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Book

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Return-Volatility Nexus in the Digital Asset Class: A Dynamic Multilayer Connectedness Analysis

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Abstract

Based on the rationale that returns and volatility are interrelated, we apply a multilayer network framework involving the return layer and volatility layer of cryptocurrencies, NFTs, and DeFi assets over the period January 1, 2018 - January 23, 2024. The results show significant connectedness in each of the return and volatility layers, with major cryptocurrencies such as Bitcoin and Ethereum playing a central role. Large spikes in the level of connectedness are noticed around COVID-19 pandemic and Russia-Ukraine conflict, and Bitcoin and Ethereum emerge are net transmitters of returns and volatility shocks, emphasizing their significant role around these crisis periods. Notably, a strong positive rank correlation exists between the return and volatility layers, highlighting the significant risk-return relationship in the digital asset class. The findings suggest that economic actors should not ignore the interconnectedness between the return and volatility layers in the system of cryptocurrencies, NFTs, and DeFi assets for the sake of a comprehensive analysis of information flow. Otherwise, a share of the information flow concerning the return-volatility nexus across these digital assets would be missed, possibly leading to inferences regarding asset pricing, portfolio allocation, and risk management.

Keywords: Multilayer networks; Spillover effects; return-volatility; cryptocurrencies; NFTs; DeFi; COVID-19; Russia-Ukraine conflict

JEL Codes: C32; G10

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1. Introduction

The academic literature examines the market dynamics of cryptocurrencies, showing significant spillover effects in return and volatility. Cryptocurrencies share some commonality regarding underlying blockchain technology, hype surrounding their market prices, and speculative nature, which increases their market integration (Ji et al., 2019). On the one hand, previous studies consider the two moments separately by building single-layer networks using information about returns (Ji et al., 2019; Omane-Adjepong et al., 2019; Zięba et al., 2019; Kumar et al., 2022) or volatility (Yi et al, 2018; Ji et al., 2019; Xu et al., 2021). On the other hand, given the pertinence of return-risk relationships and its possible asymmetry, previous studies show evidence of significant relationship between return and volatility of individual cryptocurrencies in the context of Generalized Method of Moments (Ahmed, 2020), or univariate GARCH processes (Baur and Dimpfl, 2018). However, the spillover effect between return layer and volatility layer in the digital asset class is understudied, although it could entail important insights for investors, risk managers, and policymakers about the information spillover between these two layers and its evolvement across times and around crisis periods.

This paper applies a multilayer network framework involving the return layer and volatility layer in the digital asset class. It uses several measures to assess the characteristics of the network at both return and volatility layers and the centrality of major cryptocurrencies in the networks. Furthermore, it applies a rolling window approach to examine the evolution of spillover measures during turbulent periods.

Regarding the rationale linking returns and volatility layers, a two-way relationship can associate the layer of returns with that of volatility based on two theoretical frameworks (see, Black (1976) and Christie (1982)). The first concerns the risk premium – a basic principle of the theory of finance advocating that risk-taking rational investors are compensated with higher returns – under which volatility can incur a risk premium, driving a positive association between volatility and returns. This association running from volatility to returns tends to happen instantaneously due to the efficiency of financial markets. In this regard, previous studies also indicate presence of a time-varying feature of risk premium that often varies according to market conditions. The second concerns the news or leverage effect, under which returns affects volatility, with evidence that negative returns leads to a spike in volatility exceeding the spike in volatility arising from positive returns. This asymmetric return-volatility has been challenged in the cryptocurrency market, with evidence of an inverted asymmetry, which has been linked with cryptocurrency safe-haven property (Bouri et al., 2017) and the fear of missing out (FOMO) effect (Baur and Dimpfl, 2018).

Traditional financial analysis often relies on single-layer networks primarily focusing on price movements (i.e. returns). However, this is inadequate for capturing the multifaceted nature of emerging digital assets such as cryptocurrencies, which are highly volatile possibly due to many influences, including hype, market sentiment, technological advancements, regulatory and policy trends, and changing macroeconomic conditions. A single layer solely capturing price dynamics overlooks the rich information conveyed by return volatility (Wang et al., 2023; Xiang and Borjigin, 2024). Accordingly, multilayer information spillover networks address this limitation by incorporating multiple layers of data (e.g., Battiston et al., 2014), allowing for a deeper understanding of how information cascades across different dimensions. For example, a sudden spike in volatility (one layer) can be analysed through its impact on price returns (another layer) within the same network. Such a multidimensional approach offers a more comprehensive picture of information flow and its possible influence on market dynamics within the crypto, NFT, and DeFi assets. Hence, the application of multilayer spillover networks is essential for several reasons. Firstly, it provides a more holistic and accurate financial risk assessment by capturing interconnectedness across layers reflecting various aspects of information flow. This is particularly important in young, highly volatile, and speculative markets such as cryptocurrencies, NFTs, and DeFi. Secondly, providing a comprehensive understanding on how return layer and volatility layer influence each other, especially in a time-varying setting around crisis periods, should help traders, investors, and stakeholders in making more informed decisions, potentially leading to better investment strategies and risk management practices. Thirdly, regulators can benefit from a detailed view of interconnections between return and volatility layers in the young digital asset class, which can help them identify potential vulnerabilities and thereby implement effective oversight and regulatory measures.

Our analysis differs from previous studies in various respects and enriches the existing literature in several ways. Firstly, we consider not only conventional cryptocurrencies such as Bitcoin, Ethereum, and Ripple, but also cover other segments of the digital asset class, namely NFTs, and DeFi assets. The development of NFTs and DeFi markets has been rapid, contributing to the progress and charm of the digital asset class and its smart digital applications and contracts. Therefore, our analysis belongs to recent strand of literature considering the interlinkages across cryptocurrencies, NFTs, and DeFi assets (Chowdhury et al., 2023; Corbet et al., 2023; Kumar et al., 2023; Qiao et al., 2023), but it differs through its focus on how return and volatility layers are interrelated.

Secondly, unlike most previous papers that consider spillovers in return (Ji et al., 2019; Omane-Adjepong et al., 2019; Zięba et al., 2019; Kumar et al., 2022) and volatility (Yi et al, 2018; Ji et al., 2019; Xu et al., 2021) separately, we examine the spillovers between the return layer and volatility layer, allowing to make inferences about the return-volatility linkage in the multivariate system of cryptocurrencies, NFTs, and DeFi assets. This represents an extension to studies examining the return-volatility linkage in univariate models and for individual cryptocurrencies (Baur and Dimpfl, 2018; Ahmed, 2020; Kakinaka and Umeno, 2022). our analysis shows significant evidence on the interaction between the layer of returns spillover and a layer of volatility spillovers, which helps in detecting the two-way relationship in return-volatility in the area of cryptocurrencies, NFTs, and DeFi within a multilayer-layer network. Thus, our analysis conveys useful and comprehensive information on the interaction between return and volatility layers that single-layer networks often ignore.

