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Cryptocurrency Market Efficiency Revisited: A Bibliometric Analysis

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Abstract

The aim of this comprehensive review of the papers published on the Scopus database is to gain insights into the various indicators that determine the level of market efficiency within the global cryptocurrency markets. We have employed a series of bibliometric and content analyses on 3,224 papers published during 2014–2024. Findings indicate that the scholarly literature on cryptocurrency exhibits a varied range of perspectives, frequently encompassing multiple academic disciplines such as economics, finance, accounting, technology, and engineering. We present three significant findings. *First*, despite a growing list of recent studies supporting some efficiency, cryptocurrency assets frequently deviate from conventional norms of market efficiency. Herding, co-movement, sentiment, and overconfidence are the major contributors behind the inefficient cryptocurrency market. *Second*, the intricate nature of these assets and their lack of connection to fundamental economic value contribute to inconsistencies, instability, and ambiguity. *Third,* regulators are expected to intervene with prudent and globally collaborative regulations to optimize the potential of this market. In this discourse, we analyze the potential consequences derived from various frameworks and methods, with the aim of informing forthcoming scholarly investigations.

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1. Introduction

The cryptocurrency market has been characterized by significant volatility since its inception in 2008 (Nakamoto, 2008; Urquhart, 2016). Initially perceived as a symbol of decentralized, unregulated, and economically efficient currency, scholars have identified the presence of investment prospects and hedging capabilities within the realm of cryptocurrency investment (Selgin, 2015; Dyhrberg, 2016). However, in contrast to other commodities and currencies traded in financial markets, cryptocurrencies lack a fundamental value, a characteristic widely believed to be the primary driver of their high volatility (Cheah and Fry, 2015). Furthermore, cryptocurrencies exhibit a high level of volatility, surpassing that of other assets such as precious metals and currencies (Dwyer, 2015).

However, the crypto-market efficiency is found to be time-varying and regulation sensitive (Nimalendran *et al.*, 2025); as such, some assets are found to be efficient at the initial floatation period, say the first six months (Polyzos *et al.*, 2024). Past information, such as the trading volume, also fails to predict future return (Sahoo and Sethi, 2022). These mixed bags of findings not only indicate inconsistencies and a gross deviation from the expected patterns of market efficiency but also suggest that cryptocurrencies have the potential to instigate substantial market disruptions, particularly around crisis time, such as the COVID-19 (Mokni *et al.*, 2024).

The main objective of this study is to conduct a comprehensive review of published papers to address two specific research questions. *First*, how is the literature on cryptocurrency efficiency growing? Based on a bibliometric analysis, on a variety of keywords, it is possible to create a thematic map that captures the fundamental concepts surrounding crypto-market efficiency. *Second*, what rational and irrational indicators of market efficiency are most common in cryptocurrency literature? Using a thorough content analysis of crypto-market efficiency literature found in the Scopus database, the study aims to delve deeper into the realms of market regulation, the engagement of pivotal market actors, and the resolution of relevant concerns to augment the overall efficiency of the market.

Cryptocurrencies, which emerged in 2008 (Klarin, 2020), are digital, encrypted forms of currency that function as a means of exchange in lieu of traditional physical currencies. These are results of binary codes that are stored within databases. In contrast to local currencies, cryptocurrencies are decentralized in nature, thus not issued and monitored by any central authority. Cryptocurrencies also possess characteristics that make them attractive as investment instruments (Corbet *et al*., 2019).

As of January 2025, the cryptocurrency market comprises more than 9,000 active digital currencies traded across approximately 249 spot exchanges, collectively possessing a market capitalization of approximately $3.35 trillion.[1] The market exhibited significant fluctuations, accompanied by substantial returns for certain cryptocurrencies. As an illustration, the price of a specific cryptocurrency, namely Bitcoin, experienced a notable fluctuation over a span of time. Specifically, in October 2014, the closing price of Bitcoin stood at $338.32, which subsequently escalated to $96,029 by January 2025.[2] The substantial observed rate of return has raised numerous concerns regarding the efficiency of the cryptocurrency market. This study aims to study that on a global scale.

In the subsequent sections, we provide a concise overview of the review methodology. Subsequently, we present findings pertaining to bibliographic concentrations and the literature pertaining to various facets of the cryptocurrency market that exert an influence on market efficiency. Considering the extensive number of references examined, we have included in the reference section only those materials that are most pertinent to our study. However, additional references can be obtained upon request in the form of a spreadsheet.

2. Review Approach

The review is conducted in two stages. The initial phase entails conducting a bibliometric analysis utilizing the *Biblioshiny* and *VOSviewer* packages. The process of visually representing the depth of a literary work involves several sequential stages, commencing with the selection of appropriate keywords for conducting comprehensive and targeted literature searches. The search query was conducted using the Scopus database, by employing relevant keywords. Keywords used in the search process are "*cryptocurrency and efficiency*", "*bitcoin and efficiency*", "*cryptocurrency and momentum*," "*cryptocurrency and reversal*," "*behavioural or behavioural and biases*," "*cryptocurrency and bubbles*," and "*cryptocurrency and pricing*". This corpus encompasses scholarly works such as journal papers, book chapters, and review papers. The papers in question have been gathered between 2014 and 2024.

[1]See the details in https://coinmarketcap.com

[2]Price changes can be downloaded from Yahoo Finance at https://finance.yahoo.com/quote/BTC-USD/history?p=BTC-USD

Following the bibliometric analysis, an integrative approach was conducted, as described by Torraco (2005) and Snyder (2019), focusing on a concise selection of literature pertaining to finance, economics, and business. The analysis and evaluation conducted are qualitative in nature. The examination of numerous market anomalies presents a complex challenge when conducting a systematic review. To resolve this complexity, the reviewed papers were specifically chosen based on their relevance to the sub-topics and sub-themes under investigation. Therefore, a host of research papers on purely technology and engineering-related aspects of FinTech were excluded from review. This integrative review holds significance in initiating an informed discourse regarding the efficiency surrounding cryptocurrency markets.

3. Market Efficiency and other Relevant Theories

The theory of market efficiency, as proposed by Fama (1970), has had a significant impact on the field of finance. The financial system's overall integrity may be subject to scrutiny if one of its components, namely the financial markets encompassing cryptocurrencies, exhibits deficiencies. The efficient market hypothesis (EMH) posits that the valuation of an efficient financial asset ought to incorporate all pertinent information pertaining to said asset. The EMH faces criticisms as it fails to provide a comprehensive explanation for numerous financial anomalies that have the potential to impact financial markets (De Bondt and Thaler, 1985). An increasing quantity of these irregularities is being examined within the framework of the cryptocurrency markets.

