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Research article

Do returns and volatility spillovers exist across tech stocks, cryptocurrencies and NFTs?

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ABSTRACT

This study examines the connectedness between technology stocks, cryptocurrencies, and non-fungible tokens (NFTs) using daily returns and risk data. We found that while there is strong connectedness within asset classes, connectedness between different types of assets is weak. Structural breaks in the VAR system did not change the degree of connectedness. Our findings suggest that interconnectivity between these assets is not significant enough to indicate a high level of correlation. This research provides valuable insights into the interplay between these markets and suggests diversifying portfolios to mitigate risks associated with these assets.

1. Introduction

Technology has changed the ways and means by which investors and firms operate. In 2023, Microsoft became the largest information technology firm in revenues when it generated approximately US $161 billion [1].[1] Moreover, the COVID-19 pandemic has accelerated the usage and adoption of various technology capabilities, strategies, and practices for firms to remain competitive. During the pandemic, the combined revenues of the most well-known technology firms, namely, Apple, Amazon, Alphabet, Microsoft, and Facebook rose by more than a third to $332 billion which means annual revenues of $1.3tn put them nearly level with the gross domestic product of Spain [[2]]. Advances in technology have brought about substantial changes in investor behaviour and the “big boom” in the technology sector has certainly proven attractive to investors. The world of investing has also taken a different turn with the emergence of digital assets or virtual currencies have soared in value in the last few years. In Sept 2023, the market capitalisation for the world of crypto was US$1.03 trillion [[3]]. Another growing digital asset that grew in prominence is the Non-fungible Token (NFT) market. In 2023, the projected revenues in the NFT market are US$1601.00 million [[1]].[2] Technology firms comprise businesses that sell goods and services in software, hardware, artificial intelligence, and other related information technology (IT) supplies. Digital assets are managed by blockchain technology, which allows for transparency of transactions. Hence, a common feature among the technology stocks and digital assets is their technological underpinnings.

Previous studies such as Kyriazis et al. [4] examine the transmission effects among different cryptocurrencies using M-GARCH models. They show that almost all cryptocurrencies are complementary to Bitcoin. The study focusses on one asset class i.e.,

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[1] https://www.statista.com/statistics/479308/it-services-provider-revenue-ranking/#:~:text=In%202023%2C%20Microsoft%20generated%20approximately,followed%20b%20y%20Accenture%20and%20Oracle.

[2] https://www.statista.com/outlook/dmo/fintech/digital-assets/nft/worldwide

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cryptocurrencies. In addition, other studies investigate the transmission between cryptocurrencies and other financial assets and stock market [[5,6]]. Aharon and Demir [7] explore returns' connectedness between (NFTs) and other financial assets such as equities, bonds, currencies, gold, oil, Ethereum, and the impact of the COVID-19 outbreak. They show that the connectedness between the returns for financial assets increased during the COVID-19 period. Ko et al. [8] investigate if the inclusion of NFTs in portfolios based on traditional assets offers any diversification benefit and confirms the existence of diversification benefits. Karim et al. [9] examine diversification avenues in the blockchain markets of NFTs, DeFi Tokens, and cryptocurrencies and find that NFTs provide diversification avenues. Yousaf and Yarovaya [10] and BenMabrouk et al. [11] examine the diversification benefits of NFTs compared to Bitcoin and traditional assets and provide evidence of limited return and volatility transmission between NFTs and other assets. These studies examine the transmission effects and connectedness across digital assets and other traditional asset classes but not specifically the tech stocks, ignoring the common technological feature underpinning the tech stocks and the digital assets. In this study, we present the network analysis of tech stocks and digital assets to uncover the dynamics among the technology-driven assets.

Given the growing prominence and strong presence of technology in the three asset classes, this study tackles an essential question of investigating the connectedness among these asset classes i.e., the tech stocks and the digital-based assets. To our knowledge, this study provides the first evidence of the connectedness of tech stocks and digital assets. The main objectives of this study are as follows.

a) To empirically test the returns and risk connectedness amongst technology stocks, cryptocurrencies, and NFT.
b) To analyse the existence of structural breaks and their impact on the connectedness amongst these technology-related assets.

We argue that technology underpins these assets and with changes in investors' preferences and appetite for risk, it is important and critical to analyse and understand how these asset classes are connected and if there are any benefits of diversification. Previous studies investigate the relationship between digital assets and conventional asset classes such as equities, fixed income, commodities, gold, and real estate [[12,13]]. However, these studies often overlook a shared characteristic among the digital assets and tech stocks, namely their technological underpinnings. The present study seeks to bridge this gap by systematically investigating the technological commonality that defines these digital assets and tech stocks.

Cryptocurrencies or virtual currencies have soared in value in the last few years. Bitcoin is one of the most prominent virtual currencies in the global arena. Ethereum is the world's second-largest cryptocurrency During the pandemic, Bitcoin – the world's first cryptocurrency – could be purchased for about $7300. In 2023, it costs more than $27,000 [[1]].[3] NFT is blockchain-based digital finance with a non-fungible token such as an image, characters, art, video, game, item, or even a tweet [[7,14]]. The most common types of NFTs are collectibles and artworks, and digitalised characters from sports and other games. NFTs differ from cryptocurrencies due to their non-fungibility [[15]]. Kong and Lin [16] document high volatility in the alternative asset class of NFTs.

The contribution of the paper is four-fold; first, using high-frequency data, this paper provides new evidence on the returns and volatility transmissions across three asset classes that are predominantly technology-driven, namely cryptocurrencies and NFTs and the high-performing technology stocks. This study is distinctive from the other connectedness studies that fail to consider the technology stocks separately [[17]]. We argue that as these three asset classes are technology driven, it deserves a separate analysis on their connectedness and diversification benefits. Furthermore, unlike existing literature [[8,9]], we allow for endogenous testing of common structural breaks in a seemingly unrelated process to test whether connectedness is stable over time. Second, this paper documents evidence on the growing role of digital assets in investing and this complements other studies [[10,11]]. Third, the findings will serve as a guide to policymakers, and the investment community alike on how the volatility of digital assets may impact portfolio returns and the existence of diversification benefits [[7,18]]. Finally, the findings of this paper adds to the body of evidence that show the connectedness between digital assets and conventional asset classes [[10,19]] as well as contributes to the extant finance literature specifically on alternative asset investing [[5,20]].

Our findings show, first, return spillovers from the indices, both the S&P500 and Nasdaq, to cryptocurrencies and NFTs are very small, ranging between 0.1 % and 1 %. In contrast, return spillovers from the indices to technology stocks are substantially higher ranging between 11.2 % and 19.8 %. In other words, technology stocks are more likely to be subject to shocks to indices than cryptocurrencies and NFTs. Second, we note that return spillovers from cryptocurrencies are higher than other cryptocurrencies, which range between 7.8 % and 14.3 %. The spillovers from cryptocurrencies, however, to NFTs and technology stocks are small (less than 1.1 %). Third, the spillovers from NFTs are very small and negligible and do not have any substantial to contribution to the variations in other stocks such as cryptocurrencies and technology stocks as well as other NFTs.

The remainder of the paper is organised as follows: Section 2 provides the literature review, while, in Section 3, we describe the rationale behind our sample-selection procedure, and Section 4 provides the econometric methodology. Section 5 presents the empirical results and Section 6 provides the discussion and concluding remarks.

2. Related work

2.1. Cryptocurrencies

Recent literature focuses on the transmission effect among the cryptocurrency market and between cryptocurrencies and

[3] https://www.statista.com/statistics/326707/bitcoin-price-index/.

traditional assets. The studies on the spillover impact of the cryptocurrency market and the dominance of Bitcoin provide mixed results. Some studies find support for the dominance of Bitcoin while others provide evidence of losing power. For instance, by applying the VAR model, Koutmos [21] examines the return and volatility spillover nexus for 18 cryptocurrencies, concluding that Bitcoin is the dominant cryptocurrency. Ji et al. [17] also support the dominant effect of Bitcoin by studying the volatility spillovers for 6 large cryptocurrencies but for the return shocks, not only Bitcoin but also Litecoin have an impact on the others. Yi et al. [22] provide evidence for losing the dominance of Bitcoin by applying the LASSO-VAR method. They examine volatility transmission using a small sample with 8 and a large sample with 52 cryptocurrencies. They document those 52 cryptocurrencies are closely interrelated and mega-cap cryptocurrencies are the main transmitter of volatility shocks to the others. Zieba et al. [23] analyse the returns of 78 cryptocurrencies by applying a minimum spanning tree (MST) and VAR models. They observe that Bitcoin returns do not have an impact on the price alterations of other altcoins or vice versa.

Some studies discuss the transmission impact between cryptocurrencies, especially Bitcoin, and traditional assets. Bouri et al. [24] analyse the diversification, hedging, and safe haven properties of Bitcoin by comparing it with major stock indices, bonds, oil, gold, and the dollar index. By using the dynamic conditional correlation (DCC) model, they show that Bitcoin is effective for diversification but poor for hedging. On the other hand, by applying VARMA (1,1)-DCC-GARCH, Guesmi et al. [25] document that Bitcoin offers both diversification and hedging benefits for investors when their portfolios include gold, oil, emerging stocks in addition to Bitcoin. Ji et al. [26] and Bouri et al. [27] also confirm the weak correlation between Bitcoin and traditional assets. By using a direct acyclic graph, Ji et al. [26] find time-variant causal relation between Bitcoin and traditional assets, such as equities, bonds, currencies, and commodities. Bouri et al. [27] document this weak relation by comparing Bitcoin, gold, and the commodity index against global and country stock markets by applying the wavelet coherence approach and finding support for the safe-haven property of Bitcoin. Corbet et al. [5] also provide evidence of the isolation of Bitcoin from traditional assets by examining not only Bitcoin but also Ripple and Litecoin. By using the VAR framework, they observe high connectedness among cryptocurrencies while disconnecting from traditional assets, such as stocks, government bonds, and gold indices.

2.2. NFTs

Dowling [15] shows the pricing behaviour of NFTs and documents inefficiency in NFT pricing. In another study, he amends it by analysing the relationship between cryptocurrency pricing and NFT pricing by applying the volatility spillover methodology of Diebold and Yilmaz [[28,29]] and the wavelet coherence approach to examine the co-movement [[30]]. He documents that volatility transmission between NFTs and cryptocurrencies is low and the spillover between NFT markets is small as opposed to cryptocurrencies [[31]] and stock markets [[32]]. Karim et al. [9] analyse the extreme risk transmission among NFTs, decentralized financial assets (DeFis), and cryptocurrencies by employing quantile connectedness across various volatility conditions. They find strong volatility connectedness among them while compared to cryptocurrencies and DeFis, NFTs provide better diversification. Ko et al. [8] find support for the diversification benefits of NFTs by employing the volatility spillover index based on Diebold and Yilmaz and time-varying parameter vector autoregression (TVP-VAR). They analyse the diversification benefits of NFTs, including Sandbox, Decantraland and Cryptopunks compared to traditional assets, such as stock, bonds, US dollar, commodity index, and cryptocurrencies, naming Bitcoin and Ethereum. They also apply the mean-variance approach to examine the performance of NFTs in various portfolios. Aharon and Demir [7] analyse the return connectedness between NFTs, Ethereum, and traditional assets, such as gold, bonds, equities, oil, and the USD index by employing the TVP-VAR model. They also examine the effect of COVID-19. They find that NFTs are not affected by the shocks of other assets.

Maouchi et al. [33] document price bubbles in the DeFi and NFTs markets and examine determinants for the forecast of the bubbles. They conclude that the price behaviour of DeFis and NFTs are different from the cryptocurrencies, supporting the results of Corbet et al. [34] and Dowling [30], and the occurrence of price bubbles are less but their magnitude is higher than cryptocurrencies'. They also analyse the effect of COVID-19 and conclude that COVID-19 supports bubble occurrences. Ito et al. [35] also analyse the price bubble but include a different set of NFTs compared to Maouchi et al. [33], such as Decentraland, CryptoPunks, Ethereum Name Service, and ArtBlocks, by employing the logarithmic periodic power law model. They find that NFTs in the sample and Decentraland alone suggest a decrease in prices but Ethereum Name Service and ArtBlocks anticipate increases in prices.

Moreover, Kong and Lin [16] analyse the pricing and investment performance of the NFT index, which is constructed from CryptoPunk tokens by applying a hedonic regression model. They document that the pricing of the NFTs is based on a token's scarceness and investor's aesthetic preference. For the investment returns of NFTs, they find that although the NFT returns are highly volatile, the returns are higher than the traditional financial assets[4] based on the arithmetic estimation method. Moreover, the traditional asset-pricing models fail to explain NFT returns, and Kong and Lin [16] fail to document the spillover effect among traditional assets and NFTs. Yousaf and Yarovaya [10] examine the return and volatility spillovers among NFTs, Defi assets, Bitcoin, and traditional assets, including oil, gold, and S&P500, by using the TVP-VAR model. Their findings suggest that NFTs and DeFi assets offer enhanced diversification advantages owing to their limited correlations with other assets. BenMabrouk et al. [11] analyse the dynamic spillover and hedging effectiveness between NFTs, Bitcoin, and S&P500 employing the TVP-VAR model. Their results confirm the weak relation between NFTs and other assets.

