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Global macroeconomic factors and the connectedness among NFTs and (un)conventional assets

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A B S T R A C T

This paper examines return and volatility connectedness among Non-Fungible Tokens (NFTs) and (un)conventional financial assets across various market conditions using a Quantile-VAR connectedness technique. It also explores the predictive powers of major global macroeconomic and geopolitical indicators on both connectedness across these market conditions. First, we find that return and volatility connectedness vary across market conditions, with higher levels during extreme events. Except during bullish periods, return connectedness dominates volatility connectedness. Second, NFTs are decoupled from both (un)conventional assets during normal market condition but it is a net return shocks receiver except under bullish market period, where it is a net transmitter. However, it is a net volatility shocks receiver irrespective of the market situation. Lastly, geopolitical risks, business condition and economic policy uncertainty are important predictors of return and volatility connectedness, although the strength and direction are heterogeneous. We discuss the policy implications of these findings.

1. Introduction

Although the origin of non-fungible token (NFT) dates back to 2014, it only gained momentous attention in 2021 after the artist known as Beeple sold an NFT of his work for $US 69.3 million at Christie's (Nadini et al., 2021). Since then, NFT has 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 NFT underwent a major bull session in 2021. Aharon and Demir (2021) note that NFT sales volume across multiple blockchains reached almost 2.5 billion dollars in the first half of 2021, while its sales volume was only around 95 million dollars in 2020. Further, insights from the Google Trend data show a little or no 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, NFT represents 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, an NFT is a blockchain-enabled asset. Although different blockchains have now implemented their versions of NFT, it was 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). An NFT differs 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), an NFT

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cannot be exchanged for another as each NFT is unique (Wang et al., 2021; Wilson et al., 2021; Dowling, 2022b). This intrinsic feature allows NFT to demonstrate the authenticity and ownership of different kinds of items in distinct fields. Hence, an NFT is a pure digital asset 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 NFT market behaves differently from conventional cryptocurrencies (Corbet et al., 2021; Maouchi et al., 2021; Urom et al., 2022a).

These differences between NFT and conventional cryptocurrencies imply that the knowledge gained from erstwhile studies focused on conventional cryptocurrencies cannot be easily generalized to NFT (Urom et al., 2022a). Hence, scholarly research focused on NFT has emerged alongside the growing importance of NFT. Compared to the wide literature on classical cryptocurrencies, the literature on NFT remains scanty but developing. In this paper, we contribute to this growing literature by examining how return and volatility shocks are propagated among NFT, cryptocurrency, energy, technology, equity, precious metals, and fixed income financial assets. In particular, we examine the return and volatility 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 return and volatility connectedness among these markets across different market conditions.

The motivation for our analysis draws from the growing importance of NFT as an investment option and the consequent risks and diversification roles it holds for investors and portfolio managers. As an investment option, an NFT has the added advantage of being easily transferable and tradable. It also eliminates counterfeit and improves market efficiency, as it provides an instant proof of authenticity and provenance. Studies also indicate that NFTs have higher returns than traditional financial assets (Kong and Lin, 2021). However, NFTs are highly illiquid, speculative, and extremely volatile investments (Urom et al., 2022a). 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. Considering these, it is crucial to understand the return and volatility interdependencies between NFT and other widely traded conventional and unconventional assets for a more informed portfolio diversification and hedging decision-making across these assets. Moreover, as Wang (2022, p2) rightly noted, investigating interdependencies across financial markets can uncover information transmission channels and identify risk transmitters and receivers that are helpful for developing forward-looking monitoring regulations and to facilitate financial stability.

Conceptually, the potential return and volatility connectedness between NFTs and other (un)conventional assets can be rationalized based on three hypotheses including: (i) asset substitution; (ii) hedging demand shifts; and (iii) financial contagion. Beginning with asset substitution, the hypothesis views financial assets as competing alternatives such that positive return shocks in one market will spillover as negative return shocks in the other. (Dean et al., 2010). In this case, investors would buy NFTs and sell other assets (stocks, bonds) in response to positive news about the NFTs market and vice versa. Concerning the hedging demand shifts, the mechanism of the hedging demand shifts is somewhat like that of asset substitution. More specifically, hedging demand shifts occur when price changes in one market causes hedgers to change their portfolio allocation to maintain their target hedge ratio. Like the asset substitution hypothesis, therefore, the hedging demand hypothesis also predicts that a positive shock in one market will spill over as negative shock in the other market as hedgers adjust their positions in response to price changes. Finally, the financial contagion refers to the situation where prices in one market respond not only to fundamental information but also price changes in other markets (Pham, 2021). In this case, positive and negative shocks from NFTs market can spillover to other markets and vice versa.

To address our research objectives, we employ two-prong empirical strategies. First, we use the quantile vector autoregressive (QVAR) method to analyze return and volatility interdependencies 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 (see Jena et al., 2021; Bouri et al., 2021; Liu et al., 2021; Khalfaoui et al., 2022; Ando et al., 2022). Our analysis relies particularly on three quantiles to capture three market conditions: normal (i.e., 0.5 quantiles), bearish (0.05 quantiles), and bullish (0.95 quantiles) market conditions. We refer to bearish market conditions as periods of economic crises or more generally, bad times in the paper. In the second stage analysis, we retrieve the total return and volatility connectedness across the three market conditions and employ a simple linear regression to examine their drivers. In this way, we address our second research objective that is focused on providing insights on the drivers of the return and volatility connectedness between NFT and the different conventional and unconventional assets.

Our paper contributes to the nascent literature on NFT. Empirical studies on NFT have until now focused largely on pricing efficiency and returns characteristics of the NFT market (Kong and Lin, 2021; Dowling, 2022a), diversification role or connectedness to other assets (Aharon and 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 gray 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 (2022a,b) have jointly considered the propagation of return and volatility shock between NFT and other assets. Unlike our focus, however, the assets they consider are limited to oil, gold, Bitcoin, and S&P 500. Beyond the few assets Yousaf and Yarovaya (2022a,b) consider, the roles of these other assets in providing investment options, means to optimize portfolio as well as provide hedging and diversification roles have been highlighted in the literature (see Reboredo and Ugolini, 2020; Huynh et al., 2020; Hernandez et al., 2022; Chen et al., 2022; Khalfaoui et al., 2022; Urom et al., 2022b,c). In the light of NFT's growing importance as an investment option, our study is therefore more expensive in gauging its risk-return characteristics as well as their connectedness and interdependencies with these other conventional and unconventional assets, which as noted earlier are important both from portfolio management and policy perspective.

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 (2022a,b,c) 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 NFT that employs such a method is Karim et al. (2022). However, the study only analyzes the return connectedness between NFT and the cryptocurrency markets, whereas we analyze both the volatility and return connectedness with the cryptocurrency market and a host of other conventional and unconventional assets. 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 NFT has resulted in incipient literature on NFT. 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 NFT 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 (2022a) presents one of the early empirical evidence in this regard. The author examined the pricing of NFT in Decentraland, one of the most popular NFT 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 NFT 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 NFT pricing in CryptoPunks. They found that NFT pricing largely depends on a token's scarceness and investors' esthetic preference. In addition, NFT prices surge when there is a drastic increase in the 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, NFT, and cryptocurrency markets by analyzing the existence of bubbles in these markets. They found that bubbles are less frequent but larger in Defi and NFT than cryptocurrencies. Additional analysis of the predictors of the bubbles revealed that COVID-19, trading volume, and investors' sentiment are positively associated with bubble 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 found that NFT bubbles are more recurrent and have higher magnitudes than Defi bubbles, both market price bubbles are highly correlated with market hype and the conventional cryptocurrency market uncertainty. Ito et al. (2022) applied the Logarithmic Periodic Power Law (LPPL) model to the time-series price data of major NFT projects. Among others, they found that NFT is in a small bubble.

Whereas the above studies are largely focused on NFT price formation and pricing efficiency, others analyze the return-risk characteristics as well as the propagation shocks among NFT and conventional and unconventional assets. For instance, Karim et al. (2022) examined extreme risk transmission among NFT, DeFis, and cryptocurrencies using the QVAR model. They found significant risk spillovers among cryptocurrency markets with strong disconnection of NFT, suggesting that NFT plays a diversification role with substantial risk-bearing potential among other cryptocurrency markets to shelter the investments and minimize extreme risks. Yousaf and Yarovaya (2022a,b,c) examine the return and volatility transmission between NFT, 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 NFT and Defi assets and selected markets, implying that NFT and Defi are still relatively decoupled from traditional asset classes. Moreover, they found that NFT 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 NFT 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 NFT acts as a transmitter (absorber) 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 NFT 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 NFT 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. Like Yousaf and Yarovaya (2022a,b,c) and Aharon and Demir (2021), they document an increase of coherence between NFT and major assets caused by the COVID-19 pandemic. They also found that NFT 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 NFT and the cryptocurrencies as measured by the Bitcoin and Ethereum prices. The results showed no significant effect of NFT on both cryptocurrencies, although both cryptocurrencies affect NFT in significant ways. Wang et al. (2022) The aim of this study is to investigate the volatility spillover connectedness between NFTs attention and financial markets. They found that NFT markets are volatility spillover receivers and are dominated by cryptocurrencies, DeFi, equity, bond, commodity, F.X. and gold markets. Yousaf and Goodell (2023) gauge the impact of the FTX collapse on a variety of tokens and found that abnormal returns, as well as cumulative abnormal returns (CARs) and cumulative average abnormal returns (CAARs, indicate almost all tokens initiated a persistent bearish trend on the event day.

