Lisbon School of Economics & Management
Universidade de Lisboa

MASTER

FINANCE

MASTER´S FINAL WORK

DISSERTATION

DYNAMIC CONNECTEDNESS BETWEEN NFTS AND MARKET SENTIMENT

RICARDO OLIVEIRA PINHO

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SUPERVISION:
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GLOSSARY

NFT – Non-Fungible Token

TVP-VAR – Time-Varying Parameter Vector Autoregression

MCI – Media Coverage Index

MS-VAR – Markov Switching Vector Autoregression

DeFi – Decentralized Finance

NARDL – Nonlinear Autoregressive Distributed Lag

SGXQIN01– SG Global Sentiment Index

BUZZ – BUZZ NextGen AI US Sentiment Leaders Index

AAII – American Association of Individual Investors

GIRF – Generalized Impulse Response Functions

GFEVD – Generalized Forecast Error Variance Decompositions

TCI – Total Connectedness Index

RESUMO

Neste estudo, eu investigo a conectividade dinâmica do retorno e da volatilidade entre os tokens não fungíveis (NFTs) e o sentimento do mercado de maio de 2018 a junho de 2022 usando um modelo de Autorregressão de Parâmetros Variáveis no Tempo (TVP-VAR). Nesta investigação, eu descubro que certos segmentos de NFTs, como Art, Collectibles, Metaverse, Games e Utilities, são relativamente independentes do sentimento do mercado. Também descubro que os segmentos Collectibles e Games são os principais recetores do transbordo de volatilidade enquanto os restantes segmentos de NFTs considerados são principalmente transmissores. Essas descobertas fornecem conhecimentos particularmente importantes para investidores.

ABSTRACT

I study the dynamic return and volatility connectedness between Non-Fungible Tokens (NFTs) and Market Sentiment from May 2018 to June 2022 using a Time-Varying Parameter Vector Autoregression (TVP-VAR) model. I find that certain NFT segments, such as Art, Collectibles, Metaverse, Games, and Utilities, are relatively independent from the Market Sentiment. I also find that Collectibles and Games segments are the major net receivers of volatility spillover while the other considered NFT segments are mostly net shock transmitters. These findings provide potentially useful insights important for investors.

Keywords: returns, volatility, Non-Fungible Tokens (NFTs), Market Sentiment, connectedness, Time-Varying Parameter Vector Autoregression (TVP-VAR)

JEL codes: C15, C39, G10, G14, G19, G41

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1. INTRODUCTION

Non-Fungible Tokens (NFTs) are a relatively recent investment asset. As per The Economic Times (2022), NFTs are cryptographic assets on a blockchain with unique identification codes and metadata that distinguish them from each other.

NFTs have been attracting a growing interest over the recent years. In accordance with the Google Trend (2022), there was almost no interest in NFTs until January 2021. However, the interest has rapidly increased. Breia (2022) reports the highest price ever paid for an NFT has reached $91.8M in December 2021.

For example, such a fast growth of NFTs, Wilson et al (2021) justify by its attractive characteristics such as non-interchangeability, immutability, and transparency. The non-interchangeability derives from NFT's connection to a digital or physical asset specifying the asset's value, ownership and trading rights, and other properties. This characteristic makes NFTs unique and different from cryptocurrencies. The immutability comes from the fact that NFTs cannot be easily tampered with or altered. The transparency comes from the fact that every NFT needs to be verified and recorded into a blockchain, which enables its property and ownership transparent to all parties.

On the other hand, McCormack (2021) associates the NFT's price growth with their close relationship with cryptocurrencies. However, the later study by Dowling (2022b) does not support the McCormack (2021) findings. Namely, Dowling (2022b) reveals that NFT's pricing is distinct to cryptocurrency's pricing in terms of volatility transmission. Aharon & Demir (2022), Wang (2022), Umar et al (2022b), Yousaf & Yarovaya (2022), Zhang et al (2022), among others, investigate the NFT's relationships with financial markets, such as cryptocurrencies, gold, equities, currencies, bonds, and Decentralized Finance (DeFi) assets. Aharon & Demir (2022) and Wang (2022) provide the evidence that NFTs are mainly independent from other financial markets. Umar et al (2022b), Yousaf & Yarovaya (2022) and Zhang et al (2022) examine other focus of the relationship between NFTs and Financial markets and take conclusions discussed in section 2.2.

Personally, I have curiosity for NFTs for a long time. And after reading McCormack (2021), Aharon & Demir (2022), Dowling (2022b), and Wang (2022), I gained interest in investigating NFT's relation with Market Sentiment. Market Sentiment is based on people's likes, emotions, and feelings, which can vary from one to another and this investigation could possibly result in new findings. Umar et al (2022a) investigate NFTs vs Media Coverage and Gunay & Muhammed (2022) investigate NFT's relationship with Market Sentiment. Umar et al (2022a) use a Time-Varying Parameter Vector Autoregressions (TVP-VAR) and Gunay & Muhammed (2022) use a Markov Switching Vector Autoregression (MS-VAR), respectively. Umar et al (2022a) finds Media Coverage is a net transmitter of spillover for both the return and volatility of NFT segments and that NFTs representing the Utilities segment is a major transmitter of spillover. Gunay & Muhammed finds Google Trend index has more impact on NFTs index in bear markets, whereas Fear and Greed, and Volatility Indexes are more significant in bull markets.

In order to contribute to the literature, in this Master Thesis, I explore the dynamic connectedness between NFT's and Market Sentiment from May 2018 to June 2022 studying five NFT segments (Art, Collectibles, Metaverse, Game, and Utilities) and four Market Sentiment indices (SG Global Sentiment Index, BUZZ NextGen AI US Sentiment Leaders Index and American Association of Individual Investors in a bullish – AAIIBULL – and bearish – AAIIBEAR – stock market). I use a Time-Varying Parameter Vector Autoregression (TVP-VAR) model as Antonakakis (2018, 2020), Aharon & Demir (2022), Umar et al (2022a), Wang (2022), among others. Researchers use this method to study the connectedness between markets and prove it is a comprehensive approach to capturing the dynamics of macroeconomic series.

With this study I find NFTs are mostly independent from Market Sentiment but can still suffer impacts on turbulent times. I also find the average dynamic connectedness imply a higher dependence from returns than from volatility, contradicting Umar et al (2022a). The average dynamic return connectedness reveals Games and Metaverse are the only shock transmitters whereas average dynamic volatiity connectedness reveals all segments, but utility are shock receivers.

The rest of the Thesis is organized as follows. In part 2 I explore the literature on NFTs and Market Sentiment and identify my contribution to the state-of-the-art. In part 3, I describe the dataset and explain the methodology used in my Thesis. In part 4, I present and discuss the empirical results. Part 5 concludes my Thesis.

2. LITERATURE REVIEW

Understanding what has already been investigated and what has already been found is crucial before starting another investigation. In this section I explore the existing literature on NFTs and Market Sentiment.

First, I explain what NFTs are and explore the relationship between NFTs and financial markets. After that, I explore what has already been investigated in particular, between NFTs and Market Sentiment. To finish this section, I reveal my contribution to the literature.

2.1 Non-Fungible Tokens: Definition

The definition of Non-Fungible Tokens (NFTs) doesn´t change among different research papers. Batchu et al (2022) define NFTs as tradeable tokens encoded on to a blockchain that records transactions in code, collecting data stored periodically as blocks, and cryptographically chained together. Dowling (2022a) state NFTs are blockchain-traded rights to any digital asset. Wang et al (2021) add NFTs are derived by Ethereum and can be bound with digital properties due to their unique characteristics. Dowling (2022a, 2022b) completes this idea saying this data can be images, videos, songs, objects in virtual realities, digitalized characters from sports and games, and many others. Wilson et al (2021) argue NFT's unique characteristics make them attractive and add non-fungibility is what makes NFTs unique and different from cryptocurrencies. These characteristics are non-interchangeability, immutability, and transparency. The non-interchangeability comes from the fact each NFT is linked to a digital or physical asset, specifying the asset's value, ownership and trading rights, and other properties. The immutability derives from the high difficulty to tamper with or alter an NFT and the transparency is due to the need to verify and record every NFT in a blockchain, which consequently makes its property and ownership transparent to all parties.

Ante (2022) state one of the most common blockchain nowadays used by NFTs is Ethereum. The fact is NFTs started to go mainstream using Ethereum's blockchain. However, as the interest in NFTs grew, Ethereum's blockchain started to become increasingly congested and transaction costs increased. As the interest in NFTs grew, alternative blockchains to develop more NFTs started to appear. Butcher (2021) considers Solana's blockchain as an alternative for Ethereum's blockchain as it offers high speed and performance, and low transaction costs. In the next section, I will explore the literature on NFTs and Financial Markets.

2.2. NFTs and Financial Markets

Considering the close relationship between NFTs and cryptocurrencies, McCormack (2021) argues that cryptocurrencies´ volatility should have a significant impact on NFTs´ pricing, saying its price growth would have direct consequences on NFTs´ prices. Dowling (2022b) uses correlation and wavelet coherences to investigate NFTs´ pricing and finds proofs contradicting McCormack (2021) by finding NFTs´ pricing is distinct to cryptocurrency pricing in terms of volatility transmission. Dowling (2022b) also argues there is the possibility there are common factors driving both markets as the author finds wavelet coherences suggest some co-movement between NFTs and cryptocurrencies.