[4] Traditional financial assets include ETH/USD index, NASDAQ index, S&P500 index, Dow Jones index, VIX index, Bond index, and Gold index.

2.3. Technology stocks (FAANG)

The acronym FAANG Stocks was created by CNBC's "Mad Money" host Jim Cramer in 2013. FAANG is the nickname of the four high performing American tech companies which are Facebook, Amazon, Netflix, and Alphabet (formerly known as Google), respectively. The main and common feature of these companies is their extraordinary growth which is revealed in their revenues and net profits. In 2017, Apple is added to this group and amended the acronym FAANG.

Chu et al. [36] document the association among the returns of Bitcoin, FAANG stocks, and global stock markets by using the quantile-on-quantile regression method. They find that Bitcoin and FAANG stocks show differences with regard to diversification against global stock markets and individuals perceive Bitcoin as a possible investable asset rather than a tech company or technology. By including Tesla in FAANG companies (naming as FATANG), Curto [37] examines the change in volatility among the returns of three US stock indices and FATANG stocks. Curto and Serrasqueiro [38] analyse the impact of COVID-19 on the volatility of the financial returns of S&P 500, FATANG stocks, and eleven S&P500 sector indices by using the Asymmetric Power GARCH model. They observe sectoral differences in the effect of COVID-19 on the volatility. Saleem et al. [39] employ the VAR-GARCH and DCC framework to document the volatility spillovers and conditional correlations within the daily returns of FAANG, gold, and shariah-compliant stocks. Their findings suggest that gold and shariah-compliant equities present viable options for hedging FAANG stocks.

Rather than focusing on FAANG companies, Umar et al. [40] focus on the technology sector equity indices to examine the connectedness between cryptocurrencies and the technology sector in both developed and emerging markets. By applying the network connectedness of Diebold and Yilmaz [41], they find that cryptocurrencies offer better diversification opportunities for technology sector risk.

3. Data

This work uses daily stock market index price data, specifically the closing prices, starting from March 2018 to September 2021. This period includes the post COVID-19 period, which also experienced a cryptocurrency market bubble [[9,35,42,43]]. For the purpose of this work, we collected data capturing four broader measures: market and technology measures (S&P 500 and NASDAQ 100 Technology Sector), cryptocurrency market measures (Bitcoin, Ethereum, Ripple, Litcoin, Dash, Nem, Stellar, Monero), NFTs market measures (Axie Infinity, Cryptopunks, and Decentral Land) and finally the FAANG (Facebook, Amazon, Apple, Netflix, Google). The choice of cryptocurrencies is based on those with a market value of over $1 billion as of September 2021. In addition, the selection of NFTs predominantly relies on those with sufficiently extensive historical datapoints. The starting year and month of the sample are therefore based on the earliest date from which NFTs series are being observed. A synopsis of the different time series used and the sources from which are obtained can be found in Table 1.

We acquire all data in their original form as price indices. Our objective is to assess the interconnectedness within the return and risk series. The return series for each stock is defined as the first difference of the natural logarithm of prices ($r_{it} = \Delta(ln\, P_{it})$), for $i = 1, 2, \ldots, N$ stocks, over $t = 1, 2, \ldots, T$ periods. We apply a Generalized Autoregressive Conditional Heteroskedastic model of order 1 (GARCH (1,1), hereafter) for each stock return series to generate the risk series. The model implemented is specified as follows:

$$r_{it} = \mu_i + \varepsilon_{it}, \tag{1A}$$

Table 1
Data definitions and sources.

Variable	Symbol	Definition	Sample	Source
Market Measures				
S&P 500	SNP	Price Index		https://www.spglobal.com/en/
NASDAQ 100 Technology Sector	NDXT	Price Index		https://www.nasdaq.com/
Cryptocurrency				
Bitcoin	BTC	Price Index		https://coinmetrics.io/
Ethereum	ETH	Price Index		https://coinmetrics.io/
Ripple	XRP	Price Index		https://coinmetrics.io/
Litcoin	LTC	Price Index		https://coinmetrics.io/
Dash	DASH	Price Index		https://coinmetrics.io/
Nem	XEM	Price Index		https://coinmetrics.io/
Stellar	XLM	Price Index		https://coinmetrics.io/
Monero	XMR	Price Index		https://coinmetrics.io/
Non-Fungible Tokens				
Axie Infinity	AXIE	Price Index		https://nonfungible.com/
Cryptopunks	CP	Price Index		https://nonfungible.com/
Decentraland	DCL	Price Index		https://nonfungible.com/
Technology				
Apple	APPL	Price Index		https://uk.investing.com/
Facebook	FACE	Price Index		https://uk.investing.com/
Netflix	NET	Price Index		https://uk.investing.com/
Google	GOOG	Price Index		https://uk.investing.com/
Amazon	AMZN	Price Index		https://uk.investing.com/

$$\sigma_{it}^2 = \delta_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2 + v_{it} \tag{1B}$$

where $\varepsilon_{it} \sim (0,\ \sigma_{it}^2)$, $v_{it} \sim iid\ (0,\ \sigma_{iv}^2)$; $\delta_i > 0$; $\alpha_i, \beta_i \geq 0$; $\alpha_i + \beta_i < 1$ for $i = 1, 2, \ldots, N$ and $t = 1, 2, \ldots, T$. Equation (1A) captures the conditional mean of the stock returns while Equation (1B) is the GARCH (1,1) specification.

4. Econometric methodology

This study employs an integrated framework of Vector Autoregressive modelling, network analysis and structural breaks tests to provide a multidimensional characterization of connectedness across technology stocks, cryptocurrencies, and NFTs.

The vector autoregressive (VAR) framework enables modelling predictive spillovers between returns and risks while accounting for interdependence in the data [[29]]. As Ji et al. [26] discuss, VAR models are well-suited for assessing integration in the cryptocurrency sphere. The connectivity estimates from the VAR form the basis for subsequent network visualizations. Network analysis has recently been applied to depict return and volatility spillovers [[11,40]]. Mapping the VAR results allows intuitive interpretation of the complex associations between different assets. Edges in the network represent predictive relationships rather than correlations. Finally, we endogenously test for structural breaks following Corbet et al. [5] who emphasize modelling potential distributional changes when assessing cryptocurrency dynamics. Unknown breaks are estimated using data-driven procedures [[44]]. This accounts for episodic disruptions like COVID-19 that may sever connections.

The integration of VAR modelling, networks, and break analysis provides both statistical rigor and nuanced economic insights. We posit subtler substitution effects and sentiment as drivers of connectivity. But sporadic (exogenous) shocks may overwhelm these mechanisms. By integrating the findings across methods, the study aims to comprehensively address how and why linkages emerge between assets underpinned by technology.

4.1. Measures of connectedness

For this study, we utilize the generalized variance decomposition introduced by Diebold and Yilmaz [29] (DY). The notion of connectedness, as proposed by Diebold and Yilmaz [[28,29,41]], examines the distribution of the of forecast error variation across different stock return series as a consequence of a shock of one stock returns/risk series on another stock returns/risk series. Connectedness is formalized within a Vector Autoregressive (VAR) framework.

Consider a dynamic system, $\boldsymbol{x}_t^{'} = (x_{1t}, x_{2t}, \ldots, x_{nt})$. The model is formally written in Equation (2) below:

$$\boldsymbol{x}_t = \boldsymbol{k} + \sum_{i=1}^{q} \Gamma_i \boldsymbol{x}_{t-i} + \boldsymbol{u}_t \tag{2}$$

Where the term $\boldsymbol{k}^{'} = (k_1, k_2, \ldots, k_n)$ is a $1 \times n$ vector of constants, $\Gamma_1, \Gamma_2, \ldots, \Gamma_p$ are $n \times n$ parameters matrices, $\boldsymbol{u}_t^{'} = (u_{1t}, u_{2t}, \ldots, u_{nt})$ is a $1 \times n$ vector representing the error term with zero mean, and a variance – covariance matrix, Ω, is an $n \times n$ symmetric matrix and the optimal lag length q.

The VAR (q) model accommodates interdependence and reverse causality among all endogenous time series. In addition, the model assumes covariance-stationarity for all variables within the vector $\boldsymbol{y}_t$, requiring the solutions to the characteristic equation's roots (i.e. $|\Gamma(z)|$), to be situated beyond the unit circle.

Assuming stationarity, the model in Equation (2), the VAR(q) can be stated in the form of infinite-order moving averages, denoted as MA (∞) and expressed in Equation (3):

$$\boldsymbol{y}_t = \Psi(L) \boldsymbol{u}_t \tag{3}$$

where $\Psi(L) = \Psi_0 + \Psi_1 L + \Psi_2 L^2 + \ldots$ and $\Gamma(\boldsymbol{L}) = \boldsymbol{I_N} - \Gamma_1 \boldsymbol{L} - \Gamma_2 \boldsymbol{L^2} - \ldots - \Gamma_{\boldsymbol{p}} \boldsymbol{L^p} = [\Psi(L)]^{-1}$. The term Ψ_0 captures the contemporaneous features of connectedness. The terms $\Psi_1, \Psi_2, \ldots$ encapsulate the dynamics of connectedness.

For variance decompositions, Diebold and Yilmaz [29] use Cholesky factorization, dependent on variable ordering. To overcome ordering sensitivity, Pesaran and Shin [45] propose Generalized Variance Decompositions, not reliant on variable ordering. The h-step generalized variance decomposition matrix is given by Equation (4):

$$D_t^{gH} = \left[d_{ij,t}^{gH}\right] \tag{4}$$

Has the elements shown by Equation (5)

$$d_{ij,t}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^{'} \Psi_{h,t} \Omega_t e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} \Psi_{h,t} \Omega_t \Psi_{h,t}^{'} e_j\right)^2} \tag{5}$$

where σ_{jj}^{-1} is the j-th diagonal element of Ω_t, Ψ_h is $n \times n$ of moving average coefficients at lag length h and e_j is section vector with j-th element unity and zeros elsewhere.

The expression $d_{\{ij,t\}}^{\{gH\}})$ represents the impact of the *j-th* variable on the variance of the forecast error for element *i* at horizon *h*. Considering that shocks under the generalized variance decomposition may not be orthogonal, the summation of row values in $d_{\{ij,t\}}^{\{gH\}})$ might not equate to 1. As a result, the generalized connectedness index, along with its alternative forms, depends on the normalized $d_{\{ij,t\}}^{\{gH\}})$, defined by Equation (6) as:

$$\widetilde{d_{ij,t}^{gH}} = \frac{d_{ij,t}^{gH}}{\sum_{j=1}^{N} d_{ij,t}^{gH}} \tag{6}$$

whereby definition $\sum_{j=1}^{N} \widetilde{d_{ij,t}^{gH}} = 1$ and $\sum_{i,j=1}^{N} \widetilde{d_{ij,t}^{gH}} = N$). Referring to equation (6), we can calculate the subsequent measures of connectedness:

Total Connectedness Index (TCI): This measure encapsulates the degree of connectedness between various series. Its definition is given by Equation (7):

$$C_t^{gH} = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{d_{ij,t}^{gH}}}{\sum_{j=1}^{N} \widetilde{d_{ij,t}^{gH}}} \times 100 \tag{7}$$

The directional spillover from all series j to series i as defined by Equation (8):

$$C_{i\leftarrow j}^{gH} = \frac{\sum_{j=1, i\neq j}^{N} \widetilde{d_{ij,t}^{gH}}}{\sum_{i=1}^{N} \widetilde{d_{ij,t}^{gH}}} \times 100 \tag{8}$$

The directional spillover from all series i to series j as shown by Equation (9):

$$C_{i\rightarrow j}^{gH} = \frac{\sum_{j=1, i\neq j}^{N} \widetilde{d_{ij,t}^{gH}}}{\sum_{i=1}^{N} \widetilde{d_{ij,t}^{gH}}} \times 100 \tag{9}$$

4.2. Network connectedness

We adopt a network analysis approach to investigate the transmission effects among technology stocks, cryptocurrencies, and NFTs. The variance decomposition matrix, a key component of the spillover methodology, aligns with the adjacency matrix in network theory. The degree of a node, denoted as D_i, quantifies the number of connections it maintains with other nodes in the network, and is defined by Equation (10):

$$D_i = \sum_{j=1}^{N} A_{ij} \tag{10}$$

where Aij represents the adjacency matrix. A constructed using the spillover table. The strength of interconnectedness between nodes is represented by the pairwise directional connectedness, Cij. The summation of rows in the adjacency matrix (referred to as node in-degrees) signifies the total directional connectedness 'From'. Similarly, the summation of columns in the adjacency matrix denotes the total directional connectedness 'To'. The combination of 'From' and 'To' degrees form the set of edges in the network.

