN), LSTM, and Bi-LSTM models. Wang et al. (2023) compare the contribution of various factors in forecasting Bitcoin returns using LSTM, Random Forest (RF), and Gated Recurrent Unit (GRU) models, including technological factors, economic factors, green finance factors, and media attention factors. They find that while most macroeconomic indicators do not significantly impact return prediction, investment attention using Tweets, Google, and Baidu contributes robustly and significantly to improving predictive power. Studies utilizing machine learning and deep learning methods are often sensitive to the training and testing periods, which can lead to instability in robustness.

[1] Recent studies applying machine learning techniques to study financial asset dynamics include Bang and Ryu (2023, 2024), Kelly and Xiu (2023), Kim, Park, and Ryu (2025), and Ryu, Hong, and Jo (2024).

Additional testing processes may be required to determine whether the performance improvements are statistically significant (Medeiros et al. 2021). However, these studies lack procedures addressing this aspect, which should be explored in future research. Table 4 presents notable research papers concerning investor attention and sentiment in Bitcoin.

Safe-haven properties of Bitcoin

As 'Digital gold,' Bitcoin shares many similarities with gold. It is frequently described as possessing characteristics such as scarcity, durability, divisibility, and serving as a store of value, much like gold. Theoretically, its value comes from limited supply, which is not controlled by any government, and from the mining process facilitated by independent entities and operators (Dyhrberg 2016a). Many studies have demonstrated the utility of gold as a hedge against risks as a traditional safe-haven asset. For example, gold has been effectively utilized for inflation hedging due to the negative relationship between gold

Table 4 Investor attention & sentiment in Bitcoin

References	Method	Period	Sentiment	Source
Kristoufek (2013)	VAR	May 2011 to Jun 2013	Google SVI Wikipedia	Mtgox.com
Zhang et al. (2018)	MF-DCCA	Jun 2011 to Feb 2017	Google SVI	Bitcoincharts.com
Eom et al. (2019)	AR model	Oct 2011 to May 2017	Google SVI	Bitcoincharts.com
Aalborg et al. (2019)	Heterogeneous autoregressive model	Mar 2012 to Mar 2017	Google SVI	Blockchain.com Bitcoincharts.com Bitcoinity.org
Shen et al. (2019)	VAR	Sep 2014 to Aug 2018	Tweets	Bitcoincharts.com
Philippas et al. (2019)	VAR	Jan 2016 to May 2018	Tweets Google SVI	Bloomberg.com
Cretarola and Figà-Talamanca (2021)	Mathematical theory of financial bubbles (Protter 2013) Economic theory of irrational bubbles (Shiller 2015)	Jan 2012 to Jan 2018	Google SVI	Blockchain.info
Choi (2021)	VAR	Aug 2013 to May 2018	Tweets	Bitcoincharts.com
Telli and Chen (2021)	MF-DCCA	Feb 2015 to Nov 2020	Wikipedia Reddit posts	Coinbase.com Bitstamp.net
Liu and Tsyvinski (2021)	Capital Asset Pricing Model (CAPM), Fama–French three-factor, Carhart four-factor, Fama–French five-factor, and Fama–French six-factor models	Jan 2016 to Dec 2018	Google SVI	Coinmarketcap.com Coindesk.com Blockchain.info Coinmetrics.io
Smales (2022)	Fixed Effects Model	Jan 2016 to Jun 2020	Google SVI	Coinmarketcap.com
Wang et al. (2022)	LSTM	Jan 2016 to Jun 2020	Tweets Google SVI	Coinmarketcap.com
Critien et al. (2022)	CNN, LSTM, BiLSTM	Jan 2016 to Mar 2019	Tweets	Kaggle.com
Wang et al. (2023)	LSTM, RF, GRU	Sep 2014 to Feb 2022	Tweets Google SVI Baidu	Bitcoincharts.com

This table presents key studies related to investor attention and sentiment in Bitcoin. The table includes information on the researchers (*Author*) and the publication year (*Year*) of the literature, along with methodological details (*Method*) and study periods (*Period*). *Sentiment* represents the source of investor attention and sentiment index. *Source* refers to the origin of the data used in the research and inflation (Bampinas and Panagiotidis 2015; Blose 2010; Ghosh et al. 2004; Wang et al. 2011; Worthington and Pahlavani 2007). It exhibits long-term hedging effectiveness against risks related to headline, expected, and core CPI. In the short term, while it may not respond significantly to low inflation changes, the transition to high inflation could enhance its effectiveness as an inflation hedge (Valadkhani et al. 2022). Its ability to hedge against stock market volatility, oil price fluctuation, and currency risks, among others, has also been substantiated by other researchers (Baur and McDermott 2010; Baur and Lucey 2010; Qarni and Gulzar 2021; Reboredo 2013a, 2013b; Reboredo and Rivera-Castro 2014).