Wang (2022) investigate the volatility spillovers across NFTs news attention (NFTsAI) and some financial markets from January 2018 to May 2022. The financial markets studied are the following: FTSEAWI, FTSEWGBI, PIMCOCORP, DBC, DXY and COMEX Gold represent stock, government bond, corporate bond, commodity, F.X. and gold markets, respectively, whereas Bitcoin and Ethereum represent cryptocurrency. The authors apply a Time-Varying Parameter Vector Autoregressions (TVP-VAR) model and find NFTsAI indicates NFT markets are dominated by cryptocurrency, equity, bond, commodity, F.X. and gold markets and that NFT markets are volatility spillover receivers.

Aharon & Demir (2022) study the relation between NFTs and MSCI World Index, gold, the PIMCO Investment Grade Corporate Bond Index Exchange-Traded Fund, the U.S. Dollar Index, Ethereum, crude oil, and NFTs. The period studied goes from January 2018 to June 2021. Aharon & Demir also apply a TVP-VAR model and find NFTs are mainly independent from every single variable studied, even from Ethereum, their close relation. Authors also find NFTs act as transmitters of systemic risk during normal market situations, but act as absorbers of risk spillovers during stressful times.

Umar et al (2022b) employ the wavelet approach to analyze the coherence between returns of NFTs and the bitcoin price, MSCI World Equity index, FTSE World Government Bond index, gold, and crude oil. The authors find that the returns coherence between NFTs and the other assets is high/low for the two-week-plus/below-to-weeks investment horizons.

Yousaf & Yarovaya (2022) investigate the static and time-varying herding behavior in conventional cryptocurrency market, non-fungible tokens, and Decentralized Finance (DeFi) assets from May 2020 to May 2021, a period of a cryptocurrency bubble. The authors did not find any evidence of herding in the static analysis but identify a time-varying herding in cryptocurrencies and DeFi assets for the short investment horizons. After performing a herding asymmetry analysis, the authors conclude that herding is not evident in conventional cryptocurrencies and NFT during up/down market, high/low volatility days, and high/low trading days.

Zhang et al (2022) examine whether non-fungible tokens (NFTs) can act as hedges and safe havens for stocks, bonds, US dollar, gold, crude oil, and Bitcoin using a nonlinear autoregressive distributed lag (NARDL) model from January 2018 to March 2022. The authors find that during the full sample, NFTs were hedges for bonds, US dollar and gold on average.

In order to have a better understanding of the topic examined in this Thesis, the dynamic connectedness between NFTs and Market Sentiment, during the next section, I will demonstrate the existent literature on NFTs and Market Sentiment.

2.3. NFTs and Market Sentiment

As discussed in the previous sub-section, the most NFT-related papers are focused on a comparative analysis of the NFT and financial markets. However, there is a scarce literature studying NFTs and Market Sentiment. To the best of my knowledge, Umar et al (2022a) and Gunay & Muhammed (2022) are the only studies that investigate the relationship between the NFTs and Market Sentiment.

In order to understand what Market Sentiment is, and how it can be measured, I will first explore some existent literature on Market Sentiment.

Price (2022) define Market Sentiment as the average sentiment toward a market or stock. Chari et al (2017) define it as the sentiment created by news that may change one's psychology about a certain investment asset at a given point in time. Baker & Wurgler (2006) and Chari et al (2017) argue that Market Sentiment can have an impact on market prices. These impacts can be higher or lower depending on the type of the markets and time frames studied. Baker & Wurgler (2006) consider that not all investors are rational on their investment decisions, meaning some investments happen due to likes, emotions, and other irrational reasons. Authors conclude that there are only two types of investors: rational and irrational investors. Irrational investors are defined as those who invest based on their emotions, likes. On the other hand, the rational investors follow logical thinking and thorough analysis to back their investment decisions. Baker & Wurgler (2006) argue Market Sentiment is bearish when irrational investors feel a negative sentiment and bullish, when irrational investors feel a positive sentiment. A negative (positive) sentiment causes investors to sell (buy) their positions, which makes prices decrease (increase).

Measuring Market Sentiment can be hard as it is based on likes, emotions, and feelings, which change from person to person and from situation to situation. Nonetheless, several approaches have been developed to measure the Market Sentiment. For example, Baker & Wurgler (2006) build the Market Sentiment index and uses the following proxies to build it: trading volume measured by NYSE turnover, the dividend premium, the closed-end fund discount, the number, and first-day returns on IPOs, and the equity share in new issues.

In their turn, Silva (2021) and Chen et al (2022) also build their own indexes. Silva (2021) uses four proxies to build its own sentiment index: trading volume, liquidity, the relation between the open and the adjusted closing prices, and the assets volatility. Chen et al (2022) build an index with trading volume, open interest, psychological line, futures momentum factor, and relative strength index.

Now, that I Market Sentiment is defined and I demonstrated how other authors measure Market Sentiment, I will explore the literature on NFTs versus Media Coverage and NFTs versus Market Sentiment

Umar et al (2022a) explores the return and volatility connectedness between NFTs and Media Coverage during the Covid-19 pandemic. Media Coverage means any photographing, recording, or broadcasting of court proceedings by the media using television, radio, photographic, or recording equipment. Frijns & Huynh (2018) find the frequent news flow improves investors' asset allocation. However, the effect of media on the invertor's behaviour is conditional on each person's characteristics and a person's characteristics can directly affect how one feels towards something. Following this reasoning, Media Coverage and Market Sentiment are connected and for that reason, I include Umar et al (2022a) in this section. Umar et al (2022a) apply a Time-Varying Parameter Vector Autoregressions (TVP-VAR) on the dataset composed of five NFT segments (Art, Collectibles, Games, Metaverse, and Utilities) and the RavenPack Media Coverage Index (MCI), an index based on the ratio of news sources via social media to all news sources covering the COVID-19 pandemic and that ranges from zero to one hundred, with one hundred representing the most complete COVID-19 Media Coverage. The authors find that NFT segments are particularly susceptible to the increasing flow of news related to the Covid-19 pandemic.

Gunay & Muhammed (2022) use a Markov Switching Vector Autoregression (MS-VAR) approach to explore the dependence of NFTs on investor's sentiments from January 2019 to January 2022. Authors use three proxies for the measurement of investor sentiment, namely: Google Trend, Fear and Greed Index and a Volatility Index. Google Trends is a feature that shows how frequently a given search term is entered into Google's search engine relative to the site's total search volume over a given period of time. The Fear & Greed Index is a compilation of seven different indicators that measure some aspect of stock market behavior. They are market momentum, stock price strength, stock price breadth, put and call options, junk bond demand, market volatility, and safe haven demand. The Volatility Index is a real-time market index representing the market's expectations for volatility over the coming 30 days. Gunay & Muhammed (2022) observe that Google Trend is significant when NFT's trend is falling, whereas Fear and Greed, and Volatility Indexes are more important when markets are bullish.

Now that the existent literature on NFTs and other financial markets is explored, in the next section 2.4., I will explain my contribution to the literature.

2.4. Contribution to the Literature

As explained earlier, Baker & Wurgler (2006) ague irrational investors can cause market prices to increase and decrease depending on their positive or negative feelings, respectively. Following this reasoning, Market Sentiment is an important variable to determine the movement of some markets. Adding my personal curiosity for NFTs and the importance of Market Sentiment in today's financial markets, I've decided to contribute to the literature by investigating the dynamic returns and volatility connectedness between NFTs and Market Sentiment.

At first, I calculate the correlation between all variables investigated in this paper (Art, Collectibles, Metaverse, Games, Utilities, the SG Global Sentiment Index, the BUZZ NextGen AI US Sentiment Leaders Index, the American Association of Individual Investors Bullish Index, and the American Association of Individual Investors Bullish Index). Then, I use the TVP-VAR model to study the dynamic connectedness between NFTs and Market Sentiment. Ekinci & Gençyürek (2021), Umar et al (2022a), Wang (2022), Aharon & Demir (2022), Wang (2022) and several other studies use this model to study the connectedness between markets.

In the next section 3, I explain in more detail the dataset studied in this Thesis and the method applied to the chosen empirical sample. To the best of my knowledge, this Thesis covers a larger period than any other study investigating the connectedness between NFTs and Market Sentiment. Also, no other study investigates more Market Sentiment indices than this Thesis.

3. DATA & METHODOLOGY

3.1. Data Description

In this Thesis I study the return and volatility connectedness between Market Sentiment and NFTs using indices and data collected from companies and surveys. The employed data relates to four indices focused on Market Sentiment and five NFT segments. The studied period is from May 2018 to June 2022. The historical data is analysed on a weekly basis resulting into the total of 218 observations for each variable.

The NFT data was extracted on a daily basis from *Nonfungible.com* and includes the following segments: Art, Collectibles, Game, Metaverse and Utility. The weekly price of these variables corresponds to the average price of every seven days.

All data on Market Sentiment has been extracted from *Bloomberg* on a weekly basis. Thus, the Market Sentiment dataset contains the following indexes and surveys:

- The SG Global Sentiment Index *(Bloomberg* ticker: SGXQIN01) tracks the performance of an adaptive and diverse portfolio. The strategy dynamically responds to the market environment using a simple, but robust asset allocation methodology. The Index offers diversification across global asset classes such as, global equities, government debt, and commodities within the agriculture, metals, and energy sectors, to give its portfolio resilience. In addition, it uses fundamental market signals to assess current market changes across the globe and allocate to Risk-On, Transitional, or Risk-Reduced portfolios. Plus, a built-in volatility control feature helps manage exposure in turbulent markets. As a result, the SG Global Sentiment Index combines a robust allocation model with a calibrated portfolio of assets to deliver the simple power of adaptive risk allocation in a fully systematic, rules-based index.