Further, whereas the above studies hold profound implications on the diversification and hedging roles of NFT, some studies have specifically analysed the hedging effectiveness of NFT or the performance of NFT in general. For instance, Ko et al. (2022) analyzed the portfolio implication of NFT in traditional assets and found NFT is distinct from them, potentially resulting in portfolio diversification. Using the mean-variance approach, they also found significant evidence that the inclusion of NFT improves the performance of equally weighted and tangency portfolio strategies in terms of risk-adjusted returns. Among others, Yousaf and Yarovaya (2022a) computed the static and dynamic optimal weights, hedge ratios, and hedging effectiveness for the portfolios of NFT and other assets, and Defi asset and other assets. Their results showed that investors and portfolio managers should consider adding NFT and Defi assets in their portfolios of gold, oil, and stock markets to achieve diversification benefits. Yousaf and Yarovaya (2022b) examine the static and time-varying herding behavior in three cryptocurrency classes including 'conventional' cryptocurrencies, non-fungible tokens, and DeFi assets during the most recent cryptocurrency bubble of 2021. Whereas they did not find any evidence of herding from the static analysis, the time-varying analysis shows evidence especially for short investment horizons.

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 NFT comes along with extremely high volatility, leading to a comparable Sharpe ratio to the NASDAQ index. Vidal-Tomás (2022) analysed 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. Urom et al. (2022a,b,c) examine the dependence between volume and returns for the NFT market and three sub-markets (Cryptokitties, Cryptopunks, and Decentraland). Among others, they found significant evidence of dependence between NFT return and volume, with the weakest link been for the Cryptopunks market. Yousaf and Yarovaya (2022c) examine the quantile connectedness for returns-volume and volatility-volume pairs for the three non-fungible tokens (THETA, Tezos, and Enjin Coin). They found the highest connectedness of volume with returns and volatility in the extreme upper quantile compared to other quantiles, implying the asymmetric connectedness.

Our study relates closely to the strand of literature on the propagation of shock between NFT and conventional and unconventional assets. Our innovation in this literature is threefold. First, the literature review indicates that existing studies have largely focused on return connectedness between NFTs and financial assets. Also, existing studies have only considered a few assets. We deviate from these studies by jointly studying the return and volatility connectedness between NFT and conventional and unconventional assets. In this way, we provide insights on both the risk and return characteristics of NFTs. Unlike existing studies, we also expand the set of assets under consideration, examining, the return and volatility connectedness between NFT and the technology market (artificial intelligence and FinTech), cryptocurrency (Ethereum and Bitcoin), energy market (the green and gray 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). Thus, we provide a more expansive insight on the risk-return connectedness and interdependencies between NFT and (un)conventional assets. The literature review also reveals limited empirical studies considering how the risk-return connectedness between NFT and different assets behave under different market conditions. We fill this gap by taking advantage of the QVAR method. Finally, we go beyond the conventional narrative of studying only the levels of return or risk connectedness among financial assets, and model market and geopolitical factors that drive these connectedness.

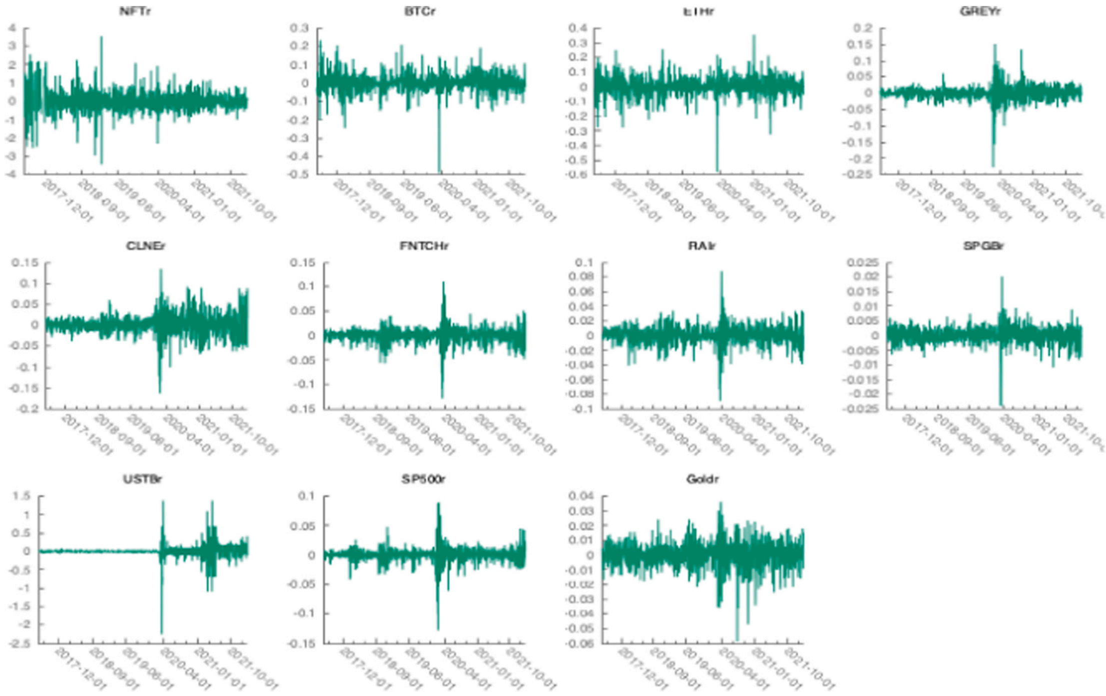
3. Empirical design

3.1. Data

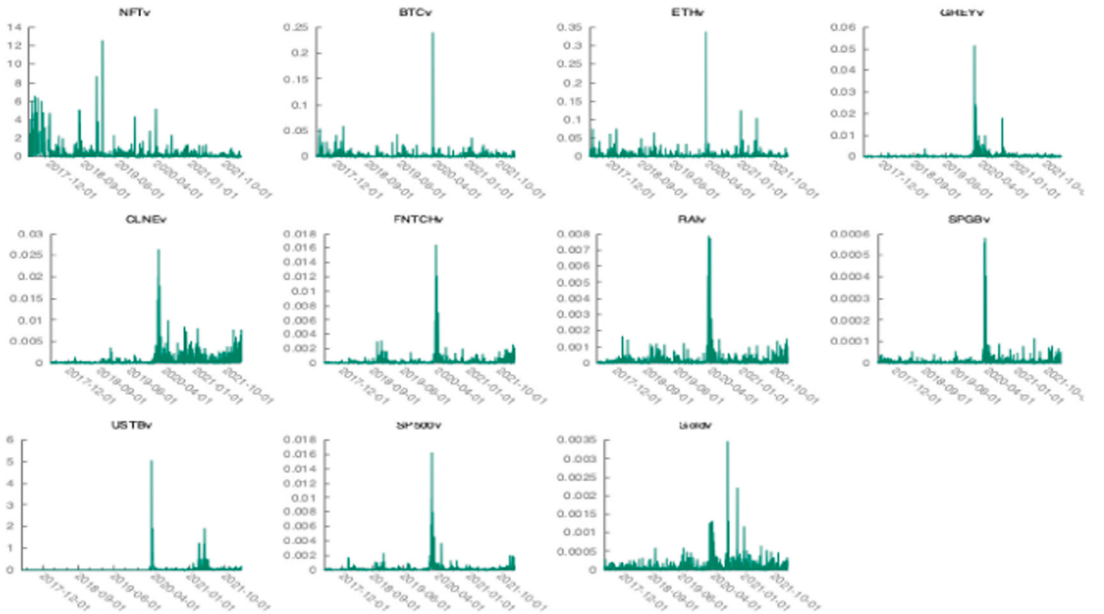
In line with our first research objective, we use daily price data of the NFT and representative indexes for the remaining markets. For the cryptocurrency market, we use both Bitcoin (BTC) and Ethereum (ETH) daily prices while for the energy market, we use both the Nasdaq Clean Edge Green Energy Index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

NFT 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 lnln (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. One advantage of using this approach to compute volatility is that it provides model-free unbiased estimates of the *ex post*



