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Volatility spillovers among leading cryptocurrencies and US energy and technology companies

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Abstract
This study investigates volatility spillovers and network connectedness among four cryptocurrencies (Bitcoin, Ethereum, Tether, and BNB coin), four energy companies (Exxon Mobil, Chevron, ConocoPhillips, and Nextera Energy), and four mega-technology companies (Apple, Microsoft, Alphabet, and Amazon) in the US. We analyze data for the period November 15, 2017–October 28, 2022 using methodologies in Diebold and Yilmaz (Int J Forecast 28(1):57–66, 2012) and Baruník and Křehlík (J Financ Economet 16(2):271–296 2018). Our analysis shows the COVID-19 pandemic amplified volatility spillovers, thereby intensifying the impact of financial contagion between markets. This finding indicates the impact of the pandemic on the US economy heightened risk transmission across markets. Moreover, we show that Bitcoin, Ethereum, Chevron, ConocoPhilips, Apple, and Microsoft are net volatility transmitters, while Tether, BNB, Exxon Mobil, Nextera Energy, Alphabet, and Amazon are net receivers Our results suggest that short-term volatility spillovers outweigh medium- and long-term spillovers, and that investors should be more concerned about short-term repercussions because they do not have enough time to act quickly to protect themselves from market risks when the US market is affected. Furthermore, in contrast to short-term dynamics, longer term patterns display superior hedging efficiency. The net-pairwise directional spillovers show that Alphabet and Amazon are the highest shock transmitters to other companies. The findings in this study have implications for both investors and policymakers.

Keywords: Volatility spillovers, Connectedness network, Cryptocurrency, Energy companies, Technology companies

JEL Classification: C58, G10, And N70

Introduction

Global markets face significant risks from volatility spillovers, an increasingly important concern for firms, countries, and global financial stability for several reasons. Financial market expansion and interconnection present new economic challenges, and accelerating globalization makes financial markets more interconnected, fostering volatility spillovers. This increases the likelihood that risk will spread rapidly from a particular region to other markets and countries (Cabrales et al. 2017), which can lead to a global recession or crisis. The 2007 global financial crisis and 2009 European debt crisis showed that a strong global economy requires thorough risk monitoring and management; still, COVID-19 posed an unusual threat as the global economy froze (Zhou et al. 2022), causing significant losses. It is important to examine the effects of this unusual situation on volatility spillover.

The term "volatility spillover" describes the extent and magnitude of risk transmission from one market to other markets (Scherer and Cho 2003; Kang et al. 2017). Volatility movements are interpreted as irregular fluctuations (Karolyi 2003). Recently, volatility spillovers have increased because of connections between financial markets, especially when influenced by external shocks. Understanding volatility spillovers is important for various reasons, as it helps to hedge risks, optimize financial portfolios, understand market efficiency, and anticipate potential market disruptions, thus guiding investors' responses (Mensi et al. 2017). The impact of spillover among markets can change due to significant policy changes and events (Wang and Guo, 2018). For example, the US subprime mortgage crisis that precipitated the 2008 financial crisis affected stock markets globally, to varying degrees (Oygur and Unal 2017). The COVID-19 pandemic also significantly impacted financial markets, resulting in simultaneous price declines and other effects for financial assets and commodities (Fang et al. 2022). The pandemic influenced financial market spillovers in new ways; for example, Fernandes et al. (2022) argue the pandemic increased the spillover effect between cryptocurrencies and traditional financial markets.

The impact of the COVID-19 pandemic led to extreme, albeit sometimes brief economic downturns during lockdowns, resulting in pronounced fluctuations and substantial losses. The pandemic affected economic fundamentals, damaging demand and supply. The emergence of cryptocurrencies as a unique financial asset class offers an outstanding opportunity to explore uncharted aspects of volatility spillover associated with them. While cryptocurrencies offer numerous advantages they also involve risks, primarily due to their substantial volatility (Guesmi et al. 2019). Separately, the energy and technology sectors play pivotal roles in the global economy. Energy is fundamental to production and consumption processes, exerting a substantial impact on a country's GDP and economic growth (Gangopadhyay and Das 2022). Additionally, technology drives a significant share of the global economy, enhancing competitiveness and economic well-being through innovation. Companies and services leverage technology to develop products, reduce costs, and increase profits. However, the energy and tech sectors were severely impacted by the COVID-19 pandemic, due to large fluctuations in oil prices that in turn influenced companies' profits and cash flows (Tuna and Tuna 2022). Pandemic-induced restrictions on the transportation, aviation, and maritime sectors reduced demand for energy commodities, affecting commodity futures markets (Zhou et al. 2022). In 2020, total energy commodity consumption decreased by 7.5%, including an 11.4% decline in oil consumption (Vaz 2022).

The pandemic also presented risks and threats to the technology sector with adverse financial consequences. Shutdowns reduced purchases from certain technological companies and cancelled conferences and meetings that typically generate new business opportunities. As a result, these companies incurred losses estimated at USD 1 billion

(Market Data Forecast 2020). A significant percentage of technology companies suffered substantial financial losses due to decreased product sales during lockdowns (Al-Skhnini 2022). However, the pandemic had a positive effect on some tech companies; those that offer products and programs related to online education and remote work flourished during this period. Our findings indicate that the effects of unconditional shocks on conditional covariance matrices during the COVID-19 period are significantly greater than those during the pre-pandemic period. The impact of the epidemic increased uncertainty in both economic and financial systems, amplifying the influence of unconditional shocks.

Cryptocurrencies are contentious and may involve significant risks and the possibility of catastrophic losses, but they have sparked considerable interest. With the interconnectedness of financial markets increasing, cross-regional and cross-market contagion has become a key focus of research. Moreover, there is a close relationship between cryptocurrencies and the energy and technology sectors for various reasons; thus, it is critical to understand spillovers among these markets. For example, renewable energy depends on technological progress, and investing in technological advancement to make the best use of available energy resources is increasingly important. Technology companies are working to develop and expand the markets for energy-related products, reinforcing the link between the two sectors (Zheng et al. 2022). Energy-related commodities are linked to cryptocurrencies in global markets (Ji et al. 2019), and energy market shocks contribute significantly to the volatility of cryptocurrencies (Libo et al. 2021). The tech sector and cryptocurrency as a trading instrument are experiencing global growth. Many companies are showing interest in blockchains and cryptocurrencies, including them in their business plans, product lines, and investment portfolios (Frankovic et al. 2021).

After the first cryptocurrency emerged in 2009, they began to spread widely (Qiu et al. 2021). By November 9, 2022, the total number of cryptocurrencies had reached 9310 and more than USD 200 billion had been traded (Statista 2022). While the cryptocurrency market has developed into a significant financial market, cryptocurrency prices continue to fluctuate dramatically (Kyriazis et al. 2020). This high volatility could limit their potential as an alternative to traditional currencies and more knowledge of their purpose and value is needed (Gandal et al. 2018). The increase in cryptocurrencies' market capitalization and high volatility has led to increased efforts to predict cryptocurrency price movements. Our study relies on the concept of spillover to explain financial market price dynamics before and during the pandemic, showing how positions in cryptocurrency, energy, and technology companies can diversify risk and predict volatility transfer. We seek to identify which of these assets act as net receivers versus transmitters of risk to help investors manage portfolio risk effectively and improve performance. Understanding spillover pathways and determining the extent of net spillover contributions from various commodities can help investors to identify sources of contagion in their portfolios. Given that prices in commodity and financial markets experience unequal upward and downward moves, the concept of an asymmetric spillover index is relevant in assessing spillover dynamics.

We investigate the existence of volatility spillovers and net-pairwise network connectedness between cryptocurrencies, energy, and technology companies in the US market using those with the four highest market capitalizations in each sector. This analysis has significant practical value in terms of understanding systemic financial risks and may serve as a reference for building cross-market portfolios, as investors could use cryptocurrencies, energy, or technology stocks for portfolio rebalancing when these spillovers occur. Our study contributes to the literature in several ways. First, we offer a comprehensive analysis of the interdependence between the four largest cryptocurrencies and the four largest energy and technology companies based on their respective market capitalizations. This novel approach allows us to shed light on the relationships between these sectors, providing valuable insights in a way that to our knowledge has not been explored before. To the best of our knowledge, our study is the first of its kind to incorporate cryptocurrencies and the energy and technology sectors into a single analysis based on market capitalization. To examine information transmission across sector markets accurately, we employ the well-established Diebold and Yilmaz (2012) spillover index, which has been widely used to assess information transmission across sector markets, unveiling the direction and strength of static spillovers and net contributors or receivers. However, during periods of financial distress static spillover measures may obscure crucial information. To address this limitation and account for the instability arising from structural breaks, we propose a rolling sample approach to examine the dynamics of the spillover index. Major events can directly impact volatility structures between strategic commodities and the certain sectors in the US stock market, making a time-sensitive analysis crucial. To address this need, we use the Baruník and Křehlík (2018) spillover index, which decomposes aggregate spillovers into short- and long-term components. This decomposition enables us to capture the effects of various factors such as investors' risk appetite, preference formation, and market anticipation. By employing this innovative index, our study contributes to a deeper understanding of the underlying dynamics driving spillover effects. By analyzing spillovers across different frequencies, our time–frequency spillover index offers market participants a global view of market interconnections, helping them to develop appropriate risk-reducing strategies. This approach enhances the understanding of market dynamics and provides valuable insights for informed decision-making by investors and policymakers. This analysis provides investors with insights into the stock market sectors that exhibit strong relationships with commodities, providing information about heterogeneity in spillover effects across different time scales.

Diebold and Yilmaz (2012) propose the spillover index approach to assess the direction of volatility spillovers across markets. This approach has garnered significant attention in the existing literature as it both quantifies the magnitude of spillover effects between markets and shows the direction of volatility spillovers. Baruník and Křehlík (2018) make a valuable contribution to understanding the relationships among economic variables by introducing a novel approach to quantifying their frequency dynamics. We present a comprehensive framework for analyzing the sources of connectedness between economic variables using spectral representations of variance decompositions and connectedness measures. Because of the varying strengths and frequencies at which shocks affect economic variables, the frequency domain is considered a suitable framework for assessing the interconnections among these variables. According to Diebold and Yilmaz (2012), variance decompositions derived by approximations provide a convenient framework for empirically quantifying interconnectedness. One possible approach to quantifying the impact of a shock in one variable on the future uncertainty of another variable within a system is to establish a natural measure focused on analyzing the frequency of responses to shocks. Specifically, we aim to evaluate the proportion of uncertainty in a particular variable that can be attributed to shocks of varying persistence levels. We also provide a detailed analysis of how the correlation of the residuals affects the level of interconnectedness. Our empirical analysis examines the interconnectivity of financial institutions in the US, which serves as a robust indicator of the systemic risk inherent in the financial sector. The data are locally approximated to obtain a detailed analysis of the time–frequency dynamics of connectedness. From an economic standpoint, in periods characterized by frequent interconnectedness stock markets demonstrate the ability to swiftly and calmly process information. Consequently, any disturbance affecting a single asset within the system is primarily felt in the short term. When connectedness occurs at lower frequencies, shocks are more persistent and are transmitted over longer time intervals. This behavior can be ascribed to changes in investor expectations, which have a lasting impact on the market. These expectations are then communicated to adjacent assets within the portfolios.

The remainder of this study is organized as follows: Sect. "Literature review" reviews the literature on the volatility of cryptocurrencies and energy and technology companies. Sect. "Data and methodology" presents the data and methodology used in this study. Sect. "Empirical finding" discusses our findings, and our conclusions are presented in Sect. 5.

Literature review

Given the growing number of global financial crises, there is increased interest in determining the extent of their impact, how they spread from one market to another, and how different market sectors interact. Many studies employ various estimation models to examine volatility spillover among markets.

The cryptocurrency, energy, and technology sectors are strongly interdependent. Previous studies examine how cryptocurrency returns affect energy and tech companies; here we investigate volatility spillovers between them. Few studies have examined volatility spillover and market returns with contagion (Edwards 1998; Edwards; Susmel 2001; Baur 2003). Yilmaz (2010) uses error variance decomposition based on the vector autoregressive (VAR) technique to investigate the relationship between a market's return and volatility spillovers. Volatility spillovers tend to be highly significant during financial crises. Neaime (2012) investigates the relationship between returns and volatility in emerging markets using a GARCH model and finds a strong relationship between returns and volatility. Zeng et al. (2019) examine connectedness in time and frequency domains to study volatility spillover and returns. They find that volatility spillovers are significant in the long term and that a US Doller index is the highest transmitter of short- to long-term return spillovers. Atenga and Mougoué (2021) used a VAR model to examine return and volatility spillovers. Habibi and Mohammadi (2022) examine return and volatility spillovers using the model in Diebold and Yilmaz (2012); they show that return and volatility spillover indexes peaked during the financial crisis, and US market shocks affected market returns and volatility in the MENA region.