- The BUZZ NextGen AI US Sentiment Leaders Index (BUZZ Index) identifies the 75 most bullish large cap US equities based on investment insights derived from the vast content generated across online platforms. The data is filtered through an analytics model which utilizes Natural Language Processing algorithms and Artificial Intelligence applications.
- The American Association of Individual Investors Bullish Market Index (AAIIBULL) measures the percentage of individual investors who are bullish on the stock market for the next six months. Individuals are polled from the ranks of AAII membership on a weekly basis. High bullish readings in the poll usually are signs of market tops and lows ones are signs of market bottoms.
- The American Association of Individual Investors Bearish Market Index (AAIIBEAR) measures the percentage of individual investors who are bearish on the stock market for the next six months. Individuals are polled from the ranks of AAII membership on a weekly basis.

To have a better understanding of the return dynamics of the variables, Figure 1 displays the weekly log returns for four Market Sentiment indices and five NFT segments. Figure 1 allows to have see how returns have changed with time.

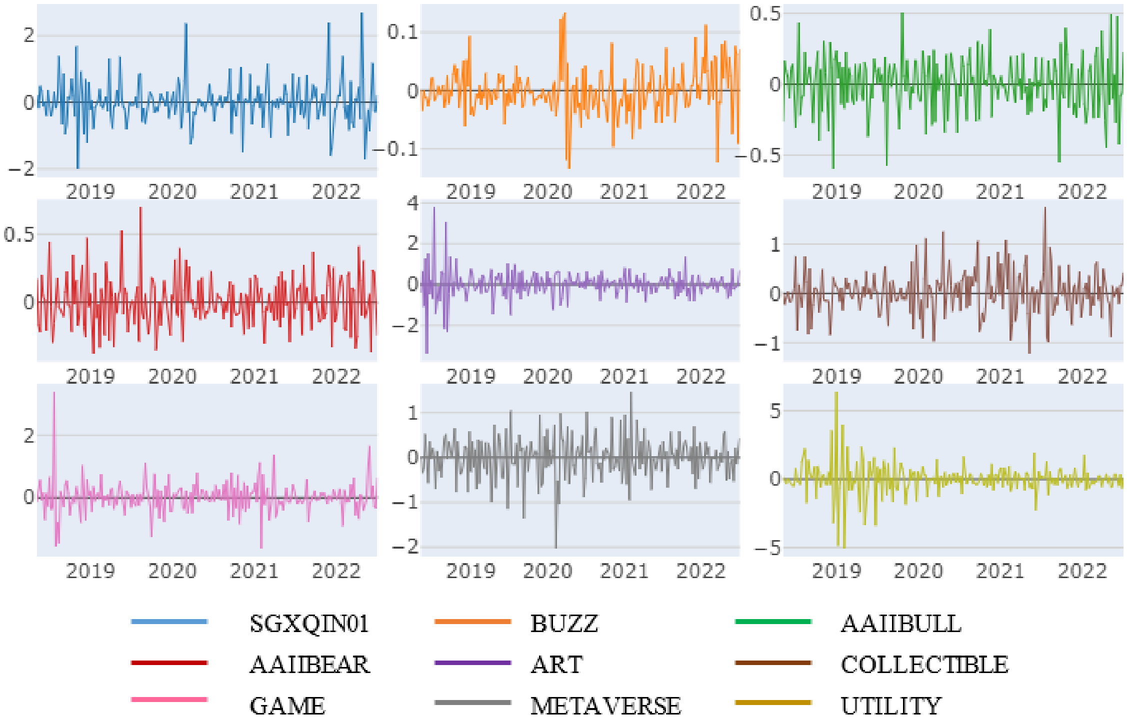

Figure 1 - Weekly Returns of all Observations

Notes: This figure demonstrates the raw data of all variable's returns. SGXQIN01 corresponds to SG Global Sentiment Index. Buzz corresponds to BUZZ NextGen AI US Sentiment Leaders Index. AAIIBULL corresponds to the American Association of Individual Investors Bullish Market. AAIIBEAR corresponds to the American Association of Individual Investors Bearish Market Index. ART, COLLECTIBLE, GAME, METAVERSE and UTLITY correspond to the NFT segments studied in this thesis.

Source: Data collected from Bloomberg and *nonfungible.com*

Additionally, Table 1 demonstrates the statistics for the entire sample of the studied variables. Table 1 demonstrates that among the NFT segments, Collectibles (2,44%) have the highest return during the studied period, followed by Games (1,63%), Art (1,61%), Utility (1,45%) and lastly Metaverse (0,35%). Between Market Sentiment indices, the SGXQIN01 Index (0,49%) shows the higher value, followed by AAIIBEAR Index (0,28%). Both BUZZ Index and AAIIBULL Index demonstrate negative values, corresponding to -0,08% and -0,22%, respectively.

Table 1 – Descriptive Statistics

stats	SGXQIN01	BUZZ	AAIIBULL	AAIIBEAR	ART	COLLECTIBLE	GAME	METAVERSE	UTILITY
mean	.0048785	-.0007935	-.0022097	.0027665	.016098	.0244081	.0162845	.0034835	.0145493
sd	.6242574	.0402848	.1915118	.1780461	.6722848	.4337841	.5025906	.4618641	1.128576
min	-1.99243	-.1342189	-.5962568	-.3758632	-3.368042	-1.214064	-1.604961	-2.019258	-5.026081
max	2.691243	.1335145	.5040078	.6948083	3.773592	1.742128	3.373339	1.455888	6.355175
variance	.3896973	.0016229	.0366768	.0317004	.4519668	.1881687	.2525973	.2133184	1.273684
skewness	.6435122	.2326827	-.2199221	.4416182	.2778912	.2582709	1.238918	-.3812181	.118651
kurtosis	6.292374	4.647123	3.413543	3.628675	11.69301	4.184288	12.51087	4.510696	11.11964

Notes: This table reports the sample statistics of the Market Sentiment Indices and NFT returns. Sd stands for standard deviation. Min and max represent the minimum and maximum observations for each variable.

Source: Stata

After understanding the dataset used, I study in the next section 3.2. whether the chosen variables demonstrate any correlation between themselves or not.

3.2. Correlation Analysis

In this section I will study how strong is the relationship between NFTs and Market Sentiment by calculating the correlations between NFT and Market Sentiment variables on a weekly, monthly, quarterly, and annual basis.

Before analysing the correlation results, and in order to avoid mistakes analysing it, we must first comprehend it. Asuero et al (2006) defines correlation as the degree of association between two variables, but adds that if the correlation between two variables equals zero, it doesn´t necessary mean they are statistically independent. Previous studies, such as Langley (1971) and Sands (1977) have already proved that the correlation results are not precise and don´t necessarily prove influence between variables. Sands (1977) backs this statement by presenting the example of the populations of Miami, Florida and Tulsa, Oklahoma. Census numbers for 1900, 1950, 1960, and 1970 indicated a correlation of 0.98 between these two cities, which suggested the growth of one city was the cause of the other one's growth. But Sands (1977) argues the increase in one city cannot be held responsible for the increase in the other. Langley (1971), after taking the same conclusion, provides more examples and explores similar situations. This conclusion suggests that correlation is not the causation. Following Langley (1971 and Sands (1977), Asuero et al (2006) state that the correlation coefficient is an estimate of association between the variables. This means that a positive correlation only indicates that it is likely that the second variable increases if the first one increases, and vice versa. The author also adds correlations are only valid when the observations are randomly drawn.

The lack of efficiency in some correlation's results can be considered as a disadvantage of this statistic. Nonetheless, Asuero et al (2006) considers this stat as simple and attractive. Sands (1977) and Asuero et al (2006) argue statistical calculations that neglect correlations often result in incorrect results and erroneous conclusions. Rummel (1976) adds to this statement that the correlation coefficient in its many forms has become the "workhorse" of several researchs and analysis. This means correlations can help improving the quality and strength of a dataset and so, it is frequently used to check variable's degree of association and model's fitness in a set of data. Correlation's relevance to achieve a correct result is one of its strongs, but when used in many variables, it can be confusing. To contradict this issue, Asuero et al (2006) suggest it is better to choose variables where errors are normal and uncorrelated.

Johnson & Wichern (2002) explore correlation in a more profound way and explain outliers can be a problem to correlation's calculations, specially when the number of observations is low.

As the number of observations for the monthly, quarterly and annual basis were significantly low, in order to demonstrate stronger results, I calculated the smoothing moving average returns for each frequency using the following formula:

$$y = x; window\ (L\ C) \tag{1}$$

$$\frac{1}{n} * \{x[t-(n-1)] + x[t-(n-2)] + \cdots + x[t-1] + 1 * x(t)\}; x(t) = x \tag{2}$$

Where x is the variable to smooth and y is the name of the variable after being smoothed. L corresponds to the number of lagged terms. I used 3, 12 and 51 lagged terms. As one term corresponds to one week, by adding 3, 12 and 51 lagged terms to the current term, I was able to obtain the monthly, quarterly, and annual smoothed moving averages, respectively. C corresponds to the current term; *t* represents the period in question and *n* is the maximum number of observations (terms).

After calculating the smoothed monthly moving average returns with 3 lagged terms, the observations obtained were exactly the same as the ones in the weekly returns. For that reason, I do not consider the smoothed monthly moving average returns in the following analysis.

In order to have a better understanding of the correlation between variables, Figure 2 displays the combination of all variables´ returns on a weekly, quarterly, and annual basis. This figure demonstrates where all observations from all the chosen variables are positioned. In this figure, it is possible to verify the existence of some outliers. Nonetheless, almost all observations from all variables are concentrated in the centre of the graph in all frequencies.

