Received 12 February 2022
Revised 12 October 2022
13 December 2022
Accepted 15 January 2023

Interlinkages of cryptocurrency and stock markets during the COVID-19 pandemic by applying a QVAR model

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Abstract

Purpose – This paper aims to study the interlinkages between cryptocurrency and the stock market by characterizing their connectedness and the effects of the COVID-19 crisis on their relations.

Design/methodology/approach – The author employs a quantile vector autoregression (QVAR) to identify the connectedness of nine indicators from January 1, 2018, to December 31, 2021, in an effort to examine the relationships between cryptocurrency and stock markets.

Findings – The results demonstrate that the pandemic shocks appear to have influences on the system-wide dynamic connectedness. Dynamic net total directional connectedness implies that Bitcoin (BTC) is a net short-duration shock transmitter during the sample. BTC is a long-duration net receiver of shocks during the 2018–2020 period and turns into a long-duration net transmitter of shocks in late 2021. Ethereum is a net shock transmitter in both durations. Binance turns into a net short-duration shock transmitter during the COVID-19 outbreak before receiving net shocks in 2021. The stock market in different areas plays various roles in the short run and long run. During the COVID-19 pandemic shock, pairwise connectedness reveals that cryptocurrencies can explain the volatility of the stock markets with the most severe impact at the beginning of 2020.

Practical implications – Insightful knowledge about key antecedents of contagion among these markets also help policymakers design adequate policies to reduce these markets' vulnerabilities and minimize the spread of risk or uncertainty across these markets.

Originality/value – The author is the first to investigate the interlinkages between the cryptocurrency and the stock market and assess the influences of uncertain events like the COVID-19 health crisis on the dynamic interlinkages between these two markets.

Keywords Stock market, COVID-19 pandemic, Cryptocurrency, QVAR, Dynamic connectedness

Paper type Research paper

1. Introduction

More than a decade after Bitcoin (BTC) was introduced; cryptocurrencies are now regarded as attractive investments. Many scholars have even emphasized that futures markets play an important role in risk hedging. There is a distinct difference between the price fluctuations experienced by cryptocurrency (a new type of exchange asset) and those experienced by other financial assets (Corbet *et al.*, 2019), in part due to the uncertainty caused by shocks such as the current COVID-19 epidemic (Wang *et al.*, 2022). Besides, based on Sharif *et al.* (2020), COVID-19 has caused unprecedented volatility in the stock market and a surge in uncertainty

This research was supported by National Economics University, Hanoi, Vietnam.

European Journal of Management and Business Economics
Vol. 33 No. 1, 2024
pp. 74-95
Emerald Publishing Limited
e-ISSN: 2444-8494
p-ISSN: 2444-8451
DOI 10.1108/EJMBE-02-2022-0035

in US. economic policy. Since the beginning of 2020, circuit breakers were frequently activated on the major United States (US) stock market indices (such as the Dow Jones industrial average index, the S&P 500 Index, and the National Association of Securities Dealers Automated Quotations Stock Market (NASDAQ) 100 Index). Furthermore, in the meantime, Ethereum (ETH) prices dropped by approximately 44%, while BTC prices dropped by up to 50% in one day, making it the worst one-day decline ever. The first bear market since active BTC trading started in COVID-19 has generated significant losses (Conlon and McGee, 2020). The cryptocurrency market exhibited idiosyncratic characteristics of higher irregularity and instability than the equity market in the aftermath of the COVID-19 epidemic, according to Lahmiri and Bekiros (2020).

A number of recent studies have shown that there are asymmetric spillover effects between the stock market and the cryptocurrency market (Corbet *et al.*, 2019; Gil-Alana and Claudio-Quiroga, 2020; Kristjanpoller *et al.*, 2020; Lamothe-Fernández *et al.*, 2020). There have been contrasting conclusions regarding crypto currency's role and inconsistent findings regarding the relationship between cryptocurrencies and stock markets. Similarly, our paper contributes to the literature by extending its scope. Initially, we examine the interaction between cryptocurrencies and stock markets and determine the influence of unforeseen circumstances, such as the COVID-19 outbreak, on these dynamic relationships. In order to achieve this, we collect daily market capitalization data of the three most valuable cryptocurrencies (BTC, ETH and Binance coin (BNB)) and six stock indexes from global markets. Aside from New York Stock Exchanges and Shanghai Stock Exchanges (SSEs), Hong Kong Stock Exchanges (HSKEs), Japan Exchange Groups (JPXGYs) and Euronext, (London Stock Exchange Groups (LSEs) are also listed.)). The data in this study were collected between January 1, 2018, and December 31, 2021.

This article's primary research objective is to assess the uncertainty shock's severe effects on the dynamic connectedness between the volatility of the cryptocurrency and stock markets in order to provide important information to policymakers in order for them to accurately comprehend the contagion effects of the pandemic shock and design and implement policies to limit the volatility of these two markets. Our paper highlights how the COVID-19 crisis negatively impacted cryptocurrencies and stocks, which is the first time anyone has investigated this issue. Since the first, second and third waves of the COVID-19 pandemic, an analysis of changes in the stock market and the cryptocurrency market has become increasingly important as both production and investment activities have been curtailed as well as all investments have turned out to be highly risky. Cryptocurrencies are safer assets under these circumstances. Our study used an up-to-date database to reveal novel findings regarding uncertain events, whereas previous studies examined the impacts of global economic recession. Second, we employ a quantile vector autoregression (QVAR) to study this dynamic connectedness. Due to its various advantages, we choose this empirical approach. First, we do not lose any insight with this practical approach. Thus, it can be performed in cases of short data spans, though that is not the case here. Second, outliers do not significantly affect our results, whereas this approach allows us to adjust for parameter changes more effectively. As part of our strategy, we computed a pairwise connectedness metric, which helps identify transmission mechanisms between these financial and commodity markets. Through the use of daily data, this paper explores the impacts of cryptocurrency market changes on stock volatility in various regions, providing critical, insightful knowledge and warnings for investors and authorities.

Our results demonstrate that the pandemic shocks appear to influence the system-wide dynamic connectedness, which peaked during the Covid-19 pandemic. Dynamic net total directional connectedness implies that BTC is a net short-duration shock transmitter during our sample. BTC is a long-duration net receiver of shocks during the 2018–2020 period and turns into a long-duration net transmitter of shocks in late 2021. ETH is a net shock transmitter in both durations. Binance turns into a net short-duration shock transmitter during the COVID-19 outbreak before receiving net shocks in 2021. The US stock market transmits net shocks in both durations before 2021 and turns into a net short-duration shock receiver from 2021. The role of the US stock market in the long duration is opposite to the short duration from 2021. Asian stock markets (including Hong Kong, Japan and Shanghai) are net receivers in both duration during our sample. Europe stocks (including Euronext and London) are net receivers of shocks during the 2018–2020 period before turning to net transmitters of shocks from 2021 in both durations. During the COVID-19 pandemic shock, pairwise connectedness reveals that cryptocurrencies can explain the volatility of the stock markets with the most severe impact at the beginning of 2020.

Following is the structure of the remainder of the study. Related works are analyzed in Section 2. A summary of statistics and data is presented in Section 3. During Section 4, we will present the analytical results or analyses of the empirical results, while Section 5 will present conclusions.

