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Informational Efficiency in Cryptocurrency Markets: A Bibliometric and Thematic Literature Review (2015–2024)

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ABSTRACT

Cryptocurrency markets are known for their wide price fluctuations, lack of central control, and fast-paced development. These characteristics present serious challenges to traditional theories about how markets work and how prices reflect available information. Understanding how information is processed in these markets is essential for investors, policy makers, and academic researchers. This paper offers a thorough review on the extent to which cryptocurrency markets reflect information, based on 977 peer-reviewed articles published between 2015 and 2024 and indexed in Scopus. Using a combined method of bibliometric analysis and thematic review, the study identifies key research directions and common methods used to explore how information affects cryptocurrency prices. The review goes beyond the Efficient Market Hypothesis (EMH) and includes related topics such as volatility modelling, behavioral dynamics, spillovers, liquidity, and institutional influences. It presents a detailed overview of the most influential publications and organises the literature into six thematic research clusters, highlighting conceptual tensions and new methodological approaches. Finally, the paper outlines a future research agenda that connects market efficiency with changing regulatory environments, innovations in market structure, and the increasing role of institutional actors in the cryptocurrency space.

JEL Classification: F30, G11, G14, G15

1 | Introduction

The rapid rise of cryptocurrencies has introduced fundamental challenges to financial economics, particularly in relation to price formation, market behavior, and informational efficiency. Since Bitcoin's inception by Satoshi Nakamoto in 2009, the cryptocurrency market has transformed from a niche technological experiment into a globally recognized asset class, marked by significant price volatility and dramatic shifts in market capitalization. For instance, the total market cap fell by over 70% between late-2021 and mid-2022, before more than doubling again by the end of 2024 (CoinMarketCap 2023). Such volatility reinforces the importance of understanding how effectively cryptocurrency prices reflect and respond to information.

The Efficient Market Hypothesis (EMH) applies in competitive markets with rational investors, but unlike traditional financial assets, cryptocurrencies operate within decentralized, largely unregulated ecosystems marked by fragmented trading venues, limited transparency, and minimal reliance on intrinsic value. These structural features challenge established theories of market behavior and complicate assessments of how information is absorbed into prices. Although a subset of studies applies formal EMH testing to cryptocurrencies, a broader stream of research investigates informational efficiency through related empirical dimensions, including volatility persistence, behavioral biases, liquidity variation, spillover effects, and regulatory responses. Collectively, this body of work illustrates the growing complexity of how information is integrated into cryptocurrency prices, highlighting the challenges of measuring informational efficiency in such a volatile and fragmented market. Unlike traditional financial markets, digital assets' data are not standardized, posing further caution in the interpretation of empirical results.

Although not proposing a formal framework, this review organizes the literature into thematic clusters that help clarify the conceptual landscape of informational efficiency in cryptocurrency markets. Drawing on 977 peer-reviewed articles published between 2015 and 2024 and indexed in the Scopus database, it examines how the literature has conceptualized, tested, and interpreted the capacity of cryptocurrency prices to incorporate information. This review encompasses both formal EMH studies and a wide array of empirical approaches that analyze price dynamics, volatility, sentiment, market linkages, and liquidity effects.

Several prior literature reviews have examined cryptocurrency-related topics such as adoption (García-Corral et al. 2022), speculative behavior (Vasudeva 2023), high-frequency trading (Anas et al. 2024), sustainability (Alqudah et al. 2023), sentiment analysis (Roumeliotis et al. 2024), or provided broad bibliometric overviews (Corbet et al. 2019). These reviews contribute valuable perspectives but do not provide clear insight into how efficiently cryptocurrency markets process and reflect information.

The two studies most closely aligned with the scope of this paper are those by Almeida and Gonçalves (2024) and Bariviera and Merediz-Solà (2021). Bariviera and Merediz-Solà (2021) employ a hybrid bibliometric and qualitative approach to survey cryptocurrency research in economics, offering a broad thematic classification but without a concentrated focus on market efficiency. Almeida and Gonçalves (2024), by contrast, conduct a systematic review of the market microstructure literature, with emphasis on trading mechanisms, order types, and platform design. This study differs in both thematic emphasis and analytical framing: it focuses explicitly on informational efficiency, that is, how, and to what extent, cryptocurrency prices reflect available information.

In doing so, this research combines bibliometric mapping with a thematic synthesis to trace the intellectual development and emerging frontiers of this literature. Its contribution is three-fold: first, it provides a topic-specific synthesis of how informational efficiency has been studied within cryptocurrency markets; second, it identifies influential publications, thematic clusters, and methodological trends; and third, it proposes a forward-looking research agenda that addresses key gaps and reflects the evolving structure and regulation of cryptocurrency markets. For researchers, the review offers a consolidated foundation for advancing theory-driven investigations. For policymakers and practitioners, it provides insights into how institutional participation, governance models, and market design influence the informational behavior of cryptocurrencies.

The remainder of the paper is structured as follows. Section 2 outlines the bibliometric methodology and dataset. Section 3 presents the key findings, including research trends, influential contributions, and a thematic comparison of informational efficiency in cryptocurrency and traditional markets. Section 4 identifies literature gaps and proposes future research directions. Section 5 concludes the paper.

2 | Methodology

This study employs bibliometric review methods to analyze the literature on cryptocurrency market information efficiency. Bibliometric techniques allow for a systematic, quantitative assessment of research trends, key authors, and influential articles within a specific field. This methodology builds upon the approaches of Jalal et al. (2021) and Vasudeva (2023) and extends their methods by incorporating a systematic literature review framework. Figure 1 shows the Scientific Procedures and Rationales for Systematic Literature Review (SPAR-4-SLR) protocol to implement the bibliometric technique.

Data for this study were sourced from Scopus, an interdisciplinary database that includes peer-reviewed literature across the social sciences (Baker et al. 2020; Kumar et al. 2025). A targeted search was performed using keywords: [("cryptocurrency" OR "Bitcoin" OR "Ethereum" OR "altcoin" OR "digital currency" OR "crypto market") AND ("market efficiency" OR "Efficient Market Hypothesis" OR "liquidity" OR "volatility")]. Several filters were applied to ensure the relevance of the dataset. The term "cryptocurrency" had to appear in at least one of the following fields: title, abstract, author keywords, or Keyword Plus (Cumming et al. 2023). This refined the search to articles that are closely aligned with the study's focus on cryptocurrency market efficiency.

Data collection was conducted in October 2024, covering publications from 2015 to 2024. The time frame was selected because significant research on cryptocurrency markets began after 2015, with the market gaining prominence during that period. The selected peer-review journals are filtered based on several criteria: publication year up to 2024, document type: "article", publication stage: "final", source type: "journal", and language restricted to English. The search yielded 977 articles published in peer-reviewed journals listed in the Academic Journal Guide (AJG) 2021[1] and in the Financial Times 50 (FT.Com 2023).

The bibliometric analysis was performed using the Bibliometric R package (Biblioshiny) (Aria and Cuccurullo 2017), which facilitates the identification of key contributors, influential articles, and research trends within the dataset. VOSViewer has been used to visualize bibliometric networks, research streams, and trends (Van Eck and Waltman 2010). This process provides valuable insights into how the field has developed and identifies critical gaps for future research.

3 | Results

3.1 | Overview of the Cryptocurrency Research Landscape

This study offers a comprehensive bibliometric and performance analysis of the cryptocurrency research domain, drawing on a dataset of 977 peer-reviewed articles authored by 1865 researchers

Stage 1 - Outline of the review (Assembling and Arranging)

- Research questions: Efficient Market Hypothesis (EMH) for cryptocurrencies
- Keywords: cryptocurrency, Bitcoin, Ethereum, altcoin, digital currency AND market efficiency, efficient market hypothesis, liquidity, volatility
- Journals ranked in the ABS list
- Data collection and filtering: article published from Jan.2015 to Oct.2024, English language, final stage of publication.

Stage 2 - Conducting the review (Assessing)

- Method of analysis - Bibliometric analysis techniques: SPAR-4-SLR protocol
  - Performance analysis: Bibliometric R package "Biblioshiny"
  - Science mapping: VOSViewer
- Visualization and selection of tools and tecniques for appropriate visualization

Stage 3 - Interpretation

- Explanation and discussion of findings: 977 articles, 1,865 Researchers, 171 journals, top contributing countries are China, the United Kingdom, the United States, Germany, France, and Australia.
- Future path of research are identified.

FIGURE 1 | **Stages of the bibliometric analysis**.

TABLE 1 | **Descriptive statistics**.

Description	Results
Main information about data	
Timespan	2015–2024
Sources (Journals, Books, etc.)	171
Documents	977
Annual growth rate %	−3.97
Document average age	3.2
Average citations per doc	37.34
References	34,448
Document contents	
Keywords plus (ID)	1031
Author's keywords (DE)	2120
Authors	
Authors	1865
Authors of single-authored docs	134
Authors collaboration	
Single-authored docs	160
Co-authors per doc	2.8
International co-authorships %	43.5
Document types	
Articles	977

Source: Scopus.

and published across 171 academic journals between 2015 and 2024 (Table 1). As illustrated in Figure 2, the field has experienced exponential growth in both publication volume and scholarly impact. The earliest Scopus-indexed contributions appeared in 2015 (Baek and Elbeck 2015; Cheung et al. 2015; Dwyer 2015), identifying the beginning of academic inquiry into digital assets. Since then, literature has progressed through two distinct phases: an exploratory period from 2015 to 2018, followed by a phase of rapid expansion beginning in 2019. In this regard, the annual publication trend, shown in Figure 2, reveals a sharp increase in output, culminating in a peak of 187 publications in 2024. Citation impact has also grown markedly, with average citations per article reaching 496.50 in 2024. This trajectory shows the increasing academic and demonstrates the continuous development of the field.

Collaboration has emerged as a defining characteristic of this research area. Although 160 articles were single-authored, the majority reflect collaborative efforts, with 43.5% involving international co-authorship (Table 1) highlighting the global and interdisciplinary nature of the field.

The dissemination of cryptocurrency research is concentrated in a relatively small number of high-impact journals, as shown in Table 2. The "nuclear zone" (Zone 1) comprises four core journals that consistently publish on cryptocurrency topics, led by *Finance Research Letters*, *International Review of Financial Analysis*, *Research in International Business and Finance*, and *Economics Letters*. These four journals alone account for nearly half of all publications in the dataset. In terms of citation impact, *Finance Research Letters* leads with 9355 citations, followed by *Economics Letters* with 5452. These outlets have played a central role in shaping discourse on market efficiency, pricing behavior, and the integration of cryptocurrencies into traditional financial systems.