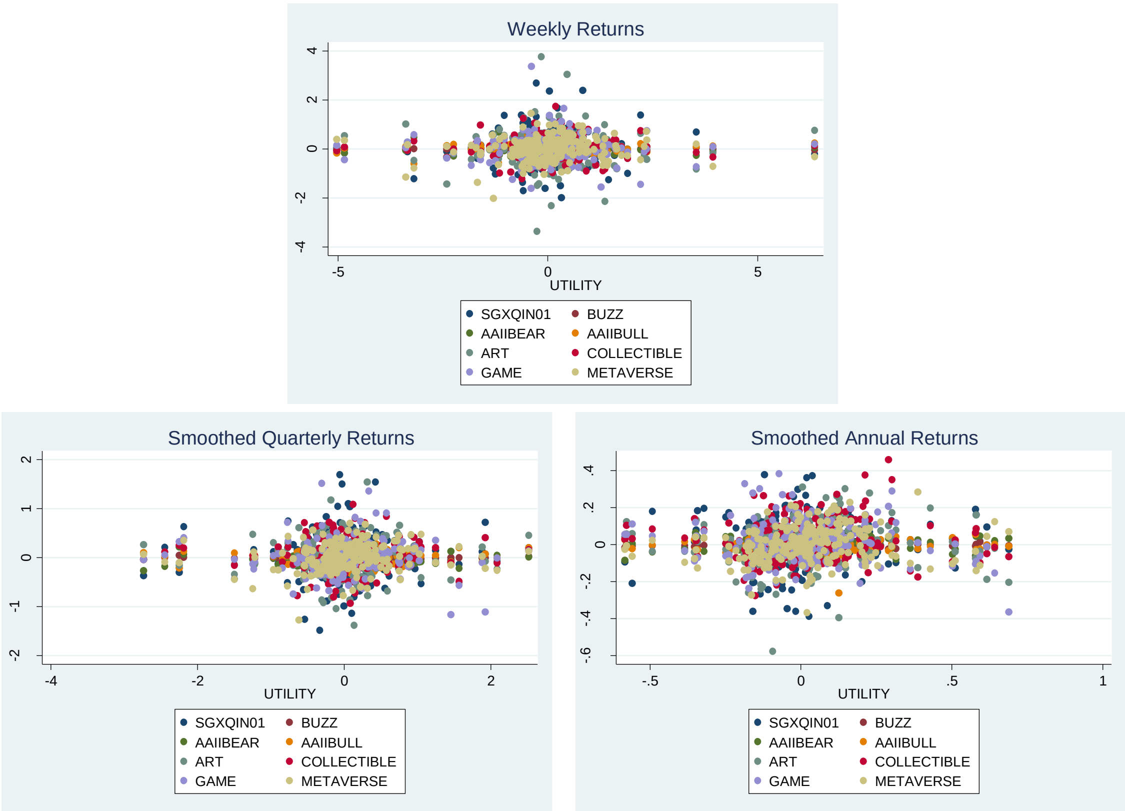

Figure 2 – Combination Of All Variable's Returns in Different Frequencies

Notes: This figure demonstrates the weekly returns, the smoothed quarterly returns and the smoothed annual returns for all variables. Each color represents a different variable.

Source: Stata

The dataset used in this study shows a low number of outliers. However, depending on the value of the outlier, it can significantly increase or decrease the correlation coefficient. Johnson & Wichern (2002) suggest correcting obvious recording mistakes with values consistent with the rest of the observations to minimize outlier's impacts or to duplicate measurements. In this paper, to reduce outlier's impacts on the dataset used, and to improve the robustness of the dataset and results of the correlations, I study the returns in a quarter and annual basis in addition to the weekly basis. The smoothed values reduce the outlier's impacts and consequently the correlation's sensitivity. To verify this, Figure 2 demonstrates more outliers on a weekly basis than on a quarter or annual basis as the returns were smoothed in the last two frequencies.

After understanding the importance of a correlation analysis, the impact it might have and the importance of reducing the number or outliers, I am now able to analyze the obtained results with this statistic. Tables 2, 3 and 4 demonstrate the correlation for all variables for the different frequencies.

Table 2 displays the weekly correlation indicating that there is a very low correlation between NFT segments. Collectible and Art have the highest correlation (0,17), followed by Game and Collectible (0,16). Between Market Sentiment indices, AAIIBULL Index and AIIBEAR Index demonstrate a highly negative correlation (-0,76). However, this correlation was already expected because these indexes represent market opposites. This result is followed by Buzz Index and SGXQIN01 Index, which show a low correlation (0,44). When comparing Market Sentiment with NFTs, I observe a low correlation. Namely, Metaverse and SGXQIN01 Index pair has the highest correlation (0,24) among all the combinations of Market Sentiment versus NFTs variables, followed by Metaverse and BUZZ Index (0,18).

Table 2 – Weekly Correlation

	SGXQIN01	BUZZ	AAIIBULL	AAIIBEAR	ART	COLLECTIBLE	GAME	METAVERSE	UTILITY
SGXQIN01	1,0000								
BUZZ	0,4419	1,0000							
AAIIBULL	0,1668	0,2159	1,0000						
AAIIBEAR	-0,1536	-0,1764	-0,7563	1,0000					
ART	0,0195	-0,0861	0,0006	0,0163	1,0000				
COLLECTIBLE	0,1391	0,0243	0,0909	-0,0806	0,1652	1,0000			
GAME	-0,0771	-0,0335	0,0186	-0,1030	-0,0045	0,1645	1,0000		
METAVERSE	0,2352	0,1791	0,0880	-0,0221	-0,0696	0,0445	0,0273	1,0000	
UTILITY	0,0207	0,0418	0,0442	0,0095	0,0067	0,0242	0,0001	0,0858	1,0000

Notes: This table reports the weekly correlation matrix of NFT returns and Market Sentiment.

Source: Stata

Table 3 displays the quarterly moving average correlation. Similarily to the weekly correlation analysis, the quarterly correlation also indicates a low correlation between NFT segments with slight differences between the previous correlations. Collectible and

Art continue to have the highest correlation (0,25), followed by Game and Collectible, and Utility and Metaverse with the same value (0,15). Among Market Sentiment indices, the relations with AAIIBEAR are the ones the highest correlation values. AAIIBULL Index and AIIBEAR Index have a correlation of -0,76, and AAIIBEAR Index with Buzz Index have 0,44. When comparing Market Sentiment and NFT segments, Metaverse and SGXQIN01 Index have again the highest correlation (0,17) between this combination of variables, followed by Collectibles and SGXQIN01 Index and Game and Buzz Index, both with the same correlation value (0,12).

Table 3 – Quarterly Moving Average Correlation

	SGXQIN01	BUZZ	AAIIBULL	AAIIBEAR	ART	COLLECTIBLE	GAME	METAVERSE	UTILITY
SGXQIN01	1,0000								
BUZZ	0,3897	1,0000							
AAIIBULL	0,3121	0,4359	1,0000						
AAIIBEAR	-0,2629	-0,3692	-0,7648	1,0000					
ART	-0,0250	-0,0823	-0,0591	0,0968	1,0000				
COLLECTIBLE	0,1150	-0,0320	0,1100	-0,1242	0,2545	1,0000			
GAME	-0,1549	-0,1216	-0,0563	-0,0174	0,0201	0,1505	1,0000		
METAVERSE	0,1727	0,0964	0,1080	0,0156	-0,1176	0,0313	-0,0273	1,0000	
UTILITY	0,0592	0,0447	0,1303	-0,0456	-0,0250	0,0313	-0,0496	0,1508	1,0000

Notes: This table reports the quarterly moving average correlation matrix of NFT returns and Market Sentiment.

Source: Stata

Table 4 shows the annual moving average correlation and also indicates an overall low correlation between all variables. The correlation between Art and Collectibles is the highest among NFTs (0,39), followed by the increase between Game and Collectibles (0,30). Once again, among Market Sentiment, the relations with highest correlation continue to be AAIIBEAR Index and AAIIBULL Index (-0,78), followed by AAIIBEAR Index with Buzz Index (0,43). Between Market Sentiment and NFT segments, the highest correlation is between Collectibles and Buzz Index (-0,36), followed by Game and Buzz Index (-0,12).

Table 4 – Annual Moving Average Correlation

	SGXQIN01	BUZZ	AAIIBULL	AAIIBEAR	ART	COLLECTIBLE	GAME	METAVERSE	UTILITY
SGXQIN01	1,0000								
BUZZ	0,1650	1,0000							
AAIIBULL	0,2357	0,4334	1,0000						
AAIIBEAR	-0,1545	-0,3012	-0,7829	1,0000					
ART	-0,0319	-0,1982	-0,0310	0,1279	1,0000				
COLLECTIBLE	-0,0176	-0,3641	0,0548	-0,0838	0,3927	1,0000			
GAME	-0,1690	-0,2077	-0,0562	0,0012	0,1009	0,2953	1,0000		
METAVERSE	-0,0277	-0,1204	-0,0415	0,0684	0,1003	0,1951	-0,0847	1,0000	
UTILITY	0,0469	-0,0491	0,0792	-0,0446	0,0682	0,1162	-0,1002	0,1461	1,0000

Notes: This table reports the annual moving average correlation matrix of NFT returns and Market Sentiment.

Source: Stata

The weekly, quarterly and annual moving average correlation analysis between NFTs and Market Sentiment was made considering the values represented in Table 5, being the size of r the value resulting from the correlation calculations.

Table 5 – Level of r (Correlation's Strength)

Size of r	Interpretation
0.90 to 1.00	Very high correlation
0.70 to 0.89	High correlation
0.50 to 0.69	Moderate correlation
0.30 to 0.49	Low correlation
0.00 to 0.29	Little if any correlation

Notes: This table demonsrates the level of r used to analyze correlation's strength.

