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Quantile return and volatility connectedness among Non-Fungible Tokens (NFTs) and (un)conventional assets

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Abstract

This paper uses the Quantile Vector-Autoregressive (Q-VAR) connectedness technique to examine the return and volatility connectedness among NFTs and (un)conventional assets including cryptocurrency, energy, technology, equity, precious metals, and fixed income financial assets across three quantiles corresponding to the normal, bearish, and bullish market conditions. It also explores the predictive powers of major macroeconomic and geopolitical indicators on the return and volatility connectedness across these three market conditions using a linear regression model. The main findings are as follows. First, the return and volatility connectedness vary across the market conditions, with the levels during the bearish and bullish market conditions being higher. Second, except under the bullish market condition, the total return connectedness is higher than those of total volatility connectedness. Third, NFTs are, at best, decoupled from (un)conventional assets during the normal market condition. Fourth, NFTs is a net return shock receivers except under the bullish market condition where it is a net transmitters. However, it is a net volatility shock receiver irrespective of the market condition. Fifth, during periods of economic crisis the total return and volatility connectedness rise (decreases) under the normal and bearish (bullish) market conditions. Finally, geopolitical risks, business environment conditions, and market and economic policy uncertainty are important predictors of return and volatility connectedness, although the predictive strength and direction vary across market conditions. We discuss the implications of our findings.

Keywords: Non-Fungible Tokens; Green energy; Grey energy; Spillovers; Quantile connectedness

JEL Classification: G12; G14; G40; C58; G11

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1. Introduction

Although the origin of Non-fungible tokens (NFTs) dates back to 2014, it only gained momentous attention in 2021 after the artist known as Beeple sold an NFTs of his work for $US 69.3 million at Christie's (Nadini et al., 2021). Since then NFTs have experienced an unprecedented rise in their market capitalization as well as application in different other sectors. Arguing along this line, Karim et al. (2022) note that the NFTs underwent a major bull session in 2021. Aharon and Demir (2021) note that NFTs sales volume across multiple blockchains reached almost 2.5 billion dollars in the first half of 2021, while the sales volume was only around 95 million dollars in 2020. Further, insights from the Google Trend data show a little or no general public interest in the term NFT up until January 2021, while insight from the LexisNexis news database shows that News media interest in the NFT market began growing around the same period (see Dowling, 2022a). Currently, NFTs represent one of the incipient disruptive technologies in the digital space that is offering investment opportunities to investors that are interested in combining different classes of assets.

Descriptively, NFTs are blockchain-enabled assets. Indeed, although different blockchains have now implemented their versions of NFTs, NFTs were originally part of the Ethereum blockchain as was firstly proposed in Ethereum Improvement Proposals (EIP)-721 and further developed in EIP-1155 (Nadini et al., 2021; Wang et al., 2021). However, NFTs differ from conventional digital assets, such as Bitcoin and Ethereum, in that they are indistinguishable and "unfungible". In particular, whereas conventional digital assets can be exchanged for another as they are worth the same (i.e., they are interchangeable and fungible, say, one bitcoin is equal to another bitcoin), NFTs cannot be exchanged for another as each NFT is unique (Wang et al., 2021; Wilson et al., 2021; Dowling, 2021b). This intrinsic feature allows NFTs to demonstrate the authenticity and ownership of different kinds of items in distinct fields. Hence, NFTs are pure digital assets, unlike traditional cryptocurrencies that are intended mainly as currencies despite some features that approximate them as financial assets. Moreover, there is evidence suggesting that the NFTs market behaves differently from conventional cryptocurrencies (Corbet et al., 2021; Maouchi et al., 2021).

The aforementioned differences between NFTs and conventional cryptocurrencies imply that the knowledge gained from erstwhile studies focused on conventional cryptocurrencies cannot be

easily generalized to NFTs. Hence, scholarly research focused on NFTs has emerged alongside the growing importance of NFTs. Compared to the wide literature on classical cryptocurrencies, however, the literature on NFTs is still scanty and underdeveloped. In this paper, we contribute to this growing literature by examining how return and volatility shocks are propagated among NFTs, cryptocurrency, energy, technology, equity, precious metals, and fixed income financial assets. In particular, we examine the volatility and return spillovers among these markets across different market conditions vis-à-vis the bearish, normal, and bullish market conditions. As a second research objective, we examine the factors that drive the connectedness among these markets across the different market conditions. The motivation for our analysis draws from the growing importance of NFTs as an investment option and the consequent risks and diversification roles it holds for investors and portfolio managers. Indeed, the literature is replete with evidence of interrelationships across financial markets driven largely by investors' desire to combine different classes of assets in their portfolios for diversification and hedging purposes.

To address our research objectives, we first employ the quantile vector autoregressive (QVAR) method recently developed by Ando et al. (2022) to analyze the connectedness among the markets under study. Whereas the widely used spillover index approach proposed by Diebold and Yilmaz (2009, 2012; 2014) only estimates the average spillover effect that prevails when an average shock affects the system, the QVAR method combines the quantile regression and spillover index to measure spillovers effects across quantiles that correspond to different market conditions. Concerning our second research objective, we employ the simple linear regression model to examine the drivers of the connectedness between NFT and the different financial markets.

Our paper contributes to the nascent literature on NFTs. Empirical studies on NFTs have until now focused largely on NFTs' pricing efficiency and returns characteristics of the NFT market (Kong & Lin, 2021; Dowling, 2022a), diversification role or connectedness to other assets (Aharon & Demir, 2021; Karim et al., 2022; Umar et al., 2022; Dowling, 2022b) and bubbles (Maouchi et al., 2021; Corbet et al., 2021). Our paper makes three innovations to this literature. First, we deviate from the predominant focus on return spillover of NFT markets by simultaneously analyzing the volatility and returns spillovers of the NFT market. Importantly, we consider how return and volatility shocks among NFTs, technology market (artificial intelligence and FinTech),

cryptocurrency (Ethereum and Bitcoin), energy market (the green and grey energy), equity market (S&P 500), precious metal market (Gold) and the fixed income market (S&P green bond and the United States treasury bill) are propagated. To our knowledge, only Yousaf and Yarovaya (2022) have jointly considered the propagation of return and volatility shock between NFT and other assets. Unlike our focus, however, the asset they consider are limited to oil, gold, Bitcoin, and S&P 500.

Another crucial innovation of our study is that we adopt an empirical framework that permits us to examine the propagation of shocks across the normal and extreme market conditions. It also suffices to note that our paper differs from Yousaf and Yarovaya (2022) along this line. The need to employ such an approach cannot be overemphasized. Extant studies employing a similar approach provide compelling evidence suggesting that the propagation of shocks across different market conditions markedly differs from the mean shock that is registered when constant-coefficient linear VAR model are employed (Jena et al., 2021; Bouri et al., 2021; Liu et al., 2021; Khalfaoui et al., 2022). To our best knowledge, the only study on NFTs that employ such a method is Karim et al. (2022). However, the study only analyzes the return connectedness between NFTs and the cryptocurrency markets, whereas we analyze both the volatility and return connectedness with the cryptocurrency market and a host of other (un)conventional markets. In this way, our analysis is more encompassing than theirs. Finally, we provide novel evidence on how internal and external factors to the NFT market influence the total spillover between NFT and the markets under study across different market conditions. It suffices to note that the study of Karim et al. (2022) also does not perform such analysis.

The rest of the paper is structured as follows. The next section presents a review of the related literature. Section 3 describes the research design by presenting the data sources, computation of variables, and estimation strategy. The third section presents the results, while we conclude with the fourth section.

2. Related Literature

The growing prominence of NFTs has resulted in incipient literature on NFTs. Wang et al. (2021) and Wilson et al. (2021) provide important insight into the market characteristics of NFTs, while

Nadini et al. (2021) quantitatively characterize the market using a variety of empirical methods. Following these studies, empirical analysis of NFTs has been on the rise with extant studies paying particular attention to its return performance, pricing efficiency, and the diversification avenues it offers to both conventional and unconventional assets.

Dowling (2021a) presents one of the early empirical evidence in this regard. The author examined the pricing of NFTs in Decentraland, one of the most popular NFTs applications, and found the price series is characterized by inefficiency and a steady rise in value. In another study, Dowling (2022b) used the spillover approach of Diebold and Yilmaz (2009; 2012) and the cross-wavelets of Torrence and Compo (1998) to analyze whether three NFTs submarkets (Decentraland, Axie Infinity, and Crytpuncts) pricing is related to cryptocurrency pricing. The results showed limited spillover between the NFTs submarkets and cryptocurrency pricing, although they tend to co-move implying that cryptocurrency pricing behaviors might be of some benefit in understanding NFT pricing patterns. Among others, Kong and Lin (2021) use the hedonic regression model to investigate the pricing of NFTs in CryptoPunks. They found that its pricing largely depends on a token's scarceness and investors' aesthetic preference. In addition, NFT prices surge when there is a drastic increase in demand for alternative investments and a search for yield in a low-interest-rate environment.

Maouchi et al. (2021) compared the price behavior of the Defi, NFTs, and cryptocurrency markets by analyzing the existence of bubbles in these markets. They found that bubbles are less frequent but larger in Defi and NFTs than cryptocurrencies. Additional analysis of the predictors of the bubbles revealed that COVID-19, trading volume, and investors' sentiment are positively associated with bubbles occurrences, while the Total Value Locked is negatively linked with it. Wang et al. (2022) use the SADF and GSADF tests to investigate price bubbles in the NFT and Defi markets. They found that both markets exhibit speculative bubbles, although there are periods without bubbles. Further, whilst they also found that NFT bubbles are more recurrent and have higher magnitudes than Defi bubbles, both markets prices bubbles are highly correlated with market hype and the conventional cryptocurrency market uncertainty. Ito et al. (2022) applied Logarithmic Periodic Power Law (LPPL) model to the time-series price data of major NFT projects. They found that the NFTs, in general, are in a small bubble, while the Decentraland

project, and the Ethereum Name Service and ArtBlocks projects are in a small negative bubble in medium and negative bubbles, respectively.