Due to the global nature of cryptocurrency marketplaces, numerous studies explore the relationship between volatility and cryptocurrencies, revealing the expected correlation. Most of these studies explore Bitcoin's volatility and its impact on traditional financial markets (Koutmos 2018; Katsiampa et al. 2019; Kumar and Anandarao 2019). Wang and Ngene (2020) use BEKK-GARCH to examine cross-market volatility shocks and volatility transmissions in the cryptocurrency market. They find that Bitcoin's daily shocks and volatility affect other currencies' conditional volatility faster and less predictably than other currencies' conditional volatility affected Bitcoin. Fakhfekh and Jeribi (2020) investigate the volatility dynamics of cryptocurrency returns using multi-GARCH models. They confirm that positive shocks increase volatility more than negative shocks. Fung et al. (2022) used multi-GARCH models to identify evidence of volatility persistence with harmful leverage effects in the return behavior of cryptocurrencies. Al-Shboul et al. (2022) use VAR models to study how cryptocurrencies interact under different market scenarios, including the COVID-19 pandemic. They found that total and net connectedness considerably affect market uncertainties; for example, when the COVID-19 pandemic hit, Litecoin became more popular and had a higher hedge ratio than Bitcoin. Khalfaoui et al. (2023) investigate the spillover effect of COVID-19 and cryptocurrency on green bond markets using the approaches in Diebold and Yilmaz (2012) and Ando et al. (2022). They find that bogus news related to COVID-19 was the highest net shock provider, followed by Bitcoin.

Studies also investigate volatility spillovers between cryptocurrencies and other markets (González et al. 2021; Wang et al. 2022; Yousaf and Yarovaya 2022). Uzonwanne (2021) studies the effect of volatility spillovers on cryptocurrencies and returns for five stock markets using a multivariate VARMA-AGARCH model and finds significant volatility and return spillovers between bidirectional and unidirectional markets. At stock market highs and lows, investors switch between market pairs to obtain the best returns with the least risk. Thus, market pairs experience spillover returns and volatility. Cao and Xie (2022) investigate dynamic spillover effects between China's financial market and cryptocurrency using time-varying parameter vector autoregressions. Their results show that China's financial market has little impact on cryptocurrencies, but cryptocurrencies have had a significant impact on cryptocurrencies. Aharon et al. (2023) examine volatility in the cryptocurrency market with structural breaks. Their results demonstrate that incorporating structural breaks diminishes volatility persistence and increases asymmetric volatility for cryptocurrencies. Moreover, ignoring structural breaks has a negative impact on hedging strategies.

Energy sectors have become commodities markets in recent years on a global scale and as a powerful financial tool to attract investors (Pham et al. 2022). Sadorsky (2012) and Zheng et al. (2022) investigate the stock market and volatility spillover impact among renewable energy, oil, and high-technology markets. Yldrm et al. (2020) use the causality-in-variance method to investigate return and volatility spillover effects between the oil and precious metals markets. Corbet et al. (2021) show that volatility spillovers are transmitted from the oil markets to the precious metals markets, and there is bidirectional volatility between silver and oil prices. Billah et al. (2022) analyze the quintile connectedness of volatility spillovers between the BRIC countries (Brazil, Russia, India, and

China) and energy commodities. They find that volatilities among energy commodities and BRIC countries' stock markets are characterized by unpredictable economic activity, time-varying characteristics, and crises. The COVID-19 pandemic and global financial and European debt crises exacerbated spillover effects.

Other studies focus on volatility spillovers between cryptocurrencies and the energy sector. Symitsi and Chalvatzis (2018) show the effects using Bitcoin and energy and technology indices. Using an asymmetric multivariate VAR-GARCH model, Cagli and Mandaci (2023) use the approaches in Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) to investigate volatility spillover among cryptocurrency, energy, and precious metals markets. This finding indicates a low degree of uncertainty in the connectedness among cryptocurrency and energy commodities and a long-term diversification potential. Finally, previous studies examine the link between Bitcoin and the energy sector (Ji et al. 2019; Okorie 2021; Zijian and Qiaoyu 2022; Lu et al. 2022).

Our study focuses on the volatility of cryptocurrencies and significant energy and technology companies, a topic that lacks precise validation. Among the four most prominent technology companies in the US, Microsoft is the highest spillover transmitter, showing the importance of the US tech sector to other markets. Similar to our study, Symitsi and Chalvatzis (2018) examine volatility spillover among Bitcoin and energy and technology indexes, while we examine volatility transmission and connectedness networks for individual cryptocurrencies and specific US energy and technology companies, selecting the top four companies with the highest market capitalization for each sector.

Table 1 provides an overview of the literature concerning volatility spillover among cryptocurrencies, energy, and technology companies. Our study is the first to examine volatility spillovers among the four largest cryptocurrencies, energy, and technology companies in terms of market value, departing from the conventional approach of analyzing market indexes to represent each sector. This shift in perspective allows us to more closely examine the dynamics of volatility spillovers within these key components of financial markets. By focusing on individual companies, we can uncover the underlying mechanisms that drive these spillover effects, thus contributing to a richer understanding of financial market behavior.

Data and methodology

Data description

We use daily price data from the Datastream database for the period from November 15, 2017 to October 28, 2022. We chose our start date based on availability of data on Ethereum and BNB in Datastream. The sample period encompasses notable economic events, specifically the COVID-19 pandemic and the Ukraine–Russia conflict. To ensure that our sample accurately reflects the sectors of interest, we use the top four cryptocurrencies and the top four energy and technology companies in the US market (Table 2). The most important companies in the US market are identified by their market capitalization, which influence US stock market returns (Farooq et al. (2022). Bitcoin, Ethereum, Tether, and BNB represent the cryptocurrency market, the energy companies in our sample are ExxonMobil, Chevron, ConocoPhillips, and Nextera Energy, and Apple, Microsoft, Alphabet, and Amazon are from the technology sector. We calculate

Table 1 Review of the literature on volatility spillovers among cryptocurrencies, energy, and technology companies

Author	Period	Variables	Methodology	Results
Symitsi and Chalvatzis (2018)	2011–2018	Bitcoin, S and P Global Clean Energy Index, MSCI World Energy Index, MSCI World Information and Technology Index	Multivariate GARCH	Spillover transmission from energy and technology stock to Bitcoin Bitcoin's influence includes long-term effects on the volatility of both fossil fuel and clean energy stocks There is a transfer of short-term volatility from technology companies to Bitcoin
Kumar and Anandarao (2019)	2015–2018	Bitcoin, Ethereum, Ripple and Litecoin Returns	GARCH model	In the short term, there exists a moderate correlation in cryptocurrency returns Volatility spillover is impacted by fluctuations in Bitcoin prices
Zeng et al. (2019)	2013–2019	Bitcoin, Crude oil, Gold and USD	Diebold and Yilmaz (2012), Barunik and Krehlik (2018) approach	In terms of return spillovers across different time horizons, the USD plays a significant role as the primary information transmitter Among various assets, crude oil stands out by contributing the highest net positive volatility spillovers, particularly in the long-term horizon
Yıldırım et al. (2020)	1990–2019	Crude oil, Gold, Silver, Platinum. Palladium	The causality-in-variance test approach	Volatility spillover impact comes from the oil markets as a transmitter to the precious metals markets Bidirectional volatility spillover between Crude oil and silver return
Al-Shboul et al. (2022)	2015–2021	Cryptocurrencies, Cryptocurrency policy, and Cryptocurrency price	The quantile VAR model	The total and net spillover index increased because of the COVID-19 crisis Litecoin was more dominant "hedger" during the crisis
Cao and Xie (2022)	2015–2020	Cryptocurrency and China's financial market	The time-varying parameter vector autoregressions (TVP-VAR) model	Financial market has week impact on cryptocurrencies Bitcoin and Ethereum have negative spillover
Zheng et al. (2022)	2012–2020	Crude oil, Renewable energy and High-technology markets	BEKK- GARCH-X approach	Spillover of volatility is observed between renewable energy and high-technology stock markets The renewable energy market in China exhibits a stronger correlation with the high-technology sector than with crude oil

Table 1 (continued)

Author	Period	Variables	Methodology	Results
Khalfaoui et al. (2023)	2020–2022	Bloomberg MSCI Global Green Bond Index, Bloomberg MSCI Euro Green Bond Index, S and P Green Bond U.S. Dollar Select Index, Coronavirus Panic Index, Coronavirus Media Hype Index, Coronavirus Fake News Index, Global Sentiment, Coronavirus Infodemic Index, Coronavirus Media Coverage Index, and cryptocurrencies	Diebold and Yilmaz (2012) and the quantile connectedness approach	COVID-19 fake news looks to be the highest net shock provider more than Bitcoin The highest net shock receiver is MSCI Euro green bond
Cagli and Mandaci (2023)	2014–2021	Cryptocurrency, Energy (Crude oil), Precious metals (Gold), Currency (Eurocurrency), Emerging Markets and China stock market volatility indices	Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) approach	The finding indicates a low degree of uncertainty in the connectedness between cryptocurrency and energy commodity Long-term diversification is potential and underscore the dynamics of the cryptocurrency market

Table 2 Data description of the US Market Based on 2022

Name	Code	Sector	Market Capitalization	Source
Bitcoin	BTC	Cryptocurrency	$ 392.59 Billion	Data stream
Ethereum	ETH	Cryptocurrency	$ 192.46 Billion	Data stream
Tether	USDT	Cryptocurrency	$ 69.42 Billion	Data stream
BNB	BNB	Cryptocurrency	$ 52.51 Billion	Data stream
Apple	AAPL	Technology	$ 2.475 Trillion	Data stream
Microsoft	MSFT	Technology	$ 1.741 Trillion	Data stream
Alphabet	GOOGL	Technology	$ 1.228 Trillion	Data stream
Amazon	AMZN	Technology	$ 1.050 Trillion	Data stream
Exxon Mobil	XOM	Energy	$ 465.31 Billion	Data stream
Chevron	CVX	Energy	$ 355.70 Billion	Data stream
ConocoPhillips	COP	Energy	$ 162.73 Billion	Data stream
Nextera	NEE	Energy	$ 152.29 Billion	Data stream

daily price returns for each one using formula (1) and take use the absolute values to calculate the volatility of the time series.

$$R_i = 100 * Ln\left(\frac{P_I}{P_{i-1}}\right) \tag{1}$$

Table 3 presents descriptive statistics along with unit root, and stationarity tests for the logarithmic returns for these cryptocurrencies and energy, and technology companies. The means are all positive except for Tether-coin. BNB coin had the highest average return over the study period. Using standard deviation (SD) as our measure of risk, BNB is also the riskiest with an SD of 7.25, while Nextera is the least risky with an SD of 1.69. Skewness is negative for all variables except Tether and BNB, and kurtosis is high, indicating leptokurtic distributions. We use the Jarque–Bera test for normality in the distributions of the series and the results reject the normality distribution hypotheses at the 1% level for every return series.

In addition, we conduct unit root and KPSS tests because the method in Diebold and Yilmaz (2012) is related to VAR and stationarity. The unit root test is significant for all series at the level of 1%; therefore, there is no unit root problem. The results of the KPSS test are not significant, indicating that all of the return series are stationary.

Methodology

Our empirical analysis is divided into three stages. First, following Diebold and Yilmaz (2012) we examine time–domain volatility spillovers among the leading cryptocurrencies and US energy, and technology companies. Second, based on Baruník and Křehlík (2018) we investigate how these markets are linked in the frequency domain. Third, we use network connectedness methods to generate a connectedness map that offers vital details about transmitters and receivers, and the degree of connectivity among them.

