

Dynamic interlinkages between cryptocurrencies, NFTs, and DeFis and optimal portfolio investment strategies

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Abstract

Purpose – This study aims to scrutinize time-varying return and volatility interlinkages among major cryptocurrencies, NFT tokens and DeFi assets between 1 July 2018 and 19 February 2023 and determine optimal portfolio allocations and hedging effectiveness under different portfolio construction techniques.

Design/methodology/approach – This work examines time-varying return and volatility interlinkages among major cryptocurrencies, NFT tokens, and DeFi assets between 1 July 2018 and 19 February 2023. To this end, the time-varying parameter-vector autoregression (TVP-VAR)-based connectedness methodology of Antonakakis *et al.* (2020) This approach is an extended version of the Diebold–Yilmaz (DY) method (Diebold and Yilmaz, 2014) and has advantages over the original DY. First, unlike the DY, it is free of the selection of a particular window size. Second, it has robustness for the outliers. Furthermore, following Broadstock *et al.* (2022), the author estimates time-varying optimal portfolio weights and hedging effectiveness under different portfolio construction scenarios.

Findings – This study's results indicate the following results: (1) The overall connectedness indices prominently capture well-known financial/geopolitical distress incidents; (2) the leading cryptocurrencies (ETH, BTC and BNB) are the largest transmitter of return shocks, while LINK and BTC are the largest transmitters/recipients of volatility shocks; (3) cryptocurrencies, NFTs and DeFi form distinct cluster groups in terms of return and volatility connectedness; (4) the connectedness networks estimated around the 2022 cryptocurrency crash and the FTX's filing for the bankruptcy are characterized by the strongest return and volatility interlinkages; (5) optimal portfolio strategies computed by different portfolio construction techniques display similar motifs and have sustained growth paths except for some short-lived drop backs.

Research limitations/implications – This study's findings imply several policy suggestions for investors, stakeholders and policymakers. First, the study's time-based dynamic interlinkages can help market participants in their optimal portfolio decisions. In particular, the persistent net receiving roles of the DeFi assets and the NFTs throughout the episode, especially around the financial/geopolitical turmoil, underpin their safe haven potentials (Umar *et al.*, 2022a, b). Finally, since the total connectedness indices (TCIs) are prone to significantly increase around financial/geopolitical burst times, these tools can be valuable for policy makers to monitor risk.

Originality/value – The contribution of knowledge is at least threefold. First, the author focuses on the dynamic time interlinkages among major cryptocurrencies, NFTs and DeFi assets in July 2018 and February 2023 considering the prominent recent financial/geopolitical incidents. Second, the author estimates network topologies of dynamic connectedness around financial/geopolitical bursts and compared them in terms of interlinkages. Finally, the author calculates the time-varying optimal portfolio allocations and hedging effectiveness under different portfolio construction techniques.

Keywords Time-varying interlinkages, NFTs, DeFi, Cryptocurrency, Hedging effectiveness, Optimal portfolio allocations

Paper type Research paper

1. Introduction

A cryptocurrency is a digital/virtual cash instrument formed to allow autonomous transactions between parties without an intermediary. Unlike conventional assets, the



price of a cryptocurrency does not rely on a tangible asset, and transactions are performed based on the design of the blockchain design. The blockchain is a shared ledger that facilitates the process of distribution of a peer-to-peer transaction network of actors participating in the system (Valdeolmillos *et al.*, 2020). Thanks to this design, transactions are verified and validated in accordance with the cryptographic protocols which render them faster, cheaper and more reliable transactions than the transactions performed with a central authority (Hossain, 2021).

However, cryptocurrencies have faced sudden surges or abrupt declines in market value, which has spurred the debate on the bubble structure of the cryptocurrency market (Frehen *et al.*, 2013; Vogel and Werner, 2015). Moreover, they are inherent to cyber criminality and regulatory disorientation issues which constitute the cryptocurrency trilemma along with their potential inherent price bubble (Corbet *et al.*, 2019).

Despite the aforementioned drawbacks, the cryptocurrency market has sustained rapid growth since the emergence of the first cryptocurrency, Bitcoin, in 2008, which triggered herding behavior and excess volatility (Jalal *et al.*, 2021). In particular, as Figure 1 indicates, the market has dramatically expanded in size in the post-COVID era despite one of the most disastrous health crises in human history.

Non-fungible tokens (NFTs) were originally derived from the smart contracts of Ethereum (EIP-721) and displayed some different features from standard coins (Wang *et al.*, 2021). NFTs' main characteristic is non-fungibility, i.e. the uniqueness that cannot be bartered, which provides personalized value for them, by giving ownership of the digital assets (Dowling, 2022; Wang *et al.*, 2023). The NFT market has overwhelmingly attracted investors and experienced \$25.1 and \$24.7 billion worth of trading volumes in 2021 and 2022 compared to \$82.5 million in 2020 [1].

Derived by blockchain as distributed ledgers and run on smart contracts, DeFi assets describe platforms that facilitate peer-to-peer designs and range from lending, borrowing, spot trading and margin trading to market making and derivatives (Corbet *et al.*, 2023). Loans obtained by DeFi are digital and provide a transaction system without a central authority (Chen and Bellavitis, 2020; Yousaf and Yarayova, 2022). This mechanism has raised interest



Figure 1.
Cryptocurrency
market capitalization

Source(s): <https://coinmarketcap.com/charts/>

from market participants and the total market capitalization of DeFi tokens reached \$59.5 billion in February 2023 [2].

Motivated by the crucial prominence of apprehension of risk transmission through financial assets, our study aims to scrutinize the time-varying interlinkages among major cryptocurrencies, NFTs and DeFi assets. It is worth remarking that a comprehensive understanding of such risk transmissions not only provides insights for portfolio managers in their investment strategies but helps policymakers in strengthening financial soundness by mitigating systemic risk (Beber and Brandt, 2010). It should be noted that understanding the spillovers among the assets is crucial for determining portfolio allocations, portfolio decisions, and designing and benefiting from hedging effectiveness among them (Kang *et al.*, 2021; Hachicha *et al.*, 2022). In particular, tight interconnectedness among financial markets offers hedging opportunities for traders (Röthig, 2009).

To achieve this, we implement the time-varying parameter-vector autoregression (TVP-VAR)-based time connectedness methodologies of Antonakakis *et al.* (2020). This approach is an extended version of the Diebold–Yilmaz (DY) method (Diebold and Yilmaz, 2014) and has advantages over the original DY. First, unlike the DY, it is free of the selection of a particular window size. Second, it has robustness for the outliers. Furthermore, following Broadstock *et al.* (2022), we estimate time-varying optimal portfolio weights and hedging effectiveness under different portfolio construction scenarios.

The contribution of knowledge is at least threefold. First, we focus on the dynamic time interlinkages among major cryptocurrencies, NFTs and DeFi assets in July 2018 and February 2023 considering the prominent recent financial/geopolitical incidents. Second, we estimate network topologies of dynamic connectedness around financial/geopolitical bursts and compared them in terms of interlinkages. Finally, we calculate the time-varying optimal portfolio allocations and hedging effectiveness under different portfolio construction techniques.

We proceed with the study as follows: Section 2 presents the literature review. Section 3 describes the data and methodology of the work. Section 4 provides and discusses the empirical findings. Section 5 delineates the main findings and concludes the study.

2. Literature review

Since the appearance of the cryptocurrency Bitcoin in 2008 in the financial system, the cryptocurrency market has sustained spectacular growth in both trading volumes and sizes. The total market capitalization has surpassed \$1 trillion with 22,695 exchanged cryptocurrencies as of February 2023, while it was around \$278.6 billion on 2 February 2020 [3]. This massive expansion in market size accompanied by the excess volatility has raised the interest of both investors and scholars.

