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Volatility spillovers across NFTs news attention and financial markets

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ABSTRACT

The aim of this study is to investigate the volatility spillover connectedness between NFTs attention and financial markets. This paper firstly proposes a new direct proxy for the public's attention in the NFT market: the non-fungible tokens attention index (NFTsAI), based on 590m news stories from the LexisNexis News & Business database and applies the historical decomposition to assess the historical variations of the NFTsAI. Then the empirical analysis is performed via a TVP-VAR volatility spillover connectedness model. The empirical results show that NFTsAI indicates NFT markets are dominated by cryptocurrency, DeFi, equity, bond, commodity, F.X. and gold markets. And NFT markets are volatility spillover receivers. In addition, NFT assets could impede financial contagion and have significant diversification benefits. Employing a panel pooled OLS regression model as a supplementary analysis and a GARCH-MIDAS model as a robustness test. This study reveals that NFTsAI has sufficient power to explain the return of NFT assets from a fixed effect perspective, and NFTsAI contains useful forecasting information for both short and long-term volatility of NFT markets, separately. The new NFTsAI and the empirical findings contain useful insights for risk-averse investors, portfolio managers, institutional investors, academics and financial policy regulators.

1. Introduction

An non-fungible token (NFT) is a non-interchange and secure unit of data on a blockchain, and it is a type of digital ledger. An NFT can be associated with a piece of reproducible digital media, including but not limited to digital arts, texts, photos, videos, audio and even bits of code. Many scholars have highlighted the connections between NFTs and the art market (e.g., Low, 2021; Suvajdzic, Stojanović, & Kanishcheva, 2022; Valeonti et al., 2021; Valera, Valdés, & Viñas, 2021; van Haaften-Schick & Whitaker, 2021). That is why NFTs can also be called digital collectables. Their lack of interchangeability can significantly distinguish NFTs from other blockchain-based cryptocurrencies, such as Bitcoin, Ethereum and Tether. Compared with physical collectables, NFTs can be copied perfectly, and they can be used infinitely. Because a digital ledger can only offer a public certificate of authenticity or proof of ownership, it cannot keep the blockchain-based recording from being shared and copied. This characteristic could limit the inherent value of an NFT. In addition, the value of an NFT is also determined by its scarcity, quality, liquidity and the size of the collector communities.

The first known NFT, Quantum, was created in May 2014. Then, NFTs are gaining increased popularity, starting from some images of cute digital cats called CryptoKitties. In March 2021, a digital collage named 'Everydays – The First 5,000 Days' was sold as a *non-fungible token* at an incredible price, \$69.3m[1]. In May 2021, a flat in Kyiv was sold as an NFT, and it even was recognised by Ukraine's authorities[2]. In August 2021, NBA superstar Steph Curry jumped into the NFT market with his \$180,000 purchase of a Twitter profile photo[3]. The NFT market hit \$41bn in 2021, up from \$340 m in 2020[4]. These examples all show the crazy boom in the NFT markets. The NFT craze is similar to the initial coin offerings (ICO) in 2018 and the sneaker transaction mania in 2019, which were full of speculation and price bubbles. Some NFT asset prices are extremely decouple from their inherent value. However, with NFT creators and investors flooding into NFT markets, now, NFTs have already received growing attention from the finance academic community.

The growing finance literature related to NFTs can be concluded into two mainstreams. Many scholars first focus on the asset pricing fields of NFTsAI. For example, price mechanism (Aharon & Demir, 2021; Ante, 2022; Dowling, 2021a; Horky, Rachel, & Fidrmuc, 2022; Vidal-Tomás, 2022), portfolio management (Ko, Son, Lee, Jang, & Lee, 2022; Vidal-Tomás, 2022; Yousaf & Yarovaya, 2022), price bubble detecting (Maouchi, Charfeddine, & El Montasser, 2022; Vidal-Tomás, 2022; Wang, Lucey, & Vigne, 2022a), among others. The other

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[1] https://www.theverge.com/2021/3/11/22325054/beeple-christies-nft-sale-cost-everydays-69-million

[2] https://cryptonews.com/news/techcrunch-founder-to-sell-his-crypto-bought-kyiv-flat-as-an-10501.htm

[3] https://markets.businessinsider.com/news/currencies/steph-curry-nft-bored-ape-yacht-club-180000-ethereum-nba-2021-8

[4] https://www.ft.com/content/e95f5ac2-0476-41f4-abd4-8a99faa7737d

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stream concentrates on the inter-connections between NFT markets and other financial markets, by using Vector Error Correction Model (VECM) and Granger causality test (Ante, 2022), wavelet coherence analysis (Dowling, 2021b; Umar, Gubareva et al., 2022; Vidal-Tomás, 2022), and spillover connectedness framework (Aharon & Demir, 2021; Dowling, 2021b; Karim, Lucey, Naeem, & Uddin, 2022; Ko et al., 2022; Mazur, 2021; Yousaf & Yarovaya, 2022).

Considering that the NFT proxy is one of the key variables that could affect the empirical analysis findings, a reliable NFT proxy is important to get accurate results and provide useful information to decision-makers, economists, and investors. Numerous proxies have been selected to represent the NFT markets. Firstly, many contributions use hot NFT assets (Dowling, 2021a; Dowling, 2021b; Karim et al., 2022; Ko et al., 2022; Maouchi et al., 2022; Yousaf & Yarovaya, 2022). Secondly, several academic studies rely extensively on the average price of NFT sectors (Aharon & Demir, 2021; Umar, Gubareva et al., 2022). Thirdly, one study employs a capitalisation-weighted composite index, NFT index[5] (Wang et al., 2022a). Fourth, some studies creatively apply their own collected data-sets (Borri, Liu, & Tsyvinski, 2022; Horky et al., 2022; Pinto-Gutiérrez, Gaitán, Jaramillo, & Velasquez, 2022; Vidal-Tomás, 2022).

However, NFTs are traded infrequently, and they differ in terms of *quality*. This characteristic of NFTs makes the development of the NFTs price composite index difficult. Only employing hot NFT asset proxies or NFT average price proxies is not sufficient, as some studies show controversial conclusions, such as Dowling (2021b) and Vidal-Tomás (2022) draw a diametrically opposite result. Umar, Gubareva et al. (2022) also suggest to improve the findings of Aharon and Demir (2021). Therefore, the lack of consistent results in the NFTs finance area indicates we may need to consider a different NFTs proxy rather than the price indices. Da, Engelberg, and Gao (2011) state that investor attention can have an impact on asset pricing statics as well as dynamics. Moreover, developing a new measure of investor attention based on online database has been proved as an accurate and efficient approach (Chen, Tang, Yao, & Zhou, 2022; Da et al., 2011; Liu & Tsyvinski, 2021), including in the digital currency area (Lucey, Vigne, Yarovaya, & Wang, 2022; Wang, Lucey, Vigne, & Yarovaya, 2022; Wang, Lucey, Vigne, & Yarovaya, 2022b). In this way, following Lucey et al. (2022), this study innovatively develops and makes available a new qualitative-based NFT proxy–the NFT attention index (NFTsAI). It is based on 590m news stories collected from the LexisNexis News & Business database to track the public attention on the NFTs. The NFTsAI covers the key periods of the development of the NFT market and the most discussed events of this new asset in the media, i.e. from January 2017 to June 2022[6].

Financial spillover connectedness as a source of systemic risk and financial market instability (Diebold & Yılmaz, 2014). Investigating financial spillover connectedness could uncover information transmission channels and identify risk transmitters and receivers. From the perspective of policymakers, considering financial spillover connectedness could help to develop forward-looking monitoring regulations and to facilitate financial stability (Hamill, Li, Pantelous, Vigne, & Waterworth, 2021). This is why, as justified above, many existing studies related to NFTs have examined the spillover connectedness between various NFT proxies and financial markets. Based on this, this study proposes the following research question. *What are the volatility spillover connectedness between NFTs attention and financial markets?*. To address the research question, this study empirically examines the volatility spillover connectedness between NFTsAI and financial markets. By doing so, this paper could uncover new channels of volatility transmission between NFT markets and other financial markets by using NFTsAI as a new indicator and further explore the diversification opportunities.

This study begins the empirical analysis with a time-varying parameter-vector autoregression (TVP-VAR) model. The financial markets are selected for the volatility spillover connectedness analysis, including the NFT markets (NFTsAI, Decentraland and CryptoPunks), the DeFi market (Chainlink and Maker), cryptocurrency market (Bitcoin, Ethereum, and Bloomberg Galaxy Crypto Index [BGCI]), the stock market (FTSE All-World Index [FTSEAWI]), the bond market (FTSE World Government Bond Index [FTSEWGBI] and PIMCO Corporate & Income Strategy Fund [PIMCOCORP]), the commodity market (Invesco DB Commodity Index Tracking Fund [DBC]), the foreign exchange (F.X.) market (U.S. Dollar Index [DXY]), and the gold market (COMEX Gold). Weekly data series between January 2018 and June 2022 are utilised.

This paper contributes to the growing literature related to NFTs and attention index in the following ways. Firstly, assisted by the Latent Dirichlet Allocation (LDA) topic modelling, this study designs a much wider attention search string related to NFTs. This study proposes the Non-Fungible Tokens Attention Index (NFTsAI) based on 590m news stories from the LexisNexis News & Business database. Moreover, NFTs attention matters to the variations of NFT markets both statistically and economically, indicating the significant role of NFTsAI as a new indicator and highlighting the important role of public attention in the NFT markets in general. Second, to the best of my knowledge, this paper is the first to propose an NFTs attention index and comprehensively examine the volatility spillover connectedness between NFTsAI and other financial markets (NFTs, DeFi, cryptocurrency, stock, bond, F.X., commodity and gold). The main findings indicate that as a proxy for NFT markets, NFTsAI is consistently an essential volatility spillover receiver in the variable system. This study's results help discover new routes of risk transmission and explore new diversification opportunities relying on NFTs attention measure. Thirdly, this study steps further to investigate the internal mechanisms between the NFTsAI and NFT markets. This study explores the effects of NFTsAI on the NFT market by using a panel pooled regression model and a GARCH-MIDAS model. This study confirms that NFTsAI has sufficient power to explain the return of NFT assets and suggests that NFTsAI contains useful forecasting information for both short and long-term volatility of NFT markets, separately. In the end, in terms of the index construction methodology contribution, this paper enhances and completes the methods used to construct a new qualitative-based index. Although many studies have proven the efficiency of referencing internet databases or newspaper archives to develop and construct new measures of financial uncertainty or attention (Baker, Bloom, & Davis, 2016; Huang & Luk, 2020; Lucey et al., 2022; Smales, 2022 and Wang et al., 2022b), designing a reasonable search string to collect comprehensive data for these qualitative-based uncertainty or attention indices has remained a thorny and unresolved issue. This study proves that the LDA topic modelling could serve as a more suitable search string design method to substitute for the traditional brainstorming method. Because this text analysis-based tool can boost the exactness of the designed search strings by capturing, sorting and generating more comprehensive search queries.

The rest of this paper is structured as follows. The Section 2 outlines previous literature on NFTs, identifies research gaps and introduces hypothesis development. Section 3 describes the method of constructing the NFTs attention index, the data for the empirical analysis and the results of NFTsAI historical variation, while Section 4 introduces the econometric models used. Section 5 presents the empirical results and robustness tests. Finally, Section 6 reviews the main findings of this study and its practical and social implications. Moreover, this section cites the limitations of the study and offers ideas for future research.

[5] The NFTI is a capitalisation-weighted composite index designed to track the performance of the non-fungible token market. It is weighted based on each NFT asset's circulating supply value. Underlying NFT assets in the NFTI including Polygon (Matic), Enjin, Decentraland, Sand, Axie Infinity, Aavegotchi, Rarible, and Meme.

[6] The latest NFTsAI weekly data can be downloaded from https://sites.google.com/view/cryptocurrency-indices/home?authuser=0.

2. Literature review

2.1. Research gap identification

In the last past 12 months, NFT assets have gained significant attention and have become one of the most popular alternative investment instruments in 2022. More and more finance researchers are beginning to pay attention to the NFT research areas. Several papers concentrate on the asset pricing field of NFTs. By adopting the VECM model, Ante (2022) demonstrates that the shocks from Bitcoin prices could increase NFT sales and that active NFT wallets respond negatively to Ethereum price shocks. Furthermore, processing the Granger causality and IRF tests, Ante (2022) further finds that the NFT market has a long-run equilibrium relationship. Additionally, significant short-run relationships can also be found among NFTs' hot assets, which indicates that the NFT market has the endogenous shock characteristic—an empirical finding consistent with Aharon and Demir (2021). Recently, Vidal-Tomás (2022) shows that his own selected 174 tokens have positive performance in the long run. It is worth noting that both Dowling (2021a) and Aharon and Demir (2021) mention inefficiency in the pricing of the NFT markets. As for the price bubble detecting in the NFT markets, Maouchi et al. (2022), Vidal-Tomás (2022) and Wang et al. (2022a) all conclude there are periods of clear bubble behaviours in the NFT markets. Mazur (2021) first investigates the risk and return profiles of NFT-based startups by using data from the cryptocurrency exchange market. He suggests that NFTs can carry more benefits than traditional investment assets. Later, based on the CryptoPunks and hedonic regression model (Rosen, 1974), Kong and Lin (2021) construct an NFT market price level index in order to analyse the pricing and NFT risk-return conditions. They suggest that NFT assets can already be valued as new alternative investment tools and could outperform traditional financial assets—the same conclusion drawn by Mazur (2021). Furthermore, they also observe that an NFT asset's scarceness and an investor's aesthetic preference can significantly impact the pricing of NFTs. In addition, Kanellopoulos, Gutt, and Li (2021) investigate the effects of NFTs on the pricing of physical products. They use eBay data to measure the dynamic relationships between the prices of basketball trading card collectables and an NFT asset named 'NBA Top Shot (NTS)'. Their findings suggest that the introduction of the NTSs' NFT could negatively impact the prices of the collectables.

One significant stream of finance studies related to NFTs is the investigation of inter-relations between NFT asset class and other classic asset classes. Dowling (2021b), Umar, Gubareva et al. (2022) and Vidal-Tomás (2022) systematically examine the co-movements between NFT assets and other financial assets by employing the wavelet analysis. Umar, Gubareva et al. (2022) believe that the co-movements between NFTs and other assets only can hold in a short-term horizon, which can refine the findings of Aharon and Demir (2021). Furthermore, Vidal-Tomás (2022) observes that his own selected 174 tokens decouple with the cryptocurrency market, which argues with the findings of Dowling (2021b), who believes co-movement trend can hold between NFT and cryptocurrency markets. It is worth noting that spillover connectedness is the most popular methodology in the NFTs area, which use to examine the interconnections between the NFT markets and other financial markets.

Through applying the TVP-VAR approach, Aharon and Demir (2021) and Dowling (2021b) suggest that NFTs are relatively independent and isolated. Dowling (2021b) observes only limited volatility transmission effects among NFTs and cryptocurrencies. Aharon and Demir (2021) state the variations of their volatilities predominantly stem from the shocks of NFTs themselves, compared with the shocks from equities, bonds, currencies, gold, oil, and cryptocurrencies. Moreover, NFTs can be valued as transmitters of systemic risk during tranquil periods. However, NFTs can act as volatility spillover receivers during turbulent financial markets. This argument is supported by Mazur (2021), who find that the NFT markets contribute to the market's recovery following the mid-2021 crash. Additionally, Dowling (2021b) and Aharon and Demir (2021)'s findings are further confirmed by Karim et al. (2022), who present a strong disconnection of volatility spillover connectedness in NFT assets and other Blockchain markets by employing the quantile connectedness technique. Recently, Ko et al. (2022) and Yousaf and Yarovaya (2022) further use the TVP-VAR model to examine the volatility and/or return transmission between NFT, DeFi, cryptocurrency, stock, bond, U.S. dollar, and commodity markets. Both of them indicate that the new alternative asset class, NFTs, disconnect from other classic assets, which is also in line with the existing literature. As expected, all of the above studies suggest significant diversification benefits in the NFT asset class.

The existing studies related to NFTs which apply the spillover connectedness analysis have compared NFT assets with other financial assets, measured the correlation between NFT asset class with other asset classes, and detected the volatility and/or return spillover transmission channels between NFT markets and other classic financial markets. All of these studies utilise the average price of NFT assets or NFT sectors as proxies to represent NFT markets. However, an issue is that NFTs are traded infrequently, and they differ in terms of *quality*. Therefore, it is imperfect just to use average price to represent NFT markets, and it is also hard to construct a comprehensive composite NFT price index by simply looking at price differences like stock, bond and cryptocurrency composite indices. To address the issue just mentioned, this study proposes to construct a qualitative-based index to capture the public attention on NFTs as a proxy for NFT markets, as tapping newspapers or online database archives to develop and issue new measures of financial or economic activities is a widely used method and one whose accuracy and efficiency have been approved (Baker et al., 2016; Huang & Luk, 2020).

2.2. Hypothesis development

Social media has become a popular venue for the public to share minds on financial markets (Da et al., 2011). Several latest papers develop new measures of attention to the digital currency literature. For example, Urquhart (2018) investigates the attention of Bitcoin by using Google trends data and demonstrates that the attention of Bitcoin is impacted by the previous day's high realised volatility and volume of Bitcoin. Then, Shen, Urquhart, and Wang (2019) examine the interconnections between investor attention and Bitcoin based on the Twitter trends, suggesting the Twitter trends can predict the next day's trading volume and realised volume of Bitcoin. Recently, Liu and Tsyvinski (2021) construct investor attention proxies for cryptocurrency based on Google trends. This research indicates that high investor attention on cryptocurrency could predict high future returns over the one-to six-week horizons. Still, in the cryptocurrency area, Wang et al. (2022) collect data from LexisNexis News & Business, and develop cryptocurrency environmental attention index (ICEA). This study measures the relative extent of media discussions surrounding the environmental concerns on the volatility of cryptocurrency market. In other digital currency areas, Wang et al. (2022b) develop the CBDC attention index (CBDCAI) based on the LexisNexis News & Business database and reveal the market reactions to central bank speeches. Therefore, this study decides to construct a new NFT proxy, named NFTs Attention Index (NFTsAI), based on texting mining to reflect the public attention on NFTs for investors, policymakers and academics. Moreover, the general consensus from the studies related to investor attention is that an attention measure and the target market for this attention measure could hold causality; co-movement relationships or spillover effects (Barber & Odean, 2008; Da, Engelberg, & Gao, 2015; Peng & Xiong, 2006). These papers inspire me to suppose that statistically and economically relationships may exist among NFT markets and the public attention related to NFT assets. Based on this, I propose hypothesis 1:

H_1: NFTsAI has financial linkages with the NFT markets.