(a) Plots of daily returns for all assets



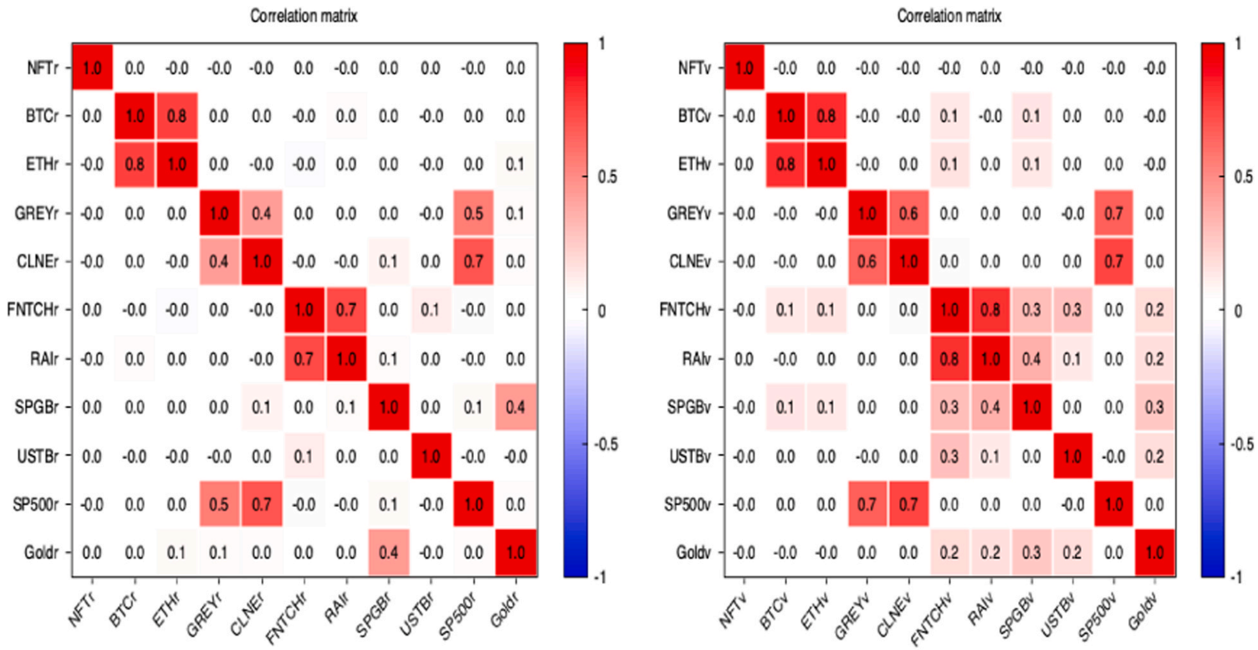
(b) Plots of daily volatility for all assets

Fig. 1. Plots of daily returns and volatility for all assets.

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***	14,928***	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	201,929***	11,866,579***	6,227,569***	4,135,823***	421,318***	1,635,150***	1,362,967***	2,968,087***	9,867,232***	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: 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.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. Each variable with “r” at the end refers to the return series of that variable.



(a) Correlation among daily returns.

(b) Correlations among daily volatility

Fig. 2. Correlation matrix of daily returns and volatility.

realized volatility. However, we do realize that it is a very noisy volatility indicator and it may limit reliable inference about the true underlying latent volatility (Andersen et al., 2001).

Fig. 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 as shown by the ADF unit roots test. As shown in Fig. 2, the correlation heatmap suggests 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 (GRAY 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 that we 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 NFT, cryptocurrency, energy, technology, equity, precious metals, and fixed income market across different market conditions, including the normal, bullish as well as bearish market periods. The Q-VAR approach offer several advantages over other measures of connectedness that focuses on estimating connectedness at the mean. For instance, as noted in Ando et al. (2022), by allowing for the estimation of relative spillover intensity in both right and left tails of the series distribution, this technique offers a very important and timely composite measure of systemic financial fragility that has important implication for risk management and monitoring. Hence, relying on the empirical design of this approach, we examine the propagation of shocks among the selected assets across different conditions, such as the normal, bearish and bullish markets. 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:

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

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 Quantile-VAR Moving Average (QVMA) (∞) following the Wold's theorem defined as follows

$$y_t = \nu(\tau) + \sum_{j=1}^{p} \vartheta_j(\tau) y_{t-j} + \upsilon_t(\tau) = \nu(\tau) + \sum_{i=0}^{\infty} \varphi_i(\tau) \upsilon_{t-i} \tag{2}$$

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:

$$\Psi_{ij}^{g}(H) = \frac{\sum(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' \varphi_h(\tau) \sum(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \varphi_h(\tau) \sum(\tau) \varphi_h(\tau)' e_j\right)} \tag{3}$$

$$\widetilde{\Psi}_{ij}^{g}(H) = \frac{\Psi_{ij}^{g}(H)}{\sum\limits_{j=1}^{k} \phi_{ij}^{g}(H)}$$

The normalization of e_i into a zero vector with unity on the i^{th} 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* denotes the overall impact variable *i* has on all other variables *j*, while the total directional connectedness *FROM* represents the overall impact on variable *i* from all other variables *j*. Eq. 4 defines both measures mathematically

$$C_{i\to j}^{g}(H) = \sum_{j=1,i\neq j}^{k} \widetilde{\Psi}_{ji}^{g}(H) and C_{i\leftarrow j}^{g}(H) = \sum_{j=1,i\neq j}^{k} \widetilde{\Psi}_{ij}^{g}(H) \quad (4)$$

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

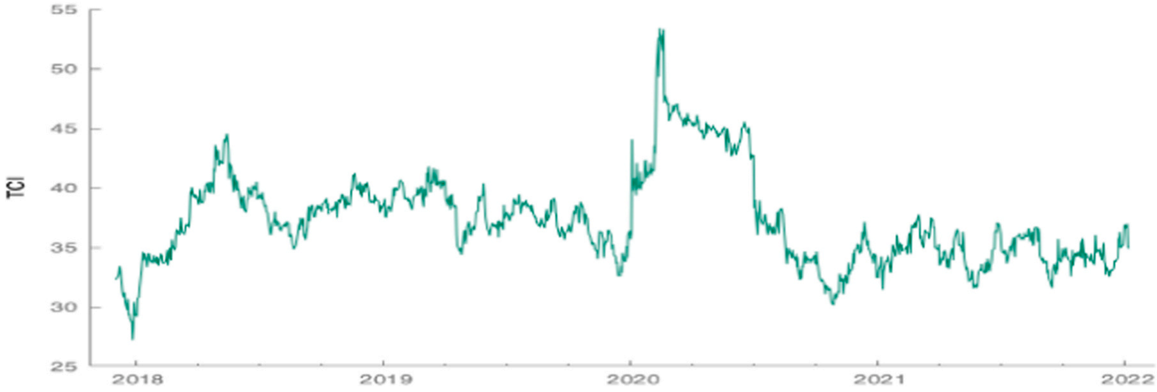
$$C_i^g = C_{i\to j}^{g}(H) - C_{i\leftarrow j}^{g}(H) \quad (5)$$

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

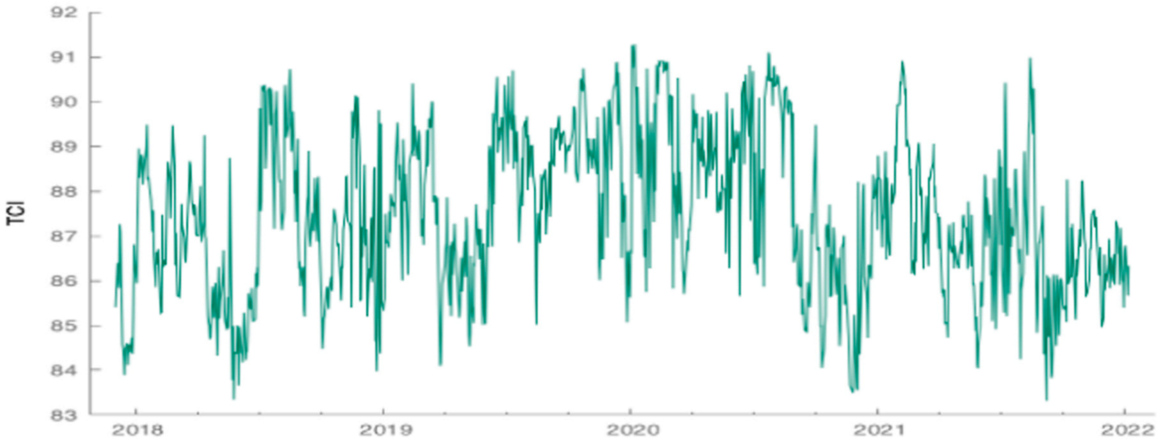
Table 2
Return connectedness across normal, bearish and bullish market conditions.

	NFTr	BTCr	ETHr	GREYr	CLNEr	FNTCH	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

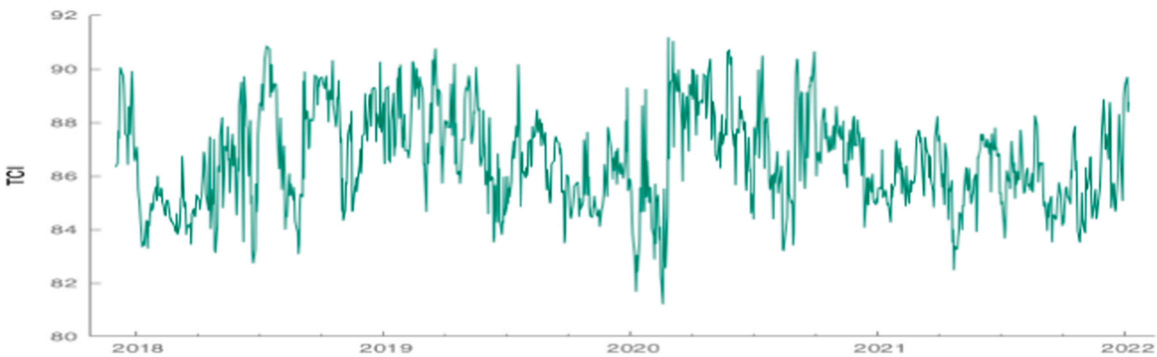
Note: NFTr, BTCr, ETHr, GREYr, CLNEr, FNTCHr, RAIr, SPGBr, USTBr, SP500r and Goldr are return indexes of Non fungible tokens, Bitcoin, Ethereum, Nasdaq Clean Edge Green Energy Index, Energy Select Sector SPDR Fund, Global Financial Technology Index (FNTCH), Global Robotics and Artificial Intelligence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



(a) Time-varying total return connectedness during normal market condition



(b) Time-varying total return connectedness during bearish market condition



© Time-varying total return connectedness during bullish market condition

Fig. 3. Time-varying total return connectedness during normal, bearish, and bullish market conditions.

may be written as:

$$TCI(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \widetilde{\Psi}_{ij}^{g}(H)}{m} \quad (6)$$

3.2.2. Drivers of 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 Eq. 6. 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:

$$TCI_t = \delta + \gamma X'_t + \mu_t \quad (7)$$

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 Eq. 6, 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, OVX, and GVZ); (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 coefficient. μ_t denotes the error term.

