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Investor attention and hype in NFTs and their connection to Bitcoin and Ethereum

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Abstract

This paper investigates the relationship between Bitcoin and Ethereum investor attention and investor attention towards non-fungible tokens (NFTs) with the use of various measures of investor attention. The research applies the two most common measures of investor attention, Google Trends and Tweets, in search of a relationship between investor attention for cryptocurrencies and NFTs. A vector autoregressive model is used to employ lagged variables for the explanation of current values of investor attention. With the use of weekly data for the year 2021, the study indicates that Bitcoin and Ethereum pricing and tweets provide the most significant influence on investor attention towards NFTs. Moreover, the lagged number of sales of a NFT can in part explain the investor attention towards that NFT. The positive nature of hypotheses posed in this study can unfortunately not be met with the current results.

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1 Introduction

Non-fungible tokens, NFTs, are digital tokens that are stored on a blockchain (Pinto-Gutiérrez et al, 2022). The token is used to represent the ownership of a digital asset, which in most cases is art, collectibles, images or music (Parham & Breitinger, 2022). Via the use of a public and transparent blockchain, the most common blockchain in the NFT world is the Ethereum blockchain, everyone can see which NFT is owned by which address or digital wallet on the blockchain (Pinto-Gutiérrez et al, 2022). NFTs can be seen as a new digital asset, which has its own characteristics that differ from other assets such as cryptocurrencies, stocks, real estate and bonds (Ante, 2021a). Each NFT, the token, can only have one rightful owner. The value of an NFT is, among other processes, based on the simple economic principle of supply and demand, where the bid- and asking prices for NFTs are denoted in cryptocurrencies (Ante, 2021b). Besides the basic supply and demand process for determining the price is the marketing around the NFT project and the public popularity an important factor for NFT pricing (Kapoor et al, 2022). Recent selling prices of similar NFTs are an important factor in evaluating the value of an NFT (White et al, 2022). Unique attributes, access to a specific community, digital content in games or for example with the NFT collection CryptoPunks a unique hat on the NFT, of a non-fungible token may increase the intrinsic value of the NFT even further (White et al, 2022). Determining the intrinsic value of a NFT is very complicated, because there are so many possibilities to put a value on a NFT (White et al, 2022). Therefore, NFT prices are very likely to experience volatility (Kapoor et al, 2022). Economists are not yet certain of a standard process to adequately put a price on NFTs (Kapoor et al 2022 and Parham & Breitinger 2022).

A possible way to examine the pricing process of NFTs is to look at other assets in the same digital realm, namely cryptocurrencies. Multiple studies research the relationship between the cryptocurrency market and the NFT market. The cryptocurrency market is found to have an impact on the NFT market (Ante 2021a, Dowling 2022, Parham & Breitinger 2022 and Umar et al 2022). Ante (2021a) and Dowling (2022) emphasize that prices in the cryptocurrency market have ripple effects in the NFT market, which is confirmed by Parham & Breitinger (2022) and Umar et al (2022). Despite both the cryptocurrency market and the NFT market rely on blockchain technology there are differences between the two assets.

An important difference is that NFTs are, unlike cryptocurrencies, non-fungible, which means that a certain NFT cannot be exchanged for another NFT, because each NFT is unique. Whereas cryptocurrencies are all worth the same and can be exchanged for other cryptocurrencies (Pinto-Gutiérrez et al, 2022). One bitcoin is worth one bitcoin for example. Cryptocurrencies are, as the name says, used as a currency to use for payments and money transfers. NFTs on the other hand are unique, there is only one NFT instead of multiple such as there is more than one bitcoin circulating in the cryptocurrency market (Dowling, 2022). This uniqueness of NFTs and the corresponding proof of ownership is the key difference between NFTs and cryptocurrencies (Dowling 2022 and Pinto-Gutiérrez et al 2022).

In the economic literature is another way of pricing an asset arising and being a subject of a growing number of studies. This method is the use of 'hype' as a measure of investor attention towards certain assets (Parham & Breitinger 2022 and Pinto-Gutiérrez et al 2022). The use of investor attention via the use of hype in the form of Tweets on Twitter and the amount of Google Searches is more and more applied in economic research (Huynh 2021, Kapoor et al 2022, Li et al 2021 and Zhang & Wang 2020). Investor sentiment and hype for NFTs and cryptocurrencies can be determined based on the Tweets on Twitter that contain information such as "#bitcoin", "#ethereum" and "#nft" (Huynh 2021 and Saurdi et al 2022). Another measures for hype is the use of Google Searches via Google Trends. Google Trends provides detailed information for the amount of searches for a specific search word or phrase (Ibikunle et al 2020, Li et al 2021 and Pinto-Gutiérrez et al 2022). Numerous examples of the application of Twitter data and Google Trends in research on investor attention and hype are available in chapter two. The hype and attention for the NFT market is possibly a by-product of the general hype concerning the blockchain technology, which as a result led to an increase of hype and attention for the NFT market (Pinto-Gutiérrez et al, 2022). Besides the hype for blockchain technology is the hype and interest in cryptocurrencies a possible explanatory factor for the immense growth and interest in the NFT market (Pinto-Gutiérrez et al, 2022). The hype and investor attention towards NFTs can possibly be explained by the hype and investor attention towards cryptocurrencies. Research that can give a definite explanation for the relationship between cryptocurrencies and NFTs would consolidate the current literature on cryptocurrencies and NFTs. Today's literature focusses on the appliance of one of the two methods of measuring investor attention and hype, either Google Trends or Tweets. This paper measures the statistical and economic relevance of Google Trends and Tweets for the NFT market dynamics in an effort to contribute to some of the unanswered puzzles in existing literature on the relationship between cryptocurrencies and the NFT market.

The main result of this study is the ability of lagged Bitcoin and Ethereum pricing and tweets of both cryptocurrencies can explain current investor attention towards NFTs. Besides the influence of the two biggest cryptocurrencies is the previous number of sales of a specific NFT also an excellent measure of investor attention towards that specific NFT.

Contribution of this research for the literature is the unifying aspect of this study. It combines and unifies the different studies on cryptocurrencies, NFTs and investor attention into a more comprehensive understanding of how NFTs and cryptocurrencies are related to each other. This study is also important for investors in digital assets such as cryptocurrencies and NFTs. Investors are enabled to make better informed investment decisions by providing them a clear interpretation of the interactions between the cryptocurrency market and the NFT market. Lastly, this research builds a foundation for future research that focusses on investor attention and

The remainder of this paper is structured as follows. Section two will provide a more elaborate theoretical background to the research. Section three describes the data sample and the methodology. Section four will present the results. Section five will discuss the results and section six concludes the paper.

2 Literature review

2.1 Current use of non-fungible tokens

Non-fungible tokens (NFTs) have become increasingly more popular over the last couple of years. Especially during the COVID-19 pandemic, NFTs gained a lot of attention (Umar et al, 2022). NFTs are currently primarily used to store the digital ownership of art and/or collections, using smart contracts on a blockchain network such as Ethereum (Parham & Breitinger, 2022). Blockchain is the technology used to store the digital asset, such as art, memes, and music, which enables the proof of ownership of the NFT in question (Kapoor et al, 2022). This means that the owner of a certain NFT can prove that he or she is the owner, as provided by blockchain technology. However, this only makes the owner of the NFT the one person with access to the content of the NFT (Kapoor et al, 2022). The owner of the NFT is not automatically the owner of the copyright of the NFT as well. NFTs can be bought, sold and traded on online marketplaces, of which OpenSea (www.opensea.io) is the most renowned (Kapoor et al, 2022 & Parham & Breitinger, 2022).

Most NFTs are based on the Ethereum blockchain and are available for trade on OpenSea.io with Ethereum as the currency for buying, selling and trading NFTs (Parham & Breitinger, 2022). Ethereum is the most common blockchain technology used for NFTs, because it supports the use of smart contracts, which is necessary for the proof of ownership of an NFT (Parham & Breitinger, 2022). Other blockchains that support the NFT space are Cardano and Polkadot (Parham & Breitingner, 2022). Blockchain technology is a decentralized network consisting of nodes that together create a block of data. The encryption method called cryptography is used to secure the different blocks on the blockchain (Parham & Breitinger, 2022). Each block of data is encrypted using cryptography and signed with a digital signature, which is called a 'private key'(Parham & Breitinger, 2022). Besides the use of the Ethereum blockchain technology is the cryptocurrency Ethereum used as the currency to buy, sell and trade NFTs on the online marketplace OpenSea. This use of the blockchain technology of Ethereum and the use of Ethereum as currency in the NFT marketplace makes it an interesting asset to investigate in relation to investor attention in the NFT space and cryptocurrency space, with Bitcoin and Ethereum as the biggest cryptocurrencies (Li et al 2021 and Sifat et al 2019).

2.2 Relationship between Bitcoin, Ethereum and NFTs

Ethereum (ETH) and Bitcoin (BTC) are the two biggest cryptocurrencies in the cryptocurrency space. Together they cover 60% of the total crypto market capitalization (www.coinmarketcap.com). Bitcoin and Ethereum are the cryptocurrencies that are most liquid and therefore get the most investor attention (Sifat et al, 2019). Bitcoin and Ethereum are interrelated themselves, because current literature suspects a lead-lag relationship between the two biggest current cryptocurrencies (Sifat et al, 2019). There is no consensus in the literature which of the two cryptocurrencies leads and which one lags. Besides the relationship between Bitcoin and Ethereum, existing literature also focusses on the efficiency of cryptocurrencies in general, possible bubble dynamics in the cryptocurrency markets, the diversification and hedge functions of cryptocurrency and lastly the relationship between investor attention and Bitcoin (Zhang & Wang, 2020). Measuring investor attention in the cryptocurrency market is an interesting take on research on returns of assets. Combining this with the booming NFT market could yield results that provide scholars and investors in digital assets with a broader understanding of the digital markets.

Using the prices and investor attention regarding both Bitcoin and Ethereum can possible explain the increasing hype towards NFTs (Ante, 2021a). Even more interesting is that the pricing behaviour of Bitcoin and Ethereum can drive the pricing in the NFT market (Ante 2021a). Dowling (2022) and Ante (2021a) report that price changes of Bitcoin and Ethereum influence the prices on the NFT market. The NFT market is thus partly driven by the cryptocurrency market. This means that the relationship between NFTs, Bitcoin and Ethereum should be explored in more detail to figure out how these two different digital asset classes behave and interact with each other with regards to investor attention.

2.3 Hype and investor attention

Hype and investor attention are becoming more widely applied in economic research (Zhang & Wang 2020 and Li et al 2021). Hype means that there is a lot more attention towards something, NFTs and cryptocurrencies in this case, than there would normally be. This can be measured in the form of investor attention. Investor attention displays the interest of investors for a certain asset (Suardi et al, 2022). Several studies have incorporated a measure of investor attention in research on cryptocurrency and NFTs. Examples of such studies are, among others, Choi (2021), Huynh

(2021), Kapoor et al (2022), Li et al (2021), Pinto-Gutiérrez et al (2022), Shen et al (2022), Urquhart (2018) and Zhang & Wang (2020). Investor attention measures used in these studies to reveal a relationship between investor attention and returns, price movements and relations to other financial markets, such as the stock market (Li et al, 2021). More recent studies incorporate investor attention measures in NFT markets to explain the hype for the NFT market. Pinto-Gutiérrez et al (2022) use Google Search activity to posit a relationship between investor attention and popular NFTs. Using tweets about NFTs to measure investor attention is applied by Kapoor et al (2022) to investigate the relationship between investor attention and NFT valuation. These two different ways of measuring investor attention are both relatively new in economic literature. The exact use of both methods is explained in more details in sections 2.4.1 and 2.4.2.

2.4 Measures of hype and investor attention

2.4.1 Google Trends

Using Google Trends (www.google.com/trends) in research on investor attention is an established research method in the research field of economics. Literature using Google Trends, or also called the GSVI (Google Search Volume Index),) in research on digital assets like NFTs and Bitcoin and Ethereum is widely employed (Da et al 2015 , Ibikunle et al 2020, Li et al 2021, Pinto-Gutiérrez et al 2022, Sifat et al 2019, Urquhart 2018, Zhang and Wang 2020,).

Da et al (2015) employ Google Trends in their research constructing a FEARS index. A Financial and Economic Attitudes Revealed by Search index, which serves as a measure of investor sentiment and attention (Da et al, 2015). Their research has an approach towards using Google Trends that is focused on determining the sentiments of US citizens towards the state of the economy. A more specific approach using Google Trends can be found in research conducted by Ibikunle et al (2020) and Zhang and Wang (2020). Ibikunle et al (2020) uses the search word 'Bitcoin' to measure investor attention to help explain the price discovery of Bitcoin. The study by Zhang and Wang (2020) is in line with the results of the previous mentioned study, because it expands the literature by including not only Bitcoin investor attention from Google Trends, but includes the top twenty cryptocurrency from the period 2013 to 2018. Besides the application of Google Trends in research on investor attention towards cryptocurrency, Pinto-Gutiérrez et al (2022) use Google Trends to explain investor attention in the NFT market by using key search words for the two most popular NFTs of that period, Cryptopunks and Decentraland respectively.

There are various studies that use the information of Google Trends as a measure of investor attention in all sorts of economic research and there are a number of reasons for it.

The first reason is that Google is the most used search machine on the internet (Li et al, 2021). Since both NFTs and the cryptocurrency market is in the digital world, it is assumed that most investors and other participants in the NFT and cryptocurrency markets gather their information online. With Google being the number one search machine online, the GSVI provides the most detailed information on search trends regarding digital assets (Li et al, 2021).

Another reason for using GSVI is that Google Trends is able to gather all search data available on a certain keyword and group all the various language and groups of search words together (Pinto-Gutiérrez et al, 2022).

Thirdly, using Google Trends data is made available in a time series format with little to no missing data. This makes statistical tests and regression analysis possible, because the data Google Trends provides is understood to be relatively objective (Li et al, 2021).

Google Trends provides the data in different formats. Standard is the format of a graph for the chosen time period. Besides the graph provides Google Trends also the option to download all the search data in the form of an Excel file. The Excel file contains the weekly data of Google searches displayed on a scale of 0 to 100, with 0 meaning no significant attention at all and 100 being the most attention the specific search word or words has seen in that chosen period (www.google.com/trends). Displaying the results for the inserted search words is accompanied by interest per region in the world and Google Trends also provides related search topics.

