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Analysis of dynamic connectedness relationships between cryptocurrency, NFT and DeFi assets: TVP-VAR approach

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ABSTRACT
The aim of this study is to analyse the dynamic connectedness relationship (DCR) between cryptocurrency, NFT, and DeFi assets. In the study, two cryptocurrencies consisting of Bitcoin and Ethereum, two NFTs consisting of Tezos and The Sandbox, and two DeFi assets consisting of Chainlink and Uniswap were analysed. The results showed that Ethereum cryptocurrency and Chainlink DeFi assets spilled volatility to other crypto assets. The other variables were assets that received volatility, and the volatility spillover relationship between NFT assets is less than other crypto assets.

KEYWORDS
DeFi; Cryptocurrency; Crypto asset; NFT; TVP-VAR approach

JEL CLASSIFICATION
G00; G11

I. Introduction

The cryptocurrency market has grown significantly over the past few years. In terms of market capitalization, the relevant market increased from USD 300 billion on 30 June 2019, to USD 1.955 billion on 15 August 2021. Besides conventional cryptocurrencies, the inclusion of NFT and DeFi has played a crucial role in the growth of the cryptocurrency market (Yousaf and Yarovaya 2022). Moreover, the high volatility of blockchain markets has led investors and market participants to concentrate on means to diversify NFT, DeFi, and cryptocurrencies (Karim et al. 2022).

The aim of this study is to analyse the DCRs among cryptocurrency, NFT, and DeFi assets. In this context, two cryptocurrencies, two NFTs, and two DeFi assets are analysed. The analysis period partly covers the period when the effects of COVID-19 continued. In this respect, the behaviour of crypto assets can be observed in times of crisis. The recently developed TVP-VAR approach is used in the analysis. Finally, NFT assets, which are relatively less discussed in the literature, are examined in the study.

There are various studies in the literature on cryptocurrencies, especially Bitcoin and Ethereum, but the number of studies on other blockchain-based crypto assets is quite limited. Alawadhi and Alshamali (2022), Karim et al. (2022), Yousaf and Yarovaya (2022), and Qiao et al. (2023) investigated the DCRs among NFT, DeFi, and cryptocurrencies. Dowling (2022a) investigated the Decentraland metaverse, whereas Dowling (2022b) investigated the relationships between NFT and cryptocurrencies.

II. Methodology

In this study, dynamic relationships between crypto assets are investigated with the recently developed TVP-VAR model. Antonakakis and Gabauer (2017) propose dynamic connectedness measures based on the TVP-VAR approach with time-varying covariance structure. The TVP-VAR model helps to make the results more concrete and understandable by showing the volatilities received and transmitted numerically. The TVP-VAR model is shown as follows (Antonakakis and Gabauer 2017):

$$Y_t = \beta_t Y_{t-1} + \epsilon_t \quad \epsilon_t|F_{t-1} \sim N(0, S_t) \tag{1}$$

$$\beta_t = \beta_{t-1} + v_t \quad v_t|F_{t-1} \sim N(0, R_t) \tag{2}$$

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In the above equations, Y_t denotes $N \times 1$ conditional volatility vector; Y_{t-1} denotes $Np \times 1$ lagged conditional vector; β_t respresents a time-varying coefficient matrix of N×Np dimension; ϵ_t stands for an $N \times 1$ dimensional error disturbance vector with an N×N S_t, a time-varying variance-covariance matrix.

$$C_t^g(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij,t}^g(J)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij,t}^g(J)} * 100 \quad (3)$$

$$= \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij,t}^g(J)}{N} * 100 \quad (4)$$

Firstly, the so-called 'total directional connectedness (TDC) to others' situation, in which variable i transmits its shock to all other variables j, is described as follows:

$$C_{i\rightarrow j,t}^g(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\phi}_{ji,t}^g(J)}{\sum_{j=1}^{N} \tilde{\phi}_{ji,t}^g(J)} * 100 \quad (5)$$

Secondly, the so-called 'TDC from others' situation, in which variable i receives from other variables j, is defined as follows:

$$C_{i\leftarrow j,t}^g(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\phi}_{ij,t}^g(J)}{\sum_{i=1}^{N} \tilde{\phi}_{ij,t}^g(J)} * 100 \quad (6)$$

Lastly, the 'net-TDC', which can be interpreted as the 'power' of the variable i or its impact on the network of all variables, is obtained by subtracting the TDC from the others from the TDC to the others as follows:

$$C_{i,t}^g = C_{i\rightarrow j,t}^g(J) - C_{i\leftarrow j,t}^g(J) \quad (7)$$

If the net TDC of the variable i is positive, it means that the variable i affects the network more than it is affected, while if the net TDC is negative, the variable i is 'network driven'.

