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The Dynamics of Connectivity between Traditional Cryptocurrencies and NFTs: Validation of the Connectivity Model by Quantiles and Frequencies

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Abstract:

Purpose: *This paper pioneers exploring the relationship between cryptocurrencies, considering the case of non-fungible tokens (NFTs) and traditional cryptocurrencies*
Design/Methodology/Approach: *The analysis is performed through an innovative TVP-VAR frequency connectedness approach, revealing a substantial level of dynamic integration and return transmission among cryptocurrencies systems.*
Findings: *Our findings are multifaceted. Firstly, that there is higher total connectedness in the bearish and bullish market conditions compared to normal conditions. Secondly, the degree of connectedness is even stronger during tranquil and turbulent times such as the Covid-19 pandemic and the Russian-Ukrainian war. Thirdly, the network's net transmission behavior is predominantly by the short-term dynamics for NFT and by the long-term dynamics for Conventional cryptocurrencies, and assets' roles as net-transmitter and net-receiver can change over time.*
Practical Implications: *These findings inform investors, traders, and portfolio managers to prioritize risk management during high-risk periods, such as COVID-19 and the Russian-Ukrainian conflict, as crises involve non-diversifiable systematic risks, demanding careful risk mitigation.*
Originality/Value: *One of the main challenges of cryptocurrencies is determining the nature of the dynamics of their connectivity. The originality and the value of this research is to investigate whether cryptocurrencies evolve in a similar manner to each other.*

Keywords: *COVID-19 pandemic, TVP-VAR, Russian-Ukrainian conflict, NFT, cryptocurrencies, frequency connectedness.*

JEL Classification: *G01, G10, C32, Q02.*

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1. Introduction

Cryptocurrencies have emerged as a revolutionary force in the financial landscape, disrupting traditional systems and challenging the concept of centralized control. These digital assets, powered by blockchain technology, have gained immense popularity and adoption in recent years.

However, the dynamic nature of cryptocurrencies extends beyond their individual existence, as they are closely interconnected within the digital economy. This study explores the concept of dynamic connectivity among cryptocurrencies. By understanding the interconnected nature of cryptocurrencies, we can gain insights into their behavior, implications, and potential to reshape the financial world Aspembitova (2021), Almeida (2023), and Poyser (2018).

In recent years, we have witnessed a significant increase in innovation in the financial services sector. This development has been driven by innovative means to meet consumer demands, leveraging digital systems. Innovations such as peer-to-peer lending, crowdfunding, and supply chain financing have reshaped the landscape of the financial sector. Cryptocurrency has become an essential component of what is now known as the financial technology industry (Thalassinos and Hakim, 2023a).

Traditional business models in the financial services market are being challenged by financial technologies, which are highly responsive to consumer needs. This rapid innovation leads to significant disruptions, creating uncertainty for many financial institutions (Thalassinos and Hakim, 2023b).

Investors have extensively debated the benefits of cryptocurrencies for portfolios and the fluctuation of their prices in the market. It is evident that cryptocurrencies are highly volatile, but this has not deterred investors from pouring substantial amounts of capital into crypto investments, which can yield significant returns or catastrophic losses Bunjaku *et al.* (2017) and Quan *et al.* (2023).

One of the main challenges of cryptocurrencies is determining the nature of the dynamics of their connectivity. The objective of this research is to investigate whether cryptocurrencies evolve in a similar manner to each other.

Indeed, the conventional cryptocurrencies and new digital currencies, like Non-Fungible Tokens (NFTs) have significantly contributed to the recent expansion of the digital market Dowling, (2022b). NFTs are created on blockchain platforms like Ethereum, offering a digital proof of ownership Chalmers *et al.* (2022). Essentially, NFTs serve as proof of ownership for distinct digital assets, often manifesting as images.

Symitsi and Chalvatzis (2018) analyzed the connection between energy and technology bitcoins. They identified a relationship between these two markets. They employed an asymmetric multivariate VAR-GARCH model to study the training effects between bitcoin and companies in the energy sector. They discovered unilateral impacts on returns and volatility, as well as bidirectional shock influences, demonstrating implications for portfolio management.

Bouri *et al.* (2019) analyzed the connections between cryptocurrencies, focusing on the relationship between volatility measures and updating transient and current causality. The analysis of contagion effects is an important tool for observing how certain financial assets are linked during extreme events such as crises or bubbles.

They indicated the explosiveness of prices in major cryptocurrencies and noted that all studied cryptocurrencies are characterized by multiple explosiveness. They determined whether the explosiveness of cryptocurrency returns can lead to the explosiveness of other cryptocurrencies. The results highlight multidirectional explosiveness behavior that does not necessarily follow a pattern from larger to smaller.

Shahzad *et al.* (2019) studied the integration of contagion risk in cryptocurrency. The results contributed to a better understanding of risk factors by emphasizing the role of flawed contagion measures in the cryptocurrency pricing model. This suggests the need to incorporate it into the application of pricing models, as it contains precise information for risk management and portfolio construction decision-making.

NFTs, or Non-Fungible Tokens, are unique asset tokens. Unlike traditional cryptocurrencies like Bitcoin, they cannot be exchanged for one another. Since each NFT is distinct, they all have different values. NFTs are frequently used to represent digital objects such as music, art, and other assets. When integrating NFTs, one trades the asset itself, whereas in cryptocurrency trading, one trades the underlying values of the assets.

The primary purpose of an NFT is to establish ownership proof of a digital asset. NFTs can be used to represent items such as audio files, digital photos, and other digital context assets.

Starting from early 2021, Bitcoin not only doubled its previous all-time high but also experienced a significant surge in Ethereum. This attracted investors to the cryptocurrency markets, with NFT and DeFi emerging as mainstream buzzwords. The markets for NFTs and DeFis expanded rapidly. Concurrently, amidst the broader economic instability that began in December 2021, prices of digital assets followed a downward trajectory.

In the second week of May 2022, cryptocurrency enthusiasts witnessed a market collapse, evolving into a meltdown reminiscent of the onset of the 2007-2008 global financial crisis. The immediate trigger was the collapse of Terra, experiencing a 96%

fall in a single day. Likewise, Bitcoin and Ethereum saw declines of 60% and 30%, respectively, from their peak in November 2021.

On November 8, 2022, cryptocurrencies experienced a decline after the cryptocurrency exchange FTX filed for bankruptcy following the withdrawal of its rival, Binance, the world's largest crypto exchange, from a deal to acquire the company.

Research on NFT assets has been relatively limited thus far. Some studies have delved into the correlation between NFTs and major cryptocurrencies. Employing wavelet coherence analysis, Pinto-Gutiérrez *et al.* (2022) propose that investor interest in NFTs tends to increase following rises in the returns of both Bitcoin and Ether. Apostu *et al.* (2022) discovered a causal relationship where the price of NFTs influenced the price of Ethereum.

Nakavachara and Saengchote (2022) observed that transactions settled in Sandbox's native utility token resulted in investors paying 3.4% more compared to Ethereum (in effective USD prices). Utilizing wavelet-based quantile causality analysis, Qiao *et al.* (2023) indicated a distinct spillover relationship, with yield farming tokens exhibiting a connection to metaverse-related NFTs as well as other DeFi tokens.

