Financial Innovation

RESEARCH

Open Access

Extreme connectedness between cryptocurrencies and non-fungible tokens: portfolio implications

Waild Mensi[1,2], Mariya Gubareva[3], Khamis Hamed Al-Yahyaee[4], Tamara Teplova[5] and Sang Hoon Kang[6,7*]

*Correspondence: sanghoonkang@pusan.ac.kr

[1] Department of Economics and Finance, College of Economics and Political Science, Sultan Qaboos University, Muscat, Oman
[2] Department of Finance and Accounting, University of Tunis El Manar and IFGT, Tunis, Tunisia
[3] Lisbon School of Economics and Management (ISEG), Research Centre in Economic and Organisational Sociology (SOCIUS)/Research in Social Sciences and Management (CSG), Universidade de Lisboa, Rua Miguel Lupi, 20, Lisbon, Portugal
[4] Muscat University, Al Ghubrah North, Muscat, Oman
[5] National Research University Higher School of Economics/HSE University, Pokrovsky Blv. 11, Moscow, Russian Federation 109028
[6] School of Business, Pusan National University, Jangjeon2-Dong, Geumjeong-Gu, Busan 46241, Republic of Korea
[7] UniSA Business School, University of South Australia, Adelaide, Australia

Abstract

We analyze the connectedness between major cryptocurrencies and nonfungible tokens (NFTs) for different quantiles employing a time-varying parameter vector autoregression approach. We find that lower and upper quantile spillovers are higher than those at the median, meaning that connectedness augments at extremes. For normal, bearish, and bullish markets, Bitcoin Cash, Bitcoin, Ethereum, and Litecoin consistently remain net transmitters, while NFTs receive innovations. However, spillover topology at both extremes becomes simpler—from cryptocurrencies to NFTs. We find no markets useful for mitigating BTC risks, whereas BTC is capable of reducing the risk of other digital assets, which is a valuable insight for market players and investors.

Keywords: Cryptocurrencies, Nonfungible tokens, Extreme quantile connectedness, Time-varying parameter vector autoregression, TVP-VAR approach

Introduction

Diversified asset allocation represents a never-ending challenge for investors and portfolio managers. To achieve this goal, knowledge about spillovers and connectedness among different markets is highly desirable (Antonakakis et al. 2020b; Choi et al. 2021; Lim and Won 2020; Umar and Gubareva 2020; Al-Yahyaee et al. 2021; Mensi et al. 2021a, b, c; Elsayed et al. 2022; Tiwari et al. 2022; Umar et al. 2022a, c). Recently, several digital assets have been widely studied by scholars and market players (Mensi et al. 2021d; Ante 2022; Dowling 2022a, b; Umar et al. 2022a, b, c; Wang 2022; Yousaf and Yarovaya 2022; Gubareva et al. 2023a; Hanif et al. 2023; Ko and Lee 2023; Kumar et al. 2023; Mensi et al. 2021f, 2023a, b; Ugolini et al. 2023; Yousaf et al. 2023a). An important strand in this research domain comprises works focused on return and volatility spillovers between cryptocurrencies and nonfungible tokens (NFTs) and decentralized finance (DeFi) instruments, emphasizing novel approaches to hedging and diversification strategies in both directions (Dowling 2022a, b; Elsayed et al. 2022; Tiwari et al. 2022; Umar et al. 2022a; Yousaf et al. 2022, 2023a).

However, the above NFT studies do not have a principal goal of investigating cryptocurrency–NFT interactions. Hence, they are limited to just one or two major cryptocurrencies and lack portfolio insights. Our motivation is to fill this gap by studying extreme return spillovers and connectedness between cryptocurrencies and NFTs and providing insights for portfolio managers. We analyze five major cryptocurrencies, namely, Bitcoin (BTC), Bitcoin Cash (BCH), Ethereum (ETH), Litecoin (LTC), and Ripple token (XRP), and three major NFT environments, namely, the Theta Network (THETA), the Tezos Platform (TEZOS), and the Enjin Ecosystem (ENJIN).

At this point, it is worth differentiating between NFTs and cryptocurrencies. In studying NFT environments, we are in fact investigating the cryptocurrencies that back the respective NFT environments but not NFTs directly. For instance, according to the Enjin website (www.enjin.com), Enjin Coin is an Ethereum-based cryptocurrency used to back the value of next-gen fungibles and NFTs. Similarly, in the case of Theta, the token is the governance token of the blockchain but not an NFT. In its turn, Tezos (www.tezos.com), is a native token of the proof-of-stake blockchain that hosts many popular NFT marketplaces. Therefore, by tracking the dynamics of the three NFT market proxies above, we can gauge the performance of NFTs and assess their hedging properties.

We are motivated to answer the question of whether NFTs could hedge cryptocurrencies and vice versa. This is especially the case with the increasing employment of digital assets as alternative instruments for portfolio management—we see an urgent necessity to assess the hedging effects of NFTs for cryptocurrencies. It is worth noting that our sample period spans major contemporaneous events transversal to financial markets, such as the COVID-19 pandemic, Russia–Ukraine conflict, and an increasing interest rate environment (Mensi et al. 2021g, 2022a; Naeem et al. 2023). These stresses have substantially affected investors´ risk appetite and, hence, altered the risk–return profiles of diverse financial instruments, including cryptocurrencies and NFTs. Thus, incorporating such events into hedging strategy studies is critically important, as hedging strategies workable under normal conditions might become infeasible during periods of economic crises and financial turmoil (Mensi et al. 2022b).

In determining spillovers and connectedness between cryptocurrency and NFT markets, it is important to highlight that NFT quotations are usually denominated in USD. In fact, NFTs can be exchanged and traded for cryptocurrencies, money, or other NFT instruments. We recognize that some NFT trading is executed by conveyance of cryptocurrencies in exchange for NFTs. However, for the meter of convenience, even in this case, NFT prices are frequently quoted in USD. Nonetheless, as most trades are enabled through conventional cryptocurrencies, it is expectable to observe the respective spillovers and alteration of connectedness, see, e.g., Aharon and Demir (2022) and Dowling (2022a, b). As our paper addresses connectedness between cryptocurrencies and NFTs, we contribute to the above-identified strand of the literature, providing new empirical evidence and insights for portfolio management.

Our main contributions to the literature are twofold. First, our paper is one of the first to scrutinize return spillovers between NFTs and cryptocurrencies and analyze the optimal hedge ratio strategy and portfolio weights for these digital assets. This subject is important for investors who continuously aim to reconfigure their digital portfolios or invest in these assets in the search for a hedge. Second, instead of examining mean-based connectedness, we employ the new quantile-based methodology of Ando et al. (2022) at the median, extreme lower, and extreme upper quantiles to investigate return spillovers corresponding to normal, bear, and bull market conditions. Researching tail effects at extreme quantiles is important for portfolio strategy and financial risk management, as it allows accounting for exceptional shocks during extraordinary market moves such as financial crises and exuberant market rallies, as seen in the crypto markets during 2021. We note that risk appetite and investors' expectations are sensitive to market price movement or market scenarios. Therefore, it is important to consider asymmetry as an important stylized fact. Our method relies on different market trends and accounts for asymmetric spillovers. Specifically, it helps market actors understand risk transfer and connectedness size and direction under various market states. Our model contains useful information that helps investors design trading strategies.

The obtained results are aligned along three strands. First, our results provide evidence of increased spillovers in the left and right tails of return distributions corresponding to bear and bull markets, respectively. Second, we report that cryptocurrencies, except XRP, are net transmitters, while NFTs are net receivers, for all quantiles and the whole sample. Third, we find that no markets can usefully mitigate BTC risks, whereas BTC can reduce the risk of other digital assets, providing valuable insights for market players and investors. The practical implications of our findings from the extreme connectedness analysis reside in showing the potential benefits of investing in digital assets and indicating how to remove the risks of such investments. Consistently acting as net recipients of spillovers, NFT markets can potentially absorb these risks. Hence, incorporating NFTs into cryptocurrency portfolios might help reduce portfolio variance and ensure the maintenance of expected portfolio returns. We provide optimal hedge ratios and portfolio weights, representing practical guidance for investors and portfolio managers.

This paper is structured as follows. "Literature review" section reviews the literature. "Methodology" section discusses the methodology. "Data" section presents the data and descriptive statistics. "Empirical results" section discusses the results and findings. "Conclusions" section concludes the paper.

Literature review

This section provides a comprehensive literature overview that embeds our research within the contemporaneous state of the art in the related research domains. Our paper is mostly related to three streams of literature: (1) general pricing dynamics in NFT and DeFi markets, (2) bubble behavior in the NFT, crypto, and DeFi markets, and (3) portfolio implications. In this context, our literature review section sheds more light on extreme connectedness and spillovers among cryptocurrencies and NFTs. We present the most recent and relevant studies that have been conducted along the three bibliographic strands identified above. Our focus is on the literature providing deeper insights into the network transmissions of the different crypto tokens and discussing their implications for crypto-NFT investment portfolios and respective hedging strategies.

General pricing dynamics in nonfungible token and decentralized finance markets

We start our excursion into the price behavior of NFT and DeFi markets with one of the pioneering studies by Dowling (2022a), which responds to the question of whether NFT pricing is driven by cryptocurrencies. Given that the NFT market emerged from cryptocurrencies, the author explores whether NFT pricing is related to cryptocurrency pricing. Dowling (2022a) documents that the crypto-NFT spillover index reveals only limited volatility transmission effects between cryptocurrencies and NFTs. However, the wavelet coherence analysis indicates co-movement between the two sets of markets. Therefore, the author argues that cryptocurrency pricing behaviors might benefit participants in understanding NFT pricing patterns. Nonetheless, low-volatility transmissions also indicate that NFTs can potentially be considered a low-correlation asset class distinct from cryptocurrencies.

In parallel, Dowling (2022b), another milestone study in NFT pricing, investigates the pricing of parcels of virtual real estate in the largest blockchain virtual world, Decentraland. The author shows that the respective NFT, termed LAND, exhibits price series characterized by both inefficiency and a steady rise in value and thus concludes that LAND pricing does not yet appear to be efficient.

Concerning digital art NFTs, NFT price determinants in the digital art market are studied by Horky et al. (2022). Using unique individual data from the online art NFT marketplace SuperRare, the authors combine econometric tools with recent machine learning approaches. This approach allows them to define explanatory variables from NFT descriptions in their hedonic pricing approach. Using these variables, they show that their hedonic pricing models exhibit relevant informational value for NFT prices. Moreover, the authors show that NFTs in the digital art market cannot be viewed as simple derivatives of cryptocurrencies.

Concerning DeFi pricing dynamics, Mohan (2022) investigates automated market makers (MMs) and decentralized exchanges. In this paper, automated MMs are treated as a neoclassical black box characterized by the conversion of inputs (tokens) to outputs (prices). Conversion is governed by the technology of automated MMs summarized by an “exchange function.” The author studies diverse automated MMs, such as constant product, constant mean, constant sum, hybrid function, and dynamic automated MMs. Mohan (2022) also investigates the impact of introducing concentrated liquidity into an automated MM. Overall, the presented framework provides an intuitive geometric representation of how an automated MM operates. This paper provides a clear delineation of the similarities and differences across various automated MMs.

