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Dynamic connectedness between non-fungible tokens, decentralized finance, and conventional financial assets in a time-frequency framework

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A B S T R A C T

This study examines how the COVID-19 pandemic has affected the connectedness between non-fungible tokens, decentralized finance coins, traditional financial assets, and cryptocurrencies. We employed a time-varying parameter vector autoregressive based frequency-dependent network connectedness approach to investigate return and volatility spillover effects between assets in time and frequency domains. The findings show that both the returns and volatility spillovers have been significantly affected by the COVID-19 pandemic, and long- and short-term connectedness vary over the course of the pandemic. These findings have implications for investors, portfolio managers, and policymakers regarding their investment strategies, portfolio allocation, and risk monitoring.

1. Introduction

Since the official declaration of the coronavirus (COVID-19) pandemic by the World Health Organization on March 11, 2020, there have been 422,188,754 confirmed cases and 5,876,766 deaths globally as of February 20, 2022.[1] The COVID-19 pandemic has had a serious impact not only on health issues, but on the global economy. Various financial measures to contain the spread of COVID-19, such as interest rate cuts and COVID-19 relief aid packages, have caused sharp market turmoil in the global financial markets.

Despite this turmoil, the cryptocurrency market, including Bitcoin, has rapidly expanded in size.[2] Furthermore, the market for non-fungible tokens (NFTs) has rapidly gained popularity. Unlike cryptocurrency, NFT's biggest feature is non-fungibility (Dowling, 2022),

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[1] Weekly epidemiological update on COVID-19 - 22 February 2022, WHO https://www.who.int/publications/m/item/weekly-epidemiological-update-on-covid-19—22-february-2022.

[2] "Centralized crypto exchanges saw over $14 trillion in trading volume this year", The Block https://www.theblockcrypto.com/linked/128526/centralized-crypto-exchanges-14-trillion-trading-volume-2021

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which gives NFTs uniqueness and individualized value, further causing people to recognize their digital scarcity.[3] Market demand for NFTs has increased rapidly. In the first half of 2021, trade volume in the NFT market reached $2.5 billion, compared to $13.7 million in the first half of 2020.[4] Like cryptocurrencies, NFTs were developed based on the blockchain technology (Umar et al., 2022a). Additionally, Decentralized Finance or "DeFi" is a new digital asset that uses blockchain technology; it is considered to be a form of evolution in finance technology. One of the most innovative aspects of DeFi is the existence of a decentralized transaction system, as opposed to transactions using a centralized financial system in traditional finance (Chen and Bellavitis, 2019; Chen and Bellavitis, 2020; Zetzsche et al., 2020; Umar et al., 2022a; Schär, 2021). DeFi has been attracting considerable interest from market participants, such as investors and policymakers, in line with the growing demand for cryptocurrency and the trend of innovation in financial technology.[5]

This study aimed to investigate how the COVID-19 pandemic has affected the connectedness between NFTs, DeFi coins (Chainlink, Maker, Basic Attention Token), and traditional financial assets including energy, industrial metals, precious metals, equities, bonds, and cryptocurrencies (Bitcoin, Ethereum, Ripple). The first motivation for this study is to investigate the impact of the COVID-19 pandemic on the financial asset market and promote the stability of the financial market. The COVID-19 pandemic has created great uncertainty in the world, including in financial markets. Resolving these uncertainties in the financial market is the main motivation for this study. Additionally, although there is abundant research on cryptocurrency, the research on NFT and DeFi assets is in its nascent stages. Academic research has yet to meet the market demand for NFTs and DeFi assets. Consequently, the second motivation for this research is to improve the understanding of the new financial landscape through the relationship between NFTs, DeFi assets and existing financial assets.

Investigation of the connectedness between financial assets provides important insights and implications for investors and policymakers. First, the dynamic linkage of cross-markets can affect portfolio management in terms of hedging or rebalancing. In particular, the dynamic connectedness of returns and volatility can improve portfolio diversification effects, which is an important issue for portfolio managers. Second, the connectivity between financial assets serves as the basis for explaining risk transmission in markets. Furthermore, the financial asset market is changing rapidly due to the COVID-19 pandemic, and the relationship between financial assets is also changing considerably. Therefore, this study helps understand these changes as well as possible responses to future crises.

Our study contributes to the relevant literature from the following perspectives. First, we have highlighted the spillover effects among new digital assets (NFT, DeFi), which have recently received great attention from market participants, and existing traditional financial assets. Second, we investigated the return and volatility spillovers among them by using both time- and frequency-based methods, through which we examined the static and dynamic connectedness between digital assets and other classical assets, as well as the short-, medium-, and long-term network structures among them in terms of return and volatility. Third, we estimated dynamic structures of connectedness that are frequency-dependent. In doing so, we identified both temporary and permanent linkages among the returns and volatilities. Lastly, we revealed how the COVID-19 pandemic has affected their relationship by examining their connectedness in the pre-pandemic and pandemic period.

Overall, one of the most notable things in this study is that digital assets, especially, NFT and DeFi assets, are investigated due to their emergence as a new asset class and as such, a relatively less explored domain in academic literature. Our choice of assets stem from the following rationale. First, the NFT and DeFi use the Ethereum smart contracts. As such, the cryptocurrency market and digital assets (NFT and DeFi) are bound to have a close relationship (Karim et al., 2022). Therefore, NFT and DeFi have the potential to become significant financial assets, as cryptocurrency has been recognized as one of the more important assets in financial markets. Second, based on the successful launch of NFT collections, NFTs are already being used in various fields, such as, digital artwork, games, metaverse, etc. (Nadini et al., 2021). Besides, the applicability of NFT is discussed in various fields. For instance, Chohan and Paschen (2021) discussed the implications of NFTs on marketing and argued that marketers should consider implementing NFTs in their marketing campaigns. Bamakan et al. (2022) examined the possibility of presenting intellectual property assets, specifically patents, as NFTs. In addition, they further proposed NFT-based patent framework. Third, DeFi can complement or replace traditional financial activities, since it excludes centralized intermediaries, such as a banks and brokerages. In other words, many financial services occurring in centralized finance can be replaced by the DeFi ecosystem. Furthermore, the decentralized networks of DeFi can reduce transaction costs and information asymmetry by platforms and codes, compared to the traditional financial system (Grassi et al., 2022). Typical fields where the Defi framework is being used or is likely to be used are stablecoins, exchanges, money markets, financial derivatives, and insurance (Abdulhakeem and Hu, 2021).

The remainder of this paper is organized as follows. Section 2 provides a literature review on the spillover effect of cryptocurrency, the COVID-19 pandemic, and the new digital assets. Section 3 describes the methods employed in this study. Section 4 shows the results of the empirical analysis. Finally, Section 5 provides concluding remarks and implications for the study.

[3] What are the copyright implications of NFTs? Reuters https://www.reuters.com/legal/transactional/what-are-copyright-implications-nfts-2021-10-29/.

[4] Howcroft, L., 2021. NFT sales volume surges to $2.5 billion in 2021 first half. Reuters, July 6, 2021. https://www.reuters.com/technology/nft-sales-volume-surges-25-bln-2021-first-half-2021-07-05.

[5] One of the Biggest Crypto Traders Is Tapping DeFi Loans for Funding, Bloomber, Feb 25, 2022. https://www.bloomberg.com/news/articles/2022-02-24/one-of-biggest-crypto-traders-is-tapping-defi-loans-for-funding.

2. Literature review

In this section, first, we discuss previous studies on the spillover effect between cryptocurrency and other assets. Second, we discuss several studies that investigated the impact of the COVID-19 pandemic on financial markets. Third, we discuss the existing literature on NFTs and DeFi.

2.1. Spillover effect of cryptocurrency

Since the introduction of Bitcoin in 2008 (Nakamoto, 2008), cryptocurrencies have received substantial attention from investors because of their new paradigm regarding financial systems. Bitcoin is now recognized as a popular financial asset. Consequently, there are abundant studies discussing cryptocurrencies. We discuss the studies that investigated the relationship between existing financial assets and cryptocurrency in terms of spillover effects. Based on the spillover analysis, they revealed how cryptocurrencies are related to conventional financial assets, as well as the features of cryptocurrencies through the relationship characteristics.

For example, various studies investigated the return or volatility spillover between cryptocurrencies and other traditional asset classes, such as stocks, bonds, commodities, and currencies (Symitsi and Chalvatzis, 2018; Mensi et al., 2019; Vardar and Aydogan, 2019; Dahir et al., 2020; Rehman, 2020; Su and Li, 2020; Aharon et al., 2021; Jiang et al., 2022; Umar et al., 2021a, 2021b; Umar et al., 2021f). Their findings indicated that the connectedness among them is strengthened during periods of high uncertainty. Furthermore, these findings have useful applications for investors and policymakers, such as Bitcoin hedging, safe haven property, and portfolio diversification. Especially, several studies have focused on the effect of the COVID-19 pandemic on the interdependency among cryptocurrencies and other financial assets (Nguyen, 2021; Guo et al., 2021; Gubareva and Umar, 2020; Gubareva et al., 2021). They showed that the linkage among them was enhanced during the COVID-19 pandemic.

On the other hand, several studies have examined the interdependency within cryptocurrencies (Yi et al., 2018; Kumar and Anandarao, 2019; Katsiampa et al., 2019; Moratis, 2021). They investigated the dynamic connectedness between various cryptocurrencies, including Bitcoin, Ethereum, and Ripple, using various approaches, such as Diebold and Yilmaz's spillover and wavelet methodology. Their findings suggested that cryptocurrencies are tightly and positively interconnected and have time-varying relationships among them. Additionally, other studies have investigated the effect of economic uncertainty on the relationship between cryptocurrencies and other financial assets (Wang et al., 2020; Fasanya et al., 2021a; Zhang et al., 2022).

2.2. Spillover effect of the COVID-19 pandemic

Many studies have analyzed how the COVID-19 pandemic affected the connectedness of global financial markets using the spillover effect among cross-border asset markets.

First, various studies have compared the spillover effects among the stock indices of different countries before and during the COVID-19 pandemic (Abuzayed et al., 2021; Samitas et al., 2022; Choi, 2022b; Umar and Gubareva, 2021; Umar et al., 2021a). They all showed that the risk contagion became stronger during the COVID-19 pandemic by measuring volatility spillovers among various stock markets. In addition, the role as net transmitter or net receiver of volatility shocks was different for each country during the pandemic. Similarly, some studies have analyzed the effect of the COVID-19 pandemic on the relationship between asset markets in the commodity, foreign exchange (FX), and cryptocurrency markets, respectively. Borgards et al. (2021) investigated the overreaction behavior of various commodity futures without considering the effects of the COVID-19 pandemic. They demonstrated that the overreactions are significantly intense in terms of both number and amplitude during the pandemic. Furthermore, according to them, this extreme overreaction can provide a profitable trading opportunity. Some studies have investigated how the COVID-19 pandemic affected the interdependence among various foreign exchange rates (Wei et al., 2020; Fasanya et al., 2021b; Gunay, 2021). They all used the volatility spillover index of the Diebold and Yilmaz framework. According to their results, the total volatility spillover increased significantly during the pandemic compared to before it. In particular, Gunay (2021) showed that the total volatility spillover index during the pandemic was much higher than in 2008 Gobal financial crisis. Additionally, Naeem et al. (2021) and Kumar et al. (2022) uncovered the spillover effect among various cryptocurrencies during the COVID-19 pandemic. They found that their total connectedness has been amplified during the COVID-19 pandemic, as in other financial asset markets. In particular, Kumar et al. (2022), using a frequency-based connectedness method, showed that the return and volatility spillovers among cryptocurrencies are more sensitive to crisis periods over short time horizons (one day to one week) than over longer horizons (one month and above).

Second, the spillover phenomenon between different asset classes during the COVID-19 pandemic has been investigated in various studies (Umar et al., 2021c,e; Umar et al., 2022d; Umar et al., 2022b; Umar et al., 2022c). Among them, some have examined spillover effects between different financial assets within individual countries. For example, spillover analysis using different asset classes was implemented by Corbet et al. (2020a), Mensi et al. (2021), and Li et al. (2021) from China, Sakurai and Kurosaki (2020) and Adekoya and Oliyide (2021) from the United States, Narayan et al. (2020) from Japan, and Rai and Garg (2021) from BRICS. The studies also found that the relationship among the financial assets was stronger during the COVID-19 pandemic than before. In addition, there are also studies using financial assets from various countries (Le et al., 2021).

Third, although the COVID-19 pandemic has substantially shocked the global financial markets, the shocks could be positive or negative depending on the industry. For example, the tourism industry suffered tremendous damage, whereas IT-related industries have benefited greatly from telecommuting during the COVID-19 pandemic. Consequently, there are studies on how the COVID-19 pandemic has affected each industry through the spillover effect (Laborda and Olmo, 2021; Shahzad et al., 2021; Si et al., 2021; Choi, 2022a; Umar et al., 2021a, 2021b). Laborda and Olmo, and Choi, examined volatility spillovers among the US stock market

Table 1
Summary statistics of returns and volatilities.

Return Series						
	Mean	Maximum	Minimum	Skewness	Kurtosis	Jarque-Bera
Energy	0.037	17.377	−30.173	−1.838	30.300	42,984.664
Industrial Metals	0.041	3.978	−4.350	−0.199	1.303	86.256
Precious Metals	0.033	5.715	−5.426	−0.438	6.114	1762.919
Chain Link	0.425	48.416	−61.754	−0.006	6.070	1702.280
MKR	0.186	45.846	−81.821	−0.478	16.359	12,393.958
BAT	0.156	51.758	−51.083	0.060	5.521	1409.300
BTC	0.151	22.512	−46.473	−0.815	10.144	4874.145
ETH	0.193	35.365	−55.071	−0.697	8.290	3263.954
XRP	0.113	62.698	−54.797	1.007	13.928	9142.083
World Equity Index	0.038	8.406	−10.442	−1.491	21.855	22,451.914
World Bonds Index	0.007	1.490	−2.200	−1.054	10.437	5234.881
NFT	0.113	62.698	−54.797	1.370	20.955	20,610.736
Volatility Series						
Energy	0.309	2.036	0.081	3.591	15.072	12,770.545
Industrial Metals	0.156	0.370	0.036	0.706	0.328	96.173
Precious Metals	0.142	0.602	0.040	2.135	6.686	2884.373
Chain Link	1.216	4.364	0.318	1.823	4.283	1450.253
MKR	1.037	3.915	0.231	2.050	4.896	1869.451
BAT	1.143	3.894	0.190	1.685	4.380	1400.197
BTC	0.667	2.413	0.098	1.481	3.944	1115.952
ETH	0.878	2.911	0.164	1.620	4.083	1245.328
XRP	1.024	5.075	0.130	2.491	7.496	3712.623
World Equity Index	0.128	1.003	0.029	4.305	24.235	30,299.165
World Bonds Index	0.035	0.184	0.010	4.911	32.051	51,469.819
NFT	0.863	5.046	0.096	2.867	9.841	5943.125

Note: This Table shows the summary statistics of the return and volatility series of the assets employed.

sectors during the COVID-19 pandemic. Their results proposed that the pandemic has intensified volatility spillovers. Both studies showed that among several sectors, energy sectors played an important role in the transfer of volatility. In addition, Si et al. (2021) investigated the effect of the COVID-19 pandemic on volatility spillovers in the Chinese energy industry. To this end, they used nine energy subsectors in China; they demonstrated that the pandemic has significantly affected the Chinese energy industry, and that each subsector was affected differently. Similarly, Shahzad et al. (2021) focused on the inter-sectoral volatility linkage in the Chinese stock market. In particular, they examined the asymmetric volatility spillovers during the pandemic. Their findings indicated that the asymmetric impact of good and bad volatilities was extensively enhanced during the pandemic period.