Referring to the latest studies about NFTs by using the TVP-VAR framework, they all suggest that NFT asset class is relatively isolated by other asset classes (Aharon & Demir, 2021; Dowling, 2021b; Karim et al., 2022; Ko et al., 2022; Yousaf & Yarovaya, 2022). This interesting finding inspires me to further explore volatility transmission between the NFT markets and other financial markets by using NFTsAI as an indicator to represent the NFT markets, via the TVP-VAR framework. First, because the TVP-VAR framework is the most widely used econometrics model to evaluate the efficiency of a new issued qualitative-based index, from the well-known Economic Policy Uncertainty Index (EPU) (Baker et al., 2016), to the latest digital currency indices (Lucey et al., 2022; Wang et al., 2022; Wang et al., 2022b). Second, the TVP-VAR model can estimate the volatility transmissions in both the static and time-varying two perspectives, which allows one to discover new channels of risk transmission between the emerging NFT markets and other financial markets. Furthermore, based on the theory of Akyildirim, Corbet, Sensoy, and Yarovaya (2020), Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) and Yousaf and Yarovaya (2022), which suggest the emerging investment assets could show a significant disconnection with other classic investment instruments because of the investment information asymmetry. NFTsAI as a new proxy to reflect investor attention on the NFT asset class. I, therefore, propose hypothesis 2:

H_2: The intensity and magnitude of volatility spillover from other financial markets to NFTsAI are higher than from NFTsAI to other financial markets.

2.3. Financial market selection

This research tries to investigate the connectedness between NFTs attention and financial market volatility. Therefore, the first financial market I want to focus on is that of NFTs. Pinto-Gutiérrez et al. (2022) study the linkages between cryptocurrency returns and NFT attention. They construct the NFT attention proxies in the Google search by using 'non-fungible token', 'NFT', 'Cryptopunk' and 'Decentraland' these four terms, separately. However, Pinto-Gutiérrez et al. (2022) just construct the NFT attention proxies in single or double search terms, not a multi-dimensional search string. Therefore, these NFT attention proxies may not capture the actual social attention on the NFTs in a comprehensive way. Moreover, Pinto-Gutiérrez et al. (2022) only focus on the effects of the NFT attention on the cryptocurrency returns but fail to explain the interconnections between the NFT attention proxies and NFT assets. Motivated by these gaps, this paper tries to study the connectedness between the NFTs attention and NFT markets.

As another special type of digital currency, DeFi tokens are always investigated with NFTs together (Karim et al., 2022, Maouchi et al., 2022, Yousaf & Yarovaya, 2022). All of these studies believe diversification avenues exist in a portfolio containing both DeFi and NFT assets. Based on this, this study comprises the DeFi market, secondly.

Thirdly, NFTs fall within the category of crypto collectables, which are based on Blockchain technology (Regner, Schweizer, & Urbach, 2019), and it is widely known that NFTs are secondary assets derived from the cryptocurrencies (Dowling, 2021b). One of the crucial reasons behind the soaring NFT asset prices could be the broad cryptocurrency enthusiasm. Therefore, NFTs can also be valued as crypto assets. Moreover, Dowling (2021a) indicates that the price mechanism and market trading behaviours of NFTs are similar to those of cryptocurrencies. Accordingly, I could suppose that NFTsAI might have a significant relationship with the cryptocurrency market.

NFTs are attracting investors due to their high speculation and fluctuation, which can bring a high return on investment (ROI). Yousaf and Yarovaya (2022) highlights that investors have valued NFTs as essential alternative assets, which can diversify their portfolios. Moreover, Karim et al. (2022) and Ko et al. (2022) believe that NFT assets have shown the characteristics of the classic financial markets, which can bring high volatility and high return, and also can transmit risks to other financial markets. Therefore, the inter-linkages between NFTs and other classic financial sectors from investment perspectives can be confirmed, for example stocks (Aharon & Demir, 2021; Ko et al., 2022; Pinto-Gutiérrez et al., 2022; Umar, Gubareva et al., 2022; Yousaf & Yarovaya, 2022) , commodities (Aharon & Demir, 2021; Ko et al., 2022; Umar, Gubareva et al., 2022; Yousaf & Yarovaya, 2022), bonds (Aharon & Demir, 2021; Ko et al., 2022; Umar, Gubareva et al., 2022), F.X. (Aharon & Demir, 2021; Ko et al., 2022) and gold (Aharon & Demir, 2021; Ko et al., 2022; Pinto-Gutiérrez et al., 2022; Umar, Gubareva et al., 2022). As justified above, investor attention indices have been proved to be statistically and economically significant in the financial markets (Da et al., 2011; Han, Lv, & Yin, 2017; Pinto-Gutiérrez et al., 2022; Vozlyublennaia, 2014; Wang et al., 2022). Therefore, there are enough theoretical and empirical supporting to allow me to investigate the transmission effects between the relative extent of media discussions surrounding NFT assets and the other classic financial markets. For these reasons, I further include the stock, commodity, bond, F.X., and Gold markets.

3. Data

3.1. NFTs Attention Index data collection

The NFTsAI is an index established on text mining, meaning that the core of its construction involved designing a rigorous and comprehensive search string to collect the necessary data. Moreover, as an attention index, it is necessary for me to gather as many relevant terms about NFTs as possible so as to capture and reflect their trends. Based on certain bibliometric studies (Aria & Cuccurullo, 2017; Corbet, Dowling et al., 2019), I choose academic papers as the optimal places for locating key terms for the NFTsAI search string due to their being straightforward, concise, and professional. Furthermore, due to its ability to extract topics from a given corpus, the LDA topic modelling is also helpful for deciding which terms could be selected for the NFTsAI search string (Blei, Ng, & Jordan, 2003). Therefore, I use [(('NFTs') AND ('Non-fungible tokens'))] to search academic papers from Scopus and then export all the corpora. Due to the many unpublished working papers about NFTs on SSRN, I also apply the web crawler to download these corpora. Finally, I combine these corpora from Scopus and SSRN, run them into a bibliometrics analysis, and sort them into a LDA topic modelling—the results of which are shown in Table 1[7].

The LDA topic modelling reveals the first topic about the official name and the abbreviation of 'Non-fungible tokens'. The second, third, and the fourth are related to the aliases of 'Non-fungible tokens'. Finally, the last topic refers to hot NFT assets and popular NFT trading platforms[8].

Combining all of the terms from topic 1 to topic 5 allows me to generate the final searching string for NFTsAI. Once done, I input the search string into the LexisNexis News & Business and collect data for the NFTsAI. As justified in the literature review, I follow (Lucey et al., 2022; Wang et al., 2022b) in using LexisNexis News & Business as the index's database. Indeed, I choose LexisNexis News & Business because it is a multi-region and multilingual source. Moreover, it can cover a wide range of sources, including the latest news articles, publication archives, and blogs.

I select 01/01/2017 as the start point for constructing the NFTsAI because only one NFT can be traced back to 2015 (the Etheria launched

[7] Plots and statistic results about the bibliometric analysis and the LDA topic modelling are not reported here for the sake of brevity. All the details are available upon reasonable request.

[8] I should note here that I have excluded all technical words, such as 'market', 'connectedness', and 'investor' from the LDA topic modelling results. I do so to optimise the results and make the final search string closer to 'Non-fungible tokens'.

Table 1
NFTsAI search string.

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
("Non-fungible tokens") ("NFTs")	("digital art") ("crypto art") ("cryptocurrency art") ("artwork tokenised") ("digital image licensing")	("digital collectibles") ("crypto collectibles") ("cryptocurrency collectibles")	("digital identity") ("IdToken") ("token unique") ("unique digital property")	("CryptoKitties") ("WCK") ("CryptoPunks") ("Axie Infinity") ("Bored Ape Yacht Club") ("The Sandbox") ("Art Blocks") ("nonfungible.com")

Notes: This table reports the search string for the NFTs attention index. Assisting by LDA topic modelling, 5 topics are sorted. Topic 1 relates to the official name and the abbreviation of Non-fungible tokens. Topic 2, 3 and 4 correspond to the aliases of Non-fungible tokens. Topic 5 refers to popular NFT assets and platforms. Importing this search string to LexisNexis News & Business, 590 million news items can be collected between January 2017 and May 2022.

on 21/10/2015). Furthermore, according to data from nonfungible.com – many hot NFTs were issued in 2017 (e.g., Curio Card, CryptoPunks, Moon Cats, and Decentraland). I build the NFTsAI using weekly data, and the reasons are as follows. First, Dowling (2021a) confirms that the NFT market is inefficient and rapidly rising in value. These findings indicate there to be market manipulations in NFT pricing, fraudulent behaviours and speculative transactions in NFT markets, thus leading to many price bubbles. Second, NFTsAI, a text mining-based index, is subject to extreme fluctuations (Wang et al., 2022). Due to these reasons, if I had constructed the NFTsAI in a high-frequency index (i.e., 5 Minutes/30 Minutes/Daily), it would have been filled with outliers and could not have shown the real trend of public attention on the NFT markets. Moreover, the famous text mining-based indices, such as EPU (Baker et al., 2016), China EPU (Huang & Luk, 2020), UCRY indices (Lucey et al., 2022), and CBDC indices (Wang et al., 2022b) are all low-frequency indices (i.e., weekly/monthly).

3.2. NFTs Attention Index construction

Following the index construction methodology of Lucey et al. (2022), Wang et al. (2022, 2022b)[9], NFTsAI can be expressed as Eq. (1):

$$NFTsAI_t = \left(\frac{N_t - \mu}{\sigma}\right) + 100, \tag{1}$$

where NFTsAI_t is the value of the NFTs attention in the week t between January 2017 and May 2022. N_t is the weekly observed value of news articles on the LexisNexis News & Business database concerning NFTs attention. If the searched terms from Table 1 appear in one article's title, keywords, main content, or the other parts, I will collect this article and record it as one unit for N_t. μ is the mean value of the collected articles related to NFTs attention range from 26/12/2016 to 05/06/2022. I collect 292,498 articles concerning NFTs attention in total from LexisNexis News & Business database, and there are 284 weekly observations between 26/12/2016 to 05/06/2022. Therefore, $\mu = 292,498/284 = 1,029.9225$. σ is the standard deviation value of such, which is equal to $1,710.3515$. Adding an average value of 100 to eliminate the potential negative impacts caused by the overall volume of articles varies across publication sources and time.

Fig. 1 shows the weekly values for the derived indices based on 590,440,560 news items collected between January 2017 and May 2022. This study also annotates which NFT flash events cause spikes on the NFTsAI in Fig. 1 and the flash events are collected according to the frequency of articles that have the same topic. These annotated events allow readers to understand new NFT developments or major events that could stimulate the newly-constructed NFT index. From the plot, NFTsAI can divide the developments of NFTs into five stages. It is worth noting that the highest value of NFTsAI is recorded in the fourth stage, wherein some hot NFTs events like the Sandbox reached a market capitalisation of \$648.35 million, Bored Ape Yacht Club 58,118% ROI, and an NFT sales volume of \$3 billion significantly heighten the NFTsAI. These events serve to indicate the NFT market's extreme prosperity and heat during this period[10].

3.3. Financial market variables' selection

Based on the research question, this study tries to investigate the volatility transmission between NFTsAI and financial markets. Therefore, this research firstly includes the average price of Decentraland and CryptoPunks, these top two most liquid and prominent NFT assets to represent the NFT markets[11]. NFTs are traded infrequently, and they differ in terms of quality, so some scholars suggest that we cannot simply look at price differences (Borri et al., 2022). However, NFTs can be divided and fractured, indicating that one NFT market price index could be constructed by adding partial shared ownership for this corresponding token in any market (Ko et al., 2022). Therefore, we can have strong evidence to utilise the average price of one popular NFT as a proxy to represent the NFT market. The existing literature of Dowling (2021a, 2021b), Karim et al. (2022), Ko et al. (2022), Maouchi et al. (2022), Pinto-Gutiérrez et al. (2022) and Yousaf and Yarovaya (2022) are all use average price of popular NFTs to represent the NFT markets[12]. Moreover, Wang et al. (2022a) creatively propose that NFT index from coinmarketcap.com can be valued as a NFTs capitalisation-weighted composite index. However, the NFT index is only available from March 2021, which cannot provide enough low-frequency observations for this study. Therefore, I exclude the NFT index.

Following the variable selection strategy similar to NFT assets' selection, I secondly select the Chainlink and Maker to represent the DeFi market. The rationales behind selecting Chainlink and Maker are also due to their trading volume and the maximum availability of data. The capitalisation-weighted composite index DeFi indices, DeFi Index from coinmarketcap.com and Bloomberg Galaxy DeFi Index are also excluded because of their limited available low-frequency observations.

I thirdly select Bitcoin as a primary variable to represent the cryptocurrency market due to it being the most popular cryptocurrency (Corbet, Lucey et al., 2018; Hossain, 2021; Klein, Pham Thu, & Walther, 2018). Bitcoin has the highest price, sales volume, and market capitalisation (Demir, Gozgor, Lau, & Vigne, 2018). Furthermore, Bitcoin tends to be viewed as a proxy for measuring the cryptocurrency

[9] For the sake of brevity, the index construction methodology will not be fully explained here. More details can be found in Lucey et al. (2022), Wang et al. (2022, 2022b).

[10] For more details about the NFTsAI and relevant big events, please see the *Appendix A - Big events related to NFTs*.

[11] The trading volume statistic decides the top two most liquid and prominent from www.nonfungible.com.

[12] Average price of NFTs in these papers. Dowling, 2021b: Decentraland, CryptoPunks, and AxieInfinity. Dowling, 2021a: Decentraland. Yousaf & Yarovaya, 2022: THETA, Tezos, EnjinCoin, Decentraland, and Digibyte. Ko et al., 2022: Sandbox, Decentraland, and CryptoPunks. Maouchi et al., 2022: THETA, Enjin Coin, and Decentraland. Pinto-Gutiérrez et al., 2022: CryptoPunks and Decentraland. Karim et al., 2022: Theta, Tezos, Enjin Coin, Decentraland, and Digibyte.

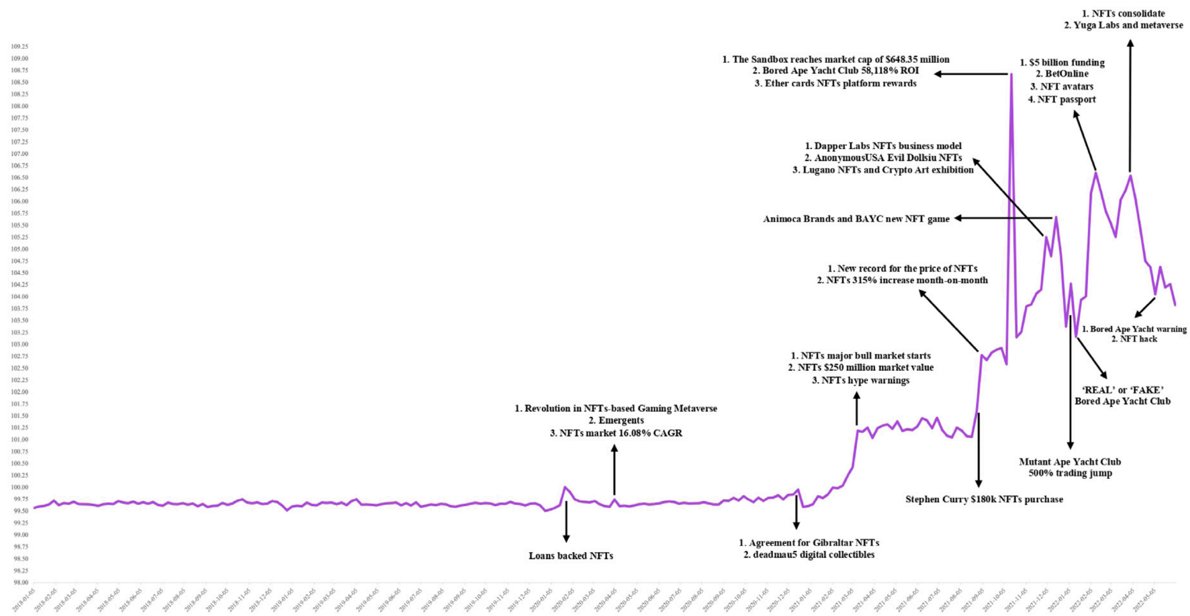

Fig. 1. NFTs Attention Index with annotated events.
Notes: This index reflected scaled weekly counts of articles containing 'Non-fungible tokens' OR 'NFTs' OR 'digital art' OR 'crypto art' OR 'cryptocurrency art' OR 'artwork tokenised' OR 'digital image licensing' OR 'digital collectibles' OR 'crypto collectibles' OR 'cryptocurrency collectibles' OR 'digital identity' OR 'IdToken' OR 'token unique' OR 'unique digital property' OR 'CryptoKitties' OR 'WCK' OR 'CryptoPunks' OR 'Axie Infinity' OR 'Bored Ape Yacht Club' OR 'The Sandbox' OR 'Art Blocks' OR 'nonfungible.com'. This series is standardised and then 100 from 26/12/2016 to 05/06/2022 based on queries. LexisNexis News & Business is the selected database. Flash events related to NFTsAI are annotated on the time series plot. Flash events are collected according to the frequency of articles that have a similar topic during week t.

market (Corbet et al., 2018). NFTs are based on the algorithm of Ethereum (Chirtoaca, Ellul, & Azzopardi, 2020), which is also one of the most popular cryptocurrencies (Corbet, Lucey et al., 2019). Therefore, I list Ethereum as another cryptocurrency proxy. The BGCI seeks to assess the performance of the largest cryptocurrencies traded in USD (Umar & Gubareva, 2020). BGCI is a comprehensive market capitalisation-weighted index that can track the cryptocurrency market (Häusler & Xia, 2021). Accordingly, BGCI is included.