Table 3 Summary of descriptive statistics, unit root, and stationarity tests for the return series

	BTC	ETH	USDT	BNB	AAPL	MSFT	GOOGL	AMZN	XOM	CVX	COP	NEE
Mean	0.09	0.12	− 0.001	0.43	0.10	0.08	0.05	0.05	0.02	0.03	0.07	0.05
Median	0.14	0.10	− 0.002	0.13	0.10	0.12	0.11	0.14	0.02	0.08	0.04	0.12
Maximum	24.38	24.75	5.660	73.35	11.32	13.29	9.190	12.69	11.94	20.49	22.49	12.83
Minimum	− 46.47	− 55.07	-5.260	− 54.31	− 13.77	− 15.95	− 12.37	− 15.14	− 13.04	− 25.01	− 28.56	− 14.41
Std. Dev	4.8415	6.1867	0.4819	7.2472	2.0692	1.9280	1.9379	2.1968	2.1311	2.2600	0.0500	0.0252
Skewness	− 0.5809	− 0.6913	0.8403	1.1238	− 0.3202	− 0.3648	− 0.3019	− 0.2678	− 0.1737	− 1.0737	− 0.6875	− 0.3345
Kurtosis	12.6681	10.4289	52.2992	24.8006	7.8918	10.4885	7.0822	7.2365	8.1398	27.2989	18.2048	14.6061
Jarque–Bera	4922.82	2964.44	126,325.60	24,936.57	1263.61	2938.98	884.06	946.69	1377.75	30,893.02	12,100.52	7016.47
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF	− 36.09***	− 35.48***	− 20.94***	− 34.56***	− 39.53***	− 44.24***	− 39.66***	− 39.80***	− 36.37***	− 11.98***	− 11.25***	− 12.47***
KPSS	0.1155	0.1417	0.0201	0.0898	0.1024	0.0940	0.1373	0.0567	0.0842	0.0502	0.0717	0.0334

*** Significant at the 1% level for ADF and KPSS

The Diebold and Yilmaz (2012) approach

Diebold and Yilmaz (2012) measure total and directional volatility spillovers using a generalized VAR approach based on forecast-error variance decompositions that are independent of the order in which the variables are presented. Diebold and Yilmaz (2009) use a VAR-approximating model to obtain variance decomposition without network theory or graphics, using a small dataset and Cholesky factor identification. In addition, empirical research emphasizes the connectedness of volatility in equity markets.

The Diebold and Yilmaz (2012) approach offers notable benefits in evaluating the interconnection of financial markets because of its comprehensive nature. The Diebold–Yilmaz Spillover Index facilitates a comprehensive examination of interconnectedness across markets, encompassing both direct and indirect connections within asset classes, portfolios, and individual assets, in a single country and internationally, identifying shocks, influences, and indirect trends and detecting instances of contagion or herd behavior. This valuable analytical tool provides insights into the transmission of shocks within a financial system, providing a holistic understanding of this phenomenon. Furthermore, Diebold and Yilmaz's (2012) generalized VAR approach ensures that forecast-error variance decompositions remain insensitive to the order of the variables and explicitly incorporates directional volatility spillovers, helping decision makers to better understand market risks.

The spillover index methodology in Diebold and Yilmaz (2009) uses the conventional VAR model, which is limited to assessing the dynamic total spillover index and lacks the ability to evaluate directional spillover. Furthermore, the findings obtained from the model are contingent on the VAR lag orders. To address these challenges, Diebold and Yilmaz (2012) proposes an enhanced DY spillover index model that mitigates the potential influence of VAR lag orders on the findings and provides a way to quantify directional spillovers between markets. To achieve this, they employ the generalized VAR framework developed by Koop et al. (1996) and Pesaran and Shin (1998), commonly referred to as KPPS. This approach determines the variance of forecast errors for variable x that can be ascribed to disturbances in another variable y (where x is not equal to y), referred to as the spillover. Moreover, the Diebold–Yilmaz approach permits the use of rolling window estimations, allowing us to examine temporal spillover patterns in terms of their magnitude and direction to identify transmission and receipt of spillovers for each variable at different time intervals.

First, we use the generalized VAR(q) approach introduced in Diebold and Yilmaz (2012) to measure directional spillover in our sample. Eq. 2 shows a vector of disturbances that are independently and identically distributed:

$$Z_t = \sum_{i=0}^{q} \psi_i Z_{t-i} + u_t \ where \ \varepsilon \sim (0, \Sigma) \tag{2}$$

Consider a stationary variance with N variables, denoted by VAR (q), where Z_t is an N-dimensional vector of regressand variables at time t, while ψ_i is an $N \times N$ autoregressive coefficient matrix and u_t is the error term. Using the VAR(q) model in Eq. (2) we can generate a moving-average (∞) representation, which can be described as follows:

$$Z_t = \sum_{n=0}^{\infty} L_n \varepsilon_{t-n} \tag{3}$$

where L_n is the $N \times N$ coefficient matrix that corresponds to the iteration of the form

$$L_n = \psi_1 L_{n-1} + \psi_2 L_{n-2} + \ldots + \psi_q L_{n-q} \tag{4}$$

where L_0 is the $N \times N$ identity matrix, while $L_n = 0 if n < 0$.

As explained in Diebold and Yilmaz (2012), understanding the system's dynamics depends on moving-average coefficients, or transformations such as variance decompositions, or impulse–response transformations. For example, we use variance decompositions to break down the forecast-error variances of each variable into parts that can be attributed to different system shocks. VAR innovations are contemporaneously related, whereas variance decompositions require orthogonal innovations. The modified VAR framework used by Koop et al. (1996) and Pesaran and Shin (1998) solves this problem. The KPPS H-step forecast-error variance decompositions can be expressed as follows:

$$\sigma_{xy}^{g}(H) = \frac{\theta_{yy}^{-1} \sum_{h=0}^{H-1} \left(b_x\prime A_h \Sigma b_y \right)^2}{\sum_{h=0}^{H-1} \left(b_x\prime A_h \Sigma A_h\prime b_x \right)}, \tag{5}$$

where θ_{yy}^{-1} represents the error term of the standard deviation for the yth equation, and Σ is the variance matrix for the error vector. The selection vector is b_x, which is one of the yth elements; otherwise, it is zero. Nevertheless, the total number of components that have been substituted in each row of the table that decomposes variance is not equal to one. Hence, every element of the variance decomposition matrix can be written as:

$$\widetilde{\sigma_{xy}^{g}}(H) = \frac{\sigma_{xy}^{g}(H)}{\sum_{y=1}^{N} \sigma_{xy}^{g}(H)}, \tag{6}$$

where $\sigma_{xy}^{g}(H) = 1$ and $\sum_{y=1}^{N} \sigma_{xy}^{g}(H) = \mathrm{N}$.

Using the KPPS variance decomposition, Diebold and Yilmaz (2012) created a total volatility spillover index as shown in Eq. 7:

$$S^{g}(H) = \frac{\sum_{\substack{xy \\ x \neq y}}^{N} \widetilde{\sigma_{xy}^{g}}(H)}{\sum_{xy}^{N} \widetilde{\sigma_{xy}^{g}}(H)} * 100 = \frac{\sum_{\substack{xy \\ x \neq y}}^{N} \widetilde{\sigma_{xy}^{g}}(H)}{N} \times 100. \tag{7}$$

Using these directional volatility spillovers in Eq. (8), we calculate volatility spillovers transmitted from all markets to one market as follows:

$$S_{x.}^{g}(H) = \frac{\sum_{\substack{y=1 \\ y \neq x}}^{N} \widetilde{\sigma_{xy}^{g}}(H)}{\sum_{x,y=1}^{N} \widetilde{\sigma_{xy}^{g}}(H)} * 100 = \frac{\sum_{\substack{y=1 \\ y \neq x}}^{N} \widetilde{\sigma_{xy}^{g}}(H)}{N} \times 100. \tag{8}$$

In addition, volatility spillovers are transmitted from one market to another market as follows:

$$S^g_{.x}(H) = \frac{\sum_{\substack{y=1 \\ y \neq x}}^{N} \widetilde{\sigma^g_{yx}}(H)}{\sum_{x,y=1}^{N} \widetilde{\sigma^g_{yx}}(H)} * 100 = \frac{\sum_{\substack{y=1 \\ y \neq x}}^{N} \widetilde{\sigma^g_{yx}}(H)}{N} \times 100. \tag{9}$$

Furthermore, we can calculate the net volatility spillover from one market to another using Eq. 10:

$$S^g_x = S^g_{.x}(H) - S^g_{x.}(H). \tag{10}$$

This shows that the net volatility spillover is the difference between the contribution to and from other markets.

Baruník and Křehlík (2018) approach

Financial market connectivity is central to risk management, portfolio allocations, and business cycle analysis. Many studies in this area focus on developing general frameworks, as correlation-based measures are often inadequate. To understand the sources of connectedness in an economic system one must comprehend its frequency dynamics because shocks to economic activity affect variables at various frequencies and strengths. Baruník and Křehlík (2018) propose a framework to measure financial connectedness across desired frequency bands, encompassing long term, medium term, and short-term shock responses. This section shows the Baruník and Křehlík (2018) approach to variance decomposition depending on the frequency of responses to shocks. The spectrum form of variance decompositions is used to determine market connectivity at various frequencies (short term, medium term, or long term).

Asset prices, driven by economic growth with different cyclical components, naturally generate shocks with heterogeneous frequency responses. This, in turn, creates systemic risk over short-, medium-, and long-term horizons from various sources of connectedness. A study of connectedness should emphasize persistent linkages that underlie systemic risk. Different variance decomposition forecast horizons can be used to examine variable connectedness at different frequencies. Heterogeneous shock responses aggregate across frequencies in the time domain. Baruník and Křehlík (2018) evaluate the distribution of forecast-error variations in variable y caused by shocks in variable x within specific frequency ranges, rather than assessing overall error variation. This approach is logical as it highlights the long term, intermediate, and immediate effects of disturbances, which can be combined to create a total impact. This generalized forecast-error variance decomposition provides a spectral representation defined for frequency-dependent measurements. Baruník and Křehlík (2018) employ Fourier transforms of impulse–response functions, referred to as frequency response. In the frequency domain, we focus on the forecast-error variance frequency band attributed to exogenous shocks in another variable.

The coefficients of the moving-average Fourier transform generate a frequency response function. $\gamma\left(e^{-ix}\right) = \sum_h e^{-ixh}\gamma_h$ is the frequency response function while γ_h is the Fourier transform, $i = \sqrt{-1}$, and x is the frequency. The Fourier transform of the moving-average (∞) filtered series gives the spectral density of y_t at frequency x as follows:

$$S_Y(x) = \sum_{h=-\infty}^{\infty} E\left(Y_t Y_{t-h'}\right)e^{-ixh} = \gamma\left(e^{-ix}\right)\sum\gamma'\left(e^{+ix}\right), \tag{11}$$

where $S_Y(x)$ is an essential quantity for clarifying frequency dynamics. Because it explains the distribution of the variance of y_t across the x-frequency components, the frequency domain equivalents of variance decomposition are defined by Eq. (12) as follows:

$$\delta_{a,b}(x) \equiv \frac{\sigma_{bb}^{-1}\left|\left(\gamma\left(e^{-ix}\right)\Sigma\right)ab\right|^2}{\left(\gamma\left(e^{-ix}\right)\Sigma\gamma'\left(e^{+ix}\right)\right)a.a}, \tag{12}$$

where $\delta_{a,b}(x)$ is a part of the spectrum of the ath at the frequency of x attributable to shock in the bth. We clarify that $x \in (-\pi, \mu)$. Equation 13 shows the weight function of the spillover of the ath variable as follows:

$$\tau_a(x) = \frac{\left(\gamma\left(e^{-ix}\right)\sum\gamma'\left(e^{+ix}\right)\right)_{a,a}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\gamma\left(e^{-i\lambda}\right)\sum\gamma'\left(e^{+i\lambda}\right)\right)_{a,a}d\lambda}, \tag{13}$$

where $\tau_a(x)$ is the weighting function and reflects the power of the ath variable at a given frequency. Using generalized variance decomposition, we can construct connectedness tables for frequency band $d, d = (w, z) : w, z \in (-\pi, \pi), w < z$) as

$$(\tilde{\delta}_d)_{a,b} = \frac{1}{2\pi}\int_{-\pi}^{\pi}\tau_a(m)\delta_{a,b}(m)dm \tag{14}$$

Next, we can defend the frequency using Eq. 15 and the connectedness of frequency band d (in Eq. 16) as follows:

$$C_d^w = \left(1 - \frac{T_r\left\{\tilde{\delta}_d\right\}}{\sum\tilde{\delta}_d}\right) * 100. \tag{15}$$

$$C_d^f = \left(\frac{\sum\tilde{\delta}_d}{\sum\tilde{\delta}_\infty} - \frac{T_r\left\{\tilde{\delta}_d\right\}}{\sum\tilde{\delta}_\infty}\right) * 100 = C_d^w * \frac{\sum\tilde{\delta}_d}{\sum\tilde{\delta}_\infty}. \tag{16}$$

In our study, we select the VAR lag length criterion to be one, in line with the information criteria of Schwarz and Hannan-Quinn. For variance decomposition, we use a forecasting horizon of 100 days (H), as using a value of (H) < 100 produces results that were deemed to be invalid based on the findings in Baruník and Křehlík (2018).

