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Quantile Time-Frequency Price Connectedness Between Classic Cryptocurrencies, NFT, DEFI, and Backed Gold Cryptocurrencies

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ABSTRACT

This study explores the quantile time-frequency connectedness for returns-volume pairs across classic cryptocurrencies, NFTs, DeFi, and backed gold cryptocurrencies from November 2, 2021, to January 5, 2023. Utilizing quantile-connectedness measures derived from a QVAR model's variance decomposition, we observe heterogeneous Total Connectedness Indices (TCIs) over time, dependent on various events. Our analysis confirms the spillover effect between return and volume across all studied cryptocurrency markets. Notably, volume exhibits predictive power for returns in most cases, shedding light on the driving forces behind price adjustments under diverse market conditions, as revealed by time-frequency analysis. Furthermore, a long-term pattern is discerned among backed gold currencies, Meta, UPUNK, Tera, and BNB, alongside a short-term pattern. Regarding net directional results, returns are predominantly received from volume, driven by transactions at both ends of the volume spectrum, with exceptions for Link, Ethereum, Fix Token, and PMGT. Additionally, our findings unveil an asymmetry in both the overall TCI and short-term and long-term net TCIs.

JEL Classifications: G10, G11, G15

Keywords: spillover effect; QVAR model; connectedness; cryptocurrencies; predictive power

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I. INTRODUCTION

Blockchain-based digital assets have gained increasing popularity among investors, policymakers, portfolio managers, and academic researchers since their inception. The rise of digital currencies, including traditional cryptocurrencies, non-fungible tokens (NFTs), decentralized finance (DeFi), and gold-backed digital currencies, has played a substantial role in driving the recent expansion of digital markets (Dowling, 2022; Yousaf and Yarovaya, 2022; Bejaoui et al., 2023; Ghosh et al., 2023; Dammak et al., 2024).

In the realm of cryptocurrency, NFTs, DeFi, and gold-backed assets are relatively new digital markets that have not been extensively investigated within the existing finance literature. Nevertheless, these digital assets have significantly contributed to the recent expansion and growth of the cryptocurrency market.

Recent studies have contributed significantly to our understanding of the resilience and efficiency of cryptocurrencies and digital assets in various economic and geopolitical contexts. Gaies et al. (2024) investigated the resilience of Bitcoin and Ethereum to inflation and financial instability amid major economic and political disruptions. Their findings, based on wavelet coherence analysis and the quantile coherence method, revealed that investors adjust their Bitcoin holdings in response to inflation expectations, driving up Bitcoin prices during turbulent times. However, Bitcoin's effectiveness as an inflation hedge diminishes in bearish market conditions, and it proves unreliable as a hedge against financial instability. Similarly, El Alaoui et al. (2019) explored the price-volume cross-correlation in the Bitcoin market, uncovering nonlinear interactions between Bitcoin prices and trading volume. Their analysis, conducted via multifractal detrended cross-correlations analysis, deepened insights into the underlying mechanisms governing Bitcoin market dynamics. Additionally, Okorie et al. (2024) examined the efficiency of the market for non-fungible tokens (NFTs) compared to fungible tokens (FTs) such as Bitcoin and Ethereum. Their study, focusing on the impact of COVID-19 and the Russia-Ukraine conflict, revealed fluctuations in market efficiency over time and heterogeneous effects of the shocks on both FTs and NFTs.

Fundamentally, NFTs are non-transferable cryptographic tokens created on the Ethereum blockchain that can be bought and sold. However, their interchangeability with other cryptocurrencies is significantly limited, as they provide a digital certificate of ownership for various forms of digital art (Chalmers et al., 2022; Wang, 2022; Chowdhury et al., 2023).

In contrast, DeFi represents a novel financial technology service that challenges the existing banking system by providing a decentralized system capable of facilitating financial transactions without the need for intermediaries (Karim et al., 2022; Chowdhury et al., 2023).

On the other hand, both traditional and gold-backed cryptocurrencies are constructed and utilized through blockchain technology. Conventional cryptocurrencies are digital currencies that rely on decentralized networks constructed using blockchain technology, and they lack any physical asset backing (Mnif et al., 2022; Trabelsi Karoui et al., 2024). Conversely, gold-backed cryptocurrencies are innovative technologies that derive their value from and are supported by gold, potentially serving as a new form of safe-haven investment, offering superior returns during turbulent times (Wasiuzzaman et al., 2023).

In this context, there is a need to analyze financial issues such as co-movements,

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connectedness, and contagion among different digital assets. Furthermore, research based on NFTs, DeFi, and gold-backed assets has remained quite limited to date compared to conventional cryptocurrencies. Using various econometric methods, few researchers have investigated the dynamic cross-market linkages and volatility spillovers between different digital asset classes. In this respect, Pinto-Gutiérrez et al. (2022) suggest that investors exhibit increased interest in NFTs following rises in the returns of Bitcoin and Ether, using wavelet coherence analysis. Additionally, the returns of these two prominent cryptocurrencies play a significant role in driving attention towards NFTs in the subsequent week. Apostu et al. (2022) investigated that the price of NFTs had a causal effect on Ethereum's price. Using wavelet-based quantile causality analysis, Qiao et al. (2023) indicate that yield farming tokens registered a pure spillover relationship with metaverse-related NFTs as well as other DeFi tokens. Alawadhi and Alshamali (2022) show that DeFi assets are relatively unconnected to traditional cryptocurrency markets. Karim et al. (2022) studied the connectedness between NFT and DeFi assets' spillovers using the quantile connectedness approach. Yousaf and Yarovaya (2022) employed the TVP-VAR framework to investigate the static and dynamic spillover effects between NFTs, DeFi, and various assets such as oil, gold, Bitcoin, and the S&P 500. The study reveals limited static return and volatility spillovers between NFTs, DeFi assets, and the selected markets, indicating that these emerging digital assets remain relatively independent from traditional asset classes.

Chowdhury et al. (2023) and Dammak et al. (2023) argue that the Covid-19 pandemic has had a pernicious impact on the functioning of digital assets. They also demonstrate that DeFi and NFTs are relatively more efficient assets than cryptocurrencies throughout the entire sample period, using the Asymmetric Multifractal Detrended Fluctuation Analysis (A-MFDFA) technique. Bejaoui et al. (2023) identify nontrivial time-varying connectedness between NFTs, DeFi, and gold based on wavelet coherence.

Other researchers have focused on the dynamic relationships among gold-backed cryptocurrencies and their interactions with other financial assets. For instance, Wang et al. (2020) analyzed three cryptocurrencies pegged to gold (DGD, HGT, and XAUR) and reported that while gold-backed cryptocurrencies may not exhibit the same level of safe-haven properties as physical gold, they can still be effectively employed to mitigate extreme losses. Jalan et al. (2021) revealed that during the COVID-19 pandemic, gold-backed cryptocurrencies exhibited similar levels of volatility and associated risks as Bitcoin. Furthermore, they demonstrated that gold-backed cryptocurrencies did not exhibit a safe-haven potential comparable to the underlying precious metal, gold. Díaz et al. (2023) investigated a minimal correlation between gold-backed currencies and conventional cryptocurrencies, validating their capacity to lower the kurtosis of cryptocurrency portfolios.

The motivation for this study arises from the evolving landscape of digital assets, encompassing a diverse range from traditional cryptocurrencies to newer forms like non-fungible tokens (NFTs), decentralized finance (DeFi), and gold-backed cryptocurrencies. Researchers have highlighted the importance of understanding the dynamic relationships and interactions among these digital assets and their implications for portfolio diversification and risk management. For instance, recent studies have examined the potential of gold-backed cryptocurrencies to mitigate extreme losses in cryptocurrency portfolios and the minimal correlation between gold-backed currencies and conventional cryptocurrencies. Furthermore, the impact of significant events such as the COVID-19

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pandemic on the volatility and risk profiles of digital assets has drawn attention. However, research on the interconnectedness and spillover effects among NFTs, DeFi, gold-backed assets, and conventional cryptocurrencies remains relatively limited.

Given this central point, it is essential to delve into the spillover between digital assets, namely NFTs, DeFi, gold-backed, and conventional cryptocurrencies using a quantile time connectedness approach. Understanding the dynamics of spillovers across different quantiles of the distribution can provide valuable insights into the asymmetric effects and transmission mechanisms among these digital asset classes, particularly in times of market stress or extreme volatility. By employing a quantile time connectedness approach, this study aims to shed light on the heterogeneous nature of spillovers and the varying degrees of interconnectedness among different digital assets, contributing to a deeper understanding of their risk-return profiles and potential implications for portfolio management strategies.

Therefore, this research paper addresses the existing gap in the literature and provides valuable insights for investors, portfolio managers, and researchers regarding the dynamic returns spillovers between new digital assets. Additionally, it takes into consideration the potential impact of the Russia-Ukraine war.

In this context, the global daily dataset used in the study covers the time span from January 4, 2016, to January 5, 2023. The research employs the quantile connectedness approach, as suggested by Chatziantoniou et al. (2021), to investigate the propagation of new digital assets on the cryptocurrency market across different quantiles. It is important to mention that the quantile connectedness method utilized in this research builds upon the foundational work of Diebold and Yilmaz (2009, 2012, 2014).

Recent advancements in frequency connectedness, as classified by Baruník and Křehlík (2018) and Chatziantoniou et al. (2022), have notably distinguished between high-frequency connectedness and low-frequency connectedness.

Therefore, our contribution serves as a significant addition to the existing body of research in this field. Specifically, we extend the literature in three key aspects. Firstly, our analysis encompasses a thorough examination of the returns spillover effects and connectedness of digital assets across various time frequencies and scales. By exploring these dynamics comprehensively, we provide insights into how digital assets interact over different time horizons, thereby enhancing our understanding of their interconnectedness and dependencies. Secondly, our study delves into the strengths and directions of spillovers, enabling market participants to identify the sources of contagion more effectively. This knowledge empowers investors and stakeholders to navigate market dynamics and manage risks associated with digital asset portfolios with greater precision. Thirdly, our research explores the dynamics of cross-market linkages during exceptional and diverse events, such as the Russia-Ukraine conflict. By examining how digital assets respond to such events, we gain valuable insights into their resilience and potential as safe-haven assets. This holistic approach contributes to a deeper understanding of the broader market dynamics surrounding digital assets and their role in times of geopolitical uncertainty.

The organization of this study is as follows: Section 2 delineates the data utilized in the research, and expounds upon the methodology. In Section 3, the empirical findings and their interpretation are presented. Finally, Section 4 provides concluding remarks.

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II. DATA AND METHODOLOGY

A. Data

We collect closing prices spanning from November 2nd, 2021, to January 5th, 2023, encompassing 18 cryptocurrencies segregated into four categories: Non-fungible tokens (NFTs), Decentralized Finance (DeFi), conventional cryptocurrencies, and gold-backed cryptocurrencies. The dataset is sourced from www.coinmarketcap.com.
To calculate returns, we used this formula:

$$R_t = \text{Ln}\left(\frac{\text{P}_t}{\text{P}_{t-1}}\right) \tag{1}$$

Where, P_t represents the price for the current day.

We calculated volatility by squaring returns, a method consistent with the approach outlined by Balcilar et al. (2017), Yousaf and Yarovaya (2022), and Dhoha et al. (2024). However, the volume data displayed deterministic time trends, including both linear and nonlinear components. To address this, we detrended the volume using the methodology described by Balcilar et al. (2017), Bouri et al. (2019), and Yousaf and Yarovaya (2022). Specifically, we took the natural log of the volume series and removed its trend by regressing it on a constant, (t/T), and (t/T)2, where T is the total sample size. The different cryptocurrencies used under these four categories of cryptocurrencies are:

- Five NFTs (Metaverse, UniclyCryptoPunks [UPUNK], Sandbox [SAND], NFTLaunch [NFTL], xNFT Protocol [XNFT]),
- Five DeFi tokens (Defi Pulse Index [DPI], Terra Classic, Avalanche [AVAX], Wrapped BTC [WBTC], ChainLink [LINK]),
- Four traditional cryptocurrencies are (Bitcoin [BTC], Ethereum [ETH], BNB [BNB], FTX Token [FTT]).
- Four gold-backed cryptocurrencies (GBC) 1 (PAX Gold [PAXG], Tether Gold [XAUT], Perth Mint Gold Token [PMGT], and Digix Gold Token [DGX]).

B. Methodology

In our study, we utilize the quantile connectedness approach and frequency connectedness measures to examine the dynamic interactions within the cryptocurrency market. These methods offer added value by capturing complex market behaviors that traditional models might overlook. Given the high volatility and susceptibility to extreme events in cryptocurrencies, it is essential to comprehend not only average interactions but also tail behaviors—how assets behave during bullish and bearish market conditions.

Our study employs the quantile connectedness approach, recommended by Chatziantoniou et al. (2021) and Ando et al. (2022), to examine how NFTs, DeFi, classic

[1]All these four GBC are built on the Ethereum blockchain and can be bought and sold on various cryptocurrency exchanges and be stored in an Ethereum wallet and can be used in various DeFi protocols. The gold backing these tokens are auditable and redeemable in the form of physical gold.

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cryptocurrencies, and backed gold cryptocurrencies propagate quantiles. These methods offer added value by capturing complex market behaviors that traditional models might overlook. Given the high volatility and susceptibility to extreme events in cryptocurrencies, understanding their propagation across quantiles is crucial for comprehending market dynamics accurately.