2. Literature review

BTC market fluctuations become erratic and unpredictable during the health crisis. Unlike stocks and the US dollar, cryptocurrencies (such as BTC) present superior hedging opportunities compared to other financial assets (Bouri *et al.*, 2019; Hu *et al.*, 2019; Kostika and Laopodis, 2019; Miglietti *et al.*, 2019; Sahoo, 2021). In response, investors diversified their portfolios throughout the outbreak of the virus to find short-term investments that were safe and profitable. Cryptocurrencies were used as a means of payment during COVID-19, which spread quickly around the world. Majdoub *et al.* (2021) and Umar *et al.* (2021) assert that cryptocurrencies can be used as investment options during unstable economic times like the COVID-19 economic crisis due to their potential link between foreign exchange and cryptocurrency markets. This plan profoundly affects managing portfolio risk, allocating strategic assets and pricing financial instruments (Umar and Gubareva, 2020). BTC's value plummeted, as well as the value of other cryptocurrencies in 2020, causing investors to change their decisions (Chen *et al.*, 2020). This has resulted in a more volatile and unpredictable crypto market during the COVID-19 crisis (Lahmiri and Bekiros, 2020) and neither did Conlon and McGee (2020). There has been significant research on BTC markets during the epidemic (Umar *et al.*, 2021). However, a small number of studies have focused explicitly on or paid close attention to cryptocurrencies due to the scattered research interests. For example, Bouri *et al.* (2021) use the daily price data of seven leading cryptocurrencies from August 8, 2015, to December 31, 2020, to indicate the connectedness measures in the left and right tails are much higher than those in the mean and median of the conditional distribution. There is evidence that return connectedness increases with shock size for both positive and negative shocks, indicating that return shocks propagate more intensely during extreme events than during calm periods. Naeem *et al.* (2022) calculate the spillover effects among seven cryptocurrencies to explore the spillover characteristics of seven cryptocurrencies, namely, BTC, ETH, Ripple, Litecoin, Monero, Stellar and New Economy Movement (NEM). The connectedness networks of returns are based on standard Vector Autoregression (VAR) and quantile VAR spillovers. In addition, the framework focuses on intact, pre-, and post-COVID-19 crisis subsample periods. They highlight that BTC, Litecoin and Ripple are the dominant transmitters to return spillover. During the outbreak of COVID-19 in Europe and the United States of America (USA), Ali *et al.* (2020) examined financial market volatility, concluding that global markets collapsed in March 2020 as the outbreak of the U.S. pandemic had significant implications on even safer commodities.

In their 2020 paper, Corbet *et al.* discuss how COVID-19 might contagiously affect gold and cryptocurrency, suggesting cryptocurrencies might serve the same purpose during economic downturns as precious metals. Gharib *et al.* (2021) demonstrated a bilateral contagion effect on gold and oil prices when COVID-19's economic effects modified the relationship between these two markets. Abakah *et al.* (2023) investigate the distributional and directional predictabilities among Fintech, BTC and artificial intelligence stocks from March 2018 to January 2021 using nonparametric causality-in-quantile and cross quantilogram approaches. They reveal the existence of bidirectional causality-in-variance between the variables in a normal market.

The eight economies' financial industries are impacted by COVID-19, according to Rizwan *et al.* (2020). It has been found that the correlation between price volatility shocks in the oil market, geopolitical risks and economic policy uncertainty is closely related to the spread of COVID-19 in the USA, according to Sharif *et al.* (2020). The researchers have identified COVID-19 as a geopolitical threat. COVID-19 is associated with cryptocurrency markets in such a way. Despite the fact that the current literature focuses primarily on the relationship between gold and cryptocurrencies, or oil and cryptocurrency markets, the authors have sought to examine the relationship between COVID-19 and the cryptocurrency market in light of the lack of research focusing entirely and mainly on this market's fluctuation.

The COVID-19 spread has also been associated with the cryptocurrency market in previous studies (Salisu and Ogbonna, 2022; Umar *et al.*, 2021). This relationship is revealed to be inconsistent, which is a concern of the authors. The literature has revealed empirical evidence of an asymmetric spillover effect between the stock market and the cryptocurrency market in regard to the correlation between the two markets. In an article published in April 2020, Lamothe-Fernández *et al.* (2020) argue that cryptocurrency price volatility is caused partly by the halving of the supply and the hash rate each year. There is a risk of spillovers occurring when there is a severe economic, financial or public health crisis, and there is also no circuit breaker on the BTC market, unlike the stock market in the USA. Therefore, there may be an end to the decline of US stocks in some manner. Unlike conventional stock markets, cryptocurrencies have maintained a downward or upward trend, increasing asymmetry. Hence, it is possible to include cryptocurrencies in investment portfolios to provide diversification of risks. This observation is supported by Corbet *et al.* (2019) and Gil-Alana and Claudio-Quiroga (2020). In most cases, cryptocurrency, however, does not provide useful hedging strategies for stock markets due to the positive correlations found in most cases (Kristjanpoller *et al.*, 2020). It is found from these analyses that cryptocurrencies' price fluctuations differ over time from those of US market indices. The spillover influences between conventional financial markets and cryptocurrency markets were investigated by Matkovskyy and Jalan (2019) using a regime-switching model. Clearly, spillover effects exist between these markets based on their results. López-Cabarcos *et al.* (2021) reported similar results.

Our paper differs from previous work by studying the dynamic interconnectedness between cryptocurrency and various global stock markets by applying the QVAR approach. We also highlight the shift in each market's role during extreme events like the COVID-19 pandemic. Our empirical approach reveals novel findings and mechanisms for the interaction between two important markets, especially during uncertain times.

3. Data and methodology

3.1 Data sample

The present article utilizes the daily data of the three largest cryptocurrencies based on market capitalization, including *BTC*, *ETH* and *BNB*, and six stock indices from the global stock market, including SP500 stock index of the U.S. (*SP500*), *SSE*, *HSKE*, *JPXGY*, Euronext (*EURONEXT*) and *LSE*. Our data is collected from January 1, 2018, to December 31, 2021. Our paper studies the dynamic interlinkages between cryptocurrency and stock markets. Since the cryptocurrency market does not close at the end of the day, we collect the daily price data, which specialized crypto companies and websites proxy cryptocurrency daily prices by using weighted prices (Vidal-Tomás, 2021). This price type represents the average of the prices across the 24-h period. We also use a similar approach to compute the weighted prices of the stock market. It is widely known that trading times for cryptocurrency markets are 24/7, and the trading day is mostly defined as 12:00 am–11:59 pm Universal Time (UTC), while conventional stock exchanges trade roughly 9/5 local time. Therefore, we must merge cryptocurrency market data (high-frequency data) with stock exchange trade data (low-frequency data). Missing data for stock market trading due to weekends, holidays and asynchronous trading times, while a similar issue does not happen for the cryptocurrency market. Merging data in this way can solve this issue. Since we used the average of the prices across the 24-h period, the difference in closing time between various stock markets (SP500 stock index of the U.S., SSE, HSKE, JPXGY, Euronext and LSE).

In terms of whole observations, all series in Table 1 are reported with a positive average return. The BNB and ETH markets have the highest variance, making the two markets the riskiest assets throughout the sample periods, as indicated in Panel A. Figure 1 demonstrates the volatility of these series. Furthermore, this research finds that all of the series are leptokurtic, which means the distributions have fatter tails than a normal distribution. According to Jarque and Bera (1980), all assets are substantially non-normally distributed. All results are at least on the 1% significance level when using the unit root test by Elliott *et al.* (1996). Finally, Fisher and Gallagher (2012) found that the returns and squared returns are autocorrelated, implying that the interlinkages of the series may be modeled using a QVAR method with a time-varying variance-covariance structure. Since the research aims to find the linkages between cryptocurrencies and the stock market, we examine the interconnectedness of these two markets before and during the COVID-19 pandemic.