Lastly, some studies have investigated the spillover effect between the COVID-19 news-related indices (Coronavirus media coverage index, sentiment index, media hype heat index, fake news index, panic emotion index, and contagion index) and financial assets (Zhang et al., 2022). Common to both studies, total interdependence among them was found to be strong when impactive events occurred.

2.3. Traditional financial assets, and NFTs and DeFi

Studies comparing new digital assets, such as NFTs and DeFi, with the traditional financial assets have recently been reported. For example, Aharon and Demir (2021) examined the dynamic connectedness among NFTs and other financial assets (equities, bonds, currencies, gold, oil, Ethereum) by using the time-varying parameter vector autoregression (TVP-VAR) model. Their empirical results indicated that NFTs are independent of the shocks from the financial assets and thus could provide portfolio diversification benefits. Dowling (2022) investigated the relationship between NFTs in terms of pricing using the DY spillover index and showed that NFT pricing was quite different from cryptocurrency pricing. They claimed that NFTs could be a low-correlation asset based on the low volatility transmission among NFTs and cryptocurrencies. Umar et al. (2022a) studied the coherence between returns of NFTs and major assets (equities, bonds, gold, oil, and Bitcoin) by using the wavelet approach. Their results proposed that the coherence of the pairwise returns between them expanded throughout the COVID-19 pandemic. Furthermore, NFTs absorbed risk during the pandemic.

Yousaf et al. (2022) recently examined the dynamic connectedness among DeFi assets and major currencies (Chinese Yuan, Japanese Yen, Euro, and Pound Sterling). The authors used Chainlink, Maker, Basic Attention Token, and Synthetix as DeFi assets in their study. Their spillover analysis results indicated that the DeFi and currency markets have low interdependence; their connectedness increased rapidly in early 2020, during the initial proliferation of the pandemic. Additionally, they showed that the DeFi markets played a predominant role in the net innovation transmitters during the first year of the COVID-19 pandemic.

To the best of our knowledge, however, no studies have examined the dynamic connectedness among NFT, DeFi, and other financial assets. Furthermore, this is the first study to compare the connectivity between the pre-pandemic and pandemic periods.

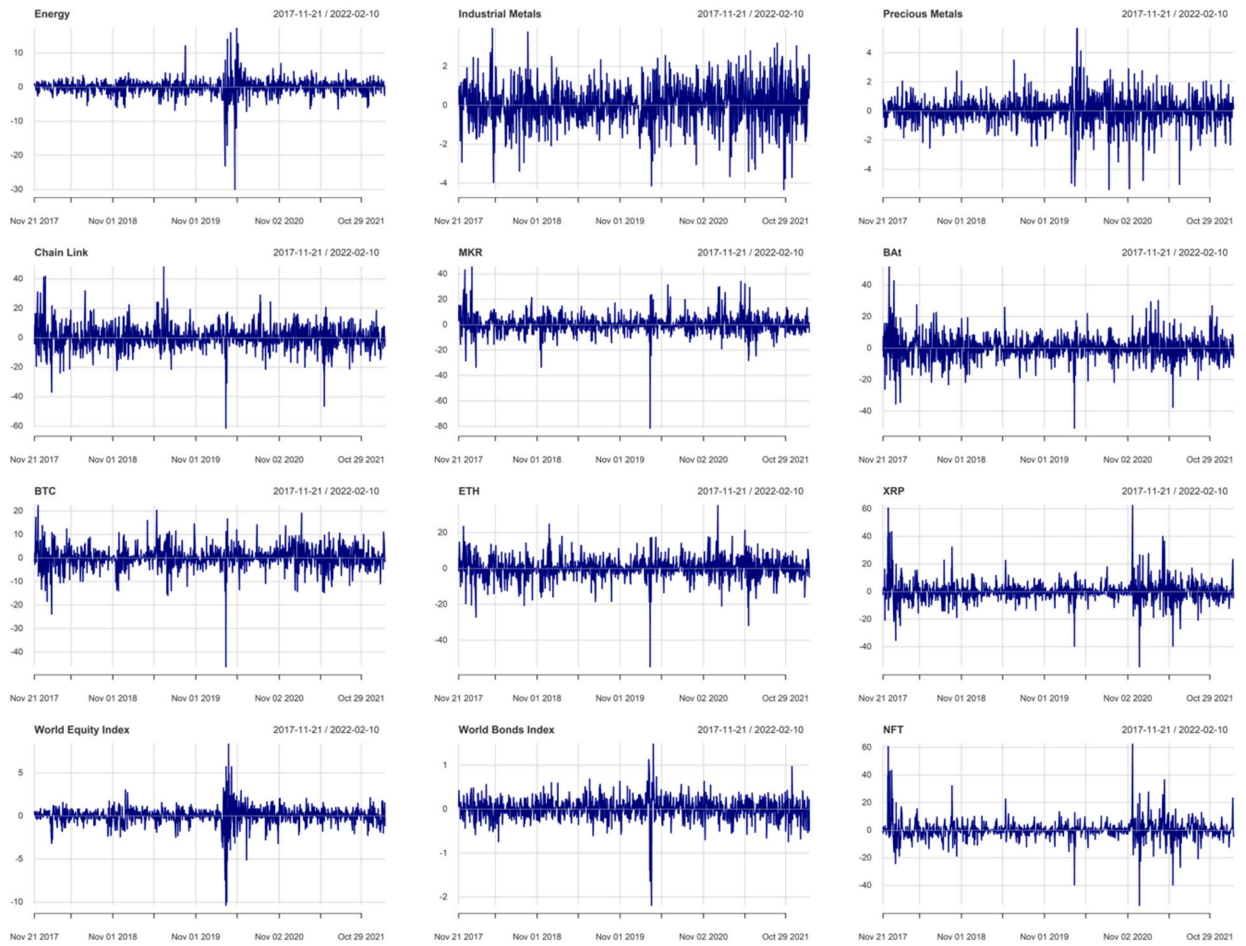

Fig. 1. Trends in return series.
Note: This figure shows the time series of the return of the assets employed.

3. Methodology

First, we employed the TVP-VAR connectedness approach introduced by Antonakakis et al. (2020) to analyze the changes in return and volatility connectedness between assets due to the COVID-19 pandemic. The method was developed by extending the Diebold and Yılmaz (2014) VAR-based connectedness approach. According to Antonakakis et al. (2020), the extended model has several advantages over the existing model. Especially, the adopted model has the advantage of not having to choose an arbitrary number of the rolling window size and having robustness for outliers. Furthermore, this method has been widely used to measure the spillover effects between financial assets (Bouri et al., 2021; Chatziantoniou et al., 2021; Foglia and Dai, 2021; Papathanasiou et al., 2022; Umar et al., 2021b). Second, in order to examine the short-, medium-, and long-term connectedness networks of return and volatilities for them, we implemented a frequency-dependent network connectedness approach developed by Barunik and Ellington (2020). This method uses a locally-stationary TVP-VAR model using Quasi-Bayesian Local Likelihood (QBLL) methods, which facilitates drawing the posterior distribution of the dynamic adjacency matrix of the network. The Bayesian framework of the methodology allows us to incorporate prior shrinkage and estimate uncertainty from the posterior distribution of the network. This novel structure of the method renders it superior to the conventional approaches that provide only point estimates by bootstrapping for confidence intervals. Additionally, this approach does not suffer from dimensionality issues with inference. By using the network framework, we further examined the frequency-based spillovers among NFTs, DeFi, and other financial assets. In accordance with these two approaches, we were able to study the effect of the COVID-19 pandemic on the linkages among assets in both time and frequency domains.

3.1. *The TVP-VAR connectedness*

Antonakakis et al. (2020) introduced a TVP-VAR connectedness approach that extends the *m* of Diebold and Yılmaz (2014) by allowing the variance-covariance matrix to vary via a Kalman filter estimation with forgetting factors based on Koop and Korobilis (2013).

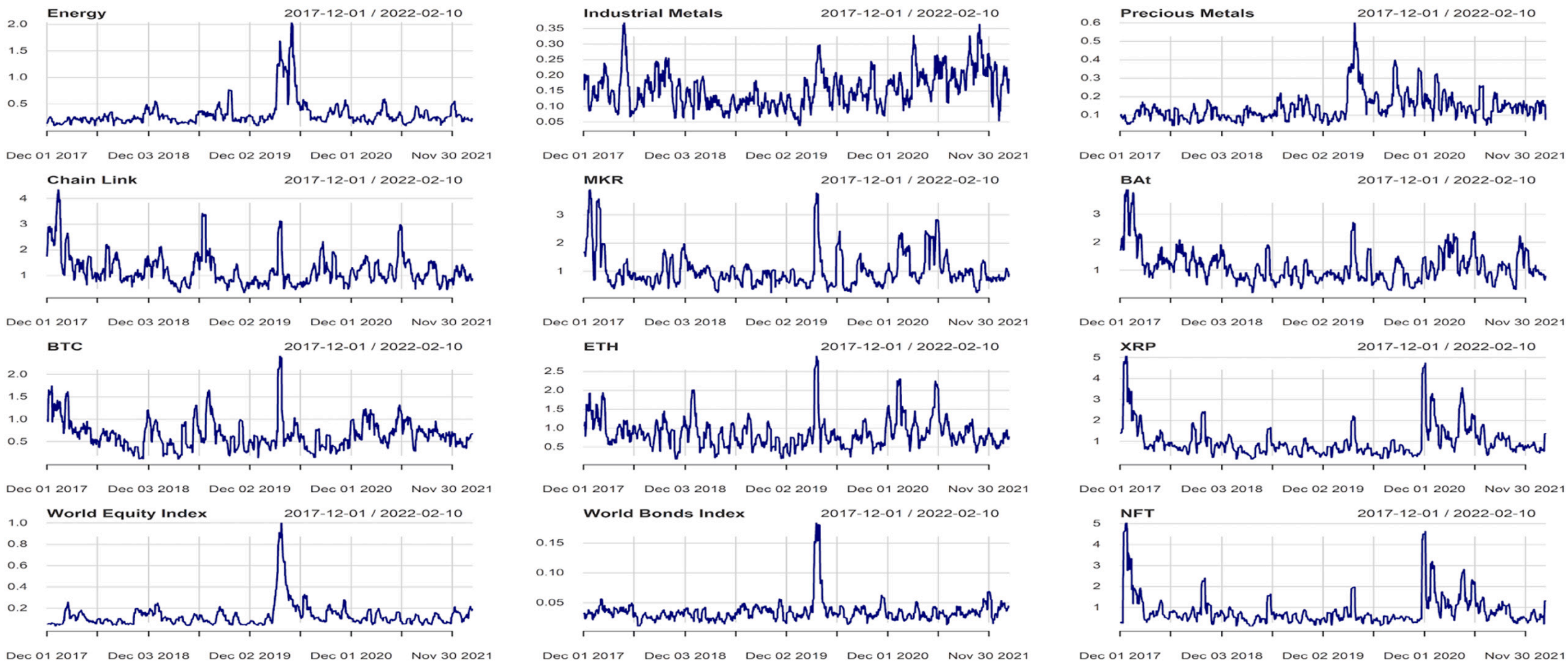

Fig. 2. Trends in volatility series.
Note: This figure shows the time series of the volatilities of the assets employed.

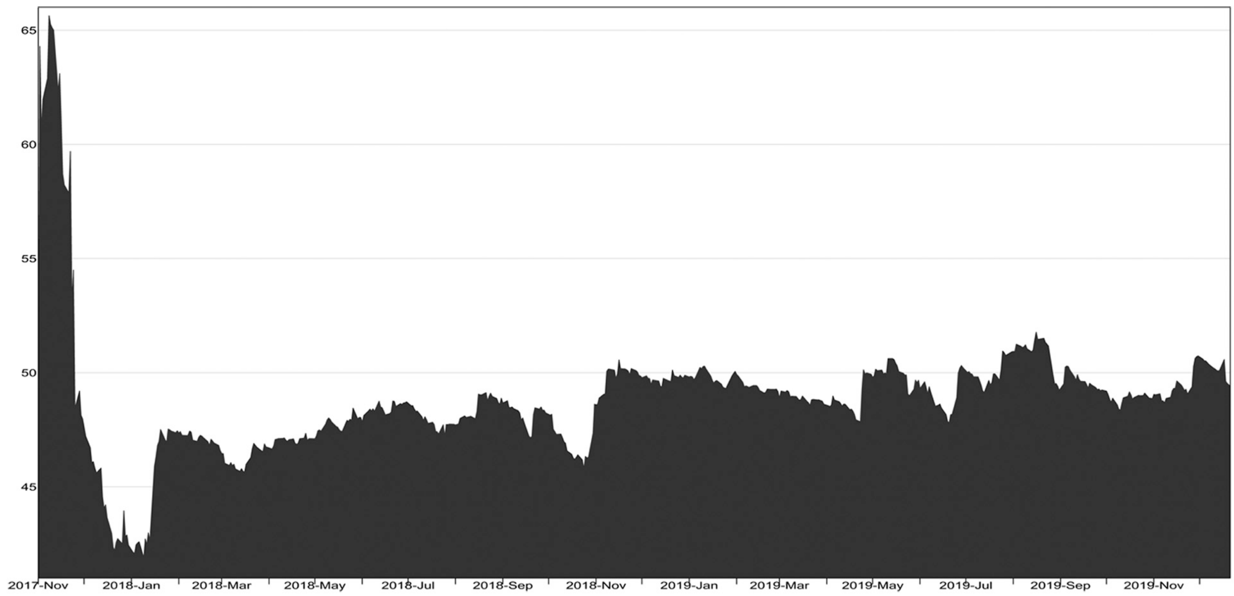

Fig. 3. Pre-COVID-19 total connectedness index for returns.
Note: This figure shows the total connectedness of the returns of assets during pre-covid period.