Alawadhi and Alshamali (2022) found that DeFi assets show relatively little connection to traditional cryptocurrency markets.Our research motivation stems from these urgent concerns of market participants and the corresponding gaps in the literature.

To fill the research gaps and provide respective references and economic implications for investors, portfolio managers, and policymakers, we incorporate cryptocurrencies, considering the case of non-fungible tokens (NFTs) and traditional cryptocurrencies, through an innovative TVP-VAR frequency connectedness approach, revealing a substantial level of dynamic integration and return transmission among cryptocurrencies systems. Moreover, it acknowledges the potential influence of the Covid-19 pandemic and the ongoing Russia-Ukraine conflict.

Within this framework, the global daily dataset used in the study covers the time span from January 4, 2016, to January 5, 2023. To examine the propagation of classic cryptocurrencies and NFTs across various quantiles and frequency particularly in the context of unprecedented and heterogeneous events like the the Covid-19 pandemic and the Russia-Ukraine conflict.

Therefore, our contribution acts as an addition to this area of study. More specifically, we expand the current body of literature in three significant areas. Firstly, we examine the relationship between cryptocurrencies, considering the case of non-fungible tokens (NFTs) and traditional cryptocurrencies, through an innovative TVP-VAR frequency connectedness approach.

Second, this paper offers intriguing analysis on the relationship between cryptocurrencies. This analysis of spillover strengths and directions allows market participants to identify the source of contagion.

Third, we elucidate policy implications and economic utility based on our empirical findings.

The next section describes the methodology and data. The third section presents the empirical analysis. Lastly, we conclude the study.

2. Data Sources and Methodology

2.1 Data Sources and Description

We have compiled closing prices within the timeframe from November 2nd, 2021, to January 5, 2023, encompassing both Non-fungible tokens (NFTs) and traditional cryptocurrencies as follows:

Five NFTs: Metaverse, UniclyCryptoPunks (UPUNK), Sandbox (SAND), NFTLaunch (NFTL) and xNFT Protocol (XNFT).

Four traditional cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), BNB (BNB) and FTX Token (FTT).

All the dataset was sourced from www.coinmarketcap.com. Covering not only the pre-COVID-19 period, but also the period of the spread of the COVID-19 pandemic due to global containment, as well as the period of the Russo-Ukrainian war. To compute the returns, we utilized the formula Rt = ln(Pt/Pt-1), where Pt represents the price on the current day.

According to the descriptive statistics of both NFT and traditional cryptocurrencies, it is evident that xNFT (FTT) exhibits the highest mean return of -0.009 (respectively, -0.010). Nevertheless, the mean returns for both categories of cryptocurrencies are negative. Notably, Play (FTT) emerges as the asset with the greatest risk at 0.020 (or 0.012).

In terms of distribution attributes, the daily returns of conventional cryptocurrencies display negative skewness, indicating a leftward asymmetry. Conversely, the daily returns of NFTs exhibit positive skewness, indicating a rightward asymmetry.

From this, it can be deduced that the exchange of net returns is a prevalent occurrence within the overall market. Therefore, it becomes crucial to investigate both highly positive and negative spillover effects and uncover any disparities that might exist among these spillovers. It's worth mentioning that the return distributions display leptokurtic tendencies during different sub-periods.

The Jarque-Bera statistics suggest that the daily returns do not adhere to a normal distribution, being statistically significant at the 1% level. Across all markets, the Ljung-Box test (Q(20)) employed to assess the autocorrelation of the return series indicates the presence of serial correlation within the residual series.

These characteristics are visually illustrated in Figure 1 and Figure 2, which highlights periods of heightened volatility, implying a robust correlation or shared movements between the variables**.**

2.2 Methodology

In order to examine how the quantile spillover mechanism across various financial markets, we employed the quantile connectedness method developed by, Bouri et al. (2021), Chatziantoniou (2021b) and Chatziantoniou (2022). To begin with, we utilized a quantile vector autoregression model called QVAR(p) to estimate the total connectedness measure. The QVAR(p) model can be summarized as follows:

$$\mathbf{x}_t = \boldsymbol{\mu}_t(\tau) + \Phi_1(\tau)\mathbf{x}_{t-1} + \Phi_2(\tau)\mathbf{x}_{t-2} + \cdots + \Phi_p(\tau)\mathbf{x}_{t-p} + \boldsymbol{u}_t(\tau) \qquad (1)$$

The variables $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-j}$ are represented as $N\times1$ dimensional vectors in the QVAR model. The parameter τ takes values within the range of [0, 1], and p is the lag length of the model. (τ) is a $N\times1$ dimensional vector that denotes the conditional mean, $\boldsymbol{\Phi}j$ (τ) is a $N\times N$ dimensional matrix of QVAR coefficients, and $\boldsymbol{u}_t(\tau)$ is a $N\times1$ dimensional error vector with an $N\times N$ dimensional error variance-covariance matrix, $\boldsymbol{\Sigma}(\tau)$.

To calculate the forward M-step Generalized Forecast Error Variance Decomposition (GFEVD), the Eq.(1) is transformed into QVMA(∞) by applying Wold's theorem. The QVMA(∞) is expressed as the following equation:

$$\mathrm{x}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \Phi_j(\tau)\mathbf{x}_{t-j} + \boldsymbol{u}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \Psi_i(\tau)\boldsymbol{u}_{t-i}.$$

The subsequent phase includes the computation of the generalized forecast error variance decomposition (GFEVD) using a forecast horizon denoted as H. This is an essential element of the connectedness approach, as outlined by Koop *et al.* (1996) and Pesaran and Shin (1998). This calculation provides insights into the influence of series j on variable i, specifically in terms of their forecast error variances.

$$\theta_{ij}(\mathrm{H}) = \frac{(\Sigma(\tau))_{jj}^{-1} \sum_{\mathrm{h}=0}^{\mathrm{H}-1} \left((\Psi_h(\tau)\Sigma(\tau))_{ij} \right)^2}{\sum_{\mathrm{h}=0}^{\mathrm{H}} \left(\Psi_h(\tau)\Sigma(\tau)\Psi_h'(\tau) \right)_{ii}} \tag{2}$$

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{k=1}^{N} \theta_{ij}(H)} \tag{3}$$

The θ_{ij} (H) rows lack a sum of one, necessitating normalization by the row sum to obtain $\tilde{\theta}_{ij}$. This normalization ensures that the row sum equals unity, signifying the impact of a shock in series i on both the series itself and all other series. Consequently, we derive the following identities.

$$\sum_{\mathrm{i}=1}^{\mathrm{N}} \tilde{\theta}_{\mathrm{ij}}(\mathrm{H})=1 \text{ and } \sum_{j=1}^{N} \sum_{i=1}^{N} \tilde{\theta}_{ij}(H) = N$$

The approach used to define the GFEVD based connectedness measures is based on Diebold and Yilmaz's (2012) method and is described below. Initially, we commence with the pairwise connectivity in the following manner:

$$NPDC_{ij}(\mathrm{H}) = \tilde{\theta}_{ij}(\mathrm{H}) - \tilde{\theta}_{ji}(\mathrm{H}). \tag{4}$$

If $NPDC_{ij}(\mathrm{H}) > 0$ $(NPDC_{ij}(\mathrm{H}) < 0$, It indicates that series j has a more (lesse) impact on series i than the other way around.

