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Research Paper

Dynamic connectedness between energy markets and cryptocurrencies: evidence from the Covid-19 pandemic

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ABSTRACT

The Covid-19 pandemic affected financial markets in several ways, influencing the dynamics of the relationships between asset classes. We investigate the connectedness between cryptocurrencies and international energy markets from 2018 to 2021 using the time-varying parameter vector autoregression approach. Net total directional connectedness suggests that the cryptocurrency and energy indexes had heterogeneous roles. Bitcoin and Ripple coin were the net receivers of shocks, while Ethereum switched from receiver to transmitter. The US energy market was a persistent net transmitter of shocks, while Asian energy markets were consistent net shock receivers. Pairwise connectedness reveals that cryptocurrencies can explain the volatility of the energy markets during the difficult period of the pandemic at the beginning of 2020. We provide insights for portfolio optimization and policy implications.

Keywords: cryptocurrency; energy markets; dynamic and joint connectedness; time-varying parameter vector autoregression; Covid-19 pandemic.

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1 INTRODUCTION

With billions of US dollars in transactions and the emergence of a futures market that provides tools for risk hedging, cryptocurrencies have garnered significant attention in recent years, not least due to their potential to revolutionize financial systems. As a novel type of trade asset, cryptocurrencies exhibit price fluctuations distinct from those seen in traditional financial assets (Corbet *et al* 2019), and these fluctuations were intensified by the Covid-19 pandemic (Wang *et al* 2021).

Besides having idiosyncratic characteristics, cryptocurrencies can influence other asset classes and markets, such as energy. One potential linkage between cryptocurrencies and energy markets arises from the process of crypto mining and the proof-of-work consensus algorithm, which requires substantial computational power and, consequently, significant energy consumption. As cryptocurrencies have gained popularity and their market value has increased, concerns have been raised about the environmental implications and sustainability of their energy-intensive mining operations.

The fact that crypto mining consumes a lot of energy has an impact on energy markets in several ways. First, the increased electricity use by miners may strain regional power grids, increasing energy costs and possibly causing blackouts in impacted areas. Second, because miners are frequently motivated to use electricity during off-peak times when it is less expensive, the concentrated demand for energy from crypto mining can potentially upset the established dynamics of energy supply and demand. Additional energy infrastructure investments, designed to meet the growing demand, could raise costs for both consumers and utility companies.

Concerns with the environmental impact of crypto mining have recently been raised (see, for example, Afjal and Clanganthuruthil Sajeev 2022; Corbet *et al* 2021; Sapra and Shaikh 2023; Yuan *et al* 2022; Zheng *et al* 2023). The electricity consumption associated with mining operations contributes to greenhouse gas emissions, exacerbating climate change. In fact, it has been estimated that the carbon footprint of mining Bitcoin is comparable to that of some small countries. This has prompted calls for developing and adopting more environmentally friendly consensus mechanisms, such as proof-of-stake, requiring less energy. As cryptocurrencies develop further, addressing the energy market linkage will be essential to ensuring their long-term viability and reducing their environmental impact.

The relationship between asset classes, including cryptocurrencies, is dynamic and state-dependent and, given that few studies have covered the pandemic period, conclusive evidence for its effect on these linkages is challenging to find. Our paper therefore makes several contributions to the literature. First, we fill a gap in the contemporary literature by investigating the relationship between volatility in the energy market and in the crypto market. In particular, our paper adds to the existing studies that focus on the impact of periods of uncertainty, such as the Covid-19 pandemic, on this relationship. Second, to study the relationships between the crypto and energy markets, we employ a novel empirical approach that combines time-varying parameter vector autoregression (TVP-VAR) with an extended joint-connectedness approach. Finally, we observe a net total directional relationship between crypto and energy markets, suggesting that each cryptocurrency and energy index has a heterogeneous role and investment implications.

We follow Balcilar *et al* (2021) in employing TVP-VAR combined with an extended joint-connectedness approach. We select this combined empirical approach due to its various advantages. Specifically, it does not reduce the number of observations. Thus, it can be used in the case of short data spanning, though this is not the case studied here.

We show that each cryptocurrency and energy index played a different role in the total net directional correspondence. Bitcoin and Ripple coin were the net receivers of shocks, while Ethereum switched from receiver to transmitter. The US energy market was persistently a net transmitter of shocks, while Asian energy markets were consistent net receivers. Pairwise connectedness reveals that cryptocurrencies can explain the volatility in the energy markets during the difficult period during the Covid-pandemic at the beginning of 2020. We provide insights for portfolio optimization and policy implications.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and models. Section 4 contains our findings and discussions. Section 5 states our conclusions and offers policy implications.

2 RELATED LITERATURE

More than a decade after their introduction, Bitcoin and other cryptocurrencies have become attractive investments for investors, with billions of US dollars in transactions and the emergence of a futures market that provides tools for risk hedging. As a novel type of trade asset, cryptocurrencies exhibit price fluctuations distinct from those seen in traditional financial assets (Corbet *et al* 2019), and these fluctuations were intensified by the Covid-19 pandemic (Wang *et al* 2021). According to related studies, Covid-19 has been the source of an exceptional surge in economic policy uncertainty and an unprecedented energy market reaction (Ashfaq *et al* 2019; Bašta and Molnár 2018; Bigerna *et al* 2021; Cevik *et al* 2020; Cui *et al* 2021; Qin 2020; Jiang and Yoon 2020; Khalfaoui *et al* 2019; Li *et al* 2020; Liu *et al* 2020; Mokni 2020; Nazlioglu *et al* 2020; Pavlova *et al* 2018; Sarwar *et al* 2020). The major energy market indexes frequently activated circuit breakers in the first quarter of 2020. During this period, the price of Ethereum decreased by roughly 44%, while the price of Bitcoin decreased by about 50% in one day, making it one of the worst one-day declines in history. The Covid-19 bear market produced the first significant losses since active Bitcoin trading began (Conlon and McGee 2020). Using the informational-efficiency framework, Lahmiri and Bekiros (2020) revealed that during the Covid-19 pandemic, crypto markets had more idiosyncratic characteristics, such as instability and irregularity, than equity markets.

It is possible there is an asymmetric spillover effect between energy and crypto markets. Many scholars contend that the hash rate[1] and half-annual supply generate price volatility in cryptocurrencies (Lamothe-Fernández *et al* 2020). Energy market price changes, however, are caused by business earnings and fundamentals. Meanwhile, news events such as severe public-health situations could change investor sentiment and the flow of capital between the two markets, thus increasing the danger of risk spillover. More specifically, even though crypto markets are mainly driven by sentiments, their connection to energy markets could be fundamental and driven by physical energy consumption during the crypto mining process and other validation procedures. Several studies have investigated such channels, providing mixed conclusions depending on the cryptocurrency type, energy market and time period (see, for example, Afjal and Clanganthuruthil Sajeev 2022; Corbet *et al* 2021; Sapra and Shaikh 2023; Yuan *et al* 2022; Zheng *et al* 2023). These studies emphasize the potential linkage and spillover effects between the two markets by focusing on the intensity of energy demand for crypto operations and the implications for sustainable development. Hence, the possible bidirectional relationship and information spillover between cryptocurrencies and energy markets remain unidentified. We therefore analyze data from 2018 to 2021, considering the periods before and after the outbreak of Covid-19 to show the dynamic connectedness between cryptocurrencies and energy markets. We use the three dominant cryptocurrencies and six global energy indexes.

It is worth emphasizing that, unlike energy markets in the United States and elsewhere, the Bitcoin market lacks a protective circuit-breaker mechanism, exacerbating the asymmetric contagion phenomena between it and other markets. According to Afjal and Clanganthuruthil Sajeev (2022) and Kumah and Mensah (2022a,b), cryptocurrencies have a weak correlation with energy indexes; therefore, portfolio diversification should reduce risk. Others, however, reveal positive correlations depending on the sample period, making cryptocurrency an unusual instrument for hedging in energy markets (Moussa *et al* 2020; Jareño *et al* 2021). For instance, Ji *et al* (2019), Das *et al* (2019) and Attarzadeh and Balcilar (2022) used regime-switching models to investigate the contagion effect between energy markets and centralized crypto

[1] The hash rate is a measure of the computational power on a blockchain network. It is based on how many guesses are made per second. The overall hash rate helps determine the security and mining difficulty of a blockchain network.

markets, documenting strong contagion from the energy market to the crypto market, as well as coskewness of returns. Okorie (2021) analyzed the information spillover between several crypto and electricity markets, concluding that the return and trading volumes of the crypto markets are net information transmitters, while the markets' volatility and the demand for electricity in the United States, China and Japan are net information receivers in the system, providing environmental implications for such a spillover.