Adaptive market efficiency (AME) has gained momentum in recent years. It challenges some assumptions of the normative market efficiency theories, assuming participants to be rational and qualified to make a quick and accurate investment decision. AME assumes that investors adapt to changing market scenarios, where assets perform non-randomly differently in different scenarios, due to competition, imitation and dynamic learning mechanism, challenging the norms of traditional market efficiency (Lo, 2005). Due to time-varying and extremely context-dependent adaptation, assets experience waxing and waning, while the performance of investment strategies differs in different contexts (Lo, 2004; Xiong *et al.*, 2019). Due to the behavior existing an early-stage investment vehicle, the volatility and differences in performance based on time, type, and environment make cryptocurrency market resemble the AME. This review contributes to our limited understanding of the cogency of the cryptocurrency market, specially of specific events, dates, locations, portfolio, and asset types that can be strategically manipulated to achieve superior market performance.

Cheah and Fry (2015) suggested that Bitcoin intrinsic price is zero, which invalidated discussion of Bitcoin bubbles, as abrupt price swings without a theoretical underpinning cannot justify or address bubbles. To overcome the theory, Tirole's (1985) anticipation of the consumption loan model, originally suggested by Samuelson (1958), explains that fiat money is intrinsically worthless but positively valued for what it fetches in exchange. García-Monleón *et al.* (2021) forward that since cryptocurrencies are essentially abstract information, Metcalfe's Law states that the usefulness of cryptocurrencies is the economic worth of the communicated information via networks. Hayes (2017) used cryptocurrency production network competitiveness, unit production rate, and mining complexity to calculate Bitcoin's fair value. Bolt and Van Oordt (2019) also examined consumer acceptability and adoption of virtual money in merchandising, the current value of virtual currency transactions, and investor forward-looking decisions and expectations of buying such a currency.

4. Results of the Bibliometric Review

4.1. Sources, collaboration, and influential author

Based on Appendix A, the average annual growth rate of publications is 15.08%, while the average number of citations per document is 17.75. About a third of the publications (29.62%) are collaborated internationally. Most of the documents analyzed are journal papers (82%; 2,646 out of 3,224).

Table 1 presents that the USA (1448) exhibited the highest level of scholarly output on the selected keywords, with China (630) and India (559) following suit. Notably, despite China's banning of the cryptocurrencies, South China Morning Post[3] reported that China had a total transaction of over US$220 billion from June 2021 until July 2022 and that Binance[4] completed an estimated US$90 billion worth of transactions in May 2023.

Figure 1 illustrates the top two literature exhibiting exceptional citation counts. *First*, a study conducted by Urquhart (2016) to examine the presence of informational inefficiency within the Bitcoin market. *Second*, extended from Urquhart (2016), Nadarajah and Chu (2017) reported an opposite finding that the Bitcoin market held the market efficiency hypothesis after changing the power transformation of the Bitcoin returns. The time- and context-varying nature of efficiency supports the AME hypothesis.

[3]See the report on the South China Morning Post at https://www.scmp.com/tech/policy/article/3196781/chinas-cryptocurrency-market-still-among-worlds-strongest-despite-beijings-crackdown-trading-mining#

[4]Report on Binance by the Wall Street Journal at https://www.wsj.com/articles/crypto-is-illegal-in-china-binance-does-90-billion-of-business-there-anyway-2a0af975?mod=business_minor_pos4#

Table 1. Top 10 countries (timespan 2014–2024).

Country	Freq.
USA	1448
CHINA	630
INDIA	559
UK	546
GERMANY	361
AUSTRALIA	212
FRANCE	212
ITALY	190
CANADA	154
SPAIN	142

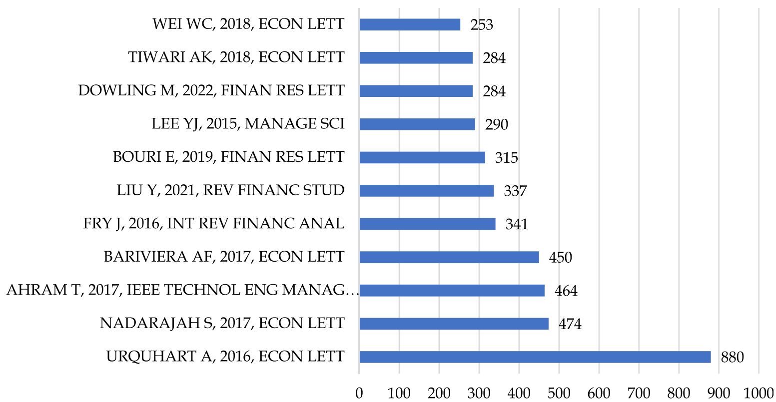

Fig. 1. Most cited global authors.

4.2. Growth and sources of scientific productions

Based on Fig. 2, the publication growth exhibits a massive increase since 2018, with the number of papers increasing from 219 in 2018 to 554 in 2024. Figure 3 shows that "Finance Research Letters" has emerged as a highly influential journal, having published a total of 87 papers, followed by "Management Science" with 65 counts of papers.

4.3. Major themes and keywords

Figure 4 depicts the interconnectedness of keywords within several distinct constructs. Table 2 provides additional information that supports the findings on keywords. The keyword that garners the highest search volume is Cryptocurrency (395), followed by the terms "behavioural finance" (302), "behavioural biases"

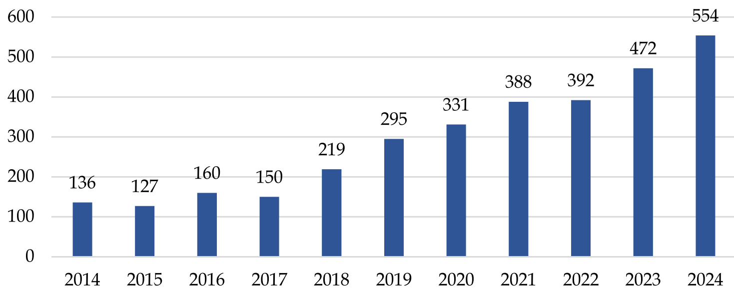

Fig. 2. Annual scientific production.

Fig. 3. Most significant publication sources (at least 20 publications).

(272), and "Bitcoin" (240). While these keywords are promising, the broader coverage in the literature warrants in-depth studies on efficiency.

Figure 5 presents a conceptual mapping of the keywords utilizing multiple correspondence analysis (MCA). The larger dimension that is toward the center of the map at the intersection of or near the dotted lines includes topics that are major contributors to cryptocurrency market. These topics include behavioural biases, decision-making, cryptocurrency, Bitcoin, heuristics, loss aversion, and so on.

Figure 6 facilitates our comprehension of three prominent themes that are categorized into four distinct quadrants (Cobo *et al*., 2011). Motor themes play a valuable role in the formulation of novel arguments. These themes encompass a compilation of robust and well-established ideas. "*Behavioural finance, biases, and overconfidence*" are among the most significant motor themes that also substantiate the aptness of this review. These themes also share quadrants with basic themes. The basic themes, although crucial, often lack in-depth development.

