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Asymmetric interactions among cutting-edge technologies and pioneering conventional and Islamic cryptocurrencies: fresh evidence from intra-day-based good and bad volatilities

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Abstract

This study examines the nexus between the good and bad volatilities of three technological revolutions—financial technology (FinTech), the Internet of Things, and artificial intelligence and technology—as well as the two main conventional and Islamic cryptocurrency platforms, Bitcoin and Stellar, via three approaches: quantile cross-spectral coherence, quantile-VAR connectedness, and quantile-based non-linear causality-in-mean and variance analysis. The results are as follows: (1) under normal market conditions, in long-run horizons there is a significant positive cross-spectral relationship between FinTech's positive volatilities and Stellar's negative volatilities; (2) Stellar's negative and positive volatilities exhibit the highest net spillovers at the lower and upper tails, respectively; and (3) the quantile-based causality results indicate that Bitcoin's good (bad) volatilities can lead to bad (good) volatilities in all three smart technologies operating between normal and bull market conditions. Moreover, the Bitcoin industry's negative volatilities have a bilateral cause-and-effect relationship with FinTech's positive volatilities. By analyzing the second moment, we found that Bitcoin's negative volatilities are the only cause variable that generates FinTech's good volatility in a unidirectional manner. As for Stellar, only bad volatilities have the potential to signal good volatilities for cutting-edge technologies in some middle quantiles, whereas good volatilities have no significant effect. Hence, the trade-off between Bitcoin and cutting-edge technologies, especially FinTech-related advancements, appear more broadly and randomly compared with the Stellar-innovative technologies nexus. The findings provide valuable insights for FinTech companies, blockchain developers, crypto-asset regulators, portfolio managers, and high-tech investors.

Highlights

- Three cutting-edge technologies and two pioneered cryptocurrencies are considered.
- The nexus of good and bad volatilities is studied using high-frequency-based volatilities.
- Causality in quantile analysis was accomplished through the first and second moments.
- Stellar's negative volatilities act as a net transmitter in all market conditions.
- Bitcoin's negative volatilities are mutually linked to FinTech's positive volatilities.

Keywords: Cryptocurrency, Blockchain, Financial technology, Volatilities, Non-parametric quantile causality

JEL Classification: Q55, O14, O32, G17

Introduction

In 1991, Haber and Stornetta introduced the concept of connecting blocks using cryptographic chains. Owing to their design, information or transactions stored with timestamps cannot be altered or tampered with. Subsequently, Bayer, Haber, and Stornetta suggested the use of a Merkle tree to verify and validate a variety of transactions between various parties. Merkle trees are used to group records made over a certain period into a single block with higher-quality recording (Bodkhe et al. 2020a, b). Based on the hash function method for creating blocks in a chain, Nakamoto (2008) devised the first blockchain network. Thereafter, he endeavored to improve the architecture and development of the blockchain so that there was no need for users and clients to sign on to it, which eventually led to the construction of a network for cryptocurrencies, now known as Bitcoin. All records of transactions that occur in the Bitcoin network are publicly available. The word blocks and chains used in his research function as separate words that are merged to form a word blockchain. By 2014, the size of the Bitcoin network file, including its transaction logs, had reached 20 GB, further increasing to 30 GB between 2014 and 2015. In January 2017, it was announced that the Bitcoin network would be expanded from 50 to 100 GB (Bodkhe et al. 2020a, b).

Digital currencies have continued to evolve in recent years, primarily driven by a strong tendency to reduce transaction costs and the time involved in the process of e-commerce and global fund transfers to increase e-commerce productivity and fund transfer efficiency (Dandapani 2017). However, with the massive adoption of cryptos in the mainstream, second-generation blockchains encountered scalability issues, and third-generation blockchains converged toward the decentralization of applications. In the process of developing decentralized applications, various research areas, such as the Internet of Things (IoT), supply chains, businesses, and smart cities, have been considered (Vora et al. 2018). Several platforms, including Hyperledger and Ethereum, were used for the creation of smart contracts for a variety of decentralized applications that could be coded (Palma et al. 2019; Yu et al. 2018). To deploy blockchain in real-time applications, a detailed taxonomy that includes digital content distribution, smart cities, the IoT, supply chains, logistics, tourism, and hospitality is needed (Bodkhe and Tanwar 2021). For example, IoT implementation can be achieved using a number of distributed ledger technologies, such as Hyperledger Fabric, Ethereum, and Internet of Things applications (IoTAs) (Pustišek and Kos 2018). However, due to technological advancements and innovations in the technology industry that have fed the digital money market and tokenization industry for many years, blockchain technology has been widely recognized as a key'component of the cryptocurrency market (Umar et al. 2021). Developed as a complex and technologically based mechanism, blockchain allows for fast, secure, decentralized, and transparent transactions. The recent dramatic growth in cryptocurrency is attributed to rapid technological improvements that make it easier for users to access digital currencies and transfer funds globally at a fraction of the cost and time. However, this has also sparked speculation among users within a general network. Although rapid technological advancements have had numerous positive effects in many aspects, swift upgrades have resulted in a substantial number of speculators participating in the market, leading to an increase in volatility in the cryptocurrency market compared with stock or other commodity markets (Hashemi Joo et al. 2020).

The finance and cryptocurrency industries use blockchain owing to its speed, security, accessibility, and confidentiality. Many companies have set up their own research centers to explore its potential applications in various industries. For example, IBM opened its Singapore Research Center in July 2016. Cryptocurrency has also attracted attention at the international level, with governance models for blockchain technology being first discussed at the World Economic Forum in November 2016 (Bodkhe et al. 2020a, b).

A fundamental feature of blockchain technology is its ability to counter a broad range of security attacks as it does not require a centralized authority to be in charge when performing various operations (Atlam and Wills 2019; Lu 2019; Morkunas et al. 2019; Muzammal et al. 2019; Wang et al. 2019a; Zhao et al. 2019). In the blockchain system, data are stored in an encrypted form across all network nodes and validated using various checks, and Merkle hash tree (MHT) and elliptical curve cryptography (ECC) are two of the techniques used (Muzammal et al. 2019). Databases are at risk of corruption or crashes because they distributed systems. Owing to the use of cryptographic keys linked to immutable ledgers for each transaction, information about transactions is protected from manipulation or deletion by malicious attackers in blockchain. Timestamps, public audits, and consensus mechanisms additionally ensure that data are stored in an immutable manner (Bodkhe et al. 2020a, b; Mingxiao et al. 2017). These mechanisms make the architecture of the blockchain security system more robust and secure and guarantee the integrity and privacy of data (Hirsh et al. 2018).

This study contributes to the rapidly growing body of literature by providing a more profound understanding of the interconnection between the negative and positive volatility associated with the two primary Islamic and conventional cryptocurrencies—Bitcoin and Stellar—and the most cutting-edge innovative technologies, including FinTech, the IoT, and artificial intelligence (AI), which are rapidly gaining popularity. To achieve this objective, we employ three different approaches: 1) the quantile cross-spectral coherence method, 2) the quantile vector autoregression (QVAR)-based connectedness measure, and 3) market-state-dependent causality analysis in the first and second moments. Our study aims to provide a comprehensive understanding of the intricate relationship between these two cryptocurrencies and the aforementioned innovative technologies, which is of great value to researchers and practitioners in this field.

This study makes a fivefold contribution to literature. In the first step, we examine three types of cutting-edge technologies, AI, the IoT, and FinTech, as well as two diverse cryptocurrencies: Bitcoin, a conventional cryptocurrency, and Stellar, a cryptocurrency that has an Islamic base. In the second step, we analyze the relationship between cryptocurrencies and modern technologies by detecting commonalities between the quantiles of the joint distributions of variables across frequencies to identify correlation patterns between each pair. Our results indicate that there are no signs of a significant association between Bitcoin and stock indices that measure modern technologies, which is consistent with the results of Gil-Alana et al. (2020) provides evidence to support the conclusion that cryptocurrency markets and stock market indices are not correlated, which contrasts the findings of Asl et al. (2021) who found that cryptocurrencies with a large market cap are positively correlated with blockchain-based technology companies. Furthermore, the results indicate that as both Bitcoin and Stellar are comparatively detached from leading technologies, they can be used for diversification purposes by investors in high-tech assets to diversify their portfolios. In the third step, we investigate the links between cryptocurrencies' good and bad volatilities and the pioneering technologies nominated throughout the paper. Our results show that, in all market states, there is substantial evidence that Stellar and Bitcoin act as powerful negative contributors to positive volatilities in the IoT, FinTech, and AI, which adds significant fresh evidence to the literature in related fields. The results also highlight that Stellar positively contributes to the positive volatilities of leading-edge technological innovations only in the bull market, which adds valuable new evidence to the related literature. In the fourth step, we investigate the connectedness of variables in the network and determine the pairwise and net roles played by each cryptocurrency and leading technology in terms of good and bad volatilities using a QVAR approach. Finally, we use a non-linear, non-parametric, quantile-based causality approach to determine the direction of causality in the cryptocurrency–technology nexus for both the first and second moments.

The remainder of this paper is organized as follows. In "Literature review" and "Background" sections briefly introducing the literature review and background, respectively. In "Research motivation and hypotheses" section explains the research motivation and hypotheses, while "Methodology" and "Data and results" sections describe the methods, data, and major empirical findings. Finally, "Conclusion" section concludes by highlighting key implications.

Literature review

A growing body of finance literature has developed in the last few years on the interaction between cryptocurrencies and FinTech in the finance industry. Cryptocurrencies and FinTech have been the subject of ongoing discussion concerning the most appropriate way to analyze the interaction between these them. With the application of blockchain technology and cryptocurrency tokens to global financial markets, FinTech innovation has transformed the world of businesses by creating a system of cross-border financial transactions (Mazambani and Mutambara 2020; Sonderegger 2015). As the name implies, blockchain is a decentralized technological platform for storing and managing data and transactions without the need for third parties (Yli-Huumo et al. 2016), and cryptocurrency refers to tokens or digital currency generated from cryptography and used in some financial transactions and functions, such as making payments and maintaining value in a blockchain (Ha and Moon 2018; Iwamura et al. 2019). Due to the fact that FinTech and cryptocurrencies share a similar market segment and rely heavily on technology for their operations (Kommel et al. 2019; Yao et al. 2018), FinTech has become intertwined with cryptocurrencies. This, in turn, presents both opportunities and challenges for investors, who are always trying to find ways to hedge, diversify, and create safe havens (Le et al. 2021b). For FinTech companies to function smoothly and in an orderly manner, a regulatory framework that addresses issues of consumer protection, market conduct, and technological impact, as well as the regulation of FinTech companies is needed (Laldin 2018). There are many implications of the recent rise of FinTech, such as the introduction of stable coins and central bank digital currencies (CBDCs). Allen et al. (2022) provided a comprehensive analysis of this topic by outlining China's experiences in FinTech, particularly in the areas of payments, digital banking, FinTech lending, and the more recent development of e-CNY pilot programs using CBDC. Mazambani and Mutambara (2020) investigated the determinants of FinTech adoption in South Africa through cryptocurrencies and developed behavioral change strategies that practitioners and policymakers can apply to improve FinTech adoption in the country. Despite the possible benefits and advantages of FinTech, Alam and Zameni (2019) pointed out some potential problems and challenges bankers and regulators race when it comes to regulating the use of FinTech and cryptocurrency, as well as possible opportunities for exploiting the technology. Considering the need for environmentally-friendly, sustainable FinTech, Kabaklarlı (2022) attempted to create a bridge between FinTech and cryptocurrencies to contribute to the development of a cashless society following the rise of digital currencies. Considering the analysis of Caprolu et al. (2021), it is evident that FinTech systems have caused the market globalization, which has directly impacted industries and tertiary services, substantially increased the dependence of the financial sector on digital information and systems, and generated new digital risks. In addition, FinTech implementation can be combined with cryptocurrencies, blockchain technology, and other areas, such as cross-border payments (Gomber et al. 2018; Michalopoulos and Tsermenidis 2018). Islamic financial institutions' adoption of FinTech should also be innovative, as the financial practices of the Islamic community affect both the Muslim and non-Muslim communities and the global financial environment (Irfan and Ahmed 2019; Rabbani et al. 2020).

Ni et al. (2020), who calculated the risks arising from upcoming regulations concerning FinTech and cryptocurrencies by constructing a Cryptocurrency Regulatory Risk Index (CRRIX) based on the frequency of policy-related news coverage, present an alternative analysis. A newly-developed strand of involvement between FinTech and Crypto-based products, non-fungible tokens (NFT) have developed rapidly since 2020, becoming one of the most popular applications in the FinTech field (Bao and Roubaud (2022). NFTs have been further developed to integrate the ERC-1155 protocol, which includes fungible tokens (FTs), and expanded to include non-Ethereum blockchains such as Flow, Wax, Hyperledger, and Fast Box. Nadini et al. (2021) investigated the development path and operating characteristics of the NFT market by studying transaction data collected via the Ethereum and Wax blockchains from June 23, 2017 to April 27, 2021 to determine the growth and performance of the NFT market.

Various studies have attempted to find evidence of a nexus between the cryptocurrency market and AI using different technical methods. By combining random forest models with Shapley values for predicting cryptographic assets, Babaei et al. (2022) implemented a methodology that achieved predictability and explainability in the allocation of AI-based cryptographic assets. According to Cho et al. (2021), there has been a growing body of research related to financial markets that apply machine learning to cryptocurrencies using blockchain technology. Considering the broad performance range of AI techniques, the choice of the most suitable algorithm is usually influenced by the composition, size, and complexity of the dataset, as well as the outcome of the analysis. It can be argued that classical portfolio diversification can be improved using AI, Bitcoins, robotic stocks, and green bonds, as suggested by Huynh et al. (2020). Bitcoin and gold are valuable assets for hedging, with gold serving as a safe haven. Yiying and Yeze (2019) studied the price dynamics of Bitcoin, Ethereum, and Ripple Yiying and Yeze (2019) revealed that artificial neural networks (ANN)s are more likely to depend on long-term data, whereas long term short-memory (LSTM) networks appear to rely more on short-term data. In similar studies, Awotunde et al. (2021) and Choithani et al. (2022) reviewed recent research in the area of AI techniques for cryptocurrency and Bitcoin. D'Amato et al. (2022) noted the high predictability power, when compared to other models designed for cryptocurrency time series (e.g., self-exciting threshold autoregressive and non-linear autoregressive neural networks), of a parsimonious recurrent neural network (RNN) called a "Jordan neural network." Silva de Souza et al. (2019) found that support vector machines (SVMs) and ANNs could be used to predict Bitcoin prices to compare and assess their capabilities and suggested that ANNs can use short-run asymmetry and information inefficiencies to produce excessive profits, which are effective in beating buy-and-hold strategies in strong bull markets. Regarding some of the challenges cryptocurrencies face, Sabry et al. (2020) examined how AI techniques can be applied to address the issues associated with the large number of transactions, trades, and news cryptos generated every day that is too large to be analyzed by humans. Based on the findings of An et al. (2021), blockchain, cryptocurrency, and AI can be implemented in the financial sector to provide various benefits. Similarly, Demiralay et al. (2021) conducted a wavelet coherence analysis in the time–frequency space to evaluate the interdependencies between AI and robotic stocks, traditional assets, and alternative assets using wavelet coherence analysis. As indicated by Ekramifard et al. (2020), it is evident that distributed management, security and efficiency enhancements, outcome prediction, and decision-making have become some of the most popular and widely applications used in the present day. While each of the aforementioned studies on the cryptocurrency market provides a thorough analysis utilizing different technical methodologies and variables, limitations on the availability of intra-day data cutting-edge technologies pose a barrier to the inclusion of various technologies and main cryptocurrencies.