It's important to note that the quantile frequency connectedness method utilized in our research builds upon the foundational work of Diebold and Yilmaz (2009, 2012, 2014). They developed this approach by implementing a generalized VAR framework that incorporates rolling-window dynamic analysis.

Hence, the concept of connectedness relies on the second moment of the VAR model, specifically the forecast error variance decomposition. This decomposition illustrates how the volatility of each variable in a network is influenced by structural shocks within that network. Essentially, strong co-movements among the variables result in high total connectedness values. Furthermore, robust connectedness may indicate the presence of contagion among the variables, which can be assessed using directional connectedness metrics.

Subsequent advancements in measuring connectedness have been achieved through empirical research, leveraging more sophisticated techniques such as time-varying parameter vector autoregressive (TVP-VAR) connectedness measures, which largely overcome the limitations of traditional rolling-window dynamic analysis (Antonakakis et al., 2020). Consequently, the quantile connectedness approach emerged as an evolution of the original methodology (Chatziantoniou et al., 2021; Dhoha et al., 2024 ; Dammak et al., 2025; Masmoudi et al., 2025).

Quantile connectedness analysis explores the interplay between variables during extreme structural shocks, encompassing both positive (higher quantiles) and negative (lower quantiles) scenarios. Its objective is to discern whether a robust co-movement between variables exists, contingent upon the severity of the shock (i.e., extreme quantile), and whether such co-movement necessitates a positive (high quantile) or negative (low quantile) shock to manifest.

In recent years, there have been significant advancements in frequency connectedness, as highlighted by Baruník and Křehlík (2018) and Chatziantoniou et al. (2022), categorizing it into high-frequency connectedness and low-frequency connectedness. High-frequency connectedness stems from transient shocks affecting network variables, while low-frequency connectedness arises from shocks inducing structural alterations in the network, with enduring effects on the variables. In our study, we incorporate these methodologies to analyze the return-volume pairs of emerging financial assets. To compute the connectedness metrics, we employ a quantile vector autoregression (QVAR(p)) by estimating its parameters:

$$x_t = \mu_t(\tau) + \Phi_1(\tau)x_{t-1} + \Phi_2(\tau)x_{t-2} + \cdots + \Phi_p(\tau)x_{t-p}\,\mu_t(\tau) \qquad (2)$$

Where x_t and x_{t-i} (where $i = 1, \ldots, p$) are vectors representing endogenous variables with dimensions $N \times 1$. The parameter τ lies within the range $[0, 1]$ aandndicates the quantile of pair return-volume, while p represents the lag length of the QVAR model. $\mu(\tau)$ is a $N \times 1$ dimensional vector that represents the conditional mean, $\Phi j\ (\tau)$ is a $N \times N$ dimensional matrix of QVAR coefficients, and $ut(\tau)$ is a $N \times 1$ dimensional error vector with an $N \times N$ dimensional error variance–covariance matrix,

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$\Sigma(\tau)$. By applying Wold's theorem, the QVAR(p) can be transformed into its quantile vector moving average representation, $QVMA\ (\infty)$, we use Wold's theorem:

$$x_t = u(\tau) + \sum_{i=0}^{n} \sum_{j=1}^{p} \Phi j\ (\tau) x_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} \Psi i(\tau)\, u_{t-i} \tag{3}$$

The next step is to compute the generalized forecast error variance decomposition (GFEVD), which is a key component of the connectedness approach (Koop et al., 1996; Pesaran and Shin, 1998). The GFEVD measures the effect of a shock in series *j* has on series i by quantifying its contribution to the forecast error variance of i. It can be expressed as follows:

$$\theta_{ij}\ (H) = \frac{(\Sigma(\tau)_{jj}^{-1} \sum_{h=0}^{H}\ ((\Psi\ h(\tau)\Sigma(\tau))_{ij}\ )^2}{\sum_{h=0}^{H}\left(\Psi h(\tau)\Sigma(\tau)\Psi' h(\tau)\right)_{ii}} \tag{4}$$

and,

$$\tilde{\theta}\mathrm{ij}\ (\mathrm{H}) = \frac{\tilde{\theta}_{\mathrm{ij}}\ (\mathrm{H})}{\sum_{\mathrm{K}=1}^{\mathrm{N}} \tilde{\theta}_{\mathrm{ij}}\ (\mathrm{H})} \tag{5}$$

Since the rows of $\tilde{\theta}$ij (H) do not add up to one, normalization is necessary. This involves dividing each element in a row by the sum of the row, resulting in $\tilde{\theta}\mathrm{ij}\ (\mathrm{H})$. Normalization gives rise to the following identities:

$$\sum_{i=1}^{N} \tilde{\theta} ij\ (H) = 1 \tag{6}$$

and,

$$\sum_{\mathrm{j}=1}^{\mathrm{N}} \sum_{i=1}^{N} \tilde{\theta} ij\ (H)\ = \mathrm{N} \tag{7}$$

Consequently, each row of $\tilde{\theta}ij$ adds up to one, indicating how a shock in series i has affected both that series and all other series j.

The following step involves the computation of all connectedness measures. The overall total directional connectedness TO others evaluates the extent to which a shock in series i affects all other series j.

$$TO_i\ (H) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ij}(H) \tag{8}$$

The overall total directional connectedness FROM others measures the degree to which series i is impacted by shocks in all other series j:

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$$\text{FROM}_\text{i}\ (\text{H}) = \sum_{\text{i}=1,\text{i}\neq\text{j}}^{\text{N}} \tilde{\theta}_{\text{ij}}(\text{H}) \tag{9}$$

The overall NET total directional connectedness reflects the disparity between the overall total directional connectedness TO others and the overall total directional connectedness FROM others, which can be interpreted as the net influence of series i on the predetermined network.

$$\text{NET}_\text{i}\ (\text{H}) = TO_i\ (H) - \text{FROM}_\text{i}\ (\text{H}) \tag{10}$$

If $NETi > 0$ ($NETi < 0$), series i has a higher (lower) impact on all other series j than it is influenced by them, respectively. Therefore, it is classified as a net transmitter (receiver) of shocks.

The overall total connectedness index (TCI), which assesses the level of network interconnectedness, can be computed by:

$$TCI\ (H) = N - 1 \sum_{i=1}^{N} iTo(H) = N - 1 \sum_{i=1}^{N} iFrom(H) \tag{11}$$

To put it differently, this measure demonstrates the average effect that a shock in one series has on all the other series. A higher TCI value indicates higher market risk, and vice versa.

Moving on from the time domain, we now turn to the frequency domain for our assessment of connectedness. We adopt Stiassny's (1996) spectral decomposition method to explore the relationship between connectedness and frequency. First, we consider the frequency response function, denoted by $(e^{-iw}) = \sum_{h=0}^{\infty} e^{-iwh}\Psi_h$,, where $i = \sqrt{-1}$ and ω is the frequency. We then move on to the spectral density of x_t at frequency ω, which can be obtained through a Fourier transformation of the $QVMA$ (∞) representation

$$\text{S}_\text{x}(\omega) = \sum_{\text{h}=-\infty}^{\infty} \text{E}(x_t x'_{t-h})\, e^{-iwh} = \left(e^{-iwh}\right)_\text{t} \Psi'\left(e^{+\text{i}\omega\text{h}}\right) \tag{12}$$

Similarly, the frequency GFEVD is a combination of the spectral density and the GFEVD. Just like in the time domain, normalization of the frequency GFEVD is necessary, and it can be expressed as follows:

$$\theta_{ij}(\omega) = \frac{\left(\Sigma(\tau)\right)_{jj}^{-1} \left|\sum_{h=0}^{\infty}\left(\boldsymbol{\Psi}(\tau)(e^{-iwh})\Sigma(\tau)\right)_{ij}\right|^2}{\sum_{h=0}^{\infty}(\boldsymbol{\Psi}(e^{-iwh})\Sigma(\tau)\boldsymbol{\Psi}(\tau)(e^{iwh}))_{ii}} \tag{13}$$

and,

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$$\tilde{\theta}ij\ (w) = \frac{\theta_{ij}\ (w)}{\sum_{K=1}^{N} \theta_{ij}\ (w)} \tag{14}$$

The symbol θ̃ij (w)refers to the fraction of the spectrum of the ith series at a specific frequency ω that can be attributed to a shock in the jth series. This measure is known as a within-frequency indicator as it helps in assessing the connectedness between the two series at a particular frequency. In order to evaluate connectedness over both short-term and long-term time frames, instead of focusing on connectedness at a single frequency, we aggregate all frequencies within a specific range, $d = (a, b): a, b \in (-\pi, \pi), a < b$:

$$\tilde{\theta}ij\ \ (d) = \int_{a}^{b} \tilde{\theta}ij\ (w)dw \tag{15}$$

We can calculate the same connectedness measures as those presented by Diebold and Yılmaz (2012, 2014) from this point. However, in this case, the measures are referred to as frequency connectedness measures and provide information on spillovers within specific frequency ranges (denoted by d) that can be interpreted in the same way.

$$TO_i\ (d) = \sum_{i=1, i \neq j}^{N} \tilde{\theta}ij\ (d) \tag{16}$$

$$FROM_i(d) = \sum_{i=1, i \neq j}^{N} \tilde{\theta}ij\ (d) \tag{17}$$

$$NET_i\ (d) = TOi(d) - \ FROMi(d) \tag{18}$$

$$TCI(d) = \ N - 1 \sum_{i=1}^{N} TO_i(d) = \ N - 1 \sum_{i=1}^{N} i\ FROM_i(d) \tag{19}$$

In our case, we have two frequency bands illustrating short-term and long-term dynamics ranging from 1 to 5 days, $d1 \ = \ (\pi\ /\ 5, \pi)$ and from 6 to infinite days, $d2 \ = \ (0, \pi\ /\ 5]$. Thus,$TOi(d1)$, $FROMi(d1)$,$NETi(d1)$, and $TCI(d1)$ illustrate short-term total directional connectedness TO others, shortterm total directional connectedness FROM others, short-term NET total directional connectedness, and short-term total connectedness index while $TOi(d2)$, $FROMi(d2)$, $NETi(d2)$, and$TCI(d2)$illustrate the long-term total directional connectedness TO others, long-term total directional connectedness FROM others, long-term NET total directional connectedness, and long-term total connectedness index. Additionally, we establish the relationship between the frequency-domain measures of Baruník and Křehlík (2018) and the time-domain measures of Diebold and Yılmaz (2009, 2012, 2014).

$$TO_i(H) = \sum_d (d) \cdot TO_i(d) \tag{20}$$

$$FROM(H) = \sum_d (d) \cdot FROM_i(d) \tag{21}$$

$$NET(H) = \sum_d (d) \cdot NET_i\,(d) \tag{22}$$

$$TCI(H) = \sum_d (d) \cdot TCI_i\,(d) \tag{23}$$

In simple terms, the total connectedness measures can be obtained by adding up the frequency connectedness measures. However, it is important to note that all these measures are computed based on a specific quantile, $\tau 2$.

C. Empirical Result

Our results yield several significant findings. Firstly, the static quantile-based spillover analysis presented in Tables 1 to 4 reveals that the total connectedness between return and volume peaks in the upper quantile, while it remains lowest in the median quantile. This observation suggests that connectedness is more pronounced in both the left and right tails, indicating that the strength of return connectedness intensifies with shock size. This outcome aligns with the conclusions drawn by Umar and Bossman (2023), Mensi et al. (2023), and Liu et al. (2024), providing insight into why stronger connectedness is observed during both bullish and bearish market conditions. Consequently, our findings confirm the spillover effect between return and volume across all studied cryptocurrency markets, including NFTs, DeFi, digital currencies, and backed gold cryptocurrencies. This underscores the necessity for investors to devise distinct strategies during extreme bullish and bearish market conditions compared to normal conditions. Additionally, our study corroborates the asymmetric tail connectedness between volume and returns of fungible cryptocurrencies, such as Bitcoin, Ethereum, and Litecoin, and non-fungible tokens like Theta, Tezos, and Enjin coin, as demonstrated by Naeem et al. (2020), Karim et al. (2022), and Yousaf and Yarovaya (2022). Hence, our research offers initial insights into the DeFi and backed gold cryptocurrencies markets.