Panel B and Panel C highlight the main statistics of two subsamples, each having identical statistics as Panel A. The data used to split the two periods (before and post-COVID) is based on the Public Health Organization's (WHO, 2020) set timeframe, which publicly revealed the coronavirus pandemic of 2019 (COVID-19) to the world for the first time on December 31, 2019. As a result, we divided the two periods into classifications: pre-COVID-19 (from January 1, 2018, to December 31, 2019) and post-COVID-19 (from January 1, 2020, to December 31, 2021). Table 1 highlights considerable distinctions in statistics of these included series in two periods. Surprisingly, a positive average return in the post-COVID-19 period is reported for all included variables except for LSE. Moreover, the mean return of *BTC, ETH* and *BNB* increased from the start of the COVID-19 health crisis, while the value of BTC and ETH changed from negative in return to positive. In addition, except for SSE, other markets became volatile during the post-COVID-19 period as all variances increased. The results of the Elliott, Rothenberg and Stock (ERS) unit root test and the weighted portmanteau test on these variables during these two periods are more likely to be the same as those obtained from tests on the entire sample, leading us to believe that modeling the interconnectedness of the series using a QVAR approach with a time-varying variance-covariance structure is a well-supported.

3.2 Empirical methodology

We use the quantile connectedness technique (Chatziantoniou *et al.*, 2021) to investigate the spreading structure between cryptocurrency volatility and renewable energy volatility. We begin to estimate a QVAR(p), and then compute all connectedness metrics using this model.

$$z_t = \boldsymbol{\mu}_t(\tau) + \mathbf{d}_1(\tau) z_{t-1} + \mathbf{d}_2(\tau) z_{t-2} + \ldots + \mathbf{d}_p(\tau) z_{t-p} + \boldsymbol{u}_t(\tau). \quad (1)$$

Table 1. Summary statistics

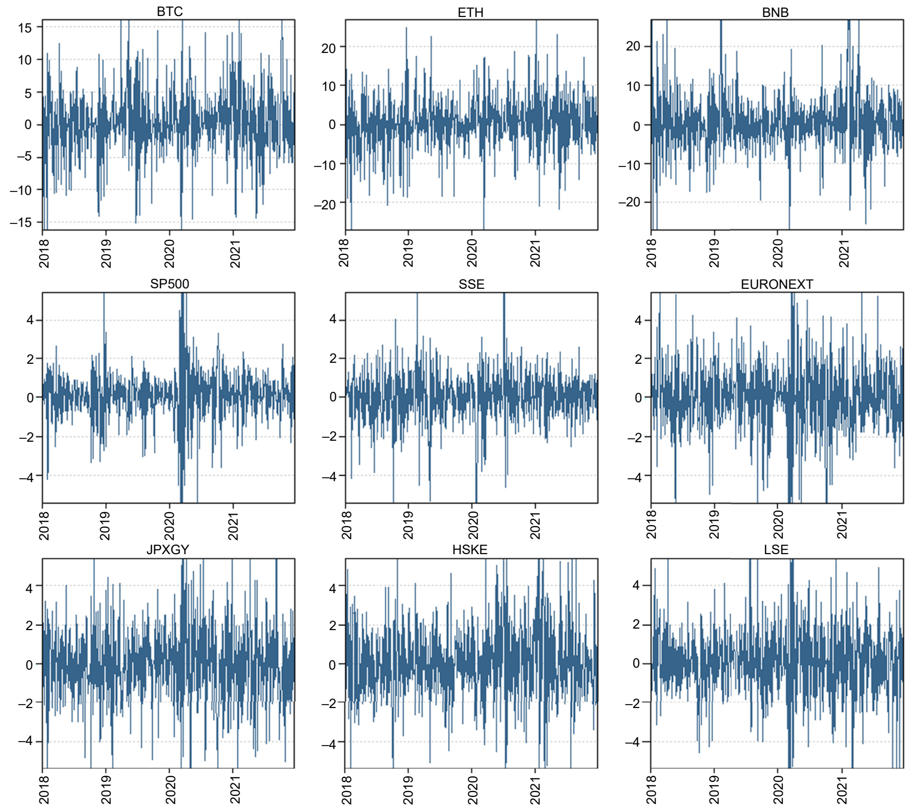
	BTC	ETH	BNB	SP500	SSE	EURONEXT	JPXGY	HSKE	LSE
Panel A: Whole sample									
Whole sample									
Mean	0.1349	0.1697	0.4562	0.062	0.0093	0.0597	0.0251	0.0654	0.0695
Variance	25.2293	43.3539	56.5131	1.9764	1.4571	3.2521	3.5031	3.588	3.6577
Skewness	−0.893***	−0.617***	0.221***	−1.004***	−0.346***	0.226***	−0.135*	0.084	−0.144*
	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	(0.006)	(0.096)	(0.300)	(0.075)
Kurtosis	10.049***	7.281***	11.495***	16.649***	5.399***	9.681***	2.289***	2.761***	10.738***
JB	3928.192***	2056.557***	4989.956***	10604.336***	1117.402***	3541.961***	200.300***	288.542***	4351.433***
ERS	−10.929***	−4.286***	−5.420***	−8.933***	−9.586***	−13.690***	−5.723***	−12.724***	−13.300***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	35.375**	31.439**	23.780*	286.692***	37.583***	40.319***	17.265	20.572	41.702***
	(0.018)	(0.050)	(0.252)	(0.000)	(0.010)	(0.005)	(0.636)	(0.423)	(0.003)
Q^2(20)	18.992**	23.390***	97.652***	1083.912***	25.756***	319.568***	31.974***	90.537***	58.800***
	(0.026)	(0.004)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Pre-COVID-19 Pandemic									
Pre-COVID-19 Pandemic									
Mean	−0.1616	−0.423	0.097	0.0399	−0.0205	0.0739	5e-04	0.0025	0.1604
Variance	23.8119	39.2743	55.1085	0.9635	1.5171	2.2228	2.6536	2.6598	2.4219
Skewness	−0.259**	−0.218*	0.256**	−0.426***	−0.301***	−0.691***	−0.265**	−0.193*	1.731***
	(0.024)	(0.057)	(0.026)	(0.000)	(0.009)	(0.000)	(0.021)	(0.091)	(0.000)
Kurtosis	3.260***	2.266***	9.807***	4.401***	2.719***	4.950***	1.648***	1.617***	15.529***
JB	206.117***	100.754***	1824.155***	380.153***	146.746***	499.570***	56.690***	52.256***	4788.632***
ERS	−7.096***	−2.824***	−3.537***	−5.544***	−6.852***	−9.659***	−3.891***	−8.840***	−10.663***
	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	36.766**	22.740	22.067	15.604	39.750***	22.188	19.413	23.196	15.173
	(0.013)	(0.302)	(0.337)	(0.741)	(0.005)	(0.330)	(0.495)	(0.279)	(0.766)
Q^2(20)	30.927***	23.409***	46.610***	78.484***	28.712***	14.344	13.452	30.831***	10.945
	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.152)	(0.202)	(0.000)	(0.407)
Panel C: Post-COVID-19 Pandemic									
Post-COVID-19 Pandemic									
Mean	0.4408	0.7718	0.8312	0.0827	0.037	0.0405	0.0473	0.1225	−0.0205
Variance	26.568	46.9366	57.8382	3.0048	1.3985	4.2932	4.3713	4.5155	4.9033

(*continued*)

Table 1.