In this strand of research, Corbet et al. (2023) answer the question of whether DeFi tokens are a separate asset class from conventional cryptocurrencies. The authors test for the existence of bubbles in conventional and DeFi-focused cryptocurrencies, searching to identify the key driving forces that separate DeFi tokens from conventional cryptocurrencies. Utilizing generalized supremum augmented Dickey–Fuller tests, they identify the presence of significant bubbles across multiple markets, with relatively more stable price developments in DeFi-focused cryptocurrencies. Finally, DCC-GARCH and Diebold–Yilmaz spillover analyses of returns and volatilities indicate that DeFi-focused cryptocurrencies possess stronger and more stable correlations with Ethereum than Bitcoin and that neither cryptocurrency influenced the significant DeFi bubble formation that occurred during 2020. Their results indicate that the DeFi market should be viewed as an asset class separate from conventional cryptocurrencies, thus providing important insights for investors seeking additional diversification opportunities.

The common conclusion of the above-reviewed papers is that NFTs and DeFi instruments represent asset classes distinct from conventional cryptocurrencies, therefore justifying further research into the interrelatedness of the former and the latter. All these researchers have attempted to describe the general pricing dynamics of these two relatively new digital asset classes. Our research represents a further step along this road, providing insights into how NTFs might be used to design cryptocurrency-based portfolios and efficient hedging strategies to avoid the negative effects of bubble formation and especially bubble busting. The second strand of our literature review addresses bubble behavior in the NFT, crypto, and DeFi markets.

Bubble behavior in the nonfungible token, cryptocurrency, and DeFi markets

A pioneering study of bubbles in cryptocurrency markets is Corbet et al. (2018), which performs date-stamping of the Bitcoin and Ethereum bubbles. The authors examine the existence and dates of pricing bubbles in the two prominent cryptocurrencies, namely Bitcoin and Ethereum. In contrast to previous papers, Corbet et al. (2018) study the fundamental drivers of the price. The authors derive economically and computationally sensible ratios and employ them to detect and date-stamp bubbles. They conclude that the analyzed cryptocurrency markets exhibit periods of clear bubble behavior.

Another relevant study by Maouchi et al. (2022) focuses on providing a better understanding of digital bubbles during the COVID-19 pandemic through an investigation of the NFT and DeFi markets. Working with a sample of nine DeFi tokens, three NFTs, Bitcoin, and Ethereum, the authors detect several bubbles in the analyzed crypto instruments and investigate potential DeFi and NFTs bubble predictors. They show that DeFi and NFTs bubbles occur less frequently but at higher magnitudes than cryptocurrency bubbles. In addition, Maouchi et al. (2022) conclude that COVID-19 and trading volume exacerbate bubble occurrences, while total value locked is negatively associated with crypto bubbles. Their results suggest that total value locked might be used as a tool for crypto market monitoring.

In their turn, Wang et al. (2022) perform detecting and date-stamping of bubble behaviors in NFT and DeFi markets, which are widely perceived as speculative. This paper identifies the existence and dates of price bubbles in the NFT and DeFi markets by applying advanced econometric tests. The authors report that both NFT and DeFi markets exhibit speculative bubbles, with NFT bubbles occurring more frequently and at higher average extreme magnitudes than DeFi bubbles. Wang et al. (2022) provide evidence that price bubbles in NFT and DeFi markets are highly correlated with market hype and more general cryptocurrency market uncertainty. The authors also identify periods within which bubbles are not observed, suggesting that these markets have intrinsic value and should not be dismissed simply as bubbles.

As could be inferred from the above-reviewed papers, cryptocurrency, NFT, and DeFi markets are prone to bubble formation and busting. Such boom and bust episodes justify paying additional attention to market dynamics during extreme market conditions, whether bullish or bearish. All these researchers tried to describe bubble formation dynamics in relatively new digital markets. Within this context, our research represents a further step that provides valuable insights into tail connectedness between cryptocurrencies and NFTs. Our results may prove useful for developing efficient hedging strategies and designing optimal portfolio allocation weights. Next, the third strand of our literature review addresses portfolio implications.

Portfolio implications of digital asset interrelatedness

Portfolio implications based on studies of static and dynamic connectedness between the NFT, Defi, and major asset classes are reported in Yousaf and Yarovaya (2022). The authors investigate return and volatility transmission between NFTs, Defi assets, oil, gold, Bitcoin, and the S&P 500 using the time-varying parameter vector autoregression (TVP-VAR) framework. The results provide evidence of weak static return and volatility spillovers between NFTs and Defi assets and the other analyzed markets, demonstrating that these new digital assets are still relatively decoupled from traditional asset classes. Yousaf and Yarovaya (2022) report that dynamic return and volatility connectedness became higher during the initial phase of the COVID-19 pandemic and the cryptocurrency bubble of 2021. In addition, the authors calculate the optimal static and dynamic weights, hedge ratios, and hedging effectiveness for NFT/other asset and Defi asset/other asset portfolios, arguing that investors and portfolio managers should consider NFTs and Defi assets for their portfolios of gold, oil, and stocks for their diversification benefits.

Further on, the hedging and safe haven properties of NFTs are addressed in Zhang et al. (2022). The authors apply a nonlinear autoregressive distributed lag model to explore whether NFTs can act as hedges and safe havens for Bitcoin, gold, stocks, bonds, the US dollar, and crude oil. In addition to examining whether NFTs can act as hedges for the analyzed asset classes during the period from January 1, 2018, to March 31, 2022, the authors examine the hedging properties of NFTs during the pre-COVID-19 period and the safe haven properties of NFTs in times of stress after the COVID-19 outbreak. Their results demonstrate that on average within the studied period, NFTs are hedges for gold, bonds, and the US dollar; in pre-COVID-19 times, on average, NFTs are hedges for stocks and the US dollar; during the COVID-19 pandemic, NFTs acted as safe havens for the US dollar. The authors claim that their outcomes provide relevant insights for investors searching for hedging and safe haven instruments for major asset classes.

In recent work, Umar et al. (2023) studied the diversification benefits of NFTs for conventional asset investors, providing empirical evidence from CoVaR with higher moments and optimal hedge ratios. The authors examine NFT risks and returns by accounting for the tail dependence of higher-order moments and portfolio characteristics. They study commodities, stocks, and bonds and report NFT hedging and portfolio attributes. The authors claim that NFTs possess beneficial investment and hedging attributes under all market conditions, including the COVID-19 pandemic, and argue that their findings provide valuable insights for regulators, portfolio managers, and investors.

As could be concluded from the above-reviewed papers, NFTs' safe haven properties and diversification attributes have recently attracted considerable attention from academic scholars. However, the beneficial role of NFTs has been investigated with respect to investment portfolios comprising conventional assets except for the two major cryptocurrencies, namely, Bitcoin and Ethereum. Therefore, the subject of the interrelatedness of NFTs and cryptocurrencies remains largely overlooked. Hence, our motivation is straightforward—to fill this gap in the literature and provide important insights for crypto investors regarding the diversification attributes of NFTs.

Methodology

To explore spillovers between cryptocurrencies and NFTs, we employ the quantile connectedness approach of Ando et al. (2022) based on the vector autoregressive (VAR) model and forecast error variance decomposition. Within the Diebold and Yilmaz (2012, 2014) framework, the quantile connectedness approach allows estimating connectedness for various quantiles (q) corresponding to bearish, normal, and bullish markets.

Following Koenker and Bassett (1978), we employ a quantile regression to examine the dependence of y_t on x_t at each quantile q of the conditional distribution of y_t/x_t. The quantile vector autoregression QVAR(p), can be expressed as

$$y_t = c(q) + \sum_{i=1}^{p} \Phi_i(q) y_{t-i} + \varepsilon_t(q), \quad q \in (0,1) \tag{1}$$

where y_t is the vector of N × 1 endogenous variables, p is the lag length, c(q) is the N × 1 mean vectors, $\Phi_i(q)$ is the N × N QVAR coefficient matrix, and $\varepsilon_t(q)$ indicates the error term for the N × N variance–covariance matrix, m $\Sigma(q)$. We estimate n $\hat{\Phi}_i$ and $\hat{c}_i$ by assuming the residuals to follow the quantile constraint, a $Q_q\left(\varepsilon_t(q)|y_{t-1}, \ldots, y_{t-p}\right) = 0$. The population qth conditional quantile of response y is defined as

$$Q_q\left(y_t|y_{t-1}, \ldots, y_{t-p}\right) = \hat{c}(q) + \sum_{i=1}^{p} \hat{\Phi}_i(q) y_{t-i} \tag{2}$$

We follow the original work of Ando et al. (2022) to construct quantile connectedness matrices at various quantiles. From Eq. (1), we define an infinite order vector moving average representation of QVAR(∞) as follows:

$$y_t = \mu(q) + \sum_{i=0}^{\infty} \Psi_i(q) \varepsilon_{t-i}(q), \mathrm{t} = 1, \ldots, \mathrm{T} \tag{3}$$

where y_t is defined by the sum of the residuals $\varepsilon_t(q)$ at every quantile q. The generalized forecast error variance decomposition (GFEVD) with a forecast horizon H is defined as follows by Koop et al. (1996) and Pesaran and Shin (1998):

$$\mathrm{C}_{ij}^{g}(H) = \frac{\sum(q)_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i\prime \Psi_h(q) \sum(q) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i\prime \Psi_h(q) \sum(\tau) \Psi_h(q)\prime e_i\right)}, \tag{4}$$

where $\mathrm{C}_{ij}^{g}(H)$ denotes the contribution of the jth variable to the variance of forecast error of the variable ith at horizon H_t and e_i is a zero vector with unity on the ith position. The normalization of each element in the decomposition matrix is

$$\tilde{C}_{ij}^{g}(H) = \frac{\mathrm{C}_{ij}^{g}(H)}{\sum_{j=1}^{k} \mathrm{C}_{ij}^{g}(H)}, \quad \text{with} \quad \sum_{j=1}^{k} \tilde{C}_{ij}^{g} = 1 \text{ and } \sum_{i,j=1}^{k} \tilde{C}_{ij}^{g}(H) = k \tag{5}$$

Following Diebold and Yilmaz (2012, 2014), the various measures of connectedness at the qth conditional quantile can be formulated using the GFEVD. Diebold and Yilmaz (2014) created an N × N spillover matrix (see Appendix, Table 5). Specifically, the total connectedness index (TCI) measures the total connectedness effect within the entire system at the qth quantile and is specified as follows:

$$TCI(q) = \frac{\sum_{i-1}^{k}\sum_{j=1,i\neq j}^{k}\tilde{C}_{ij}^{g}(q)}{\sum_{i-1}^{k}\sum_{j=1}^{k}\tilde{C}_{ij}^{g}(q)} \times 100 \tag{6}$$

The "TO" directional spillover index from index i to all indices j at quantile (q) is

$$TO_{i\rightarrow j}(q) = \frac{\sum_{j=1,i\neq j}^{k}\tilde{C}_{ji}^{g}(q)}{\sum_{j=1}^{k}\tilde{C}_{ji}^{g}(q)} \times 100 \tag{7}$$

The "FROM" directional spillover index from all indices j to index i at quantile (q) is

$$FROM_{i\leftarrow j} = \frac{\sum_{j=1,i\neq j}^{k}\tilde{C}_{ij}^{g}(q)}{\sum_{j=1}^{k}\tilde{C}_{ij}^{g}(q)} \times 100 \tag{8}$$

The "NET" directional spillover index at quantile (q) is

$$NET_i(q) = TO_{i\rightarrow j}(q) - FROM_{j\leftarrow i}(q) \tag{9}$$

A positive (negative) value for $NET_i(q)$ indicates a net transmitter (net recipient) from other markets. Practically, the quantile connectedness index is estimated on a QVAR with a lag order of 1 (selected based on the Bayesian information criterion) and a forecast horizon of 10. We adopt a 200-day rolling window to estimate dynamic connectedness at the quantile.[1]

Data

We consider five prominent cryptocurrencies, namely, BCH, BTC, ETH, LTC, and XRP, and three major proxies for NFT markets, namely THETA, TEZOS, and ENJIN. THETA, TEZOS, and ENJIN, which constitute a sample for gauging NFT markets, are referred to as NFTs throughout our paper, but in a strict sense, they cannot properly be said to be NFTs. They represent most of the start-ups that may use NFTs within their operating strategies. However, the three chosen proxies host many popular NFT marketplaces and thus represent the NFT markets. For advanced reading on this subject, we recommend consulting the study by Mazur (2021) linking NFTs to these types of start-ups.