In the end, as justified in the literature review part, to investigate the connectedness between the NFTs attention and financial markets. I not only include NFT, cryptocurrency and DeFi these three digital currency markets, but I also consider the stock, bond, commodity, F.X., and gold as aiming financial markets. Following the selected variables in the existing literature about NFTs, I include FTSEAWI (Aharon & Demir, 2021; Ko et al., 2022; Umar, Gubareva et al., 2022), FTSEWGBI (Umar, Gubareva et al., 2022), PIMCOCORP (Aharon & Demir, 2021; Ko et al., 2022), DBC (Ko et al., 2022), DXY (Aharon & Demir, 2021; Ko et al., 2022), and COMEX Gold (Aharon & Demir, 2021; Pinto-Gutiérrez et al., 2022; Umar, Gubareva et al., 2022; Yousaf & Yarovaya, 2022) to represent stock, government bond, corporate bond, commodity, F.X. and gold markets, respectively.

As the NFT markets are beginning to emerge, it necessary to extend the research period to collect more data to ensure the results' accuracy. The time span of this study ranges from 05/Jan/2018 to 03/June/2022. The reasons for selecting this sample period are as follows. Firstly, the data of all the selected financial variables, including the NFTsAI, are available from this date. Secondly, this time interval comprises the bull and turbulent periods in the cryptocurrency, DeFi and NFT markets. In the end, this sample period includes the 2018 financial crisis and recent pandemics. These special events mentioned above could have significantly influential connectedness among financial markets. The data related to the NFT and DeFi assets are obtained from nonfungible.com and coinmarketcap.com, separately. I obtain the BGCI from the Bloomberg database and download Bitcoin, Ethereum, FTSEAWI, FTSEWGBI, PIMCOCORP, DBC, DXY and COMEX Gold data from Thomson Reuters.

3.4. NFTsAI evolution

NFTsAI is a newly issued index. In order to assess the characteristics of the NFTsAI and prove it can be deeply used do to further empirical analysis. It is essential to analyse the historical evolution of NFTsAI and the contribution of each of the structural shocks to variations in NFTsAI following significant historical episodes. Therefore, this study decomposes the historical variations of NFTsAI by following the methods of Lucey et al. (2022); Wang et al. (2022, 2022b)[13].

Fig. 2 shows the historical variations of NFTsAI with annotated events[14]. The variations of NFTsAI are highlighted in purple. To identify NFTsAI disturbances' cumulative contributions, this study sets the historical variations of NFTsAI on the right-hand axis as a secondary axis. Historical variations of the other variables' are on the left-hand axis as the primary axis. NFTsAI is constructed based on text mining, so historical decomposition analysis in the NFTsAI takes significant historical episodes as the entry point. Several novelty findings are highlighted in the following sections:

First, there is a trend of the representative of the NFT market, CryptoPunks and Decentraland, co-move with NFTsAI. This finding suggests that the higher the NFTs attention, the higher NFT asset volatility. This finding also proves that NFTsAI can serve as an NFT market proxy. In this way, H_1 can hold. Second, the historical variations of NFTsAI reasonably match exceptions. The positive news concerning the NFT markets produces a positive shock on the historical variations of NFTsAI, and the negative news concerning the NFT markets contributes to a negative shock in the results. For example, NFTs' $2.5 billion sales volume and 315% trading volume increased month-on-month; Bored Ape Yacht Club's 58,118% return on investment, are positive news events reflecting the prosperity of the NFT market, which, in

[13] For the sake of brevity, the historical decomposition methodology will not be fully explained here. More details can be found in (Lucey et al., 2022; Wang et al., 2022, 2022b).

[14] The details of these events are listed in the *Appendix A - Big events related to NFTs*.

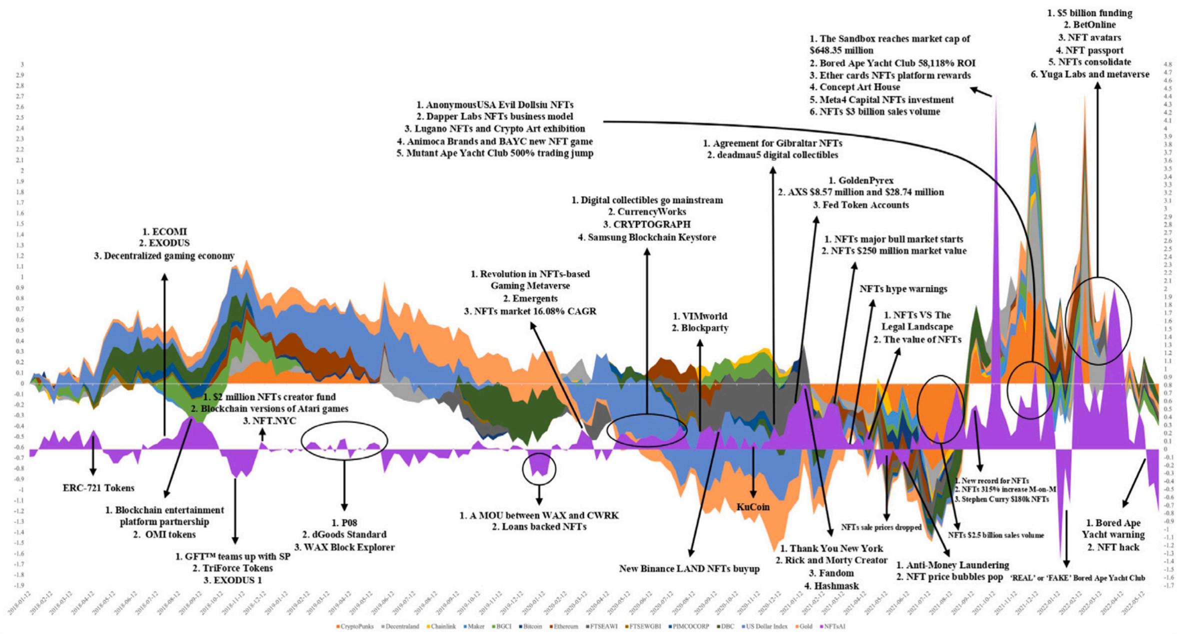

Fig. 2. NFTs Attention Index historical decomposition.

Notes: The horizontal axis represents the time sample period, and the vertical axis represents the variations of NFTsAI, CryptoPunks, Decentraland, Chainlink, Maker, BGCI, Bitcoin, Ethereum, FTSEAWI, FTSEWGBI, PIMCO CORP, DBC, US Dollar Index and COMEX Gold volatility in per cent after NFTsAI shocks. Lag = 1. The variations of NFTsAI are highlighted in purple. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

turn, cause significant spikes in the historical variations of NFTsAI. Following NFT market hype warnings, NFT sale prices dropped, new regulations on anti-money laundering concerning trading NFTs were implemented, NFTs price bubbles popped, and the NFT platform was hacked. These negative news events reveal that the volatility and uncertainty of the NFT markets can cause the historical variations of NFTsAI to plummet. Third, the historical variation results of the NFTsAI show a volatile trend between January 2021 and June 2022. There are three potential reasons for this. Firstly, with the development of the NFT markets since 2021, more investors have seized the speculation opportunities of the NFT markets. These kinds of speculation activities in the NFT markets contribute to the volatilities of NFT markets. Secondly, the volatility cryptocurrency markets also contain a significant amount of cryptocurrency uncertainties between January 2021 and June 2022 (Lucey et al., 2022). These cryptocurrency uncertainties could transmit to the NFT markets as the speculators will reduce their net long positions in cryptocurrencies and search for alternative digital assets to hedge the uncertainty from cryptocurrency markets. These behaviours may affect the trading volume of NFT assets and bring more speculation activities to NFT markets, causing further volatilities in the NFT markets. Thirdly, NFT assets can be valued as digital art assets, and art markets always show volatility during periods of financial uncertainty (Rezaee & Sequeira, 2021).

4. Methodology

Many econometrics models can measure the interconnections between different financial markets. In the digital currency area, wavelet analysis, DCC-GARCH, and VAR are the three most popular and efficient models used to achieve this goal (Wang et al., 2022b). This study applies the TVP-VAR model for the volatility spillover connectedness analysis. First, because the TVP-VAR model can estimate the volatility transmissions in both the static and time-varying two perspectives[15]. With the help of the volatility spillovers in the time domain, the effects of flash events on volatility spillovers can be uncovered. Second, TVP-VAR model can capture the dynamic interconnections with a small and low-frequency dataset because the econometrics framework is based on variance decomposition of the prediction error (Primiceri, 2005; Diebold & Yilmaz, 2009; Diebold & Yilmaz, 2012; Hamill et al., 2021)[16]. NFT markets are still in their infancy, meaning that the research period is relatively short—not to mention that the NFTsAI is a weekly-frequency index based on text mining. Therefore, these limitations mean that this study has to use a short time period and low-frequency dataset, which matches the TVP-VAR model's characteristics. In the end, the TVP-VAR model allows one to examine bidirectional volatility spillover connectedness because it can achieve (a) Totally volatility spillover analysis, (2) Net directional volatility spillover analysis, (3) Directional volatility spillover from each variable to all others, (4) Directional volatility spillover to each variable from all others, (5) Net pairwise directional volatility spillover[17]. By using the TVP-VAR model, this study can examine the effects of NFTsAI on financial markets and capture the impacts of the financial markets on NFTsAI.

4.1. *Spillover connectedness in time domain*

A vector autoregression (VAR) is a standard econometric model used within a wide range of financial analyses, especially for characterising dynamic relationships (Lütkepohl, 2005). Based on the VAR framework proposed by (Sims, 1980), Primiceri (2005) further includes stochastic

[15] GARCH models only can capture the static volatility linkages.

[16] GARCH models are based on the ARCH model. In this case, the conditional variance trend can rapidly fade—requires a high order of the stochastic process when measuring the conditional variance of a time series over time (Andersson-Säll & Lindskog, 2019). Furthermore, the wavelet analysis suffers from insufficient stage information, poor directionality, and shift sensitivity (Fernandas, Van Spaendonck, & Burrus, 2003). Although a few optimisation wavelet transformations can significantly reduce these disadvantages, this requires a high frequency and a large volume of data.

[17] While GARCH model and VAR-IRF (Impulse Response Function), FEVD (Forecast Error Variance Decomposition) and HD (Historical Decomposition) tests only can capture the unidirectional volatility spillover connectedness.

volatility into it, thus creating the TVP-VAR model. This model can measure prolonged time variation in the VAR model by applying coefficients and variance–covariance matrix (Nakajima et al., 2011). The TVP-VAR model framework can be denoted as follows Eq. (2):

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_{p-1} y_{t-(p-1)} + \Delta y_{t-p} + \Xi^{+} D_t + u_t, \tag{2}$$

where y_t is a $K \times 1$ dimensional vector of variables observed at time t. $A_1, A_2, \ldots, A_{p-1}, A_p$ are $K \times K_p$ time-varying parameter coefficient matrix. D_t is a time-varying parameter vector of deterministic terms, and Ξ^{+} is the time-varying parameter coefficient matrix corresponding with D_t. u_t is a k-dimensional unobservable zero mean vector white noise process, and has the covariance matrix Σ_u. u_t also denotes the reduced form disturbance.

In order to investigate the time-varying volatility spillover connectedness between the NFTsAI and financial markets. I establish a variable system based on Eq. (2), which includes the 14 variables justified and selected in Section 3, each of which has 230 observations. Moreover, I calculate the optimal lag based on the AIC, HQ, SC, and FPE information criteria. Finally, the baseline VAR specification includes one lag of all variables[18]. To assess the TVP-VAR spillover connectedness, three more procedure calculations are required:

4.1.1. Convert TVP-VAR to TVP-VMA

First, this study needs to convert the TVP-VAR model into a time-varying parameter vector moving average (TVP-VMA) representation in order to compute the impulse response function (IRF) and forecast error variance decomposition (FEVD), which can be written as follows Eq. (3):

$$y_t = u_t + \sum_{i=1}^{\infty} \Phi_i u_{t-i}, \Phi_0 = I_k, \tag{3}$$

where u_t is a k-dimensional unobservable zero mean vector white noise process and has covariance matrix Σ_u. $\Phi_i = J A^i J'$ and $J = [I_k : 0 : 0 : \cdots : 0]$. A^i are summable.

4.1.2. Derive IRF from TVP-VMA

Second, based on the TVP-VMA in Eq. (3), the IRF could trace the marginal effect of a shock to one variable by counterfactual experiment. Indeed, the IRF for each variable j on variable i can be computed as Eq. (4):

$$IRF = \sum_{p=0}^{\infty} (e_i' A_p \sum e_j)^2, \tag{4}$$

where both e_i' and e_j are fundamental $N \times 1$-dimensional vectors with unity at i and j, separately. A is still the $K \times K_p$ time-varying parameter coefficient matrix. The impulse response is equal to the cumulative forecast error from a shock to the variable i from j at time t-p.

4.1.3. Compute FEVD using the IRF

Third, the forecast error variance of the kth element of the forecast error vector can be denoted as Eq. (5):

$$E(y_{j,t+h} - y_{j,t}(h))^2 = \sum_{j=1}^{K} (\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2), \tag{5}$$

where $\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2$ can represent the contribution of the jth ε_t innovation to the h-step forecast error variance of variable k. $\frac{\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2}{E(y_{j,t+h} - y_{j,t}(h))^2}$ can compute the contribution % of the jth ε_t innovation to the h-step forecast error variance of variable k. $\omega_{kj,h}$ can decompose the contribution of the jth ε_t innovation to the h-step forecast error variance of variable k.

[18] The optimal lag selection process will not be detailed here for the sake of brevity. All the details are available upon reasonable request.

In order to more comprehensively understand the linkages between the FEVD Eq. (5), the IRF Eq. (4), and the spillover connectedness, the FEVD can also be re-written as Eq. (6):

$$\theta_{ij,t}(h) = \frac{\sigma_{jj}^{-1} \sum_{p=0}^{n} (e_i' A_p \sum e_j)^2}{\sum_{p=0}^{n} (e_i' A_p \sum A_p' e_i)} = \frac{\theta_{ij,t}(H)}{\sum_{j=1}^{N} \theta_{ij,t}(H)}, H = 1, 2, 3 \ldots, \tag{6}$$

where σ_{jj}^{-1} represents the standard deviation of the jth ε_t innovation to the h-step forecast error variance of variable k. $\tilde{\theta}_{ij,t}(h)$ is the standardised results of $\theta_{ij,t}(h)$, and can provide the magnitude of pairwise-directional spillover connectedness from i to j at horizon h. Based on Eq. (6), this study can propose that $\sum_{j=1}^{N} \tilde{\theta}_{ij,t}(h) = 1$, and $\sum_{i,j=1}^{N} \tilde{\theta} = N$. Following (Karim et al., 2022), and also considering the short-term and low-frequency data series used in this study, then H is set to be 10.

4.1.4. Total spillover index

As the mathematical framework of spillover connectedness has been clearly explained, this study can (according to the FEVD in Eq. (6)) construct the total spillover connectedness index (TSCI) as Eq. (7):

$$TSCI(h) = \frac{\sum_{ij=1, i \neq j}^{N} \tilde{\theta}_{ij,t}(h)}{\sum_{ij=1}^{N} \tilde{\theta}_{ij,t}(h)} \times 100 = \frac{\sum_{ij=1, i \neq j}^{N} \tilde{\theta}_{ij,t}(h)}{N} \times 100 \tag{7}$$

The TSCI can reveal the dynamic interconnection between a system's variables. It is similar to the system shock analysis. For example, one unit (A_1) has the highest amount of momentum, and can transfer momenta to those units closest to it. These units then subsequently pass the momenta to those nearest them, and so on. The whole process can propagate fast (high values) or attenuate slow (low values).

4.1.5. Directional spillover connectedness indices

According to Eqs. (6) and (7), this study could still partially compute directional spillover connectedness (DSC). DSC refers to the directional spillovers received by each variable i 'From' all other variables in a variable system, or those transmitted by each variable i 'To' all other variables in a variable system. Put simply, DSC can be valued as processing a decomposition on the TSCI 'From' or 'To' a particular source.

There are four different measures of DSC: from-spillover connectedness (DSC^f), to-spillover connectedness (DSC^t), net-spillover connectedness (DSC^n), and net-pairwise directional spillover connectedness (DSC^{np}). It is worth noting that the DSC^n is the difference between DSC^f and DSC^t. Moreover, the DSC^{np} between variable i and j is the difference between the directional spillovers transmitted from variables i to j, as well as those transmitted from j to i. The formula details of the four different DSC measures are shown as follows:

The DSC^f can be expressed as Eq. (8):

$$DSC_{i \leftarrow j,t}^{f}(h) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ji,t}(h)}{\sum_{j,i=1}^{N} \tilde{\theta}_{ji,t}(h)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ji,t}(h)}{N} \times 100 \tag{8}$$

The DSC^t can be defined as Eq. (9):

$$DSC_{i \rightarrow j,t}^{t}(h) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij,t}(h)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij,t}(h)} \times 100 = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij,t}(h)}{N} \times 100 \tag{9}$$

The DSC^n can be written as Eq. (10):

$$DSC_{ij,t}^{n}(h) = DSC_{i \rightarrow j,t}^{t}(h) - DSC_{i \leftarrow j,t}^{f}(h) = \left(\frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij,t}(h)}{N} - \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ji,t}(h)}{N} \right) \times 100 \tag{10}$$

The DSC^{np} can be given as Eq. (11):

$$DSC_{ij,t}^{np}(h) = \left(\frac{\tilde{\theta}_{ij,t}(h)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij,t}(h)} - \frac{\tilde{\theta}_{ji,t}(h)}{\sum_{j,i=1}^{N} \tilde{\theta}_{ji,t}(h)} \right) \times 100 = \frac{\tilde{\theta}_{ij,t}(h)}{N} \times 100 \tag{11}$$

Table 2
Generalised volatility spillover connectedness table.