The field is also shaped by a relatively concentrated group of highly productive and influential scholars. As detailed in Table 3, Professor Elie Bouri (Lebanese American University) leads in both publication volume (33 articles) and scholarly impact (h-index of 21). His research spans topics such as Bitcoin's hedging properties, volatility under economic uncertainty, and dynamic connectedness in crypto markets. Other leading contributors include Professor Shaen Corbet (Dublin City University), Professor Brian Lucey (Trinity College Dublin), and Dr. Larisa Yarovaya (University of Southampton). Corbet's work focuses on financial crises, FinTech, and the interconnectedness of digital and traditional assets. Lucey has made significant contributions to the literature on gold, cryptocurrencies, and market efficiency, while Yarovaya's research on financial contagion, herding behavior, and

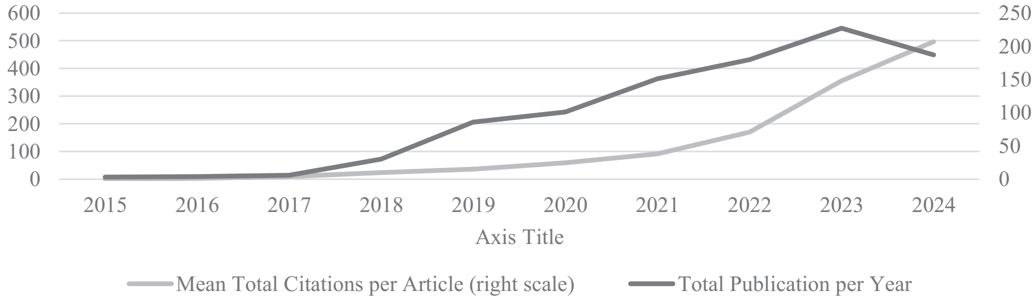

FIGURE 2 | **Year wise publications and citations**. This figure represents the trends of publications and citations over the years. On the left y-axis, the mean total citations per article are displayed, indicating the average citation impact of the published works each year. On the right y-axis, the total number of publications per year is shown, reflecting the annual research output. *Source:* Scopus.

TABLE 2 | Most influential journals.

Journals	Publications (no. of articles)	Citations	FT50 and AJG	H_Index	Zone (Brad Law)
Finance Research Letters	185	9355	2	52	Zone 1
International Review of Financial Analysis	69	4038	3	29	Zone 1
Research in International Business and Finance	48	1773	2	22	Zone 1
Economics Letters	36	5452	3	25	Zone 1
North American Journal of Economics and Finance	34	803	2	17	Zone 2
International Review of Economics and Finance	31	652	2	13	Zone 2
Applied Economics Letters	30	730	1	11	Zone 2
Applied Economics	25	977	2	12	Zone 2
Quarterly Review of Economics and Finance	22	718	2	13	Zone 2
Journal of International Financial Markets, Institutions and Money	20	708	3	13	Zone 2
Technological Forecasting and Social Change	19	1231	3	15	Zone 2
International Journal of Finance and Economics	17	346	3	9	Zone 2
Expert Systems with Applications	15	493	1	9	Zone 2
Computational Economics	15	139	1	7	Zone 2
Studies In Economics and Finance	15	129	1	7	Zone 2
Resources Policy	12	380	2	9	Zone 2
Quantitative Finance	12	130	3	5	Zone 2
Journal of Risk Finance	11	237	1	7	Zone 2
Economic Modelling	10	674	2	5	Zone 2
Annals of Operations Research	10	258	3	8	Zone 2

Source: Scopus.

geopolitical risk has garnered over 1000 citations. Together, these scholars have advanced theoretical understanding, influenced policy debates, and driven methodological innovation.

Figure 3 shed light on the structure of scholarly collaboration. Prominent clusters centered around Bouri, Corbet, and Yarovaya reveal tightly knit research communities, and the emergence of yellow nodes signals the entry of new contributors and recent collaborations. This visualization shows the dynamic and increasingly interconnected nature of the cryptocurrency research community.

Institutional collaboration has also played a pivotal role in shaping the field. Figure 4 illustrates the network of academic institutions engaged in cryptocurrency research. Institutions such as Trinity College Dublin, University of Economics Ho Chi Minh City, Dublin City University, and University of Southampton have central positions in the network. Their high betweenness

TABLE 3 | Most influential authors.

Author	Latest/last reported affiliation	Publications	Citations	H-Index
Bouri Elie	Lebanese American University	33	2803	21
Corbet Shaen	Dublin City University	26	2346	21
Lucey Brian	Trinity College Dublin	26	2472	21
Yarovaya Larisa	University of Southampton	18	1222	16
Urquhart Andrew	University of Birmingham	14	2013	13
Baur Dirk G	The University of Western Australia	12	870	8
Goodell John W	University of Akron	12	415	9
Mensi Walid	Sultan Qaboos University, Oman	12	805	11
Sensoy Ahmet	Bilkent University	12	764	11
Gupta Rangan	University of Pretoria	11	1505	9

Source: Scopus.

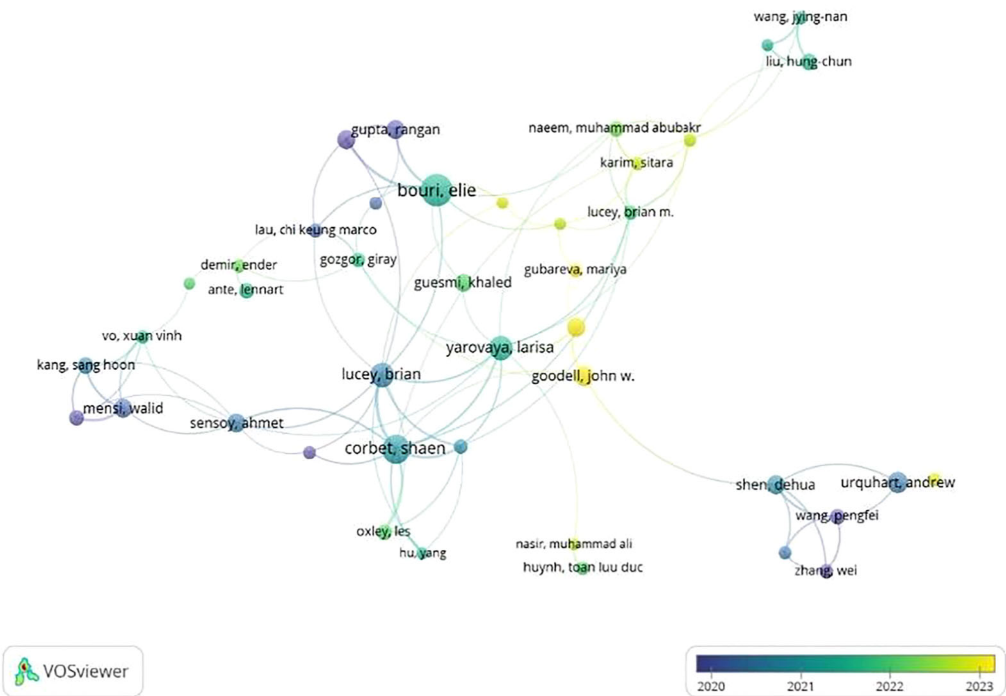

FIGURE 3 | **Authors' network over time**. This figure illustrates the evolution of the authors' collaboration network from 2020 to 2023, as visualized using VOSviewer. Each node in the network represents an individual author, and the lines connecting them indicate co-authorship relationships. The color of each node reflects the average year of publication, transitioning from blue for earlier years to yellow for more recent ones. This temporal gradient allows for a clear view of how collaboration patterns have shifted over time. *Source:* Scopus. [Colour figure can be viewed at wileyonlinelibrary.com]

and PageRank scores suggest they function as key hubs, facilitating knowledge exchange and bridging otherwise disconnected research communities. This institutional network complements the author-level analysis by revealing the broader structural architecture of global academic collaboration, which matters because it provides a comprehensive view of how institutions collectively contribute to the research landscape, identifying key institutions and understanding the dynamics of academic partnerships.

Overall, the bibliometric and performance analysis reveals a rapidly maturing field characterized by high-impact publications, robust international collaboration, and a growing body of interdisciplinary research disseminated through a concentrated set of leading journals.

3.2 | Most Influential Articles

This section presents a critical synthesis of the 40 most cited studies in cryptocurrency research, identified through bibliometric analysis. As the most frequently referenced contributions in the field, these articles are widely recognized for shaping prevailing empirical approaches and theoretical perspectives. Their

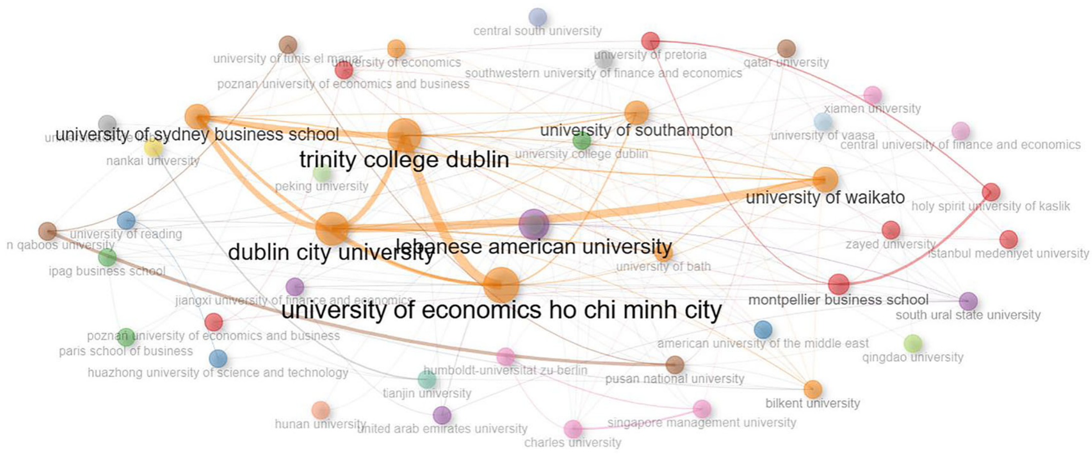

FIGURE 4 | **Top contributing institutions**. In this figure, each node represents a university or business school, with node size reflecting the institution's centrality or influence within the network. Edges between nodes indicate collaborative relationships, such as co-authorships, with thicker lines denoting stronger or more frequent partnerships. The nodes are color-coded into clusters, representing communities of institutions that collaborate more frequently with each other than with those outside their group, often reflecting geographic proximity or shared research agendas. *Source:* Scopus. [Colour figure can be viewed at wileyonlinelibrary.com]

prominence across citation networks makes them analytically valuable for uncovering broader patterns in how efficiency is conceptualized and tested. In addition to summarizing their key elements (see Table 4), the analysis shows that across the 40 papers, there is considerable variation in empirical methods and inconsistencies in findings, arising from differences in modelling approaches, data sources, and the way efficiency is interpreted.

Among the most prominent theoretical frameworks employed, the EMH serves as a benchmark for evaluating informational efficiency in cryptocurrency markets. Foundational studies such as Nadarajah and Chu (2017) and Urquhart (2016) apply classical weak-form efficiency tests, including autocorrelation, variance ratio (VR), and the wild-bootstrapped automatic variance ratio (AVR) tests, to Bitcoin price data. Urquhart (2016) finds that Bitcoin was inefficient in its early years (2010–2013) but exhibited signs of improving efficiency in the sub-period 2013–2016. Nadarajah and Chu (2017) revisit the findings using the same tests but introduce an odd-power transformation of returns, showing that Bitcoin appears efficient under the transformed series. The treatment of Bitcoin in these studies reflects its growing maturity, aligning its behavior more closely with traditional financial assets. However, this view is contested by studies that emphasizes behavioral and structural anomalies. Bariviera (2017), for example, employs the Hurst exponent to detect long memory and volatility clustering, indicating persistent inefficiencies even in more recent periods. Similarly, Bouri, Roubaud and Kristoufek (2019) and Shen et al. (2019), introduce behavioral finance perspectives, documenting herding behavior and sentiment-driven volatility using logistic regression and Vector Autoregression (VAR) models, respectively. These findings suggest that informational efficiency in crypto markets is not a binary condition, but a dynamic and context-dependent phenomenon shaped by liquidity, investor composition, and technological infrastructure.