The $TVP - VAR(q)$ model is defined as follows:

$$z_t = A_t y_{t-1} + \varepsilon_t \ \varepsilon_t \mid \Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$vec(A_t) = vec(A_{t-1}) + \xi_t \ \xi_t \mid \Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

with

$$y_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-q} \end{pmatrix} A_t^{'} = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \vdots \\ A_{qt} \end{pmatrix} \tag{3}$$

where Ω_{t-1} denotes all information available until $t-1$; z_t and y_t represent $m \times 1$ and $mq \times 1$ vectors, respectively. The variables A_t and A_{it} are $m \times mq$ and $mq \times 1$ dimensional matrices, respectively. The variables ε_t and ξ_t are $m \times 1$ and $m^2q \times 1$ dimensional vectors, respectively. The variables Σ_t and Ξ_t are $m \times m$ and $m^2q \times m^2q$ dimensional matrices, respectively. The variable $vec(A_t)$ is the vectorization of A and is an $m^2q \times 1$ dimensional vector.

We transformed TVP-VAR to its vector moving average (VMA) form that was relied on in the Wold representation theorem. Subsequently, we estimated the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD). Accordingly, the VMA representation of z_t can be defined as $\sum_{j=0}^{\infty} A_{jt} \mu_{t-j}$, where A_{jt} is the $m \times m$ dimensional matrix.

The $GIRF(\Psi_{ij,\ t}(H))$ denotes the responses of all variables j, following a shock in i calculated with an $H - step$ ahead of forecast. $GIRF$ $(\Psi_{ij,\ t}(H))$ can be given as follows:

$$GIRF\left(H, \sigma_{j,t}, \Omega_{t-1}\right) = E\left(z_t + H \middle| e_j = \sigma_{j,t}, \Omega_{t-1}\right) - E\left(z_{t+j} \middle| \Omega_{t-1}\right) \tag{4}$$

$$\Psi_{j,t}(H) = \frac{A_{H,t} \Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\sigma_{j,t}}{\sqrt{\Sigma_{jj,t}}} \ \sigma_{j,t} = \sqrt{\Sigma_{jj,t}} \tag{5}$$

$$\Psi_{j,t}(H) = \Sigma_{jj,t}{}^{-1/2} A_{H,t} \Sigma_t e_j \tag{6}$$

where e_j is an $m \times 1$ selection vector which takes 1 with the selection of the jth element, and 0 otherwise. Consequently, the $GFEVD\left(\widetilde{\Phi}_{ij,t}(H)\right)$ was estimated, relying on $\widetilde{\Phi}_{ij,t}(H)$, which has the following form:

$$\widetilde{\Phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_t^2}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \Psi_t^2} \tag{7}$$

Table 2
Pre-COVID-19 average connectedness results for returns.

	Energy	Industrial Metals	Precious Metals	Chain link	MKR	BAT	BTC	ETH	XRP	World Equity Index	World Bonds Index	NFT	FROM Others
Energy	76.04	6.45	0.88	0.46	1.38	1.04	1.56	1.43	0.92	7.76	1.1	0.98	23.96
Industrial Metals	6.48	71.87	4.61	1.13	0.96	0.78	1.32	0.8	1.68	6.1	1.74	2.53	28.13
Precious Metals	1.23	3.78	63.63	0.44	0.57	0.38	1.44	0.93	0.96	1.15	24.42	1.08	36.37
Chain Link	0.33	0.52	0.11	48.38	7.71	10.64	7.61	11.08	7.36	0.43	0.11	5.72	51.62
MKR	0.15	0.24	0.18	6.2	38.18	10.49	11.32	18.95	8.39	0.42	0.18	5.32	61.82
BAT	0.27	0.26	0.22	8.85	10.77	39.91	8.25	16.39	9.28	0.67	0.23	4.9	60.09
BTC	0.25	0.19	0.49	7.44	10.99	8.01	38.13	17.1	10.17	0.35	0.27	6.6	61.87
ETH	0.33	0.25	0.31	7.09	15.28	12.72	13.83	30.48	11.44	0.73	0.27	7.28	69.52
XRP	0.11	0.25	0.18	4.6	7.51	7.4	8.99	12.36	33.13	0.24	0.09	25.15	66.87
World Equity Index	7.36	5.77	2.27	0.88	1.2	1.44	1.54	2.06	0.95	72.04	3.1	1.4	27.96
World Bonds Index	1.49	1.34	25.57	0.67	0.55	1.19	0.9	1.12	0.99	2.12	63.08	0.98	36.92
NFT	0.14	0.57	0.17	3.83	5.65	4.58	6.81	9	29.62	0.35	0.06	39.21	60.79
TO Others	18.13	19.62	34.99	41.58	62.56	58.66	63.57	91.22	81.76	20.33	31.57	61.92	585.92
NET	−5.83	−8.52	−1.38	−10.04	0.74	−1.43	1.7	21.7	14.9	−7.63	−5.35	1.14	**TCI = 48.83**

Note: This table shows the average connectedness of the returns of assets during the pre-Covid-19 period.

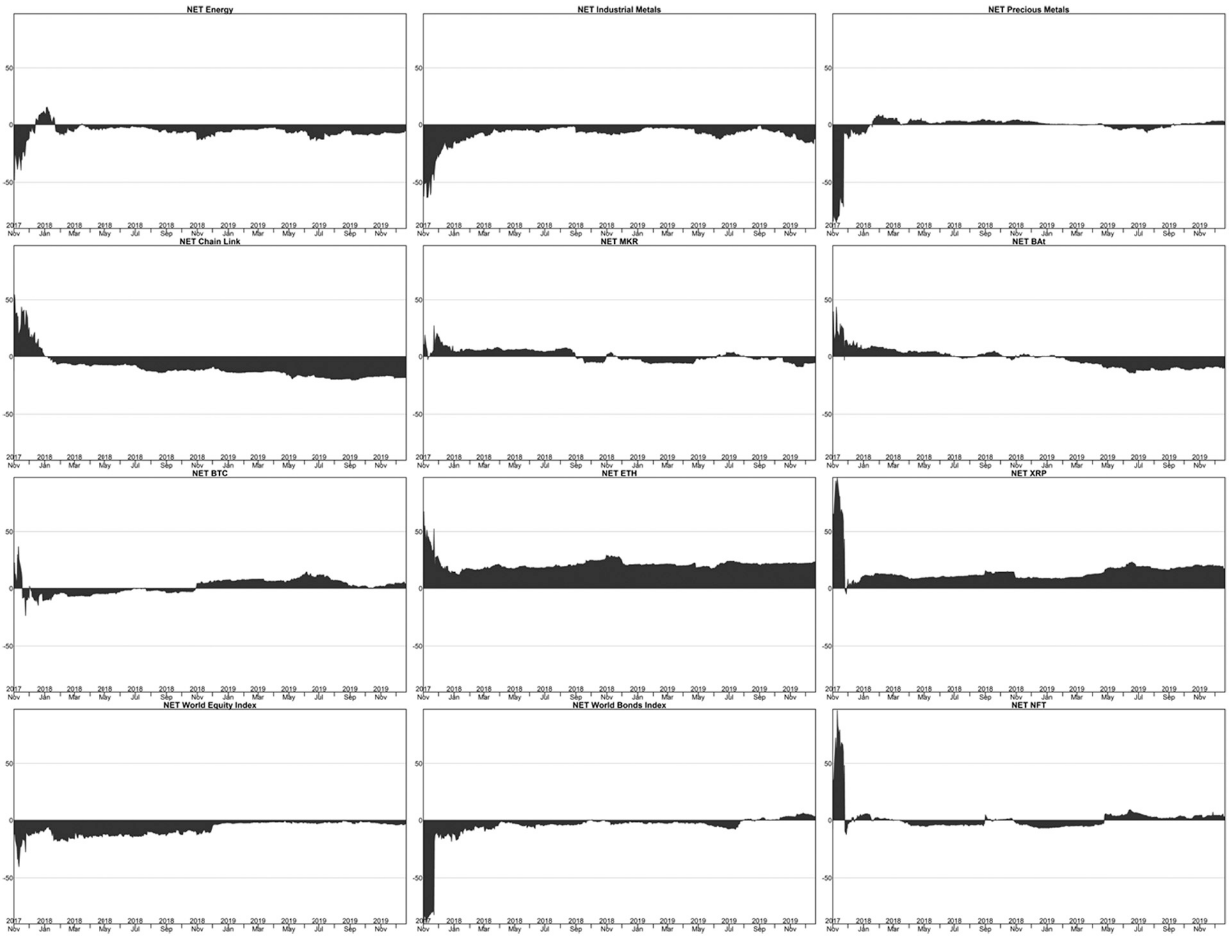

Fig. 4. Pre-COVID-19 total net connectedness for returns.
Note: This figure shows the total net connectedness of the returns of assets during the pre-Covid-19 period.

with $\sum_{j=1}^{m}\widetilde{\Phi}_{ij,t}(H) = 1$, and $\sum_{i,j=1}^{m}\widetilde{\Phi}_{ij,t}(H) = m$.

In line with the above formulation the total connectedness index (TCI) was introduced as:

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{m}\widetilde{\Phi}_{ij,t}(H)}*100 = \frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\Phi}_{ij,t}(H)}{m}*100 \tag{8}$$

Total directional connectedness to others, i.e., how i propagates its shock to all other variables j, is defined as:

$$C_{i\to j,t}(H) = \frac{\sum_{j=1,i\neq j}^{m}\widetilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{m}\widetilde{\Phi}_{ji,t}(H)}*100 \tag{9}$$

Total directional connectedness from others, i.e., how i receives shock from all other variables j, is given as:

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{m}\widetilde{\Phi}_{ij,t}(H)}{\sum_{i=1}^{m}\widetilde{\Phi}_{ij,t}(H)}*100 \tag{10}$$

Net total directional connectedness is defined as:

$$C_{i,t}(H) = C_{i\to j,t}(H) - C_{i\leftarrow j,t}(H) \tag{11}$$

3.2. The frequency-based TVP-VAR network connectedness

Barunik and Ellington (2020) introduced a dynamic network form using spectral decomposition of time-varying variance decomposition matrices. The network structure reflects the impact of transitory (short-term frequency) and permanent (long-term frequency) shocks from variable j to future variance of variable i. The model structures a dynamic adjacency matrix, constituting all

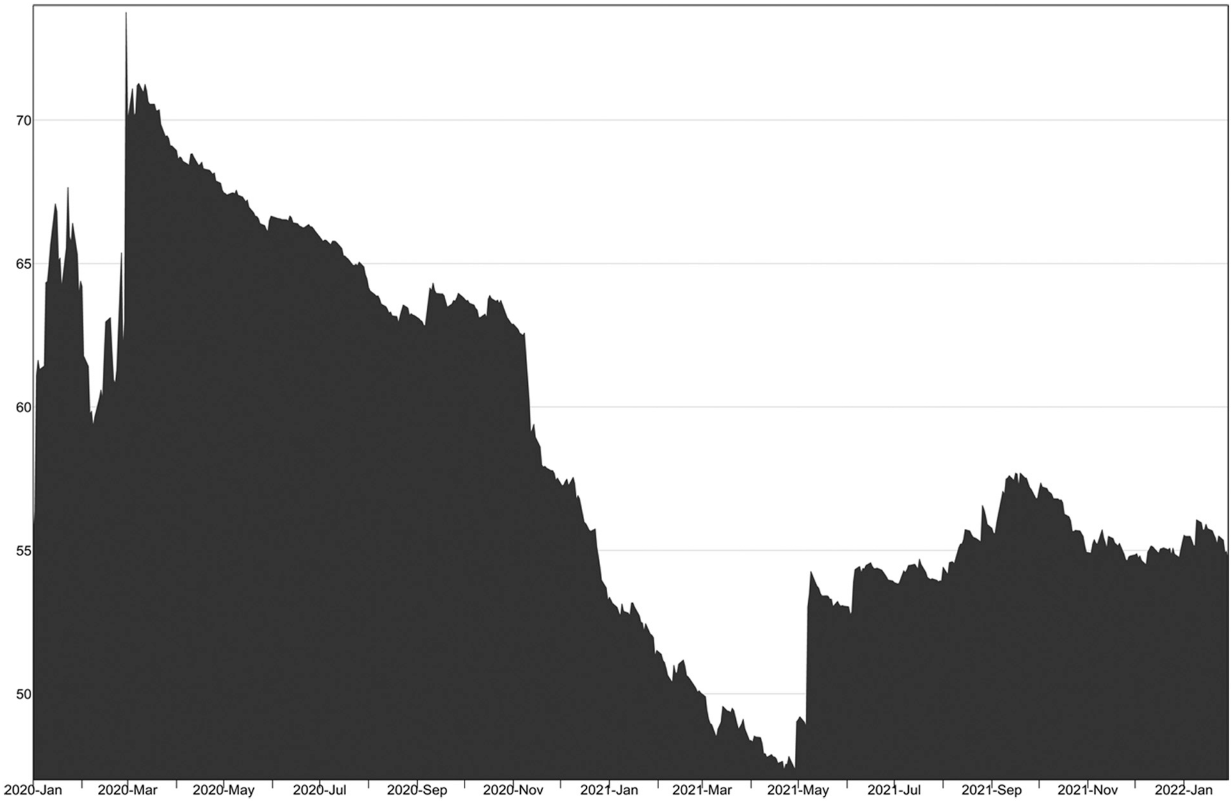

Fig. 5. COVID-19 total connectedness index for returns.
Notes: This figure shows the total connectedness of the returns of assets during covid period.

information indicating the network.

Let $(Z_{t,\ T})_{1 \leq t \leq T,\ T\epsilon N}$ be the N-variate time series with elements of $Z_{t,\ T} = (Z^1_{t,\ T}, \ldots, Z^N_{t,\ T})^T$. Herein, t denotes the time index; T is an additional index representing the "sharpness of the local approximation of the time series $(Z_{t,\ T})_{1 \leq t \leq T,\ T\epsilon N}$ by a stationary one" (Barunik and Ellington, 2020:7).