The total directional connectedness to other series measures how much a shock in series i impacts all other series j.

$$TO_i(H) = \sum_{i=1, i \neq j}^{N} \tilde{\theta}_{ji}(\mathrm{H}) \tag{5}$$

The total directional connectedness from other series measures the extent to which series i is affected by shocks in all other series j.

$$FROM_i(\mathrm{H}) = \sum_{i=1, i \neq j}^{N} \theta_{ij}(\mathrm{H}) \tag{6}$$

To investigate the NET impact between the To and From measures, the directional connectedness net measure is defined as follows:

$$NET_i(H) = TO_i(\mathrm{H}) - FROM_i(\mathrm{H}) \tag{7}$$

This disparity can be interpreted as the net impact of series i on the predefined network.

When $NETi > 0$ ($NETi < 0$), it means that series i has a greater (lesser) influence on all other series j compared to how much it is influenced by them. As a result, it is categorized as a net transmitter (receiver) of shocks.

The computation of the overall total connectedness index (TCI), which evaluates the degree of interconnectedness within the network. A higher value of TCI signifies increased market risk, while a lower value indicates the opposite.

The degree of network interconnectedness is determined by the overall total connectedness index (TCI), which can be calculated using the following formula:

$$TCI(H) = N^{-1}\sum_{i=1}^{N} TO_i(H) = N^{-1}\sum_{i=1}^{N} FROM_i(H) \tag{8}$$

To examine connectivity in the time domain, we evaluate connectivity in the frequency domain. We use the spectral decomposition method of Stiassny (1996). First, we examine the frequency response function, expressed as $\boldsymbol{\Psi}\ (e^{-i\omega})= \sum_{\mathrm{h}=0}^{\infty} e^{-iwh}\,\Psi_{\mathrm{h}}$,where $i = \sqrt{-1}$ and ω is the frequency. Next, we analyze the spectral density of $x_t$at a specific frequency ω. This can be obtained by applying the Fourier transform to QVMA(∞):

$$\boldsymbol{S}_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h})\, e^{-iwh} = \boldsymbol{\Psi}\left(e^{-i\omega h}\right)\sum\nolimits_t \boldsymbol{\Psi}'\left(e^{+i\omega h}\right) \tag{9}$$

Likewise, frequency-based generalized prediction error variance decomposition (GFEVD) is a fusion of spectral density and GFEVD. GEVD should be normalized in the frequency domain, similar to the requirement for time domain normalization. He is represented by:

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1}\left|\sum_{h=0}^{\infty}\left(\boldsymbol{\Psi}(\tau)(e^{-iwh})\Sigma(\tau)\right)_{ij}\right|^2}{\sum_{h=0}^{\infty}(\boldsymbol{\Psi}(e^{-iwh})\Sigma(\tau)\boldsymbol{\Psi}(\tau)(e^{iwh}))_{ii}} \tag{10}$$

$$\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^{N}\theta_{ij}(\omega)} \tag{11}$$

The expression $\tilde{\theta}ij\ (\omega)$ refers to the fraction of the spectrum of the ith series at a given frequency ω that is attributable to the effect on the jth series. This measurement is often called an intra-frequency indicator. To assess connectivity over short and long time scales, we do not focus on individual frequencies but aggregate all frequencies within a specific range, called d= (a, b): a, $b \in (-\pi, \pi)$, $a<b$:

$$\tilde{\theta}ij\ (d) = \int_a^b \tilde{\theta}ij\ (w)dw \tag{12}$$

From this stage we have the opportunity to calculate connectivity measures similar to those mentioned previously and can be evaluated using the same methods. However, in this case these measures are called frequency composite measures. They provide insights into the propagation of effects within a specific frequency range (represented by d), which can be explained in a similar way :

$$NPDC_{ij}(d) = \tilde{\theta}_{ij}(d) - \tilde{\theta}_{ji}(d) \tag{13}$$

$$TO_i(d) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ji}(d) \tag{14}$$

$$FROM_i(d) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ij}(d) \tag{15}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{16}$$

$$TCI(d) = N^{-1}\sum_{i=1}^{N} TO_i(d) = N^{-1}\sum_{i=1}^{N} FROM_i(d) \tag{17}$$

In our analysis, we define two frequency bands that capture short-term and long-term dynamics. The first range $d1$ = (π/5, π) covers the range from 1 to 5 days, while the second range $d2$ = (0, π/5] covers the time range from 6 days to infinity. Therefore: NPDCij(d1), $TOi(d1)$, $FROMi(d1)$, $NETi(d1)$, and $TCI(d1)$ represent the short-term general direction connectivity with other short-term general direction connectivity of others, short-term network overall direction connectivity or short-term overall Connectivity index.

On the flip side, $NPDC_{ij}(d2)$, $TO_i(d2)$, $FROM_i(d2)$, $NET_i(d2)$, and $TCI(d2)$) illustrate prolonged total directional connectedness towards others, prolonged total directional connectedness from others, prolonged net total directional connectedness, and prolonged total connectedness index, respectively. Additionally, we establish a correlation between the frequency-domain measures proposed by Baruník and Křehlík (2018) and the time-domain measures introduced by Diebold and Yılmaz (2009; 2012; 2014).

$$NPDC_{ij}(H) = \cdot \sum_{d} NPDC_{ij}(d) \tag{18}$$

$$TO_i(H) = \sum_d (\mathrm{d}) \cdot TO_i(d) \tag{19}$$

$$FROM_i(d) = \sum_d (\mathrm{d}) \cdot FROM_i(d) \tag{20}$$

$$NET_i(H) = \sum_d (\mathrm{d}) \cdot NET_i(d) \tag{21}$$

$$TCI(H) = \sum_d (\mathrm{d}) \cdot TCI(d) \tag{22}$$

In simpler terms, the total connectedness metrics can be obtained by consolidating the frequency connectedness metrics. It's important to emphasize that all these metrics are computed using a specific quantile, identified as τ.2.

3. Empirical Results and Discussion

In this research, we initially delve into examining the evolving static and dynamic nature of spillovers between the NFT cryptocurrency system and the conventional cryptocurrency system. These spillover effects are evaluated at the conditional median (τ = 0.5). This reference point will be utilized to contrast the connectedness findings in periods characterized by bearish and bullish market conditions, specifically at (τ = 0.05) and (τ = 0.95).

Additionally, our second objective is to explore the time-varying dynamics that shed light on the mechanisms of propagation, considering both time and frequency dimensions, between NFT and between conventional cryptocurrencies. Table 1 presents the summery statistics of the variables.