4. Results and discussion

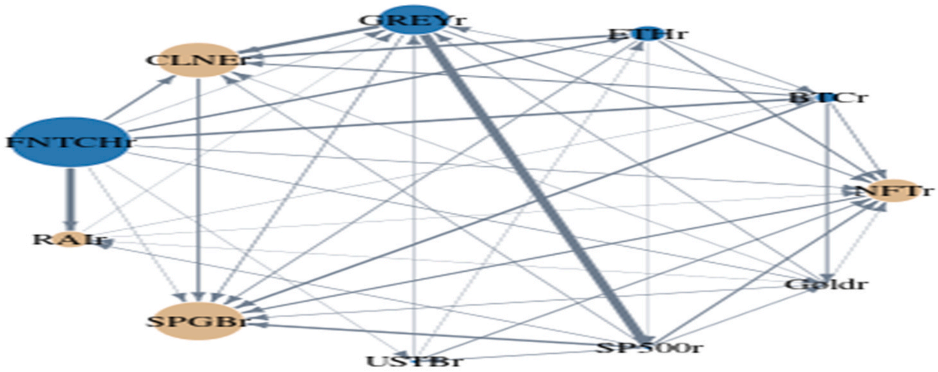
This section proceeds in three steps. First, we present and discuss the results for the return connectedness across three quantiles corresponding to the normal (i.e., 0.5 quantiles), bearish (0.05 quantiles), and bullish (0.95 quantiles) market conditions, respectively. In the second section, we focus 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 three market conditions.

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

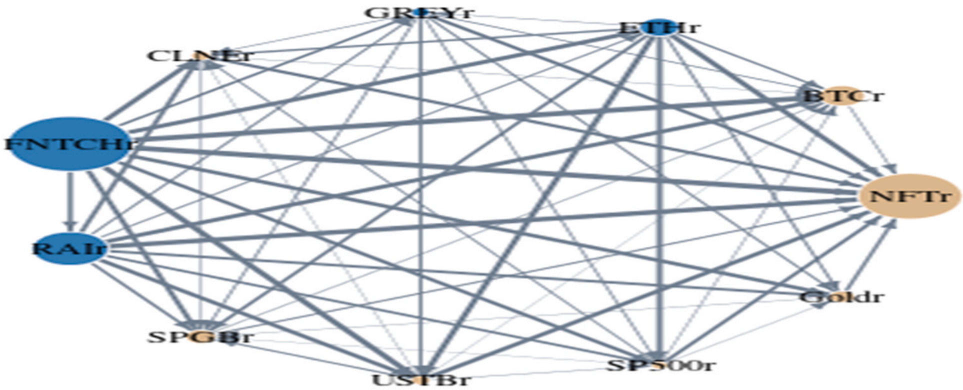
Table 2 reports the results for the return connectedness. In line with Section 3.2, the table contains different connectedness measures such as the total connectedness index (TCI), Pairwise directional connectedness, net directional connectedness (NDI), the directional TO, and the directional FROM. Beginning 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 to 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. Focusing on NFTs return-volume and volatility-volume connectedness, similar evidence of higher connectedness at extreme quantiles is documents in Yousaf, I., & Yarovaya, L. (2022c). In a broad sense, this result and conclusion are consistent with previous studies suggesting higher connectedness among different assets during extreme market conditions (e.g. Urom et al., 2020; Jena et al., 2021; Bouri et al., 2021; Liu et al., 2021; Khalfaoui et al., 2022; Mzoughi 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 Fig. 3a, b and c where we plot the dynamic TCI shows time-varying patterns, especially 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 NFT, 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 NFT 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 NFT returns that show 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 NFT 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.

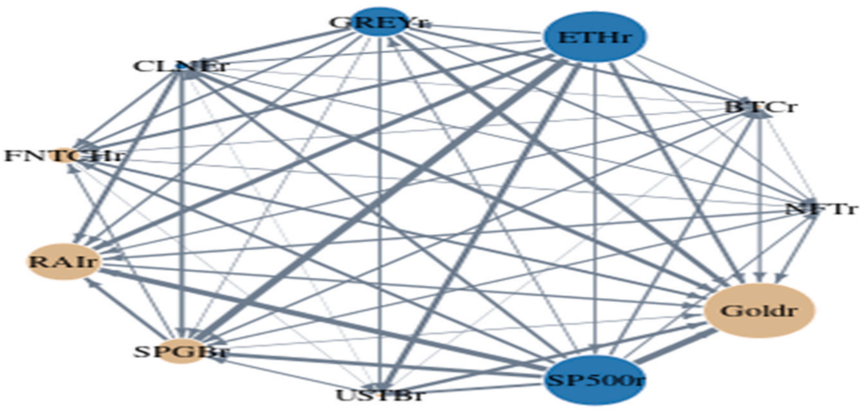
Next, we look at the pairwise directional connectedness, which shows the bilateral connectedness among the markets. Evidence in the table suggests a low pairwise spillover among NFT and the other studied assets during the normal market condition than in other periods. In particular, the shock received from or transmitted by NFT during normal periods ranges from 1.05 % to 2.32 %. However, this is between 7.67 % and 9.26 % during the bearish market condition and between 8.19 % and 9.10 % during the bullish market