	$\text{NFTsAI}_{\mathbf{1,z}}$	$\text{CryptoPunks}_{\mathbf{2,z}}$	$\text{Decentraland}_{\mathbf{3,z}}$	…	$\text{DBC}_{\mathbf{12,z}}$	$\text{DXY}_{\mathbf{13,z}}$	$\text{Gold}_{\mathbf{14,z}}$	FROM OTHERS
$\text{NFTsAI}_{1,z}$	$\text{NFTsAI}^{h}_{11,z}$	$\text{NFTsAI}^{h}_{12,z}$	$\text{NFTsAI}^{h}_{13,z}$	…	$\text{NFTsAI}^{h}_{112,z}$	$\text{NFTsAI}^{h}_{113,z}$	$\text{NFTsAI}^{h}_{114,z}$	$\sum_{j=1}^{N}\ \text{NFTsAI}^{h}_{1j,z}, j \neq 1$
$\text{CryptoPunks}_{2,z}$	$\text{CryptoPunks}^{h}_{21,z}$	$\text{CryptoPunks}^{h}_{22,z}$	$\text{CryptoPunks}^{h}_{23,z}$	…	$\text{CryptoPunks}^{h}_{212,z}$	$\text{CryptoPunks}^{h}_{213,z}$	$\text{CryptoPunks}^{h}_{214,z}$	$\sum_{j=1}^{N}\ \text{CryptoPunks}^{h}_{2j,z}, j \neq 2$
$\text{Decentraland}\ _{3,z}$	$\text{Decentraland}\ ^{h}_{31,z}$	$\text{Decentraland}\ ^{h}_{32,z}$	$\text{Decentraland}\ ^{h}_{33,z}$	…	$\text{Decentraland}\ ^{h}_{312,z}$	$\text{Decentraland}\ ^{h}_{313,z}$	$\text{Decentraland}\ ^{h}_{314,z}$	$\sum_{j=1}^{N}\ \text{NFTsPWI}^{h}_{3j,z}, j \neq 3$
⋮	⋮	⋮	⋮	⋱	⋮	⋮	⋮	⋮
$\text{DBC}_{12,z}$	$\text{DBC}^{h}_{121,z}$	$\text{DBC}^{h}_{122,z}$	$\text{DBC}^{h}_{123,z}$	…	$\text{DBC}^{h}_{1212,z}$	$\text{DBC}^{h}_{1213,z}$	$\text{DBC}^{h}_{1214,z}$	$\sum_{j=1}^{N}\ \text{DBC}^{h}_{12j,z}, j \neq 12$
$\text{DXY}_{13,z}$	$\text{DXY}^{h}_{131,z}$	$\text{DXY}^{h}_{132,z}$	$\text{DXY}^{h}_{133,z}$	…	$\text{DXY}^{h}_{1312,z}$	$\text{DXY}^{h}_{1313,z}$	$\text{DXY}^{h}_{1314,z}$	$\sum_{j=1}^{N}\ \text{DXY}^{h}_{13j,z}, j \neq 13$
$\text{Gold}_{14,z}$	$\text{Gold}^{h}_{141,z}$	$\text{Gold}^{h}_{142,z}$	$\text{Gold}^{h}_{143,z}$	…	$\text{Gold}^{h}_{1412,z}$	$\text{Gold}^{h}_{1413,z}$	$\text{Gold}^{h}_{1414,z}$	$\sum_{j=1}^{N}\ \text{Gold}^{h}_{14j,z}, j \neq 14$
TO OTHERS	$\sum_{i=1}^{N}\ a^{h}_{i1,z}, i \neq 1$	$\sum_{i=1}^{N}\ a^{h}_{i2,z}, i \neq 2$	$\sum_{i=1}^{N}\ a^{h}_{i3,z}, i \neq 3$	…	$\sum_{i=1}^{N}\ a^{h}_{i12,z}, i \neq 12$	$\sum_{i=1}^{N}\ a^{h}_{i13,z}, i \neq 13$	$\sum_{i=1}^{N}\ a^{h}_{i14,z}, i \neq 14$	**Grand average =**

Notes: This table displays the variance decomposition matrix for this study. The 14×14 matrix contains the 14 forecast error variance decomposition from a connectedness perspective. This matrix can be denoted as: $A^{h}_{p,ijz}$. The rightmost 'FROM OTHERS' column presents the sums of off-diagonal row. The bottom 'TO OTHERS' row displays the sums of off-diagonal column. The inter-variables' information transmission level can be found in the bottom right, as 'GRAND AVERAGE'.

4.2. Generalised volatility spillover connectedness table

Developing the time-varying volatility spillover connectedness econometrics framework allows one to formulate its generalised table. This table allows one to understand the various connected measures and their relationships in terms of time. The variance and spectral decomposition matrix, defined as $A^{h}_{p,ijz}$, is listed on the main upper-left $N \times N$ block, and contains the variance and spectral decomposition results. In this type of table, the summing of columns can contribute to increasing $A^{h}_{p,ijz} = [a^{h}_{p,ijz}]$ with a bottom row. The row sums are shown in the rightmost column, and the grand average can be found in the bottom-right. The generalised table can be found in Table 2.

5. Empirical results and discussions

5.1. Summary statistics

NFTsAI is a weekly frequency index, and the TVP-VAR model requires one to process this model in the same frequency data series. Moreover, the daily return of NFTs and cryptocurrencies contain significant outliers (Dowling, 2021a; Ko et al., 2022; Urquhart, 2016; Urquhart & Lucey, 2022), but the weekly average price can address this issue. In the end, Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012) have proven that TVP-VAR can generate solid and reliable empirical results by using the low-frequency data. Based on the above reasons, this research applies weekly frequency data for all the collected variables.

Table 3 Panel A-1 and Panel A-2 display the descriptive statistics for the raw data. As a key NFT asset in the NFT markets, CryptoPunks has the largest mean and standard deviation value, even higher than the well-known high fluctuation asset, Bitcoin (Urquhart & Lucey, 2022). These results reflect the prosperity and fluctuation of the NFT markets. There is no skewness value equal to 0, which indicates asymmetry. The kurtosis values of NFTsAI, CryptoPunks, Decentraland, Chainlink, Maker, and DBC are greater than 0, especially for Decentraland and CryptoPunks, indicating a leptokurtic distribution. The kurtosis values of the other variables are all negative, which means that the distributions of these variables have lighter tails than the normal distributions. The Jarque–Bera (J.-B.) test also confirms these findings. The statistical results from the Ljung–Box test indicate that all of the variables' residuals are not independently distributed and confirm the presence of serial correlations in all return series. Considering the results of the ADF, KPSS, and PP unit root tests, this study can confirm the presence of unit roots in all the variables.

In the VAR model, all the variables should keep stationary without unit roots (Lütkepohl, 2005). Moreover, volatility spillover connectedness analysis requires one to use data in its logarithm return level (Diebold & Yilmaz, 2012). To measure the logarithm return (volatility) for each variable, I calculate the logarithm returns by processing the first-difference in the logarithmic values of two consecutive prices, denoted as: $CCR_{i,t} = ln(P_{i,t}/P_{i,t-1}) \times 100$, where $CCR_{i,t}$ denotes the logarithm percentage returns for variable i at time t, while $P_{i,t}$ denotes the price level of variable i at time t.

Table 3 Panel B-1 and Panel B-2 show the descriptive statistics for the logarithm returns of the variables used for empirical analysis. CryptoPunks still has the largest value of mean and standard deviation. Decentraland is ranked as the second, indicating the risk-return tradeoff in the NFT markets. All return series are still asymmetry distributed, and all of them have a peak and thick tail. Serial correlations are not present in the BGCI, Bitcoin, Ethereum, FTSEAWI, FTSEWGBI and DBC these six variables at their logarithm return levels. Finally, the three different unit root tests can confirm that all the return series are stationary without unit-roots. Fig. 3 shows the weekly price and logarithm return on each asset. NFT markets skyrocketed in late 2021, and then NFT markets took a nosedive in 2022, indicating that NFT markets exhibit higher fluctuations and uncertainties than the other financial markets.

5.2. Volatility spillover connectedness analysis

5.2.1. Static volatility spillover connectedness using the full sample

Table 4 summarises the static estimations of the TVP-VAR spillover connectedness model. The total spillover index can assess the systemic risk transmission. The value of the total spillover index is 50.7%, implying that the internal 14 variables' risk transmission contributed to approximately half of the overall volatility and mutual shocks in the examined variable system. The following sections further explain the degree of system volatility spillover connectedness.

Considering the static total directional volatility spillover connectedness 'FROM', its values are listed in the rightmost column of Table 4. 'FROM' represents the volatility shocks received from the other 13 variables to each variable in the gross forecast error variance decompositions for each variable. Based on the formulas of Eq. (8), 'FROM' is equal to 100% minus the share of the gross forecast error variance decompositions. The 'FROM' values in Table 4 range between 4.7% (BGCI) to 1.8% (CryptoPunks). The 'FROM' values of these three variables are over 4.5%, including BGCI (4.7%), Ethereum (4.6%), and Bitcoin (4.5%). These three variables all belong to cryptocurrency indices, indicating that cryptocurrency markets are significantly affected by other financial markets. This finding echoes the results of Ji, Bouri, Roubaud et al. (2019) and Ji, Bouri, Lau et al. (2019), who believe that cryptocurrency markets are driven by global financial markets. NFT market proxies hold the lowest 'FROM' values, which are NFTsAI (2.6%), Decentraland (2.3%) and CryptoPunks (1.8%). These interesting statistical results indicate that NFT markets are less affected by cryptocurrency, DeFi, equity, bond, commodity, F.X. and gold markets, which suggests the validity of the Hypothesis$_2$. These findings are in line with the empirical findings of Aharon and Demir (2021); Dowling (2021b); Karim et al. (2022) and Yousaf and Yarovaya (2022), who believe that NFT markets are relatively independent and isolated from

Table 3
Descriptive statistics.
Notes: Ljung–Box test for the distribution of residuals in a variable (Box & Pierce, 1970) and (Ljung & Box, 1978), and it can examine the autocorrelation of squared returns series; Jarque–Bera (J.-B.) statistics can be used to check the normal distribution characteristic of the data (Jarque & Bera, 1980) and (Bera & Jarque, 1981); ADF, PP and KPSS these three unit root tests refer to Augmented Dickey–Fuller test (Dickey & Fuller, 1979), Phillips–Perron test (Phillips & Perron, 1988) and Kwiatkowski–Phillips–Schmidt–Shin test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). *p<0.1; **p<0.05; ***p<0.01.

Panel A-1: raw data

	NFTsAI	CryptoPunks	Decentraland	Chainlink	Maker	BGCI	Bitcoin
Observation	231	231	231	231	231	231	231
Mean	100.70	63326.13	2833.57	9.55	1197.99	1098.98	20404.71
Min	99.51	23.46	15.25	0.19	240.46	197.59	3252.84
Max	108.67	619540.07	25069.90	47.77	5385.07	3715.11	65466.84
Std. Dev.	1.93	129476.99	4057.41	10.99	1018.51	953.62	18080.07
Skewness	1.85	2.30	2.92	1.08	1.44	1.02	0.96
Kurtosis	2.37	4.50	9.57	0.14	1.47	−0.31	−0.61
Ljung–Box	207.9***	208.11***	190.57***	225.15***	224.26***	225.96***	228.22***
J.-B.	189.63***	406.76***	1234***	45.998***	102.55***	41.627***	39.035***
ADF	−1.3883	−2.2527	−2.3498	−1.6461	−2.1389	−2.2439	−2.369
KPSS	2.8885***	2.2605***	1.7326***	3.3172***	2.4178***	2.8496***	3.3723***
PP	−15.513	−15.309	−23.493	−9.8733	−12.121	−9.8306	−9.3374

Panel A-2: raw data

	Ethereum	FTSEAWI	FTSEWGBI	PIMCOCORP	DBC	DXY	Gold
Observation	231	231	231	231	231	231	231
Mean	1119.25	384.11	999.36	101.49	16.82	95.25	1589.02
Min	85.26	262.18	887.46	88.00	10.70	89.07	1176.50
Max	4626.36	498.35	1098.56	113.07	29.88	104.56	2010.10
Std. Dev.	1272.00	60.70	52.85	8.68	3.73	3.25	256.10
Skewness	1.16	0.51	−0.05	−0.23	1.35	0.06	−0.13
Kurtosis	−0.01	−1.17	−1.13	−1.47	2.02	−0.50	−1.56
Ljung–Box	227.3***	227.9***	223.61***	226.79***	217.88***	212.34***	227.78***
J.-B.	52.741***	23.136***	11.947***	22.626***	112.21***	2.3336	23.555***
ADF	−2.1138	−1.9971	0.40736	0.48669	0.585	−1.6664	−1.9632
KPSS	3.0493***	3.6678***	2.1362***	3.7443***	1.8593***	1.45573**	4.1705***
PP	−8.0897	−9.268	3.559	−2.0615	2.2736	−4.4275	−8.7041

Panel B-1: volatility

	NFTsAI	CryptoPunks	Decentraland	Chainlink	Maker	BGCI	Bitcoin
Observation	230	230	230	230	230	230	230
Mean(%)	0.02	2.41	0.21	0.90	0.05	−0.09	0.26
Min(%)	−5.22	−204.84	−151.65	−47.45	−45.02	−55.83	−40.79
Max(%)	5.76	222.36	160.69	42.64	60.69	34.51	26.07
Std. Dev.(%)	0.59	48.22	56.78	15.47	12.92	11.55	10.42
Skewness	1.17	−0.12	0.09	−0.09	0.21	−0.82	−0.60
Kurtosis	65.97	4.15	0.38	0.53	2.76	3.12	1.39
Ljung–Box	43.639***	18.741***	36.128***	16.387***	20.922***	1.4539	2.0929
J.-B.	42528***	170.35***	19.328**	32.528**	77.599***	122.36***	33.637***
ADF	−6.9025***	−6.2508***	−5.8573***	−5.9406***	−6.8288***	−5.8926***	−5.0742***
KPSS	0.0997	0.2416	0.0619	0.1826	0.1074	0.3451	0.2584
PP	−292.29***	−269.46***	−298.66***	−165.87***	−151.73***	−213.47***	−204.71***

Panel B-2: volatility

	Ethereum	FTSEAWI	FTSEWGBI	PIMCOCORP	DBC	DXY	Gold
Observation	230	230	230	230	230	230	230
Mean(%)	0.19	0.09	−0.03	0.03	0.27	0.05	0.15
Min(%)	−53.10	−13.30	−3.81	−11.64	−10.16	−4.42	−9.74
Max(%)	42.77	9.88	3.24	10.97	14.05	4.04	9.01
Std. Dev.(%)	13.90	2.59	0.80	1.42	2.68	0.89	2.03
Skewness	−0.63	−1.01	−0.29	−0.91	−0.13	−0.11	−0.20
Kurtosis	1.79	7.04	3.74	37.79	4.01	3.60	3.92
Ljung–Box	0.91401	0.1226	0.7854	2.8486*	0.2281	10.554***	7.4761***
J.-B.	47.412***	526.43***	141.54***	13978***	159.6***	128.4***	153.59***
ADF	−5.9156***	−5.8277***	−4.8521***	−6.2658***	−4.9103***	−5.7896***	−4.8444***
KPSS	0.4289	0.0817	0.4774	0.2838	0.1614	0.1815	0.1149
PP	−219.18***	−236.81***	−247.69***	−231.16***	−232.4***	−269.67***	−266.18***

other financial markets. The findings above suggest diversification opportunities when considering NFT assets in portfolios.

Regarding the static total directional volatility spillover connectedness 'TO', which is displayed in the third-to-last row in Table 4. 'TO' represents the total volatility spillover connectedness from each variable's volatility to other variables' volatility. In other words, it represents each variable's contribution to the other's forecast error variance decompositions. The directional spillover 'TO' values can range from 6.1% (BGCI) to CryptoPunks (1.2%). The BGCI transmits the highest level of volatility (6.1%), followed by Ethereum (5.0%) and Bitcoin (4.7%). These findings prove that NFTs are created based on the algorithm of Ethereum (Chirtoaca et al., 2020). Unsurprisingly, NFT group variables have the three lowest 'TO' values, which are Decentraland (2.0%), NFTsAI (1.4%) and CryptoPunks (1.2%), and these statistical results also suggest the validity of the Hypothesis_2.