The IoT and blockchain-based cryptocurrencies are expected to interact strongly and have thus been the subject of numerous influential research contributions. Currently, the IoT is applied to an array of applications, including residential, industrial, manufacturing, distribution, commerce, education, supply chain management, e-commerce, smart cities, and almost anything else that we can imagine (Khan and Salah 2018; Meng et al. 2018a, b; Mobile 2016; Restuccia et al. 2018; Zhu et al. 2016). By integrating blockchain technology with recent innovations, such as the IoT, it is possible to improve techniques to create permanent records, thereby ensuring that information is shared throughout a product supply chain and action can be taken when the need arises (Banerjee 2019; Sodhro et al. 2018). Integrating blockchain-based systems systems can enhance the legitimacy and authenticity of products by improving how businesses trace and monitor goods (Al-Rakhami and Al-Mashari 2021; Sodhro et al. 2020). With the belief that blockchain, a technology that emerged from the emergence of the cryptocurrency Bitcoin and is capable of fulfilling the requirements of the IoT, Alzubi et al. (2019) outlined the advantages of cryptocurrencies written over blockchain as a solution to the IoT micropayment problem and highlighted the fact that cryptocurrency technologies have facilitated the implementation of automatic data micropayment mechanisms. Radhakrishnan and Krishnamachari (2018) proposed a redesigned architecture of the streaming data payment protocol (SDPP) using a transmission control protocol (TCP) for data transfer, IoTA,[1] which functions as both a cryptocurrency and a distributed ledger. There is a huge potential for cryptocurrencies and digital payment networks powered by blockchain technology to become major players in IoT rapidly growing market segment. Considering the time-consuming processing of the Society for Worldwide Interbank Financial Telecommunication (SWIFT) mechanism and the Single Euro Payments Area (SEPA) system, the implementation of payment systems based on blockchain could potentially have a tremendous impact on global transactions (Hashemi Joo et al. 2020). However, there exists a common and widespread problem in cryptocurrency trading—cybercriminal activities or cybercrime—which include different types of hacking. Ransomware and black nets are among the most significant problems. This is one of the main issues addressed in "Background" section, which covers the main ways in which cryptocurrencies can be stored securely, how to avoid ransomware attacks, and how to monitor the relationship between investors and transactions to avoid illegal business (Ghalwesh et al. 2020). Furthermore, as the IoT develops over the coming years, cryptocurrency can play a critical role in contributing to the creation of such a secure infrastructure by acting as a form of digital currency. By successfully integrating the IoT and cryptocurrency technologies, we will be able to develop new consumer applications, enhance consumers' shopping experiences, automate payments between sensors, and allow electric vehicles or drones to perform financial transactions that were previously impossible to achieve (Mercan et al. 2022). Ozyilmaz and Yurdakul (2019) demonstrated an example of integrating the IoT and cryptocurrency technologies through the use of Ethereum and low-power wide area networks (LPWANs). It is worth noting that some popular ledger platforms, such as Hyperledger, use gateway-based methods to integrate their systems with IoT devices in order to input their data into the system through peer-to-peer communication. Yu et al. (2019) developed *LRCoin*, a leakage-resistant cryptocurrency based on Bitcoin specifically designed for IoT data trading that implements an efficient bilinear-based continuous-leakage-resistant elliptic curve digital signature algorithm (ECDSA), which prevents the algorithm from being manipulated by adaptively

[1] It is important to note that IoTA is the first distributed ledger designed specifically for the "Internet of Everything," a network that involves exchanging value and data between humans and machines. For more information, see Khan et al. (2020).

selected messages under continuous leakage in the generic bilinear group model. Noyen et al. (2014) provided an in-depth analysis of the process of data exchange using Bitcoin and how sensing-as-a-service can benefit from it. Dua (2022) reported that a newly developed algorithm could mine cryptocurrencies, such as Bitcoin, on low-power IoT equipment without connecting them to an external device, and Delgado-Segura et al. (2020) proposed a framework for developing a fair protocol for the trading of data based on the Bitcoin script language and double encryption.

Recent panel data studies conducted on the association of different markets, including Li et al. (2021a), Wang et al. (2023a, b, c), serve as good samples for designing empirical studies. For example, Li et al. (2021a) used the Granger causality test to analyze the situation of 147 countries and four income groups from 1990 to 2015, and Wang et al. (2023a) developed threshold effect regression estimation approaches based on the panel data of 139 countries for the period 1998–2018.

Several studies have attempted to formulate a multivariate volatility analysis. Özdurak (2021) examined how volatile crude oil prices relate to clean energy investments, technology companies, and energy democracy. Liow et al. (2021) investigated the spillover effects of the Chinese economy across various markets, including stock, public real estate, bond, commodity futures, and foreign exchange. Dong et al. (2020) evaluated the asymmetric volatility spillover among six markets for virtual financial assets (VFAs), and López-Cabarcos et al. (2021) analyzed Bitcoin behavior and whether the effects of investor sentiment and S&P 500 and CBEO Volatility Index (VIX) returns on Bitcoin volatility could be classified in this area. Related studies have focused on the tools and capabilities of cryptocurrency and technology for risk management. Among them, Le et al. (2021a) claimed that Bitcoin and FinTech companies are innovative assets that were subject to the most volatility spillovers during the COVID-19 pandemic, and therefore should not be considered safe havens, while Kamran et al. (2022) and Bouri et al. (2017c) disagreed, contending that that Bitcoin should be regarded as a diversifier. Additionally, Shahzad et al. (2019) demonstrated that the safe haven roles provided by Bitcoin, gold, and commodities vary depending on the stock market indices studied. White et al. (2020) argued that Bitcoin is a hybrid techno-financial instrument, and Baur et al. (2018) similarly believed that Bitcoin is primarily used as a speculative investment rather than a financial asset.

Another group of studies examined univariate volatility analysis. Li et al. (2022) assessed the heterogeneity in Bitcoin volatility using a Markov regime-switching model, and Bouri et al. (2017a) explored the relationship between price returns and volatility changes in the Bitcoin market using a daily database denominated in US dollars. Similarly, Conrad et al. (2018) analyzed Bitcoin volatility over the long and short term using the GARCH-MIDAS model (mixed-data sampling). Finally, using change point analysis, Chen and Dong (2020) argued that there is significant asymmetry between systematic and idiosyncratic volatility spillovers in the Bitcoin market, and Li et al. (2021c) expressed Bitcoin-related events as change points.

As the literature review shows, this is the first study to investigate intra-day-based good and bad volatilities in an attempt to fill a gap in the literature on the interconnectedness between blockchain-based cryptocurrencies and leading-edge technological breakthroughs and to examine the interconnectivity between them in the form of a quantile cross-spectral approach, a quantile-based connectedness method, and a quantile causality test for first and second moments.

In light of certain limitations identified in the prior research, there is a pressing need to reevaluate and delve deeper into several aspects that have not yet been thoroughly examined. First, it is crucial to highlight that previous studies have fallen short in comprehensively exploring innovative Industry 4.0, technologies, specifically those related to blockchain platforms, which have emerged as prominent players in the industry in recent years. Remarkably, these studies predominantly viewed cryptocurrencies solely as financial markets, disregarding their intricate technological foundations and significant interconnections with sectors such as FinTech, which are widely recognized as technology-based industries within the financial domain. Thus, we first seek to rectify this oversight. Another key limitation lies in the analysis of innovations' impacts on cryptocurrency exchanges while simultaneously considering the prevailing market states to better understand their interrelationships. By examining how innovation in technology and other factors influence cryptocurrency exchanges, we obtain a more comprehensive and accurate understanding of these markets' dynamics. Moreover, it is crucial to emphasize an oft-overlooked aspect in prior research pertaining to the common distribution of variables across different frequencies. By accounting for distribution patterns across varying time intervals, researchers can obtain a more nuanced and robust analysis of the dynamics at play.

It is worth noting that the fourth and fifth limitations identified represent the most significant gaps that previous studies have failed to adequately address. Bridging these gaps is crucial to enhance our understanding of the complex relationships between cryptocurrencies, technological advancements, and financial markets. To overcome these limitations and propel research forward, utilizing precise intra-day data is imperative. Intra-day data serve as a powerful tool employed by traders, investors, and analysts to monitor, analyze, and develop effective trading strategies and make informed decisions based on short-term market trends. By harnessing the insights offered by intra-day data, market participants gain a real- and near-real-time perspective on price dynamics, enabling them to navigate the intricacies of the market and plan for future investments. Notably, intra-day data provide a more detailed and granular perspective than historical or daily data as they capture the nuanced price movements, fluctuations, and market behavior occurring within each trading session to unveil underlying patterns that may go unnoticed when broader timeframes are used. This richer level of detail facilitates a comprehensive understanding of market dynamics and enables researchers to identify both positive and negative volatilities at the intra-day level.

In conclusion, addressing the aforementioned limitations and leveraging the potential of intra-day data allow researchers and market participants to delve deeper into the interplay between technology, financial markets, and cryptocurrencies. By adopting a more comprehensive and nuanced approach, this study sheds light on the intricacies of these relationships, enabling the development of innovative strategies and a deeper understanding of the evolving financial industry landscape.

Table 1 Comparison of AI and Blockchain. *Source*: Kumar et al. (2022b) and Singh et al. (2020) with modifications

AI	Blockchain
Driven by centralized infrastructure	Predicated on decentralized infrastructure
Unexplainable to human users (Decision-making by machine learning systems)	Explainable to human users
Non-transparent/non-trackable	Transparent/trackable
Probabilistic	Deterministic
Modeling and adaption over time	Immutable
Concentrated power	Distributed power
Protocol-based	Task-based
Data feeds AI to continuously improve itself	Encrypted storage of data
Closed access	Open access

Background

In the technological environment, AI is a significant innovation owing to its ability to more efficiently and effectively perform tasks that normally require human input (Kumar et al. 2022b), and its potential to surpass human capabilities is astounding (Agarwal et al. 2020; Pandl et al. 2020). As a driver of industrial development, AI is one of the main factors on which the Fourth Industrial Revolution (IR 4.0) is based as it promotes the integration of emerging technologies (Goodell et al. 2021; Lim 2020; Zhang et al. 2021), including blockchains, cryptocurrencies, cloud computing, and the IoT (Ehrenberg and King 2020; Ghaleb et al. 2021; Hsu 2022; Li and Whinston 2020). Blockchains provide users with maximum privacy and confidence, and AI can be employed to design and execute machine learning applications on top of them, thus ensuring efficiency, scalability, and security. Although there are technical differences between AI and blockchain (see Table 1) and inherent disparities and distinctions, the two can be effectively combined to address each other's shortcomings (Kumar et al. 2022b). Indeed, there are numerous new opportunities that can be exploited due to the close integration of AI and blockchain in a practical setting (Makarius et al. 2020).

The use of AI is seen in a variety of applications, including day-to-day living operations (Dermody and Fritz 2019), systems and services for financial and banking processes (Agarwal 2019), medical care (Mamoshina et al. 2018), public health (Wang et al. 2021), and transportation service providers (Machin et al. 2018). According to recent news reports, it is widely predicted that by 2030, AI will be worth 13 trillion dollars according (Ekramifard et al. 2020).

In addition to facilitating the integration of AI and blockchain technologies into one platform, blockchain provides a secure, trusted, and distributed platform for sharing large volumes of data between parties to analyze, study, adapt, and make informed decisions. Naturally, no central authority or intermediary is required (Ekramifard et al. 2020). Integration could also lead to the large-scale creation of new applications and technologies (Parizi et al. 2018). It goes without saying that owing to blockchain's ability to ensure the accuracy of data, it is a valuable tool that can be used to feed data into AI systems and record the results generated by these systems (Rabah 2018).

In summary, AI and blockchain are the two of the most important factors driving modern innovation worldwide. It is estimated that both of these technologies will revolutionize every aspect of our lives, adding trillions of dollars to the global economy. Blockchain has several shortcomings and weaknesses, such as problems with scaling, reliability, efficiency, and cost-effectiveness, and AI is subject to some privacy and security concerns. The combination of these two technologies will undoubtedly revolutionize each other as they complement one another in many ways. Using blockchain is a convenient way to offer user privacy and confidence. AI can be employed to design and execute machine learning applications on top of a blockchain that are safe, scalable, and highly efficient. Hence, it can be seen that integrating AI and blockchain can be viewed as creating AI for blockchain and vice versa. As blockchain technology and AI merge, there are some issues that need to be addressed when it comes to their convergence, including security and privacy, threats and attacks, smart infrastructure, technical and business challenges, a lack of standards, the inability to integrate regulations, vulnerabilities in smart contracts, and issues concerning deterministic executions and good governance (Singh et al. 2020).

Considering another strand of blockchain-based usage, cryptocurrency is essentially a form of electronic cash that is used in lieu of traditional money as a medium of exchange. When it comes to conducting financial transactions with a degree of security, ease of tracking, and irreversibility, a blockchain-based approach is by far the most effective strategy. Blockchain technology can also be used to create new units (Polansek 2019). As soon as Bitcoin rose to prominence in the world monetary system, it was hailed as an innovation that would reduce transaction fees by eliminating the need for third parties to conduct transactions and enabling real-time transactions (Khan et al. 2019).

Although the price of Bitcoin has increased to record highs, it does not imply that it violates Sharia principles in any way; rather, it is a sign that Bitcoin is becoming more popular and trustworthy, as well as a sign of the hope people have for the future (Oziev and Yandiev 2017; Rabbani et al. 2020). It is possible that a Bitcoin transaction could be characterized as *gharar* transaction because the real value of a Bitcoin is unknown, its price fluctuates, and the method used for storing the Bitcoin value differs significantly (Bakar et al. 2017). According to the Arabic language, *gharar* signifies an unacceptably high level of uncertainty or deception, which may be used to market non-existent products that have not yet been made (Cattelan 2009; Wan Ahmad 2008). Meera (2018) states that since Bitcoin does not have an intrinsic value and is not regulated by any central bank, it can be easily mishandled. In addition, because Bitcoin is used in contravention of the basic principle of Islamic economics, namely the rule of social justice, some have regarded it as violating Shariah, which is why it has been prohibited (Meera 2018; Rabbani et al. 2020). As Kusuma (2020) points out, Bitcoin cannot be used as a commodity in Shariah derivative contracts because it involves a great deal of speculation. In addition, some have characterized it as *maysir*, the Arabic term for speculation or gambling, both of which are forbidden by Islamic finance because they generate wealth from chance rather than from productive activities and are vulnerable to abuse. Given the external factors that may influence Bitcoin, according to Islamic rules, it is advisable to avoid its use.

Accordingly, Muslim scholars have varying views on whether the use of cryptocurrencies is in accordance with Shariah law. The fundamental grounds for the rejection of cryptocurrency are based on the principle that it violates the basic principles of Islam, which has been endorsed by scholars such as the Egyptian grand mufti Shaikh Shaki Alam. For something to be declared *halal*, it must follow the rules of maqasid al Shariah (Rabbani et al. 2020). It is estimated that there are more than 2,800 cryptocurrencies in use today, none of which are currencies but rather cryptographic assets. A cryptographic asset is a financial asset that can be used for various purposes and is not limited to coins. There are several criteria for judging whether a cryptocurrency is a currency, including the features that define a currency as a store of value, a unit of account, and a medium of exchange (Yakubowski 2019).

To cope with and understand the changes brought about by the technological revolution, all sectors of society, including consumers, governments, financial institutions, and investors, must develop effective strategies. There is a need for greater insights into the concepts of blockchain and cryptocurrencies to gain a deeper understanding of them (Mohamed and Ali 2018). Moreover, it should be a top priority for Shariah scholars to find a way to use this financial revolution to increase the community's comfort level with digital currencies because they can be used for a variety of sustainable and diversified projects that benefit the entire Muslim community. Investing in cryptocurrency has real potential for people to not only reap financial benefits but also to change the course of their lives for the better in the long run (Noordin 2018).

Several scholars have investigated the possibility of developing an Islamic digital currency using blockchain technology to finance Islamic enterprises (Alzubaidi 2017). There is great potential for blockchain to revolutionize Islamic banking by converting standard Islamic finance contracts into smart contracts, which will reduce the costs of services by up to 95% and allow an immutable record of ownership and assets to be maintained (Wintermeyer and Abdul 2017). In July 2018, the Stellar blockchain, considered one of the largest and most well-known cryptocurrencies based on market capitalization and popularity, became the first digital ledger technology (DLT) protocol to obtain Shariah confirmation for asset tokenization and secure payment processing. A press release used by the Stellar Development Foundation reported that after evaluating the technology's properties and financial applications, the Shariyah Review Bureau (SRB), which is a registered with the Central Bank of Bahrain and provides international Shariah advisory services, has been approved as a Shariah-compliant vehicle for transfers and accredited to tokenize real-world assets via Stellar. To this end, the Stellar Foundation stated that this prestigious certificate, the 48th issued by the SRB, will help the organization form prosperous partnerships with Islamic financial service providers operating across the Middle East and Southeast Asia (Alexandre 2018; Mohamed and Ali 2018; Rabbani et al. 2020). It is also worth mentioning that the Sakkex Sukuk issuance is based on the Stellar blockchain (Khan et al. 2022; r3 2019).

With Stellar, people will have access to a blockchain-based micropayment system that enables low-cost cross-border payments between financial institutions and individuals in only a few seconds. In addition to the possibility of making smaller payments and micropayments, Stellar provides an increased level of efficiency. In the analysis of payment transactions, most were micropayments (83%), whereas path payment transactions had a greater mixture of payment amounts reflecting a greater variety of payments. To expand its user base and increase trust in Stellar, greater focus on micropayment systems that account for characteristics that are not technical, rather than technical, is needed.