It is also observed that the different methodologies across these studies reflect a lack of consensus on how to effectively measure efficiency in decentralized and highly volatile markets. Volatility modelling dominates the field, with Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models employed in over half of the top-cited studies. Baur et al. (2018), Dyhrberg (2016), and Katsiampa (2017) rely on variants of GARCH to model time-varying volatility in Bitcoin and other cryptocurrencies. These models are well-suited for capturing conditional heteroskedasticity but often assume linearity and stationarity, assumptions that may not hold in crypto markets characterized by regime shifts, structural breaks, and non-normal return distributions. Even within this modelling family, results diverge. For instance, while Dyhrberg (2016) concludes that Bitcoin behaves similarly to gold and may serve as a hedge for risk-averse investors, Klein et al. (2018) challenge this interpretation using dynamic correlation models, finding that Bitcoin lacks the safe-haven properties of gold. Baur et al. (2018) build on Dyhrberg (2016)'s work and find that Bitcoin's return and volatility characteristics are distinct from both gold and fiat currencies.

Other studies adopt more flexible or non-linear approaches. Balcilar et al. (2017) demonstrate that trading volume can predict returns under certain market regimes using a causality-in-quantiles framework. Mnif, Jarbouri and Mouakahr (2020) apply multifractal analysis to examine efficiency before and after the COVID-19 pandemic. These methods are better equipped to capture the heavy-tailed distributions and non-linear dependencies typical of crypto assets. Taking a different approach, Shen et al. (2019, p. 201) and Urquhart (2018) incorporate sentiment proxies such as Twitter activity and Google Trends into VAR models, highlighting the role of investor attention in driving volatility and volume. Urquhart (2018) finds that realized volatility and trading volume influence public attention to Bitcoin, though attention itself does not predict returns. Shen et al. (2019) show that Twitter activity predicts volatility and volume but not price direction. Bouri et al. (2019) further expand the behavioral perspective by identifying herding behavior in the cryptocurrency market using a logistic regression, and demonstrate that trading volume can predict returns under certain market regimes using a causality-in-quantiles framework. These studies challenge the rational expectations underpinning EMH and suggest that behavioral

TABLE 4 | Most influential articles.

Author(s) (Year)	Title	Journal	TC	Research question	Period	Data type	Research approach	Key findings
Ali et al. (2020)	BTC, gold and the dollar—A GARCH volatility analysis	Finance Research Letters	959	Explores the financial asset capabilities of Bitcoin (BTC) using GARCH models	2010–2015	Daily closing price of BTC (Coindesk), gold price and US stock index	Quantitative. Asymmetric GARCH and volatility analysis	The asymmetric GARCH showed that BTC may be useful in risk management and ideal for risk averse investors in anticipation of negative shocks to the market.
Urquhart (2016)	The inefficiency of BTC.	Economics Letters	855	Is the BTC market efficient?	2010–2016	Daily closing prices of BTC in USD	Quantitative. Autocorrelation of returns tests; variance ratio test; AVR; Wild-bootstrapped AVR test	The BTC market was inefficient in 2010–2016; however, it seems to be becoming less inefficient in the sub-period 2013–2016.
Katsiampa (2017)	Volatility estimation for BTC: A comparison of GARCH models.	Economics Letters	660	Which conditional heteroscedasticity model can better explain the BTC data?	2010–2016	Daily closing prices of BTC Coin- desk Index	Quantitative. ARCH model for the conditional mean and a first-order GARCH-type model for the conditional variance.	The ARCH-GARCH is the model that fits the data, short- and a long-run component of conditional variance are relevant.
Corbet et al. (2020)	The contagion effects of the COVID-19 pandemic: Evidence from gold and cryp-tocurrencies	Finance Research Letters	593	How did the volatility of main Chinese stock markets and BTC evolved during this pandemic crisis?	March 11, 2019–March 10, 2020	Hourly price of BTC, Gold, the DJIA and Chinese stock indices (Shanghai, Shenzen)	Quantitative. GARCH and volatility analysis	In times of serious financial and economic disruption cryptos do not act as hedges, or safe havens, but rather as amplifiers of contagion.
Klein et al. (2018)	BTC is not the New Gold—A comparison of volatility, correlation, and portfolio performance.	International Review of Financial Analysis	523	How does cryptocurrency' volatility differ from that of stock indices and commodities? use a dynamic correlation analysis to examine the hedging and safe haven capacity of cryptocurrencies in comparison to Gold	2011–2017	Daily price of BTC, Gold and Silver prices in USD per oz, of crude oil prices for the WTI, of the S&P 500 index, of MSCI World and of the MSCI Emerging Markets 50 index	Quantitative. GARCH models	The BTC, unlike gold, does not serve as a safe-haven asset in portfolio.

(Continues)

TABLE 4 | (Continued)

Author(s) (Year)	Title	Journal	TC	Research question	Period	Data type	Research approach	Key findings
Dwyer (2015)	The economics of BTC and similar private digital currencies	Journal of Financial Stability	485	Provides an overview of BTC and similar private digital currencies	No data	No empirical analysis	Qualitative description of the market; no empirical investigation	The structure of BTC makes it conceivable for an equilibrium with a positive value for such a currency; it has the potential to eliminate the need for banks and payment processors in such applications. Major obstacles are raised by regulation. The government's capacity to inflate the economy can be undermined by the BTC and other digital currencies.
Balcilar et al. (2017)	Can volume predict BTC returns and volatility? A quantiles-based approach	Economic Modelling	473	Use a non-parametric causality-in-quantiles test to analyze the causal relation between trading volume and Bitcoin returns and volatility, over the whole of their respective conditional distributions	December 9, 2011–April 25, 2016	Daily data on BTC from bitcoincharts.com	Quantitative. Non-linear relationship between returns and volumes; VAR and ADF tests.	BTC returns and volumes are not normally distributed. Causality-in-quantiles test reveals that volume of BTC can predict returns—except in Bitcoin bear and bull market regimes.
Ali et al. (2020)	Coronavirus (COVID-19) — An epidemic or pandemic for financial markets	Journal of Behavioral and Experimental Finance	470	Investigate the reaction of financial markets (decline and volatility) as Coronavirus epicenter moved from China to Europe and then to the US.	1 January 2020–20 March 2020	Daily prices of stock markets (US, China, European, Asian), gold and oil, and BTC.	Quantitative. Exponential GARCH model.	The earlier epicentre China has stabilized while the global markets have gone into a freefall. Even the relatively safer commodities have suffered as the pandemic moves into the US.
Nadarajah and Chu (2017)	On the inefficiency of BTC	Economics Letters	461	Is the BTC market efficient?	2010–2016	Daily closing prices of BTC in USD	Quantitative. Replication of Urquhart (2016); run's test; Ljung–Box test for serial autocorrelation; Bartel's test; wild-bootstrapped automatic variance ratio test.	A simple power transformation of BTC returns satisfies the efficiency hypothesis through the use of eight different tests, with no loss of information.

(Continues)

TABLE 4 | (Continued)

Author(s) (Year)	Title	Journal	TC	Research question	Period	Data type	Research approach	Key findings
Bariviera (2017)	The inefficiency of BTC revisited: A dynamic approach	Economics Letters	434	Is the BTC market efficient?	2011–2017	Daily closing prices of BTC in USD	Quantitative. Study the long memory of the BTC market using the Hurst exponent, computed using two alternative methods.	Volatility clustering is an important characteristic of the BTC.
Guesmi et al. (2019)	Portfolio diversification with virtual currency: Evidence from BTC.	International Review of Financial Analysis	421	Are virtual currencies useful to diversify portfolios?	2012–2018	Daily prices of USD of stock markets (MSCI Emerging Markets Index and MSCI Global Market Index), Euro and Chinese exchange rate, gold and oil (gold bullion and WTI), BTC (Bitstamp) and the VIX.	Quantitative. GARCH models; VARMA (1,1)-DCC-GJR-GARCH	BTC may offer portfolio diversification and hedging benefits for investors.
Baek and Elbeck (2015)	BTCs as an investment or speculative vehicle? A first look	Applied Economics Letters	399	Which are the drivers of BTC returns?	July 2010–February 2014	BTC (bitcoincharts.com) and S&P 500 Index daily returns	Quantitative. Use BTC and S&P 500 Index daily return to examine relative volatility using detrended ratios.	BTC volatility is internally (buyer and seller) driven leading to the conclusion that the Bitcoin market is highly speculative.
Ji et al. (2019)	Dynamic connectedness and integration in cryptocurrency markets	International Review of Financial Analysis	395	Quantifying the time spillover effects across six large cryptocurrencies (BTC, Ether (ETH), Ripple (XRP), Litecoin (LTC), Stellar(XLM) and Dash (DASH)) to better understand the spillover nature of each cryptocurrency.	2015–2018	Daily data of largest cryptocurrencies by market capitalization from https://coinmarketcap.com.	Return and volatility connectedness networks	The findings highlight the significance of trading volume, the impact of global and investment substitution, and the impact of uncertainty in determining the net directional spillover across cryptocurrency returns. Highly capitalized cryptocurrencies have relatively different levels of integration, which means that shocks to one cryptocurrency typically do not result in significant spillovers to the others, reducing the possibility of diversification.