4.3. Common structural breaks

We also extend the analysis by investigating whether the stock returns in our dataset exhibit any meaningful common breaks. For this purpose, we apply Qu and Perron [46] – QP hereafter – test for multiple structural breaks in multivariate systems. Suppose the DGP of the stock returns can be expressed in a system of equations as in Equation (11):

$$\boldsymbol{r_t} = \left(I_n \bigotimes z_t^{'}\right) S\beta_j + \boldsymbol{\epsilon_t} \tag{11}$$

where the vector $\boldsymbol{r_t} = (r_{1t}, \ldots, r_{nt})^{'}$ contains the *n*-vector of stock returns, *I* is an identity matrix of the dimension $n \times n$, the vector of *k* regressors from all equations $z_t^{'} = (z_{1t}, \ldots, r_{kt})^{'}$ where $z_{it} = \{1\}$ for $i = 1, 2, \ldots, n$ and over $t = 1, 2, \ldots, T$; and an $nk \times q$ full column rank selection matrix *S*. The vector $\boldsymbol{\epsilon_t} = (\varepsilon_{1t}, \ldots, \varepsilon_{nt})$ contains the *n*-vector of white noise errors. Given the DGP specified above, the selection matrix S is simply an identity matrix of order $n \times n$. Thus, the DGP for each equation is defined as: $r_{it} = \mu_i + \varepsilon_{it}$, where the ε_{it} is an *iid* error term.

The QP tests the null of l breaks versus l+1 breaks using a battery of tests including the sequential test (that allows for selecting the number of breaks) and double maximum test (that tests for the unknown number of changes up to a pre-defined maximum number of breaks).

In summary, our methodology is implemented as follows. We start by testing for the presence of unit root in the return series. If all series do not contain unit roots, we proceed to estimate connectedness using the VAR model of the order specified by the HJC. If one or more returns series exhibit a unit root, we apply the approach proposed by Toda and Yamamoto [47], which allows modelling a VAR model with integrated variables by augmenting the selected lag length by one lag. Finally, we extend the analysis to estimate the connectedness under structural breaks.

4.4. Other empirical Considerations

The measure of connectedness as described above is sensitive to a number of parameters and pre-estimation settings including the stationarity of the series, lag-length, and the stability of the VAR model. To ensure the robustness of our results, we apply various robust methods to deal with the pre-estimation settings mentioned above.

4.4.1. Lag length selection

Standard approaches to determining the optimal lag length of a VAR model – and indeed univariate ARIMA models – involve using information criteria such as Akaike Information Criterion [48], Bayesian Information Criterion [49], and Hannan and Quinn [50] Information Criterion (AIC, BIC, and HQIC, respectively). These standard information criteria may perform poorly when the process considered may be unstable or suffer from nonstationary of some or all the series in the system [[51]]. Furthermore, the performance of these information criteria may vary in terms of accuracy, especially in a VAR model that may suffer from some form of nonstationary [[52–54]] leading to different information criteria reporting different lag lengths. In this context, the literature offers alternative or modified versions of the standard information criteria. For example, literature such as Ng and Perron [51] and Perron and Qu [52] propose a modified version of the AIC to deal with the lag length selection problem when data contain a unit root and suffer from nonstationarity. Hatemi-J [55] proposes an alternative information criterion known as HJC, which attempts to overcome the weaknesses of standard AIC and BIC. HJC is found to perform better than standard AIC and BIC under both stable and unstable VAR with and without autoregressive conditional heteroskedastic volatility [[56,57]]. Therefore, we use the HJC for lag length selection.

4.4.2. Unit root tests

The VAR model and proposed measure of connectedness require that the variables within the system are covariance stationary. Thus, we need to test whether the return series are indeed covariance stationary. One common approach to test for non-stationarity is to apply unit root tests such as Dicky and Fuller [57] test (ADF), Phillips and Perron [58] test (PP), and/or stationarity tests such as Kwiatkowski et al. [59]. In the context of this paper, we apply two tests: the ADF and KPSS tests. When the null of unit root is rejected by the ADF test; this does not necessarily imply stationarity. Thus, applying the KPSS test will help in confirming the conclusion of the ADF test if the null cannot be rejected.

The ADF test is performed using the following DGP for each stock return series is given by Equation (12):

$$\Delta r_{it} = \mu_i + \alpha_i r_{it-1} + \sum_{j=1}^{k-1} \varphi_{ij} \Delta r_{it-j} + v_{it} \tag{12}$$

where $\Delta r_{it} = r_{it} - r_{it-1}$ for stock i and over $t = 1,2,\ldots,T$. Note that the DGP is consistent with a random walk with drift process, where it consists of only intercept (μ) and the term associated with the lagged returns: $\alpha = \rho - 1$, where ρ is the persistence of an autoregressive process of order 1. The terms $\sum_{j=1}^{k-1} \varphi_{ij} \Delta r_{it-j}$ are added to correct for autocorrelation. The lag length is selected using one of the information criteria available in the literature. For the unit root test, we follow Ng and Perron [51] and use Modified AIC since it has better properties than the others such as BIC.

The test is based on whether the process contains a unit root, then $\rho = 1$ or $\alpha = 0$. The ADF test has the following null and alternative hypotheses:

$$H_{0:} \alpha = \rho - 1 = 0 \ (unit\ root)$$

$$H_{1:} \alpha = \rho - 1 < 0 \ (no\ unit\ root)$$

The test statistic is a t statistic from the OLS regression on (10) defined by Equation (13):

$$\widehat{t}_{\widehat{\alpha}} = \frac{\widehat{\alpha}}{se(\widehat{\alpha})} \sim DF \tag{13}$$

where DF refers to Dickey-Fuller distribution.

The KPSS test assumes under the null that the process is stationary, while the alternative states that the process contains a unit root. The test statistic is based on the following OLS regression in Equation (14):

$$r_{it} = x_{it}^{'}\delta_i + v_{it} \tag{14}$$

where x_{it} is the set of exogenous variables. The LM statistic is defined by Equation (15):

$$LM = \frac{\sum_{i=1}^{T} S_t^2}{\widehat{\sigma}_e^2} \tag{15}$$

where e_t are the residuals from the regression of r_{it} on a constant, $\widehat{\sigma}_e^2$ is the residuals variance from this regression and S_t is the partial sum of e_t defined by $S_t = \sum_{i=1}^{T} e_t$. The asymptotic distribution of the test is derived by, and Kwiatkowski et al. [59].

5. Empirical results

5.1. Primary results and structural breaks

Table 2 reports key descriptive statistics including measures of centre and dispersion. In general, most return series have a positive average return except DASH, XEM, and AXIE, two of which are cryptocurrencies, and one is an NFT. In addition, we note that NFTs have higher variations, followed by cryptocurrencies. Technology stocks behave – in terms of means and dispersion – similar to the market (both S&P 500 and Nasdaq). In terms of risk, NFTs have the highest average volatility where it ranges between about 21 % and 90 %. The range of estimated volatility is also substantially wider for NFTs compared to other stocks and market. While the estimated volatility of cryptocurrencies is much smaller compared to NFTs, it remains higher (by about 3.8 % on average) than technology stocks and the overall volatility of the market. In short, NFTs and cryptocurrencies have higher risk than technology stocks and the market.

We also report the ADF and KPSS test statistics in Table 1. According to the ADF test, the unit root hypothesis is strongly rejected. This implies that the data do not follow a random walk process. This, however, does not rule out the presence of some form of nonstationarity. The KPSS test may act as a confirmatory or a robustness check test. According to the finding, all the return series follow a stationary process at all levels of significance. One exception is Ethereum where the null of stationarity I rejected at 5 % but not at a 10 % level of significance. This implies in general that returns follow a (covariance) stationary process. Similarly, the ADF test applied to estimated volatility rejects the null of unit root for all series. The KPSS, however, rejects the null of stationarity of five series. This, again, does not imply the presence of a unit root. It may also imply the presence of some form of nonstationarity in the data such as the presence of structural breaks.

Furthermore, a simple pairwise correlation assessment – as reported in Table 2, Panel A – Panel shows little evidence of cross-markets associations. For example, we find evidence that cryptocurrencies returns are highly correlated, while their association with the market, NFTs, and technology stock returns is relatively weak. Similarly, some technology stock returns are highly correlated among each other including Apple, Amazon and Google, but uncorrelated with cryptocurrencies and NFTs. Table 2, Panel B reports the pairwise statistical association among the estimated volatility of the stock returns. There is little evidence that volatility across the market is statistically correlated. There are a few exceptions including the high correlation (as shown in Table 3) between the estimated volatility of the technology stocks.

We perform the QP structural break test on the data using the DGP defined by Equation (15), which specifies each stock return/risk as a process that is a function of a mean subject to shifts over time (i.e. $r_{it} = \mu_i + \varepsilon_{it}$). We set the maximum number of breaks to two breaks given the small span of the data (e.g. from 2018 to 2021). We report three statistics including *SupLR*, *WDmax* and *Seq* tests for both return and risk series. All results are reported in Table 4.

According to our findings, the 18-stock return and their estimated risk series have experienced two common structural breaks[5] in the period 2018–2021. The common breaks estimated for the return series are dated to have occurred on July 30, 2019 and August 12, 2020 respectively. The common breaks for the risk series are also estimated to have occurred around similar dates as with returns. In other words, the first break occurred on April 25, 2019 while the second break occurred on July 29, 2020. We note that the breaks of the risk series occurred earlier than those of the return series. This, however, does not inform us much about whether the break in the risk series caused the breaks in the returns series. The QP test as implemented in this paper does not offer further insights.[6] Second, the difference in the dating of breaks between risk and returns series may be due to purely the computational structure of the algorithms as argued by Crafts and Mills [60] when testing for structural breaks endogenously.

The breaks estimated in the year 2019 coincide with the announcement of Facebook's project Libra in June 2019, which has been an important development for the cryptocurrency market as argued by Telli and Chen [61], and leading to a bubble [[42]]. The break identified in 2020 may reflect the effect of the COVID-19 period and possibly the cryptocurrency bubble during the same period [[9, 43]]. In other words, we have three regimes for both returns and risk. We incorporate these regimes when examining the issue of

[5] The discussion here should be centred on the notion of 'common' breaks, which are different from the breaks each individual series may exhibit. In this context, common breaks should be taken to express the change in these series when put in a 'seemingly unrelated' system framework, where these variables are somehow related via their error terms. This latter is a plausible way to capture the effect of unobserved exogenous shocks such as COVID-19.

[6] This can be tested using different frameworks starting with the causal link between returns and risk. Furthermore, this issue is beyond the scope of this paper and left for future research.

Table 2
Descriptive statistics and unit root tests.

Variable	Obs	Mean	Std. Dev.	Min	Max	ADF	KPSS	Lags
Panel A: Returns								
SNP	1263	.0008	.0129	−.1032	.107	−7.31***	0.14	22
DXT	1263	.0006	.0138	−.1043	.0971	−7.31***	0.12	22
BTC	1263	.0013	.0395	−.4706	.1697	−7.31**	0.27	19
ETH	1263	.0015	.0525	−.5656	.2448	−7.37***	0.57**	18
XRP	1263	.0005	.0613	−.5213	.4234	−7.57***	0.18	22
LTC	1263	.0001	.0543	−.4588	.2531	−7.58***	0.26	22
DASH	1263	−.0006	.0609	−.4745	.4394	−7.64***	0.23	21
XEM	1263	−.0003	.0603	−.415	.2783	−7.14***	0.28	20
XLM	1263	.0003	.06	−.415	.5593	−8.03***	0.22	22
XMR	1263	.0002	.0531	−.4922	.3193	−7.58***	0.32	19
AXIE	1262	−.0007	.2152	−1.6336	2.1537	−8.98***	0.19	22
CP	1263	.007	.5987	−3.4814	3.6534	−10.86***	0.17	22
DCL	1263	.0014	.9445	−6.1235	8.0366	−10.21***	0.06	22
APPL	1263	.0011	.016	−.1049	.1132	−6.48***	0.11	22
FACE	1263	.0007	.0178	−.2108	.1483	−7.07***	0.08	22
NET	1263	.0005	.0196	−.1084	.1558	−7.68***	0.07	22
GOOG	1263	.0008	.014	−.0863	.0994	−6.98***	0.27	22
AMZN	1263	.0007	.015	−.0825	.0712	−8.12***	0.06	22
Panel B: Risk								
SNP	1263	.01144	.00648	.00536	.05873	−4.18***	0.25	18
DXT	1263	.0123	.00612	.00653	.05409	−3.90***	0.28	18
BTC	1263	.03909	.00986	.0289	.14155	−6.58***	0.34	3
ETH	1263	.05163	.01246	.03846	.17255	−6.50***	0.30	3
XRP	1263	.05918	.03425	.03352	.35661	−4.75***	0.81***	22
LTC	1263	.0535	.01035	.04154	.12666	−5.92***	0.94***	3
DASH	1263	.05884	.02547	.03342	.20989	−6.99***	1.73***	3
XEM	1263	.05906	.01743	.04008	.16058	−5.00***	1.01***	16
XLM	1263	.05817	.02231	.03967	.31905	−5.40***	0.33	21
XMR	1263	.05215	.01725	.03411	.20026	−6.67***	0.15	3
AXIE	1263	.20943	.01394	.05807	.29281	−7.44***	0.15	22
CP	1263	.57168	.28845	.39781	2.65747	−5.99***	0.18	18
DCL	1263	.89892	.38052	.50684	4.98162	−5.93***	1.46***	22
APPL	1263	.01505	.0063	.00849	.05509	−3.90***	0.26	19
FACE	1263	.01817	.0128	.00942	.22271	−5.77***	0.16	21
NET	1263	.01952	.00407	.01775	.07381	−5.49***	0.29	21
GOOG	1263	.01331	.0036	.00993	.03796	−4.40***	0.28	11
AMZN	1263	.01427	.00511	.00856	.04103	−4.66***	0.24	14

Notes: (***), (**) refer to the rejection at 1 % and 5 % levels of significance. ADF tests the null of unit root against the alternative of no unit root. KPSS tests the null of stationarity against the alternative of unit root. Lag length is selected using Modified AIC.

connectedness in the following section.