Table 2 Comparison of Bitcoin and Stellar. *Source*: Khan et al. (2019) and McGuire (2018) with modifications

Cryptocurrency	Bitcoin	Stellar
Anonymity	Anonymous	Pseudonymous
Scalability	Billions of transactions per second (envisaged)	1000+Transactions per second (1 billion users)
Ease of use	High technical knowledge	High technical knowledge
Validation	True (payment transfer through intermediaries)	True
Security	Timelocks	Cryptography based on public keys (Ed25519), offline storage of the secret seed to generate a pair of public–private keys
Latency	1200+s (minimum)	3–5 s
Interoperability	Yes for Blockchains with the same hash function	Yes for fiat and crypto
Privacy	Users are known only by their Blockchain addresses for offline transfers (except the initial and final transfers), and there is no payment information available	Anchors access data for regulatory compliance
Market penetration	9102 nodes	1 million active user accounts in 3 years
Prepaid/postpaid	Prepaid	Prepaid
Payment Threshold	Upper bound (restricted by channel capacity)	No limits
Shariah compatibility	No	Yes (shariah-compliant license)
Money laundering	Yes	No

In terms of its potential to contribute to the digital economy, the Stellar blockchain platform can function as a micropayment system and has considerable capacity to contribute to the creation of a more digitally connected world in a meaningful manner (Khan et al. 2019). The Stellar blockchain is used by Tempo, a payment system, to send money internationally between Europe and other parts of the globe, and 600,000 transactions can be executed for less than $0.01 USD, making it one of the most popular micropayment options (Stellar Network Overview 2022). Stellar Core is the heart of the network and is supported by the Horizon application processing interface (API), which is made up of multiple Stellar cores owned by different individuals or organizations to ensure decentralization (Mazieres 2015). By integrating with the compliance protocol (Compliance Protocol 2019), Stellar supports regulatory compliance as well as anti-money laundering/know your customer (AML/KYC) procedures (Khan et al. 2019). As shown in Table 2, there are some major differences between Bitcoin and Stellar in terms of their structure.

Research motivation and hypotheses

Blockchain-based ecosystems are considered one of the most suitable technologies for use in conjunction with the IoT at the current stage of development because they are seen as secure and distributed ecosystems (Huckle et al. 2016). In fact, the revolution of blockchain technology is widely acknowledged to be the result of an anonymous person (or group of individuals) named S. Nakamoto, who formally developed it fin 2008 and introduced it to the public in 2009 (Nakamoto 2008). Blockchain technology is one of the major components of digital currencies, especially Bitcoin, and a public ledger serves as the central repository of all the transactions that take place throughout the network (Tschorsch and Scheuermann 2016). Several researchers have explored ways to leverage blockchain technology to improve the efficiency of IoT communications and eliminate the need for centralized trusted authorities by applying it to decentralize IoT communications as it lays the foundation for serverless record-keeping (Ali et al. 2019). Centralized service providers currently provide IoT services to users of in exchange for surrender of their data. Once the data is communicated over public blockchains, users can participate in a new marketplace for data and providers can monetize the data that is being transmitted over blockchains.

Technically, blockchain can be viewed as a decentralized data infrastructure comprising cryptographic hash functions used by a decentralized network to process data (Du et al. 2020). Often referred to as the infrastructure layer, it serves as an additional layer of confidentiality in Internet transactions as it presides over an infrastructure layer.

There is no better way to maintain records and tabs, track assets, and perform worldwide transactions than to have an infrastructure layer capable of maintaining all types of asset records and handling all types of transactions (Wang et al. 2019b). In recent years, as blockchain applications have become increasingly complex, the wave of "Blockchain+," focusing on improving the efficiency of financial transactions by reducing the risks involved in settlements, has gradually emerged (Ren 2022). In the early days of blockchain technology, cryptocurrency was the most popular application.

Blockchain technology is expected to revolutionize a broad range of fields by providing faster, more secure, and more efficient end-to-end transactions between individual users without the intervention of a central authority or trusted third parties (Kim and Deka 2020). From a conceptual standpoint, a blockchain is a distributed ledger that records all transactions that take place within a network and preserves an immutable record. In a world where cryptocurrency is an application of blockchain record-keeping capabilities, a distributed ledger has the potential to be applied anywhere there is some form of data exchange, including in networks with various types of payment systems.

Peer-to-peer (P2P) networks based on blockchain technology maintain identical copies of the ledger shared between peer nodes. A distributed consensus among peers enables new entries comprising information about transactions to be added to the blockchain using a non-centrally controlled method (Ali et al. 2019). As these technologies (including blockchain data structure and regular consensus algorithms) have grown in popularity, it soon became evident they could be used to track and keep secure not only storable data (e.g., how much money each user has) but also programs to be executed by nodes as they gain prominence, without any possibility of modifying the code (Blockchain 2.0) (Chondrogiannis et al. 2022; Yaga et al. 2019). One of the key elements of blockchain technology is its capacity integrate cryptocurrencies with IoT and AI. Despite the absence of a central authority, blockchain technologies are some of the most efficient technologies in the marketplace for secure communication among distributed entities. They have also been adapted for relevant applications in the health sector (Kuo et al. 2017). Thanks to technological advances, individuals are now able to fully control the information collected during their visits to healthcare institutions, as well as the secondary use of such information (Azaria et al. 2016; Zyskind et al. 2015).

Smart contracts, which consist of a predefined set of rules employed in blockchain networks to execute transactions in a predetermined manner agreed on by both participating parties, represent a distinctive and innovative utilization of blockchain technology. The concept of smart contracts encompasses a rule system that governs the transactional behavior in blockchain networks. These rules are determined in advance by the parties involved, forming an integral part of the contractual agreement, and are selected through voluntary participation. Bitcoin, the pioneering cryptocurrency that introduced blockchain technology, does not inherently support the deployment or execution of smart contracts. However, it offers a limited degree of programmatic capability through scripting language, albeit with limitations such as a lack of user friendliness and the need for Turing compliance (Tschorsch and Scheuermann 2016).

Unlike traditional cryptocurrency implementations that rely on serialized tokens, Bitcoin adopts an alternative approach. During the initial stages of a blockchain, a predetermined number of tokens are allocated to each address based on a systematic numbering scheme. Ownership tracking occurs through subsequent transactions in which tokens associated with each participant's address are added or subtracted to maintain accurate ownership records. Although the use of digital signatures in blockchain implementation now extends beyond ensuring the assignment of digital asset ownership, their primary purpose was to guarantee the integrity and security of data exchanges between the parties involved. Digital signatures employ cryptographic techniques to verify the authenticity and protect the confidentiality of the exchanged data, thereby fostering trust and reliability within blockchain networks (Ali et al. 2019). Thus, smart contracts offer a unique and innovative application of blockchain technology by establishing a set of rules that governs transactions within such networks. As aforementioned, while Bitcoin does not inherently support smart contracts, it provides limited programmatic capabilities through scripting languages. Additionally, Bitcoin's implementation differs from that of traditional cryptocurrencies as it allocates tokens to addresses during the initial phases of the blockchain using a numbering scheme. In sum, the use of digital signatures goes beyond the assignment of digital asset ownership and ensures the integrity and safety of data exchange between parties. By understanding the capabilities and characteristics of smart contracts, we can harness the full potential of blockchain technology in various domains.

A glimpse into the future reveals the potential necessity of adopting blockchain technology to effectively address future financial challenges (Rakshit et al. 2022). Blockchain has gained widespread recognition for its numerous advantages in the financial sector, positioning it as one of the leading technologies in this domain (Ahluwalia et al. 2020). Its advantages now include increased protection, security, complete transaction reversibility, rapid processing, comprehensive visibility, and exceptional reliability. Collectively, these attributes contribute to blockchain's reputation as a transformative technology in the financial industry.

A pivotal element of blockchain technology is its anti-double spending function, which serves as a critical security measure (Ioannou and Demirel 2022). This mechanism ensures that the outputs of an unspent transaction are securely transferred, along with the asset being exchanged (Tancini et al. 2012). It also plays a significant role in maintaining equivalency within financial statements and preventing the duplication of asset transfers (Antonopoulos and Wood 2018). This unique feature ensures that assets can only be transferred once, thereby establishing an unparalleled mode of asset transfer (Tasca and Tessone 2019). Accordingly, as previously mentioned, the future adoption of blockchain technology has immense potential to overcome future financial challenges. Its advantages, including enhanced protection, transaction reversibility, rapid processing, complete visibility, and high reliability, have made it a leading technology in the financial sector. In addition, its anti-double spending function serves as a crucial security measure that guarantees the integrity of asset transfers in various contexts. Thus, embracing the potential of blockchain can pave the way for a future in which financial transactions are secure, transparent, and efficient.

In sum, this study aims to explore the hypothesis that blockchain-based technologies, particularly cryptocurrencies, have the potential to deliver both benefits and risks when integrated with cutting-edge technologies such as IoT, FinTech, and AI. By investigating the interplay between these domains, we gain a deeper understanding of the implications and opportunities arising from the convergence of blockchain and transformative technologies. First, concerning its potential benefits, the decentralized and transparent nature of blockchain can enhance the security and integrity of data exchange within IoT ecosystems. By leveraging blockchain's immutable ledger, IoT devices can securely communicate, verify, and record transactions, thereby facilitating trust and eliminating the need for intermediaries. Furthermore, integrating blockchain with FinTech can revolutionize financial services, enabling faster, more secure, and cost-effective transactions. Blockchain's ability to streamline payment processes, establish smart contracts, and facilitate cross-border transactions can enhance financial inclusion, reduce fraud, and increase efficiency. In addition, the fusion of blockchain technology and AI has the potential to revolutionize data management and privacy. Blockchain can provide a trusted framework for securely storing and sharing large volumes of data, whereas AI can analyze and derive valuable insights from these data, leading to improved decision-making and innovative solutions.

Second, it is important to consider the potential risks and challenges associated with the integration of blockchain-based technologies, the primary concern being scalability. As the adoption of IoT, FinTech, and AI continues to expand, blockchain networks may face scalability issues owing to the increasing volume of transactions and computational requirements. Additionally, the complexity of implementing and managing blockchain infrastructure can pose technical challenges, requiring robust governance and regulatory frameworks to ensure compliance and mitigate potential risks (e.g., data breaches or vulnerabilities in smart contracts). Moreover, blockchain's inherent transparency may conflict with privacy requirements in certain applications, necessitating careful consideration of data protection and anonymization techniques. Furthermore, the emergence of decentralized finance (DeFi), NFTs, and tokenization represent disruptive innovations within the financial landscape, demonstrating the potential of blockchain technology to reshape traditional industries. As organizations and entrepreneurs explore novel use cases and business models, they contribute to the advancement and maturation of blockchain ecosystems. Moreover, collaborations among academia, industry, and policymakers can drive research and development initiatives, paving the way for enhanced scalability, interoperability, and sustainability of blockchain-based solutions.

In summary, this study proposes the hypothesis that integrating blockchain-based technologies, particularly cryptocurrencies, with IoT, FinTech, and AI can yield both benefits and risks. By understanding these dynamics, we can unlock blockchain's transformative potential while addressing the challenges associated with its implementation. Furthermore, this study posits that innovation in the new economy can propel the growth of the blockchain industry as disruptive applications and collaborations contribute to its evolution. Through rigorous research and analysis, we provide valuable insights that inform decision-making and drive the responsible adoption of blockchain-based technologies in the context of emerging cutting-edge domains.

Methodology

This study empirically examines the relationship between Bitcoin and Stellar, two pioneering cryptocurrencies, and the financial performance of emerging technologies in the stock market to identify spillover patterns between these markets and to guide decision-making based on good and bad volatility.

First, we examine the asymmetric properties of the multivariate links between conventional and Islamic cryptocurrencies and technology-based investments. In doing so, we contribute to the literature examining the relationship between heterogeneous cryptocurrencies and high-tech assets. A quantitative cross-spectral coherence approach is used to determine the degree of interconnectedness of the new cryptocurrencies with each budding knowledge-based stock. We first determine the degree of interconnectedness during different time horizons and market states using a bivariate framework based on a quantile cross-spectral coherence approach. Then we look at cryptocurrencies and innovative advancements in a QVAR-based framework to analyze their relationship. Studies of this nature are crucial for making informed investment decisions and because they establish patterns of interconnectedness between cryptocurrency markets and new technologies. Finally, we attempt to determine the cause-effect relationship between volatilities in a non-linear, non-parametric quantile-based causality framework for both the first and second moments. Specifically, we examine the intensity of the nexus between variables within a quantile framework and from the viewpoint of a step-by-step analysis of synergistic interactions, spillover effects, and non-linear quantile-based causality.

Quantile cross-spectral coherence approach

The distinguished studies of Baruník et al. (2016), use positive and negative semi-variances for the asymmetric connectedness approach, but squaring values often generate outliers. Therefore, following Ghaemi Asl et al. (2021), we compute daily positive and negative absolute returns using the following equation:

$$v_t = \frac{1}{T}\sum_{t=1}^{T}|x_t - \overline{x}| \tag{1}$$

$$v_t = \left(\frac{1}{T}\sum_{t=1}^{T}(1-W_t)|x_t-\overline{x}|\right) + \left(\frac{1}{T}\sum_{t=1}^{T}W_t|x_t-\overline{x}|\right) \tag{2}$$

$$W_t = \begin{cases} 0, & if\ x_t < 0 \\ 1, & if\ x_t \geq 0 \end{cases} \tag{3}$$

$$v_t = v_t^P + v_t^N \tag{4}$$

where x_t represents the percentage of hourly change, T is the number of observations per day, and $\overline{x}$ is the average daily return. v_t denotes the average daily absolute percentage change, which is the sum of the daily positive absolute return, v_t^P, and daily negative absolute return, v_t^N.

In the first step, we use the quantile coherency method introduced by Baruník and Kley (2019), which was recently applied in different studies (e.g., Chai et al. (2022) to determine the general dependence between the joint distributions at different frequencies using quantiles of their corresponding distributions. Specifically, we study the dependence between the positive and negative volatilities of Stellar and Bitcoin and cutting-edge technologies as the frequencies and quantiles change.

We set the $v_t^{1,P}$ (or $v_t^{1,N}$) and $v_t^{2,P}$ (or $v_t^{2,N}$) as stationary series. This can be interpreted as a dynamic association between the two variables as follows:

$$\varrho^{v_t^{1,P}\left(orv_t^{1,N}\right),v_t^{2,P}\left(orv_t^{2,N}\right)}\left(\omega,q_{1,\tau},q_{2,\tau}\right) = \frac{\Psi^{v_t^{1,P}\left(orv_t^{1,N}\right),v_t^{2,P}\left(orv_t^{2,N}\right)}\left(\omega,q_{1,\tau},q_{2,\tau}\right)}{\left(\Psi^{v_t^{1,P}\left(orv_t^{1,N}\right),v_t^{1,P}\left(orv_t^{1,N}\right)}\left(\omega,q_{1,\tau},q_{2,\tau}\right).\Psi^{v_t^{2,P}\left(orv_t^{2,N}\right),v_t^{2,P}\left(orv_t^{2,N}\right)}\left(\omega,q_{1,\tau},q_{2,\tau}\right)\right)^{\frac{1}{2}}} \tag{5}$$

where $\Psi^{v_t^{1,P}\left(orv_t^{1,N}\right),v_t^{2,P}\left(orv_t^{2,N}\right)}$, $\Psi^{v_t^{1,P}\left(orv_t^{1,N}\right),v_t^{1,P}\left(orv_t^{1,N}\right)}$ and $\Psi^{v_t^{2,P}\left(orv_t^{2,N}\right),v_t^{2,P}\left(orv_t^{2,N}\right)}$ denote quantile cross-spectral and quantile spectral densities of the $v_t^{1,P}$ (or $v_t^{1,N}$) and $v_t^{2,P}$ (or $v_t^{2,N}$) processes, respectively. Additionally, we have $-\pi \ll \omega \ll \pi$, and $q_{1,\tau}, q_{2,\tau} \in [0,\ 1]$.

Quantile-VAR approach

Next, we examine the volatility spillover technique (Diebold and Yilmaz 2012; Diebold and Yılmaz 2014) based on the QVAR approach (Ando et al. 2018, 2022) used by various studies such as Bouri et al. (2020), Chatziantoniou et al. (2021), Chatziantoniou and Gabauer (2021), Shahzad et al. (2023), Dai and Zhu (2023), and Lorente et al. (2023).

The QVAR-based framework is a valuable and innovative tool for forecasting and stress testing in finance and economics. Quantile models such as QVAR can capture the tail risk of a distribution, which is crucial for risk management and stress testing. By modeling the interaction among endogenous variables at any quantile, a QVAR-based framework can provide a more precise and nuanced picture of potential downside risks. Furthermore, this framework can investigate asymmetry in downside and upside risks by considering different quantile levels, which, in turn, provides a more sophisticated understanding of potential risks and opportunities in a given market or economy. This approach has been proven effective in various studies.

The QVAR-based framework can be particularly useful in situations where traditional methods may fall short. For instance, it can provide a more accurate and flexible approach to risk management and forecasting, particularly in scenarios where potential downside risks are significant. This framework can also be used to investigate the impact of systemic financial stress on growth and derive policy implications from scenario analyses (Chavleishvili and Manganelli 2019; Iacopini et al. 2022).