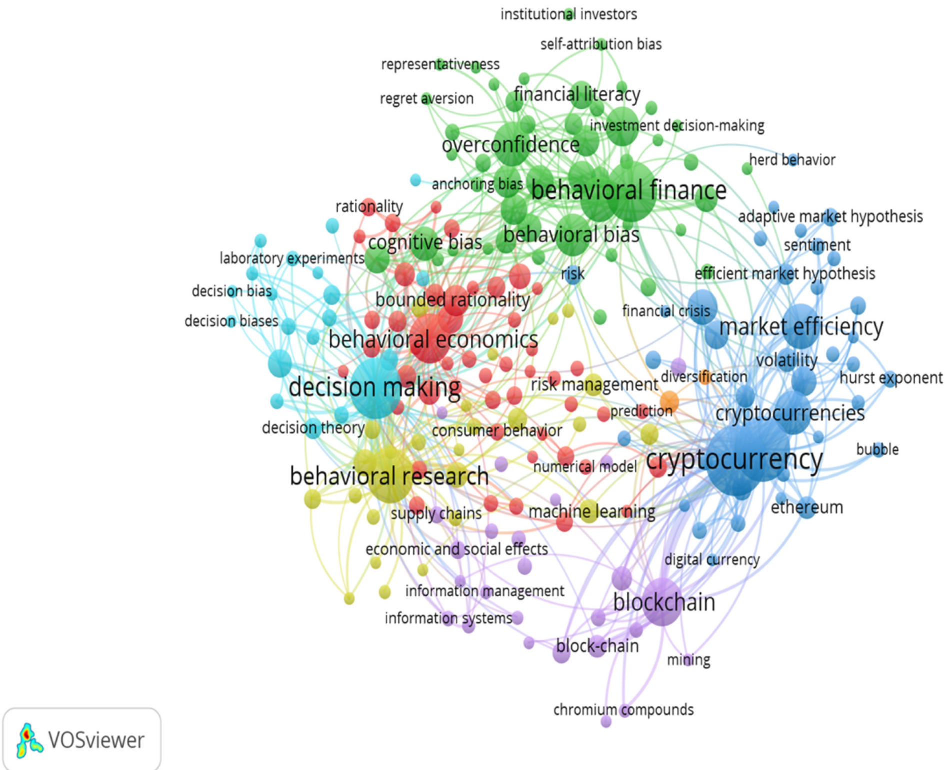

Fig. 4. Network of keywords.

Table 2. Occurrences of the keywords (minimum of 50 occurrences).

Words	Occurrences	Words	Occurrences
Cryptocurrency	395	loss aversion	63
Behavioural finance	302	disposition effect	60
Behavioural biases	272	heuristics	59
Bitcoin	240	cognitive bias	55
Behavioural economics	191	prospect theory	55
Market efficiency	118	asset pricing	52
Overconfidence	114	decision-making	52
Blockchain	109	financial literacy	50
COVID-19	69		

Such sharing between two themes — motor and basic — indicates the strength as well as newness of these ideas that require more research. Additionally, emerging and declining themes encompass ideas that are either gaining prominence or losing significance. A host of these themes also share place with basic themes.

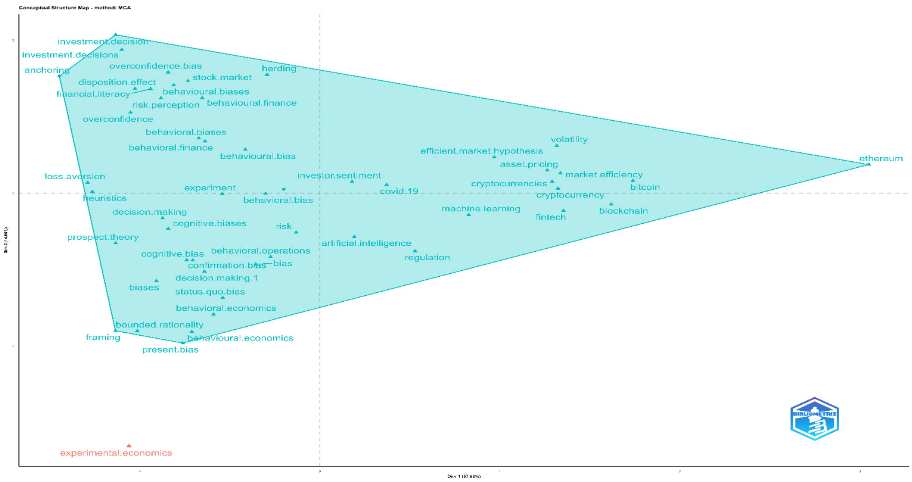

Fig. 5. Conceptual structure map using MCA.

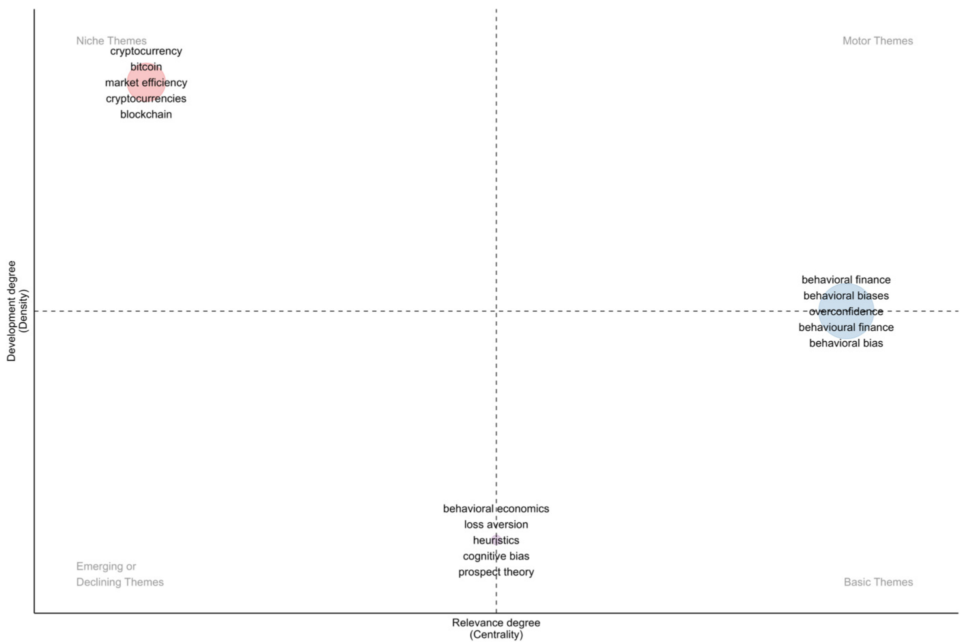

Fig. 6. Major themes.

These include contents like *"behavioural economics, cognitive biases, and prospect theory."*

Themes with a high level of density can be classified into two categories: motor themes and niche themes. Among these, the contents of *"cryptocurrency, Bitcoin, market efficiency, and blockchain"* stand out as relatively more prominent niches.