Moreover, we acknowledge that THETA, TEZOS, and ENJIN tokens are defined by most professionals as NFT-enabling or NFT-related cryptocurrencies, as some features of these instruments, such as the absence of an easily recognizable value-generating mechanism, resemble those of genuine NFTs. In contrast, the potentially unlimited number of units—e.g., THETA has one billion units outstanding—makes them more like a cryptocurrency. Note that the NFTs analyzed in this paper may easily serve as "mediums of exchange," whereas true NFTs may not. For further consideration of this issue, we recommend the two insightful discussions on this subject matter that can be found in

[1] The quantile connectedness is estimated by the R code of Connectedness Approach (https://davidgabauer.shinyapps.io/connectedness_approach/).

Frye (2022) and Houser and Holden (2022), who argue that a real NFT is a transferable token recognized by the internet-enabled NFT market as a legitimate representation of ownership either of an author´s work or of a certain collectible. However, to overcome the difficulties of accessing individual data for extremely large numbers of genuine individual tokens and still tracking the dynamics of NFT markets, we follow the approach recently employed in several research works on this subject. That approach consists of using appropriate proxies; see Aharon and Demir (2022), Dowling (2022a, b), Umar et al. (2022a, b), Kumar et al. (2023), Yousaf et al. (2023a), and the references therein.

It is worth noting that in this research, we employ end-of-the-day prices for both conventional cryptocurrencies and NFT markets. As we are interested in short to medium, or at least interday, time horizons and not in intraday high-frequency patterns, we circumvent the necessity to assure perfect synchronization of the data needed in the case of intraday trading studies. We explain our position by analogy, comparing the asynchronized exchange of messages by e-mails to the almost perfectly synchronized exchange of messages via chat. We may learn different information on a minute-long timescale, but by the end-of-the-day, all these momentary differences cancel out, corroborating our point of using end-of-the-day prices to study interday dynamics.

At the time of writing, October 8, 2022, the joint market capitalization of the five analyzed cryptocurrencies equals \$569.04 billion, representing 60.3% of the total crypto market capitalization of \$943.82 billion. The total market capitalization of collectibles and NFTs is more modest and equals \$17.64 billion, while the three considered NFTs jointly account for 15.9% of the market.[2] Our dataset (July 2018–July 2022) is obtained from the CoinMarketCap (https://coinmarketcap.com/) database. The motivation behind our choice to start our dataset in July 2018 is inherently linked to the launch of one of the three studied proxies of the NFT market, TEZOS (www.tezos.com), a proof-of-stake blockchain that hosts many popular NFT marketplaces, on June 30, 2018. In a certain way, this was the beginning of a relatively mature NFT market state. To further support our decision, we note that many prominent adherents of the NFT movement were launched during the first half of 2018, including Axie Infinity (March 2018), KnownOrigin (April 2018), and SuperRare (May 2018). Thus, we posit that the possibility of studying the NFT market, which already incorporates the important abovementioned players, also justifies our choice to start our dataset in July 2018. The end of our data sample is July 2022, when the work on the papers commenced. It is also worth noting that the sample period includes at least two major events (COVID-19 and the Russia–Ukraine military conflict). Continuously compounded daily returns are $r_t = ln(P_t/P_{t-1}) \times 100$. Figure 1 shows the prices and returns of the analyzed assets.

Table 1 provides sample statistics. The mean returns are positive for all assets except BTC. BCH, TEZOS, and XRP present the most elevated average returns, respectively; 0.317, 0.28, and 0.20. As indicated by the variances, the NFT returns are the most volatile. All return series are asymmetric and leptokurtic; see their positive skewness and elevated kurtosis exceeding 3. The Jarque–Bera statistics reject the normality of the return series.

[2] These information are collected from the https://coinmarketcap.com/ website.

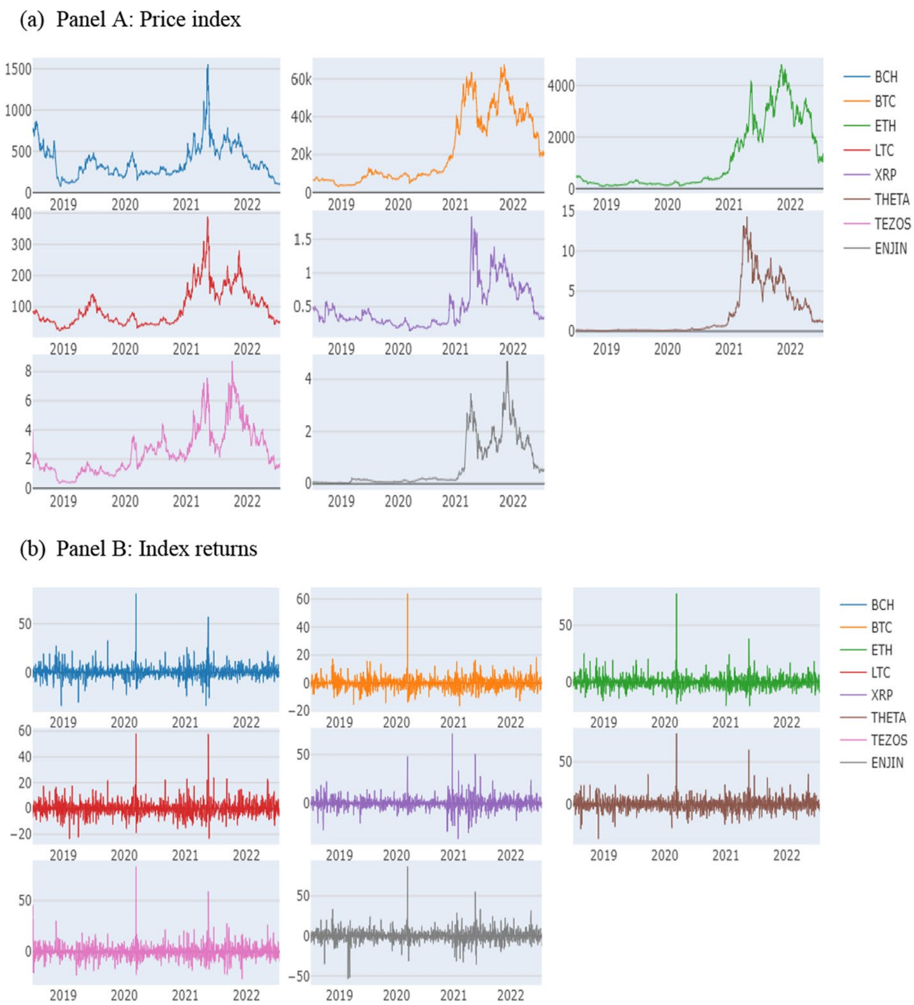


Fig. 1 Dynamics of prices (**A**) and returns (**B**) of cryptocurrency and NFT markets

Table 1 Descriptive statistics and unit root tests

	BCH	BTC	ETH	LTC	XRP	THETA	TEZOS	ENJIN
Mean	0.317	0.058	0.064	0.175	0.2	0.12	0.28	0.135
Variance	39.44	16.853	29.358	31.436	36.877	54.413	47.584	57.469
Skewness	1.960***	2.757***	2.559***	1.726***	1.459***	1.537***	2.011***	0.739***
Ex.Kurtosis	26.15***	40.93***	31.39***	16.43***	21.92***	16.22***	19.90***	18.19***
JB	43,053.***	104,996.***	62,252.***	17,356.***	30,109.***	16,780.***	25,372.***	20,507.***
ERS	− 6.591***	− 6.290***	− 6.738***	− 5.526***	− 6.735***	− 16.140***	− 1.225	− 5.335***
Q(10)	23.04***	22.35***	29.14***	25.77***	6.541	26.63***	14.75***	12.12**
Q2(10)	13.89***	5.033	11.08**	25.46***	35.791***	11.64**	26.65***	17.35***

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

Empirical results

Extreme quantile connectedness index

We analyze conditional connectedness at the median (0.5), lower (0.05), and upper (0.95) quantiles, corresponding, respectively, to normal, bear, and bull markets. The outcomes at the median percentile provide a comparison of outcomes at the lower and upper tails. We present the results for the three abovementioned quantiles in Table 2.[3] From Panel B, we see that under normal market conditions, TCI is rather elevated (74.08), implying strong conditional connectedness within the system even during market stability.

The bottom line of Panel B reports the net conditional connectedness metrics. ETH (12.95%), LTC (10.98%), BCH (9.22%), and BTC (3.79%) are net transmitters of return spillovers, while XRP (−0.93%) and three NFTs, namely, THETA (−15.23%), TEZOS (−6.19%), and ENJIN (−14.59%), are spillover recipients. Therefore, under normal market conditions, net-transmitting cryptocurrencies help forecast the three NFT markets.

To investigate return spillovers in bearish and bullish markets, we compute the connectedness metrics at the extreme left (Panel A) and right (Panel C) tails. Comparing Panels A and C with Panel B, we observe that the quantile TCI at the lower (84.28%) and upper (84.42%) quantiles is higher than at the median percentile (74.98%), meaning that connectedness augments at extremes. These estimates corroborate the studies that stronger shocks make systems more connected (Londono 2019; Mensi et al. 2021e; Raham et al. 2021; Olofsson et al. 2021; Yousaf et al. 2022). Interestingly enough, the net transmitters and receivers remain the same for normal, bearish, and bullish conditions. Nonetheless, the TCI outcomes highlight the substantial influence of extreme market states on the strength of network interactions and support employing the market-sensitive quantile VAR methodology.

Because the four cryptocurrencies always remain net transmitters for all analyzed quantiles, we infer that they are valuable predictors for NFTs, signaling a consistent lack of efficiency in the considered digital markets for all market states. This could be explored for forecasting NFT markets based on cryptocurrencies and obtaining excess returns from NFTs during all market conditions.

Figure 2 confronts network connectedness for the median, lower, and upper quantiles. The TCI values at the extremes are consistently higher than at the median quantile, corroborating our conclusions from Table 2. Figures 4 and 5 present directional connectedness ("TO" and "FROM") and net connectedness at different quantiles. The TCI for the extreme quantiles is seemingly less responsive to the influence of COVID-19 in 2020 and to the rally in digital markets during the second half of 2021, the impact of which is well pronounced at the medium quantile. For example, the pandemic impact on the median quantile connectedness appears in the form of the "rectangular" unit impulse signal function ( ), representing an abrupt increase from 60% to above 80% around the COVID-19-fueled meltdown in March 2020 (Gubareva 2021), followed by a commensurate abrupt decline a half year later. Successful news concerning vaccine development allowed for containment of the economic impacts of the pandemic (Rouatbi et al. 2021; Yousaf et al. 2023b).

[3] This paper applies the QVAR R code of Ando (2022), which is available on the GabauerDavid/ConnectednessApproach (https://sites.google.com/view/davidgabauer/econometric-code).