Table 1.
Static Quantile Based Spillovers Between Return and Volume (NFTs)

	Median (0.5)	**Lower Quantile (0.05)**	**Upper Quantile (0.95)**
1 : Metaverse			
Total Spillovers	0.26	27.78	28.61
To :			
Return	0.34	26.67	27.60
Volume	99.66	73.33	72.41

From:			
Return	0.18	28.88	29.61
Volume	99.82	71.12	70.39
Net:			
Return	0.16	-2.20	-2.02
Volume	-0.16	2.20	2.02
2: UPUNK			
Total Spillovers	0.68	31.19	27.91
To :			
Return	0.65	24.89	20.54
Volume	99.35	75.11	79.46
From:			
Return	7.81	37.48	35.27
Volume	92.19	62.52	64.73
Net:			
Return	-7.55	-12.59	-14.74
Volume	7.55	12.59	14.74
3: SAND			
Total Spillovers	4.04	35.49	34.00
To :			
Return	0.26	27.71	32.71
Volume	99.74	72.29	67.29
From:			
Return	7.81	34.27	35.30
Volume	92.19	56.73	64.70
Net:			
Return	-7.55	-15.56	-2.59
Volume	7.55	15.56	2.59
4: Launch			
Total Spillovers	2.22	26.10	31.95
To :			
Return	0.08	23.00	30.85
Volume	99.92	77.00	69.15
From:			
Return	4.36	29.20	33.06
Volume	95.64	70.80	66.954
Net:			
Return	-4.28	-6.21	-2.21
Volume	4.28	6.21	2.21
5: X NFT Protocol			
Total Spillovers	1.71	26.30	24.25
To :			
Return	1.02	28.26	19.52
Volume	98.98	71.74	80.48
From:			
Return	2.40	24.33	28.99
Volume	97.60	75.67	71.01
Net:			
Return	1.38	3.93	-9.47
Volume	-1.38		9.47

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Notes: "Total spillover" refers to the overall connectedness between the return and volume of NFTs. "To returns" indicates the spillover effect from volume to returns, while "to volume" represents the spillover effect from returns to volume. Positive "net returns" spillovers indicate that returns act as a net transmitter of spillover effects to volume, and vice versa. The length of the rolling window used is 200 days.

Table 2.
Static Quantile-Based Spillovers Between Return and Volume (DEFI)

	Median (0.5)	**Lower Quantile (0.05)**	**Upper Quantile (0.95)**
1 : Defi Pulse			
Total Spillovers	3.46	31.05	30.18
To :			
Return	0.36	27.99	24.59
Volume	99.64	72.01	75.41
From:			
Return	6.56	34.11	35.77
Volume	93.44	65.89	64.23
Net:			
Return	-6.19	-6.13	-11.18
Volume	6.19	6.13	11.18
2: Terra Classique			
Total Spillovers	0.28	39.83	18.41
To :			
Return	0.32	61.54	14.56
Volume	99.68	38.64	85.44
From:			
Return	0.25	18.12	22.26
Volume	99.75	81.88	77.74
Net:			
Return	3.36	43.42	-7.70
Volume	-3.36	-43.42	7.70
3: Avax			
Total Spillovers	2.56	36.45	34.12
To :			
Return	0.97	37.20	33.20
Volume	99.03	62.80	66.80
From:			
Return	4.16	35.70	35.04
Volume	95.84	64.30	64.96
Net:			
Return	-3.19	1.50	-1.84
Volume	3.19	-1.50	1.84
4: WBTC			
Total Spillovers	2.31	30.53	30.46
To :			
Return	0.93	24.44	29.74
Volume	99.07	75.56	70.26
From:			
Return	3.69	36.63	31.19
Volume	96.31	63.37	68.81
Net:			

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Return	-2.76	-12.19	-1.45
Volume	2.76	12.19	1.45
5: Link			
Total Spillovers	14.45	38.29	33.56
To :			
Return	0.14	31.43	31.22
Volume	99.86	68.57	68.78
From:			
Return	28.75	45.15	35.89
Volume	71.25	54.85	64.11
Net:			
Return	-28.61	0.89	-4.66
Volume	28.61	-0.89	4.66

Notes "Total spillover" refers to the overall connectedness between the return and volume of DEFIs. "To returns" indicates the spillover effect from volume to returns, while "to volume" represents the spillover effect from returns to volume. Positive "net returns" spillovers indicate that returns act as a net transmitter of spillover effects to volume, and vice versa. The length of the rolling window used is 200 days.

Table 3.
Static Quantile-Based Spillovers Between Return and Volume (Cryptocurrencies)

	Median (0.5)	**Lower Quantile (0.05)**	**Upper Quantile (0.95)**
1 : BTC			
Total Spillovers	0.67	33.94	32.10
To :			
Return	0.11	29.78	30.51
Volume	99.89	70.22	69.49
From:			
Return	1.23	38.10	33.69
Volume	98.97	61.90	66.31
Net:			
Return	-1.12	-8.32	-3.18
Volume	1.12	8.32	3.18
2: ETH			
Total Spillovers	4.66	33.03	32.62
To :			
Return	0.29	30.15	32.26
Volume	99.71	69.85	67.74
From:			
Return	9.03	35.92	32.99
Volume	90.97	64.08	67.01
Net:			
Return	-8.74	-5.78	-0.74
Volume	8.74	5.78	0.74
3: BNB			
Total Spillovers	1.02	34.29	31.41
To :			
Return	0.80	37.03	30.97
Volume	99.20	62.97	69.03
From:			
Return	1.24	31.55	31.84

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Volume	98.76	68.45	68.16
Net:			
Return	-0.44	5.48	-0.08
Volume	0.44	-5.48	0.08
4: Fix Token			
Total Spillovers	2.37	25.19	28.35
To :			
Return	0.14	22.18	27.81
Volume	99.86	77.82	72.19
From:			
Return	4.60	28.19	28.89
Volume	95.40	71.81	71.11
Net:			
Return	-4.46	-6.01	-1.08
Volume	4.46	6.01	1.08

Notes "Total spillover" refers to the overall connectedness between the return and volume of classic Cryptocurrencies. "To returns" indicates the spillover effect from volume to returns, while "to volume" represents the spillover effect from returns to volume. Positive "net returns" spillovers indicate that returns act as a net transmitter of spillover effects to volume, and vice versa. The length of the rolling window used is 200 days.

Table 4.

Static Quantile Based Spillovers Between Return and Volume (Backed Gold Cryptocurrencies)

	Median (0.5)	**Lower Quantile (0.05)**	**Upper Quantile (0.95)**
1 :PAXG			
Total Spillovers	0.59	34.30	30.71
To :			
Return	0.38	33.33	27.20
Volume	99.62	66.67	72.80
From:			
Return	0.81	35.26	34.21
Volume	99.19	64.74	65.79
Net:			
Return	-0.43	-1.93	-7.01
Volume	0.43	1.93	7.01
2: Tether Gold			
Total Spillovers	0.84	23.87	33.25
To :			
Return	0.81	20.10	26.62
Volume	99.19	79.90	73.38
From:			
Return	0.87	27.63	39.89
Volume	99.13	72.36	60.11
Net:			
Return	-0.06	-7.35	-13.28
Volume	0.06	7.35	13.28
3: PMGT			
Total Spillovers	6.08	36.38	38.15
To :			
Return	0.12	34.71	40.68

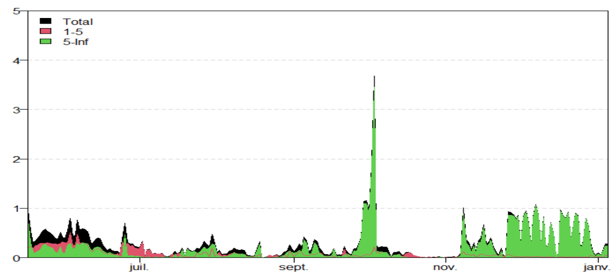
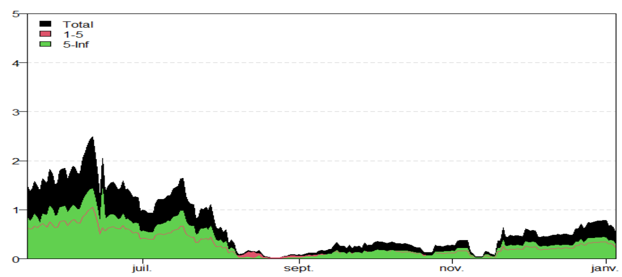
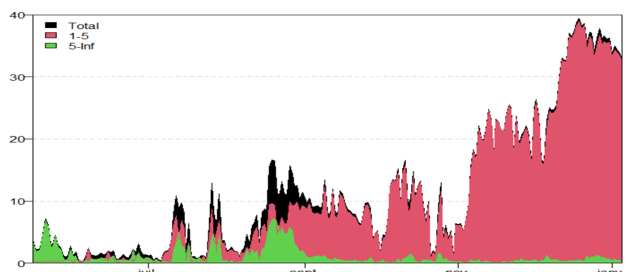
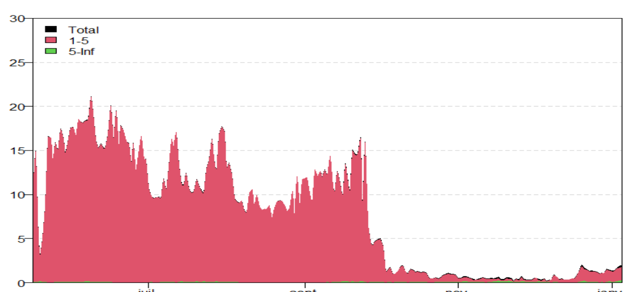
Volume	99.88	65.29	59.32
From:			
Return	12.05	38.06	35.62
Volume	87.95	61.94	64.38
Net:			
Return	-11.93	-3.35	5.06
Volume	11.93	3.35	-5.06
4: Digix Global			
Total Spillovers	0.37	21.79	27.53
To :			
Return	0.37	23.42	20.75
Volume	99.63	76.58	79.25
From:			
Return	0.38	20.16	34.32
Volume	99.62	79.84	65.68
Net:			
Return	0.00	3.27	-13.56
Volume	0.00	-3.27	13.56

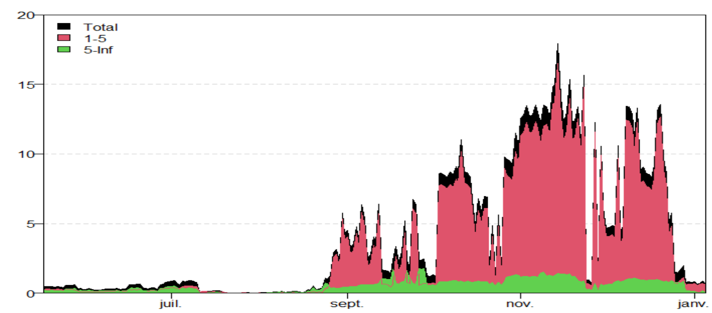
Notes: "Total spillover" refers to the overall connectedness between the return and volume of Backed Gold Cryptocurrencies. "To returns" indicates the spillover effect from volume to returns, while "to volume" represents the spillover effect from returns to volume. Positive "net returns" spillovers indicate that returns act as a net transmitter of spillover effects to volume, and vice versa. The length of the rolling window used is 200 days.

Secondly, we observe figures 1 to 4 that the net spillover of returns exhibits negativity across the median and extreme lower and upper quantiles for all examined assets, except for Metaverse and Tera in the median, and for Metaverse, Protocol, Tera, Link, PMGT, and DIGIX in the lower quantile. Thus, the spillover direction is from volume to returns in the median quantile, with exceptions seen in Metaverse and Tera, where the spillover effect is from return to volume. Conversely, at extreme upper and lower quantiles, the spillover direction is from volume to return, barring exceptions such as Metaverse, Protocol, Tera, Link, PMGT, and DIGIX in the bearish quantile. These findings align with the anti-efficiency market hypothesis and sequential information arrival hypothesis, indicating negative net spillover in the median and extreme quantiles. However, exceptions exist where the net spillover of returns is positive at the median quantile and extreme market conditions, demonstrating that the direction of spillovers is from return to volume. Generally, these results indicate that volume possesses predictive power for returns, albeit with a few exceptions, leading us to infer the inefficiency of these markets, as highlighted by Yousaf and Yarovaya (2022) in the NFT market and Bouri et al. (2019) in leading classic cryptocurrencies. The examination of spillover direction proves beneficial in evaluating the predictive ability of volume for returns in extreme market or stable conditions, thereby aiding in guiding trading decisions.

Thirdly, we establish through time-varying spillover analysis that returns consistently received from volume across the entire observation period for the four studied markets, with exceptions noted for Metaverse and Tera. In extreme upper and lower quantiles, the status of returns as a net recipient or net transmitter exhibits frequent variations over time, particularly for Protocol, Tera, Link, BNB, and Digix, echoing the findings of Naeem et al. (2020) in traditional cryptocurrencies. This variability in the status of net transmitter or receiver underscores the dynamic nature of these relationships over time.

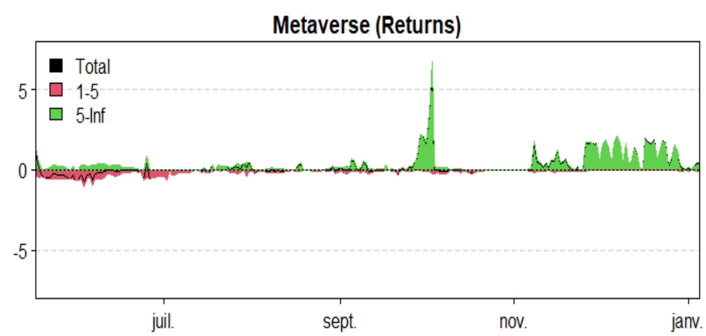
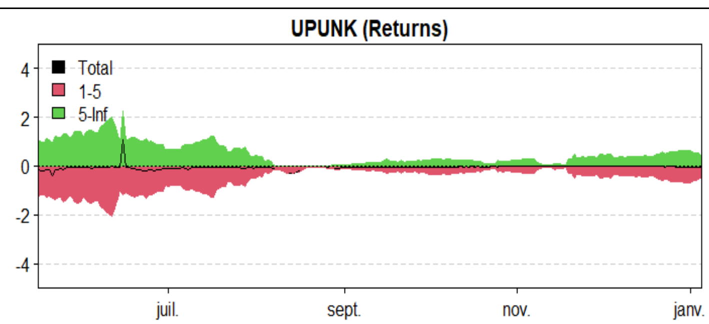
Figure 1.
Short-term, Long-Term and Overall Dynamic Total Connectedness for NFT's

	Volume/ Returns
Metaverse	
UPUNK	
SAND	
Launch	

Protocol	

Notes: The results of NFTs are derived from a QVAR model using a rolling window of 200 days, with a lag length of one (determined by BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area displays the time dynamic connectedness values, while the green and red areas indicate the short-term and long-term results, respectively. The corresponding lines show the outcomes from the standard VAR time-domain approach (Diebold and Yılmaz, 2012, 2014) and the frequency-domain connectedness approach (Baruník and Křehlík, 2018).