5. Cryptocurrency Market (in)Efficiency: General Overview

5.1. Evidence of inefficiency

A growing list of studies reported gross violation of the assumptions of market efficiency surrounding cryptocurrency markets and assets (Kristoufek, 2018). Zhang *et al.* (2018) conducted a comprehensive examination of nine cryptocurrencies, employing several efficiency tests on both individual cryptocurrencies and a value-weighted index of cryptocurrencies. The findings indicated that all the examined cryptocurrency marketplaces exhibited inefficiencies. To a greater extent, most cryptocurrencies violate the assumptions of the *random walk hypothesis* (Aggarwal, 2019), and as such, the daily returns of crypto assets, such as Bitcoin, exhibit predictability. Grobys *et al.* (2020) employed technical trading methods on a sample of 11 cryptocurrencies. Their findings indicated that the implementation of a simple moving average rule resulted in the generation of excess returns.

Sapkota and Grobys (2021) found that cryptocurrencies, such as Bitcoins, demonstrated a discernible state of market equilibrium. This implies that there is an absence of any inherent inclination for the market to undergo changes, since each buyer can locate a seller at the prevailing price, and conversely, each seller is able to find a buyer. The herding behavior observed in bitcoin pricing may be attributed to this factor. Vidal-Tomás *et al.* (2019) conducted an analysis of *herding behavior* within cryptocurrency markets. Their findings revealed instances of herding behavior during periods of market decline. Additionally, they observed that smaller cryptocurrencies exhibited herding tendencies toward larger ones. However, Goczek and Skliarov (2019) reported that the price of Bitcoin exhibited heterogeneity in supply and demand dynamics, which might affect market liquidity.

5.2. Evidence of efficiency

After analyzing over 1,000 cryptocurrencies utilizing the low volatility-factor model, Burggraf and Rudolf (2021) revealed that the efficiency of cryptocurrency markets surpassed the prevailing assertions in the literature. Apopo and Phiri (2021) offered opposing views from Aggarwal (2019), explaining the prevalence of *random walk* behavior in the daily series of the five leading cryptocurrencies.

Liew *et al.* (2019) examined the top 100 cryptocurrencies from 2015 to 2018 and indicated that the cryptocurrency markets exhibit a degree of semi-strong form of efficiency in the short-term. On similar notes, Bartos (2015) found that prices of Bitcoin promptly reacted to the publicly available information, exhibiting signs of market efficiency. Nevertheless, the outcomes of these studies indicate support toward adaptive market hypothesis more than the EMH.

Zhang *et al.* (2020) studied Bitcoin, Ethereum, and Litecoin, and reported efficiency of the three currencies during bullish periods using hourly returns. Using the price-volume framework, Sahoo and Sethi (2022) examined the performance of the leading eight cryptocurrencies between the years 2015 and 2022. They confirmed the inability to predict Bitcoin returns using trading volume, which indicated at least weak-form efficiency. Hattori and Ishida (2020) examined the arbitrage tactics utilized by investors in the spot and futures markets of Bitcoin. Their findings suggest that the spot and futures market for Bitcoin exhibits a predominantly efficient nature.

Kyriazis (2019) offered two primary conclusions. *First*, most of the data suggest that cryptocurrencies exhibit inefficiency. *Second*, there has been a notable trend toward enhanced efficiency within the realm of cryptocurrencies in recent years. This finding aligns with the research conducted by Tran and Leirvik (2020), which also indicates that prior to 2017, the efficiency of Bitcoin marketplaces was predominantly deficient. Kang *et al.* (2021) found a subset (54) of 893 cryptocurrencies to adhere to the weak-form efficiency, and only 24 cryptocurrencies were observed to comply with the semi-strong market hypothesis. The time-varying and context-dependent nature of the efficiency in cryptocurrency market offers strong support toward the AME hypothesis.

6. Biases in Cryptocurrency Market

It may be observed that a significant proportion of participants in the cryptocurrency markets lack experience, which consequently gives rise to certain psychological biases (Fonseca *et al.*, 2019). In this section, we discuss the behavioural biases of the cryptocurrency markets.

6.1. Herding behavior

Vidal-Tomás *et al.* (2019) noted the potential occurrence of herding behavior in periods of market decline. Ballis and Drakos (2020) conducted an analysis of six prominent cryptocurrencies between the years 2015 and 2018, and confirmed a tendency to rise in tandem. Akyildirim *et al.* (2020) found that a contagion effect in cryptocurrency markets, where fear and uncertainty increased herding. Shrotryia and Kalra (2021) also claimed that herding occurs in the cryptocurrency market during bullish and high volatility. Kumar (2020), however, argued that anti-herding behavior replaced herding in stable or bullish markets.

6.2. Co-movement and interdependence

Several studies, including Katsiampa (2019), Katsiampa *et al.* (2019), and Qiao *et al.* (2020), have found a positive co-movement or interdependency between cryptocurrencies. Bouri *et al.* (2021) found that severe positive or negative events have higher connectivity than average or median conditions. Bouri *et al.* (2019b) found that when one digital currency's value fluctuates, another can too. However, Manahov (2020) found cryptocurrency market co-movement to be dynamic. Antonakakis *et al.* (2019) found that cryptocurrencies' interdependence or correlated behavior can vary by 25–75%. Like other markets, the cryptocurrency market is highly contagious too (Ferreira and Pereira, 2019).

6.3. Investor sentiment

Gurdgiev and O'Loughlin (2020) explained how investor sentiment affects cryptocurrency market herding and anchoring heuristics. Emotions affected Bitcoin trading volume and volatility, causing price fluctuations (Ahn and Kim, 2021). Investors' optimism about Bitcoin can predict price fluctuations (Anamika *et al.*, 2021). Akyildirim *et al.* (2021) found large cryptocurrencies dominating the connection between attitudes and cryptocurrency returns, which lasted only for about 15 min, making it difficult to exploit these for a meaningful investment strategy. Investors paid more attention to media-covered cryptocurrencies like Bitcoin and Ethereum (Guégan and Renault, 2020; Subramaniam and Chakraborty, 2019).

6.4. Announcement effect

Joo *et al.* (2020) revealed that there is a delay (up to 6 days) in price adjustment following the release of significant news events in prominent cryptocurrency markets, indicating gradual diffusion of information and overreaction to negative news. News sentiment carried relatively higher influence on cryptocurrencies that were younger, smaller in market capitalization, and characterized by higher levels of volatility (Anamika and Subramaniam, 2022).

Unlike traditional currencies, Rognone *et al.* (2020) observed that Bitcoin's value demonstrates an increase in both negative and positive market announcements, indicating an early adopter enthusiasm among individuals for Bitcoin. Narratives on social media and search engines also offered measurable influence on the cryptocurrency prices and volatility in the form of social attention (Zhang *et al.*, 2021; Sabalionis *et al.*, 2020; Azqueta-Gavaldón, 2020). Industry-specific negative news, such as the cyber-attacks or fraudulent activities, negatively impacted the value of Bitcoin and contributed to its price volatility (Corbet *et al.*, 2020).