2.4.2 Twitter and tweets

Besides using Google Trends in research on digital assets as a proxy for investor attention, Twitter provides useful insights regarding investor attention as well. Sifat et al. (2022) point out that Twitter data has been be mined for “cues on actionable economic decisions” for more than ten years. Huynh (2021) investigated the effect of tweets of Donald Trump on the price of Bitcoin. In the light of research on the influence of social media (Urquhart 2016, Urquhart 2018 and Choi 2021), Huynh (2021) finds that Trump’s tweet are correlated with a price change in Bitcoin’s price. An increase in Trump’s negative sentiment in his tweets results in a one day lagged result of a positive price increase of Bitcoin (Huynh, 2021). This small example of the influence of social media, Twitter in this case, makes Twitter data another interesting source of measuring investor attention towards digital assets.

Using tweets on Twitter to measure investor attention towards NFTs is attracting scholar's attention in the field of economic research. One study, conducted by Kapoor et al (2022), measures investor attention towards NFTs by analyzing tweets that contain a URL linked to a NFT on OpenSea to gather data on sales and price information. The authors find that tweets on Twitter can be used as a determinant of the price of a NFT on the online marketplace OpenSea.

Tweets are more commonly used in relation to investor attention towards Bitcoin (Shen et al 2019, Choi 2021 and Huynh 2021). The existing literature suggests that there is a relationship between tweets involving "Bitcoin" and returns, volatility and trading volume of Bitcoin. The same principle can be applied to "Ethereum".

2.5 Using both Google Trends and Tweets in research on the relationship between NFTs, Bitcoin and Ethereum

As discussed earlier there is an increasing interest in the understanding of the NFT market and the relationship with cryptocurrencies such as Bitcoin and Ethereum. Current literature has conducted research to either the relationship between NFTs and Bitcoin, the relationship between Bitcoin and Ethereum and the use of various measures of investor attention in the cryptocurrency market. Investor attention or hype is measured with either Google Trends or Tweets from Twitter. Present literature uses one of those two methods. A combination of both Google Trends and Tweets as proxies for investor attention has not been used before. Combining both measures of hype is a first of a kind in the economic literature. This unifying approach will contribute to a better and more complete understanding of the relationship between investor attention towards NFTs, Bitcoin and Ethereum and the relations between these digital assets.

Since the NFT space is still relatively young, but booming and expanding at a fast pace, this research will take eleven of the biggest and renowned NFTs into consideration when studying the dynamics of investor attention and the relationship between the NFT market and the two biggest cryptocurrencies Bitcoin and Ethereum. Selection criteria for the NFTs is explained in more detail in section three.

2.6 Hypotheses

From the literature review follows that investor attention is measured with either Google Trends or tweets. Bitcoin and Ethereum are the biggest cryptocurrencies that have an influence on the NFT market. Combining these two measures of investor attention and their relationship with the two biggest cryptocurrencies, yields the hypotheses below that are tested in this research. For each way of measuring investor attention towards assets has its own hypothesis to make interpretation of the results easier. Given the positive results of current literature, all hypotheses below are stated in such manner that a positive influence on investor attention towards NFTs is expected. NFT investor attention represents the Google Trends data of each selected NFT in this research.

- H1: Bitcoin and Ethereum Google Trends investor attention has a positive influence on NFT investor attention .
- H2: Bitcoin and Ethereum tweets investor attention has a positive influence on NFT investor attention.
- H3: Bitcoin and Ethereum returns has a positive influence on NFT investor attention.

3 Data and methodology

3.1 Data and sample

The sample of all the data gathered and used is the year 2021 (the 3th of January until the 31th of December 2021). All the data is on a weekly basis, since most databases provide data on a weekly basis, which is common practice in existing literature (Pinto-Gutiérrez et al 2022 and Li et al 2021). The year 2021 captures 52 weeks of data on all the included variables, which are explained in more detail below.

The data on investor attention, NFT attention in Equation (1) and (2), is gathered via the use of Google Trends (www.google.com/trends) and Twitter from Bitinfocharts (www.bitinfocharts.com) . The prices and returns of the two biggest cryptocurrencies, Bitcoin and Ethereum, are collected from Coinmarketcap (www.coinmarketcap.com). The use of Coinmarketcap as the source of data on cryptocurrencies is widely applied in existing literature (Pinto-Gutiérrez et al 2022, Huynh 2021 and Li et al 2021).

Eleven NFTs are selected for this study. The eleven NFTs are Art Blocks, Axie Infinity, Bored Ape Yacht Club, Cool Cats, CryptoKitties, CryptoPunks, Decentraland, Hashmasks, Meebits, SuperRare and The Sandbox. The data regarding the sales and trading volume of these eleven NFTs are extracted from nonfungible.com (www.nonfungible.com/market-tracker). Nonfungible.com provides data on trading volume, number of sales and prices of NFTs. For this research is trading volume and number of sales of a NFT used. Using the online database of nonfungible.com is applied in Pinto-Gutiérrez et al (2022) and Ante (2021a). Selection criteria for the NFTs that are used are as follows. The NFTs selected are screened on Opensea.io (www.opensea.io) first to look at their history. Each NFT has to be at least half a year old, being available for sale on Opensea, in 2021. Since the NFT market is still in early stages, NFTs that are selected for this study need to have some data available to work with. Each NFTs is stored on the Ethereum blockchain, except for Art Blocks. The selected eleven NFTs have a variety of applications. Bored Ape Yacht Club, Cool Cats, CryptoPunks, Hashmasks and Meebits are art collectibles in the NFT space, whereas CryptoKitties and Axie Infinity share the collectability, but are also used in their accompanying metaverse game. Another form of an NFT are Art Blocks and SuperRare, which fulfils the purpose of an online art market where producers and consumers sell and buy online art, like NFTs. The Sandbox and Decentraland are NFTs that sell pieces of land in a virtual world or game to its user. This variety of NFTs and their own unique use cases provides this study with a unifying layer in research on the NFT market due to its inclusiveness.

The data from Google Trends are scaled from zero to one hundred. If the value is zero it means that for that particular moment in time there were no Google Searches. If the value of the GSVI is one hundred, it means that at that moment in time the Google Searches were at the highest point possible. The keywords used for gathering the data regarding investor attention on NFTs, BTC and ETH consists of multiple search terms together. For the keywords Bitcoin, Ethereum and selected eleven NFTs, Table 1 will state the used search terms that are used and aggregated into an average measure for the different data of Google Trends. The Google Trend data will consist of the weekly data, which is how Google Trends presents the trendline.

The Twitter data is from bitinfochart (www.bitinfocharts.com). Since this online database presents the data on a daily basis, the weekly average will be calculated and used to match with the weekly data from Google Trends and the data on the selected NFTs from Nonfungible.com. Previous research that consulted bitinfochart for Twitter data is displayed in Huynh (2021), Shen et al (2018) and Suardi et al (2022).

3.2 Description of the variables

The database used in this study consists of different types of data. All the data is either obtained on a weekly basis or on a daily basis and then transformed into weekly data via calculating the mean of the daily data. This method is also applied in Dowling (2021a,b).

First of all there is the data from coinmarketcap.com on the price, return and volume of Bitcoin and Ethereum. Second, the calculated mean of the used Google Trends search words or phrases. Used keywords and/or phrases are displayed in Table 1 below. Table 1 also provides the abbreviations for each NFT, Bitcoin and Ethereum which will return in later tables containing statistical results. Note that some NFTs have more search words or phrases than others. This is due to possible nicknames (e.g. Bored Ape for the NFT collection of Bored Ape Yacht Club) and other possibilities of the NFT (e.g. the game Axie Infinity). Thirdly is the data provided by nonfungible.com (www.nonfungible.com), which contains the volume and number of sales in USD of each selected NFT. At last is the number of tweets containing “#Bitcoin” and “#Ethereum” from bitinfocharts.com (www.bitinforcharts.com).

Table 2 provides the descriptive statistics of Bitcoin, Ethereum and Google Trends of NFT. Table 3 provides the descriptive statistics of selected NFTs. Figures one to fourteen present a graphical presentation of the Google Search Volume Index for each variable listed in Table 1.

TABLE 1: EXPLANATION OF VARIABLES

Variable	**Abbreviation**	**Search words or phrases Google Trends**
Bitcoin	BTC	Bitcoin, bitcoin crypto, bitcoin cryptocurrency, BTC
Ethereum	ETH	Ethereum, Ethereum crypto, Ethereum cryptocurrency, ETH
NFT[1]	NFT	Non fungible token, non-fungible token, non-fungible tokens, NFT, NFTs
Art Blocks	AB	Art block nft, art block opensea, art blocks
Axie Infinity	AI	Axie infinity coin, axie infinity nft, axie infinity opensea, axie infinity
Bored Ape Yacht Club	BAYC	Ape nft, bored ape nft, bored ape yacht club nft, bored ape yacht club, bored ape yacht club opensea, bored ape
Cool Cats	CC	Cool cats nft, cool cats opensea
Cryptokitties	CK	Cryptokitties nft, cryptokitties opensea, cryptokitties
CryptoPunks	CP	Punks nft, cryptopunks nft, crypto punks, cryptopunk opensea, cryptopunks
Decentraland	D	Decentraland, decentraland game, decentraland nft, decentraland opensea
Hashmasks	HM	Hashmasks, hashmasks nft, hashmasks opensea.
Meebits	MB	Meebits, meebits nft, meebits opensea
SuperRare	SR	SuperRare, superrare nft, superrare opensea
The Sandbox	TS	The Sandbox, the sandbox nft, the sandbox opensea, the sandbox crypto

Notes: The abbreviation of each variable is stated, which will used in other tables. Search words or phrases of Google Trends is the input used in Google Trends with regards to each variable.
1 NFT is a variable that measures general investor attention towards NFTs.

TABLE 2: DESCRIPTIVE STATISTICS BITCOIN, ETHEREUM AND NFT ATTENTION

	Mean	**Std. Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
Bitcoin Google Trends	45.538	15.188	26.500	100	1.227	4.679
Bitcoin Price	47506.515	9933.627	31796.810	65466.84	-.038	1.737
Bitcoin Volume in USD	4.061e+10	1.823e+10	1.879e+10	9.747e+10	1.146	3.73
Bitcoin Return (%)	1.9	11.235	-25.150	25.23	-.16	2.78
Bitcoin Tweets	113635.49	25804.339	67349.429	192751.29	.979	4.478
Ethereum Google Trends	39.721	15.404	22.750	100	2.279	8.698
Ethereum Price	2770.814	1036.563	975.510	4626.36	.172	1.783
Ethereum Volume in USD	2.405e+10	1.101e+10	1.120e+10	5.601e+10	1.281	3.909
Ethereum Return (%)	4.597	14.965	-41.200	42.9	-.115	3.932
Ethereum Tweets	26710.422	9138.477	11448.571	48521.714	.207	2.311
NFT Google Trends	27.738	18.486	1.000	67.4	.465	2.178

Note: this table report the descriptive statistics for the variables regarding Bitcoin, Ethereum and general NFT investor attention

TABLE 3: DESCRIPTIVE STATISTICS OF SELECTED NFTS

	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Art Blocks Google Trends	28.218	21.416	6.667	93.333	1.196	3.76
Art Blocks Number Of Sales	296344.09	386774.4	12626.714	1316471.6	1.465	3.7
Art Blocks Volume in USD	2.717e+08	3.163e+08	3039196.213	1.701e+09	2.226	9.6
BAYC Google Trends	18.971	27.961	0.000	94.5	1.499	3.966
BAYC Number Of Sales	1505.834	3164.613	0.000	19347.714	4.488	23.81
BAYC Volume in USD	32872574	65712750	0.000	4.258e+08	4.475	26.144
Cryptopunks Google Trends	30.935	26.073	0.200	99.8	.619	2.254
CryptoPunks Number Of Sales	296121.42	386895.3	12626.714	1316471.6	1.465	3.699
Cryptopunks Volume in USD	2.717e+08	3.163e+08	3039196.213	1.701e+09	2.226	9.6
SuperRare Google Trends	38.038	21.951	4.000	78	.076	1.757
SuperRare Number Of Sales	273.183	193.521	92.286	803.143	1.451	3.839
SuperRare Volume in USD	4187384.8	3495589.7	435180.383	13810053	.912	3.008
Axie Infinity Google Trends	29.957	27.273	0.000	78.5	.233	1.381
Axie Infinity Number Of Sales	386878.11	392910.57	871.571	1033361.7	.254	1.251
Axie Infinity Volume in USD	66791491	67906930	116600.573	2.073e+08	.497	1.818
Cool Cats Google Trends	22.192	25.099	0.000	81.5	.655	2.108
Cool Cats Number Of Sales	647.121	1887.921	0.000	12477.714	5.127	31.397
Cool Cats Volume in USD	3790577.8	5551528.1	0.000	26123796	1.925	6.929
Crypto Kitties Google Trends	37.821	18.356	3.667	82	.36	2.879
Crypto Kitties Number of Sales	1240.85	777.128	264.571	3586.143	1.2	4.169
Crypto Kitties Volume in USD	357559.28	873107.69	24412.609	5282661.5	4.546	23.896
Decentraland Google Trends	20.567	24.974	1.250	86.75	1.662	4.15
Decentraland Number of Sales	410.235	218.098	110.714	1150.429	1.364	5.439
Decentraland Volume in USD	2101814.2	2923652.1	93715.333	14596182	2.591	9.547
Hashmasks Google Trends	17.359	17.925	0.000	77	1.327	4.315
Hashmasks Number Of Sales	605.076	1966.31	0.000	14019.286	6.319	43.356
Hashmasks Volume in USD	1842371.4	3329461.2	0.000	19763074	3.607	18.075
Meebits Google Trends	17.212	21.32	0.000	98.667	1.758	6.487
Meebits Number Of Sales	487.082	1598.856	0.000	11194.167	6.016	40.324
Meebits Volume in USD	6650542.1	17583736	0.000	1.112e+08	4.594	25.988
The Sandbox Google Trends	15.837	20.804	2.750	80.5	2.029	5.727
The Sandbox Number Of Sales	1255.234	854.477	174.000	4452.286	1.646	6.572
The Sandbox Volume in USD	6007465.8	12749870	23867.751	59844564	3.187	13.006

Notes: this table displays the descriptive statistics of the selected eleven NFTs. BAYC is an abbreviation of Bored Ape Yacht Club NFT.