Figure 2.
Short-term, Long-term and Overall Net Total Directional Connectedness for NFT's

	Volume/ Returns
Metaverse	
UPUNK	

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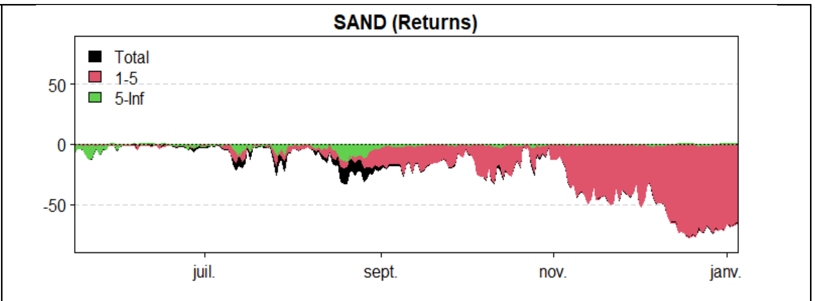
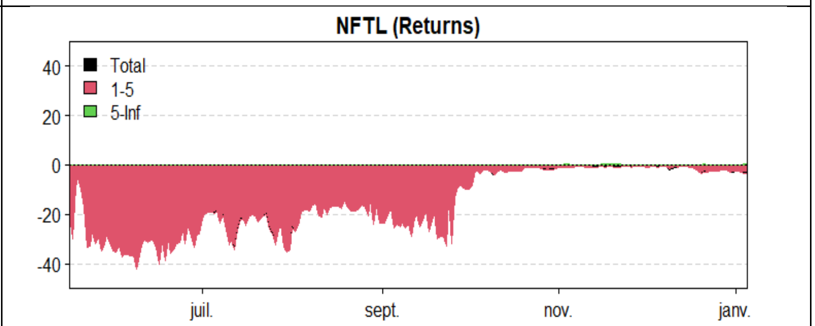
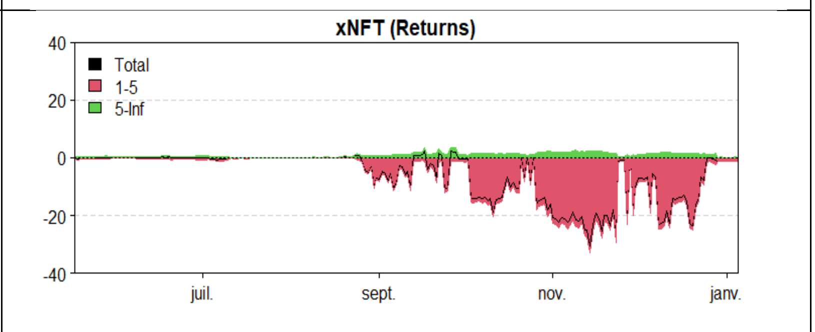
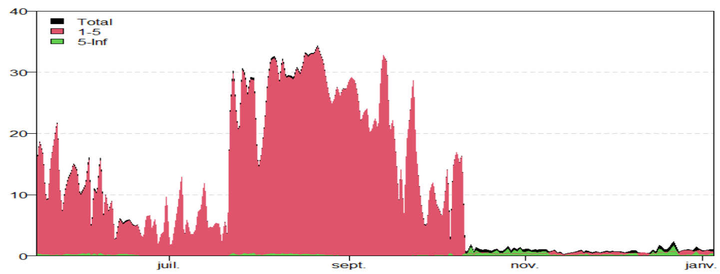
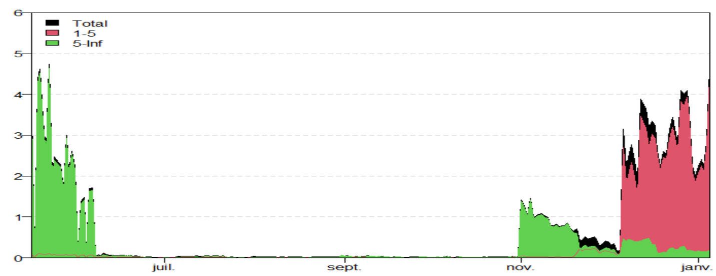
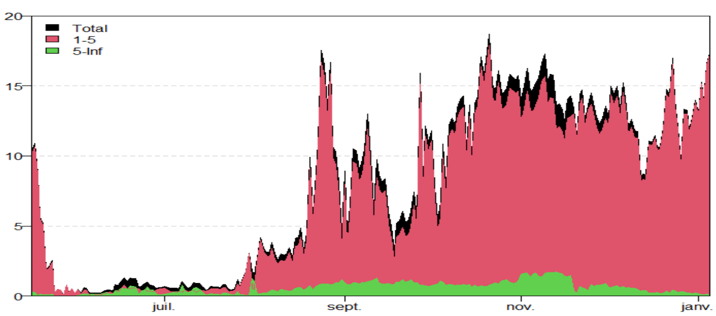
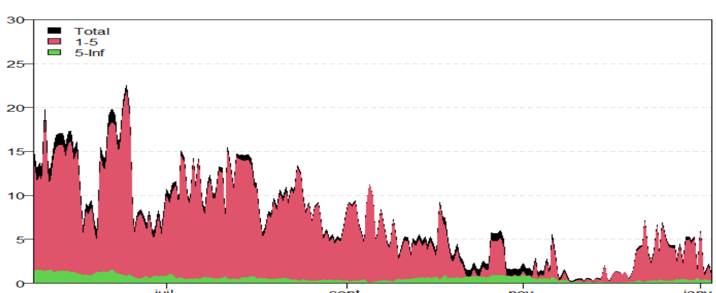
SAND	
Launch	
Protocol	

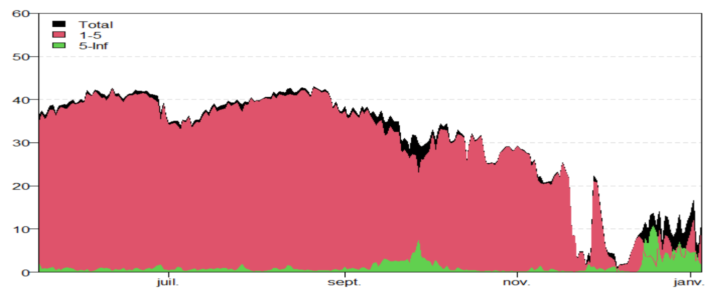
Notes: The results of NFTs are based on a QVAR model with a rolling window size of 200 days, a lag length of one (determined by BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area illustrates the time dynamic connectedness values, while the green and red areas depict the short-term and long-term results.

Figure 3.
Short-term, Long-term and Overall Dynamic Total Connectedness for DEFI.

	Volume/ Returns

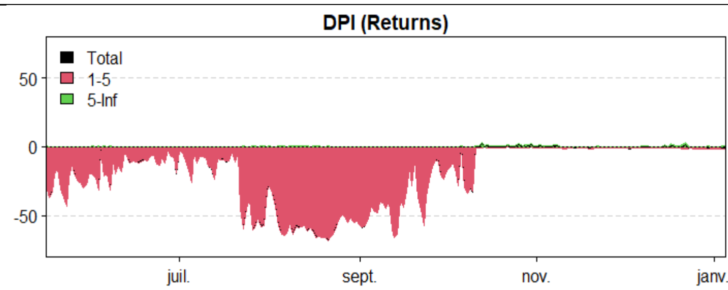
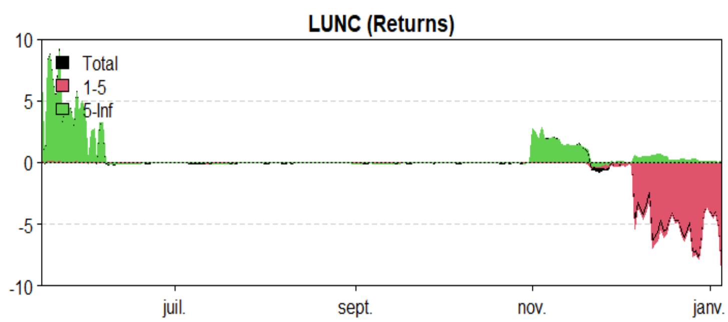
Pulse	
Terra Classique	
AVAX	
WBTC	

https://doi.org/10.55802/IJB.030(1).001

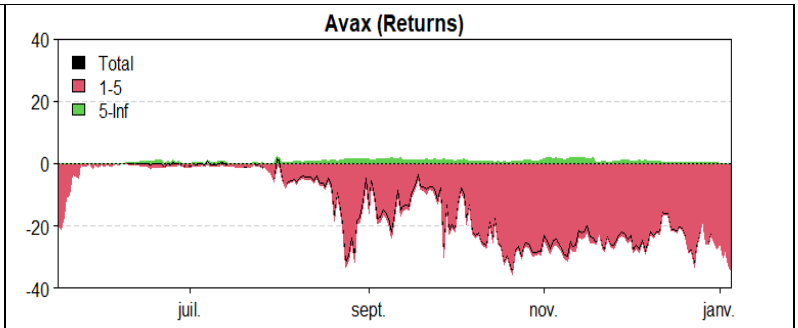
LINK	

Notes: The results of DEFIs are derived from a QVAR model using a rolling window of 200 days, with a lag length of one (determined by BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area displays the time dynamic connectedness values, while the green and red areas indicate the short-term and long-term results, respectively. The corresponding lines show the outcomes from the standard VAR time-domain approach (Diebold and Yılmaz, 2012, 2014) and the frequency-domain connectedness approach (Baruník and Křehlík, 2018).

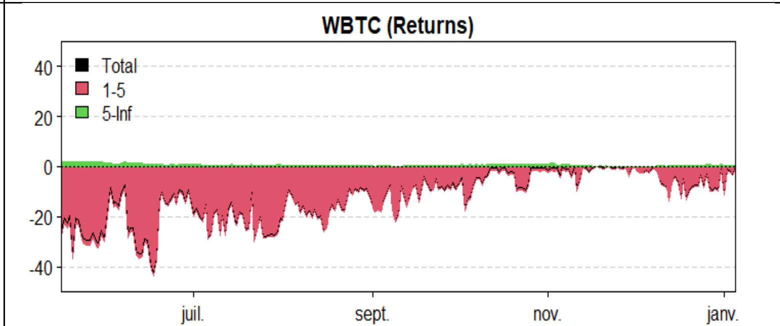
Figure 4.
Short-term, Long-term and Overall Net Total Directional Connectedness for DEFI.

	Volume/ Returns
Pulse	
Terra Classique	

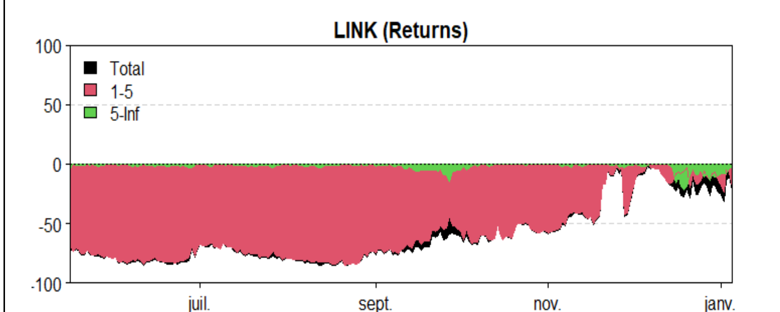
AVAX



WBTC



LINK



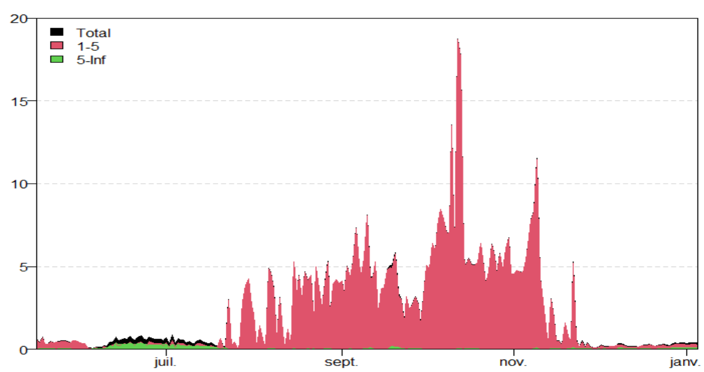
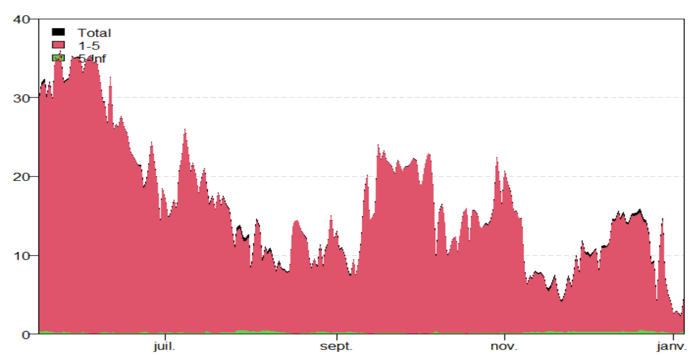
Notes: The results of DEFIs are based on a QVAR model with a rolling window size of 200 days, a lag length of one (determined by BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area illustrates the time dynamic connectedness values, while the green and red areas depict the short-term and long-term results.