6.5. Disposition effect, ambiguity aversion, and gambler's fallacy

In the presence of a disposition effect, investors exhibit a reluctance to divest their underperforming assets, while displaying a greater propensity to sell their profitable assets (Shefrin and Statman, 1985). Bitcoin demonstrated a tendency toward a positive disposition impact when experiencing negative market conditions, and conversely, a reverse disposition effect during bullish market periods (Haryanto *et al.*, 2019).

To streamline the decision-making process when faced with two bets, investors are faced with and should rationally avoid ambiguities (Ellsberg, 1961). Luo *et al.* (2021) suggested that, on average, market participants displayed a tendency to ambiguity aversion, and when the ambiguity aversion is kept minimum, investors have the potential to achieve anomalous gains.

Despite the inherent ambiguity of cryptocurrency markets, investors often fall victim to the gambler's fallacy, as described by Rogers (1998). Gemayel and Preda (2021) provided empirical evidence that investors who have encountered poor rates of trading success or low returns in past transactions tend to augment their future trading volume. Senarathne (2019) reported a consistent positive connection between risk and investors' motivation to invest in Bitcoin while examining gambling behavior.

6.6. Overconfidence and overreaction

Heuristics can be described as a cognitive process that involves substituting complex problems with simpler ones (Kahneman, 2003). An example of a commonly seen phenomenon in bitcoin trading is the presence of a widespread illusion of control (Delfabbro *et al.*, 2021), which manifests as an overconfidence heuristic relating to overstating someone's capacity to have an impact. Borgards and Czudaj (2020) found the presence of price overreaction among 12 cryptocurrencies. The instances of negative overreactions were more prevalent than those of positive overreactions. Nonetheless, there is a growing list of heuristics to be explored further, which include take-the-best, recognition, availability, and representativeness.

7. Other Indicators of Market Inefficiency

7.1. Cryptocurrency momentum reversals and anomalies

Common anomalies like Momentum and Reversal, extensively studied by De Bondt and Thaler (1985), Chan *et al.* (1996), Jegadeesh (1990), Jegadeesh and Titman (1993), and Lee and Swaminathan (2000), have challenged the explanatory power of the efficient market theory. The concept of momentum suggests that financial assets that have exhibited strong performance in the past are likely to continue outperforming assets that have performed poorly in subsequent time periods. On the other hand, the concept of reversal proposes the opposite, suggesting that assets with poor past performance may generate positive abnormal returns compared to assets with strong past performance.

Lee *et al.* (2020a) argued that speculative motives of cryptocurrency investors who employed a momentum trading strategy in the Bitcoin market during higher volatility and a contrarian strategy during low volatility.

Several studies reported a strong presence of a momentum effect in cryptocurrency market (Borgards, 2021; Liu and Tsyvinski, 2020). Caporale *et al.* (2018) examined the concept of price persistence as a measure of momentum of Bitcoin, Litecoin, Ripple, and Dash cryptocurrencies from 2013 to 2017. The research findings indicate a good association between the historical and future prices of various digital currencies. Omane-Adjepong *et al.* (2019) extended this analysis, including Ethereum, Stellar, Monero, and Nem coins and found similar results. Cheng *et al.* (2019) also confirmed the above results using both Bitcoin and Ethereum.

Li *et al.* (2021) argued that maintaining a long position in a cryptocurrency is more probable to yield greater future gains. Nguyen *et al.* (2020), however, their findings did not offer conclusive proof that integrating a momentum-based investment strategy into cryptocurrency portfolio management can yield positive abnormal returns. Caporale and Plastun (2020) indicated otherwise: abnormal profit is possible in cryptocurrency markets using the momenturm strategy.

Kozlowski *et al.* (2020) studied the reverse effect on a sample of 200 cryptocurrencies, examining their performance across various time durations. The findings verified that the impact endured for 50% of the duration of the sample period. Zaremba *et al.* (2021) conducted an analysis on the daily returns of a substantial sample size of 36,000 cryptocurrencies that revealed the presence of a robust reversal signal.

Shen *et al.* (2020) employed the three-factor model proposed by Fama and French (1993) on a sample of 1,700 cryptocurrencies and found a higher probability of reversal returns for larger cryptocurrencies. Using the size effect (see Banz, 1981), Li *et al.* (2019) found that cryptocurrencies with smaller market values exhibit a tendency to outperform those with larger market values in subsequent periods.

Ozdamar *et al.* (2021) observed that cryptocurrencies exhibiting the most substantial daily returns throughout the preceding month generally exhibit more favorable anticipated returns. The disparity in average weekly returns amongst cryptocurrencies is approximately 3.03%. Even after controlling for other variables such as size, price, and momentum, the observed disparity remains approximately 1.99%.

Kosc *et al.* (2019) investigated the top 100 cryptocurrencies based on market capitalization and found that the impact of a contrarian strategy, characterized by the act of opposing prevailing market trends, exhibits greater prominence in the short-term as compared to the momentum effect and other conventional investment benchmarks.

Grobys and Sapkota (2019) presented some early challenges against momentum and reversal-related anomalies. Although the research findings did not provide any empirical proof of substantial momentum returns, the prevailing sentiment among the majority still favors the inefficiencies of Bitcoin markets.

7.2. Cryptocurrency seasonality

Seasonality is a term used to describe the recurrent patterns — positive and negative — observed in the returns of financial assets. The months of July and August are deemed unfavorable for cryptocurrency acquisition due to the observed data set, which indicates significantly lower returns during these two months compared to the remaining duration of the year (Plastun *et al.*, 2019). Long *et al.* (2020) indicated that the average returns of cryptocurrencies on the same weekday in the past had a positive predictive effect on future returns. The repatriation of Bitcoin on Mondays is higher compared to other days of the week (Aharon and Qadan, 2019; Caporale and Plastun, 2019b; Fraz *et al.*, 2019). The values of Bitcoins tend to cluster more frequently around whole numbers on Fridays compared to the other days of the week (Mbanga, 2018).

Qadan *et al.* (2022) examined four anomalies, namely calendar patterns, natural conditions, holidays coinciding with the closure of the New York Stock Exchange, and holidays coinciding with the simultaneous operation of the New York Stock Exchange and the Chicago Exchanges. They found a favorable correlation between the occurrence of New Year's Day and the performance of Ethereum and Monero cryptocurrencies, but not for the Chinese New Year's Day.

Several recent findings align with the concept of AME, indicating that efficiency is not fixed but rather dynamic and subject to change. While the weak form of market efficiency cannot be rejected outright (Kaiser, 2019), seasonality patterns were shown to be significant but lacked consistency. Other studies (Khuntia and Pattanayak, 2021; Shahzad *et al.*, 2022) blamed dynamism and erratic fluctuations in cryptocurrency market for seasonality, indicating signs of adaptations.