FIGURE 1: GOOGLE TRENDS ART BLOCKS

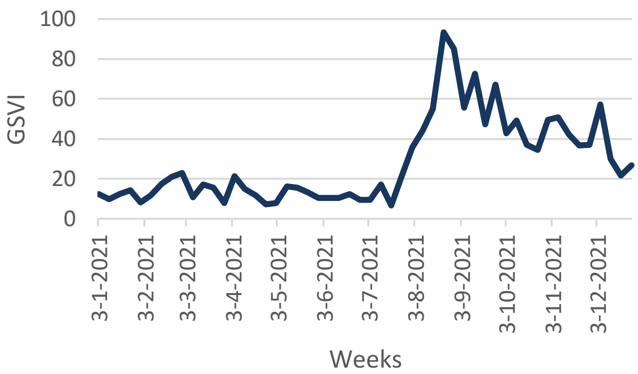


FIGURE 2: GOOGLE TRENDS AXIE INFINITY

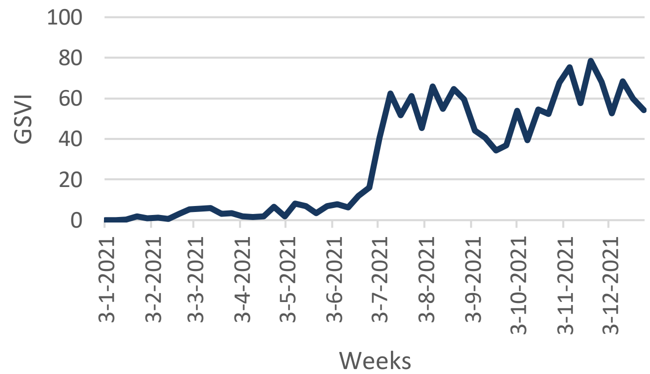


FIGURE 3: GOOGLE TRENDS BITCOIN

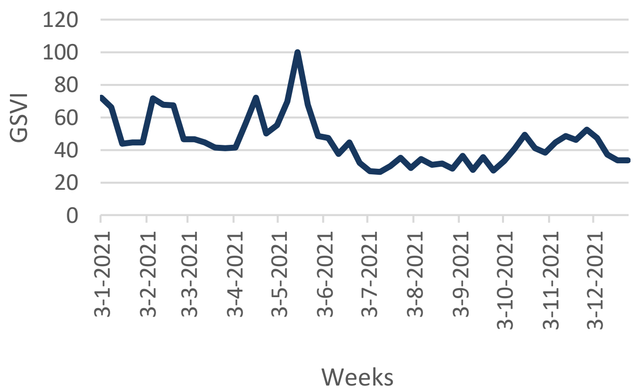


FIGURE 4: GOOGLE TRENDS BORED APE

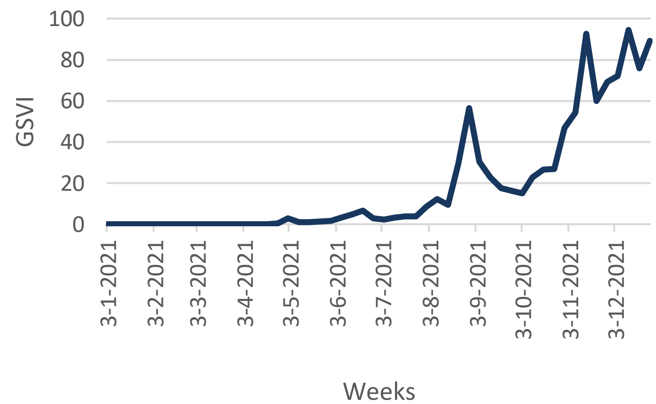


FIGURE 5: GOOGLE TRENDS COOL CATS

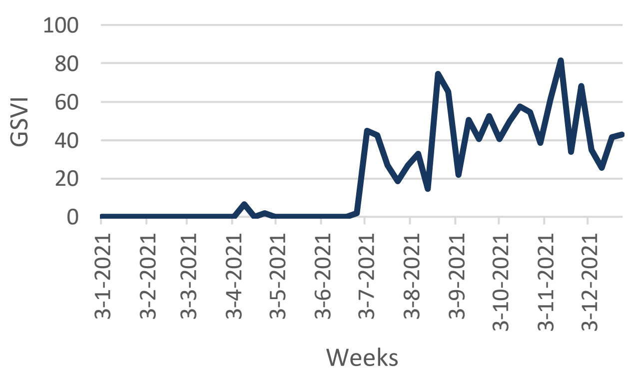


FIGURE 6: GOOGLE TRENDS CRYPTOKITTIES

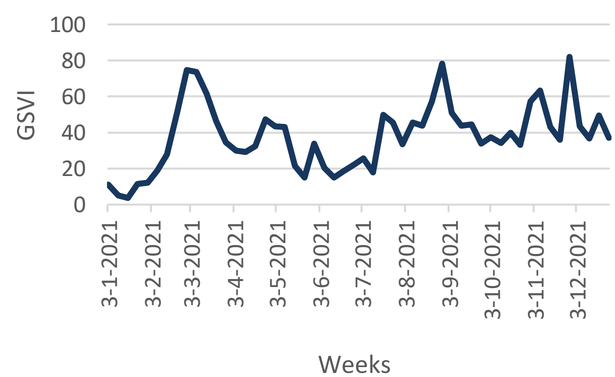


FIGURE 7: GOOGLE TRENDS CRYPTO PUNKS

FIGURE 8: GOOGLE TRENDS DECENTRALAND

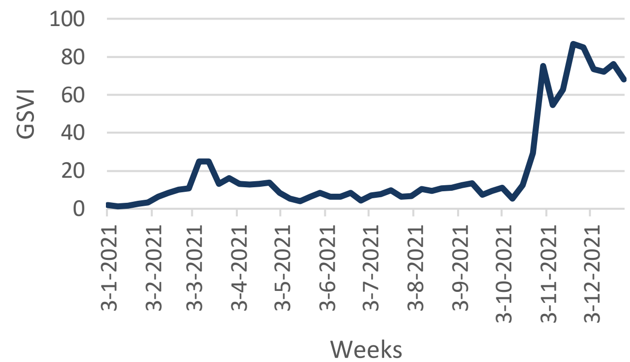


FIGURE 9: GOOGLE TRENDS ETHEREUM

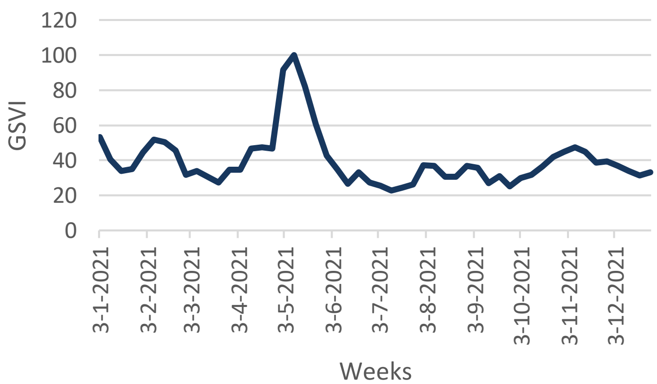


FIGURE 10: GOOGLE TRENDS HASHMASKS

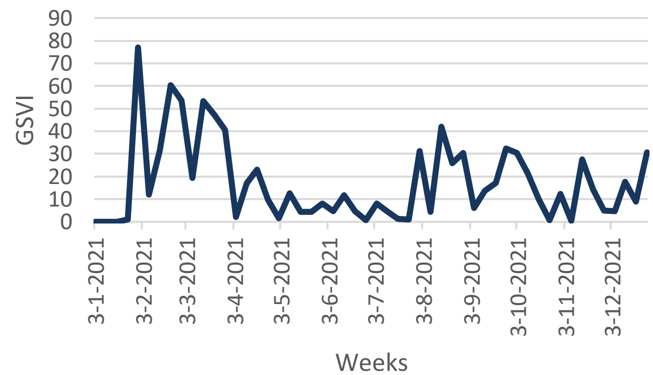


FIGURE 11: GOOGLE TRENDS MEEBITS

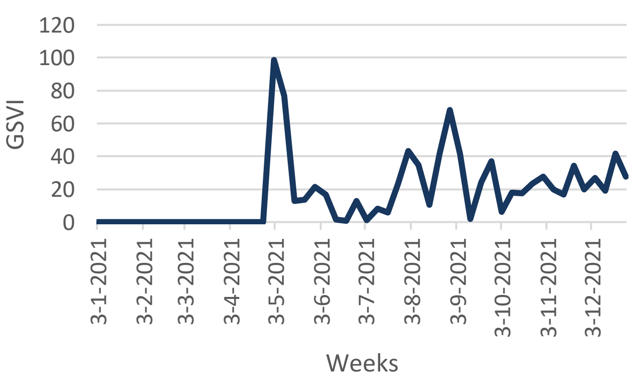


FIGURE 12: GOOGLE TRENDS NFT

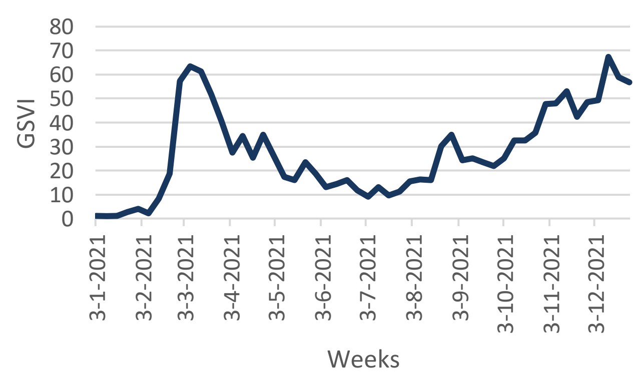


FIGURE 13: GOOGLE TRENDS SUPERRARE

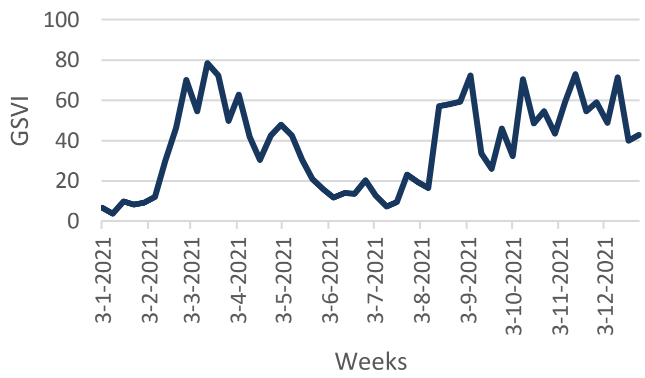
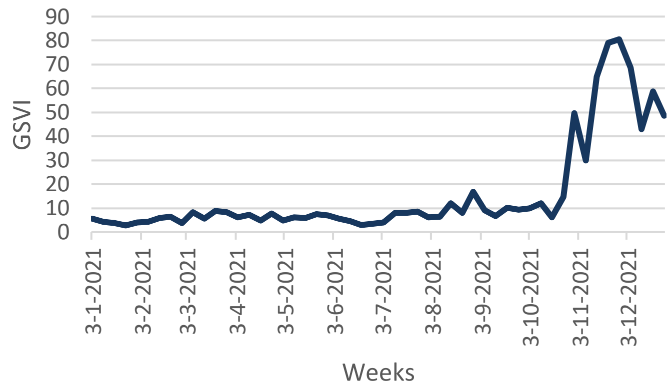


FIGURE 14: GOOGLE TRENDS THE SANDBOX



3.3 Methodology

The methodology is based on methods applied in Pinto-Gutiérrez et al (2022) and Shen et al (2019), which is the use of a vector autoregressive (VAR) model and Granger causality tests. Using a VAR model for the research on investor attention is widely used in existing literature (Ante 2021a, Ante 2021b, Huynh 2021 and Choi 2021). A VAR model is useful for understanding multiple time series data via the use of the lagged versions of the variables to explain the current values of the variables (Pinto-Gutiérrez et al, 2022). For this research The VAR model consists of the following equations:

$$NFT\ attention_t = \alpha + \sum_{j=1}^{p} \beta NFT\ attention_{t-j} + \sum_{j=1}^{p} \beta Crypto\ return_{t-j} + \mu_t \tag{1}$$

$$Crypto\ return_t = \alpha + \sum_{j=1}^{p} \beta NFT\ attention_{t-j} + \sum_{j=1}^{p} \gamma Crypto\ return_{t-j} + \mu_t \tag{2}$$

Equation (1) and (2) are the basic equations on which the equations that are used in this study based on. Equations (3) and (4) provide an extensive example with the selected variables included. Not all the used equations are spelled out to save space. The example equations will provide an adequate interpretation of the equations used in the statistical analyses.

$$ABGT_t = a + \sum_{j=1}^{2} \beta ABGT_{t-j} + \sum_{j=1}^{2} \beta ABsales_{t-j} + \sum_{j=1}^{2} \beta ABvolume_{t-j} + \sum_{j=1}^{2} \beta BTCGT_{t-j} + \sum_{j=1}^{2} \beta BTCreturn_{t-j} + \sum_{j=1}^{2} \beta BTCreturn_{t-j} + \sum_{j=1}^{2} \beta BTCvolume_{t-j} + \sum_{j=1}^{2} \beta BTCprice_{t-j} + \sum_{j=1}^{2} \beta BTCtweets_{t-j} + \sum_{j=1}^{2} \beta ETHGT_{t-j} + \sum_{j=1}^{2} \beta ETHreturn_{t-j} + \sum_{j=1}^{2} \beta ETHvolume_{t-j} + \sum_{j=1}^{2} \beta ETHprice_{t-j} + \sum_{j=1}^{2} \beta ETHtweets_{t-j} + \sum_{j=1}^{2} \beta NFTGT_{t-j} + \mu_t \tag{3}$$

$$BTCreturn_t = a + \sum_{j=1}^{2} \beta ABGT_{t-j} + \sum_{j=1}^{2} \gamma BTCreturn_{t-j} + \sum_{j=1}^{2} \gamma BTCprice_{t-j} + \sum_{j=1}^{2} \gamma BTCvolume_{t-j} + \sum_{j=1}^{2} \gamma BTCtweets_{t-j} \sum_{j=1}^{2} \gamma BTCGT_{t-j} + \sum_{j=1}^{2} \gamma ETHreturn_{t-j} + \sum_{j=1}^{2} \gamma ETHprice_{t-j} + \sum_{j=1}^{2} \gamma ETHvolume_{t-j} + \sum_{j=1}^{2} \gamma ETHtweets_{t-j} + \sum_{j=1}^{2} \gamma ETHGT_{t-j} + \sum_{j=1}^{2} \gamma NFTGT_{t-j} + \mu_t \tag{4}$$

The primary variable is NFT attention, which represents investor attention, as measured by Google Trends and Twitter data. NFT attention consists of variables that represent the Google Trends for the selected NFTs, Bitcoin, Ethereum and NFTs investor attention in general. α represents the vector of constants, β is a vector of coefficients on the first endogenous variable, which is NFT attention, and γ is a vector of the coefficients on the second endogenous variables, Crypto returns (Pinto-Gutiérrez et al 2022 and Shen et al 2019). μ_t represents the vector of white noise innovations. Finally, p is the number of lags in both Equation (1) and (2).

The optimal number of lags is determined by applying the Akaike information criterion (AIC) and the Schwarz-Bayesian information criteria (SBIC) in compliance with Ante (2021a), Pinto-Gutiérrez et al (2022) and Shen et al (2019).