Source: Asuero et al (2006)

According to Langley (1971), Sands (1977) and Asuero et al (2006), a low correlation between variables only indicate that there is, in general, a low probability of one variable influencing another. Following this reasoning, it is never guaranteed there is low correlation between the studied variables, but a low probability instead.

The highest results obtained were between AAIIBEAR Index and AAIIBULL Index, which always showed a high correlation. However, this result does not impact in any way the conclusions I take from the relations between NFTs and Market Sentiment since this specific result was already expected as these indexes study market opposites.

I notice in general a low or little to any correlation between NFT segments and Market Sentiment, which indicate that Market Sentiment barely influence NFT's returns. On a deeper note, the obtained results indicate that, in general, Collectibles and Metaverse are the NFT segments that reflect more impact from the Market Sentiment indices. It is also possiblie to verify that Buzz Index and SGXQIN01 Index seem to be the indexes with higher impacts on the NFT segments. These findings are in line with Asuero et al (2006), who suggest it is better to choose uncorrelated variables to obtain better results, and accordingly to this reasoning, the final conclusions of this study should be strong.

In the next section, I explain the necessary methodology used in order to study the Dynamic connectedness between NFTs and Market Sentiment.

3.3 Time-Varying Parameter Vector Autoregressions (TVP-VAR)

To study the dynamic connectedness between NFTs and Market Sentiment, I use a Time-Varying Parameter Vector Autoregression (TVP-VAR). This approach was proposed by Antonakakis et al (2018, 2020) and extends the originally proposed connectedness approach of Diebold & Yılmaz (2009, 2012, 2014). This method overcomes the problem of arbitrarily choosing the window size, which could lead to wrong or flattened parameters, and avoids losing observations as it is uses a Kalman filter procedure in the spirit of Koop & Korobilis (2014) to calculate the variance-covariance matrix. It can also be used to examine dynamic connectedness measures for both low-frequency data and limited time-series data.

The TVP-VAR model can be written as follows:

$$W_t = \beta_t W_{t-1} + \varepsilon_t;\ \varepsilon_t | F_{t-1} \sim N(0, A_t) \tag{3}$$

$$\beta_t = \beta_{t-1} + v_t;\ v_t | F_{t-1} \sim N(0, B_t) \tag{4}$$

Where W_t represents a N x 1 vector, F_{t-1} indicates the array of data accessible at time *t-1*. W_{t-1} is the Np × 1 lagged array of dependent parameters. β_t denotes an N × Np time-varying coefficient matrix. ε_t and v_t are the N × 1 dimensional arrays of error terms. A_t and B_t are *N* × *N* and *Np* × *Np* variance-covariance matrices, respectively, for ε_t and v_t, respectively.

According to Diebold & Yilmaz (2014), the time-varying coefficients and time-varying variance-covariance matrices are used to estimate the generalized connectedness.

The generalized connectedness approach is based on the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) developed by Koop et al (1996) and Pesaran & Shin (1998). In order to estimate the GIRF and GFEVD, it's important to transform the time-varying-parameter vector-autoregressive model to its vector moving averages using the time-varying coefficients and error covariances in order to estimate the GIRF and GFVED. As a result of that, the equation is presented as follows:

$$W_t = \beta_t W_{t-1} + \varepsilon_t = Z_t \varepsilon_t \tag{5}$$

Where $Z_t = (Z_{1,t}, Z_{2,t}, \dots Z_{p,t})'$ is a $N \times N$ variance-covariance matrix. The GIRFs demonstrate the responses of all variables following a shock in variable *i*, and the GFVED represents the pairwise directional connectedness from *j* to *i*. These variances together explain 100% of variable's i forecast error variance, which means the forecast-error variance can be expressed as follows:

$$\psi_{ij,t}^{g}(J) = \frac{\Sigma_{t=1}^{j-1} \varphi_{ij,t}^{2,g}}{\Sigma_{j=1}^{N} \Sigma_{t=1}^{J-1} \varphi_{ij,t}^{2,g}} \tag{6}$$

With $\Sigma_{j=1}^{N} \psi_{ij,t}^{N}(J) = 1$ and $\Sigma_{i,j=1}^{N} \psi_{ij,t}^{N}(J) = N$.

The Total Connectedness Index (TCI) is built using the GFVED, which represents the total interconnectedness in the framework and shows how a shock in one variable spill over to other variables. The TCI can be expressed as:

$$C_t^g(J) = \frac{\Sigma_{i,j=1,i\neq j}^{N} \psi_{ij,t}^{g}(J)}{N} * 100 \tag{7}$$

When total directional connectedness goes from *i* to *j*, we can express the equation as follows:

$$C_{i\to j,t}^{g}(J) = \frac{\Sigma_{i,j=1,i\neq j}^{N} \psi_{ij,t}^{g}(J)}{\Sigma_{j=1}^{N} \psi_{ij,t}^{N}(J)} * 100 \tag{8}$$

When total directional connectedness goes from *j* to *i*, we can express the equation as follows:

$$C_{i\leftarrow j,t}^{g}(J) = \frac{\Sigma_{i,j=1,i\neq j}^{N} \psi_{ij,t}^{g}(J)}{\Sigma_{j=1}^{N} \psi_{ij,t}^{N}(J)} * 100 \tag{9}$$

Finally, we can calculate a net total directional connectedness, which can be interpreted as the influence variable *i* has over the other variables:

$$C^{g}_{i,t}(J) = C^{g}_{i\rightarrow j,t}(J) - C^{g}_{i\leftarrow j,t}(J) \qquad (10)$$

If $C^{g}_{i,t}(J) > 0$, the variable *i* is a transmitter, whereas if $C^{g}_{i,t}(J) < 0$, the variable *i* is a receiver of spillover.

4. EMPIRICAL RESULTS

This section explores the results obtained from the Time-Varying Parameter Vector Autoregression (TVP-VAR) model and finds the connectedness between the NFTs and Market Sentiment. I start by presenting the results of the Average Dynamic Return Connectedness and Average Dynamic Volatility Connectedness. After that, I discuss the dynamic total return and volatility connectedness. Then I analyze the dynamic total spillover to find whether the NFTs are shock transmitters or shock receivers in terms of returns and volatility. Then I explore which variables contribute more to others and which variables receive more from the system. To finish the dynamic connectedness analysis, I study the net pairwise connectedness.

4.1. Dynamic Connectedness

In this part, I present the results obtained from Tables 6 and 7. I start by explaining the Total Connectedness Index (TCI), which illustrates the average impact a shock in one series has on all others. Then I talk about the intrinsic variation in NFT's returns and volatilities and later I reveal which variables are transmitters and receivers.

Table 6 – Average Dynamic Return Connectedness

	SGXQIN01	BUZZ	AAIIBULL	AAIIBEAR	ART	COLLECTIBLE	GAME	METAVERSE	UTILITY	FROM
SGXQIN01	63.51	16.92	3.90	5.51	0.72	2.01	2.28	4.70	0.45	36.49
BUZZ	14.02	68.24	5.33	5.67	0.69	1.34	1.22	2.63	0.85	31.76
AAIIBULL	5.72	9.08	50.71	26.72	2.55	2.06	1.37	0.41	1.38	49.29
AAIIBEAR	10.00	15.57	23.56	44.53	1.41	1.19	0.91	1.71	1.11	55.47
ART	1.30	1.01	3.41	1.43	86.29	3.12	1.44	1.36	0.64	13.71
COLLECTIBL	2.84	1.18	0.75	1.63	3.63	86.28	3.08	0.41	0.21	13.72
GAME	2.57	1.20	1.85	0.29	0.92	2.56	89.29	0.51	0.81	10.71
METAVERSE	2.07	3.29	0.70	1.95	2.08	0.67	0.44	87.35	1.44	12.65
UTILITY	0.83	0.90	0.68	1.04	1.04	0.32	0.56	2.43	92.20	7.80
TO	39.35	49.15	40.18	44.25	13.05	13.27	11.29	14.16	6.90	231.60
Inc.Own	102.87	117.39	90.89	88.78	99.33	99.55	100.58	101.51	99.10	TCI
NET	2.87	17.39	-9.11	-11.22	-0.67	-0.45	0.58	1.51	-0.90	25.73
NPT	6.00	6.00	3.00	4.00	3.00	4.00	4.00	3.00	3.00	

Notes: This table shows the average dynamic analysis of the return series of NFT segments and Market Sentiment. Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author's calculations

Table 7 – Average Dynamic Volatility Connectedness

	SGXQIN01	BUZZ	AAIIBULL	AAIIBEAR	ART	COLLECTIBLE	GAME	METAVERSE	UTILITY	FROM
SGXQIN01	84.93	9.36	1.63	1.11	0.11	0.61	0.21	1.55	0.49	15.07
BUZZ	10.82	75.49	6.40	0.99	0.98	0.86	1.27	1.58	1.59	24.51
AAIIBULL	3.08	7.12	58.24	25.96	2.16	1.28	0.37	0.85	0.94	41.76
AAIIBEAR	2.59	2.01	29.52	60.20	0.77	0.67	0.34	0.71	3.17	39.80
ART	0.36	1.14	1.70	1.79	93.01	0.58	0.19	0.87	0.36	6.99
COLLECTIBL	1.82	7.14	1.19	0.58	0.47	85.82	0.17	0.57	2.25	14.18
GAME	0.33	2.67	3.79	0.94	0.78	0.33	90.18	0.65	0.33	9.82
METAVERSE	1.87	1.11	0.80	0.88	0.83	3.65	0.45	89.91	0.50	10.09
UTILITY	0.92	4.33	0.85	0.97	0.12	1.15	0.08	0.56	91.01	8.99
TO	21.79	34.88	45.86	33.22	6.22	9.15	3.09	7.35	9.64	171.20
Inc.Own	106.72	110.38	104.10	93.42	99.23	94.97	93.26	97.26	100.65	TCI
NET	6.72	10.38	4.10	-6.58	-0.77	-5.03	-6.74	-2.74	0.65	19.02
NPT	8.00	6.00	2.00	3.00	2.00	5.00	0.00	5.00	5.00	