Whereas the above studies are largely focused on NFTs' price formation and pricing efficiency, others analyze the return-risk characteristics as well as the propagation shocks among NFTs and (un)conventional asset markets. For instance, Karim et al. (2022) examined extreme risk transmission among NFTs, DeFis, and cryptocurrencies using the QVAR model by Ando et al. (2022). They found significant risk spillovers among cryptocurrency markets with strong disconnection of NFTs which suggests that NFTs play a diversification role with substantial risk-bearing potential among other cryptocurrency markets to shelter the investments and minimize extreme risks. Yousaf and Yarovaya (2022) examine the return and volatility transmission between NFTs, Defi assets, and other assets (oil, gold, Bitcoin, and S&P 500) using the TVP-VAR framework. While they found that the dynamic return and volatility connectedness become higher during the initial phase of the COVID-19 pandemic, their results generally show weak return and volatility spillovers between NFTs and Defi assets and selected markets, implying that NFTs and Defi are still relatively decoupled from traditional asset classes. Moreover, they found that NFTs and Defi assets are net transmitters of return and volatility spillovers, implying both markets influence others more than they are being influenced by others.

Aharon and Demir (2021) analyzed the return connectedness between NFTs and other financial assets (equities, gold, cryptocurrencies, currencies, oil, and bonds) using the TVP-VAR framework. Results from their static analysis showed that the majority of NFT returns are attributable to endogenous shocks, whilst the dynamic analysis results showed that NFTs act as transmitters (absorbers) of systemic risk to some degree during normal (stressful) times. Moreover, they also found that the overall connectedness between the returns for financial assets increased during the COVID-19 period with NFTs offering diversification avenues during turbulent times as apparent during the COVID-19 crisis. Umar et al. (2022) used the squared wavelet coherence (SWC) technique to analyze the returns coherence for NFTs and major assets (bitcoin price, MSCI World Equity Index, FTSE World Government Bond index, gold, and crude oil) for three subintervals: pre-pandemic, the first year and the second year of the pandemic. Similar to Yousaf and Yarovaya (2022) and Aharon and Demir (2021), they document an increase of coherence

among NFTs and major assets caused by the COVID-19 pandemic. They also found that NFTs absorbed risk during the outbreak of Covid-19 only in the short-run for the below-two-week investment horizons. Ante (2021) used the vector error correction model (VECM) to analyze the interrelationship between NFTs and the cryptocurrency market as measured by the Bitcoin and Ethereum prices. The results showed no significant effect of NFT on both cryptocurrencies, although both cryptocurrencies affect NFTs in significant ways.

Finally, whereas the above studies hold profound implications on the diversification and hedging roles of NFTs, some studies have specifically analyzed the hedging effectiveness of NFTs or the performance of NFTs in general. For instance, Ko et al. (2022) analyzed the portfolio implication of NFTs in traditional assets and found that NFTs are distinct from them, potentially resulting in portfolio diversification. Using the mean-variance approach, they also found significant evidence that the inclusion of NFTs improves the performance of equally weighted and tangency portfolio strategies in terms of risk-adjusted returns. Among others, Yousaf and Yarovaya (2022) computed the static and dynamic optimal weights, hedge ratios, and hedging effectiveness for the portfolios of NFTs and other assets, and Defi asset and other assets. Their results showed that investors and portfolio managers should consider adding NFTs and Defi assets in their portfolios of gold, oil, and stock markets to achieve diversification benefits. Kong and Lin (2021) investigated NFTs returns and found that they have higher returns than traditional financial assets. Their results, however, showed that investing in NFTs comes along with extremely high volatility, leading to a comparable Sharpe ratio to the NASDAQ index. Vidal-Tomás et al. (2022) analyzed the performance and dynamics of 174 tokens and found that they are characterized by a positive performance in the long run and an absence of high co-movements with the cryptocurrency market, among others.

3. Empirical Design

3.1. Data

In line with our first research objective, we use daily price data of the NFTs market (NFT) and representative indexes for the remaining markets. For the cryptocurrency market, we use both Bitcoin (BTC) and Ethereum (ETH) daily prices while for the energy market, we use both the Nasdaq Clean Edge Green Energy Index (CLNE) and the Energy Select Sector SPDR Fund

(GREY). Further, for the technology market, we rely on the Indxx Global Robotics and Artificial Intelligence (RAI) and Indxx Global Financial Technology Index (FNTCH) while we use the S&P 500 (SP500) and Gold (Gold) price indexes to capture the equity and precious metals markets, respectively. For the fixed income market, we used both the S&P green bond index (SPGB) and the United States Treasury bill index (USTB). The SPGB index enables us to capture the green energy fixed income market, while the USTB measures the traditional fixed income market dynamics.

Data on NFTs comprise secondary market trades retrieved from https://nonfungible.com/ while data on BTC and ETH were collected from https://www.coindesk.com. We follow Aharon and Demir (2021) that use the mean value of transaction prices daily for all trades in the NFT market, which offers a higher number of observations for analysis while circumventing empirical issues associated with extreme volatility present in sub-markets. The remaining indexes were retrieved from the Thompson Reuters database. Our data sample spans the period from June 23, 2017 to February 11, 2022. The start period is determined by the availability of data on the NFT market. However, it enables us to capture the major developments in the NFTs market as well as the period of the recent financial market turmoil caused by the COVID-19 pandemic, which may have significantly affected the degree of network connectedness among NFTs and other financial assets. To capture the daily return of each asset r_t, we use the logarithmic differences of daily prices defined as $r_t = \ln(P_t) - \ln(P_{t-1})$, where $\ln(P_t)$is the natural logarithm of closing price at time, t while $\ln(P_{t-1})$, is the natural logarithm of closing price at time $t-1$. We retrieve the volatility series for each market by taking the square of daily returns of the respective markets.

Figure 1 shows the evolution of daily returns and volatility for all the assets included in this study over the sample period. The notable effects of the COVID-19 pandemic on both returns and volatility series may be seen across all the markets, especially the traditional fixed income market, where changes in return and volatility became more notable during the first wave of the pandemic. In Table 1, we present the descriptive statistics for all the series. As may be seen in Table 1, among all the markets in our sample, the NFT market possesses both the highest mean return and volatility as well as the mean return and volatility standard deviations. The coefficients of main test statistics for normality and stationarity suggest that all return and volatility series depart from the normality

conditions as shown by both the kurtosis and Jarqua-Bera tests and that all series are stationary at first difference as shown by the ADF unit roots test. As shown in Figure 2, the correlation heatmaps suggest that correlations are stronger among the daily volatility series of the chosen assets. However, in both cases, cross-market correlation is strongest between the equity (SP500) and energy markets (GREY and CLNE).

Regarding our second research objective which relates to drivers of return and volatility connectedness across the various market conditions, we source variables that are internal and external to the studied markets. To achieve this, we use the composite NFT market's sales volume (NFTVOL), the Chicago Board Options Exchange (CBOE) volatility index on S&P 500 (VIX), Oil market volatility index (OVX), Gold market volatility index (GVZ), Merrill Lynch Option Volatility Estimate (MOVE), and the U.S economic policy uncertainty index (EPU) to capture the influence of uncertainty related to equity, oil, gold, fixed income markets and economic policy on return and volatility connectedness among these markets. Additionally, we use the Aruoba-Diebold-Scotti business conditions index (ADS) of Aruoba et al. (2009), the term spread between the 10-year and 3-month U.S. Treasury bonds (Terms), and the Geo-political Risk index (GPRI) of Caldara and Matteo (2021) as proxies for the global macroeconomic and geopolitical conditions. The data for these indicators were retrieved from St. Louis FRED, except for ADS business condition index which was taken from the Federal Reserve Bank of Philadelphia database, and GPRI which was retrieved from policyuncertainty.com. Lastly, we control for the influence of the COVID-19 pandemic using a dummy variable which takes the value of 1 for the period from January 1, 2020 to August 1, 2020, and 0 otherwise. This enables us to capture the periods of financial market turmoil due to the first wave of the global health crisis.

3.2.Research Methods

3.2.1. Quantile return and volatility connectedness

Following the first objective of this study, we rely on the Q-VAR connectedness approach of Ando et al. (2022). This approach extends the VAR-based spillover models of Diebold and Yilmaz (2012, 2014); Antonakakis and Gabauer (2017) by accounting for the tail behavior of the topology of financial assets. With this approach, we explore the shock propagation mechanism among NFTs, cryptocurrency, energy, technology, equity, precious metals, and fixed income market

across different market conditions, including the normal, bullish as well as bearish market periods. As noted in Chatziantoniou et al. (2021), the Q-VAR(p) model from where all the connectedness indicators are retrieved may be expressed as follows:

$$y_t = \nu(\tau) + \sum_{j=1}^{p} \vartheta_j(\tau)\, y_{t-j} + \upsilon_t(\tau) \qquad (1)$$

where y_t, and y_{t-1} are $m \times 1$ dimensional vectors associated with the concerned returns series;τ is of range $[0, 1]$ corresponding to the quantile of interest. In this study, we focus on three quantiles namely 0.5, 0.05, and 0.95 corresponding to the normal, bearish, and bullish market conditions. Besides, p represents the lag length of the Q-VAR model; $\nu(\tau)$ is an $m \times 1$ dimensional vector of conditional mean while $\vartheta_j(\tau)$ is an $m \times m$ dimensional matrix of Q-VAR coefficients. $\upsilon_t(\tau)$ is the $m \times 1$ dimensional vector of error terms relating to a $m \times m$ dimensional matrix of variance-covariance, $\sum(\tau)$. Next, the Q-VAR(p) model is transformed into Quantiile-VAR Moving Average (QVMA) (∞) following the Wold's theorem defined as follows

$$y_t = \nu(\tau) + \sum_{j=1}^{p} \vartheta_j(\tau)\, y_{t-j} + \upsilon_t(\tau) = \nu(\tau) + \sum_{i=0}^{\infty} \varphi_i(\tau)\, \upsilon_{t-i}$$