Although there is a large body of econometric literature characterizing the mean performance of time-series data, quantile regression is generally used, particularly when evaluating the cyclical behavior of stock prices. The below formula shows QVAR(q) at τ ($0 < \tau < 1$) quantile:

$$\nu_t = c(\tau) + \sum_{j=1}^{q} \beta_j(\tau)\nu_{t-j} + \varepsilon_t(\tau) \tag{6}$$

where ν_t and $c(\tau)$ show market volatility at time t and the intercept of the model at τ quantile, respectively. β_{j} and $\varepsilon_t(\tau)$ show the matrix of lagged coefficients and residual at quantile τ, which meets the population quantile constraints specified below:

$$Q_\tau(\varepsilon_\tau(\tau)|\nu_{t-1}, ..., \nu_{t-p}) = 0 \tag{7}$$

As seen below, the τth population conditional quantile in response ν creates:

$$Q_\tau(\nu_t|\nu_{t-1}, ..., \nu_{t-p}) = c(\tau) + \sum_{j=1}^{q} \beta_j(\tau)\nu_{t-j} \tag{8}$$

This arrangement suggests an equation for each quantile computed using quantile regression (Cecchetti and Li 2008). To extract the quantile volatility spillover across data in the network environment, we use the generalized variance decomposition technique (Diebold and Yilmaz 2012; Diebold and Yılmaz 2014) based on QVAR. The following equation depicts the vector moving average model with infinite order in quantiles, and A(τ) displays moving average parameters. A moving average model is constructed based on these coefficients:

$$\nu_t = \mu(\tau) + \sum_{l=0}^{\infty} A_l(\tau)\varepsilon_{t-s}(\tau), \tag{9}$$

Quantile causality approach

Finally, we perform a non-linear causality-in-quantile test. Our analysis follows Adekoya and Oliyide (2021), Li et al. (2021b), Das et al. (2018), and Bhatia et al. (2018) by approximating the quantile causality using the non-linear method offered in Balcilar et al. (2017). It might be that causality tests based on mean values are unable to accurately reflect the actual dependence structure. To arrive at the quantile causality approach proposed by Balcilar et al. (2017), the tests are closely aligned with the frameworks proposed by Nishiyama et al. (2011) and Jeong et al. (2012).

Additionally, a second moment is considered in the analysis of causality-in-variance between financial assets. Although there may not be causality in the assets' means (as in the first moment), there may be predictive power in their variances (i.e., assets' volatility), which might lead to greater benefits for portfolio diversification strategies if volatility predictions are more precise (Bhatia et al. 2018). Using the quantile causality test, it is possible to estimate whether a non-linear causal relationship exists between variables ν_{1t} and ν_{2t}. To explain how quantile-based causality works, Jeong et al. (2012) defined the lag vector as $\left\{\nu_{2,t-1}, ..., \nu_{2,t-\mathrm{p}}, \nu_{1,t-1}, ..., \nu_{1,t-\mathrm{p}}\right\}$ when the expressed $\nu_{1,t}$ does not lead to the measured $\nu_{2,t}$ in the given quantity, θth:

$$Q_\theta\left(\nu_{2,t}|\nu_{2,t-1},\ldots,\nu_{2,t-p},\nu_{1,t-1},...,\nu_{1,t-p}\right)=Q_\theta\left(\nu_{2,t}|\nu_{2,t-1},\ldots,\nu_{2,t-p}\right) \tag{10}$$

Moreover, it may be justifiable to assume that $\nu_{1,t}$ is likely to cause $\nu_{2,t}$ to be in the type of θth quantile where the extent of the quantile calculates as $\left\{\nu_{2,t-1}, ..., \nu_{2,t-\mathrm{p}}, \nu_{1,t-1}, ..., \nu_{1,t-\mathrm{p}}\right\}$, depending on whether:

$$Q_\theta\left(\nu_{2,t}|\nu_{2,t-1},\ldots,\nu_{2,t-p},\nu_{1,t-1},...,\nu_{1,t-p}\right)\neq Q_\theta\left(\nu_{2,t}|\nu_{2,t-1},\ldots,\nu_{2,t-p}\right) \tag{11}$$

In this case, $Q_\theta\left(\nu_{2,t}|.\right)$ will correspond to the θ t conditional quantile of $\nu_{2,t}$; that is, the conditional quantile will depend on period t, and quantiles appear only in the range of 0–1 (i.e., $0 \prec \theta \prec 1$). Therefore, it is plausible that the historical values of $\nu_{1,t}$, considering the causal relationship between $\nu_{1,t}$ and $\nu_{2,t}$ at the qth quantile, can be used to assist in predicting the values of $\nu_{2,t}$ at the qth quantile. However, this does not apply to other quantiles due to the quantile-associated relationship between $\nu_{1,t}$ and $\nu_{2,t}$.

Data and results

In this study, the raw data are based on a one-hour frequency and the volatilities are based on realized absolute returns over that period. Based on the studies of Wen et al. (2022), Hu et al. (2019), Ma and Tanizaki (2022), and Sifat et al. (2019) and the limited time coverage of intra-day observations with high and low frequencies for technology stocks and cryptocurrencies in different databases, we selected hourly data to provide the best possible coverage. Furthermore, using an hourly frequency to determine liquidity for Bitcoin, Urquhart and Zhang (2019) concluded that higher frequencies do not provide liquidity, and Zhang et al. (2019) demonstrated that the prices of selected cryptocurrencies—Bitcoin, Ethereum, Ripple, and Litecoin—are relatively efficient on an hourly basis. To collect data on technology stocks, we accessed the Bloomberg terminal in a manner similar to Hu et al. (2019), Wen et al. (2022), Wang et al. (2020), and Urquhart and Zhang (2019), and collected cryptocurrency data from the Bitstamp exchange since it was one of the first, liquid, and most established exchanges and is regarded as a relatively safe exchange by market participants worldwide (Bouri et al. 2017b). In accordance with the data access, the time period in which the hourly data for innovative stocks are available for reporting begins on January 25, 2019 at 15:00:00, when the first hourly data for innovative stocks becomes available, and ends on July 1, 2022 at 23:00:00, when the paper begins modeling the smart stock price. Several types of Global

Table 3 Abbreviations

Symbol	Variable
XLM	Stellar
BTC	Bitcoin
FINX	FinTech
SNSR	Internet of Things
AIQ	Artificial Intelligence & Technology
XLMN	Negative volatility of Stellar
BTCN	Negative volatility of Bitcoin
FINXN	Negative volatility of FinTech
SNSRN	Negative volatility of the Internet of Things
AIQN	Negative volatility of Artificial Intelligence & Technology
XLMP	Positive volatility of Stellar
BTCP	Positive volatility of Bitcoin
FINXP	Positive volatility of FinTech
SNSRP	Positive volatility of the Internet of Things
AIQP	Positive volatility of Artificial Intelligence & Technology

X exchange-traded funds (ETFs) are used in our analysis of technology-driven stocks. The Global X Internet of Things ETF (SNSR) seeks to invest in companies that are positioned to benefit from the broader adoption of the IoT, which is enabled by technologies such as Wi-Fi systems, 5G telecommunications infrastructure, and fiber optics. The Global X FinTech ETF (FINX) is designed to invest in leading companies in the emerging FinTech sector, which encompasses a range of innovations that have helped transform established industries (e.g., insurance, investing, fundraising, and third-party lending) by providing customized mobile and digital solutions. In addition, the Global X AI and Technology ETF (AIQ) specializes in companies that may reap the benefits of further development and use of AI technologies to enhance the quality of their products and services, as well as companies that provide hardware that facilitates the use of AI to analyze extensive data. Table 3 lists the full names and abbreviations.

Table 4 presents an overview of the statistics related to positive and negative volatilities. Interestingly, all average positive volatilities are greater than the average negative positive volatilities. Additionally, all three series are non-normal at the 1% significance level as they are positively skewed and have leptokurtic distributions (Jarque and Bera 1980). Moreover, all series are stationary and autocorrelated as assessed by the Elliott, Rothenberg, and Stock (ERS) unit root test (Elliott et al. 1996), have autoregressive conditional heteroskedasticity (ARCH)/generalized autoregressive conditional heteroskedasticity (GARCH) errors and are significantly autocorrelated. Finally, the Kendall correlation coefficients indicate the strongest correlation between negative volatilities. It is noteworthy that all correlation coefficients are between 0.420 and 0.913. Figure 1 shows the positive and negative volatilities of each series.

Quantile cross-spectral coherence results

In Figs. 2, 3, 4, 5, 6 and 7 (and Table 6 in the "Appendix") we present only the real part of the quantile coherency estimates across multiple quantile levels (e.g., 0.05|0.05, 0.5|0.5, and 0.95|0.95), as well as over a variety of frequencies over an extended time period [0,

Table 4 Summary statistics

	Mean	Variance	Skewness	Kurtosis	JB	ADF	PP	KPSS	ERS	Q(10)
Descriptive statistics										
XLMP	10.133	65.595	3.919	26.461	23,578.48***	− 14.1***	− 14.99***	0.0782	− 4.643***	442.094***
XLMN	9.808	46.085	2.955	14.183	7308.919***	− 11.4***	− 17.07***	0.0649	− 5.256***	450.590***
BTCP	6.681	23.129	2.945	17.960	11,060.11***	− 7.49***	− 18.84***	0.0971	− 4.319***	576.199***
BTCN	6.236	25.469	3.522	21.043	15,244.28***	− 8.02***	− 17.82***	0.0855	− 5.445***	472.002***
FINXP	1.69	2.215	2.705	11.860	5260.226***	− 3.81***	− 26.37***	0.0916	− 5.111***	501.249***
FINXN	1.615	3.445	3.166	16.425	9593.305***	− 5.37***	− 25.48***	0.0868	− 3.698***	602.028***
SNSRP	1.582	2.136	2.451	8.464	2961.538***	− 5.38***	− 29.50***	0.0845	− 3.801***	239.301***
SNSRN	1.463	2.675	2.961	14.888	7947.959***	− 8.72***	− 27.46***	0.0680	− 4.603***	369.524***
AIQP	1.465	2.291	3.599	18.630	12,349.51***	− 7.80***	− 30.40***	0.1008	− 5.791***	165.881***
AIQN	1.341	2.591	3.003	12.667	6083.666***	− 6.88***	− 27.95***	0.0600	− 4.866***	258.733***
	Q = 0.1	**Q = 0.2**	**Q = 0.3**	**Q = 0.4**	**Q = 0.5**	**Q = 0.6**	**Q = 0.7**	**Q = 0.8**	**Q = 0.9**	
Quantile unit root test										
XLMP	− 2.794***	− 5.331***	− 3.411***	− 4.025***	− 2.686***	3.561***	− 3.140***	− 3.648***	− 3.751***	− 4.389***
XLMN	− 2.195***	2.255***	6.208***	4.704***	− 2.252***	3.666***	− 2.491***	− 4.036***	3.044***	− 3.074***
BTCP	− 5.253***	3.531***	2.461***	2.526***	5.930***	3.774***	5.237***	3.039***	2.057***	− 4.772***
BTCN	4.943***	3.189***	2.570***	4.829***	2.342***	3.419***	2.778***	5.968***	5.108***	− 5.886***
FINXP	3.060***	3.632***	6.058***	2.143***	3.180***	3.622***	3.381***	4.341***	3.487***	− 2.633***
FINXN	3.228***	3.702***	4.377***	4.509***	4.857***	3.530***	3.538***	5.262***	3.097***	3.004***
SNSRP	5.257***	− 3.147***	− 2.351***	2.484***	5.056***	2.025***	− 5.075***	4.693***	− 3.955***	− 2.152***
SNSRN	2.345***	− 4.292***	3.810***	4.502***	3.383***	4.952***	− 4.866***	− 3.110***	− 3.023***	− 5.149***
AIQP	− 2.015***	− 3.857***	− 5.958***	2.538***	4.438***	4.780***	− 4.805***	− 5.959***	− 5.152***	− 5.049***
AIQN	5.188***	4.041***	− 5.508***	3.849***	4.638***	− 3.082***	− 3.882***	− 4.897***	− 5.653***	− 3.936***

Table 4 (continued)

	XLMP	XLMN	BTCP	BTCN	FINXP	FINXN	SNSRP	SNSRN	AIQP	AIQN
Ordinary correlations										
XLMP	1.0000									
XLMN	0.6611	1.0000								
BTCP	0.4897	0.4165	1.0000							
BTCN	0.3749	0.6895	0.6031	1.0000						
FINXP	0.1213	0.0871	0.2234	0.1683	1.0000					
FINXN	0.0512	0.2186	0.1175	0.3141	0.3268	1.0000				
SNSRP	0.1350	0.0538	0.1921	0.1133	0.6155	0.1309	1.0000			
SNSRN	0.0487	0.2159	0.1317	0.3176	0.1708	0.7346	0.2856	1.0000		
AIQP	0.0876	0.0465	0.1909	0.1227	0.5591	0.1137	0.4718	0.0529	1.0000	
AIQN	0.0317	0.1637	0.1442	0.2452	0.1392	0.6785	0.0966	0.6597	0.2868	1.0000

***Denotes significance at the 1% level. Skewness, Kurtosis, JB, ADF, PP, KPSS, ERS, and Q(10) are related to the D'Agostino (1970) test, Anscombe and Glynn (1983) test, Jarque and Bera (1980) normality test, Dickey and Fuller (1979) unit root test, Phillips and Perron (1988) unit root test, Kwiatkowski et al. (1992) unit root test, Elliott et al. (1996) unit root test, and Fisher and Gallagher (2012) weighted portmanteau test, respectively. Finally, the quantile unit root test of Galvao (2009) confirms the previous unit root test results for each quantile, and we can reject the null hypothesis of a unit root at all quantiles

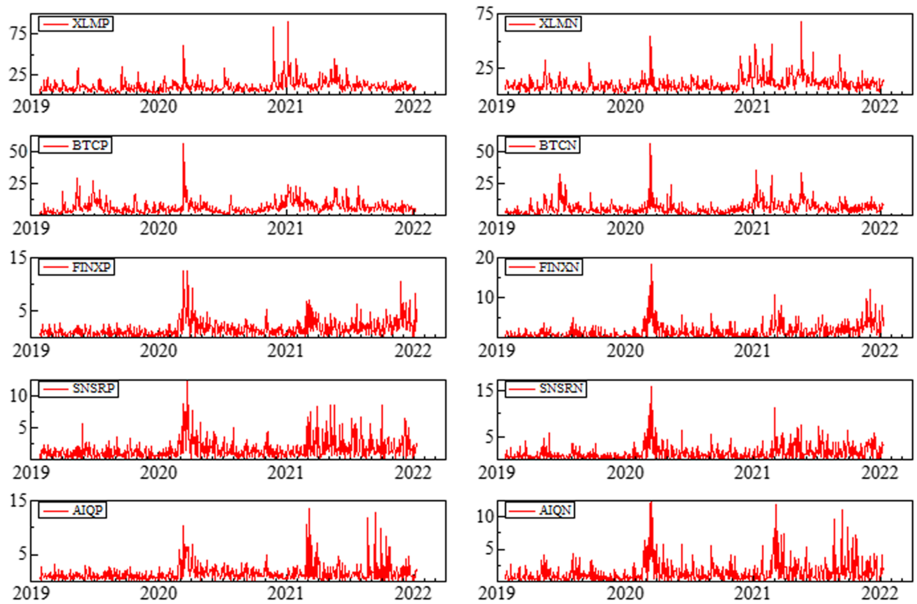

Fig. 1 Volatilities dynamics

0.5]. The horizontal axis was rescaled to emphasize the importance of the daily cycle. The abbreviations Y, M, and W refer to the annual, monthly, and weekly periods, respectively.

Because of the wide variety of quantiles, we used only the three quantiles that were retained as coherent (0.5, 0.05, and 0.95) and their combinations (i.e., the middle, left tail, and right tail of the distributions). By studying these quantiles, we can identify the degree of dependence in different parts of the distributions. Another aspect of this study is that it focuses on three different frequency periods: the short run (one week), medium run (one month), and long run (one year).

Four eye-catching findings are observed when examining the relationship between the volatility of the combination of cryptocurrencies and innovative technologies. First, in the long run, the coherence of the pair does not appear to be perfect in most cases; interestingly, the highest and weakest associations were found in the middle and lower quantiles of the FINXP-XLMN pair. Alternatively, our findings suggest that there is significant positive and negative co-movement (i.e., in the same direction) between FINX's good volatility and Stellars (XLM's) bad volatility over the long term in the middle- and low-volatility markets, respectively (Hereafter, XLM is an acronym for Stellar).