Empirical finding

Diebold and Yilmaz (2012) model

We use our framework to estimate volatility spillovers using the time-invariant volatility transmission between the largest cryptocurrencies and the largest energy and

Table 4 Volatility spillovers among leading cryptocurrencies and energy and technology companies

	BTC	ETH	USDT	BNB	AAPL	MSFT	GOOGL	AMZN	XOM	CVX	COP	NEE	From others
BTC	50.49	25.38	4.36	16.09	0.49	0.50	0.33	0.31	0.45	0.21	0.61	0.87	49.6
ETH	25.42	50.66	3.52	15.34	0.75	0.64	0.38	0.28	0.84	0.58	0.97	0.61	49.3
USDT	8.28	9.32	72.96	4.19	0.60	1.02	0.40	0.13	0.34	0.84	0.43	1.48	27.0
BNB	18.53	17.84	2.92	57.93	0.30	0.44	0.36	0.15	0.51	0.12	0.64	0.26	42.1
AAPL	0.62	1.15	0.58	0.33	39.72	17.65	13.20	9.25	3.32	4.52	3.90	5.77	60.3
MSFT	0.66	1.24	1.14	0.41	15.00	34.03	16.76	10.82	3.91	4.89	4.46	6.68	66.0
GOOGL	0.32	0.50	0.24	0.22	12.96	20.39	38.88	10.78	3.16	3.78	3.46	5.31	61.1
AMZN	0.27	0.46	0.08	0.08	11.89	16.75	13.73	47.22	1.96	2.21	1.81	3.52	52.8
XON	0.34	0.61	0.03	0.34	3.79	4.84	2.90	2.03	37.08	21.00	20.31	6.73	62.9
CVX	0.17	0.54	0.69	0.09	4.71	5.82	3.37	2.19	19.99	33.88	20.10	8.45	66.1
COP	0.44	0.77	0.29	0.41	3.48	4.47	2.62	1.49	20.08	21.69	37.56	6.70	62.4
NEE	0.85	0.97	0.60	0.24	7.40	9.44	6.10	3.04	5.62	7.58	6.70	51.47	48.5
Contribution to other	55.9	58.8	14.4	37.7	61.4	81.9	60.2	40.5	60.2	67.4	63.4	46.4	648.2
Contribution including own	106.3	109.5	87.4	95.7	101.1	116.0	99.0	87.7	97.3	101.3	101.0	97.9	**54.0%**
Net volatility spillovers	6.3	9.4	− 12.6	− 4.4	1.1	15.9	− 0.9	− 12.3	− 2.7	1.3	1	− 2.1	

technology stocks in the US market using Diebold and Yilmaz (2012). Table 4 shows the resulting volatility spillovers. The major diagonal component in the matrix provides information on how market returns contribute to forecast-error variation. Our results show the estimated contributions (To—From) in the US market for the selected sectors. The total spillover is the sum of the off-diagonal elements in a specific column or row divided by the sum of all elements in that column or row, including the diagonal elements. According to the total volatility spillover indicator across our sample, an average of 54% of the variance in volatility forecast errors across all three markets can be attributed to spillover effects. The extent of directional spillovers over the entire sample period was relatively high, which means that the volatility forecast-error variance in all of the cryptocurrencies, energy, and technology companies in our sample largely comes from spillovers. This overview of all contributions *to* and *from* the other assets shows the highest volatility spillover transmitter is Microsoft, with a value of 81.9% to others, followed by Chevron, with a value of 67.4% to others. In other words, Microsoft and Chevron exert a significant influence on the other assets in the sample. Of the cryptocurrencies in our sample, Ethereum exhibits the greatest spillover effect on other asset classes. Similarly, within the energy sector Chevron demonstrates the highest spillover effect and Microsoft displays the highest spillover effect of the technology stocks. While Microsoft, Bitcoin, and Ethereum make the largest contributions to the shocks and volatility connectedness in our study sample, the highest transmission percentage comes from Microsoft. Given that Microsoft has a higher market value than Bitcoin, which has a higher market value than Ethereum, this indicates that practitioners should pay attention to entities of various sizes. Furthermore, USDT and Amazon contribute less to shocks and volatility than the others. Investors should consider entities which may be "too big to fail" and may be "too interconnected" when estimating systemic risk across financial institutions. Despite their small market capitalizations, Bitcoin and Ethereum are significant (net) contributors to volatility connectedness and shocks, meaning they substantially contribute to risk in our sample (Wang et al. 2018). In contrast, Tether (USDT) has a weight of 14.4%, making it the lowest transmitter. In addition, Chevron is the highest receiver with a value of 66.1%, and Tether is the lowest, with volatility spillovers of 27.0% in terms of the variance of its forecast error.

Further, net volatility spillovers are the difference between contributions *to* and *from* others. Therefore, positive net volatility spillovers identify net transmitters and negative net volatility spillovers identify net receivers. Bitcoin and Ethereum have positive net volatility spillovers from cryptocurrencies; hence, they are net transmitters, a finding consistent with Li et al. (2023) who investigate the volatility of cryptocurrencies and financial assets in China. Tether and BNB Coin have negative net volatility spillovers; therefore, they are net receivers. Among the four energy stocks, ExxonMobil and Nextera Energy are net receivers, while Chevron and ConocoPhilips are net transmitters, which is consistent with Bouri et al. (2021), who suggest that crude oil is the primary shock transmitter in the network. Tech companies Apple and Microsoft are net transmitters, and Alphabet and Amazon are net receivers in the system. Microsoft is the highest net transmitter and Tether is the highest net receiver.

Figure 1 illustrates the dynamics of total volatility spillovers among the leading cryptocurrencies (Bitcoin, Ethereum, Tether, and BNB coin), US energy companies (Exxon

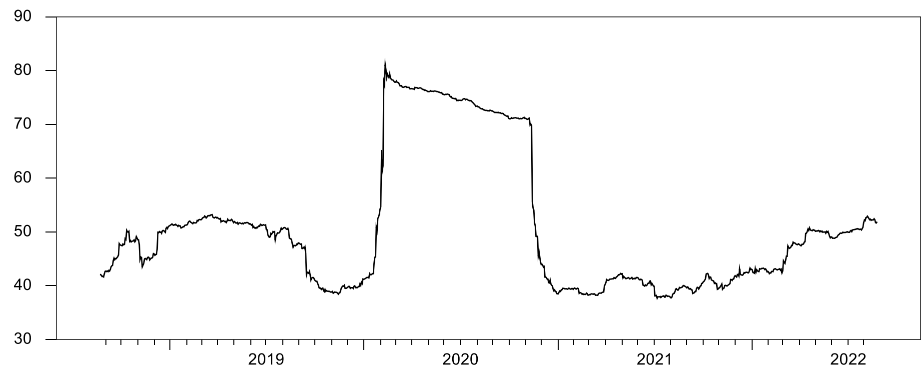

Fig. 1 Total Volatility Spillovers for the US Study Sample

Mobil, Chevron, ConocoPhillips, and Nextera Energy), and US technology companies (Apple, Microsoft, Alphabet, and Amazon). Table 3 shows the comprehensive spillover and spillover index for the entire sample. It is worth noting that this summary may overlook significant sectoral and cyclical fluctuations in spillover patterns. To address this, we calculate volatility spillovers using 200-day rolling sample periods. In addition, we evaluate the magnitude and characteristics of spillover fluctuations over time by examining the corresponding time series of spillover indices. Over the study period, 200-day total volatility spillovers were between 40 and 85%, whereas the static total spillover index was 54%, in line with (Kang et al. 2019; Fang et al. 2022; Khalfaoui et al. 2023). Compared with static analyses, which produce strong indicators, the time-varying technique offers more information on the volatility connections among the cryptocurrency, energy, and technology markets. Total spillovers are between 40 and 50% until 2019. Thereafter, we see significant changes as the magnitude of spillovers surpasses 50% in the middle of 2019 and reaches a high of 85% during the COVID-19 pandemic, which started on March 11, 2020 (WHO, 2021). The highest total volatility spillovers occur between 2020 and 2021 due to the COVID-19 pandemic, which led to closures in all aspects of economic and social life that were reflected in stock prices and cryptocurrencies. Several factors made volatility spillovers decline in 2021, the most important of which was the announcement of the COVID-19 vaccine in the last quarter of 2020. This led countries to gradually reduce restrictions and end closures. Our results align with those in prior studies (Bouri et al. 2021; Coskun and Taspinar 2022), which show that the outbreak of COVID-19 affected financial markets, resulting in increased volatility. The spillovers during the COVID-19 pandemic were significantly larger than those observed before and after, indicating the impact of COVID-19 on the US economy increased risk transmission across markets.

Figure 2 shows trends in directional volatility spillovers among the cryptocurrencies and stocks in our sample. Again, the highest volatility spillovers were in the COVID-19 period in 2020, rising by roughly 40%, which is consistent with Mensi et al. (2022). Bitcoin's volatility transmissions varied over time, as did Ethereum's, Tether's, and BNB's during COVID-19. Apple, Microsoft, Alphabet, and Amazon transmit volatility to others in a time-variant manner Similarly, Exxon Mobil, Chevron, ConocoPhillips, and Nextera Energy from the energy sector transmitted volatility to others. Their volatility spillovers then dropped slightly for a short time, then rose again in 2022 due Russia's

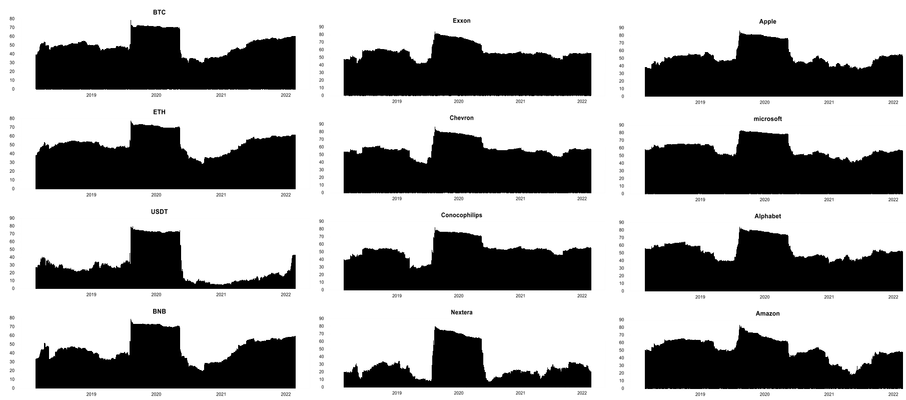

Fig. 2 Directional Volatility Spillovers from Companies to Others in the US Market Return

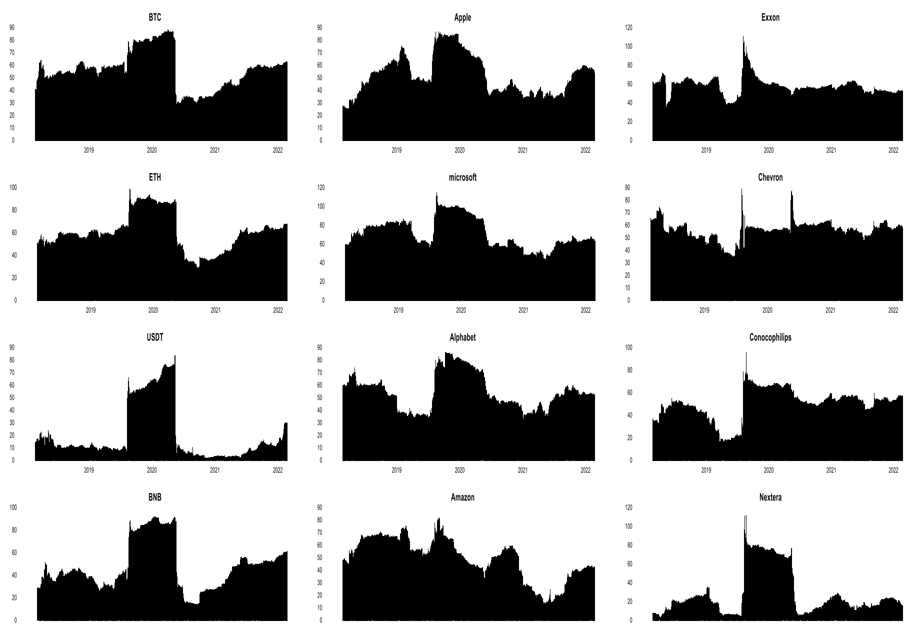

Fig. 3 Directional Volatility Spillovers to Companies from Others

invasion of Ukraine and the resulting food crisis and price inflation, which is consistent with Chaaya et al. (2022).