Suppose $(Z_{t,\ T})_{1 \leq t \leq T,\ T\epsilon N}$ follows a locally stationary TVP-VAR of lag order of q:

$$Z_{t,T} = \varphi_1(t/T)Z_{t-1,T} + \ldots + \varphi_q(t/T)Z_{t-q,T} + \omega_{t,T} \tag{12}$$

where, $\omega_{t,T} = \Sigma^{-\frac{1}{2}}(t/T)\rho_{t,T}$ with $\rho_{t,\ T} \sim NID(0, I_M)$, and $\varphi(t/T) = (\varphi_1(t/T), \ldots, \varphi_q(t/T))^T$are time-varying autoregressive coefficients. In a neighborhood of fixed time $\mu_0 = t_0/T$, the process $Z_{t,\ T}$ is estimated by a stationary process $\widetilde{Z}_t(\mu_0)$ as:

$$\widetilde{Z}_t(\mu_0) = \varnothing_1(\mu_0)\widetilde{Z}_{t-1}(\mu_0) + \ldots + \varnothing_q(\mu_0)\widetilde{Z}_{t-q}(\mu_0) + \rho_t \tag{13}$$

with $t \in \mathbb{Z}$, and satisfying $\left| Z_{t,T} - \widetilde{Z}_t(\mu_0) \right| = O_q(|t/T - \mu_0| + 1/T)$. The time-varying $VMA(\infty)$ representation of the process is:

$$Z_{t,T} = \sum_{h=-\infty}^{\infty} \Psi_{t,T}(h)\rho_{t-h} \tag{14}$$

where $\Psi_{t,\ T} \approx \varphi(t/T, h)$ is a stochastic process with $sup_l \|\Psi_t - \Psi_l\|^2$ for $1 \leq h \leq t$ as $t \to \infty$. The spectral density of $Y_{t,\ T}$ at frequency w is defined as:

$$S_Z(\mu, w) = \sum_{h=-\infty}^{\infty} \mathrm{E}\left[\widetilde{Z}_{t+h}(\mu)\widetilde{Z}_t^{\ T}(\mu)\right]e^{-iwh} = \left\{\Psi(\mu)e^{-iw}\right\}\Sigma(\mu)\left\{\Psi(\mu)e^{+iw}\right\}^T \tag{15}$$

Let us assume that $Z_{t,\ T}$ is a weakly local stationary process with $\sigma_{kk}^{-1}\sum_{h=0}^{\infty}\left|[\Psi(\mu)e^{-iw}\Sigma(\mu)]_{j,\ k}\right|^2 < \infty$, $\forall\, j, k$. Then, "the time-frequency variance decompositions of the jth variable at a rescaled time $\mu = t_0/T$ due to shock in the kth variable on the frequency band $d = (a, b) : a,\ b\epsilon(-\pi, \pi)$, $a < b$ form a dynamic adjacency matrix" (Barunik and Ellington, 2020:8) as:

Table 3
COVID-19 average connectedness results for returns.

	Energy	Industrial Metals	Precious Metals	Chain link	MKR	BAT	BTC	ETH	XRP	World Equity Index	World Bonds Index	NFT	FROM Others
Energy	66.36	7.74	1.29	1.55	1.6	2.02	2.41	2.33	1.72	11.39	0.92	0.68	33.64
Industrial Metals	7.43	59.89	3.7	2.81	1.97	2.76	2.89	2.62	2.44	9.69	2.06	1.73	40.11
Precious Metals	1.87	4.07	63.05	2.06	2.69	2.38	3.41	2.94	1.16	4.05	10.93	1.39	36.95
Chain Link	0.53	1.21	0.59	27.57	10.72	12.42	12.02	15.72	8.66	2.84	0.42	7.29	72.43
MKR	0.57	0.84	0.75	12.21	32.07	9.28	10.29	15.53	7.24	3.57	1.1	6.55	67.93
BAT	0.75	1.05	0.87	12.86	8.4	28.86	12.25	12.99	9.98	3.27	0.37	8.34	71.14
BTC	0.8	1.2	0.86	12.04	8.94	11.66	27.13	17.28	8.38	3.65	0.92	7.15	72.87
ETH	0.6	0.97	0.71	14.14	12.1	11.21	15.61	24.65	8.98	3.01	0.61	7.42	75.35
XRP	0.51	0.83	0.29	8.84	6.49	9.97	8.74	10.32	28.22	1.94	0.3	23.55	71.78
World Equity Index	8.25	6.77	2.82	4.53	5.52	5.32	6.3	5.72	3.39	47.29	0.77	3.32	52.71
World Bonds Index	2.14	2.34	10.59	2.56	4.52	2.18	3.43	3.14	2.48	3.05	60.95	2.61	39.05
NFT	0.14	0.59	0.33	7.96	6.38	8.96	8.07	9.23	25.38	2.02	0.5	30.44	69.56
TO others	23.59	27.6	22.79	81.55	69.34	78.17	85.42	97.83	79.81	48.49	18.91	70.02	703.52
NET	−10.05	−12.51	−14.15	9.12	1.41	7.03	12.55	22.47	8.04	−4.23	−20.14	0.46	**TCI = 58.63**

Note: This table shows the average connectedness of the returns of assets during the Covid-19 period.

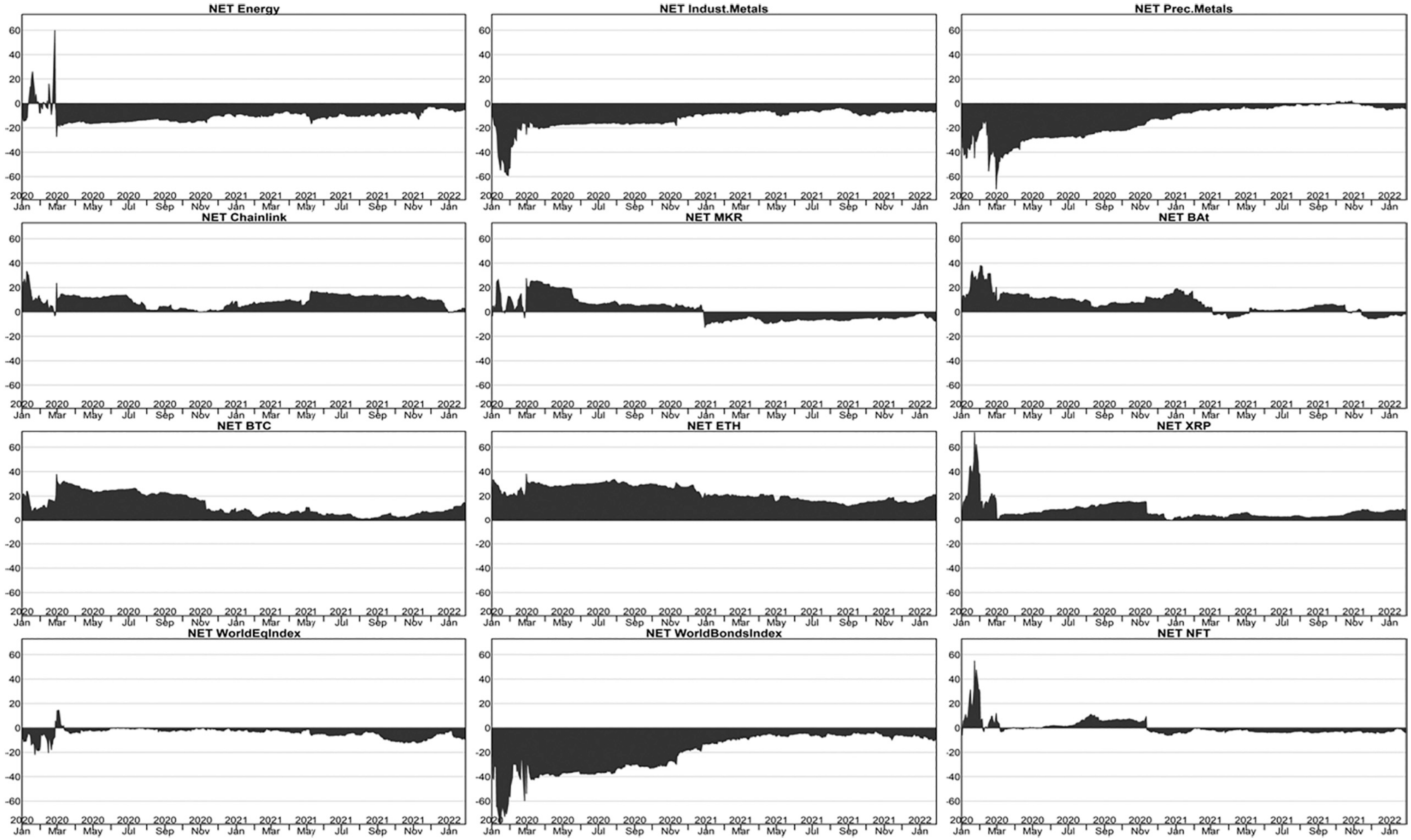

Fig. 6. COVID-19 total net connectedness for the returns.
Note: This figure shows the total net connectedness of the returns of assets during the Covid-19 period.

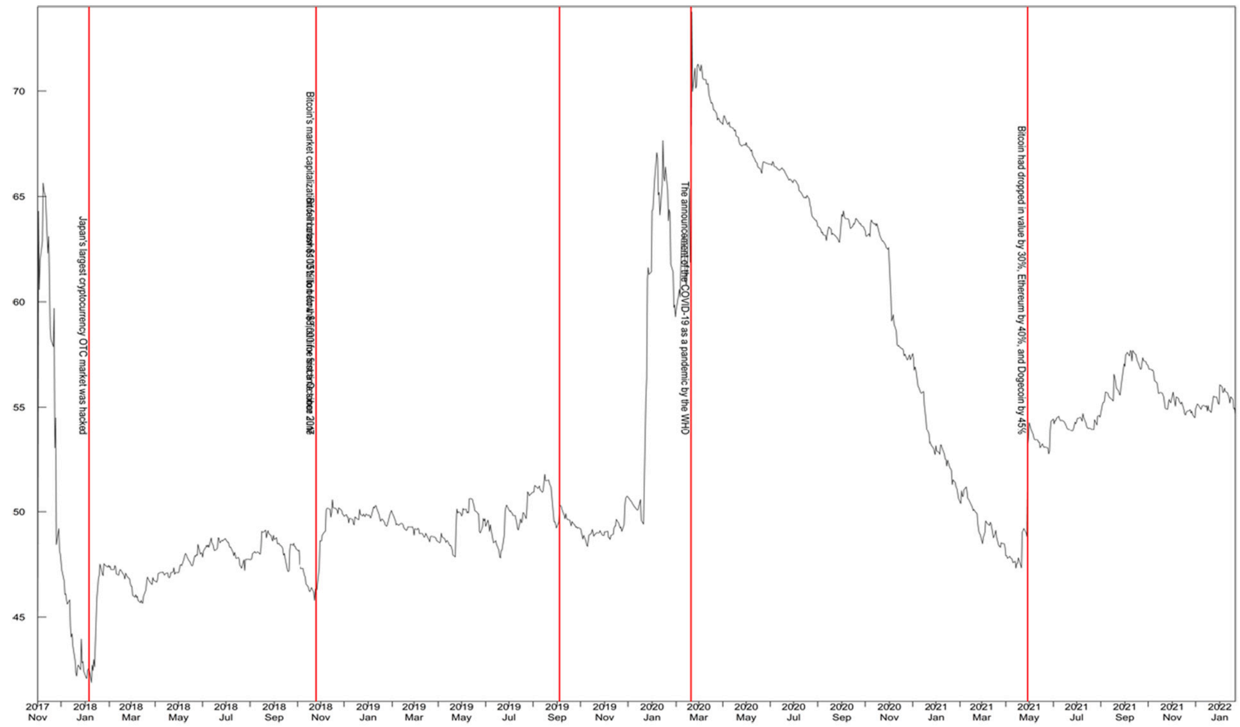

Fig. 7. TCI for the returns and well-known incidents.

$$[\theta(\mu,d)]_{j,k} = \frac{\sigma_{kk}^{-1}\int_a^b \left|[\Psi(\mu)e^{-iw}\Sigma(\mu)]_{j,k}\right|^2 dw}{\int_{-\pi}^{\pi}\left[\{\Psi(\mu)e^{-iw}\}\Sigma(\mu)\{\Psi(\mu)e^{-iw}\}^T\right]_{j,j} dw} \tag{16}$$

We normalize each element in the row of the network by the corresponding row sum as:

$$\left[\widetilde{\theta}(\mu,d)\right]_{j,k} = [\theta(\mu,d)]_{j,k} \Big/ \sum_{k=1}^{N}[\theta(\mu,d)]_{j,k} \tag{17}$$

The local network connectedness is introduced as:

$$C(\mu,d) = 100 \times \sum_{j,k=1\ j\neq k}^{N}\left[\widetilde{\theta}(\mu,d)\right]_{j,k} \Big/ \sum_{j,k=1}^{N}\left[\widetilde{\theta}(\mu)\right]_{j,k} \tag{18}$$

The local directional connectedness (FROM connectedness) that gauges how much of each indicator's j varies due to shocks in other indicators $k \neq j$ is defined as:

$$C_{j\leftarrow\bullet}(\mu,d) = 100 \times \sum_{\substack{k=1\\k\neq j}}^{N}\left[\widetilde{\theta}(\mu,d)\right]_{j,k} \Big/ \sum_{j,k=1}^{N}\left[\widetilde{\theta}(\mu)\right]_{j,k} \tag{19}$$

Similarly, the contribution of j to variances in other indicators is calculated as:

$$C_{j\rightarrow\bullet}(\mu,d) = 100 \times \sum_{\substack{k=1\\k\neq j}}^{N}\left[\widetilde{\theta}(\mu,d)\right]_{k,j} \Big/ \sum_{k,j=1}^{N}\left[\widetilde{\theta}(\mu)\right]_{k,j} \tag{20}$$

4. Results and discussion

4.1. Data and preliminary findings

We sourced our data from multiple sources. We employed the S&P GSCI commodity indices for energy, industrial metals, and precious metals. The S&P GSCI indices are widely used as benchmarks for tracking commodity markets. We used the MSCI World

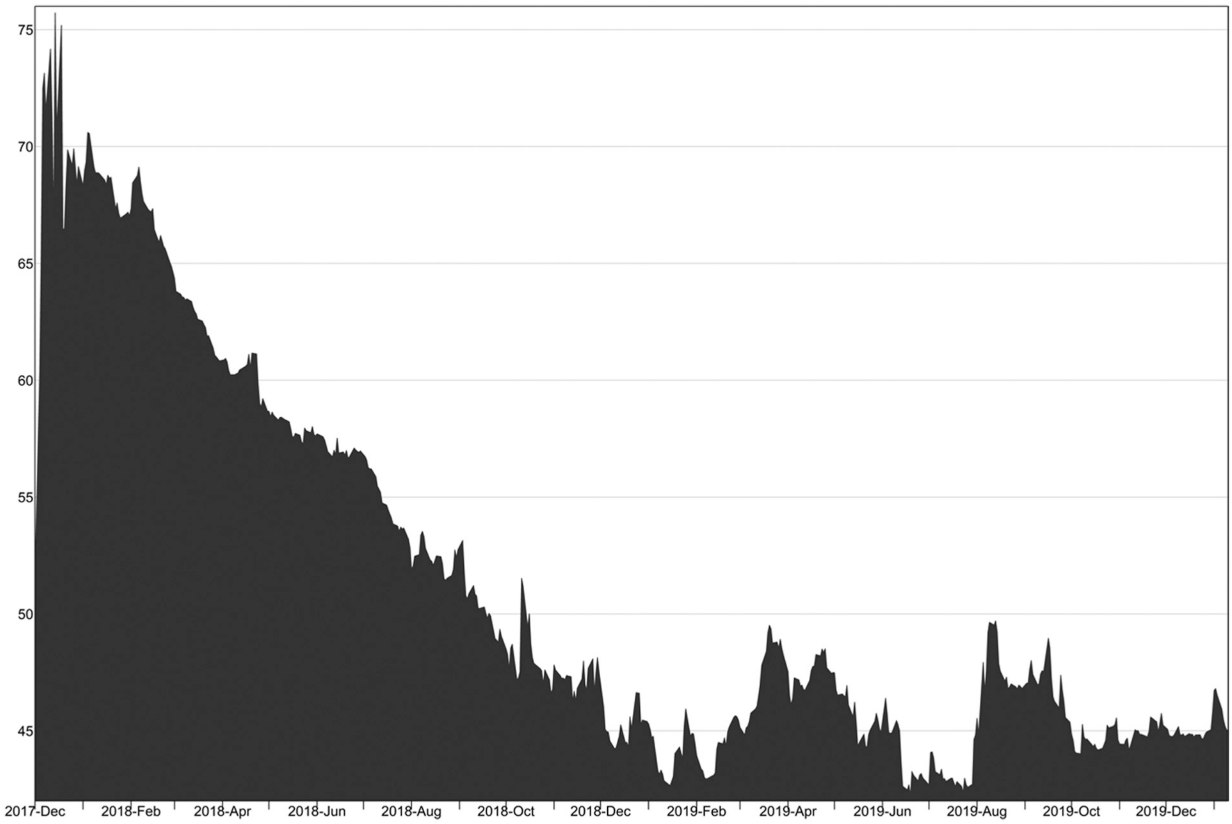

Fig. 8. Pre-COVID-19 total connectedness index for volatilities.
Note: This figure shows the total connectedness of the volatility of assets during the pre-Covid-19 period.