Notes: This table shows the average dynamic analysis of the volatility series of NFT segments and Market Sentiment. Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author's calculations

The Total Connectedness Index (TCI) results presented in Tables 6 and 7 demonstrate a general average dynamic connectedness of 25,73% for returns 19,02% for volatilities. The TCI is calculated as the off-diagonal column sum or row sum totalled across all the variables over the column sum or row sum, including the diagonals totalled across all variables, and is expressed as a percentage. Following the reasoning of Umar et al (2022a), the results obtained for the average dynamic connectedness imply a higher dependence from returns than from volatility. However, these results are not in line with Umar et al (2022a) which obtained an opposite result for average dynamic connectedness. The different result can be justified by differences in the dataset between this Thesis and Umar et al (2022a). Umar et al (2022a) only study one Market Sentiment index (MCI) while this Thesis studies four Market Sentiment indices (SGXQIN01 Index, BUZZ Index, AAIIBULL Index, and AAIIBEAR Index). The time frames are also different. This Thesis examines a period that goes from May 2018 to June 2022 whereas Umar et al (2022a) only covers the period of Covid-19 that goes from January 2020 to December 2021. This was a turbulent period and can help justify the differences found.

The intrinsic variation in NFT's returns and volatilities demonstrated in the diagonal of the Tables 6 and 7 equals to 86,29%, 86,28%, 89,29%, 87,35% and 92,20% for Art, Collectibles, Games, Metaverse and Utilities, respectively, in the return connectedness and 93,01%, 85,82%, 90,18%, 89,91% and 91,91% for Art, Collectibles, Games, Metaverse and Utilities, respectively, in the volatility connectedness. These high percentages reveal a small portion of systemic risk spillover, a risk determined by interactions from NFT segments with the other variables studied, and not by interactions with themselves. This shows that NFTs are almost independent from returns and volatilities from the Market Sentiment indices chosen for this study analyze.

Tables 6 and 7 also demonstrate how much each variable transmits (receives) TO (FROM) other considered variables. The net total directional connectedness, NET, presented in the next to the last row of the tables, results from the difference between the total directional connectedness TO and FROM others. A positive (negative) value in this row corresponds to a shock transmitter (receiver) variable. The total directional connectedness TO others, TO, represents the impact one variable has on all other variables and the total directional connectedness FROM others, FROM, demonstrates the impact all variables have on one variable.

According to the values seen in Tables 6 and 7, the returns spillover indicates that Games (0,58%) and Metaverse (1,51%) are shock transmitter NFT segments whereas Art (-0,67%), Collectibles (-0,45%) and Utilities (-0,90%) are shock receivers. However, the volatility spillover indicates all segments but Utility (0,65%) are shock receivers, with Art, Collectibles, Games and Metaverse presenting the following negative results, respectively, -0,77%, -5,03%, -6,74% and -2,74%.

Figures 3, 4, 5 and 6 allow a better understanding of how much each variable contributes (receives) TO (FROM) others in both return and volatility. Figure 3 displays the total directional return connectedness TO others, figure 4 represents the total directional return connectedness FROM others, figure 5 demonstrates the total directional volatility connectedness TO others and lastly, figure 6 reveals total directional volatility connectedness FROM others.