The combination of TVP-VAR with total connectedness appears to be an appropriate approach for investigating the interrelationships both between individual cryptocurrencies and between cryptocurrencies and other asset classes. Using this approach, Ersan *et al* (2022) studied the linkage between fan tokens and football stocks and found that the shocks transmitted to any token are larger than those transmitted to the stocks, and that tokens are the net transmitters of shocks; a decrease in total connectedness was also documented. Jiang *et al* (2022) used the same methodology to investigate the connectedness between cryptocurrencies and financial markets; they found that Bitcoin is an investment hedge rather than a safe haven, and that external market attention is the cause of volatility spillover movement. In contrast, Al-Shboul *et al* (2023) found that cryptocurrencies remained safe-haven tools against market uncertainty during Covid-19, and that Covid-19 played an important role in the impact of policy uncertainty on the connectedness between asset classes. Giannellis (2022), providing a similar result, found that the connectedness between cryptocurrencies is time-varying and appeared to decline during Covid-19.

Testing the dynamic connectedness between cryptocurrencies and other asset classes is not limited to VAR models. Using wavelet techniques and quantile models, Kumah and Mensah (2022a,b) provided evidence that cryptocurrencies are hedges for gold investment regardless of the market regime in the medium to long term; Demiralay and Bayracı (2021) confirmed the similar result that adding cryptocurrencies to equity market portfolios enhances portfolio diversification. Elsayed *et al* (2022) used Bayesian models to find a significant causal relationship between cryptocurrencies. Except for the Chinese yuan, however, major traditional currencies were not found to significantly affect cryptocurrencies. Ghabri *et al* (2022) revisited the volatility spillover among several asset classes, including cryptocurrencies, during the early stages of the Covid-19 pandemic. They documented the safe-haven function of gold and Bitcoin, but found Bitcoin's safe-haven function to have been unstable over the pandemic lockdown period. They concluded that gold is the most promising hedge and safe-haven asset, as it remained stable and thus exhibited superiority over both Bitcoin and Tether.

The dynamic linkage between asset classes, including cryptocurrencies, is not determined a priori. The relationship depends on the horizon, the market condition (bear or bull) and the technical approach. Few studies investigating such linkages have covered the pandemic lockdown period. Our paper is therefore timely because it covers an extended pandemic period (before and during) and investigates the dynamic linkage between energy markets and cryptocurrencies, offering practical implications for portfolio balancing and for policymakers. Thus, we fill a gap in the contemporary literature by examining the relationship between energy market and crypto market volatility using novel methodologies and including the uncertain Covid-19 period.

3 DATA AND MODELS

3.1 Data and preliminary analysis

Our overall sample period is January 1, 2018 to December 31, 2021. We study three cryptocurrencies, chosen on the basis of market capitalization: Bitcoin (BTC), Ethereum (ETH) and Ripple coin (XRP).[2] We study six global energy indexes (specifically, Morgan Stanley Capital International (MSCI) energy equity indexes): the MSCI USA Energy Index (USA), MSCI China A Energy Index (CHN), MSCI Korea Energy Index (KOR), MSCI Japan Energy Index (JPN), MSCI Europe Energy Index (EUR) and MSCI UK Energy Index (UK).[3]

Regarding the entire sample, all series in Table 1 show positive average returns. As indicated in part (a), the XRP and ETH markets have the highest variance, making them the two riskiest assets throughout the sample periods. Further, all series are leptokurtic, which indicates that the distributions have fatter tails than a normal distribution. According to the Jarque–Bera test (Jarque and Bera 1980), all assets are substantially nonnormally distributed. All results are at least at the 1% significance level when the unit-root test by Elliott *et al* (1996) is used. Finally, the Fisher–Gallagher test (Fisher and Gallagher 2012) finds that the returns and squared returns are autocorrelated, implying that the interrelationships of the series may be modeled using a TVP-VAR method with a time-varying variance–covariance structure. Since the study aims to find the linkages between crypto and energy markets, we examine these markets' interconnectedness before and during the Covid-19 pandemic.

Parts (b) and (c) of Table 1 highlight the main statistics of two subsamples. We use the World Health Organization's (WHO) time line to split the sample into before and after the Covid-19 outbreak. The WHO publicly revealed the coronavirus to the world for the first time on December 31, 2019. Accordingly, we assume that the pre-Covid-19 outbreak subperiod is from January 1, 2018 to December 31, 2019 and the post-Covid-19 outbreak subperiod is from January 1, 2020 to December 31, 2021.

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[2] Prices of crypto assets were collected from Bloomberg: www.bloomberg.com/crypto.

[3] Values of energy indexes were collected from MSCI: www.msci.com.

TABLE 1 Summary statistics of the cryptocurrency and energy index returns. [Table continues on next page.]

(a) Whole sample

	BTC	**ETH**	**XRP**	**USA**	**CHN**	**EUR**	**JPN**	**KOR**	**UK**
Mean	0.146	0.181	0.467	0.073	0.010	0.071	0.036	0.077	0.081
Var.	36.340	54.465	67.624	2.088	2.568	4.363	4.614	4.699	4.769
Skew.	–0.994***	–0.728***	0.332***	–1.115***	–0.457***	0.337***	–0.246*	0.095	–0.255*
Kurt.	11.060***	8.392***	12.606***	17.760***	6.500***	10.792***	3.398***	3.872***	11.849***
JB	5039.303***	3167.668***	6101.067***	21 715.447***	2228.513***	4653.072***	311.411***	399.653***	5462.544***
ERS	–12.040***	–5.397***	–6.531***	–10.044***	–10.697***	–14.801***	–6.834***	–13.835***	–14.411***
Q(20)	46.486**	42.550**	34.891*	397.803***	48.694***	51.430***	18.376	21.683	42.813***
Q2(20)	30.003**	34.501***	108.763***	2 195.023***	36.867***	430.679***	43.085***	101.648***	69.911***

TABLE 1 Continued.

(b) Pre-Covid-19 pandemic

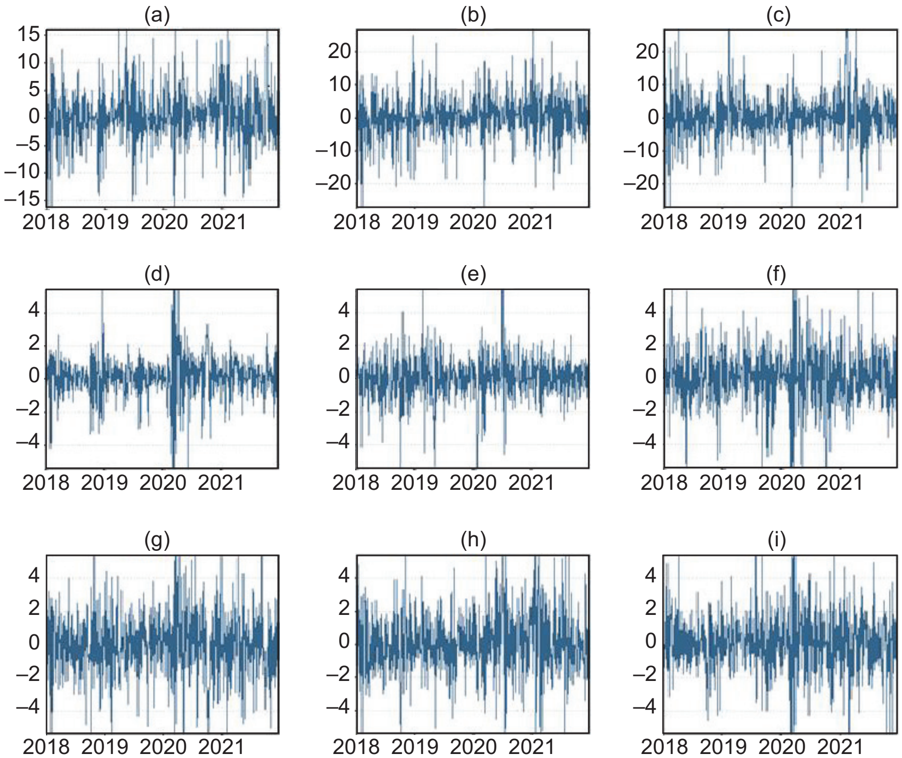
	BTC	ETH	XRP	USA	CHN	EUR	JPN	KOR	UK
Mean	−0.273	−0.534	0.208	0.051	−0.032	0.085	0.001	0.004	0.272
Var.	34.923	50.385	66.220	2.075	2.628	3.334	3.765	3.771	3.533
Skew.	−0.370**	−0.329*	0.367**	−0.537***	−0.412***	−0.802***	−0.376**	−0.304*	2.842***
Kurt.	4.371***	3.377***	10.918***	5.512***	3.830***	6.061***	2.759***	2.728***	26.640***
JB	317.228***	211.865***	2935.266***	491.264***	257.857***	610.681***	67.801***	63.367***	5899.743***
ERS	−8.207***	−3.935***	−4.648***	−6.655***	−7.963***	−10.770***	−5.002***	−9.951***	−11.774***
Q(20)	47.877**	33.851	33.178	26.715	50.861***	33.299	30.524	34.307	26.284
Q2(20)	42.038***	34.520***	57.721***	89.595***	39.823***	25.455	24.563	41.942***	22.056