Second, by appreciating moderate volatility in a long-term time frame, one can notice that the positive volatilities of XLM are synchronous with the negative volatilities of FINX. When moving from reasonably volatile markets to rarely volatile states, the positive volatilities of XLM are synchronous with the negative volatilities of FINX, and considering the same long-term horizon (i.e., annually), the good and bad volatilities of XLM rarely follow one another, given that they are inversely correlated. Second, the bad volatilities of Bitcoin (BTC) and XLM always parallel the bad and good volatilities of FINX, respectively, when considering two specific pairs

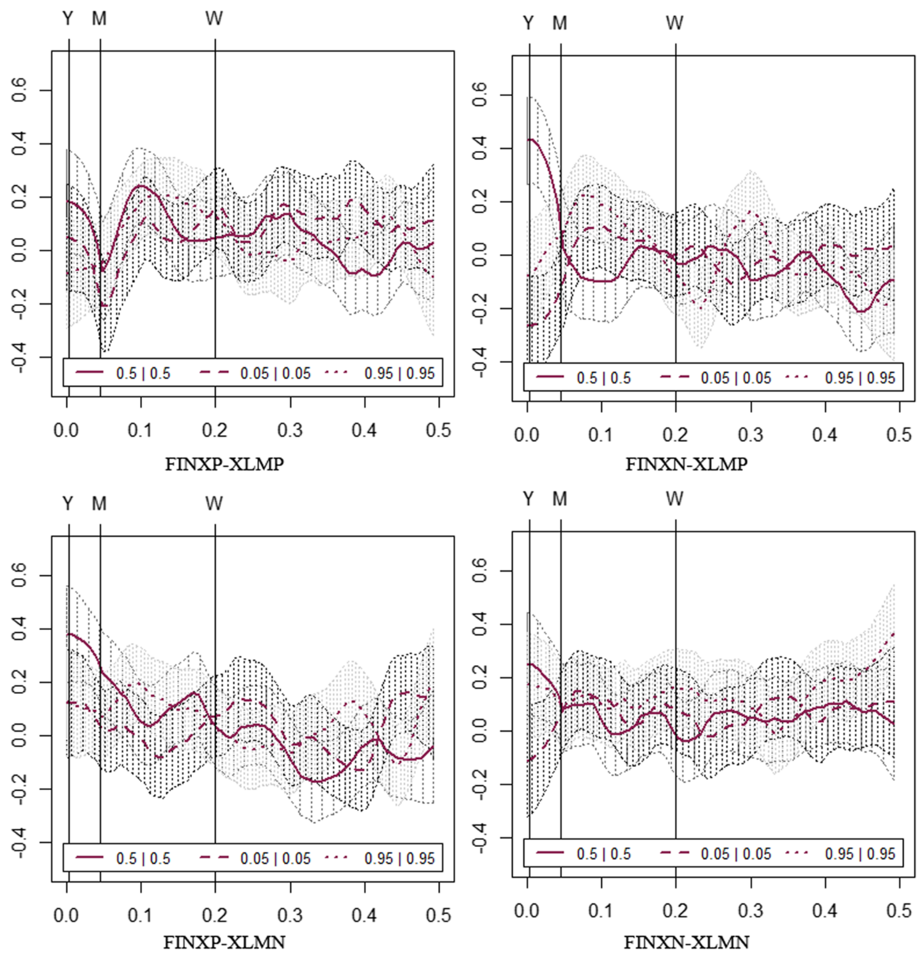

Fig. 2 Association of FINX and XLM. *Notes*: The series of graphs show how quantile coherency estimates differ across many quantile levels (e.g., 0.05|0.05, 0.5|0.5, and 0.95|0.95), as well as over several frequencies across an extended period of time [0, 0.5]. The graphs were rescaled to emphasize the significance of the daily cycle along the horizontal axis. The abbreviations Y, M, and W refer to annual, monthly, and weekly periods, respectively

of FINXN-BTCN and FINXP-XLMN. As a result, if we observe signs of negative volatility in XLM, we might interpret the anticipation of good volatility in FINX as a straightforward approach.

Third, in most low-volatility conditions, cryptocurrencies do not depend on high-tech equipment, especially when it comes to monthly and yearly horizons; for example, all possible good and bad volatility pairs between the SNSR-XLM and XLM (or BTC) and the AIQ-XLM (or BTC) are negatively correlated over the long run (yearly), except for the AIQN-BTCP pair, which exhibits a positive relationship. Finally, various pairs of AIQ and BTC, with all ascertainable types of volatility, are the only ones that show a positive connection in high-volatility market conditions, irrespective of any exception, within these heterogeneous market conditions.

Our findings are consistent with those of Huynh et al. (2020), who demonstrated that BTC serves as a valuable asset for hedging. However, it should be noted that Bitcoin is also influenced by its historical volatility, a characteristic it shares with AI and

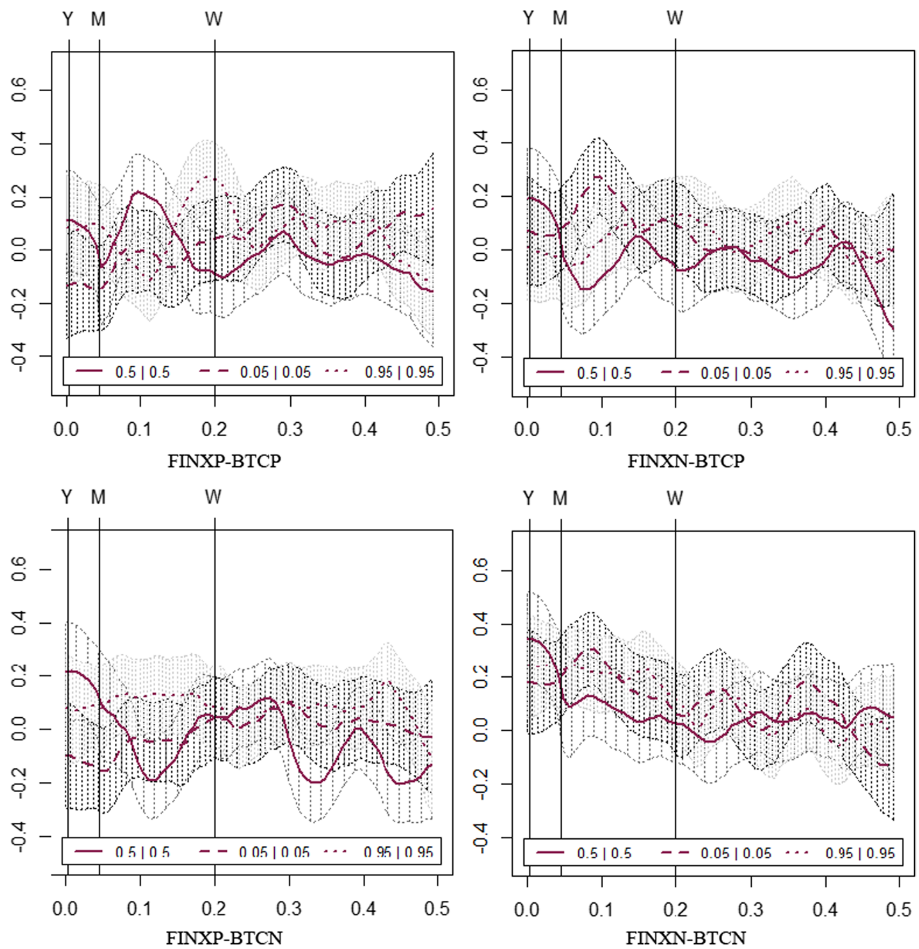

Fig. 3 Association of FINX and BTC. *Notes*: See notes in Fig. 2

certain environmentally-friendly assets. Nevertheless, AI and general equity indices are not effective hedging instruments for each another. Furthermore, our results align with those of previous studies examining AI-based assets, such as Jareño and Yousaf (2023), who revealed that the system is more responsive to extreme values in the distribution (specifically, the lower and upper quantiles) rather than the median (Q = 0.50).

Our results suggest that the potential for asset diversification in emerging markets is significantly limited, which is consistent with the findings of Huynh et al. (2020), Kamran et al. (2022), and Abakah et al. (2023). However, our results contradict those of Umar et al. (2021), who found that the cryptocurrency market is less integrated with technological systems and is structurally less exposed to systemic risk. Our study confirms the asset diversification characteristics of BTC and XLM over time, as proposed by previous studies focusing on BTC (Gil-Alana et al. 2020; Le et al. 2021a; Smales 2019) and reveals asymmetry in the underlying behaviors, which are time-varying and diverse across cryptocurrency and high-tech markets, as noted by Abakah et al. (2023).

Ultimately, it can be said that, overall, the quantile cross-spectral coherence results show that, from a volatility standpoint, the correlation between cryptocurrencies with

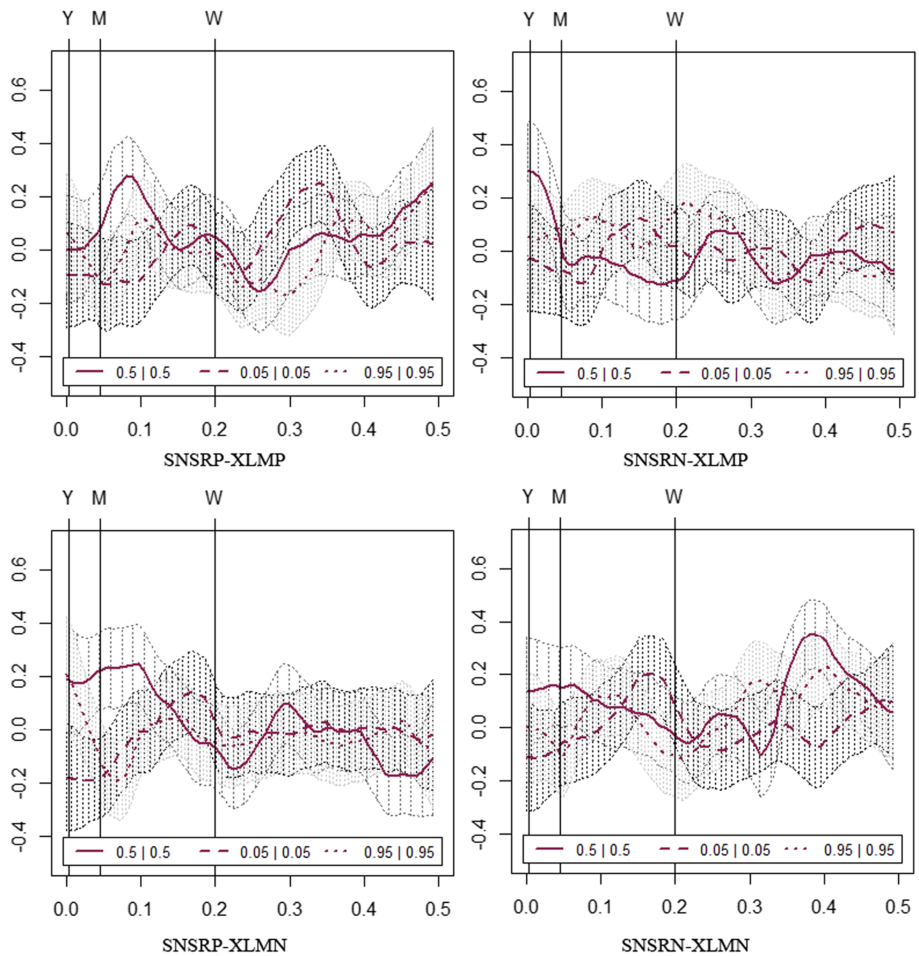

Fig. 4 Association of SNSR and XLM. *Notes*: See notes in Fig. 2

AIQ, SNSR, and FINX is heterogeneous across a variety of cryptocurrencies (Islamic and conventional), different horizons, and varying volatility classes. It is clear from the above description that one of the problems with this method is that it emphasizes correlation, and the results are ineffective in recognizing spillover directions and the composition of followers and leaders. Accordingly, we now turn to analyzing the connectedness and investigating spillovers.

Quantile-VAR approach: Connectedness results

Initially, we explain the average dynamic connectedness measures for good and bad volatilities as a starting point. Figure 8 shows how the total connectedness varies over time because the averaged total connectedness index (TCI) in Table 5 does not sufficiently reflect the dynamic nature of the network. Dynamic total connectedness for each quantile is observed to be highly variable over time, ranging from 42.15% (belongs to Q = 0.5) to 99.51% (belongs to Q = 0.95) over the studied time period. In the early months of 2020, the level of total connectedness peaked during the COVID-19 outbreak, whereas the lowest level of overall interconnectedness occurred at the end of 2021. In November, the cryptocurrency market reached an unprecedented

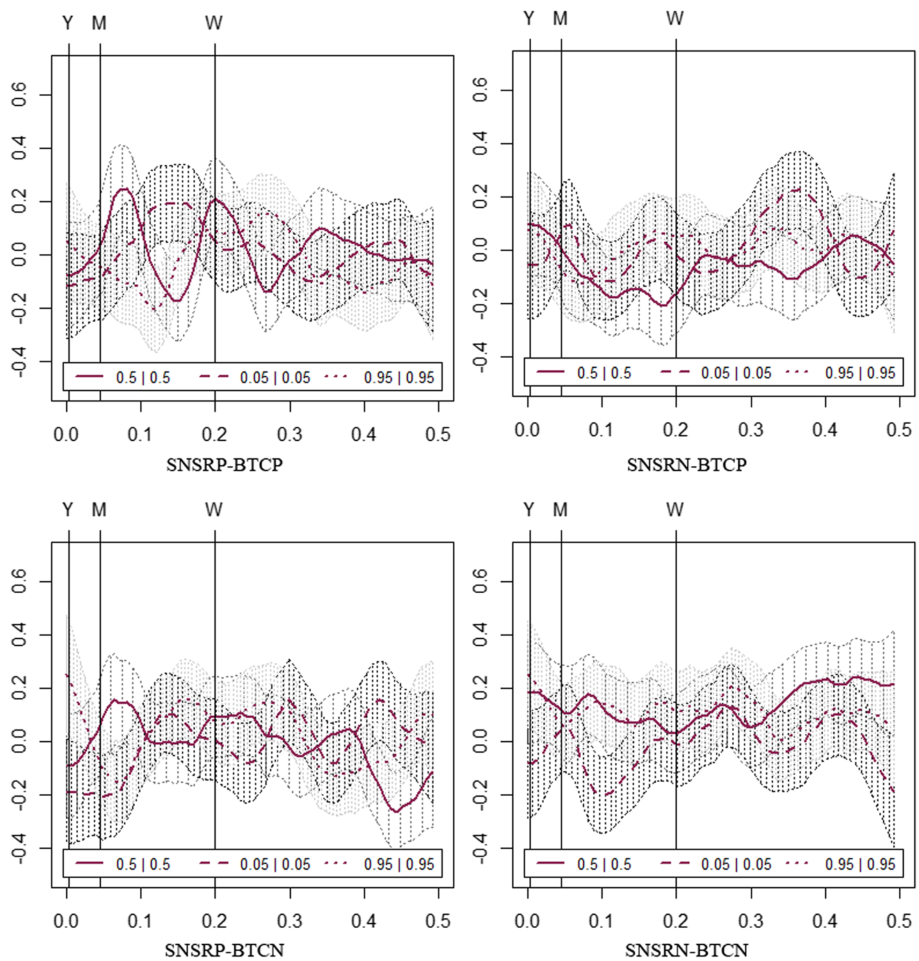

Fig. 5 Association of SNSR and BTC. *Notes*: See notes in Fig. 2

milestone, surpassing a total value of $3 trillion. This remarkable feature highlights the significant level of interconnectivity in the market. However, the emergence of a new variant of COVID-19, known as Omicron, has had a contrasting effect on stock markets. The ongoing COVID-19 pandemic has resulted in increased risk spillover, both among and within emerging markets, leading to a sharp decline in stock market performance (Kumar et al. 2022a). Studies examining the correlation between Asian technology stock indices and cryptocurrencies during the COVID-19 pandemic have revealed a significant level of co-movement (Rijanto 2023). Additionally, Almeida et al. (2023) note that the pandemic has had a notable impact on the interconnection between cryptocurrencies and emerging markets, with strong cross-correlations observed in cryptocurrency-based markets during turbulent periods of the pandemic. Moreover, the COVID-19 pandemic has influenced the flow of information between cryptocurrencies and traditional financial assets (Rijanto 2023). For further insights into the relationship between emerging and alternative industries in the context of COVID-19, refer to Naeem et al. (2022), Yousaf et al. (2023), and Li and Meng (2022).