	BTC	ETH	BNB	SP500	SSE	EURONEXT	JPXGY	HSKE	LSE
Skewness	−1.466***	−0.980***	0.179	−1.024***	−0.387***	0.574***	−0.079	0.174	−0.733***
	(0.000)	(0.000)	(0.118)	(0.000)	(0.001)	(0.000)	(0.486)	(0.128)	(0.000)
Kurtosis	15.902***	11.162***	13.145***	13.410***	8.580***	9.541***	2.114***	2.672***	7.615***
JB	4902.485***	2408.121***	3242.086***	3450.172***	1391.426***	1731.673***	84.261***	136.153***	1127.532***
ERS	−4.358***	−5.550***	−6.278***	−6.063***	−10.164***	−10.721***	−8.071***	−4.004***	−7.190***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q(20)$	30.159*	25.804	29.320*	236.510***	18.789	33.751**	23.144	27.757	39.520***
	(0.067)	(0.172)	(0.082)	(0.000)	(0.536)	(0.028)	(0.282)	(0.115)	(0.006)
$Q^2(20)$	9.270	11.324	88.582***	544.370***	15.512	190.787***	15.250	45.970***	39.520***
	(0.586)	(0.370)	(0.000)	(0.000)	(0.102)	(0.000)	(0.111)	(0.000)	(0.000)

Note(s): ***,**,* denote significance at 1%, 5% and 10% significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott *et al.* (1996) unit-root test with constant; $Q(10)$ and $Q2(10)$: Fisher and Gallagher (2012) weighted portmanteau test
Source(s): Authors' calculations



Source(s): Authors' calculations

Figure 1.
Changes in volatility degrees in the cryptocurrency and stock market

where $\mathbb{z}_t$ and $\mathbb{z}_{t-i}$, $i = 1, \ldots, p$ are $N \times 1$ dimensional endogenous variable vectors, τ is between [0, 1] and describes the quantile of indicator, p illustrates the lag length of the QVAR model, $\boldsymbol{\mu}(\tau)$ is an $N \times 1$ dimensional conditional mean vector, $\mathbf{d}_j(\tau)$ is an $N \times N$ dimensional QVAR coefficient matrix, and $\boldsymbol{u}_t(\tau)$ demonstrates the $N \times 1$ dimensional error vector, which has an $N \times N$ dimensional variance-covariance matrix, $\sum(\tau)$. The approach of Wold is employed to convert the QVAR(p) to its Quantile Vector Moving Average (QVMA)(∞) description: $\mathbb{z}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \mathbf{d}_j(\tau)\mathbb{z}_{t-j} + \boldsymbol{u}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \mathbf{Z}_i(\tau)\boldsymbol{u}_{t-i}$.

Consequently, our research estimate the generalized forecast error variance decomposition (GFEVD) (Koop *et al.*, 1996; Pesaran and Shin, 1998), which is the center of the connectedness technique [1]. The GFEVD, which has the general structure, may be used to determine the effect that a shock in series j has on variable i with regard to the variance of its forecast error:

$$\Upsilon_{ij}(\breve{U}) = \frac{(\boldsymbol{\Sigma}(\tau))_{jj}^{-1} \sum_{\breve{u}=0}^{\breve{U}-1} \left((\mathbf{Z}_h(\tau)\boldsymbol{\Sigma}(\tau))_{ij}\right)^2}{\sum_{\breve{u}=0}^{\breve{U}} (\mathbf{Z}_h(\tau)\boldsymbol{\Sigma}(\tau)\mathbf{Z}_h'(\tau))_{ii}} \quad (2)$$

$$\widetilde{\Upsilon}_{ij}(H) = \frac{\Upsilon_{ij}(\breve{\text{U}})}{\sum_{k=1}^{N}\Upsilon_{ij}(\breve{\text{U}})} \tag{3}$$

where $\widetilde{\Upsilon}_{ij}(\breve{\text{U}})$ illustrates the effects of the j th series on the variance of the forecast error of the i th series at horizon Ŭ. We must standardize the rows of $\widetilde{\Upsilon}_{ij}(\breve{\text{U}})$ because they do not even add up to one, which yields $\widetilde{\Upsilon}_{ij}$. We achieve the next identities by standardization: $\sum_{i=1}^{N}\widetilde{\Upsilon}_{ij}(\breve{\text{U}}) = 1$ and $\sum_{j=1}^{N}\sum_{i=1}^{N}\widetilde{\Upsilon}_{ij}(H) = N$.

All connectedness metrics can be calculated in a subsequent phase. We begin by computing the net pairwise connectedness as follows:

$$NPDC_{ij}(\breve{\text{U}}) = \widetilde{\Upsilon}_{ij}(\breve{\text{U}}) - \widetilde{\Upsilon}_{ji}(\breve{\text{U}}). \tag{4}$$

If $NPDC_{ij}(\breve{\text{U}}) > 0$ ($NPDC_{ij}(\breve{\text{U}}) < 0$, it denotes that series j impacts series i more (less) than the other way around.

The effect of a shock in indicator i transmitted to all other indicators j is described by the *total directional connectedness TO others:*

$$TO_i(\breve{\text{U}}) = \sum_{i=1, i\neq j}^{N}\widetilde{\Upsilon}_{ji}(\breve{\text{U}}) \tag{5}$$

The effect of a shock in indicator i receiving to all other indicator j is described by the *total directional connectedness FROM others:*

$$FROM_i(\breve{\text{U}}) = \sum_{i=1, i\neq j}^{N}\widetilde{\Upsilon}_{ij}(\breve{\text{U}}) \tag{6}$$

The *net total directional connectedness* may be considered the impact series i has on the system under study since it is the difference between TO others and FROM others.

$$NET_i(\breve{\text{U}}) = TO_i(\breve{\text{U}}) - FROM_i(\breve{\text{U}}) \tag{7}$$

If the $NET_i > 0$ ($NET_i < 0$), all other series i have a greater (lesser) impact on them than they have on us. As a result, it is regarded as a net shock transmitter (receiver).

The following formulas can be used to determine the total connectedness index (TCI), which gauges the degree of network interconnectedness:

$$TCI(\breve{\text{U}}) = N^{-1}\sum_{i=1}^{N} TO_i(\breve{\text{U}}) = N^{-1}\sum_{i=1}^{N} FROM_i(\breve{\text{U}}) \tag{8}$$

This metric, then, shows the average effect of a shock in one series on all others. The risk associated with the market increases as its value increases, and vice versa.

Our research has been concentrating on the time domain connectedness assessment so far. In a similar vein, we keep up with the connectedness evaluation in the frequency area. We may investigate the connectivity connection in the frequency domain by employing a spectral decomposition technique. We start by exploring function: $Z(\boldsymbol{e}^{-\boldsymbol{i\omega}}) = \sum_{\breve{\text{u}}=0}^{\infty} e^{-iwh} Z_{\breve{\text{u}}}$, where $i = \sqrt{-1}$ and ω illustrates the frequency to keep up with the spectral density of x_t at frequency ω which can be illustrated as a Fourier transformation of the QVMA(∞):

$$\boldsymbol{S}_{\mathbb{z}}(\omega) = \sum_{\breve{\text{u}}=-\infty}^{\infty} E(\mathbb{z}_t \mathbb{z}'_{t-h})\, e^{-iwh} = Z(e^{-i\omega h})\sum\nolimits_t Z(e^{+i\omega h}) \tag{9}$$

Combining the spectral density and the GFEVD yields the frequency GFEVD. Similar to the time domain situation, the frequency GFEVD has to be normalized. This may be done by formulating it regards:

$$\Upsilon_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1}\left|\sum_{\breve{u}=0}^{\infty}(Z(\tau)(e^{-iwh})\Sigma(\tau))_{ij}\right|^2}{\sum_{\breve{u}=0}^{\infty}(Z(e^{-iwh})\Sigma(\tau)Z(\tau)(e^{iwh}))_{ii}} \tag{10}$$

$$\widetilde{\Upsilon}_{ij}(\omega) = \frac{\Upsilon_{ij}(\omega)}{\sum_{k=1}^{N}\Upsilon_{ij}(\omega)} \tag{11}$$

where $\widetilde{\Upsilon}_{ij}(\omega)$ denotes the portion of the ith variable's spectrum at a certain frequency ω that may be assigned to a shock in the jth series. As a within-frequency indication, it may be understood.