III. Datasets and descriptive statistics

The daily frequency closing datasets, which are used in the study and obtained from the internet address 'finance.yahoo.com', cover the periods 09.-18.2020–11.17.2022 for all variables. Among the variables used in this study, Bitcoin and Ethereum are the two largest cryptocurrencies by market capitalization, representing more than 65% of the market. At the same time, Ethereum is a next-generation smart contract and decentralized application platform, unlike Bitcoin, which is just money. DeFi products mostly use the Ethereum blockchain as infrastructure. Chainlink is both the first and largest service provider (oracle), while Uniswap is the oldest decentralized cryptocurrency exchange in the related ecosystem. The Sandbox and Tezos are among the best NFTs in terms of market capitalization.

As can be seen from Table 1, the daily data are used in accordance with the literature. The datasets of the variables are converted into return series with the formula $\ln(P_t/P_{t-1})*100$, and then volatility series are obtained by taking the squares of the return series.

Upon examining the price series graphs of the variables in Figure 1, a great deal of price volatility is observed. In general, price increases occurred in

Table 1. Descriptive statistics of volatility series of variables.

	Cryptocurrencies		NFTs		DeFis	
	BTC	ETH	XTZ	SAND	LINK	UNI
Mean	14.49142	25.86069	41.76609	75.65566	41.80201	49.61049
Median	3.382428	7.578077	11.04382	14.93660	13.05061	15.35815
Maximum	302.9429	1007.802	2135.977	4917.309	2170.002	1627.911
Minimum	3.74E−06	1.55E−06	6.95E−05	0.000000	0.000145	0.000184
Std. Dev.	30.78221	61.66789	110.0208	251.9246	103.8660	121.2735
Skewness	4.703455	7.947867	10.60930	11.47773	12.25832	7.712243
Kurtosis	32.72610	99.19026	176.7447	189.0089	230.0324	83.23477
Jarque-Bera	31999.32 (0.000000)	312880.80 (0.000000)	1008482.20 (0.000000)	1156239.46 (0.000000)	1716432.23 (0.000000)	219736.30 (0.000000)
Observations	790	790	790	790	790	790
ADF	−26.32323*** (0.0000)	−8.946320*** (0.0000)	−15.99923*** (0.0000)	−13.01334*** (0.0000)	−6.803095*** (0.0000)	−8.795344*** (0.0000)
PP	−26.63874*** (0.0000)	−27.06380*** (0.0000)	−26.27925*** (0.0000)	−25.88441*** (0.0000)	−27.27456*** (0.0000)	−28.10569*** (0.0000)

Note: *** indicates a 1% significance level. Values in parentheses are probability values. In the ADF unit root test, the lag length is determined by the SIC.