Moreover, the dynamics of TCI in different quantiles show a more undulating nature of total connectedness in normal markets than in bear and bull markets, such

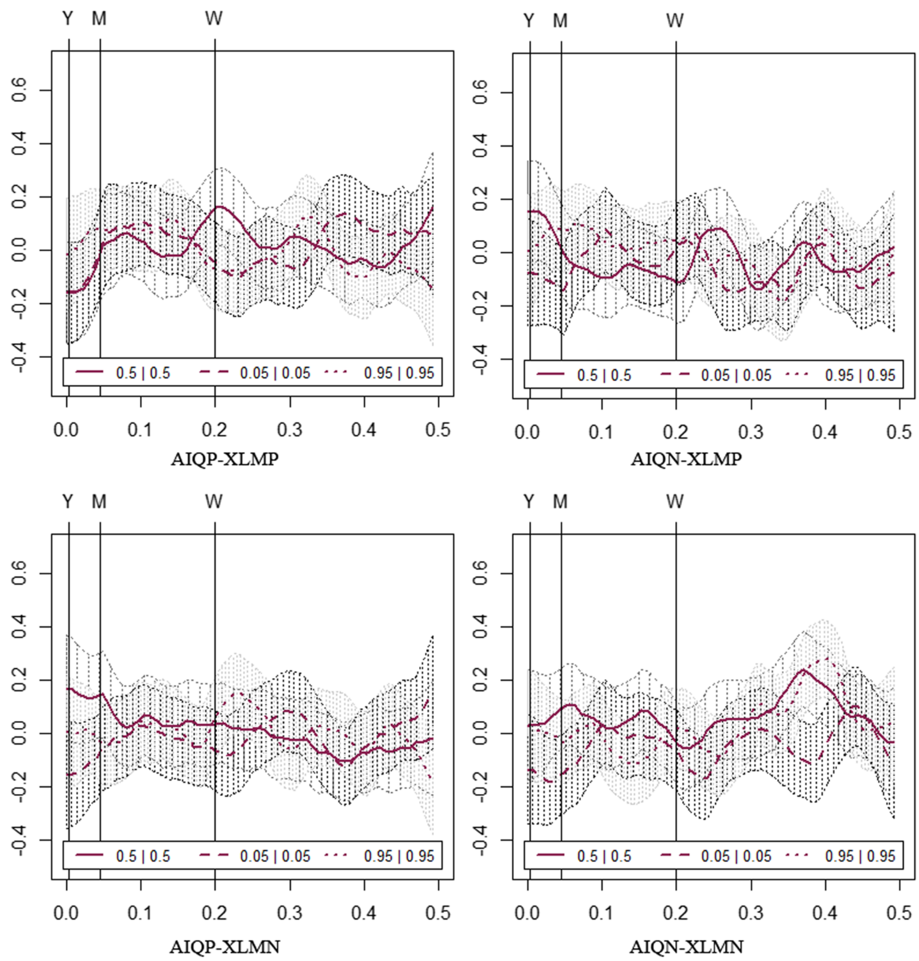

Fig. 6 Association of AIQ and XLM. *Notes*: See notes in Fig. 2

that the range of motion in Q = 0.95 and Q = 0.05 is [99.81%, 89.32%] and [80.93%, 87.22%], respectively, but varies from 42.15 to 77.22% in the normal market. The level of connectedness in the upper and lower tails is higher than that in the middle quantile, which aligns with the findings of previous studies such as Bouri et al. (2021) and Yousaf et al. (2022). The increase in connections between the bear and bull markets can be attributed to several factors. Cryptocurrencies are digital assets that rely on blockchain technology, a decentralized and distributed ledger technology (Anwer et al. 2023) and are closely associated with cutting-edge technologies such as FinTech and AI. Blockchain is closely tied to the technology sector, and its development and adoption can significantly impact the cryptocurrency market. The cryptocurrency market is highly volatile as prices are influenced by various factors, including market sentiment, regulatory changes, and technological advancements (Gupta and Chaudhary 2022; Mensi et al. 2023). These factors are closely linked to the technology sector and any changes can impact the market. Furthermore, cryptocurrencies are predominantly traded on technology platforms and their trading volumes are influenced by the availability and adoption of these platforms (Attarzadeh and Balcilar 2022). The development of new cryptocurrencies and their adoption by the technology sector

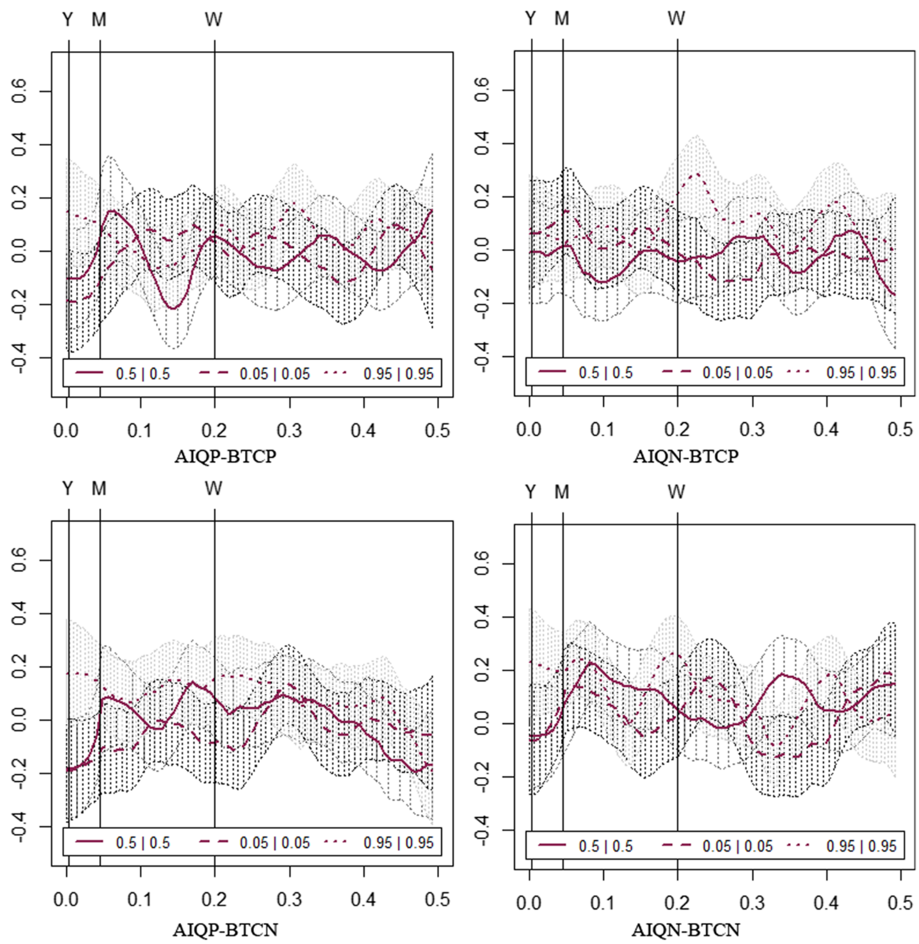

Fig. 7 Association of AIQ and BTC. *Notes*: See notes in Fig. 2

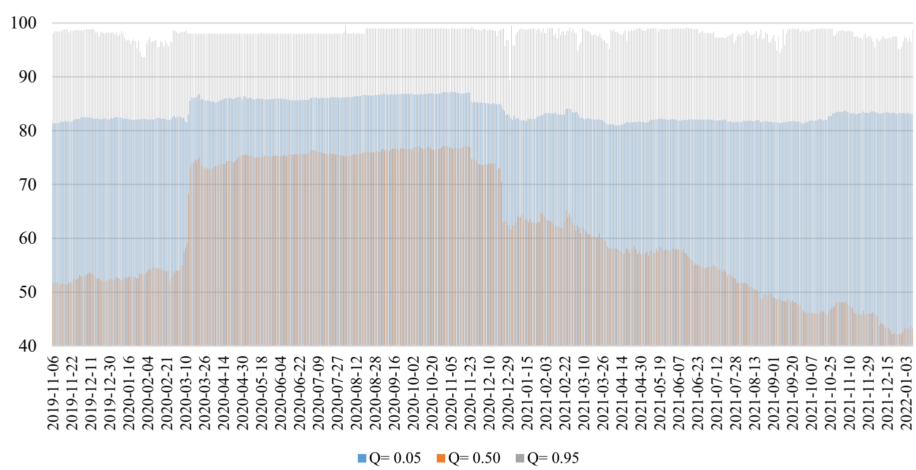

Fig. 8 Dynamics of total connectedness index for each quantile. *Notes*: Q = 0.05, Q = 0.5, and Q = 0.95 indicate bear, normal, and bull markets, respectively

Table 5 Averaged dynamic connectedness

Q= 0.05	XLMP	XLMN	BTCP	BTCN	FINXP	FINXN	SNSRP	SNSRN	AIQP	AIQN	FROM others
XLMP	26.79	15.97	11.65	9.89	6.97	5.44	6.70	5.43	5.92	5.23	73.21
XLMN	13.29	23.56	9.78	15.86	6.29	7.00	5.18	7.03	5.32	6.68	76.44
BTCP	10.59	11.25	24.32	13.61	7.97	6.00	6.66	6.14	7.49	5.96	75.68
BTCN	7.72	16.09	12.47	23.33	6.65	7.75	5.37	7.88	5.81	6.93	76.67
FINXP	5.98	6.58	7.40	6.60	23.80	6.53	15.58	5.60	16.00	5.93	76.20
FINXN	4.10	7.29	4.83	8.01	6.41	24.14	5.04	17.87	4.56	17.74	75.86
SNSRP	5.96	5.79	6.59	5.61	16.83	5.74	25.59	7.85	14.64	5.41	74.41
SNSRN	4.11	7.35	4.95	8.15	5.40	18.03	6.98	24.32	4.22	16.49	75.68
AIQP	5.34	5.83	7.18	5.95	17.17	5.04	14.41	4.61	26.39	8.10	73.61
AIQN	4.08	7.03	5.09	7.16	5.91	17.78	4.88	16.32	7.19	24.57	75.43
TO others	61.18	83.18	69.93	80.84	79.62	79.31	70.80	78.72	71.16	78.46	
Inc.Own	87.97	106.74	94.25	104.18	103.42	103.45	96.39	103.03	97.54	103.03	TCI= 83.69
NET	−12.03	6.74	−5.75	4.18	3.42	3.45	−3.61	3.03	−2.46	3.03	
Q= 0.50	XLMP	XLMN	BTCP	BTCN	FINXP	FINXN	SNSRP	SNSRN	AIQP	AIQN	FROM others
XLMP	56.98	20.06	9.06	8.17	0.84	0.94	0.76	1.28	0.81	1.11	43.02
XLMN	19.92	43.51	5.90	19.99	0.55	3.15	0.61	3.07	0.57	2.73	56.49
BTCP	11.06	12.25	49.14	18.18	1.57	1.72	0.77	1.85	1.50	1.96	50.86
BTCN	5.44	22.74	14.88	43.02	0.65	4.34	0.42	4.74	0.59	3.18	56.98
FINXP	1.40	2.24	1.97	2.41	44.14	6.83	12.40	6.84	15.29	6.49	55.86
FINXN	0.67	3.48	1.17	4.88	2.29	41.16	1.49	21.11	1.73	22.02	58.84
SNSRP	1.05	1.89	1.32	2.54	13.02	8.65	42.82	10.56	11.34	6.80	57.18
SNSRN	0.95	3.29	1.43	4.88	2.22	21.58	5.00	40.15	2.26	18.23	59.85
AIQP	1.02	2.07	1.79	2.12	14.98	5.79	10.08	6.45	43.94	11.76	56.06
AIQN	0.67	2.90	1.64	3.46	2.60	21.47	1.94	17.66	7.31	40.36	59.64
TO others	42.19	70.91	39.15	66.64	38.71	74.47	33.47	73.56	41.42	74.28	
Inc.Own	99.17	114.42	88.29	109.65	82.85	115.63	76.29	113.71	85.36	114.64	TCI= 61.64
NET	−0.83	14.42	−11.71	9.65	−17.15	15.63	−23.71	13.71	−14.64	14.64	
Q= 0.95	XLMP	XLMN	BTCP	BTCN	FINXP	FINXN	SNSRP	SNSRN	AIQP	AIQN	FROM others
XLMP	15.35	13.71	10.24	12.43	7.71	8.94	7.58	9.15	6.21	8.68	84.65
XLMN	15.25	13.89	10.28	12.57	7.58	8.92	7.56	9.12	6.16	8.67	86.11
BTCP	15.11	13.59	10.29	12.39	7.62	9.09	7.57	9.26	6.29	8.79	89.71
BTCN	14.28	13.49	10.21	12.73	7.74	9.26	7.67	9.38	6.34	8.91	87.27
FINXP	13.88	12.34	9.47	11.39	8.34	10.14	7.89	9.98	7.00	9.57	91.66
FINXN	14.19	12.82	9.77	11.89	7.75	10.11	7.67	9.88	6.48	9.43	89.89
SNSRP	12.73	12.40	9.74	11.71	8.03	10.00	8.51	10.19	7.10	9.58	91.49
SNSRN	13.43	12.76	9.74	11.94	7.65	9.94	7.96	10.15	7.03	9.39	89.85
AIQP	12.16	12.01	9.76	11.95	8.32	10.27	8.10	10.02	7.63	9.79	92.37
AIQN	14.49	13.03	9.81	12.04	7.78	9.57	7.71	9.63	6.60	9.34	90.66
TO others	125.53	116.16	89.04	108.31	70.18	86.14	69.71	86.61	59.21	82.80	
Inc.Own	140.88	130.05	99.33	121.03	78.52	96.24	78.22	96.76	66.83	92.14	TCI= 89.09
NET	40.88	30.05	−0.67	21.03	−21.48	−3.76	−21.78	−3.24	−33.17	−7.86	

a color gradient can be observed in vectors as the numbers increase from lower to higher values. The color transition follows a shift from red to blue. In matrices, a similar pattern is observed, where the colors transition from yellow to green as the numbers increase

can also affect the connectedness between cryptocurrencies and the technology sector (Kumar et al. 2022a, b). Considering these characteristics, new technologies and cryptocurrencies exhibit similar and integrated behaviors under extreme market conditions, with their co-movement intensifying in abnormal markets.

As shown in Table 5, the average dynamic connectedness and pairwise spillover results for three different quantiles, Q = 0.05, Q = 0.50, and Q = 0.95, are also shown in Fig. 9 respectively. From these measures, it is evident that the poor volatilities of all variables are net transmitters of shocks to other variables in the system. A striking amount of evidence suggests that the negative volatilities of all variables have a stronger net spillover effect on the connectedness system than the positive volatilities in the normal market. In a bear market, the same results can be observed, except that both good and bad volatilities for FINX are net transmitter shocks of the system. However, the results of the bull market are vastly different for both types of XLM

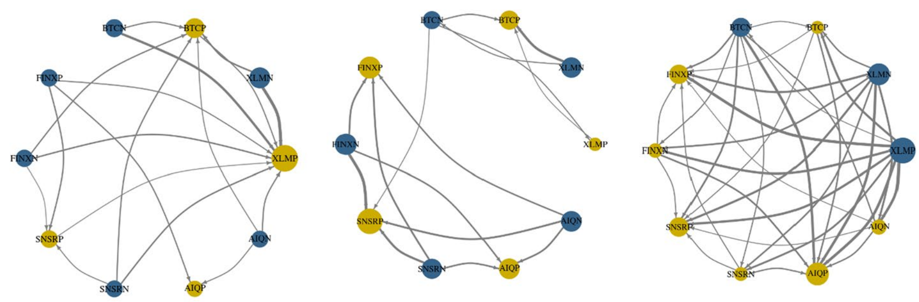

Fig. 9 Average of pairwise spillovers and connectedness networks. *Note*: Arrows indicate positive directionality from the source to the edge of the arrow. A greater number of arrows indicates that the network is more connected. The blue (beige) nodes in the diagram represent net shock transmitters (receivers). The weights of the vertices are determined using the averaged pairwise directional connectedness measures of the vertices. The size of the nodes is a measure of the weighted average of their net total directionality

volatility, along with the negative volatility of BTC, which is the primary transmitter of all other volatilities.

It should also be noted that when we consider bad volatility in a normal market, we find that cryptocurrencies and innovative technologies influence others more than they are influenced by others. Thus, the own-variance share on the diagonal is lower for negative volatilities than it is for positive ones. By considering the middle quantile and negative volatilities, AIQ and XLM can transmit 74.28% and 70.91% of a shock to all their trading partners, respectively, and receive 59.64% and 56.49% of the shocks from all their competitors.

The negative volatilities of XLM and BTC are the net transmission leaders of shocks to the network of volatilities, regardless of the market state. Furthermore, the positive volatility of SNSR and AIQ, with a continuous net-recipient role, suffers from a large spillover effect from FINXP, AIQN, and XLMP in a bear, normal, and bull market, respectively, all of which have net-transmitting scores under different market conditions. In the upper tail, both the positive and negative volatilities of technologies are net shock recipients, with both the positive and negative volatilities of XLM dominating technologies and the BTCP dominating the positive volatilities of all cutting-edge technologies. In all market states, FINX, SNSR, and AIQ are considered the boldest net shock recipients among innovative stocks, with the exception of FINXP in bear markets, which is considered a net shock transmitter. It is important to stress that, regardless of market conditions, BTCP (BTCN) performs as an uninterrupted shock recipient (shock transmitter) in the system and plays the steadiest role among all of the variables.

In addition to analyzing the overall directional connectedness of the network, as depicted in Fig. 9, we examine pairwise directional connectedness to gain a more comprehensive understanding of the network's total directional connectedness. Through our measurement of pairwise directional connectedness, we can precisely identify the exact position of each pair studied, enabling us to determine which series primarily influence each other in terms of volatility spillovers. The empirical findings demonstrate that the negative volatilities of BTC and XLM consistently outweigh the positive and negative volatilities of innovation supplies across all quantiles of the distribution. This implies that, in both normal and bear markets, BTCN and XLMN exhibit the highest transmission of positive volatility in the technology sector, whereas BTCP and XLMP exhibit the lowest spillover of negative volatility in smart inventions. Notably, these results contradict the findings of Umar et al. (2021), who suggest that, contrary to previous belief, cryptocurrencies have not been integrated into global technology sectors. Furthermore, our results provide additional insights into Umar et al. (2021), who found significant interconnectedness between technology sectors globally but minimal contributions from and to the cryptocurrency market. They concluded that cryptocurrencies appear to have less integration with the overall technological system framework and are structurally less exposed to systemic risk, indicating that Bitcoin may offer diversification benefits for investors to hedge against technology sector risk. Additionally, in line with Umar et al. (2021), the network analysis conducted by Goodell et al. (2022) demonstrates a strong correlation between FINX and conventional asset classes and green equity indices, while BTC does not exhibit such a strong association. This suggests that Bitcoin can serve as a diversification vehicle.