Instead of measuring connectedness at a single frequency, we combine all frequencies within a certain range to evaluate both short-duration and long-duration connectedness, $d = (a, b) : a, b \epsilon (-\pi, \pi), a < b :$

$$\widetilde{\Upsilon}_{ij}(d) = \int_a^b \widetilde{\Upsilon}_{ij}(\omega)d\omega \tag{12}$$

From this point, we can compute the accurate same connectedness estimates as Diebold and Yilmaz (2012, 2014), which may be evaluated the same way. Nevertheless, in this instance, frequency interconnectedness estimates provide details on spread within a specific frequency range d:

$$NPDC_{ij}(d) = \widetilde{\Upsilon}_{ij}(d) - \widetilde{\Upsilon}_{ji}(d) \tag{13}$$

$$TO_i(d) = \sum_{i=1, i\neq j}^{N} \widetilde{\Upsilon}_{ji}(d) \tag{14}$$

$$FROM_i(d) = \sum_{i=1, i\neq j}^{N} \widetilde{\Upsilon}_{ij}(d) \tag{15}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{16}$$

$$TCI(d) = N^{-1}\sum_{i=1}^{N} TO_i(d) = N^{-1}\sum_{i=1}^{N} FROM_i(d) \tag{17}$$

All measurements offer data on the precise range but not on the overall impact. In accordance with the overall methodology, Baruník and Křehlík (2018) recommend weighing all contribution metrics of each frequency band by, $\Gamma(\mathrm{d}) = \sum_{i,j=1}^{N}\widetilde{\Upsilon}_{ij}(d)/N$.

$$\widetilde{NPDC}_{ij}(d) = \Gamma(\mathrm{d}) \cdot NPDC_{ij}(d) \tag{18}$$

$$\widetilde{TO}_i(d) = \Gamma(\mathrm{d}) \cdot TO_i(d) \tag{19}$$

$$\widetilde{FROM}_i(d) = \Gamma(\mathrm{d}) \cdot FROM_i(d) \tag{20}$$

$$\widetilde{NET}_i(d) = \Gamma(\mathrm{d}) \cdot NET_i(d) \tag{21}$$

$$\widetilde{TCI}(d) = \Gamma(\mathrm{d}) \cdot TCI(d) \tag{22}$$

Finally, we demonstrate the correspondence between the Baruník and Křehlík (2018) frequency-domain measurements and the Diebold and Yilmaz (2012, 2014) time-domain estimates:

$$NPDC_{ij}(\breve{U}) = \sum_{d} NPDC_{ij}(d) \tag{23}$$

$$TO_{i}(\breve{U}) = \sum_{d} TO_{i}(d) \tag{24}$$

$$FROM_{i}(\breve{U}) = \sum_{d} FROM_{i}(d) \tag{25}$$

$$NET_{i}(\breve{U}) = \sum_{d} NET_{i}(d) \tag{26}$$

$$TCI(\breve{U}) = \sum_{d} TCI(d) \tag{27}$$

4. Results

The average and dynamic results for the connectedness metrics are shown in the next section. The TCI average value is calculated based on the whole sample of data. TCI is first presented, after which a dynamic evolution of the TCI over time is demonstrated. Understanding how the TCI responds to different economic scenarios requires the latter approach. Political patterns are also seen within the time frame of our investigation. We evaluate net pairwise and net total connectedness data in our suggested framework. This relationship improves our understanding of the market for four indicators, including the geopolitical risks index and prices of corn, wheat and rice. Remembering that each indication can act as either a transmitter or receiver of net shocks is crucial. Finally, we employ the dynamic spillover index created by Chatziantoniou *et al.* (2021) and Diebold and Yilmaz (2012, 2014). These results might be used to investigate the reasons for changes in the networks connecting various measures.

4.1 Variation in average dynamic connectivity over time

Table 2 shows the average outcomes for the interlinkages of various indicators inside the network using the entire data set from January 1, 2018, to December 31, 2021. The diagonal part of this table describes the change of a single indicator driven by its own shocks. In comparison, the off-diagonal components describe how the instability of this indicator influences that of other indicators (FROM) and how other indicators impact the instability of this indicator (TO). The columns display the independent effects of each type of indicator on one another, whereas Table 2 specifically displays the influence of each indicator on the forecast error variance of each other.

The TCI average value for the entire set of data is 40.95%. It is proven that changes to this network might be responsible for 40.95% of the volatility in the network of indicators under investigation. This shows that idiosyncratic causes cause about 60% of the system's error variation. The contribution of each indicator is displayed in the last row of Table 2. The transmission of shocks and volatility to other system indicators is significantly influenced by ETH, SP500. Many previous studies also reached the same conclusion as our paper, such as Shahzad *et al.* (2021), Sui *et al.* (2022). Moreover, BTC, BNB and LSE are net shock transmitters in the network. In contrast, *JPXGY* is the most susceptible to shocks. It is worth noting that the *JPXGY, SSE, EURONEXT* and *HSKE* absorb the net of shocks in our network. Most cryptocurrencies play a major role in transmitting shocks to the stock market.

Table 2. Averaged Joint connectedness

	BTC	ETH	BNB	SP500	SSE	EURONEXT	JPXGY	HSKE	LSE	FROM
Panel A: Total										
Whole sample										
BTC	45.10	29.10	19.22	2.77	0.53	0.70	0.90	0.34	1.34	54.90
ETH	28.43	44.15	20.43	2.76	0.59	0.81	1.09	0.82	0.92	55.85
BNB	20.56	22.39	49.14	2.78	0.90	0.96	1.32	0.77	1.19	50.86
SP500	3.46	3.80	3.31	62.64	3.90	5.47	7.77	3.75	5.91	37.36
SSE	1.42	1.61	1.58	5.47	62.45	2.21	1.60	20.48	3.18	37.55
EURONEXT	1.19	1.62	1.47	6.29	2.06	67.40	1.65	3.76	14.56	32.60
JPXGY	1.86	2.54	2.58	11.04	2.37	2.25	72.75	2.28	2.33	27.25
HSKE	0.68	1.47	1.09	6.98	19.68	3.94	2.33	60.22	3.62	39.78
LSE	1.75	1.39	1.63	7.40	2.02	14.31	1.33	2.56	67.60	32.40
To	59.35	63.92	51.32	45.49	32.04	30.63	17.98	34.77	33.05	TCI
NET	4.45	8.07	0.46	8.13	−5.51	−1.97	−9.27	−5.02	0.65	40.95
Panel B: 1–5										
1–5										
BTC	39.11	25.37	16.67	2.40	0.44	0.59	0.79	0.28	1.20	47.75
ETH	25.18	38.55	17.94	2.42	0.50	0.65	0.97	0.65	0.82	49.13
BNB	18.00	19.59	42.54	2.48	0.76	0.79	1.17	0.59	1.04	44.42
SP500	3.20	3.45	3.11	55.40	3.59	4.93	7.09	3.28	5.31	33.96
SSE	1.24	1.32	1.22	4.21	53.94	1.77	1.32	17.32	2.57	30.96
EURONEXT	0.98	1.36	1.21	5.35	1.82	57.90	1.42	3.17	12.74	28.05
JPXGY	1.63	2.19	2.34	9.82	2.16	1.85	62.88	2.04	1.95	23.97
HSKE	0.58	1.15	0.89	5.41	17.31	3.19	1.89	51.96	2.88	33.30
LSE	1.51	1.24	1.44	6.16	1.92	12.46	1.12	2.34	58.78	28.19
To	52.32	55.68	44.81	38.25	28.50	26.22	15.77	29.68	28.51	TCI
NET	4.57	6.54	0.39	4.30	−2.46	−1.84	−8.20	−3.62	0.32	35.53
Panel C: 5-inf										
5-inf										
BTC	5.99	3.73	2.56	0.37	0.09	0.11	0.11	0.05	0.13	7.15
ETH	3.25	5.60	2.49	0.34	0.09	0.16	0.12	0.18	0.10	6.72

(*continued*)

Table 2.