Fourthly, we employ the classification of frequency connectedness into high and low frequency as proposed by Baruník and Křehlík (2018). This method allows for the analysis of connectedness across various frequencies, offering a more comprehensive examination compared to the traditional time-domain connectedness approach. Additionally, by incorporating quantiles, it provides further insights into tail dependencies. Consequently, this framework facilitates an analysis of whether short-term and long-term connectedness vary across quantiles. We begin by interpreting short-term and long-term total dynamic connectedness, followed by the median. Indeed, solely examining the total TCI could obscure the origins of movements, underscoring the importance of separately considering short-term and long-term dynamics. This distinction holds significance for investors and risk managers, as a substantial change in long-term TCI typically signifies a significant alteration in the overall market structure, as discussed in Chatziantoniou et al. (2021).

We observe that in Figures 5 and 7, for the studied digital currencies, the Total Connectedness Index (TCI) is predominantly influenced by short-term connectedness rather than long-term connectedness, with the exception of Metaverse, UPUNK, Tera, BNB, and all backed gold cryptocurrencies, where connectedness is notably driven by long-term dynamics.

This prevalence of short-term connectedness suggests that the market responds swiftly to news and events. This finding is consistent with the conclusions of Mensi et al. (2022) and Zhu et al. (2024), who illustrate that long-term spillovers are linked with passive investors, while short-term spillovers involve active investors.

Figure 5.
Short-term, Long-term and Overall Dynamic Total Connectedness for Cryptocurrencies.

	Volume/ Returns
BTC	
ETH	

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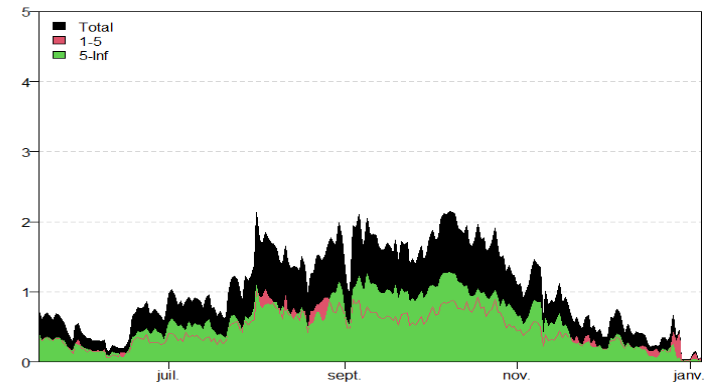
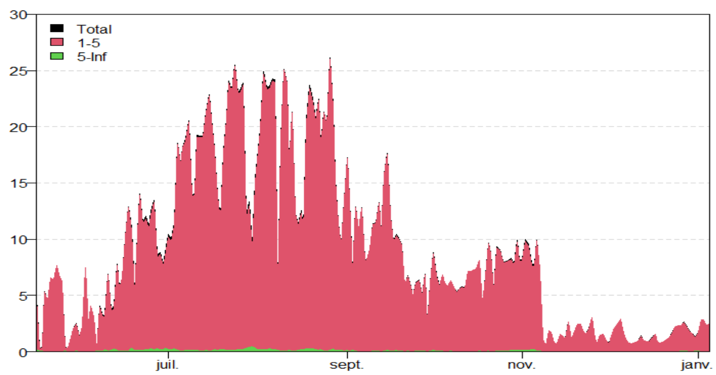
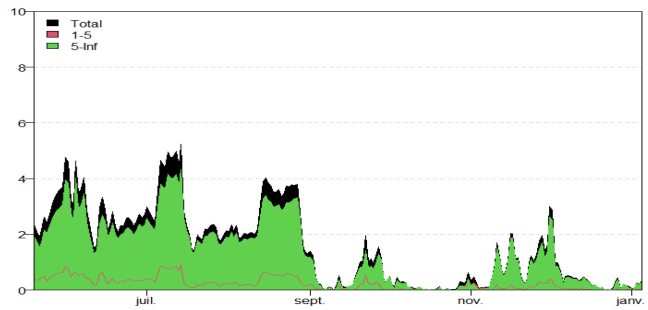
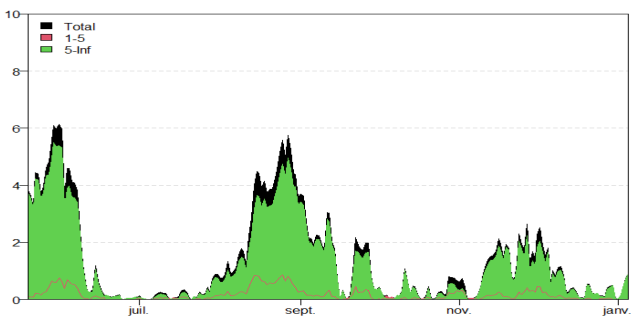
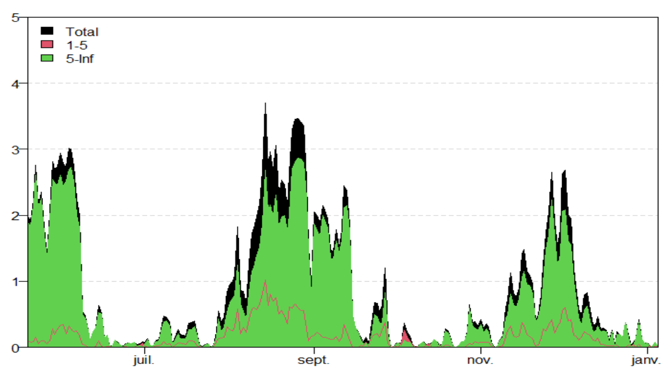
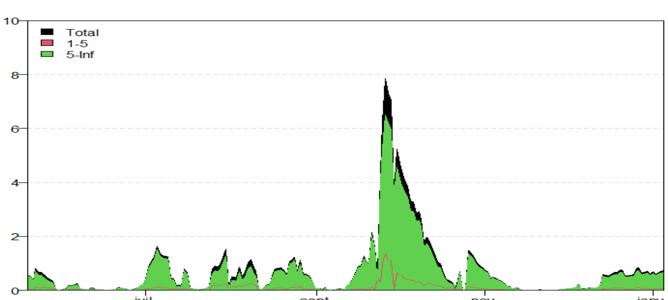
BNB	
Fix Token	

Notes: The results of classic cryptocurrencies are derived from a QVAR model using a rolling window of 200 days, with a lag length of one (determined by BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area displays the time dynamic connectedness values, while the green and red areas indicate the short-term and long-term results, respectively. The corresponding lines show the outcomes from the standard VAR time-domain approach (Diebold and Yılmaz, 2012, 2014) and the frequency-domain connectedness approach (Baruník and Křehlík, 2018).

Figure 7.
Short-term, Long-term, and Overall Dynamic Total Connectedness for Backed Gold Cryptocurrencies

	Volume/ Returns

https://doi.org/10.55802/IJB.030(1).001

PAXG	
XAUT	
PMGT	
DGX	

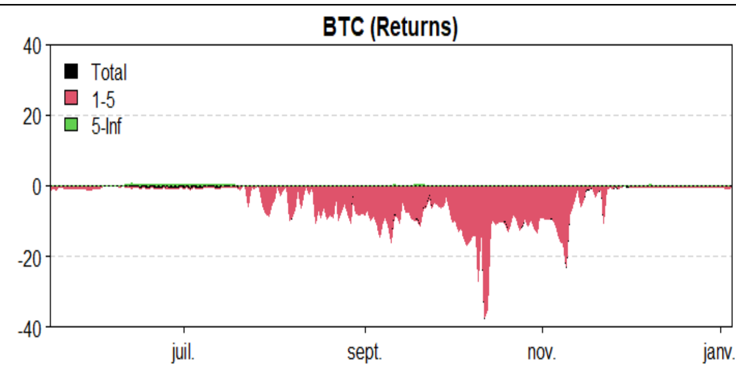
https://doi.org/10.55802/IJB.030(1).001

Notes: The results of Backed gold cryptocurrencies are derived from a QVAR model using a rolling window of 200 days, with a lag length of one (determined by BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area displays the time dynamic connectedness values, while the green and red areas indicate the short-term and long-term results, respectively. The corresponding lines show the outcomes from the standard VAR time-domain approach (Diebold and Yılmaz, 2012, 2014) and the frequency-domain connectedness approach (Baruník and Křehlík, 2018).

When examining the short and long-term net connectedness, we observe in Figures 6 and 8 that nearly all studied assets act as short-term net receivers of shocks, except for Metaverse, UPUNK, TERA, and PNB, where there appears to be a balancing effect between the "from" and "to" components. Interestingly, all studied backed gold cryptocurrencies exhibit long-term net transmitter characteristics. Furthermore, our analysis reveals asymmetry in the Total Connectedness Index (TCI) and both short-term and long-term TCIs, underscoring the impact of various economic and financial events across different time horizons.

Additionally, our investigation into market risk across time and quantiles unveils mixed results, with dynamic total connectedness being more pronounced at the extremes. This indicates that market risk fluctuates over time and across different quantiles, suggesting the need for adaptive risk management strategies to navigate varying market conditions effectively.

Figure 6.
Short-term, Long-term and Overall Net Total Directional Connectedness for Classic Cryptocurrencies

<table>
<tr><td></td><td>Volume/ Returns</td></tr>
<tr><td>BTC</td><td>
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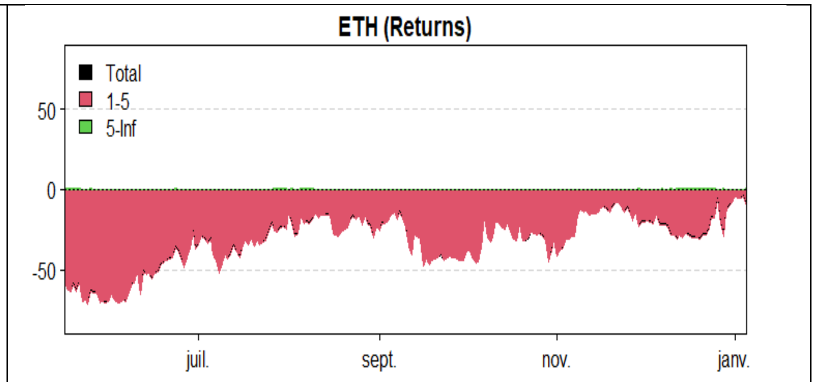
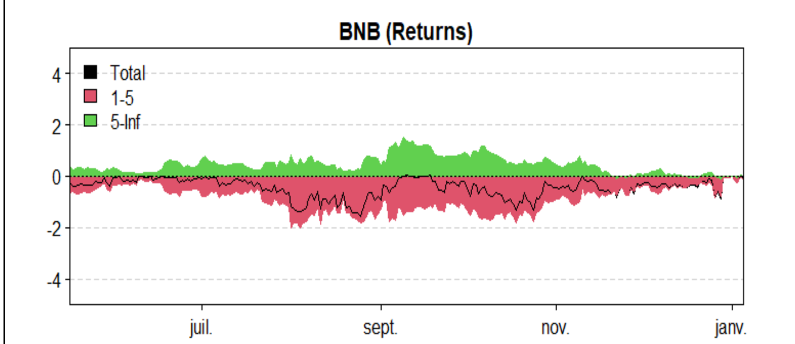
https://doi.org/10.55802/IJB.030(1).001