Following this, the H-step ahead Generalized Forecast Error Variance Decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998) that may be interpreted as the impact that a shock in variable j has on a variable i, may be estimated as follows:

$$\psi_{ij}^{g}(H) = \frac{\sum(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' \varphi_h(\tau) \sum(\tau)\, e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \varphi_h(\tau) \sum(\tau) \varphi_h(\tau)'\, e_j\right)} \qquad (2)$$

$$\widetilde{\psi}_{ij}^{g}(H) = \frac{\psi_{ij}^{g}(H)}{\sum_{j=1}^{k} \phi_{ij}^{g}(H)}$$

The normalization of e_i into a zero vector with unity on the ith position offers the following two equalities: $\sum_{j=1}^{k} \psi_{ij}^{g}(H) = 1$ and $\sum_{j=1}^{k} \phi_{ij}^{g}(H) = K$. The total directional connectedness TO others denotes the overall impact variable i has on all other variables j while the total directional connectedness $FROM$ others which represents the overall impact on variable i from shocking all other variables j may be defined respectively as:

$$C_{i\to j}^{g}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}_{ji}^{g}(H) \qquad and \;\; C_{i\leftarrow j}^{g}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}_{ij}^{g}(H) \tag{3}$$

Next, the *net total directional connectedness* defined as the difference between the total directional connectedness TO others and the total directional connectedness $FROM$ others or the net effect variables i has on the network of interest may be written as:

$$C_{i}^{g} = C_{i\to j}^{g}(H) - C_{i\leftarrow j}^{g}(H) \tag{4}$$

where $C_i^g > 0$; $\left(C_i^g < 0\right)$ implies that variable i is a net transmitter (receiver) of shocks since it is influencing all others more (less) than it is being influenced by then. Lastly, the total connectedness index (TCI), which is the average amount of one variable's forecast error variance share explained by all other variables, expresses how much a shock in one variable influences all other variables on average. This is an indicator of the degree of market risk, because the higher the TCI, the higher the level of network interconnectedness. This may be written as:

$$TCI(H) = \frac{\sum_{i,j=1, i\neq j}^{m} \tilde{\psi}_{ij}^{g}(H)}{m} \tag{5}$$

3.2.2. Drivers of quantile return and volatility connectedness

To address our second research objective, we proceed in two steps. First, we retrieve the time series of the return and volatility connectedness for each market condition from Equation 5. Second, we then regress the retrieved series on a vector of factors as listed in section 3.1. To achieve the latter, we specify the following regression model:

$$TCI_t = \delta + \gamma X'_t + \mu_t \quad (6)$$

where depending on the equation, TCI_t represents the total Q-VAR return (volatility) connectedness index for the normal, bearish, and bullish market conditions estimated in Equation 5, while X'_t is a vector of control variables. As indicated in section 3.1, this includes NFT market's sales volume (NFTVOL); the set of macroeconomic and geopolitical variables including (i) equity, oil, and gold market volatility captured by the implied volatility indexes (VIX, GVZ, and OVX); (ii) Economic Policy Uncertainty (EPU) represented by the U.S. economic policy uncertainty index; (iii) fixed income market uncertainty proxied by the Bank of America Merril Lynch MOVE index; (iv) the term spread between the ten-year and three-month Treasury Bonds (Term); (v) the ADS business condition index (ADS)); (vi) geopolitical risk index (GPRI) and the COVID-19 dummy (COVID). Lastly, δ is the intercept while γ is the regression coefficients. μ_t denotes the error term.

4. Results and discussion

This section proceeds in three steps. First, we present and discuss the results for the return connectedness across three quantiles corresponding to the normal (i.e. 0.5 quantiles), bearish (0.05 quantiles), and bullish (0.95 quantiles) market conditions, respectively. In the second section, we focus on the results for the volatility connectedness, while the third section focuses on the drivers of return and volatility connectedness between NFT and the chosen assets across the aforementioned three market conditions.

4.1.NFTs and (un)conventional assets: Return connectedness

Table 2 reports the results for the return connectedness. In line with section 3.2, the table contains different connectedness measures such as the total connectedness index (TCI), Pairwise directional connectedness, net directional connectedness (NDI), the directional TO, and the directional FROM. Beginning with TCI, it is 37.27% during the normal market condition and 87.48% and 86.64% during the bearish and bullish market conditions, respectively. The TCI varies from 1-100 and measures how much a shock or market risk in one variable influences all other variables in the system, on average. Hence, the obtained TCI values indicate that the return connectedness among NFT and the chosen assets is relatively weak during normal market conditions as the TCI is only

about one-third of the possible total forecast error variance. However, the level of TCI is strong during extreme downside and upside market conditions as they are considerably higher than half of the possible total forecast error variance, implying that the intensity of return connectedness rises with shock size for both extreme positive and extreme negative shocks. In which case, the levels of connectedness among the returns of NFTs and the chosen markets are stronger during extreme market conditions when the boom and burst together. Put together, this result and conclusion are consistent with previous studies suggesting higher connectedness among different assets during extreme market conditions (e.g. Jena et al., 2021; Bouri et al., 2021; Liu et al., 2021; Khalfaoui et al., 2022; Chen et al., 2022) as well as previous studies highlighting the stronger impact of large shocks as compared to small shocks (e.g., Dendramis et al., 2015; Saeed et al., 2021).

Furthermore, the level of TCI in both extreme market conditions does not show any clear evidence of distinction, suggesting an average symmetric tail interaction among the studied assets. Albeit not focused on NFT, similar results have also been documented in other studies (Jena et al., 2021; Wei et al., 2022). Nevertheless, evidence in Figures 3b(i) and c(i) where we plot the dynamic TCI shows time-varying patterns under both extreme market conditions. Hence, while the average TCI shows evidence of symmetric tail interactions, notable deviations exist under dynamic settings reflecting, among others, the influence of economic, political, and social factors. Although not focused on NFTs, such observed asymmetric tail interactions under dynamic settings have also been documented in other studies (Bouri et al., 2021; Umar et al., 2021; Iqbal et al., 2022). Returning to Table 2, evidence in the table also shows that in contrast to the periods of extreme market conditions the shock received from or contributed to the system by either the returns of NFTs or those of other assets understudy during normal market conditions are, on average, lower than the TCI. Akin to this, the figures in the diagonal cells which represent the magnitude of own shock spillovers are consistently higher than the TCI during the normal market condition. During extreme market conditions, however, they reduce significantly while the levels of TCI increase significantly. This includes the returns of NFTs that showed strong own shock dynamics in the normal period. These cumulatively imply the share of own shock spillover decreases and systemwide shock increases, confirming the fact that there is an influence of external shock impacting the return connectedness among NFTs and the chosen markets. As Londono (2019)

rightly noted, these extreme shocks are the results of the arrival of unexpected good or bad news, which are described as beneficial or adverse shocks in the market.

Next, we look at the pairwise directional connectedness, which shows the bilateral connectedness among the markets. Evidence in the table suggests a low pairwise spillover among NFT and the other studied assets during the normal market condition than in other periods. In particular, the shock received from or transmitted by NFT during normal periods ranges from 1.11% to 2.32%. However, this is between 7.67% to 9.26% during the bearish market condition and between 8.19% to 9.10% during the bullish market state. During the normal period, the highest received shock is from the returns of Gold (2.43%) while the highest transmitted shock is to clean energy (2.32%). Under extreme conditions, the highest received shock is from FinTech (9.26%) for the bearish and Ethereum (9.10) for the bullish, while the highest transmitted shock is to Gold (8.14%) during bearish and SPGBr (8.94) during bullish market conditions. Akin to these, the result shows that in terms of the cryptocurrency market NFT is more connected to Ethereum than Bitcoin across all market conditions. As noted in Nadini et al. (2021), the strong interaction between NFT and the cryptocurrency market, especially Ethereum is expected given that NFT is generally encoded within smart chain contracts enabled by blockchain technology.

Moving on to the net directional "return" connectedness (NDI), evidence in the table suggests that except for a bullish market, NFT is a net shock transmitter, implying that it transmits more shock to the system than it receives from the system. These results on NFT are largely in line with those of Karim et al. (2022) which use similar methods as ours albeit focused only on the return connectedness between NFT, Defi, and cryptocurrency. Our result that NFT is a net shock receiver during the bearish period is also in line with Aharon and Demir (2021) who albeit use the spillover approach of Diebold and Yilmaz (2009, 2012, 2014) found that NFT is a net shock transmitted during COVID-19 period. Our result shows that such contagion effect is not only limited to the COVID pandemic but more generally to crises with extreme negative effects on the financial market. Regarding other studied assets, except for clean energy, artificial intelligence, green bond (SPGBr), and gold, they are net shock transmitters during normal market conditions suggesting that they are driving the market risks during this period. Hence, they influence others more than they are being influenced. Notable differences, however, occur when we consider the two extreme

market conditions. In particular, we observe that whilst the returns on Ethereum and grey energy (clean energy, green bond, and gold) remain net shock transmitter (receivers) during bearish and bullish market conditions, the returns on traditional bond (USTBr) becomes a net shock receiver during both extreme market conditions. On the other hand, the returns on stocks (SP500r) become a net shock receiver (transmitter) during a bearish (bullish) market, whilst the two technology market indices are net shock transmitters (receivers) during the bearish (bullish) market condition. Portfolio and risk managers are more interested in assets that are driving the market than those that are being driven by the market as the latter are exposed to more risk sources compared to the former. This suggests that the roles and attractiveness vary across market conditions, with NFTs yielding the best benefits during bullish market conditions. At the same time, our results also suggest that except for Ethereum and grey energy, the roles and attractiveness of other assets in our sample vary across market conditions.

Figures 3a(ii), b(ii), and c(ii) plot the net pairwise directional connectedness among the markets under study. Blue nodes in the figures illustrate net shock transmitters, whilst yellow nodes illustrate net shock receivers. The sizes of the nodes represent weighted average net total directional connectedness. Hence, depending on whether a market is a net shock transmitter or net shock receiver of risks, the sizes of the node rank the net directional connectedness with larger nodes being markets with stronger net directional connectedness. The figures reemphasize the varying structural characteristics of the market during normal and extreme market conditions. In particular, the vertices are mostly light in Figure 3a(ii) implying that the observed market connectedness in the figure is hardly strong. This is different from Figures 3b(ii) and c(ii) where a significant number of the vertices are thicker and bolder suggesting a stronger connectedness among those markets during extreme market conditions. Furthermore, insights from the figures indicate that during normal market periods, green bond and clean energy markets are the main shock receiver from the system, especially from grey (Greyr), Ethereum (ETHr), and Bitcoin (BTCr) markets, respectively.