It should be worth remarking that the debate on whether a cryptocurrency is a commodity or an alternative to fiat currency is still going on in academic domains. In this vein, some studies argued that a cryptocurrency would be a candidate for fiat money in the near future (Carrick, 2016; Kirkby, 2018), while some scholars asserted it as a commodity (Bariviera *et al.*, 2017; Bouri *et al.*, 2018; Dyhrberg, 2016).

Unlike traditional financial assets, cryptocurrencies experience abrupt price and volatility movements, which motivate scholars to scrutinize their stylized facts. In this context, studies have examined different aspects of cryptocurrencies such as herding behavior (Baur and Hoang, 2021; Bouri *et al.*, 2019; Mnif *et al.*, 2020; Shrotryia and Kalra, 2022), hedge and safe haven properties (Corbet *et al.*, 2020; Karim *et al.*, 2022b), and efficiencies (Fernandes *et al.*, 2022; Kakinaka and Umeno, 2022; Vidal-Tomás, 2022).

It should be noted that the interdependencies among global financial markets are prone to markedly augment around financial/geopolitical bursts (Diebold and Yilmaz, 2014).

Furthermore, a comprehensive understanding of cross-market interconnectedness would help the market participants in their hedging and portfolio management strategies. Consequently, an abundant strand of literature has examined interlinkages among cryptocurrencies and other asset classes (Yi *et al.*, 2018; Ji *et al.*, 2019; Bouri *et al.*, 2021; Polat and Kabakçı Günay, 2021; Umar *et al.*, 2021, 2022a; Elsayed *et al.*, 2022; Attarzadeh and Balcilar, 2022; Kumar *et al.*, 2022; Le, 2023; Ugolini *et al.*, 2023). Most of these studies have determined strengthening interlinkages around burst episodes, such as the outbreak of the COVID-19 pandemic in early 2020.

Despite the rich literature on cryptocurrency connectedness, only a limited number of studies have focused on this research topic considering NFTs and/or DeFi assets. In this vein, Aharon and Demir (2022) analyzed time-varying interconnectedness among the returns of NFTs and asset classes between January 2018 and June 2021 by utilizing the TVP-VAR connectedness approach. Their results indicated that NFTs are mainly independent of shocks from common assets and accountable for their own shocks. Likewise, Karim *et al.* (2022a) analyzed the interlinkages among NFTs, DeFi tokens and cryptocurrencies on 15 March 2018 and 24 October 2021 by implementing quantile connectedness. The authors found significant risk transmissions between blockchain markets with tightly disconnected NFTs. Along similar lines, Umar *et al.* (2022b) analyzed the time and frequency-based connectedness between NFTs, DeFi tokens and asset classes in December 2017 and January 2022. Their findings suggest that the time and frequency-dependent transmissions among them notably escalate with the pandemic and the dominance of transitory connectedness throughout the episode. Youssaf and Yarayova (2022) examined return and volatility transmissions between NFTs, DeFi assets and other assets (oil, gold, S&P500, and Bitcoin) between May 2018 and July 2021 by employing the TVP-VAR connectedness approach. They determined weak interdependencies between NFTs and DeFi tokens with other assets. Similarly, Yousaf and Yaroyaya (2022) investigated static and time-varying return interdependencies between DeFi coins and four foreign exchange rates in March 2018 and October 2021 by utilizing the TVP-VAR connectedness methodology. Their results reported weak interdependencies between DeFi assets and currencies, particularly in early 2020.

It should be worth mentioning that recent studies have examined the diversification roles or hedging properties of NFTs of DeFi assets. In this vein, Ko *et al.* (2022) examined the diversification roles of NFTs in portfolio investing strategies and found that NFTs are distinct from traditional assets, suggesting portfolio diversification of them. Likewise Karim *et al.* (2023) found that NFTs exhibit greater diversification attributes compared to DeFi assets and cryptocurrencies. Along similar lines, Umar *et al.* (2023) determined that NFTs offer beneficial investment and hedging attributes. Similarly, Cevik *et al.* (2022) analyzed interconnectedness among DeFi assets and natural resource assets (crude oil, and gold) and found the hedging effectiveness of DeFi assets for gold and crude oil investors.

3. Data and methodology

3.1 Data

We collected the data from CoinMarketCap and considered cryptocurrencies, NFT data and DeFi tokens with the largest market capitalization on the study date and the longest availability of data matches [4]. Consequently, our data set constitutes three cryptocurrencies, Bitcoin (BTC), Ethereum (ETH) and Binance Coin (BNB); three DeFi assets, Maker (MKR), Basic Attention Token (BAT) and Chain Link (LINK); and two NFT tokens, Decentraland (MANA) and Tezos (XTZ). The data ranges from 1 July 2018 to 19 February 2023. We compute the log returns of cryptocurrencies, NFTs and DeFi assets for date t by employing $\frac{\log(P_t) - \log(P_{t-1})}{\log(P_{t-1})}$ formula. Following Attarzadeh and Balcilar (2022), we

calculate the daily realized volatilities by implementing the method of [Rogers and Satchell \(1991\)](#) that uses the High (H), Low (L), Open (O) and Close (C) in the following formulation:

$$RV_t = 100 \times \sqrt{N \times \left[\ln\left(\frac{H_t}{O_t}\right) \times \ln\left(\frac{H_t}{C_t}\right) + \ln\left(\frac{L_t}{O_t}\right) \times \ln\left(\frac{L_t}{C_t}\right) \right]}$$

The summary statistics and trends in the returns and volatilities are provided in [Table 1](#) and [Figures 2 and 3](#), respectively.

All return series are featured by positive returns on average and the highest return is recorded by MANA (0.564) and followed by LINK (0.423). Contrariwise, XTZ, and BTC provide the lowest returns. All return series exhibit leptokurtic distributions. Except for BTC and ETH, all returns tail to the left. Moreover, the JB values manifest abnormal distributions. Additionally, all series are significantly auto-correlated and they display ARCH/GARCH errors.

Regarding the volatilities, BTC records the highest volatility on average, while BAT manifests the lowest average volatility. All volatilities tail to the right and exhibit abnormal distributions. Likewise the returns, all volatilities are significantly auto-correlated and manifest ARCH/GARCH errors.

Return and volatility series exhibit notable spikes around prominent financial/geopolitical incidents such as the sudden drop in market capitalization of Bitcoin on 15 November 2018 [\[5\]](#), the proclamation of the SARS-CoV-19 pandemic by the World Health Organization (WHO) on 11 March 2020, the crypto collapse on 19 May 2021 [\[6\]](#), the Russian invasion on Ukraine on 24 February 2022, and the filing for bankruptcy by the crypto exchange FTX on 11 November 2022 [\[7\]](#).

3.2 Methodology

3.2.1 TVP-VAR-based connectedness methodologies. In this work, we utilize the TVP-VAR-based time connectedness methodology of [Antonakakis et al. \(2020\)](#). [Table 2](#) briefly describes this approach and the details of the approach are provided in [Appendix A.1](#).

3.2.2 Dynamic portfolio approach. Following [Broadstock et al. \(2022\)](#), we employ multivariate portfolio construction methodologies, the minimum variance portfolio (MVP) and minimum correlations portfolio (MCP), and focus on the time-varying optimal portfolio weights and hedging effectiveness under them. [Table 3](#) summarizes optimal portfolio weights under MVP, and MCP and more details are presented in [Appendix A.2](#).