Besides checking for the optimal amount of lags, the Dickey-Fuller test (DF) is conducted to examine the chosen variables for stationarity in the time-series data and variables. Checking for stationarity is necessary as non-stationary data could result in spurious regression results (Pinto-Gutiérrez et al, 2022). The VAR model is suitable for this research if the data is proven to be stationary by the Dickey-Fuller test (Ante, 2021a).

The final step in the methodology is to run the regression as given in Equation (3) and (4) via the Granger causality test. The Granger causality test is conducted to examine the formulated equations on a causal relationship between NFT attention and Crypto returns (Pinto-Gutiérrez et al 2022 and Shen et al 2018). The causal relationship means that lagged, past, values of variables help to explain or predict current or future values of other variables, which is explained in Equations (1) and (2).

Equations (3) and (4) represent an example, with Art Blocks as the specific NFT, of the extensive equations used in the statistical analyses. For the other NFTs, specified in Table 1, AB will be replaced with the abbreviation of the other selected non-fungible tokens in Equations (3) and (4). Variables used are the Google Trends of each selected NFT as the independent variable, ABGT in equation (3), the lagged variables of investor attention towards the NFT, number of sales and volume of the NFT, ABGT, ABsales and ABvolume respectively. Cryptocurrency variables are the investor attention towards Bitcoin and Ethereum denoted as BTCGT, BTCtweets, ETHGT and ETHtweets and the return, price and volume of both cryptocurrencies, which are displayed as BTCreturn, BTCprice, BTCvolume, ETHreturn, ETHprice, ETHvolume. The last variable included is the general investor attention towards NFTs, which is captured in the Google Trends variable denoted as NFTGT. Each NFT has the same equation as in the example of Equation (3). The only changes made are the NFT specific variables, Google Trends, sales and volume of the NFT respectively. The same principle applies to the set up of extensive Equation (4).

The optimal number of lags according to the Akaike and Schwarz-Bayesian information criterion for this research is two lags, which translates to using the one and two weeks ago values of the variables to explain current values of investor attention towards NFTs and cryptocurrency returns. The tables in section four report the optimal number of lags in each table note.

4 Empirical results

4.1 Results Dickey-Fuller test and correlation matrix

Table 4 displays the results of the Dickey-Fuller test on all variables included in the study. The Z-value shows the test value for the variable, whereas the p-value determines if this test value is significant at any level of significance, the 1 percent, 5 percent and 10 percent level respectively.

Table 5 provides a correlation matrix of all variables included in this study. There is some correlation between a few of the Google Searches for the NFTs included in this study. Art Blocks and CryptoPunks Google Searches and The Sandbox and Decentraland Google Searches are the most noteworthy highly correlated NFT Google Searches.

TABLE 4: DICKEY-FULLER TEST RESULTS

Variables	Z	p-value
ArtBlocks Google Trends	-2.157	0.222
ArtBlocks Number of Sales	-1.020	0.746
ArtBlocks Volume in USD	-2.402	0.141
Bored Ape Yacht Club Google Trends	-0.329	0.921
Bored Ape Yacht Club Number of Sales	-6.296	0.000***
Bored Ape Yacht Club Volume in USD	-4.538	0.000***
Cryptopunks Google Trends	-1.958	0.305
Cryptopunks Number of Sales	-1.019	0.746
Cryptopunks Volume in USD	-2.402	0.141
SuperRare Google Trends	-2.919	0.043***
SuperRare Number of Sales	-1.732	0.415
SuperRare Volume in USD	-3.196	0.020***
Axie Infinity Google Trends	-1.404	0.580
Axie Infinity Number of Sales	-1.044	0.737
Axie Infinity Volume in USD	-1.220	0.665
Cool Cats Google Trends	-2.635	0.086*
Cool Cats Number of Sales	-3.891	0.002***
Cool Cats Volume in USD	-2.837	0.053*
Cryptokitties Google Trends	-3.350	0.013**
Cryptokitties Number of Sales	-2.168	0.218
Cryptokitties Volume in USD	-4.150	0.001***
Decentraland Google Trends	-0.711	0.844
Decentraland Number of Sales	-3.170	0.022**
Decentraland Volume in USD	-1.709	0.426
Hashmasks Google Trends	-5.166	0.000***
Hashmasks Number of Sales	-5.796	0.000***
Hashmasks Volume in USD	-3.911	0.002***
Meebits Google Trends	-4.129	0.001***
Meebits Number of Sales	-5.686	0.000***

Meebits Volume in USD	-5.223	0.000***
The Sandbox Google Trends	-1.307	0.626
The Sandbox Number of Sales	-2.922	0.043**
The Sandbox Volume in USD	-1.882	0.341
Bitcoin Google Trends	-3.106	0.026**
Bitcoin Tweets	-4.585	0.000***
Bitcoin Price	-2.194	0.208
Bitcoin Volume in USD	-3.550	0.007***
Bitcoin Return	-5.985	0.000***
Ethereum Google Trends	-2.374	0.149
Ethereum Tweets	-1.895	0.335
Ethereum Price	-1.598	0.485
Ethereum Volume in USD	-3.560	0.007***
Ethereum Return	-7.109	0.000***
NFT Google Trends	-1.638	0.463

Notes: The Z- and p-values of the Dickey-Fuller test for all the variables. *, **, *** denote significance at the 10%, 5% and 1% level, respectively. Of each variable that is insignificant at the 5% level, the first difference will be used. All first difference variable are significant at the 5% level, but not reported to save space.

TABLE 5: MATRIX OF CORRELATIONS

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Art Blocks Google Trends	1.000													
(2) Bored Ape Yacht Club Google Trends	0.496	1.000												
(3) Cryptopunks Google Trends	0.819	0.764	1.000											
(4) SuperRare Google Trends	0.451	0.462	0.627	1.000										
(5) Axie Infinity Google Trends	0.656	0.720	0.759	0.284	1.000									
(6) Cool Cats Google Trends	0.749	0.687	0.769	0.337	0.845	1.000								
(7) Crypto Kitties Google Trends	0.471	0.375	0.632	0.680	0.435	0.422	1.000							
(8) Decentraland Google Trends	0.247	0.867	0.576	0.446	0.597	0.467	0.405	1.000						
(9) Hashmasks Google Trends	0.103	-0.056	0.114	0.347	-0.150	-0.078	0.249	-0.057	1.000					
(10) Meebits Google Trends	0.396	0.338	0.442	0.233	0.368	0.331	0.328	0.182	-0.158	1.000				
(11) The Sandbox Google Trends	0.292	0.869	0.554	0.383	0.609	0.516	0.348	0.956	-0.080	0.229	1.000			
(12) Bitcoin Google Trends	-0.423	-0.258	-0.423	-0.119	-0.553	-0.481	-0.248	-0.127	-0.078	-0.137	-0.100	1.000		
(13) Ethereum Google Trends	-0.236	-0.127	-0.199	-0.007	-0.333	-0.294	-0.081	-0.073	-0.135	0.439	-0.054	0.737	1.000	
(14) NFT Google Trends	0.252	0.631	0.614	0.791	0.352	0.338	0.671	0.716	0.242	0.133	0.592	-0.179	-0.118	1.000

Note: This table presents the correlation coefficients among all the Google Trends of the selected variables.

4.2 VAR results and Granger causality

Tables six to sixteen show the results of the vector autoregression (VAR) models for each NFT separately. The tables display the t-value of each coefficient, with the corresponding significance in asterisks in Panel A. Panel B displays the Granger-causality values and significance. For each estimation is a maximal amount of two lags used, which means that the previous two and one week values are used to explain the current value of the dependent variable, which in all cases in the investor attention for the NFT in question measured by Google Trends. The use of two lags is applied, because the Aikake and Schwarz-Bayesian Information Criterion results showed significance at two lags. Including a maximum of two lags also has an economic explanation behind it. The past three, four or more weeks explaining current investor attention is far stretched, whereas one or two weeks lag would fit an economic explanation better.

Each VAR estimation is checked for stationarity, stability and autocorrelation. All VAR estimations displayed in Tables six to sixteen are stationary, stable and have no autocorrelation detected at the selected lags.

TABLE 6: VAR ESTIMATION AND GRANGER-CAUSALITY RESULTS ART BLOCKS

Panel A: VAR estimation Art Blocks	
	ABGT
$ABGT_{t-1}$	-0.3683343***
$ABGT_{t-2}$	0.0621242
$ABsales_{t-1}$	-9.19e-06
$ABsales_{t-2}$	.0000658***
$ABvolume_{t-1}$	-1.12e-08
$ABvolume_{t-2}$	-2.41e-09
$BTCPrice_{t-1}$	-0.0009639
$BTCPrice_{t-2}$	-0.0025952*
$BTCReturn_{t-1}$	0.7712379
$BTCReturn_{t-2}$	1.138744
$BTCVolume_{t-1}$	-1.63e-10
$BTCVolume_{t-2}$	-6.17e-12

$BTCGT_{t-1}$		0.3354758	
$BTCGT_{t-2}$		-0.2229817	
$BTCTweets_{t-1}$		-0.0001325*	
$BTCTweets_{t-2}$		.0000685	
$ETHPrice_{t-1}$		0.0139066	
$ETHPrice_{t-2}$		-0.0049492	
$ETHReturn_{t-1}$		-0.1322144	
$ETHReturn_{t-2}$		0.1091561	
$ETHVolume_{t-1}$		5.38e-11	
$ETHVolume_{t-2}$		1.87e-11	
$ETHGT_{t-1}$		0.2393951	
$ETHGT_{t-2}$		-0.2841851	
$ETTweets_{t-1}$		0.0002834	
$ETHTweets_{t-2}$		0.0001767	
$NFTGT_{t-1}$		-0.0745737	
$NFTGT_{t-2}$		-0.2530765*	
Constant		8.609703	
Panel B: Granger Causality			
ABGT does not Granger-cause BTCreturn	10.042***	BTCReturn does not Granger-cause ABGT	3.6477
ABGT does not Granger-cause BTCGT	0.96842	BTCGT does not Granger-cause ABGT	2.5826
ABGT does not Granger-cause BTCTweets	5.2086**	BTCTweets does not Granger-cause ABGT	2.7119
ABGT does not Granger-cause ETHReturn	9.7978***	ETHReturn does not Granger-cause ABGT	.35176
ABGT does not Granger-cause ETHGT	6.915**	ETHGT does not Granger-cause ABGT	3.9083
ABGT does not Granger-cause ETHTweets	1.3965	ETHTweets does not Granger-cause ABGT	1.1073
ABGT does not Granger-cause NFTGT	7.8982**	NFTGT does not Granger-cause NFTGT	3.3106

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results. The Aikake and Schwarz-Bayesian Information Criterion is significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 7: VAR ESTIMATION AND GRANGER-CAUSALITY RESULTS AXIE INFINITY

Panel A: VAR estimation Axie Infinity	
	AIGT
$AIGT_{t-1}$	-0.4339333***
$AIGT_{t-2}$	-0.1111539
$AIsales_{t-1}$	2.20e-06
$AIsales_{t-2}$	-0.0000354
$AIvolume_{t-1}$	5.60e-08
$AIvolume_{t-2}$	2.00e-07*

$BTCPrice_{t-1}$		0.0008326	
$BTCPrice_{t-2}$		0.00194	
$BTCReturn_{t-1}$		-0.3067607	
$BTCReturn_{t-2}$		-0.8955162	
$BTCVolume_{t-1}$		8.77e-11	
$BTCVolume_{t-2}$		6.27e-12	
$BTCGT_{t-1}$		-0.1601643	
$BTCGT_{t-2}$		0.0774091	
$BTCTweets_{t-1}$		-0.0000539	
$BTCTweets_{t-2}$		0.0001048	
$ETHPrice_{t-1}$		0.0079715	
$ETHPrice_{t-2}$		0.0087898	
$ETHReturn_{t-1}$		-0.2311149	
$ETHReturn_{t-2}$		-0.3682281	
$ETHVolume_{t-1}$		5.79e-11	
$ETHVolume_{t-2}$		1.85e-11	
$ETHGT_{t-1}$		-0.0144224	
$ETHGT_{t-2}$		0.0299376	
$ETTweets_{t-1}$		0.0000601	
$ETHTweets_{t-2}$		0.0001545	
$NFTGT_{t-1}$		0.0168621	
$NFTGT_{t-2}$		-0.0347363	
Constant		-3.178917	
Panel B: Granger Causality			
AIGT does not Granger-cause BTCreturn	1.0596	BTCReturn does not Granger-cause AIGT	1.4401
AIGT does not Granger-cause BTCGT	0.02901	BTCGT does not Granger-cause AIGT	0.50631
AIGT does not Granger-cause BTCTweets	0.04282	BTCTweets does not Granger-cause AIGT	1.6788
AIGT does not Granger-cause ETHReturn	0.67891	ETHReturn does not Granger-cause AIGT	1.3538
AIGT does not Granger-cause ETHGT	0.3404	ETHGT does not Granger-cause AIGT	0.02466
AIGT does not Granger-cause ETHTweets	1.8657	ETHTweets does not Granger-cause AIGT	0.28625
AIGT does not Granger-cause NFTGT	0.58547	NFTGT does not Granger-cause AIGT	0.04678

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results The Aikake and Schwarz-Bayesian Information Criterion is significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 8: VAR ESTIMATION AND GRANGER-CAUSALITY RESULTS BORED APE YACHT CLUB