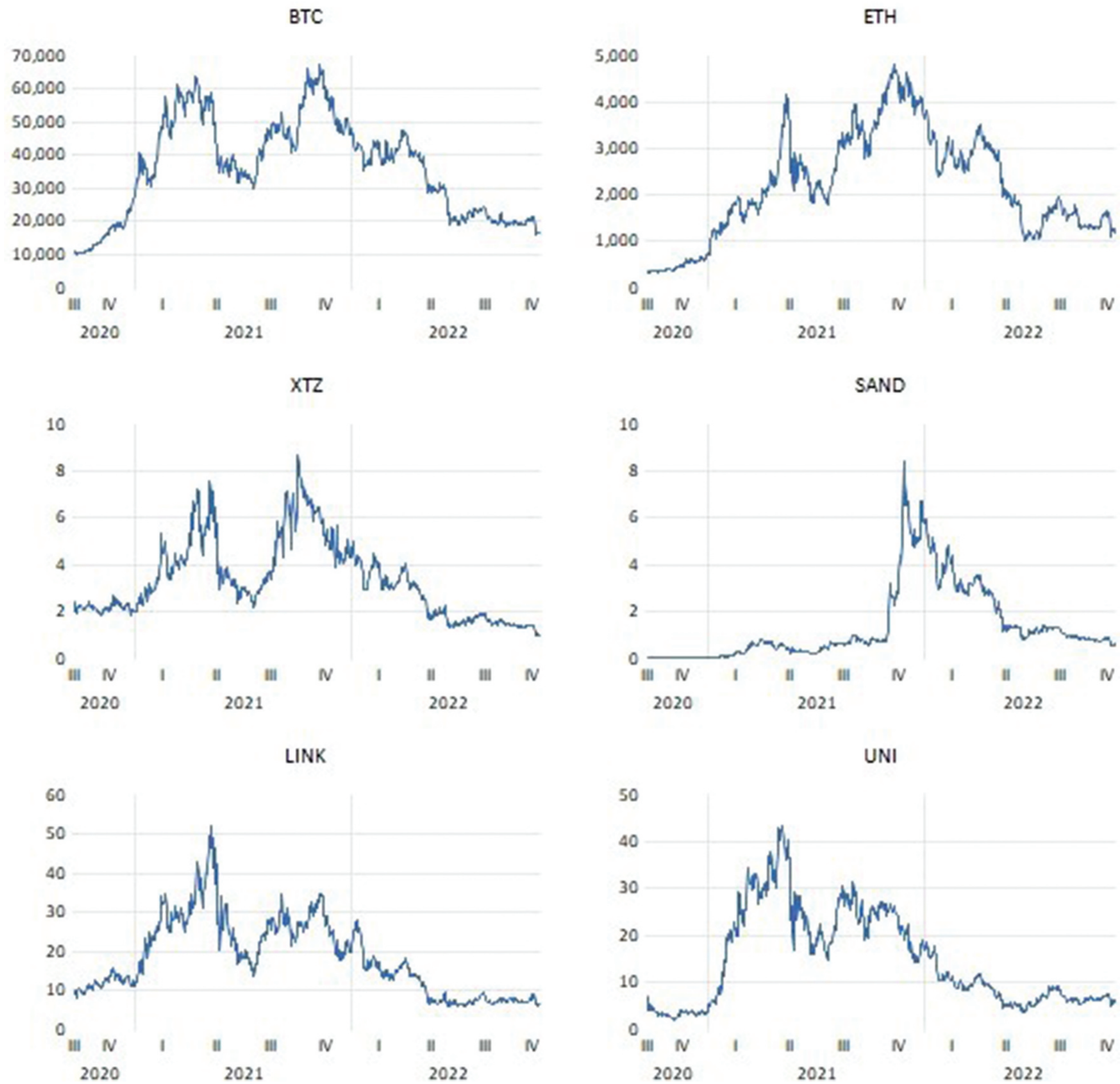

Figure 1. Price series charts of the variables used in the study.

cryptocurrencies until May 2021, but significant price decreases were observed over the period May 2021 - July 2021.

Upon examining Figure 2, it can be seen that the volatilities of cryptocurrencies are quite different from of other crypto assets. On the other hand, in the second quarter of 2021, extreme increases in the volatility of all crypto assets drew attention.

IV. Empirical findings

As a result of the TVP-VAR analysis obtained, the results of the total DCR, net TDC, average dynamic connectedness table and network plot between the related variables are presented below. Figure 3, firstly, illustrates the results of total DCR.

According to Figure 3, it can be seen that there has been a great deal of volatility spillover regarding crypto assets during the relevant period. Although the spillover increased in the second half of 2021, there was a relative decline at the beginning of 2022, but then it began to rise again. Figure 4 illustrates the net TDC results.

According to the net DCR graph, the coloured areas below zero indicate the volatility received in the corresponding date or period, and the coloured areas above the zero point indicate the volatility spillover in the corresponding date or period. In Figure 4, BTC, SAND, and UNI are, in general, seen as volatility receiver variables, whereas ETH and LINK are seen as volatility transmitter variables in the entire sample period.