Regarding the static 'NET' total directional volatility spillover connectedness, which is displayed in the second-to-last bottom row of Table 4, the 'NET' values show the difference between static total directional volatility spillover connectedness to others and static total directional volatility spillover connectedness from others. The 'NET'

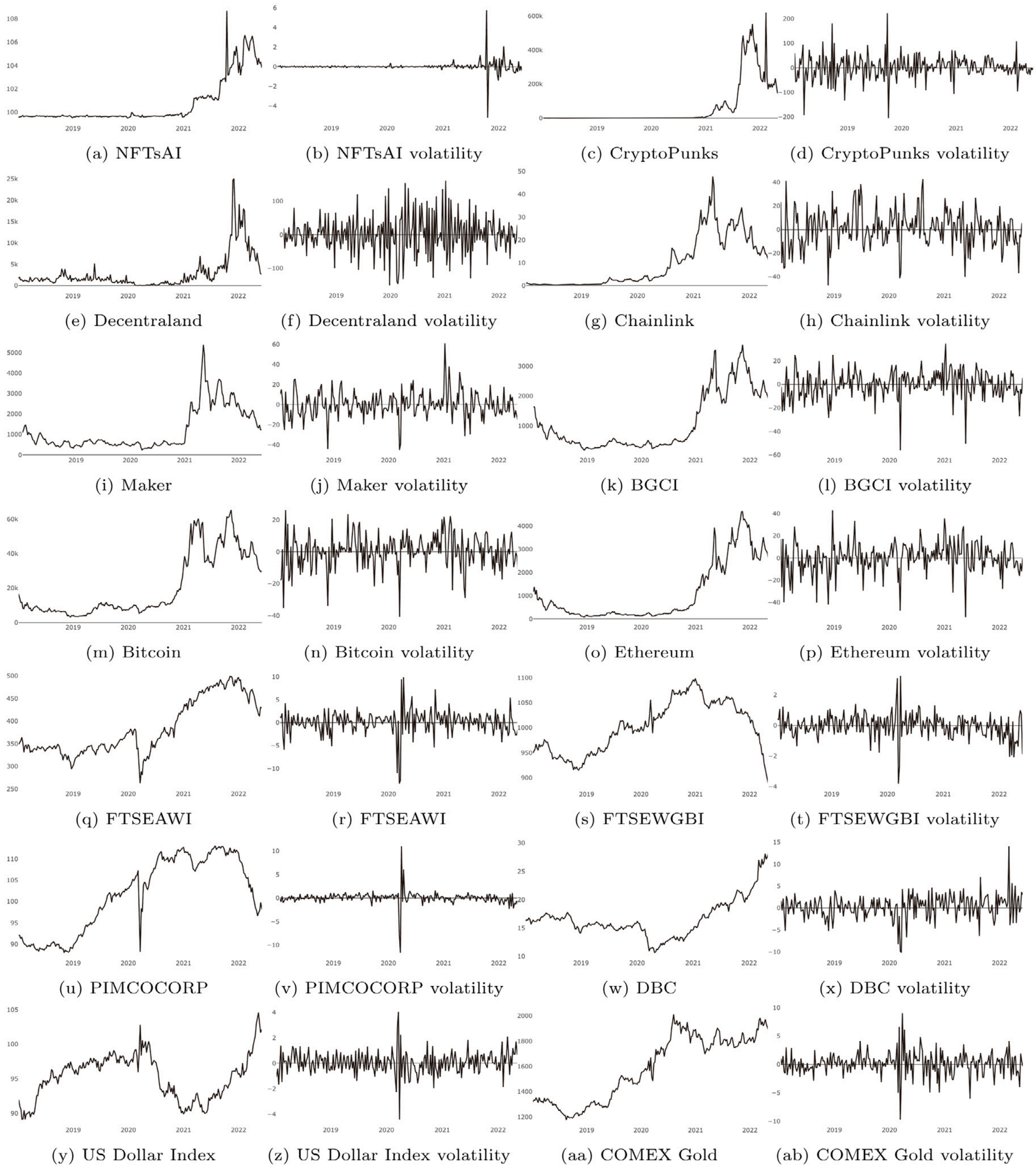

Fig. 3. Time series of price and volatility of each index on a weekly basis.
Notes: The graphs displayed above are the weekly price and logarithm return across time for each of the system variables. The sample period visualised is 26/Dec/2016 to 05/Jun/2022.

value of NFTsAI is negative at -1.1%, illustrating that the impact of the NFTsAI on the other 13 variables' volatility is less than that of the other 13 variables' volatility. In summary, the NFT market is a volatility receiver, and this finding can be further confirmed by the representative NFT assets, CryptoPunks and Decentraland, which hold a 'NET' value of -0.6% and -0.3%, separately. These findings support the conclusion of Aharon and Demir (2021), Karim et al. (2022) and Yousaf and Yarovaya (2022), who find that NFTs can act as risk spillover receivers during stressful times. Conversely, BGCI is the largest volatility transmitter, contributing 6.1%, followed by Ethereum (5.0%) and Bitcoin (4.7%). The statistical results of the static 'NET' total directional volatility spillover connectedness could confirm the Hypothesis$_2$ can hold.

The off-diagonal elements of the 14×14 matrix in Table 4 illustrate the static net pairwise directional volatility spillover connectedness between the volatility of two variables. For example, the value 0.3 in row 10, column 2 stands for the percentage of forecast error variance decomposition of the volatility of Ethereum due to the shocks from NFTsAI. Regarding the shocks from NFTsAI, the static net pairwise directional volatility spillover connectedness between NFTsAI and the other financial markets is extremely low, ranging between 0.3% (Ethereum) and 4.1% (PIMCO CORP). The majority of NFTsAI volatility is attributable to endogenous shocks (64.2%), which can provide evidence to support Hypothesis$_2$. These findings are confirmed by the selected NFT assets, CryptoPunks (75.0%) and the Decentraland (72.6%). Previous studies also support this view and scholars have suggested that NFT assets may have significant diversification benefits

Table 4
Static volatility spillover connectedness table.

To (i)	From (j)													
	NFTsAI	CP	DL	Chainlink	Maker	BGCI	Bit	Eth	FTSEAWI	FTSEWGBI	PIMCOCORP	DBC	DXY	Gold	FROM
NFTsAI	64.2	2.4	4.4	1.0	2.1	3.2	2.2	1.7	1.9	4.6	4.5	1.8	3.9	2.2	2.6
CP	2.1	75.0	5.8	1.7	0.9	2.7	2.1	1.6	1.4	1.3	1.0	1.5	1.1	1.7	1.8
DL	2.1	2.8	72.6	1.0	3.0	2.4	1.3	1.5	3.0	1.2	3.5	0.8	1.8	2.8	2.3
Chainlink	0.8	1.2	1.9	46.4	9.4	11.2	8.6	8.1	3.3	1.0	2.9	3.3	1.3	0.6	3.6
Maker	1.3	0.5	2.0	8.5	43.3	14.6	6.4	9.1	2.9	2.2	2.6	5.0	0.9	0.7	4.1
BGCI	0.5	1.0	1.4	9.1	11.3	33.7	14.8	17.4	2.1	2.2	1.5	2.5	0.8	1.8	4.7
Bit	0.6	0.8	1.8	7.4	5.8	16.9	38.2	19.7	2.6	1.4	1.0	2.4	0.8	0.5	4.5
Eth	0.3	0.5	1.0	7.1	7.5	19.2	18.7	36.8	2.1	1.9	0.6	2.5	0.5	1.2	4.6
FTSEAWI	1.2	1.1	2.1	3.6	3.3	2.5	3.4	2.9	45.7	4.9	6.3	13.6	4.8	4.7	3.9
FTSEWGBI	2.0	1.9	1.1	1.2	2.9	2.9	1.7	2.2	6.8	42.1	9.1	5.4	9.9	11.0	4.1
PIMCOCORP	4.1	1.0	3.0	2.3	3.0	2.1	1.4	0.9	5.9	12.0	48.8	4.1	6.6	4.9	3.7
DBC	1.4	1.1	2.2	3.6	5.2	3.7	2.9	3.0	13.4	4.1	3.0	47.7	4.3	4.4	3.7
DXY	2.4	1.0	1.3	3.2	2.6	1.8	1.3	0.8	6.2	11.2	7.4	5.7	47.6	7.6	3.7
Gold	1.3	1.1	3.6	0.8	1.6	2.6	0.7	1.5	7.6	13.1	4.5	5.2	8.6	47.5	3.7
TO	1.4	1.2	2.0	3.8	4.2	6.1	4.7	5.0	4.2	4.4	3.4	3.9	3.2	3.2	710.4
NET	−1.1	−0.6	−0.3	0.2	0.1	1.4	0.3	0.5	0.3	0.2	−0.2	0.1	−0.5	−0.6	**TCI =**
NPDC	0.0	2.0	6.0	7.0	10.0	13.0	10.0	12.0	6.0	5.0	6.0	7.0	4.0	3.0	**50.7%**

Notes: This table displays the static volatility spillover connectedness results. There are 230 observations. All of the results are given in percentages, and all of the variables are in the logarithmic return form. The model includes 1 lag based on the AIC, HQ, SC and FPE information criteria. The term 'FROM' in the rightmost column indicates volatility spillover receiver. The term 'TO' in the third-to-last row indicates volatility spillover contributor. The term 'NET' in the second-to-last row reveals the net directional spillover connectedness. The term 'NPDC' in the last row shows the net pairwise directional connectedness. The total connectedness index of the variable system is presented by the term 'TCI' in the bottom right corner. CryptoPunks (CP) and Decentraland (DL).

(Aharon & Demir, 2021; Dowling, 2021b; Karim et al., 2022; Yousaf & Yarovaya, 2022).

Two factors may contribute to the isolation of NFTs. Firstly, NFTs are new investment assets with an inefficiency price mechanism (Dowling, 2021a). Few investors become involved in the NFT markets compared with the cryptocurrency markets (Mazur, 2021). The trading volume of NFT assets confirms this in nonfungible.com. Therefore, NFT has not been widely used as a hedge asset by risk-averse investors, portfolio managers or institutional investors. Secondly, the unique properties of NFTs also contribute to their isolation. NFTs can be valued as digital art, making these assets popular among specific culture circles (Valera et al., 2021). Therefore, NFT assets have low liquidity; this low liquidity condition reduces their impact on other financial assets.

5.2.2. Dynamic total volatility spillover connectedness using the rolling sample

The above empirical analysis demonstrates the static connectedness by using the full sample data. How this volatility spillover connectedness evolves in time-varying and low-frequency data should also be investigated to reveal the dynamic connectedness between NFTsAI and other financial markets. Fig. 4 displays the time-varying dynamics of the total volatility spillover connectedness between NFT markets and the other selected financial markets and suggests how spillover effects change over time. Although the static TSCI from Table 4 is 50.7%, it should be noted that the actual TSCI is in the range of 39.97% and 72.18%. This is another reason why the time-varying TSCI should be fully investigated. It can provide a valuable summary of the 'average' volatility spillover information to NFT investors, stakeholders and policymakers.

The highest peak in Fig. 4 occurred in the first quarter of 2020. Considering the timespan, a plausible explanation of the high level of volatility spillover connectedness could be due to the effects of COVID-19 on financial markets (Marobhe, 2021; Yousaf & Yarovaya, 2022). This explanation is confirmed by the volatility plots in Fig. 3 as COVID-19 caused fluctuations in the stock (Nguyen, Anh, & Gan, 2021; Sharif, Aloui, & Yarovaya, 2020), commodity (Ji, Zhang, & Zhao, 2020), bond (Bouri, Cepni, Gabauer, & Gupta, 2021; Mezghani, Boujelbène, & Elbayar, 2021), F.X. (Aslam, Aziz, Nguyen, Mughal, & Khan, 2020), and gold (Corbet, Larkin, & Lucey, 2020) markets. In addition, total volatility transmissions also soared in the first quarter of 2021. This period matches the collapse of cryptocurrency prices, which was caused by the bear market of the cryptocurrency as a result of the crash in Bitcoin price. Interestingly, plummeting NFT prices in the first and second quarters of 2022 have aroused violent fluctuations in the total volatility spillover connectedness. Therefore, it can be inferred that price bubbles of NFT markets contributed to these fluctuations.

5.2.3. Dynamic directional volatility spillover connectedness using the rolling sample

To further identify the volatility spillover transmission, the dynamic net directional volatility spillover connectedness is displayed in Fig. 5[19]. As a proxy for NFT markets, NFTsAI highlights the importance of media coverage on NFTs because NFTsAI is consistently an essential volatility spillover receiver in the variable system, thus indicating that NFT markets receive more volatility spillovers than it spreads and could impede the financial contagion. This finding can prove the validity of the Hypothesis$_2$ and also is in line with the results of Umar, Abrar et al. (2022). NFT markets are volatility spillover receivers can be further confirmed by the represented NFT assets, CryptoPunks and Decentraland, as they keep a volatility spillover receiver role in general (Although Decentraland, one major NFT asset in the Metaverse NFT market. It plays a role as a volatility spillover transmitter in the early stage of the NFT market, but with the prosperity of the NFT market after 2020, the role of Decentraland has transferred to a volatility spillover receiver). Moreover, the statistical results in the dynamic directional volatility spillover connectedness of NFT markets match that in the static directional volatility spillover connectedness. Both of them suggest that the NFT markets can generally act as a volatility spillover receiver. In addition, regarding the popularity of NFT assets in 2021, particularly after the price of the cryptocurrency market plummeted in May 2021, the role of NFTsAI has shifted from volatility spillover receiver to transmitter, indicating that NFT markets are spreading more and more volatilities with the prosperity of the NFT markets. Please note that referring to the results of Umar, Abrar et al. (2022), NFTsAI could serve as a better indicator for Art, Games and Utilities tokens than that for Collectibles and Metaverse tokens. Because NFTsAI, Art, Games and Utilities show a volatility spillover transmitter role from the third quarter of 2021. This has been caused by cryptocurrency

[19] For the sake of brevity, the plots of directional volatility spillovers from each variable i to all others and directional volatility spillovers to each variable i from all others are listed in the *Appendix—Figures*.

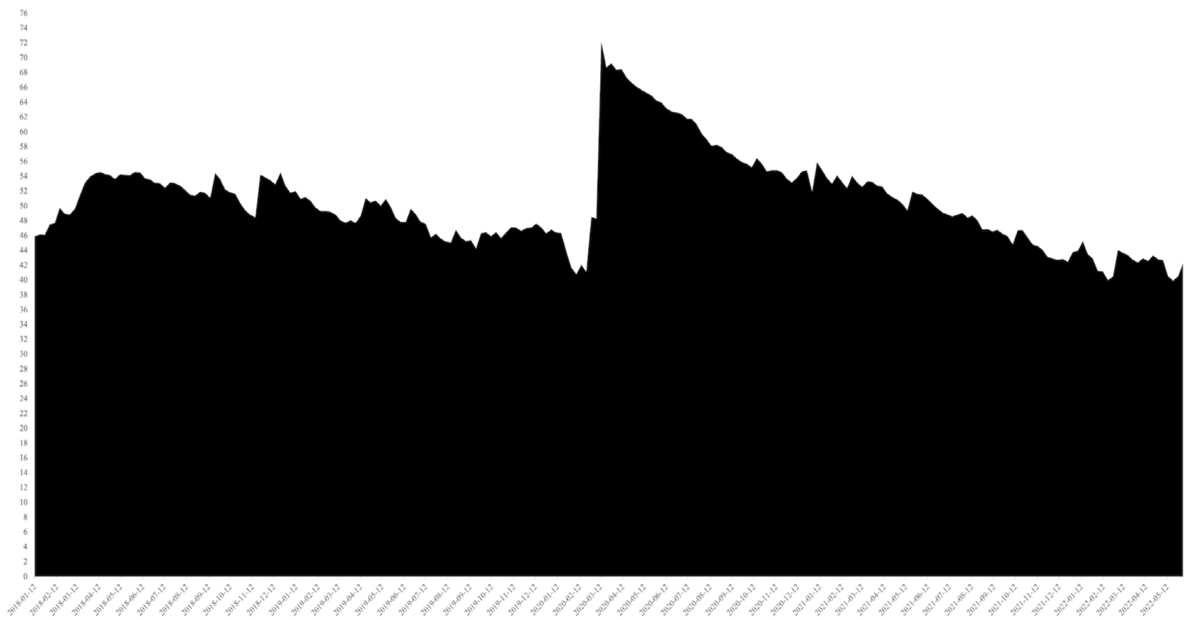

Fig. 4. Total volatility spillover.
Notes: The total volatility spillover connectedness index measures the connectedness of the whole variable system. The figure displays the dynamic connectedness of the variables of volatility across time using a TVP-VAR approach with AR(1) based on the information criteria. The predictive horizon for the underlying variance decomposition is 10 weeks (H = 10). The sample is from 26/Dec/2016 to 05/Jun/2022.

market uncertainty, which is confirmed by Lucey et al. (2022) and Wang et al. (2022a). Investors lose confidence in cryptocurrency's high uncertainty periods, and then they begin to search for alternative investment assets to hedge the risks of cryptocurrencies. NFT assets as new digital collectables closely related to cryptocurrencies, which can perfectly serve the aim of hedging the risks of cryptocurrencies. Furthermore, during the periods when the NFT markets can serve as a volatility spillover transmitter, the DeFi, bond, F.X. and Gold markets act as volatility spillover receivers.

In addition, BGCI is the most giant volatility transmitter across the variable system. And the cryptocurrency markets generally spreads more volatility spillovers than it receives as the cryptocurrency group variables, BGCI, Ethereum and Bitcoin, appear to have a significant positive value of dynamic net directional volatility spillovers for most of the sample time. However, as NFTs are part of the Ethereum blockchain (Nadini et al., 2021), Ethereum spread more volatilities than Bitcoin, especially after 2020 with the developments of the NFT markets. CryptoPunks, US Dollar Index, and Gold appear to be volatility spillover receivers for most of the sample span. In addition, when the COVID-19 as a time point, Decentraland, Chainlink, Bitcoin, Ethereum, and FTSE World Government Bond Index spread more volatilities than they receive before the COVID-19. However, Bloomberg Galaxy Cryptocurrency Index, FTSE All-World Index, Investment Grade Corporate Bond Index Exchange-Traded Fund and Invesco DB Commodity Index Tracking Fund spread more volatilities than they receive after the COVID-19.

To identify the linkages between NFTsAI and the volatilities of other selected financial markets, net pairwise volatility spillover connectedness should be further investigated. One advantage of this index over the other measures of directional spillover connectedness indices is that it can extract and focus on the dynamic relationships between NFTsAI and the other variables, allowing one to construct the transmitter and receiver volatility spillover connectedness framework at a net pairwise level. The net pairwise volatility spillover connectedness network results are presented in Fig. 6.

Fig. 6 helps to understand the direction of directional volatility spillovers across NFTsAI and NFT, DeFi, cryptocurrency, stock, bond, F.X., commodity and Gold markets. The direction of the arrows displays a 'to' or 'from' connection between each variable. The size of an arrow indicates the weight of the connection between two variables (the wider the arrow, the stronger the connection). The node colour represents whether a variable is a net volatility spillover transmitter (red) or receiver (green). Node size denotes the weight of the net pairwise spillover (the higher the new pairwise spillover value, the larger the node).