5.2. *Connectedness of returns and volatility*

The results of applying the methods described in Section 4.1 on returns are reported in Table 5, while Table 6 reports the results on risk (volatility). Both sets of results are based on the VAR model expressed by Equation (3). The lag length is selected using HJC, which works well for models that are unstable or subject to structural breaks. The optimal lag length is 1. Therefore, all the results reported in Tables 5 and 6 (Panels A – Panel D) are based on a VAR (1). As mentioned above, the variance decomposition method implemented is the generalized variance decomposition. We use rolling window estimation with a window width of 200 days when using the full sample and 100 days when using regimes-based samples. The predictive horizon for the underlying variance decomposition is 10 days.

Panel A of Table 5 reports the estimates of connectedness using the full sample (from March 24, 2018 to September 07, 2021). Table 5, Panels B, C, and D report connectedness estimates for the estimated regimes using the QP test. Regime 1 covers the period March 24, 2018–July 30, 2019, Regime 2 covers the period July 31, 2019–August 12, 2020, and Regime 3 covers the period August 13, 2020–September 07, 2021. The connectedness is measured as the estimated contribution to the forecast error variance of a stock return *i* due to the shock to stock return *j*. The column 'From Others' displays the total spillover coming from other stock returns, which is the sum of values in each row. The row 'Contribution to others' shows the total spillover going to other stock returns, obtained by summing values in each column. Both are derived using Equation (7). In addition, the values in the centre of the table, referred to as *ij-th* entries, represent the decomposition of the Spillover Index for each pair of stocks, calculated using Equations (8) and (9).

In general, the total Spillover Index 'From Others' is ranging between 3.4 % and 80.5 %. In this context, the cryptocurrencies' returns receive the highest spillovers from other assets compared to technology stocks and NFTs. The latter receives the least spillovers, which are estimated to range between 3.4 % and 5.2 %. A closer look into the contribution of each variable to the returns of the other yield the following findings. First, return spillovers from the market, both the S&P500 and Nasdaq, to cryptocurrencies and NFTs are

Table 3
Pairwise correlation matrix of the overall sample.

Variables	SNP	DXT	BTC	ETH	XRP	LTC	DASH	XEM	XLM	XMR	AXIE	CP	DCL	APPL	FACE	NET	GOOG	AMZN
Panel A: Returns																		
SNP	1.000																	
DXT	**0.951**	1.000																
BTC	0.216	0.219	1.000															
ETH	0.218	0.215	**0.829**	1.000														
XRP	0.165	0.171	**0.610**	**0.677**	1.000													
LTC	0.192	0.191	**0.812**	**0.848**	**0.683**	1.000												
DASH	0.140	0.135	**0.687**	**0.722**	**0.613**	**0.748**	1.000											
XEM	0.142	0.150	**0.620**	**0.661**	**0.611**	**0.642**	**0.597**	1.000										
XLM	0.174	0.180	**0.661**	**0.714**	**0.744**	**0.707**	**0.647**	**0.668**	1.000									
XMR	0.187	0.178	**0.765**	**0.760**	**0.609**	**0.762**	**0.750**	**0.611**	**0.659**	1.000								
AXIE	−0.005	−0.011	0.042	0.048	0.048	0.045	0.018	0.053	0.059	0.019	1.000							
CP	−0.047	−0.035	0.006	0.027	−0.006	0.034	0.014	0.024	0.029	0.010	−0.029	1.000						
DCL	0.000	−0.015	−0.006	0.021	−0.004	0.001	0.016	−0.006	−0.030	0.014	0.058	0.003	1.000					
APPL	**0.869**	**0.769**	0.172	0.177	0.135	0.160	0.105	0.100	0.131	0.167	−0.031	−0.049	0.001	1.000				
FACE	0.462	0.393	0.117	0.098	0.072	0.096	0.058	0.071	0.099	0.076	−0.024	0.011	0.012	0.376	1.000			
NET	0.596	0.541	0.108	0.115	0.099	0.095	0.082	0.076	0.079	0.103	−0.012	−0.073	0.009	0.492	0.283	1.000		
GOOG	**0.832**	**0.741**	0.161	0.169	0.107	0.136	0.103	0.111	0.139	0.142	0.020	−0.051	0.017	**0.657**	0.421	0.527	1.000	
AMZN	**0.757**	**0.682**	0.140	0.143	0.102	0.125	0.091	0.087	0.113	0.132	−0.013	−0.065	0.024	**0.651**	0.412	**0.638**	**0.665**	1.000
Panel B: Risk																		
SNP	1.000																	
DXT	**0.969**	1.000																
BTC	0.516	0.530	1.000															
ETH	0.516	0.492	**0.843**	1.000														
XRP	0.074	0.083	0.360	0.442	1.000													
LTC	0.380	0.382	**0.782**	**0.859**	0.483	1.000												
DASH	0.249	0.255	**0.614**	**0.678**	0.435	**0.750**	1.000											
XEM	0.196	0.213	0.505	0.570	0.479	**0.635**	0.541	1.000										
XLM	0.131	0.114	0.459	0.524	**0.693**	0.496	0.476	0.505	1.000									
XMR	0.329	0.316	**0.767**	**0.838**	0.429	**0.856**	**0.780**	**0.603**	0.490	1.000								
AXIE	0.011	0.007	−0.014	0.001	0.002	−0.007	−0.030	0.001	−0.003	−0.010	1.000							
CP	0.067	0.052	0.054	0.074	0.030	0.058	0.039	0.003	0.016	0.039	−0.003	1.000						
DCL	0.026	0.043	0.036	−0.010	0.036	0.007	−0.001	−0.044	0.056	−0.048	−0.015	0.086	1.000					
APPL	**0.909**	**0.844**	0.434	0.477	0.079	0.348	0.216	0.177	0.116	0.290	0.011	0.082	0.038	1.000				
FACE	0.277	0.256	0.144	0.116	0.004	0.076	0.057	0.051	0.050	0.079	−0.021	0.012	−0.004	0.256	1.000			
NET	0.284	0.237	0.163	0.187	0.032	0.107	0.079	0.064	0.095	0.122	0.002	0.006	−0.055	0.246	0.261	1.000		
GOOG	**0.885**	**0.852**	0.472	0.449	0.066	0.331	0.194	0.124	0.102	0.270	0.002	0.073	0.021	**0.813**	0.271	0.274	1.000	
AMZN	**0.750**	**0.676**	0.245	0.285	0.000	0.148	0.079	0.059	0.046	0.149	0.013	0.066	−0.022	**0.720**	0.234	0.309	**0.709**	1.000

Notes: numbers in bold refer to strong linear association.

Table 4
QP structural breaks test output.

	Return Series	Risk Series
SupLR (0 vs 1)	1864.25***	465.15***
SupLR (0 vs 2)	2899.08***	957.37***
WDmax	1864.25***	613.25***
Seq (2/1)	1161.84***	0.00***
Break 1 Date	July 30, 2019	April 25, 2019
Break 2 Date	August 12, 2020	July 29, 2020

Notes: (***) refers to significance at 1 % level. *SupLR*: tests the null of zero breaks against a fixed number of changes. *WDmax*: double maximum test. It tests the null of no breaks against an unknown number of breaks up to some prespecified maximum. *Seq (2/1):* tests the null of 1 break against the alternative of two breaks. The tests allow for breaks in the error covariance matrix. Distributions across regimes are allowed to change. Test statistics are robust to autocorrelation. Trimming rate is set at 30 %.

very small, ranging between 0.1 % and 1 %. In contrast, return spillovers from the market to technology stocks are substantially higher ranging between 11.2 % and 19.8 %. In other words, technology stocks are more likely to be subject to shocks to markets than cryptocurrencies and NFTs. Second, we note that return spillovers from cryptocurrencies are higher than other cryptocurrencies, which range between 7.8 % and 14.3 %. The spillovers from cryptocurrencies, however, to NFTs and technology stocks are small (less than 1.1 %). Third, the spillovers from NFTs are very small and negligible and do not have any substantial to contribution to the variations in other stocks such as cryptocurrencies and technologies as well as other NFTs. In this context, our findings suggest that return spillovers from NFTs' only contribute to their own returns. Finally, return spillovers from technology stocks have a higher contribution to the variations and returns of other technology stocks than NFTs and cryptocurrencies.

Similar remarks can be made about the sources of spillovers. We note, according to our findings, that S&P500 receives the highest return spillovers (about 105 % of forecast error variance) followed by Ethereum and DASH (94 % and 92 % respectively). In general, cryptocurrencies are subject to higher spillovers from others (ranging between 64 % and 94 %), followed by technology stocks (ranging between about 27 % and 73 %), while NFTs are the least affected by spillovers from others. It is also important to highlight that the source of these spillovers is from stocks of the same type. That is to say that the spillovers to cryptocurrencies are from other cryptocurrencies. The same applies to technology stocks.

The overall conclusions are the same when accounting for structural breaks and estimated regimes as to the full sample. In other words, there is no evidence of strong connectedness across different stock returns. There is, however, evidence to suggest stronger spillover effects among cryptocurrencies and technology stocks during regime 2 compared to other regimes and the full sample.

Fig. 1 depicts the network pairwise spillover among technology stocks, cryptocurrencies, and NFTs using the full sample. Figs. 2–4 exhibit the network connectedness for Regimes 1, 2, and 3, respectively. The network connectedness is assessed using the return spillover matrix presented in Table 5. The network's attributes are evaluated under five categories: node size, node colour, node location, link arrow size, and edge colour. Node size is determined by node degree,[7] with larger nodes indicating a higher degree. Node colour denotes the type of asset, with blue representing cryptocurrencies, yellow representing NFTs, and red representing technology stocks. Node location is determined by employing the ForceAtlas2 algorithm in Gephi [[62]]. This algorithm situates each node based on its degree of relatedness, positioning more closely related nodes in closer proximity and less related nodes farther apart. The width of the arrows in the figure signifies the strength of the transmission effects, with broader arrows indicating greater magnitudes of spillover. The edge colours, whether dark or light gray, indicate the strength of directional spillover. Dark gray signifies a strong relationship, whereas light gray represents a weaker connection.

The results reveal clustering in the connectedness network among technology stocks, cryptocurrencies, and NFTs. Within each asset group, strong interconnections are observed, whereas the relationships between different groups of assets are less pronounced. For example, technology stocks and cryptocurrencies exhibit strong internal connections, while NFTs are moderately related to each other. Technology stocks are closely linked, though not to the same extent as cryptocurrencies. Our findings remain robust across changes in regimes. This visual representation serves a valuable tool for identifying the primary pathways of spillovers and the key drivers of interconnectivity among technology stocks, cryptocurrencies, and NFTs.

Table 6 reports connectedness estimates of stock volatility. The table has the same structure as Table 5 and reports the same type of output, spillovers 'from' and 'contribution to' as well as the pairwise spillovers from *i*-th variable to *j-th* variable vice versa. The estimates report a similar pattern to those of returns. In other words, the overall volatility spillovers – as reported in Table 6, Panels A, B, C and D, the column 'From Others' range between 4.3 % to about 81 %. Cryptocurrencies variations are subject to volatility spillovers from others the highest (ranging between 65.9 % and 80.9 %), while NFTs receive the least volatility spillovers from others (ranging between 4.3 % and 6.6 %). Technology stocks vary in terms of the level of volatility spillovers received from others as it ranges between 33.4 % and 71.3 %. Similar remarks can be made about the contribution to others. We note, according to our findings, that S&P500 contributes to the volatility spillovers to others the highest (about 111 % of forecast error variance) followed by Monero and Ethereum (about 92 % and 90 % respectively). In general, volatility spillovers from cryptocurrencies to others are the highest (ranging between

[7] The node's degree indicates its number of connections with other nodes.