Figure 3 shows the directional volatility spillovers to the companies in our sample. The transmission of effects from others exhibits noticeable temporal variations. However, the pattern of relative variation is reversed compared to the increases in their directional volatility spillovers to asset classes. Hence, the highest volatility spillovers were received during the COVID-19 period during 2020, consistent with Wei et al. (2022). Volatility spillovers rose for all companies in the market. Bitcoin received the volatility from others in a time-variant, the same for Ethereum, Tether, and BNB, and volatility spillovers reached 100% during the COVID-19 period. In the technology sector, Apple, Microsoft, Alphabet, and Amazon received volatility spillovers from

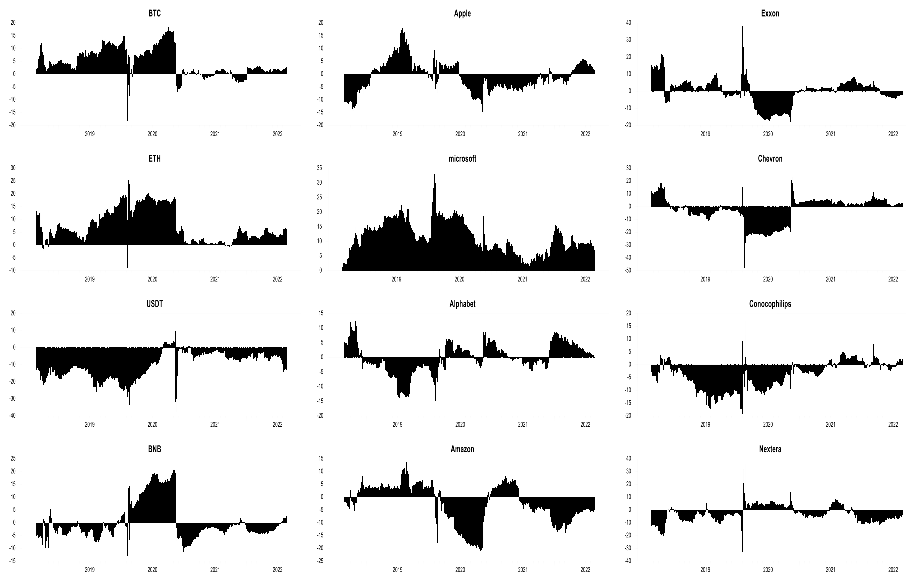

Fig. 4 Net Volatility Spillovers over Time-Variant

others in a time-variant. Moreover, Exxon Mobil, Chevron, ConocoPhillips, and Nextera Energy from the energy sector received volatility spillovers from others. Exxon and Amazon had an effect for a short time. Then the volatility spillovers dropped in cryptocurrency, Nextera in the energy sector, and the technology companies, while Exxon Mobil, Chevron, and ConocoPhillips dropped slightly and still received volatility spillovers. Furthermore, we find that Bitcoin, Ethereum, BNB, technology companies, and energy companies (except Nextera) received volatility spillovers again during 2022 because of the Russia–Ukraine crisis, consistent with Chaaya et al. (2022).

Figure 4 shows the net volatility spillovers for each asset in our study. Before the COVID-19 pandemic, the net volatility spillovers between each of the assets were below 20%. Nevertheless, there was a significant shift in circumstances following January 2018. The net transmission of volatility spillover from Bitcoin, Ethereum, and Microsoft remained positive during various phases of the panadmic, peaking at 30% following the COVID-19 pandemic in 2020. Accordingly Bitcoin, Ethereum, and Microsoft had a positive net volatility spillover, which means they were transmitters and they were a transmission of the volatility spillovers. Also, the net receiving of volatility spillover from the Apple, Amazon, Exxon, Chevron and ConocoPhillips remained negative during various phases of the panadmic, peaking at mines 40% in 2020. Hence, Apple, Amazon, Exxon, Chevron and ConocoPhillips had negative net volatility spillovers during the COVID-19 period, which means they were receiving the volatility spillovers. BNB and Nextera experienced a shift from being net receivers to becoming net transmitters in the COVID-19 period and subsequently reverted back to receiving spillover.

The Baruník and Křehlík (2018) model

In this section we estimate the dynamics of volatility spillovers for both short- and long-term horizons using the method in Baruník and Křehlík (2018), and present the results in Table 5. The table shows time–frequency spillovers of different terms (short, medium,

Table 5 Results of Total Volatility Spillovers Using Baruník and Křehlík (2018) Model

The spillover band: 3.14 to 0.79 (short term, 1 day to 4 days)													
	BTC	**ETH**	**USDT**	**BNB**	**AAPL**	**MSFT**	**GOOGL**	**AMZN**	**XOM**	**CVX**	**COP**	**NEE**	**FROM ABS**	**FROM WTH**
BTC	0.19	0.08	0.02	0.07	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.02	4.25
ETH	0.09	0.16	0.02	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	4.10
USDT	0.00	0.01	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.80
BNB	0.05	0.04	0.01	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	2.38
APPL	0.00	0.00	0.00	0.00	0.19	0.07	0.05	0.04	0.01	0.03	0.01	0.01	0.02	4.79
MSFT	0.00	0.00	0.00	0.00	0.04	0.14	0.07	0.03	0.01	0.01	0.00	0.01	0.01	3.58
GOOGL	0.00	0.00	0.00	0.00	0.05	0.08	0.20	0.03	0.00	0.01	0.00	0.01	0.02	4.37
AMZN	0.00	0.00	0.00	0.00	0.03	0.04	0.04	0.17	0.00	0.00	0.00	0.00	0.01	2.69
XON	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.15	0.08	0.05	0.00	0.01	3.69
CVX	0.01	0.01	0.01	0.00	0.02	0.01	0.01	0.00	0.09	0.28	0.12	0.01	0.02	6.23
COP	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.10	0.14	0.21	0.01	0.03	6.90
NEE	0.01	0.00	0.01	0.00	0.02	0.02	0.01	0.01	0.03	0.05	0.01	0.44	0.02	4.03
TO ABS	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.03	0.02	0.00	0.18	
TO WTH	4.03	3.54	1.57	3.52	3.76	5.51	4.36	2.73	5.71	7.41	4.42	1.24		TGI: 47.81
The spillover band: 0.79 to 0.31 (Medium term, 4 days to 10 days)														
	BTC	ETH	USDT	BNB	AAPL	MSFT	GOOGL	AMZN	XOM	CVX	COP	NEE	FROM ABS	FROM WTH
BTC	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.77
ETH	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.59
USDT	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21
BNB	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.61
APPL	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.03
MSFT	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.80
GOOGL	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	4.27
AMZN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	2.38
XON	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	3.16

Table 5 (continued)

The spillover band: 3.14 to 0.79 (short term, 1 day to 4 days)														
	BTC	**ETH**	**USDT**	**BNB**	**AAPL**	**MSFT**	**GOOGL**	**AMZN**	**XOM**	**CVX**	**COP**	**NEE**	**FROM ABS**	**FROM WTH**
CVX	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	5.71
COP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	6.76
NEE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	1.51
TO ABS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	
TO WTH	3.61	3.22	0.96	2.71	3.67	4.57	3.83	2.34	3.95	7.16	4.78	1.01		TGI: 41.82
The spillover band: 0.31 to 0.00 (Long term, 10 days to Infinite days)														
	BTC	ETH	USDT	BNB	AAPL	MSFT	GOOGL	AMZN	XOM	CVX	COP	NEE	FROM ABS	FROM WTH
BTC	53.94	25.23	2.92	14.89	0.16	0.03	0.17	0.13	0.28	0.24	0.90	0.67	3.80	3.82
ETH	24.38	56.36	2.20	13.92	0.36	0.05	0.12	0.04	0.37	0.66	1.13	0.03	3.61	3.62
USDT	7.82	8.54	77.36	3.28	0.16	0.10	0.05	0.110	0.28	0.00	0.60	1.59	1.88	1.89
BNB	18.51	17.81	1.02	60.69	0.09	0.11	0.19	0.02	0.37	0.06	0.80	0.04	3.25	3.26
APPL	1.16	1.25	0.23	0.73	54.80	14.93	11.56	10.08	0.17	0.04	0.04	4.56	3.73	3.75
MSFT	0.66	0.73	0.41	0.48	14.27	48.41	18.10	11.42	0.34	0.11	0.33	4.42	4.27	4.29
GOOGL	0.23	0.25	0.02	0.09	10.69	20.72	50.87	10.55	0.48	0.07	0.00	5.61	4.06	4.08
AMZN	0.18	0.13	0.01	0.09	12.20	14.07	10.81	59.68	0.13	1.23	0.28	0.88	3.33	3.35
XON	0.03	0.12	0.00	0.08	0.36	0.52	0.28	0.34	46.16	24.96	25.45	1.37	4.46	4.48
CVX	0.17	0.68	0.00	0.09	0.18	0.34	0.01	1.46	30.76	36.69	18.28	10.74	5.23	5.25
COP	0.69	1.11	0.34	0.43	0.00	0.27	0.10	0.23	26.52	14.86	46.32	8.57	4.43	4.45
NEE	0.25	0.04	0.35	0.04	5.92	5.70	6.94	1.12	0.22	8.36	6.40	63.99	2.95	2.96
TO ABS	4.51	4.66	0.63	2.85	3.70	4.74	4.03	2.96	4.99	4.22	4.52	3.21	44.99	
TO WTH	4.53	4.68	0.63	2.86	3.71	4.76	4.04	2.97	5.01	4.23	4.54	3.22		TGI:45.17

and long). The results show total volatility spillovers over the short term (1–4 days) are 47.81%, while in the medium term (from 4 to 10 days) they are 41.82%, and in the long term (from 10 days) they are 45.17%. The highest value for volatility spillovers occurs in the short term horizon, indicating that the effects of volatility spillover transmission from one market to another are of brief duration, in contrast to the findings of Coskun and Taspinar (2022) who find the highest spillover values in the long term. Naeem et al. (2020) and Mensi et al. (2022) find that in the short term, the transfer of volatility between stocks and commodities increases due to speculation, investor sentiment, and exaggerated responses to news related to both the real and financial sectors of an economy. In our results, we observe the lowest value over the medium term. Our findings show that market volatility spillovers tend to concentrate in less than four days, and volatility spillovers in the short term over the whole period dominate the medium- and long-term spillovers. As a result, cryptocurrencies, energy, and technology respond to shocks more quickly in the short term than in the long and intermediate terms. In the short term, it is plausible that cryptocurrencies, energy, and technology, could display swift and occasionally unforeseeable reactions to external disturbances, including market occurrences, economic fluctuations, or geopolitical advancements. Investors derive advantages from their capacity to promptly evaluate and respond to these transient disruptions, thereby potentially minimizing financial losses or capitalizing on advantageous circumstances. Investors can enhance the safeguarding of their portfolios against abrupt adverse movements by promptly acknowledging and addressing short-term shocks; our results align with those of Mensi et al. (2021). Chevron contributed the most to short and medium-term volatility spillovers by 7.16% and 7.41%, respectively, while Exxon contributed the most to long-term volatility spillovers by 5.01%.

Moreover, Exxon had the second highest contribution in the short term, followed by Microsoft (5.51%), ConocoPhillips (4.42%), Alphabet (4.36%) and Bitcoin (4.03%), so they were the highest transmitter of volatility to the others. Energy companies have the most contribution volatility spillovers in our sample. In the long term, Exxon, Microsoft, ConocoPhillips, and Bitcoin were the highest transmitter of volatility to the others, while USDT was the highest receiver from the others.