Table 1. *Summary statistics*

Panel A : NFT					
	PLAY	**UPUNK**	**SAND**	**NFTL**	**xNFT**
Mean	-0.006	-0.003	-0.004	-0.007	-0.009**
	(0.400)	(0.209)	(0.243)	(0.111)	(0.038)
Variance	0.020***	0.003***	0.004***	0.007***	0.008***
Skewness	0.237**	-0.568***	0.488***	0.929***	1.447***
	(0.044)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	16.003***	6.450***	4.327***	11.830***	13.745***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

JB	4592.256***	768.531***	352.593***	2569.340***	3535.094***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel B : Conventional cryptocurrencies				
	BTC	**ETH**	**BNB**	**FTT**
Mean	-0.003*	-0.003*	-0.002*	-0.010*
	(0.062)	(0.177)	(0.403)	(0.070)
Variance	0.001***	0.002***	0.002***	0.012***
Skewness	-0.580***	-0.381***	-0.576***	-12.878***
	(0.000)	(0.001)	(0.000)	(0.000)
Ex.Kurtosis	4.180***	2.763***	4.822***	226.389***
	(0.000)	(0.000)	(0.000)	(0.000)
JB	337.073***	147.184***	440.370***	930145.789***
	(0.000)	(0.000)	(0.000)	(0.000)

Note: **, **, and *** represent significance at 10%, 5%, and 1%, respectively. Values in parentheses indicate the probability of significance.*
Source: *Own study.*

3.1 Analysis of the Connectivity Among Assets

3.1.1 Conditional median spillovers

The connectedness measure can be computed at the conditional median (τ = 0.5). Subsequently, this permits a comparison of connectedness outcomes in the higher and lower extremities. It's important to recall that the empirical findings are derived using the method introduced by Diebold and Yilmaz (2012; 2014). The estimation outcomes of the tail connectedness measures for the median quantile are presented in Table 2. It is noteworthy that the connectedness measue at the conditional median for NFTs demonstrates a value of 31.95% (respectively, 56.44%) for digital currencies.

Overall, over the entire study duration, net spillovers are negative exclusively for PLAY and NFTL (Table 2 and Figure 5), as well as for BNB and FTT (Table 2 and Figure 6). This observation implies that PLAY, NFTL, BNB, and FTT predominantly act as recipients of return spillovers.

Conversely, net spillovers are positive for PLAY, SAND, and NFTL (Table 2 and Figure 5), along with BTC and ETH (Table 2 and Figure 6). This indicates that PLAY, SAND, NFTL, BTC, ETH, and BSE primarily function as generators or sources of return spillovers.

3.1.2 Connectedness Measures at Lower (τ=0.05) and Upper (τ=0.95) Quantiles

The results from estimating the connectedness measures at the extreme upper and lower quantiles are displayed in Tables 3 and 4. Notably, scrutinizing the quantile-connectedness across both upper and lower tails serves to enhance comprehension and identification of exceptional negative and positive shocks. It is intriguing to observe that the values of connectedness measures appear to surpass those found for the median quantile in the cases of both right and left tails of the conditional distribution.

Particularly noteworthy is that at the lower (and respectively upper) quantile, the comprehensive return spillover indices for NFTs seem to amount to 71.17% (and 71.03% respectively). Conversely, for digital currencies, at the lower (and respectively upper) quantile, the overall return spillover indices appear to be approximately 73.56% (and 68.21% respectively).

Table 2. *Spillovers measures based on the quantile VAR (median quantile τ=0.5)*

Panel A: NFT						
	PLAY	**UPUNK**	**SAND**	**NFTL**	**xNFT**	**FROM**
PLAY	67.99	4.11	15.34	8.38	4.18	32.01
UPUNK	5.37	74.13	8.65	8.43	3.43	25.87
SAND	15.02	7.25	56.76	17.43	3.54	43.24
NFTL	8.89	7.23	18.43	60.91	4.54	39.09
xNFT	5.72	3.58	4.50	5.74	80.46	19.54
TO	35.01	22.17	46.92	39.98	15.69	159.76
Inc.Own	103.00	96.29	103.68	100.89	96.14	cTCI/TCI
NET	3.00	-3.71	3.68	0.89	-3.86	39.94/31.95
NPT	3.00	1.00	4.00	2.00	0.00	
Panel B : Conventional cryptocurrencies						
	BTC	**ETH**	**BNB**	**FTT**		**FROM**
BTC	42.11	33.29	12.44	12.17		57.89
ETH	32.70	41.53	13.35	12.43		58.47
BNB	16.53	18.37	43.16	21.94		56.84
FTT	16.24	17.34	18.97	47.46		52.54
TO	65.47	69.00	44.75	46.53		225.74
Inc.Own	107.57	110.52	87.91	93.99		cTCI/TCI
NET	7.57	10.52	-12.09	-6.01		75.25/56.44
NPT	2.00	3.00	0.00	1.00		

Note: **, **, and *** represent significance at 10%, 5%, and 1%, respectively. Values in parentheses indicate the probability of significance.*
Source: *Own study.*

Table 3. *Spillovers measures based on the quantile VAR (lower quantile τ=0.05)*

Panel A: NFT						
	PLAY	**UPUNK**	**SAND**	**NFTL**	**xNFT**	**FROM**
PLAY	29.51	16.69	20.65	18.15	14.99	70.49
UPUNK	16.76	28.65	20.04	19.45	15.09	71.35
SAND	19.29	17.38	27.31	20.45	15.58	72.69

NFTL	17.52	17.77	21.47	27.26	15.97	72.74
xNFT	16.23	17.06	17.81	17.47	31.44	68.56
TO	69.80	68.91	79.98	75.51	61.63	355.83
Inc.Own	99.31	97.56	107.28	102.78	93.07	cTCI/TCI
NET	-0.69	-2.44	7.28	2.78	-6.93	88.96/71.17
NPT	2.00	1.00	4.00	3.00	0.00	
Panel B : Conventional cryptocurrencies						
	BTC	**ETH**	**BNB**	**FTT**		**FROM**
BTC	25.38	24.55	23.12	26.95		74.62
ETH	24.12	25.67	23.03	27.17		74.33
BNB	23.42	24.33	24.71	27.54		75.29
FTT	23.05	23.42	23.54	29.99		70.01
TO	70.58	72.31	69.69	81.66		294.25
Inc.Own	95.96	97.98	94.41	111.65		cTCI/TCI
NET	-4.04	-2.02	-5.59	11.65		98.08/73.56
NPT	1.00	2.00	0.00	3.00		

Note: **, **, and *** represent significance at 10%, 5%, and 1%, respectively. Values in parentheses indicate the probability of significance.*
Source: *Own study.*