(a) Net pairwise returns spillover during normal market condition

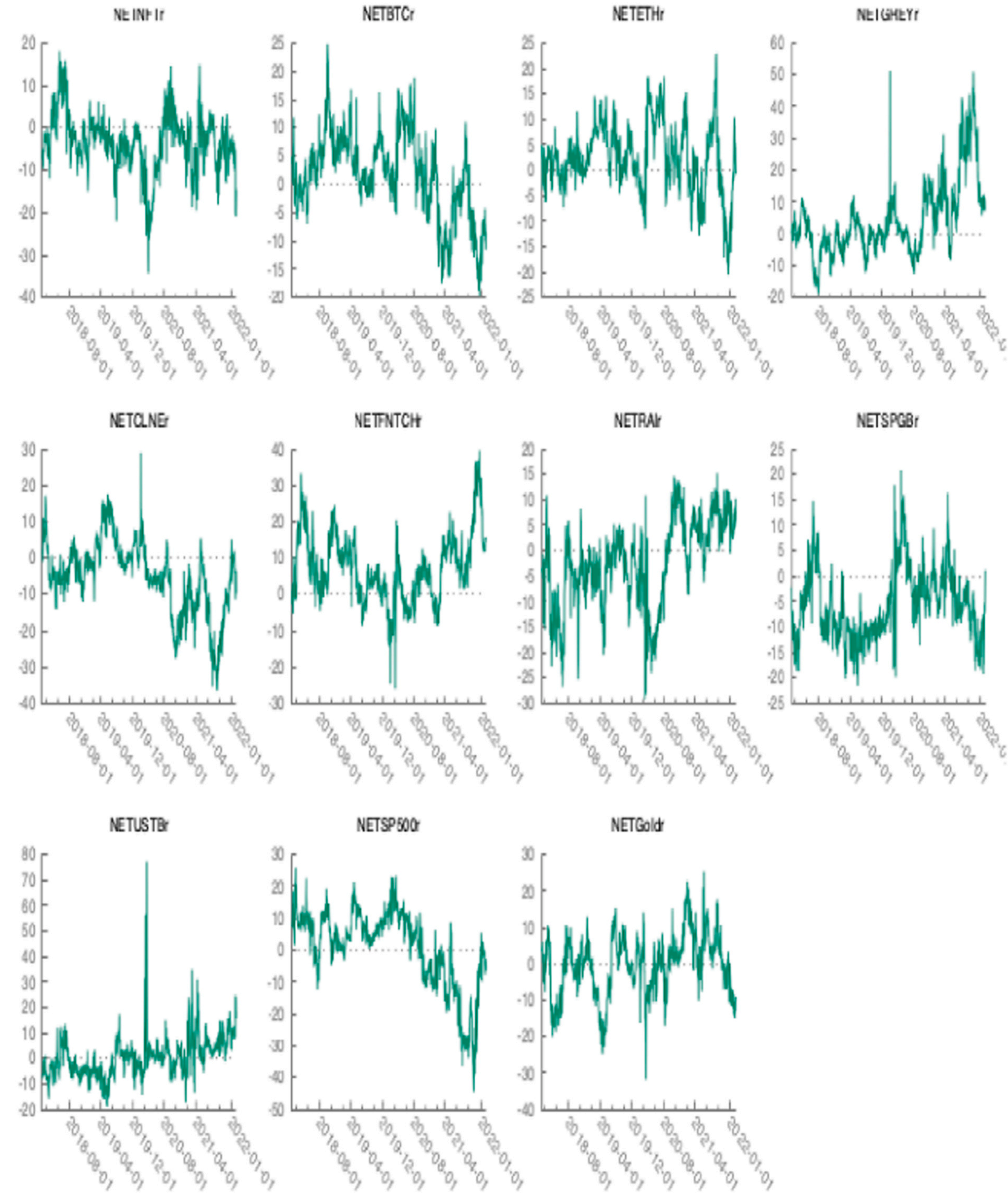


(b) Net pairwise returns spillover during bearish market condition



© Net pairwise returns spillover during bullish market condition

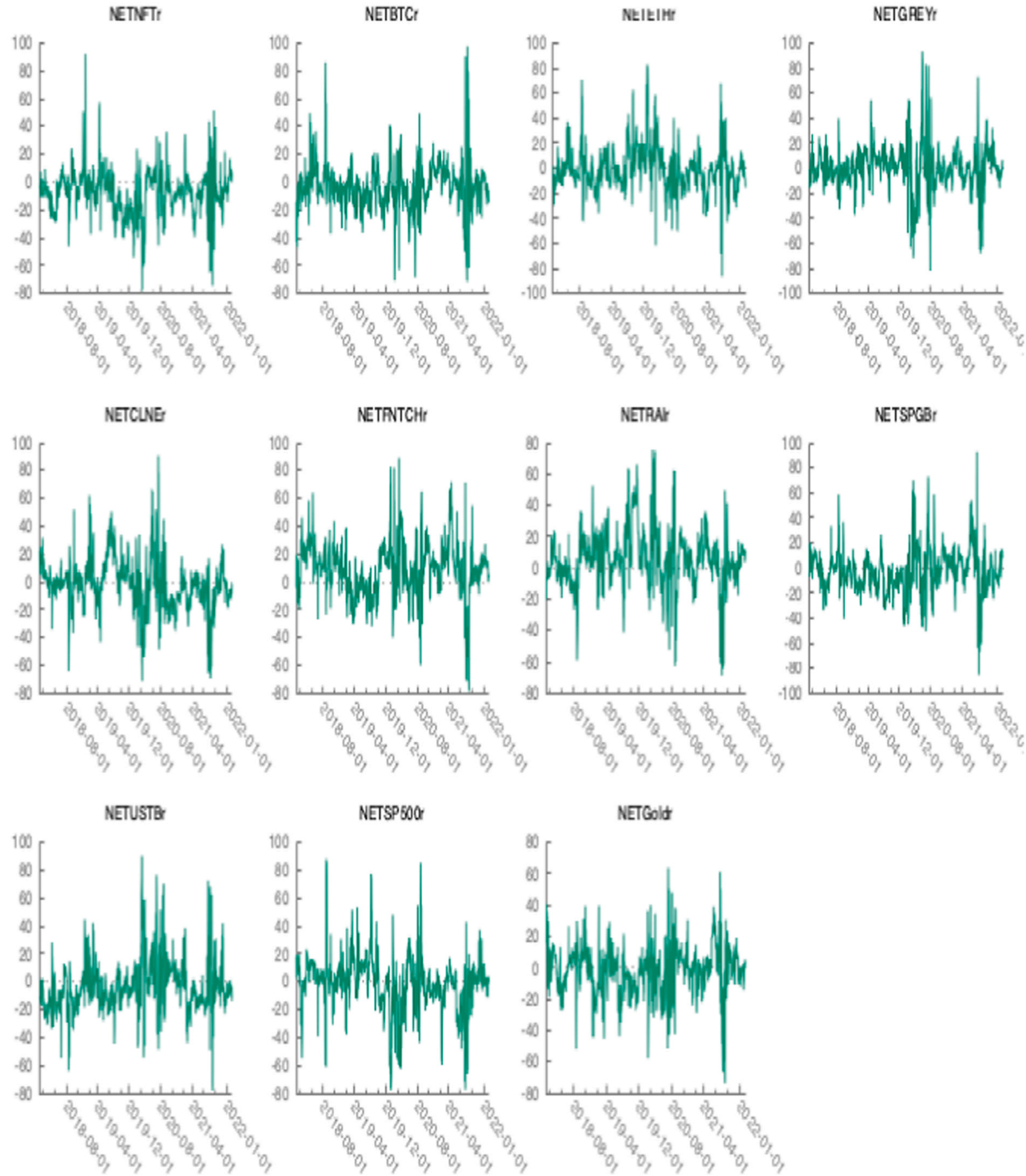
Fig. 4. Net pairwise return spillover during normal, bearish, and bullish market conditions. Note: Blue/yellow node denotes a pairwise transmitter/receiver of risks while the node sizes correspond to the level of risk received/transmitted.



(a) Time varying net return spillovers during normal market condition

Fig. 5. Time-varying net return spillover during normal, bearish, and bullish market conditions.

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, except under the bearish market condition, the result shows that for the cryptocurrency market NFT is more



(b) Time varying net return spillovers during bearish market condition

Fig. 5. (*continued*).

connected to Ethereum than Bitcoin. As noted in Nadini et al. (2021), strong interaction between NFT and the cryptocurrency market is expected, 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

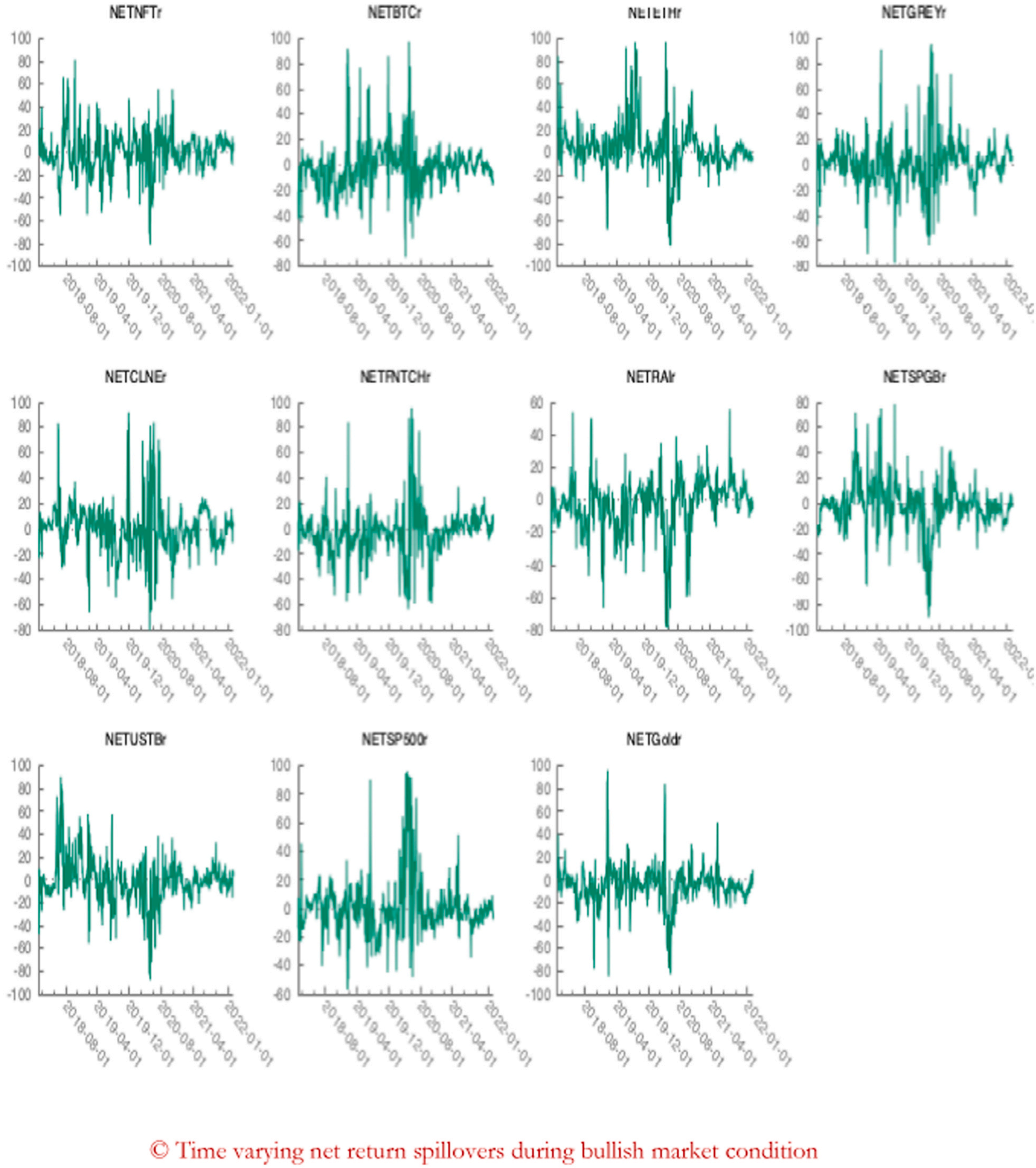


Fig. 5. (*continued*).

a net shock receiver, implying that it receives more shock from the system than it transmits to 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 receiver during COVID-19 period. Our result shows that such contagion effects are 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

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

	NFTv	BTCv	ETHv	GREYv	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
GREYv	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
FNTCv	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	103.2	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
GREYv	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
GREYv	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
FNTCv	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, GREYv, 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. "v" at the end refers to the volatility series of that variable

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 gray 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 NFT yielding the best benefits during bullish market conditions. At the same time, our results also suggest that except for Ethereum and gray energy, the roles and attractiveness of other assets in our sample vary across market conditions.