Bitcoin can be utilized for portfolio diversification or hedging, depending on its relationship with other assets and market conditions. If Bitcoin exhibits a significantly negative correlation with other asset classes, it can be used for portfolio diversification. Furthermore, if it demonstrates asymmetric tail dependence with those asset classes, it can act as an effective safe haven against extreme movements (In and Kim 2006). Firstly, a negative relationship between assets typically indicates that when one asset declines, the other asset tends to rise both in terms of returns and stability. Such a negative correlation can help reduce portfolio risk and stabilize returns. Secondly, asymmetric tail dependence measures the extent to which extreme events in one variable are associated with extreme events in the other variable. This means that when one asset moves sharply in a certain direction, the other asset tends to exhibit similar extreme movements. For example, if there is a significant decrease in the returns of specific stocks or commodities in the lower quantiles, and there is a tendency for Bitcoin returns to be high, this indicates that Bitcoin serves as a useful hedging asset.

Negative correlation with other assets

Previous studies provide evidence that Bitcoin exhibits a negative correlation with other asset classes, suggesting its potential use for portfolio diversification and hedging risks. Dyhrberg (2016a) analyzes the similarities in the time series volatility of Bitcoin, the dollar, and gold. As a result, Bitcoin proves useful in risk management and is particularly suited for risk-averse investors preparing for adverse market events. It suggests a position within financial markets and portfolio management, straddling the characteristics of both gold and the dollar. Moreover, Dyhrberg (2016b) argues that Bitcoin has the potential as a hedge against stocks in the Financial Times Stock Exchange (FTSE) index, as well as against the American dollar in the short term. Guesmi et al. (2019) demonstrate that incorporating Bitcoin into hedging strategies alongside gold, oil, and emerging stock markets significantly reduces portfolio risk compared to strategies that exclude Bitcoin. Wang et al. (2019) explore the mean and volatility spillover effects between Bitcoin and six financial assets in China, including stocks, commodity futures (commodities), gold, foreign exchange, monetary assets, and bonds. The study aims to explore whether Bitcoin can be utilized as either a hedging asset or a safe haven. Their empirical findings suggest that Bitcoin can be hedged against stocks, bonds, and the Shanghai Interbank Offered Rate (SHIBOR). Jin and Tian (2024) examine Bitcoin's safe-haven property during the Silicon Valley Bank collapse. Their findings suggest Bitcoin's role as a safe haven amidst US banking market uncertainty, showing superior short-term performance and outperforming gold in return and stabilizing hedged positions. Bitcoin maintained its safe-haven status over 50 days, even during periods of reduced market uncertainty, solidifying its position as a better safe-haven asset for hedging purposes.

Some studies identify that Bitcoin primarily exhibits negative correlations with financial instruments, particularly showing a high level of negative relationship with Asian stock markets, including China. Bouri et al. (2017b) investigate if Bitcoin could function as a hedge and safe haven for major global stock indices, bonds, oil, gold, the general commodity index, and the US dollar index. Their empirical findings suggest that Bitcoin performs inadequately as a hedge and is primarily suitable for diversification purposes. It only demonstrates safe-haven characteristics during weekly extreme downtrends in Asian stocks, but not in other asset classes.