Equity Index and the Bloomberg Global Aggregate Bond Index as proxies for world equity and fixed income markets, respectively. These series were sourced from Bloomberg. We sourced the NFT data from https://nonfungible.com/, whereas the DeFi assets (Chain Link, Maker-MKR, Basic attention token- BAT) and cryptocurrencies (Bitcoin-BTC, Ethereum-ETH, Ripple- XRP) data was sourced from https://coinmarketcap.com. and is motivated by the longest availability of the matched time series.

We first report basic statistical settings of the returns, volatilities, and dynamics of the aforementioned series through Table 1, and Figs. 1 and 2. The summary statistics for the return series indicate that Ripple and NFT provided the highest returns (62.698), while the World Bonds Index gained the lowest returns (1.49). Unsurprisingly, all cryptocurrencies and DeFi coins provided higher returns compared to other assets in the data sample, accompanied by considerable volatility (Kyriazis et al., 2020). Cryptocurrencies had the highest volatility values as presented by Table 1, while the World Bonds Index had the lowest volatility with an average value of 0.035. Except for industrial metals, all series are characterized by excess kurtosis, which is more prominent for energy, World Equity Index, and World Bonds Index. Nevertheless, excess JB values for all series indicate that they are all non-normally distributed. Except for Bat, XRP, and NFT, all return series have a fatter tail on the left side of their distribution. On the other hand, the distributions of all volatility series are right-skewed.

At first glance, all cryptocurrencies seem highly volatile particularly in late 2017 due to the 2017–2018 cryptocurrency bubble. Sharing a common feature, all return series exhibit significant spikes in March–April 2020 triggered by the COVID-19 pandemic. Additionally, return series for cryptocurrencies, and industrial and precious metals have fluctuated markedly in the recent period.

Fig. 2 reveals that all series are highly volatile around financial/geopolitical burst episodes. The volatility for industrial metals exhibits a sharp spike in April–May 2018 due to the remarkable price surge observed in the same period. All volatility series experienced a monumental rise around March–April 2020 due to the COVID-19 pandemic. Furthermore, all series except the World Equity/Bonds indices observe significant spikes in the recent period probably owing to the second, third, and fourth COVID-19 waves.

4.2. Time-varying connectedness

Both time dynamics of returns and volatilities reveal a significant impact of COVID-19 on the series. Departing from this phenomenon, we estimated time-varying connectedness for returns and volatility series for the pre-COVID-19 and COVID-19 periods. Fig. 3 displays the pre-COVID-19 total connectedness index (TCI) for returns. Overall time-varying connectedness between returns fluctuated between 41% and 66% over the pre-COVID-19 period. The index skyrocketed in late 2017 and peaked on November 11,

Table 4
Pre-COVID-19 average connectedness results for volatilities.

	Energy	Industrial Metals	Precious Metals	Chain link	MKR	BAT	BTC	ETH	XRP	World Equity Index	World Bonds Index	NFT	FROM Others
Energy	71.18	1.82	1.49	2.68	2.71	4.44	1.49	1.41	4.32	4.01	0.62	3.84	28.82
Industrial Metals	4.75	70.39	1.83	2.75	1.09	4.82	2.5	3.09	2.87	1.9	1.54	2.47	29.61
Precious Metals	3.1	1.94	62.88	2.83	2.34	2.93	1.51	2.5	3.23	5.41	7.88	3.43	37.12
Chain Link	0.66	0.97	1.03	52.4	2.77	8.57	12.27	4.24	8	0.91	0.59	7.6	47.6
MKR	0.76	0.74	0.69	2.43	39.18	13.32	8.4	12.29	11.9	0.16	0.4	9.73	60.82
BAT	1.32	0.83	0.85	7.39	9.43	37.75	7.5	8.39	14.6	0.25	0.23	11.45	62.25
BTC	1.51	0.68	1.19	8.67	7.46	11.22	36.77	14.94	9.51	1.08	1.04	5.93	63.23
ETH	3.89	1.19	0.75	3.45	11.6	10.49	14.79	31.08	12.84	1.07	0.27	8.61	68.92
XRP	1.03	1.61	0.55	5.43	10.19	13.46	6.76	9.05	28.61	0.24	0.17	22.91	71.39
World Equity Index	8.04	1.72	4.89	2.31	2.88	2.59	3.29	4.31	2.46	62.06	3.71	1.74	37.94
World Bonds Index	4.45	4.95	8.38	2.01	3.01	2.57	1.67	2.17	1.7	5.39	61.75	1.96	38.25
NFT	0.91	1.64	0.71	4.73	9.6	11.95	4.92	7.1	27.27	0.35	0.17	30.64	69.36
TO Others	30.41	18.09	22.35	44.67	63.09	86.37	65.11	69.49	98.7	20.76	16.61	79.67	615.31
NET	1.59	−11.52	−14.78	−2.93	2.26	24.12	1.88	0.57	27.31	−17.19	−21.64	10.32	**TCI = 51.28**

Note: This table shows the total connectedness of the volatility of assets during the pre-Covid-19 period.

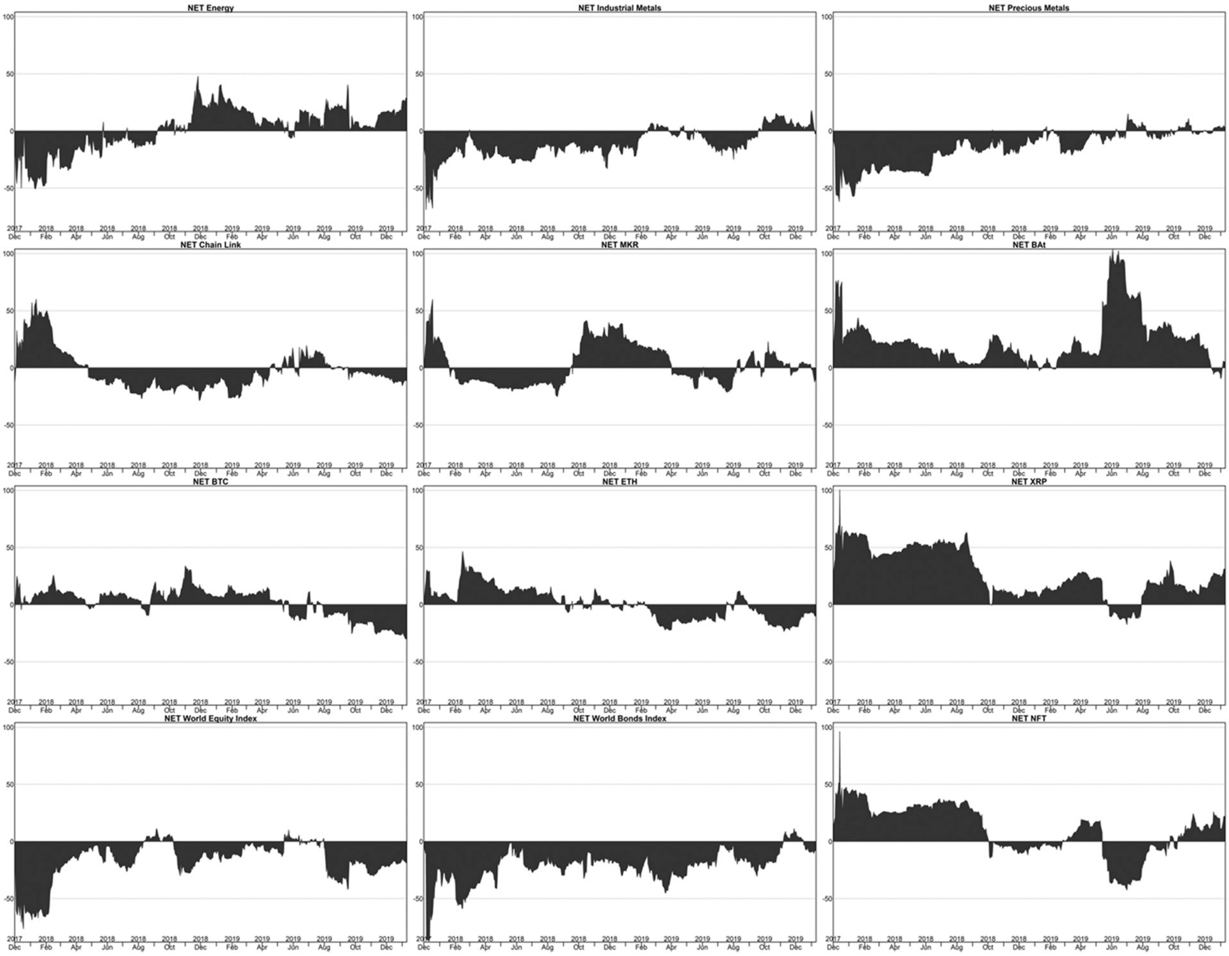

Fig. 9. Pre-COVID-19 total net connectedness for volatilities.
Note: This figure shows the total net connectedness of the volatility of assets during the pre-Covid-19 period.

2017 with 65.63% returns. The TCI dropped to around 42% in late January 2018, and slightly rose to approximately 50%.

Table 2 reports the average connectedness results for returns for the pre-COVID-19 period. Return spillover results for the pre-COVID-19 period reveal that all series contributed their own shocks. ETH was the largest transmitter/receiver of shocks to/from other returns (91.2%, and 69.5%, respectively). This finding is related to the strong connectedness among cryptocurrencies in the pre-COVID-19 era. Additionally, ETH, BTC, XRP, MKR were net transmitters of shocks, while the rest of the returns were net receivers of shocks. Fig. 4 displays the pre-COVID-19 period total net connectedness for the returns.

Sharing a common feature, all cryptocurrencies, DeFi coins, and NFTs transmitted notable net spillovers in late 2017; concurrently, industrial metals, precious metals, energy, and World Bonds Index received a vast number of net shocks. Among all return series, only ETH and XRP kept their role as net transmitters of shocks over the pre-COVID-19 period.

Next, we estimated time-varying connectedness for returns for the COVID-19 period. Fig. 5 shows the TCI for the returns series for the COVID-19 period.

The TCI fluctuated between 47% and 74% over the COVID-19 period. The index skyrocketed in early March and peaked on March 12, 2020 (73.75%), which was one day after the official announcement of the COVID-19 outbreak as a pandemic by the World Health Organization (WHO). The index moderately plummeted in March and May and reached its trough on May 5, 2020, with 47.32%. The TCI slightly surged afterward and swung between 53% and 57%. Table 3 presents the average connectedness results for returns for the COVID-19 period.

Unsurprisingly, interdependencies between financial indicators intensified due to the pandemic. As seen in the spillovers for the pre-COVID-19 period, all returns series contributed to their own spillovers, more than the others on average. The TCI notably escalated to 58.63% compared to the pre-COVID-19 period. ETH kept its role of being the largest transmitter and receiver of shocks (97.83%, and 75.35%, respectively) during the COVID-19 period. On the other hand, energy received the lowest spillover from other indices on average (33.64%). Energy, industrial metals, precious metals, World Equity Index, and World Bonds Index were net receivers of shocks in the COVID-19 period, while the rest of the indicators transmitted more shocks than they received. Fig. 6 displays the COVID-19 total

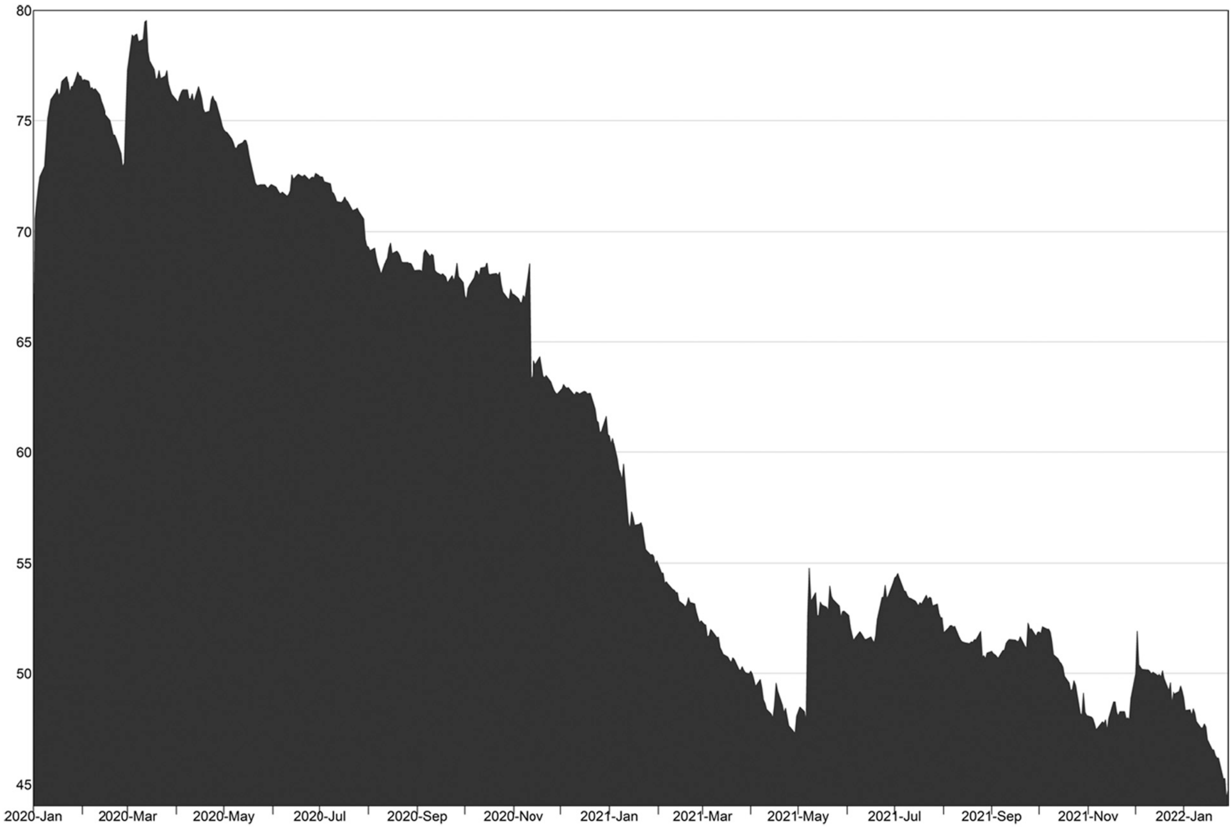

Fig. 10. COVID-19 total connectedness index for volatilities.
Note: This figure shows the total connectedness of the volatility of assets during the Covid-19 period.

net connectedness for the returns.