7.3. Arbitrage in cryptocurrency market

Arbitrage opportunities arise when cryptocurrency exchanges have large price disparities. A trend in trade volumes across exchanges explains 80% of Bitcoin's return, say, in the USA. However, exchange-specific changes affect arbitrage prices (Makarov and Schoar, 2020). Lee *et al.* (2020b) found that deviations, or price discrepancies between spot and future values, do occur and become more evident during disturbances like Bitcoin thefts or the introduction of new cryptocurrencies. This exhibit locational arbitrage — traders may theoretically acquire Bitcoin at a cheaper price in one market and sell it at a higher price in another — reaping a profit without risk — essentially arbitrage.

7.4. Information asymmetry

Ante (2020) used blockchain transparency to study trade volume and knowledge asymmetry in large Bitcoin transactions. The study found favorable trading volume changes linked to 2,132 large Bitcoin transactions between September 2018 and November 2019. Public dissemination of high-information-asymmetry transactions reduced abnormal trading activity. Less information asymmetry has opposite impacts. The findings show that knowledgeable traders use blockchain transaction data to shape Bitcoin's market dynamics. This observation suggests that market information is not always consistently absorbed or acted upon. On a similar note, Alexander *et al.* (2020) found that institutional investors are better informed, suggesting lower information asymmetry.

7.5. Market bubbles

Short-term speculators often cause reasonable bubbles (Wei and Dukes, 2021). Speculative investors and cryptocurrency users may engage more, increasing the risk of a bubble. According to Eom (2021), fundamental uncertainty divides investors. Trading based on significant differences in belief can cause speculative bubbles. Dogecoin's price boom and crash were strongly connected to social media comments by Elon Musk (Cary, 2021; Shahzad *et al.*, 2022). Researchers suggested using the bubbles carefully to explain the explosive character of the cryptocurrency market (Gronwald, 2021). Similar to other assets, crypto valuation should go beyond its financial fundamentals (Abraham, 2019).

Cryptocurrency bubbles can occur when the market value of a currency differs from its intrinsic worth. Bitcoin and Ethereum prices have shown bubble behavior for multiple periods (Corbet *et al.*, 2018). Bitcoin has been in a bubble since its price rose beyond $1000 (Phillips and Yu, 2011). However, several studies concluded that Bitcoin bubbles are widespread, but their testing methods did not prove their persistence (Geuder *et al.*, 2019; Filimonov and Sornette, 2013; Phillips *et al.*, 2015).

8. Adaptive Market Efficiency Hypothesis

The AME hypothesis combines the EMH and behavioural finance. Ferreira *et al.* (2020) emphasized that investors cannot consistently profit from cryptocurrency price movements as they are close to the random walk. Due to the dynamic random walk, bitcoin markets are not efficient. Market efficiency changes over time in cryptocurrency markets (Noda, 2020; Khuntia and Pattanayak, 2018, 2020). AME theory, a novel version of the EMH (Lo, 2004), explains this dynamic state.

Dynamic adaptation is supported by several studies: by López-Martín *et al.* (2021) in Bitcoin, Ripple, Stellar, and Monero cryptocurrencies; and by Chu *et al.* (2019) in Ethereum. Keshari Jena *et al.* (2020) and Khursheed *et al.* (2020) ranked several cryptocurrencies. Ethereum, Ripple, Bitcoin, Dash, and Nem are ranked from most to least efficient (Keshari Jena *et al.*, 2020). Bitcoin, Monaro, and Litecoin have the longest efficiency periods (Khursheed *et al.*, 2020).

Sentimental investing during extreme market conditions (e.g., the COVID-19 pandemic, cryptocurrency heist) contradicts static market efficiency and is more consistent with the AME (Skwarek, 2025; Aslam *et al.*, 2023; Maghyereh and Al-Shboul, 2024; Li *et al.*, 2025). These incidents align with AME, as investors struggle to process information, triggering emotional reactions like panic selling. This dynamic state of inefficiency is influenced not only by external conditions but also by internal ones, such as liquidity and volatility, further supporting the AME framework (Polyzos *et al.*, 2024).

However, due to a nonlinear structure, the AME in cryptocurrency markets is more complex than in traditional financial markets. The absence of a central clearing mechanism makes cryptocurrency markets more dependent on their network structure, leading to complex, nonlinear dynamic adaptive dynamics (Zhu *et al.*, 2025). While linear and nonlinear behaviors may appear similar, they diverge during certain periods, such as the early 2018 Bitcoin breakdown (Bundi and Wildi, 2019). Furthermore, adaptive efficiency behavior may vary across cryptocurrencies. While the market efficiency of Bitcoin and Ripple evolves over time, Ethereum tends to move toward a more inefficient state (Ghazani and Jafari, 2021).

While the AME remains more applicable than the EMH due to the frequent occurrences of price bubbles across different time scales (Alvarez-Ramirez *et al.*, 2018), critiques of AME reject this notion (Jiang *et al.*, 2018) as they did not find evidence of improvements in Bitcoin's efficiency over time.

9. What Contributes to (in)Efficiency?

Convergence occurs when an efficient market prevents simultaneous trading of a financial instrument at two prices, reducing arbitrage opportunities. Apergis *et al.* (2021) found that market microstructure drives the convergence of eight cryptocurrencies. Among other factors, range volatility, market capitalization, and mining fees increase convergence due to price uncertainty, but information and news trade volume, and network addresses failed to contribute to convergence.

Contrary to trade volume, Güleç and Aktaş (2019) found that market volume increases efficiency. Trading volume also positively correlated with speculative cryptocurrency booms (Eom, 2021).

Market capitalization plays an efficiency function by lowering momentum impact in cryptocurrency marketplaces (Jia *et al.*, 2022; Liu *et al.*, 2020). Köchling *et al.* (2019) found high correlations between bid-ask spreads, market cap, and weak-form cryptocurrency market efficiency. A highly liquid, low-volatility cryptocurrency market is efficient (Al-Yahyaee *et al.*, 2020). Dong *et al.* (2022) explained that a fall in cryptocurrency liquidity increases anomalous returns, inversely affecting market efficiency. Wei (2018) confirmed that liquidity is a key factor in market efficiency, while Fakhfekh and Jeribi (2020) justified the volatility result by arguing that increased volatility may cause uninformed investors to herd. Also, volatility (trading volume) increases (decreases) herding behavior in the cryptocurrency market (Youssef, 2020). Low-priced cryptocurrencies are also more volatile than high-priced ones (Aloosh and Ouzan, 2020), making efficient cryptocurrencies more costly.