Table 5
Spillover table, stock returns.

TO		From																	
	SNP	DXT	BTC	ETH	XRP	LTC	DASH	XEM	XLM	XMR	AXIE	CP	DCL	APPL	FACE	NET	GOOG	AMZN	From Others
Panel A: Full Sample																			
SNP	20.7	18.7	1.2	1.2	0.5	1.0	0.5	0.5	0.7	0.9	0.0	0.0	0.1	15.6	4.7	7.3	14.2	12.0	79.3
DXT	21.1	23.2	1.4	1.3	0.7	1.1	0.6	0.7	0.8	0.9	0.0	0.0	0.1	13.8	3.9	6.8	12.7	11.0	76.8
BTC	1.0	1.0	20.8	14.3	7.8	13.7	9.8	8.1	9.0	12.2	0.0	0.0	0.0	0.6	0.3	0.3	0.6	0.4	79.2
ETH	0.9	0.9	13.4	19.5	9.0	14.0	10.2	8.7	9.8	11.3	0.0	0.0	0.0	0.6	0.2	0.3	0.6	0.4	80.5
XRP	0.7	0.7	9.2	11.2	24.3	11.5	9.2	9.2	13.5	9.1	0.1	0.0	0.0	0.5	0.1	0.2	0.2	0.3	75.7
LTC	0.7	0.7	13.0	14.2	9.3	19.7	11.1	8.3	9.8	11.5	0.0	0.0	0.0	0.5	0.2	0.2	0.4	0.3	80.3
DASH	0.5	0.4	10.9	11.9	8.6	12.8	23.0	8.4	9.5	13.0	0.0	0.0	0.1	0.3	0.1	0.1	0.3	0.2	77.0
XEM	0.5	0.6	10.0	11.4	9.6	10.7	9.2	25.8	11.4	9.6	0.1	0.1	0.0	0.2	0.1	0.2	0.3	0.2	74.2
XLM	0.7	0.7	10.0	11.4	12.5	11.3	9.4	10.2	22.4	9.8	0.1	0.0	0.0	0.4	0.2	0.1	0.4	0.3	77.6
XMR	0.7	0.7	12.6	12.5	8.0	12.4	12.1	8.2	9.2	21.7	0.0	0.0	0.1	0.6	0.1	0.2	0.4	0.4	78.3
AXIE	0.1	0.1	0.2	0.3	0.2	0.2	0.0	0.3	0.4	0.0	96.6	0.1	0.5	0.3	0.0	0.3	0.1	0.3	3.4
CP	0.2	0.1	0.4	0.2	0.1	0.3	0.2	0.1	0.5	0.4	0.2	96.1	0.2	0.3	0.1	0.2	0.1	0.3	3.9
DCL	0.1	0.1	1.0	0.3	0.7	0.4	0.5	0.1	0.5	0.4	0.1	0.5	94.8	0.0	0.2	0.1	0.1	0.1	5.2
APPL	19.8	15.5	1.0	1.1	0.5	0.8	0.4	0.3	0.5	0.9	0.1	0.1	0.0	26.1	4.0	6.4	11.3	11.2	73.9
FACE	11.2	8.0	0.7	0.5	0.3	0.5	0.2	0.3	0.6	0.3	0.0	0.1	0.2	7.5	47.5	4.1	9.4	8.7	52.5
NET	12.8	10.5	0.6	0.6	0.3	0.5	0.3	0.3	0.3	0.5	0.0	0.2	0.1	8.9	3.1	36.1	9.9	14.8	63.9
GOOG	18.4	14.6	0.9	0.9	0.3	0.6	0.4	0.4	0.6	0.7	0.0	0.1	0.0	11.5	5.1	7.3	26.5	11.7	73.5
AMZN	15.9	13.0	0.6	0.6	0.3	0.4	0.3	0.2	0.4	0.5	0.0	0.2	0.0	11.7	4.9	11.3	12.1	27.5	72.5
Contribution to others	105.3	86.2	87.0	94.0	68.8	92.3	74.3	64.1	77.5	82.1	0.9	1.6	1.6	73.2	27.6	45.6	73.1	72.5	1127.7
Contribution including own	126.0	109.4	107.8	113.5	93.0	112.0	97.3	89.9	99.9	103.8	97.5	97.7	96.4	99.4	75.0	81.7	99.6	100.0	62.7 %
Panel B: Regime 1 (February 24, 2018–July 30, 2019)																			
SNP	22.1	19.3	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.3	0.0	15.1	3.3	10.0	13.9	15.0	77.9
DXT	22.5	25.7	0.0	0.1	0.1	0.2	0.1	0.1	0.2	0.1	0.2	0.4	0.0	13.8	2.2	9.5	11.1	13.9	74.3
BTC	0.1	0.1	18.8	13.3	9.5	12.4	11.1	11.0	10.4	12.6	0.0	0.0	0.2	0.2	0.1	0.0	0.0	0.1	81.2
ETH	0.1	0.1	12.4	17.4	11.4	12.7	11.5	11.5	10.6	11.8	0.0	0.0	0.1	0.2	0.0	0.1	0.0	0.1	82.6
XRP	0.1	0.1	10.1	13.1	19.6	11.2	10.1	11.1	12.5	11.3	0.0	0.1	0.1	0.3	0.0	0.0	0.0	0.2	80.4
LTC	0.1	0.1	12.4	13.7	10.6	18.5	10.8	10.6	10.6	11.9	0.0	0.0	0.0	0.2	0.1	0.1	0.0	0.1	81.5
DASH	0.1	0.1	11.6	12.9	10.0	11.3	19.3	10.7	10.6	13.0	0.0	0.0	0.1	0.2	0.0	0.0	0.0	0.1	80.7
XEM	0.0	0.0	11.6	13.0	10.7	11.2	10.6	19.8	11.6	10.9	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.1	80.2
XLM	0.1	0.1	10.8	11.9	12.2	10.9	10.5	11.6	19.4	11.5	0.1	0.1	0.1	0.2	0.1	0.0	0.1	0.2	80.6
XMR	0.0	0.0	12.5	12.6	10.4	11.8	12.3	10.4	10.9	18.3	0.0	0.1	0.1	0.2	0.0	0.1	0.0	0.1	81.7
AXIE	0.8	0.7	0.5	0.6	0.2	0.4	0.5	1.1	0.3	0.1	90.3	0.5	0.5	1.7	0.1	0.3	0.4	0.9	9.7
CP	0.5	0.6	0.3	0.5	0.9	0.5	0.4	0.9	1.8	0.6	1.0	88.9	0.6	0.6	0.6	0.6	0.2	0.5	11.1
DCL	0.4	0.4	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.1	0.7	0.3	96.2	0.1	0.7	0.3	0.1	0.1	3.8
APPL	20.3	15.9	0.2	0.2	0.3	0.4	0.2	0.1	0.3	0.3	0.6	0.3	0.0	29.7	1.9	7.1	10.2	12.2	70.3
FACE	8.8	5.0	0.1	0.1	0.1	0.4	0.3	0.1	1.2	0.1	0.1	0.1	0.3	3.4	58.9	4.3	6.6	10.0	41.1
NET	15.4	12.6	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	8.1	2.8	34.1	10.6	15.7	65.9
GOOG	18.9	12.9	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.5	0.0	10.5	3.3	9.3	30.0	14.3	70.0
AMZN	17.8	14.2	0.1	0.2	0.2	0.2	0.1	0.1	0.3	0.1	0.1	0.5	0.0	10.8	4.4	12.1	12.6	26.2	73.8
Contribution to others	106.0	82.4	82.9	92.4	77.1	83.9	78.8	79.3	81.7	84.4	3.4	3.6	2.2	65.7	19.7	54.0	65.8	83.5	1146.6
Contribution including own	128.1	108.0	101.8	109.8	96.7	102.4	98.0	99.1	101.1	102.7	93.7	92.5	98.4	95.3	78.6	88.1	95.8	109.7	63.7 %
Panel C: Regime 2 (July 31, 2019–August 12, 2020)																			
SNP	17.5	16.3	2.7	2.8	1.6	2.2	1.1	1.3	1.7	2.5	0.0	0.0	0.1	14.2	5.5	6.1	13.8	10.4	82.5
DXT	17.8	18.8	2.9	2.9	1.7	2.4	0.9	1.5	1.8	2.4	0.0	0.0	0.1	12.8	5.1	5.6	13.5	9.9	81.2
BTC	2.3	2.3	18.2	13.7	9.1	12.9	9.1	5.9	7.8	12.4	0.0	0.0	0.0	1.6	0.8	1.0	1.7	1.3	81.8
ETH	2.3	2.2	13.0	17.0	10.8	13.1	8.8	6.4	8.8	11.6	0.1	0.0	0.0	1.7	0.4	1.1	1.6	1.2	83.0

(*continued on next page*)

Table 5 (*continued*)