Quantile causality results

Based on the findings presented in Figs. 10, 11, 12 and 13, it can be inferred that XLM and BTC compete with advanced technologies in terms of their impact on market dynamics. This conclusion is drawn from the quantile causality results in the first moment, which indicate that the negative volatility of each cryptocurrency has the potential to generate positive volatility in technology stocks. This relationship is evident under normal market conditions, specifically in the middle quantiles. For these associations, there are only three exceptional cases in which the positive volatilities of XLM cannot cause any negative volatility in innovative technologies, whereas the positive volatilities of BTC can. Thus, the competitive nature of BTC

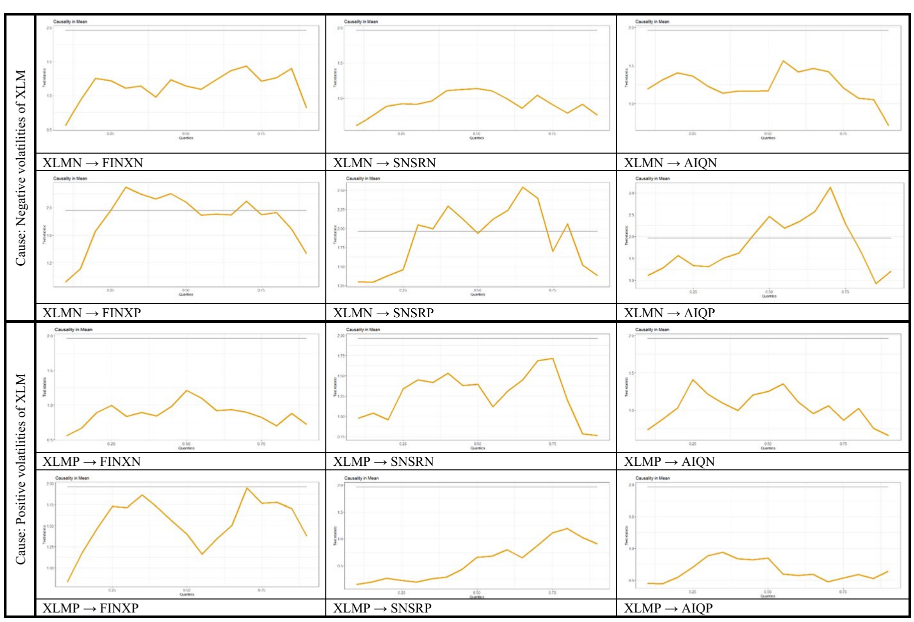

Fig. 10 Quantile causality in the first moment (causality-in-mean of XLM volatilities)

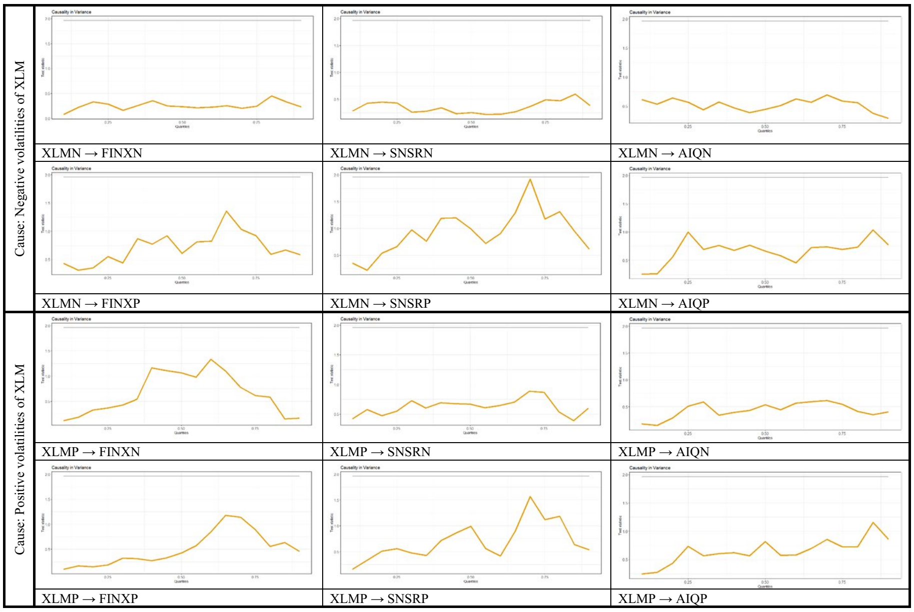

Fig. 11 Quantile causality in the second moment (causality-in-variance of XLM volatilities)

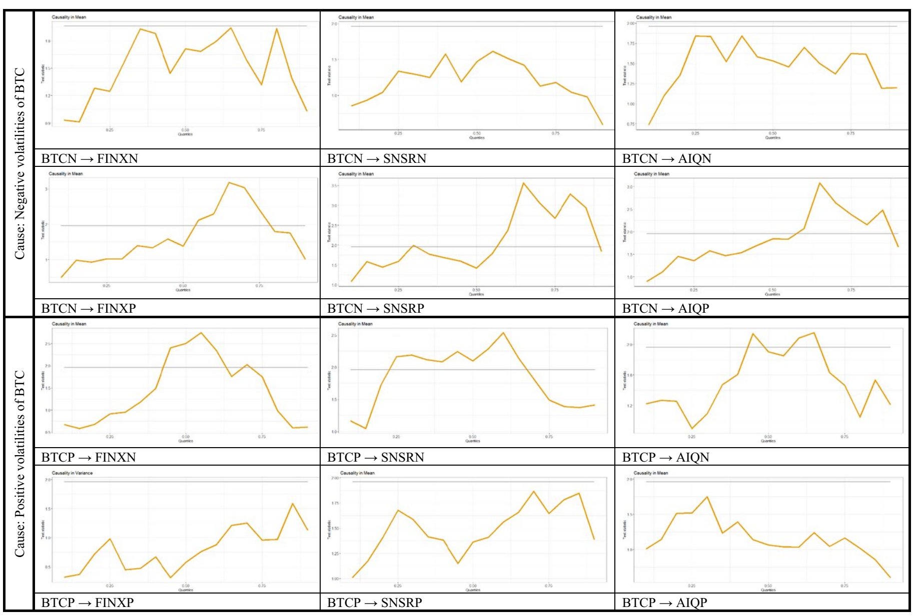

Fig. 12 Quantile causality in the first moment (causality-in-mean of BTC volatilities**)**

and other technologies can be observed in a wider range of reactions than that in XLM. Contextualizing cryptocurrency with technologies provides new insights into the implications of Hughes et al. (2019), who emphasize that blockchain technologies consist of software and web technologies, which are traditionally used to build and configure websites. In addition, Hung (2020) emphasized that Bitcoin is strongly

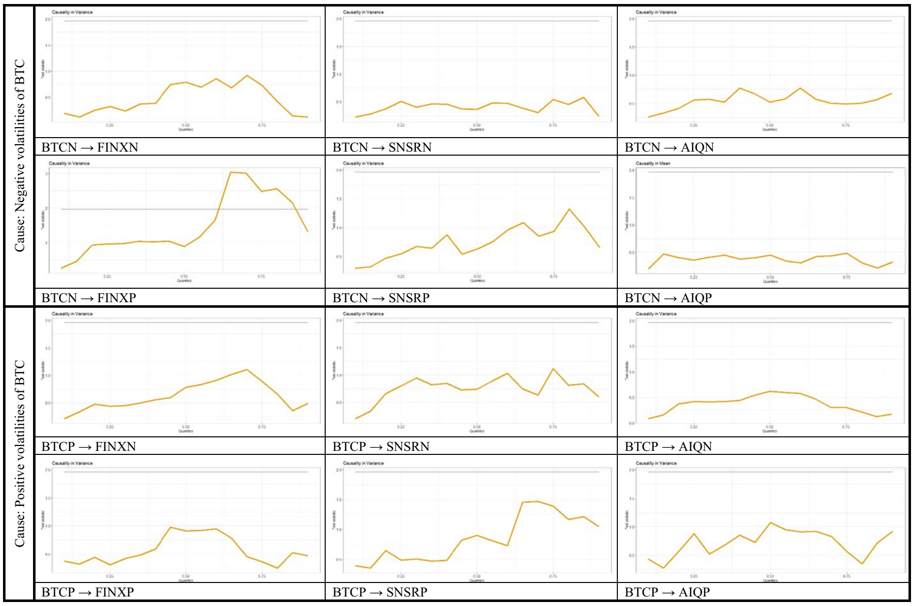

Fig. 13 Quantile causality in the second moment (causality-in-variance of BTC volatilities)

associated with the equity market in a unidirectional manner, which is consistent with our findings.

According to Barigozzi et al. (2019), the second moment of volatility, which refers to the variance in volatilities, can be interpreted as shocks resulting from variability in volatilities. By examining the quantile causality results in the second moment, specifically, causality-in-variance, we can provide evidence for this implication and conclude that there is a relationship between BTCN and FINXP, the causal and dependent variables, respectively, particularly in the upper quantiles. This suggests a trade-off between the volatilities of BTC and FINX under favorable market conditions, especially when negative volatilities in BTC lead to positive shocks in FINX. However, there is no evidence of a shock-generating interaction between new technologies and XLM. Figures 14, 15, 16, 17 in the "Appendix" summarize the results of the reverse causality investigations from cutting-edge technologies to cryptocurrencies. Among these results, there are only a few significant cases in which technology is causally linked with cryptocurrencies, specifically in a unique quantile of FINXP and BTCN, indicating bidirectional causality-in-mean around the normal market ($q=0.55$). Abakah et al. (2023) partially support our findings by revealing limited evidence of causality-in-mean from FINX to BTC across all conditional quantiles, which differs from the findings of Le et al. (2021a), who examined the spillovers between FinTech and other assets, including Bitcoin. In other words, the tests strongly reject the null hypothesis of Granger non-causality-in-variance from FINX to AI and Bitcoin in all distributions, except at extremely low and high quantiles. This finding indicates that FINX has predictive power for the volatility of AI and Bitcoin returns, primarily under normal market conditions, with diminishing intensity as markets move toward extreme conditions. Consequently, the information content about FinTech leading the other two technology markets decreases under extremely bearish and bullish conditions. In summary, our findings align with the implications of Abakah et al. (2023) and support the emergence of Bitcoin as a predictor of FinTech stocks, consistent with the conclusion of Symitsi and Chalvatzis (2019), but differ from the findings of Le et al. (2021a).

Conclusion

Over the last few years, the popularity of cryptocurrencies, such as Bitcoin, has increased substantially. Blockchain technologies, which form the base for most cryptocurrencies, have the potential to extend even deeper and more profoundly beyond cryptocurrencies to other business applications than they have thus far. Even though blockchain-based technologies can be applied to a wide range of industries (e.g., digital art management, supply chains, and healthcare), technical, organizational, and regulatory hurdles must be overcome before mass adoption can take place. Meanwhile, AI (the act of simulating the processes of human intelligence by machines, especially computer systems), the IoT (an electronic system that is connected to any mechanical digital machine, object, animal, or person that has a unique identifier (UID) associated with it), and the FinTech industry (businesses and consumers that use technology to modify, enhance, or automate the delivery of financial services to businesses or consumers) are some of the most important emerging technologies closely associated with blockchain platforms.

By contributing to the rapidly growing body of literature, we aim to provide a deeper understanding of how the negative and positive volatilities associated with the two main Islamic and conventional cryptocurrencies (i.e., Bitcoin and Stellar) are interconnected with the most cutting-edge innovative technologies, including FinTech, the IoT, and AI, which are rapidly growing in popularity. Three different approaches were used to achieve this objective: the quantile cross-spectral coherence method, the QVAR-based connectedness measure, and the market state-dependent causality analysis in the first and second moments.

According to the results, not only does the overall positive quantile cross-spectral connection relate to the pair of FinTech's positive volatility and Stellar's negative volatility when compared to different pairs of volatility between technologies and cryptocurrencies at all volatility states and time horizons but also, this pair reaches the highest quantile dependency among all pairs under normal long-run market conditions.

Furthermore, it is important to note that, on the one hand, in a bear market, the negative volatilities of Bitcoin and Stellar have the highest pairwise transmission to the positive volatility of technologies, whereas Stellar's positive and negative volatilities spill over to both types of volatilities in smart inventions in higher quantiles.

It is undeniable that cryptocurrencies play a key role in volatility transmission, especially in the normal market, as we see that XLM and BTC function as warriors for cutting-edge technologies that create negative volatility in high-tech stocks by virtue of their positive volatility. Interestingly, the competition nexus between BTC and technologies could be seen in a wider range of reactions than XLM, since negative volatility in Bitcoin may cause positive volatility in all new technologies; however, this was not the case for XLM. Aside from XLM, among all second-moment-related pairs, the only significant shock-causing relationship was the change from negative Bitcoin volatility to positive FinTech volatility in many higher quantiles. Therefore, a substantial connection between the positive volatilities of FinTech and the negative volatility of Bitcoin is evident when the results of the quantile causality-in-mean test clearly demonstrate a bidirectional causality relationship between them under normal market conditions.

We observe a clear trade-off between cryptocurrencies and the FinTech industry in terms of volatility creation. However, Bitcoin has a more conflicting nature than Stellar with respect to new technologies, especially FinTech, and it seems that Bitcoin can emerge as a new vanguard alongside new financial technologies, AI, and the IoT (see Table 7 in the "Appendix"). It appears that Bitcoin is searching for a special place next to other technologies, and rather than playing a complementary role, presents itself as belligerent competitor seeking a share in the technology market. Thus, we can classify Bitcoin as an emerging technology-based product, as mentioned in White et al. (2020), who examined Bitcoin as a hybrid techno-financial instrument. While Stellar also experiences bad volatilities, it has a supportive and particularly positive alignment with new financial technologies and provides opportunities for good volatilities in other intelligent technologies. This implies that the use of Stellar in the world of new technologies, especially financial technologies, is an alternative and optimal solution. In case of disruption in this modern financial crypto-based solution, other technologies can be extended and improved.

Stellar and Bitcoin can be used simultaneously as a smart financial sector supporter and a modern financial sector competitor, respectively. Therefore, convincing more small and medium-sized banks, microfinance institutions, and businesses involved in blockchain development, all of whom have a stake in the success of its implementation, to utilize Stellar could make it easier to integrate it more effectively into the official financial system.

This study found that, in general, Bitcoin is integrated with new technologies in a converse manner. We draw several conclusions from the adverse connection between good and bad volatility in Bitcoin-technology pairs, which have implications for investors, regulatory bodies, and interested parties from various perspectives. Specifically, we find that Bitcoin serves as a good hedge for technology investments and is an attractive option for investors looking for exposure to this sector. This finding adds new insights to the analysis of Umar et al. (2021), indicating that cryptocurrencies are viewed as a means of diversifying global technology investments.

Our study presents a valuable opportunity for individuals involved in the digital market and technical investors as it offers new understandings that can assist in making informed decisions. The findings reveal an intriguing relationship between Bitcoin volatility and its impact on the volatility of companies operating in the FinTech, IoT, and AI domains. Negative and positive Bitcoin volatility can significantly influence the volatility of these high-tech industries, albeit with opposite effects (positive or negative). Consequently, monitoring Bitcoin volatility can serve as a potent indicator of decision-making within the high-tech sector.

By comprehending the relationship between Bitcoin volatility and that of high-tech industries, market participants can enhance their decision-making processes. Monitoring Bitcoin price fluctuations offers valuable signals that can inform investment strategies and facilitate informed choices within a dynamic digital landscape. This study serves as a crucial resource for individuals seeking to navigate the intricate interplay between cryptocurrency markets and evolving high-tech sectors.

Furthermore, the relationship between the FinTech industry and the Bitcoin market displays an intriguing dynamic, wherein the FinTech sector exhibits a unique inverse correlation. This peculiar association implies that this industry can potentially harness more benefits from the negative or positive signals originating from Bitcoin. Similar conclusions can be drawn regarding the cryptocurrency Stellar, with the notable distinction being that negative volatility in Stellar may positively and unidirectionally impact cutting-edge technology companies. Therefore, Stellar does not play a disruptive role in its interaction with emerging technologies, and it can only provide a favorable foundation for positive developments in other technological domains when facing unfavorable volatilities.

Moreover, Stellar's divisibility into fractions of a cent facilitates microtransactions that were previously impractical. This capability has sparked the proliferation of innovative approaches for monetizing online resources. The advent of microtransactions has the potential to contribute significantly to poverty reduction by expanding economic opportunities for individuals at lower income levels.