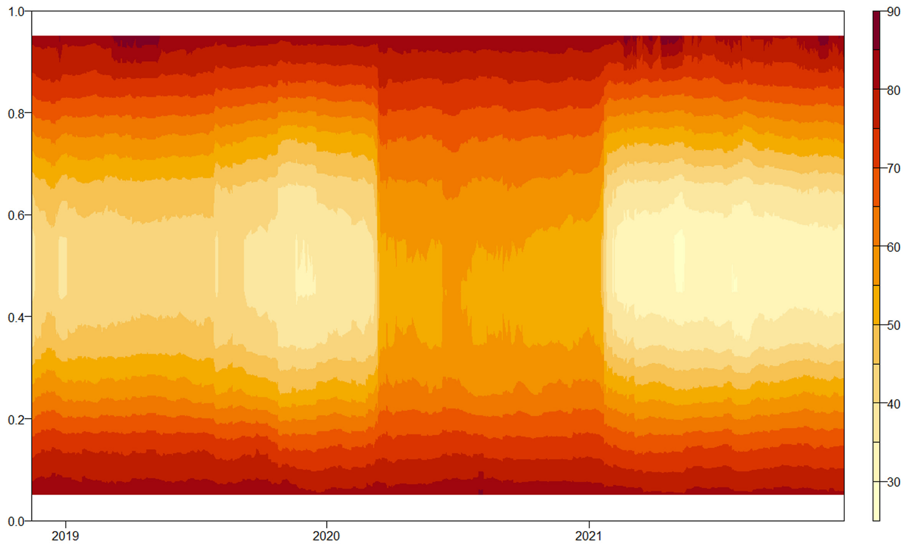
	BTC	ETH	BNB	SP500	SSE	EURONEXT	JPXGY	HSKE	LSE	FROM
BNB	2.56	2.80	6.60	0.30	0.14	0.17	0.15	0.18	0.15	6.44
SP500	0.27	0.35	0.20	7.24	0.31	0.54	0.67	0.47	0.60	3.40
SSE	0.18	0.28	0.36	1.27	8.51	0.44	0.28	3.16	0.61	6.59
EURONEXT	0.22	0.26	0.26	0.94	0.24	9.49	0.23	0.59	1.82	4.55
JPXGY	0.23	0.35	0.24	1.22	0.21	0.40	9.87	0.23	0.39	3.27
HSKE	0.09	0.32	0.20	1.57	2.37	0.75	0.44	8.26	0.74	6.48
LSE	0.24	0.15	0.20	1.23	0.11	1.85	0.21	0.22	8.82	4.22
To	7.03	8.24	6.51	7.24	3.54	4.42	2.21	5.09	4.54	TCI
NET	−0.11	1.52	0.07	3.84	−3.05	−0.13	−1.07	−1.39	0.32	5.42

Note(s): Results are based on a QVAR model with a lag length of order one (Bayesian Information Criterion (BIC)) and a 20-step-ahead generalized forecast error variance decomposition. Panel B and C are the results of the fluctuation in the system's forecast uncertainty in the short run and long run
Source(s): Authors' calculations

This analysis explores the notion that each indicator has a varied role throughout various times by dividing the observational portions into short duration and long duration. The system of all indicators (TCI is 35.53%) can partially explain the short-duration history of the system. Similarly, idiosyncratic effects can account for around 65% of the system's forecast uncertainty fluctuation in the short duration. Long-term, nevertheless, this number has significantly dropped to 5.42%. These findings support the notion that these indicators commonly move in lockstep, especially for short-duration or long-term. *SSE, EURONEXT, JPXGY* and *HSKE* have been net receivers of network shocks in both durations, respectively. On the contrary, *ETH, BNB, SP500* and *LSE* are net transmitters of shocks in both two durations. In the long term, BTC changes from a net transmitter of shocks in short duration to a net receiver of shock. We can empirically show that, except for BTC, the connectedness of cryptocurrency and stock markets in short duration is similar to long duration. Moreover, cryptocurrency helps to describe the erratic nature of the stock markets.

4.2 Dynamic total connectedness

Figure 2 displays the findings for total dynamic connectedness over a quantile. Warmer colors on the graph indicate larger levels of interconnectedness. An intense correlation occurs between changes in the geopolitical risks and the commodities market that are strongly negative and those that are strongly positive (below the 20% quantile and above the 80% quantile). In other words, it appears that the impact is symmetrical. Additionally, 50% is the median quantile of connectedness throughout the whole time. Colors along the vertical axis represent times when there is greater uncertainty across quantiles, indicating a generalized financial and economic crisis. In our situation, it is easy to distinguish between the COVID-19 epidemic. Additionally, we find that market risk is higher since the start of the COVID-19 epidemic when market interconnection dramatically increased across all quantiles. The interconnectedness around the y-axis is interestingly quite symmetric, suggesting that spillovers between very positive and negative returns behave similarly.



Source(s): Authors' calculations

Figure 2. Dynamic net total directional connectedness over a quantile

The findings about the net spread shocks of each indicator are of great importance in the literature on connectedness. In this particular instance, it carries crucial data for risk managers and investors. The long-duration dynamics are fully accountable for the roles of nine indicators, being a net shock transmitter or receiver, while the short-duration net spread mechanism paints a helpful overview. Our article analyses the net total directional connectedness in both two durations in Figure 3. For BTC, we notice that its role depends on the study period. BTC is a net short-duration shock transmitter during our sample. BTC is a long-duration net receiver of shocks during the 2018–2020 period and turns into a long-duration net receiver of shocks from late 2021. ETH is a net shock transmitter in both durations. BNB turns into a net short-duration shock transmitter during the COVID-19 outbreak before receiving net shocks in 2021. SP500 transmits net shocks in both durations before 2021 and turns into a net short-duration shock receiver from 2021. The role of SP500 in long duration is opposite to short duration from 2021. SSE, HSKE and JPXGY are net receivers in both duration during our sample. Specifically, TCI values of JPXGY and HSKE reach a peak at the beginning of the COVID-19 epidemic. EURONEXT and LSE are net receivers of shocks during the 2018–2020 period before turning to net transmitters of shocks from 2021 in both durations.