Thirdly, we consider both static and time-varying analysis covering calm and turbulent periods, which allows us to capture the evolution and instability of the spillover effect around crisis periods. Our results show high spikes in the connectedness around COVID-19 pandemic and Russia-Ukraine conflict. Notably, there is evidence of a strong positive rank correlation between the return and volatility layers, underscoring the significant risk-return relationship in the digital asset class. Major cryptocurrencies, such as Bitcoin and Ethereum, are net spillover transmitters of returns and volatility shocks, emphasizing their significant role during the COVID-19 pandemic and Russia-Ukraine conflict.

2. Research background

In less than 15 years of history, the cryptocurrency market has become mainstream, constituting a well-established and appealing digital asset class. It has grown in price, size, and constituents, reaching a total market capitalization of almost 2.3 trillion USD by the end of April 2024. The decentralization and scarcity features of most cryptocurrencies, built around mass collaboration and blockchain technology, allow holders of a cryptocurrency to avoid the adverse impact of enlarged balance sheets of major central banks, especially the Fed, and to diversify the downside risk of the global financial system, including stock markets (Bouri et al., 2017). The related literature highlights the close co-movement in the price dynamics of cryptocurrencies, with Bitcoin playing a significant role, and shows evidence of co-jumps (Zhang et al., 2023), co-bubbling (Bouri, Shahzad, & Roubaud, 2019), contagion effect (Antonakakis et al., 2019), and the importance of media attention (Philippas et al., 2019), uncertainty conveyed in social media (Aharon et al. (2022), and sentiment and emotions

(Gurdgiev and O'Loughlin, 2020; Ahn and Kim, 2021; Mokni et al., 2022; Almeida and Gonçalves, 2023).

Besides major cryptocurrencies such as Bitcoin, Ethereum, Ripple, often labelled conventional cryptocurrencies, other segments of the digital asset class have emerged over the past years, experiencing historical development. These include Non-Fungible Tokens (NFTs) and Decentralized Finance (DeFi) assets, which have recently supported the growth of the digital asset class. NFTs represent digital assets with built-in authentication feature serving as proof of ownership (Ante, 2022; Borri et al., 2022; Nadini et al., 2021; Wang et al., 2021; Gosh et al., 2023). Different from conventional cryptocurrencies which exhibit a fungible or interchangeable feature, NFTs are not fungible, and are considered as collectibles of various forms such as artworks, games, music, and videos (Ante, 2022; Borri et al., 2022; Dowling, 2022; Gosh et al., 2023). Although in a pre-mature stage, NFTs price, sales, and attractiveness have increased substantially, notably around the COVID-19 outbreak during which the demand for digital assets and digital artworks spiked under the lockdown and the shift to work from home. Specifically, NFT tokens are coins related to a digital asset and used for buying a digital asset such as a NFT within its respective platform. As for DeFi, it represents a new financial technology service constructed around blockcahin networks, replicating conventional financial functions via smart digital contracts. It offers financial instruments and investments without the intermediary role of conventional financial institutions, which has been appealing to many market participants especially under the global economic slump and COVID-19 outbreak. DeFi has managed to produce considerable returns for investors in a short periods, such as the yield farming craze around mi-2020, with billions of USD being locked in DeFi protocols in 2020 and 2021.

The development of NFTs and DeFi markets has been rapid but these markets are still young and subject to large price fluctuations, often accentuated by speculative activities and the presence of limited number of market participants. Okorie et al. (2024) provide evidence that market efficiency of NFTs and conventional cryptocurrencies varies over time and is affected by the COVID-19 pandemic and the Russia-Ukraine conflict. Wang et al. (2022) highlight the presence of price bubbles in NFT and DeFi markets. The digital asset class is highly sensitive to hype, news, and investment sentiment, which facilitates return and volatility spillovers. Corbet et al. (2022) indicate the importance of investor attention to DeFi prices. Wang (2022) underlines the role of news attention for the volatility connectedness among NFTs.

The markets of conventional cryptocurrency and NTFs are interrelated and can effect each other. In this regard, Ethereum[1] is often used as a payment for NFT marketplaces, which contributes to strong interrelation between these cryptocurrency and NFT markets (Nadini et al., 2021). Compared to NFTs, which are somewhat detached from the global financial system and conventional assets (Aharon and Demir, 2022; Umar et al., 2022b), DeFi is generally more sensitive to the return volatility in conventional assets than to volatility from major cryptocurrencies.

A recent strand of literature considers the interlinkages across cryptocurrencies, NFTs, and DeFi assets (Karim et al., 2022; Umar et al., 2022a; Chowdhury et al., 2023; Kumar et al., 2023; Qiao et al., 2023[2]), showing significant increases in spillover effects around the pandemic and evidence on the importance of major cryptocurrencies in the system of information transmission. For example, Karim et al. (2022) show significant risk transmission across cryptocurrencies, DeFi and NFTs markets based on a quantile-based approach of connectedness. They show that NFTs offer higher diversification possibilities. Umar et al. (2022a) highlight the significant impact of the pandemic on the return and volatility spillovers across cryptocurrencies, NFTs, DeFi coins, and conventional assets using a VAR-based approach of connectedness. Chowdhury et al. (2023) apply an Asymmetric Multifractal Cross-Correlations approach and show that the volatility dynamics of cryptocurrencies, NFTs, and DeFi tokens pursue nonlinear cross-correlation dynamics. Furthermore, NFTs and DeFi show high sensitivity to events in bull market state. Considering the three digital assets, Kumar et al. (2023) apply a time-varying approach of connectedness based on VAR models and notice an increase in the level of connectedness before the Russia-Ukraine conflict and a change in the network of connectedness. Furthermore, cryptocurrencies absorb the volatility shocks arising from NFTs and DeFi markets, and DeFi tokens are the least connected to cryptocurrencies. However, the existing literature lacks an analysis of the spillover effect in returns and volatility in a multilayer network framework, capable of revealing possible relationship between the return layer and volatility layer, especially in a time-varying setting. This is where we aim to contribute.

[1] Ethereum ecosystem offers generally more application and innovation potentials than Bitcoin ecosystem.
[2] Qiao et al. (2023) employ a wavelet-quantile causality approach and their main results indicate that well-established coins control the network of upside and downside risk among cryptocurrencies and that yield farming tokens in the area of DeFi aggravate decentralized finance's reduction risk.

3. Methodology: A multilayer network framework

To analyse the information spillover between returns and volatility for cryptocurrency, NFTs and DeFi, we use the information multilayer network method developed by Wang et al. (2023). Thanks to this model, based on the Diebold and Yilmaz (2012, 2014) design, we are able to deeply investigate the nexus between returns and volatility of these digital assets in a multilayer prospective.