Multivariate GARCH-family models including Dynamic Conditional Correlation (DCC) and Asymmetric Dynamic Conditional Correlation (ADCC) models have been widely used in the field of financial economics (Chun et al. 2019, 2023; Park et al. 2017; Song et al. 2018). Urquhart and Zhang (2019) combine the DCC and ADCC models with extended GARCH models to assess Bitcoin's hedge, diversifier, and safe-haven capabilities against currencies worldwide. Bitcoin demonstrates hedging abilities against CHF, EUR, and GBP, diversification capabilities against AUD, CAD, and JPY, and functions as a safe-haven in times of severe volatility for CAD, CHF, and GBP. This suggests that Bitcoin acts as a safe-haven only for certain foreign exchange assets. Corbet et al. (2020a, b) examine whether Bitcoin acts as a hedge asset in response to nine COVID-19-related events in China. Their results indicate that the volatility relationship between the main Chinese stock markets and Bitcoin significantly evolved during the COVID-19 period of immense financial stress, with Bitcoin playing a role in significantly destabilizing market stability. Ustaoglu (2023) suggests that Bitcoin exhibits weaker hedging capabilities compared to gold but demonstrated hedging abilities against certain commodities like wheat and natural gas during a period of significant price volatility caused by the Russia–Ukraine war (Habib and Kayani 2024). Table 5 presents notable research papers concerning Bitcoin's negative correlation with other assets.

Asymmetric tail dependence

There is a significant body of literature suggesting that Bitcoin can serve as a weak safe-haven asset, as it demonstrates increased returns and stability during periods of rising economic uncertainty or risk factors. This is the case even though there is little economic rationale for such a relationship. Bouri et al. (2017a, b) explore the potential of Bitcoin to act as a hedge against World VIX, assessed through the first principal component of the VIX of 14 developed and developing equity markets. Employing a quantile-on-quantile methodology, they find evidence of heavy tails suggesting that Bitcoin can be a hedge asset against global uncertainty, displaying a positive response to heightened uncertainty levels and shorter-term fluctuations in Bitcoin returns. Demir et al. (2018) analyze the predictive power of the Economic Policy Uncertainty Index (EPU) over Bitcoin returns using OLS and quantile-on-quantile estimations. As a result, Bitcoin returns generally exhibit a negative relationship with the EPU. However, they may show a positive relationship in highly uncertain situations, indicating that Bitcoin can be useful for hedging risk. Baur et al. (2018) explore how Bitcoin interacts with different financial variables,

Table 5 Negative correlation with other assets

References	Method	Period	Asset	Source
Dyhrberg (2016a)	Exponential GARCH	Jul 2010 to May 2015	Bitcoin, USD-EUR exchange rate, USD-GBP exchange rate, FTSE index, Gold futures, Gold cash	Mtgox.com
Dyhrberg (2016b)	Threshold GARCH	Jul 2010 to May 2015	Bitcoin, USD-EUR exchange rate, USD-GBP exchange rate, FTSE index	Bitcoincharts.com
Bouri et al. (2017b)	DCC-GARCH	Jul 2011 to Dec 2015	Bitcoin, S&P 500, FTSE 100, DAX 30, Nikkei 225, Shanghai A-share, MSCI World, MSCI Europe, MSCI Pacific, bond index, US dollar index, Commodity index, Oil, Gold spot	Bitcoincharts.com
Guesmi et al. (2019)	Multivariate GARCH	Jan 2012 to May 2018	Bitcoin, MSCI World, MSCI DM, MSCI EM, VIX, WTI, Gold spot	Blockchain.com Bitcoincharts.com Bitcoinity.org Bitcoinity.org
Wang et al. (2019)	VAR-GARCH-BEKK	Jan 2013 to Sep 2017	Bitcoin, CSI 300 Index, Commodity futures (Nanhua Commodity Index), Gold spot, USD/CNY exchange rate, interest rate of SHIBOR, ChinaBond Aggregate Index (Full Price Index)	Bitcoincharts.com
Urquhart and Zhang (2019)	DCC –GARCH DCC –GJRGARCH DCC -EGARCH DCC –EGARCH ADCC -GARCH ADCC –GARCH ADCC -GJRGARCH ADCC –GJRGARCH ADCC -EGARCH ADCC -EGARCH	Nov 2014 to Oct 2017	Australian dollar (AUD), Canadian dollar (CAD), the Swiss franc (CHF), the Euro (EUR), the British pound (GBP) and the Japanese yen (JPY), all per one US dollars (USD)	Bloomberg.com
Corbet et al. (2020a, b)	GARCH, DCC-GARCH	Mar 2019 to Mar 2020	Bitcoin, Shanghai and Shenzhen Stock Exchanges, DJIA, WTI, Gold spot	Blockchain.info
Ustaoglu (2023)	ADCC-GARCH	Feb 2022 to Oct 2022	Bitcoin, Gold spot, US (S&P500), Canada (S&P TSX), England (FTSE100), Japan (Nikkei225), France (CAC40), Germany (DAX), Italy (FTSE MIB), China (SZSE Component), Russia (Moex), MSCI Europe, Brent Oil, Natural Gas, Wheat	Bitcoincharts.com