Panel A: VAR estimation Bored Ape Yacht Club	
	BAYCGT

$BAYCGT_{t-1}$		-0.1875895	
$BAYCGT_{t-2}$		0.2077277	
$BAYCsales_{t-1}$		-0.0005547	
$BAYCsales_{t-2}$		-0.0003767	
$BAYCvolume_{t-1}$		-5.24e-08	
$BAYCvolume_{t-2}$		-2.87e-08	
$BTCPrice_{t-1}$		-0.0009391	
$BTCPrice_{t-2}$		-0.0001025	
$BTCReturn_{t-1}$		0.3868722	
$BTCReturn_{t-2}$		0.1352025	
$BTCVolume_{t-1}$		-1.75e-10	
$BTCVolume_{t-2}$		-1.00e-10	
$BTCGT_{t-1}$		0.0509872	
$BTCGT_{t-2}$		-0.0044874	
$BTCTweets_{t-1}$		-1.44e-06	
$BTCTweets_{t-2}$		6.31e-06	
$ETHPrice_{t-1}$		0.0315662*	
$ETHPrice_{t-2}$		0.0161081	
$ETHReturn_{t-1}$		-0.6449106	
$ETHReturn_{t-2}$		-0.376234	
$ETHVolume_{t-1}$		2.23e-10	
$ETHVolume_{t-2}$		-1.81e-10	
$ETHGT_{t-1}$		0.0859843	
$ETHGT_{t-2}$		-0.207436	
$ETTweets_{t-1}$		-0.0000858	
$ETHTweets_{t-2}$		-0.0005094*	
$NFTGT_{t-1}$		0.0006972	
$NFTGT_{t-2}$		0.1133027	
Constant		13.55826	
Panel B: Granger Causality			
BAYCGT does not Granger-cause BTCreturn	1.6657	BTCReturn does not Granger-cause BAYCGT	0.21606
BAYCGT does not Granger-cause BTCGT	3.0078	BTCGT does not Granger-cause BAYCGT	0.05028
BAYCGT does not Granger-cause BTCTweets	0.87921	BTCTweets does not Granger-cause BAYCGT	0.00512
BAYCGT does not Granger-cause ETHReturn	0.61215	ETHReturn does not Granger-cause BAYCGT	2.9163
BAYCGT does not Granger-cause ETHGT	3.7939	ETHGT does not Granger-cause BAYCGT	0.78632
BAYCGT does not Granger-cause ETHTweets	3.6032	ETHTweets does not Granger-cause BAYCGT	2.8531
BAYCGT does not Granger-cause NFTGT	2.0703	NFTGT does not Granger-cause BAYCGT	0.31213

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results The Aikake and Schwarz-Bayesian Information Criterion is significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

Table 9: VAR estimation and Granger-causality results Cool Cats

Panel A: VAR estimation Cool Cats

	CCGT
$CCGT_{t-1}$	-0.6306623***
$CCGT_{t-2}$	-0.4824467**
$CCsales_{t-1}$	0.0033203**
$CCsales_{t-2}$	-0.0010959
$CCvolume_{t-1}$	-5.29e-07
$CCvolume_{t-2}$	2.35e-07
$BTCPrice_{t-1}$	-0.0000706
$BTCPrice_{t-2}$	0.0017325
$BTCReturn_{t-1}$	0.1930841
$BTCReturn_{t-2}$	-0.7112474
$BTCVolume_{t-1}$	2.50e-10
$BTCVolume_{t-2}$	2.73e-10
$BTCGT_{t-1}$	-0.4848707
$BTCGT_{t-2}$	-0.0708073
$BTCTweets_{t-1}$	0.00013
$BTCTweets_{t-2}$	-0.0000114
$ETHPrice_{t-1}$	-0.0042127
$ETHPrice_{t-2}$	0.004664
$ETHReturn_{t-1}$	0.1278221
$ETHReturn_{t-2}$	0.1066136
$ETHVolume_{t-1}$	-9.83e-12
$ETHVolume_{t-2}$	-8.49e-13
$ETHGT_{t-1}$	0.1017497
$ETHGT_{t-2}$	-0.0738378
$ETTweets_{t-1}$	-0.0009725***
$ETHTweets_{t-2}$	-0.0011871***
$NFTGT_{t-1}$	-0.0383213
$NFTGT_{t-2}$	0.2074938
Constant	-9.423764

Panel B: Granger Causality

CCGT does not Granger-cause BTCreturn	1.06	BTCReturn does not Granger-cause CCGT	0.38736
CCGT does not Granger-cause BTCGT	0.4748	BTCGT does not Granger-cause CCGT	3.1523
CCGT does not Granger-cause BTCTweets	0.42947	BTCTweets does not Granger-cause CCGT	1.1597
CCGT does not Granger-cause ETHReturn	1.6235	ETHReturn does not Granger-cause CCGT	0.09915
CCGT does not Granger-cause ETHGT	0.41924	ETHGT does not Granger-cause CCGT	0.27646
CCGT does not Granger-cause ETHTweets	8.5568**	ETHTweets does not Granger-cause CCGT	13.475***
CCGT does not Granger-cause NFTGT	1.8881	NFTGT does not Granger-cause CCGT	0.69897

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results. The Aikake and Schwarz-Bayesian Information Criterion is significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 10: VAR ESTIMATION AND GRANGER-CAUSALITY RESULTS CRYPTO PUNKS

Panel A: VAR estimation Crypto Punks			
		CPGT	
$CPGT_{t-1}$		-0.1288357	
$CPGT_{t-2}$		-0.0348747	
$CPsales_{t-1}$		-0.0000479**	
$CPsales_{t-2}$		0.0000853***	
$CPvolume_{t-1}$		4.13e-09	
$CPvolume_{t-2}$		-4.88e-09	
$BTCPrice_{t-1}$		0.0013205	
$BTCPrice_{t-2}$		-0.0008321	
$BTCReturn_{t-1}$		-0.4154655	
$BTCReturn_{t-2}$		0.541173	
$BTCVolume_{t-1}$		2.49e-11	
$BTCVolume_{t-2}$		1.30e-10	
$BTCGT_{t-1}$		0.1091854	
$BTCGT_{t-2}$		-0.2456501	
$BTCTweets_{t-1}$		0.0000526	
$BTCTweets_{t-2}$		0.0000787	
$ETHPrice_{t-1}$		0.0078029	
$ETHPrice_{t-2}$		-0.0106993	
$ETHReturn_{t-1}$		-0.0976941	
$ETHReturn_{t-2}$		0.1689201	
$ETHVolume_{t-1}$		1.92e-10	
$ETHVolume_{t-2}$		-1.90e-10	
$ETHGT_{t-1}$		0.062622	
$ETHGT_{t-2}$		-0.02244	
$ETTweets_{t-1}$		0.0001827	
$ETHTweets_{t-2}$		-0.0004523	
$NFTGT_{t-1}$		0.2176686	
$NFTGT_{t-2}$		-0.1070634	
Constant		-14.18768	
Panel B: Granger Causality			
CPGT does not Granger-cause BTCreturn	0.77843	BTCReturn does not Granger-cause CPGT	0.47797
CPGT does not Granger-cause BTCGT	1.1184	BTCGT does not Granger-cause CPGT	0.54574
CPGT does not Granger-cause BTCTweets	1.7639	BTCTweets does not Granger-cause CPGT	1.4825

CPGT does not Granger-cause ETHReturn	0.19727	ETHReturn does not Granger-cause CPGT	0.26381
CPGT does not Granger-cause ETHGT	2.3115	ETHGT does not Granger-cause CPGT	0.08475
CPGT does not Granger-cause ETHTweets	5.0141*	ETHTweets does not Granger-cause CPGT	1.6058
CPGT does not Granger-cause NFTGT	3.5178	NFTGT does not Granger-cause CPGT	1.0576

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results. The Aikake and Schwarz-Bayesian Information Criterion is significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 11: VAR ESTIMATION AND GRANGER-CAUSALITY RESULTS CRYPTOKITTIES

Panel A: VAR estimation CryptoKitties	
	CKGT
$CKGT_{t-1}$	0.4105754***
$CKGT_{t-2}$	-0.0601238
$CKsales_{t-1}$	-0.0079957
$CKsales_{t-2}$	0.0037507
$CKvolume_{t-1}$	4.66e-07
$CKvolume_{t-2}$	1.63e-07
$BTCPrice_{t-1}$	-0.0038827**
$BTCPrice_{t-2}$	-0.0002969
$BTCReturn_{t-1}$	1.834127**
$BTCReturn_{t-2}$	0.4794445
$BTCVolume_{t-1}$	-3.11e-10
$BTCVolume_{t-2}$	-1.12e-10
$BTCGT_{t-1}$	0.3295044
$BTCGT_{t-2}$	0.0710168
$BTCTweets_{t-1}$	-0.0002472**
$BTCTweets_{t-2}$	0.000129
$ETHPrice_{t-1}$	-0.0463958**
$ETHPrice_{t-2}$	0.0003551
$ETHReturn_{t-1}$	0.9509644*
$ETHReturn_{t-2}$	0.272483
$ETHVolume_{t-1}$	-4.84e-10*
$ETHVolume_{t-2}$	-1.01e-10
$ETHGT_{t-1}$	0.1084501
$ETHGT_{t-2}$	0.35277
$ETTweets_{t-1}$	-0.000505
$ETHTweets_{t-2}$	-0.0001536
$NFTGT_{t-1}$	0.445042*
$NFTGT_{t-2}$	0.413178
Constant	35.48312***

Panel B: Granger Causality			
CKGT does not Granger-cause BTCreturn	2.2217	BTCReturn does not Granger-cause CKGT	4.2186
CKGT does not Granger-cause BTCGT	1.0846	BTCGT does not Granger-cause CKGT	2.0398
CKGT does not Granger-cause BTCTweets	2.2435	BTCTweets does not Granger-cause CKGT	5.1187*
CKGT does not Granger-cause ETHReturn	0.09481	ETHReturn does not Granger-cause CKGT	3.5767
CKGT does not Granger-cause ETHGT	0.81216	ETHGT does not Granger-cause CKGT	1.6883
CKGT does not Granger-cause ETHTweets	1.3136	ETHTweets does not Granger-cause CKGT	1.9761
CKGT does not Granger-cause NFTGT	0.34081	NFTGT does not Granger-cause CKGT	5.3201*

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results The Aikake and Schwarz-Bayesian Information Criterion was significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 12: VAR ESTIMATION AND GRANGER-CAUSALITY RESULTS DECENTRALAND

Panel A: VAR estimation Decentraland	
	DGT
DGT_{t-1}	-0.3101668**
DGT_{t-2}	-0.244631*
$Dsales_{t-1}$	-0.0139211*
$Dsales_{t-2}$	0.003723
$Dvolume_{t-1}$	1.02e-06
$Dvolume_{t-2}$	-2.25e-07
$BTCPrice_{t-1}$	0.0009302
$BTCPrice_{t-2}$	0.0054295***
$BTCReturn_{t-1}$	-.2963417
$BTCReturn_{t-2}$	-2.350307***
$BTCVolume_{t-1}$	-1.61e-10
$BTCVolume_{t-2}$	3.56e-12
$BTCGT_{t-1}$	0.1596812
$BTCGT_{t-2}$	0.1466905
$BTCTweets_{t-1}$	-0.0000695
$BTCTweets_{t-2}$	0.0001267*
$ETHPrice_{t-1}$	0.0246664**
$ETHPrice_{t-2}$	0.0202411**
$ETHReturn_{t-1}$	-0.6228611**
$ETHReturn_{t-2}$	-0.5218975**
$ETHVolume_{t-1}$	-1.28e-12
$ETHVolume_{t-2}$	8.52e-11
$ETHGT_{t-1}$	-0.199766

ETHGT$_{t-2}$		0.0315537	
ETTweets$_{t-1}$		0.0009345***	
ETHTweets$_{t-2}$		0.0002258	
NFTGT$_{t-1}$		0.1931113	
NFTGT$_{t-2}$		0.3225286**	
Constant		-6.657104	
Panel B: Granger Causality			
DGT does not Granger-cause BTCreturn	2.2636	BTCReturn does not Granger-cause DGT	12.99***
DGT does not Granger-cause BTCGT	1.3061	BTCGT does not Granger-cause DGT	2.2991
DGT does not Granger-cause BTCTweets	0.3138	BTCTweets does not Granger-cause DGT	3.6608
DGT does not Granger-cause ETHReturn	2.1667	ETHReturn does not Granger-cause DGT	6.4394**
DGT does not Granger-cause ETHGT	2.2723	ETHGT does not Granger-cause DGT	2.2019
DGT does not Granger-cause ETHTweets	3.1658	ETHTweets does not Granger-cause DGT	17.773***
DGT does not Granger-cause NFTGT	1.8275	NFTGT does not Granger-cause DGT	6.4928**

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results The Aikake and Schwarz-Bayesian Information Criterion was significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 13: VAR ESTIMATION AND GRANGER-CAUSALITY RESULTS HASHMASKS

Panel A: VAR estimation Hashmasks	
	HMGT
HMGT$_{t-1}$	0.1258978
HMGT$_{t-2}$	-0.18486
HMsales$_{t-1}$	-0.0062147
HMsales$_{t-2}$	-0.0027155
HMvolume$_{t-1}$	3.31e-06
HMvolume$_{t-2}$	2.52e-06
BTCPrice$_{t-1}$	0.0009554
BTCPrice$_{t-2}$	0.0010473
BTCReturn$_{t-1}$	-0.2441457
BTCReturn$_{t-2}$	-0.6591893
BTCVolume$_{t-1}$	2.67e-10
BTCVolume$_{t-2}$	-1.23e-10
BTCGT$_{t-1}$	-0.3129059
BTCGT$_{t-2}$	0.2782667
BTCTweets$_{t-1}$	0.0000768
BTCTweets$_{t-2}$	-0.0002788**
ETHPrice$_{t-1}$	-0.0670375***

ETHPrice$_{t-2}$		-0.0078606	
ETHReturn$_{t-1}$		2.197762***	
ETHReturn$_{t-2}$		0.375412	
ETHVolume$_{t-1}$		1.41e-10	
ETHVolume$_{t-2}$		-3.87e-10	
ETHGT$_{t-1}$		-0.1134339	
ETHGT$_{t-2}$		-.1943315	
ETTweets$_{t-1}$		-0.0003415	
ETHTweets$_{t-2}$		-0.0003685	
NFTGT$_{t-1}$		-0.0618021	
NFTGT$_{t-2}$		0.2634977	
Constant		33.01345**	
Panel B: Granger Causality			
HMGT does not Granger-cause BTCreturn	3.0154	BTCReturn does not Granger-cause HMGT	0.26364
HMGT does not Granger-cause BTCGT	2.1002	BTCGT does not Granger-cause HMGT	0.79751
HMGT does not Granger-cause BTCTweets	0.02069	BTCTweets does not Granger-cause HMGT	4.887*
HMGT does not Granger-cause ETHReturn	1.2131	ETHReturn does not Granger-cause HMGT	10.62***
HMGT does not Granger-cause ETHGT	5.1373*	ETHGT does not Granger-cause HMGT	0.54996
HMGT does not Granger-cause ETHTweets	2.2149	ETHTweets does not Granger-cause HMGT	1.0782
HMGT does not Granger-cause NFTGT	2.9823	NFTGT does not Granger-cause HMGT	0.95264

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results. The Aikake and Schwarz-Bayesian Information Criterion was significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

TABLE 14: VAR ESTIMATION AND GRANGER-CAUSALITY RESULTS MEEBITS

Panel A: VAR estimation Meebits	
	MBGT
MBGT$_{t-1}$	0.7320313***
MBGT$_{t-2}$	-0.4559617*
MBsales$_{t-1}$	-0.0001676
MBsales$_{t-2}$	-0.0032536
MBvolume$_{t-1}$	7.49e-08
MBvolume$_{t-2}$	6.06e-07
BTCPrice$_{t-1}$	-0.0039877
BTCPrice$_{t-2}$	-0.0016288
BTCReturn$_{t-1}$	1.506444
BTCReturn$_{t-2}$	0.4434692
BTCVolume$_{t-1}$	-5.74e-10**