In contrast, while FinTech dominates risk spillovers in the system, especially towards Bitcoin, Ethereum, and artificial intelligence, the NFT market is relatively isolated from the system. This is shown by remarkably low levels of net directional pairwise spillover between the NFT and all

the remaining assets in the system. This hints that the NFT may possess different features with very little variations in NFT returns being driven by innovations within the system. Under the bearish market period, the NFT market becomes the strongest net receiver of shocks, with significant risk spillovers from innovations in all other assets, especially the FinTech and artificial intelligence while the FinTech index (FNTCH) retains its relevance as the main source of shocks into the system. This suggests that the financial technology index (FNTCH) may not be a good choice for an investor that is seeking diversification benefits for a portfolio containing the concerned assets, especially during both normal market periods and during market downturns. During the bullish period, Ethereum (ETHr) and stocks (SP500) become the main transmitters of spillover to the system, while Gold becomes the Net transmitter with the NFT market being relatively isolated from the system in both cases.

Figures 3a(i), b(i), and c(i) display the time-varying total return connectedness index across the sample period for the three market conditions. The three figures show significant evidence of a time-varying pattern although is higher for the extreme market conditions. Except for the total connectedness under the bullish market condition, there is also a remarkable increase in the level of system connectedness under the normal and bearish market quantile during the first wave of the COVID-19 crisis. As per the bullish market total connectedness, it falls considerably instead during this period. Finally, consistent with the evidence reported in Table 2, the total connectedness of normal market conditions remained significantly below the levels of both the bearish and bullish market connectedness levels.

4.2.NTFs and (un)conventional assets: Volatility connectedness

Table 3 reports the results of the volatility connectedness among NFT and the assets under study. The TCI during the normal market condition is approximately 33.3%, and 47.86%, and 90.49% during the bearish and bullish periods, respectively. This result is in line with those of the return connectedness in suggesting that the level of connectedness among the studied assets is stronger when we move from the normal period to either of the periods of extreme market conditions. As discussed in the previous section, this result implies that extreme shocks have a greater impact on the spillovers among these assets. However, there are notable differences between the volatility and return connectedness results. Except for the bullish period, the TCI for the return

connectedness is relatively higher than their corresponding TCI estimates for those of volatility connectedness. This implies that the return connectedness among the studied assets is stronger than their volatility connectedness. That is, the return shocks among these assets spread more vigorously than their volatility shocks during the normal and bearish period. In contrast, during the bullish period volatility shock spread more vigorously than their return shocks. Indeed, using the TVP-VAR framework, Yousaf and Yarovaya (2022) find that the return linkages between NFTs and other assets are stronger than the volatility linkages. Our finding refines theirs by suggesting that this is only during normal and bearish market conditions as the opposite effect takes precedence during the bullish period.

Further, unlike the return connectedness, the TCI for both the extreme market conditions shows clear evidence of differentiation, indicating average asymmetric interaction among the volatility indices of the studied assets. In addition, we also find that, unlike the return connectedness, the figures in the diagonal cells which represent the magnitude of own shock spillovers are mostly higher than the TCI during both the normal and bearish periods. This implies that own volatility shock accounts for most shock observed in each asset market during these periods. Similar to the return connectedness, however, during the bullish period, own volatility shock reduces significantly and is considerably lower than the TCI of that period, implying the influence of the external positive event. Concerning the pairwise connectedness, we find that except for the bearish period, the pairwise connectedness both in terms of the volatility spillover NFT transmits to the assets understudy or that it receives from them are somewhat similar to those of the return connectedness.

Moving on to the results for net directional connectedness (NDI), the NFT realized volatility is a net shock receiver across the entire period, unlike the NFT return which was only a net shock receiver in the normal and bearish periods. Further, evidence in the table suggests that the green bond (SPGBv) is also a net shock receiver throughout the entire period, while the volatility of clean energy assets (CLNEv) and stock market (SP500) are net shock transmitters. Concerning the other assets, their roles vary across the market periods. The volatility of Bitcoin and Ethereum are net shock transmitters during the normal and bearish market conditions and net shock receivers during the bullish market condition, whilst the volatility of grey energy, FinTech, and Artificial

intelligence is net shock receivers during the normal period and net shock transmitter during both extreme market periods. Traditional bond (USTBv), on the other hand, is a net shock transmitter during the normal and bullish period and a net shock receiver during the bearish period.

Figures 4a(ii), b(ii), and c(ii) present the network system of net directional pairwise connectedness among all the series. The description of the figure is similar to Figures 3a(i), b(ii), and c(ii). Similar to the results of the return connectedness, the plots show that the connectedness among the assets is stronger during the extreme market periods as the vertices during the normal period are mostly light. Insights from the figure also show that during normal times, shock absorption is dominated by NFTs volatility, receiving the most shock from tradition bond (USTBv) and FinTech. On the other hand, Ethereum and Bitcoin dominate the shock transmission with FinTech being the most recipient of this shock. During the bearish market period, clean energy dominates shock transmission with NFT being a major recipient of the transmitted shock, while traditional bond (USTBv) dominates the shock absorption with most absorbed shock coming from the clean energy market almost in the same order as those received by NFT. For the bullish period, the assets are well integrated among each other. However, Bitcoin dominates the risk absorption while FinTech dominates the risk transmission. Put together, these results suggest that the market connectedness among NFTs and (un)conventional assets vary not only across market conditions but also whether we focus on return or volatility connectedness among these markets, with the market that are either being driven by others or drive others depending on whether we focus on the returns or volatility connectedness.

Figures 4a(i), b(i), and c(i) display the time-varying total volatility connectedness index across the sample period for the three market conditions. The three figures show significant evidence of a time-varying pattern although is higher for the extreme market conditions. Except for the total volatility connectedness under the bullish market condition, there is also a remarkable increase in the level of system connectedness under the normal and bearish market quantile during the first wave of the COVID-19 crisis. As per the bullish market total volatility connectedness, it falls considerably instead during this period. Finally, consistent with the evidence reported in Table 3, the total connectedness of normal market conditions remained significantly below the levels of both the bearish and bullish market connectedness levels.

4.3.Drivers of return and volatility connectedness among NFT and (un)conventional assets

Table 4 presents the results of the drivers of total return and volatility connectedness indexes for the different market conditions. Columns 1-3 present the results for the return connectedness, while columns 4-6 present the results for volatility connectedness. Beginning with the return connectedness, only the business environment (ADS) and the gold (GVZ) and fixed-income (MOVE) market uncertainty consistently predict return connectedness across the three market conditions. Among these three variables, only the estimated coefficient of fixed income market uncertainty is positive across the three market conditions, with the size of the estimated coefficient being higher during the normal market condition. This implies that the fixed income market uncertainty increases the return connectedness among NFT and the studied market across all market conditions. Results for the bearish and bullish market conditions further indicate the positive changes in fixed income market uncertainty (MOVE) expose the returns of the studied assets to large positive and negative shocks. As per the gold market uncertainty (GVZ), it negatively predicts the return connectedness under the normal and bullish market conditions, while during bearish it positively predicts the return connectedness. Hence, positive changes in gold market uncertainty is a driver of small shocks and large positive shock on the studied assets return, whilst it significantly reduces the studied assets returns exposure to large negative shocks.

Business environment (ADS) on the other hand, negatively predict the return connectedness under the normal and bearish market conditions, but positively predicts it under the bullish market conditions. This implies that a good business environment reduces (increases) the returns of the studied assets' exposure to large negative (positive) shocks. Regarding other variables, except for equity market uncertainty (VIX), COVID-19 and the bond terms spread (Term) which do not predict return connectedness across the market conditions, the predictive powers of other variables vary across market conditions. In particular, the results indicate that oil market uncertainty (OVX), NFTs volume (NFTVOL), and geopolitical risk (GPRI) only predict return TCI under the normal with the effect being positive for OVX and GPRI and negative for NFTVOL. This suggests that oil market uncertainty and geopolitical risks increase cross-market shocks between NFTs and the studied assets, especially during normal market conditions. However, a well-functioning NFT market as captured by large trading NFT volume decouples its returns from those of (un)conventional assets during the normal market condition. Increases in economic policy

uncertainty significantly reduce (increase) return connectedness during bearish (bullish) periods. Implications of the results are as given for ADS.

Moving on to columns 4-6 that report the results on the drivers of volatility connectedness, we first observe that equity market uncertainty (VIX) unlike in return connectedness possesses predictive power although limited to the bullish market condition where it is significantly positive. Oil market uncertainty (OVX) is the only variable that significantly predicts volatility connectedness across all the market conditions with the effect under the normal market conditions being the highest. In particular, its estimated coefficient during the normal and the bearish market condition is significantly positive, implying that as it rises the volatility connectedness among NFTs and the studied assets rises. As per the bearish period result, it also implies that increases in oil market uncertainty expose the volatility of the studied assets to more negative shocks. However, the estimated coefficient during the bullish period is significantly negative, suggesting that under this market condition it reduces the volatility connectedness of the studied assets and by extension reduces their exposure to positive shock that induces intensifies their volatility. Unlike the return connectedness, we find a limited effect for both fixed income market uncertainty (MOVE), gold market uncertainty (GVZ), and business environment (ADS). In particular, gold market uncertainty is a significant predictor of volatility connectedness under the normal and bullish market conditions with positive changes in the variable being associated with a decrease in volatility connectedness during both market conditions.

Concerning the fixed income market uncertainty (MOVE) and business environment (ADS), their predictive power of volatility connectedness is limited to the normal and bullish market conditions. For the fixed income market uncertainty (MOVE), the estimated coefficient is only significant and positive for the normal market condition. The business environment, on the other hand, exerts opposing effects on both periods with its estimated coefficient being negative under the normal market condition and positive under the bullish market condition. The estimated coefficient of NFTs volume is significant and negative under the normal market condition and positive under the bullish market condition. Geopolitical risk on the other hand increases volatility connectedness during the bullish and bearish market conditions. Finally, the estimated coefficient for COVID is statistically insignificant under the normal market condition but turns statistically significant under

both extreme market conditions. In particular, it is negative during the bearish market condition and positive during the bullish market condition. The remaining estimated coefficient show no evidence of statistical significance at all conventional level.