Our methodological framework has three steps. Firstly, we estimate the spillovers using the Diebold-Yilmaz methodology (2012, 2014). Secondly, we calculate single- and multi-layer network measures. Thirdly, by the block aggregation methodology developed by Greenwood-Ninno et al. (2021), we investigate the spillovers between the two layers (in our case, between returns and volatility)

3.1. Spillover model

Using the Diebold-Yilmaz (2012, 2014) model, we calculate the spillover indices for returns and volatility layers, respectively. The framework is founded upon the vector autoregression (VAR):

$$Y_t = \sum_{i=1}^{p} \Theta_i Y_{t-i} + \varepsilon_t \tag{1}$$

where, Y_t denotes an $N \times 1$ vector of endogenous variables at time t, Θ_i represents $N \times N$ coefficient matrices for each lag, p indicates the lag order, and finally $\varepsilon_t \sim (0, \Sigma)$ is an $N \times 1$ white noise vector. The VAR (p) model can be expressed as a moving average process, given by: $Y_t = \sum_{j=0}^{\infty} \Psi_j \, \varepsilon_{t-j}$ where, Ψ_j is a an $N \times N$ coefficients matrix defined as $\Psi_j = \Theta_1 \Psi_{j-1} + \Theta_2 \Psi_{j-2} + \ldots + \Theta_k \Psi_{j-k}$ with Ψ_0 as an $N \times N$ identity matrix, and $\Psi_j = 0$ for $j < 0$.

By the generalized variance decomposition (GVD) developed by Koop et al., (1996), and Pesaran and Shin (1998), we assess the contribution of each variable to the forecast error variance. Therefore, the H-step ahead generalized forecast error variance can be defined as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' B_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' B_h \Sigma B_h' e_i\right)} \tag{2}$$

where, Σ represents the $N \times N$ covariance matrix of the error vector ε, σ_{jj} denotes the standard deviation of the error term, and e_i is an $N \times 1$ selection vector. Finally, we normalise each element of the H-step ahead matrix:

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

3.2. Network measures

First, we calculate the average connection strength (ACS), that quantifies the average spillover effect of each layer. The ACS is computed as:

$$ACS = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ij}(H) \tag{4}$$

Second, from a multilayer perspective, we calculate the average edge overlap ⟨O⟩. This measure quantifies the average number of edges present among all pairs of nodes within the M layers. In our studies, since the multilayer networks include two layers, the overlap index spans from 1 to 2. Values close to 2 indicate a strong interconnection between two layers, whereas values around 1 imply that each edge exists solely within one layer. Conversely, if each edge is unique to one layer, the average edge overlap is 1. This network metric is able to measure the similarity between edge structures within a multiplex. The overlap index is defined as follows:

$$O = \frac{1}{K}\sum_{i=1}^{N}\sum_{j=1,i\neq j}^{N}\sum_{\alpha=1}^{M} a_{ij}^{[\alpha]} \tag{5}$$

where $a_{ij}^{[\alpha]} = \sin(g\left(\tilde{\theta}_{ij}\right))$, and k is the number of edges for layers.

To assess node importance in multilayer networks, we calculate the average overlapping strength of each layer. The average overlapping strength of a financial asset includes average overlapping in-strength ($O_{IN,i}$), average overlapping out-strength ($O_{OUT,i}$) and average overlapping net-strength ($O_{NET,i}$), which are defined as the averages of in-strength, out-strength and net-strength of financial asset *i* over all layers, i.e:

$$O_{IN,i} = \frac{1}{M}\sum_{\lambda=1}^{M} IS_i^{\lambda} \tag{6}$$

$$O_{OS,i} = \frac{1}{M}\sum_{\lambda=1}^{M} OS_i^{\lambda} \tag{7}$$

$$O_{NET,i} = O_{OS,i} - O_{IN,i} \tag{8}$$

After determining the system's connectedness, we examine structural similarity between pairs of layers using Spearman's rank correlation between layers α and β, as:

$$\rho^{[\alpha,\beta]} = 1 - \frac{6\sum_i\left(R_i^{[\alpha]} - R_i^{[\beta]}\right)^2}{N(N^2-1)} \tag{9}$$

where N denotes the number of financial assets, $R_i^{[\alpha]}$ and $R_i^{[\beta]}$ are the degree rankings of financial assets i on layers α and β, respectively.

In final step, following Wang et al. (2023), we quantify spillover between layers (returns and volatility) using the block aggregation methodology (Greenwood-Ninno et al., 2021):

$$S_{i\leftarrow j}(H) = \frac{1}{d}\sum_{i=1}^{d} G_{\leftarrow j}\,(H) = \frac{1}{d}\sum_{i=1}^{d}\sum_{ij=1,i\neq j}^{d} \tilde{\theta}_{ij}\,(H) \tag{10}$$

where, by definition, $S_{i\leftarrow j}(H) + S_{i\leftarrow i}(H) = 1$. The cross-layer connectedness matrix is then defined as:

$$\begin{bmatrix} \Theta^{g}_{R\to \mathrm{R}} & \Theta^{g}_{\mathrm{V}\to \mathrm{R}} \\ \Theta^{g}_{R\to \mathrm{V}} & \Theta^{g}_{\mathrm{V}\to \mathrm{V}} \end{bmatrix} \tag{11}$$

where $\Theta^{g}_{R\to \mathrm{V}}$ and $\Theta^{g}_{\mathrm{V}\to R}$ are the total cross-risk spillover from the return layer to the volatility layer and vice versa.

4. Empirical results

4.1. Data

The dataset used in this research paper includes the closing prices in USD of 23 digital assets, covering cryptocurrencies (Bitcoin, Litecoin, XRP, Dogecoin, Dash, Monero, Stellar, NEM, Ethereum, Waves, Ethereum Classic, Neo[3], Zcash, Bitcoin Cash, TRON, and Cardano), NFT tokens (Tezoz, Decentraland, Enjin Coin, and WAX), and DeFi (LINK, Decred, and EOS[4]), over the period January 1, 2018 - January 23, 2024, collected from https://coinmarketcap.com/. These selected assets in the three segments of the digital asset class are leaders in their respective segments, based on market capitalization. Furthermore, they are generally associated with a large trading volume, somewhat reflecting their market liquidity.

Using the closing prices, we calculate the log-returns. As for time-varying volatility, we measure it as $0.361\times\ln(H_t/L_t)$ based on Parkinson (1980), where in H_t and L_t stands for high and low prices

[3] Although Neo is often classified as a conventional cryptocurrency, recent developments show that it boards DeFi protocols such as Flamingo Finance, and an NFT marketplace named GhostMarket.
[4] EOS facilitates several functions such as transactions on DeFi protocols (https://eosnetwork.com/introducing-eos/). It also allows for trading digital art through NFTs.

respectively on a particular date (day) t. Note that, Parkinson (1980) created this metric by assuming an underlying geometric Brownian motion with no drift for the prices, and is considered to be as much as 8.5 times more efficient than logarithmic values of squared returns (Chan and Lien, 2003).[5].

Table 1 shows the summary statistics for our two layers, i.e., the log-returns and volatility. The descriptive statistics show that Dogecoin and Decentraland exhibit the highest average values in both layers, indicating a significant impact of financial turmoil on these assets. The Kurtosis values confirm that all series follow non-Gaussian distributions, as validated by the Jarque–Bera (J-B) statistic. Additionally, the augmented Dickey-Fuller (ADF) test indicates no evidence of a unit root, thereby satisfying the stationarity requirement for VAR modelling.