4. Results

4.1 Time-varying connectedness for the returns

We start our analysis with the time-varying connectedness for the return series with well-known financial/geopolitical incidents and plot the TCI in [Figure 4](#).

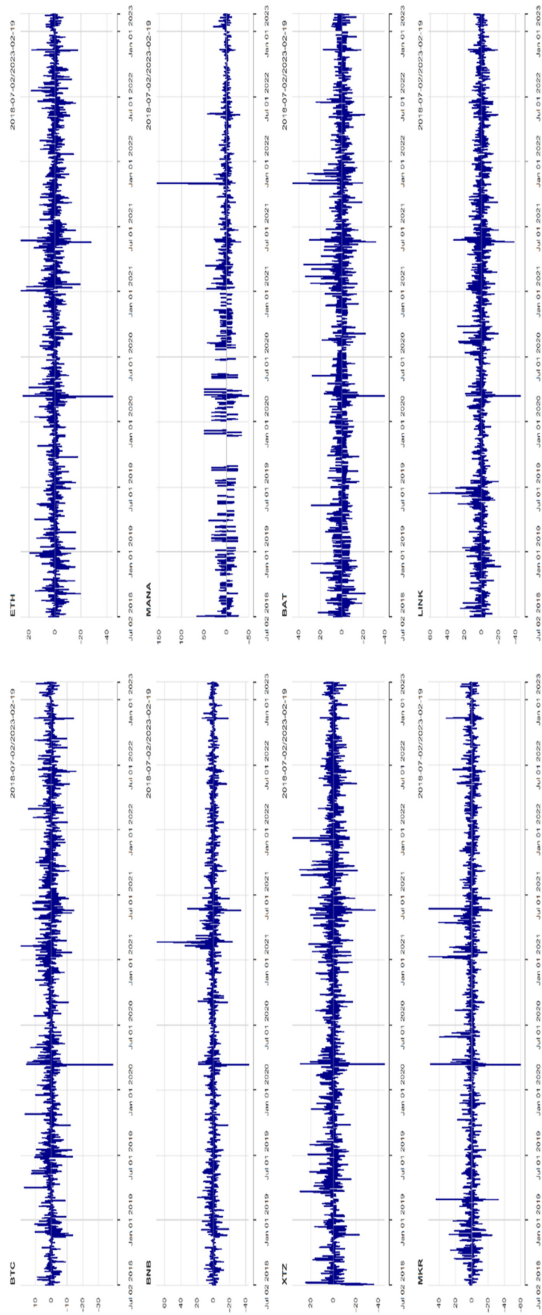
The TCI oscillates between 36 and 83% and peaks on 5 May 2022 (82.54%), which coincides with 400\$ billion crypto crash followed by sudden plunges in major cryptocurrencies [\[8\]](#). It is worthwhile noting that the TCI markedly escalates around well-known financial/geopolitical incidents over the study episode. The index noticeably amplifies with the significant drop in Bitcoin's price in November 2018 and hits its first peak on 1 December 2018 (71.23%). The TCI then moderately plummeted and reached around 37% in May 2019. Afterward, the index gradually surges and skyrockets with the proclamation of the pandemic on 11 March 2020. The index experiences noticeable escalations around the 2021 cryptocurrency crash on 19 May 2021, the Russian invasion of Ukraine on 24 February

	Mean	Variance	Skewness	Ex. Kurtosis	JB	ERS	Q(20)	Q2(20)
<i>Returns</i>								
BTC	0.150*	13.935***	-0.484***	9.723***	6739.301***	-6.56***	19.15**	52.89***
ETH	0.203*	24.563***	-0.298***	7.014***	3497.770***	-6.74***	35.92***	101.66***
BNB	0.322**	28.457***	1.236***	23.905***	40767.231***	-15.41***	42.99***	186.30***
MANA	0.564**	98.816***	3.232***	40.192***	116970.580***	-20.16***	20.66**	23.66***
XTZ	0.122	39.379***	0.041	5.534***	2161.959***	-4.32***	24.70***	170.57***
BAT	0.214	40.348***	0.674***	5.930***	2610.113***	-5.40***	46.66***	63.25***
MKR	0.232	43.237***	1.207***	15.391***	17130.395***	-17.69***	55.53***	128.53***
LINK	0.423***	43.027***	0.602***	8.203***	4851.786***	-9.02***	14.50	73.72***
<i>Volatilities</i>								
BTC	21546.80***	29541.4109.27***	0.884***	-0.525***	240.349***	-0.826***	17346.62***	16823.57***
ETH	1203.14***	1528309.20***	1.013***	-0.115	290.883***	-1.039***	17315.24***	16636.36***
BNB	170.063***	34665.817***	0.755***	-0.753***	200.904***	-0.835***	17180.91***	16120.74***
MANA	0.602***	0.832***	2.183***	4.574***	2823.717***	-1.646***	16702.94***	14878.96***
XTZ	2.360***	2.467***	1.229***	1.156***	521.029***	-1.377***	16150.94***	14857.17***
BAT	0.413***	0.099***	1.587***	1.777***	934.473***	-1.989***	16444.16***	14895.08***
MKR	1167.04***	1007697.53***	1.574***	1.984***	977.467***	-1.54***	16723.96***	15187.49***
LINK	10.12***	107.910***	1.176***	0.637***	419.264***	-1.385***	16814.19***	15036.36***

Note(s): JB denotes the Jarque-Bera statistics, and ***, **, and * represent 1%, 5% and 10% statistical significance levels. ERS: *Stock et al. (1996)* unit root test. Q(20) and Q2(20) denote the Ljung-Box statistics for serial correlation in raw series and squared residuals

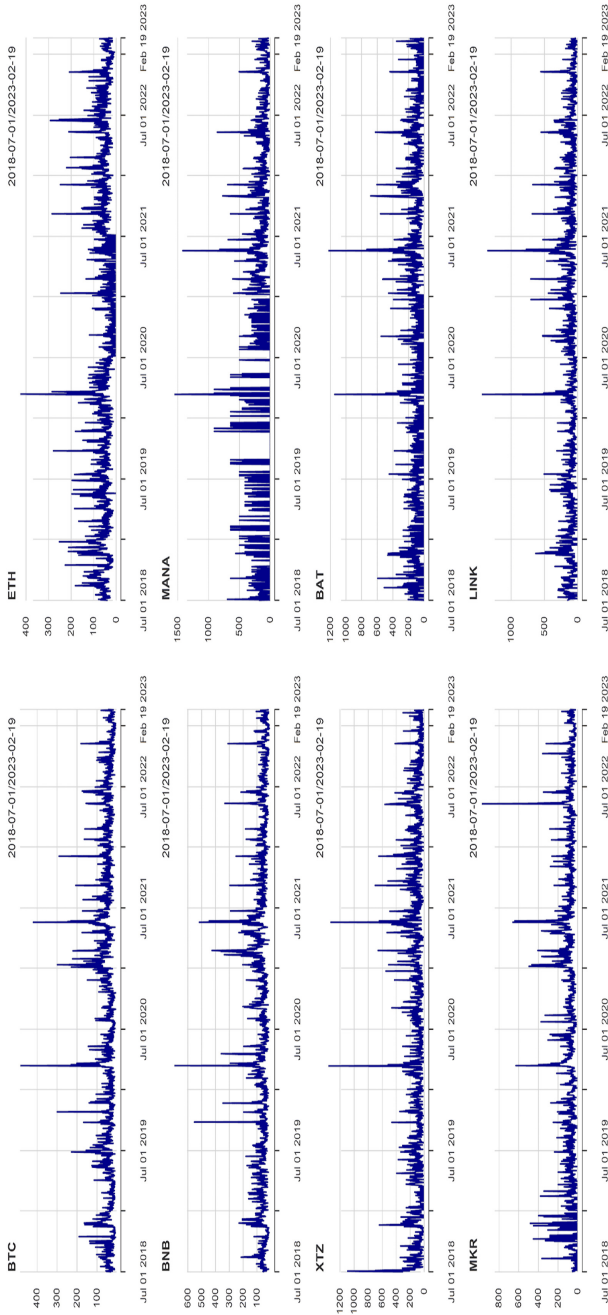
Source(s): Author's own creation

Table 1.
Descriptive statistics



Source(s): Authors own creation

Figure 2.
Trends in the returns



Source(s): Authors own creation

Figure 3.
Trends in the
volatilities

Total connectedness index (TCI)

$$C_t(H) = \frac{\sum_{i=1,t \neq j}^n \tilde{\Phi}_{y,i,t}(H)}{\sum_{i=1}^n \tilde{\Phi}_{y,i,t}(H)} = \frac{\sum_{i=1,t \neq j}^n \tilde{\Phi}_{y,i,t}(H)}{n} \times 100$$