5. Conclusion

NFT has gained significant prominence as well as grown in importance among market participants, policymakers, and the general public in recent times. Hence, there is now a growing literature focused on NFT as an alternative digital asset. Among others, this literature examines the pricing characteristics and the diversification role of NFT. The current paper contributes to this literature by examining how return and volatility shocks are propagated among NFT and (un)conventional assets including the technology market (artificial intelligence and FinTech), cryptocurrency (Ethereum and Bitcoin), energy market (the green and grey energy), equity market (S&P 500), precious metal market (Gold) and the fixed income market (S&P green bond and the United States treasury bill). We consider the return and volatility shock among these markets across three quantiles corresponding to the normal (i.e. 0.5 quantiles), bearish (0.05 quantiles), and bullish (0.95 quantiles) market conditions, respectively. We address our research question by employing the quantile vector autoregressive (Q-VAR) connectedness approach that is recently developed by Ando et al. (2022). Akin to this, we also employed the linear regression model to examine the drivers of return and volatility connectedness across the three aforementioned market conditions. Our main findings and the implications can be summarized as follows.

First, we found that the return and volatility connectedness vary across the market condition, with the levels of total connectedness during extreme downside and upside market conditions being higher, which implies higher propagation of return and volatility shocks among NFT and the studied assets during extreme market conditions when the boom and burst together. It also refined the conventional narrative that NFT is decoupled from (un)conventional assets. At best, our result indicates that NFT is decoupled from (un)conventional assets only during the normal market condition. In fact, our estimates suggest that during the normal market condition for both the return and volatility connectedness, more than 80% of the NFT forecast error variance is explained by endogenous shock - i.e., return and volatility shocks that are internal to or emanate from the NFT market. Second, except under the bullish market conditions, the return total connectedness is

higher than those of volatility total connectedness, implying that the return connectedness is stronger than volatility connectedness. That is, the return shocks among the studied assets spread more vigorously than their volatility shocks during the normal and bearish market conditions. In contrast, during the bullish market condition, the volatility shock spread more vigorously than the return shocks. Third, the NFT is a net return shock receiver except under the bullish market condition where it is a net transmitter. However, the NFT is a net volatility shock receiver irrespective of the market condition, implying that the attractiveness and role of NFT vary not only across the market condition but also on the performance and risks associated with NFT. In which case, investors and market participants interested in the studied assets need to account for both in their trading strategy. Fourth, in line with previous studies, we find that the dynamic total return and volatility connectedness varies over time. However, during periods of economic crisis the total return and volatility connectedness rise (decreases) under the normal and bearish (bullish) market conditions.

Finally, geopolitical risks, economic policy uncertainty, business environment condition, and uncertainties about the oil, gold, and fixed-income market are important predictors of return connectedness although the predictive power and direction vary across different market conditions. In particular, positive changes in fixed–income market uncertainty increase return connectedness across all the market conditions, whilst increases in geopolitical risk only predict return connectedness under the normal market condition with the effect being positive. Increases in economic policy uncertainty significantly reduce (increase) return connectedness during the bearish (bullish) market condition. NFT volume significantly reduces return connectedness during the normal market condition. Increased uncertainty about the oil market significantly increases the return connectedness during the normal market condition, while increased uncertainty about the gold market significantly reduces the return connectedness during the normal and bullish market conditions and is positive during the bearish market condition. Concerning the volatility connectedness, oil, gold, and fixed-income market uncertainty, NFT volume, and business environment conditions significantly predict it with the predictive power and direction also varying across the market conditions. In particular, oil market uncertainty significantly predicts volatility connectedness across all market conditions with the effect being positive under the normal and bearish market conditions but turning negative under the bullish market condition. Gold market

uncertainty reduces volatility connectedness under the normal and bullish market conditions and has no effect under the bearish market condition. Fixed-income market uncertainty, on the other hand, increases the volatility connectedness under the normal market conditions but leaves the volatility connectedness under the bearish and bullish market conditions unaffected. NFT volume and a better business environment reduces (increases) volatility connectedness under the normal (bullish) market conditions but leaves the volatility connectedness under the bearish market condition unaffected.

Our results hold profound implications for investors and market participants seeking diversification with NFT and policymakers and financial regulators that may be interested in monitoring developments in the NFT market and how it impacts the financial and commodity markets. For instance, our results that return and volatility shocks have higher impacts during extreme downside and upside market conditions have useful implications for NFT-traders and investors making decisions regarding short- or long-term positions during extreme bullish or bearish markets. It particularly recommends against using a mean-based measure while formulating and evaluating diversified portfolios with stated risk-return profiles. The results of time-varying total return and volatility connectedness measures also imply that investors adjust their positions under various market conditions such as the COVID-19 outbreak period. From a policy perspective, the varying results across market conditions imply that policymakers and financial regulators interested in market risk monitoring should pay attention to cross-market risk transmission between NFT and the studied assets, especially the tail risk connectedness. Finally, our result on the drivers of return and volatility connectedness suggests that policymakers and financial regulators pay close attention to them in making policies aimed at (de)coupling NFT and the studied assets. In which case, they are appropriate policy and surveillance tools for managing small and extreme shocks. At the same time, investors could also examine their developments to make a more informed decision in adjusting their portfolio strategy, because hedging strategies depend on market conditions.

Table 1: Descriptive statistics for return and volatility time series

	NFTr	BTCr	ETHr	GREYr	CLNEr	FNTCHr	RAIr	SPGBr	USTBr	SP500r	Goldr
Return series											
Mean	0.0173	0.0023	0.0019	0.0002	0.0008	0.0006	0.0004	0.0001	-0.0017	0.0005	0.0003
Min.	-3.4339	-0.4903	-0.5817	-0.2272	-0.1625	-0.1284	-0.0888	-0.0241	-2.2513	-0.1277	-0.0589
Max.	3.5531	0.2345	0.3555	0.1514	0.1340	0.1103	0.0879	0.0201	1.3863	0.0897	0.0363
Std. Dev.	0.5817	0.0501	0.0650	0.0221	0.0247	0.0157	0.0126	0.0029	0.1609	0.0129	0.0084
Skewness	0.149**	-0.769***	-0.667***	-1.049***	-0.371***	-0.862***	-0.503***	-0.943***	-1.671***	-0.892***	-0.634***
Ex.Kurtosis	5.389***	10.328***	7.949***	17.366***	5.107***	10.008***	5.971***	10.843***	48.286***	17.324***	4.700***
JB	1421.5***	5319.7***	3169.8***	14928***	1299.6***	5032.1***	1789.0***	5909.7***	114306***	14798***	1155.9***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	120.842***	9.975*	9.984*	46.725***	23.917***	16.698***	49.614***	73.178***	135.653***	152.670***	11.075**
	(0.000)	(0.071)	(0.071)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.042)
Q2(10)	262.917***	18.541***	40.525***	435.248***	512.122***	600.614***	283.433***	368.408***	158.689***	1062.141***	81.545***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF	-33.637***	-36.079***	-36.906***	-23.740***	-22.235***	-21.832***	-20.148***	-20.832***	-30.597***	-24.545***	-33.505***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility series											
Mean	0.3383	0.0025	0.0042	0.0005	0.0006	0.0002	0.0002	0.0000	0.0259	0.0002	0.0001
Min.	0	1.25E-08	1.15E-09	0	0	0	0	0	0	4.76E-11	0
Max.	12.6240	0.2404	0.3383	0.0516	0.0264	0.0165	0.0079	0.0006	5.0683	0.0163	0.0035
Std. Dev.	0.9209	0.0086	0.0131	0.0022	0.0016	0.0009	0.0004	0.0000	0.1865	0.0007	0.0002
Skewness	6.792***	18.861***	15.597***	14.921***	8.070***	12.056***	11.142***	14.285***	18.723***	13.255***	9.363***
Ex.Kurtosis	62.882***	491.718***	355.897***	289.611***	91.513***	181.470***	165.644***	244.981***	448.140***	226.840***	135.169***
JB	201929***	11866579***	6227569***	4135823***	421318***	1635150***	1362967***	2968087***	9867232***	2544928***	908562***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	262.917***	18.541***	40.525***	435.248***	512.122***	600.614***	283.433***	368.408***	158.689***	1062.141***	81.545***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q2(10)	201.584***	0.098	0.613	58.863***	454.495***	377.376***	169.581***	226.088***	14.099***	279.070***	10.577*
	(0.000)	(1.000)	(0.999)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.053)
ADF	-22.401***	-32.324***	-20.949***	-17.818***	-15.411***	-12.675***	-18.191***	-19.586***	-30.182***	-11.401***	-20.675***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Skewness, Ex. Kurtosis., J-B, LB-Q and ADF denote the Skewness, Kurtosis, Jarque-Bera, Ljung-Box Q and Augmented Dickey-Fuller tests for skewness, normality, autocorrelation and stationarity. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Table 3: Return connectedness across normal, bearish and bullish market conditions