Similar to the empirical findings which are mentioned above. Fig. 6 shows that BGCI can dominate all the other 13 variables, and NFTsAI is dominated by all the other variables. This evidence also can confirm the validity of the Hypothesis$_2$. Moreover, NFTsAI receives a significant amount of volatilities from cryptocurrency markets (BGCI, Bitcoin and Ethereum), indicating that the NFT market is sensitive to shocks from cryptocurrency price volatilities. Decentraland and CryptoPunks are all spread volatilities to the NFTsAI. This finding is consistent with the former empirical analysis results. The higher the NFT attention, the higher the volatility of NFT assets. Therefore, Hypothesis$_1$ also can hold. Interestingly, government bond sectors (FTSE WGBI) spread more volatilities to NFTsAI than stock markets (FTSEAWI). Among the NFT group variables, the representer of the Metaverse token, Decentraland, is a prominent transmitter to the other NFT proxies. In addition, Decentraland spreads a small volume of volatilities to Bitcoin (cryptocurrency), Chainlink (DeFi), DBC (commodity market) and gold (safe-haven). Cryptocurrency group variables (including BGCI, Bitcoin and Ethereum), FTSEAWI, FTSEWGBI, DBC and Maker also play a crucial role in spreading volatility spillovers. Except for the NFTsAI, Chainlink, CryptoPunks, safe-haven (gold), F.X. markets (DXY), and corporate bond sectors (PIMCO CORP) all serve as volatility spillover receivers in the variable system.

5.3. Supplementary analysis

Although the previous findings suggest that the majority of NFTsAI volatility is attributable to endogenous shocks and NFT assets are relatively independent and isolated from other financial markets, there are significant spillover transmissions that exist among NFTsAI and NFT markets referring to the net pairwise spillover network. Moreover, the NFTsAI is a new index, and a natural question is whether such

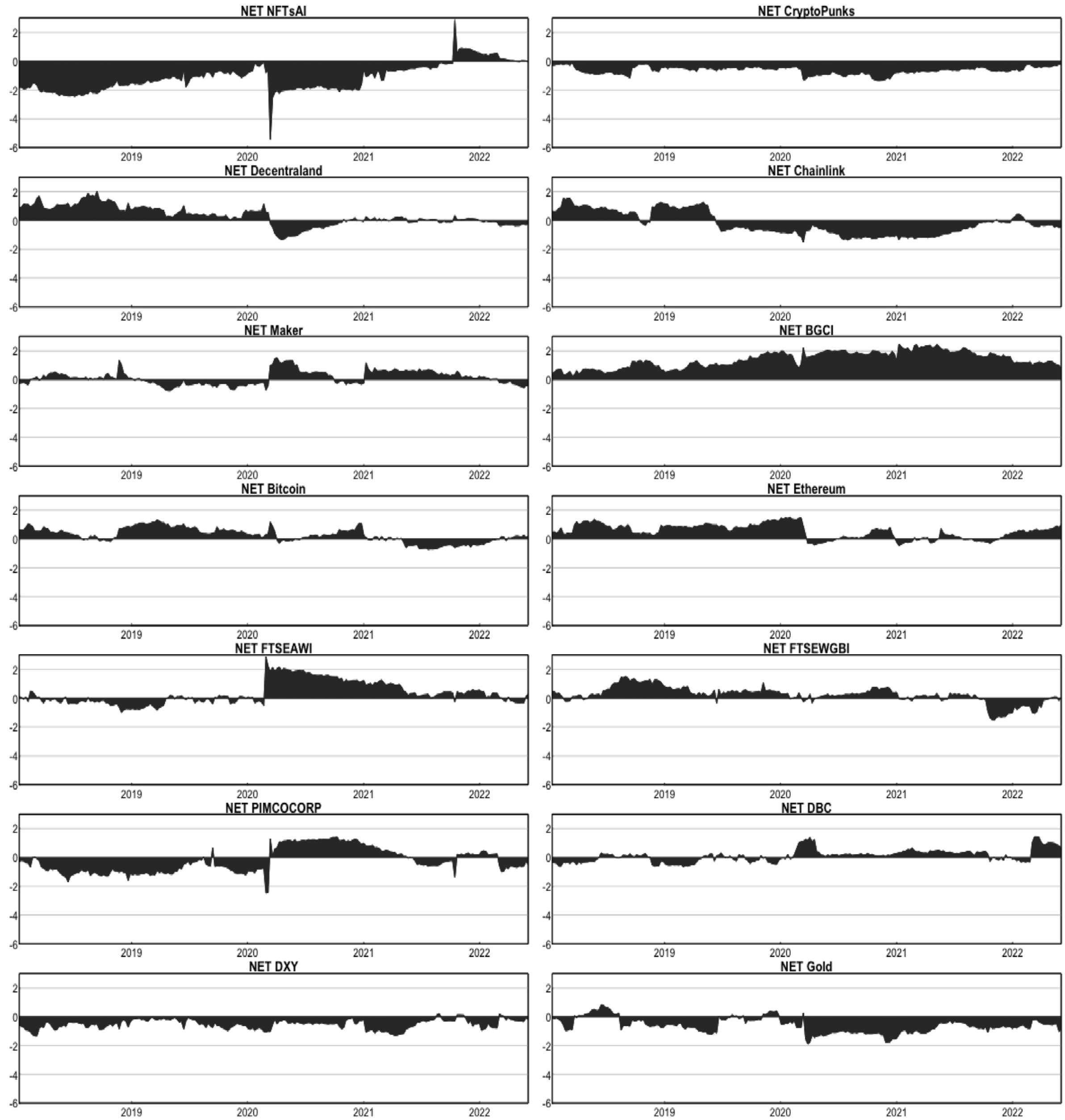

Fig. 5. Net directional volatility spillover.
Notes: The net directional volatility spillover connectedness depicts the difference between dynamic total directional volatility spillover connectedness to others and dynamic total directional volatility spillover connectedness from others. Positive values imply that the variable acts as a transmitter of systemic shocks, while negative values indicate that the role of the variable is a receiver in terms of systemic risk shocks. The predictive horizon for the underlying variance decomposition is 10 weeks ($H = 10$). The sample is from 26/Dec/2016 to 05/Jun/2022.

attention can have an impact on NFT asset prices. Therefore, it is essential to test the effects of NFTsAI on NFT markets. I follow the methodology of Pastor and Veronesi (2012), which investigates the relationship between the economic policy uncertainty index and the stock market by utilising a panel pooled OLS regression model. The regression model for this paper can be constructed as Eq. (12):

$$\Delta NFT_{i,t} = \beta_1 \Delta NFTsAI_{i,t} + \beta_2 \Delta NFT_{i,t-1} + \Delta CV_{i,t} + c + \varepsilon_{i,t}, \tag{12}$$

where the $\Delta\mathrm{NFT}_{i,t}$ is the log return of NFT asset price at time t, the $\Delta\mathrm{NFTsAI}_{i,t}$ is the log return of NFTs attention index at time t, $\Delta\mathrm{NFT}_{i,t-1}$ is used to remove any potential serial correlation in the log return of $\mathrm{NFT}_{i,t}$, $\Delta\mathrm{CV}_{i,t}$ is the K × K matrix of control variables. $\Delta\mathrm{CV}_{i,t}$ is equal to removing the explanatory variable, $\Delta\mathrm{NFTsAI}_{i,t}$, and one aimed explained variable, $\Delta\mathrm{NFT}_{i,t}$, other remaining variables which are used in the volatility spillover connectedness analysis[20]. c is a constant and $\varepsilon_{i,t}$ is an error term.

Due to the limitations of the research sample period in the TVP-VAR volatility spillover, the main empirical analysis only selects the CryptoPunks and Decentraland to represent NFT markets. Fortunately,

[20] Control variables are: log return of CryptoPunks, log return of Decentraland, log return of Chainlink, log return of Maker, log return of BGCI, log return of Bitcoin, log return of Ethereum, log return of FTSEAWI, log return of FTSEWGBI, log return of PIMCOCORP, log return of DBC, log return of DXY, and log return of Gold.

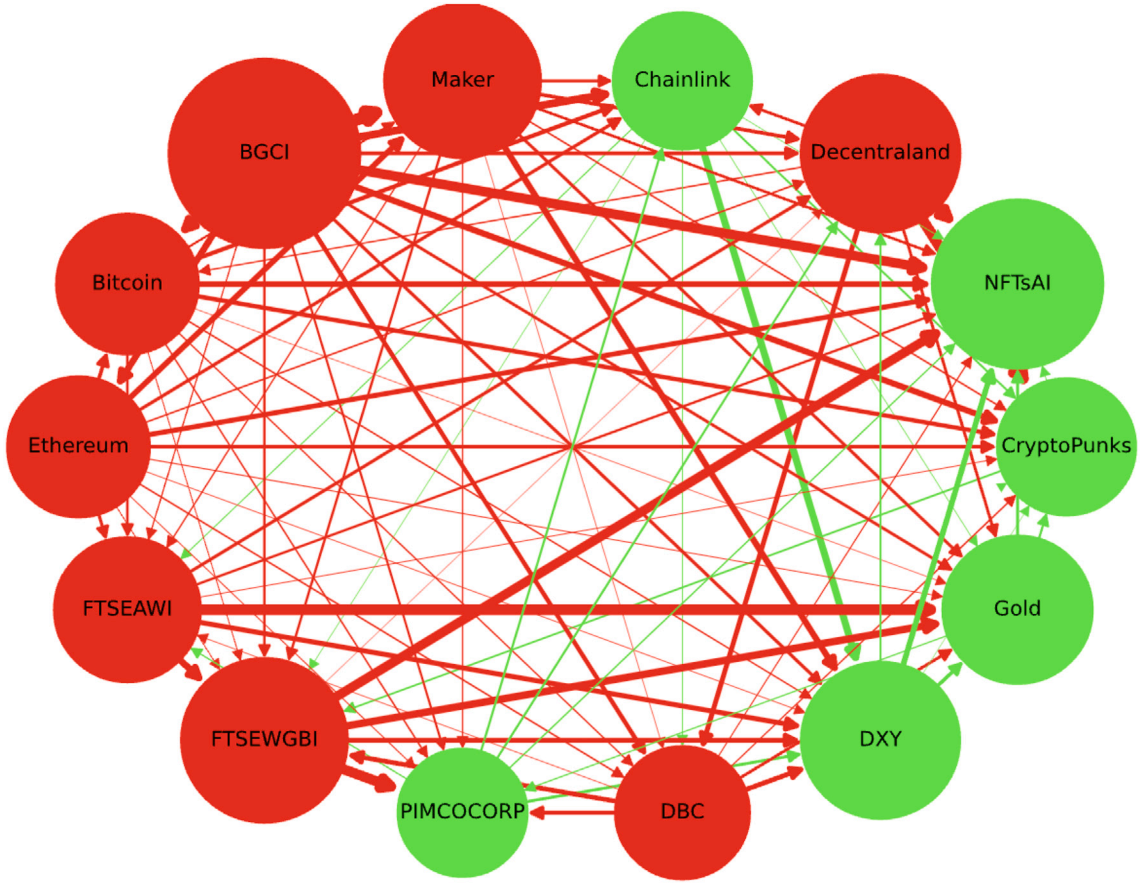

Fig. 6. Net pairwise spillover network.
Notes: Net pairwise spillover network can depict the dynamic relationships between NFTsAI and the other variables. It helps to understand the direction of directional volatility spillovers across the variable system. A variable that dominates the other 13 variables is marked with a red node. A variable that is dominated by the other 13 variables is marked with a green node. Node size denotes the weight of the net pairwise spillover (the higher the new pairwise spillover value, the larger the node). The direction of the arrows displays a 'to' or 'from' connection between each variable. The size of an arrow indicates the weight of the connection between two variables (the wider the arrow, the stronger the connection). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

a panel pooled OLS regression model does not have such special requirements for the research sample period. Therefore, I select the weekly data of NFTI (2021-03-05 to 2022-06-05), All NFT segments (All) average price (2018-01-01 to 2022-06-05), Art NFT segment (Art) average price (2018-04-23 to 2022-06-05), Collectible NFT segment (Collectible) average price (2018-01-01 to 2022-06-05), Game NFT segment (Game) average price (2018-01-01 to 2022-06-05), Metaverse NFT segment (Metaverse) average price (2018-03-19 to 2022-06-05) and Utility NFT segment (Utility) average price (2018-04-30 to 2022-06-05). NFTI is collected from coinmarket.com, and All, Art, Collectible, Game, Metaverse and Utility are all can be downloaded from nonfungible.com.

The model regression results are presented in Table 5. These statistical results confirm that NFTsAI has a positive impact on NFT markets. The higher the attention on NFT assets, the higher the return of NFT asset prices. Model (1) in Table 5 shows the impacts of NFTsAI on NFT markets without control variables. All the β_1 values in Model (1) are significant and positive. The residual standard error values are relatively low, being above 0 but below 1.7. The values of R^2 are approximately 50%. This statistical evidence indicates that these regression models are fitted well and that NFTsAI has sufficient power to explain the return of NFT assets. Moreover, Model (2) in Table 5 presents the impacts of NFTsAI on NFT markets with control variables. The β_1 values are robust because they still keep positive at a 1% significance level. The residual standard error values in Model (2) are lower than in Model (1). The values of R^2 in Model (2) are significantly higher than in Model (1) at approximately 90%. These statistical numbers not only suggest that the regression models are fitted better but also indicate that NFTsAI could explain the positive return of NFT assets in a better way when the control variables are added. These findings perfectly align with the previous empirical analysis results regarding volatility spillover connectedness and can further confirm Hypothesis$_1$ that NFTsAI could positively impact NFT markets.

5.4. Robustness test

In this paper, two robustness tests are designed to check the reliability of empirical results and re-confirm the effects of NFTsAI on NFT markets.

First, the main econometrics model in this paper is TVP-VAR volatility spillover connectedness. The only two uncertainties in this model are the selection of the forecast horizon (H) and the VAR estimation thresholds. Therefore, the robustness of the TVP-VAR volatility spillover connectedness results can be verified by setting different values to the forecast horizon and parameters in the VAR model. Suppose the new forecast horizons and VAR thresholds could not significantly change the general trend of the dynamic total volatility spillover connectedness. In that case, the robustness of the main empirical findings can be confirmed. In the main empirical section, the forecast horizon is set as 10 weeks. The forecast horizon is changed by 13 weeks as 13 is a multiple of 52 *(One year has 52 transaction weeks)*.

Table 5
The impacts of NFTsAI on NFT markets.

	ΔNFTsAI	
	Model (1)	Model (2)
ΔNFTI β_1	22.201***	6.887***
	(0.4423)	(0.1293)
Control variables	No	Yes
R^2	47.26%	95.49%
Observations	66	66
ΔAll β_1	70.691***	43.9237***
	(1.207)	(0.5251)
Control variables	No	Yes
R^2	55.8%	91.44%
Observations	231	231
ΔArt β_1	733.33***	70.5095***
	(1.550)	(0.5848)
Control variables	No	Yes
R^2	46.56%	92.19%
Observations	215	215
ΔCollectible β_1	124.760***	41.4867***
	(1.693)	(0.5267)
Control variables	No	Yes
R^2	65.78%	96.69%
Observations	231	231
ΔGame β_1	36.041***	9.21702***
	(1.097)	(0.5139)
Control variables	No	Yes
R^2	57.45%	84.09%
Observations	231	231
ΔMetaverse β_1	1407.45***	10.2082***
	(0.4495)	(0.2029)
Control variables	No	Yes
R^2	64.89%	88.81%
Observations	220	220
ΔUtility β_1	27.511***	25.0038***
	(1.58)	(1.076)
Control variables	No	Yes
R^2	57.99%	88.16%
Observations	214	214

Notes: This table displays the impacts of NFTsAI on NFT markets, including NFTI, All NFT segment, Art NFT segment, Collectible NFT segment, Game NFT segment, Metaverse NFT segment and Utility NFT segment. Weekly log return data is applied. Model (1) shows the impacts of NFTsAI on NFT markets without control variables. Model (2) presents the impacts of NFTsAI on NFT markets with control variables. Control variables are log return of CryptoPunks, log return of Decentraland, log return of Chainlink, log return of Maker, log return of BGCI, log return of Bitcoin, log return of Ethereum, log return of FTSEAWI, log return of FTSEWGBI, log return of PIMCOCORP, log return of DBC, log return of DXY, and log return of Gold. The parameter β_1 explicitly indicates the impacts of NFTsAI on NFT markets. These statistical results reveal that NFTsAI has sufficient power to explain the return of NFT assets and can confirm that NFTsAI has a positive impact on NFT markets. *p<0.1; **p<0.05; ***p<0.01

The robustness of the main empirical findings is firstly assessed by utilising alternative forecast horizons (i.e. 13-week, 26-week, 39-week, 52-week, 65-week, 78-week, 91-week, and 104-week ahead forecast horizons). The calculated results indicate that the eight new dynamic total volatility spillover indices are quantitatively similar to that in the main empirical findings, and the static total spillover connectedness indices can always keep the same as 50.7%. In this case, this study can confirm that different forecast horizons could not change the volatility spillover connectedness and the main empirical findings are robustness in terms of the forecast horizon variations. Secondly, considering it is not easy to set different VAR parameters in the TVP-VAR spillover connectedness model as it does not require one to set rolling-windows (R). In this way, this study applies the DY-VAR spillover connectedness model to test the effects of different VAR parameters on the total spillover connectedness index (Diebold & Yilmaz, 2009; Hamill et al., 2021; Li et al., 2021). As justified above, the variations in the forecast horizon in this study will not significantly change the total volatility spillover index. Therefore, the further robustness tests could fix the forecast horizon to 10-ahead in the DY-VAR spillover connectedness model and then measure the total volatility spillover connectedness index by using a different rolling-window size (i.e. R = 26, 39, 52, 65, 78, 91 or 104 weeks).

Fig. 7 displays the robustness test results for the TVP-VAR volatility spillover connectedness model. The TVP-VAR dynamic total volatility spillover index is highlighted in red colour. Regarding the DY-VAR dynamic total volatility spillover indices with different rolling-windows, they can co-move with the TVP-VAR dynamic total volatility spillover index, and they do not vary significantly with a variation in rolling-window sizes. Therefore, the TVP-VAR volatility spillover connectedness model can hold, and the main empirical findings of this study are robust regarding the selection of different forecast horizons and VAR thresholds.