Robustness tests

Verifying our empirical analysis is crucial to ensure its robustness and validity, particularly because of the arbitrary selection of the rolling window (RW) size. Choosing a relatively low RW size can make the analysis sensitive to extreme outliers in total connectedness. Conversely, opting for a high RW size may smooth out the potential impact of different outcomes (Diebold and Yilmaz 2012). To assess the reliability of our empirical findings we examine various RW sizes, specifically 200, 300, and 400 days. By analyzing the time-varying total spillovers presented in Fig. 5A show no sensitivity across different RW sizes. This implies that our results are not merely coincidental; they remain consistent regardless of whether we use low or high RW sizes, thereby indicating robust empirical findings. The spillover index is computed for VAR orders 2 to 6, and the resulting minimum, maximum, and median values in Fig. 5B. We also determine the spillover index for forecast horizons ranging from 4 to 10 days, as shown in Fig. 5C. Figures 5B

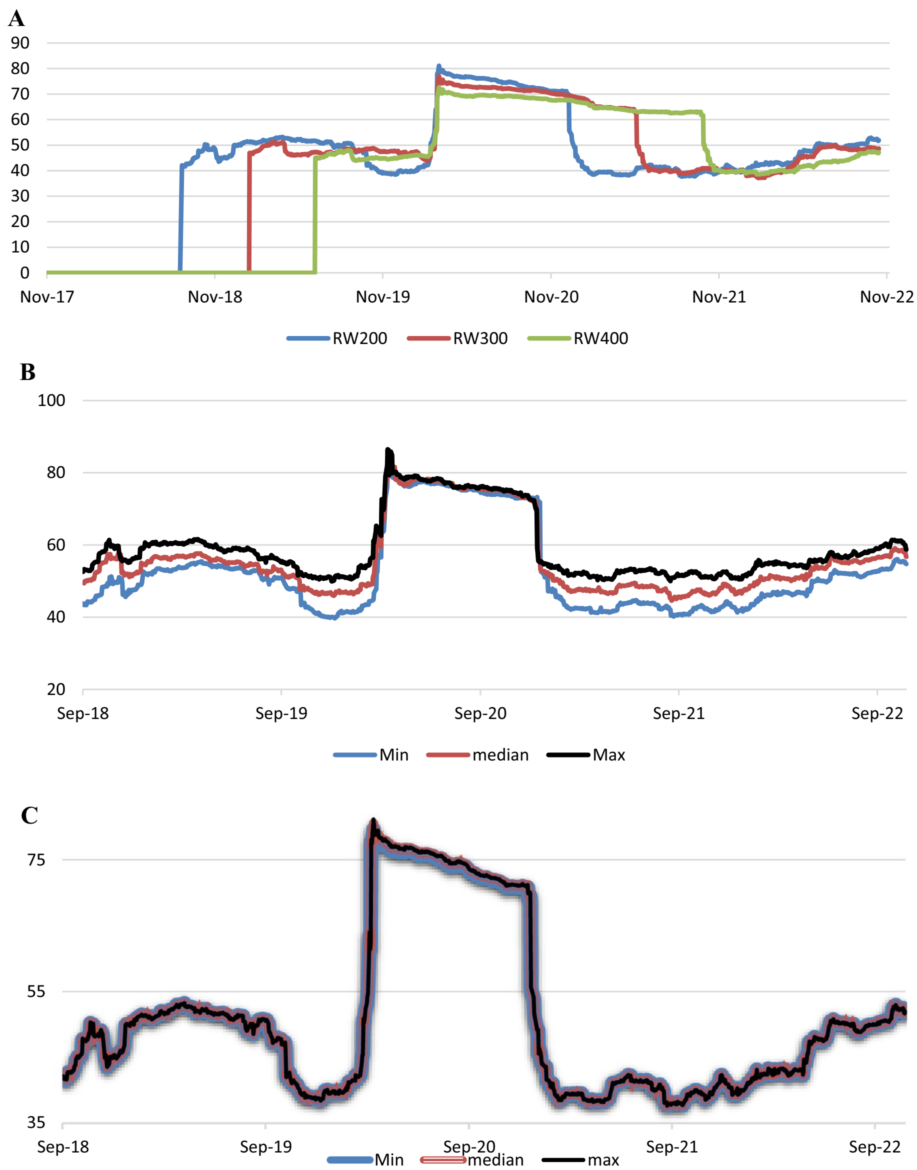

Fig. 5 **A** Total spillover plots using different rolling windows (RW) sizes. **B** Sensitivity test of the spillover index across different vector autoregression lag structure (max, median, and min values of the index for VAR orders of 2–6). **C** Sensitivity test of the spillover index across different forecast horizons (max, median, and min values over 4 to 10 days horizon)

and C confirm the overall spillover plot is not sensitive to the choice of VAR order or forecast horizon, which is consistent with Diebold and Yilmaz (2012).

Connectedness network results

Connectedness networks show directional volatility spillovers, and the connectedness network between variables provides information about the receiver and transmitter for each. In Fig. 6, a darker color and bolder font indicate a strong influence, while less darkening indicates a more minor influence. In addition, we calculate volatility spillover networks after measuring extreme volatility spillovers.

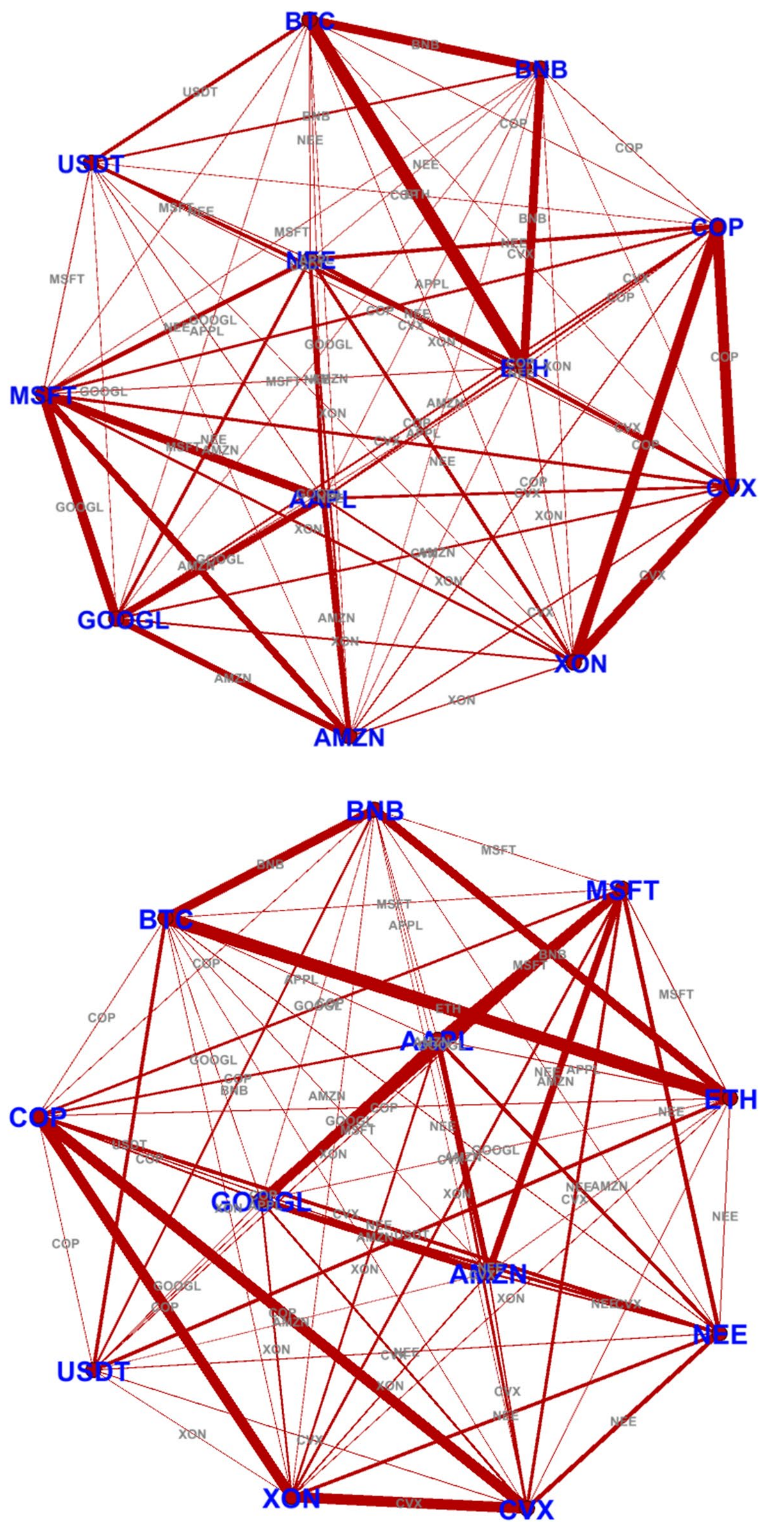

Fig. 6 Connectedness Network FROM-TO, Respectively

Figure 6 indicate the risks associated with extreme volatility spillovers across cryptocurrencies, energy and technology companies and connectedness networks from one variable to another, using the method in Diebold and Yilmaz (2012). We can see that Bitcoin, BNB, and Ethereum strongly receive and transmit volatility (FROM-TO) to each other, i.e., Bitcoin receives and transmits (FROM-TO) Ethereum and BNB. Ethereum receives and transmits (FROM-TO) Bitcoin and BNB. In contrast, BNB receives and transmits (FROM-TO) Bitcoin and Ethereum. All four technology companies (Apple, Microsoft, Alphabet, and Amazon) strongly affect (FROM-TO) each other in the technology sector. Finally, Chevron, ConocoPhillips, and ExxonMobil each have a strong influence (FROM-TO) on each other, whereas Nextera has a moderate effect (FROM-TO) on technology companies ConocoPhillips, Tether, and Chevron. In sum, all of the assets in our sample face significant volatility spillovers.

Figure 7 illustrate the extreme volatility spillovers across cryptocurrencies and energy and technology companies over the long term (from 10 to infinity) network according to Baruník and Křehlík (2018). Volatility spillover for all four technology companies is high for (FROM-TO). Cryptocurrency Bitcoin, Ethereum, and BNB have high volatility spillover effects (FROM-TO), and Chevron, ConocoPhillips, and ExxonMobil exhibit high volatility spillover. In contrast, Nextera shows moderate volatility spillover effects (FROM-TO), with Microsoft, Apple, Alphabet, Chevron, and ExxonMobil.

Figure 8 show extreme volatility spillovers across cryptocurrency, energy, and technology companies over the medium-term (from 4 to 10 days) network, according to Baruník and Křehlík (2018). We can note the volatility spillover effect in the medium term is low between variables; as a result, the volatility spillover is deficient in this period of study.

Figure 9 show the high volatility spillover among cryptocurrency, energy, and technology companies over the short term (from 1 to 4 days), following the method in Baruník and Křehlík (2018). We note that volatility spillovers for energy companies other than Nextera have the highest volatility (FROM-TO) in the short term, between Chevron, ConocoPhillips, and ExxonMobil. The volatility spillover (FROM-TO) effect between cryptocurrencies other than Tether is also substantial. Finally, among the four technology companies, there is a strong effect (FROM-TO) for Alphabet, Microsoft, and Apple, whereas the effect is less (FROM-TO) for Amazon..

Connectedness network for net-pairwise directional spillovers

In this section, we use various colors to define the relationships between nodes in the network. The node color corresponds to the function of a particular group in the system, and the size of the nodes reflects the magnitude of the net-pairwise directional spillovers. Red represents the strongest relationship, light green indicates a moderate relationship, and blue is the weakest. Edge colors reflect the strength of the net-pairwise directional connectedness, ranging from red, the most potent effect, to green, to blue, and lastly light blue, which shows the weakest spillover effect.

Figure 10 shows the net-pairwise directional spillovers among the cryptocurrencies, energy, and technology companies in our sample. The map evidence in Table 3 depends on Diebold and Yilmaz 2012. Alphabet and Amazon are the highest transmitters of shocks to other companies, energy companies are in the middle, and cryptocurrencies

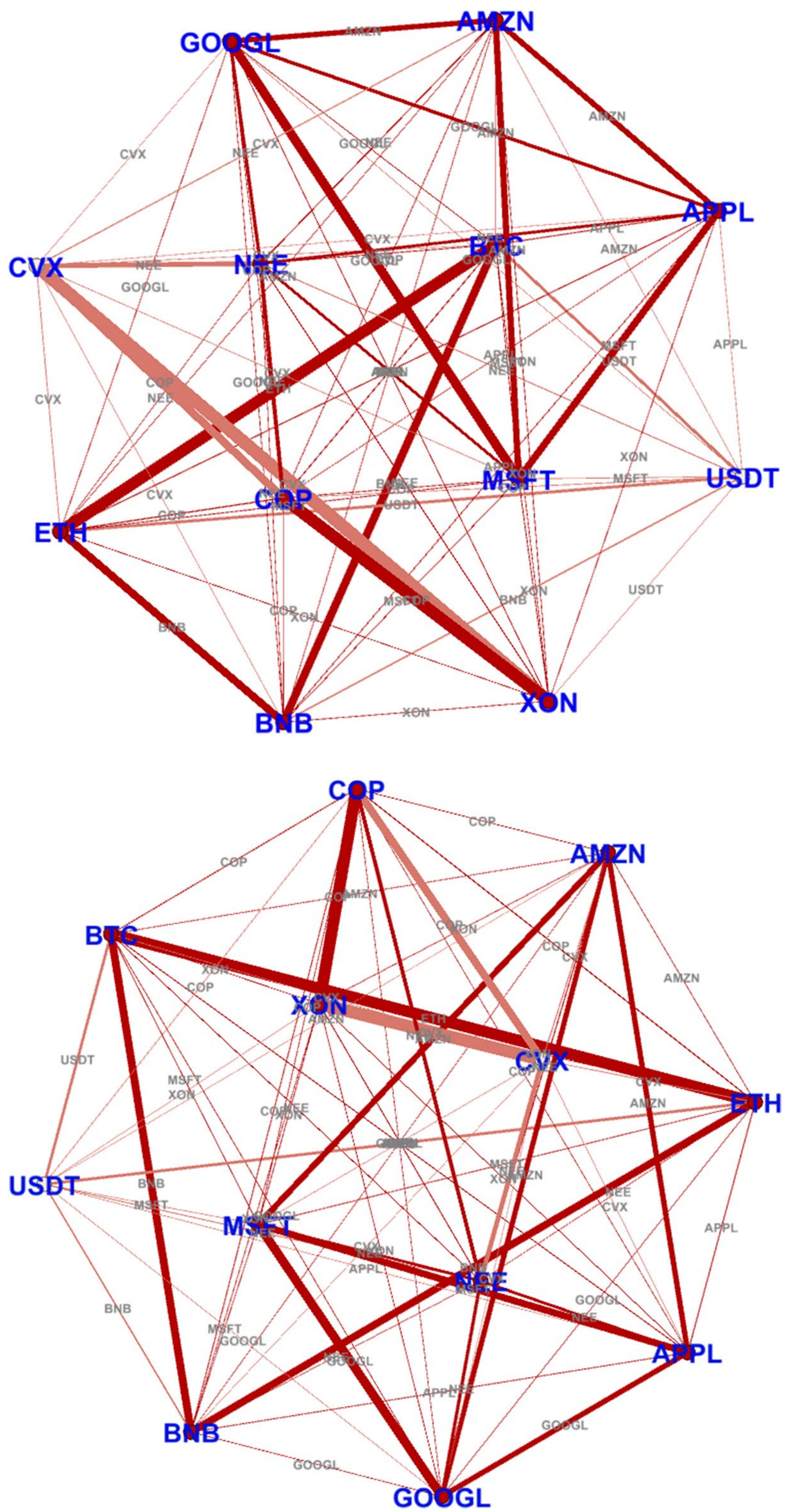

Fig. 7 Connectedness Networks FROM-TO for the Long Term (from 10 to Infinity), Respectively