TO	From																	
	SNP	DXT	BTC	ETH	XRP	LTC	DASH	XEM	XLM	XMR	AXIE	CP	DCL	APPL	FACE	NET	GOOG	AMZN	From Others
XRP	1.6	1.6	10.0	12.3	19.1	12.1	8.8	7.4	13.0	10.1	0.1	0.0	0.0	1.1	0.3	0.7	1.0	0.7	80.9
LTC	2.0	1.9	12.8	13.7	11.0	17.4	9.4	6.1	9.3	11.3	0.0	0.0	0.0	1.4	0.4	0.7	1.3	1.0	82.6
DASH	1.2	0.9	11.3	11.7	10.2	12.1	22.3	6.0	9.3	11.6	0.1	0.1	0.0	0.9	0.2	0.6	0.9	0.7	77.7
XEM	1.8	2.0	8.8	10.2	10.0	9.2	7.1	26.6	9.5	8.9	0.3	0.1	0.1	1.1	0.4	1.0	1.4	1.2	73.4
XLM	1.8	1.8	9.4	10.8	13.8	10.9	8.7	7.6	20.4	10.0	0.1	0.0	0.1	1.2	0.5	0.8	1.4	0.8	79.6
XMR	2.2	2.0	12.7	12.5	9.6	11.6	9.6	6.1	8.7	19.0	0.0	0.0	0.0	1.8	0.3	1.0	1.5	1.2	81.0
AXIE	0.0	0.0	0.1	0.2	0.4	0.3	0.3	0.8	0.7	0.2	94.1	0.7	1.3	0.1	0.1	0.4	0.1	0.3	5.9
CP	0.5	0.3	0.7	0.3	0.2	0.4	0.7	0.5	0.2	0.3	0.5	92.7	1.4	0.7	0.2	0.1	0.1	0.3	7.3
DCL	0.2	0.2	1.6	0.4	0.1	1.2	1.4	0.7	0.8	1.4	0.1	0.5	89.9	0.2	0.3	0.4	0.4	0.2	10.1
APPL	17.1	14.1	2.3	2.6	1.4	2.0	1.0	1.0	1.4	2.3	0.0	0.0	0.0	20.7	5.8	6.1	11.6	10.4	79.3
FACE	12.0	10.0	1.7	1.1	0.9	0.9	0.8	0.6	0.9	0.8	0.0	0.4	0.4	10.5	37.3	3.4	10.5	7.8	62.7
NET	10.9	9.1	2.4	2.6	1.5	1.7	1.1	1.4	1.6	2.1	0.0	0.2	0.3	9.1	2.7	31.6	8.3	13.3	68.4
GOOG	16.8	15.0	2.3	2.4	1.1	1.8	0.9	1.2	1.5	2.1	0.1	0.0	0.1	11.7	5.8	5.8	21.3	10.0	78.7
AMZN	14.4	12.4	1.9	1.9	0.9	1.5	0.7	1.1	0.9	1.6	0.1	0.3	0.1	11.9	4.8	10.2	11.4	23.9	76.1
Contribution to others	104.9	92.1	96.5	102.4	84.0	96.5	70.1	55.7	77.9	91.6	1.7	2.4	4.2	82.0	33.8	45.3	80.5	70.6	1192.1
Contribution including own	122.5	110.9	114.7	119.3	103.1	113.9	92.4	82.3	98.3	110.6	95.7	95.1	94.1	102.7	71.1	76.9	101.8	94.6	66.2 %
Panel D: Regime 3 (August 13, 2020–September 07, 2021**)**																			
SNP	21.2	18.2	1.3	0.7	0.3	0.8	0.5	0.5	0.2	0.7	0.1	0.1	0.0	15.2	8.1	7.0	12.4	12.7	78.8
DXT	21.5	25.3	1.7	0.8	0.5	1.1	0.7	0.9	0.4	0.7	0.0	0.0	0.1	11.8	6.6	6.2	10.8	10.7	74.7
BTC	1.2	1.4	25.1	13.8	6.4	15.0	9.6	6.0	8.1	10.2	0.6	0.0	0.2	0.5	0.3	0.6	0.7	0.2	74.9
ETH	0.7	0.7	13.3	24.7	7.2	15.2	10.2	7.1	9.1	9.6	0.2	0.0	0.1	0.4	0.2	0.5	0.5	0.2	75.3
XRP	0.7	0.7	7.6	8.7	30.9	10.8	9.1	7.9	15.3	6.4	0.3	0.1	0.1	0.5	0.1	0.4	0.2	0.1	69.1
LTC	0.5	0.6	13.8	14.2	8.0	23.0	13.0	6.1	8.9	10.6	0.2	0.1	0.1	0.3	0.1	0.2	0.2	0.2	77.0
DASH	0.4	0.5	9.7	10.4	7.6	14.5	26.8	7.1	8.6	13.5	0.1	0.1	0.1	0.1	0.0	0.3	0.2	0.0	73.2
XEM	0.5	0.7	7.7	9.3	8.7	8.9	9.0	34.2	11.8	7.3	0.3	0.1	0.0	0.2	0.4	0.3	0.4	0.1	65.8
XLM	0.4	0.5	8.9	10.1	13.7	10.8	9.4	9.8	27.6	7.1	0.1	0.1	0.1	0.1	0.1	0.5	0.4	0.1	72.4
XMR	0.8	0.7	10.7	10.8	5.7	12.5	14.5	6.4	6.7	28.6	0.1	0.1	0.2	0.4	0.1	0.6	0.6	0.4	71.4
AXIE	0.0	0.0	2.3	0.8	0.9	0.6	0.0	0.8	0.4	0.1	93.2	0.2	0.0	0.0	0.1	0.5	0.0	0.1	6.8
CP	0.3	0.2	0.9	0.1	0.2	0.4	0.1	0.1	0.2	0.3	0.3	94.5	0.1	0.4	0.1	0.9	0.7	0.3	5.5
DCL	0.1	0.2	2.7	0.9	1.9	0.9	0.9	0.1	1.4	0.5	0.0	1.7	87.7	0.3	0.1	0.3	0.1	0.2	12.3
APPL	20.3	13.5	1.0	0.6	0.2	0.6	0.3	0.3	0.0	0.6	0.1	0.2	0.2	28.4	6.2	6.6	8.0	12.9	71.6
FACE	14.0	9.4	0.5	0.2	0.1	0.1	0.1	0.6	0.1	0.1	0.0	0.7	0.1	8.5	36.9	6.2	11.3	11.1	63.1
NET	12.8	9.5	0.5	0.1	0.2	0.2	0.3	0.3	0.0	0.5	0.1	0.2	0.3	9.1	6.5	38.8	7.5	13.0	61.2
GOOG	17.8	12.9	0.9	0.6	0.2	0.4	0.3	0.4	0.3	0.6	0.0	0.4	0.1	8.9	9.4	5.7	30.3	10.9	69.7
AMZN	16.9	11.9	0.3	0.2	0.1	0.2	0.1	0.1	0.1	0.4	0.1	0.1	0.1	13.0	8.4	9.3	10.2	28.2	71.8
Contribution to others	108.8	81.6	83.9	82.4	62.0	93.1	78.1	54.3	71.8	69.3	2.7	4.3	2.0	69.6	46.9	46.0	64.3	73.4	1094.4
Contribution including own	130.0	106.9	108.9	107.1	93.0	116.2	104.9	88.4	99.4	97.9	96.0	98.8	89.7	98.0	83.8	84.8	94.6	101.6	60.8 %

Table 6
Spillover table, stock volatility.

TO	From																	
	SNP	DXT	BTC	ETH	XRP	LTC	DASH	XEM	XLM	XMR	AXIE	CP	DCL	APPL	FACE	NET	GOOG	AMZN	From Others
Panel A: Full Sample																			
SNP	24.7	20.1	2.8	2.5	0.3	1.4	0.8	0.8	1.2	1.4	0.0	0.0	0.2	13.7	3.0	5.8	12.0	9.3	75.3
DXT	23.6	24.5	3.6	3.0	0.5	1.7	1.0	1.2	1.2	1.6	0.0	0.0	0.3	11.0	2.4	5.5	11.0	8.1	75.5
BTC	3.2	2.9	21.1	14.3	4.7	12.7	8.0	6.7	7.0	13.2	0.0	0.0	0.0	1.4	0.3	1.5	2.1	0.8	78.9
ETH	2.7	2.0	13.2	19.1	6.2	13.8	9.2	7.6	7.0	14.5	0.0	0.0	0.0	1.5	0.2	1.1	1.4	0.6	80.9
XRP	0.4	0.5	6.4	9.0	35.1	10.2	6.5	7.8	14.8	8.1	0.0	0.1	0.2	0.4	0.1	0.1	0.1	0.1	64.9
LTC	1.5	1.2	11.4	13.2	7.1	19.9	10.8	8.7	7.9	15.2	0.0	0.0	0.0	0.9	0.1	0.6	0.9	0.3	80.1
DASH	1.0	1.0	8.6	10.4	6.5	11.8	28.1	6.5	8.9	15.2	0.3	0.0	0.0	0.6	0.0	0.3	0.4	0.1	71.9
XEM	0.6	0.6	6.8	8.2	8.8	10.5	7.5	34.1	10.6	11.1	0.0	0.0	0.1	0.4	0.1	0.2	0.1	0.1	65.9
XLM	0.8	0.7	8.2	10.7	13.9	10.1	7.2	9.1	28.6	9.0	0.0	0.0	0.1	0.5	0.1	0.6	0.2	0.2	71.4
XMR	1.6	1.3	10.9	11.8	5.7	13.4	13.4	7.8	8.0	23.6	0.1	0.0	0.0	0.8	0.0	0.6	0.8	0.3	76.4
AXIE	0.0	0.0	0.4	0.0	0.0	0.0	1.1	0.0	0.1	0.1	94.9	0.0	3.2	0.0	0.0	0.0	0.0	0.0	5.1
CP	0.2	0.1	0.5	0.4	0.1	0.3	0.3	0.1	0.1	0.2	0.1	95.7	1.0	0.3	0.1	0.1	0.0	0.2	4.3
DCL	0.1	0.1	0.0	0.0	2.3	0.0	0.1	0.0	1.0	0.0	1.9	0.1	93.4	0.2	0.4	0.1	0.1	0.1	6.6
APPL	20.8	14.6	2.1	2.2	0.3	1.1	0.5	0.6	0.9	1.2	0.0	0.0	0.0	28.7	3.6	4.3	10.6	8.6	71.3
FACE	7.2	5.0	0.7	0.3	0.1	0.2	0.1	0.2	0.3	0.2	0.0	0.0	0.2	4.8	66.6	3.8	5.2	5.1	33.4
NET	10.5	8.1	1.9	1.3	0.2	1.0	0.3	0.2	0.6	0.7	0.0	0.0	0.1	3.8	2.7	48.8	8.0	11.8	51.2
GOOG	19.5	14.0	2.1	1.8	0.3	1.0	0.3	0.3	0.5	0.7	0.0	0.2	0.1	9.8	3.4	7.0	30.6	8.3	69.4
AMZN	17.8	12.9	0.5	0.3	0.0	0.2	0.1	0.1	0.2	0.2	0.0	0.1	0.1	9.2	5.6	9.2	11.7	31.8	68.2
Contribution to others	111.4	85.3	80.2	89.6	57.1	89.3	67.4	57.8	70.3	92.6	2.6	0.9	5.8	59.2	22.0	40.7	64.6	53.8	1050.5
Contribution including own	136.2	109.7	101.3	108.7	92.2	109.3	95.4	91.9	98.8	116.2	97.6	96.6	99.1	87.9	88.7	89.5	95.2	85.7	58.4 %
Panel B: Regime 1 (February 24, 2018–April 25, 2019**)**																			
SNP	24.6	21.4	0.0	0.0	0.1	0.2	0.0	0.5	0.0	0.0	0.0	0.0	0.2	9.9	2.0	11.3	14.8	15.1	75.4
DXT	24.0	26.8	0.0	0.0	0.1	0.1	0.0	0.4	0.1	0.1	0.0	0.1	0.2	9.7	1.2	10.8	13.2	13.1	73.2
BTC	0.5	0.5	24.4	12.2	5.3	11.8	7.7	11.7	7.3	16.2	0.0	0.2	1.1	0.7	0.2	0.0	0.0	0.0	75.6
ETH	0.5	0.2	12.4	20.2	7.3	10.4	11.8	10.4	6.6	16.8	0.0	0.1	2.1	0.7	0.2	0.1	0.0	0.2	79.8
XRP	0.1	0.1	7.5	11.5	33.5	6.7	6.0	9.1	11.4	10.5	0.2	1.2	1.6	0.3	0.0	0.1	0.0	0.2	66.5
LTC	0.5	0.5	15.5	13.2	5.5	24.9	7.0	11.9	5.2	12.4	0.0	0.0	1.5	1.4	0.2	0.0	0.1	0.1	75.1
DASH	0.7	0.7	9.1	10.2	4.5	5.9	34.1	5.9	5.4	16.7	0.0	0.1	5.5	0.7	0.4	0.1	0.0	0.2	65.9
XEM	0.0	0.1	13.2	11.0	10.9	9.2	6.3	26.9	8.7	11.9	0.1	0.3	0.8	0.1	0.1	0.1	0.1	0.1	73.1
XLM	0.2	0.2	12.9	10.7	12.3	7.0	6.5	10.3	24.6	12.5	0.2	0.3	1.7	0.1	0.1	0.1	0.3	0.1	75.4
XMR	0.6	0.4	14.8	11.9	5.9	8.5	13.7	9.6	7.5	23.4	0.0	0.1	2.5	0.7	0.2	0.0	0.0	0.1	76.6
AXIE	0.0	0.0	0.0	0.1	0.4	0.0	0.0	0.2	0.5	0.1	97.5	0.6	0.1	0.1	0.0	0.0	0.0	0.2	2.5
CP	0.5	0.3	2.0	2.0	1.7	1.2	0.9	0.8	0.4	2.1	0.1	85.6	0.6	0.0	0.1	0.3	1.3	0.0	14.4
DCL	1.6	2.6	0.1	0.5	0.7	0.2	0.6	1.6	0.8	0.3	0.0	0.3	86.0	1.5	0.2	0.8	0.9	1.1	14.0
APPL	20.5	19.2	0.0	0.2	0.0	0.1	0.3	0.4	0.0	0.5	0.0	0.0	0.2	32.8	0.9	5.8	8.0	11.0	67.2
FACE	3.5	1.5	0.3	0.1	0.1	0.3	0.1	0.7	0.7	0.2	0.3	0.2	0.0	0.4	80.3	2.2	3.2	5.6	19.7
NET	16.1	13.3	0.1	0.0	0.0	0.1	0.0	0.2	0.0	0.1	0.0	0.1	0.2	2.7	0.9	33.5	17.0	15.5	66.5
GOOG	20.7	17.2	0.1	0.2	0.2	0.6	0.1	0.6	0.1	0.2	0.0	0.3	0.1	6.1	1.7	13.1	22.3	16.5	77.7
AMZN	19.2	16.4	0.1	0.1	0.0	0.4	0.0	0.5	0.0	0.1	0.0	0.4	0.2	4.4	3.1	14.0	15.3	25.7	74.3
Contribution to others	109.4	94.6	88.1	84.0	55.1	62.8	61.1	74.7	54.8	100.8	1.1	4.2	18.6	39.6	11.6	58.7	74.4	79.1	1072.8
Contribution including own	134.0	121.4	112.6	104.2	88.6	87.7	95.2	101.6	79.4	124.2	98.6	89.8	104.6	72.4	91.9	92.3	96.7	104.8	59.6 %
Panel C: Regime 2 (26/04/2019–July 29, 2020**)**																			
SNP	18.3	14.5	4.0	4.7	4.3	4.2	2.0	2.6	3.3	4.8	0.0	0.0	0.1	15.3	2.4	4.3	7.5	7.5	81.7
DXT	17.6	15.9	4.5	5.1	4.3	4.5	2.3	2.8	3.4	5.2	0.0	0.0	0.1	13.6	2.4	4.3	6.8	7.3	84.1
BTC	5.0	4.3	13.5	11.6	8.5	10.9	7.2	8.3	7.3	12.3	0.0	0.1	0.0	3.5	0.5	2.7	2.2	2.1	86.5
ETH	5.0	4.2	10.9	12.4	9.5	10.6	7.5	8.4	8.2	11.4	0.0	0.1	0.0	4.1	0.6	2.6	2.1	2.4	87.6