Table 5 (continued)

References	Method	Period	Asset	Source
Jin and Tian (2024)	CEEMDAN-based event analysis	Jul 2022 to Jun 2023	Bitcoin, gold, KBW Nasdaq bank index, S&P 500 Financials Index, Nasdaq Composite Index, Dow Jones Industrial Average Index, S&P 500 Index, US dollar index, VIX, and U.S. Aggregate Bond Index	Coinbase.com Bitstamp.net

This table presents key studies related to the relationship between Bitcoin and other assets. The table includes information on the researchers (*Author*) and the publication year (*Year*) of the literature, along with methodological details (*Method*), and study periods (*Period*). *Asset* represents the assets used to assess the correlation with Bitcoin. *Source* refers to the origin of the data used in the research

using a quantile regression model. Ultimately, the lack of an effect from the financial crisis suggests that Bitcoin does not serve as a safe-haven asset. Shahzad et al. (2019) examine the potential of Bitcoin as a safe-haven asset for the US, China, and other developed and emerging economies using a cross-quantilogram approach. They find that gold, Bitcoin, and commodities are all weak safe-haven assets but play different roles as safe havens across various assets. Bitcoin exhibits weak safe-haven property in China and the global stock market index, but it fails to hedge risks in developed, emerging, and US stock markets. Jareño et al. (2020) investigate how Bitcoin returns react to variations in gold price returns and other global risk factors. This research indicates that Bitcoin returns demonstrate a notable and statistically significant positive sensitivity, particularly at higher quantiles when acting as a hedge against fluctuations in the performance of the US stock market throughout all observed time frames. Consequently, the magnitude of the coefficient suggests an exaggerated response of Bitcoin returns to shifts in stock market performance during periods of expansion. Das et al. (2020) argue that Bitcoin emerged as a safe-haven for OVX at the extreme 99th percentile and exhibited characteristics of a weak safe-haven at the 90th percentile. The superiority of hedging performance varied depending on the economic conditions or the nature of the risks (demand shock, supply shock, and risk shock). Shahzad et al. (2020) assess the hedging capabilities during extreme fluctuations using the conditional diversification benefit (CDB) measure. The results indicate that while gold is effective across all stock markets, Bitcoin demonstrated superiority only in the Canadian stock index, showing that its hedging ability is somewhat inferior to that of gold. Urom et al. (2020) analyze the relationship of Bitcoin with equity markets of 12 countries, as well as gold and WTI (West Texas Intermediate) crude oil. Their research indicates that Bitcoin serves as a safe-haven, and it also highlights the portfolio diversification benefits of Bitcoin for international investors during bear markets. Corbet et al. (2020a, b) analyzed Granger-causality in distribution (GCD) and Granger-causality in quantiles (GCQ) tests for the S&P500 and WTI crude oil. They find evidence indicating that Bitcoin serves as a strong safe haven for oil and a weak one for the S&P500. Maghyereh and Abdoh (2020) demonstrate that Bitcoin is not the causal factor for the returns of financial assets; rather, the returns of financial assets can influence Bitcoin returns. Specifically, they find that the S&P 500, gold, and the bond index impact Bitcoin returns only in low return quantiles.

Hau et al. (2021) used the Quantile-on-quantile regression to analyze the relationship between Bitcoin and the USD. They found a positive relationship in the higher quantiles of Bitcoin returns and a negative relationship in the lower quantiles between Bitcoin and the dollar. Mokni (2021) analyzes the Symmetric and Asymmetric causality in quantiles between Bitcoin prices and the EPU. The research findings indicate that Bitcoin prices tend to increase in higher quantiles of EPU, suggesting that Bitcoin can be used as a hedging vehicle against increased asset volatility caused by heightened uncertainty in all considered countries, particularly during bearish and bullish Bitcoin market conditions. Although some results indicate that Bitcoin lacks stability, most studies support the claim that Bitcoin serves as a safe haven. Table 6 presents notable research papers concerning Bitcoin's asymmetric tail dependence.