(Continues)

TABLE 4 | (Continued)

Author(s) (Year)	Title	Journal	TC	Research question	Period	Data type	Research approach	Key findings
Urquhart and Zhang (2019)	Is BTC a hedge or safe haven for currencies? An intraday analysis	International Review of Financial Analysis	335	Examine the intraday hedge and safe haven properties of BTC	2014–2017	Intraday data of BTC (Bitstamp); intraday currency data (Bloomberg) of CHF, EUR, GBP, AUD, CAD, JPY.	Quantitative. Dynamic conditional correlation analysis	BTC is a hedge for the CHF, EUR and GBP, is a diversifier for AUD, CAD and JPY, and safe heaven during turmoil for CAD, CHF and GBP.
Baur et al. (2018)	BTC, gold and the US dollar—A replication and extension	Finance Research Letters	318	Explores the financial asset capabilities of BTC using GARCH models	2010–2015 extended to July 14, 2017	Daily closing price of BTC (Coindesk), gold price and US stock index	Quantitative. Replication and Extension of Dyhrberg (2016)	BTC returns, volatility and correlation characteristics are distinctively different compared to gold and fiat currencies.
Yi et al. (2018)	Volatility connectedness in the cryptocurrency market: Is BTC a dominant cryptocurrency?	International Review of Financial Analysis	302	Volatility connectedness among cryptos; BTC dominance	2013–2018	Daily prices of cryptocurrencies.	Quantitative; LASSO VAR of connectedness using the volatility index	Volatility connectedness among cryptos fluctuated periodically over the sample period, and increased when the market is experiencing unstable economic conditions or unpredictable exogenous shocks; BTC does not dominate the crypto market.
Bouri et al. (2019)	Herding behavior in cryptocurrencies	Finance Research Letters	299	Is there herding behavior in the crypto market?	April 28, 2013—May 2, 2018	Daily prices of BTC, ETH, XRP, Litecoin, Stellar, Dash, Nem, Monero, Bytecoin, Verge, Siacoin, BitShares, Decred, and Dogecoin from coinmarketcap.com	Quantitative. Logistic regression of cross-sectional absolute standard deviations (CSAD).	The cryptocurrency market is subject to herding behavior that seems to vary over time
Dowling (2022)	Is non-fungible token pricing driven by cryptocurrencies?	Finance Research Letters	267	Is NFT pricing related to cryptocurrency pricing?	March 2019–March 2021	Daily data on BTC, ETH, Non-Fungible Tokens (NFTs) (Cryptopunk, AxieInfinity, Decentraland)	Quantitative. Volatility spillovers between the markets and wavelet coherence analysis.	NFT pricing seems quite distinct to cryptocurrency pricing in terms of volatility transmission and also between NFTs; wavelet coherences suggest some co-movement between crypto and NFTS.

(Continues)

TABLE 4 | (Continued)

Author(s) (Year)	Title	Journal	TC	Research question	Period	Data type	Research approach	Key findings
Cheung et al. (2015)	Crypto-currency bubbles: an application of the Phillips–Shi–Yu (2013) methodology on Mt. Gox BTC prices	Applied Economics	257	Are there bubbles in the BTC market?	July 17, 2010–February 18, 2014	Daily data on BTC from bitcoincharts.com	Quantitative. Use the technique of Phillips, Shi and Yu that is robust in detecting bubbles.	In 2010–2014, short-lived bubbles have been detected. Three huge bubbles were in the latter part of the period 2011–2013 due to market crash (MtGox exchange crash)
Urquhart (2018)	What causes the attention of BTC?	Economics Letters	253	What causes the attention of BTC?	2010-2017	Google trend data for the keyword 'BTC'.	VAR models with daily realized volatility data at 5-minutes level	Realized volatility and the volume of BTC significantly influence the next day's attention; however, attention offers no significant predictive power for realized volatility or returns.
Le et al. (2021)	Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocur-rencies in the age of the fourth industrial revolution	Technological Forecasting and Social Change	248	Investigate the time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies.	2018–2020	Daily data of KBW NASDAQ, BTC, MSCI equity indices (MSCI US and MSCI World), US Dollar, Crude oil (S&P GSCI WTI), gold (S&P GSCI), and CBOE volatility (VIX).	VAR models; spillover analysis.	Traditional and digital assets are connected. BTC, MSCIW, MSCI US, and KFTX are net contributors to volatility shocks and US Dollar, Oil, Gold, VIX, Green Bond and Green Bond Select are net receivers. Volatility is higher in the short, than in the long term.
Wei (2018)	Liquidity and market efficiency in cryptocurren-cies	Economics Letters	247	Test the efficient market hypothesis of 456 crypto returns	2017	Returns (log of prices) of cryptos ranked according to their liquidity.	Quantitative; efficient pricing	Market efficiency is stronger and volatility is lower in liquid markets.

(Continues)

TABLE 4 | (Continued)

Author(s) (Year)	Title	Journal	TC	Research question	Period	Data type	Research approach	Key findings
Shen et al. (2019)	Does twitter predict BTC?	Economics Letters	237	Does Twitter predict BTC? Look at the link between investor attention and BTC returns, trading volume and realized volatility	2014–2018	Intraday data of BTC.	Quantitative. VAR models with daily data	The number of previous day tweets are significant drivers of BTC RV and volume, but not returns.
Phillip et al. (2018)	A new look at cryptocurren-cies	Economics Letters	233	Which are the characteristics of cryptocurrencies prices?	2008–2014	Daily data of largest cryptocurrencies sourced from Brave New Coin (BNC) Digital Currency indices (BTC, ETH, ZRP, DEM, Dash).	Quantitative. Time series model of generalized long memory (GLM), stochastic volatility (SV), leverage (LVG) and heavy tails (HT).	Cryptocurrencies exhibit long memory, leverage, stochastic volatility and heavy tailedness.
Chen et al. (2020)	Fear Sentiment, Uncertainty, and BTC Price Dynamics: The Case of COVID-19	Emerging Market and Trade	228	Which is the impact of fear sentiment caused by the coronavirus pandemic on BTC price dynamics?	January 15, 202–April 24, 2020	Hourly data of BTC in USD, VIX and Google Trend search of pandemic sentiment.	Quantitative. Following Urquhart (2018) use VAR models to investigate the relationship between fear sentiment, uncertainty, and Bitcoin returns and trading volume.	An increase in search interest in the pandemic is correlated with increased financial market uncertainty; however, increasing fear of the coronavirus leads to negative Bitcoin returns and high trading volume.
Brauneis and Mestel (2018)	Price discovery of cryptocur-rencies: BTC and beyond	Economics Letters	225	Investigate efficiency, predictability and liquidity of a large number of cryptocurrency returns time series.	August 31, 2015–November 30, 2017	Daily data from coinmarketcap.com of prices of 10 largest cryptocurrencies (BTC, ETH, XRP, Dash, Litecoin, Monero, Nem, Stellar, Monacoin).	Quantitative. Follow Urquhart (2016) and extend to other tests.	Efficiency is positively related to liquidity
Borri (2019)	Conditional tail-risk in cryptocurrency markets.	Journal of Empirical Finance	219	Vulnerability of BTC, Ripple, Ether, and Litecoin to tail-risk (CoVar)	2015–2018	Daily prices of cryptocurrencies.	Quantitative. CoVar	Cryptos are exposed to tail-risk with other cryptos, but not with other financial assets.
Aysan et al. (2019)	Effects of the geopolitical risks on BTC returns and volatility	Research in International Business and Finance	218	Analyze the predictive power of the GPR on returns and volatility of Bitcoin	July 18, 2010–May 31, 2018	Daily prices of BTC and geopolitical risk index	Quantitative. Bayesian Graphical Structural Vector Autoregressive (BSGVAR) technique	Bitcoin can be considered as a hedging tool against global geopolitical risks

(Continues)

TABLE 4 | (Continued)

Author(s) (Year)	Title	Journal	TC	Research question	Period	Data type	Research approach	Key findings
Fang et al. (2019)	Does global economic uncertainty matter for the volatility and hedging effectiveness of BTC?	International Review of Financial Analysis	217	Does global economic uncertainty matter for the volatility and hedging effectiveness of BTC?	2010-2018	Daily prices of BTC and monthly data of Economic Policy Uncertainty index.	Whether the long-run volatilities of BTC, global equities, commodities, and bonds are affected by global economic policy uncertainty with GARCH-Midas model	Global Economic Policy Uncertainty (EPU) negatively impacts BTC-bonds correlation; global EPU positively impacts BTC-equities and BTC-commodities correlations; BTC is hegde under specific economic uncertainty conditions.
Bouri et al. (2018)	Spillovers between BTC and other assets during bear and bull markets	Applied Economics	212	Relations between BTC and conventional investments in bear and bull market conditions	July 19, 2010–October 31, 2017	Daily prices of BTC and market indices	Quantitative. Return and volatility spillovers between BTC and four asset classes (equities, stocks, commodities, currencies, and bonds) with VAR GARCH-in-mean model.	BTC returns are related quite closely to those of most of the other asset studies, particularly commodities.
Baur and Dimpfl (2018)	Asymmetric volatility in cryptocurren-cies	Economics Letters	210	Analyze asymmetric volatility effects for the 20 largest cryptocurrencies	2010–2018	Daily prices of c20 largest cryptocurrencies	Quantitative. TGARCH model of volatility	Volatility increases by more in response to positive shocks than in response to negative shocks implying an asymmetric effect.
Mariana et al. (2021)	Are BTC and Ethereum safe-havens for stocks during the COVID-19 pandemic?	Finance Research Letters	211	Utilize the WHO COVID-19 pandemic announcement as the setting to test the safe-haven properties of Bitcoin and Ethereum	July 1, 2019–April 6, 2020	Daily price of BTC, ETH from coindesk and S&P500 and gold from Datastream.	Quantitative. DCC-GARCH methodology to model the dynamic correlation	Bitcoin and Ethereum exhibit short-term safe-haven properties. Ethereum is potentially a better safe-haven than Bitcoin. However, both cryptocurrencies exhibit high volatilities.
Mnif, Jarbouri and Mouakahr (2020)	How the cryptocurrency market has performed during COVID 19? A multifractal analysis	Finance Research Letters	203	Exploration of the cryptocurrencies market efficiency before and after the COVID-19 pandemic through a multifractal analysis	2010–2020	Daily prices of BTC; ETH, XRP, Litecoin and Binance from coindesk	Quantitative. Fractal analysis	COVID-19 was revealed to have an impact on the efficiency of all the five cryptocurrencies.

(Continues)

TABLE 4 | (Continued)

Author(s) (Year)	Title	Journal	TC	Research question	Period	Data type	Research approach	Key findings
Katsiampa et al. (2019)	Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis	Finance Research Letters	205	Examine the conditional dynamic volatility dynamics and conditional correlations between large cryptocurrencies.	August 7, 2015–July 10, 2018	Daily prices of cryptocurrencies.	Quantitative. BEKK-MGARCH methodology	Evidence of bi-directional shock transmission effects between Bitcoin and both Ether and Litecoin. Bi-directional volatility spillovers between all analyzed pairwise relationships
Huynh et al. (2020)	Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds and cryptocurrencies	Technological Forecasting and Social Change	200	Investigate the role of AI, robotics stocks and green bonds in portfolio diversification.	2017–2020	Daily data of BTC, stock market index, volatility, gold, and crude oil price.	Employ tail dependence as copulas and the Generalized Forecast Error Variance Decomposition to examine the volatility connectedness.	Portfolios consisting of these assets exhibit heavy-tail dependence, volatility transmission is higher in the short-term, and BTC and gold can hedge portfolios.
Koutmos (2018)	Return and volatility spillovers among cryptocurrencies	Economics Letters	197	Measure return and volatility spillovers among 18 major cryptocurrencies	August 7, 2015–July 17, 2018	Daily data of cryptocurrencies	Quantitative. VAR and GARCH models	BTC is the dominant transmission catalyst for shocks in the remaining sampled currencies
Su et al. (2020)	Financial implications of fourth industrial revolution: Can BTC improve prospects of energy investment?	Technological Forecasting and Social Change	184	Can BTC improve prospects of energy investment? Focus on oil market	2010–2020	Daily data of BTC and oil price	Bootstrap full- and sub-sample rolling-window Granger causality tests.	Results show that shocks originated in crude oil prices and transmitted toward BTC price can be both positive or negative.