Table 2 The quantile connectedness table

	BCH	BTC	ETH	LTC	XRP	THETA	TEZOS	ENJIN	FROM
Panel A: Lower quantile ($q = 0.05$)									
BCH	16.24	13.15	12.32	13.56	12.21	10.52	11.13	10.86	83.76
BTC	13.44	15.46	12.67	13.2	12.03	10.64	11.46	11.08	84.54
ETH	12.99	13	14.65	13.38	12.36	10.84	11.7	11.08	85.35
LTC	13.65	13.15	12.71	15.26	12.2	10.84	11.18	11	84.74
XRP	13.19	12.5	12.22	12.82	15.39	10.72	11.92	11.24	84.61
THETA	12.01	11.97	12.14	12.22	11.59	16.55	11.64	11.89	83.45
TEZOS	12.57	12.36	12.11	12.46	12.04	11.05	15.8	11.61	84.2
ENJIN	12.23	11.96	12.04	12.06	11.65	11.67	12	16.4	83.6
TO	90.09	88.07	86.21	89.72	84.08	76.29	81.03	78.77	674.26
ALL	106.32	103.54	100.86	104.98	99.47	92.84	96.82	95.17	**TCI**
NET	6.32	3.54	0.86	4.98	−0.53	−7.16	−3.18	−4.83	84.28
Panel B: Median quantile ($q = 0.5$)									
BCH	21.93	13.33	14.33	15.68	11.65	7.03	9.66	6.39	78.07
BTC	14.1	22.73	15.54	14.72	10.49	6.79	8.98	6.66	77.27
ETH	13.87	14.3	21.05	14.66	11.68	6.99	9.92	7.53	78.95
LTC	15.47	13.78	14.84	21.18	11.72	7.03	9.25	6.74	78.82
XRP	13.13	11.16	13.5	13.34	25.42	6.61	9.95	6.89	74.58
THETA	9.96	9.06	10.46	10.21	8.7	33.3	8.85	9.46	66.7
TEZOS	11.72	10.62	12.34	11.51	10.63	7.37	27.88	7.92	72.12
ENJIN	9.03	8.81	10.9	9.69	8.78	9.64	9.31	33.83	66.17
TO	87.29	81.06	91.9	89.8	73.65	51.47	65.93	51.57	592.67
ALL	109.22	103.79	112.95	110.98	99.07	84.77	93.81	85.41	**TCI**
NET	9.22	3.79	12.95	10.98	−0.93	−15.23	−6.19	−14.59	74.08
Panel C: Upper quantile ($q = 0.95$)									
BCH	15	12.96	12.95	13.35	12.25	11.2	11.63	10.66	85
BTC	12.99	15.31	13.14	13.11	11.95	10.96	11.66	10.89	84.69
ETH	12.76	12.96	14.95	13.13	12.22	11.04	11.67	11.27	85.05
LTC	13.21	12.95	13.1	14.89	12.42	11	11.51	10.92	85.11
XRP	12.66	12.33	12.83	12.97	15.54	11.02	11.63	11.02	84.46
THETA	12.05	11.83	12.25	12.14	11.29	16.63	11.68	12.14	83.37
TEZOS	12.21	12.21	12.59	12.46	11.99	11.51	15.59	11.45	84.41
ENJIN	11.57	11.81	12.45	12.08	11.57	12.13	11.66	16.72	83.28
TO	87.45	87.05	89.3	89.23	83.7	78.86	81.44	78.34	675.36
ALL	102.45	102.35	104.25	104.13	99.24	95.48	97.02	95.07	**TCI**
NET	2.45	2.35	4.25	4.13	−0.76	−4.52	−2.98	−4.93	84.42

The table presents pairwise connectedness measures along with the total connectedness index (TCI) for the lower (Panel A), median (Panel B) and the upper (Panel C) quantiles. Quantile VAR model uses a lag length of order 1 (BIC) and a 10-step-ahead forecast

It is worth noting that at all quantiles, XRP, acting as a net recipient, behaves differently from the other four cryptocurrencies, which are consistent net transmitters. A possible explanation for such a difference could be found in the inherent properties of XRP, which is not a mineable cryptocurrency, unlike Bitcoin and many others. Instead, every one of the 100 billion Ripple coins that have ever or will ever exist had already been created by Ripple (www.ripple.com). This makes a difference, as mining costs may result in digital coin fragility (Taleb 2021). Moreover, according to Ripple, XRP is a virtual coin designed as a native currency of the XRP Ledger, which purports to settle transactions

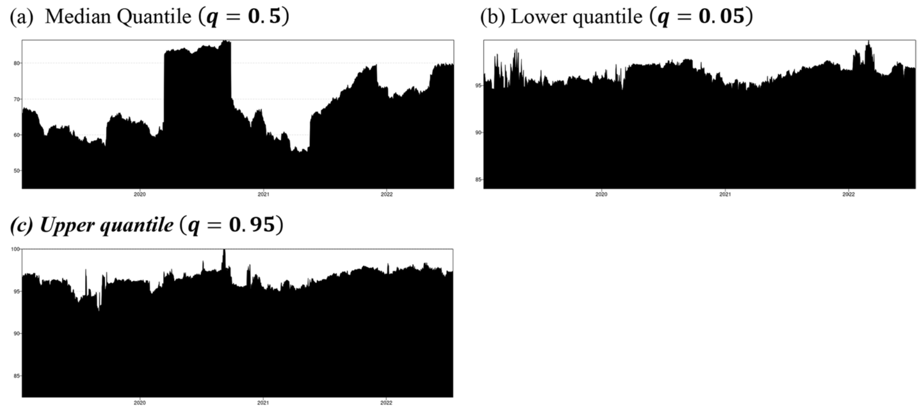


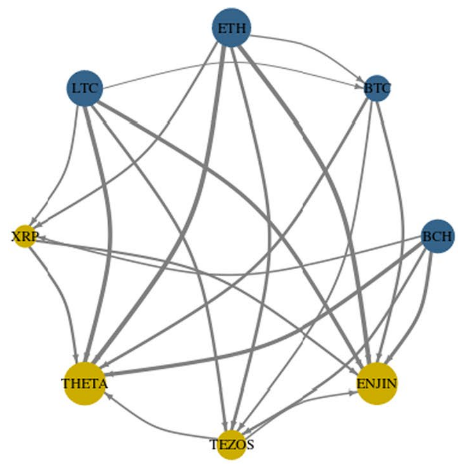
Fig. 2 Quantile total connectedness. *Note*: The total connectedness index (TCI) is computed based on a rolling window of 200 days and 10 step-ahead forecast horizons

in 3–5 s. We posit that settlement timeliness may affect connectedness patterns. In addition, about 50 Bi XRP are in circulation, which is a relatively large number compared with Bitcoin and other true blockchain cryptocurrencies. The trade-off is that Ripple is not expected to reach the price heights of cryptocurrencies like BTC or ETH. However, this does not signify that XRP cannot climb or drop by a considerable amount in relative terms. In theory, XRP holders can obtain substantial profits or suffer considerable losses on Ripple without the XRP coin itself being worth that much. Unlike BTC and others, the idea behind Ripple is to speed up the international transfer of money, i.e., become a medium of exchange rather than serve as a store of value. All the abovementioned aspects may help in understanding the differences in XRP behavior vis-à-vis other cryptocurrencies. Further research within this domain seems highly desirable.

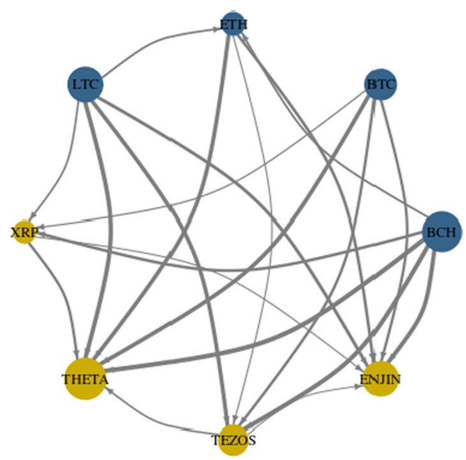
Connectedness network analysis

The network graphs for net connectedness within the network for different quantiles comprise five cryptocurrencies and three NFTs. The net bilateral connectedness is estimated according to the TVP-VAR approach (Antonakakis et al. 2020a). Figure 3 presents the net connectedness plots, representing linkages for distinct percentiles based on the whole sample. Figure 6 displays the quantile connectedness network based on pairwise directional connectedness (see Appendix). The plots map the topology of systemic risk transmission and illustrate the net magnitude and flow of innovations within the bilateral sets of the nodes. Blue (yellow) tonality signifies that the node is a net contributor (receiver) of innovations to the system of the analyzed digital assets. The thickness of the connectors represents the magnitude of the influence.

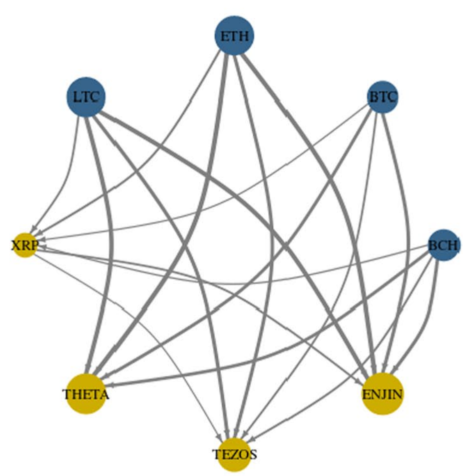
From Fig. 3, we conclude that all cryptocurrencies except XRP are the net contributors to the network, whereas the three NFTs and XRP are net recipients of innovation at all quantiles, with THETA and ENJIN consistently behaving as the most important receivers of innovations. We observe that the links between the nodes, representing flows of innovations, vary depending on the quantile under analysis. For instance, for the median and upper quantiles, ETH plays the role of the strongest innovations transmitter to the system. This outcome is somewhat expected, as a major proportion of NFTs are quoted



(a) Median quantile (q = 0.5)



(b) Lower quantile (q = 0.05)



(c) Upper quantile (q = 0.95)

Fig. 3 The network of net pairwise connectedness between cryptocurrency and NFT markets. *Notes*: Blue (yellow) nodes designate the net transmitters (receivers) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. The size of nodes represents weighted average net connectedness and traded in the ETH cryptocurrency (Dowling 2022a, b). At the median quantile, we observe the most complex topology of network connectedness and the maximum number of observed bilateral connections. Despite the more elevated values of the connectedness index found at the lower and upper quantiles (see Table 2), the subjacent network topology becomes simpler. For instance, at the lower quantile, the LTC → BTC linkage disappears, while at the upper quantile, the LTC → BTC channel also ceases to exist. This means that while spillovers exist between net-transmitting cryptocurrencies under normal market conditions, they disappear when a bullish market appears, with only an influence on XRP and NFTs remaining. At the same time, in the bullish upper quarter, the channels of influence within NFTs, such as TEZOS → THETA and TEZOS → ENJIN, also disappear. Wrapping up, vis-à-vis the medium quantile, during bearish and bullish market conditions, the influence transmission from cryptocurrencies to FNTs strengthens while within-crypto and within-NFT spillovers fade.

Portfolio design and hedging strategy analysis

Concerning portfolio management analysis, the optimal hedge ratios and hedging effectiveness between two assets are calculated following Kroner and Sultan (1993), while the estimates of the pairwise asset weights and hedge effectiveness are obtained following Kroner and Ng (1998).

In Table 3, we present the optimal hedge ratios and hedging effectiveness (HE) between the left and the right assets. Table 3 informs the average value of the hedge ratio percentage of the short position in the right asset to hedge the one-dollar long exposure to the left asset. For example, our estimate of the BTC/BCH hedge ratio is 0.47, implying that a 1-dollar exposure to BTC may be hedged by shorting a $0.47 position in BCH. As per Table 3, we observe that the system of crypto and NFT assets provides fair pairwise hedging opportunities to a different degree. The highest HE value (70%) of LTC/ETH indicates the best effective hedging ratio.