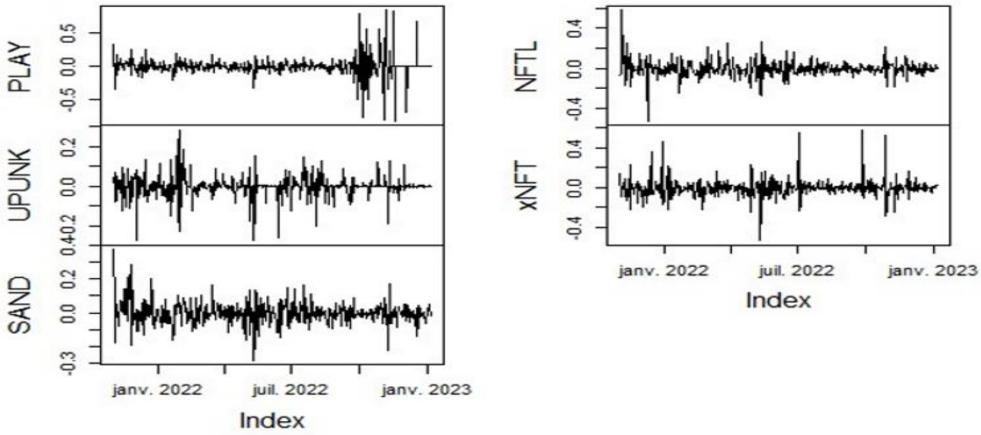
Table 4. *Spillovers measures based on the quantile VAR (upper quantile τ=0.95)*

Panel A: NFT						
	PLAY	UPUNK	SAND	NFTL	xNFT	FROM
PLAY	30.23	16.98	18.79	19.23	14.78	69.77
UPUNK	18.45	29.80	16.94	20.12	14.69	70.20
SAND	20.86	17.61	26.00	21.43	14.10	74.00
NFTL	18.42	19.18	19.60	27.65	15.15	72.35
xNFT	17.39	16.12	16.75	18.56	31.18	68.82
TO	75.12	69.89	72.08	79.34	58.71	355.15
Inc.Own	105.36	99.69	98.08	106.99	89.89	cTCI/TCI
NET	5.36	-0.31	-1.92	6.99	-10.11	88.79/71.03
NPT	3.00	2.00	1.00	4.00	0.00	
Panel B : Conventional cryptocurrencies						
	BTC	ETH	BNB	FTT		FROM
BTC	29.50	31.78	19.03	19.69		70.50
ETH	25.06	33.73	19.78	21.44		66.27
BNB	22.21	27.00	28.41	22.38		71.59
FTT	20.18	25.79	18.50	35.52		64.48
TO	67.45	84.57	57.31	63.51		272.84
Inc.Own	96.95	118.30	85.73	99.03		cTCI/TCI
NET	-3.05	18.30	-14.27	-0.97		90.95/68.21
NPT	2.00	3.00	0.00	1.00		

Note: **, **, and *** represent significance at 10%, 5%, and 1%, respectively. Values in parentheses indicate the probability of significance.*
Source: *Own study.*

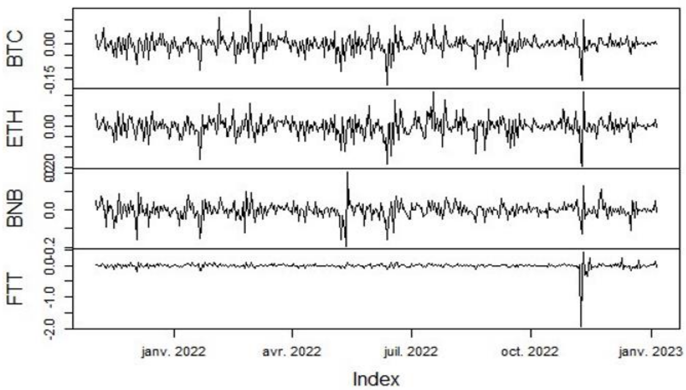
This indicates that the overall interconnectedness between returns and volume exhibits its highest values at the extreme upper and lower quantiles, while showing the lowest values at the median quantile (Figure 3 and Figure 4). These findings underscore that the connectedness in both the left and right tails is elevated, indicating that return interconnectedness becomes more pronounced with larger shocks. Interestingly, these outcomes align with the conclusions of a prior study conducted by Mensi *et al.* (2023).

Figure 1. *Time-varying price returns of NFT in the entire time frame of the study*



Source: *Own study.*

Figure 2. *Time-varying price returns of conventional cryptocurrencies in the entire time frame of the study*

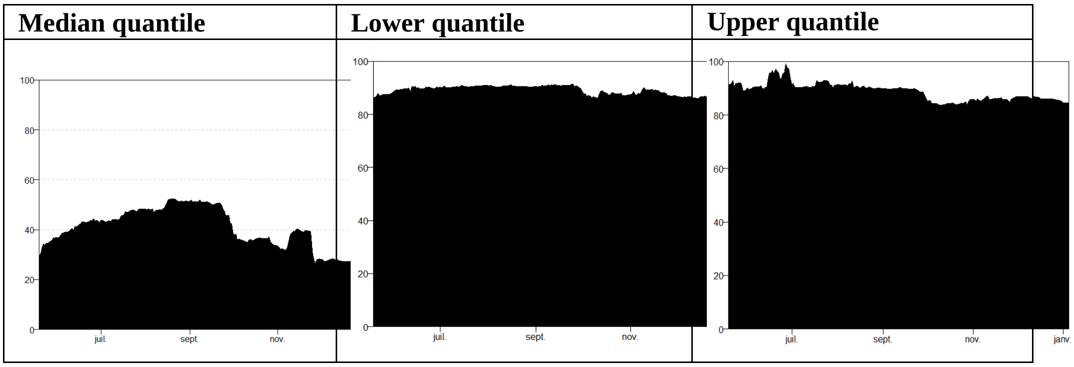


Source: *Own study.*

Additionally, the outcomes demonstrate asymmetric tail connectedness between NFTs and between digital currencies. As a result, we substantiate the presence of spillover effects between returns of NFTs and returns of digital currencies. Consequently, investors are encouraged to devise distinct strategies during periods of extreme bullish and bearish market conditions, distinct from normal conditions. This further aligns our findings with the conclusions reached by Naeem *et al.* (2020)

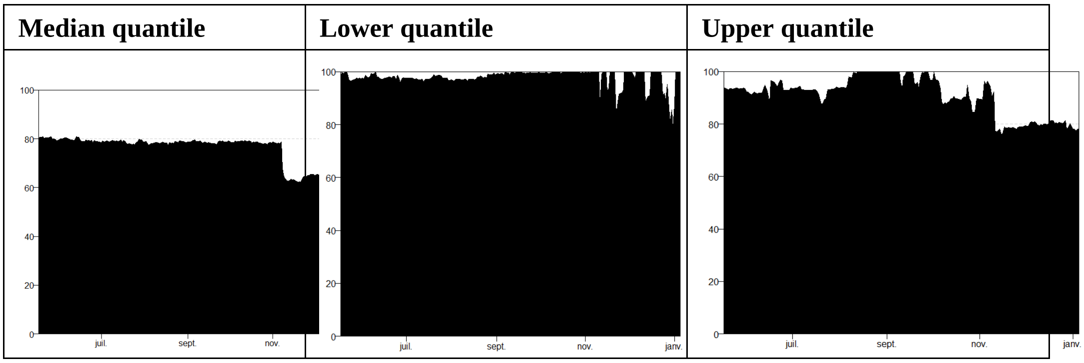
Karim *et al.* (2022) and Yousaf and Yarovaya (2022), who demonstrated the asymmetric tail connectedness between fungible cryptocurrencies like Bitcoin, Ethereum, and Litecoin, and non-fungible tokens like Theta, Tezos, and Enjin Coin.