(c) During the Covid-19 pandemic

	BTC	ETH	XRP	USA	CHN	EUR	JPN	KOR	UK
Mean	0.552	0.883	0.942	0.094	0.048	0.052	0.058	0.234	−0.032
Var.	37.679	58.048	68.949	4.116	2.510	5.404	5.482	5.627	6.014
Skew.	−2.577***	−2.091***	1.290	−2.135***	−1.498***	1.685***	−1.190	1.285	−1.844***
Kurt.	27.013***	22.273***	24.256***	24.521***	9.691***	10.652***	3.225***	3.783***	8.726***
JB	6013.596***	3519.232***	4353.197***	4561.283***	2502.537***	2842.784***	95.372***	247.264***	2238.643***
ERS	−5.469***	−6.661***	−7.389***	−7.174***	−11.275***	−11.832***	−9.182***	−5.115***	−8.301***
Q1(20)	41.270*	36.915	40.431*	347.621***	29.900	44.862**	34.255	38.868	50.631***
Q2(20)	10.381	22.435	99.693***	655.481***	26.623	301.898***	26.361	55.081***	50.631***

BTC, ETH, and XRP denote the cryptocurrencies Bitcoin, Ethereum and Ripple. USA, CHN, EUR, JPN, KOR and UK denote the MSCI energy indexes for the United States, China, Europe, Japan, Korea and the United Kingdom. JB, Jarque–Bera test. ERS, Elliott–Rothenberg–Stock test. Q1 and Q2 are the first and second quartiles. * $p < 0.01$; ** $p < 0.05$; *** $p < 0.1$.

FIGURE 1 Volatilities of returns of the crypto and energy markets.



(a) BTC. (b) ETH. (c) XRP. (d) USA. (e) CHN. (f) EUR. (g) JPN. (h) KOR. (i) UK.

Surprisingly, all indexes show positive performance during the Covid-19 pandemic except for the UK energy index.

Moreover, the mean returns of BTC, ETH and XRP all increased following the start of the Covid-19 crisis, with the value of BTC and ETH returns changing from negative to positive. Further, the investigated energy markets became volatile during the pandemic, except for CHN. The unit-root and weighted-portmanteau test results for the subperiods are similar to those for the whole sample, confirming that the TVP-VAR approach with a time-varying variance–covariance structure is appropriate for modeling interconnectedness between our chosen asset classes and markets.

The volatilities of all markets are show in Figure 1.

3.2 Models

Previous empirical papers usually employ generalized VAR methods, as in Diebold and Yılmaz (2012). However, one limitation of this approach is its reliance on an arbitrarily chosen rolling-window size for time-variant connectedness. Several suggestions have been introduced to resolve this issue, such as using the mean squared prediction error of the rolling-window VAR employed (Antonakakis *et al* 2020) or the joint spillover index (Lastrapes and Wiesen 2021). We follow Balcilar *et al* (2021) in using time-varying parameter vector autoregression (TVP-VAR), combined with an extended joint-connectedness approach. We select this combined empirical approach due to its various advantages. Specifically, it does not reduce the number of observations. Thus, it can be used in the case of short-spanning data, although this case is beyond the scope of this paper.

Moreover, the presence of an outlier does not cause a significant change in our results, and this approach also provides a better adjustment to parameter changes than generalized VAR. The most important step in our chosen strategy is computing the net pairwise connectedness, which detects transmission mechanisms between energy and crypto markets. The findings of this paper bring critical, insightful knowledge and warnings for investors and authorities.

3.2.1 TVP-VAR

In this subsection, we outline the TVP-VAR connectedness approach of Antonakakis *et al* (2020), in combination with the work of Diebold and Yılmaz (2012). For our paper, the Bayesian information criterion suggests a lag length of 1 for estimating the TVP-VAR model:

$$y_t = M_t y_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Sigma_t), \tag{3.1}$$

$$\mathrm{vec}(M_t) = \mathrm{vec}(M_{t-1}) + \mu_t, \quad \varepsilon_t \sim N(0, R_t), \tag{3.2}$$

where y_t, y_{t-1} and ε_t are $(Z \times 1)$-dimensional vectors and M_t and Σ_t are $(Z \times Z)$-dimensional matrixes; (M_t) and μ_t are $(Z^2 \times 1)$-dimensional vectors, whereas R_t is a $(Z^2 \times Z^2)$-dimensional matrix. This model is designed to allow a time-varying series of all parameters (M_t). The model also assumes time-varying variance–covariance matrixes, Σ_t and R_t. Most previous studies show that variances and covariances – especially in the energy market – are time-dependent, adding market and investment risks. In the following step, we adopt the Wold representation theorem to transform TVP-VAR into a time-varying parameter vector moving-average (TVP-VMA) model:

$$y_t = \sum_{h=0}^{\infty} N_{h,t} \varepsilon_{t-1},$$

where $N_0 = I_z$ and ε_t is a vector of white-noise shocks (symmetric but not orthogonal), with $Z \times Z$ time-varying covariance matrix $E(\varepsilon_t \varepsilon_t') = \Sigma_t$. Thus, the L-step forecast error can be written as

$$\varphi_t(L) = y_{t+1} - E(y_{t+L} \mid y_t, y_{t-1}, \dots), \tag{3.3}$$

with a forecast-error covariance matrix equal to

$$E((\varphi_t(L)\varphi_t'(L))) = N_{l,t} \Sigma_t N_{h,t}'. \tag{3.4}$$

Koop *et al* (1996) and Pesaran and Shin (1998) proposed the L-step-ahead generalized forecast-error variance decomposition (GFEVD), which will be useful in developing our framework. The impact of a shock in variable j on $\mathrm{gST}_{ij,t}$, denoting the (scaled) GFEVD, is formulated as follows:

$$\varphi_{ij,t}^{\text{gen}}(L) = \frac{E(\varphi_{i,t}^2(L) - E[\varphi_{i,t}(L) - E(\varphi_{i,t}(L) \mid \varepsilon_{j,t+1}, \dots, \varepsilon_{j,t+1})]^2)}{E(\varphi_{i,t}^2(L))}, \tag{3.5}$$

$$\varphi_{ij,t}^{\text{gen}}(L) = \frac{\sum_{l=0}^{L-1} E(e_i' N_{lt} \Sigma_t e_j)^2}{(e_j' \Sigma_t e_j) \sum_{l=0}^{L-1} E(e_i' N_{lt} \Sigma_t N_{lt}' e_i)^2}, \tag{3.6}$$

$$\mathrm{gST}_{ij,t} = \frac{\varphi_{ij,t}^{\text{gen}}(L)}{\sum_{j=1}^{L} \varphi_{ij,t}^{\text{gen}}(L)}, \tag{3.7}$$

where e_i is an $e_i Z \times 1$ zero-selection vector with unity in its ith position, and $\varphi_{ij,t}^{\text{gen}}(L)$ is the proportional reduction in the L-step forecast-error variance of variable i due to conditioning on the future shocks of variable j. As

$$\sum_{j=1}^{Z} \varphi_{ij,t}^{\text{gen}} \neq 1,$$

Diebold and Yılmaz (2012) proposed to normalize it to unity by the row sum, resulting in the generalized spillover table, $\mathrm{gST}_{ij,t}$.

The generalized spillover table shows the total directional connectedness between several variables, which illustrates the magnitude of the network's effect on variable i and how much variable i influences the whole network, respectively. These metrics can be written as

$$X_{i \leftarrow \bullet,t}^{\text{gen,from}} = \sum_{j=1,\ i \neq j}^{Z} \mathrm{gST}_{ij,t}, \tag{3.8}$$

$$X_{i \rightarrow \bullet,t}^{\text{gen,to}} = \sum_{j=1,\ i \neq j}^{Z} \mathrm{gST}_{ij,t}. \tag{3.9}$$

In addition to the total connectedness measure, the net total directional connectedness shows whether variable i is a net influencer or influenced by the network:

$$X_{i,t}^{\text{gen,net}} = X_{l\to\bullet,t}^{\text{gen,to}} - X_{i\leftarrow\bullet,t}^{\text{gen,from}}.$$

If $X_{i,t}^{\text{gen,net}} > 0$, then variable i is a net shock transmitter (affecting the network), and if $X_{i,t}^{\text{gen,net}} < 0$, then it is a net shock receiver (influenced by the network).