Conclusions

Theoretical implications

This study makes a significant contribution to existing financial theories by comprehensively summarizing scattered literature on Bitcoin-related research in the finance field through bibliometrics. It explores Bitcoin's dual characteristics, namely its speculative nature and its hedging effect as a safe-haven asset, thereby providing an important conceptual contribution. We present the possibility of Bitcoin transcending traditional asset categories, offering a new perspective on the position and role of cryptocurrencies like Bitcoin in financial markets. By organizing and presenting studies showing that Bitcoin can function as a safe-haven asset in times of economic uncertainty, this research suggests the potential for expanding existing frameworks. The understanding of Bitcoin's high volatility and the investment strategies based on it contributes to reinforcing theories related to volatile assets and provides insights for analyzing the investment characteristics of similar cryptocurrencies. This analysis offers foundational material for developing investment strategies and risk management in the cryptocurrency market, and further lays the theoretical groundwork necessary for predicting market trends in cryptocurrencies.

Managerial/policy implications

From a managerial perspective, this study provides important insights for investors to understand the characteristics of Bitcoin and adjust their investment strategies accordingly. Leveraging Bitcoin's high volatility for aggressive investment and utilizing its negative correlation with other assets for diversification strategies can be valuable approaches in portfolio management. From a policy perspective, the study highlights the need to regulate and manage Bitcoin appropriately, recognizing that, despite being a high-risk asset, it can also function as a safe-haven asset. Governments and financial regulators must strengthen investor protection considering Bitcoin's volatility while also implementing policies that allow Bitcoin to be used as a tool for portfolio diversification. Regulatory environments should be developed to offer stable investment options to investors, especially through advancements such as the approval of cryptocurrency spot ETFs.

Table 6 Asymmetric tail dependence

References	Method	Period	Asset	Source
Bouri et al. (2017a, b)	Quantile-on-quantile regression	Mar 2011 to Oct 2016	Bitcoin, World VIX, US dollars	Coindesk.com
Demir et al. (2018)	OLS Quantile-on-quantile regression	Jul 2010 to Nov 2017	Bitcoin, EPU	Coindesk.com
Baur et al. (2018)	Quantile regression	Jul 2010 to Jun 2015	WinkDex (Bitcoin exchange rate index), S&P500, S&P600, Gold Spot, Silver Spot, EUR/USD, AUD/USD, JPY/USD, GBP/USD, CNY/USD, HUF/USD, Trade weighted US dollar index, WTI, HH(Natural gas index), Bloomberg UsS Corporate Bond Index	Winkdex.com
Shahzad et al. (2019)	Cross-quantilogram	Jul 2010 to Feb 2018	Bitcoin, Gold spot, Commodities, S&P GSCI, MSCI World, MSCI DM, MSCI EM, MSCI China, MSCI US	Coindesk.com
Jareño et al. (2020)	Quantile regression NARDL approach	Jan 2010 to Dec 2018	Bitcoin, S&P500, 10-year nominal interest rates, Crude oil prices, Gold spot, VIX, STLFSI	Coindesk.com
Das et al. (2020)	GARCH Quantile regression	Jul 2010 to Jun 2019	Bitcoin, Gold, Commodity, Dollar, OVX (CBOE Crude Oil Volatility Index)	Bloomberg.com
Shahzad et al. (2020)	AGDCC-GARCH Conditional Diversification Benefit (CDB) measure	Jul 2010 to Dec 2018	Bitcoin, Gold spot, MSCI—G7 (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States)	Coindesk.com
Urom et al. (2020)	TVP-VAR Cross-quantilogram	Apr 2013 to May 2018	Bitcoin, 12 Equity markets index (France, Finland, Germany, Ireland, the Netherlands, Spain, Sweden, Switzerland, the United Kingdom, Australia, Japan, and the United States of America, Gold spot, WTI	Coindesk.com
Corbet et al. (2020a, b)	Granger-causality in distribution (GCD) Granger-causality in quantiles (GCQ)	Aug 2015 to Jan 2019	Bitcoin, WTI, S&P500	Coinmarketcap.com
Maghyereh and Abdoh (2020)	Quantile cross-spectral (coherency) approach Granger non-causality test in quantiles Granger non-causality test in quantiles	Aug 2011 to Jan 2020	Bitcoin, S&P 500, FTSE 100, DAX 30, Shanghai A-share, Bond index, EUR/USD exchange rate, Commodity index, Crude Oil-Brent, Gold, Silver	Bitstamp.net