Local network connectedness

Total directional connectedness TO others

$$C_{i \rightarrow j,t}(H) = \frac{\sum_{j=1,t \neq i}^n \tilde{\Phi}_{y,i,t}(H)}{\sum_{j=1}^n \tilde{\Phi}_{y,i,t}(H)} \times 100$$

total directional connectedness FROM others

$$C_{i \leftarrow j,t}(H) = \frac{\sum_{i=1,t \neq j}^n \tilde{\Phi}_{y,i,t}(H)}{\sum_{i=1}^n \tilde{\Phi}_{y,i,t}(H)} \times 100$$

Table 2.
Summary of
methodology

NET total directional connectedness

Source(s): Author's own creation

$$C_{i,t}(H) = C_{i \rightarrow j,t}(H) - C_{i \leftarrow j,t}(H)$$

Optimal portfolio weights

MVP

$$w_t = \frac{\sum_l I}{\sum_{l=1}^I I}$$

Table 3.
Optimal portfolio
weights

MCP

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

Source(s): Author's own creation

2022 and the FTX's filing for bankruptcy on 11 November 2022. [Table 4](#) presents the average connectedness results for the returns.

Average connectedness results in [Table 4](#) indicate that all return series contribute more to their own shocks than to others on average. Moreover, the overall connectedness of returns on average is 62.91%, which underpins a relatively strong interdependence among the return series. Expectedly and in line with the previous studies ([Ha, 2022](#); [Umar *et al.*, 2022a, b](#)), the leading cryptocurrencies (ETH, BTC and BNB) are the largest transmitters of return shocks. On the other hand, LINK and XTZ are the largest recipients of shocks. Additionally, BTC, ETH, BNB and MKR are the net transmitter of return shocks, while the rest of the series are the net recipients of the shocks.

Next, we focus on the net directional return connectedness with prominent incidents and depict them in [Figure 5](#).

In line with our previous findings, major cryptocurrencies such as BTC, ETH and BNB are the net transmitters of the return shocks throughout the episode. This result is consistent with previous studies ([Yi *et al.*, 2018](#); [Katsiampa *et al.*, 2019](#), [Umar *et al.*, 2022a, b](#)). Likewise, MKR is the net transmitter of the shocks, whereas the rest returns are the net receivers of shocks over the study period. Manifestly, the net spillover indices accurately capture prominent incidents over the episode. Moreover, increasing/decreasing trends in net transmitting/receiving returns shocks are worth noting particularly through the end of the episode.

4.2 Time-varying connectedness for the volatilities

Continuing our analysis of the time-varying connectedness for the volatilities, [Figure 6](#) plots the TCI with well-known financial/geopolitical events.

Table 4.
Average
connectedness table for
the returns

	BTC	ETH	BNB	MANA	XTZ	BAT	MKR	LINK	FROM
BTC	38.38	25.65	18.72	0.97	0.99	0.79	13.66	0.84	61.62
ETH	24.16	36.01	19.94	0.96	1.06	0.81	16.06	0.98	63.99
BNB	19.4	21.93	41.15	1.04	1.14	0.93	13.26	1.16	58.85
MANA	10.4	10.95	10.74	50.44	3.22	3.99	7.51	2.74	49.56
XTZ	15.53	18.52	16.25	2.33	28.34	3.31	12.43	3.29	71.66
BAT	15.34	18.76	16.65	3.04	3.71	29.09	11.07	2.33	70.91
MKR	15.7	19.71	14.95	1.13	1.11	0.97	45.24	1.17	54.76
LINK	15.87	19.93	16.59	1.87	3.44	1.94	12.3	28.06	71.94
TO	116.4	135.45	113.86	11.34	14.68	12.74	86.3	12.51	503.28
NET	54.78	71.46	55.01	-38.22	-56.98	-58.17	31.54	-59.42	TCI = 62.9

Note(s): The off-diagonal values indicate the shocks from the i th element to the j th element in the network. Results are estimated based on the TVP-VAR (1) model with lag 1 (BIC) and a 10-step ahead FEVD

Source(s): Author's own creation

The TCI for the volatilities oscillates between 39 and 77% and peaks on 16 March 2020 (76.78%), shortly after the proclamation of the COVID-19 pandemic by the WHO. The index accurately captures well-known financial/geopolitical incidents over the episode. [Table 5](#) presents the average connectedness results for the volatilities.

Examining the results in [Table 5](#), LINK and BTC are the largest transmitter/recipient of volatility shocks on average, respectively. Concerning the net transmitting/receiving roles, BTC, XTZ, BAT and LINK are the net transmitter of shocks, while the rest of them are the net recipient of shocks. Note that the results of the largest transmitter of volatility shocks as LINK is consistent with the findings of [Fasanya et al. \(2021\)](#). The average overall connectedness of volatilities is 61.42%, which is very close to the TCI found for the returns. [Figure 7](#) depicts the net directional volatility connectedness with prominent incidents.

In turn, XTZ, BAT and LINK are the persistent net transmitters of volatility shocks, whereas MKR is the main recipient of shocks throughout the period. On the other hand, BTC, ETH, BNB and MANA shift between the roles of a net transmitting or a net receiving over the period. It is worth remarking that the magnitudes of the net spillovers mainly amplify around the well-known incidents of the episode.

4.3 Time-varying connectedness networks

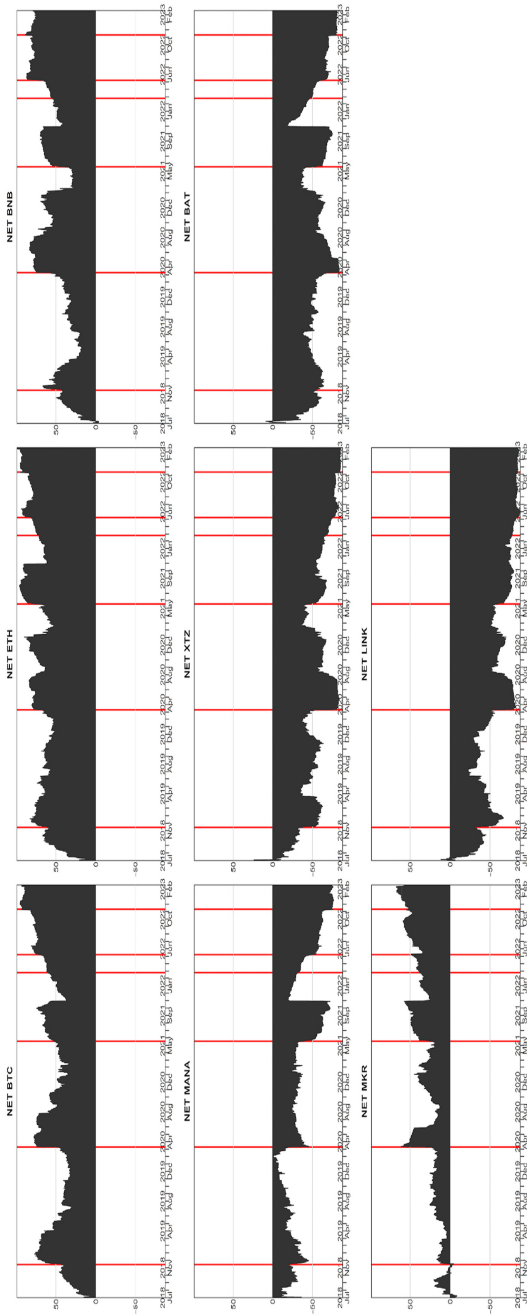
Proceeding with our analysis of the connectedness of returns and volatilities around prominent events of the episode, we plot the connectedness networks in [Figures 8 and 9](#).