Table 1. Summary statistics of returns and volatility series

Assets	Mean	Min	Max	Std. Dev.	Skewness	Ex. kurtosis	J-B	ADF
Log-return series								
Bitcoin	0.0005	-0.4647	0.17182	0.03677	-1.0516	14.198	18960.940***	-12.034***
Litecoin	-0.0005	-0.4491	0.29059	0.05032	-0.5487	8.2874	6432.404***	-12.906***
XRP	-0.0007	-0.5505	0.54856	0.05668	0.32699	16.945	26468.604***	-12.935***
Dogecoin	0.00099	-0.5151	1.5164	0.07122	5.2583	104.6	1017168.727***	-12.981***
Dash	-0.0016	-0.4655	0.4513	0.05488	-0.1071	10.497	10146.902***	-12.971***
Monero	-0.0004	-0.5342	0.34495	0.0495	-1.1335	13.819	18048.803***	-12.781***
Stellar	-0.0007	-0.41	0.55918	0.05484	0.8974	15.061	21175.800***	-13.635***
NEM	-0.0015	-0.4227	0.4338	0.05804	0.0027	8.1784	6156.277***	-12.333***
Ethereum	0.00053	-0.5507	0.2307	0.0474	-1.0158	11.259	12046.583***	-12.121***
Decred	-0.0009	-0.5108	0.70964	0.05557	0.46728	18.171	30471.711***	-12.371***
Waves	-0.0008	-0.4871	0.53412	0.06528	0.49272	10.149	9570.318***	-12.161***
Ethereum Classic	-0.0001	-0.5064	0.35247	0.05787	-0.052	8.9675	7402.644***	-12.621***
Neo	-0.0009	-0.4656	0.33429	0.05783	-0.5021	6.5039	3986.236***	-12.594***
Zcash	-0.0014	-0.5394	0.26072	0.05611	-0.618	7.4288	5220.110***	-12.837***
EOS	-0.0011	-0.5042	0.4396	0.0591	-0.2751	9.7839	8838.531***	-13.259***
Bitcoin Cash	-0.0011	-0.5614	0.42081	0.05755	-0.2147	12.65	14745.602***	-12.887***
TRON	0.00034	-0.5232	0.78667	0.05749	0.88869	24.2	54193.766***	-13.465***
Decentraland	0.0007	-0.6298	0.93507	0.07198	1.2187	20.089	37691.961***	-12.442***
LINK	0.00134	-0.6146	0.48062	0.06504	-0.1741	8.3738	6465.233***	-12.786***
Cardano	-0.0002	-0.5037	0.3218	0.05554	-0.0189	5.9851	3297.165***	-11.561***

[5] As outlined in Floros (2009), we also considered alternative metrics of volatility considered in the literature, based on not only high- and low-prices but also opening and closing prices, as well as conditional volatility from the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (Bollerslev, 1986), but our main empirical findings continued to be robust, with these results available upon request from the authors.

Tezos	-0.0007	-0.6073	0.30587	0.06196	-0.6822	8.3701	6619.727***	-13.101***
Enjin Coin	0.00022	-0.6242	0.76822	0.07262	1.0911	17.898	29923.980***	-12.003***
WAX	-0.0012	-0.7249	0.81541	0.07342	0.90724	21.206	41692.732***	-12.262***
Volatility series								
Bitcoin	0.00121	4.65E-06	0.08648	0.00307	14.051	315.14	9213546.447***	-9.519***
Litecoin	0.00239	1.36E-05	0.16932	0.006	13.69	303.85	8566479.092***	-9.601***
XRP	0.00317	1.14E-05	0.18981	0.01051	10.462	141.22	1875861.033***	-9.427***
Dogecoin	0.00459	2.08E-05	0.85242	0.0254	22.136	635.5	37352253.202***	-10.132***
Dash	0.00274	1.88E-05	0.21484	0.00748	14.366	326.9	9912180.018***	-9.634***
Monero	0.00234	1.71E-05	0.23741	0.00701	20.286	601.84	33490181.954***	-9.847***
Stellar	0.00308	2.38E-05	0.21472	0.00944	12.507	212.57	4216542.582***	-8.524***
NEM	0.00365	2.10E-05	0.15927	0.00885	8.9716	116.97	1288895.536***	-8.374***
Ethereum	0.00199	4.55E-06	0.11556	0.00499	13.071	253.06	5956972.053***	-9.827***
Decred	0.00327	2.34E-05	0.2729	0.0094	15.292	354.99	11684917.678***	-11.059***
Waves	0.00423	3.84E-05	0.16208	0.00932	7.584	83.704	666053.568***	-9,057***
Ethereum Classic	0.00328	1.75E-05	0.22488	0.00926	12.285	224.94	4712533.713***	-7.341***
Neo	0.00333	3.06E-05	0.21195	0.00822	12.344	235.55	5162927.341***	-9.607***
Zcash	0.00314	4.99E-05	0.30304	0.00875	20.532	640.28	37888403.268***	-9.576***
EOS	0.0031	2.40E-05	0.21575	0.00801	12.037	248.65	5744026.581***	-8.013***
Bitcoin Cash	0.00286	1.61E-05	0.22112	0.00811	13.257	277.21	7137717.302***	-8.974***
TRON	0.00316	7.12E-06	0.24713	0.01033	11.903	202.11	3811857.792***	-10.056***
Decentraland	0.00527	2.67E-05	0.60303	0.01777	20.454	608.36	34218269.134***	-10.289***
LINK	0.00428	2.63E-05	0.18488	0.00951	9.2063	124.14	1449706.696***	-8.916***
Cardano	0.00311	2.85E-05	0.16666	0.00697	10.234	173.25	2801376.597***	-9.248***
Tezos	0.00396	2.01E-06	0.17885	0.00914	9.3239	126.43	1503252.364***	-9.285***
Enjin Coin	0.00543	3.23E-05	0.34423	0.01532	11.21	178.32	2973053.641***	-8.331***
WAX	0.00579	3.04E-05	0.38363	0.01719	11.206	182.49	3111555.964***	-9.478***

Note: The descriptive statistics cover daily log-return and volatility series for 23 digital assets from January 1, 2018, to January 23, 2024. The augmented Dickey-Fuller (ADF) statistic tests the null hypothesis of a unit root. Each augmented Dickey-Fuller (ADF) statistic is negative and less than the critical value at the 1% significance level, leading to the rejection of the null hypothesis of a unit root in each return/volatility series. For all series, Jarque-Bera (J-B) statistics are significant at the 1% level, rejecting the null hypothesis of Gaussian distribution.

Before we move on to our multilayer spillover analysis formally, to motivate the approach further we used the factor-adjusted network estimation, i.e., FNETS method of Barigozzi et al. (2024), to show that there is strong causal influence between the returns and volatilities, as well as across the two moments in particular, of the 23 digital currencies, as observed from Figure A1 in the Appendix of the paper. Hence, the need to consider a multilayer approach. Note that, our decision to use Parkinson's (1980) approach to compute volatilities based on high- and low-prices are also motivated by Barigozzi et al. (2024).