To grasp deeper insights into the efficient allocation of funds among crypto assets, Table 4 presents estimates of pairwise asset weights and hedge effectiveness, obtained from following Kroner and Ng 1998. It is observable that except for the pairwise weights between BTC and the remaining digital markets (0.84–0.98), investment in the digital assets across all other analyzed pairs reduces portfolio volatility per the HE values. Besides acknowledging that no markets are useful to mitigate BTC risks, BTC is capable of diminishing the risk of exposure to all other analyzed digital assets. The ENJIN/BTC pair provides the highest value (78%) of HE, implying the best effective portfolio weight to minimize exposure of the NFT-BTC portfolio.

Conclusions

This paper studies extreme return spillovers and connectedness between cryptocurrencies and NFTs and provides relevant insights for portfolio management. Our network comprises five cryptocurrencies and three NFTs analyzed at various quantiles. Net bilateral connectedness is estimated with the TVP-VAR approach. We find that quantile connectedness at the lower and upper quantiles is higher than quantile TCI at the median quantile, meaning that connectedness is augmented at extremes. Moreover, the four most prominent cryptocurrencies, BCH, BTC, ETH, and LTC, are

Table 3 Performance of optimal hedge ratio strategy for portfolio

	Mean	SD	5%	95%	HE (%)	*p* value
BTC/BCH	0.47	0.12	0.29	0.67	57	0
ETH/BCH	0.63	0.11	0.42	0.8	57	0
LTC/BCH	0.7	0.11	0.53	0.85	65	0
XRP/BCH	0.64	0.24	0.39	1.05	44	0
THETA/BCH	0.54	0.18	0.25	0.81	22	0
TEZOS/BCH	0.56	0.18	0.29	0.88	36	0
ENJIN/BCH	0.51	0.18	0.21	0.81	15	0
BCH/BTC	1.35	0.35	0.91	1.99	59	0
ETH/BTC	1.1	0.24	0.78	1.54	66	0
LTC/BTC	1.19	0.27	0.83	1.61	64	0
XRP/BTC	1.01	0.38	0.58	1.68	41	0
THETA/BTC	0.93	0.31	0.45	1.47	20	0
TEZOS/BTC	0.92	0.32	0.5	1.54	35	0
ENJIN/BTC	0.9	0.34	0.41	1.39	21	0
BCH/ETH	1.02	0.18	0.81	1.3	61	0
BTC/ETH	0.63	0.14	0.42	0.87	67	0
LTC/ETH	0.9	0.12	0.72	1.11	70	0
XRP/ETH	0.83	0.26	0.61	1.3	52	0
THETA/ETH	0.73	0.19	0.42	1.02	26	0
TEZOS/ETH	0.78	0.2	0.5	1.12	44	0
ENJIN/ETH	0.74	0.21	0.41	1.09	18	0
BCH/LTC	0.99	0.16	0.76	1.25	67	0
BTC/LTC	0.58	0.13	0.39	0.79	65	0
ETH/LTC	0.78	0.12	0.57	0.99	69	0
XRP/LTC	0.76	0.24	0.5	1.19	50	0
THETA/LTC	0.68	0.19	0.4	0.96	26	0
TEZOS/LTC	0.68	0.2	0.38	1.02	39	0
ENJIN/LTC	0.65	0.2	0.33	0.96	19	0
BCH/XRP	0.85	0.25	0.39	1.19	37	0
BTC/XRP	0.48	0.18	0.16	0.77	36	0
ETH/XRP	0.69	0.21	0.25	0.97	42	0
LTC/XRP	0.73	0.21	0.3	1	46	0
THETA/XRP	0.62	0.23	0.16	0.94	18	0
TEZOS/XRP	0.65	0.22	0.3	1.01	34	0
ENJIN/XRP	0.63	0.28	0.2	0.95	16	0
BCH/THETA	0.47	0.15	0.24	0.73	24	0
BTC/THETA	0.29	0.12	0.13	0.5	26	0
ETH/THETA	0.39	0.13	0.19	0.62	26	0
LTC/THETA	0.42	0.13	0.22	0.63	27	0
XRP/THETA	0.4	0.18	0.18	0.72	24	0
TEZOS/THETA	0.43	0.18	0.18	0.78	22	0
ENJIN/THETA	0.55	0.21	0.28	0.83	26	0
BCH/TEZOS	0.63	0.21	0.3	0.95	33	0
BTC/TEZOS	0.36	0.14	0.16	0.6	31	0
ETH/TEZOS	0.54	0.17	0.25	0.79	37	0
LTC/TEZOS	0.54	0.17	0.26	0.78	35	0
XRP/TEZOS	0.56	0.27	0.24	1.07	31	0
THETA/TEZOS	0.55	0.2	0.2	0.84	23	0
ENJIN/TEZOS	0.57	0.2	0.25	0.84	23	0

Table 3 (continued)

	Mean	SD	5%	95%	HE (%)	*p* value
BCH/ENJIN	0.41	0.15	0.16	0.66	18	0
BTC/ENJIN	0.26	0.11	0.09	0.46	22	0
ETH/ENJIN	0.37	0.12	0.15	0.56	24	0
LTC/ENJIN	0.37	0.13	0.15	0.56	22	0
XRP/ENJIN	0.37	0.19	0.13	0.7	19	0
THETA/ENJIN	0.51	0.15	0.23	0.72	13	0.01
TEZOS/ENJIN	0.42	0.16	0.16	0.71	19	0

The table presents pairwise optimal hedge ratios and hedge effectiveness (HE) for portfolio composed of crypto and NFT assets

consistent net transmitters of return spillovers, whereas NFTs act as net receivers, for all considered quantiles corresponding to normal, bearish, and bullish markets. The connectedness network analysis reveals that despite the more elevated values of the connectedness index found for the lower and upper quantiles, the subjacent network topology becomes simpler, primarily from cryptocurrencies to NFTs. In terms of portfolio implications, we observe that no markets are useful for mitigating BTC risks, whereas BTC can diminish the risk of exposure for all other analyzed digital assets, which is a valuable insight for market players and investors.

It is worth noting that our paper focuses on identifying certain types of ex ante spillovers, which is not an especially useful observation in isolation. The possibility of detecting an ex ante change in the market trend, i.e., identifying a turning point and locating it correctly on a time scale, would be considerably more valuable; see Gubareva and Borges (2016) and Gubareva et al. (2023b). Although the task of providing strategy rules to enhance the ability of a diversifying investor to detect upcoming changes in market trends lies outside the scope of our research, it makes sense to address it in greater detail for the cryptocurrency and NFT markets in the same manner as it is addressed for fixed income markets in the two papers cited above. While this domain of studies will be covered in future research, certain implications can be highlighted here. Instead of attempting to predict a future change in the market trend, a diversifying investor may well try to construct an all-weather portfolio capable of withstanding a wide range of adverse future occurrences. For instance, we find that for normal, bearish, and bullish markets, BCH, BTC, ETH, and LTC consistently remain net transmitters, while NFTs receive innovations. This consistent result evidences the risk absorption potential of NFT instruments. Therefore, adding NFTs to investment portfolios consisting of cryptocurrencies would likely provide diversification benefits. Moreover, we find that no markets are useful for mitigating BTC risks, whereas BTC can reduce the risks of other digital assets. Hence, our advice to the diversifying investor is to include BTC exposure in crypto portfolios comprising NFT instruments.

Wrapping up, we find it worth repeating that, in the literature overview, we identified three important strands of research for exploring the implications of adding NFTs to investment portfolios. These topical areas are related to the general pricing dynamics of NFT markets, NFT bubble formation, and portfolio implications. Concerning NFT pricing, previous researchers have limited themselves to just describing general

Table 4 Performance of an optimal portfolio weights strategy

	Mean	SD	5%	95%	HE (%)	*p* value
BCH/BTC	0.02	0.07	0	0.11	60	0
BCH/ETH	0.1	0.15	0	0.42	31	0
BCH/LTC	0.15	0.21	0	0.56	26	0
BCH/XRP	0.29	0.32	0	1	26	0
BCH/THETA	0.58	0.2	0.17	0.88	17	0
BCH/TEZOS	0.44	0.25	0.05	0.9	21	0
BCH/ENJIN	0.6	0.18	0.28	0.9	0	0.97
BTC/BCH	0.98	0.07	0.89	1	0	0.98
BTC/ETH	0.89	0.21	0.36	1	−2	0.67
BTC/LTC	0.93	0.16	0.6	1	0	0.99
BTC/XRP	0.84	0.22	0.35	1	0	0.99
BTC/THETA	0.91	0.13	0.64	1	0	0.93
BTC/TEZOS	0.87	0.15	0.58	1	−1	0.83
BTC/ENJIN	0.91	0.12	0.67	1	−1	0.8
ETH/BCH	0.9	0.15	0.58	1	0	0.97
ETH/BTC	0.11	0.21	0	0.64	40	0
ETH/LTC	0.66	0.28	0.03	1	5	0.37
ETH/XRP	0.56	0.3	0.05	1	10	0.04
ETH/THETA	0.79	0.16	0.45	1	1	0.79
ETH/TEZOS	0.7	0.22	0.3	1	6	0.26
ETH/ENJIN	0.81	0.15	0.55	1	−11	0.04
LTC/BCH	0.85	0.21	0.44	1	3	0.57
LTC/BTC	0.07	0.16	0	0.4	47	0
LTC/ETH	0.34	0.28	0	0.97	14	0
LTC/XRP	0.47	0.32	0	1	12	0.02
LTC/THETA	0.73	0.17	0.41	0.97	3	0.51
LTC/TEZOS	0.62	0.23	0.23	1	9	0.09
LTC/ENJIN	0.74	0.16	0.46	0.98	−7	0.2
XRP/BCH	0.71	0.32	0	1	24	0
XRP/BTC	0.16	0.22	0	0.65	59	0
XRP/ETH	0.44	0.3	0	0.95	38	0
XRP/LTC	0.53	0.32	0	1	32	0
XRP/THETA	0.69	0.25	0.14	0.97	25	0
XRP/TEZOS	0.6	0.29	0	1	30	0
XRP/ENJIN	0.71	0.24	0.15	0.98	14	0
THETA/BCH	0.42	0.2	0.12	0.83	40	0
THETA/BTC	0.09	0.13	0	0.36	71	0
THETA/ETH	0.21	0.16	0	0.55	51	0
THETA/LTC	0.27	0.17	0.03	0.59	47	0
THETA/XRP	0.31	0.25	0.03	0.86	47	0
THETA/TEZOS	0.39	0.23	0.09	0.83	39	0
THETA/ENJIN	0.53	0.18	0.24	0.89	16	0
TEZOS/BCH	0.56	0.25	0.1	0.95	30	0
TEZOS/BTC	0.13	0.15	0	0.42	64	0
TEZOS/ETH	0.3	0.22	0	0.7	43	0
TEZOS/LTC	0.38	0.23	0	0.77	38	0
TEZOS/XRP	0.4	0.29	0	1	39	0
TEZOS/THETA	0.61	0.23	0.17	0.91	25	0
TEZOS/ENJIN	0.63	0.21	0.22	0.93	18	0

Table 4 (continued)

	Mean	SD	5%	95%	HE (%)	*p* value
ENJIN/BCH	0.4	0.18	0.1	0.72	47	0
ENJIN/BTC	0.09	0.12	0	0.33	78	0
ENJIN/ETH	0.19	0.15	0	0.45	60	0
ENJIN/LTC	0.26	0.16	0.02	0.54	57	0
ENJIN/XRP	0.29	0.24	0.02	0.85	55	0
ENJIN/THETA	0.47	0.18	0.11	0.76	39	0
ENJIN/TEZOS	0.37	0.21	0.07	0.78	51	0

The table presents pairwise optimal portfolio weight ratios and hedge effectiveness (HE) for portfolio composed of crypto and NFT assets

pricing dynamics, whereas our work represents a further advancement by providing knowledge on how NFTs might be used to design cryptocurrency-based portfolios and efficient hedging strategies. Concerning the boom and bust episodes of bubble formation and collapse, earlier research studies have had a restricted focus of describing bubble dynamics and providing evidence that NFT markets are prone to bubble formation and busts. Within this context, our research represents important enhancements and provides valuable insights into tail connectedness between cryptocurrencies and NFTs. Such insights could prove useful when developing efficient hedging strategies and designing optimal portfolio allocation weights. Our research has further portfolio implications because previous investigations into the beneficial role of NFTs have largely looked at investment portfolios comprising conventional assets, except for the two major cryptocurrencies, namely, Bitcoin and Ethereum. Therefore, the subject of the interrelatedness of NFTs and cryptocurrencies has been largely overlooked until now. By analyzing tail connectedness among the five prominent cryptocurrencies and the three major NFTs, our research effectively bridges the gap in the literature and provides practical insights into optimal hedge ratios and portfolio weights for crypto investors interested in the diversification attributes of NFTs.