Several results are worth noting based on the connectedness networks of the returns. First, mainly in all networks, BTC, ETH and BNB have the strongest interlinkages. Second, cryptocurrencies, DeFi assets and NFT tokens form different cluster groups in terms of return interdependencies. Third, the network estimated on 11 November 2022 has the tightest interconnectedness of returns (represented by the red and green colors) among all connectedness topologies.

As per volatility connectedness topologies, the networks estimated on 5 May 2022, and 11 November 2022 have more red and green linkages, indicating stronger interdependencies among the volatilities. Moreover, similar to the findings for the returns, cryptocurrencies, DeFi assets and NFT tokens structure distinct cluster groups.

4.4 Time-varying portfolio weights

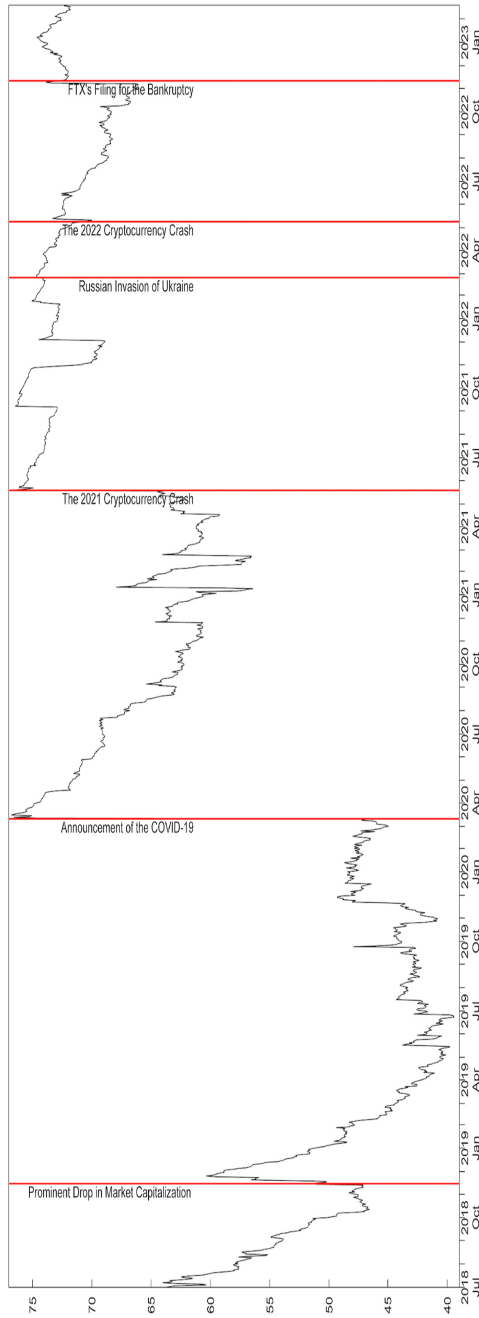
The final phase of the study scrutinizes the dynamic portfolio weights computed by MVP and MCP techniques. In this sense, we compute the optimal portfolio weights under each approach and display them in [Figure 10](#).



Note(s): Vertical red lines indicate the following incidents over the episode: A significant drop in Bitcoin's price on 15 November 2018, the announcement of the COVID pandemic on 11 March 2020, the 2021 cryptocurrency crash on 19 May 2021, the RIU on 24 February 2022, the 2022 cryptocurrency crash on 5 May 2022, FTX's filing for bankruptcy on 11 November 2022, respectively. Results are estimated based on the TVP-VAR (1) model with lag 1 (BIC) and a 10-step ahead FEVD

Source(s): Author's own creation

Figure 5.
Net directional
spillovers for the
returns



Note(s): Results are estimated based on the TVP-VAR (1) model with lag 2 (BIC) and a 10-step ahead forecast error variance decomposition (FEVD)

Source(s): Authors own creations

Figure 6.
TCI for the volatilities

	BTC	ETH	BNB	MANA	XTZ	BAT	MKR	LINK	FROM
BTC	31.94	15.24	11.83	5.76	8.71	8.37	8.39	9.76	68.06
ETH	17.16	37.81	11.17	4.34	7.56	6.96	7.15	7.85	62.19
BNB	12.72	10.07	37.82	5.8	8.07	8.2	7.24	10.07	62.18
MANA	5.76	3.98	5.12	46.77	10.04	12.78	4.65	10.91	53.23
XTZ	7.4	5.19	5.76	8.82	37.22	15.62	4.03	15.97	62.78
BAT	6.61	5.01	6.17	11.06	15.5	36.39	4.18	15.08	63.61
MKR	11.13	8.21	8.52	5.7	6.08	6.76	46.17	7.43	53.83
LINK	7.98	5.82	7.75	9.2	15.56	14.22	4.9	34.56	65.44
TO	68.75	53.53	56.33	50.68	71.52	72.92	40.55	77.06	491.32
NET	0.69	-8.66	-5.85	-2.56	8.75	9.3	-13.28	11.62	TCI = 61.42

Note(s): The off-diagonal values indicate the shocks from the i th element to the j th element in the network. Results are estimated based on the TVP-VAR (1) model with lag 2 (BIC) and a 10-step ahead forecast error variance decomposition (FEVD)

Source(s): Author's own creation

Table 5.
Average
connectedness table for
the volatilities

Predominantly, time-varying portfolio allocations for the returns estimated by MVP and MCP exhibit some discrepancies. However, corroborating our findings for the average connectedness results, BTC constitutes a higher proportion in the optimal portfolio construction under the MVP. Moreover, sharing a common trend, all weights of the returns are positive under two different portfolio construction techniques.

Optimal investment portfolios estimated under MVP and MCP are given in Figure 11. Optimal portfolio strategies obtained by the two distinct portfolio construction approaches display similar motifs, while the allocations under the MVP are lower than the weights estimated by the MCP. Furthermore, all portfolios experienced a sustained growth path except for short-lived drops induced by financial/geopolitical upheavals such as the pandemic and the 2021 crypto crash until the end of 2021. However, they have plummeted since then with a gradual increase through the end of the episode.

Finally, we provide the average portfolio allocations under these portfolio construction techniques in Table 6. On average, we invest in BTC 38%, in ETH 0%, in BNB 9%, in MANA 2%, in XTZ 18%, in BAT 14%, in MKR 1%, in LINK 17%, then the contributions of volatilities in the portfolio will be statistically significant lowered by 34% from BTC, 62% from ETH, 67% from BNB, 91% from MANA, 76% from XTZ, 77% from BAT, 79%, from MKR and 78% from LINK. The high proportion of the BTC in the optimal portfolio allocation by the MVP underpins its significant role in portfolio decision strategy.