4.2. Static analysis

Table 2 reports the static network metrics among the cryptocurrency, DeFi and NTF markets using a 300-day rolling window (corresponding to one trading year) and 10-day-ahead forecast horizon[6]. The optimal lag length for the VAR model is selected based on the Schwarz and Akaike information criteria (lag order k=1).

Table 2: Network metrics

Panel A: Average connection strength and overlap index		
Layer	ACS	⟨O⟩
Returns spillover layer	88.3	1.9
Volatility spillover layer	88.1	
Panel B: Correlation between layers		
Layer-Layer	Spearman Rank correlation	
Returns layer and Volatility layer	0.904***	
Panel C: Cross-spillover layer		
Layer	Returns spillover layer	Volatility spillover layer
Returns spillover layer	84	20
Volatility spillover layer	16	80

Note: ACS (average connection strength); ⟨O⟩ (overlap index); *** denotes statistical significance at the 1% significance level.

As we can note from Table 1, the returns and the volatility of the cryptocurrency, NFT and DeFi are fairly connected and integrated, as evidenced by Average connection strength (ACS) of 88.3 and 88.1, respectively. This suggests a strong integration between the returns and volatility of these digital assets. From the multilayer measurements, ⟨O⟩ and Spearman rank correlation quantify the overlap of edges in multilayer information spillover networks and the correlation between being hubs in one layer and in the other, respectively. The ⟨O⟩ measurement shows that almost every edge in each layer

6 As a robustness check, we estimate the model based on alternative rolling windows (250, 300, and 500 days), and forecast horizons (20, 30, and 60 days). The test results show that our empirical results are robust.

also exists in the other, indicating that the directional spillover between the two assets of each layer also exists in the other. The Spearman Rank correlation coefficient, with a value of 0.904 statistically significant at the 1% level of significance, indicates a strong positive correlation between returns and volatility layers. This suggests that assets exhibiting centrality or importance in one layer tend to maintain similar importance in the other layer. Thus, the risk-return relationship appears to be symmetrical across the digital assets. This finding corroborates the works of Yousaf and Yarovaya (2022) and Chowdhury et al., (2023) which show this characteristic of these digital assets. However, when focusing on cross-layer spillovers, it is interesting to note how the two layers transmit between 16% and 20% of information flows. Therefore, it is significant to analyse individual behaviour characteristics, especially for assets that behave differently on each level in multilayer information spillover networks.

In Table 3, we report the top 10 assets in terms of Out-strength, In-strength, and Net-strength, in descending order during the entire sample period, respectively. The average overlapping out-strength (O_{OUT}) ranges between 20.50 and 23.44, while the average in-strength overlapping (O_{IN}) varies from 18.03 to 18.21. The distribution of $O_{IN,i}$ is much more diverse than that of the O_{OUT}. This finding suggests a pattern of heterogeneous out-strength spillover effects compared to a more homogeneous pattern of in-strength spillover effects for assets. In simpler terms, the shocks transmitted by individual assets to other assets are more varied, while the shocks received by individual assets from others are more evenly distributed. As we can note, the most important transmitters and receivers are Ethereum, Litecoin, Neo, Cardano, Bitcoin, and Dash.

Table 4 shows the top 10 assets by PageRank centrality[7]. As we can note, the ranking is perfectly in line with the analysis above. This shows that assets with higher return and volatility spillovers also have higher PageRank versatility. The findings emphasize the significance of cryptocurrency due to its highly speculative nature and the relative dominance of its market value. Cryptocurrencies exhibit high sensitivity to investor sentiment (e.g., Taleb, 2021). As evidenced by Kumar et al. (2023), the influence of human emotions plays a determinant role in price movements within the cryptocurrency market. The results provide evidence that most cryptocurrencies act as net spillover transmitters to NFT and DeFi assets. This reinforces the notion that cryptocurrencies serve as key assets facilitating the transfer of spillover across the decentralized financial markets. In other words, changes in cryptocurrency prices tend to influence the price changes of NFTs and DeFi assets, suggesting that the market dynamics of NFTs and DeFi assets often follow the market dynamics of cryptocurrencies.

[7] For the sake of brevity, we do not report the methodological aspects of the PageRank method. However, they are available on request.

These results align with the literature (e.g., Yousaf and Yarovaya, 2022; Mensi et al., 2024), which similarly identified cryptocurrencies as net transmitters of returns to NFT. Moreover, the predominant influence of Ethereum, Litecoin, and Bitcoin as net transmitters can be attributed to their leading positions in the cryptocurrency market. Notably, Ethereum functions as a central hub for the exchange of many NFTs and underpins numerous DeFi applications (Kumar et al., 2023; Dowling, 2022). Consequently, changes in Ethereum prices have a significant ripple effect on related markets.

Table 3: Top 10 assets

Rank	Average overlapping strength					
	Financial assets	Out-strength	Financial assets	IN-strength	Financial assets	Net-strength
1	Ethereum	2.344	Ethereum	1.821	Ethereum	0.520
2	Litecoin	2.265	Litecoin	1.820	Litecoin	0.444
3	Neo	2.251	Neo	1.812	Neo	0.438
4	Cardano	2.115	Cardano	1.811	Cardano	0.304
5	Bitcoin	2.106	Bitcoin	1.808	Bitcoin	0.296
6	Dash	2.091	Dash	1.807	EOS	0.291
7	EOS	2.081	Monero	1.806	Dash	0.290
8	Monero	2.076	EOS	1.805	Monero	0.289
9	Bitcoin Cash	2.051	Zcash	1.804	Bitcoin Cash	0.248
10	Zcash	2.050	Bitcoin Cash	1.803	Zcash	0.245

Table 4: PageRank Centrality

Rank	Top 10 assets ranked by PageRank Centrality	
	return layer	volatility layer
1	Ethereum	Ethereum
2	Litecoin	Neo
3	Neo	Litecoin
4	Bitcoin	Monero
5	EOS	Bitcoin
6	Dash	Cardano
7	Bitcoin_Cash	Dash
8	Cardano	EOS
9	Zcash	Ethereum_Classic
10	Ethereum_Classic	Bitcoin_Cash

4.3.Dynamic analysis

In this section we consider the dynamics of the multilayer network. Figure 1 plots the evolution of the return and volatility connectedness, i.e., the average connection strength (ACS). The analysis of connectivity dynamics in cryptocurrency, DeFi, and NFT systems shows several key insights into the behaviour of these markets, particularly during periods of significant events such as the COVID-19 pandemic, the cryptocurrency market bubble of 2021, and the Russia-Ukraine conflict.

The observed high levels of connectivity, ranging from 75% to 90% for the returns layer and from 70% to 88% for the volatility layer, indicate a strong interdependence among cryptocurrencies, DeFi, and NFTs. This suggests that movements in one asset can significantly influence others within the system, highlighting the interconnectedness of these markets. We observe peaks in connectivity during periods of major global events, such as the COVID-19 pandemic and the Russia-Ukraine conflict. The COVID-19 pandemic, in particular, led to a rapid increase in total system connectivity, reflecting heightened market uncertainty and investor concerns. Similarly, the Russia-Ukraine conflict contributed to increased connectivity.