Our research provides timely implications in the middle of the currently ongoing crypto crash, which has been unfolding in different ways for the various and diverse crypto assets. This asset-specific unfolding reflects the diverse perceptions of economic agents and academy scholars on the role of digital assets in eventually mitigating diverse downside and wrong-way risks. In terms of employing digital assets, downside risk mitigation may be implemented through purchases of targeted amounts of cryptocurrencies. In theory, partial reliance on cryptocurrencies, on the one hand, may help reduce economic policy uncertainty risks, whereas, on the other hand, it may provide hedging against sanctions risks for the central banks of countries facing higher risks of US sanctions (Bossman et al. 2023). Concerning the economic policy implications of cryptocurrencies, it is impossible to ignore a seminal paper by Taleb (2021), who claims that, for instance, bitcoin failed to satisfy the notion of currency without a government. In fact, it was suitable for neither short-term nor long-term value storage, as its expected value is no higher than zero. Therefore, it does not represent a reliable inflation hedge, constitute a safe haven for investments, serve as a shield against government tyranny, or provide tail protection from catastrophic events. However, Ferranti (2022) explores the potential for Bitcoin to serve as an alternative hedging asset for hedging sanctions risk in countries facing a higher risk of US financial sanctions. Ferranti (2022) shows that a modest risk of sanctions significantly increases optimal gold and bitcoin allocations of central banks concerned about being sanctioned. Thus, sanctions risk may bolster the use of cryptocurrencies.

Finally, a few comments should be made about the crypto crash that unfolded in May 2022, when crypto markets went into a free fall. This crypto slump was triggered by the collapse of FTX, which handled around $1 billion in transactions each day. Diverse digital assets have exhibited huge declines in their prices. Even the prices of so-called stablecoins have presented certain unpleasant surprises. During this crypto collapse, stablecoins proved not so stable. For instance, Terra USD, a cryptocurrency pegged to the USD, declined from $1 to effectively $0 in a matter of days. However, also important is that the overall monetary volume placed in so-called stablecoins has demonstrated a certain resilience against the generalized collapse in the prices of digital assets (Cecchetti and Schoenholtz 2022; Klement 2022). As shown by Cecchetti and Schoenholtz (2022), the aggregate capitalization of stablecoins was only slightly diminished during the turbulent crypto times of 2022, remaining at a solid level of approximately 200 billion USD. Therefore, new avenues of future research should perhaps be dedicated to studies of stablecoin inflows and outflows and trade volumes, as stablecoins, despite recently observed collapses in the prices of some instruments, may still have the potential to provide diversification features to diverse investment portfolios. It is worth noting that diversified, and hence more stable, portfolios promise improvements in financial stability, which in turn reduces economic policy uncertainty, making economic policies more predictable and transparent and benefiting the well-being of both developed and developing economies and societies.

Appendix

See Table 5 and Figs. 4, 5 and 6.

Table 5 Spillover matrix of Diebold and Yilmaz (2014)

	X_1	X_2	$\cdots$	X_N	FROM
X_1	$C^g_{11}(H)$	$C^g_{12}(H)$	$\cdots$	$C^g_{1N}(H)$	$\sum_{j=1, j\neq 1}^{N} C^g_{1j}(H)$
X_2	$C^g_{21}(H)$	$C^g_{22}(H)$	$\cdots$	$C^g_{2N}(H)$	$\sum_{j=1, j\neq 2}^{N} C^g_{2j}(H)$
$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$
X_N	$C^g_{N1}(H)$	$C^g_{N2}(H)$	$\cdots$	$C^g_{NN}(H)$	$\sum_{j=1, j\neq N}^{N} C^g_{Nj}(H)$
TO	$\sum_{i=1, i\neq 1}^{N} C^g_{i1}(H)$	$\sum_{i=1, i\neq 2}^{N} C^g_{i2}(H)$	$\cdots$	$\sum_{i=1, i\neq N}^{N} C^g_{iN}(H)$	$\frac{1}{N}\sum_{i,j=1, i\neq j}^{N} C^g_{ij}(H)$