The average weights and hedging effectiveness found by the MCP are somewhat similar and statistically significant (except for BTC). Notice that the negative values for BTC indicate that if we invest in this asset then the volatility of each asset in the portfolio would increase.

Table 7 reports the whole sample portfolio performances (the Sharpe ratio) of each portfolio construction methodologies. MCP records a higher average return (0.33%), compared to the MVP (0.18%). Moreover, the MCP has a higher SR value (0.087), indicating a better portfolio performance compared to the MVP.

5. Concluding remarks

In this work, we examined the dynamic time connectedness among the returns and volatilities of major cryptocurrencies, NFT tokens and DeFi assets. Additionally, we performed a portfolio backtesting analysis to determine time-varying optimal portfolio allocations under different portfolio construction techniques.

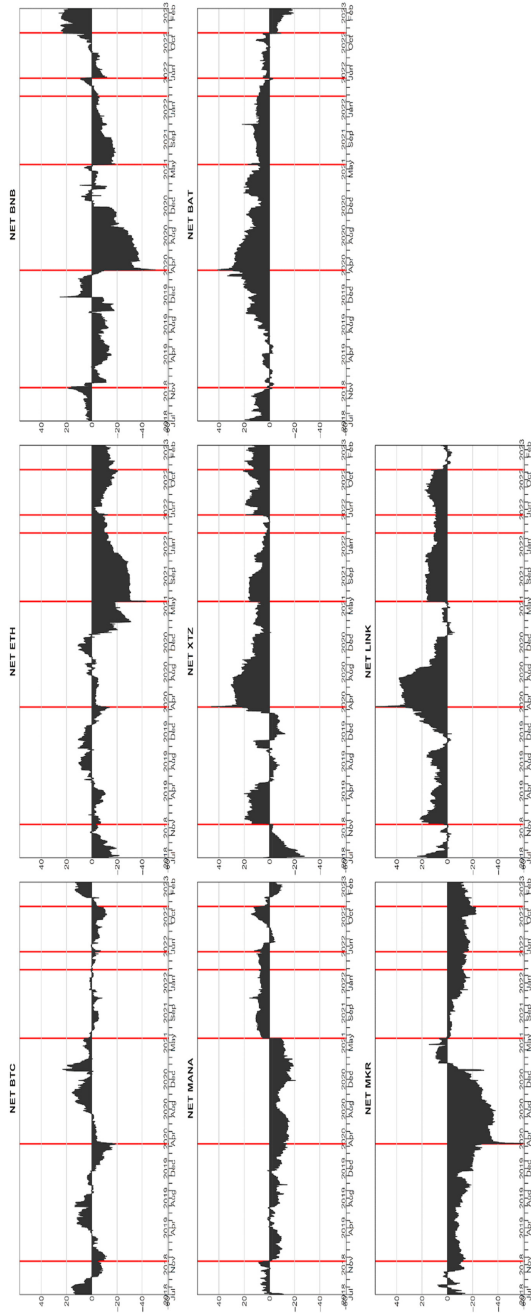
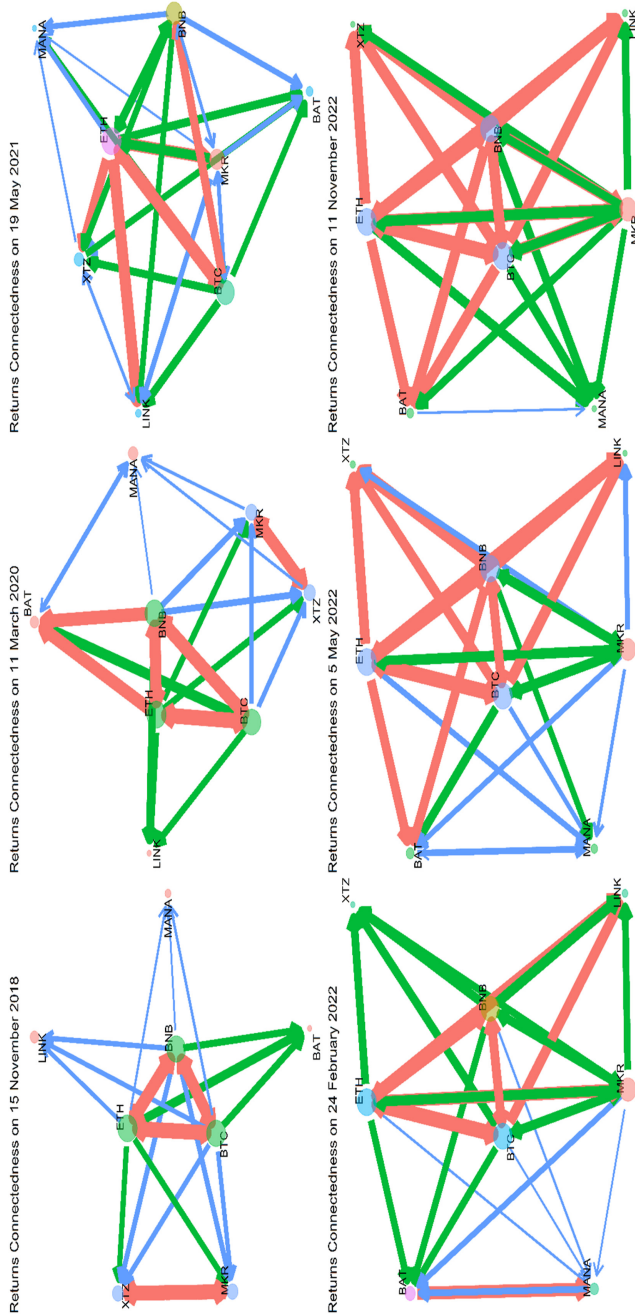


Figure 7.
Net directional
spillovers for the
volatilities

Note(s): Results are estimated based on the TVP-VAR (1) model with lag 2 (BIC) and a 10-step ahead FEVD

Source(s): Authors own creation



Note(s): In this figure, arrows show the direction of the connectedness, the size, and color (red, green, and blue, respectively) of the lines indicate the magnitude of the interlinkages, and the sizes of the vertices are denoted by total TO spillovers pertaining to that node