	NFTr	BTCr	ETHr	GREYr	CLNEr	FNTCHr	RAIr	SPGBr	USTBr	SP500r	Goldr	**FROM**
Normal market												
NFTr	80.75	1.59	2.06	1.90	2.35	2.15	1.62	1.11	2.16	1.88	2.43	19.25
BTCr	1.06	54.89	32.14	0.88	1.21	3.16	1.99	0.89	1.42	1.14	1.23	45.11
ETHr	1.29	31.69	54.42	1.06	0.99	3.12	2.16	1.29	1.49	0.87	1.61	45.58
GREYr	1.29	1.29	1.18	59.16	12.44	1.57	1.56	1.58	1.87	16.20	1.88	40.84
CLNEr	2.32	2.04	2.38	14.50	50.47	2.43	1.72	1.11	1.69	19.99	1.35	49.53
FNTCHr	1.69	1.81	1.97	1.30	1.53	61.45	23.32	1.88	2.20	1.48	1.36	38.55
RAIr	1.40	1.74	2.31	1.37	1.64	25.59	58.67	2.03	1.67	1.63	1.96	41.33
SPGBr	1.98	1.99	1.81	2.08	1.92	2.16	2.02	65.90	1.56	2.42	16.15	34.10
USTBr	1.53	1.47	1.23	1.56	1.67	2.44	1.54	1.63	83.81	1.74	1.37	16.19
SP500r	1.05	1.12	1.07	19.27	19.57	1.58	1.19	1.20	1.18	51.43	1.34	48.57
Goldr	2.17	1.93	1.75	1.43	1.05	1.83	1.73	15.69	1.49	1.81	69.12	30.88
TO	15.78	46.66	47.91	45.35	44.37	46.03	38.86	28.40	16.73	49.17	30.67	409.94
Inc. own	96.53	101.55	102.32	104.50	94.84	107.48	97.53	94.31	100.54	100.61	99.79	
NET	-3.47	1.55	2.32	4.50	-5.16	7.48	-2.47	-5.69	0.54	0.61	-0.21	TCI = 37.27
Bearish market												
NFTr	13.30	8.26	8.81	8.57	8.45	9.26	9.12	8.35	8.85	8.42	8.61	86.70
BTCr	8.05	11.41	10.61	8.67	8.36	9.65	9.37	8.59	8.52	8.38	8.39	88.59
ETHr	7.92	10.21	12.33	8.58	8.13	9.76	9.45	8.29	8.57	8.43	8.33	87.67
GREYr	7.83	8.40	8.75	12.42	9.47	9.43	9.11	8.38	8.42	9.41	8.37	87.58
CLNEr	7.67	8.23	8.63	9.67	12.50	9.26	8.87	8.13	8.50	10.30	8.24	87.50
FNTCHr	7.90	8.29	8.72	8.90	8.39	12.95	10.80	8.49	8.54	8.48	8.53	87.05
RAIr	7.88	8.35	9.15	8.78	8.25	11.37	12.72	8.34	8.44	8.37	8.35	87.28
SPGBr	7.99	8.41	8.84	8.65	8.30	9.18	8.82	12.78	8.53	8.51	9.97	87.22
USTBr	7.95	8.43	9.37	8.82	8.38	9.52	9.31	8.15	13.28	8.34	8.46	86.72
SP500r	7.81	8.21	9.12	9.68	10.02	9.26	8.97	8.42	8.49	11.62	8.41	88.38
Goldr	8.14	8.44	8.67	8.72	8.29	9.47	9.06	9.85	8.41	8.52	12.44	87.56
TO	79.12	85.24	90.66	89.04	86.04	96.16	92.88	84.99	85.27	87.17	85.67	962.23
Inc. own	92.43	96.65	102.99	101.46	98.54	109.11	105.60	97.77	98.55	98.79	98.11	
NET	-7.57	-3.35	2.99	1.46	-1.46	9.11	5.60	-2.23	-1.45	-1.21	-1.89	TCI = 87.48
Bullish market												
NFTr	13.11	8.77	9.10	9.03	8.67	8.52	8.19	8.63	8.80	8.75	8.44	86.89
BTCr	8.86	12.64	11.00	8.58	8.30	8.58	8.33	8.24	8.69	8.63	8.15	87.36
ETHr	8.90	10.78	13.78	8.34	8.38	8.26	8.05	8.31	8.38	8.52	8.30	86.22
GREYr	8.69	8.10	8.65	13.44	9.59	8.16	8.15	8.38	8.69	10.14	7.99	86.56
CLNEr	8.44	8.42	8.66	10.21	12.97	7.99	8.01	7.97	8.61	10.87	7.84	87.03
FNTCHr	8.69	8.43	8.83	8.54	8.35	13.53	10.47	8.21	8.62	8.55	7.79	86.47
RAIr	8.57	8.62	8.79	8.48	8.54	10.51	13.09	8.42	8.44	8.65	7.88	86.91
SPGBr	8.94	8.57	9.27	8.52	8.42	7.96	7.95	13.33	8.45	8.67	9.92	86.67
USTBr	8.77	8.61	9.02	8.98	8.56	8.69	8.42	8.16	13.94	9.02	7.84	86.06
SP500r	8.51	8.30	8.77	9.95	10.42	8.08	7.71	7.94	8.53	14.02	7.78	85.98
Goldr	8.74	8.42	8.77	8.65	8.50	8.26	8.26	10.08	8.45	8.77	13.10	86.90
TO	87.11	87.03	90.86	89.28	87.71	85.02	83.55	84.33	85.65	90.55	81.93	953.03
Inc. own	100.22	99.67	104.64	102.73	100.68	98.56	96.64	97.67	99.60	104.57	95.03	
NET	0.22	-0.33	4.64	2.73	0.68	-1.44	-3.36	-2.33	-0.40	4.57	-4.97	TCI = 86.64

Note: NFTr, BTCr, ETHr, GREYr, CLNEr, FNTCHr, RAIr, SPGBr, USTBr, SP500r and Goldr are return indexes of Non fungible tokens, Bitcoin, Ethereum, Nasdaq Clean Edge Green Energy Index, Energy Select Sector SPDR Fund, Global Financial Technology Index (FNTCH), Global Robotics and Artificial Intelligence (RAI), S&P green bond index (SPGB), United States Treasury bill index, S&P 500, and Gold.

Table 3: Volatility connectedness across normal, bearish and bullish market condition

	NFTv	BTCv	ETHv	GvEYv	CLNEv	FNTCHv	RAIv	SPGBv	USTBv	SP500v	Goldv	**FROM**
Normal market												
NFTv	83.22	0.68	1.85	1.53	2.13	2.23	2.10	1.16	2.13	1.03	1.94	16.78
BTCv	0.45	61.51	28.03	0.96	1.56	1.10	1.23	1.58	1.23	1.42	0.92	38.49
ETHv	1.41	27.83	60.96	0.78	0.95	1.59	1.61	1.49	1.83	1.00	0.56	39.04
GvEYv	1.22	1.15	0.88	61.96	12.49	1.24	1.10	1.45	1.17	15.41	1.92	38.04
CLNEv	1.88	2.23	1.90	11.77	56.05	1.31	1.13	0.94	1.19	20.29	1.30	43.95
FNTCHv	1.67	2.65	3.03	1.31	1.55	61.06	20.15	2.76	1.97	1.70	2.16	38.94
RAIv	1.95	1.30	1.45	1.18	1.43	22.30	62.21	2.46	1.67	1.35	2.71	37.79
SPGBv	1.14	1.98	1.50	1.70	1.25	2.96	3.03	73.82	2.03	1.15	9.44	26.18
USTBv	1.15	1.35	2.21	0.94	1.63	2.37	1.43	1.82	83.73	1.08	2.30	16.27
SP500v	0.60	1.40	0.97	14.97	19.92	0.87	0.87	0.99	1.47	56.51	1.42	43.49
Goldv	1.38	1.16	0.87	2.32	1.44	2.09	2.53	9.45	2.30	2.00	74.47	25.53
TO	12.85	41.73	42.70	37.45	44.35	38.07	35.18	24.09	16.98	46.44	24.67	364.50
Inc. own	96.07	103.23	103.66	99.41	100.40	99.12	97.39	97.91	100.71	102.95	99.14	
NET	-3.93	3.23	3.66	-0.59	0.40	-0.88	-2.61	-2.09	0.71	2.95	-0.86	TCI = 33.14
Bearish market												
NFTv	65.24	1.84	3.34	3.47	4.81	4.16	4.34	3.44	2.53	2.88	3.96	34.76
BTCv	1.58	50.88	26.55	2.50	3.98	2.30	2.52	3.07	1.76	3.03	1.82	49.12
ETHv	2.88	26.33	50.38	2.42	3.04	2.96	3.00	3.06	2.22	2.36	1.34	49.62
GvEYv	2.81	2.34	2.29	47.26	14.35	3.35	3.07	3.64	1.96	15.26	3.67	52.74
CLNEv	3.31	3.49	2.64	13.16	42.52	2.66	3.32	3.21	2.71	20.17	2.81	57.48
FNTCHv	3.30	2.43	3.00	3.35	3.12	48.53	21.73	5.11	3.07	2.57	3.80	51.47
RAIv	3.34	2.41	2.94	3.04	3.88	21.70	47.44	5.04	2.78	3.05	4.38	52.56
SPGBv	3.03	3.32	3.11	4.25	4.19	5.60	5.79	53.29	3.23	3.08	11.13	46.71
USTBv	2.73	2.32	2.78	2.73	4.12	4.18	3.68	3.83	66.80	2.58	4.25	33.20
SP500v	2.34	2.86	2.18	14.82	21.15	2.38	2.85	2.55	1.90	44.42	2.55	55.58
Goldv	3.67	2.08	1.51	4.55	3.74	4.34	5.18	11.30	3.60	3.27	56.76	43.24
TO	28.98	49.42	50.35	54.29	66.38	53.62	55.47	44.25	25.76	58.25	39.72	526.49
Inc. own	94.22	100.30	100.74	101.56	108.89	102.15	102.91	97.53	92.56	102.68	96.47	
NET	-5.78	0.30	0.74	1.56	8.89	2.15	2.91	-2.47	-7.44	2.68	-3.53	TCI = 47.86
Bullish market												
NFTv	9.53	7.23	8.43	9.63	9.39	9.80	9.30	8.34	9.52	9.83	8.99	90.47
BTCv	8.30	7.57	8.49	9.75	9.14	9.73	9.63	8.82	9.69	9.71	9.16	92.43
ETHv	8.97	7.32	8.71	9.15	8.69	9.85	9.66	8.88	9.77	9.45	9.56	91.29
GvEYv	8.40	7.37	8.31	10.51	9.92	9.89	9.54	8.28	8.89	9.93	8.97	89.49
CLNEv	8.44	7.36	8.55	9.94	9.61	9.73	9.60	8.43	9.25	10.13	8.97	90.39
FNTCHv	8.54	7.45	8.28	9.55	9.03	10.26	9.60	8.83	9.67	9.65	9.16	89.74
vRAIv	8.69	7.46	8.41	9.61	9.11	10.03	9.91	8.79	9.27	9.60	9.12	90.09
SPGBv	8.31	7.67	8.63	9.16	8.81	10.12	9.67	8.88	9.64	9.41	9.70	91.12
USTBv	8.70	7.58	8.79	9.12	8.58	9.93	9.43	9.10	9.75	9.62	9.40	90.25
SP500v	8.53	7.58	8.41	10.24	9.54	9.70	9.03	8.40	9.20	10.53	8.84	89.47
Goldv	8.62	7.46	8.32	9.50	8.81	10.11	9.36	9.01	9.86	9.57	9.38	90.62
TO	85.49	74.48	84.63	95.65	91.03	98.88	94.81	86.88	94.77	96.89	91.86	995.37
Inc. own	95.03	82.05	93.34	106.16	100.63	109.13	104.72	95.76	104.51	107.43	101.24	
NET	-4.97	-17.95	-6.66	6.16	0.63	9.13	4.72	-4.24	4.51	7.43	1.24	TCI = 90.49

Note: NFTv, BTCv, ETHv, GvEYv, CLNEv, FNTCHv, RAIv, SPGBv, USTBv, SP500v and Goldv are volatility indexes of Non fungible tokens, Bitcoin, Ethereum, Nasdaq Clean Edge Green Energy Index, Energy Select Sector SPDR Fund, Global Financial Technology Index (FNTCH), Global Robotics and Artificial Intelligence (RAI), S&P green bond index (SPGB), United States Treasury bill index, S&P 500, and Gold.