(Continues)

TABLE 4 | (Continued)

Author(s) (Year)	Title	Journal	TC	Research question	Period	Data type	Research approach	Key findings
Goodell and Goutte (2021)	Diversifying equity with cryptocurrencies during COVID-19.	International Review of Financial Analysis	153	Whether cryptocurrencies provide a diversification for equities during the COVID-19 pandemic crisis and soon after.	2019–2021	Daily data of cryptocurrencies (BTC, ETH, Litecoin and Tether), VIX, stock market index (Swiss, IBEX, DAX, CAC, FTSE UK, Eurstoxx and S&P500).	Wavelet coherence, and neural network analyses to examine the role of COVID-19 on the paired co-movements of four cryptocurrencies, with seven equity indices.	Results show co-movements between cryptocurrencies and equity indices gradually increased as COVID-19 progressed. However, most of these co-movements are either modestly positively correlated, or minimal, suggesting cryptocurrencies in general do not provide a diversification benefit during either normal times or downturns. An exception, however, is the co-movement of Tether.
Elsayed et al. (2022)	Risk transmissions between BTC and traditional financial assets during the COVID-19 era: The role of global uncertainties.	International Review of Financial Analysis	117	Risk transmissions between BTC and traditional financial assets during the COVID-19 era.	2013–2020	Daily data of cryptocurrencies, bonds, stocks, US dollar, Gold and US crude oil.	Time-Varying Parameter Vector Autoregressive (TVP-VAR) model to analyse the volatility spillovers among BTC, financial assets and uncertainty measures.	BTC has a significant price volatility transmission to traditional financial markets during the COVID-19 period, and its price volatility has been driven by economic policy uncertainty.
Kumar et al. (2025)	Connectedness among major cryptocurrencies in standard times and during the COVID-19 outbreak.	Journal of International Financial Markets, Institutions & Money	101	Connectedness among major cryptocurrencies in standard times and during the COVID-19 outbreak. Examine how cryptocurrencies interact and whether there is a leader.	2017–2021	Daily data of largest cryptos (from coinmarketcap)	Volatility connectedness and spillovers	The total connectedness intensifies during the COVID-19 outbreak period; BTC is not a dominant crypto, while Ether passes its shocks to other cryptos. BTC cash also played a leading role during the pandemic period.

Source: Scopus.

dynamics play a significant role in shaping price formation, factors often overlooked in traditional financial models.

Moreover, several studies extend the analysis to macroeconomic and geopolitical uncertainty. Aysan et al. (2019) and Fang et al. (2019) show that Bitcoin's volatility and hedging effectiveness are influenced by global economic policy and geopolitical risks. These findings suggest that external shocks and systemic uncertainty can disrupt informational efficiency. Borri (2019) uses the CoVaR framework to highlight exposure to tail-risk, while Bouri et al. (2018) link Bitcoin's return dynamics to commodities, especially during bear markets. This strand of research shows how cryptocurrencies interact with traditional financial markets, influencing and being influenced by macroeconomic trends, commodity prices, and technological innovation. Huynh et al. (2020) and Le et al. (2021) explore Bitcoin's integration with fintech, green bonds, and AI-related assets, revealing complex interdependencies and volatility spillovers that suggest cryptocurrencies are increasingly embedded in broader financial networks.

Based on the review, it is found that methodological and data-related differences have significant impact on how information efficiency is examined and interpreted in cryptocurrency research. Crucially, the choice of data sources, whether price series, trading volume, sentiment indicators, or macroeconomic proxies, often determines the selection of empirical methods. For instance, studies using high-frequency price data tend to use GARCH family models to capture volatility clustering and partial efficiency. Studies using sentiment or behavioral proxies such as Twitter activity or Google Trends employ VAR or logistic regression to highlight the influence of non-fundamental factors such as media attention and investor sentiment. This variation is especially evident in debates about Bitcoin's role during systemic crises. Some studies report hedging potential under specific conditions (Urquhart and Zhang 2019), while others show it amplifies contagion during crises (Ali et al. 2020; Elsayed et al. 2022). Such contradictions reflect not only difference in modelling approaches and crisis periods, but also in asset scope and data inputs. A few studies extend the analysis beyond Bitcoin to include other leading cryptocurrencies such as Ether or Tether, revealing asset-specific behavior and further complicating generalizations about market efficiency.

Finally, based on the review, the 40 most cited studies reveal a set of recurring themes that reflect the diversity of research methods and the evolving topics of efficiency in cryptocurrency market. Four broad areas emerge: (1) the evolving efficiency of cryptocurrency markets, particularly Bitcoin, often framed through the lens of EMH and tested using econometric tools such as VR tests and GARCH models (Urquhart 2016; Nadarajah and Chu 2017); (2) volatility dynamics and contagion effects, especially during systemic crises such as COVID-19, where cryptocurrencies are alternately portrayed as amplifiers of risk or potential safe havens (Ali et al. 2020; Elsayed et al. 2022); (3) the role of digital assets in portfolio diversification and hedging, with mixed evidence on their effectiveness across market regimes (Goodell and Goutte 2021; Guesmi et al. 2019); and (4) the influence of behavioral and informational factors, including herding, sentiment, and attention, which challenge assumptions of investor rationality (Bouri et al. 2019; Shen et al. 2019).

Although these themes provide useful structure for understanding the field, they also reveal ongoing methodological heterogeneity and unresolved conceptual tensions, particularly in relation to how the EMH is applied in decentralized and sentiment-driven markets. This mix of continuity and divergence across studies highlights the importance of tracing how emerging research builds on, challenges, or reinterprets foundational debates.

Accordingly, the next section develops a thematic map that traces how emerging research streams build on, diverge from, and extend these foundational debates, capturing both established lines of inquiry and newer directions that contribute to a more detailed understanding of informational efficiency in crypto markets.

3.3 | Research Streams

This section shifts from citation-based analysis to a broader thematic synthesis, organizing the literature into six clusters. These clusters reflect key areas of focus in the literature including market efficiency, volatility, contagion effects, and portfolio diversification. It also illustrates how the filed has expanded in scope and depth over time. Figure 5 illustrates how literature progressed through three key periods. In the early phase (2015–2018), research focused primarily on *Bitcoin price* and *spillovers*. Subsequent periods (2019–2021 and 2022–2024) expanded these themes to broader areas such as *cryptocurrencies*, *Bitcoin volatility*, and *liquidity risk*, marking a shift from asset-specific studies to systemic financial inquiries.

Figure 6 presents a keyword co-occurrence map generated using VOSviewer, based on bibliometric data from Scopus. The map visualizes the thematic structure and temporal evolution of cryptocurrency research. The central keyword, "cryptocurrency", is prominently positioned, with strong connections to terms such as "blockchain", "covid-19", "market efficiency", and "spillover". The color gradient, ranging from blue (2021) to yellow (2023), reflects the average publication year of each keyword, highlighting shifts in research focus over time. The spatial and temporal patterns revealed in the keywords co-occurrence map provide the foundation for identifying six major research clusters. These clusters reflect both established and emerging areas of analysis, and they align with the evolving thematic structure of the literature. Each cluster is examined in detail below, highlighting its core focus, representative studies, and methodological or theoretical contributions.

3.3.1 | Cluster 1: Volatility Modelling and Predictive Complexity

Volatility is one of the most intensively studied aspects of cryptocurrency pricing. Early research relied heavily on GARCH-based models, which are effective for modelling conditional heteroskedasticity but rely on assumptions, such as linearity and stationarity, that are often challenged by the behavior of crypto assets. As discussed in Section 3.2, these models may struggle to account for regime shifts, structural break, and the heavy-tailed nature of return distributions. More recent studies have responded to these limitations by adopting hybrid approaches and

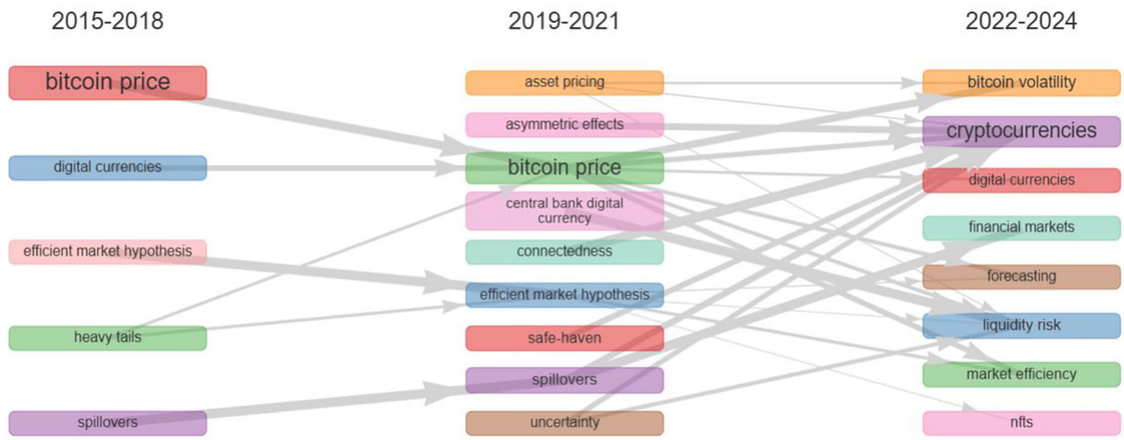

FIGURE 5 | **Thematic evolution**. *Source:* Scopus. [Colour figure can be viewed at wileyonlinelibrary.com]

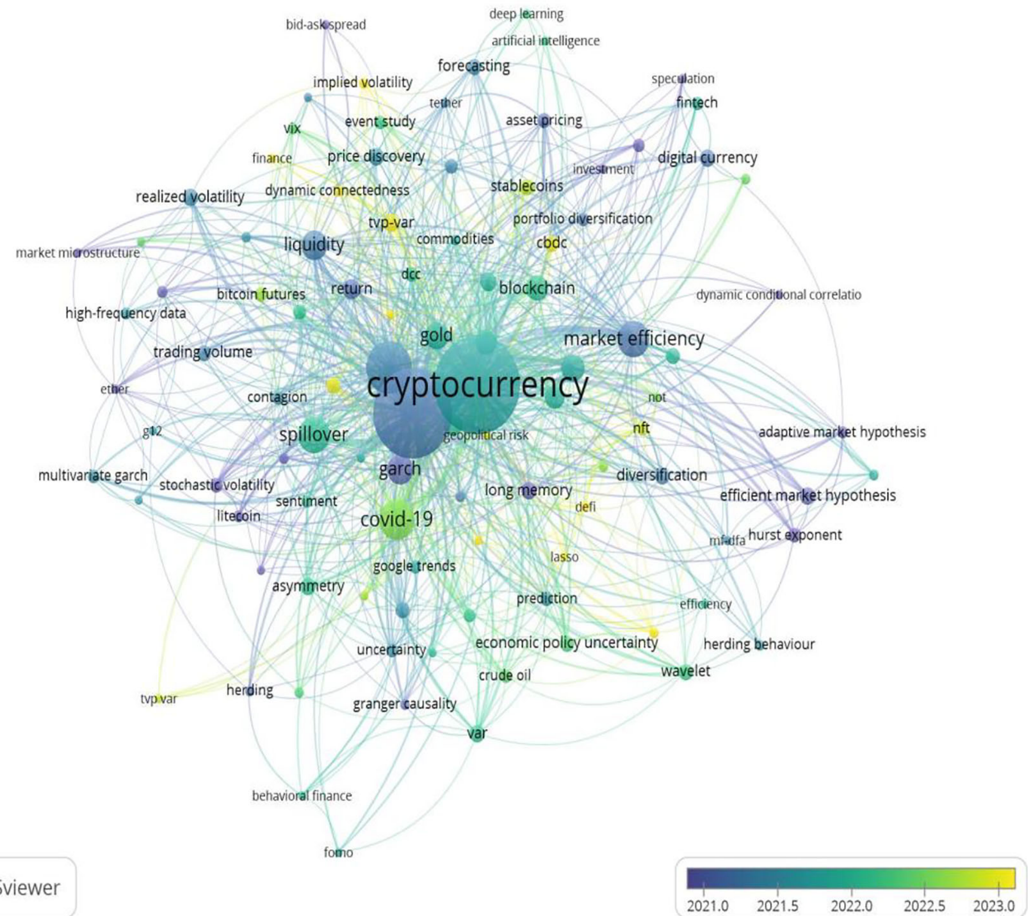

FIGURE 6 | **Keywords map**. *Source:* Scopus. [Colour figure can be viewed at wileyonlinelibrary.com]

machine learning (ML) techniques, which offer greater flexibility in capturing the nonlinear, high-frequency fluctuations, and influences.