Another noteworthy indicator of connectedness is the total connectedness index (TCI), which is a measure of interconnectedness within the network and can also be viewed as market risk. The TCI is used by portfolio and risk managers as a useful tool for diversification. It is calculated as the average total directional influence from (or to) others, formulated as follows:

$$\text{gST}_t = \frac{1}{Z}\sum_{i=1}^{Z} X_{i\leftarrow\bullet,t}^{\text{gen,from}} = \frac{1}{Z}\sum_{i=1}^{Z} X_{i\to\bullet,t}^{\text{gen,to}}. \tag{3.10}$$

A higher TCI represents greater market risk due to the spillover effect directly affecting portfolio balancing.

Finally, the pairwise directional spillover also occurs at a more disaggregated level; it offers information about the bilateral interrelationships of two variables and is defined by

$$X_{ij,t}^{\text{gen,net}} = \text{gST}_{ij,t}^{\text{gen,to}} - \text{gST}_{ij,t}^{\text{gen,from}}.$$

If $X_{ij,t}^{\text{gen,net}} > 0$ or $X_{ij,t}^{\text{gen,net}} < 0$, this definition implies that variable i dominates variable j when $\text{gST}_{ij,t}^{\text{gen,to}}$ has a greater impact on $\text{gST}_{ij,t}^{\text{gen,from}}$.

3.2.2 Extended joint-connectedness method

Here, we try to find the equivalent of $\text{gST}_{ij,t}$ for the joint-connectedness method, namely, $\text{jST}_{ij,t}$, under the following conditions:

$$X_{i\leftarrow\bullet,t}^{\text{jnt,from}} = \sum_{j=1,\ i\neq j}^{Z} \text{jST}_{ij,t}, \tag{3.11}$$

$$X_{\bullet\leftarrow i,t}^{\text{jnt,to}} = \sum_{j=1,\ i\neq j}^{Z} \text{jST}_{ji,t}, \tag{3.12}$$

$$\text{jST}_i = \frac{1}{Z}\sum_{i=1}^{Z} X_{i\leftarrow\bullet,t}^{\text{jnt,from}} = \frac{1}{Z}\sum_{i=1}^{Z} X_{i\to\bullet,t}^{\text{jnt,to}}. \tag{3.13}$$

In this context, Lastrapes and Wiesen's (2021) scaling approach is generalized, indicating that (3.11) must hold. In addition, the diagonal elements of the joint-connectedness table must stay the same since the row sums of the original table and the joint-connectedness table are 1. Thus, the scaling factor η is different for each row, which leads to the following equations:

$$\eta_i = \frac{X^{\text{jnt,from}}_{i\leftarrow\bullet,t}}{X^{\text{gen,from}}_{i\leftarrow\bullet,t}}, \tag{3.14}$$

$$\eta = \frac{1}{Z}\sum_{i=1}^{Z}\eta_i. \tag{3.15}$$

Our η scaling and the one from the joint-connectedness method are the same, except that our approach is more flexible because each row has its own scaling factor. Thus, the following steps have to be performed:

$$\begin{aligned}
\text{jST}_{ij,t} &= \eta_i\,\text{gST}_{ij,t},\\
\text{jST}_{ii,t} &= 1 - X^{\text{jnt,from}}_{i\leftarrow\bullet,t},\\
X^{\text{jnt,to}}_{i\rightarrow\bullet,t} &= \sum_{j=1,\ i\neq j}^{Z}\text{jST}_{ij,t}.
\end{aligned}$$

Finally, because the scaling factor varies by row, the net total and pairwise directional connectedness can be computed by the following measures:

$$X^{\text{jnt,net}}_{i,t} = X^{\text{jnt,to}}_{i\rightarrow\bullet,t} - X^{\text{jnt,from}}_{i\leftarrow\bullet,t}, \tag{3.16}$$

$$X^{\text{jnt,net}}_{ij,t} = \text{gST}_{ji,t} - \text{gST}_{ij,t}. \tag{3.17}$$

In this way we extend the joint-connectedness approach to overcome the limitations of the row-sum normalization method (Caloia *et al* 2019). The extended method deals with multiple issues of the original connectedness approach through the following improvements, among others.

- The rolling-window size is not arbitrarily chosen.
- The estimation results are not outlier-sensitive, thanks to the multivariate Kalman filter method.
- VAR coefficients and variance–covariance matrixes are allowed to vary over time in order to better reflect financial market volatility, providing crucial information to portfolio and risk managers.
- The row-sum normalization issue has been addressed according to Lastrapes and Wiesen (2021).
- The flexible version of the joint-connectedness approach aligns with the original joint-connectedness approach, allowing the computation of net pairwise directional connectedness measures. Such measures are important in showing the relative bilateral strength of variables.

4 EMPIRICAL FINDINGS AND DISCUSSIONS

We evaluate the effects of the uncertain Covid-19 period on the interrelationships between crypto and energy markets by analyzing changes in the TCI before and during Covid-19. We also discuss the net total connectedness and net pairwise connectedness of assets' returns,[4] offering insights into the influence of each market within our proposed framework. Consequently, each market can be classified as a net shock transmitter or a net receiver. Finally, following Lastrapes and Wiesen (2021), we find that joint spillover is a helpful index for exploring the reasons behind interrelationship changes. A similar procedure is also applied to two subsamples to indicate the influence of the Covid-19 pandemic on the network.

4.1 Average time-variant dynamic connectedness

Using the full set of observations and the subsets based on the day the Covid-19 pandemic was declared by the WHO, the average results regarding interrelationships of all markets in the network are reported in Table 2. The diagonal elements report the volatility of returns of a particular market, accounted for by its own shocks. The bilateral contributions of one market to others' volatility are summarized in the off-diagonal elements. Note that each row corresponds to the contributions that a particular market's forecast-error variance receives from the markets heading each column, while each column corresponds to the effects of a particular market on the markets labeling each row.

Regarding the entire sample, the average TCI is 45.97%, suggesting that idiosyncratic effects can explain 54% of the forecast-error variance of the system. The average results presented in Table 2 indicate that comovement occurs between the studied markets, with CHN, EUR, JPN, KOR and UK tending to be shock receivers. Among the net receivers, the only cryptocurrency is BTC. With a tendency to influence other markets rather than be influenced, ETH, XRP and USA are the three net transmitters of shocks.

By considering the two subsets of observations, this paper sheds light on how a market can act differently according to the given periods (ie, state-dependence). Before Covid-19, each market in the network was still the primary factor in its own development and evolution (TCI $=$ 45.23%). It is worth noting that the TCI increased to 46.13% when the Covid-19 pandemic started, and that idiosyncratic effects were responsible for 56.09% of volatility in the network during the pandemic. These findings show that, during a time of uncertainty, substantial comovements occurred. Pre-Covid-19, the average joint connectedness of BTC, ETH, CHN, KOR and UK showed them to be shock receivers. During the same sample period, XRP,

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[4] We use "returns" to refer to log returns, calculated as $\log \mathrm{Ret} = \log(P_t/P_{t-1})$.

TABLE 2 Averaged joint connectedness. [Table continues on next page.]