Table 4: Results of drivers of total return and volatility connectedness for the normal, bearish and bullish markets

	Return TCI			Volatility TCI		
Variables	Normal market (0.5)	Bearish market (0.05)	Bullish market (0.95)	Normal market (0.5)	Bearish market (0.05)	Bullish market (0.95)
ln(VIX)	0.369	-0.098	-0.285	-0.147	-1.719	0.774**
	(1.017)	(0.557)	(0.691)	(1.697)	(1.229)	(0.331)
ln(OVX)	5.341***	-0.382	-0.101	8.597***	2.727**	-1.804***
	(1.183)	(0.544)	(0.573)	(2.538)	(1.333)	(0.394)
ln(GVZ)	-3.939***	1.346**	-1.654**	-4.167*	1.594	-0.889**
	(1.185)	(0.673)	(0.694)	(2.521)	(1.845)	(0.407)
ln(EPU)	0.115	-0.479***	0.403**	-0.382	0.429	-0.023
	(0.232)	(0.149)	(0.201)	(0.444)	(0.305)	(0.096)
ln(MOVE)	6.057***	2.254**	3.234***	7.883*	-2.366	1.01
	(2.231)	(0.928)	(0.779)	(4.241)	(2.031)	(0.697)
ln(GPRI)	0.498**	0.058	0.046	0.217	0.655**	0.207*
	(0.247)	(0.168)	(0.167)	(0.464)	(0.317)	(0.124)
ln(NFTVOL)	-0.397***	-0.047	0.011	-0.423*	-0.129	0.148***
	(0.133)	(0.058)	(0.052)	(0.253)	(0.136)	(0.045)
COVID	-1.078	0.085	-0.084	-0.172	-4.656***	0.730***
	(0.853)	(0.504)	(0.393)	(1.514)	(0.976)	(0.237)
d(Term)	3.335	1.431	-0.973	3.847	-0.224	-1.372
	(2.765)	(0.973)	(1.049)	(4.459)	(2.837)	(1.233)
d(ADS)	-1.780*	-0.682**	0.572**	-4.627**	-1.345	0.569***
	(0.914)	(0.322)	(0.231)	(2.304)	(0.840)	(0.186)
Constant	21.54***	85.02***	85.55***	-8.961*	39.81***	92.87***
	(3.311)	(1.768)	(1.774)	(5.309)	(3.408)	(1.190)
d Mean	37.26	87.47	86.64	33.13	47.87	90.49
d Max	53.47	91.3	91.21	80.83	59.19	94.67
d Min	27.2	83.31	81.19	21.28	38.83	83.12
d Std. Dev.	3.859	1.751	1.813	6.552	3.703	1.449
R-squared	0.538	0.135	0.172	0.406	0.261	0.121

Note: Robust standard errors are presented in brackets while ***, ** and * represent significance at 1%, 5% and 10% levels, respectively. Ω Mean, Ω Max and Ω Min are the mean, maximum and minimum values of total return and volatility connectedness indexes for the three market conditions while Std. Dev. is the standard deviation of total return and volatility connectedness indexes.

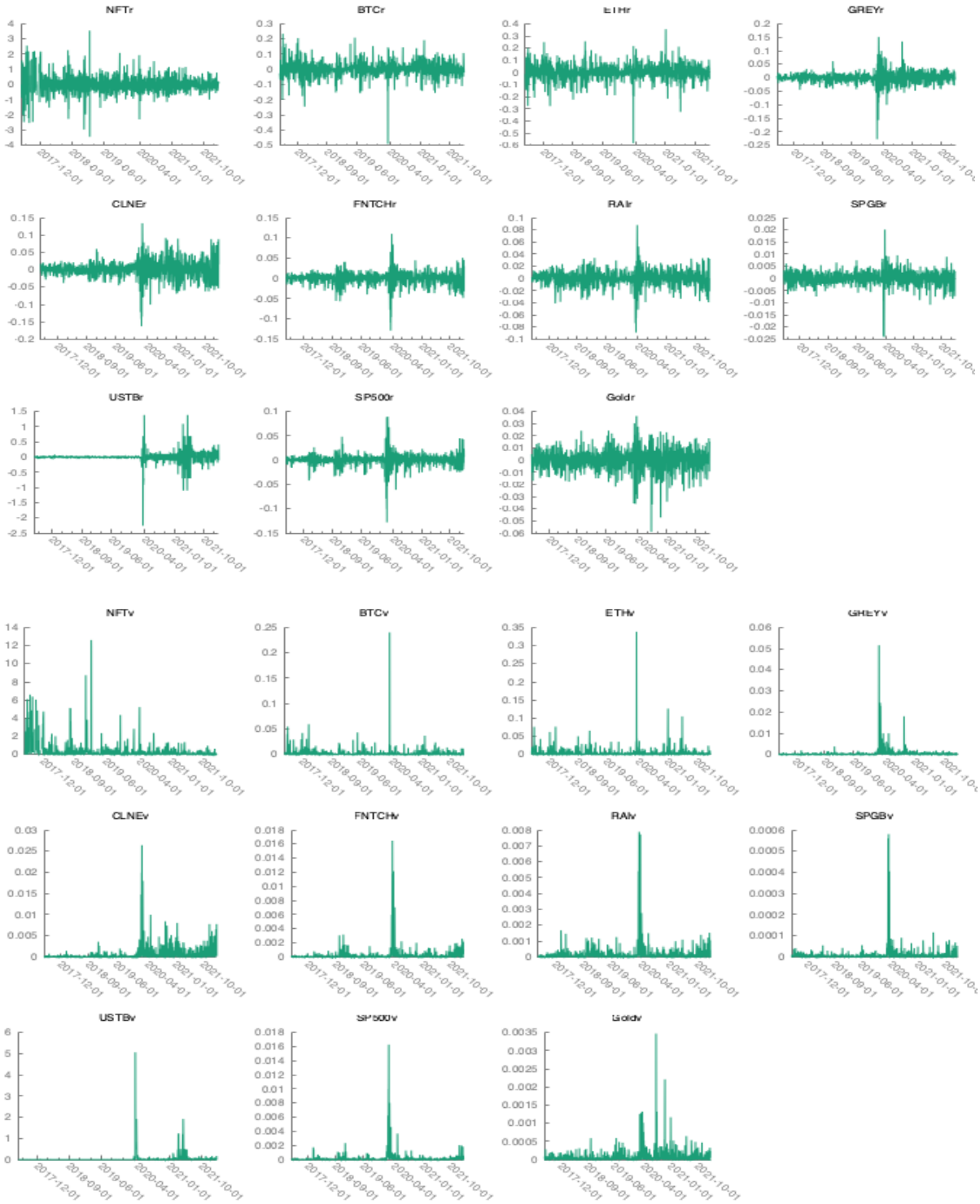
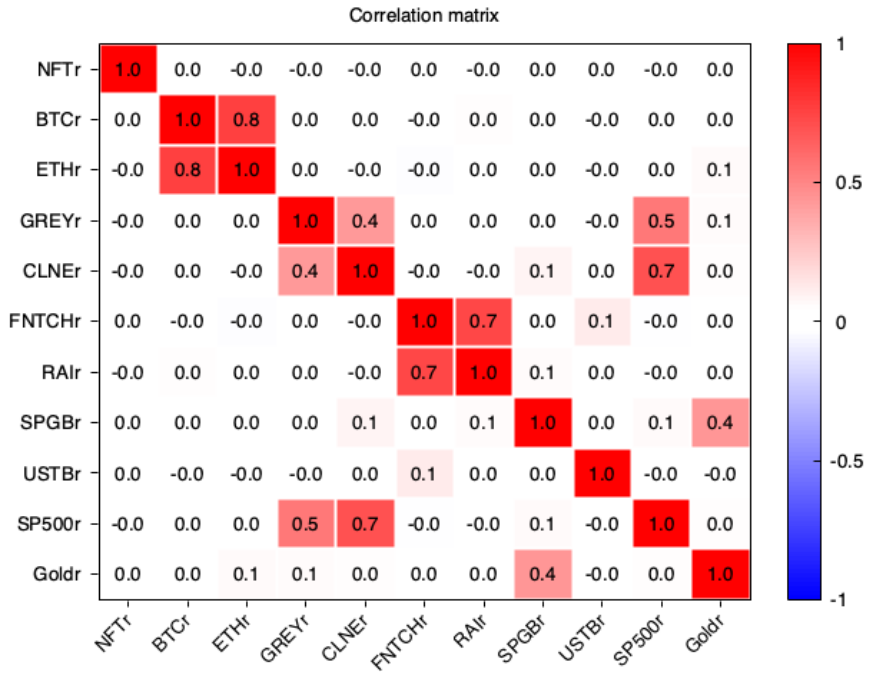