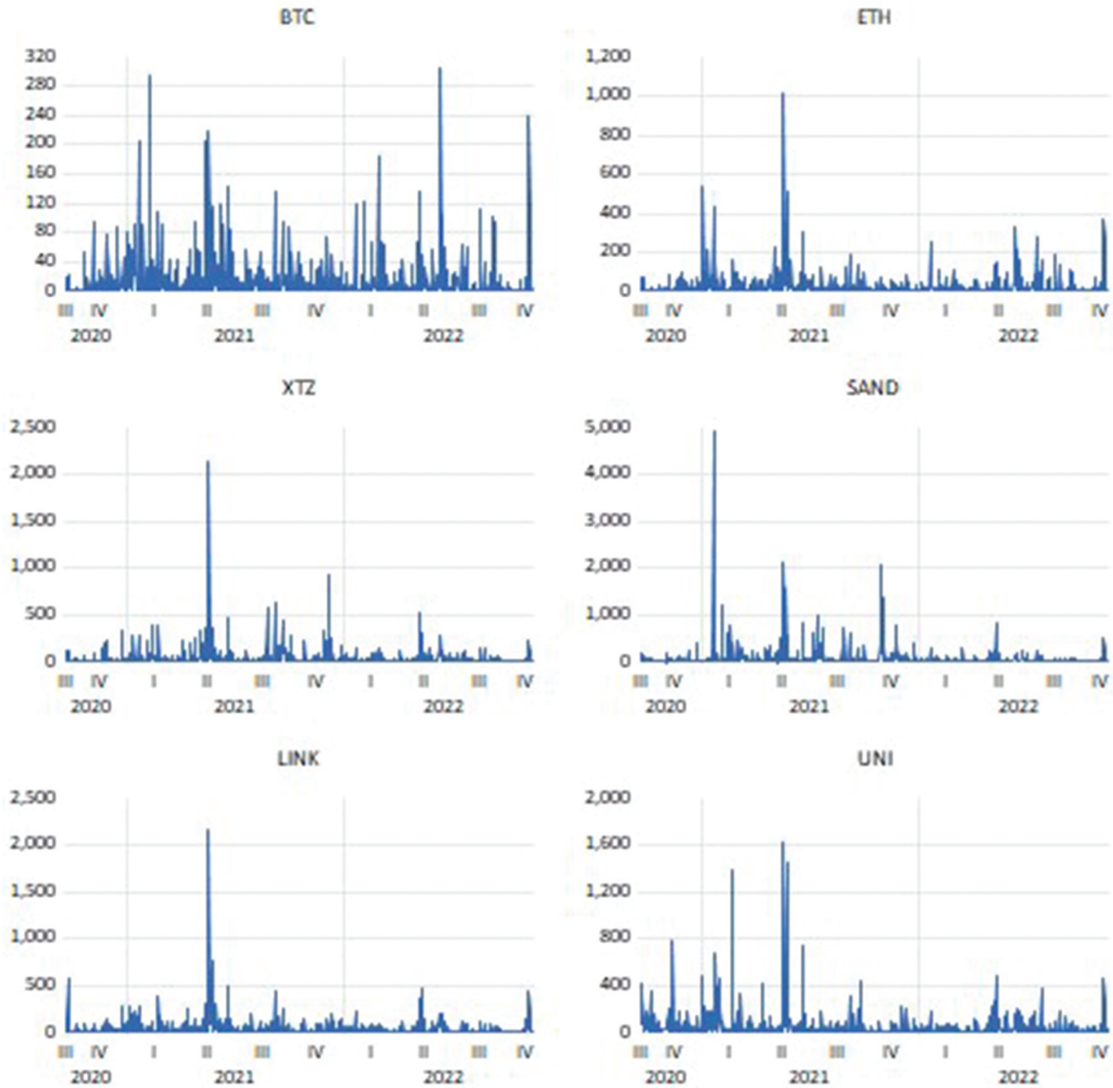

Figure 2. VolaTility series graphs of the variables used in the study.