Figure 3. *Total connectedness for NFT at median, lower and upper quantiles*



Source: *Own study.*

Figure 4. *Total connectedness for Conventional cryptocurrencies at median, lower and upper quantiles*



Source: *Own study.*

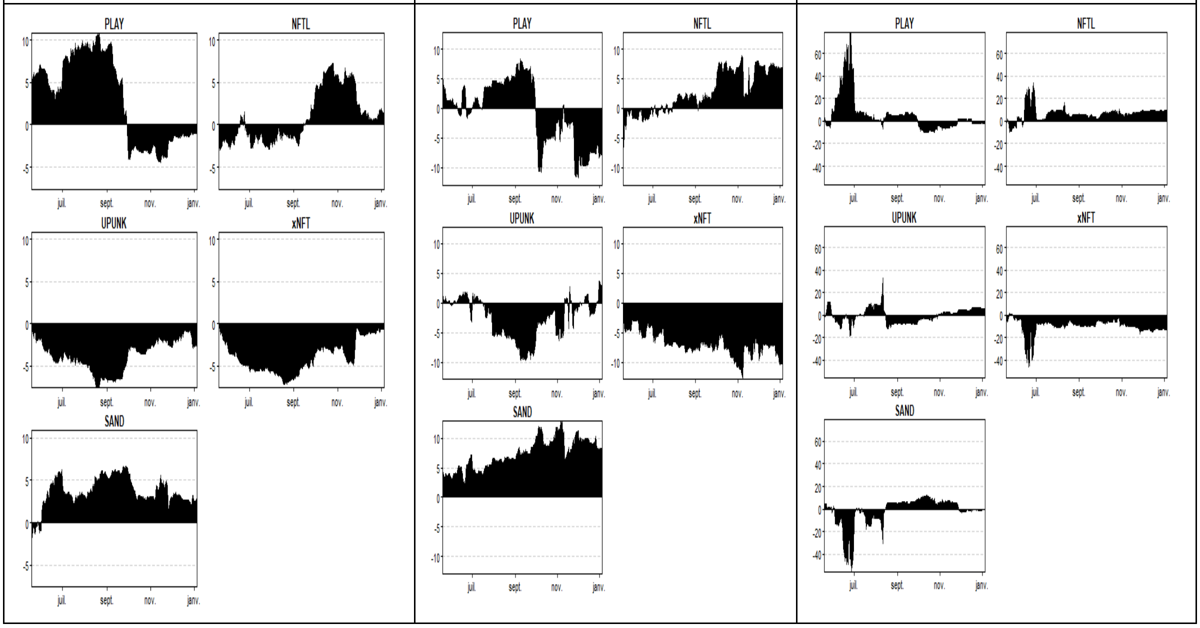
The findings suggest that the influence of extreme shocks on the spillover patterns of returns is notably pronounced. Remarkably, the upper and lower tails play a significantly more substantial role in both transmitting and receiving spillovers as compared to the median. Moreover, when contrasting the extreme upper and lower tails with the median quantile, variations emerge regarding which groups act as net recipients and transmitters of spillovers.

In the context of the left tail of the conditional distribution for Non-Fungible Tokens, SAND and NFTL are identified as net transmitters of return spillovers. Furthermore, in the right tail, PLAY and NFTL are observed to function as net transmitters (refer to Figure 5).

For Conventional cryptocurrencies, specifically focusing on the left tail of the conditional distribution, only FTT retains its role as a net transmitter of return spillovers. Additionally, within the upper quantile, ETH operates as a net transmitter (as depicted in Figure 6).

Figure 5. *Net total connectedness for NFT at lower and upper quantiles*

Median quantile	**Lower quantile**	**Upper quantile**



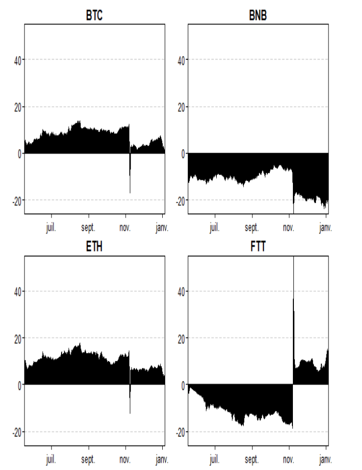
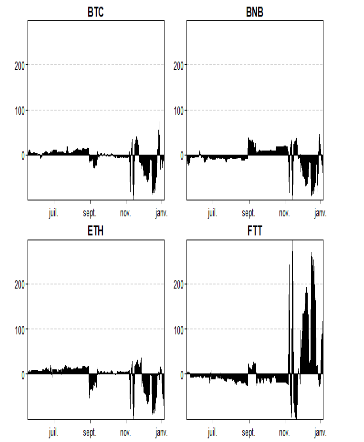
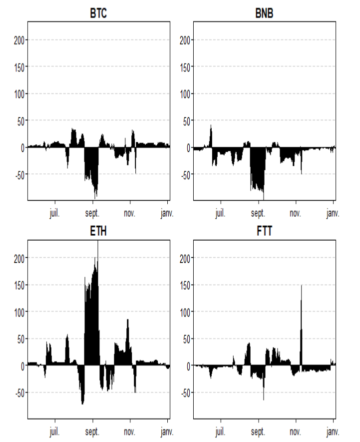
Source: *Own study.*

5.2 Short-term and Long-term Analysis of Overall Dynamic Total Connectedness

Within this section, our exploration unfolds in two sequential phases: first, we delve into the time-frequency dynamics of connectedness for NFTs, followed by the investigation of the same for Conventional cryptocurrencies.

To encompass the connectedness across varying time scales, we introduce two frequency ranges within the frequency domain. Specifically, the high-frequency band corresponds to the short term, while the low-frequency band corresponds to the long term, a concept previously introduced by Baruník and Křehlík (2018) and Chatziantoniou (2022). The outcomes of our estimations across all time periods are visually presented in Figures 7 and Figure 8.

Figure 6. *Net Total connectedness for Conventional cryptocurrencies at lower and upper quantiles*

Lower quantile	**Lower quantile**	**Upper quantile**
		

Source: *Own study.*

The additional insights into the dynamics of short-run and long-run Total Connectedness Index (TCI) across various time periods unveil that the overarching TCI dynamics are predominantly influenced by short-term dynamics, which exhibit higher volatility in contrast to long-term dynamics (as depicted in Figure 7). It's important to note that the outcomes highlighted in the shaded black region correspond to the total connectedness, while the red and green shaded outcomes delineate the division of the analysis into long-term and short-term connectedness, respectively.