$BTCVolume_{t-2}$		9.98e-10***	
$BTCGT_{t-1}$		0.4601249	
$BTCGT_{t-2}$		-1.252427***	
$BTCTweets_{t-1}$		-0.0000815	
$BTCTweets_{t-2}$		0.0004177 ***	
$ETHPrice_{t-1}$		-0.004268	
$ETHPrice_{t-2}$		0.0651014***	
$ETHReturn_{t-1}$		0.1318573	
$ETHReturn_{t-2}$		-1.705776***	
$ETHVolume_{t-1}$		-4.73e-10	
$ETHVolume_{t-2}$		1.11e-09***	
$ETHGT_{t-1}$		0.6787377	
$ETHGT_{t-2}$		-0.0494005	
$ETTweets_{t-1}$		-0.0008532*	
$ETHTweets_{t-2}$		-0.0008732*	
$NFTGT_{t-1}$		0.7386578***	
$NFTGT_{t-2}$		-.8777751***	
Constant		-10.97566	
Panel B: Granger Causality			
MBGT does not Granger-cause BTCreturn	0.04878	BTCReturn does not Granger-cause MBGT	1.8285
MBGT does not Granger-cause BTCGT	0.61658	BTCGT does not Granger-cause MBGT	8.499**
MBGT does not Granger-cause BTCTweets	3.0002	BTCTweets does not Granger-cause MBGT	10.867***
MBGT does not Granger-cause ETHReturn	2.9303	ETHReturn does not Granger-cause MBGT	13.493***
MBGT does not Granger-cause ETHGT	6.499**	ETHGT does not Granger-cause MBGT	2.6192
MBGT does not Granger-cause ETHTweets	9.29***	ETHTweets does not Granger-cause MBGT	5.8487*
MBGT does not Granger-cause NFTGT	2.0967	NFTGT does not Granger-cause MBGT	10.199***

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results. The Aikake and Schwarz-Bayesian Information Criterion was significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

TABLE 15: VAR ESTIMATION AND GRANGER-CAUSALITY RESULTS SUPERRARE

Panel A: VAR estimation SuperRare	
	SRGT
$SRGT_{t-1}$	0.3853929***
$SRGT_{t-2}$	0.2805118**
$SRsales_{t-1}$	0.0050701
$SRsales_{t-2}$	0.0172277
$SRvolume_{t-1}$	2.08e-06***

$SRvolume_{t-2}$		-8.39e-07	
$BTCPrice_{t-1}$		0-.001362	
$BTCPrice_{t-2}$		-0.0029087	
$BTCReturn_{t-1}$		0.7578487	
$BTCReturn_{t-2}$		1.427395	
$BTCVolume_{t-1}$		-8.31e-11	
$BTCVolume_{t-2}$		2.60e-10	
$BTCGT_{t-1}$		0.4961285*	
$BTCGT_{t-2}$		-0.6610666**	
$BTCTweets_{t-1}$		-0.0001104	
$BTCTweets_{t-2}$		0.0001405	
$ETHPrice_{t-1}$		-0.0117968	
$ETHPrice_{t-2}$		0.0089675	
$ETHReturn_{t-1}$		0.4173449	
$ETHReturn_{t-2}$		-0.0906999	
$ETHVolume_{t-1}$		-2.86e-10	
$ETHVolume_{t-2}$		2.08e-10	
$ETHGT_{t-1}$		0.2001595	
$ETHGT_{t-2}$		0.0580098	
$ETTweets_{t-1}$		-0.0009125***	
$ETHTweets_{t-2}$		0.0000718	
$NFTGT_{t-1}$		0.0879453	
$NFTGT_{t-2}$		0.5732289***	
Constant		5.035859	
Panel B: Granger Causality			
SRGT does not Granger-cause BTCreturn	4.5281	BTCReturn does not Granger-cause SRGT	3.1014
SRGT does not Granger-cause BTCGT	1.1831	BTCGT does not Granger-cause SRGT	5.3819*
SRGT does not Granger-cause BTCTweets	3.1074	BTCTweets does not Granger-cause SRGT	2.2393
SRGT does not Granger-cause ETHReturn	3.0834	ETHReturn does not Granger-cause SRGT	1.0572
SRGT does not Granger-cause ETHGT	1.8828	ETHGT does not Granger-cause SRGT	1.0872
SRGT does not Granger-cause ETHTweets	1.1189	ETHTweets does not Granger-cause SRGT	7.1675**
SRGT does not Granger-cause NFTGT	5.7724*	NFTGT does not Granger-cause SRGT	8.0244**

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results. The Aikake and Schwarz-Bayesian Information Criterion was significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 16: VAR ESTIMATION AND GRANGER-CAUSALITY RESULTS THE SANDBOX

Panel A: VAR estimation The Sandbox

	TSGT		
$TSGT_{t-1}$	-0.7718712***		
$TSGT_{t-2}$	-0.1992516		
$TSsales_{t-1}$	-0.0021714		
$TSsales_{t-2}$	0.0008264		
$TSvolume_{t-1}$	1.02e-06***		
$TSvolume_{t-2}$	3.65e-08		
$BTCPrice_{t-1}$	0.0015797		
$BTCPrice_{t-2}$	0.0033953***		
$BTCReturn_{t-1}$	-0.6724694		
$BTCReturn_{t-2}$	-1.486334**		
$BTCVolume_{t-1}$	-1.94e-10		
$BTCVolume_{t-2}$	1.76e-11		
$BTCGT_{t-1}$	0.3129179*		
$BTCGT_{t-2}$	-0.0800657		
$BTCTweets_{t-1}$	-0.0001092*		
$BTCTweets_{t-2}$	0.0001417**		
$ETHPrice_{t-1}$	0.0206759*		
$ETHPrice_{t-2}$	0.0250933***		
$ETHReturn_{t-1}$	-0.4181051		
$ETHReturn_{t-2}$	-0.5856844**		
$ETHVolume_{t-1}$	-3.86e-11		
$ETHVolume_{t-2}$	1.50e-10		
$ETHGT_{t-1}$	-0.1152365		
$ETHGT_{t-2}$	-0.0408226		
$ETTweets_{t-1}$	0.0005694**		
$ETHTweets_{t-2}$	-0.0000219		
$NFTGT_{t-1}$	0.1587911		
$NFTGT_{t-2}$	0.1303837		
Constant	-2.734133		
Panel B: Granger Causality			
TSGT does not Granger-cause BTCreturn	0.11789	BTCReturn does not Granger-cause TSGT	6.7298**
TSGT does not Granger-cause BTCGT	1.714	BTCGT does not Granger-cause TSGT	3.459
TSGT does not Granger-cause BTCTweets	0.79934	BTCTweets does not Granger-cause TSGT	5.8253*
TSGT does not Granger-cause ETHReturn	0.69974	ETHReturn does not Granger-cause TSGT	6.8635**
TSGT does not Granger-cause ETHGT	1.5955	ETHGT does not Granger-cause TSGT	1.0162
TSGT does not Granger-cause ETHTweets	1.9724	ETHTweets does not Granger-cause TSGT	6.3837**
TSGT does not Granger-cause NFTGT	4.8158*	NFTGT does not Granger-cause TSGT	3.0738

Notes: abbreviations of the variables can be found in Table 1. Panel A presents the statistical results of the VAR analysis, whereas panel B present the Granger-causality test results The Aikake and Schwarz-Bayesian Information Criterion was significant at two lags, therefore T-1 and T-2 represent the lag at one and two weeks.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

5 Discussion

5.1 Discussion of results

Tables six to sixteen present the results of the vector autoregressive models with a two week and one week lag for the eleven selected NFTs, Bitcoin and Ethereum prices, returns, volume and investor attention, as well as general investor attention towards NFTs. Granger causality test results are reported to investigate the relationship between NFT attention and investor attention and returns of Bitcoin and Ethereum in more depth.

5.1.1 Bitcoin and Ethereum prices, return and volume

Bitcoin returns influence the investor attention towards Decentraland (Table 12) and the Sandbox (Table 16) at the two weeks lag. Results are significant at the one percent and five percent level respectively. The significant influence of Bitcoin returns for investor attention towards Decentraland is supported by the Granger causality test at the one percent level (Table 12), since the null hypothesis that Bitcoin returns does not Granger cause Decentraland investor attention cannot be rejected at the one percent level. Dowling (2021b) finds similar results, where Bitcoin and Ethereum returns impact for about 25% of the investor attention towards the NFT Decentraland.

Ethereum returns at the one week and two weeks lags yield more significant results than Bitcoin returns. The one week lag of Ethereum returns helps explain investor attention towards CryptoKitties (Table 11), Decentraland (Table 12), Hashmasks (Table 13), Meebits (Table 14) and the Sandbox (Table 16). Granger causality results support the findings of influence of Ethereum returns for Hashmasks, Meebits and the Sandbox at the five percent, one percent and five percent level of significance respectively. The influence of Ethereum returns on investor attention towards NFTs is greater than the influence of Bitcoin returns, as these results suggest. The Ethereum returns and the influence on investor attention towards NFTs results obtained with the VAR model are the opposite of what Pinto-Gutiérrez et al (2022) find, but are in line with findings reported in Ante (2021a,b). The difference in methodology between the two aforementioned authors is the use of VAR estimation and wavelet coherence analysis versus a solely appliance of VAR estimation in Ante (2021a,b).

The results above can partly confirm hypothesis three (H3) that Bitcoin and Ethereum returns has a positive influence on NFT investor attention. Bitcoin and Ethereum returns do have an influence on NFT investor attention, but the Bitcoin and Ethereum returns do not have a positive influence on each different NFT. Examples of positive influence of cryptocurrency returns are the coefficients 1.834127**[1] and 0.4794445 of Bitcoin return at the one and two week lag for the NFT CryptoKitties. Although only the first result is statistically significant, it does show that Bitcoin return does have a positive influence on the investor attention towards NFTs, in this case for the NFT CryptoKitties. Bitcoin returns can also have a negative influence on investor attention, as the results in Table 12 suggest. The coefficients of -0.2963417 and -2.350307***[2] for the NFT Decentraland suggest that an increase of 1% in Bitcoin returns roughly leads to a 0.3% and 2.4% decrease of investor attention towards Decentraland. Similar positive (negative) results for Ethereum returns are found for the NFTs Hashmasks (Decentraland) and Meebits (Bored Ape Yacht Club).

All in all can be concluded here that Bitcoin and Ethereum returns do have an influence on NFT investor attention, but it is not a positive influence for each selected NFT, which results in a rejection of H3, as it cannot be fully accepted.

Bitcoin and Ethereum prices at the one week and two week lag provide more significant results than the lagged returns of both cryptocurrencies. Bitcoin prices of the previous week influence the investor attention towards CryptoKitties (Table 11), whereas the two weeks Bitcoin prices can help explain the investor attention of Art Blocks (Table 6), Decentraland (Table 12) and the Sandbox (Table 16). Ethereum prices will lead to more Google Searches for Bored Ape Yacht Club (Table 8), CryptoKitties (Table 11), Decentraland (Table 12), Hashmasks (Table 13), Meebits (Table 14) and the Sandbox (Table 16). In line with Ante's (2021a) conjecture, Bitcoin and Ethereum pricing is of important influence on the NFT market, which the results in this study prove as well. Ante (2021a) find that Ethereum pricing does not significantly results in more investor attention towards NFT, despite Ethereum being the currency NFTs are denoted in, whereas the results of this study suggest otherwise. This difference in results may be due to the use of less lags, two lags on a weekly basis in this study, whereas Ante (2021a) uses four lags on a daily basis.

[1] ** means that this results is significant at the five percent level.

[2] *** means that this results is significant at the one percent level.

Besides the weekly prices and returns of Bitcoin and Ethereum, is the volume of both cryptocurrencies also included in the study. Previous volume of Bitcoin can for some part explain the investor attention towards Meebits (Table 14), with the previous week volume being significant at the five percent level, while the two weeks ago volume of Bitcoin is significant at the one percent level. Meebits is the only NFT out of the eleven that is influenced by the volume of Bitcoin. For the Ethereum volume, there are more NFTs being influenced. The one week lagged Ethereum volume has a significant impact on the investor attention towards Cryptokitties (Table11), whereas the two week lagged Ethereum volume is responsible for contributing to investor attention towards Meebits (Table 14). Including trading volume of Bitcoin and Ethereum in research on NFT investor attention is more common in research on the influence of investor attention on Bitcoin and Ethereum volume, as is seen in Choi (2021), Huynh (2021) and Shen et al (2019). In that type of research, investor attention towards Bitcoin and Ethereum, be it via Google Trends or Tweets, is found to have a positive influence on Bitcoin and Ethereum volume the days after. The results of this research show that this does not necessarily spills over towards the NFT market. This can best be seen in the coefficient of 9.83e-12 and -8.49e-13 for the one and two week lagged Ethereum volume for the NFT Cool Cats (Table 9). Although both results are not significant, the very low coefficients suggest that including Ethereum volume does not impact investor attention towards Cool Cats. The same principle applies to Bitcoin volume in for example Table 8 (Bored Ape Yacht Club). The one exception is the NFT Meebits, for which Bitcoin and Ethereum volume does provide significant results, as can be seen in Table 14.

Existing literature included Axie Infinity, Crypto Punks, Decentraland and SuperRare in their research on investor attention and possible influence of the cryptocurrency market (Ante 2021a,b, Dowling 2021a,b, Pinto-Gutiérrez et al 2022 and Schaar & Kampakis 2022). With including larger and different types of NFTs, the results so far suggest that Bitcoin and Ethereum pricing, returns can help further explain investor attention towards NFTs. Bitcoin and Ethereum volume has little explanatory power when it comes to influencing investor attention towards NFTs.

5.1.2 Influence of tweets and Google Searches about Bitcoin, Ethereum and NFTs on investor attention towards NFTs

Investor attention towards Bitcoin and Ethereum can help explain investor attention towards the NFT market (Ante, 2021b) In the VAR model and Granger-causality test results, this is displayed in the variables BTCGT and ETHGT, with also NFTGT as a proxy for general investor attention towards NFTs. Investor attention towards NFTs in general (NFTGT) is of significant influence for the NFTs Art blocks (Table 6), CryptoKitties (Table11), Decentraland (Table 12), Meebits (Table 14) and SuperRare (Table 15). Noticeable is that the two week lagged investor attention towards NFTs is significant for Art Blocks, Decentraland and SuperRare, in contrast to the NFTs CryptoKitties and Meebits, where the one week lagged NFTGT is of significant influence. Overall can be concluded that Google searches towards NFTs and other versions of the word NFT, see Table 1 for more possible Google search terms, can explain more investor attention towards NFTs, but not every NFT is susceptible for it.