Although low volatility improves market efficiency, high volatility can improve it, especially during pre- and post-crash periods (Yaya *et al.*, 2020). Diaconaşu *et al.* (2022) also found that pandemics boost cryptocurrency efficiency. Wang and Wang (2021) analyzed the COVID-19 pandemic using Entropy-based analysis and found that Bitcoin markets are more robust and less inefficient than stock markets. These traits made it a safe haven. Naeem *et al.* (2021) used asymmetric multifractal detrended fluctuation (MF-DFA) and time-varying deficit on 1-h Bitcoin, Ethereum, Litecoin, and Ripple data. Bitcoin and Ethereum were the least efficient of the four cryptocurrencies due to the COVID-19 epidemic. The COVID-19 pandemic had a greater impact on bitcoin market efficiency than bubble episodes in late 2017, early 2018, and July 2020 (Montasser *et al.*, 2022).

Caporale and Plastun (2019a) revealed that transaction costs (mining fees) may reduce profit potential that drives investors to overbuy or oversell a coin due to fear or greed. Leveraged trading affects cryptocurrency market efficiency (Strych, 2022). Also, margin trading and short selling diminish market pricing efficiency. Financial derivatives may improve bitcoin market information efficiency. The Bitcoin futures increased the spot price's information efficiency (Shynkevich, 2020). Cryptocurrencies have no fundamental worth, except for their utility as a tool for exchange. Speculative bubbles occur when investors overvalue or undervalue cryptocurrencies (Latif *et al.*, 2017).

10. Decentralized Finance and Non-Fungible Tokens

Cryptocurrencies are often designed around decentralized principles, aiming to eliminate the need for central intermediaries. They are traded in decentralized exchanges (DEXs) like Uniswap-V2, but they can also be traded in centralized exchanges (CEXs) like Binance. Almeida *et al.* (2025) found that Ethereum-Bitcoin pair exhibits a superior level of weak form efficiency in DEXs over CEXs. Therefore, DeFi enhances cryptocurrency market efficiency. This is driven by DEX's inherent transparency, facilitation of arbitrage, global accessibility, algorithmic trading, fewer regulatory hurdles, and rapid adaptation to market conditions.

In contrast, Momtaz (2024) agreed that decentralized finance (DeFi) aims to enhance cryptocurrency market efficiency by reducing intermediation and transaction costs. However, in practice, DeFi exhibits significant inefficiencies due to search frictions driven by market granularity, asymmetric information, moral hazard in signaling, and cyber risks. While transactions are technically efficient, distributed ledger technology (DLT) and asset tokenization lead to highly granular markets, increasing search intensity and effort required to find optimal matches. High information asymmetry can cause under- or overinvestment, while moral hazard signaling can facilitate fraudulent signaling. Additionally, most users lack the expertise to detect cyber-attacks, further undermining efficiency. Consequently, a certain degree of centralization, such as intermediation by crypto funds, is often necessary for efficient functioning within the cryptocurrency ecosystem, indicating that perfectly DeFi may not be optimal for market efficiency.

The relationship between DeFi and cryptocurrency market efficiency is multi-faceted. Makridis *et al.* (2023) observed that DEXs experience the front-running phenomenon, where some transactions are executed ahead of others to secure risk-free profits. Their design also exposes users to front-running cyber-attacks. Additionally, mechanisms like "airdrops", while driving growth, can increase volatility when "yield farmers" cash out tokens rapidly after price surges. These factors hinder efficiency. On the other hand, DEXs reduce information asymmetry through integral smart contracts. Notably, growth does not appear to stem from speculation or regulatory arbitrage (e.g., hiding illicit gains). These features suggest that while certain aspects in DEXs hinder efficiency, others promote it.

Cryptocurrencies like Bitcoin and Ethereum are fungible tokens (FTs), while non-fungible tokens (NFTs) represent unique, non-fungible assets that allow for the creation, registration, and transfer of ownership. Okorie *et al.* (2024) find that both FTs and NFTs exhibit AME, with increased inefficiency during the COVID-19 pandemic. However, NFTs demonstrate greater resilience and improved efficiency during Russia–Ukraine conflict. Similarly, Chowdhury *et al.* (2023) observe that DeFi-based FTs are more efficient than centralized FTs, and NFTs are generally more efficient than FTs. Despite this, inefficiencies persist. Tekin (2025) notes that NFT markets remain sentiment-driven, influenced by behavioural biases such as the bandwagon effect, herding, and speculative bubbles and hype. Benedek and Nagy (2025) highlight the role of information asymmetries influencing NFTs.

Although NFT markets are more mature than FT markets, NFT prices are unidirectionally caused by FTs prices (Apostu *et al*., 2022). Christopher Westland (2024) showed that Bitcoin and Ether prices are strongly correlated with NFT prices and volume due to hedging strategies, sentiment, and holdings transfer and transaction dynamics.

11. Regulatory Frameworks

Cryptocurrencies, due to inherently weak regulatory frameworks and limited nformation disclosures, are highly influenced by psychological and sociological factors (Naeem *et al*., 2021). Regulations, often perceived as uncertain events and bad news, tend to increase market volatility, affecting prices, liquidity, and returns, thereby reducing market efficiency. However, during periods of heightened investor greed, regulation can enhance efficiency by curbing excessive sentiment. Notably, the impact of regulatory policies on volatility diminishes during crises or epidemics, as investors view cryptocurrencies as safe-haven assets regardless of regulatory actions. These actions often include trading bans, risk warnings, and restrictions on virtual currency mining (Zhang *et al*., 2023). Tight and strict regulations may reduce cryptocurrency market efficiency by hindering efficient information dissemination and increasing price distortion and uncertainty (Yi *et al*., 2023). In contrast, Bouteska *et al*. (2025) demonstrated that introducing regulatory reforms in cryptocurrency markets can enhance efficiency by reducing regulatory uncertainty, increasing market trust, improving liquidity, and providing clearer guidelines for market participants. Examples of such reforms include tax clarity, anti-money laundering (AML) and know-your-customer (KYC) compliance, transparent auditing, governance standards, liquidity pooling, smart contract regulation, improved scalability and interoperability, information disclosure, and support for institutional investment tools and central bank digital currencies. Meanwhile, some studies report neutral effects. For instance, Feinstein and Werbach (2021) found almost entirely null results regarding the impact of regulatory actions, such as securities classifications AML and anti-fraud enforcement, and bespoke licensing, on trading dynamics or overall market participation.

12. Implications for Cryptocurrency Investors and Risk Managers

Essentially, the most important question regarding crypto asset investment surrounds its extreme volatility and lack of regulation to protect the interest of the investors. Nimalendran *et al*. (2025) found that regulation and compliance, at this initial stage of market development, can significantly boost public confidence, leading to an efficient cryptocurrency market. Additionally, assets voluntarily following regulations can achieve efficiency almost similar to the government-regulated assets.

Technical indicators related to Blockchain offer traders valuable insights (Lahmiri *et al.*, 2021). Technical trading tactics were more profitable than buy-and-hold, protecting against large losses (Hudson and Urquhart, 2019). However, simplistic technical trading may not be as profitable as a buy-and-hold strategy (Ahmed *et al.*, 2020). The 20-day moving average trading method (Grobys *et al.*, 2020) is successful. The use of candlestick patterns is found to be ineffective and misleading for cryptocurrency trading (Ho *et al.*, 2021). Every minute counts in crypto trading. Traders who trade every 1 or 60 min can generate an abnormal return (Aslan and Sensoy, 2020).