Fig. 4a, b, and c 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 nodes 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,

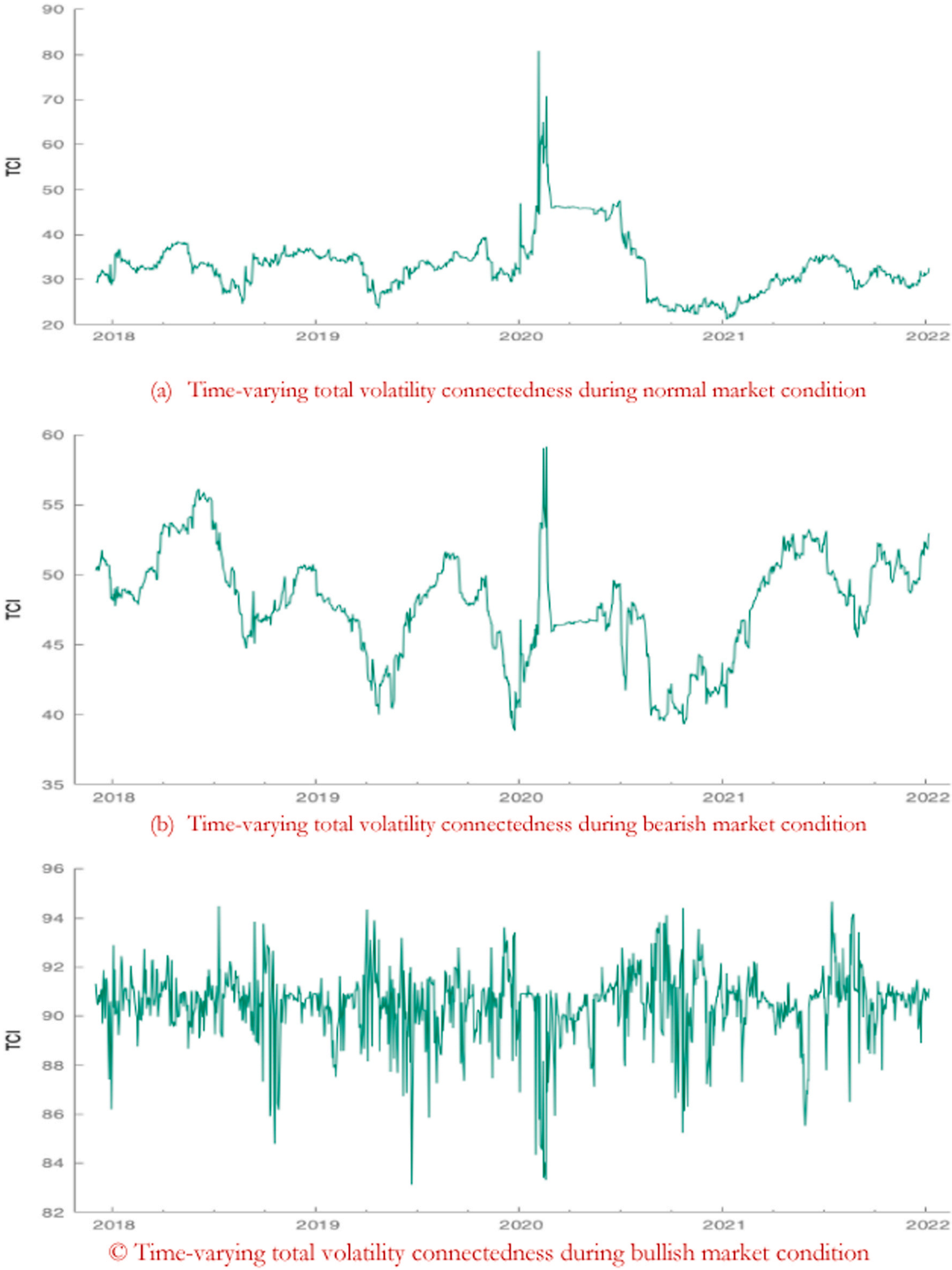
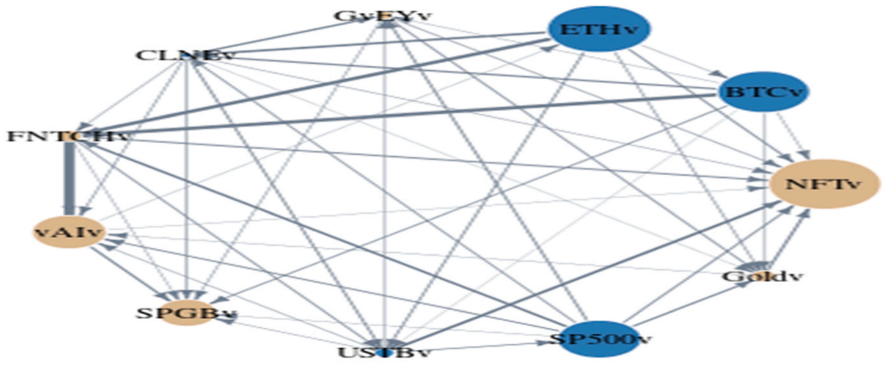
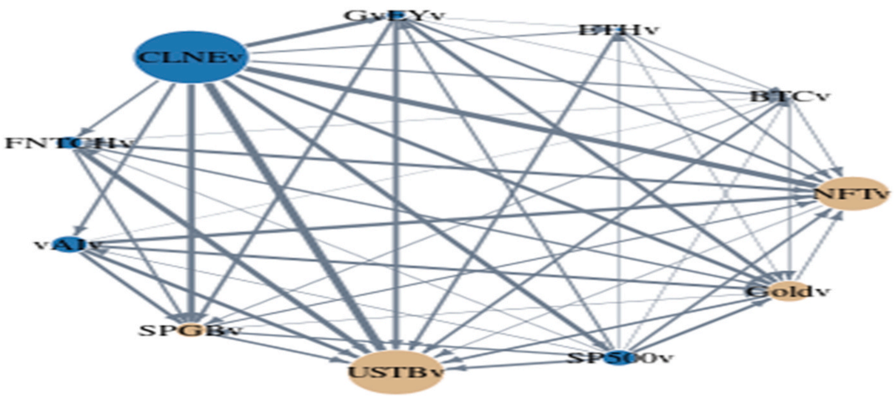


Fig. 6. Time-varying total volatility connectedness during normal, bearish, and bullish market conditions.

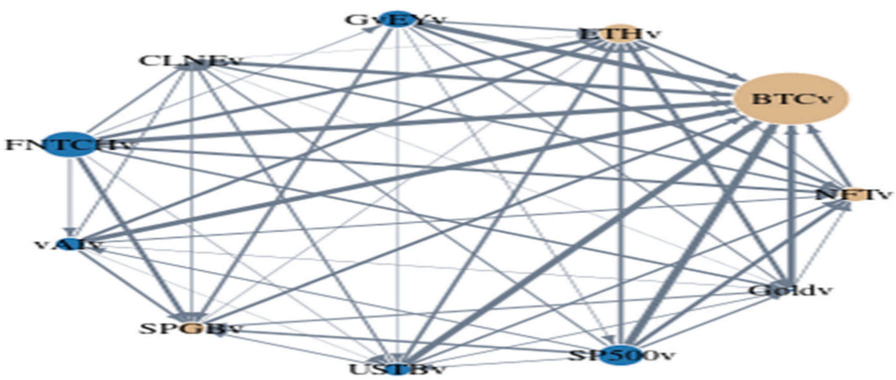
the vertices are mostly light in Fig. 4a implying that the observed market connectedness in the figure is hardly strong. This is different from Fig. 4b and c where a significant number of the vertices are thicker and bolder suggesting a stronger connectedness among those markets during extreme market conditions. Furthermore, insights from the figures indicate that during normal market periods, green bond and clean energy markets are the main shock receivers from the system, especially from gray (Greyr), Ethereum (ETHr), and