During the peak of the COVID-19 pandemic in early 2020, a sharp increase in connectivity was observed, followed by a subsequent decline after the approval of vaccines later in the year. The subsequent decline in connectivity reflects a gradual return to normalcy as confidence in the global economy improved.

The cryptocurrency market bubble of 2021 led to increased volatility and connectivity within the cryptocurrency, DeFi, and NFT systems. This period of exuberant market behaviour was characterized by significant speculative trading activity. The observed increase in volatility layer connectivity during this period indicates heightened market uncertainty and risk aversion among investors (see, Yousaf et al., 2023; Kumar et al. 2023; Mensi et al., 2024).

From 2023 onwards, a downward trend in connectivity and volatility is observed, particularly in the volatility layer. This trend suggests a potential shift towards more stability and normalization in the cryptocurrency, DeFi, and NFT markets. Factors contributing to this trend may include regulatory interventions, such as the approval of Regulation (EU) 2023/1113 in Europe and the approval of the first US Bitcoin Spot ETFs in January 2024.

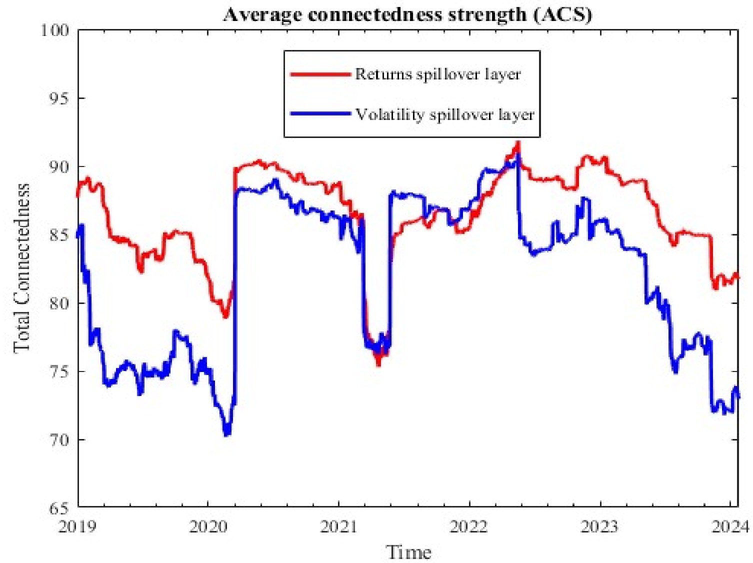


Figure 1: The ACS evolution for each layer

Figure 2 illustrates the average edge overlap ⟨O⟩ in multilayer networks. During periods of market tension, ⟨O⟩ reaches near-maximum values close to 2, indicating that almost all edges are joined across every layer. The value of ⟨O⟩ increases rapidly during market downturns and remains low during stable market conditions.

Figure 3 displays changes in the inter-layer rank correlation in multilayer networks. The Spearman rank correlation coefficients between the return and volatility layers exhibit similar trends, fluctuating in the range of 0.7-0.95. This implies a strong positive rank correlation between the two layers, indicating that assets serving as hubs in the return spillover layer are likely also to be hubs in the volatility layer. The strong positive correlations between the return and volatility layers indicate that assets with high returns also tend to exhibit high volatility. This underscores the risk-return solid relationship in these assets.

An interesting observation is the downward trend in correlation starting from mid-2022. While on the aggregate level, we observe an increase in connections, the role of each asset in the network has changed. This trend shift may be attributed to the impact of the Russia-Ukraine conflict, which triggered a paradigm shift in the risk-return relationship, stimulating arbitrage opportunities (Bouteska et al., 2023; Abakah et al., 2024).

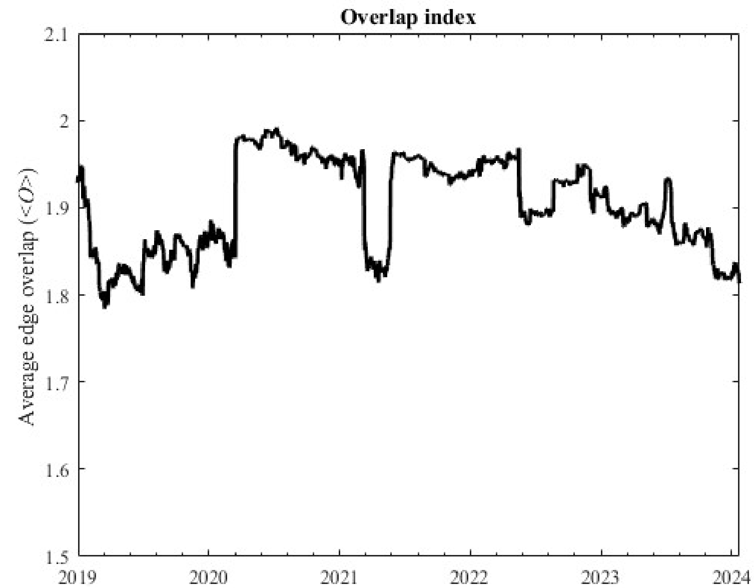


Figure 2: The dynamics of Overlap index

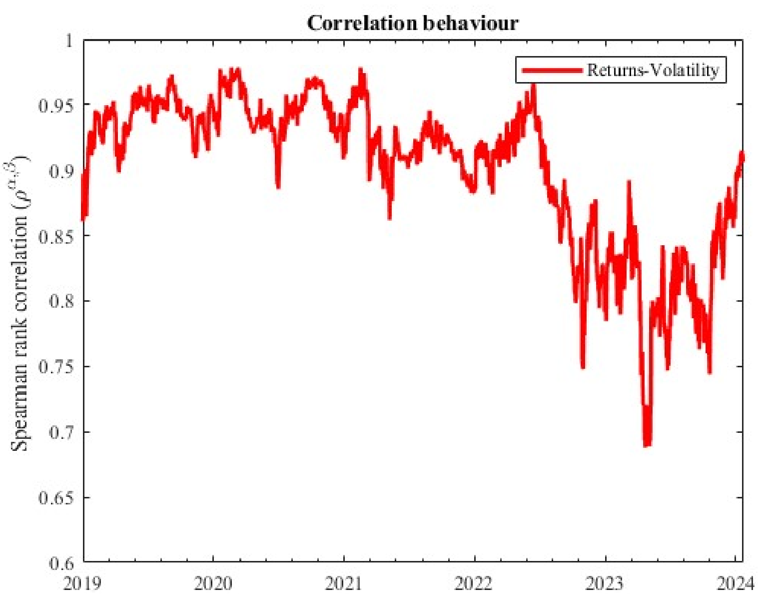
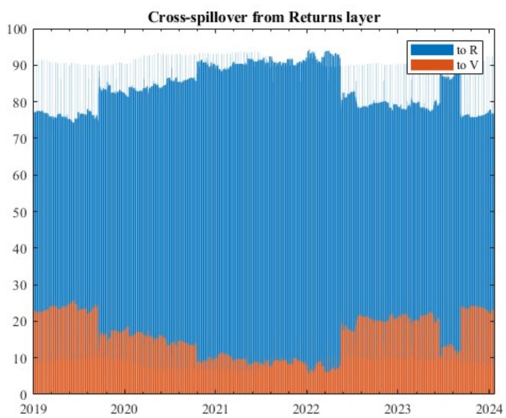