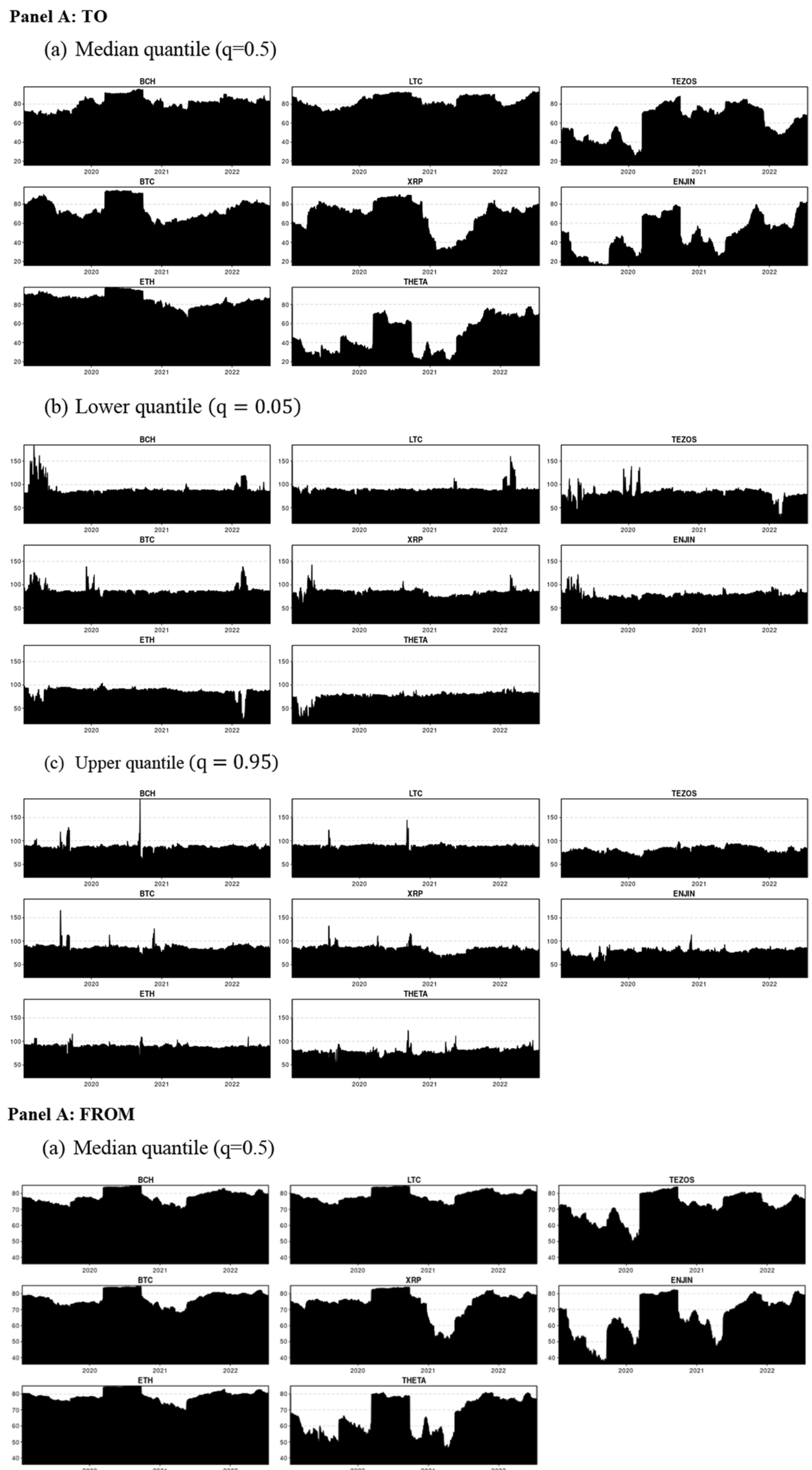


Fig. 4 Quantile directional inbound and outbound connectedness

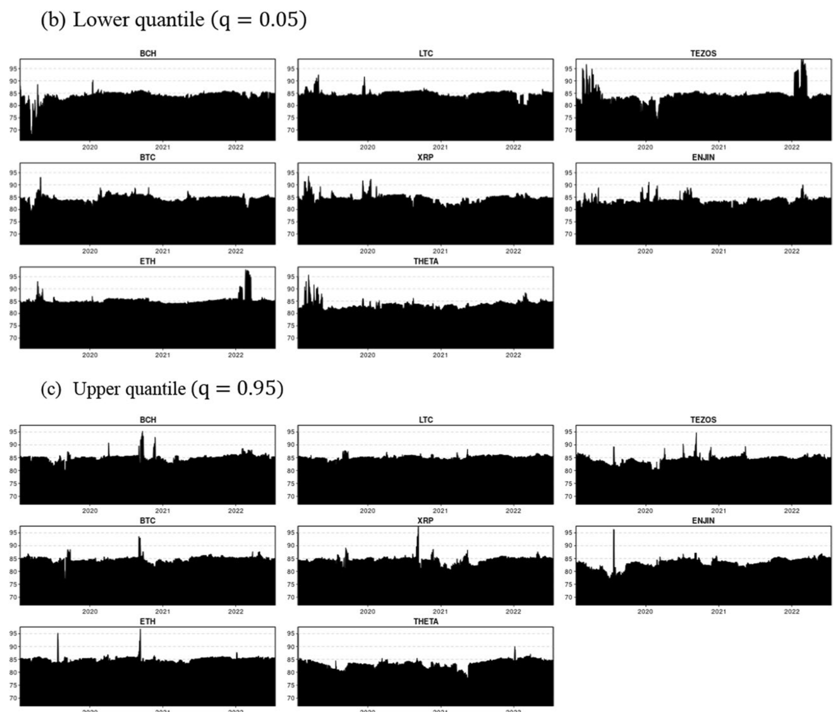


Fig. 4 continued

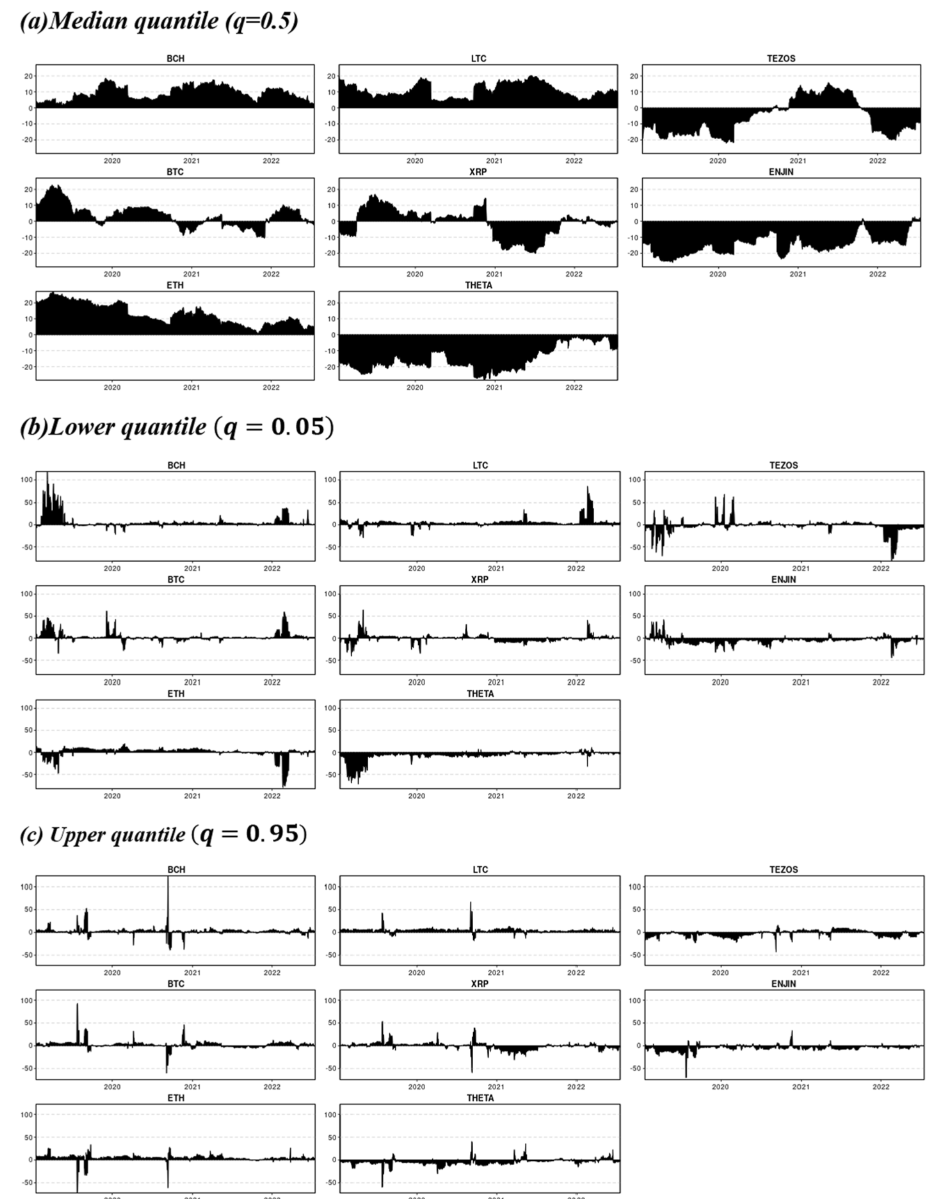


Fig. 5 Quantile net connectedness. This figure displays the quantile dynamics of the net directional return connectedness using the quantile connectedness approach of Ando et al. (2022). The net directional return connectedness measures are calculated by subtracting directional "FROM" spillovers from directional "TO" spillovers. Positive (negative) values of connectedness indicate that the corresponding variable is a net transmitter (receiver) of return connectedness to (from) all the other variables

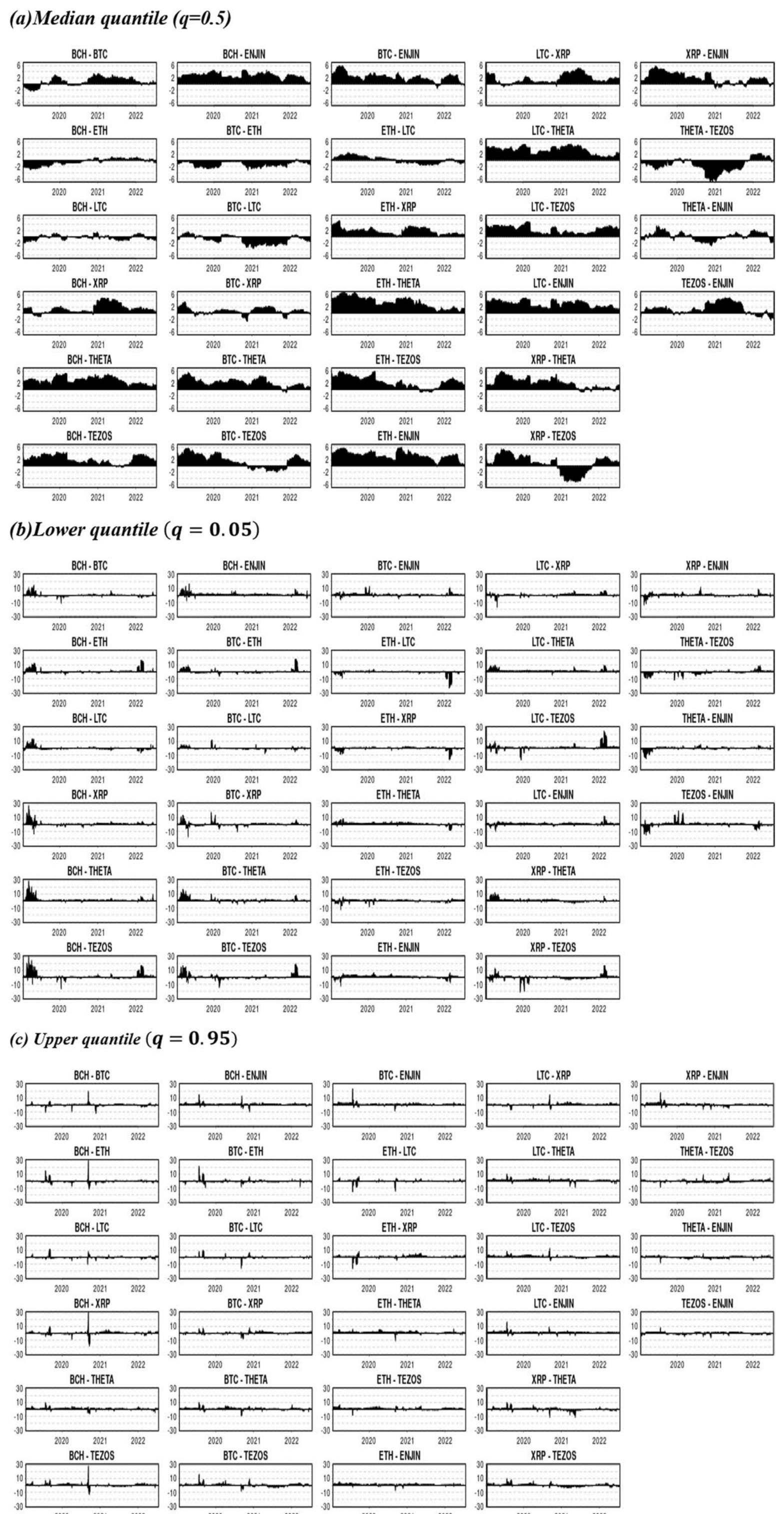


Fig. 6 Dynamic pairwise connectedness in different quantiles

Abbreviations

BCH	Bitcoin Cash
BTC	Bitcoin
DeFi	Decentralized finance
ENJIN	Enjin Ecosystem
ETH	Ethereum
GFEVD	Generalized forecast error variance decomposition
HE	Hedging effectiveness
LTC	Litecoin
NFT	Non-fungible tokens
QVAR	Quantile vector auto regression
TCI	Total connectedness index
TEZOS	Tezos platform
THETA	Theta network
TVP-VAR	Time-varying-parameter vector auto-regression
XRP	Ripple

Acknowledgements
This work was supported by FCT, I.P., the Portuguese national funding agency for science, research and technology, under the Project UIDB/04521/2020. The article was prepared within the framework of the Basic Research Program at HSE University.

Author contributions
WM: conceptualization, writing original draft. MG: methodology, writing original draft, writing-review and editing. KHAl-Y: data curation, data analysis and investigation. TT: methodology, writing-review and editing. SHK: supervision, data analysis, funding acquisition.

Funding
This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2022S1A5A2A01038422). This research is partly funded by the University of Economics Ho Chi Minh City, Vietnam.

Availability of data and materials
The datasets generated and/or analysed during the current study are not publicly available due to data security but are available from the corresponding author on reasonable request.

Declarations

Competing interests
There are no conflict of interest to declare.

Received: 12 January 2023 Accepted: 18 December 2023
Published online: 08 April 2024

References

Aharon DY, Demir E (2022) NFTs and asset class spillovers: lessons from the period around the COVID-19 pandemic. Finance Res Lett 47(A):102515. https://doi.org/10.1016/j.frl.2021.102515
Al-Yahyaee KH, Mensi W, Ko H-U, Caporin M, Kang SH (2021) Is the Korean housing market following Gangnam style? Empir Econ 61(4):2014–2072
Ando T, Greenwood-Nimmo M, Shin Y (2022) Quantile connectedness: modeling tail behavior in the topology of financial networks. Manag Sci 68(4):2377–3174. https://doi.org/10.1287/mnsc.2021.3984
Anscombe FJ, Glynn WJ (1983) Distribution of the kurtosis statistic b2 for normal samples. Biometrica 70(1):227–234
Ante L (2022) The non-fungible token (NFT) market and its relationship with bitcoin and ethereum. FinTech 1(3):216–224. https://doi.org/10.3390/fintech1030017
Antonakakis N, Chatziantoniou I, Gabauer D (2020a) Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J Risk Financ Manag 13(4):84. https://doi.org/10.3390/jrfm13040084
Antonakakis N, Cunado J, Filis G, Gabauer D, de Gracia FP (2020b) Oil and asset classes implied volatilities: investment strategies and hedging effectiveness. Energy Econ 91:104762. https://doi.org/10.1016/j.eneco.2020.104762
Bossman A, Gubareva M, Teplova T (2023) Asymmetric effects of geopolitical risk on major currencies: Russia-Ukraine tensions. Financ Res Lett 51:103440. https://doi.org/10.1016/j.frl.2022.103440
Cecchetti S, Schoenholtz K (2022) Let crypto burn. Financial Times. https://www.ft.com/content/ac058ede-80cb-4aa6-8394-941443eec7e3
Choi K-H, McIver RP, Ferraro S, Xu L, Kang SH (2021) Dynamic volatility spillover and network connectedness across ASX sector markets. J Econ Finance 45(4):677–691

Corbet S, Lucey B, Yarovaya L (2018) Datestamping the Bitcoin and Ethereum bubbles. Finance Res Lett 26:81–88. https://doi.org/10.1016/j.frl.2017.12.006

Corbet S, Goodell JW, Gunay S, Kaskaloglu K (2023) Are DeFi tokens a separate asset class from conventional cryptocurrencies? Ann Oper Res 322:609–630. https://doi.org/10.1007/s10479-022-05150-z

D'Agostino RB (1970) Transformation to normality of the null distribution of g1. Biometrika 57:679–681