(a) Net pairwise volatility spillover during normal market condition

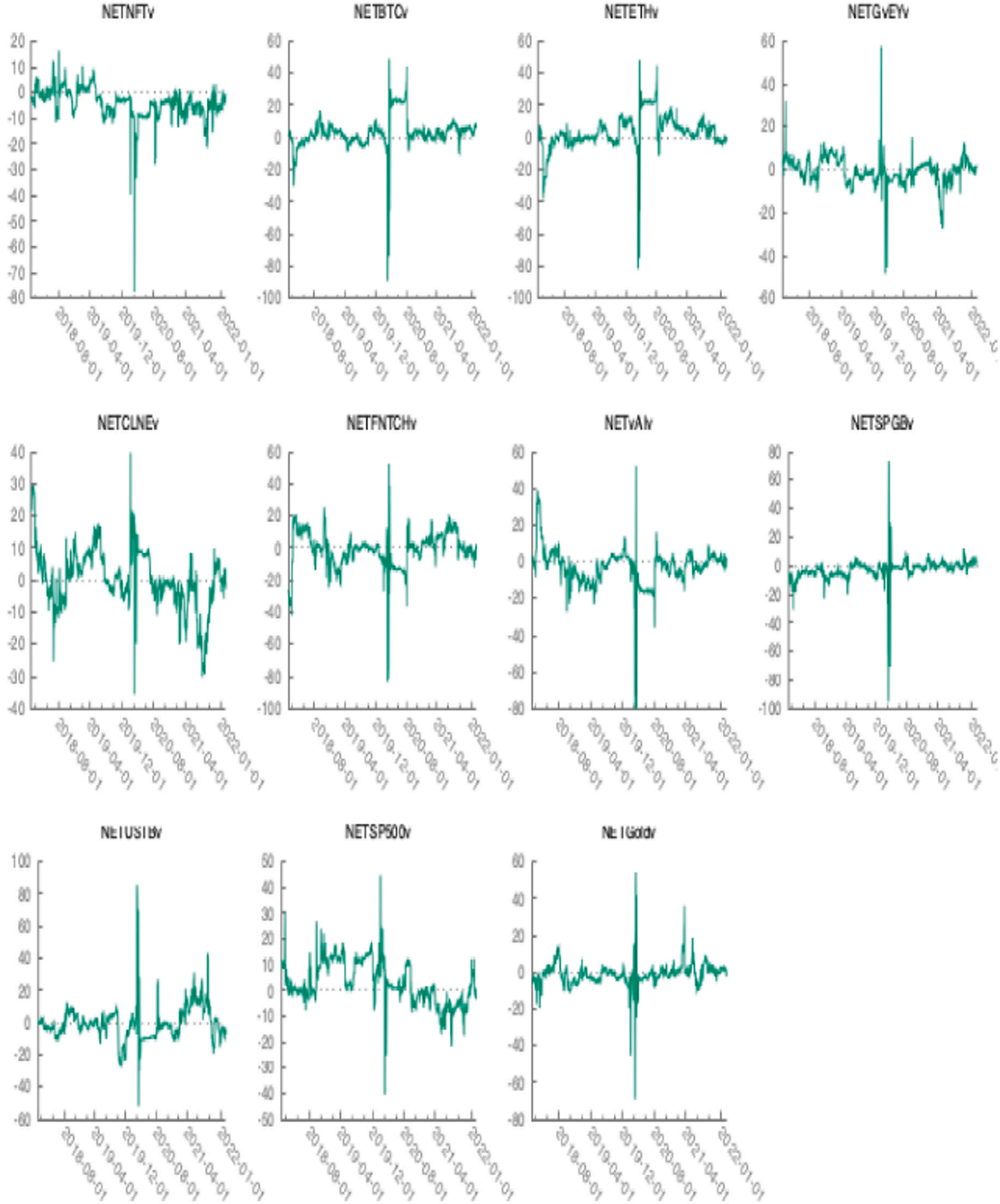


(b) Net pairwise volatility spillover during bearish market condition



© Net pairwise volatility spillover during bullish market condition

Fig. 7. Net pairwise volatility spillover during normal, bearish, and bullish market conditions. Note: Blue/yellow node denotes a pairwise transmitter/receiver of risks while the node sizes correspond to the level of risk received/transmitted.

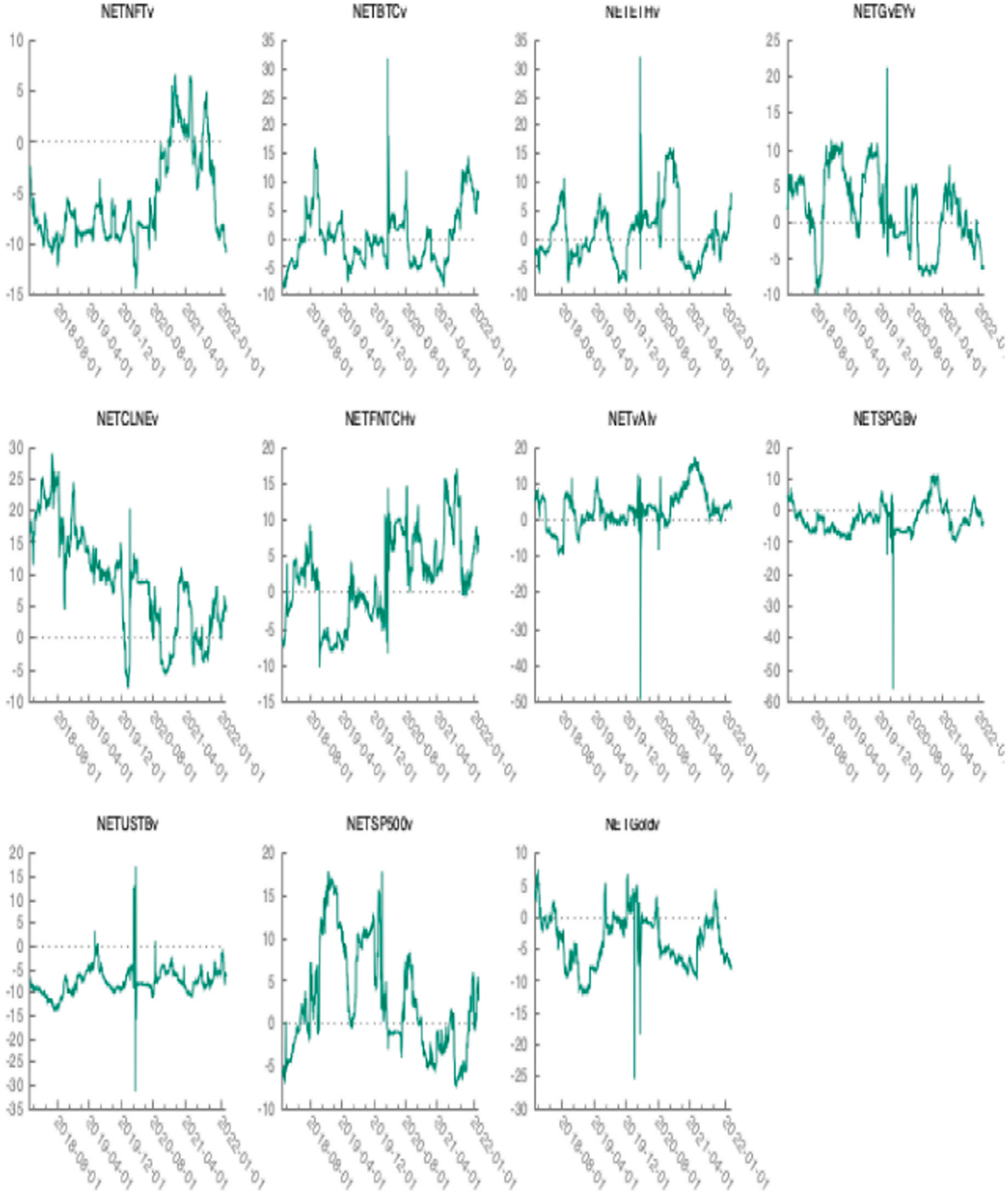


(a) Time varying net volatility spillovers during normal market condition

Fig. 8. Time-varying net volatility spillover during normal, bearish, and bullish market conditions.

Bitcoin (BTCr) markets, respectively.