(a) Whole sample

	BTC	ETH	XRP	USA	CHN	EUR	JPN	KOR	UK	From
BTC	33.33	37.06	24.65	4.45	0.72	1.10	1.10	0.75	1.83	68.89
ETH	36.71	29.93	27.75	4.63	0.94	1.12	1.31	1.28	1.32	72.29
XRP	21.62	25.43	48.29	4.05	1.01	1.01	1.18	1.06	1.35	53.93
USA	3.31	3.41	3.04	66.81	3.50	5.05	8.65	4.40	6.81	35.41
CHN	1.33	1.54	1.53	7.52	57.57	3.40	3.08	23.35	3.65	44.65
EUR	1.48	1.76	1.61	6.93	2.23	67.53	2.03	4.19	16.35	34.80
JPN	1.30	1.82	1.61	9.52	1.80	1.81	80.03	2.04	2.05	22.19
KOR	0.85	1.78	2.12	8.43	22.67	4.85	2.78	55.79	3.71	46.43
UK	2.04	1.47	1.71	7.91	2.19	16.57	1.97	2.36	66.78	35.44
To	66.88	72.50	62.25	50.68	34.30	34.13	21.33	36.66	35.29	
Net	−2.12	0.32	8.42	16.38	−11.46	−0.78	−0.97	−10.88	−0.26	
									TCI:	46.00

(b) Pre-Covid-19 pandemic

	BTC	ETH	XRP	USA	CHN	EUR	JPN	KOR	UK	From
BTC	37.45	39.18	23.19	0.91	0.51	0.76	0.81	0.55	0.62	64.77
ETH	38.92	31.14	29.32	1.14	0.85	0.72	0.86	0.71	0.35	71.08
XRP	20.25	27.09	52.40	0.73	0.88	0.78	0.79	0.72	0.35	49.82
USA	1.45	1.63	1.02	71.17	2.88	5.23	9.86	3.09	5.66	31.05
CHN	0.82	1.06	1.22	6.91	53.28	4.28	4.41	27.79	3.22	48.94
EUR	1.21	1.57	1.34	6.79	2.80	69.66	2.97	4.43	12.11	32.56
JPN	1.08	1.62	1.45	12.21	1.88	2.17	77.62	2.14	2.82	24.60
KOR	0.82	1.57	2.66	12.03	25.86	6.70	3.39	47.53	3.43	54.69
UK	0.86	0.55	0.54	7.01	2.50	13.26	3.09	2.51	72.67	29.55
To	63.65	72.50	58.96	45.96	37.41	33.11	26.40	41.27	27.78	
Net	−1.23	1.53	9.25	15.03	−12.64	0.67	1.91	−14.53	−1.88	
									TCI:	45.23

USA, EUR and JPN were the markets most affecting others, being the net transmitters. However, with the appearance of Covid-19, things changed. While CHN and KOR were persistent net receivers and XRP remained a net transmitter, roles shifted for all other markets, with BTC, ETH and UK becoming net transmitters during the pandemic.

Our findings align with the previous related studies (Corbet *et al* 2021; Sapra and

TABLE 2 Continued.

(c) During the Covid-19 pandemic

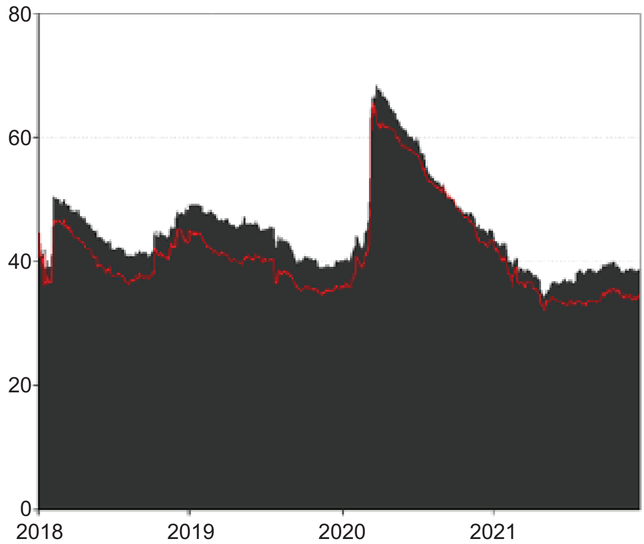
	BTC	ETH	XRP	USA	CHN	EUR	JPN	KOR	UK	From
BTC	31.20	34.70	25.60	5.51	0.58	1.33	1.24	0.66	3.16	70.00
ETH	34.70	31.50	25.10	5.53	0.65	1.36	1.50	1.39	2.31	70.69
XRP	22.50	22.40	48.10	4.74	0.71	0.94	1.34	0.99	2.26	54.00
USA	5.84	5.48	5.32	61.35	3.99	4.45	6.85	3.09	5.63	40.87
CHN	1.66	1.88	1.83	6.83	62.90	2.71	1.85	19.49	3.85	39.32
EUR	1.86	1.97	1.64	6.66	1.71	64.01	1.01	2.08	22.10	38.21
JPN	1.81	2.09	1.86	8.93	1.92	1.60	80.48	1.84	1.47	21.74
KOR	1.05	1.94	1.73	4.47	19.36	3.01	1.74	65.51	4.16	36.71
UK	3.67	2.85	3.29	7.73	1.77	20.37	1.12	2.54	59.70	42.56
To	71.30	71.60	64.50	50.63	29.92	34.99	16.88	31.30	44.10	
Net	0.36	1.01	11.50	10.87	−10.50	−3.34	−4.97	−5.51	1.67	
									TCI:	46.13

The table demonstrates the average results regarding interrelationships of different markets within the network. The diagonal elements report the volatility of returns of a particular market, accounted for by its own shocks. The bilateral contributions of one market to others' volatility are summarized in the off-diagonal elements. Each row corresponds to the contributions that a particular market's forecast-error variance receives from the markets heading each column, while each column corresponds to the effects of a particular market on the markets labeling each row.

Shaikh 2023; Yuan *et al* 2022; Zheng *et al* 2023). We show that the three cryptocurrencies had heterogeneous roles in impacting other markets but were generally considered net transmitters during times of uncertainty. Covid-19 contributed to markets' uncertainty, inducing investors to rebalance their portfolios by short-selling cryptocurrencies and buying safe-haven assets such as gold. Such behavior reduced the pressure on crypto mining, thus lowering energy demand and contributing to lower energy prices.

The linkage between cryptocurrencies and energy markets appears to be dynamic and state-dependent. In a bull market, the greater demand for cryptocurrencies increases the pressure on mining, causing energy prices to rise, and vice versa. Such a situation would not last long, since lower energy prices, for example, would encourage crypto investments again and reactivate the cycle. In a nutshell, regardless of whether they are net receivers or transmitters in the network, there is a linkage between energy and crypto markets; thus, combining cryptocurrencies and energy investments does not provide beneficial diversification and thus would not be helpful for portfolio optimization.

FIGURE 2 Time-variant total connectedness.



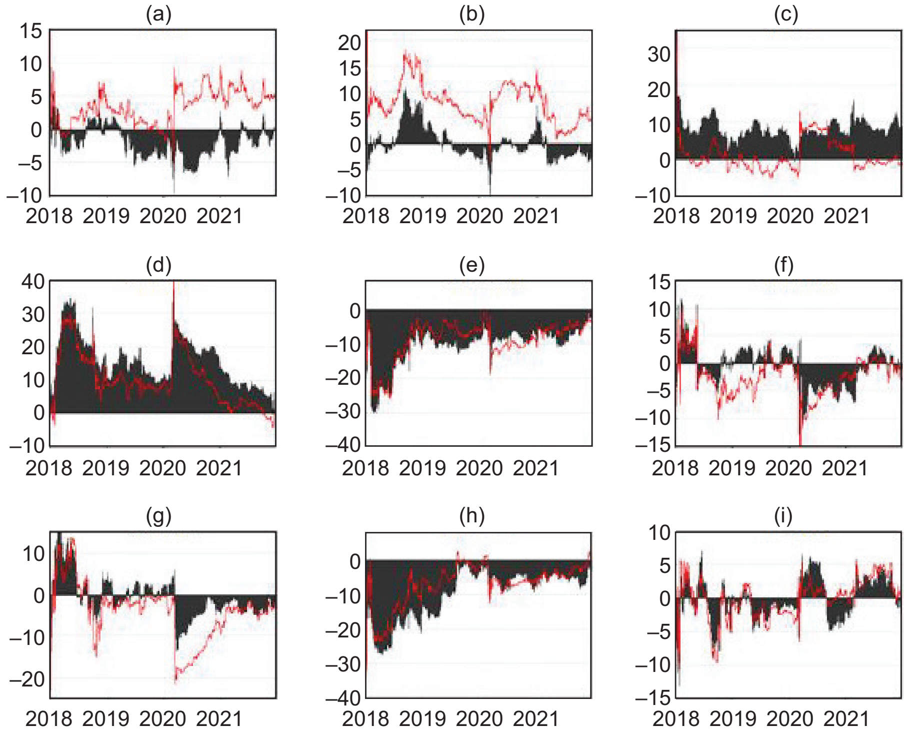
Robustness checks were also conducted by changing these values. The black shaded area displays the joint interrelationships, and the red line displays the original interrelationships.