Diebold FX, Yilmaz K (2012) Better to give than to receive: predictive directional measurement of volatility spillovers. Int J Forecast 28(1):57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold FX, Yılmaz K (2014) On the network topology of variance decompositions: measuring the connectedness of financial firms. J Econom 182(1):119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Dowling M (2022a) Is non-fungible token pricing driven by cryptocurrencies? Financ Res Lett 44:102097. https://doi.org/10.1016/j.frl.2021.102097

Dowling M (2022b) Fertile land: pricing non-fungible tokens. Finance Res Lett 44:102096. https://doi.org/10.1016/j.frl.2021.102096

Elliott G, Rothenberg TJ, Stock JH (1996) Efficient tests for an autoregressive unit root. Econometrica 64(4):813–836

Elsayed AH, Gozgor G, Yarovaya L (2022) Volatility and return connectedness of cryptocurrency, gold, and uncertainty: evidence from the cryptocurrency uncertainty indices. Finance Res Lett 47(B):102732. https://doi.org/10.1016/j.frl.2022.102732

Ferranti M (2022) Hedging sanctions risk: cryptocurrency in central bank reserves. Department of Economics, Harvard University, Working Paper. https://sites.google.com/view/matthewferranti/research

Fisher TJ, Gallagher CM (2012) New weighted promanteau statistics for time series goodness of fit testing. J Am Stat Assoc 107(498):777–787

Frye BL (2022) After copyright: Pwning NFTs in a clout economy. Columbia J Law Arts. https://doi.org/10.52214/jla.v45i3.10008

Gubareva M (2021) The impact of Covid-19 on liquidity of emerging market bonds. Finance Res Lett 41:101826. https://doi.org/10.1016/j.frl.2020.101826

Gubareva M, Borges R (2016) Typology for flight-to-quality episodes and downside risk measurement. Appl Econ 48(10):835–853. https://doi.org/10.1080/00036846.2015.1088143

Gubareva M, Bossman A, Teplova T (2023a) Stablecoins as the cornerstone in the linkage between the digital and conventional financial markets. N Am J Econ Finance. https://doi.org/10.1016/j.najef.2023.101979

Gubareva M, Umar Z, Teplova T, Vo XV (2023b) Flights-to-quality from EM bonds to safe-haven US Treasury securities: a time-frequency analysis. Emerg Mark Financ Trade 59(2):338–362. https://doi.org/10.1080/1540496X.2022.2103399

Hanif W, Ko HU, Pham L, Kang SH (2023) Dynamic connectedness and network in the high moments of cryptocurrency, stock, and commodity markets. Financ Innov 9(1):1–40

Horky F, Rachel C, Fidrmuc J (2022) Price determinants of non-fungible tokens in the digital art market. Finance Res Lett 48:103007. https://doi.org/10.1016/j.frl.2022.103007

Houser KA, Holden JT (2022) Navigating the non-fungible token. Utah Law Rev 5:1. https://doi.org/10.26054/0d-r48b-sq13

Jarque CM, Bera AK (1980) Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Econ Lett 6(3):255–259

Klement J (2022) Another tail wagging the dog. Klement on Investing. https://klementoninvesting.substack.com/p/another-tail-wagging-the-dog

Ko H, Lee J (2023) Non-fungible tokens: a hedge or a safe haven? Appl Econ Lett. https://doi.org/10.1080/13504851.2023.2182402

Koenker R, Bassett G (1978) Regression quantiles. Econometrica 46:33–50

Koop G, Pesaran MH, Potter SM (1996) Impulse response analysis in nonlinear multivariate models. J Econ 74(1):119–147

Kroner KF, Ng VK (1998) Modeling asymmetric movements of asset prices. Rev Financ 11(4):844–871. https://doi.org/10.2307/2331164

Kroner KF, Sultan J (1993) Time-varying distributions and dynamic hedging with foreign currency futures. J Financ Quant Anal 28(4):535–551

Kumar S, Patel R, Iqbal N, Gubareva M (2023) Interconnectivity among cryptocurrencies, NFTs, and DeFi: evidence from the Russia-Ukraine conflict. N Am J Econ Finance 68:101983. https://doi.org/10.1016/j.najef.2023.101983

Lim J, Won DH (2020) How Las Vegas' tourism could survive an economic crisis? Cities 100:102643

Londono JM (2019) Bad bad contagion. J Bank Finance 108:105652. https://doi.org/10.1016/j.jbankfin.2019.105652

Maouchi Y, Charfeddine L, El Montasser G (2022) Understanding digital bubbles amidst the COVID-19 pandemic: evidence from DeFi and NFTs. Finance Res Lett 47-A:102584. https://doi.org/10.1016/j.frl.2021.102584

Mazur M (2021) Non-fungible tokens (NFT). The Analysis of Risk and Return. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3953535

Mensi W, Al-Yahyaee KH, Vo VX, Kang SH (2021a) Dynamic spillover and connectedness between oil futures and European bonds. N Am J Econ Finance 56:101342

Mensi W, Hammoudeh S, Vo VX, Kang SH (2021b) Volatility spillovers between oil and equity markets and portfolio risk implications in the US and vulnerable EU countries. J Int Finan Markets Inst Money 75:101457

Mensi W, Vo XV, Kang SH (2021c) Multiscale spillovers, connectedness, and portfolio management among precious and industrial metals, energy, agriculture, and livestock futures. Resour Policy 74:102375

Mensi W, Rehman MU, Shafiullah M, Al-Yahyaee KH, Sensoy A (2021d) High frequency multiscale relationships among major cryptocurrencies: portfolio management implications. Financ Innov 7:75. https://doi.org/10.1186/s40854-021-00290-w

Mensi W, Vo XV, Kang SH (2021e) Precious metals, oil, and ASEAN stock markets: from global financial crisis to global health crisis. Resour Policy 73:102221

Mensi W, Maitra D, Vo XV, Kang SH (2021f) Asymmetric volatility connectedness among main international stock markets: A high frequency analysis. Brosa Istanb Rev 21(3):291–306

Mensi W, Vo XV, Kang SH (2021g) Upside downside multifractality and efficiency of Green bond. Finance Res Lett 43:101995
Mensi W, Sensoy A, Vo XV, Kang SH (2022a) Pricing efficiency and asymmetric multifractality of major asset classes before and during COVID-19 crisis. N Am J Econ Finance 62:101773
Mensi W, Al SRM, Vo XV, Kang SH (2022b) Multiscale dependence, spillovers, and connectedness between precious metals and currency markets: a hedge and safe-haven analysis. Resour Policy 77:102752
Mensi W, Gubareva M, Ko H-U, Vo XV, Kang SH (2023a) Tail spillover effects between cryptocurrencies and uncertainty in the gold, oil, and stock markets. Financ Innov 9:92. https://doi.org/10.1186/s40854-023-00498-y
Mensi W, El Khoury R, Ali SRM, Vo XV, Kang SH (2023b) Quantile dependencies and connectedness between the gold and cryptocurrency markets: effects of the COVID-19 crisis. Res Int Bus Financ 65:101929
Mohan V (2022) Automated market makers and decentralized exchanges: a DeFi primer. Financ Innov 8(1):20. https://doi.org/10.1186/s40854-021-00314-5
Naeem MA, Farid S, Yousaf I, Kang SH (2023) Asymmetric efficiency in petroleum markets before and during COVID-19. Resour Policy 86:104194
Olofsson P, Råholm A, Uddin GS, Troster V, Kang SH (2021) Ethical and unethical investments under extreme market condtions. Int Rev Financ Anal 78:101951
Pesaran HH, Shin Y (1998) Generalized impulse response analysis in linear multivariate models. Econ Lett 58(1):17–29
Raham ML, Hedström A, Uddin GS, Kang SH (2021) Qunatile relationship between Islamic and non-Islamic equity markets. Pac Basin Finance J 68:101586
Rouatbi W, Demir E, Kizys R, Zaremba A (2021) Immunizing markets against the pandemic: COVID-19 vaccinations and stock volatility around the world. Int Rev Financ Anal 77:101819. https://doi.org/10.1016/j.irfa.2021.101819
Taleb NN (2021) Bitcoin, currencies, and fragility. Quant Finance 21(8):1249–1255. https://doi.org/10.1080/14697688.2021.1952702
Tiwari AK, Abakah EJA, Gabauer D, Dwumfour RA (2022) Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: implications for hedging and investments strategies. Glob Financ J 51:100692. https://doi.org/10.1016/j.gfj.2021.100692
Ugolini A, Reboredo JC, Mensi W (2023) Connectedness between DeFi, cryptocurrency, stock, and safe-haven assets. Financ Res Lett 53:103692. https://doi.org/10.1016/j.frl.2023.103692
Umar Z, Gubareva M (2020) A time-frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets. J Behav Exp Financ 28:100404. https://doi.org/10.1016/j.jbef.2020.100404
Umar Z, Gubareva M, Teplova T, Tran DK (2022a) Covid-19 impact on NFTs and major asset classes interrelations: insights from the wavelet coherence analysis. Finance Res Lett 47(B):102725. https://doi.org/10.1016/j.frl.2022.102725
Umar Z, Abrar A, Zaremba A, Teplova T, Vo XV (2022b) The return and volatility connectedness of NFT segments and media coverage: fresh evidence based on news about the COVID-19 pandemic. Finance Res Lett 49:103031. https://doi.org/10.1016/j.frl.2022.103031
Umar Z, Yousaf I, Gubareva M, Vo XV (2022c) Spillover and risk transmission between the term structure of the US interest rates and Islamic equities. Pac Basin Financ J 72:101712. https://doi.org/10.1016/j.pacfin.2022.101712
Umar Z, Usman M, Choi S-Y, Rice J (2023) Diversification benefits of NFTs for conventional asset investors: evidence from CoVaR with higher moments and optimal hedge ratios. Res Int Bus Finance. https://doi.org/10.1016/j.ribaf.2023.101957
Wang Y (2022) Volatility spillovers across NFTs news attention and financial markets. Int Rev Financ Anal 83:102313. https://doi.org/10.1016/j.irfa.2022.102313
Wang Y, Horky F, Baals LJ, Lucey BM, Vigne SA (2022) Bubbles all the way down? Detecting and date-stamping bubble behaviours in NFT and DeFi markets. J Chin Econ Bus Stud 20(4):415–436. https://doi.org/10.1080/14765284.2022.2138161
Yousaf I, Yarovaya L (2022) Static and dynamic connectedness between NFTs, Defi and other assets: portfolio implication. Glob Financ J 53:100719. https://doi.org/10.1016/j.gfj.2022.100719
Yousaf I, Nekhili R, Gubareva M (2022) Linkages between DeFi assets and conventional currencies: evidence from the COVID-19 pandemic. Int Rev Financ Anal 81:102082. https://doi.org/10.1016/j.irfa.2022.102082
Yousaf I, Gubareva M, Teplova T (2023a) Connectedness of non-fungible tokens and conventional cryptocurrencies with metals. N Am J Econ Finance 68:101995. https://doi.org/10.1016/j.najef.2023.101995
Yousaf I, Qureshi S, Qureshi F, Gubareva M (2023b) Connectedness of COVID vaccination with economic policy uncertainty, oil, bonds, and sectoral equity markets: evidence from the US. Ann Oper Res. https://doi.org/10.1007/s10479-023-05267-9
Zhang Z, Sun Q, Ma Y (2022) The hedge and safe haven properties of non-fungible tokens (NFTs): evidence from the nonlinear autoregressive distributed lag (NARDL) model. Finance Res Lett 50:103315. https://doi.org/10.1016/j.frl.2022.103315

Publisher's Note