Figure 3: The Spearman Rank correlation

Figure 4 shows the dynamic evolution of information spillover decomposition, distinguishing between internal spillover within the layer (blue) and cross-layer spillover (red). The analysis highlights that internal spillovers dominate in magnitude compared to cross-layer spillovers. Most information flow is disseminated within the same layer (about 80%), with relatively minor transfer between layers (about 20%). This indicates that information spillover is primarily transmitted within the same layer. Although internal spillovers dominate, the intensity of spillovers varies over time. The dynamics of information spillover exhibit fluctuations influenced by external events and market conditions. Specifically, the intensity of cross-layer spillover between the volatility and return layers fluctuates, with notable changes observed around significant events. Moreover, the intensity of cross-layer spillover from the volatility layer to the return layer is stronger than the reverse connection, particularly from late 2022 onwards, coinciding with the Russia-Ukraine conflict. This event triggered an increase in financial market volatility, marking a shift in the interconnectedness between the layers. This shift is further evidenced by the dynamics of Spearman rank correlation, which reflects changes in the relationship between layers in response to external shocks.



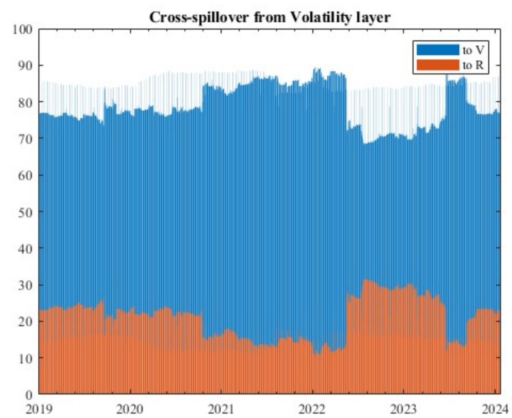


Figure 4: Cross-spillover indexes over time.

Note: R stands for Return layers, while V for Volatility layers.

In what follows, we analyse the dynamic behaviour of the financial assets in our multiplex spillover network. Figure 5 presents the overlapping dynamic average of the strength-out (O_{OUT}), strength-in (O_{IN}), and strength-net (O_{NET}) for the 23 assets, respectively. In the overlapping strength (out and in), the darker the colour, the larger the strength. In the overlapping net strength, 'red' represents a positive value, and 'blue' represents a negative value.

We can note a dynamic character in all three measures across the period under consideration. Interestingly, the distribution of O_{IN}, across the 23 assets appears relatively uniform. This suggests that the overlapping average strength shows no difference, although all assets received large spillover shocks during these periods. Therefore, the evolution of the average overlapping net strength (O_{NET}) is similar to the evolution of O_{OUT}. For simplicity, we only focus on the evolution of O_{NET}. In fact, the net-strength measure provides a comprehensive framework to inspect dynamic market behaviour in terms of spillover information. Among cryptocurrencies, Bitcoin, Litecoin, and Ethereum emerge as the assets exhibiting the highest overall overlapping strength. On the other hand, we find Neo and EOS, possibly due to their multifaceted use and rich applications. For example, Neo boards DeFi protocols such as Flamingo Finance, and an NFT marketplace named GhostMarket. EOS facilitates transactions on DeFi protocols and allows for trading digital art through NFTs. The evolution of net-strength confirms our finding in the static analysis that cryptocurrencies are the main emitter of return and volatility spillover shocks. These findings underscores cryptocurrency instruments' role as net spillover transmitters, emphasizing their speculative nature during financial and economic turbulence (such as the COVID-19 pandemic and Russia-Ukraine conflict). This observation suggests that cryptocurrencies tend to transmit the main fluctuations in the network and pricing changes across various assets. Furthermore, from a dynamic point of view, we can note the dominant influence of Ethereum and Bitcoin as transmitters of spillover.

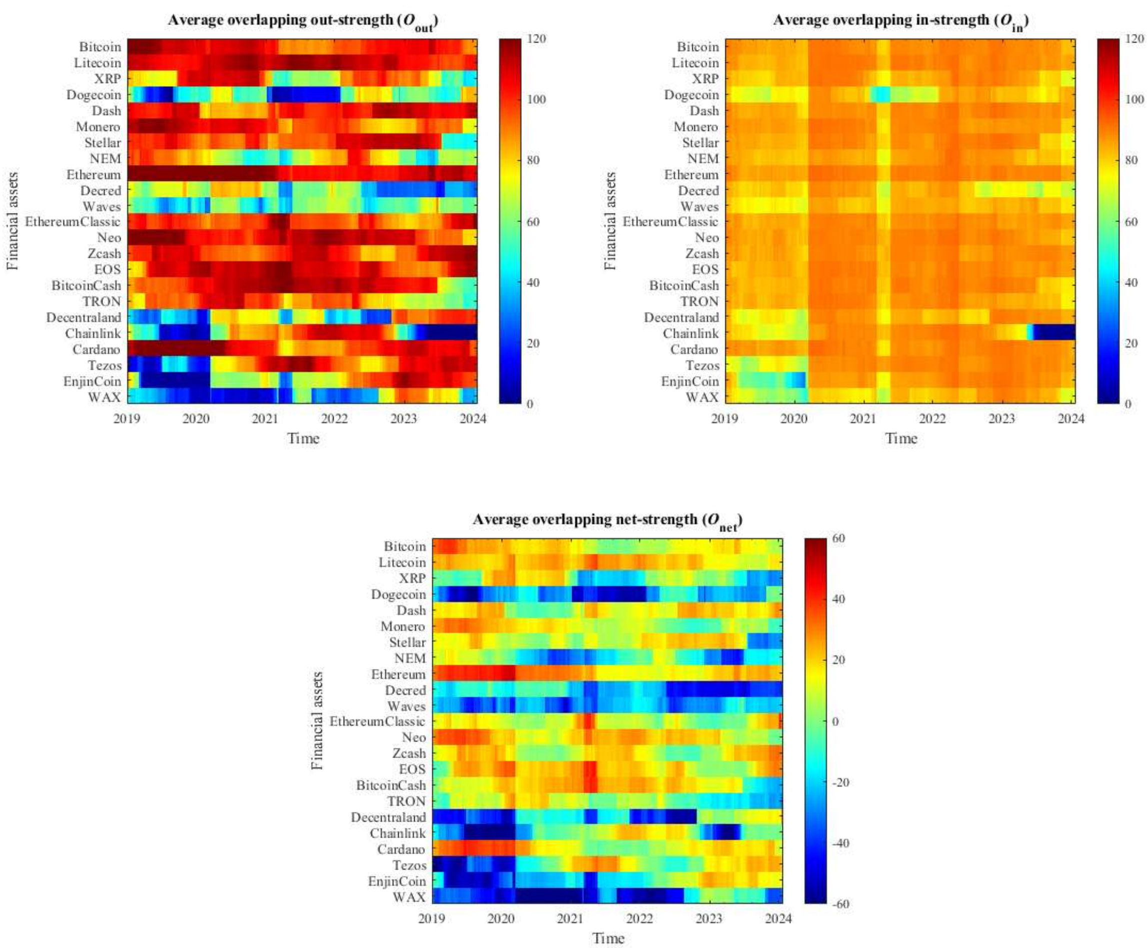


Figure 5: Overlapping indexes over time

5. Conclusion

This paper applies a multilayer approach to examine the network spillover between returns and volatility for cryptocurrency, NFTs and DeFi markets, by integrating the spillover approach of Diebold and Yilmaz (2012, 2014) with the multilayer network model of Wang et al. (2023). Notably, it considers both single- and multi-layer network measures, allowing for an examination of the spillover effects between the return layer and volatility layer, which is new to the related literature on digital assets.