Figure 1: Plot of return and volatility NFTs and (un)conventional Assets



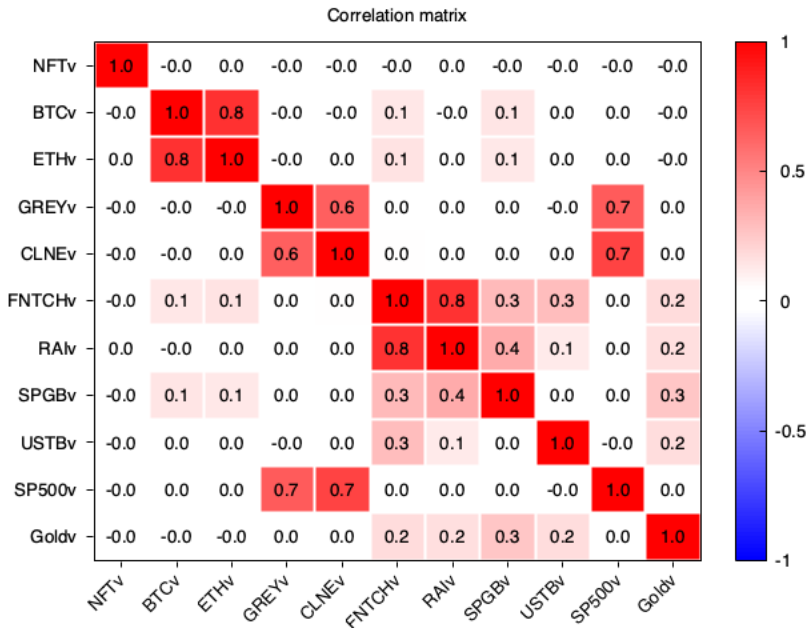
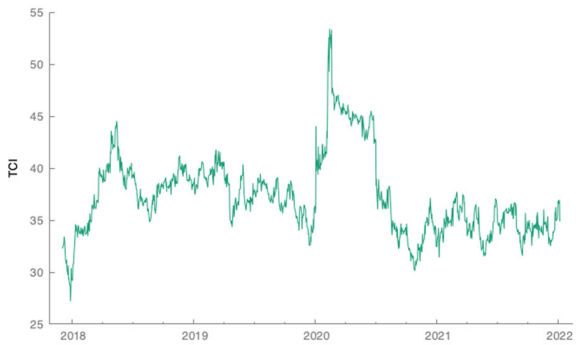
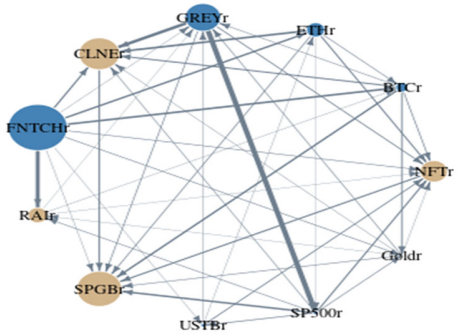


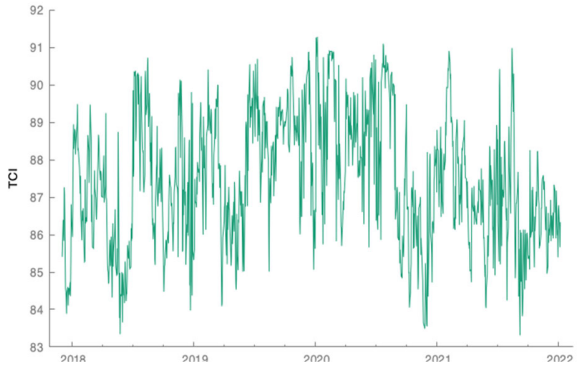
Figure 2: Correlation of NFTs and (un)conventional assets return and volatility



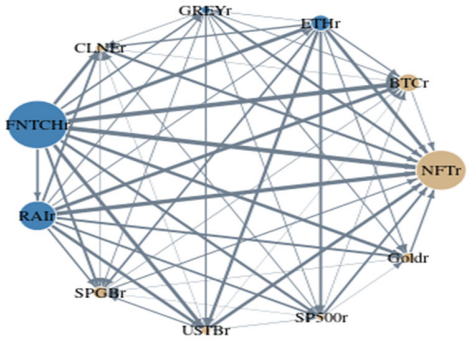
a(i) TCI under normal market



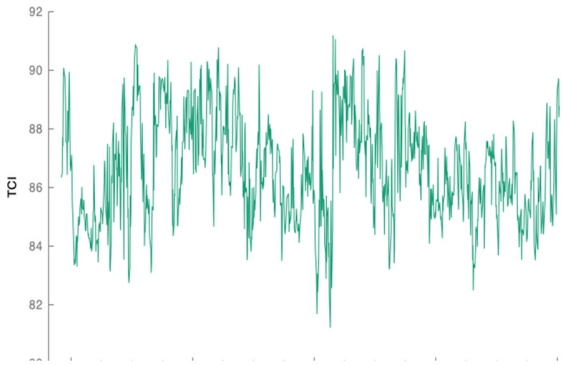
a(ii) Network plot for normal market



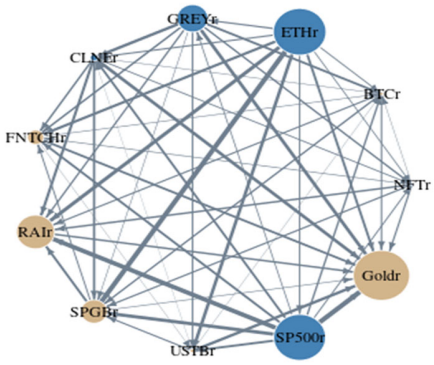
b(i) TCI under bearish market



b(ii) Network plot for bearish market



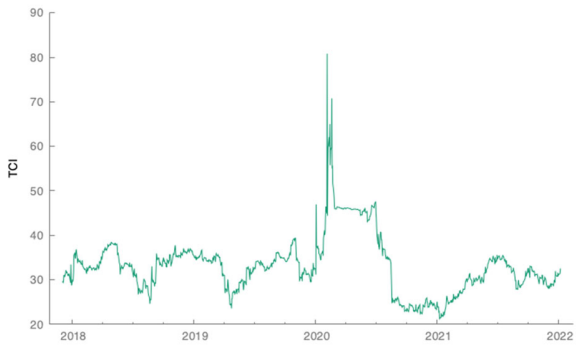
c(i)TCI under bullish market



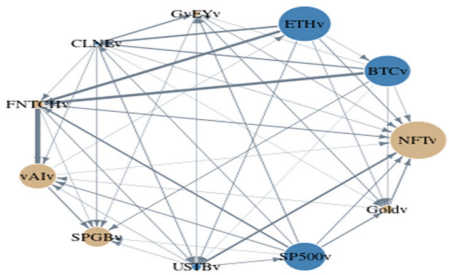
c(ii) Network plot for bullish market

Figure 3: Time-varying total return connectedness (TCI) and network system plot under normal, bearish and bullish markets

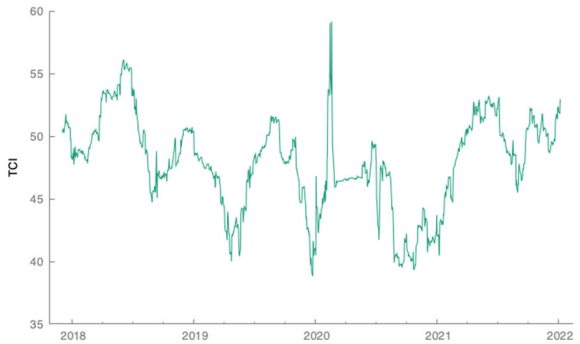
Notes: Panel (ii) is the network of pairwise directional connectedness under normal, bearish and bullish market conditions. Blue (yellow) nodes illustrate net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. Size of nodes represent weighted average net total directional connectedness.



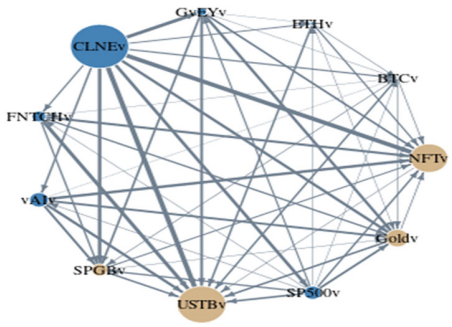
a(i) TCI under normal market



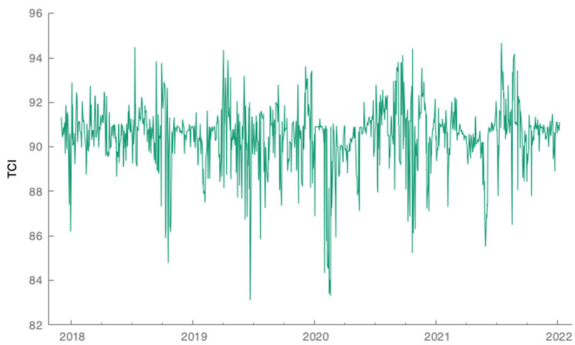
a(ii) Network plot for normal market



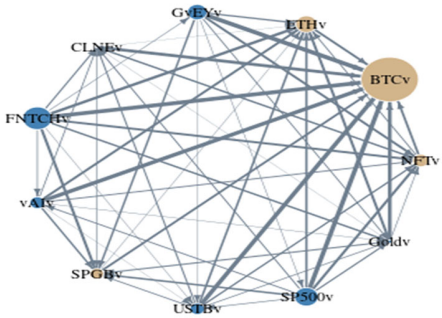
b(i) TCI under bearish market



b(ii) Network plot for bearish market



c(i)TCI under bullish market



c(ii) Network plot for bullish market

Figure 4: Time-varying total volatility connectedness (TCI) and network system plot under normal, bearish and bullish markets

Notes: Panel (ii) is the network of pairwise directional connectedness under normal, bearish and bullish market conditions. Blue (yellow) nodes illustrate net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. Size of nodes represent weighted average net total directional connectedness.

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