4.2 Total time-variant connectedness

It is worth noting that the average findings are mainly used to summarize the fundamental interconnections. Such findings do not help investigate a single incident or a big shock, such as the Covid-19 pandemic. As a result, employing dynamic or time-variant total connectivity is critical for examining market dynamics and role changes through time. One of the instances demonstrating the effectiveness of using this model is the necessity of investigating the switching roles of net transmitter and net receiver. The TCI's temporal development is seen in Figure 2.[5] Overall, the TCI varies during the sample period. However, except for 2020, the figures for the TCI over the four years are relatively stable. A visible trend from 2018 to 2020 shows that the TCI values typically peak at the beginning of the year and move downward toward the year's end, before increasing slightly at the beginning of the following year. However, after Covid-19 started to spread at the beginning of 2020, the TCI peaked at around 72%, before rapidly decreasing toward the end of 2020. This downward trends appears to have stopped in 2021, with the pattern being broken by a slight

[5] In Figures 2–5 we follow Balcilar *et al* (2021) in using a lead of 20 and a lag of 1 for the forecast-error variance decomposition in our TVP-VAR system.

FIGURE 3 Net total directional time-variant connectedness of returns.



(a) BTC. (b) ETH. (c) XRP. (d) USA. (e) CHN. (f) EUR. (g) JPN. (h) KOR. (i) UK.

increase in the TCI. The increase witnessed at the beginning of 2020 is similar to the reported rise in commodity market connectedness during the global financial crisis of 2007–9.

4.3 Net total and pairwise directional time-variant connectedness

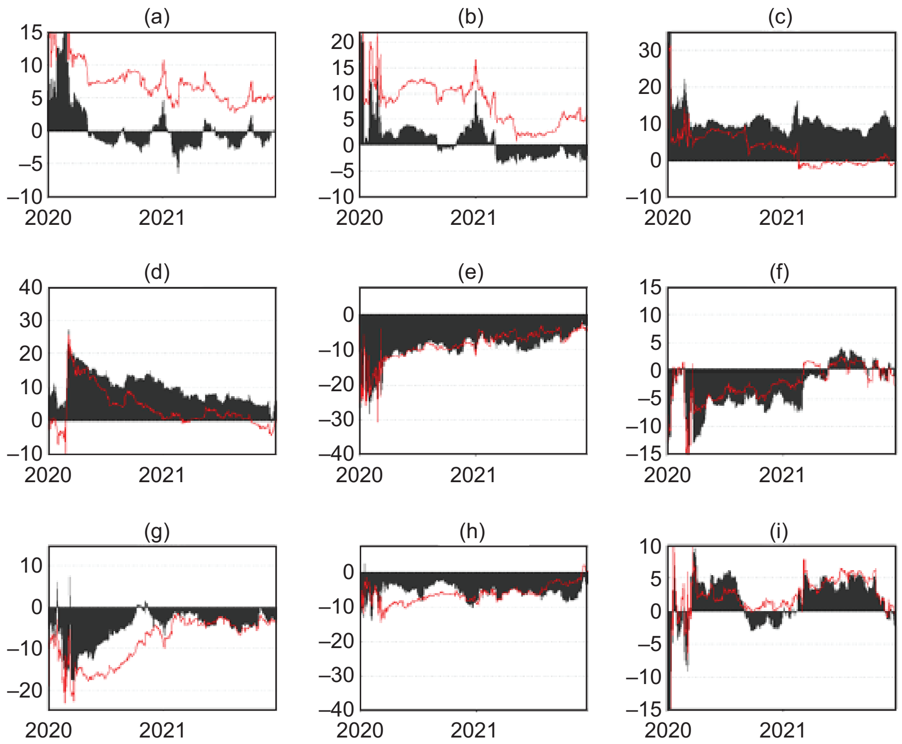
The connectedness results in the following analysis are an additional indication for distinguishing different markets as net transmitters or receivers. The dynamic method also reveals the possibility of different markets switching between the two roles. We show that the role a market plays in the system is determined by the time interval and market type.

We start with net total connectedness, which allows us to see whether a market's role has changed over time compared with other markets. We next go through our findings of pairwise net connectedness to scrutinize the evolution of interrelationship over time and the two roles mentioned above by looking at pairs of markets. Figure 3 depicts the findings for net total connectedness. Positive values indicate net transmission, and negative values indicate net receipt. The previous average joint-connectedness analysis shows alignments with the dynamic connectedness analysis. For BTC, the market was a net receiver of shocks for most of the sample period. ETH, EUR, JPN and UK all shared the same pattern of fluctuation between receiving and transmitting. Among them, JPN and EUR witnessed a trend of considerable net shock receipt after the pandemic hit. This means that, before the beginning of 2020, the TCIs of these two markets was mostly positive. After the pandemic began, their TCIs dropped to negatives values, and from 2020 to 2021 they remained mainly net receivers of shocks. Among the nine markets, XRP and USA were persistent net transmitters of shocks, while CHN and KOR were the two consistent net receivers. Therefore, it can be concluded from the findings that CHN and KOR are the two long-term net receivers of shocks, while XRP and USA are the long-term transmitters.

Such dynamics are not surprising. China is considered the largest source of crypto mining, accounting for about 80% of mining activity (Corbet *et al* 2021). Thus, it is highly connected to crypto investment. Further, China was where the exogenous shock of Covid-19 first appeared, causing lockdowns. This may have made China a long-term net shock receiver, since investors replace risky assets with safe-haven ones. The United States, on the other hand, has the world's largest financial sector, which may explain its role as a net shock transmitter. Understanding such dynamics could help investors determine how quickly they would need to adjust their portfolios before the shocks are realized. It would also benefit policy makers and regulators by helping to establish mechanisms to absorb the impact of such shocks – for example, by introducing circuit breakers in markets for highly connected traded assets.

Figure 4 illustrates the connectedness during the Covid-19 pandemic. BTC was a net transmitter at the beginning of 2020, while ETH played a role as a net transmitter from the beginning of 2020 to the beginning of 2021, before returning to being a net receiver of shocks. XRP and USA, as expected, were still the two long-term net transmitters, while CHN and KOR remained the long-term net receivers. After the Covid-19 pandemic had started, JPN turned into a net receiver of shocks, with only a few brief moments as a net transmitter at the beginning of 2020. Note that Japan was the largest source of crypto mining after China. Therefore, the pandemic and the falling demand for cryptocurrencies made JPN a net receiver. As for Europe, EUR witnessed the same trend, except that by 2021 the market had become a net transmitter again. These dynamics for EUR were mainly due to the pandemic: Europe was the first bloc to impose a lockdown after China, putting pressure on energy markets in the European Union; then, in 2021, lockdown measures were eased, and energy

FIGURE 4 Net total directional time-variant connectedness of returns during the Covid-19 pandemic.

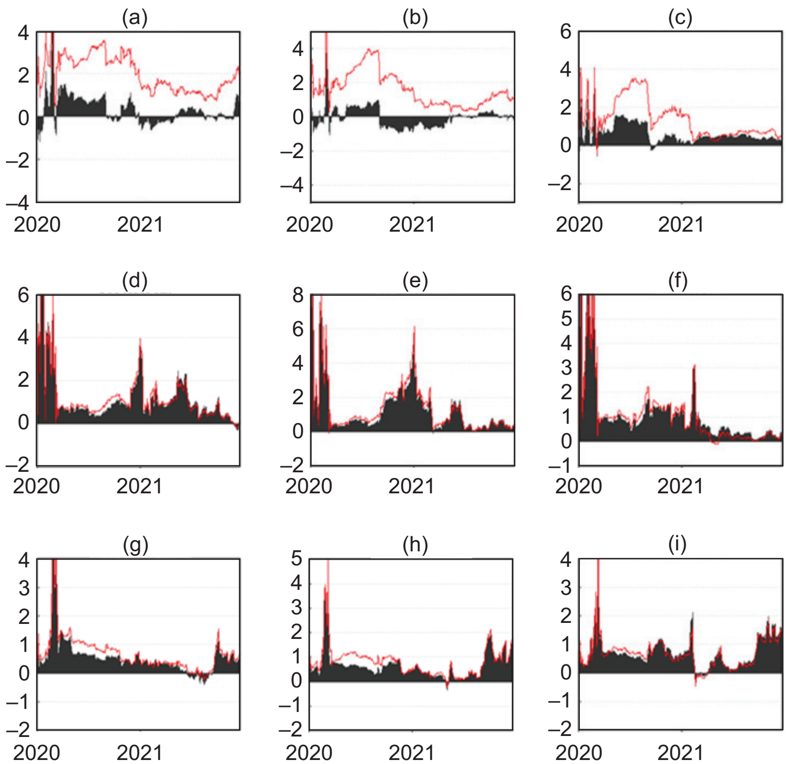


(a) BTC. (b) ETH. (c) XRP. (d) USA. (e) CHN. (f) EUR. (g) JPN. (h) KOR. (i) UK.

demand started to soar again. While the fluctuation in the TCI values of the UK market appeared mostly at the beginning and end of 2020, the UK market played the role of a net transmitter for much of the time during the pandemic, due to less-stringent Covid-19 restrictions than other European countries as well as the fact that many European commodities exchanges are based in London.