Representative studies include García-Medina and Aguayo-Moreno (2024), who propose a Long Short-Term Memory–Generalized Autoregressive Conditional Heteroskedasticity-GARCH (LSTM–GARCH) hybrid model integrating deep learning with traditional volatility features, achieving superior predictive performance during the COVID-19 period. Similarly, Peng et al. (2024) develop an attention-based Convolutional Neural Network—Long Short Term Memory (CNN–LSTM) model for multi-currency trend prediction, addressing the instability of high-frequency crypto data and reducing overtrading through novel labelling techniques.

Other contributions build on influential work, further exploring the role of macroeconomic and external shocks. Tzeng and Su

(2024) examine the forecasting power of U.S. macroeconomic indicators on crypto volatility, finding that variables like consumer confidence and exports significantly improve GARCH model performance. Yin et al. (2021) link oil market shocks to long-term crypto volatility, highlighting the growing relevance of macro-financial spillovers for understanding crypto risk dynamics.

This cluster is defined by methodological innovation and an implicit critique of the EMH. Although EMH assumes that volatility reflects new information, these studies suggest that crypto volatility is often driven by structural frictions, external shocks, and algorithmic trading patterns, factors that challenge traditional notions of informational efficiency. This echo concerns raised in Section 3.2 about applying EMH in its classical form to decentralized, sentiment-driven markets.

Nonetheless, many of these technically sophisticated studies remain primarily empirical in focus and lack robust theoretical grounding. Few engage directly with broader theoretical debates in finance, such as Adaptive Market Hypothesis (AMH) (Almeida and Gonçalves 2023) or behavioral volatility models (Bouri et al. 2019; Haykir and Yagli 2022; Nepp and Karpeko 2024; Yao et al. 2024). Moreover, while these models are technically advanced, their focus on predictive accuracy often comes at the expense of interpretability. This raises questions about what kind of theoretical insights they really offer. So, even though this cluster pushes the boundaries of crypto research methods, it also shows the need for stronger theoretical grounding.

3.3.2 | Cluster 2: Market Efficiency and Asset Design

This cluster extends the foundational debates discussed in Section 3.2, moving beyond Bitcoin to examine informational efficiency across a broader set of digital assets, including Ether, stablecoins, and carbon-linked cryptocurrencies. It highlights how structural features, such as asset design, environmental externalities, and regulatory contexts, shape market behavior and efficiency.

For instance, Kim and Park (2023) apply a non-linear quantile framework to test weak-form efficiency across 15 cryptocurrencies, showing asymmetric behavior across different quantile intervals. Their findings challenge the binary classification of markets as simply efficient or inefficient, showing instead that efficiency varies across distributional tails. This introduces a consideration often missing from traditional unit root tests. Similarly, Wei et al. (2024) investigate how carbon market dynamics affect the efficiency of clean and dirty cryptocurrencies. By bringing environmental factors into the pricing discussion, their work broadens the conceptual boundaries of how efficiency is understood, which moves beyond purely financial metrics.

Other studies focus on asset-specific dynamics. Kim et al. (2024) employ a quantum harmonic oscillator framework to assess the weak-from market efficiency of Bitcoin and Bitcoin Cash. Their findings suggest that Bitcoin Cash adjusts long-term equilibrium nearly three times faster than Bitcoin and operate with lower uncertainty. This indicates a higher degree of market efficiency despite its shorter history and greater volatility. Sahoo and Sethi (2024) adopt a price–volume framework to examine predictability across eight major cryptocurrencies. Although most show no significant causal link between trading volume and returns, supporting weak-form efficiency, they identify notable exceptions, including XRP and DASH, where volume-based signal suggests potential inefficiencies. What brings these studies is a shared recognition of the heterogeneity of crypto assets and the standard efficiency tests often fall short. Although the EMH remains a conceptual reference point, many papers in this cluster critique its assumptions, particularly the notion of homogeneous investor behavior and frictionless markets. Instead, they highlight how asset design (e.g., stablecoin mechanisms, carbon linkage), market maturity, and external shocks (themes that also appear in Cluster 1) interact to produce varying degrees of efficiency.

Conceptually, this cluster advances the literature by integrating efficiency analysis with broader economic and policy considerations (Kim et al. 2024; Wei et al. 2024). This cluster move beyond purely financial metrics to consider how asset design and regulatory context shape efficiency outcomes. However, it also reveals a degree of fragmentation. Few studies attempt to synthesize findings across asset types or connect efficiency outcomes to wider concerns such as investor welfare or systemic risk. Although these themes occasionally intersect with macroeconomic and volatility-focused research, the core contribution here lies in highlighting the need for a more integrated theoretical framework.

3.3.3 | Cluster 3: Central Bank Digital Currencies (CBDCs) and Institutional Design

The emergence of CBDCs has introduced a distinct dimension to the cryptocurrency literature, linking digital asset research with macro-financial theory and institutional economics. Unlike studies focused on asset-level dynamics, this cluster addresses systemic design questions such as monetary policy transmission, financial stability, and regulatory architecture.

Representative studies include Moro and Nispi Landi (2024), who use a Dynamic Stochastic General Equilibrium (DSGE) model to assess the macroeconomic consequences of foreign CBDC adoption in small open economies. Their findings suggest that CBDCs can induce structural reductions in economic activity, depending on their design and interaction with domestic deposits. Dong and Xiao (2024) develop a theoretical model to assess how interest-bearing CBDCs interact with traditional banking. They find that under certain conditions, CBDCs can complement rather than crowd out bank deposits, particularly by mobilizing idle liquidity and enhancing lending capacity.

Other contributions focus on the informational and behavioral dimensions of CBDCs. Wang et al. (2022) construct two novel indices (i.e., the CBDC Attention Index and the CBDC Uncertainty Index), based on over 660 million news articles. Their analysis shows CBDC-related news significantly affects volatility across asset classes, with uncertainty having a stronger impact than attention. These findings suggest that market participants respond not only to CBDC developments but also to the tone and clarity of public discourse, positioning CDBCs as informational barometers in global finance. Complementing this perspective, van Egmond and de Vries (2024) use a system-dynamics model to explore the macroeconomic implications of full CBDC adoption in the Eurozone. They argue that issuing 100% CBDC could stabilize monetary policy and reduce public debt, provided the central bank becomes the sole monetary authority. Their simulations show that such a reform could enable countercyclical money creation and targeted fiscal interventions.

This cluster stands out for its conceptual depth and policy relevance. Unlike most crypto studies, which examine micro-level trading behaviors or asset-specific pricing, CBDC research engages directly with institutional design and macroeconomic theory. It reflects a broader shift in scholarly attention from decentralized finance to state-backed digital infrastructure. However, the cluster remains somewhat peripheral within the broader crypto literature. Few studies link CBDC dynamics to behavioral finance, investor sentiment, or market microstructure theory. And while the policy implications are clear, the empirical foundations are still emerging, with many models relying on simulations rather than observed market data. As such, this cluster represents a promising frontier but one that requires deeper empirical grounding and stronger theoretical integration.

3.3.4 | Cluster 4: Contagion, Spillovers, and Systemic Risk

This cluster captures the literature's growing attention to inter-market connectedness, particularly during periods of systemic stress. Although Section 3.2 highlighted volatility spillovers as a recurring theme in top-cited studies, the papers in this cluster go further by modelling dynamic transmission mechanisms across asset classes, geographies, and time horizons.

Several studies use advanced econometric techniques to trace these spillovers. Yousaf et al. (2024) apply a Time-varying Parameter Vector Autoregression (TVP-VAR) model to examine volatility transmission between Islamic cryptocurrencies and metal markets during COVID-19. Their findings show intensified spillovers and time-varying hedging effectiveness, suggesting that crisis periods amplify cross-market linkage and challenge traditional safe-haven assumptions. Patel et al. (2023) explore the interaction between green and dirty cryptocurrencies and socially responsible investments during the Russia–Ukraine war. Using a dynamic connectedness framework, they find role-switching behavior, where assets alternate between being transmitters and receivers of shocks.

Other contributions focus on higher-order or multiscale dynamics. Apergis (2023) builds on influential studies such as Elsayed et al. (2022), Corbet, Larking and Lucey (2020), and Mnif, Jarbouri and Mouakhar (2020), investigating intraday spillovers in realized skewness and kurtosis across major cryptocurrencies. The study finds that connectedness in higher-order moments intensified during crisis periods, with skewness playing a particularly prominent role in capturing tail risk and asymmetry. This approach extends the insights of Elsayed et al. (2022), who demonstrated the importance of third and fourth order moments in capturing contagion dynamics and complements Corbet, Larking and Lucey (2020)'s focus on volatility spillovers during cyber shocks. Like Mnif, Jarbouri and Mouakhar (2020), Apergis (2023) also highlights the time-varying nature of spillovers and the directional roles of different assets, reinforcing the need for multidimensional models that go beyond standard volatility measure. In contrast, Wang et al. (2024) contribute to this cluster by adopting a multilevel complex network approach to visualize spillover structures between cryptocurrencies and energy markets. Their model captures both direct and indirect transmission channels, revealing significant heterogeneity in how risk transmits across asset classes. Some cryptocurrencies consistently act as shock transmitters (e.g., BTC, ETH), while others serve as buffers (e.g., USDT), depending on market conditions and energy price dynamics. Collectively, these studies challenge the notion of cryptocurrencies as isolated or self-contained markets. Instead, they consider crypto assets as deeply embedded in global financial networks, where spillovers are asymmetric, time-varying, and often amplified during crises. This has important implications for both market efficiency and financial stability, suggesting that informational shocks are not fully absorbed within crypto markets but transmit across asset classes.