Using daily data of 23 assets (including cryptocurrencies, NFTs and Defi assets) from January 1, 2018 to January 23, 2024, the main results are summarized as follows: Firstly, the static analysis shows significant spillover effects in the layer of returns and the layer of volatility. The main transmitters and receivers of return and volatility spillovers are Ethereum, Litecoin, Neo, Cardano, Bitcoin and Dash, which also have a high PageRank versatility, possibly due to their high speculative nature and large market value. A strong positive correlation exists between returns and volatility layers. Assets exhibiting centrality in one layer tend to maintain a similar centrality in the other layer. This suggests that the risk-return relationship is symmetrical across the digital assets. Cryptocurrencies act as net spillover transmitters to NFT and DeFi assets, reflecting their key role as facilitators of returns spillovers across the decentralized financial markets. Secondly, the dynamic analysis of the multilayer network shows high levels of interconnectivity for both return and volatility layers among cryptocurrencies, DeFi, and NFTs, with peaks in interconnectivity noticed during the COVID-19 pandemic and the Russia-Ukraine conflict. Notably, a strong positive rank correlation exists between the two layers, indicating that assets serving as hubs in the return spillover layer are also hubs in the volatility layer. Such a strong positive correlations between the return and volatility layers is indicative that assets with high returns also tend to exhibit high volatility, which underscores the risk-return nexus in these assets. Spillovers within each layer are larger than spillovers across layers, but the intensity of spillovers varies over time and is affected by external events and shocks. Among cryptocurrencies, Bitcoin, Litecoin, and Ethereum emerge as the assets exhibiting the highest overall overlapping strength. Among NTFs, Neo and EOS are influential. Again, major cryptocurrencies, such as Bitcoin and Ethereum, are net spillover transmitters of returns and volatility shocks, emphasizing their speculative nature during the COVID-19 pandemic and Russia-Ukraine conflict. This is not surprising given their large market value, concurring with previous studies.

These findings hold substantial implications for risk portfolio management and investment strategies. They provide valuable insights for evaluating return and volatility risk spillover flow within digital financial markets during periods of increased uncertainty and conflict. Notably, single-layer networks conducted for returns and volatility separately should be accompanied with an analysis of multilayer-layer networks to capture the interaction between return and volatility layers among cryptocurrencies, NFTs, and DeFi assets, otherwise useful and comprehensive information on the return-volatility nexus would be ignored. More specifically, the findings suggest that market participants should not ignore the interconnectedness between the return and volatility layers in the system of cryptocurrencies, NFTs, and DeFi assets for the sake of a comprehensive analysis of information flow and systemic risk. Otherwise, a share of the information flow between return and volatility in the growing digital asset class would be missed, possibly affecting asset pricing, portfolio allocation, and risk management.

Some questions can be addressed in future research. The first considers the multilayer networks of positive and negative returns. The second involves the multilayer networks of good and bad volatility. The third considers a broader set of assets classes covering both conventional and digital assets.

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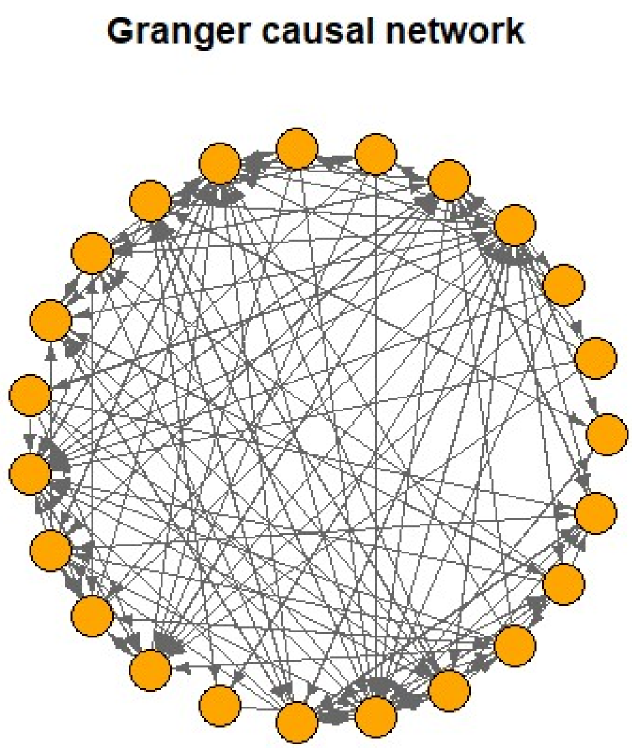
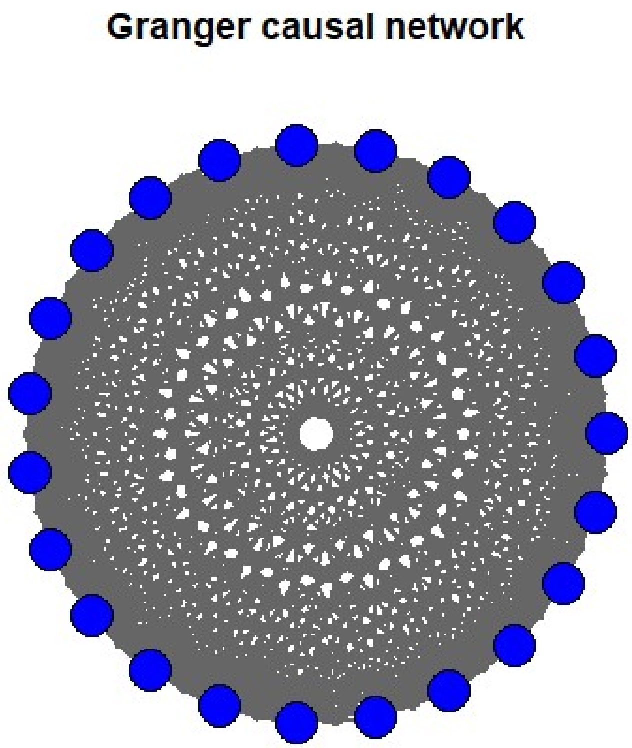
APPENDIX:

Figure A1. FNETS results

(a). Returns



(b). Volatilities



(c). Returns and Volatilities