(*continued on next page*)

Table 6 (*continued*)

TO	From																		
	SNP	DXT	BTC	ETH	XRP	LTC	DASH	XEM	XLM	XMR	AXIE	CP	DCL	APPL	FACE	NET	GOOG	AMZN	From Others
XRP	3.2	2.8	9.8	11.3	16.1	10.4	7.5	9.1	10.9	10.6	0.0	0.0	0.0	2.9	0.5	1.9	1.3	1.6	83.9
LTC	4.4	3.5	11.1	11.6	9.3	12.2	8.0	8.9	7.9	11.8	0.0	0.1	0.0	3.8	0.5	2.6	2.2	2.1	87.8
DASH	2.7	2.6	9.9	11.7	10.0	11.0	19.8	7.7	7.2	11.8	0.0	0.0	0.0	2.2	0.1	1.3	0.8	1.2	80.2
XEM	2.7	2.6	9.0	9.9	10.7	9.4	7.2	19.6	9.2	10.8	0.0	0.0	0.2	2.9	0.6	2.1	0.8	2.1	80.4
XLM	3.2	3.0	9.3	10.8	12.8	9.8	7.2	8.7	16.2	10.4	0.0	0.0	0.1	2.9	0.4	2.3	1.3	1.5	83.8
XMR	4.5	3.9	11.5	11.3	8.9	10.4	8.0	9.0	8.2	14.0	0.0	0.1	0.0	3.8	0.4	2.3	1.8	1.9	86.0
AXIE	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	87.7	0.0	12.0	0.0	0.0	0.0	0.0	0.0	12.3
CP	0.4	0.7	0.8	1.0	1.3	0.5	2.2	0.3	1.3	0.9	0.1	88.7	0.8	0.2	0.0	0.1	0.1	0.4	11.3
DCL	0.1	0.3	0.1	0.0	0.2	0.1	0.0	0.6	0.1	0.0	6.3	0.2	91.1	0.5	0.1	0.0	0.1	0.1	8.9
APPL	16.6	12.4	3.8	4.7	4.2	4.5	2.0	2.8	3.3	4.9	0.0	0.1	0.1	19.4	2.7	4.0	7.6	6.8	80.6
FACE	8.2	8.1	2.0	1.9	1.7	1.8	0.7	1.5	1.2	1.7	0.0	0.8	0.1	4.9	53.3	4.4	4.2	3.4	46.7
NET	6.0	5.1	5.4	5.6	4.6	5.7	2.6	4.0	5.4	5.6	0.0	0.1	0.2	4.4	2.7	34.7	2.8	5.3	65.3
GOOG	15.5	10.1	3.0	3.6	4.0	4.0	1.1	1.9	2.7	3.5	0.0	0.0	0.1	11.5	2.8	5.3	25.1	5.9	74.9
AMZN	16.2	12.2	2.0	2.5	3.0	2.5	0.7	1.7	2.1	2.3	0.0	0.0	0.1	12.7	4.1	5.5	9.0	23.3	76.7
Contribution to others	111.5	90.4	97.2	107.5	97.3	100.4	66.3	78.2	81.8	108.0	6.5	1.6	14.2	89.2	20.7	45.6	50.7	51.5	1218.6
Contribution including own	129.8	106.3	110.7	119.9	113.4	112.6	86.1	97.8	98.0	122.0	94.2	90.3	105.3	108.7	74.0	80.3	75.8	74.8	67.7 %
Panel D: Regime 3 (30/07/2020–September 07, 2021**)**																			
SNP	26.9	20.7	0.2	0.3	1.2	0.1	0.4	0.7	0.3	0.1	0.0	1.1	0.3	13.2	7.7	3.7	14.6	8.5	73.1
DXT	25.2	33.1	0.7	0.6	0.7	0.1	0.1	1.4	0.3	0.1	0.0	0.7	0.5	7.6	5.4	3.2	13.5	6.5	66.9
BTC	0.4	0.7	25.2	12.1	4.3	13.3	9.5	6.2	6.6	14.6	0.8	0.7	2.4	0.3	0.1	1.0	0.9	0.8	74.8
ETH	0.5	0.2	9.0	26.5	5.0	17.0	8.4	7.3	5.5	16.9	0.2	1.4	0.9	0.1	0.0	0.2	0.3	0.5	73.5
XRP	0.6	0.1	3.5	6.1	44.4	11.1	3.7	4.5	17.5	4.6	0.0	0.1	0.7	0.5	0.5	0.2	0.4	1.6	55.6
LTC	0.1	0.1	7.0	12.8	7.2	23.9	13.5	6.6	7.3	18.5	0.1	1.5	0.3	0.0	0.2	0.0	0.0	0.8	76.1
DASH	0.1	0.1	5.0	8.0	5.0	13.3	32.1	4.1	10.0	18.4	1.0	0.2	0.5	0.1	0.4	0.0	0.1	1.4	67.9
XEM	0.5	0.9	4.1	6.3	5.7	11.2	5.9	42.0	10.7	11.0	0.0	0.9	0.0	0.0	0.0	0.0	0.0	0.7	58.0
XLM	0.7	0.5	4.0	10.7	15.2	9.0	5.6	7.5	37.9	4.6	0.2	0.3	0.9	0.6	0.3	0.4	0.6	1.0	62.1
XMR	0.2	0.1	5.9	9.9	4.2	15.8	18.0	5.7	6.1	31.9	0.1	1.0	0.1	0.1	0.4	0.0	0.1	0.3	68.1
AXIE	0.0	0.0	6.6	0.2	0.1	0.0	4.1	0.0	0.3	0.4	87.5	0.2	0.1	0.0	0.0	0.2	0.1	0.1	12.5
CP	3.0	1.1	0.2	0.9	1.0	0.8	0.7	0.5	0.4	0.9	0.4	82.3	1.3	0.8	1.2	0.1	3.9	0.5	17.7
DCL	1.1	0.1	1.3	0.9	9.1	1.0	0.7	0.0	8.6	0.2	0.4	0.1	66.8	5.2	3.5	0.0	0.2	0.7	33.2
APPL	17.6	8.2	0.6	0.1	1.6	0.2	1.4	0.0	0.3	0.4	0.0	0.9	0.3	34.6	10.9	3.1	13.1	6.8	65.4
FACE	9.8	5.1	0.1	0.3	0.9	0.4	0.3	0.0	0.1	0.2	0.1	1.0	1.1	11.2	48.4	4.9	9.5	6.4	51.6
NET	7.4	4.4	0.4	0.0	0.5	0.3	0.2	0.1	0.5	0.0	0.1	0.2	0.1	2.7	7.0	58.5	9.9	7.5	41.5
GOOG	16.0	12.0	0.1	0.2	0.3	0.2	1.0	0.0	0.2	0.2	0.1	3.0	0.0	8.2	9.4	5.8	37.2	6.1	62.8
AMZN	15.2	9.0	0.6	0.6	1.7	1.7	1.2	0.3	0.7	0.5	0.0	0.3	0.4	9.5	10.3	4.3	13.2	30.5	69.5
Contribution to others	98.4	63.4	49.5	70.1	63.8	95.5	74.6	45.1	75.5	91.6	3.6	13.8	9.8	60.4	57.2	27.3	80.3	50.3	1030.3
Contribution including own	125.3	96.5	74.7	96.6	108.2	119.5	106.7	87.1	113.4	123.5	91.1	96.1	76.6	95.0	105.6	85.8	117.5	80.7	57.2 %

64 % and 94 %), followed by technology stocks (ranging between about 22 % and 65 %), while the NFTs are the least contributors (ranging between about 0.9 % and 5.8 %). This pattern is also observed across regimes. However, the Spillover Indices during Regime 2 (April 26, 2019–July 29, 2020) are the highest compared to the full sample, and Regime 1 (February 24, 2018–April 25, 2019) and Regime 3 (July 30, 2020–September 07, 2021).

Similar to returns, volatility spillovers are the highest when the spillovers are from or to stocks of the same types. Cross types (sectors) spillovers are very small. The only exception is that technology stocks are highly connected to market indices (both S&P500 and Nasdaq). This is true for the full sample and across regimes.

Fig. 5 presents how the volatility of technology stocks, cryptocurrencies, and NFTs are interconnected. Figs. 6–8 further elaborate on this relationship under varying regimes. In the network, nodes represent individual assets, and the edges connecting them signify the strength of their risk interconnection. Notably, the risks associated with NFTs exhibit weaker connections to technology stocks and cryptocurrencies. Conversely, the strongest connections are observed within each respective asset group. Regime changes also offer evidence of clustering, with the exception of NFTs. Given the diverse nature of NFTs, their risk and return characteristics are distinctly unique [[63]]; therefore, they demonstrate heterogeneity across different regimes. This aligns with the findings of Xia et al. [64], who document that NFTs form distinct subgroups with other NFTs under different market conditions.

Our findings depart from existing literature in several ways. First, our results are more focused on digital assets and their connectedness. Thus, the effect of financial assets of different classes is not accounted for. In other words, our findings are not directly comparable to literature such as Curto and Serrasquiro [38], Chu et al. [36], Curto [37], Bouri et al. [27], Corbet et al. [5] and Jie et al. [26], which consider more diverse classes of assets. Second, our findings are based on a larger sample in terms of number of assets, which is more than much of the existing literature. In line with the existing literature, we show that cryptocurrencies are dominant source of shocks and variations. However, in contrast to the existing literature, the spillovers are limited to assets of the same class. In other words, shocks of assets affect only those on the same class. Similarly, shocks affecting these assets are due to spillovers from assets of the same class. Finally, we offer some insights on the role of exogenous shocks and estimate common breaks for a seemingly unrelated system of equations of both stock returns and volatility which was never done in the literature.

6. Discussion and concluding remarks

The above analysis highlights some of the statistical properties of technology, cryptocurrencies, and NFTs assets, both individually and within a system. According to the unit root tests, return series exhibit stationarity in the conditional mean. This may seem to have confirmed that returns are covariance stationary, but this argument is flawed to a certain extent. In fact, standard unit root and stationarity tests assume the constancy of the variances and therefore do not offer much insight on whether stock returns consist also of time varying volatility. We mitigate this by (i) estimating GARCH (1,1)- based volatility and (ii) allowing for the covariance matrix to shift over time when testing for multiple structural breaks for the system in Equation (15). The former allows to explicitly analyse the properties of volatility spillovers. The latter, on the other hand, captures regimes shifts in the mean – and volatility – accounting for the distributional changes across regimes.

The estimated regimes coincide with the relevant events. In this context, we estimate one break in 2019 and another in 2020 for both returns and volatility. The break dates, however, occur on different days. For example, the first break occurs on April 25, 2019 for volatility and July 30, 2019 for returns. Similarly, the second break occurs on July 29, 2020 for volatility and July 30, 2020 for returns. We cannot, however, confirm whether this gap in the timing is of economic or financial significance due to the limitations of the

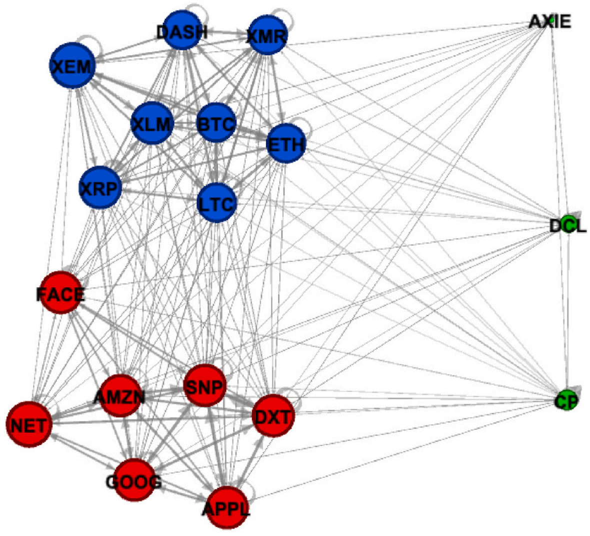

Fig. 1. Network representation of estimated connectedness (return-full sample).

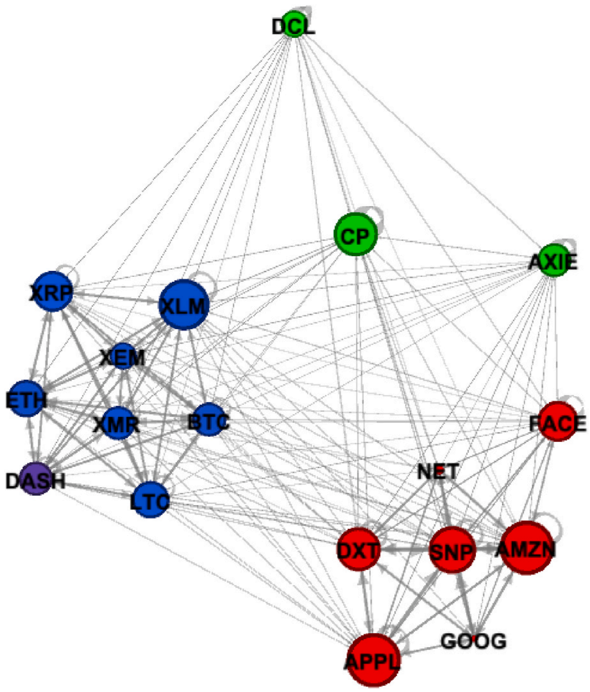

Fig. 2. Network representation of estimated connectedness (Return-Regime1).