As shown in Fig. 6, major cryptocurrencies such as BTC, ETH, and XRP transmitted a significant number of spillovers during the COVID-19 period. This finding corroborates the massive surge in both traded returns and volumes owing to the safe haven view of the cryptocurrency market during the pandemic (Corbet et al., 2020b), and is in line with previous studies (Polat and Günay, 2021; González et al., 2021). Energy, industrial metals, precious metals, and the World Bonds Index received notable spillovers during the pandemic.

To analyze the performance of the TCI for the returns, Fig. 7 depicts the dynamics of the total net return connectedness index with prominent financial/geopolitical incidents.

Fig. 7 corroborates that the TCI for the returns prominently responds to the well-known financial/geopolitical events over the study period.

In the next phase of the study, we estimated the total time-varying connectedness for 10-day volatilities for the pre-COVID-19 period; Fig. 8 depicts the TCI.

The TCI oscillated between 42% and 76% over the pre-COVID-19 period. The index sharply surged in December 2017 and hit its apex on December 14, 2017, with 75.71%. This tremendous rise in the TCI can be attributed to the 2017–2018 cryptocurrency bubble since cryptocurrencies constitute the largest portion of our data set. The TCI sharply dropped to around 43% and reached its trough on June 19, 2019, with 42.24%. The index slightly fluctuated over the rest of the pre-COVID-19 period between 42% and 51%. Table 4 shows the average connectedness results for volatilities for the pre-COVID-19 period.

As shown in Table 4, contributing more than others on average is more prominent for the volatilities. XRP was the largest transmitter/receiver of spillovers (98.7%, and 71.39%). Contrary to this, the World Bonds Index received the lowest number of spillovers for the pre-COVID-19 period. Cryptocurrencies transmitted/received the highest shocks probably owing to the 2017–2018 cryptocurrency bubble. Industrial metals, precious metals, Chainlink, World Equities Index, and World Bonds Index were net receivers of spillovers, while the rest of the financial indicators were net transmitters of spillovers. Fig. 9 plots the pre-COVID-19 total net connectedness for the volatilities. Except for BTC and ETH, all cryptocurrencies were net transmitters of spillovers at the beginning of the period. This was probably triggered by the immense connectedness among cryptocurrencies in late 2017, where massive short selloffs took place in the cryptocurrency market. Meanwhile, energy, industrial metals, and precious metals were net receivers of shocks until late 2018 or early 2019. Energy became a net transmitter of spillovers starting from late 2018. The World Equities Index and the World Bonds Index were mostly net receivers of shocks over most of the period.

Table 5
COVID-19 average connectedness results for volatilities.

	Energy	Industrial Metals	Precious Metals	Chain link	MKR	BAT	BTC	ETH	XRP	World Equity Index	World Bonds Index	NFT	FROM Others
Energy	52	1.24	4.84	0.86	0.91	1.14	1.99	1.6	2.43	22.24	8.82	1.93	48
Industrial Metals	1.56	51.92	2.59	8.33	6.15	5.41	4.59	6.11	4.32	2.82	2.55	3.65	48.08
Precious Metals	4.88	1.38	50.13	4.65	3.46	3.44	3.13	4.69	1.66	10.83	10.35	1.41	49.87
Chain Link	0.72	2.1	0.99	35.65	7.31	8.82	8.34	16.32	8.17	2.14	1.46	7.98	64.35
MKR	0.73	1.04	2.3	10.46	31.97	6.76	9.39	16.65	7.89	3.05	3	6.75	68.03
BAT	0.68	3.39	1.05	8.53	9.14	37.2	10	9.13	9.1	1.25	2.23	8.31	62.8
BTC	1.29	1.98	1.57	9.17	10.3	8.22	29.34	16.92	6.33	4.11	3.9	6.87	70.66
ETH	0.71	1.27	1.02	13.19	9.38	7.66	11.29	31.33	9.47	2.66	2.22	9.81	68.67
XRP	0.43	0.8	0.6	4.03	3.93	6.49	3.98	7.06	38.45	0.27	0.3	33.66	61.55
World Equity Index	13.66	1.25	6.08	4.73	5.19	2.35	5.48	5.56	0.91	40.8	13.34	0.64	59.2
World Bonds Index	7.37	1.97	7.75	3.6	5.23	3.37	7.25	5.26	2.5	18.24	34.91	2.55	65.09
NFT	0.36	0.58	0.47	4.6	3.69	6.82	3.97	6.92	35.42	0.25	0.29	36.62	63.38
TO Others	32.39	17	29.25	72.16	64.7	60.46	69.42	96.23	88.19	67.85	48.47	83.56	729.68
NET	−15.61	−31.07	−20.62	7.81	−3.33	−2.34	−1.24	27.56	26.64	8.65	−16.62	20.18	**TCI = 60.81**

Note: This table shows the average connectedness of the volatility of assets during the Covid-19 period.

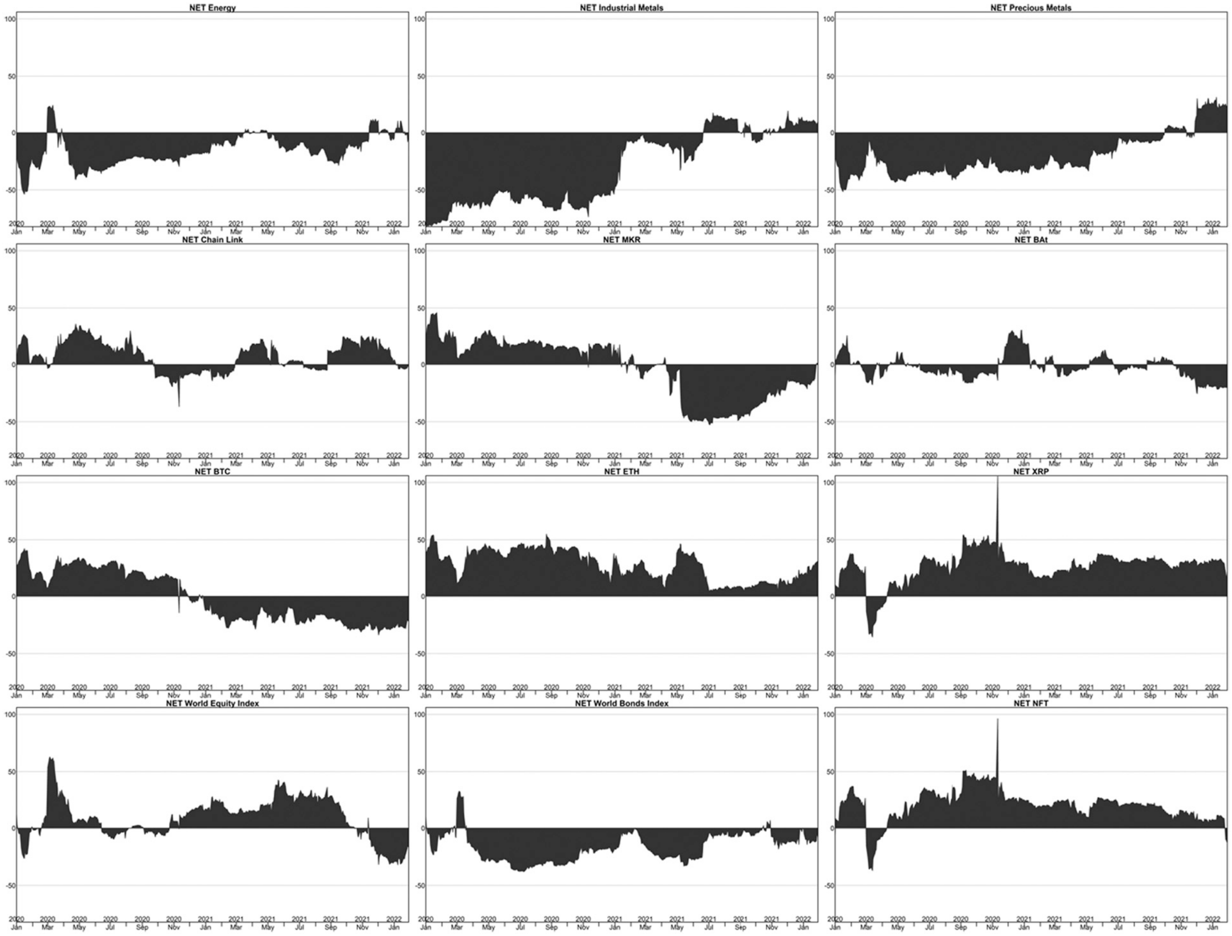

Fig. 11. COVID-19 total net connectedness for volatilities.
Notes: This figure shows the total net connectedness of the volatility of assets during covid period.

In the final step of this section, we estimated the total time-varying connectedness index for 10-day volatilities for the COVID-19 period; Fig. 10 depicts the same.

The TCI noticeably intensified at the beginning of the COVID-19 era and surpassed 75% starting from March 2020. The index hit its apex on March 25, 2020 (79.54%) and gradually alleviated until May 11, 2021 (47.3%). The TCI reached its trough on February 9, 2020, with 44.36%. Table 5 unveils the average connectedness results for volatilities for the COVID-19 period.

All volatility series contributed more to own shocks than others on average for the COVID-19 period. The overall connectedness index amplified significantly to 60.81% due to the pandemic. ETH was the largest transmitter of shocks (96.23%), while BTC received the highest spillover (70.66%). Additionally, industrial metals transmitted the lowest amount of spillover (17%), whereas energy received the lowest shocks from other financial indicators (48%). Connectedness among financial indicators intensified owing to the pandemic. Chainlink, ETH, XRP, NFT, and the World Equity Index were net transmitters of spillovers, while the other indicators were net receivers of spillovers. Fig. 10 displays the total net connectedness for the volatilities during the COVID-19 period.

As depicted in Fig. 11, energy, industrial metals, precious metals, and the World Bonds Index were the net receiver of shocks over the COVID-19 period. Except for BTC, other major cryptocurrencies such as ETH and XRP transmitted more than they received over the period. Additionally, NFT and XRP displayed very similar patterns, particularly in the first half of the COVID-19 period.

To evaluate the performance of the TCI for the volatilities, Fig. 8 displays the dynamics of the total net volatility connectedness index with well-known financial/geopolitical incidents.

As shown in Fig. 12, the TCI for the volatilities creates proper signs to the well-known financial/geopolitical incidents.

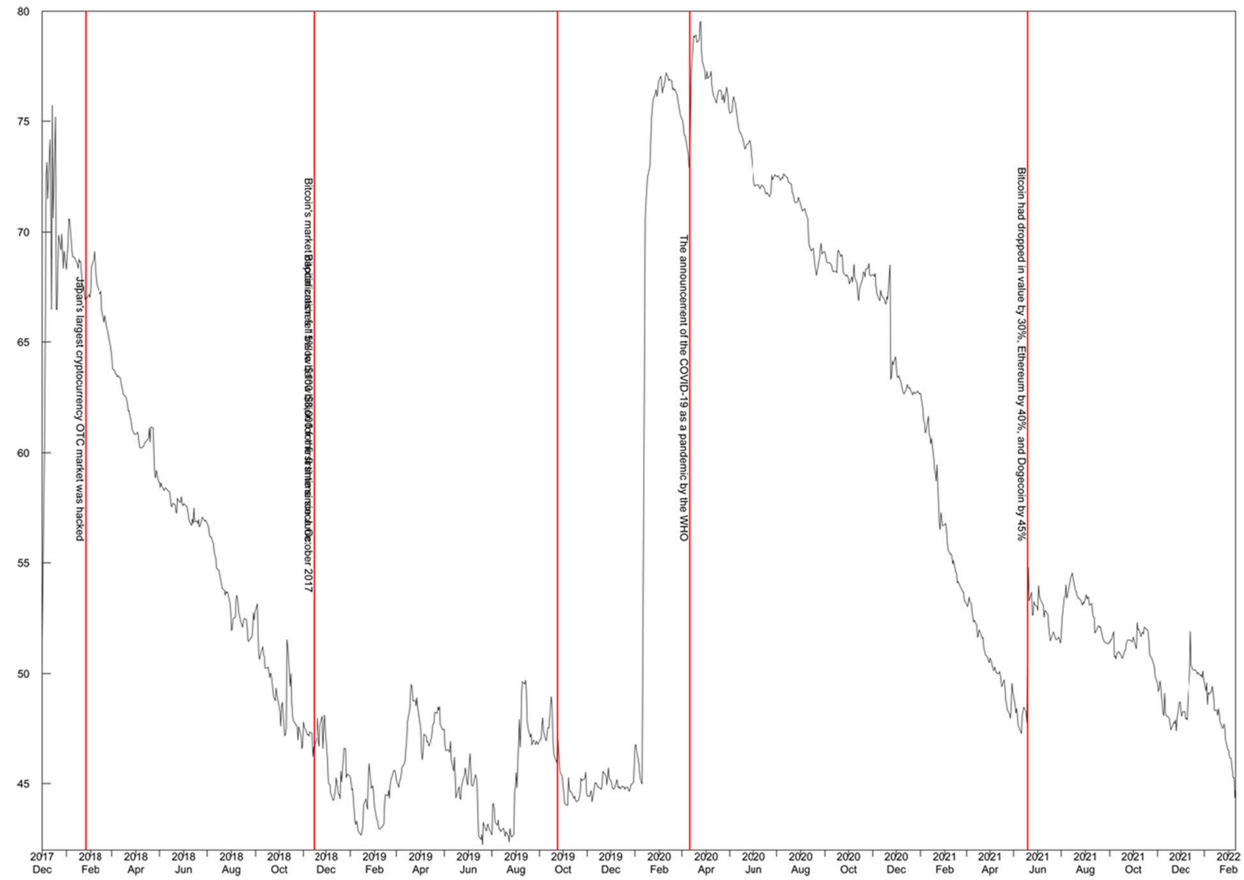

Fig. 12. TCI for the volatilities and well-known events.

4.3. Frequency-dependent TVP-VAR network connectedness

In this sub-section, we estimated the short-, medium-, and long-term network structures of returns and volatilities connectedness for the pre-COVID-19 and COVID-19 periods by employing the TVP-VAR connectedness methodology of Barunik and Ellington (2020).[6] In doing so, we highlighted the frequency-dependent network structures of connectedness for returns and volatilities. Fig. 11 shows pre-COVID-19 and COVID-19 short-, medium-, and long-term connectedness for returns.