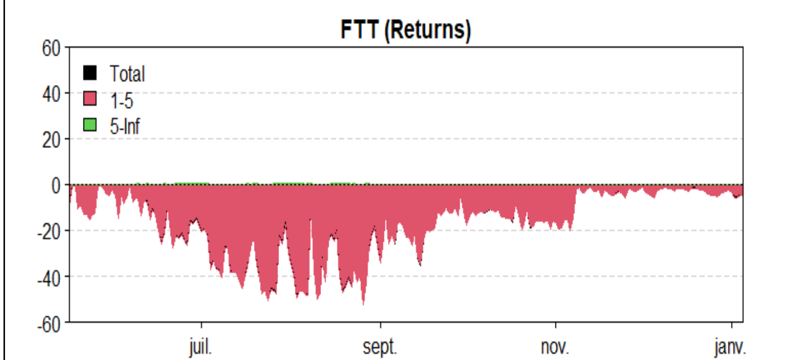
ETH



PNB



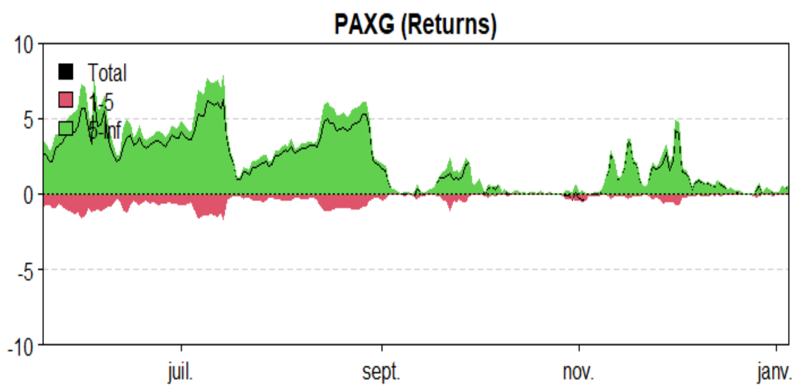
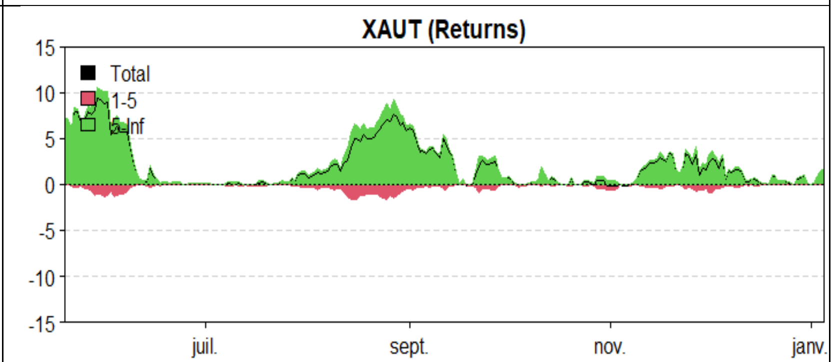
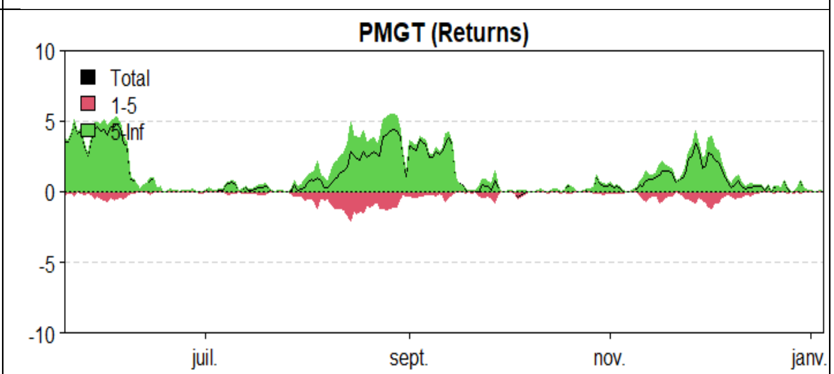
FIX Token



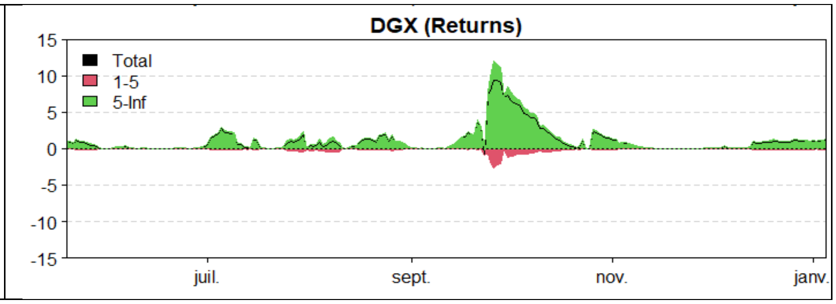
Notes: The results of classic cryptocurrencies are based on a QVAR model with a rolling window size of 200 days, a lag length of one (determined by BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area illustrates the time dynamic connectedness values, while the green and red areas depict the short-term and long-term results.

Figure 8.
Short-term, Long-term and Overall Net Total Directional Connectedness for Backed Gold Cryptocurrencies

	Volume/ Returns

PAXG	
XAUT	
PMGT	

https://doi.org/10.55802/IJB.030(1).001

DGX	

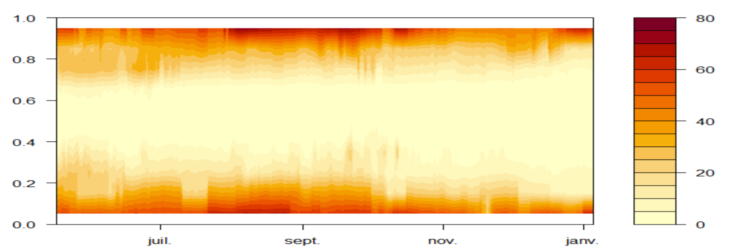
Notes: The results of Backed gold cryptocurrencies are based on a QVAR model with a rolling window size of 200 days, a lag length of one (determined by BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area illustrates the time dynamic connectedness values, while the green and red areas depict the short-term and long-term results

Furthermore, our nuanced investigation of connectedness contributes to understanding the transmission mechanisms of shocks within a highly integrated international financial system. We find that substantial price returns or volume changes, in either direction, significantly influence connectedness in financial markets. Additionally, our results shed light on which digital currency drives changes based on the direction of price adjustments, providing valuable insights for market participants seeking to understand and navigate dynamic market conditions.

Figures 9 to 16 depict the outcomes regarding total dynamic connectedness. In the plots, warmer shades signify higher levels of connectedness. Notably, we observe robust connectedness for both highly negative return changes (below the 20% quantile) and highly positive changes (above the 80% quantile) across all cryptocurrencies. Overall, the connectivity between returns and volume appears to exhibit asymmetry, except for Protocol, Fix Token, and SGX, where connectivity is lower in the upper and lower quantiles. Moreover, the results do not exhibit significant values at specific intervals, except for Sand (around January 2023), PULSE (around August 2022), LINK (from May to November), and PMGT (during almost the entire period), indicating higher connectedness in these instances. Finally, we do not observe a cyclical pattern of connectedness across time, suggesting that connectedness is not highly dependent on specific events.

Figure 9.
Dynamic Total Connectedness (NFT)

	Volume/ Returns

<table>
<tr><td>Metaverse</td><td>
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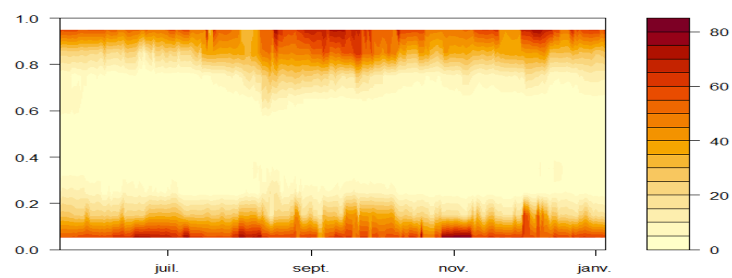
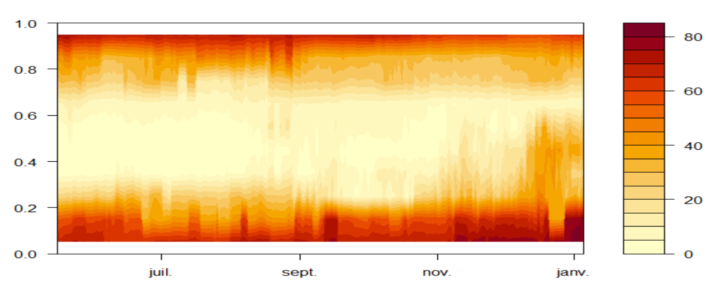
<tr><td>UPUNK</td><td>
</td></tr>
<tr><td>SAND</td><td>
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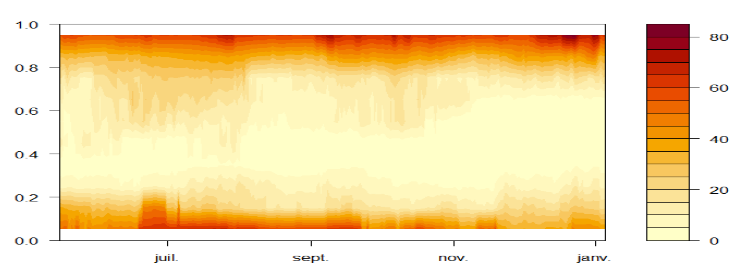
<tr><td>Launch</td><td>
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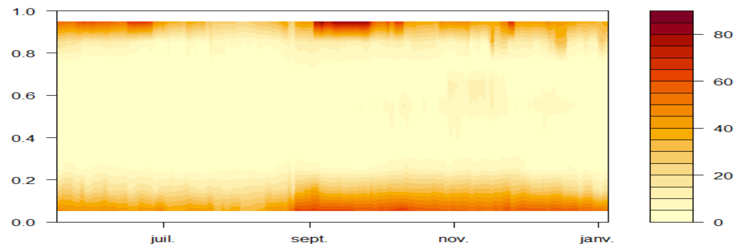
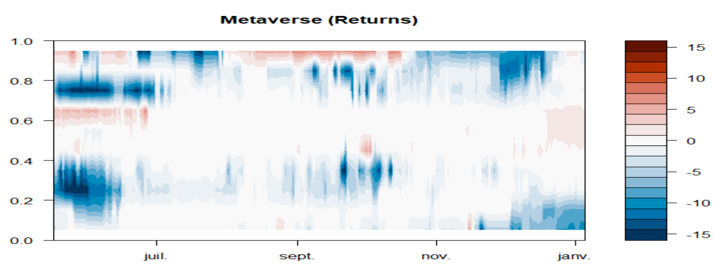
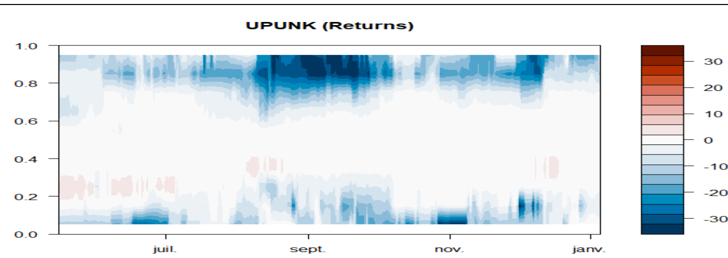
Protocol	

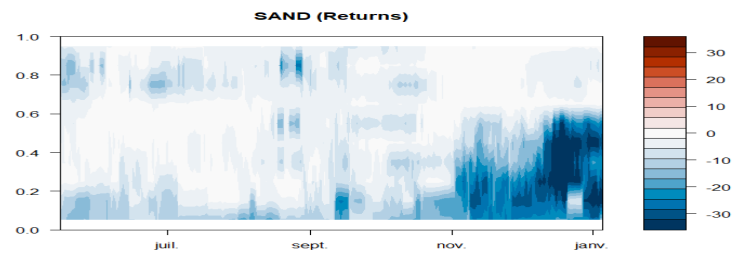
Notes: These figures display the total dynamic connectedness for NFTs across different market conditions, represented by a color-coded spectrum, with warmer hues indicating increasing degrees of interconnectedness.

Figure 10.
Net Total Directional Connectedness (NFT)

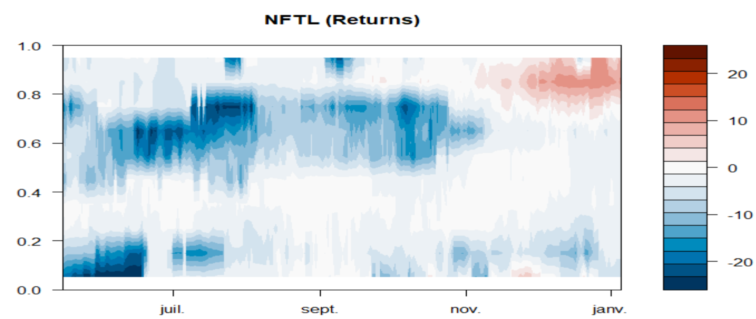
	Volume/ Returns
Metaverse	
UPUNK	

https://doi.org/10.55802/IJB.030(1).001

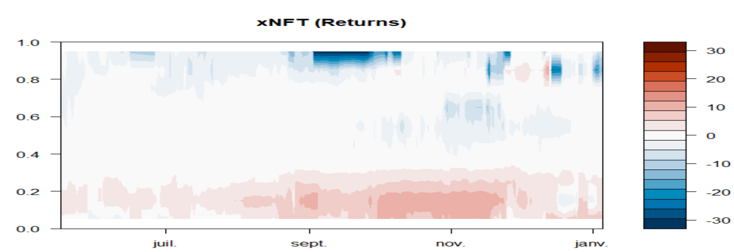
SAND



Launch



Protocol

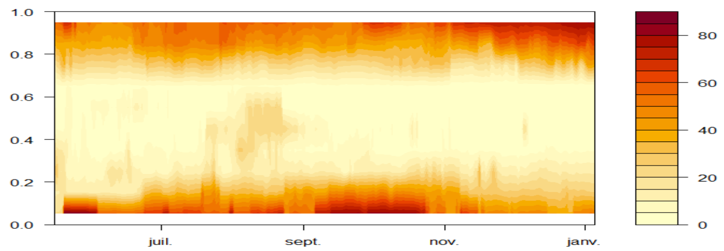
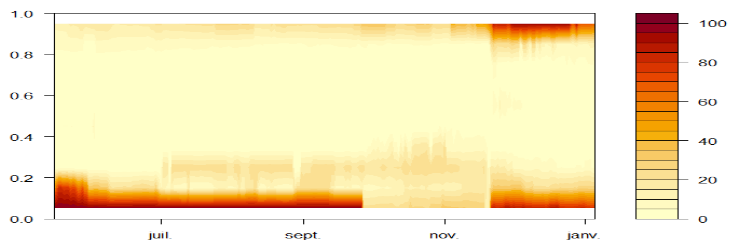
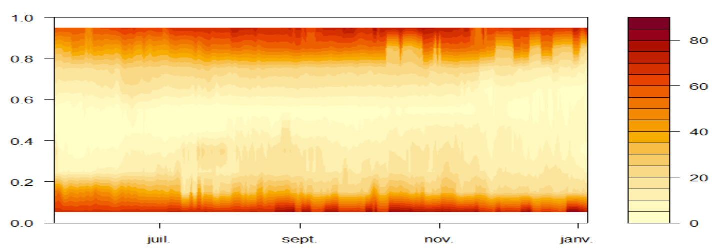
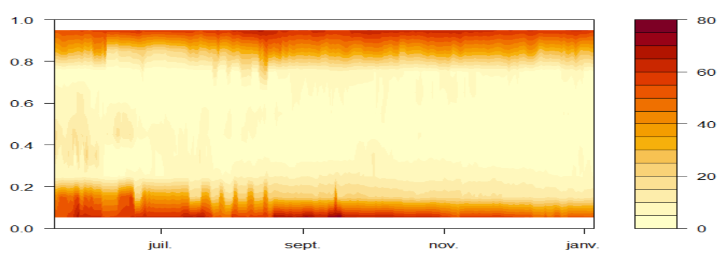


Notes: These figures display the Net Total Directional Connectedness for NFTs, represented by a spectrum of colors to distinguish the roles of assets: warmer hues signify assets acting as net transmitters of shocks, whereas cooler tones suggest assets functioning as net receivers.