Second, the supplementary analysis results indicate that NFTsAI has sufficient power to explain the return of NFT assets and can confirm that NFTsAI positively impacts NFT markets from a fixed effect perspective. In the robustness test, it is worth evaluating the prediction power of NFTsAI on the short and long-term volatility of the NFT markets to re-confirm the effects of NFTsAI on the NFT markets. This study still selects the NFTI to represent the NFT markets. Referring to the NFTI is a daily frequency index, but NFTsAI is constructed in weekly frequency. This study utilises the GARCH-MIDAS model of Engle, Ghysels, and Sohn (2013) to detect the predictive power of NFTsAI on the volatility of NFT markets. This model can decompose the total conditional volatility of asset returns into short-term and long-term components, where the short-term volatility part is driven by a simple GARCH (1,1) process, and the long-term one is determined by a MIDAS regression of low-frequency exogenous series. In the GARCH-MIDAS model, the asset return on day i of week t, $r_{i,t}$ is defined as Eq. (13):

$$r_{i,t} - \omega = \sqrt{g_{i,t}\tau_t} z_{i,t},\ \forall i = 1, \dots, N_t, \tag{13}$$

where, ω is the unconditional mean of the return, and N_t is the number of trading days in a week t. $g_{i,t}$ and τ_t are the short-term and long-term components of the conditional volatility, respectively, and can be expressed as Eqs. (14) and (15):

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \omega)^2}{\tau_t} + \beta g_{i-1,t}, \tag{14}$$

$$log(\tau_t) = m + \theta_{RV} \sum_{k=1}^{K} \varphi_k(w_{RV}) RV_{t-k} + \theta_X \sum_{k=1}^{K} \varphi_k(w_X) X_{t-k}, \tag{15}$$

where, K is the number of lags for smoothing the long-term volatility; $RV_{t-k} = \sum_{i=1}^{N_t} r_{i,t-k}^2$ is the realised volatility in a week $t-k$. X_{t-k} is the attention measure in this paper (NFTsAI) and $\varphi_k(w)$ is a weighting function that is set by a Beta polynomial as Eq. (16):

$$\varphi_k(w) = \frac{(1 - k/K)^{w-1}}{\sum_{j=1}^{K} (1 - j/K)^{w-1}}. \tag{16}$$

Fig. 8 displays the estimated total daily volatility and long-term volatility of GARCH-MIDAS. The green dashed line indicates the NFTI total daily volatility, and the blue line means the NFTI long-term volatility determined by NFTsAI. Fig. 8 reveals that NFTsAI can depict the long-term components of volatility in NFT markets, and these long-term components vary significantly over time. Fig. 8 indicates that NFTsAI could capture different aspects of long-term price fluctuations in NFT markets. Table 6 presents the estimation results of the GARCH-MIDAS model for NFT markets by using NFTsAI. All the coefficients in Table 6 are statistically significant, suggesting the capability of the GARCH-MIDAS model in capturing the short and long-term volatility of the NFT markets by using NFTsAI as a proxy. β parameter measuring

Table 6
The estimation results of GARCH-MIDAS model for NFT markets by using NFTsAI.

	μ	α	β	θ_{RV}	θ_X	w_{RV}	w_X	m	BIC
NFTI	0.031804*	0.23187***	0.40766***	0.00040289***	0.31497**	4.5163*	2.0731*	3.6846***	2993.79
	(0.30402)	(0.060036)	(0.11859)	(0.00011817)	(0.13986)	(10.148)	(2.478)	(0.10903)	

Notes: θ_{RV} and θ_X indicate the impacts of lagged RV and NFTsAI on the long-term volatility of NFT markets, respectively. BIC is the Bayesian info criterion of the estimation. The bracketed numbers are the standard errors of the estimations. *p<0.1; **p<0.05; ***p<0.01. NFTI estimation results have 455 sample size and the sample is from 08/Mar/2021 to 03/July/2022.

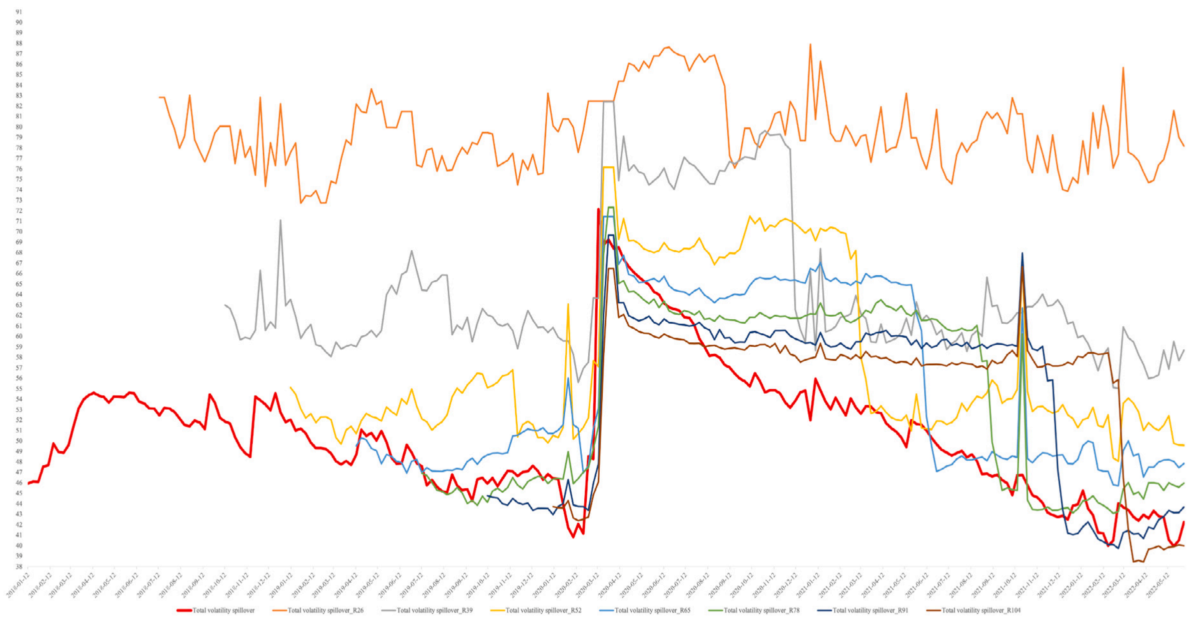

Fig. 7. Robustness test.
Notes: This figure depicts the robustness test results for this study. TVP-VAR dynamic total volatility spillover index is highlighted in red colour. DY-VAR dynamic total volatility spillover connectedness indices with different rolling-windows (i.e. rolling-window = 26, 39, 52, 65, 78, 91 or 104 weeks) are in different colours. TVP-VAR and DY-VAR models are all with AR(1) based on the information criteria. The predictive horizon for the underlying variance decomposition is 10 weeks (H = 10). The sample is from 26/Dec/2016 to 05/Jun/2022. Suppose the new forecast horizons and VAR thresholds could not significantly change the general trend of the dynamic total volatility spillover connectedness. In that case, the robustness of the main empirical findings can be confirmed. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the GARCH effects. β parameter is positive at 1% significance level, and the value is 0.4077, which indicates NFTsAI can cause strong short-term volatility in NFT markets. The θ_{RV} coefficient is positive at a 1% significance level, implying that higher historical volatility of NFTsAI will lead to higher long-term volatility of NFT markets. The estimation result of θ_X coefficient can evaluate the predictive power of the NFTsAI on the long-term volatility of NFT markets. From the statistical value of the θ_X, this study finds that NFTsAI significantly positively impacts the long-term volatility of NFT markets. In a nutshell, the empirical findings from the GARCH-MIDAS model suggest that NFTsAI contains useful forecasting information for both short and long-term volatility of NFT markets, which can further re-confirm and prove the robustness of the former empirical findings.

6. Conclusions

This study develops an NFTs attention index using over 590m news items collected from the LexisNexis News & Business database. Employing NFTsAI as a new indicator and TVP-VAR model, this study further enriches the existing NFTs literature by estimating the volatility spillover connectedness between NFT markets and other classic financial markets. The empirical results of this study suggest that the new qualitative-based measure of attention for NFT markets can be used by risk-averse investors, portfolio managers, institutional investors, researchers and financial policy regulators in their subsequent works.

Several findings can be made from the empirical analysis. Firstly, the historical decomposition results suggest that the historical variations of CryptoPunks and Decentraland could co-move with that of NFTsAI, indicating that the NFTsAI could serve as an NFT market proxy. Secondly, NFTsAI indicates that NFT markets have a relatively independent and isolated characteristic in comparison to other financial markets. In other words, NFTsAI consistently suggests that NFT markets are less affected by cryptocurrency, DeFi, equity, bond, commodity, F.X. and gold markets, and NFT markets are volatility spillover receivers. Moreover, the majority of volatility in the NFT markets is attributable to endogenous shocks, suggesting that NFT assets could impede financial contagion and have significant diversification benefits. It is also worth noting that the net dynamic volatility spillover results show that NFT markets are spreading more and more volatility to the other financial markets with the prosperity of the NFT assets. Thirdly, the net pairwise volatility spillover connectedness network uncovers that Decentraland and CryptoPunks are all spread volatilities to the NFTsAI. In addition, the panel pooled OLS regression model results confirm that NFTsAI has sufficient power to explain the return of NFT assets, and NFTsAI could positively impact NFT markets from a fixed effect perspective. In the end, robustness test results suggest that the empirical findings from the TVP-VAR are robust, and NFTsAI contains useful forecasting information for both short and long-term volatility of NFT markets.

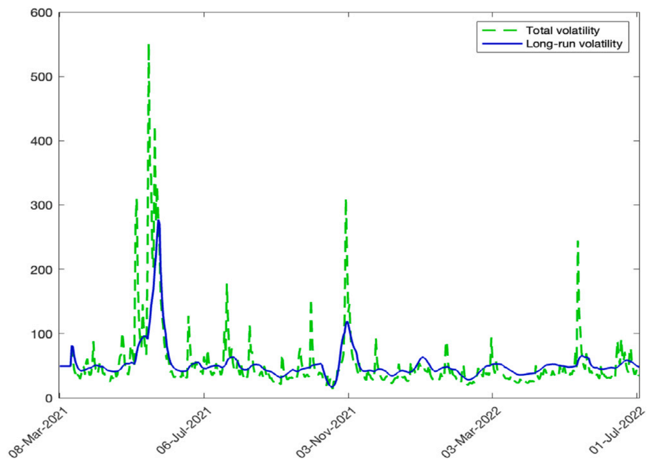

Fig. 8. Volatility for NFTI estimated by NFTsAI.
Notes: This plot shows the estimated total daily volatility and long-term volatility of GARCH-MIDAS. The green dashed line indicates the NFTI total daily volatility, and the blue line means the NFTI long-term volatility determined by NFTsAI. NFTI is in a high-frequency daily data, and NFTsAI is in a low-frequency weekly data. The sample is from 08/Mar/2021 to 03/July/2022.

This study's empirical findings could interest risk-averse investors, portfolio managers, institutional investors, researchers and financial policy regulators. For risk-averse investors, considering the volatility spillover connectedness among the NFTs market and other financial markets, also with its time-varying characteristic, is helpful for forecasting and judging the trends and relationships of different financial asset prices. This information could help to identify more arbitrage opportunities, adjust net long/short positions, and avoid unacceptable investment failures. From the perspective of portfolio managers and institutional investors, the NFTsAI could help to improve portfolio performances and optimise investment portfolios because the strong/weak volatility spillover connectedness between NFT markets and other classic financial markets could affect passive and active portfolio managers. From a policy-making perspective, the empirical findings indicate that NFTsAI has significant information contents that can signal impending turbulence in the NFT markets early. Therefore, NFTsAI can be used to trace unusual fluctuations in the NFT markets in real-time by market regulators and also can raise an early warning call to policymakers to remind them to launch more effective stabilisation policies and prevent possible NFT crises. Researchers can apply the newly issued NFTsAI to the applied finance and economics fields to further enrich the research field of NFTs.

This paper provides new insights into understanding the NFT markets. However, there are some shortcomings. Firstly, the NFT markets are just beginning to emerge, and thus, the amount of research data is not large enough. This study has tried to extend the research sample period as much as possible. However, the relatively short research sample period due to objective reasons is unavoidable. In the future, more researchers can conduct further studies based on some of the arguments in this paper, using the same or different econometrics models, longer research observation periods, and the same or higher-frequency data, in order to confirm or argue some of the findings and viewpoints in this study. Secondly, this study does not estimate the spillover connectedness in different periods and quantiles using NFTsAI. Hence, future research could concentrate on these unexplored fields. Thirdly, this study is limited to assessing the predictive power of NFTsAI. Future studies not only can expand the GARCH-MIDAS model to other financial markets by using the NFTsAI but also could measure whether the volatility of financial markets is driven by NFTs attention by using different prediction power evaluation methods.

Declaration of competing interest

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

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Appendix A. Big events related to NFTsAI

• The First Wave (26/12/2016–07/03/2021)
•04/06/2018–10/06/2018

(1). ERC-721 Tokens (08/06/2018).
Explanation: ERC-721 Tokens (CryptoKitties) shake up blockchain technology.

•25/06/2018–15/07/2018

(1). ECOMI (10/07/2018).
Explanation: ECOMI is bringing Licensed and Brand-name Collectables to Blockchain Technology.
(2). EXODUS (11/07/2018).
Explanation: HTC Blockchain phone. HTC launches the world's first major blockchain phone—the Exodus, and cooperates with the world's first and most popular NFT game on the blockchain, CryptoKitties.
(3). Decentralized gaming economy (12/07/2018).
Explanation: Blockchain game 'War Riders' partners with WAX and OPSkins Marketplace.

•06/08/2018–12/08/2018

(1). Blockchain entertainment platform partnership (10/08/2018).
Explanation: WAX and Terra Virtua set up strategic partnership. It is the world's first Reality/Virtual Reality blockchain entertainment platform.
(2). OMI tokens (10/08/2018).
Explanation: Ecomi launches crowd sale for OMI tokens.

•15/10/2018–28/10/2018

(1). TriForce Tokens (22/10/2018).
Explanation: Bitcoin gaming platform TriForce Tokens developing unique blockchain ecosystem.
(2). EXODUS 1 (23/10/2018).
Explanation: HTC formally launches the Blockchain phone, EXODUS 1.
(3). Greenfence Consumer teams up with Sony Pictures (22/10/2018).
Explanation: Blockchain leader Greenfence consumer cooperates with Sony Pictures to distribute digital collectibles for Goosebumps 2: Haunted Halloween.

•03/12/2018–23/12/2018

(1). $2 million NFTs creator fund (14/12/2018).
Explanation: the Sandbox blockchain gaming platform launches $2 million NFTs creator fund for artists.
(2). Blockchain versions of Atari games (19/12/2018).
Explanation: Atari partners with Animoca Brands to make blockchain versions of Atari games RollerCoaster Tycoon Touch and Goon Squad. The new titles will feature the integration of NFTs.
(3). NFT.NYC (20/02/2019).
NFT.NYC brings the Digital Collectibles Ecosystem to Times Square, New York City.

•21/01/2019–27/01/2019

(1). P08 (22/01/2019).
Explanation: P08, a tech company, earned the Creative Business Cup Award for innovative and impact-driven solutions in blockchain technology and NFTs.
(2). dGoods Standard (23/01/2019).
Explanation: Mythical Games, EOS Lynx, and Scatter cooperates for dGoods Standard to set a new benchmark for virtual items on the EOS Blockchain.

•11/02/2019–10/03/2019

(1). WAX Block Explorer (28/02/2019).
Explanation: WAX Block Explorer takes the NFT market openness to a whole new level.

•09/12/2019–26/01/2020

(1). A MOU between WAX and CWRK (19/12/2019).
Explanation: Worldwide Asset eXchange announces the signing of a Memorandum of Understanding with CurrencyWorks. They will work together to provide a turnkey offering for NFTs.
(2). Loans backed NFTs (21/01/2020).
Explanation: a new kind of dApp, named Rocket, that will allow DeFi users to receive undercollateralized loans by putting up (NFTs).

•30/03/2020–05/04/2020

(1). Revolution in NFTs-based Gaming Metaverse (30/03/2020).
Explanation: Atari new partnership with Animoca Brands and TSB Gaming.
(2). Emergents (30/03/2020).
Explanation: Emergents is a crypto collectible card game that will comprise non-fungible tokens so the players will have full ownership over.
(3). NFT market 16.08% CAGR (02/04/2020).
Explanation: NFT market is expected to achieve 16.08% compound annual growth rate.

•22/06/2020–26/07/2020

(1). Digital collectibles go mainstream (30/06/2020).
Explanation: digital collectibles go mainstream on the WAX Blockchain.
(2). CurrencyWorks (07/07/2020).
Explanation: the limited edition branded digital collectibles is now available on the CurrencyWorks Collectibles blockchain platform.
(3). CRYPTOGRAPH (08/07/2020).
Explanation: Cryptograph, a Blockchain based digital collectible auction platform, officially launches.
(4). Samsung Blockchain Keystore (23/07/2020).
Explanation: crypto token developers Decentraland announced that Samsung had added its token to the Samsung Blockchain Keystore.

•17/08/2020–30/08/2020

(1). VIMworld (18/08/2020).
Explanation: 8Hours Foundation announces launch date of VIMworld, a smart NFT Collectible & Gaming platform.
(2). Blockparty (19/08/2020).
Explanation: Blockparty launches a digital collectibles marketplace for art, sports, and music that enables users to own, sell, and trade digital assets.

•07/09/2020–27/09/2020

(1). New Binance LAND NFTs Buyup (09/09/2020).
Explanation: Blockchain technology has great potential in the gaming industry, and Blockchain gaming hits cryptoeconomy primetime.

•16/11/2020–29/11/2020

(1). KuCoin (16/11/2020).
KuCoin enters NFT markets with the proposal of launching NFT exchange.

•14/12/2020–20/12/2020

(1). deadmau5 digital collectibles (15/12/2020).
Explanation: first-ever deadmau5 digital collectibles to be released on WAX Blockchain.
(2). Agreement for Gibraltar NFTs (17/12/2020).
Explanation: new agreement for Gibraltar cryptocurrency stamp and digital collectible NFTs.