The short-term connectedness was stronger than the medium- and long-term connectedness for returns for both pre-COVID-19 and COVID-19 periods. The Pre-COVID-19 connectedness networks graphs indicate that the medium- and short-term network connectedness indices peaked in November and December 2018 (54.29%, and 12.40%), respectively, coinciding with the 2017–2018 cryptocurrency bubble. Meanwhile, the long-term network connectedness index hit its apex on February 16, 2018 (4.31%). COVID-19 significantly amplified the frequency-based network linkages between financial indicators (except for the long-term connectedness). The short-term network connectedness index peaked on March 5, 2020 (59.12%), while the medium- and long-term connectedness indices hit their apexes on January 20, 2022 (10.4%) and October 1, 2021 (3.46%), respectively.

Next, we compute the short-, medium-, and long-term connectedness for volatilities for the pre-COVID-19 and COVID-19 periods; Fig. 12 displays them.

As exhibited in Fig. 14, the short-, medium-, and long-term connectedness indices intertwined in late 2017 and early 2018, probably due to the 2017–2018 cryptocurrency bubble. Short-term interdependencies between assets were stronger than the medium- and long-term linkages over most of the rest of the pre-COVID-19 period. For the pre-COVID-19 period, the short-term connectedness index peaked on January 8, 2020 (46.71%), while the medium- and long-term connectedness indices hit their apexes on July 30, 2019 (30.38%) and December 11, 2017 (24.04%), respectively.

The long-term connectedness index skyrocketed at the beginning of the COVID-19 period, and peaked on March 28, 2020 (63.68%). The long-term interdependencies among financial assets were stronger than the short- and medium-term linkages until April

[6] The short-, medium-, and long-term connectedness roughly corresponds to 1 to 5 days (1 week), 5 to 20 days (1 week to 1 month), and more than 20 days, respectively.

Fig. 13. Short-, medium-, and long-term connectedness for returns.

13, 2020. On the other hand, the short-term connectedness was higher than the medium- and long-term connectedness over the rest of the COVID-19 period. The short-term connectedness index peaked on January 13, 2020 (46.62%), while the medium-term connectedness index peaked on March 24, 2020 (33.95%).

In the final phase of the study, we followed Barunik and Ellington (2020) and computed transitory (short-term) and persistent (long-term) connectedness networks on a time of turmoil in the COVID-19 pandemic. In line with the previous studies (Polat and Günay, 2021; Umar et al., 2021d), we chose this date as March 11, 2020, which was when the WHO officially announced the COVID-19 outbreak as a pandemic. Fig. 13 shows the transitory and persistent connectedness networks of returns as on March 11, 2020.

Fig. 15 reveals that the transitory linkages are larger relative to the persistent connections, indicating shocks between assets create connections that dominate the short-run. Additionally, major cryptocurrencies, DeFi coins, and NFTs stand at the epicenter of the short-term connectedness network. On the contrary, the World Bonds Index, industrial metals, and precious metals form another cluster group transmitting relatively low spillovers from/to each other. Energy and industrial metals are strongly linked in the transitory connectedness network. As for the persistent connectedness network, surprisingly, the World Bonds Index-MKR, NFT, BTC, and precious metals transmitted/received the largest spillovers from/to each other. However, our finding of strong connectedness between BTC and precious metals during the COVID-19 pandemic is consistent with previous studies (Mariana et al., 2021).

Finally, we computed transitory and persistent network connectedness for volatilities as on March 11, 2020; Fig. 16 depicts them.

Likewise, transitory connections for returns, cryptocurrencies, DeFi coins, and NFTs stand at the center of the short-term connectedness network. Energy-World Equities Index, Precious Metal-World Equities Index, and Energy-World Bonds Index pairs follow cryptocurrencies in terms of directional to/from spillovers in the transitory connectedness network. Additionally, persistent

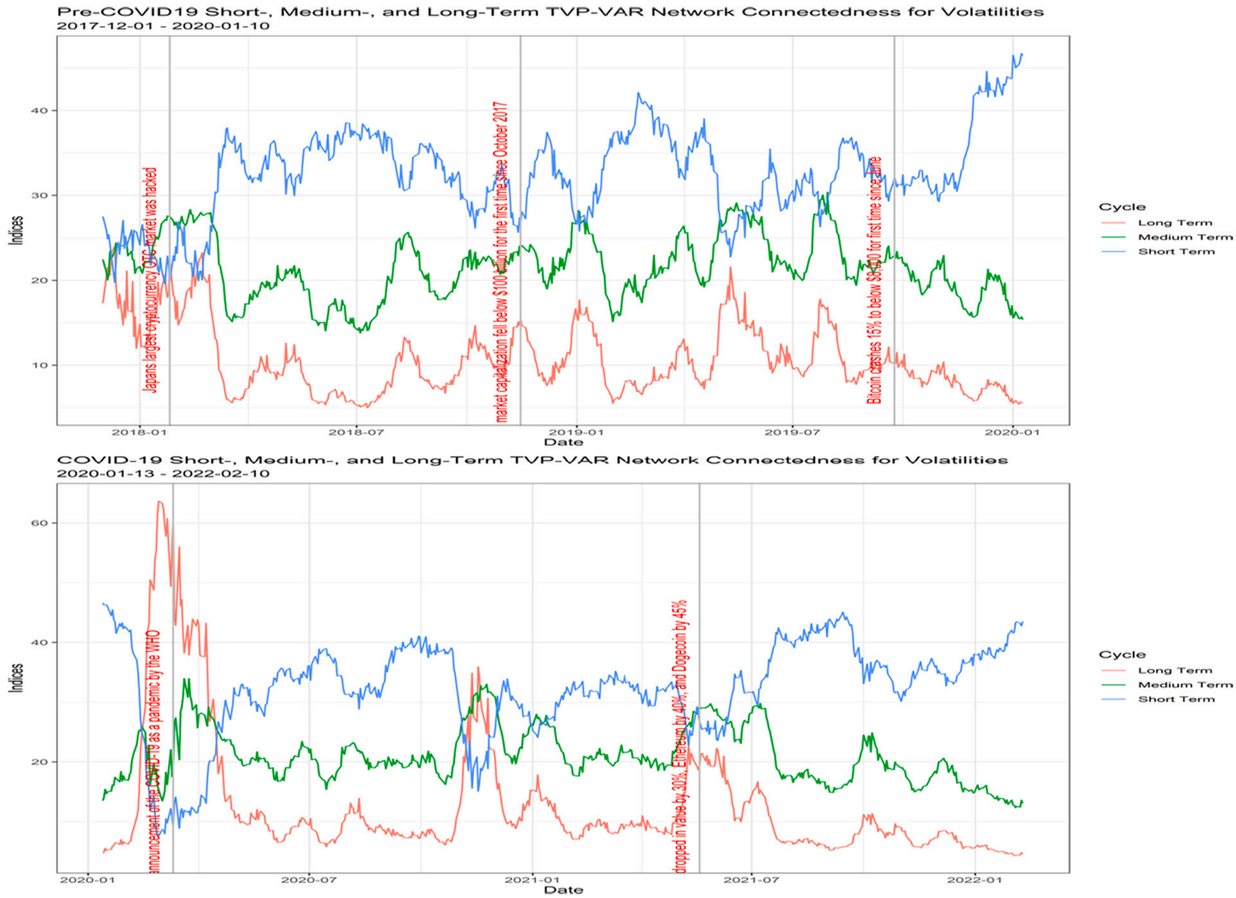

Fig. 14. Short-, medium-, and long-term connectedness for volatilities.

connections are larger relative to transitory connections among volatilities, meaning that the volatility interdependencies are related to long-term horizons, which is consistent with the finding of Barunik and Ellington (2020).

5. Dynamic portfolio analysis

We follow Broadstock et al. (2022) and investigate historical investment performance of our findings by employing back-testing portfolios. We implemented the Minimum Variance Portfolio, the Minimum Correlation Portfolio, and the Minimum Connectedness Portfolio Approaches.

5.1. Minimum Variance Portfolio (MVP)

The aim of this methodology is to minimize risk for expected portfolio returns by allocating weights to the included assets (Markowitz, 1952). The portfolio weighs are computed by the following formula:

$$w_{Ht} = \frac{H_t^{-1} I}{I H_t^{-1} I} \tag{21}$$

Here, w_{Ht} is an $n \times 1$ dimensional portfolio weight, I is an n-dimensional vector of ones, and H_t is an $n \times n$ dimensional conditional variance-covariance matrix in t.

5.2. Minimum Correlation Portfolio (MCP)

We define the conditional correlation matrix as follows:

$$R_t = diag(H_t)^{-0.5} H_t diag(H_t)^{-0.5} \tag{22}$$

where R_t is an $n \times n$ dimensional matrix, The minimum correlation portfolio weights are computed as:

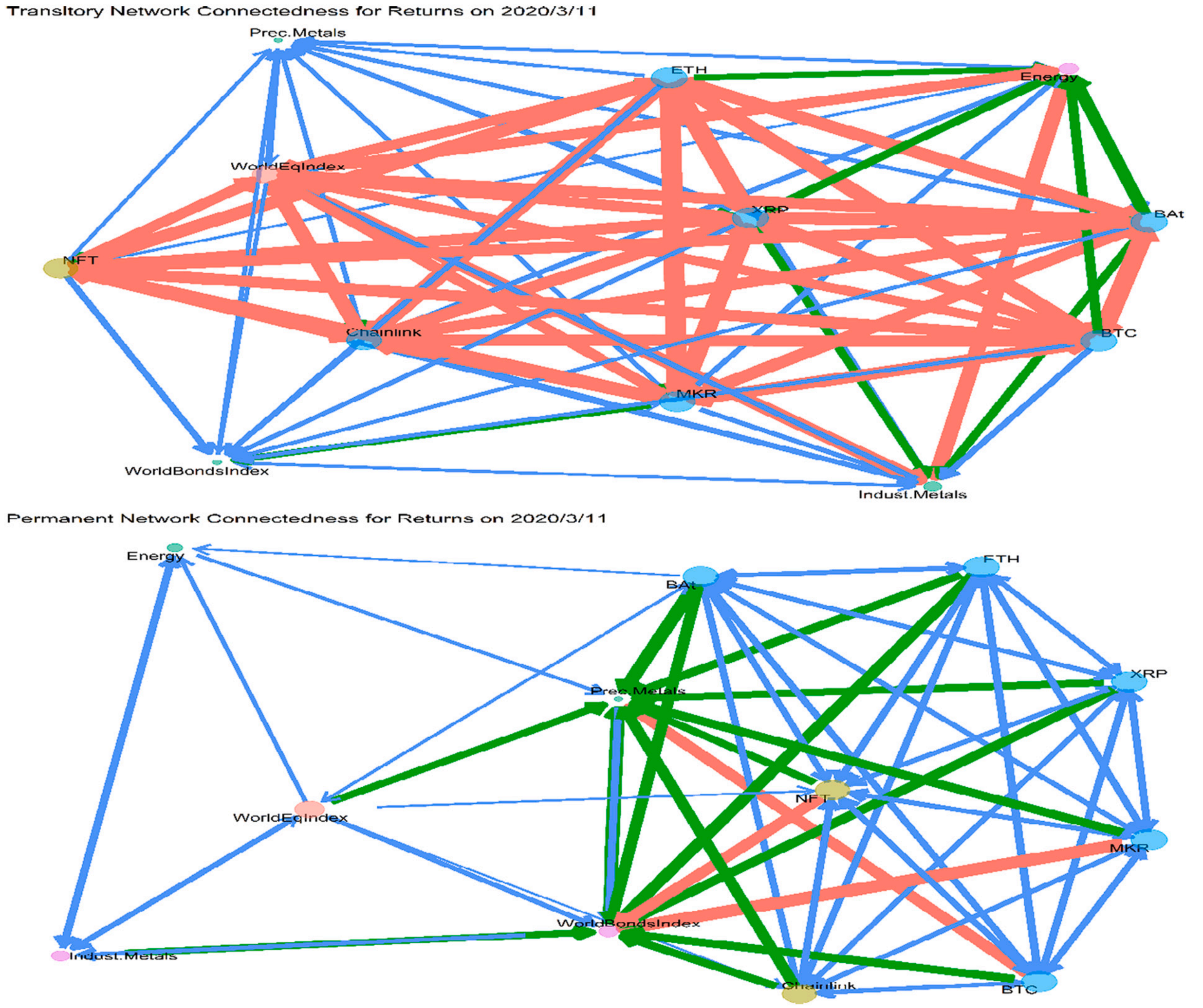

Fig. 15. Temporary and persistent network connectedness for returns as on March 11, 2020.

$$w_{Rt} = \frac{R_t^{-1}I}{IR_t^{-1}I} \tag{23}$$

5.3. Minimum Connectedness Portfolio (MCoP)

The minimum connectedness portfolio (MCoP) is introduced by using all pairwise connectedness (Broadstock et al., 2022). The approach minimizes the interconnectedness among variables and constructs portfolio by using spillovers between them. Therefore, the portfolio weights are more resilient to network shocks and given as follows:

$$w_{Rt} = \frac{PCI_t^{-1}I}{IPCI_t^{-1}I} \tag{24}$$

here, PCI is the pairwise connectedness index matrix, and I is an n-dimensional vector of ones.

5.4. Dynamic portfolios

We constructed investment portfolios by implementing three portfolio strategies: MVP, MCP, and MCoP. Fig. 17 diplays these three investment portfolios.

The figure indicates that MCoP, and MCP exhibit similar patterns, underlining an equivalance performance of these investment strategies. However, the MVP strategy clearly disperates from them. Moreover, sharing a common trend, the of MCP and MCoP strategies have exhibited a sustained growth since the first quarter of 2021.