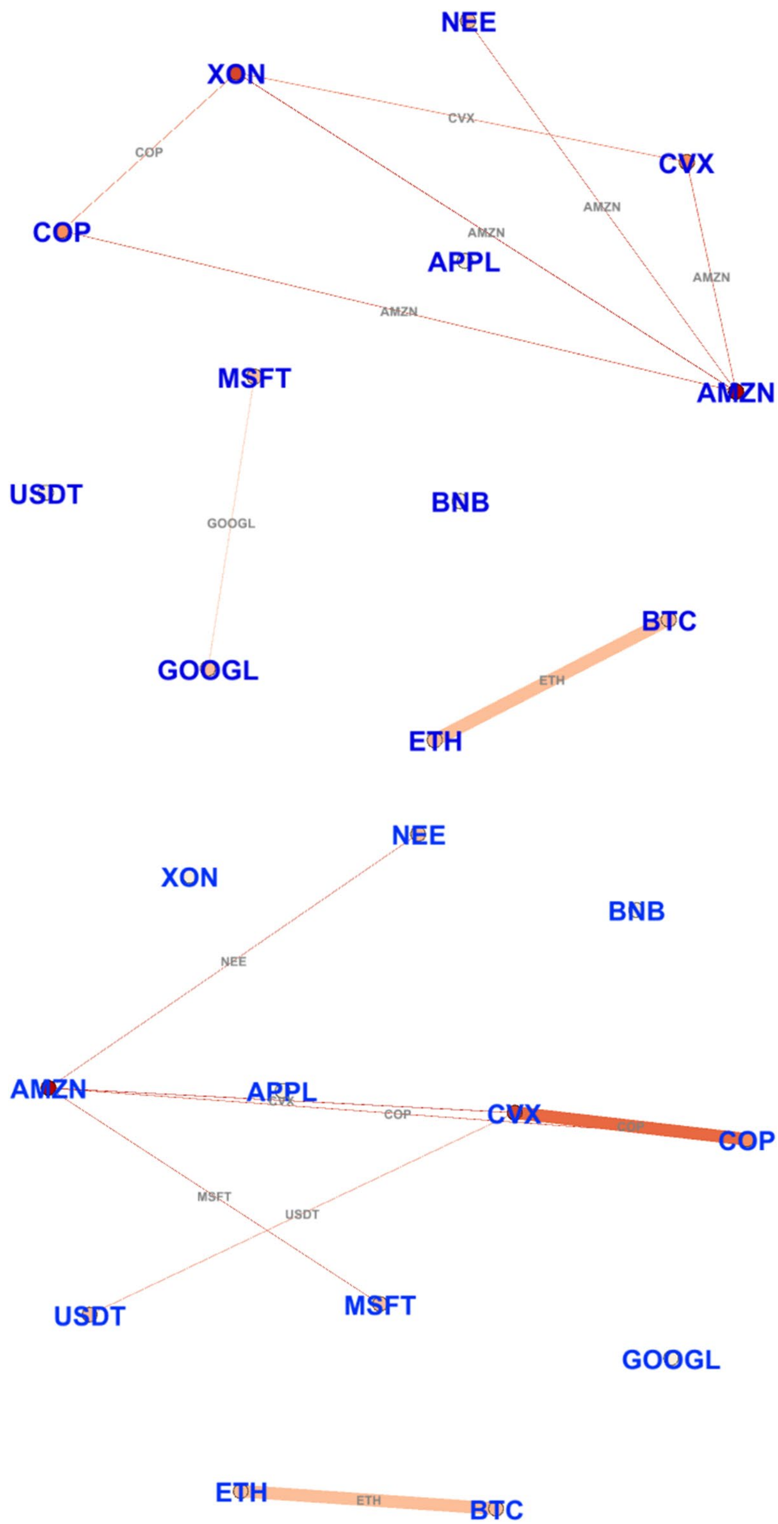

Fig. 8 Connectedness Networks FROM-TO over the Medium Term (from 4 to 10 Days) Respectively

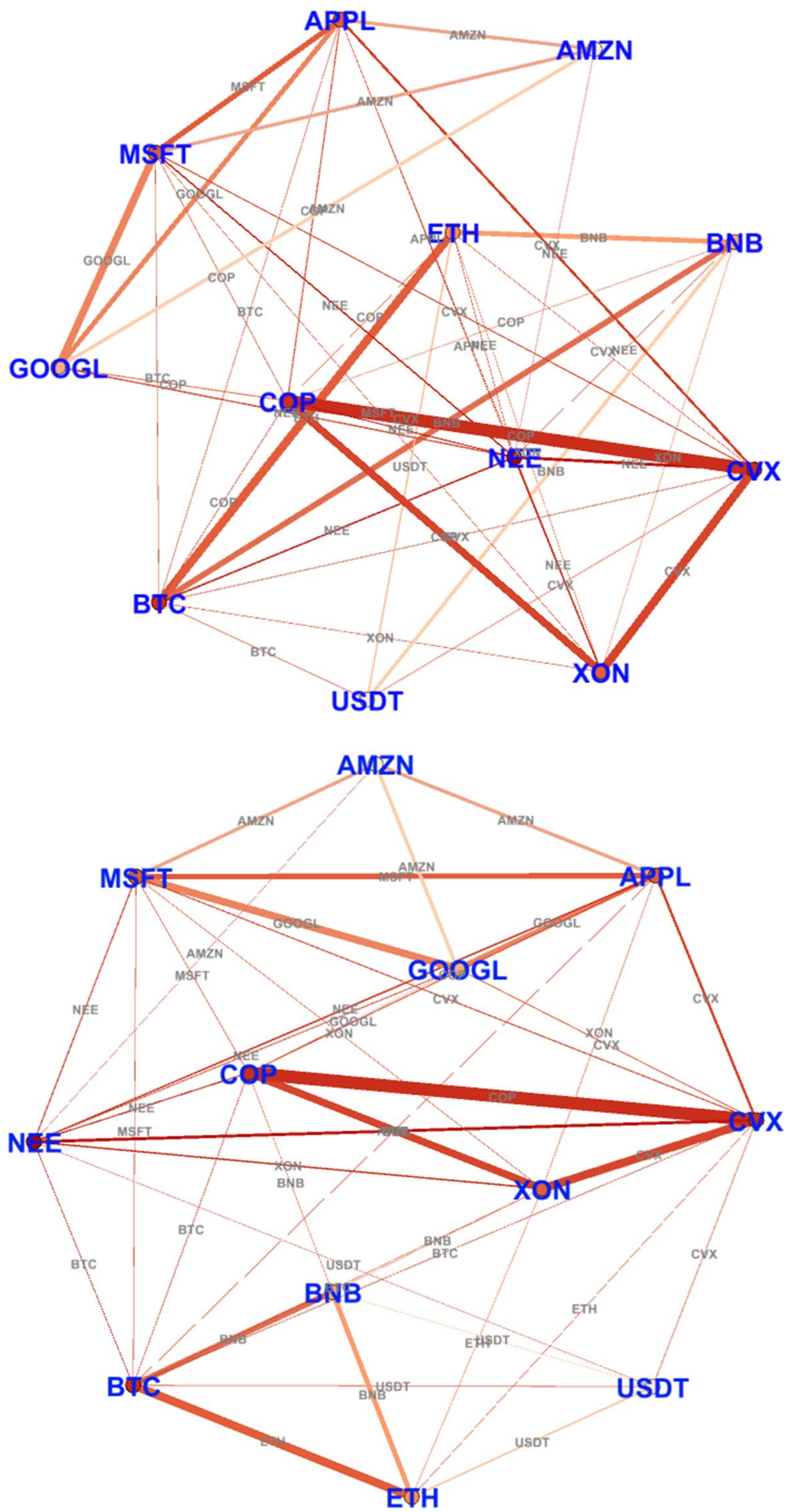

Fig. 9 Connectedness Networks FROM-TO over Short Term (1 to 4 Days), Respectively

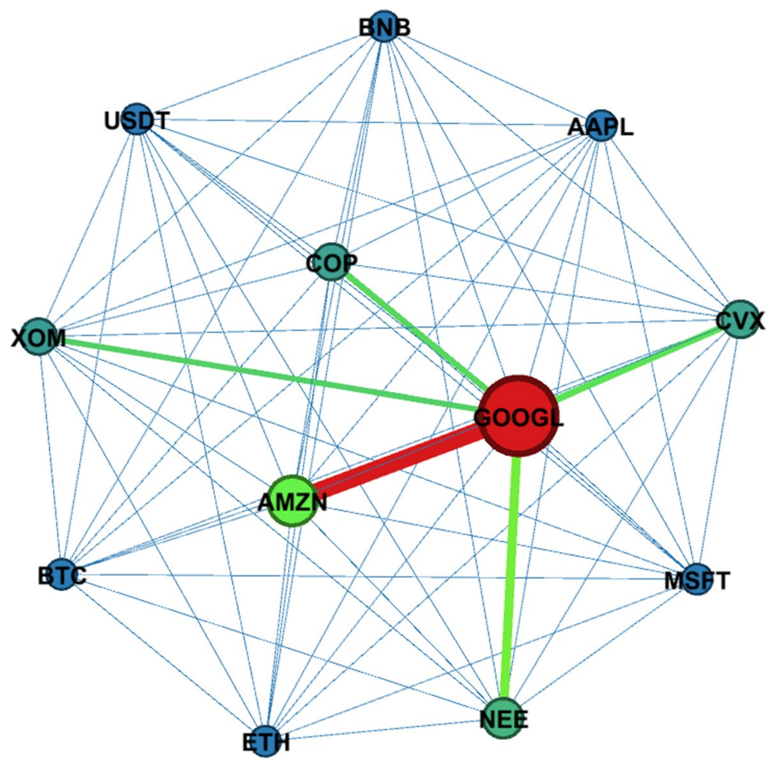

Fig. 10 Connectedness Network for Net-Pairwise Directional Spillovers according to Diebold and Yilmaz (2012)

were mostly shocked by the energy and technology stocks in the sample. Alphabet transfers the greatest shock to all companies, with the most significant direct transmission to Amazon.

Figure 11 present the connectedness network for net-pairwise directional spillovers depending on frequency time with different terms (short and long term), following Baruník and Křehlík (2018). The short- and long-term results confirm that Alphabet transfers the highest shocks to all of the other companies. Moreover, analyzing the market conditions indicates that most of the transmission of the shock into Amazon originates from Alphabet. Alphabet transmits less spillover to Chevron and Nextera in the short term and minor spillover to others. Notice that in the time horizon, the node sizes for Alphabet and Amazon are large during this period.