The normalization approach employed in the original TVP-VAR methodology is not theory-based and thus represents an arbitrary way of normalizing connectedness. Therefore, the theoretically derived measures suggested by Lastrapes and Wiesen (2021) are recommended. Our study now focuses on the net pairwise connectedness results presented in Figure 5, which are based on these measures. In particular, we scrutinize the spillover effects of the crypto markets on different energy markets. The results indicate that the three cryptocurrencies account for the volatility of

FIGURE 5 Net pairwise directional connectedness of returns during the Covid-19 pandemic, showing the influence of cryptocurrencies on energy markets.



(a) BTC–USA. (b) ETH–USA. (c) XRP–USA. (d) BTC–CHN. (e) ETH–CHN. (f) XRP–CHN. (g) BTC–EUR. (h) ETH–EUR. (i) XRP–EUR.

the energy markets. After the start of the Covid-19 pandemic, BTC and XRP were the cryptocurrencies that most influenced USA, while for most of the time between 2020 and 2021, ETH was a net receiver of USA's influence. This means that USA had more impact on ETH than ETH had on USA. However, at the beginning of 2020, all three crypto markets peaked in their TCI values, indicating that at that time USA was significantly impacted by cryptocurrencies. In addition, XRP was the only cryptocurrency to remain a consistent net transmitter of shocks to USA. As one of the long-term net receivers of shocks, CHN was consistently influenced by all three cryptocurrencies, with the TCI values also peaking at the beginning of 2020. The three cryptocurrencies were also net transmitters of shocks to EUR from the start of the pandemic onward. These results indicate that cryptocurrencies explain the volatility of the energy markets during the pandemic.

5 CONCLUSION AND POLICY IMPLICATIONS

We adopted a network connectedness approach using a TVP-VAR methodology to estimate the interrelationships between cryptocurrencies and energy markets in a time-varying regime. We also introduced flexibility to the model by following the method of Balcilar *et al* (2021), enabling us to attain metrics for net pairwise connectedness. We collected daily observations for the three largest cryptocurrencies and six largest energy indexes from January 1, 2018 to December 31, 2021. Using the complete data set, we proved that the two asset classes were somewhat interconnected. However, during the Covid-19 pandemic, their interrelationship becomes stronger, as illustrated by the relatively high TCI values of around 45% for the entire sample and 46% during Covid-19. The results suggest that market risk dominates our constructed network. In particular, we found time-variant interrelationships within the system that were triggered by the Covid-19 pandemic. Our findings emphasize the influence of the pandemic on the system-wide dynamic connectedness due to fundamental public-health, economic and financial changes. Net total directional connectedness revealed that each cryptocurrency and energy index had heterogeneous roles, depending on their internal characteristics and external shocks. Notably, BTC and XRP were found to be net receivers of shocks, while ETH shifted from a receiver to a transmitter. As for the energy markets, USA was a persistent net transmitters of shocks, while CHN and KOR were the two consistent net receivers. Pairwise connectedness revealed that cryptocurrencies can explain most of the volatility of the energy markets at the beginning of 2020, during the start of the Covid-19 pandemic.

The findings provide practical implications for investors and authorities, offering insights into contagion across diverse markets and its connection to policy. Knowing the connectedness between various markets and asset classes can help policy makers design adequate policies to reduce market vulnerabilities and minimize negative spillovers. Policy makers should examine the spillover of information from the BTC market to prevent the market becoming a source of systemic risks. Improving the regulatory system of the BTC market, mainly through the hash rate, is an effective way to lessen the risk of contagion in the system. The dynamic supervision of energy consumption through the sustainable reform of cryptocurrencies can also help reduce the risk of spillovers.

We find considerable relationships between crypto and energy markets, emphasizing the potential impacts on diversification and portfolio balancing. This paper highlights the increasing market interrelationships during unexpected and highly uncertain events such as the recent Covid-19 pandemic. Through these findings, we show that each asset class has its specific role within the overall network, which implies that investors and portfolio managers should be more cautious in managing their investments. By monitoring the contagion of uncertainty and risk, they could obtain early-warning signals for consideration in investment strategies and dynamic portfolio rebalancing. Understanding the dynamics of shock transmitters and receivers would help investors determine how quickly they need to adjust their portfolios before shocks are realized. It would also benefit policy makers and regulators by helping to establish mechanisms to absorb the impact of such shocks – for example, by introducing circuit breakers in markets for highly connected traded assets.

Besides highlighting cryptocurrencies' role in financial contagion, we also open up the discussion of their socioeconomic and environmental viability, as crypto mining exerts a severe drain on electricity and thus disrupts energy supply chains and prices. Finally, there is also a public welfare implication to our results, which can help inform policies intended to prevent crypto markets from transmitting socially adverse effects to energy markets. Hence, our results are invaluable for designing policies that enhance the welfare of vulnerable groups and society at large.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

REFERENCES

Afjal, M., and Clanganthuruthil Sajeev, K. C. (2022). Interconnection between cryptocurrencies and energy markets: an analysis of volatility spillover. *OPEC Energy Review* **46**(3), 287–309 (https://doi.org/10.1111/opec.12227).

Al-Shboul, M., Assaf, A., and Mokni, K. (2023). Does economic policy uncertainty drive the dynamic spillover among traditional currencies and cryptocurrencies? The role of the COVID-19 pandemic. *Research in International Business and Finance* **64**, Paper 101824 (https://doi.org/10.1016/j.ribaf.2022.101824).

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., and de Gracia, F. P. (2020). Oil and asset classes implied volatilities: investment strategies and hedging effectiveness. *Energy Economics* **91**, Paper 104762 (https://doi.org/10.1016/j.eneco.2020.104762).

Ashfaq, S., Tang, Y., and Maqbool, R. (2019). Volatility spillover impact of world oil prices on leading Asian energy exporting and importing economies' stock returns. *Energy* **188**, Paper 116002 (https://doi.org/10.1016/j.energy.2019.116002).

Attarzadeh, A., and Balcilar, M. (2022). On the dynamic connectedness of the stock, oil, clean energy, and technology markets. *Energies* **15**(5), Paper 1893 (https://doi.org/10.3390/en15051893).

Balcilar, M., Gabauer, D., and Umar, Z. (2021). Crude oil futures contracts and commodity markets: new evidence from a TVP-VAR extended joint connectedness approach. *Resources Policy* **73**, Paper 102219 (https://doi.org/10.1016/j.resourpol.2021.102219).

Bašta, M., and Molnár, P. (2018). Oil market volatility and stock market volatility. *Finance Research Letters* **26**, 204–214 (https://doi.org/10.1016/j.frl.2018.02.001).

Bigerna, S., Bollino, C. A., and Polinori, P. (2021). Oil import portfolio risk and spillover volatility. *Resources Policy* **70**, Paper 101976 (https://doi.org/10.1016/j.resourpol.2020.101976).

Caloia, F. G., Cipollini, A., and Muzzioli, S. (2019). How do normalization schemes affect net spillovers? A replication of the Diebold and Yılmaz (2012) study. *Energy Economics* **84**, Paper 104536 (https://doi.org/10.1016/j.eneco.2019.104536).

Cevik, N. K., Cevik, E. I., and Dibooglu, S. (2020). Oil prices, stock market returns and volatility spillovers: evidence from Turkey. *Journal of Policy Modeling* **42**(3), 597–614 (https://doi.org/10.1016/j.jpolmod.2020.01.006).

Conlon, T., and McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. *Finance Research Letters* **35**, Paper 101607 (https://doi.org/10.1016/j.frl.2020.101607).

Corbet, S., Lucey, B., Urquhart, A., and Yarovaya, L. (2019). Cryptocurrencies as a financial asset: a systematic analysis. *International Review of Financial Analysis* **62**, 182–199 (https://doi.org/10.1016/j.irfa.2018.09.003).

Corbet, S., Lucey, B., and Yarovaya, L. (2021). Bitcoin–energy markets interrelationships: new evidence. *Resources Policy* **70**, Paper 101916 (https://doi.org/10.1016/j.resourpol.2020.101916).

Cui, J., Goh, M., Li, B., and Zou, H. (2021). Dynamic dependence and risk connectedness among oil and stock markets: new evidence from time–frequency domain perspectives. *Energy* **216**, Paper 119302 (https://doi.org/10.1016/j.energy.2020.119302).