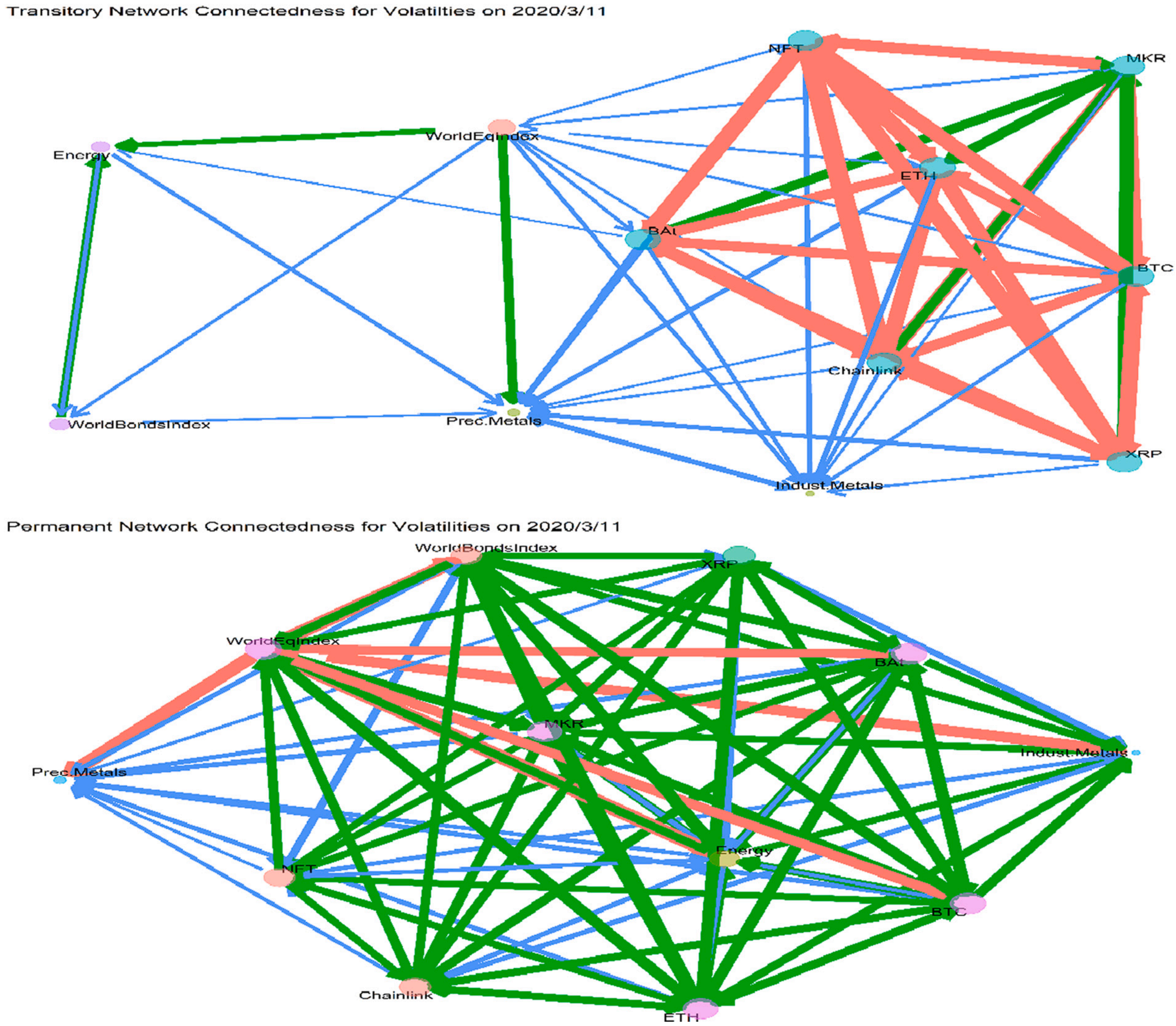

Fig. 16. Temporary and persistent network connectedness for volatilities as on March 11, 2020.

To better understand the composition of assets in individual portfolios, we plot dynamic potfolio weights in Fig. 18.

Similar to Broadstock et al. (2022) findings, the MVP composition differs significantly from MCP, or MCoP. MCP and MCoP share more close constitutions. However, the weights of some assets in MCP and MCoP have some differences. For instance, the weights for NFT in MCP exhibit a sharp increase around February–March 2020, while the weights for NFT in MCoP process a much lower surge.

In the final step, we present the avarage portfolio weights for three alternative investment portfolios in Table 6.

The average weights for MVP are as follows. MVP: Energy: 1%, industrial metals: 3%, world equity index: 5%, and world bond index: 90%. As clearly shown in Table 6, the diversifications are much higher for both MCP and MCoP. The highest weights for MCP, and MCoP correspond to the world bond index, and NFT (15%), respectively. Conversely, the lowest weights for MCP, and MCoP belong to XRP, and ETH. Additionally, sharing a common feature, the compositions of assets for MCP and MCoP on average are close.

6. Concluding remarks and implications

In this study, we investigated the time and frequency connectedness among the returns and volatility of NFT, Defi, cryptocurrencies and other traditional financial assets (Energy, Metals, Equity, and Bond) using time- and frequency-based connectedness approaches. In particular, we employed Chainlink, Maker, Basic Attention Token as Defi assets and Bitcoin, Ethereum, and Ripple for cryptocurrencies. Furthermore, we calculated transitory and persistent connectedness among them during the COVID-19 pandemic and compared their connectedness during the pre-pandemic and pandemic periods.

The time- and frequency-based connectedness methods provided several interesting conclusions, with useful practical implications. Our main findings can be summarized as follows.

Fig. 17. Dynamic Portfolio Weights.
Notes: Dynamic portfolio weighs are estimated by time-varying variance-covariance matrices obtained by the TVP-VAR(0.99,0.99) with one lag and a-20-step-ahead generalized forecast error variance decompositions.

First, both the returns and volatility spillovers were significantly affected by the COVID-19 pandemic. In other words, the interdependencies between the new digital assets and other financial assets intensified due to the pandemic. This result is consistent with the results of many previous studies as discussed in Section 2.2. Interestingly, during the pandemic period, energy received the lowest shocks from other financial assets for both return and volatility spillovers. This was because the shock within the energy industry was large at that time, which was primarily due to the decline in demand for crude oil owing to the spread of COVID-19 and the Russia-Saudi Arabia oil price war (See Choi, 2022a).

Second, the short-term connectedness among financial assets returns was stronger than the medium-, and the long- term connectedness during both pre-pandemic and COVID-19 pandemic periods. However, the long-term connectedness among financial asset volatility was stronger than the short-, and medium-term linkages until April 13, 2020. In general, the longer-term components become more important in a bear market (See Kumar et al., 2022). Therefore, this result suggests that when long-term volatility connectivity was stronger than short- and medium-term linkages, the market was a definite bear market.

Third, the spread of COVID-19 caused a shift in the direction of return and volatility spillovers among assets, which can be assessed by comparing the connectedness between the pre-pandemic and pandemic periods.

The return connectedness during the two periods (Tables 2 and 3) showed the MKR and NFT to experience the first (= 0.67) and second (= −0.68) smallest change in NET values, respectively. In addition, their NET values were almost zero during the two periods. That is, they had balanced return transmission with others even during the pandemic period. However, Chainlink and BTC were the first (=19.16) and second (=10.85), respectively, to show an increase in NFT values. That is, global investments were transferred to Chainlink and BTC from the other markets, causing the increase in return net spillovers.

Regarding volatility connectedness during the two periods (Tables 4 and 5), all show bigger changes than that in the return connectedness. This indicates that the financial assets transmitted or received other significant shocks during the pandemic period. In particular, BAT was the first to show a decrease (= −26.46) in NFT value. This change suggests that BAT exhibits the safe haven effect (See Wang et al., 2022; Zhang et al., 2021). In addition, XRP experienced the smallest change (= −0.67) in NET values, and it was the net transmitter of volatility spillovers during both pre-pandemic and pandemic periods.

We analyzed historical investment performance of our estimates by employing back-testing portfolios. Based on dynamic portfolio analysis, we determined that MCP, and MCoP share common portfolio weights compositions, while MVP differs from them. Moreover, sharing a common trend, MCP and MCoP investment portfolio have proceeded a growth since the first quarter of 2020, while the MVP has remained silent. Furthermore, MCP and MCoP investment portfolio strategies provide a much more diversified option compared to the MVP.

We suggest several implications for financial market participants based on these findings. First, our findings on the dynamic

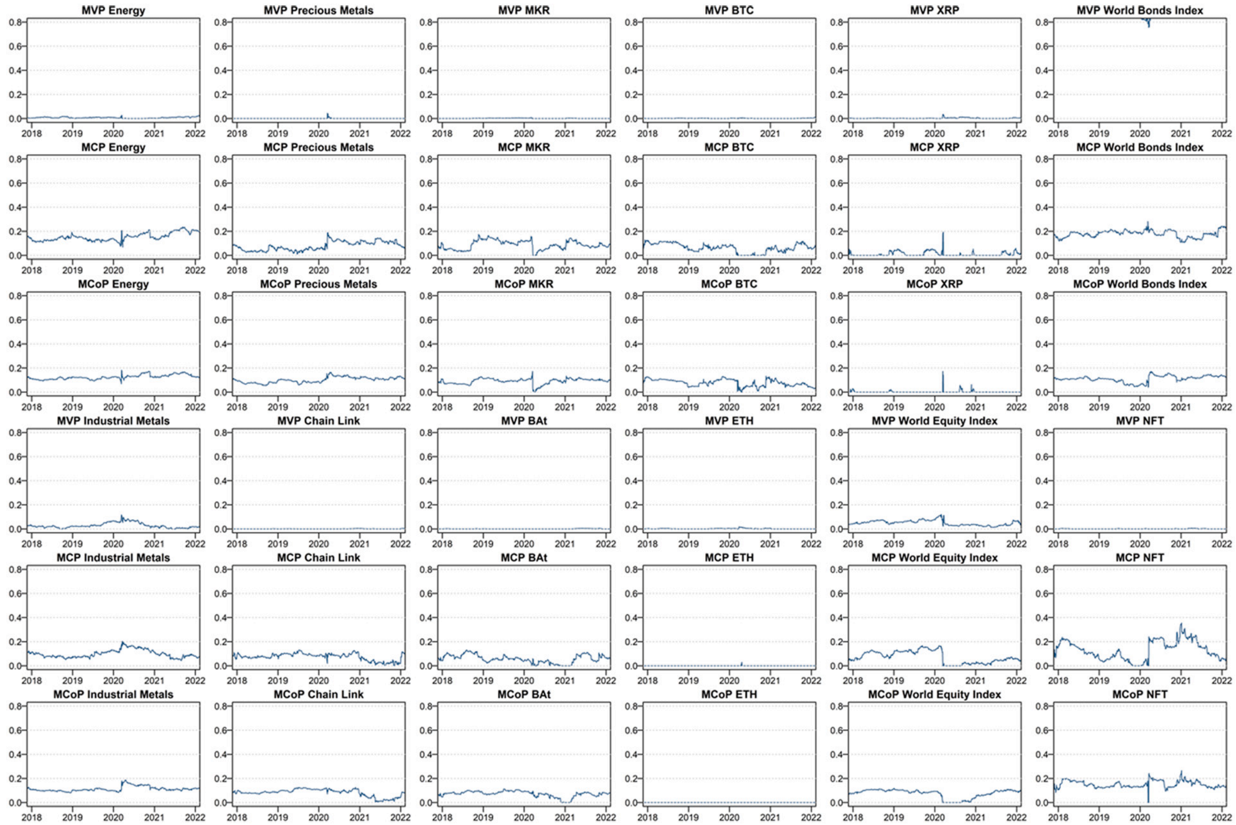

Fig. 18. Dynamic multivariate portfolio weights.
Notes: Dynamic portfolio weighs are estimated by time-varying variance-covariance matrices obtained by the TVP-VAR (0.99,0.99) with one lag and a-20-step-ahead generalized forecast error variance decompositions.

connectedness may help portfolio managers, investors, and policymakers to establish effective portfolio allocation strategies. For example, BAT becoming a net receiver due to the COVID-19 pandemic has revealed its potential as a safe haven. Furthermore, the frequency-based connectedness results provide insight into transaction strategies to long-term investors or short-term speculators. Second, the understanding of the interrelationship between digital assets and other financial assets provides flexible regulatory bandwidth to policymakers for stabilizing financial systems. NFTs and Defi have been of great interest to market participants as new technological innovations. Therefore, the financial authorities need to establish appropriate regulations to prevent side effects in the financial system caused by excessive interest. Third, our findings may be used to predict financial crises, as an early risk indicator. For example, the relationship between long-term connectedness, and short- and medium-term connectedness can be used to predict whether the market has entered a bearish trend. There is also a study that showed that volatility spillover has the capability of a financial crisis indicator (See Laborda and Olmo, 2021).

The topic explored in this paper can be further extended by future studies in several ways. First, it is necessary to investigate whether NFT and Defi have the characteristics of hedge, safe-haven, and portfolio diversification. Second, since each country has a different financial system, it will be valuable to investigate the dynamic connectedness among NFT, Defi and other financial assets within each country. Third, the varying effects of good and bad news on connectedness, such as the study of Shahzad et al. (2021) should be further considered. Lastly, the welfare effects of portfolio choice in the spirit of (Spierdijk and Umar, 2014) may be explored.

CRediT authorship contribution statement

Zaghum Umar: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Supervision, Investigation, Project administration, Writing - original draft, Writing - review & editing. **Onur Polat:** Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing - original draft, Writing - review & editing. **Sun-Yong Choi:** Conceptualization, Validation, Formal analysis, Writing - original draft, Writing - review & editing. **Tamara Teplova:** Conceptualization, Validation, Formal analysis, Writing - original draft, Writing - review & editing.

Table 6
Dynamic portfolio weights.

MVP				
	Mean	**Std.Dev.**	**5%**	**95%**
Energy	0.010	0.010	0.000	0.020
Industrial Metals	0.030	0.020	0.000	0.070
Precious Metals	0.000	0.000	0.000	0.000
Chain Link	0.000	0.000	0.000	0.000
MKR	0.000	0.000	0.000	0.000
BAt	0.000	0.000	0.000	0.000
BTC	0.000	0.000	0.000	0.000
ETH	0.000	0.000	0.000	0.010
XRP	0.000	0.000	0.000	0.010
World Equity Index	0.050	0.020	0.020	0.080
World Bonds Index	0.900	0.040	0.830	0.950
NFT	0.000	0.000	0.000	0.000
MCP				
	Mean	**Std.Dev.**	**5%**	**95%**
Energy	0.150	0.030	0.110	0.210
Industrial Metals	0.100	0.030	0.060	0.160
Precious Metals	0.080	0.040	0.030	0.140
Chain Link	0.070	0.030	0.020	0.110
MKR	0.090	0.040	0.030	0.140
BAt	0.060	0.030	0.000	0.110
BTC	0.060	0.040	0.000	0.110
ETH	0.000	0.000	0.000	0.000
XRP	0.010	0.020	0.000	0.050
World Equity Index	0.070	0.050	0.000	0.150
World Bonds Index	0.180	0.030	0.130	0.230
NFT	0.130	0.080	0.000	0.250
MCoP				
	Mean	**Std.Dev.**	**5%**	**95%**
Energy	0.130	0.020	0.100	0.160
Industrial Metals	0.110	0.020	0.090	0.150
Precious Metals	0.100	0.020	0.070	0.140
Chain Link	0.080	0.030	0.020	0.120
MKR	0.090	0.020	0.050	0.120
BAt	0.070	0.020	0.000	0.100
BTC	0.080	0.030	0.030	0.120
ETH	0.000	0.000	0.000	0.000
XRP	0.000	0.010	0.000	0.010
World Equity Index	0.070	0.040	0.000	0.110
World Bonds Index	0.110	0.030	0.060	0.150
NFT	0.150	0.030	0.120	0.200

Notes: Dynamic portfolio weighs are estimated by time-varying variance-covariance matrices obtained by the TVP-VAR(0.99,0.99) with one lag and a-20-step-ahead generalized forecast error variance decompositions.

Declaration of Competing Interest

The authors have declared that there are no conflicts of interest.

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