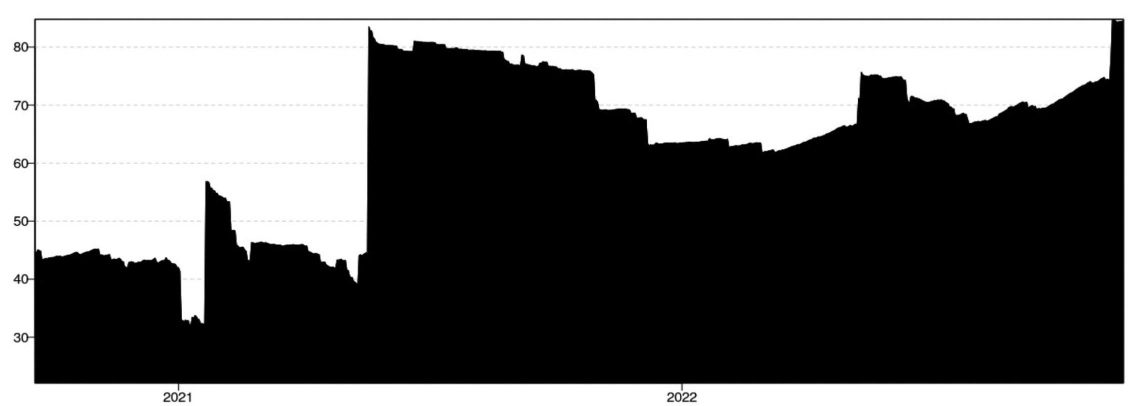

Figure 3. ToTal dynamic connectedness graph of variables.

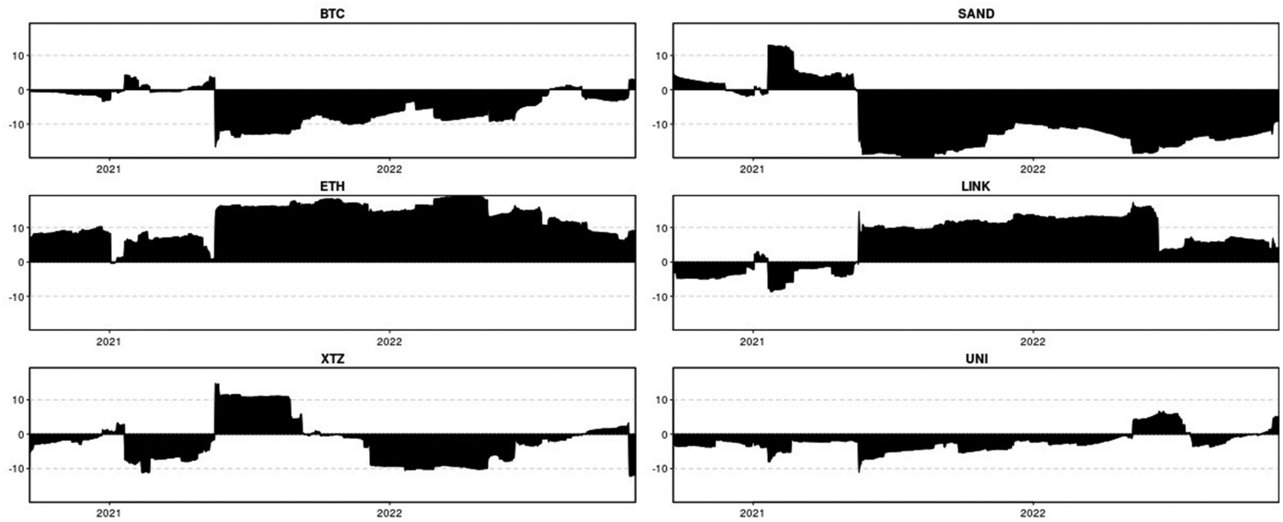

Figure 4. Net TDC graph of the variables.

Table 2. Table of average dynamic connectedness for the variables.