Our examination of volatility spillovers between prominent cryptocurrencies and US energy and technology companies offers various practical applications and implications. First, gaining insight into the interplay between cryptocurrency volatility and its impact on the energy and technology sectors, as well as the reciprocal influence of these sectors on cryptocurrency volatility, is important in the realm of risk management. The cryptocurrency Ethereum exhibits the greatest spillover effect to the other assets in our sample, Chevron demonstrates the highest spillover effect within the energy sector, and Microsoft displays the highest spillover effects among the technology stocks. Investors and portfolio managers can use this information to implement portfolio diversification strategies. In the event of heightened volatility in a particular

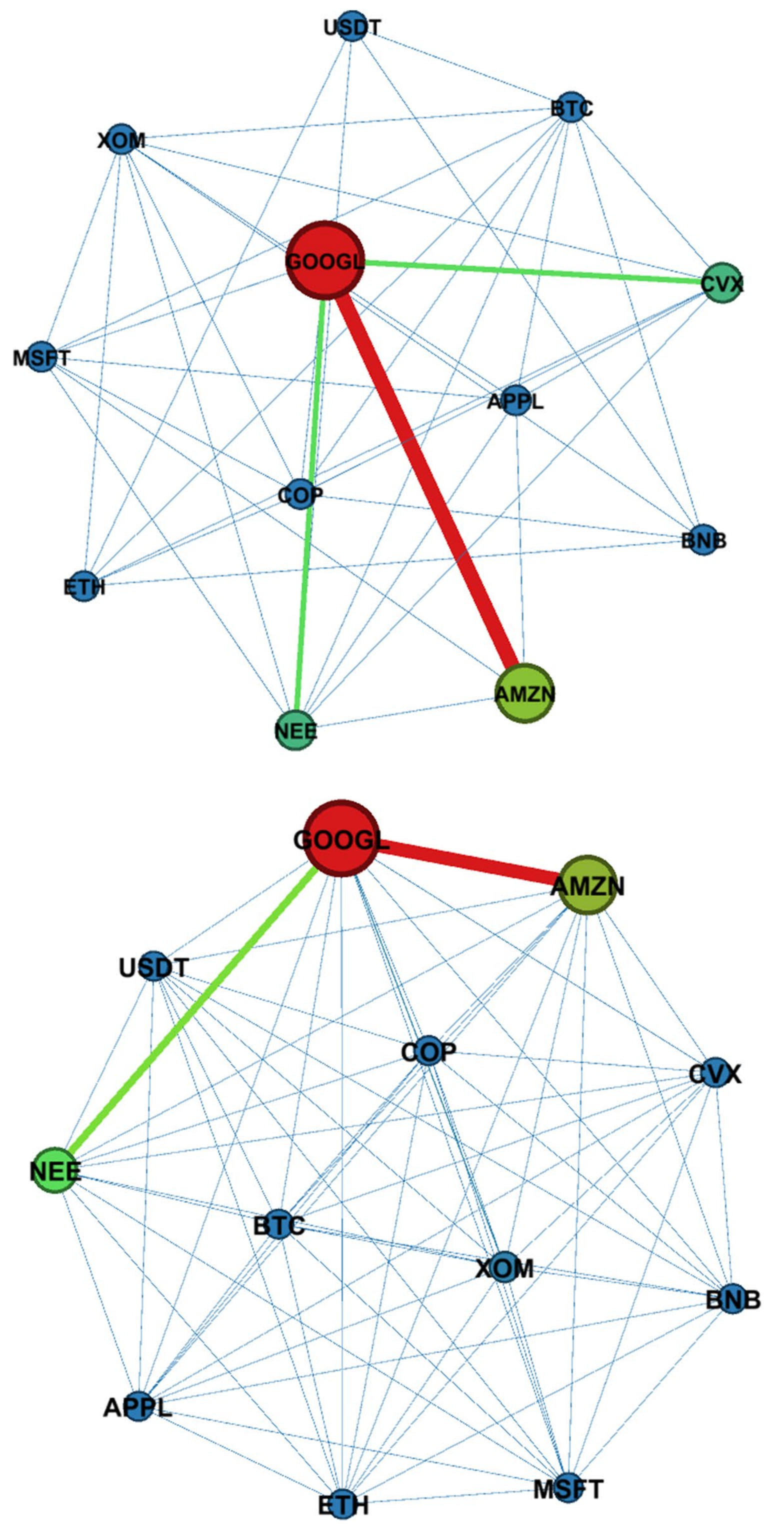

Fig. 11 Connectedness Network for Net-Pairwise Directional Spillovers (Short and Long Term), According to Baruník and Křehlík (2018), Respectively

asset class, investors could modify their allocations to mitigate overall portfolio risk. Second, the results provides valuable insights that can assist investors in making the optimal allocations to cryptocurrencies, energy, and technology sectors, given that Bitcoin, Ethereum, Chevron, ConocoPhillips, Apple, and Microsoft are net transmitters of volatility shocks while others are net receivers. Investors could use this to modify their asset allocations to maximize returns and mitigate risk, based on their respective risk tolerance levels and investment objectives. The information can be utilized by investors to mitigate their positions. Individuals with substantial holdings in cryptocurrencies might use options or other derivatives to hedge against potential adverse effects resulting from the transmission of cryptocurrency volatility. Third, financial institutions and investment firms can use the findings in this study within their asset allocation models to guide investment decisions that reflect the interconnections among cryptocurrencies and energy and technology stocks. Fourth, robustly quantifying systemic risk is important from the standpoint of market supervision. While it is beneficial to employ targeted measures for assessing regulatory tools in relation to specific risk channels, it is imperative to utilize comprehensive measures that aim, to quantify the extent to which financial institutions contribute to overall systemic risk. This is essential in order to identify institutions that hold significant importance in the broader system. In situations where the impact of institutions is enduring rather than limited to the immediate term, the systemically important financial institutions may be subjected to elevated capital requirements or a tax aimed at

Table 6 Comparison of results using the Diebold and Yilmaz (2012) Model and the Baruník and Křehlík (2018) Model

Diebold and Yilmaz (2012)	Baruník and Křehlík (2018)
Total volatility spillover indicator, it is observed that, on average, within the entirety of our sample equals 54% The highest volatility spillover transmitter is Microsoft, with a value of 81.9% to others, followed by Chevron, which has a value of 67.4% to others Tether (USDT) has a weight of 14.4%, which is the lowest transmutation for the other Chevron is the highest receiving with a value of 66.1%, and Tether is the lowest receiving with volatility spillovers of 27.0% The magnitude of the dynamics spillovers surpassed the threshold of 50% in the middle of 2019 and reached 85%. Significantly, during the COVID-19 pandemic The period characterized by the most pronounced directional volatility spillovers from – to companies was observed during the COVID-19 pandemic in the year 2020 and the volatility spillovers rise about 40% for each Then the volatility spillovers witnessed resurgence in 2022 because of the Russia–Ukraine crisis and the resulting food crisis and price inflation Bitcoin, Ethereum, Chevron, ConocoPhilips, Apple and Microsoft are net sender, while other is net receiver	Baruník and Křehlík (2018) approach shows time–frequency spillovers with different terms (short, medium, and long) The total volatility spillovers for the short-term period (from 1 to 4 days) are 47.81%, while in the medium term (from 4 to 10 days) they are 41.82%, and in the long-term (from 10 days) they are 45.17% The highest value for volatility spillovers occurs in the short-term horizon The effects of volatility spillover transmission from one market to others are of brief duration Chevron contributed the most to short and medium-term volatility spillovers by 7.16% and 7.41%, respectively Exxon contributed the most to long-term volatility spillovers by 5.01% Exxon had the second highest contribution in the short term, followed by Microsoft (5.51%), ConocoPhillips (4.42%), Alphabet (4.36%) and Bitcoin (4.03%), so they were the highest transmitter of volatility to the others Energy companies have the most contribution volatility spillovers in our sample In the long term, Exxon, Microsoft, ConocoPhillips, and Bitcoin were the highest transmitter of volatility to the others, while USDT was the highest receiver from the others

mitigating systemic risks. The identification of the specific sources of instability at different frequencies is crucial for policymakers seeking effective tools to monitor the accumulation of risk, as systemic risk poses a significant threat to the overall stability of the financial sector.

Table 6 compares the outcomes derived from the approaches used in Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), providing insights into disparities observed in our findings and enhancing the understanding of the relevant dynamics in these markets.

Conclusion

This study analyzes volatility spillovers for a subset of assets traded in US markets using generalized VAR and variance decomposition (frequency response) models. We focus on the cryptocurrency, energy, and technology sectors using daily prices from November 15, 2017, to October 28, 2022. Based on Diebold and Yilmaz (2012), our main finding is that the average total volatility spillover for our sample is approximately 54% of the variance in volatility forecast errors across all of the assets in our sample. The magnitude of the directional spillovers observed over the entire duration of the sample period was relatively high. We find that Chevron and Microsoft have bidirectional spillover strength, Microsoft is the highest net transmitter, and Tether is the highest net receiver. Bitcoin, Ethereum, Chevron, ConocoPhilips, Apple, and Microsoft are net volatility transmitters and the other six are net receivers (e.g., Wang et al. 2018; Bouri et al. 2021; Li et al. 2023). Total volatility spillover ranges between 40 and 85% over time (e.g., Fang et al. 2022; Khalfaoui et al. 2023). The most significant volatility spillover occurred between 2020 and 2021, indicating the COVID-19 pandemic strongly influenced volatility spillover, and during 2022 the volatility spillover. Spillover started to increase slightly in 2022 because of the Russian–Ukrainian crisis (Mensi et al. 2022; Chaaya et al. 2022). To offer another perspective, we follow Baruník and Křehlík (2018), which allows us to extract detailed time–frequency dynamics within the connectedness network. Periods characterized by frequent connectivity are associated with stock markets that are efficiently and calmly processing information. During such periods, a shock to one asset primarily affects the system in the short term, but is not notable in the intermediate terms, resulting in the short term dominating. Hence, volatility spreads with a short-term frequency and spillovers intensify during extreme events. Within our sample, Bitcoin, Ethereum, Nextera Energy, ConocoPhillips, Alphabet, and Apple are the net receivers of spillovers, while Tether, BNB, Microsoft, Amazon, ExxonMobil, and Chevron are net transmitters of spillovers. The connectedness network shows that in terms of net-pairwise directional spillovers, Alphabet and Amazon are the biggest transmitters of shocks to other companies.

Our findings imply several policy recommendations for decision makers and investors. Investors must always be prepared for fluctuations in market conditions, as careful analysis of stock prices requires predicting future shocks. However, the study shows that investors should primarily focus on short-term effects because they do not have enough time to make quick decisions to protect themselves from market risks when the US market is affected. Hence, we can suggest to. Based on our limited sample of cryptocurrencies and large energy and technology stocks, investors should be aware that volatility spillovers intensify during global crises. Regulators and investors should be aware of the connections among the cryptocurrency, energy, and technology markets should be brought to the attention of regulators and investors and should be considered when making policies. Volatilities in these markets influence each other and may exacerbate a decline in stock prices, as volatility usually rises when prices are falling. Our results also highlight the growing connections between unexpected and wildly unpredictable events such as the COVID-19 outbreak and the Russia–Ukraine conflict. Hence, governments should consider measures to mitigate the detrimental effects caused by external shocks and to focus on frequency-specific sources of risk.

Our study's limitations include insufficient data for cryptocurrencies, as most started trading only recently. As a result, we could not examine shocks to the US market before 2017 due to the lack of data available before that period. Thus, the researchers were unable to investigate the events and shocks adequately and thoroughly in the U.S. market. Moreover, our approach does not permit us to calculate portfolio weights and optimal hedge ratios to address portfolio diversification. In addition, the methodologies we follow here do not fully utilize the advantages of Bayesian shrinkage techniques in estimating high-dimensional systems while avoiding the need for computationally intensive simulation methods. The dynamic connectedness index and directional connectedness measures exhibit immunity to the persistence observed in rolling window estimation (Attarzadeh and Balcilar 2022).

Further studies on this topic could include risk-free government bonds, corporate bonds, and/or green bonds to the sample and incorporate new cryptocurrencies and other companies traded in the US market. By expanding the sample, a more comprehensive representation of the US market can be achieved, allowing for a more complete analysis of information transmission and spillovers across sectors. Studies could also compare other markets to the US to determine volatility spread patterns beyond what we studied here.

Abbreviations

BTC	Bitcoin
ETH	Ethereum
USDT	Tether
BNB	BNB
AAPL	Apple
MSFT	Microsoft
GOOGL	Alphabet
AMZN	Amazon
XOM	Exxon Mobil
CVX	Chevron
COP	ConocoPhillips
NEE	Nextera
VAR	Vector autoregressive

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Author contributions
A.A.: Conception and design of the study, Acquisition of data, Software, Formal analysis, Writing—Original Draft, Investigation, Visualization. K.G.: Writing—Review & Editing, Supervision. N.T.: Writing—Review & Editing, Co-Supervision.

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Availability of data and materials
The study uses daily price data from the Data Stream database between November 15, 2017, and October 28, 2022.

Declarations

Competing interests
The authors declare that they have no competing interests.

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