Like Cluster 1, this cluster advances modelling techniques, but is also falls short when it comes to connecting those models to wider theories. Although spillover models are often built on frameworks such as contagion theory or network analysis, few studies explicitly link spillover dynamics to EMH, AMH, or behavioral finance (e.g., Apergis 2023; Patel et al. 2023; Wang et al. 2024; Yousaf et al. 2024). Moreover, concentrating on specific events, such as COVID-19 or geopolitical shocks, can lead to a fragmented body of research, where studies become isolated case analyses rather than contributing to a cohesive understanding. Therefore, a more integrated framework is needed to connect these findings to broader theories of market structure and systemic risk.

3.3.5 | Cluster 5: Behavioral Dynamics and Investor Sentiment

This cluster builds on the behavioral finance strand identified in Section 3.2 but focuses more explicitly on the role of investor attention, hype, and sentiment in shaping liquidity and volatility. These studies challenge the rational expectations underpinning EMH and highlight the social and psychological dimensions of crypto trading.

Nepp and Karpeko (2024) explore the impact of social media activity on Bitcoin prices, focusing on how different types of user engagement, such as likes, reports, and comments that affect market sentiment. Their analysis identifies patterns of "collective hysteria", where surges in social media attention correlate with sharp price movements, often disconnected from fundamental value. This effect is particularly pronounced during periods of heightened volatility, suggesting that investor sentiment amplified through digital platforms can drive speculative bubbles. The study also shows asymmetric sentiment effects across market regimes.

Complementing the perspective, Yao et al. (2024) examine the role of investor attention in shaping liquidity across nearly 600 cryptocurrencies. They distinguish between static attention, which tends to enhance liquidity by attracting sustained interest, and abnormal attention, which can lead to crowding and deterioration in market depth. Their study suggests that sentiment-driven behavior not only affects price volatility, but also the structural functioning of crypto markets, particularly under conditions of low economic policy uncertainty. These findings resonate with earlier studies discussed in Section 3.2 (Urquhart 2018; Shen et al. 2019) but go further by quantifying the dual role of attention as both a liquidity enhancer and a source of instability. They also highlight the importance of platform-specific dynamics, such as the influence of Twitter, Reddit, or Google Trends, in shaping investor behavior.

Conceptually, this cluster aligns with the AMH and bounded rationality models. However, most empirical studies do not clearly explain or highlight these connections. There is also a tendency to treat sentiment as an exogenous variable rather than exploring its feedback loops with price formation and market microstructure.

Nonetheless, this cluster is crucial for advancing our understanding of the behavioral foundations of crypto markets, especially given their decentralized, retail-driven, and hype-sensitive nature. It also points to the need for more interdisciplinary approaches that combine finance, psychology, and data science.

3.3.6 | Cluster 6: Diversification, Hedging, and Portfolio Roles

The last cluster focuses on the role of cryptocurrencies in portfolio construction, risk management, and asset allocation, particularly under conditions of market stress. Although Section 3.2 noted the mixed evidence on crypto's safe-haven properties, the studies here adopt a more comparative and dynamic perspective, emphasizing regime-dependence and methodological diversity.

Huynh et al. (2024) examine the connectedness between Bitcoin and oil using copula models. Their findings reveal strong left-tail dependence, suggesting that during extreme market downturns, Bitcoin and oil exhibit co-movement that undermines their diversification potential. Shaik et al. (2024) extend these findings by examining volatility transmission across crypto, Islamic finance, and commodity markets during COVID-19. Their dynamic connectedness analysis shows that Bitcoin became a major volatility transmitter during the crisis. This suggests that its integration into portfolios may amplify rather than mitigate systemic risk. These two papers highlight the negative role in portfolio diversification under crisis condition.

Other studies explore the time-varying nature of diversification benefits. For instance, Cheng et al. (2024) compare the predictive performance of LSTM, Seasonal Auto-Regressive Integrated Moving Average (SARIMA), and Facebook Prophet models for Bitcoin volatility. Their findings suggest that ML models offer better forecasts during turbulent periods. The study, however, raises questions about the interpretability of these models and their practical relevance for portfolio strategy. It also reinforces the idea that crypto's portfolio role is highly regime-dependent and sensitive to modelling choice.

This cluster contributes to the literature by situating crypto assets within broader investment strategies, rather than treating them as standalone phenomena. It also highlights the methodological diversity in assessing diversification, ranging from TVP-VAR models and quantile-based analysis (e.g., Shaik et al. 2024), wavelet decomposition and multiscale techniques (e.g., Cheng et al. 2024), and copula modelling (e.g., Huynh et al. 2024).

However, the conceptual framing often remains narrow. Few studies engage meaningfully with theories of market integration, liquidity risk, or investor utility, leaving a gap between empirical modelling and strategic portfolio design. Moreover, the focus on short-term hedging effectiveness may overlook longer-term structural dynamics, such as the institutionalization of crypto or its correlation with macroeconomic variables.

3.4 | Fragmented Frontiers of Informational Efficiency

Taken together, the thematic clusters mapped in this review reveal a literature that is both expanding in scope and fragmenting in structure. Although the studies span diverse topics, from volatility modelling and behavioral dynamics to CBDCs and systemic spillovers, they are unified by a shared research questions about how information is processed, transmitted, and priced in cryptocurrency markets.

Furthermore, the notion of informational efficiency is interpreted in markedly different ways across clusters. In the volatility and forecasting literature, efficiency is often implicit, measured through the predictability of returns or volatility regimes. In the market efficiency and asset design cluster, it is tested more directly but with growing attention to asset-specific features and structural asymmetries. Behavioral studies challenge the rational expectations underpinning EMH. Although CBDC research reframes efficiency at the institutional level, focusing on liquidity provision and macroeconomic stability, spillover and contagion studies, emphasize the cross-asset spillover dynamics that challenge the notion of market segmentation.

Building on the foundational insight from Section 3.2, the thematic clusters in this review further illustrate the informational efficiency in crypto markets is not a fixed condition, but a spectrum shaped by asset design, investor behavior, institutional context, and methodological lens. Rather than reinforcing a binary efficient/inefficient divide, the literature increasingly reflects a more detailed understanding of how information is interpreted and incorporate into market pricing across different context.

This thematic structure thus complements the citation-based analysis in Section 3.2 by revealing how the field is evolving beyond its most cited contributions. It also sets the stage for the next section, which outlines a future research agenda aimed at integrating these fragmented insights into a more coherent framework for understanding efficiency in cryptocurrency markets.

4 | Future Research Direction

The analysis of the most influential studies (Section 3.2) and thematic clusters (Section 3.3) reveals a field that is methodologically rich but conceptually fragmented. Although the EMH remains a reference point, the cryptocurrency literature in the area reflects a proliferation of methodological approaches, data sources, and theoretical framings, often developed in isolation and rarely integrated.

To advance the field, future research must move beyond descriptive modelling and engage more rigorously with the causal mechanisms underpinning informational inefficiency. This section outlines six interrelated research priorities; each grounded in the gaps and tensions identified in the previous sections.

4.1 | Theoretical Integration: From EMH to Pluralistic Efficiency Models

Despite the widespread adoption of the EMH as a benchmark in financial economics, limited empirical work has explicitly tested or refined its core assumptions within the distinct context of cryptocurrency markets. These markets are characterized by high volatility, limited regulation, retail dominance, and sentiment-driven trading. Such conditions diverge markedly from the assumptions underpinning classical EMH, raising questions about its continued relevance for cryptocurrency pricing.

To move the field forward, future research should develop hybrid theoretical frameworks that integrate EMH with the AMH and behavioral finance. The AMH introduces an evolutionary perspective, suggesting that market efficiency is not static but changes as investors adapt to new conditions, a particularly relevant notion in the rapidly transforming crypto ecosystem. Concurrently, behavioral finance provides a foundation for explaining persistent anomalies such as volatility clustering, herding, and sentiment-driven trading (Bouri et al. 2019; Almeida and Gonçalves 2023).

Future studies could potentially embed these theories within contagion and spillover models. For example, EMH could be examined through the lens of cross-market spillovers. If shocks are not immediately and proportionally reflected across assets, this may indicate inefficiencies. AMH could help interpret time-varying spillover intensities as evidence of evolving market efficiency in response to changing investor behavior or macroeconomic conditions. Behavioral finance could be integrated by modelling how investor sentiment and herding contribute to contagion effects, especially during episodes of extreme volatility or market stress. Linking these theoretical perspectives with volatility and spillover analysis would move beyond purely statistical measurement and allow researchers to better understand the underlying mechanisms driving interdependencies in cryptocurrency markets. There is also scope for integrating models of bounded rationality and, algorithmic trading to better capture structural inefficiencies and informational frictions. These elements challenge the assumption of fully rational, homogeneously informed agents, and may help explain the persistent deviations from equilibrium pricing observed in crypto markets. In this context, regime-switching models, which accommodate shifts between periods of relative efficiency and inefficiency, may also help capture the episodic, and context-dependent nature of crypto market behavior (Shen et al. 2019; Urquhart 2016). Advancing such integrative and adaptive frameworks will be essential to accurately characterizing the informational properties of digital asset markets and refining our theoretical understanding of market efficiency in non-traditional financial systems.

4.2 | Methodological Innovation With Interpretability

Although ML and hybrid modelling approaches, such as LSTM–GARCH and CNN–LSTM models, have significantly enhanced the predictive accuracy of asset price and volatility forecasts, these models often lack interpretability and theoretical grounding (García-Medina and Aguayo-Moreno 2024; Peng et al. 2024). These models operate as complex "black boxes", making it difficult to identify the economic mechanism driving volatility, contagion, or regime shifts. This limits their utility in advancing our theoretical understanding of informational efficiency.

To address these concerns, future research should aim to integrate explainable artificial intelligence (AI) methodologies with established economic and financial theories. Methods such as Shapley Additive Explanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and attention-based visualizations can enhance transparency by revealing feature importance and model behavior. Embedding such interpretability tools within hybrid architectures would help uncover latent drivers of market anomalies, including investor sentiment and liquidity fragmentation.

Moreover, greater use of causal inference frameworks, such as structural vector autoregressions (SVARs), Granger causality analysis, and counterfactual simulation techniques, can facilitate a deeper understanding of the channels through which information propagates across assets and time. These methods allow researchers to move beyond correlation and test causal hypotheses related to contagion, arbitrage breakdowns, and behavioral asymmetries.

Ultimately, methodological innovation in this space must not only enhance forecasting performance but also produce models that offer theoretical insight and policy relevance. Bridging the gap between computational sophistication and economic interpretability will be essential for developing empirically rigorous and conceptually coherent understandings of efficiency in cryptocurrency markets.

4.3 | Blockchain-Level Data and Structural Market Features

The vast majority of empirical studies on cryptocurrency markets rely on exchange-level data, such as order books, trade volumes, and price feeds, which, while useful, offer only a partial view of how information flows and price discovery occur in decentralized systems. This exchange-centric focus tends to overlook market microstructure of decentralized finance, where structural and technological features, rather than centralized trading mechanics, govern liquidity, execution, and price discovery.