Table 5. *Averaged dynamic connectedness table*

Panel A : NFT						
	PLAY	**UPUNK**	**SAND**	**NFTL**	**xNFT**	**FROM**
PLAY	67.99 (56.79 ,11.20)	4.11 (3.24 ,0.87)	15.34 (12.32 ,3.03)	8.38 (7.29 ,1.09)	4.18 (3.52 ,0.66)	32.01 (26.36 ,5.65)
UPUNK	5.37 (4.28, 1.09)	74.13 (60.53 ,13.6)	8.65 (6.84 ,1.81)	8.43 (6.83 ,1.59)	3.43 (2.79 ,0.64)	25.87 (20.74 ,5.13)
SAND	15.02	7.25	56.76	17.43	3.54	43.24

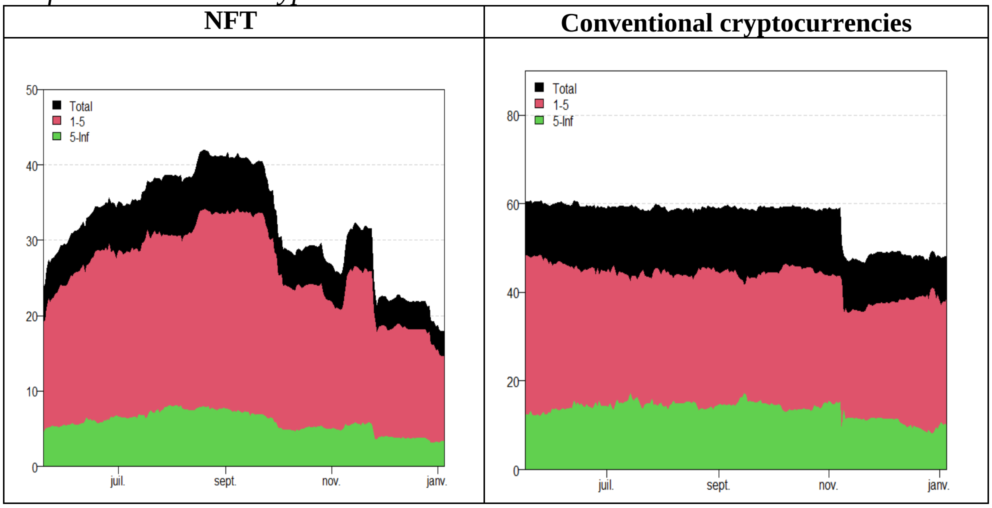
	(12.33 ,2.69)	(5.87 ,1.38)	(47.96 ,8.8)	(14.89 ,2.55)	(3 ,0.54)	(36.09 ,7.15)
NFTL	8.89 (7.07 ,1.82)	7.23 (5.73 ,1.5)	18.43 (14.7 ,3.73)	60.91 (51.13 ,9.78)	4.54 (3.7 ,0.84)	39.09 (31.2 ,7.89)
xNFT	5.72 (4.78 ,0.94)	3.58 (2.95 ,0.63)	4.50 (3.75 ,0.75)	5.74 (4.92 ,0.82)	80.46 (70.3 ,10.16)	19.54 (16.4 ,3.14)
TO	35.01 (28.47,6.53)	22.17 (17.79,4.38)	46.92 (37.60,9.32)	39.98 (33.93,6.05)	15.69 (13.00,2.68)	159.76 (130.80,28.96)
Inc.Own	103.00 (85.26,17.74)	96.29 (78.32,17.97)	103.68 (85.57,18.11)	100.89 (85.06,15.83)	96.14 (83.30,12.84)	cTCI/TCI
Net	3.00 (2.11,0.88)	-3.71 (2.95,-0.76)	3.68 (1.52,2.16)	0.89 (2.73,-1.84)	-3.86 (-3.40,-0.46)	39.94/31.95 (32.70/26.16, 7.24/5.79)
NPDC	3.00 (3.00,3.00)	1.00 (1.00,0.00	4.00 (2.00,4.00	2.00 (4.00,1.00)	0.00 (0.00,2.00)	
Panel B: Conventional cryptocurrencies						
	BTC	**ETH**	**BNB**	**FTT**	**FROM**	
BTC	42.11 (34.31 ,7.79)	33.29 (26.63 ,6.66)	12.44 (10.14 ,2.29)	12.17 (10.36, 1.81)	57.89 (47.14, 10.76)	
ETH	32.70 (26.98 ,5.72)	41.53 (33.79 ,7.73)	13.35 (11.34, 2)	12.43 (10.46, 1.97)	58.47 (48.79, 9.68)	
BNB	16.53 (10.48 ,6.05)	18.37 (11.97 ,6.39)	43.16 (34.1 ,9.07)	21.94 (17.92 ,4.02)	56.84 (40.37 ,16.47)	
FTT	16.24 (10.02 ,6.22)	17.34 (10.73 ,6.61)	18.97 (15.18 ,3.79)	47.46 (37.97 ,9.49)	52.54 (35.93 ,16.62)	
TO	65.47 (47.48,17.98)	69.00 (49.33,19.66)	44.75 (36.67,8.08)	46.53 (38.74,7.80)	225.74	
Inc.Own	107.57 (81.79,25.78)	110.52 (83.12,27.40)	87.91 (70.77,17.15)	93.99 (76.70,17.29)	cTCI/TCI	
Net	7.57 (0.35,7.23)	10.52 (0.54,9.98)	-12.09 (-3.70,-8.39)	-6.01 (2.81,-8.82)	75.25/56.44 (57.51,13.38)	
NPDC	2.00 (2.00,2.00)	3.00 (2.00,3.00)	0.00 (0.00,0.00)	1.00 (2.00,1.00)		

Note: **, **, and *** represent significance at 10%, 5%, and 1%, respectively. Values in parentheses indicate the probability of significance.*
Source: *Own study.*

Furthermore, we discern an asymmetry in both short-term TCIs and long-term TCIs, characterized by distinct effects related to different economic and financial events in both the short and long term. This observation is in alignment with the findings of Jareño *et al.* (2022).

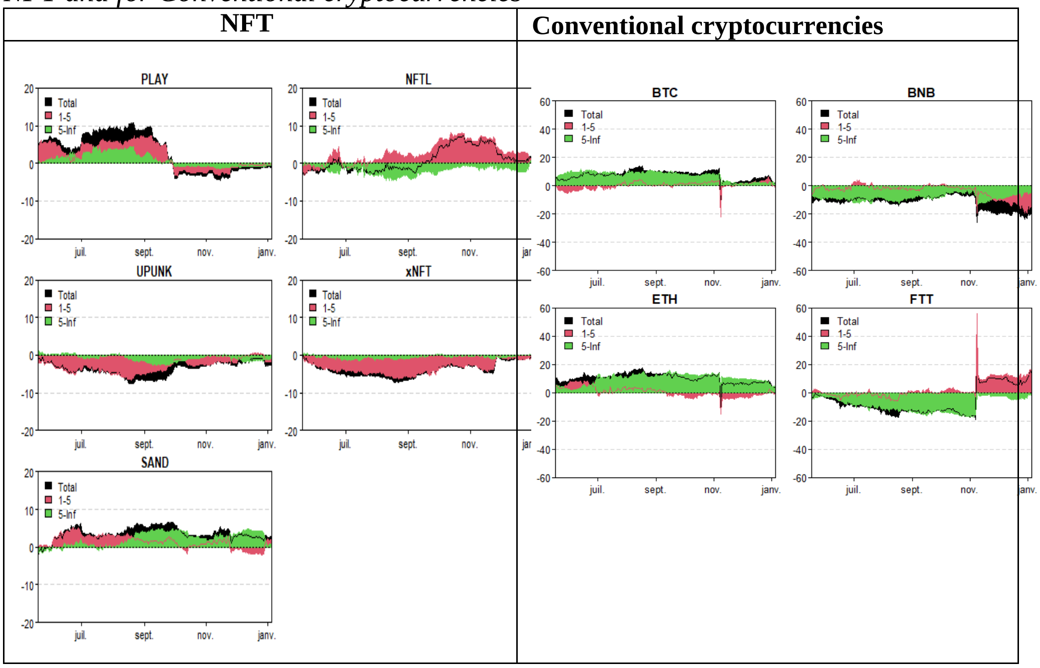
Examining the net connectedness in both short and long terms within the cryptocurrency markets (NFTs and classical cryptocurrencies), we observe that almost all NFTs exhibit short-term net effects of shocks, with the exception of SAND. In contrast, all the studied digital currencies manifest long-term net effects of shocks. Additionally, we ascertain that both short-term and long-term TCIs exhibit asymmetry, shedding light on diverse economic and financial events and their repercussions in both short and long timeframes (as illustrated in Figure 8 and Table 6).