Table 6 (continued)

References	Method	Period	Asset	Source
Hau et al. (2021)	Quantile-on-quantile regression	Jan 2013 to Dec 2018	Bitcoin, USD	Bitcoincharts.com
Mokni (2021)	Symmetric causality in quantiles Asymmetric causality in quantiles	Sep 2010 to Oct 2019	Bitcoin, EPU	Coindesk.com

This table presents key studies related to the asymmetric tail dependence of Bitcoin. The table includes information on the researchers (*Author*) and the publication year (*Year*) of the literature, along with methodological details (*Method*), and study periods (*Period*). *Asset* denotes asset classes used to compare the distribution symmetry of Bitcoin. *Source* refers to the origin of the data used in the research

Limitations and future research directions

This study focuses on comparing Bitcoin's dual characteristics as a speculative asset and a safe-haven asset. However, the complexity and volatility of the Bitcoin market may limit the theoretical analysis. For instance, Bitcoin's price volatility can be influenced by various external factors, and its characteristics may vary depending on specific time-frames or economic conditions. The limitations of the data and models used in the studies presented in this research may restrict the generalizability of the results to specific market conditions. More experiments and validations are needed to improve the accuracy of predictions regarding Bitcoin's characteristics. Environmental, Social, and Governance (ESG) issues are becoming increasingly important and a popular research topic in the financial field (Bang et al. 2025; Bang et al. 2023; Bang et al. 2023a, b; Cheng et al. 2024; Choi et al. 2024 Habib 2024; Habib et al. 2024; Kang et al. 2024; You et al. 2025). Bitcoin faces ESG-related challenges, such as energy consumption due to mining and its use in illicit activities (Foley et al. 2019; Papp et al. 2023). However, despite their importance, these issues are not addressed in this study. Future research could consider more refined methodologies to analyze Bitcoin's characteristics. It would also be valuable to explore the asset's characteristics from an ESG perspective. Specifically, a deeper analysis of the external economic factors affecting Bitcoin's price volatility is necessary (Bouri et al. 2023). As digital assets like Bitcoin expand their role in the global financial markets, it is crucial to closely analyze potential risks and continuously conduct research to establish appropriate levels of investor protection and regulation, considering both the asset's characteristics and ESG aspects (Habib 2023).

Acknowledgements

We appreciate helpful comments from Alexander Webb (University of Wollongong).

Author contributions

DY, DR: proposal and original idea. DY, DR, RW: conceptualization; DY: methodology; DY: DR: validation; DR: resources; DY, RW: literature review; DR, RW: economic and business implication; DY, DR: writing—original draft preparation; RW: writing—review and editing; RW: discussion; DR: project administration. All authors have read and agreed to the published version of the manuscript. Daeyun Kang is the first author. Doojin Ryu and Robert Webb are the corresponding authors.

Funding

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT; Ministry of Science and ICT) [No. 2022R1A2C1010596] [NRF-2022R1A2C1010596].

Availability of data and materials

We use Web of Science (WoS) data. Over the period from 2014 to 2024, we collect 2,349 papers with journal categories limited to "Business, Finance" OR "Business & Economics" OR "Economics," and the topic specified as "Bitcoin." Using the R package bibliometrix 4.2.1, we extract data from the WoS dataset including the number of articles published per year, the number of articles per topic over the years, and the most frequently cited studies. We employ Word Cloud analysis to identify key topics. Co-occurrence, co-authorship, and co-citation analyses are conducted using VOSviewer software 1.6.20.

Declarations

Competing interests
There is no conflict of interest. All authors read and approved the final manuscript.

Received: 14 May 2024 Accepted: 13 February 2025
Published online: 20 March 2025

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