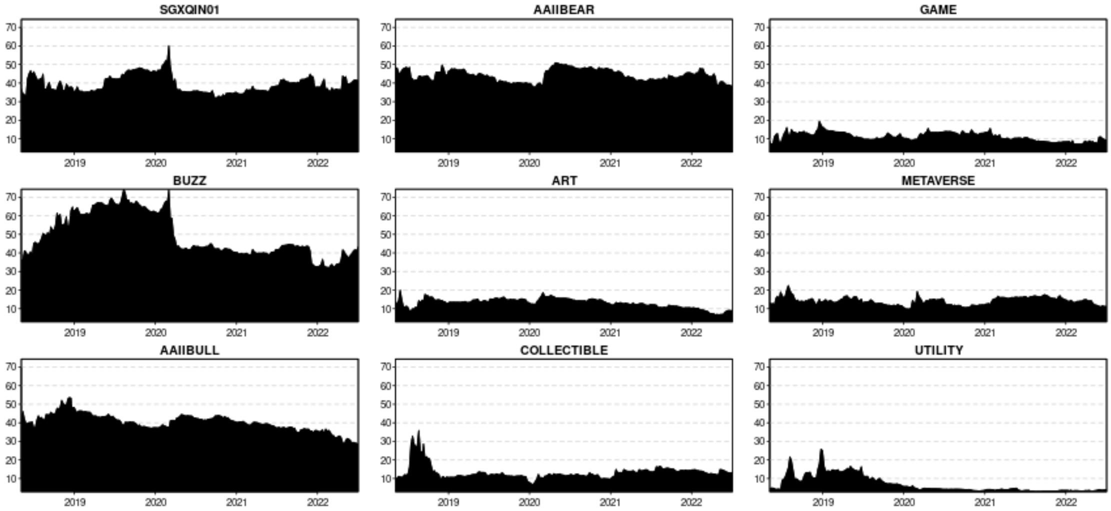

Figure 3 - Total Directional Return Connectedness TO Others

Notes: Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author's calculations

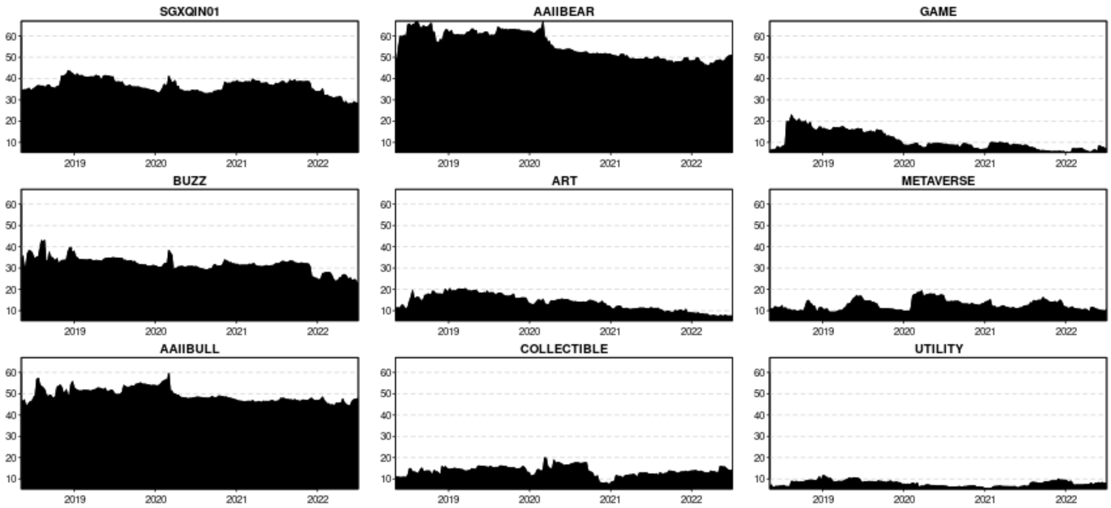

Figure 4 - Total Directional Return Connectedness FROM Others

Notes: Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author's calculations

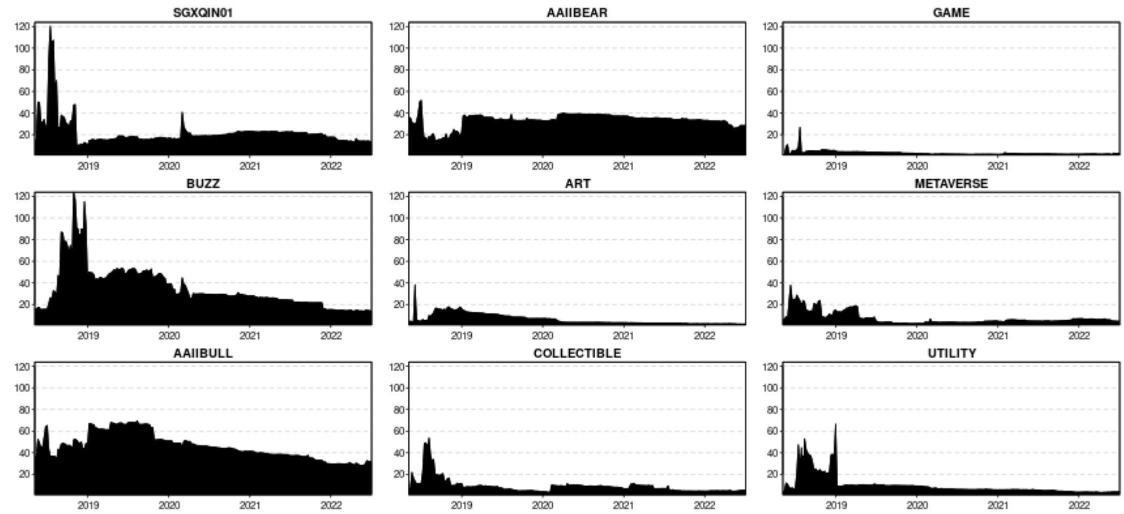

Figure 5 - Total Directional Volatility Connectedness TO Others

Notes: Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author’s calculations

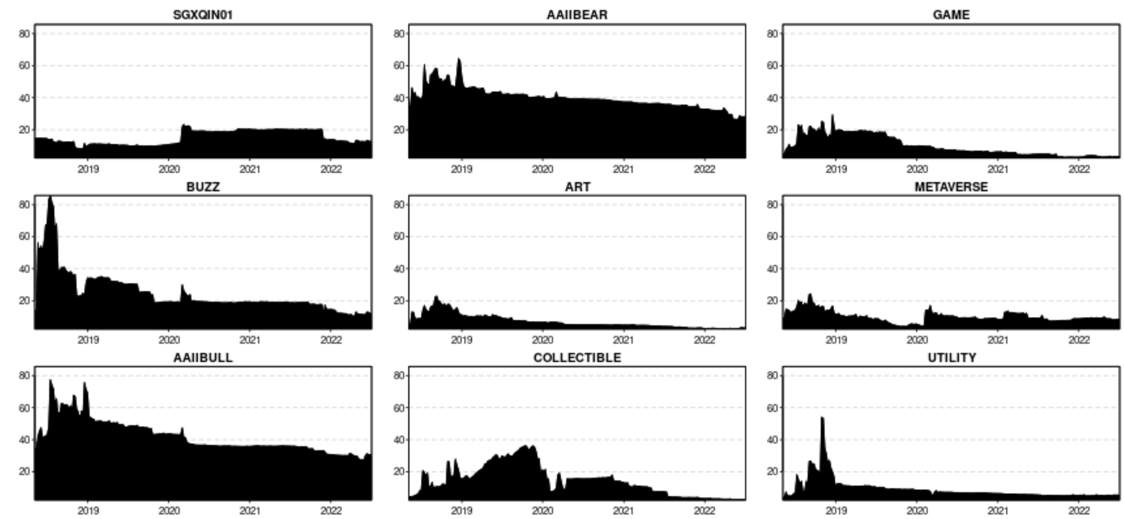

Figure 6 - Total Directional Volatility Connectedness FROM Others

Notes: Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author’s calculations

4.1.1. Dynamic Total Connectedness

In this topic, I explore and discuss the results obtained from the dynamic total connectedness. Figures 7 and 8 display the time-varying dynamics of the total return and volatility spillover connectedness, respectively, between NFT segments and the studied Market Sentiment indices and suggests how spillover effects change over time.

Figure 7 - Dynamic Total Return Connectedness

Notes: This figure shows the time-varying total connectedness of the returns of NFT segments and Market Sentiment. Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author's calculations

In Figure 7, it is possible to observe a return spillover's growth of almost 10% during 2018 and Figure 8 demonstrates a growth of around 25% in the volatility spillover over the same period. According to Hamilton (2022) this spike, and fast growth coincide with the period when NFTs started to go mainstream which justifies the significant spikes in both return and volatility's connectedness. Another spike is observed in the first quarter of 2020, again in both dynamic total return and volatility connectedness, as it coincides with the beginning of the Covid-19 pandemic which lead to lockdowns and closed services. During this period, the number of sales in NFT segments decreased, which is possible to verify in *nonfungible.com*, and consequently the overall return and volatility connectedness between the studied variables increased significantly. After the spike noticed during the beginning of the Covid-19 pandemic, both returns, and volatility spillover decreased with the volatility spillover demonstrating a more consisting decrease

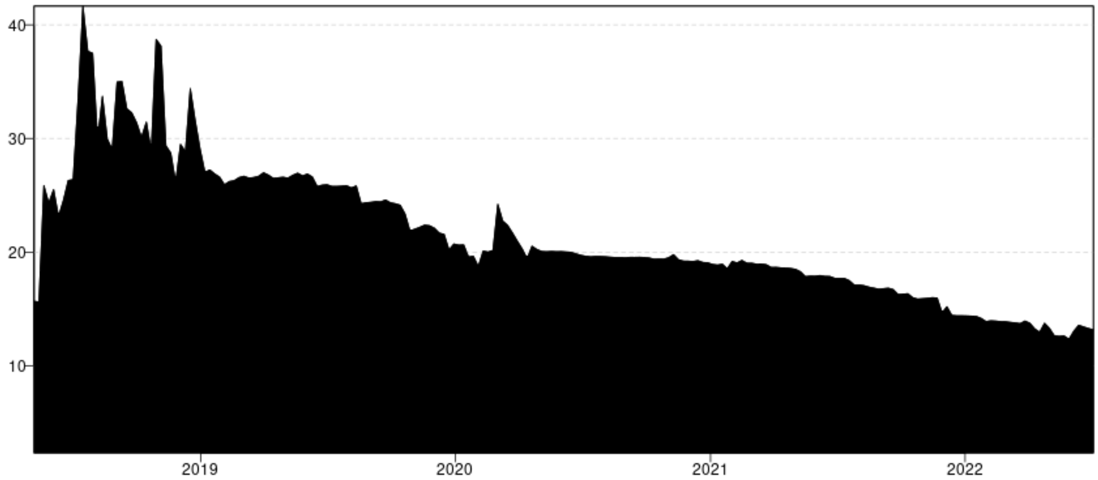

Figure 8 - Dynamic Total Volatility Connectedness

Notes: This figure shows the time-varying total connectedness of the volatilities of NFT segments and Market Sentiment. Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author's calculations

than the returns spillover.

These findings suggest both NFTs returns, and volatility responded to the Covid-19 pandemic news. Umar et al (2022a) and Wang (2022) reached the same observations. These findings also indicate there is an increase in the dynamic total connectedness between NFTs and Market Sentiment during turbulent period and are supported by Aharon & Demir (2021). The achieved results suggest risk averse investors should avoid having NFTs in their portfolios during turbulent times.

After studying the average impact a shock in one variable has on all others, in the next section 4.1.2., I discuss on a deeper note the direction each variable takes over time.

4.1.2. Net Total Directional Connectedness

Figures 9 and 10 display the net total directional connectedness in returns and volatility, respectively, and are in line with the 'NET' values of Tables 6 and 7. These figures demonstrate the direction each variable takes over time allowing a better understanding of the variable's transmissions and receptions.

Namely, Figure 9 indicates BUZZ index is the largest transmitter across the return network whereas AAIIBULL and AAIIBEAR indexes appear to be the largest receptors. NFT segments demonstrate relatively low return connectedness. However, it is possible to verify that the NFT segments are mostly receptors during 2020, which again coincides with the Covid-19 pandemic. Nonetheless, before the pandemic, and from the beginning of 2021 onwards, the return spillover analysis indicates that NFT segments are mostly shock transmitters, besides the low connectedness. These finding confirms that the NFT's return connectedness suffers more during turbulent periods and indicate that NFTs are mostly transmitters in the periods of normal market conditions. Overall, these findings suggest diversification opportunities when considering NFT assets in portfolios.

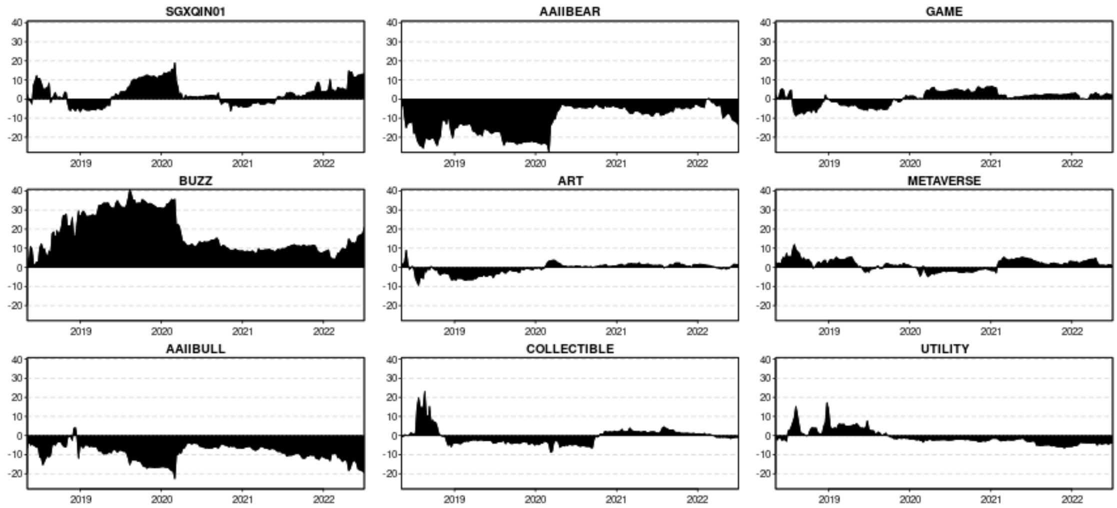

Figure 9 - Net Total Directional Return Connectedness

Notes: This figure shows the time-varying net directional spillover from each of the returns of NFT segments and Market Sentiment to all other variables. The net directional return spillover connectedness depicts the difference between dynamic total directional return spillover connectedness to others and dynamic total directional reurn spillover connectedness from others. Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author's calculations

Figure 10 indicates that all Market Sentiment indices have a significantly higher volatility connectedness before 2020 than afterwards. These period not only coincides with a period before the pandemic, but also with the appearance and fast growth of NFTs. The decrease in the connectedness from 2020 onwards can be justified by the lockdowns implemented all over the world after the announcement of the pandemic. Until the pandemic hit, Market Sentiment indices were mostly volatility shock transmitters, but from then on, all indexes demonstrate little to any connectedness. NFT's connectedness also suffered a hit after the beginning of the pandemic. Besides indicating to be receivers, Figure 10 demonstrates little to any connectedness since the start of 2020. Before the pandemic Collectibles and Games were the largest and more consistent receivers with the other segments varying from transmitters to receptors from time to time. These findings indicate NFTs are volatility spillover receivers. Aharon and Demir (2021), Karim et al (2022), and Wang (2022), support these findings as these papers find NFTs can act as risk spillover receivers during stressful times.