Then we focus on net total directional connectedness over a quantile. As illustrated in Figure 4, this. On these graphs, a currency net transmitter is indicated by warmer colors. Figure 4c demonstrates that, among all the indicators, the geopolitical risks index has had the most consistent reaction. The incident between 2020 and 2021 (COVID–19) is significant. BTC and ETH are significant transmitters of shocks all over quantiles during the outbreak of COVID-19. BNB is a net shock transmitter during 2020 in the median quantile, while BNB has almost no impact on the system in other periods. SP500 is a net transmitter of shocks before 2021 and turns into a net shock receiver from 2021 all over quantiles. SSE, HSKE and Japan Exchange Group (JPXGX) are net shock receivers during the COVID-19 outbreak over all quantiles. EURONEXT is a net shock receiver from 2020 all over quantiles and turns into a

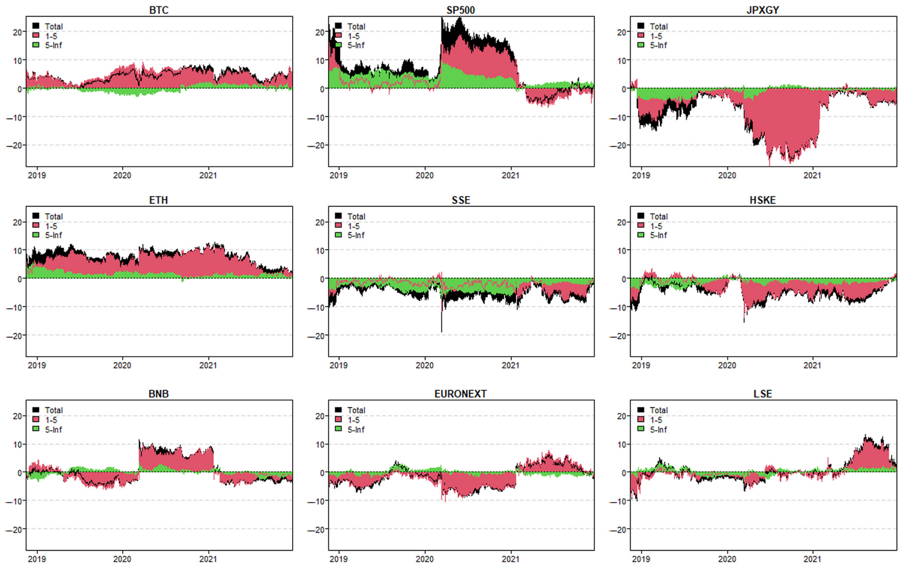
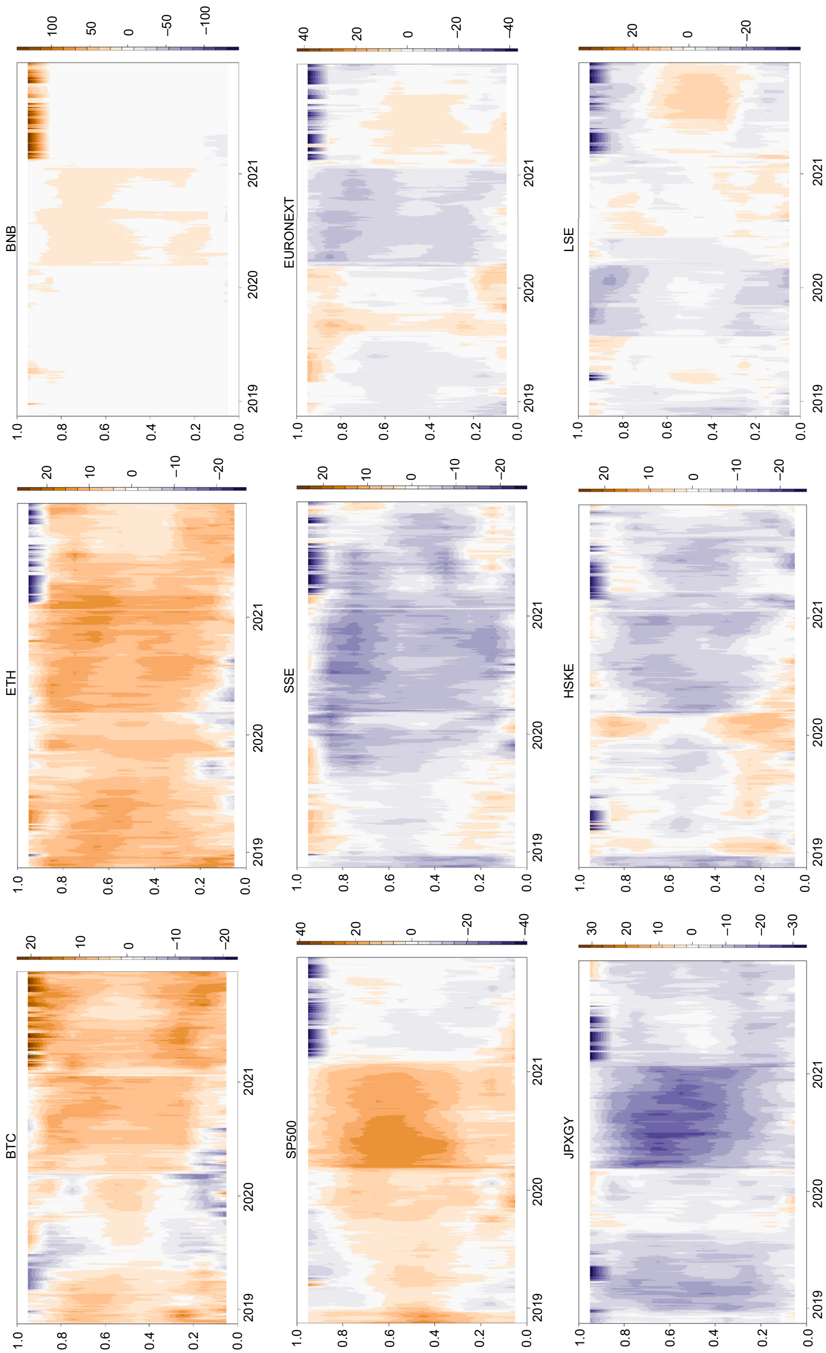


Figure 3.
Dynamic net total directional connectedness: QVAR

Source(s): Authors' calculations



Source(s): Authors' calculations

Figure 4.
Dynamic net total directional connectedness: QVAR

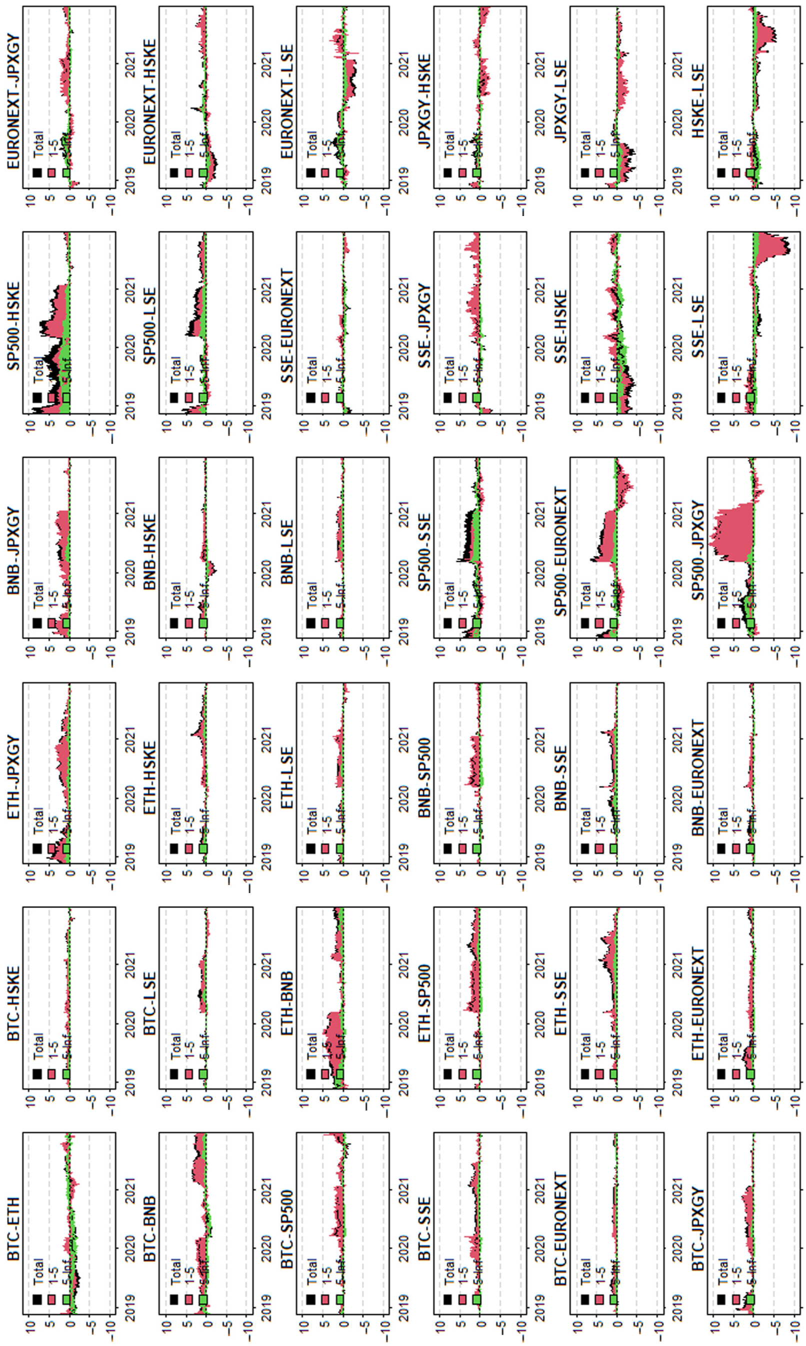
net transmitter of shocks from 2021 below 60% quantile. LSE is a net shock transmitter of shocks during 2020 below the 20% quantile and over 80% quantile.