	Cryptocurrencies		NFTs		DeFis		
	BTC	ETH	XTZ	SAND	LINK	UNI	Volatility Received
BTC	48.83	17.96	9.05	6.27	10.78	7.11	51.17
ETH	14.42	38.51	12.00	7.79	15.70	11.57	61.49
XTZ	8.82	13.92	43.57	7.02	18.76	7.91	56.43
SAND	7.19	11.39	7.55	59.92	8.45	5.50	40.08
LINK	9.41	16.57	17.03	6.19	39.57	11.24	60.43
UNI	6.40	14.14	8.54	3.75	12.76	54.41	45.59
Volatility Spilled Over	46.25	73.99	54.16	31.01	66.45	43.33	315.20
NET	−4.92	12.50	−2.27	−9.07	6.02	−2.26	52.53

According to Table 2, although BTC explains 48.83% of the volatility change within itself, other variables explain the remaining 51.17%. The volatility of 17.96%, 9.05%, 6.27%, 10.78%, and 7.11% from ETH, XTZ, SAND, LINK, and UNI, respectively, spreads to BTC. On the other hand, a 46.25% volatility from BTC spreads to other crypto asset variants. Accordingly, BTC receives a net volatility spread of 4.92%. Other variables in Table 2 are interpreted in this way in detail. Interestingly, Bitcoin is in the position of a net volatility receiver. While many studies have generally determined that Bitcoin is a net volatility transmitter, Naeem et al. (2022) states that during the post-Covid-19 panic period, Bitcoin's role has turned into a net receiver, while Ethereum has become a net transmitter.

SAND stands out as the variable that transmits and receives the least volatility among all variables. However, the volatility spillover relationship between NFT assets is less than other crypto assets. Here, it can be stated that NFTs can provide potential benefits in terms of diversification in a portfolio of cryptocurrencies and DeFis. Results similar to those of this study on NFT are also seen in the studies of Dowling (2022b), Alawadhi and Alshamali (2022), Karim et al. (2022).

There is a volatility spillover relationship among all crypto assets. However, it may be more explanatory to focus on the net results in the bottom line of Table 2 without going into more details here. ETH and LINK are net volatility transmitters, other variables are net volatility receivers according to Table 2.

In Figure 5, the volatility spillovers among the volatility series of the relevant crypto assets are illustrated in the form of network graphs. The blue dots on the graph indicate the volatility transmitter variables, whereas the yellow dots show the volatility spillover-receiving variables. Moreover, the sizes of the dots indicate the sizes of the spillover effects. Apart from the dots in the chart, the arrows indicate the direction of

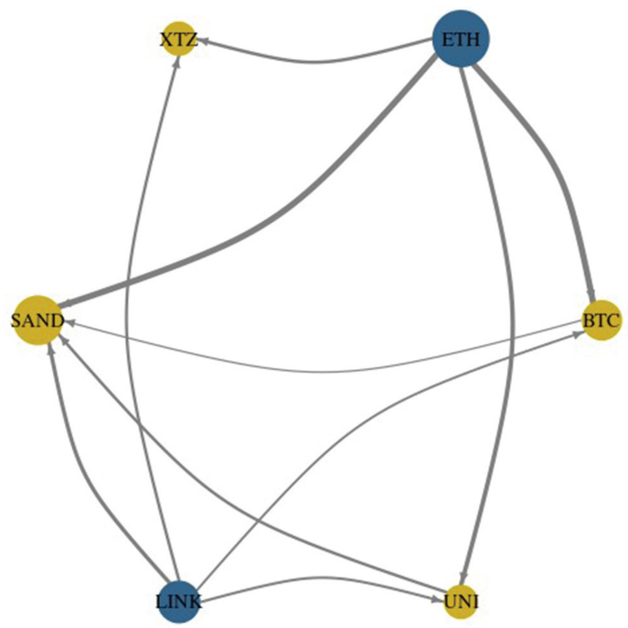

Figure 5. NetWork graph representation of volatility spillover to the variables.

the volatility spillover and the thickness of the lines with the arrows indicate the magnitude of the volatility spillovers.

V. Conclusion and evaluation

The findings in the study assume an essential role in supporting the modern portfolio theory, confirming the importance of studying the co-movement of NFT, DeFi, and cryptocurrencies, which are relatively new assets that can exhibit varying behaviours. By diversifying cryptocurrencies and DeFis with NFTs, investors can reduce portfolio risk. In other words, by investing in NFTs, risk-averse investors, institutional investors, and portfolio managers may reduce the risk of cryptocurrencies and DeFis. In addition, it is important to consider the volatility spillover behaviour of crypto assets and the changes in volatility spillover behaviour in different market conditions. NFT assets can provide potential portfolio diversification among other crypto assets.

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