Figure 11.
Dynamic Total Connectedness (DEFI)

	Volume/ Returns

https://doi.org/10.55802/IJB.030(1).001

Pulse	
Terra Classiqu e	
AVAX	
WBTC	

https://doi.org/10.55802/IJB.030(1).001

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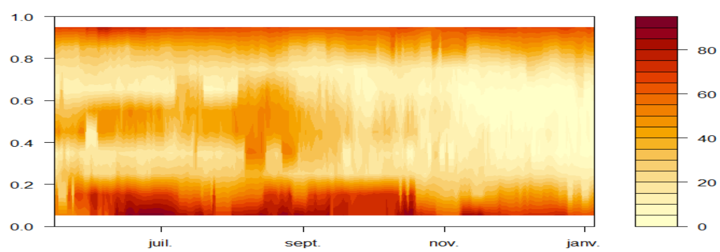
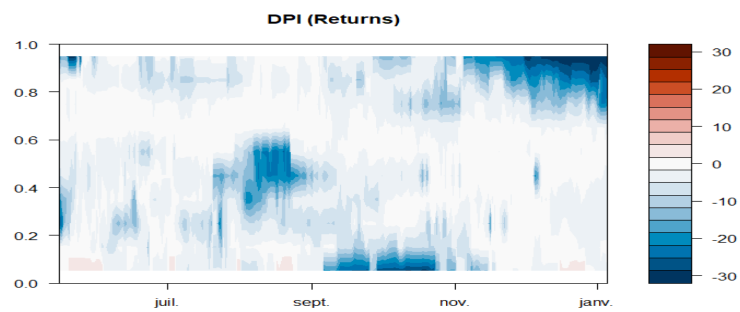
<tr><td>LINK</td><td>
</td></tr>
</table>

Notes: These figures display the total dynamic connectedness for DEFIs across different market conditions, represented by a color-coded spectrum, with warmer hues indicating increasing degrees of interconnectedness.

Figure 12.
Net Total Directional Connectedness (DEFI)

<table>
<tr><td></td><td>Volume/ Returns</td></tr>
<tr><td>Pulse</td><td>
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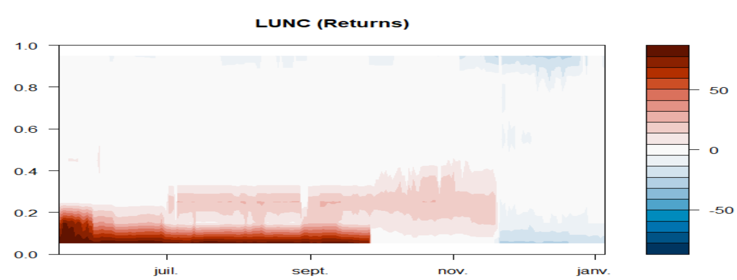
<tr><td>Terra Classique</td><td>
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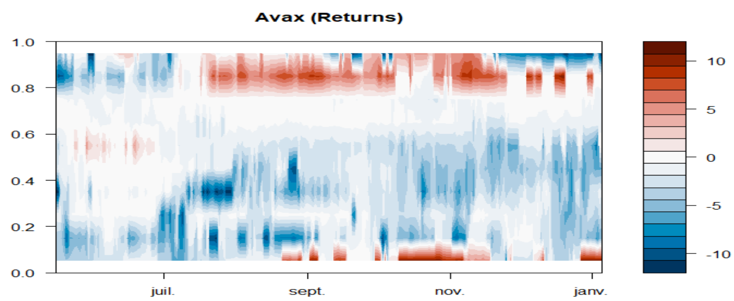
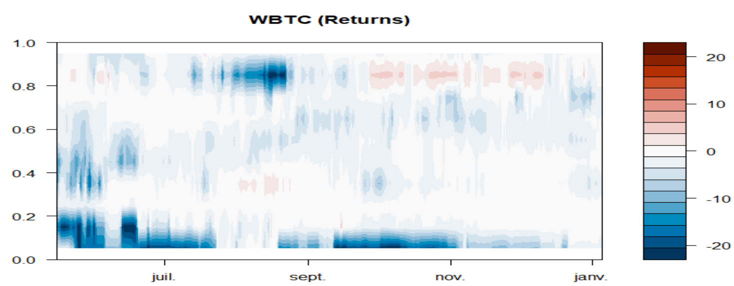
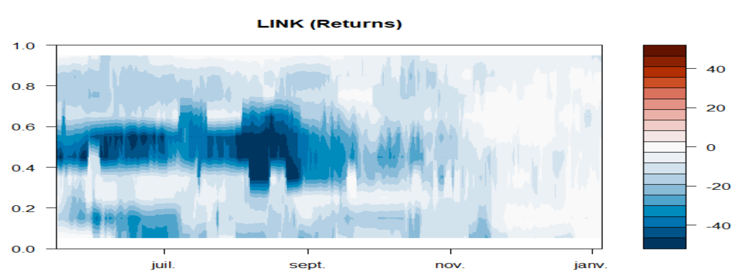
https://doi.org/10.55802/IJB.030(1).001

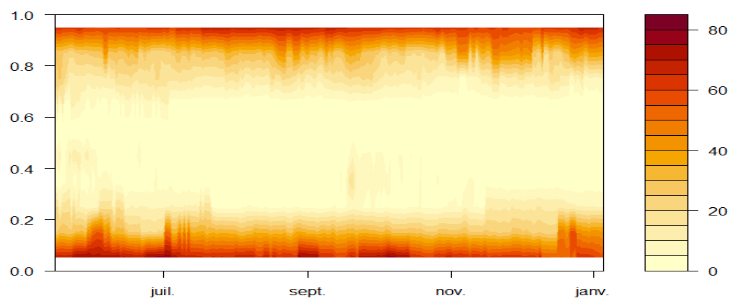
AVAX	
WBTC	
LINK	

Notes: These figures display the Net Total Directional Connectedness for DEFIs, represented by a spectrum of colors to distinguish the roles of assets: warmer hues signify assets acting as net transmitters of shocks, whereas cooler tones suggest assets functioning as net receivers

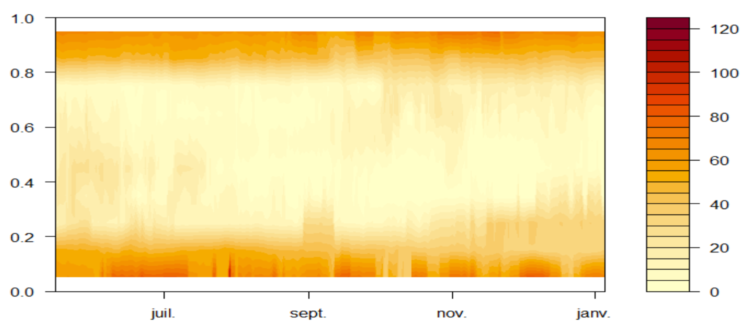
Figure 13.
Dynamic Total Connectedness (Classic cryptocurrencies)

	Volume/ Returns

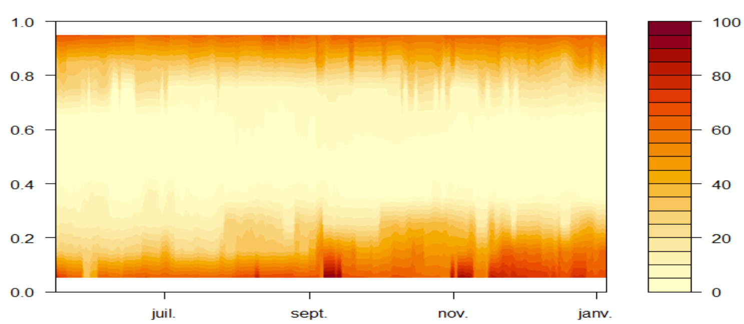
BTC



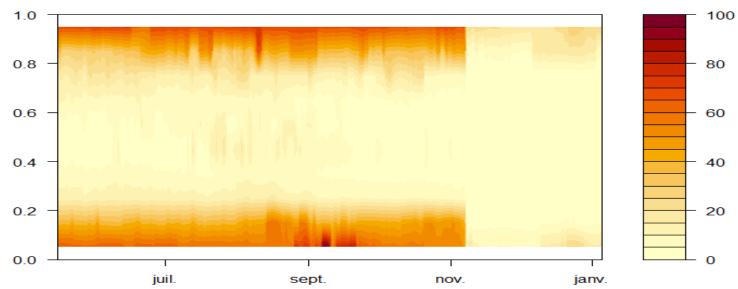
ETH



BNB

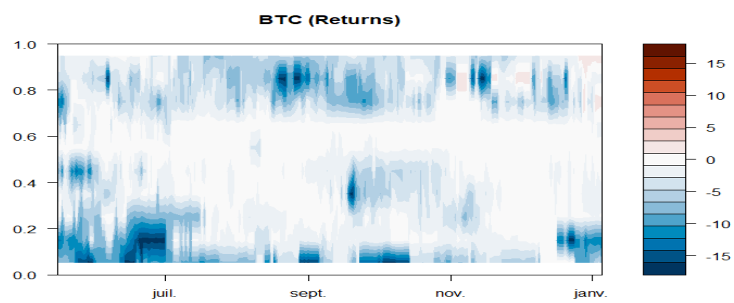


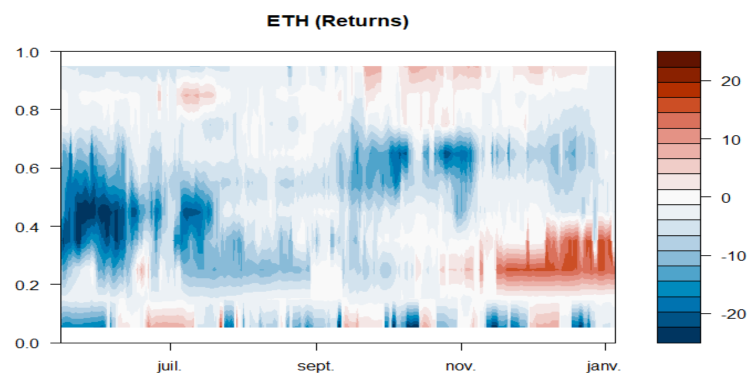
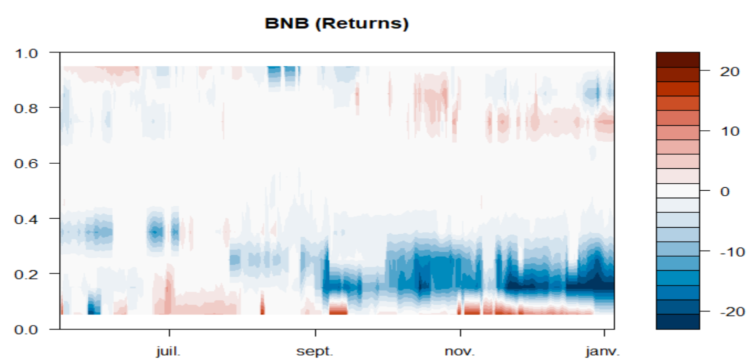
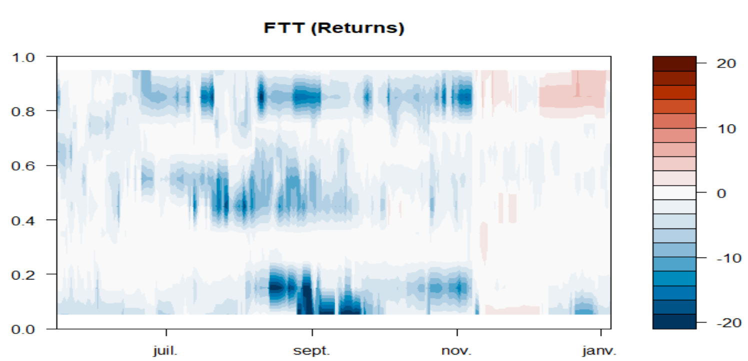
https://doi.org/10.55802/IJB.030(1).001

Fix Token	

Notes: These figures display the total dynamic connectedness for Classic cryptocurrencies across different market conditions, represented by a color-coded spectrum, with warmer hues indicating increasing degrees of interconnectedness.