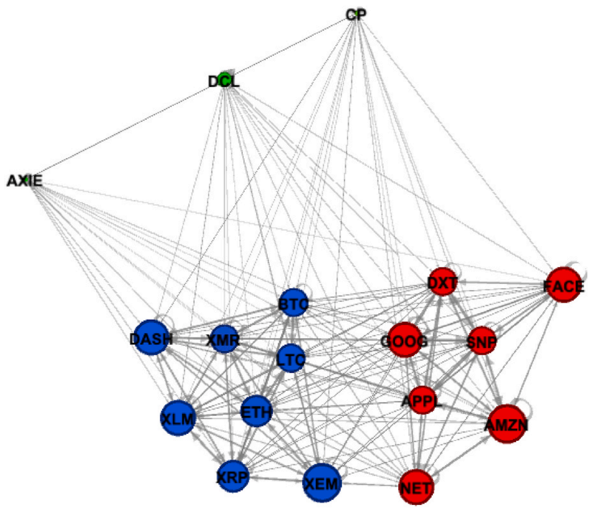

Fig. 3. Network representation of estimated connectedness (Return-Regime2).

econometric tools we employ. It is, however, typical to have different dates when breaks are determined endogenously. The break dates become an approximation more than an exercise of identifying the exact date. Nonetheless, the breaks are consistent with a cryptocurrency bubble as documented in the literature of Telli and Chen [61] and Diniz et al. [42]. The second break is also consistent with the post COVID-19 period Karim et al. [9] and Montasser et al. [43]. Thus, the stock returns and volatility are not stable and have been subject to exogenous shocks. This also implies that connectedness when measured needs to account for the effect of these exogenous shocks.

The results from connectedness show several interesting patterns. First, using the full sample or regime-based samples, the findings are relatively robust and stable. There is, however, evidence suggesting that spillovers may differ from one regime to another. Our findings suggest that for both returns and volatility, the second regime (February 24, 2018–July 30, 2019 for returns and 26/04/2019–July 29, 2020 for volatility), reports higher spillovers compared to the other two regimes. This is consistent with the findings in Karim et al. [9], which highlight the 'dramatically enhanced' connectedness in the cryptocurrency and NFTs market during 2019.

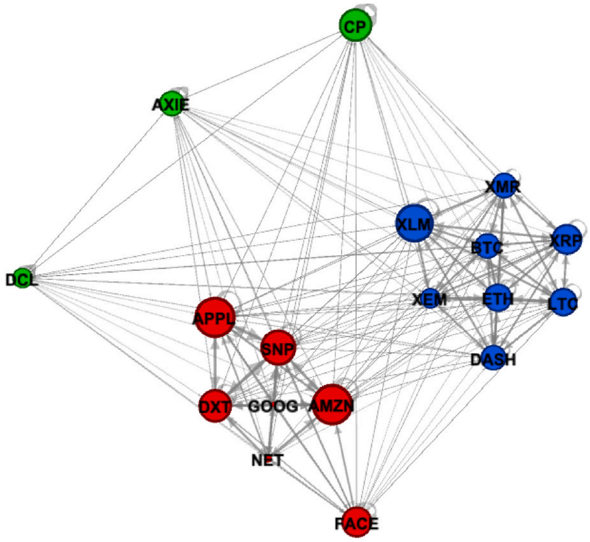

Fig. 4. Network representation of estimated connectedness (Return-Regime3).

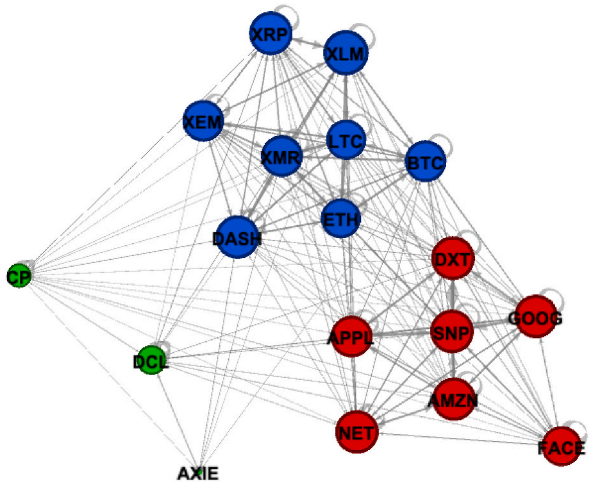

Fig. 5. Network representation of estimated connectedness (volatility-full sample).

Second, our findings suggest a form of the group (or type) wise connectedness. While many stocks or indicators exhibited very high contribution or exposure to return/volatility spillovers, the spillovers are often limited within the assets of the same type. For example, shocks to Bitcoin contribute to about 87 % of return spillovers to other assets. However, about 79 % of these return towards other cryptocurrency assets, while the remaining 8 % are received by assets other than cryptocurrencies. This applies to technology, while NFTs do not show any relevant connectedness. In conclusion, there is no cross assets connectedness in the wider sense. Connectedness is strong only among assets of the same type.

The paper finds limited return and volatility spillovers between the technology stocks, cryptocurrencies, and NFTs. These results align with some recent studies, though differ from others. For instance, Yousaf and Yarovaya [10] and BenMabrouk et al. [11] also document limited return and volatility transmission between NFTs and other assets like Bitcoin and stocks. However, Karim et al. [9] find strong volatility connectedness among NFTs, DeFis, and cryptocurrencies.

One potential economic rationale for the limited spillovers is that these assets remain fairly segmented in terms of investor bases and use cases. NFTs, represent a niche market driven more by hype and speculation than fundamentals [[19]]. As Kong and Lin [16] discuss, NFT prices are influenced by factors like scarcity and aesthetics rather than traditional valuation models.

Cryptocurrencies also trade on sentiment without clear anchors for valuation [[34]], so shocks may remain confined within each asset group rather than spreading more systemically across categories. As Bouri et al. [27] explain, this makes cryptocurrencies weak conduits for cross-market volatility transmission. In contrast, the stronger internal connectedness likely reflects greater substitution effects within asset classes. For instance, cryptocurrency returns are highly correlated since investors can easily switch between coins

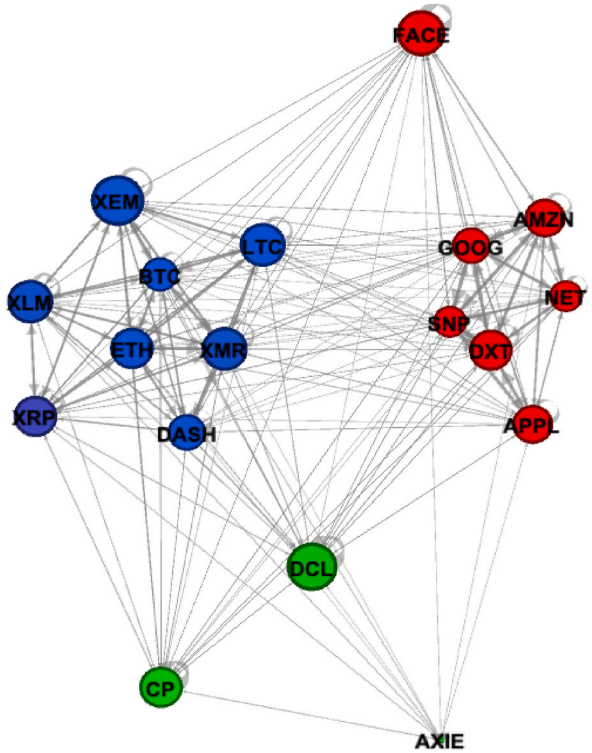

Fig. 6. Network representation of estimated connectedness (Volatility-Regime1).

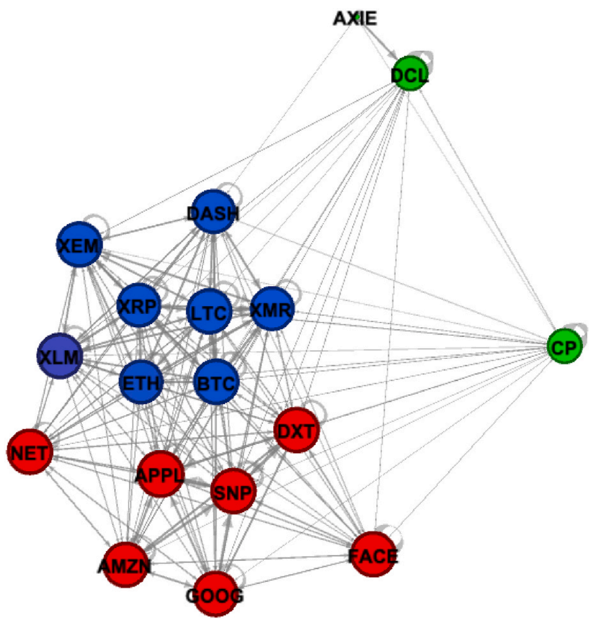

Fig. 7. Network representation of estimated connectedness (Volatility-Regime2).

based on momentum and narratives [[21]]. As Dowling [15] notes, this drives significant volatility spillovers among cryptos. The same holds for technology stocks which compete in overlapping markets [[36]]. Demand shocks can propagate among tech companies with similar offerings and investor bases.

This paper makes two main contributions to literature. First, it examines the connectedness between technology stocks, cryptocurrencies, and NFTs in a joint framework—an analysis that existing works do not provide. While past studies explore linkages between

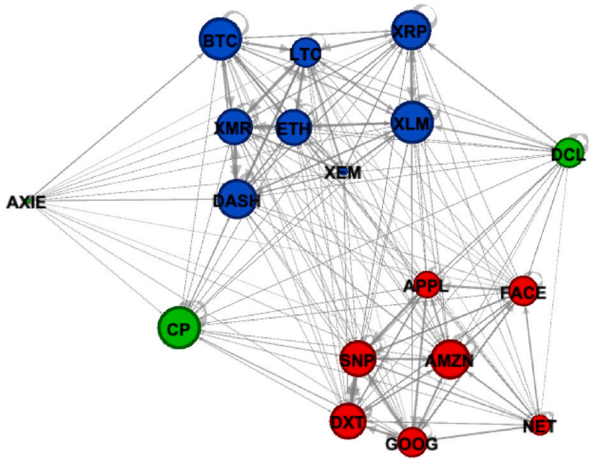

Fig. 8. Network representation of estimated connectedness (Volatility-Regime3).

cryptocurrencies and tech stocks or NFTs and tech stocks, they do not consider the interplay between all three asset classes simultaneously as done in this paper. Second, this study incorporates common structural break analysis to account for distributional changes in connectedness over time. Prior literature such as [7] relies on single-equation break tests, whereas we model unknown common shifts among the assets using seemingly unrelated equations. This enables capturing common sporadic shifts in response to exogenous shocks. In summary, by connecting all three technology-driven assets and estimating their joint structural breaks, this paper delivers unique evidence to advance the finance literature. The findings offer insights into risk management and diversification strategies involving tech stocks, cryptocurrencies, and NFTs.

The evidence that volatility and return spillovers primarily remain confined within tech stocks, cryptocurrencies, and NFTs has notable policy implications. For regulators, these limited cross-asset spillovers suggest emerging digital assets such as cryptocurrencies and NFTs currently pose limited systemic risk to broader financial markets, providing cautious justification for ongoing monitoring over pre-emptive interventions as discussed by Auer and Claessens [65]. However, as Guesmi et al. [25] argue, policymakers remain concerned about potential contagion between cryptos and traditional assets. Our findings indicate such risk transmission has so far been contained.

For investors and managers, the segmented nature of connectedness underscores benefits in diversifying across these asset categories, as Liu and Tsyvinski [66] highlight. Portfolios can tap into the high growth potential of tech stocks, cryptos, and NFTs while partly insulating against category-specific volatility. However, Liu and Tsyvinski [66] note the strong internal spillovers also highlight the need for mitigating concentrated exposures. As regulators debate crypto regulation amid its growing adoption, our evidence offers timely insights into risk planning as portfolios increasingly incorporate both digital and technology-based assets. Overall, the nuanced connectivity suggests a measured approach to managing portfolio exposures and oversight.

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Tugba Bas: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Issam Malki:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Sheeja Sivaprasad:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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