Future research should incorporate blockchain-native data, including wallet activity, staking behavior, validator concentration, smart contract execution, and inter-address fund flows. These dimensions of on-chain activity can provide granular insights into endogenous liquidity formation, the potential for price manipulation, and the strength of network effects. For instance, wallet clustering and inter-address flow analysis can reveal concentration or coordination among market participants, while smart contract usage patterns may indicate protocol health or speculative intensity, insights unavailable through exchange data alone.

In addition, technological infrastructure such as Layer 2 scaling solutions, automated market makers (AMMs), and oracle infrastructures plays a crucial role in shaping crypto market microstructure. AMMs introduce novel price formation mechanisms, diverging from traditional order-book dynamics and creating distinct arbitrage and slippage patterns. Layer 2 protocols reduce transaction latency and costs, which in turn influence trading strategies and liquidity provision. Oracles, which bridge off-chain and on-chain data, affect information timing and reliability, critical inputs for price efficiency.

Furthermore, the network congestion, gas fees, and validator incentive structures deserve closer academic scrutiny. These structural elements can distort market efficiency by delaying settlement, creating transaction prioritization disparities, or weakening consensus mechanisms, particularly under stress conditions.

By shifting analytical focus from surface-level trading metrics to the underlying market microstructure, future research can more accurately model how information is transmitted, distorted, or delayed in decentralized systems. This shift is essential to developing empirically robust and theoretically grounded insights into informational efficiency in crypto markets.

4.4 | Asset Diversity and Comparative Efficiency

A significant limitation of the current literature is its overwhelming focus on the Bitcoin, with over 90% of empirical studies concentrating exclusively on this crypto (see Section 3). Although Bitcoin is the most well-known cryptocurrency and often used to represent the whole market, its dominance has led to a narrow conceptual and empirical understanding of other digital asset market's behavior. Future research should prioritize comparative studies across a broader spectrum of cryptocurrencies and digital asset classes, including Ether, stablecoins, NFTs, CBDCs, and tokens associated with DeFi protocols (Kim et al. 2024; Wei et al. 2024). Such comparative analyses are essential for capturing the heterogeneity in market efficiency, return volatility, liquidity structure, and investor behavior that exists across different blockchain platforms and asset types.

Digital assets differ markedly in their technological foundations, use cases, governance models, and user demographics. For instance, stablecoins, particularly algorithmic versus collateralized variants, exhibit divergent price stabilization mechanisms and risk profiles, which may have distinct implications for volatility clustering, arbitrage opportunities, and systemic stability. Similarly, comparing consensus mechanisms such as proof-of-stake (PoS) and proof-of-work (PoW) can yield valuable insights into how energy usage, validator incentives, and security assumptions influence transaction finality, processing capacity, and susceptibility to market manipulation. Ether, functioning as the native asset of a smart contract platform, exhibits price dynamics that are influenced not only by macro-financial trends, but also by on-chain application activity, network congestion, and gas fee volatility, distinguishing it from Bitcoin's store-of-value narrative.

Ethereum's role as a smart contract platform introduces further complexity: its valuation is not only influenced by macro-financial trends, but also by on-chain application usage, gas fee dynamics, and protocol upgrades. This makes it a fundamentally different asset from Bitcoin, whose primary narrative is as a decentralized store of value. Similarly, NFTs and DeFi tokens exhibit idiosyncratic trading behaviors, governance models, and community dynamics, all of which warrant independent scrutiny. Comparative research across these diverse assets is crucial for building a more detailed theoretical framework that reflects the structural diversity of the digital asset ecosystem.

By expanding beyond Bitcoin and examining how asset-specific features influence market behavior, future studies can offer a richer understanding of the design-driven dynamics shaping informational efficiency. Such efforts will not only enhance the theoretical breadth of the literature, but also provide a practical insight for regulators, developers, and institutional investors engaging with an increasingly complex and diversified crypto-financial landscape.

4.5 | Institutional Adoption, Regulation, and Market Maturity

The existing literature has not systematically addressed the implications of institutionalization and regulatory evolution in cryptocurrency markets. As digital assets increasingly migrate from speculative niche instruments to components of mainstream financial portfolios, institutional participation and regulatory oversight are becoming central to the structure, efficiency, and resilience of these markets. However, academic research remains underdeveloped in evaluating how these shifts shape market dynamics and behavioral responses.

Future research should critically examine how regulatory frameworks, such as the European Union's Markets in Crypto-Assets Regulation (MiCA) and the U.S. Securities and Exchange Commission's (SEC) emerging guidelines on crypto asset classification and trading, influence key market attributes such as efficiency, investor protection, and technological innovation. These regulatory regimes are likely to affect not only market entry and compliance costs but also broader issues of transparency, standardization, and legal certainty, which are fundamental to sustainable market development.

Moreover, the growing institutional participation in digital finance, manifested through instruments such as exchange-traded funds (ETFs), custodial and prime brokerage services, and CBDCs presents new dynamics that warrant close academic scrutiny. Although institutional entry may deepen liquidity and reduce idiosyncratic volatility, it also raises concerns around systemic risk, ownership concentration, and the erosion of decentralization (Dong and Xiao 2024; Moro and Nispi Landi 2024). For example, the approval of spot Bitcoin ETFs may increase market integration with traditional finance but also expose crypto markets to correlated sell-offs and liquidity spirals during financial stress.

Importantly, the interactions between regulation, institutionalization, and market structure are dynamic, path-dependent, and context-specific. Future research should investigate these feedback loops, particularly how investor expectations, asset design, and trading behavior responds to evolving policy environments. Cross-jurisdictional and longitudinal studies can reveal divergent outcomes across regulatory regimes, including unintended consequences such as regulatory arbitrage, innovation displacement, or shadow market emergence.

A more rigorous, interdisciplinary agenda that links financial regulation, market microstructure, and investor behavior is critical. Such work will not only enhance theoretical models of informational efficiency in institutionalizing markets, but also generate insights for evidence-based policymaking aimed at building stable, transparent, and inclusive digital financial ecosystems.

4.6 | Systemic Risk, Spillovers, and Financial Stability

The current literature on spillover effects in cryptocurrency markets remains highly fragmented and predominantly event-driven, often focusing on discrete crises or regulatory announcements without developing broader theoretical frameworks (Patel et al. 2023; Yousaf et al. 2024). Although such studies provide valuable insights into the short-term transmission of shocks across digital assets or between crypto and traditional markets, they often lack generalizable frameworks capable of capturing the structural and behavioral interlinkages that define the modern digital financial system.

Future research should prioritize the development of generalized models of inter-market connectedness that account for the non-linear, time-varying, and multi-layered transmission across crypto and traditional asset classes (Apergis 2023; Wang et al. 2024). Such models must reflect the increasing complexity of both crypto-native and cross-asset interactions, where traditional econometric tools often fall short in detecting higher-order dependencies, feedback mechanisms, and dynamic regimes. Incorporating frameworks such as Markov-switching models, and quantile connectedness approaches may enhance the ability to trace the evolution of contagion and interdependence over time and under different market conditions.

An important direction is to explicitly link spillover effects with macroprudential concerns, such as liquidity dry-ups, fire-sale dynamics, and flight-to-safety behavior, particularly during periods of geopolitical conflict or monetary tightening. As digital assets interact more deeply with traditional markets, understanding how instability in one segment (e.g., a stablecoin depegging or a DeFi protocol failure) reverberates through global financial channels is essential for effective risk management and regulatory oversight.

Incorporating network theory and complex systems modelling represents a promising avenue to visualize and quantify systemic vulnerabilities. Multilayer networks, for instance, can map interactions among exchanges, tokens, stablecoins, and investor cohorts, identifying potential chokepoints or amplifiers of systemic stress. Agent-based models can simulate feedback loops under heterogeneous liquidity constraints, allowing for more granular stress-testing of decentralized systems under different regulatory and technological regimes.

Finally, to enhance policy relevance, future work should align with real-world developments such as the phased implementation of the MiCA in the European Union (EU) or the growing adoption of Layer 2 scaling solutions. These structural shifts reshape both market architecture and institutional behavior, with implications for arbitrage, information flows, and cross-border contagion. The field must therefore evolve from isolated empirical episodes to a more integrated understanding of systemic dynamics, grounded in theory, enriched by diverse data sources, and attuned to the shifting institutional landscape.

5 | Conclusions

This paper has provided a comprehensive bibliometric and thematic review of the literature on informational efficiency in cryptocurrency markets, synthesizing 977 peer-reviewed articles published between 2015 and 2024. By combining citation analysis with thematic clustering, the study has mapped the intellectual evolution of the field and identified six major research streams: volatility modelling, market efficiency and asset design, CBDCs and institutional frameworks, contagion and systemic risk, behavioral dynamics, and portfolio roles. The standardization of digital assets' data is necessary to provide researchers with homogenous data, supporting the generalization of results.

This review contributes to the conceptual understanding of informational efficiency in cryptocurrency markets by mapping thematic clusters and methodological trends, thereby laying the foundation for a more integrated framework. Initially centered on foundational tests of the EMH, the field has progressively diversified in response to the unique characteristics of cryptocurrency markets, namely, decentralization, high volatility, and technological innovation. This has led to the emergence of a pluralistic understanding of informational efficiency, where efficiency is no longer treated as a binary condition but as a spectrum shaped by behavioral, structural, and technological factors.

The review also reveals that the field is maturing along three dimensions. First, there is a shift from asset-specific studies (primarily focused on Bitcoin) to comparative analyses across a broader range of digital assets, including stablecoins, NFTs, and CBDCs. Second, methodological approaches have evolved from traditional econometric models to include ML, network theory, and blockchain analytics. Third, there is growing recognition of the importance of institutional and regulatory developments, such as the MiCA regulation and Layer 2 scaling solutions, in shaping market behavior and efficiency.

Despite these contributions, the literature remains conceptually fragmented. Few studies integrate insights across clusters or engage with the causal mechanisms that highlight inefficiency. For example, while behavioral studies highlight the role of sentiment and attention, they are rarely linked to systemic risk models or regulatory frameworks. Similarly, spillover analyses often lack theoretical anchoring in EMH or AMH, limiting their explanatory power.

The theoretical implications are clear: existing models of market efficiency must consider for the adaptive, decentralized, and heterogeneous nature of crypto markets. This calls for the development of hybrid frameworks that combine EMH with behavioral finance, complexity economics, and institutional theory. Nevertheless, the findings highlight the need for more robust regulatory frameworks, improved data infrastructure, and interdisciplinary approaches that can inform policy design, risk management, and market governance.

Therefore, this paper not only maps the current state of the literature but also provides a forward-looking agenda that connects informational efficiency to the broader evolution of digital finance.

As the field continues to grow, addressing the conceptual, methodological, and empirical gaps identified here will be essential for building a more coherent and policy-relevant understanding of how information is processed and priced in cryptocurrency markets.

Author Contributions

Giulia Fantini: conceptualization, formal analysis, methodology, data curation, writing, reviewing and editing. **Joy Jia**: writing, reviewing, and editing. **Chiara Oldani**: conceptualization, data curation, writing, reviewing and editing.

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Data Availability Statement

Data come from Scopus and are available from authors upon request.

Endnotes

[1] Academic Journal Guide 2021 - Chartered Association of Business Schools (charteredabs.org)

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