The results in tables six to sixteen also suggest that for some NFTs Google searches on Bitcoin and Ethereum can predict investor attention towards NFTs. Notable results are the influence of Bitcoin Google searches on Meebits (Table 14), SuperRare (Table 15) and the Sandbox (Table 16). Granger causality test confirms these statistical results. For Ethereum Google searches, there are no NFTs that receive investor attention after people search for Ethereum, or Ethereum related search terms, on Google, as none of the displayed results suggest an influence of Ethereum Google Trends on any of the NFTs, which is confirmed by Granger causality test results. A possible explanation for this phenomenon can be based on findings reported in Thorton and Batten (1985). When applying a VAR model, choosing the right amount of lags for the model is crucial. Including more lags than currently applied, could yield in reversed or more significant effects (Thorton & Batten, 1985). In this case, including more than two lags in this study, could possibly result in significant influence of Ethereum Google Searches on investor attention towards certain NFTs or NFTs in general.

However, Google searches for Art Blocks and Meebits do Granger-cause Google Searches for Ethereum, as both results are significant at the five and ten percent level respectively. The insight that Google searches towards Bitcoin and Ethereum influences the Google searches towards certain NFTs can provide a more comprehensive way of understanding the relationship between investor attention towards cryptocurrencies and NFTs, as they are both types of digital assets.

The results of Bitcoin, Ethereum and NFT investor attention measured with Google Trends does not provide enough significant results to fully accept hypothesis one (H1), which states that Bitcoin and Ethereum Google Trends investor attention has a positive influence on NFT investor attention. There are some significant and positive results for Bitcoin and Ethereum investor attention, but also some significant negative coefficients such as -1.252427***[3] for the influence of Bitcoin Google Trends on Meebits Google Trends. A further dive into the two-sided influence of Bitcoin and Ethereum investor attention measured via the use of Google Trends can perhaps in future research provide researchers with more clarity on this relationship.

Bitcoin and Ethereum searches measured via Google Trends yield a couple significant results. Tweets containing '#bitcoin' and / or '#ethereum' provide more significant results in this study. Bitcoin tweets influence the investor attention towards Art Blocks (Table 6), CryptoKitties (Table 11), Decentraland (Table 12), Hashmasks (Table 13), Meebits (Table 14) and the Sandbox (Table 16). The results for Art Blocks, CryptoKitties, Hahsmaks, Meebits and the Sandbox are confirmed by the Granger causality tests as well. Ethereum tweets are significant for the NFTs Bored Ape Yacht Club (Table 8),Cool Cats (Table 9), Decentraland (Table 12), Meebits (Table 14), SuperRare (Table 15) and the Sandbox (Table 16). Significant Granger causality tests confirms the influence of Ethereum tweets for Cool Cats at the one percent level, Decentraland at the one percent level, Meebits at the ten percent level, SuperRare and the Sandbox at the five percent level.

Among aforementioned results are the most noteworthy the coefficients of Ethereum tweets on investor attention towards Cool Cats. With the one week lagged Ethereum tweets coefficient at -0.0009725***[4] and the two week lagged coefficient -0.0011871***[5], there results suggest that that a 1% increase in the tweets containing '#ethereum' would result in a 0.001% drop in Google Searches for Cool Cats one week later. Bitcoin tweets with a two weeks lag can in part explain investor attention towards the NFT Meebits, as the significant coefficient of 0.0004177***[6] suggest. The mixed results of Bitcoin and Ethereum tweets results in a rejection of hypothesis two (H2) as it is not possible to reach a clear conclusion of positive influence of Bitcoin and Ethereum tweets on investor attention towards NFTs.

Research that incorporates tweets containing Bitcoin and Ethereum (Al Guindy 2021, Choi 2021, Huynh 2021 and Kraaijeveld & De Smedt 2020) prove that tweets can drive investor attention towards Bitcoin and Ethereum. By adding the appliance of Bitcoin and Ethereum tweets to research on investor attention towards NFTs, this strand in the literature gets widened. Future

[3] *** means that this results is significant at the one percent level.
[4] *** means that this result is significant at the one percent level.
[5] *** means that this result is significant at the one percent level.
[6] *** means that this result is significant at the one percent level.

research can build further on this foundation when trying to find similar or contrasting results as presented in this study.

5.1.3 NFT specific investor attention, number of sales and volume

NFT specific variables, which are investor attention measured with Google Trends, number of sales and volume in USD, can also help, in the lagged variant, predict today or future values of NFT attention for that specific NFT. For every NFT, except for Bored Ape Yacht Club, Crypto Punks and Hashmasks, is either the one week lagged investor attention variable or both the one and two week lagged variable of investor attention significant in the vector autoregressive model. With coefficients of -0.3683343***[7] for Art Blocks, -0.4339333***[8] for Axie Infinity, 0.4105754***[9] for CryptoKitties, the results suggest a binary influence. For some NFTs, previous investor attention will increase the investor attention one or two weeks later, whereas for other NFTs this works in the opposite way. The negative coefficients of the examples Art Blocks and Axie Infinity, both at the one week lag, are difficult to interpret. Economic literature would suggest that previous investor attention towards a digital asset, such as cryptocurrencies and NFTs, would result in an increase of investor attention in the days of weeks afterwards. The results of this study do not confirm the findings of Google Searches having a solely positive influence as is for example presented in Lin (2021), Urquhart (2018), but it does confirm the finding of both positive and negative coefficients as presented by Han et al (2018).

Previous number of sales of a specific NFT can also generate more investor attention towards that specific NFT. This is the case for Art Blocks (Table 6), Cool Cats (Table 9), Crypto Punks (Table 10)and Decentraland (Table 12). Volume in USD for a NFT has a significant influence on investor attention towards SuperRare (Table 15) and the Sandbox (Table 16) only. These results complement the results of Ante (2021b) in which the author finds that the number of NFT sales of the NFT CryptoPunks has a significant impact on other NFTs such as CryptoKitties, The Sandbox and Art Blocks. The conjecture posed in Ante (2021b) that NFT markets are driven by other NFT markets can be deepened by adding that NFT specific sales and volume in USD can help explain the investor attention towards that NFT.

[7] *** means that this result is significant at the one percent level.
[8] *** means that this result is significant at the one percent level.
[9] *** means that this result is significant at the one percent level.

Whereas mostly Bitcoin and Ethereum returns, volume, tweets and Google Trends Granger-cause investor attention towards NFTs, the results suggest relationships the other way around. The Granger causality tests reveal that Art Block Google Search Granger-cause Bitcoin return and tweets, Ethereum returns and investor attention and also investor attention towards NFTs in general. Cool Cats and Crypto Punks, Tables 9 and 10, also Granger-cause Ethereum tweets. This is an odd result, because common economic literature on NFTs and cryptocurrencies find evidence for the other way around, where Bitcoin and Ethereum investor attention causes NFT specific investor attention.

5.2 Limitations

There are some limitation to this study that could alter the interpretation of the results and repetition of the same research in the future.

First of all, weekly interval data is standard for Google Trends. The widespread appliance of Google Trends in economic research all experience the same limitation when including Google Trends in research., which makes this limitation a common and acceptable limitation in this strand of economic literature.

Secondly, linear regression results, included in Appendix A in Tables 17 to 27, suggest that not every variable used in this study has a significant impact on the independent variable, investor attention for each NFT, which could therefore be excluded from the further VAR analysis conducted in this research. By only using the significant variables for each NFT, the VAR analysis and accompanying Granger causality tests would result in different outcomes, which would make comparing and generalization more difficult.

Another limitation is the missing of a measure for tweets containing the name or nick-name of the NFTs into account, as is the case for Bitcoin and Ethereum. Reason being is because this research focusses on the relationship and influence of Bitcoin and Ethereum on the NFT market. The possible influence of the NFT market on itself and the cryptocurrency market is recommendation for future research. Granger causality results of this study suggest that that investor attention, measured with Google Trends, can explain the investor attention towards Bitcoin and Ethereum. Deeper exploration of these uncommon results in future research will provide a better understanding of the interactions between the cryptocurrency and NFT market.

The data in this study is all the available data for the year 2021. Since the NFT market is still very young and expanding, not every NFT included has a full year of available data. The year 2021 is a year with record-high prices and activity in the NFT market (Pinto-Gutiérrez et al, 2022), however, the market itself being immature and not having a complete dataset on NFTs could alter the result and their implication of this research. Future datasets with more data series can provide a comprehensive interpretation of the results suggested in this study.

A final implication and recommendation for future research is to include the relationship and interrelatedness of Bitcoin and Ethereum and the effect of that specific relationship on the NFT market in research on investor attention towards NFTs. An example of this relationship between Bitcoin and Ethereum is the lead-lag relationship between the two cryptocurrencies, as suggested in Sifat et al (2019). By excluding either of the two biggest cryptocurrencies or adding other cryptocurrencies to the data sample can possibly provide different results with regards to investor attention towards NFTs.

6 Conclusion

This paper uses Google Searches and tweets concerning the topics Bitcoin, Ethereum and NFTs to analyze investor attention towards various NFTs. Weekly data for the year 2021 on Google Searches for specific NFTs, Bitcoin and Ethereum, tweets containing Bitcoin and Ethereum and NFT specific activity show that Bitcoin and Ethereum pricing results in more investor attention towards NFTs than Bitcoin and Ethereum returns do. Granger causality tests results confirm this. Unfortunately, the posed hypotheses in this study cannot be fully accepted due to the results not unanimous suggesting positive influence of Bitcoin and Ethereum investor attention on NFT investor attention. The results provide economic literature with more knowledge on investor attention with combining the appliance of Google Trends and tweets as a measure of investor attention for cryptocurrencies and NFTs. Bitcoin tweets and Ethereum tweets, mostly, result in more significant investor attention towards NFTs, which is a complementary result for the literature strand. Besides various measures of investor attention explaining investor attention towards NFTs is the lagged number of sales of a specific NFT also a good measure of explaining investor attention towards that specific NFT.

The research in this paper contributes to the existing literature by providing a deeper insight and analysis of the relationship between the NFT market and the cryptocurrency market by unifying the use of Google Trends and tweets into the same research. Despite some limitations, this research is the first step into combining existing methods and resources into a unifying study, on which future research will be build.

The results of this study are of importance for investors in digital assets such as NFTs and cryptocurrency. This research provides them with a better understanding of the interrelatedness of both type of digital assets, which could help make investors better informed investment decisions. Policymaker and legal enforces can use the results of this study to provide the public with protection and education where seemed fit.

For future study, researchers may want to construct and use a database with more detailed data, include tweets about specific NFTs as well and find a way to correct for the relationship between Bitcoin and Ethereum and the influence of that relationship on the NFT market.

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Appendices

Appendix A: linear regression tables for every included NFT, which are shown in table 1.

TABLE 17: LINEAR REGRESSION ART BLOCKS

ABGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
ABvolume	8.745e-06	7.205e-06	1.21	.23233491	-5.841e-06	.00002333	
ABsales	3.700e-08	8.000e-09	4.49	.00006511	2.000e-08	5.400e-08	***
BTCGT	.20043687	.27271457	0.73	.46687	-.35164492	.75251865	
BTCTweets	-.00015712	.00009473	-1.66	.10543353	-.00034889	.00003465	
BTCPrice	.00030072	.00032621	0.92	.36241597	-.00035966	.00096109	
BTCVolume	0	0	0.14	.89169769	-1.000e-09	1.000e-09	
BTCReturn	.02034212	.23125314	0.09	.93036664	-.44780539	.48848963	
ETHGT	-.46756608	.21012732	-2.23	.03208259	-.89294659	-.04218557	**
ETHTweets	-.00062526	.00026495	-2.36	.02351976	-.00116163	-.00008889	**
ETHPrice	.01462444	.00359116	4.07	.0002277	.00735452	.02189436	***
ETHVolume	0	1.000e-09	0.49	.62385921	-1.000e-09	1.000e-09	
ETHReturn	-.15564553	.17128403	-0.91	.36923673	-.50239193	.19110086	
NFTGT	-.11472022	.13074016	-0.88	.38574701	-.37938984	.1499494	
Constant	-.08104064	11.79234	-0.01	.99455268	-23.953384	23.791303	

Mean dependent var	28.217948718	SD dependent var	21.415678965
R-squared	0.853415034	Number of obs	52
F-test	17.018101226	Prob > F	0.000000000
Akaike crit. (AIC)	389.380889464	Bayesian crit. (BIC)	412.795814087

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 18: LINEAR REGRESSION AXIE INFINITY

AIGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
AIvolume	-.00001042	.00001381	-0.75	.45498399	-.00003838	.00001753	
AIsales	2.720e-07	6.600e-08	4.14	.00018406	1.390e-07	4.050e-07	***
BTCGT	.40832792	.23456901	1.74	.0898187	-.06653221	.88318806	*
BTCTweets	-.00021784	.00008555	-2.55	.01505827	-.00039102	-.00004466	**
BTCPrice	-.00090278	.00028032	-3.22	.00262201	-.00147025	-.00033531	***
BTCVolume	0	0	0.49	.63029202	0	1.000e-09	
BTCReturn	-.03690283	.2007467	-0.18	.85512598	-.44329328	.36948762	
ETHGT	-.30063292	.19750954	-1.52	.13625836	-.70047007	.09920423	
ETHTweets	.00017542	.00024709	0.71	.48208617	-.00032479	.00067562	
ETHPrice	.01550945	.004272	3.63	.00083081	.00686124	.02415767	***
ETHVolume	-1.000e-09	0	-1.48	.14649412	-2.000e-09	0	

ETHReturn	.08069539	.14618204	0.55	.58416698	-.21523468	.37662545	
NFTGT	.23485696	.11071045	2.12	.04047234	.01073536	.45897855	**
Constant	32.879073	9.6111034	3.42	.00150559	13.422411	52.335734	***

Mean dependent var	29.956730769	SD dependent var	27.272756335
R-squared	0.933090866	Number of obs	52
F-test	40.764186176	Prob > F	0.000000000
Akaike crit. (AIC)	373.742417462	Bayesian crit. (BIC)	397.157342085

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 19: LINEAR REGRESSION BORED APE YACHT CLUB

BAYCGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
BAYCvolume	-.00091393	.00104897	-0.87	.38908237	-.00303745	.0012096	
BAYCsales	1.110e-07	5.000e-08	2.24	.03107647	1.100e-08	2.110e-07	**
BTCGT	.76783257	.31049054	2.47	.01798699	.13927734	1.3963878	**
BTCTweets	-.00027555	.00010226	-2.69	.01043976	-.00048257	-.00006852	**
BTCPrice	-.00201495	.0003421	-5.89	8.060e-07	-.0027075	-.00132241	***
BTCVolume	1.000e-09	0	2.50	.01670021	0	2.000e-09	**
BTCReturn	.07023525	.23705468	0.30	.7686273	-.40965686	.55012737	
ETHGT	-.16681813	.28403241	-0.59	.56046214	-.74181168	.40817542	
ETHTweets	.00051319	.00027983	1.83	.07451134	-.00005331	.00107968	*
ETHPrice	.02539913	.00422452	6.01	5.480e-07	.01684704	.03395121	***
ETHVolume	-2.000e-09	1.000e-09	-3.27	.00229873	-3.000e-09	-1.000e-09	***
ETHReturn	.16434082	.17580651	0.93	.35580305	-.19156086	.5202425	
NFTGT	.77457283	.12374878	6.26	2.510e-07	.52405653	1.0250891	***
Constant	17.331158	12.184454	1.42	.16306768	-7.3349796	41.997295	

Mean dependent var	18.971153846	SD dependent var	27.961257845
R-squared	0.903882637	Number of obs	52
F-test	27.488462016	Prob > F	0.000000000
Akaike crit. (AIC)	395.171501134	Bayesian crit. (BIC)	418.586425757

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 20: LINEAR REGRESSION COOL CATS

CCGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CCvolume	.00230882	.00096384	2.40	.02163356	.00035762	.00426002	**
CCsales	1.958e-06	4.130e-07	4.74	.0000299	1.122e-06	2.795e-06	***
BTCGT	.80431446	.32566394	2.47	.01812557	.14504229	1.4635866	**
BTCTweets	-.00022748	.00011244	-2.02	.05013871	-.0004551	1.450e-07	*

BTCPrice	.00005852	.00037941	0.15	.87823408	-.00070955	.0008266	
BTCVolume	0	0	-0.58	.56376086	-1.000e-09	1.000e-09	
BTCReturn	.21757557	.27032443	0.80	.42590306	-.32966762	.76481876	
ETHGT	-.56508555	.24289527	-2.33	.02542584	-1.0568013	-.07336978	**
ETHTweets	.000586	.000321	1.83	.0757878	-.00006384	.00123584	*
ETHPrice	.01148441	.00452123	2.54	.01529162	.00233165	.02063716	**
ETHVolume	0	1.000e-09	-0.42	.67936567	-2.000e-09	1.000e-09	
ETHReturn	-.14889868	.20255675	-0.74	.46679376	-.55895339	.26115603	
NFTGT	-.0476518	.14585247	-0.33	.74567826	-.3429147	.24761109	
Constant	-8.2392427	14.42928	-0.57	.57135558	-37.449793	20.971308	

Mean dependent var	22.192307692	SD dependent var	25.098659023
R-squared	0.848962171	Number of obs	52
F-test	16.430199988	Prob > F	0.000000000
Akaike crit. (AIC)	407.440869081	Bayesian crit. (BIC)	430.855793704

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 21: LINEAR REGRESSION CRYPTOKITTIES

CKGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CKvolume	.00982461	.0042019	2.34	.02474446	.0013183	.01833091	**
CKsales	3.362e-06	2.461e-06	1.37	.17994729	-1.620e-06	8.344e-06	
BTCGT	.51100808	.33461979	1.53	.13501017	-.16639427	1.1884104	
BTCTweets	-.00023618	.00011229	-2.10	.04212112	-.00046351	-8.854e-06	**
BTCPrice	.00057766	.00039803	1.45	.15489986	-.00022811	.00138343	
BTCVolume	-1.000e-09	0	-1.09	.28279665	-1.000e-09	0	
BTCReturn	.04403797	.29146852	0.15	.88070398	-.54600921	.63408515	
ETHGT	-.07291199	.25445806	-0.29	.77602233	-.58803542	.44221142	
ETHTweets	.00010353	.00034968	0.30	.76878443	-.00060436	.00081143	
ETHPrice	.00478834	.0048109	1.00	.32588166	-.00495082	.0145275	
ETHVolume	0	1.000e-09	0.39	.69673321	-1.000e-09	2.000e-09	
ETHReturn	-.10161335	.20972822	-0.48	.63081202	-.52618594	.32295924	
NFTGT	.25403744	.16475204	1.54	.13137606	-.07948562	.58756051	
Constant	-5.2747131	18.21513	-0.29	.77371277	-42.149316	31.599889	

Mean dependent var	37.820512821	SD dependent var	18.355774921
R-squared	0.702232253	Number of obs	52
F-test	6.893556860	Prob > F	0.000001435
Akaike crit. (AIC)	410.199110976	Bayesian crit. (BIC)	433.614035599

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level

** Significant at the 5% level
*** Significant at the 1% level

TABLE 22: LINEAR REGRESSION CRYPTO PUNKS

CPGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CPvolume	2.045e-06	6.964e-06	0.29	.77056397	-.00001205	.00001614	
CPsales	4.100e-08	8.000e-09	5.09	9.977e-06	2.500e-08	5.700e-08	***
BTCGT	.34988868	.26358177	1.33	.19228375	-.18370471	.88348207	
BTCTweets	-.00017448	.00009156	-1.91	.06428576	-.00035984	.00001088	*
BTCPrice	-.00027581	.00031546	-0.87	.38743467	-.00091442	.0003628	
BTCVolume	0	0	0.52	.60895471	-1.000e-09	1.000e-09	
BTCReturn	.01926416	.2235278	0.09	.93177394	-.43324422	.47177254	
ETHGT	-.3045225	.20312652	-1.50	.14209053	-.71573063	.10668564	
ETHTweets	.00025541	.00025609	1.00	.32490684	-.00026302	.00077385	
ETHPrice	.01128597	.0034711	3.25	.0024098	.00425909	.01831285	***
ETHVolume	0	1.000e-09	-0.65	.52070788	-1.000e-09	1.000e-09	
ETHReturn	.09340706	.16557593	0.56	.57597751	-.2417839	.42859801	
NFTGT	.52407527	.12648349	4.14	.00018409	.26802283	.78012771	***
Constant	-3.4148792	11.393517	-0.30	.76602317	-26.479848	19.65009	

Mean dependent var	30.934615385	SD dependent var	26.072710432
R-squared	0.907609143	Number of obs	52
F-test	28.715085362	Prob > F	0.000000000
Akaike crit. (AIC)	385.842525389	Bayesian crit. (BIC)	409.257450012

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 23: LINEAR REGRESSION DECENTRALAND

DGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Dvolume	.01038204	.01186451	0.88	.38704392	-.0136364	.03440048	
Dsales	4.085e-06	8.950e-07	4.56	.00005157	2.273e-06	5.898e-06	***
BTCGT	.670106	.32755671	2.05	.04774591	.00700211	1.3332099	**
BTCTweets	-.00022347	.00010707	-2.09	.04363461	-.00044023	-6.719e-06	**
BTCPrice	-.00080439	.00033369	-2.41	.02087221	-.00147991	-.00012887	**
BTCVolume	0	0	1.12	.27120657	0	1.000e-09	
BTCReturn	-.01133966	.21105546	-0.05	.95743308	-.43859911	.41591979	
ETHGT	-.28276391	.22394026	-1.26	.21439954	-.73610727	.17057945	

ETHTweets	.00053427	.00025835	2.07	.04549907	.00001126	.00105728	**
ETHPrice	.01138152	.00487962	2.33	.02507354	.00150324	.02125979	**
ETHVolume	-1.000e-09	0	-1.79	.08220991	-2.000e-09	0	*
ETHReturn	.13297119	.15670314	0.85	.40144297	-.18425774	.45020011	
NFTGT	.39744946	.14092371	2.82	.00758326	.11216433	.68273459	***
Constant	2.0367156	11.026388	0.18	.85443656	-20.285039	24.358471	

Mean dependent var	20.567307692	SD dependent var	24.973864544
R-squared	0.907941949	Number of obs	52
F-test	28.829462904	Prob > F	0.000000000
Akaike crit. (AIC)	381.176704857	Bayesian crit. (BIC)	404.591629480

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 24: LINEAR REGRESSION HASHMASKS

HMGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
HMvolume	.003011	.00225003	1.34	.18878196	-.00154394	.00756594	
HMsales	1.515e-06	1.380e-06	1.10	.27899444	-1.278e-06	4.309e-06	
BTCGT	-.05309153	.33140963	-0.16	.87357279	-.72399524	.61781218	
BTCTweets	-.00010144	.00010972	-0.92	.3610507	-.00032355	.00012068	
BTCPrice	.00098352	.00040452	2.43	.01986838	.00016462	.00180242	**
BTCVolume	0	0	-1.18	.24481617	-1.000e-09	0	
BTCReturn	.56433089	.29603586	1.91	.06419606	-.03496236	1.1636242	*
ETHGT	-.25225383	.26445051	-0.95	.3461736	-.78760589	.28309823	
ETHTweets	-.00073458	.00032969	-2.23	.03187268	-.00140201	-.00006714	**
ETHPrice	.00005696	.00393106	0.01	.9885152	-.00790105	.00801497	
ETHVolume	1.000e-09	1.000e-09	1.50	.14160923	0	2.000e-09	
ETHReturn	-.57308731	.20978524	-2.73	.00950253	-.99777532	-.14839929	***
NFTGT	.17284208	.13876063	1.25	.22053223	-.10806412	.45374828	
Constant	2.0317677	13.771958	0.15	.88349425	-25.848104	29.911639	

Mean dependent var	17.358974359	SD dependent var	17.924660312
R-squared	0.705226567	Number of obs	52
F-test	6.993274413	Prob > F	0.000001210
Akaike crit. (AIC)	407.201811698	Bayesian crit. (BIC)	430.616736321

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 25: LINEAR REGRESSION MEEBITS

MBGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MBvolume	-.00638053	.00308816	-2.07	.04568242	-.01263219	-.00012888	**
MBsales	1.274e-06	2.860e-07	4.46	.00007162	6.950e-07	1.853e-06	***
BTCGT	-.41565251	.29014502	-1.43	.16015704	-1.0030204	.17171538	
BTCTweets	.00002674	.00008841	0.30	.76392334	-.00015223	.00020571	
BTCPrice	-.00046206	.00030541	-1.51	.13857412	-.00108033	.00015621	

BTCVolume	0	0	0.15	.88373977	-1.000e-09	1.000e-09	
BTCReturn	.05908269	.21749672	0.27	.7873626	-.38121639	.49938178	
ETHGT	.45986561	.27482602	1.67	.10248284	-.09649059	1.0162218	
ETHTweets	.0000999	.00025344	0.39	.69566321	-.00041316	.00061296	
ETHPrice	.00721523	.00332786	2.17	.03647793	.00047833	.01395212	**
ETHVolume	0	1.000e-09	0.07	.94438244	-1.000e-09	1.000e-09	
ETHReturn	.05722312	.1600402	0.36	.72265494	-.26676133	.38120757	
NFTGT	.13063779	.11247171	1.16	.2526759	-.09704929	.35832486	
Constant	2.0101013	10.65135	0.19	.85131815	-19.552429	23.572631	

Mean dependent var	17.211538462	SD dependent var	21.319749438
R-squared	0.863985102	Number of obs	52
F-test	18.567781616	Prob > F	0.000000000
Akaike crit. (AIC)	385.022262429	Bayesian crit. (BIC)	408.437187052

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 26: LINEAR REGRESSION SUPERRARE

SRGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SRvolume	.02729472	.01541432	1.77	.0846261	-.00390994	.05849938	*
SRsales	4.280e-07	6.130e-07	0.70	.4889077	-8.130e-07	1.669e-06	
BTCGT	-.09515928	.29482457	-0.32	.74864194	-.69200042	.50168185	
BTCTweets	-.00001925	.00009859	-0.20	.8462417	-.00021884	.00018034	
BTCPrice	.00090952	.00038658	2.35	.02391403	.00012694	.0016921	**
BTCVolume	0	0	-0.29	.77694638	-1.000e-09	1.000e-09	
BTCReturn	-.03306322	.23674752	-0.14	.88966937	-.51233352	.44620708	
ETHGT	.0176019	.21223726	0.08	.93433855	-.41204998	.44725378	
ETHTweets	-.00072888	.00028915	-2.52	.01602719	-.00131423	-.00014353	**
ETHPrice	.00843295	.00413597	2.04	.04845732	.00006012	.01680578	**
ETHVolume	0	1.000e-09	0.31	.75576121	-1.000e-09	1.000e-09	
ETHReturn	-.05161771	.17835153	-0.29	.77383664	-.41267151	.3094361	
NFTGT	.38600424	.12624767	3.06	.0040735	.13042919	.64157929	***
Constant	-22.8845	12.880663	-1.78	.08363161	-48.96004	3.1910402	*

Mean dependent var	38.038461538	SD dependent var	21.950891302
R-squared	0.849472966	Number of obs	52
F-test	16.495872937	Prob > F	0.000000000
Akaike crit. (AIC)	393.328018073	Bayesian crit. (BIC)	416.742942696

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

TABLE 27: LINEAR REGRESSION THE SANDBOX

TSGT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
TSvolume	.00028611	.0019645	0.15	.8849743	-.0036908	.00426303	
TSsales	1.081e-06	1.510e-07	7.14	1.600e-08	7.740e-07	1.387e-06	***
BTCGT	.15346519	.20229164	0.76	.45275185	-.25605281	.5629832	
BTCTweets	-.00008431	.00006478	-1.30	.20088976	-.00021544	.00004682	
BTCPrice	-.00076458	.0002204	-3.47	.00131503	-.00121075	-.00031841	***
BTCVolume	0	0	1.91	.06406469	0	1.000e-09	*
BTCReturn	-.03158853	.15024301	-0.21	.83459619	-.33573959	.27256253	
ETHGT	-.017802	.14006923	-0.13	.89953596	-.30135732	.26575333	
ETHTweets	.00021303	.00017982	1.18	.24349618	-.000151	.00057706	
ETHPrice	.00829984	.00237775	3.49	.00123738	.00348635	.01311334	***
ETHVolume	-1.000e-09	0	-1.80	.07965503	-1.000e-09	0	*
ETHReturn	.11855907	.11187455	1.06	.29594806	-.10791911	.34503726	
NFTGT	.34342994	.08321817	4.13	.00019346	.17496356	.51189633	***
Constant	8.3527577	7.7096443	1.08	.28545021	-7.2546011	23.960117	

Mean dependent var	15.836538462	SD dependent var	20.803756532
R-squared	0.931818538	Number of obs	52
F-test	39.948941713	Prob > F	0.000000000
Akaike crit. (AIC)	346.563465207	Bayesian crit. (BIC)	369.978389830

Notes: explanation of variable abbreviations can be found in Table 1.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level