Figure 7. *Short-term, long-term and overall dynamic total connectedness for NFT and for Conventional cryptocurrencies*



Source: *Own study.*

Figure 8. *Short-term, long-term and overall net total directional connectedness for NFT and for Conventional cryptocurrencies*



Source: *Own study.*

As an illustration, we ascertain that the most substantial proportions of spillovers in terms of their own-variance share, for NFTs, are observed with PLAY, accounting for 67.99%. However, in the case of digital currencies, this share escalates to 75.97%, particularly for BTC.

To delve deeper, focusing on individual NFTs, UPUNK, SAND, NFTL, and XNFT exert influences on PLAY amounting to 5.37%, 15.02%, 8.89%, and 5.72% respectively. Each shock can be dissected into its short-term and long-term spillover components. Taking SAND as an example, which significantly impacts PLAY, we identify that 12.33% of the impact originates from short-term spillovers, while 2.69% stems from long-term SSE stock market spillovers.

Similarly, for digital currencies, specifically ETH, BNB, and FTT, their impacts on BTC are calculated at 32.70%, 16.53%, and 16.24% respectively. Taking ETH's impact on BTC, which is the most pronounced, we deduce that 26.98% arises from short-term spillovers, whereas 5.72% emanates from long-term ETH stock market spillovers.

Collectively, we observe that PLAY exerts an influence on the market at 35.01% and is itself influenced by 32.01%, implying a net transmitter role (3%). Diving deeper, we find that it acts as both a short-term and long-term net transmitter of shocks, with short-term net spillovers amounting to 2.11% and long-term net spillovers reaching 0.88%.

Turning to the series of NFTs under scrutiny, we discover that among them, SAND emerges as the primary net transmitter of shocks in the long term. It holds sway over the market by 46.92% while being influenced by 43.24%, indicating a net transmitter role with a differential of 3.68%. Specifically, it serves as a net transmitter of shocks, both in the short term (1.52% short-term net spillovers) and long term (2.16% long-term net spillovers).

In the case of NFTL, its impact on the market stands at 39.98%, while it is itself influenced by 39.09%, showcasing a net transmitter status with a marginal 0.89% difference. Delving into specifics, we observe its dual role as a short-term and long-term net transmitter of shocks, with short-term net spillovers at 2.73% and long-term net spillovers at -1.84%.

Regarding XNFT, it emerges as the primary net receiver of shocks in the short term (-3.86), closely followed by UPUNK at -3.71%.

In the realm of investigated digital currency series, we observe that BTC wields an influence over the market at 65.47%, while being influenced by 57.89%, indicating its role as a net transmitter of shocks with a difference of 7.57%. More specifically, we find that it serves as both a short-term and long-term net receiver of shocks, with short-term net spillovers accounting for 0.35% and long-term net spillovers amounting to 7.23%.

Shifting focus to ETH, its sway on the market stands at 69%, while it is itself influenced by 58.47%, pointing towards its status as a net transmitter of shocks, characterized by a margin of 10.52%. In more detail, it acts as both a short-term and long-term net transmitter of shocks, with short-term net spillovers at 0.54% and long-term net spillovers equaling 98.9%.
Contrastingly, BNB emerges as the primary net receiver of shocks in the long term (-12.09), closely trailed by FTT at -6.01%.

The study highlights that the network's net transmission behavior is largely influenced by short-term dynamics for NFTs and long-term dynamics for Conventional cryptocurrencies. Moreover, the roles of assets as net transmitters or net receivers can evolve over time. This knowledge bears significant relevance for both investors and policymakers. Investors can utilize these insights to enhance their decision-making and risk management particularly during periods of extreme market conditions. Policymakers, on the other hand, can harness these findings to navigate diverse market circumstances more effectively.

6. Conclusion

In summary, the research provides a comprehensive analysis of the dynamic relationship and interconnectedness between the returns of conventional cryptocurrencies and NFTs across extreme and median quantiles during the period from November 2, 2021, to January 5, 2023. Utilizing the quantile TVP-VAR method and time-frequency analysis, we delve into these dynamics. The findings confirm an elevated level of spillover effects across all studied cryptocurrency markets.

Significantly, the total return spillover index underscores a more pronounced impact of extreme negative and positive shocks on the interconnected system compared to periods of relative stability, revealing a symmetric spillover effect during extreme market conditions. These dynamics undergo significant changes, especially during periods of extreme market turmoil such as pandemics and wars.

Furthermore, total connectivity indices for overall transmissions exhibit variations over time and are influenced by unexpected events, with short-term effects prevailing for NFTs and long-term effects for traditional cryptocurrencies, resulting in asymmetric connectivity. These results lead us to conclude the inefficiency of these markets. Additionally, the roles of assets as net transmitters or net receivers can evolve over time.

These findings have significant implications in blockchain markets for professionals in the field and provide them with valuable insights into network intermediaries. This knowledge can assist asset allocation decisions and enable regular adjustments to respond to the severity of the COVID-19 pandemic and the economic impact of the Russia-Ukraine conflict.

This is particularly beneficial for portfolio managers seeking a clear understanding of repatriation transfer patterns, particularly during periods of extreme market conditions. Policymakers interested in the economic impact of the COVID-19 pandemic and the war conflict between Russia and Ukraine can also benefit from these insights. This information can help investors optimize financial returns, make informed investment decisions, and differentiate between companies that generate net spillovers and those that experience them.

While our research carries practical and theoretical implications, there are numerous areas that could be further investigated in future studies. By encompassing a wider range of assets and employing diverse analytical methodologies, a more thorough understanding of spillover dynamics can be achieved. It is crucial to highlight that we cannot discern any consistent pattern universally applicable to how risk events impact total or net spillovers across frequency quantile connectedness.

Conflict of interest statement : On behalf of all authors, the corresponding author states that there is no conflict of interest.

Declaration of interests : The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. There is no funding.

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