Finally, to fully comprehend the dynamics of volatility in cryptocurrency and stock markets, we display the pairwise dynamics in Figure 5 and discuss the results in detail. All the stock markets have had an important interaction with cryptocurrency during the COVID-19 outbreak. The short-duration and long-duration net pairwise connectedness emphasize the dominance of cryptocurrency during the COVID-19 outbreak. BTC and ETH dominated SSE, EURONEXT, JPXGY and HSKE during the COVID-19 outbreak in both durations, while the effect of BTC and ETH on these stock markets decreased at the end of our sample. BTC and ETH dominate SP500 for a short duration from 2020, while their role in a long duration is the opposite. BTC and ETH were significant net transmitters of shocks to LSE at the beginning of COVID-19 and turned into net shock receivers in 2021. The domination of ETH is more preponderant than BTC. BNB dominated SSE, EURONEXT, JPXGY and LSE during the COVID-19 outbreak in both durations, while its effect on these stock markets decreased at the end of our sample. BNB dominates SP500 in short duration during the COVID-19 outbreak, while their role in long duration is the opposite. Regarding HSKE, BNB is a net transmitter of shock during our sample except at the beginning of COVID-19. Therefore, it can be indicated that the volatility of the stock markets can be explained by cryptocurrencies, with the impact most severe at the beginning of 2020. The pairwise dynamics between cryptocurrency and stock markets in a short duration are more preponderant than in a long duration. In other words, the dominance of cryptocurrency in a crisis has little impact on stock markets for a long duration. Our results are consistent with the findings in the literature. The growth of some commodity markets has been noted before in conjunction with various financial crises (2007–2009), as indicated by Balcilar *et al.* (2021) and Zhang and Broadstock (2020).

5. Conclusions and policy implications

Our study includes a QVAR framework to measure the network connectedness of nine indicators, including *BTC*, *ETH*, and *BNB*, and six stock indices from the global stock market, including SP500 stock index of the U.S. (*SP500*), *SSE*, *HSKE*, *JPXGY*, Euronext (*EURONEXT*) and *LSE*, in a time-varying manner. We also use the strategy proposed by Baruník and Křehlík (2018), which offers greater flexibility and lets us achieve the net pairwise connectedness measurements. These indicators are among the daily datasets we gathered for this study. Our time series covers from January 1, 2018, to December 31, 2021.

Our findings demonstrate that all the investigated indicators are just marginally related when considering the entire set of data. This research specifically demonstrates the existence of a temporal variation of systemic connectedness driven by the COVID-19 outbreak. According to the dynamic net total directional connectedness, BTC is a net short-duration shock transmitter during our sample period. From 2018 to 2020, BTC was a long-duration net receiver of shocks and became a long-duration net transmitter of shocks in late 2021. In both durations, ETH acts as a shock transmitter. During the COVID-19 outbreak, Binance became a net short-duration shock transmitter before receiving net shocks in 2021. Before 2021, the US stock market transmits shocks of both durations and then becomes a net short-duration shock receiver from 2021. The U.S. stock market plays a different role in the long term than in the short term, beginning in 2021. Stock markets in Asia (including Hong Kong, Japan and Shanghai) are net receivers of both durations during our sample. Stocks in Europe (including Euronext and London) are net recipients of shocks during the period 2018–2020 before becoming net transmitters of shocks from 2021. Following the COVID-19 pandemic shock, pairwise connectedness revealed that cryptocurrencies explained the most severe impact on stock markets at the beginning of 2020.



Source(s): Authors' calculations

Figure 5.
Dynamic net pairwise directional connectedness: cryptocurrency to other indicators

5.1 Theoretical contributions

In our research, we are the first to offer a unique deep explanation of the interconnectedness between these indicators, namely cryptocurrency and stock markets, specifically in chaotic events like the COVID-19 epidemic on the dynamic connectedness over quantile among these indicators. The special method uses the net pairwise connectedness over a quantile estimate spread channels between cryptocurrency and stock markets. We contribute crucial information and warnings about the spread of uncertain occurrences and policies for regulators and investors.

5.2 Practical applications

As a result of the interconnections between the various determinants and their spillover effects, our findings have significant policy repercussions for investors and authorities. We also provide suggestions based on these interactions. By being well-informed about the primary sources of the spillovers between cryptocurrency and stock markets, policymakers can develop the most effective policies to lessen the vulnerabilities of these indicators and minimize how widely the market is exposed to risk or uncertainty. By showing the substantial linkages between nine variables, our findings indicate the risk of either insufficient or excessive variety in evaluations of authorities. Our analysis draws attention to the rising relationships between unanticipated and wildly unpredictable events, such as the COVID-19 outbreak. Our research suggests that cryptocurrency promotes the volatility of stock markets since a shock to one typical indication impacts the entire network. Additionally, it is meant that crises like the COVID-19 outbreak will affect cryptocurrency movements and stock markets in the short duration with little impact on their trend in the long duration. Clarifying the connectedness between cryptocurrency and stock markets in short and long duration enables the authorities to establish policies to stabilize cryptocurrency and stock markets. The results of this study may also benefit politicians in improving social welfare, which is directly influenced by cryptocurrency and stock markets. In order to promote the welfare of society, it is crucial to incorporate them while creating policies for disadvantaged groups.

5.3 Limitations and directions for future research

The outcomes of the research still have three limitations. Prior to all else, it is important to highlight that we cannot find any general principle or pattern that applies to all cases on how risk occurrences impact total, net or pairwise spillovers over a quantile. Second, the extent of the spread is significant from the standpoint of indicator association. If the spread is large, changes and shocks brought on by other indicators will majorly influence a particular market system. The government must take a variety of steps to lessen the negative consequences of outside shocks. Authorities should concentrate on frequency-specific danger sources. In the integration of global regulatory guidelines for different metrics, more focus should be made on reducing the negative consequences of long-duration fluctuation spread and short-duration return spread. Last but not least, considering that many researchers consider the spillover influence across several metrics, evaluating the portfolio advantages of diversity is a substantial extension. In the meanwhile, we placed it on the back burner.

Note

1. Because the recovered results are entirely independent of the variable ordering, the GFEVD is preferable to its orthogonal equivalent. Furthermore, Wiesen *et al.* (2018) emphasize that the GFEVD is able to be used in the absence of a theoretical framework that would make it possible to detect the error pattern.

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