Given Stellar's distinct position within the cryptocurrency market and its acceptance in Islamic society, coupled with its notably positive relationship with modern technologies, there is a clear need to pay special attention to Islamic FinTech principles. Therefore, it would be prudent to propose the development of a more efficient and compatible cryptocurrency that fully incorporates the Islamic FinTech algorithm and adheres to regulations based on Shariah's ethos and values. Embracing Islamic principles in the design and implementation of cryptocurrencies has significant potential (Laldin 2018; Rabbani et al. 2020; Wintermeyer and Abdul 2017). Some of the major advantages of Islamic FinTech are its transparency, user friendliness, and comprehensibility. By aligning with Shariah principles, Islamic FinTech fosters an environment of trust and clarity among users. Adherence to ethical guidelines and the integration of transparency in financial transactions reassure users, ensuring that the financial activities conducted through Islamic FinTech platforms are easily understandable and comply with the principles of fairness and justice. Developing a cryptocurrency specifically tailored to meet the needs and requirements of Islamic FinTech presents an opportunity to address the unique concerns and preferences of the Islamic community. Incorporating the ethical dimensions of Shariah (e.g., the prohibition of interest (*riba*) and adherence to ethical investments (*halal*)) can lead to the creation of a more compatible and inclusive cryptocurrency, enabling individuals in Islamic society to participate in the digital economy while still adhering to their religious beliefs and values. There is growing interest in Islamic FinTech as a means of improving the finance world and establishing an alternative finance vehicle with a higher level of transparency and ethical values than that of the traditional finance industry (Rabbani et al. 2020; Setyawati et al. 2017). The success of Islamic FinTech can be attributed to the number of financial service areas linked to it. For example, it can be paired with cryptocurrencies, blockchain, and other areas such as cross-border payments (Gomber et al. 2018; Michalopoulos and Tsermenidis 2018). As a responsible way to ensure that Islamic FinTech continues to grow and maintain its sustainability, awareness programs can be implemented among students who use this technology (Rabbani et al. 2020; Saad et al. 2019). Furthermore, FinTech adoption by Islamic financial institutions should be innovative as its adoption by the Islamic community affects not only Muslim and non-Muslim communities but also the global financial environment (Irfan and Ahmed 2019; Rabbani et al. 2020).

The integration of Stellar's microtransaction functionality opens up new avenues for financial inclusion and economic empowerment for policymakers. Previously, the lack of feasible denominations hindered their ability to engage in small-scale transactions. However, with Stellar's divisibility, individuals can engage in microtransactions, thereby unlocking the potential for economic growth and improving access to financial resources. This has implications for poverty reduction because it enables previously underserved individuals to participate in economic activities and leverage their resources more effectively. Thus, the relationship between the FinTech industry and the Bitcoin market presents unique characteristics, with the FinTech sector benefiting from Bitcoin-associated signals. Similarly, Stellar demonstrates a unidirectional impact with negative volatility potentially leading to positive effects for cutting-edge technology companies. Stellar's divisibility enables microtransactions, which have the potential to revolutionize online monetization and contribute to poverty alleviation. These advancements in FinTech hold promise for promoting economic inclusivity and creating new opportunities for previously marginalized individuals.

Concerning the new policy implications, blockchain-based cryptocurrencies and their interaction with Industry 4.0 presents numerous unanswered questions and future research opportunities. The existing literature on this subject is limited, particularly regarding the direction of value creation for cryptocurrencies and blockchain technologies. Therefore, there is a pressing need to develop a systematic approach that clarifies the fundamental assumptions and uncertainties surrounding the valuation of these assets. By establishing a structured process, researchers can clarify the factors driving the value of cryptocurrencies and blockchain-related technologies to enable the identification and prediction of both positive and negative characteristics associated with these technologies. Such insights would be invaluable to investors, especially during market fluctuations, as cryptocurrencies transition from emerging and ambiguous technologies to highly valued investments in crypto-derived assets and blockchain-based solutions.

Furthermore, it is essential to emphasize the potential of non-parametric non-linear quantile-based causality methods in FinTech research. This methodology provides a robust platform for investigating relationships and causalities within financial markets, and its ability to handle non-linear relationships and capture subtle nuances opens up new possibilities for exploring various aspects of the financial ecosystem. In conclusion, the exploration of blockchain-based cryptocurrencies, different types of blockchains, and their interaction with Industry 4.0 presents fertile ground for future research. The development of a systematic valuation process can address existing knowledge gaps and provide insights into value creation in this evolving domain. Additionally, leveraging advanced methodologies, such as non-parametric non-linear quantile-based causality analysis, holds immense potential for investigating the complexities of FinTech and expanding our understanding of financial markets.

Appendix

See Figs. 14, 15, 16, 17 and Tables 6, 7.

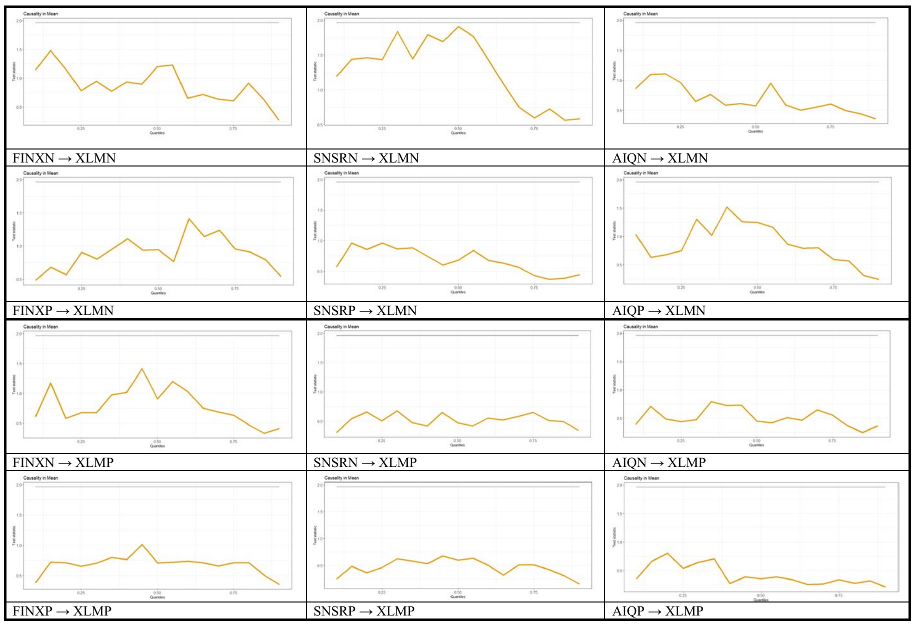

Fig. 14 Quantile causality in the first moment with XLM as the dependent variable (causality-in-mean of volatilities)

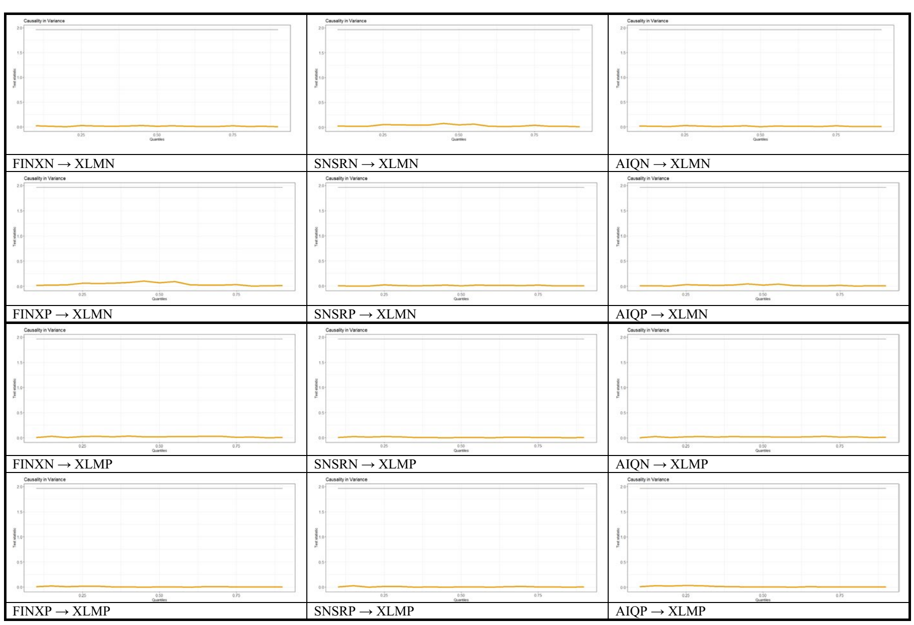

Figure15 Quantile causality in the second moment with XLM as the dependent variable (causality-in-variance of volatilities)

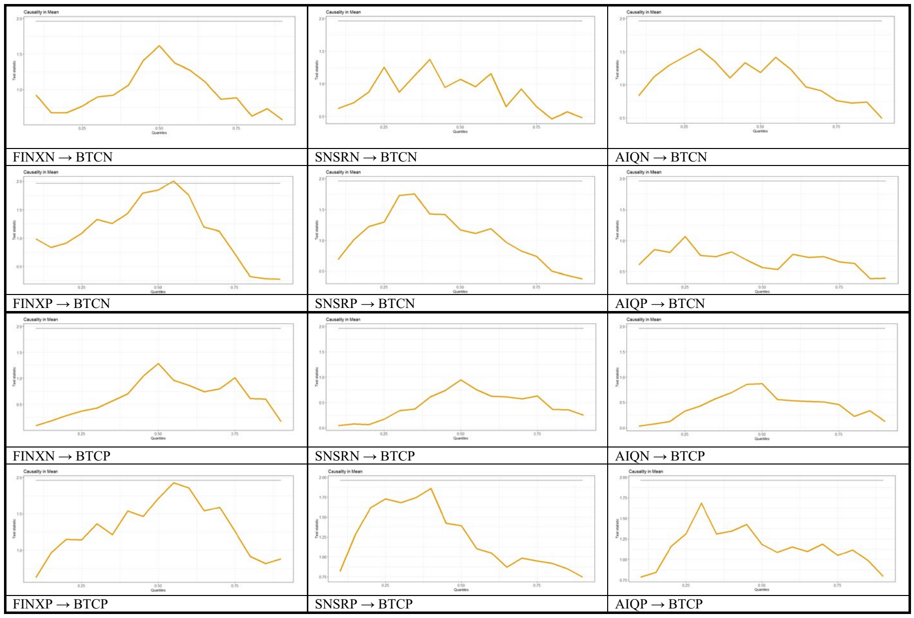

Fig. 16 Quantile causality in the first moment with BTC as the dependent variable (causality-in-mean of technologies volatilities)

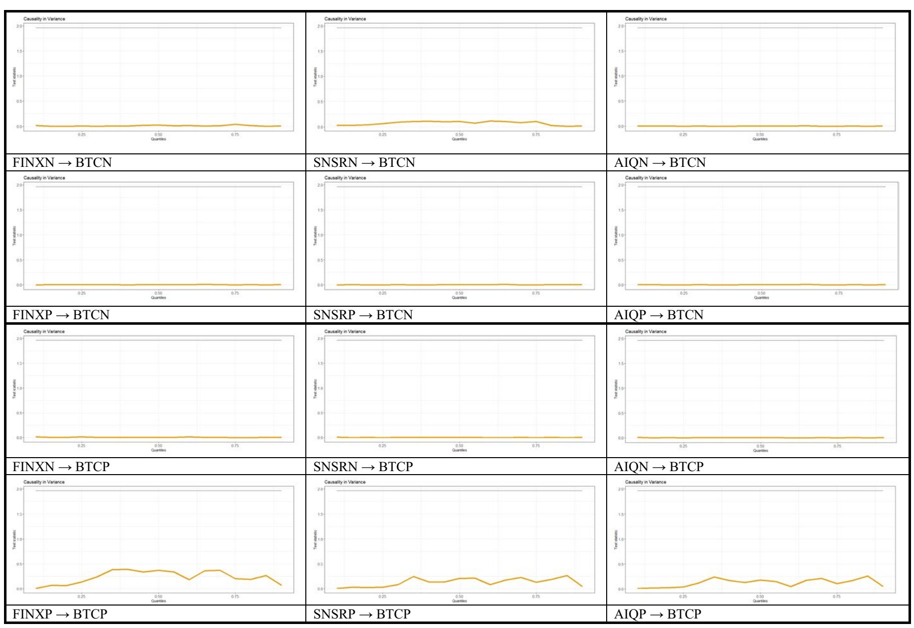

Fig. 17 Quantile causality in the second moment with BTC as the dependent variable (causality-in-variance of technologies volatilities)

Table 6 Summary of quantile cross-spectral coherence results

	FINX-XLM			FINX-BTC			SNSR-XLM			SNSR-BTC			AIQ-XLM			AIQ-BTC		
Horizon / Pairs	FINXP-XLMP-05	FINXP-XLMP-50	FINXP-XLMP-95	FINXP-BTCP-05	FINXP-BTCP-50	FINXP-BTCP-95	SNSRP-XLMP-05	SNSRP-XLMP-50	SNSRP-XLMP-95	SNSRP-BTCP-05	SNSRP-BTCP-50	SNSRP-BTCP-95	AIQP-XLMP-05	AIQP-XLMP-50	AIQP-XLMP-95	AIQP-BTCP-05	AIQP-BTCP-50	AIQP-BTCP-95
Y	0.050	0.185	−0.086	−0.134	0.111	0.083	−0.094	0.002	0.065	−0.117	−0.077	0.053	−0.161	−0.159	−0.018	−0.183	−0.104	0.146
M	−0.112	0.031	−0.059	−0.145	0.019	0.094	−0.110	0.061	−0.094	−0.086	0.009	−0.041	−0.037	−0.058	0.079	−0.137	−0.003	0.103
W	0.135	0.044	0.131	0.034	−0.078	0.276	0.017	0.056	−0.014	0.072	0.197	0.093	−0.031	0.137	−0.067	0.049	0.053	0.055
Horizon / Pairs	FINXN-XLMP-05	FINXN-XLMP-50	FINXN-XLMP-95	FINXN-BTCP-05	FINXN-BTCP-50	FINXN-BTCP-95	SNSRN-XLMP-05	SNSRN-XLMP-50	SNSRN-XLMP-95	SNSRN-BTCP-05	SNSRN-BTCP-50	SNSRN-BTCP-95	AIQN-XLMP-05	AIQN-XLMP-50	AIQN-XLMP-95	AIQN-BTCP-05	AIQN-BTCP-50	AIQN-BTCP-95
Y	−0.265	0.429	−0.079	0.073	0.191	0.009	−0.030	0.304	0.051	−0.055	0.099	0.079	−0.074	0.151	0.005	0.060	−0.009	0.077
M	−0.162	0.196	0.065	0.063	0.085	−0.027	−0.078	0.075	0.038	0.038	0.027	−0.048	−0.129	0.043	0.092	0.119	0.007	0.038
W	−0.005	−0.002	−0.067	0.109	−0.050	0.126	0.016	−0.114	0.132	0.005	−0.179	0.052	−0.009	−0.099	0.041	0.010	−0.037	0.184
Horizon / Pairs	FINXP-XLMN-05	FINXP-XLMN-50	FINXP-XLMN-95	FINXP-BTCN-05	FINXP-BTCN-50	FINXP-BTCN-95	SNSRP-XLMN-05	SNSRP-XLMN-50	SNSRP-XLMN-95	SNSRP-BTCN-05	SNSRP-BTCN-50	SNSRP-BTCN-95	AIQP-XLMN-05	AIQP-XLMN-50	AIQP-XLMN-95	AIQP-BTCN-05	AIQP-BTCN-50	AIQP-BTCN-95
Y	0.120	0.380	0.124	−0.099	0.214	0.077	−0.180	0.191	0.210	−0.187	−0.091	0.254	−0.157	0.170	0.006	−0.191	−0.184	0.172
M	0.057	0.293	0.085	−0.140	0.147	0.081	−0.185	0.215	−0.071	−0.199	0.028	−0.047	−0.091	0.139	−0.015	−0.138	−0.060	0.148
W	0.067	0.063	0.050	0.032	0.050	0.077	0.073	−0.055	−0.038	0.007	0.091	0.090	−0.052	0.030	0.017	−0.087	0.102	0.139
Horizon / Pairs	FINXN-XLMN-05	FINXN-XLMN-50	FINXN-XLMN-95	FINXN-BTCN-05	FINXN-BTCN-50	FINXN-BTCN-95	SNSRN-XLMN-05	SNSRN-XLMN-50	SNSRN-XLMN-95	SNSRN-BTCN-05	SNSRN-BTCN-50	SNSRN-BTCN-95	AIQN-XLMN-05	AIQN-XLMN-50	AIQN-XLMN-95	AIQN-BTCN-05	AIQN-BTCN-50	AIQN-BTCN-95
Y	−0.112	0.250	0.173	0.183	0.347	0.242	−0.110	0.135	0.002	−0.084	0.184	0.252	−0.134	0.032	0.028	−0.061	−0.049	0.230
M	0.032	0.145	0.119	0.186	0.218	0.233	−0.082	0.157	−0.079	0.028	0.129	0.081	−0.165	0.084	−0.018	0.059	0.016	0.195
W	0.088	0.011	0.160	0.083	0.028	0.127	0.124	−0.013	−0.104	0.002	0.029	0.124	−0.051	−0.010	0.018	0.017	0.068	0.259

A similar color transition occurs as the numbers progress from lower to higher values, as Table 5. In this case, the colors shift from red to green

Table 7 Summary of non-linear causality tests

	M1			M2		
BTC	BTCN → FINXP BTCP → FINXN FINXP → BTCN	BTCN → SNSRP BTCP → SNSRN	BTCN → AIQP BTCP → AIQN	BTCN → FINXP	–	–
XLM	XLMN → FINXP	XLMN → SNSRP	XLMN → AIQP	–	–	–

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Declarations

Competing interests
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