Source(s): Authors own work

Figure 8.
Connectedness
networks for the
returns

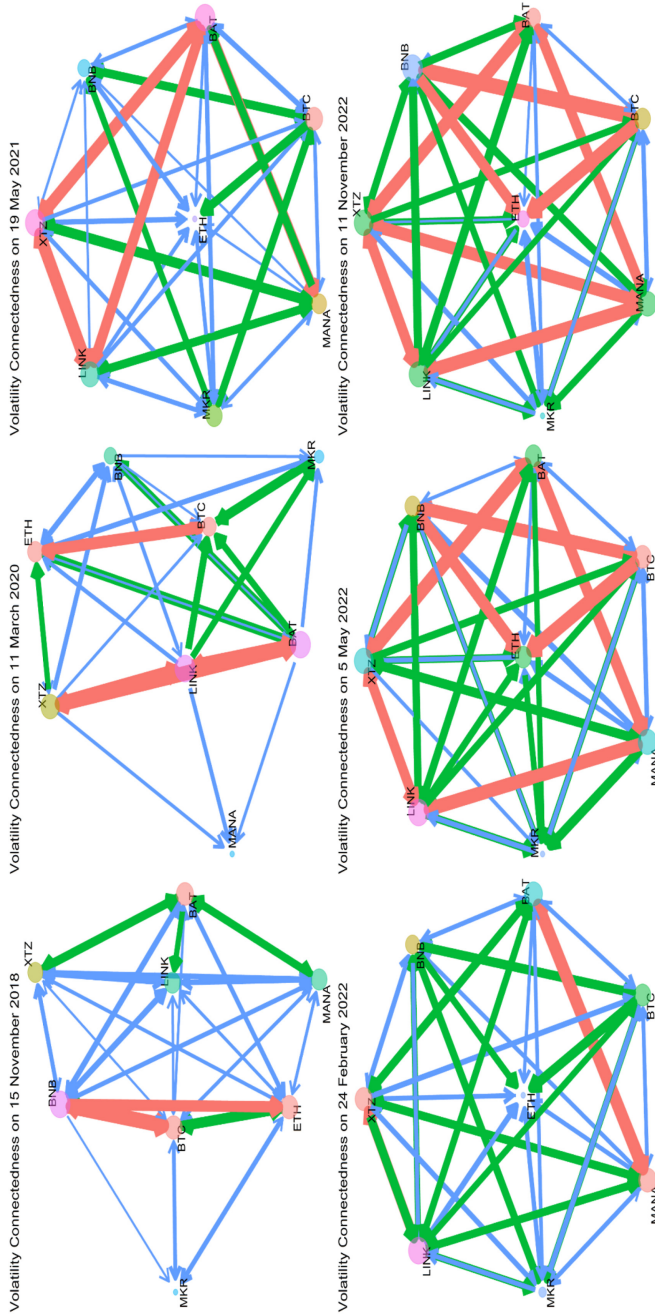
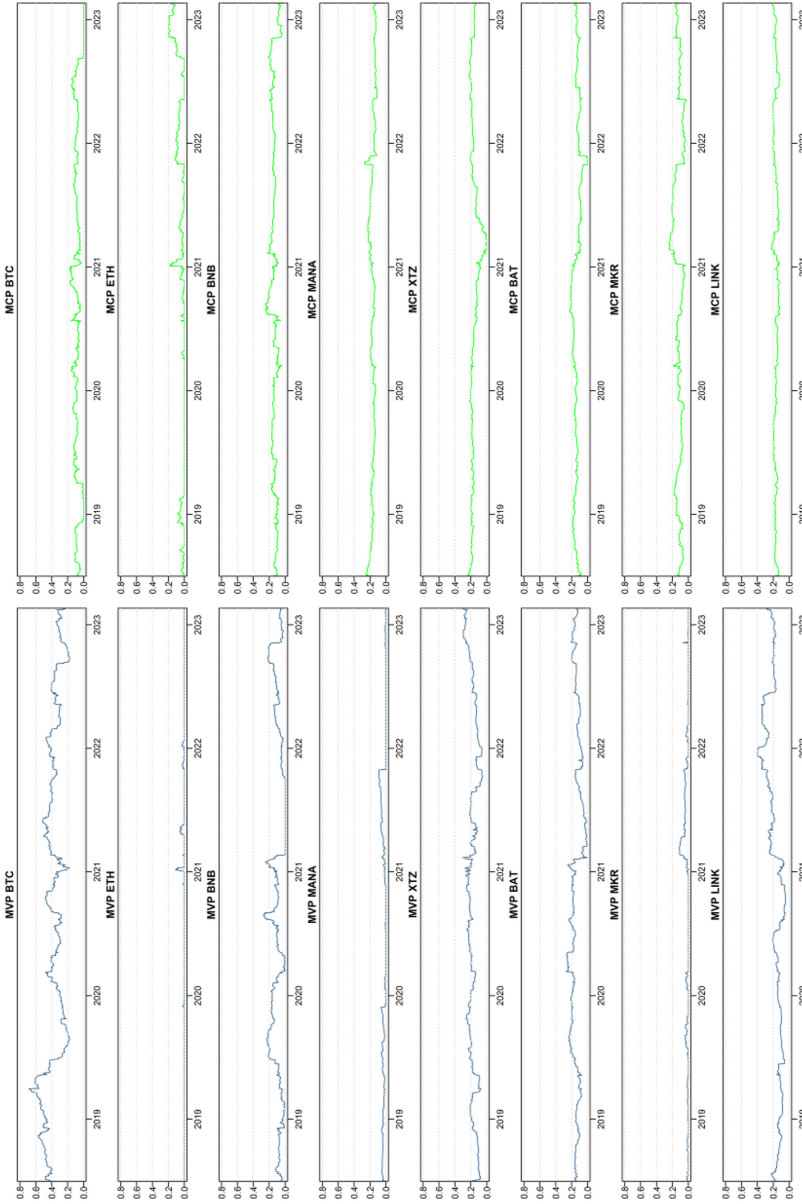


Figure 9.
Connectedness
networks for the
volatilities

Note(s): In this figure, arrows show the direction of the connectedness, the size, and color (red, green, and blue, respectively) of the lines indicate the magnitude of the interlinkages, and the sizes of the vertices are denoted by total TO spillovers pertaining to that node
Source(s): Authors own creation



Note(s): Results of MVP and MCP are based on Broadstock *et al.* (2020) and estimated based on the TVP-VAR (1) model with lag 2 (BIC) and a 20-step ahead FEVD. Vertical axis represent the weights of returns
Source(s): Authors own creation

Figure 10.
Dynamic portfolio
weights



Figure 11.
Optimal portfolio strategies

Source(s): Authors own creation

	Mean	Standard dev	5%	95%	Hedging effectiveness	<i>p</i> -value
<i>MVP</i>						
BTC	0.38	0.10	0.21	0.55	0.34	0.00
ETH	0.00	0.01	0.00	0.01	0.62	0.00
BNB	0.09	0.07	0.00	0.21	0.67	0.00
MANA	0.02	0.02	0.00	0.06	0.91	0.00
XTZ	0.18	0.05	0.09	0.27	0.76	0.00
BAT	0.14	0.06	0.04	0.23	0.77	0.00
MKR	0.01	0.02	0.00	0.05	0.79	0.00
LINK	0.17	0.08	0.06	0.34	0.78	0.00
<i>MCP</i>						
BTC	0.08	0.04	0.00	0.14	-0.03	0.59
ETH	0.03	0.05	0.00	0.15	0.42	0.00
BNB	0.14	0.04	0.08	0.20	0.50	0.00
MANA	0.17	0.03	0.13	0.22	0.86	0.00
XTZ	0.16	0.05	0.05	0.21	0.64	0.00
BAT	0.14	0.04	0.08	0.20	0.65	0.00
MKR	0.12	0.05	0.05	0.20	0.67	0.00
LINK	0.17	0.02	0.13	0.20	0.67	0.00

Table 6.
Dynamic portfolio allocations

Note(s): Results are based on the the TVP-VAR (0.99, 0.99) with 1 lag. The hedging effectiveness (HE) is computed in the spirit of Ederington (1979) by the following formula: $HE = 1 - \frac{Var(y_t)}{Var(y_{unhedged})}$

Source(s): Author's own creation

	MVP	MCP
Mean	0.18%	0.33%
Std. Dev	3.04%	3.78%
SR	0.060	0.087

Table 7.
Portfolio performances

Note(s): SR represents the Sharpe ratio

Source(s): Author's own creation

Based on our time-varying connectedness results, the TCIs notably capture well-known financial/geopolitical distress incidents and sharply escalate around them. Moreover, the TCI index estimated for the returns hits its apex on 5 May 2022, which coincides with the massive \$400 billion crypto crash. On the other hand, the TCI computed for the volatilities peaks on 16 March 2020, shortly after the declaration of the COVID-19 pandemic. Moreover, in line with previous studies (Ji *et al.*, 2019; Mensi *et al.*, 2021; Umar *et al.*, 2022a, b), we determined that major cryptocurrencies are the largest transmitters of the returns shocks, while LINK is found to be the largest transmitter of volatility shock. Moreover, these cryptocurrencies along with MKR were the persistent transmitters of return shock throughout the episode.