Das, D., Kumar, S. B., Tiwari, A. K., Shahbaz, M., and Hasim, H. M. (2019). On the relationship of gold, crude oil, stocks with financial stress: a causality-in-quantiles approach. *Finance Research Letters* **27**, 169–174 (https://doi.org/10.1016/j.frl.2018.02.030).

Demiralay, S., and Bayracı, S. (2021). Should stock investors include cryptocurrencies in their portfolios after all? Evidence from a conditional diversification benefits measure. *International Journal of Finance and Economics* **26**(4), 6188–6204 (https://doi.org/10.1002/ijfe.2116).

Diebold, F. X., and Yılmaz, K. (2012). Better to give than to receive: predictive directional measurement of volatility spillovers. *International Journal of Forecasting* **28**(1), 57–66 (https://doi.org/10.1016/j.ijforecast.2011.02.006).

Elliott, G., Rothenberg, T. J., and Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica* **64**, 813–836 (https://doi.org/10.2307/2171846).

Elsayed, A. H., Gozgor, G., and Lau, C. K. M. (2022). Causality and dynamic spillovers among cryptocurrencies and currency markets. *International Journal of Finance and Economics* **27**(2), 2026–2040 (https://doi.org/10.1002/ijfe.2257).

Ersan, O., Demir, E., and Assaf, A. (2022). Connectedness among fan tokens and stocks of football clubs. *Research in International Business and Finance* **63**, Paper 101780 (https://doi.org/10.1016/j.ribaf.2022.101780).

Fisher, T. J., and Gallagher, C. M. (2012). New weighted portmanteau statistics for time series goodness of fit testing. *Journal of the American Statistical Association* **107**(498), 777–787 (https://doi.org/10.1080/01621459.2012.688465).

Ghabri, Y., Huynh, L. D. T., and Nasir, M. A. (2022). Volatility spillovers, hedging and safe-havens under pandemics: all that glitters is not gold! *International Journal of Finance and Economics* (https://doi.org/10.1002/ijfe.2738).

Giannellis, N. (2022). Cryptocurrency market connectedness in Covid-19 days and the role of Twitter: evidence from a smooth transition regression model. *Research in International Business and Finance* **63**, Paper 101801 (https://doi.org/10.1016/j.ribaf.2022.101801).

Jareño, F., González, M. O., López, R., and Ramos, A. R. (2021). Cryptocurrencies and oil price shocks: a NARDL analysis in the COVID-19 pandemic. *Resources Policy* **74**, Paper 102281 (https://doi.org/10.1016/j.resourpol.2021.102281).

Jarque, C. M., and Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters* **6**(3), 255–259 (https://doi.org/10.1016/0165-1765(80)90024-5).

Ji, Q., Bouri, E., Roubaud, D., and Kristoufek, L. (2019). Information interdependence among energy, cryptocurrency and major commodity markets. *Energy Economics* **81**, 1042–1055 (https://doi.org/10.1016/j.eneco.2019.06.005).

Jiang, Z., and Yoon, S.-M. (2020). Dynamic co-movement between oil and stock markets in oil-importing and oil-exporting countries: two types of wavelet analysis. *Energy Economics* **90**, Paper 104835 (https://doi.org/10.1016/j.eneco.2020.104835).

Jiang, S., Li, Y., Lu, Q., Wang, S., and Wei, Y. (2022). Volatility communicator or receiver? Investigating volatility spillover mechanisms among Bitcoin and other financial markets. *Research in International Business and Finance* **59**, Paper 101543 (https://doi.org/10.1016/j.ribaf.2021.101543).

Khalfaoui, R., Sarwar, S., and Tiwari, A. K. (2019). Analyzing volatility spillover between the oil market and the stock market in oil-importing and oil-exporting countries: implications on portfolio management. *Resources Policy* **62**, 22–32 (https://doi.org/10.1016/j.resourpol.2019.03.004).

Koop, G., Pesaran, M. H., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* **74**(1), 119–147 (https://doi.org/10.1016/0304-4076(95)01753-4).

Kumah, S. P., and Mensah, J. O. (2022a). Do cryptocurrencies and crude oil influence each other? Evidence from wavelet-based quantile-in-quantile approach. *Cogent Economics and Finance* **10**(1), Paper 2082027 (https://doi.org/10.1080/23322039.2022.2082027).

Kumah, S. P., and Mensah, J. O. (2022b). Are cryptocurrencies connected to gold? A wavelet-based quantile-in-quantile approach. *International Journal of Finance and Economics* **27**(3), 3640–3659 (https://doi.org/10.1002/ijfe.2342).

Lahmiri, S., and Bekiros, S. (2020). The impact of COVID-19 pandemic upon stability and sequential irregularity of equity and cryptocurrency markets. *Chaos, Solitons and Fractals* **138**, Paper 109936 (https://doi.org/10.1016/j.chaos.2020.109936).

Lamothe-Fernández, P., Alaminos, D., Lamothe-López, P., and Fernández-Gámez, M. A. (2020). Deep learning methods for modeling Bitcoin price. *Mathematics* **8**(8), Paper 1245 (https://doi.org/10.3390/math8081245).

Lastrapes, W. D., and Wiesen, T. F. P. (2021). The joint spillover index. *Economic Modelling* **94**, 681–691 (https://doi.org/10.1016/j.econmod.2020.02.010).

Li, H., Semeyutin, A., Lau, C. K. M., and Gozgor, G. (2020). The relationship between oil and financial markets in emerging economies: the significant role of Kazakhstan as the oil exporting country. *Finance Research Letters* **32**, Paper 101171 (https://doi.org/10.1016/j.frl.2019.04.028).

Liu, Z., Tseng, H.-K., Wu, J. S., and Ding, Z. (2020). Implied volatility relationships between crude oil and the US stock markets: dynamic correlation and spillover effects. *Resources Policy* **66**, Paper 101637 (https://doi.org/10.1016/j.resourpol.2020.101637).

Mokni, K. (2020). A dynamic quantile regression model for the relationship between oil price and stock markets in oil-importing and oil-exporting countries. *Energy* **213**, Paper 118639 (https://doi.org/10.1016/j.energy.2020.118639).

Moussa, W., Regaïeg, R., and Mgadmi, N. (2020). Estimating the hedging potentials of Bitcoin and energy returns. *The Journal of Energy Markets* **13**(4), 101–115 (https://doi.org/10.21314/JEM.2020.212).

Nazlioglu, S., Gupta, R., and Bouri, E. (2020). Movements in international bond markets: the role of oil prices. *International Review of Economics and Finance* **68**, 47–58 (https://doi.org/10.1016/j.iref.2020.03.004).

Okorie, D. I. (2021). A network analysis of electricity demand and the cryptocurrency markets. *International Journal of Finance and Economics* **26**(2), 3093–3108 (https://doi.org/10.1002/ijfe.1952).

Pavlova, I., de Boyrie, M. E., and Parhizgari, A. M. (2018). A dynamic spillover analysis of crude oil effects on the sovereign credit risk of exporting countries. *Quarterly Review of Economics and Finance* **68**, 10–22 (https://doi.org/10.1016/j.qref.2018.03.003).

Pesaran, H. H., and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters* **58**(1), 17–29 (https://doi.org/10.1016/S0165-1765(97)00214-0).

Qin, X. (2020). Oil shocks and financial systemic stress: international evidence. *Energy Economics* **92**, Paper 104945 (https://doi.org/10.1016/j.eneco.2020.104945).

Sapra, N., and Shaikh, I. (2023). Impact of Bitcoin mining and crypto market determinants on Bitcoin-based energy consumption. *Managerial Finance*, forthcoming (https://doi.org/10.1108/MF-03-2023-0179).

Sarwar, S., Tiwari, A. K., and Tingqiu, C. (2020). Analyzing volatility spillovers between oil market and Asian stock markets. *Resources Policy* **66**, Paper 101608 (https://doi.org/10.1016/j.resourpol.2020.101608).

Wang, H., Wang, X., Yin, S., and Ji, H. (2021). The asymmetric contagion effect between stock market and cryptocurrency market. *Finance Research Letters* **46**(A), Paper 102345 (https://doi.org/10.1016/j.frl.2021.102345).

Yuan, X., Su, C.-W., and Peculea, A. D. (2022). Dynamic linkage of the bitcoin market and energy consumption: an analysis across time. *Energy Strategy Reviews* **44**, Paper 100976 (https://doi.org/10.1016/j.esr.2022.100976).

Zheng, M., Feng, G. F., Zhao, X., and Chang, C. P. (2023). The transaction behavior of cryptocurrency and electricity consumption. *Financial Innovation* **9**(1), 1–18 (https://doi.org/10.1186/s40854-023-00449-7).