Cryptocurrency investment is significant for risk managers for its volatility, capacity to mitigate idiosyncratic risk and effect price volatility (Al Guindy, 2021; Subramaniam and Chakraborty, 2019; Yao *et al.*, 2021; Zhu *et al.*, 2021; Kim, 2022). Specialized technical indicators can be developed to capitalize on extreme market conditions (Chan *et al.*, 2022). Traders' misinterpretation could lead to illiquid cryptocurrency markets and dramatic price volatility. Combining trading indicators, like moving averages, with social factors like user sentiment, improves cryptocurrency price prediction by over 50% (Ortu *et al.*, 2022).

Lucey *et al.* (2022) found that professional investors react to policy changes, while amateur investors react to general media hype. To better understand investor conduct in turbulent cryptocurrency markets, they created Cryptocurrency Uncertainty Indexes that capture these two sorts of uncertainties. Addressing these uncertainties will generate higher returns. Investors should also be aware of the herding behavior as it may reduce crypto investment return and may expose crypto-only investors to risk (Bouri *et al.*, 2019a). For correct risk assessment, forecasting, and strategic portfolio building, investors and portfolio managers should include the long-memory behavior of cryptocurrencies under the Fractal Markets Theory (Assaf *et al.*, 2022).

The Three-Factor Model comprises the cryptocurrency market, size, and momentum. The model can predict returns on crypto assets (Liu *et al.*, 2022). They identified ten 10 cryptocurrency traits that were explained well by the three-factor model. An extension to the four-factor model by adding a contagion risk factor to Fama–French's three-factor model was found to outperform both the cryptocurrency-CAPM and the original three-factor models (Shahzad *et al.*, 2021).

13. Conclusion

This review investigates published literature on efficiency in and drivers of the cryptocurrency market. Based on the bibliometric review, China dominates the bitcoin market and efficiency publications. Bitcoin is the most studied cryptocurrency. The systematic review suggests that cryptocurrency markets are inefficient and easier to spot. Despite claims of market efficiency, they were rare, and outcomes varied by sample. Opponents of cryptocurrency market efficiency found emotions, herding, co-movements, explosivity, disposition effect, size effect, heuristics, ambiguity, gambler's fallacy, momentum, reversal, seasonality, and market bubbles to support the presence of market inefficiency. Controlling for Bitcoin market efficiency drivers, such the range volatility, market capitalization, mining fees, trading volume, and network addresses, helps minimize market inefficiency.

Major implications are as follows. First, stock exchange regulators should regulate cryptocurrency markets to safeguard investors from manipulation and fraud. They should strengthen market cybersecurity to mitigate security breaches and heists. Regulators should require clear and accessible disclosures from token issuers to reduce information asymmetry, moral hazard signals and behavioural biases like herding. Perfectly DeFi-based cryptocurrency is not optimal for market efficiency, and some centralizing is beneficial such as establishing centralized clearing houses for cryptocurrencies or further support establishing and investing in crypto funds. Furthermore, regulatory interventions should be timed based on market sentiment — tightening oversight when investor greed is high to reduce speculation, and avoiding hasty intervention during panic to prevent further volatility. Policymakers can implement sentiment index-based warning systems, such as the Crypto Fear and Greed Index (FGI), this can support timely and effective regulatory responses.

Second, despite the lack of robustness, technical investment tactics might give speculators abnormal returns. Third, to avoid arbitrageurs, speculators, and financial "criminals," investors should choose cryptocurrencies with efficiency boosters. Fourth, diversification may reduce unsystematic risk, but bitcoin portfolio managers should be wary of strong cryptocurrency co-movement. Furthermore, investors should adopt adaptive strategies to crypto market inefficiencies and apply active trading approaches. They should also assume that, despite differences in market inefficiency strength between DeFi-based cryptocurrencies and centralized ones, or between FTs and NFTs assets. All remain inefficient and require similar technical investment tactics. Finally, academics should not assume cryptocurrency markets behave like stock markets or other financial markets. Furthermore, it seems that the literature regarding comparisons between DeFi-based and centralized-based cryptocurrencies, as well as FTs and NFTs in the context of market efficiency, are relatively few. Therefore, more fundamental investigations should be conducted on relevant topics.

This paper provides an overview and establishes a foundation for examining the efficiency of cryptocurrency marketplaces. Nevertheless, it is important to acknowledge that the realm of cryptocurrency is vast and dynamic, which has imposed certain constraints on the scope of our study. The current landscape of cryptocurrencies encompasses a vast array of thousands of digital currencies. However, the body of published academic literature pertaining to market efficiency in this domain is limited in scope, since it addresses just a fraction of the whole cryptocurrency population. Furthermore, this study employs a representativeness framework, hence necessitating the acknowledgment that the findings pertaining to a specific cryptocurrency should not be extrapolated to other cryptocurrencies. Furthermore, while there exists a sufficient body of research examining the prominent abnormalities within cryptocurrency markets, numerous behavioural phenomena remain unexplored. Hence, it is recommended that forthcoming researchers broaden the scope of their investigations by encompassing a wider range of cryptocurrencies and incorporating other behavioural phenomena. Furthermore, this study is an initial attempt to examine the concept of market efficiency in the realm of bitcoin. Subsequent researchers may consider broadening the scope of this investigation to encompass a more comprehensive analysis of this subject matter.

Appendix A: Key Statistics of the Literature Considered for Bibliometric review

Description	Information/Freq.
Core information	
Timespan	2014:2024
Sources (Journals, Books, etc.)	1177
Documents	3224
Annual Growth Rate %	15.08
Document Average Age	4.53
Average citations per doc	17.75
Contents	
Keywords Plus (ID)	4440
Author's Keywords (DE)	7974
Authors	
Authors	6831
Authors of single-authored docs	565
Collaboration	
Single-authored docs	621
Coauthors per Doc	2.66
International co-authorships %	29.62
Document types	
Paper	2646
Book chapter	238
Conference paper	161

(*Continued*)

Description	Information/Freq.
Book	48
Review	131

Notes: Scopus search specifications: (TITLE-ABS-KEY (cryptocurrency AND efficiency) OR TITLE-ABS-KEY (bitcoin AND efficiency) OR TITLE-ABS-KEY (cryptocurrency AND momentum) OR TITLE-ABS-KEY (cryptocurrency AND reversal) OR TITLE-ABS-KEY (behavioral OR behavioural AND biases) OR TITLE-ABS-KEY (cryptocurrency AND bubbles) OR TITLE-ABS-KEY (cryptocurrency AND pricing)) AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO (SUBJAREA, "ECON") OR LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ch") OR LIMIT-TO (DOCTYPE, "re") OR LIMIT-TO (DOCTYPE, "bk")) AND (LIMIT-TO (LANGUAGE, "English")).

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