Delving deep into the connectedness networks of returns on prominent financial/geopolitical incidents provided important insights. First, predominantly, major cryptocurrencies have the strongest interdependencies in all return connectedness topologies. Second, cryptocurrencies, NFT tokens and DeFi assets structure connectedness cluster groups. Third, the connectedness networks estimated on 5 May 2022 and on 11 November 2022 is characterized by the strongest interlinkages among the returns.

In the final phase of the study, we carried out a portfolio backtesting exercise to determine the optimal allocations of returns under three different portfolio construction approaches. Our results indicate that optimal portfolio strategies estimated by three different approaches exhibit similar patterns and have sustained growth paths except for some short-lived dropbacks. However, average optimal portfolio weights computed by MVP and MCP display discrepancies, while all weights of the returns in portfolios are positive and with an exception for BTC in MCP, statistically significant. Furthermore, the MCP provides a higher portfolio performance than the MVP overall.

Our findings imply several policy suggestions for investors, stakeholders and policymakers. First, our time-based dynamic interlinkages can help the market participants in their optimal portfolio decisions. In particular, the persistent net receiving roles of the DeFi assets and the NFTs throughout the episode, especially around the financial/geopolitical turmoil, underpin their safe haven potentials (Umar *et al.*, 2022a, b). Finally, since the TCIs are prone to significantly increase around financial/geopolitical burst times, these tools can be valuable for policy makers to monitor risk.

Notes

1. <https://finance.yahoo.com/news/nft-sales-2022-nearly-matched-231149675.html#:~:text=The%20NFT%20market%20generated%20around,marketplaces%2C%20DappRadar%20shared%20with%20Decrypt.>
2. [https://coinmarketcap.com/view/defi/.](https://coinmarketcap.com/view/defi/)
3. <https://www.investing.com/crypto/charts.>
4. We collected the data of the work from <https://coinmarketcap.com> on 23 February 2023.
5. <https://www.cnbc.com/2018/11/14/bitcoin-plummets-under-6000-to-a-low-of-the-year-after-months-of-stability.html>.
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7. [https://www.reuters.com/business/ftx-start-us-bankruptcy-proceedings-ceo-exit-2022-11-11/.](https://www.reuters.com/business/ftx-start-us-bankruptcy-proceedings-ceo-exit-2022-11-11/)
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Further reading

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Appendix

Appendix A.1 TVP-VAR connectedness

Antonakakis *et al.* (2020) introduced a TVP-VAR connectedness methodology which is an extension of the Diebold and Yi Imaz (2014) approach. In this approach, the variance-covariance matrix varies via a Kalman filter estimation with forgetting factors in the sense of Koop and Korobilis (2013).

TVP – VAR(*q*) model is defined as follows:

$$x_t = B_t y_{t-1} + \varepsilon_t \mid \Omega_{t-1} \sim N(0, \Sigma_t) \tag{A.1}$$

$$vec(B_t) = vec(B_{(t-1)}) + \mathbf{q}_t \mid \Omega_{t-1} \sim N(0, \Xi_t) \tag{A.2}$$

with

$$y_{t-1} = \begin{pmatrix} x_{t-1} \\ x_{t-2} \\ \vdots \\ x_{t-q} \end{pmatrix} B'_t = \begin{pmatrix} B_{1t} \\ B_{2t} \\ \vdots \\ B_{qt} \end{pmatrix} \tag{A.3}$$

wherein Ω_{t-1} denotes all information available until $t - 1$; x_t and y_{t-1} denote $n \times 1$ and $nq \times 1$ vectors, respectively. B_t and B_{it} are $n \times nq$ and $n \times n$ dimensional matrices, respectively. ε_t and \mathbf{q}_t are $n \times 1$ and $n^2q \times 1$ dimensional vectors, respectively. Σ_t and Ξ_t are $n \times n$ and $n^2q \times n^2q$ dimensional matrices, respectively. $vec(B_t)$ is the vectorization of B_t and is an $n^2q \times 1$ dimensional vector.

We transform the TVP-VAR to its vector moving average (VMA) form based on the Wold representation theorem, and thus the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) are computed. Consequently, the VMA representation of x_t can be defined as $\sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j}$, where A_{jt} is the $n \times n$ dimensional matrix.

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

$$GIRF_t(H, \rho_{j,t}, \Omega_{t-1}) = E(x_t + H \mid e_j = \rho_{j,t}, \Omega_{t-1}) - E(y_{t+H} \mid \Omega_{t-1}) \tag{A.4}$$

$$\Psi_{j,t}(H) = \frac{A_{H,t} \Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\rho_{j,t}}{\sqrt{\Sigma_{jj,t}}} \rho_{j,t} = \sqrt{\Sigma_{jj,t}} \quad (A.5)$$

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

where e_j is an $m \times 1$ selection vector which takes 1 with the selection of the j th element and 0 o.w. Therefore, the $GFEVD(\tilde{\Phi}_{ij,t}(H))$ is estimated based on $\tilde{\Phi}_{ij,t}(H)$ as follows:

$$\tilde{\Phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^n \sum_{t=1}^{H-1} \Psi_{ij,t}^2} \quad (A.7)$$

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

The TCI:

$$C_t(H) = \frac{\sum_{i,j=1,i \neq j}^n \tilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^n \tilde{\Phi}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1,i \neq j}^n \tilde{\Phi}_{ij,t}(H)}{n} * 100 \quad (A.8)$$

Total directional connectedness to others, i.e. how i transmits its shock to all other variables j :

$$C_{i \rightarrow j,t}(H) = \frac{\sum_{j=1,i \neq j}^n \tilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^n \tilde{\Phi}_{ji,t}(H)} * 100 \quad (A.9)$$

Total directional connectedness from others, i.e. how i retrieves shock from all other variables j :

$$C_{i \leftarrow j,t}(H) = \frac{\sum_{j=1,i \neq j}^n \tilde{\Phi}_{ij,t}(H)}{\sum_{j=1}^n \tilde{\Phi}_{ij,t}(H)} * 100 \quad (A.10)$$

Net total directional connectedness:

$$C_{i,t}(H) = C_{i \rightarrow j,t}(H) - C_{i \leftarrow j,t}(H) \quad (A.11)$$

Appendix A.2. Multivariate portfolio construction

A.2.1. Minimum variance portfolio (MVP)

The MVP is based on maximizing the expected portfolio return while minimizing the portfolio risk. The MVP proposes an optimal trade-off between risk and return (Markowitz, 1952). The portfolio allocations of assets are calculated as

$$w_t = \frac{\sum I}{I \Sigma_t^{-1} I} \quad (A.12)$$

wherein, w_t is $n \times 1$ dimensional portfolio weight vector, I is an n -dimensional unit vector, and Σ_t is an $n \times n$ dimensional conditional variance-covariance matrix.

A.2.2. Minimum correlation portfolio (MCP)

The correlation matrix is defined as follows:

$$R_t = \text{diag}\left(\sum_t\right)^{-0.5} H_t \text{diag}\left(\sum_t\right)^{-0.5} \quad (\text{A.13})$$

R_t is an $n \times n$ dimensional matrix. The portfolio weights are computed as

$$w_{Rt} = \frac{R_t^{-1} \mathbf{1}}{\mathbf{1} R_t^{-1} \mathbf{1}} \quad (\text{A.14})$$

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