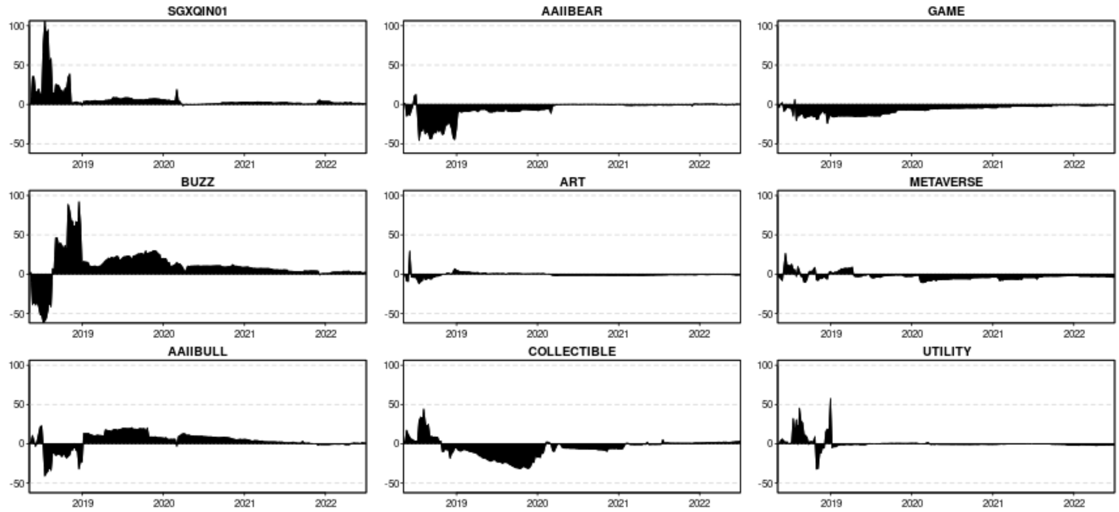

Figure 10 - Net Total Directional Volatility Connectedness

Notes: This figure shows the time-varying net directional spillover from each of the volatilities of NFT segments and Market Sentiment to all other variables. 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. Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author's calculations

4.1.3. Net Pairwise Connectedness

Figures 11 and 12 confirm the findings from the intrinsic variation discussed in section 4.1. The findings suggest NFTs are almost independent from returns and volatilities from the Market Sentiment indices chosen for this study analyze. As it is possible to verify in these figures, every relationship between the NFT segments and the

Market Sentiment indices studied indicate little to any connectedness, both in the dynamic pairwise returns and volatility connectedness.

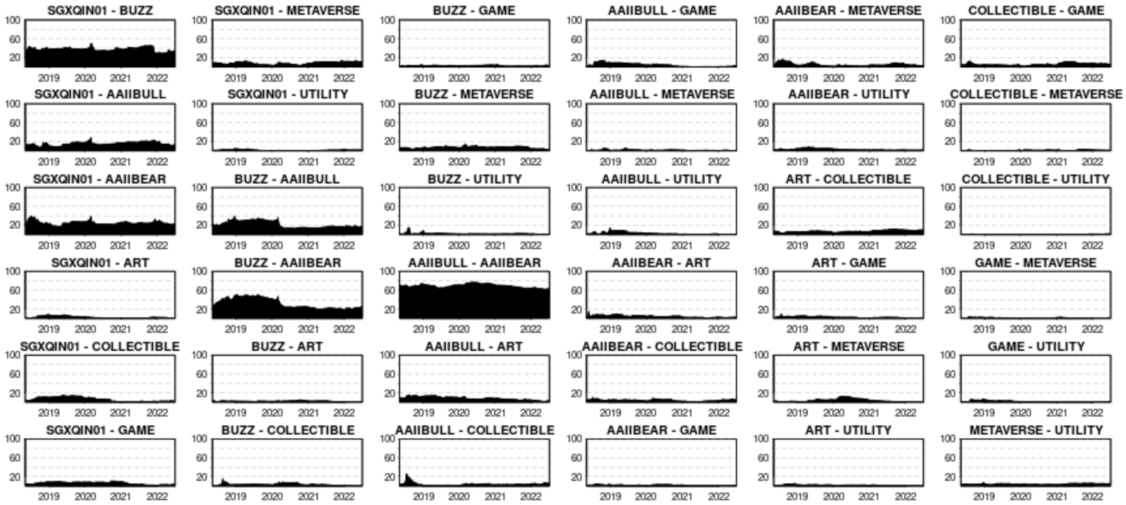

Figure 11 - Dynamic Pairwise Return Connectedness

Notes: The dynamic pairwise return connectedness can depict the dynamic relationships between NFTs and Market Sentiment. It helps to understand the direction of directional return spillovers across the variable system. Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author’s calculations

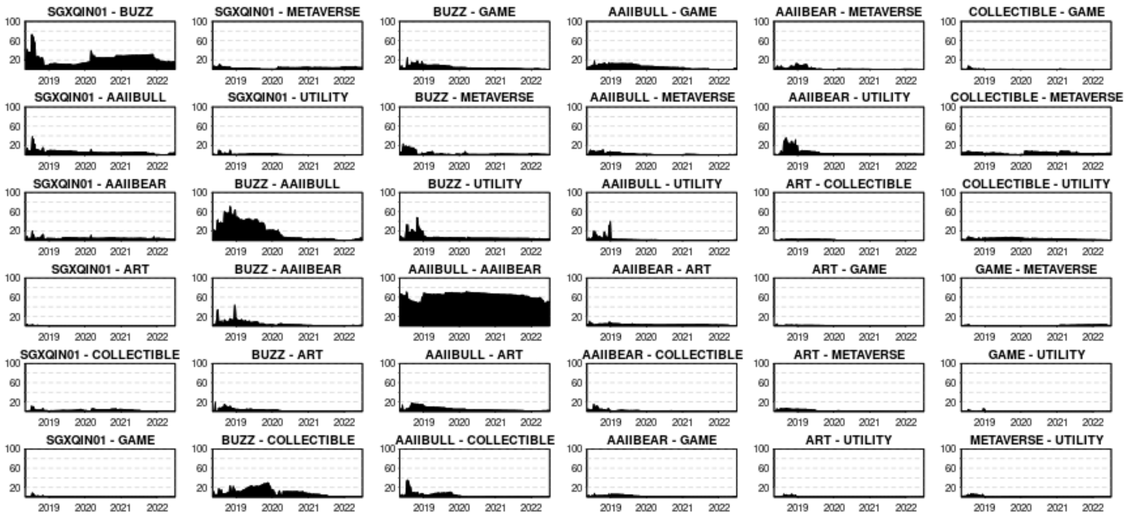

Figure 12 - Dynamic Pairwise Volatility Connectedness

Notes: The dynamic pairwise volatility connectedness can depict the dynamic relationships between NFTs and Market Sentiment. It helps to understand the direction of directional volatiity spillovers across the variable system. Results are based on a TVP–VAR model using a Bayes prior with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Source: The data used is from Bloomberg and *nonfungible.com*. Author’s calculations

This NFT’s independence from Market Sentiment is in line with Aharon & Demir (2022) and Dowling (2022b). Aharon & Demir (2022) conclude NFTs are mainly independent of shocks from Gold, Equities, Ethereum, Oil, Bonds, and the US Dollar and Dowling (2022b) concludes there is a low volatility transmission between NFTs and cryptocurrencies. Adding the findings in this Thesis to the findings from Aharon & Demir (2022) and Dowling (2022b), NFTs are indicating to be very independent from any other finance market. Dowling (2022b) says this independence is related to the pricing mechanism of NFTs, which is still inefficient as NFTs are still a recent investment asset. Wang (2022) adds to this statement saying the low liquidity NFTs offer are also one of the reasons NFTs are so isolated.

5. CONCLUSIONS

In this Thesis, I investigate the dynamic returns and volatility connectedness between NFTs and Market Sentiment through correlations and a TVP-VAR model from May 2018 to June 2022.

The correlations reveal that there is barely any correlation between Market Sentiment and NFT's returns. However, correlation analysis indicates: i) in general, Collectibles and Metaverse reflect a higher correlation with the investigated Market Sentiment indices and ii) Buzz Index and SGXQIN01 Index are the indices, which are the most correlated with the NFT segments.

The TVP-VAR model indicates that there is some connectedness between NFTs and Market Sentiment as it is possible to see the impacts on NFTs during the beginning of the pandemic. On a deeper note, the return spillover indicates that the NFT segments are mostly shock transmitters and the volatility spillover suggests that Collectibles and Games are the major receivers.

These findings are especially important for investors as they indicate whether the NFT segments are net transmitters or net receivers of spillover in both returns and volatility and indicate that the NFT's returns, and volatility can suffer impacts in turbulent times. These conclusions are in line with Umar et al (2022a), who find that there are differences in the return and risk characteristics of various NFT segments with the identification of net transmitter and net receiver of spillover.

This research is limited to the maximum available time window, as there is no information on the studied NFT segments from before the studied period.

Future investigations may use a larger time window and include other financial markets to verify whether the conclusions are still the same in the future or if there are any significant changes.

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