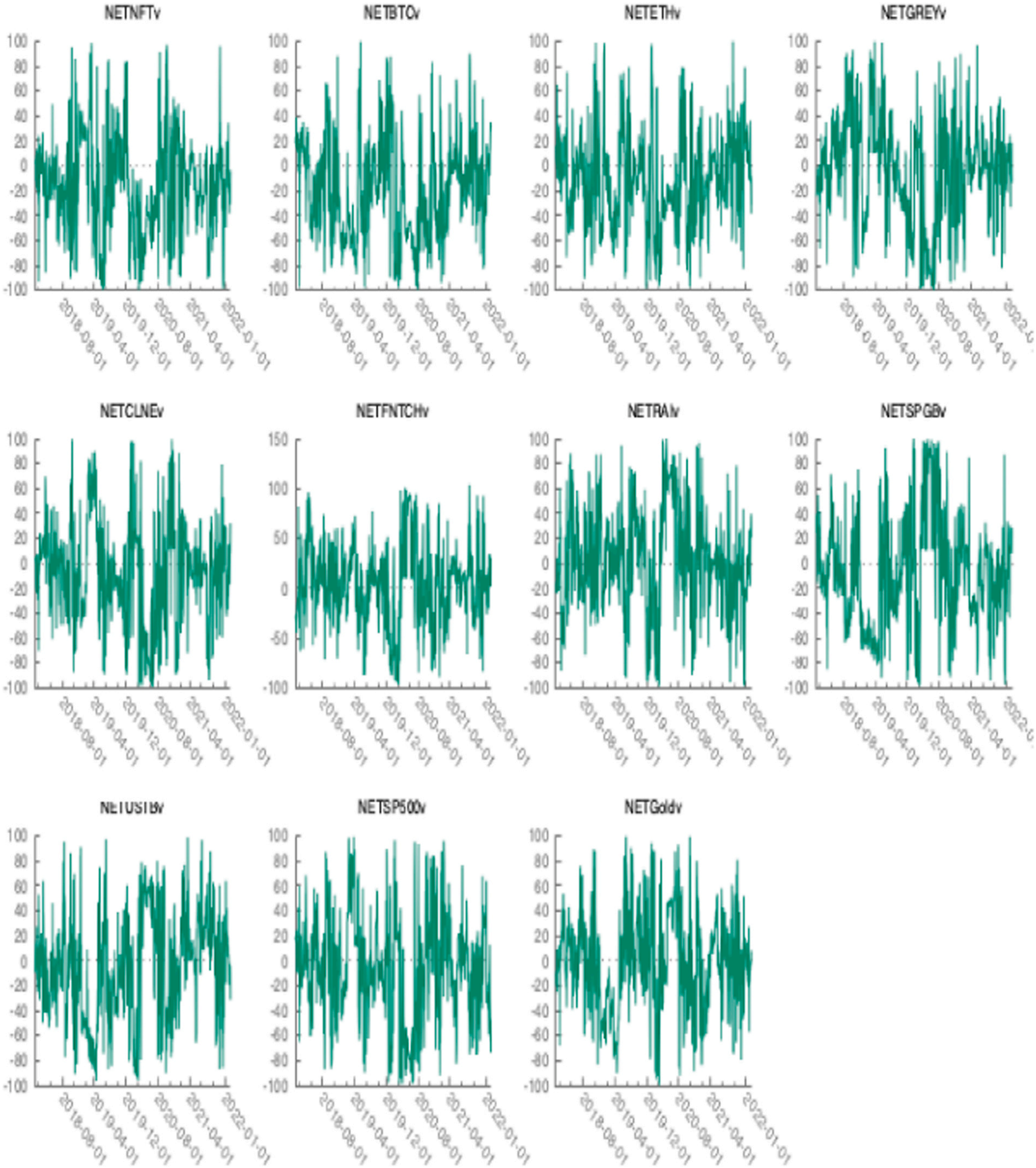
In contrast, while FinTech dominates risk spillovers in the system, especially towards Bitcoin, Ethereum, and artificial intelligence, the NFT market is relatively isolated from the system. This is shown by remarkably low levels of net directional pairwise spillover between the NFT and all the remaining assets in the system. This hints that the NFT may possess different features with very little



(b) Time varying net volatility spillovers during bearish market condition

Fig. 8. (*continued*).

variation 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 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



© Time varying net volatility spillovers during bullish market condition

Fig. 8. (*continued*).

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.

Fig. 5a, b, and c display the time-varying net return spillover between each asset and the system across the sample period for the

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)
Ω Mean	37.26	87.47	86.64	33.13	47.87	90.49
Ω Max	53.47	91.3	91.21	80.83	59.19	94.67
Ω Min	27.2	83.31	81.19	21.28	38.83	83.12
Ω 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: TCI refers to Total Connectedness Index; VIX, OVX, and GVZ are equity, oil, and gold market volatility indexes; Economic Policy Uncertainty (EPU) index; MOVE is the Bank of America Merril Lynch MOVE index; Term is term spread; ADS is the business condition index; GPRI is geopolitical risk index;; NFTVOL is the NFTs market's sales volume while COVID is the COVID-19 dummy. 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.

three market conditions. The three figures show significant evidence of a time-varying pattern, which becomes more pronounced under extreme market conditions. In all cases, the figures show that none of these assets is consistently a net receiver of shocks or net shocks transmitter across all the study period and market condition. Indeed, this implies that there are periods during which shocks from each asset are stronger than shocks sent from the system towards each asset and vice versa. There is a more remarkable increase in the switch from being net shocks transmitter to being net shocks receiver from the system for each asset during the first and second waves of the COVID-19 crisis and this is stronger for the bullish market conditions.

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 33.34 %, 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 bullish market periods, volatility shocks spread a bit more vigorously than their return shocks. Indeed, using the TVP-VAR framework, Yousaf and Yarovaya (2022a,b,c) 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. This may be explained in terms of the evolving pricing behavior of non-traditional asset classes such as NFTs, cryptocurrencies and other assets in our sample, which are still less efficient, with possible effects on the evolution of return and volatility spillovers across market conditions.

Further, unlike the return connectedness, the TCI for both the extreme market conditions show 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. Like 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 like 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 gray 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.

Fig. 6a, b, and c 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 it 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. Lastly, volatility connectedness (90.49) is a bit stronger than return connectedness (86.64) under bullish market conditions. This is not consistent with previous papers which show that return connectedness between NFT and other assets is higher than volatility connectedness. This may be explained from two fronts. First, previous papers such as Yousaf and Yarovaya (2022a,b,c) have employed empirical techniques that do not decompose the levels of connectedness into different market conditions. Indeed, we extend this literature by demonstrating that weaker volatility connectedness among NFTs and other assets is associated with market conditions. Secondly, this may be connected with the unique features and evolution of pricing behavior of non-traditional assets in our sample (especially, NFTs and cryptocurrencies), which is still not efficient.

Fig. 7a, b, and c present the network system of net directional pairwise connectedness among all the volatility series. The description of the figure is like that of Fig.4 a, b, and c. Like 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 traditional bonds (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.

Lastly, Fig. 8a, b, and c display the time-varying net volatility spillover between each asset and the network across the period covered and for the three market conditions. Like the time-varying net return spillover, the figures show strong evidence of a time-variation in the pattern of influence between each asset and the system especially under extreme market conditions. While in all cases the figures show that none of these assets is consistently a net receiver of shocks or net shocks transmitter across all the study period and market condition, some interesting patterns may be deduced. First, for both normal and bearish market periods, the NFT market appears to be a consistent net receiver of volatility shocks from the system except for brief periods during which it sent more shocks than it received from the system. This may also be said of the USTB, green bond and the gold market, especially during the bearish market state. However, such pattern is difficult to deduce under the bullish market condition due to high oscillations in the switch from being net shocks transmitter to being net shocks receiver from the system for all the assets across all the period of the study.

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 are a driver of small shocks and large positive shocks 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 predicts 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 NFT 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 coefficients show no evidence of statistical significance at all conventional levels.

A number of explanations may be offered regarding the mixed signs of the coefficients associated with these market factors across both return and volatility connectedness as well as market conditions. First, increase in the volatility of energy and fixed-income markets' volatility as well as heightened geopolitical tensions affect the rebalancing decisions of investors to allocate funds to non-traditional assets such as NFTs, cryptocurrencies and others in our analysis. This may increase the level of risk spillovers among existing traditional assets and new assets classes included in the portfolio. As expected, given the evolving pricing patterns and efficiency of new assets' markets, the effects of increase in traditional equity market volatility (VIX) is shown to matter for volatility connectedness only when the market condition is bullish. These results show that increased uncertainty of macroeconomic and financial conditions impacts positively on return and volatility connectedness among NFTs and other assets and that improvements in the global business condition as shown by the business conditions index will mostly decrease the level of shocks and spillovers. On the other hand, given the well-established role of gold as a safe-haven, increase in gold market volatility generally signifies an increase in attention and allocation of funds into the gold market, which is expected to decrease the connectedness among conventional and non-conventional assets that previously served as means of diversification strategy. Lastly, as hinted earlier, observed asymmetries in the magnitude and directions of effects of these market factors may be explained in terms of relative inefficiency in pricing patterns and the unique features of most of the assets in our sample.

5. Conclusion

This paper contributes to the growing literature on NFT by examining how return and volatility shocks are propagated among NFT and (un)conventional assets across different market conditions viz-a-viz the bearish, normal and bullish market conditions. It also examines the drivers of these shock propagation. 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. Secondly, we find that total return and volatility connectedness vary over time and that geopolitical risks, economic policy uncertainty, business environment condition, and uncertainties in the oil, gold, and fixed-income markets are important predictors of return connectedness. On the other hand, oil, gold, and fixed-income markets uncertainty, NFT volume, and business environment conditions significantly predict the time-varying total volatility connectedness.

Our results hold profound implications for several stakeholders, including investors and market participants who seek 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.

Moreover, 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.

Going forward, our work creates precedence for future studies. First is that the analysis thus far has been correlational. Future studies can focus on causal relation on the risk-return connectedness between the NFT and the assets under study, say, using the granger causality test. Future studies can also investigate the mechanisms that lead to the pairwise risk-return connectedness that are documented in our analysis and how this relationship differs across different market conditions and investment horizons. Indeed, analysis on the short, medium and long-run risk or return connectedness between NFT and other financial assets are yet to be analysed. Finally, whereas our results highlight the portfolio diversification roles of NFT, future studies could consider more sophisticated techniques to test the robustness of our findings. Future studies can consider using similar technique to derive the optimal portfolio weights, hedge ratios, and hedging effectiveness of NFT for the assets in this study as well as for different asset pairs. Finally, we only used squared returns over the relevant return horizon as a volatility measure. While this approach has the advantage that the volatility it provides is a model-free unbiased estimate, it is often noisy and it may limit reliable inference about the true underlying latent volatility.

CRediT authorship contribution statement

Khaled Guesmi: Writing – review & editing, Supervision, Software. **Gideon Ndubuisi:** Writing – review & editing, Writing – original draft, Software, Data curation, Conceptualization. **Christian Urom:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

There are no conflicts of interests regarding this study.

Data availability

Data will be made available on request.

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