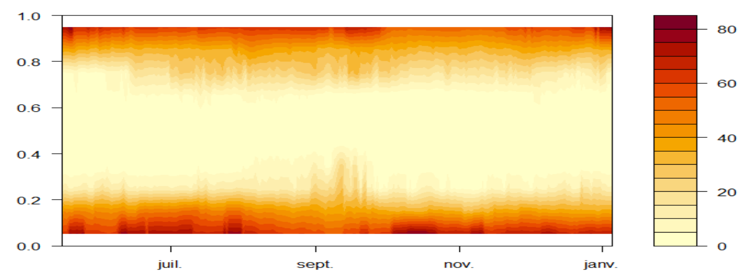
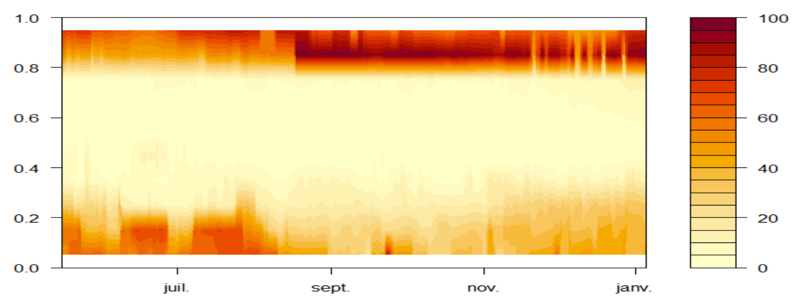
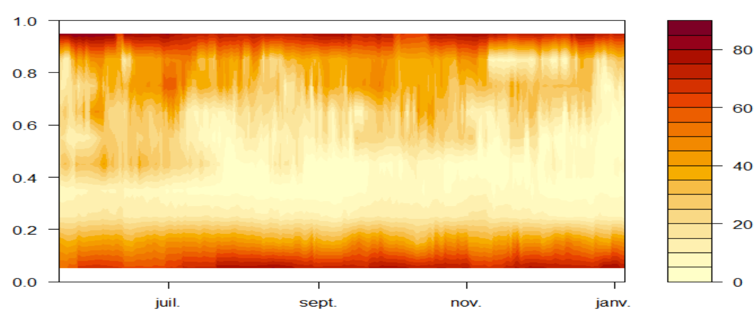
Figure 14.
Net Total Directional Connectedness (Classic Cryptocurrencies)

	Volume/ Returns
BTC	

ETH	
BNB	
FIX Token	

Notes: These figures in this table display the Net Total Directional Connectedness for Classic cryptocurrencies, *represented by a spectrum of colors to distinguish the roles of assets: warmer hues signify assets acting as net transmitters of shocks, whereas cooler tones suggest assets functioning as net receivers*

Figure 15.
Dynamic Total Connectedness (Backed Gold Cryptocurrencies)

	Volume/ Returns
PAXG	
XAUT	
PMGT	

https://doi.org/10.55802/IJB.030(1).001

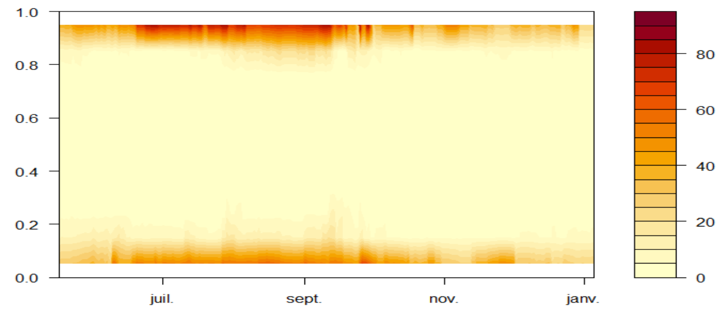
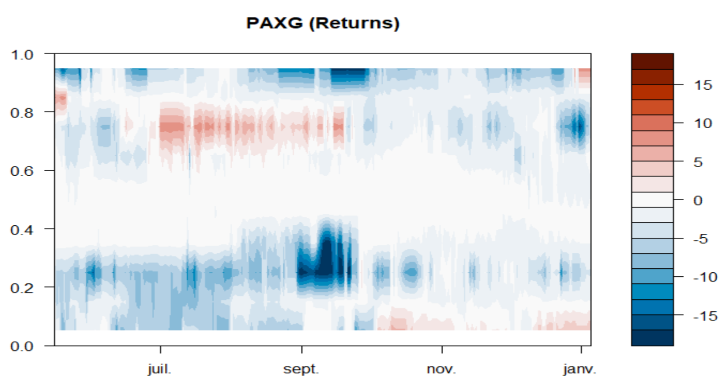
DGX	

Figure 16.
Net Total Directional Connectedness (Backed Gold cryptocurrencies)

	Volume/ Returns
PAXG	

<table>
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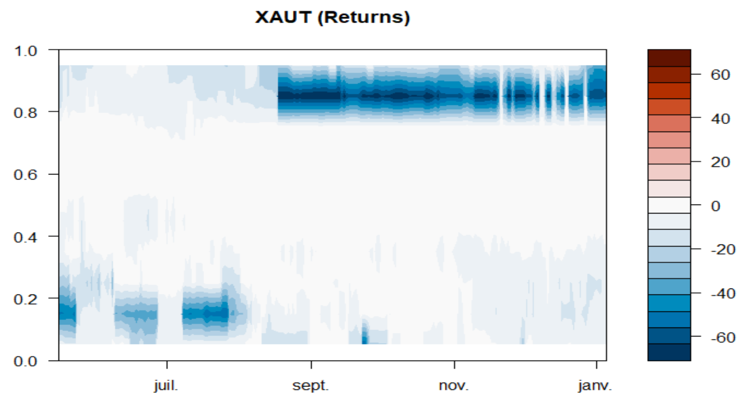
<td>XAUT</td>
<td>


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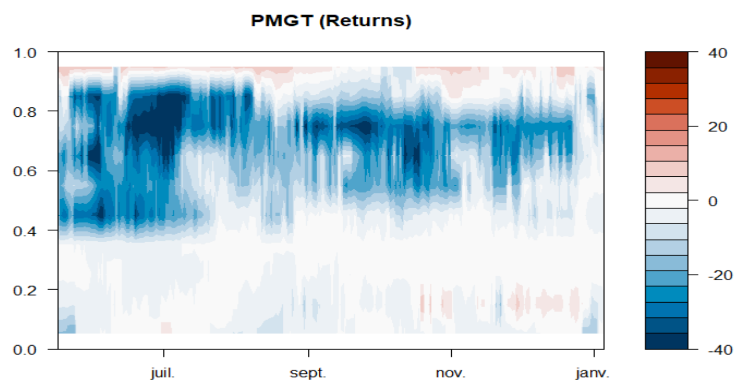
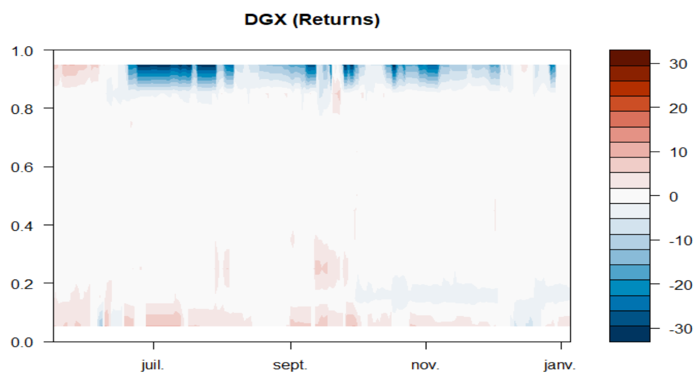
</tr>
<tr>
<td>PMGT</td>
<td>


</td>
</tr>
</table>

https://doi.org/10.55802/IJB.030(1).001

DGX	

Notes: These figures display the Net Total Directional Connectedness for Backed gold cryptocurrencies, represented by a spectrum of colors to distinguish the roles of assets: warmer hues signify assets acting as net transmitters of shocks, whereas cooler tones suggest assets functioning as net receivers.

In turn, we shift our focus to the net directional outcomes. In these plots, warmer shades denote a net-transmitting currency. Notably, our analysis reveals a consistent pattern across all digital currencies, where they predominantly receive from volume. This net receiving role is particularly pronounced during periods of both very low and very high transaction volumes. Interestingly, exceptions are observed for Link, Ethereum, Fix Token, and PMGT, where this role persists even during median quantiles, indicative of stable periods. Conversely, TERA emerges as predominantly a net transmitter to volume throughout nearly the entire observation period. Specifically, regarding backed gold cryptocurrencies, our findings indicate that PAXG exhibits shifts across quantiles, alternating between a net transmitting and a net receiving role, first observed between July and October, and then again between November and January 2023. On the other hand, XAUT, DGX, and PMGT predominantly assume a net receiving role, driven primarily by very high-volume transactions.

III. CONCLUSION

This paper empirically investigates the dynamic return-volume spillover pairs of classic cryptocurrencies, NFTs, DeFi, and gold-backed cryptocurrencies over the period from November 2, 2021, to January 5, 2023, utilizing the novel TVP-VAR frequency connectedness approach. Our findings confirm the presence of spillover effects between returns and volume for all the studied cryptocurrency markets. Generally, volume is found to have predictive power for returns, with few exceptions, leading us to conclude the inefficiency of these markets. Additionally, we provide insights into which digital currencies drive changes depending on the direction of price adjustments, even amidst varying market conditions, through time-frequency analysis.

Moreover, the volatility spillover decomposition in the frequency domain reveals a distinct pattern throughout the period for all backed gold currencies, Meta, UPUNK, Tera, and BNB, characterized by both long-term and short-term dynamics. This pattern

https://doi.org/10.55802/IJB.030(1).001

suggests significant shifts in market expectations and the presence of both short and long-term uncertainty. The Total Connectedness Index (TCI) predominantly reflects short-term connectedness across most cryptocurrencies, except for Metaverse, UPUNK, Tera, BNB, and all backed gold cryptocurrencies, where connectedness is primarily driven by long-term factors. Additionally, our analysis indicates that digital currencies consistently receive from volume, with their net receiving role being driven by both very low and very high transaction volumes, except for Link, Ethereum, Fix Token, and PMGT, where this role is observed even during stable market periods. Furthermore, we observe asymmetries in both the overall TCI and short-term and long-term net TCI. Lastly, we identify that the role of cryptocurrency returns in volatility transmission to volume is contingent upon the nature of the cryptocurrency.

The results highlight that the network's net transmission behavior predominantly stems from short-term dynamics, with the roles of assets as net-transmitters and net-receivers evolving over time. Given the increasing emphasis on volatility transmission between different assets in portfolio diversification and risk hedging strategies, such insights hold critical importance for both investors and policymakers. Investors can utilize these findings to enhance decision-making processes and refine risk management strategies, particularly during periods of extreme market conditions. Meanwhile, policymakers can leverage these insights to effectively navigate and manage diverse market conditions, contributing to overall market stability and resilience.

The detailed examination of the network's net transmission behavior and the evolving roles of assets as net-transmitters and net-receivers holds significant implications for both investors and policymakers. Understanding the dominance of short-term dynamics in driving transmission behaviors allows investors to better refine their decision-making processes and risk management strategies, particularly during periods of heightened market volatility. By leveraging this insight, investors can adjust their portfolios to mitigate risks effectively and capitalize on emerging opportunities. Moreover, policymakers can utilize these findings to inform regulatory frameworks and interventions aimed at maintaining market stability and resilience. Additionally, our analysis sheds light on the implications for asset pricing and price discovery mechanisms. The evolving roles of assets in transmitting volatility suggest dynamic shifts in market dynamics and information dissemination processes. This has important implications for asset pricing models, as traditional frameworks may need to account for the changing nature of transmission behaviors across different time horizons. Furthermore, understanding the intricacies of price discovery mechanisms in the context of evolving transmission dynamics can enhance market efficiency and transparency. Policymakers can use these insights to implement measures that foster a more efficient and resilient market environment, ultimately benefiting both investors and the broader economy. Integrating these policy implications into our analysis enriches the paper, providing a more comprehensive understanding of the implications of our findings for both financial markets and regulatory frameworks.

While our research offers practical and theoretical insights, there are avenues for future exploration. One limitation lies in our study's focus on a restricted set of assets, potentially limiting the breadth of market dynamics captured. Expanding the scope to include a wider array of assets and employing diverse analytical methods could yield a more nuanced understanding of spillover dynamics. Additionally, it's crucial to acknowledge that no consistent pattern can universally explain how risk events impact

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total or net spillovers across quantiles.

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