•21/12/2020–27/12/2020

(1). GoldenPyrex (21/12/2020).
Explanation: GoldenPyrex is building a sustainable and independent token ecosystem, and will lead in the next era in DeFi with a robust ecosystem.
(2). AXS $8.57 million and $28.74 million (24/12/2020).
Explanation: Axie Infinity hits 1-Day trading volume of $8.57 million. Furthermore, market capitalisation of Axie Infinity hits $28.74 million.
(3). Fed Token Accounts (24/12/2020).
Explanation: The Federal Reserve issued the Fed Notes article about Token Accounts in the context of digital currencies.

•28/12/2020–07/03/2020

(1). Thank You New York (29/12/2020).
Explanation: Photographer JN Silva and artist ThankYouX cooperates for digital art, 'Thank You New York' NFT portraying by using Blockchain technology.
(2). Rick and Morty Creator (14/01/2020).
Explanation: Rick and Morty Creator releases NFT artwork on Ethereum's Blockchain.
(3). Fandom (19/01/2020).
Explanation: Fandom outlines NFTs strategy for Esports Fan rewards.
(4). Hashmask (10/02/2021).
Explanation: one kinds of digital art, hashmasks, raised about $10 million four days after its launch. A hashmask sold for $130,000.

•The Second Wave (08/03/2021–22/08/2021)
•08/03/2021–14/03/2021

(1). NFTs major bull market starts (08/03/2021).
(2). NFTs $250 million market value (09/03/2021).
Explanation: investments in NFTs rose 299% in 2020, and NFTs have made nearly 1,000% profit in some cases. NFTs have a market value of $250 million. Furthermore, Christie's auction house and Paris Hilton, these legacy auction house are involving in on the NFTs boom.
(3). NFTs hype warnings (09/03/2021).
Explanation: NFTs are also dangers attached to the current level of hysteria, and the NFT market is full of price bubbles, hypes, and speculative transactions. Some experts remind NFTs investors should be aware of volatility, illiquidity, and fraud in the NFTs budding market.

•15/03/2021–28/03/2021

(1). NFTs VS The Legal Landscape (22/03/2021).
Explanation: concerns about NFTs could disrupt the legal landscape, especially in patent, ownership right, copyright and security fields.
(2). The value of NFTs (27/03/2021).
Explanation: questions remain over how investors should assess monetary worth of NFTs.

•19/04/2021–25/04/2021

(1). NFTs sale prices dropped (24/04/2021).
Explanation: the average price of NFTs dropped over 60% in April compared to February highs.

•10/05/2021–06/06/2021

(1). Anti-Money Laundering (19/05/2021).
Explanation: a collision between the anti-money laundering and NFTs. As NFTs gain popularity, buyers and sellers should consider the potential issues related to anti-money laundering laws.
(2). NFT price bubbles pop (04/06/2021).
Explanation: NFT market implodes with sales falling 90% in a month as the NFTs transaction craze fades.

•28/06/2021–18/07/2021

(1). NFTs $2.5 billion sales volume (07/07/2021).
Explanation: NFTs sales volume surges to $2.5 billion in the first half of the year.

•The Third Wave (23/08/2021–10/10/2021)
•23/08/2021–29/08/2021

(1). Stephen Curry $180k NFTs purchase (28/08/2021).
Explanation: NBA superstar Stephen Curry purchased a Bored Ape NFT for $180,000.

•06/09/2021–12/09/2021

(1). NFTs 315% increase month-on-month (09/09/2021).
Explanation: according to the data from DappRadar, August was a phenomenal month for NFTs with over $5 billion in total sales volume, a 315% increase month-on-month.
(2). New record for the price of NFTs (10/09/2021).
Explanation: a collection of BoredApes NFTs sold for $24.4 million at a Sotheby's auction.

•The Fourth Wave (11/10/2021–31/10/2021)
•11/10/2021–17/10/2021

(1). The Sandbox reaches market cap of $648.35 million (13/10/2021).
(2). Bored Ape Yacht Club 58,118% ROI (13/10/2021).
(3). Ether cards NFTs platform rewards (13/10/2021).
Explanation: Ether cards NFTs platform rewards early users with dust tokens worth $10.6 million.
(4). Concept Art House (19/10/2021).
Explanation: Concept Art House raises $25M to create NFT art.
(5). Meta4 Capital NFTs investment (21/10/2021).
Explanation: Meta4 Capital will invest up to $100M in rare NFTs.
(6). NFTs $3 billion sales volume (26/10/2021).
Explanation: NFTs sales volume in 2021 has exceeded $3 billion.

•The Fifth Wave (01/11/2021–Present)
•22/11/2021–28/11/2021

(1). AnonymousUSA Evil Dollsiu NFTs (23/11/2021).
Explanation: AnonymousUSA Evil Dollsiu NFTs sold at Sotheby's auction for $35.6 million.
(2). Dapper Labs NFTs business model (25/11/2021).
Explanation: Dapper Labs is developing blockchain technology and bringing it to the public, the innovative NFTs business model worth multi-billion dollar.
(3). Lugano NFTs and Crypto Art exhibition (26/11/2021).
Explanation: Lugano is trying to be a Blockchain & Crypto-friendly city. The digital innovation laboratory of Lugano has promoted an exhibition that explores the NFTs and Crypto Art with an exhibition, events and dedicated workshops.

•13/12/2021–19/12/2021

(1). Animoca Brands and BAYC new NFT game (14/12/2021).
Explanation: Animoca Brands Corporation Ltd and Bored Ape Yacht Club (BAYC) have joined forces to develop and publish a blockchain game using BAYC's popular Bored Ape non-fungible tokens (NFTs).

•27/12/2021–02/01/2022

(1). Mutant Ape Yacht Club 500% trading jump (29/12/2021).
Explanation: Mutant Ape Yacht Club has become the hottest NFT collection. The trading volume has surged by about 500% over the past seven days. The average price of a Mutant Ape increased from about $32,000 to about $50,000 during the past seven days.
(2). 'REAL' or 'FAKE' Bored Ape Yacht Club (31/12/2021).
Explanation: A pair of NFT projects are testing the boundary between plagiarism and parody. Digital marketplace OpenSea has banned the PHAYC and Phunky Ape Yacht Club collections, both of which are based on the same gimmick.

•07/02/2022–20/02/2022

(1). $5 billion funding (03/02/2022).
Explanation: The start-up behind the popular Bored Ape Yacht Club non-fungible token collection is in talks with Andreessen Horowitz for a $5 billion funding.
(2). BetOnline (07/02/2022).
Explanation: A sports betting giant, BetOnline, bought Bored Ape Yacht Club NFT for $375,000.
(3). NFT avatars (10/02/2022).
Explanation: from CryptoPunks to Bored Ape Yacht Club, avatars are providing a hit in the NFT market. A collection of images of disillusioned monkeys can sell for several hundred thousand dollars.
(4). NFT passport (20/02/2022).
Explanation: Harmony launched Bored Ape Yacht Club passport. Harmony's Passport doesn't move assets, but it also proves asset ownership across multiple blockchains that guarantee their authenticity.

•14/03/2022–10/04/2022

(1). NFTs consolidate (14/03/2022).
Explanation: NFTs consolidate as Bored Ape Yacht Club creator acquires CryptoPunks and Meebits.
(2). Yuga Labs and metaverse (23/03/2022).
Explanation: Yuga Labs, creators behind the Bored Ape Yacht Club is now stepping into the world of metaverse.
(3). Bored Ape Yacht warning (01/04/2022).
Explanation: Bored Ape Yacht Club warned users not to mint any NFTs after its Discord was hacked.

•02/05/2022–05/06/2022

(1). NFT hack (04/06/2022).
Explanation: Bored Ape Yacht Club Discord server hacked, NFT stolen.

Appendix B. Tables

See Table 7.

Appendix C. Figures

See Figs. 9 and 10.

Table 7
Nomenclature table.

NFTs	Non-Fungible Tokens	**NFTsAI**	Non-Fungible Tokens Attention Index	**VAR**	Vector Autoregression
TVP-VAR	Time-Varying Parameter–Vector Autoregression	**F.X.**	Foreign Exchange	**OLS**	Ordinary Least Squares
ICO	Initial Coin Offering	**BGCI**	Bloomberg Galaxy Crypto Index	**FTSEAWI**	FTSE All-World Index
FTSEWGBI	FTSE World Government Bond Index	**PIMCOCORP**	PIMCO Corporate & Income Strategy Fund	**DBC**	Invesco DB Commodity Index Tracking Fund
DXY	U.S. Dollar Index	**LDA**	Latent Dirichlet Allocation	ICEA	Cryptocurrency Environmental Attention Index
CBDCAI	CBDC Attention Index	**EPU**	Economic Policy Uncertainty	**ROI**	Return on Investment
CBDC	Central Bank Digital Currency	**IRF**	Impulse Response Function	**FEVD**	Forecast Error Variance Decomposition
HD	Historical Decomposition	**TSCI**	Total Spillover Connectedness Index	**DSC**	Directional Spillover Connectedness
DSC^f	From-Spillover Connectedness	**DSC^t**	To-Spillover Connectedness	**DSC^n**	Net-Spillover Connectedness
DSC^{np}	Net-Pairwise Directional Spillover Connectedness	**J.-B.**	Jarque–Bera Test	**CP**	CryptoPunks
DL	Decentraland	**H**	Forecast Horizon	**R**	Rolling-Window
All	All NFT Segments	**Art**	Art NFT Segment	**Collectible**	Collectible NFT Segment
Game	Game NFT Segment	**Metaverse**	Metaverse NFT Segment	**Utility**	Utility NFT Segment

Notes: This table displays all the terminology and proper nouns shown in this paper with their abbreviations.

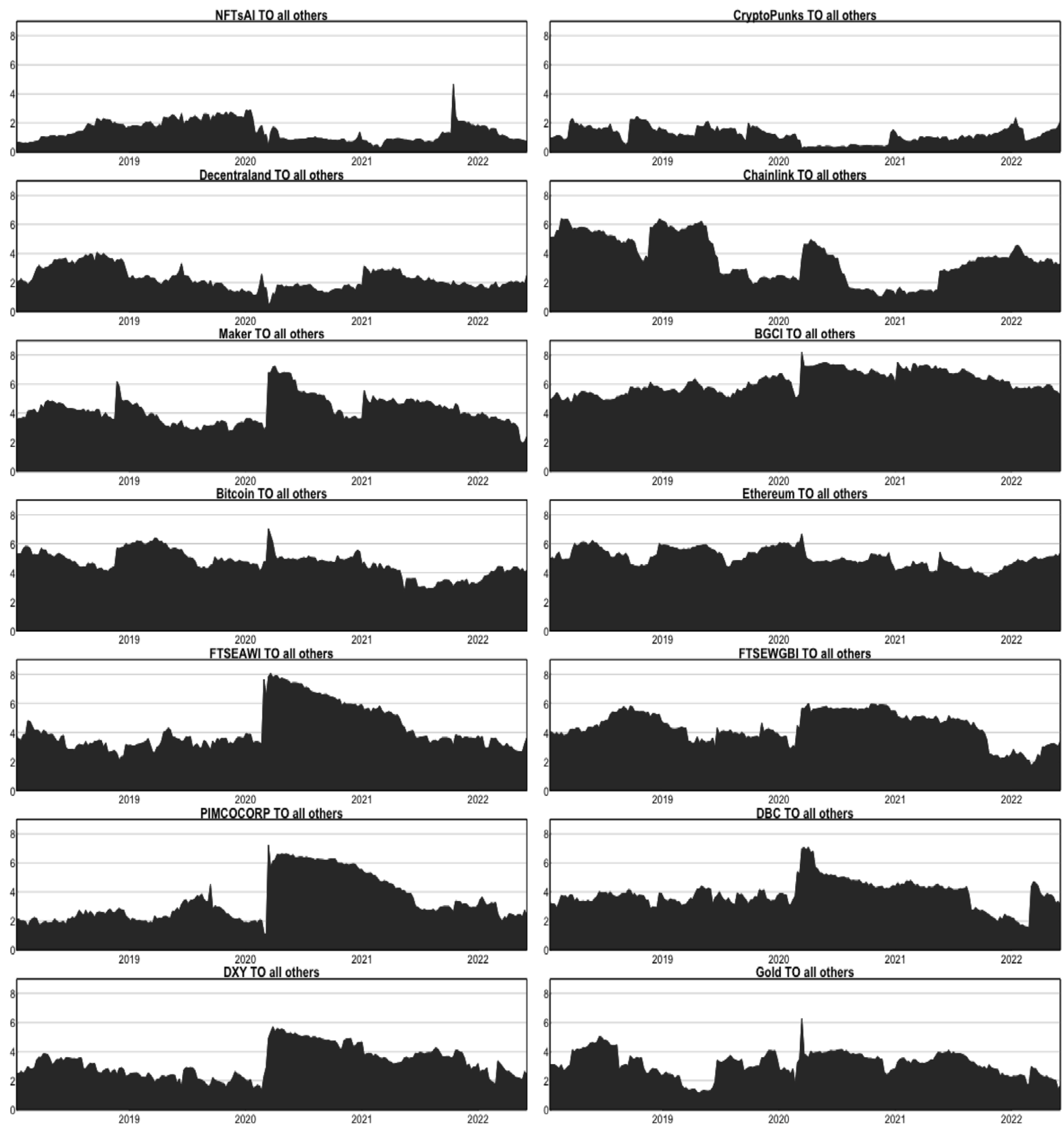

Fig. 9. Directional volatility spillovers to each variable i from all others.
Notes: The TO directional spillover connectedness quantifies the contribution of variable i to all other variables. The predictive horizon for the underlying variance decomposition is 10 weeks ($H = 10$). The sample is from 26/Dec/2016 to 05/Jun/2022. These figures indicate that (1). The cryptocurrency markets transmit more volatility spillover effects than it receives. (2). NFT markets are relatively independent and isolated. The cryptocurrency market holds the dominant role that arouses the NFT markets' volatility, compared with the stock, commodity, bond, F.X., and gold markets.

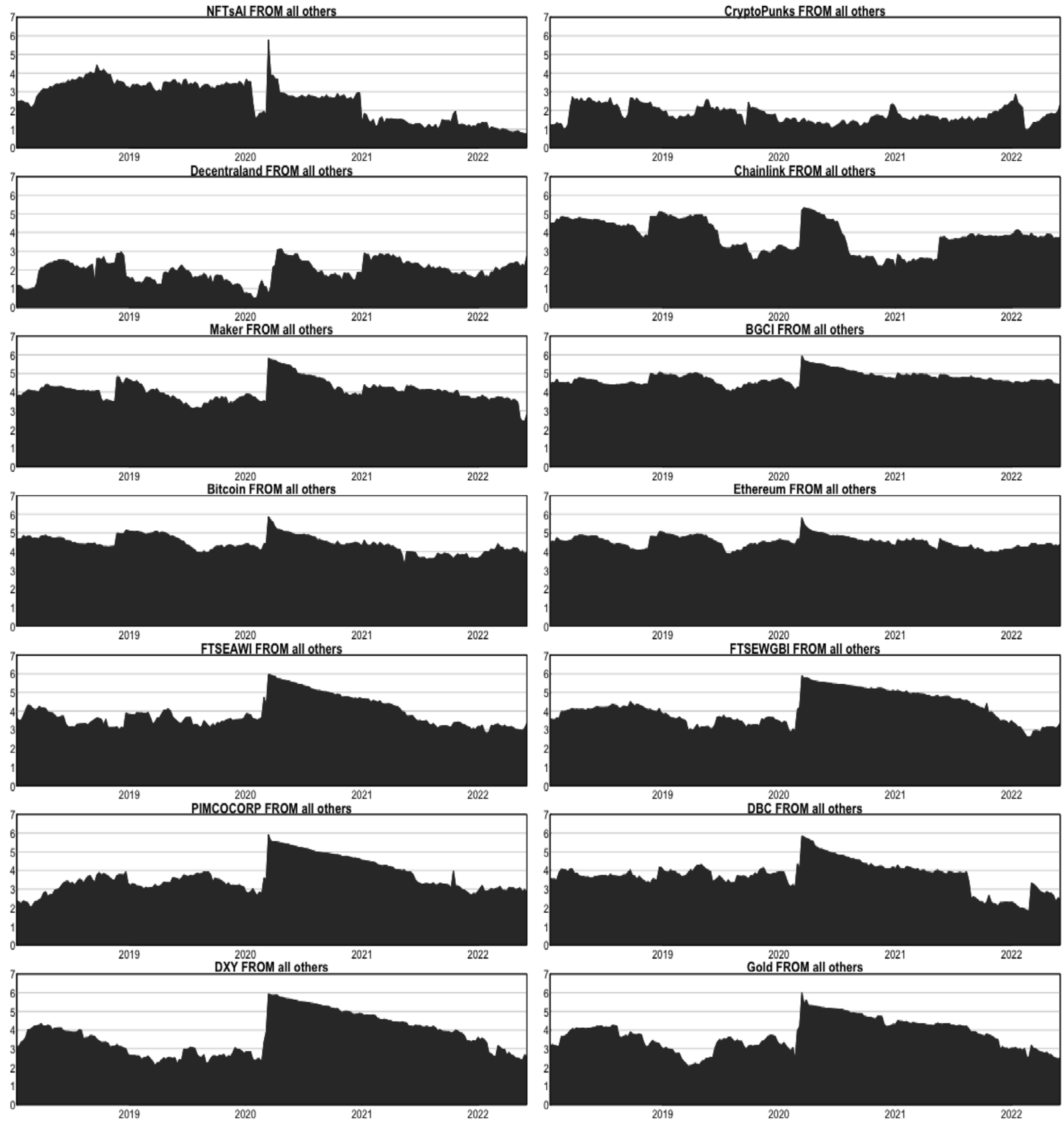

Fig. 10. Directional volatility spillovers from each variable i to all others.
Notes: The FROM directional spillover connectedness measures the spillovers received by variable i from all other variables. The predictive horizon for the underlying variance decomposition is 10 weeks ($H = 10$). The sample is from 26/Dec/2016 to 05/Jun/2022. These figures re-confirm the existing viewpoint that NFT assets have diversification benefits (Aharon & Demir, 2021; Dowling, 2021b; Karim et al., 2022; Yousaf & Yarovaya, 2022).

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