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The NFT Hype: What Draws Attention to Non-Fungible Tokens?

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Abstract: Non-fungible tokens (NFTs) can be used to represent ownership of digital art or any other unique digital item where ownership is recorded in smart contracts on a blockchain. NFTs have recently received enormous attention from both cryptocurrency investors and the media. We examine why NFTs have gotten so much attention. Using vector autoregressive models, we show that Bitcoin returns significantly predict next week's NFT growth in popularity, measured by Google search queries. Moreover, wavelet coherence analysis suggests that Bitcoin and Ether returns are significant drivers of next week's attention to NFTs. These results indicate that the remarkable increases in prices of major cryptocurrencies can explain the hype around NFTs.

Keywords: NFT; non-fungible tokens; investor attention; cryptocurrency

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1. Introduction

The non-fungible token (NFT) market has shown a significant increase in popularity in 2021. In just one year, the NFT market went from total daily sales of about USD 183,121 in 2020 to an average of USD 38 million in 2021 (data from https://nonfungible.com/market/history, accessed on 22 December 2021). Some NFT examples include the sale made by the artist Beeple, who sold a piece of digital art for USD 69 million, or the sale of the first Tweet made by Twitter CEO Jack Dorsey for USD 2.9 million. Two others popular NFTs are the CryptoPunks and Decentraland. The entire CryptoPunks collection, created in 2017 by Larva Labs, surpassed USD 1 billion in sales in 2021. Meanwhile, MANA, the native token of Decentraland, a metaverse platform where users can buy and sell virtual properties, spiked 400% and hit an all-time high market capitalization of more than USD 6 billion after Facebook announced it was changing its name to Meta.

NFTs are tokens stored on a blockchain that can be used to represent ownership of digital assets like artworks, recordings, virtual real estate and pets. NFTs are sold on specialized marketplaces, such as OpenSea, Axie Marketplace, and Rarible. On these platforms, investors can also exchange the property right to the asset underlying the NFT. And because NFTs use smart contract technology, they can be set up so that the original artist can earn a percentage of all subsequent sales. The main difference between NFTs and cryptocurrencies, such as bitcoin, is that cryptocurrencies are fungible or interchangeable; they are all worth the same amount. However, NFTs are non-fungible, meaning that an NFT cannot be exchanged for another since each one is unique. Precisely, this uniqueness enables the use of NFTs to authenticate ownership of digital assets. Furthermore, each NFT is stored on a public and transparent blockchain (often Ethereum's). Thus, NFTs are decentralized applications with high levels of verifiability, tamper resistance, usability, atomicity, and traceability. For additional details about the technicalities of NFTs, please see Wang et al. (2021) [1].

In 2021, public attention towards NFTs exploded, and the NFT market has become quite popular among investors and collectors. For instance, the largest NFT marketplace, OpenSea, has more than one million users buying and selling digital art and collectibles via their platform (data from https://dune.xyz/rchen8/opensea, accessed on 22 December 2021). Thus, why have NFTs received such attention? In this paper, we examine the factors that explain investor attention to non-fungible tokens. This rise in awareness can be attributed to several factors, including the excitement around blockchain technology. We argue that rising cryptocurrency prices may have played a role in the surge of NFTs. We posit that NFT markets have benefited from the hype around major cryptocurrencies, particularly Bitcoin, as the digital currency with the largest market capitalization. Bitcoin has attracted significant attention recently, and it has undeniably assumed an important role in global financial markets. We also examine the effects of Ether, as NFTs are primarily registered on Ethereum smart contracts and often valued in Ether.

The literature on NFT markets is scarce. Prior papers have examined the factors that determine the prices of NFTs, finding a positive relationship between the prices of cryptocurrencies and the prices of NFTs [2,3]. The literature has also suggested that NFTs are difficult assets to value. For instance, Dowling (2021a) [4] shows that Decentraland is inefficiently priced and characterized by a steady rise in value. Chohan (2021) [5] claims that demand forces determining NFT prices are fundamentally dependent upon inherent scarcity and a buyer's readiness to purchase a one-of-a-kind item. Oppositely, other studies contradict this, stating that scarcity is not necessarily relevant in all NFTs. For example, Serada et al. (2020) [6] analyze CryptoKitties, an online game where players collect, breed, buy, and sell various kinds of virtual cats. They found that the least common game tokens experience rapid devaluation quickly if not enough players are in the game. Nadini et al. (2021) [7] created a superb overview of some central NFT features that span the six main NFT categories, including art, games, and collectibles. The findings show that past sale history is the best predictor of NFT prices, as one would expect. In addition, NFT-specific properties like a digital object's appearance also increase price predictability.

This paper provides novel evidence for the factors that draw investors' attention to the NFT market. To our knowledge, this is the first study to examine the levels of attention to non-fungible tokens. The NFT market started getting mainstream attention in early 2021, coinciding with a price run-up in all major cryptocurrencies. Accordingly, using a database featuring weekly data on Google search activity for the topic "non-fungible token" and two of the most popular NFTs, "Cryptopunk" and "Decentraland," between 2017 and 2021, we explore if NFT attention is related to cryptocurrency pricing. We test this hypothesis using various time-series econometric models, ranging from vector autoregressive (VAR) regressions to wavelet coherence analysis. We select the empirical models based on the experience of prior literature. Other studies examining investor attention to cryptocurrencies have primarily used VAR models (see, for example, [8–12]). Meanwhile, wavelet coherence models have recently been used in the financial literature to examine the dynamic relations among cryptocurrencies (see, for instance, [2,13–16]).

Using vector autoregressive (VAR) models, we find that the previous week's bitcoin returns significantly drive attention to NFTs. Moreover, when wavelet coherence analysis is used, we find that investors are more attracted to NFTs after increases in both Bitcoin and Ether returns. These results are consistent with the notion that as Bitcoin and other cryptocurrencies have boomed in price and popularity over the last few years, NFTs have also soared. In other words, the results suggest that the hype around cryptocurrencies could explain the NFT growth in popularity.

Our study has implications for financial practices, particularly for digital artists, collectors, and cryptocurrency investors. We believe our results will help NFT market participants better understand this disruptive innovation and the impacts that the accelerated growth of NFTs has on decentralized markets.

We organize the rest of the paper as follows. First, Section 2 provides the materials and methods used. Then, Section 3 presents our main results. Finally, Section 4 shows the conclusion and examines the implications of our findings.

2. Materials and Methods

2.1. Methodology

We first study the dynamics between cryptocurrency returns and NTF attention by estimating vector autoregressive (VAR) models with exogenous variables. VAR models are used to capture the complex dynamics of multiple time series. Prior studies analyzing investor attention to cryptocurrencies have mainly used VAR models (see, for example, [8–12]). In this paper, we estimate VAR models with exogenous variables. These exogenous variables include economic factors that could also determine investor attention to NFT markets. For example, we have variables such as CBOE Volatility Index (VIX), gold, and S&P 500 returns. We also control for the level of attention toward Bitcoin and Ethereum. The VAR model we evaluate in this study consists of the following two equations:

$$NFT\ attention_t = \alpha + \sum_{j=1}^{p} \beta' NFT\ attention_{t-j} + \sum_{j=1}^{p} \beta' Crypto\ return_{t-j} + \delta' Z_{t-1} + \mu_t, \quad (1)$$

$$Crypto\ return_t = \alpha + \sum_{j=1}^{p} \beta' NFT\ attention_{t-j} + \sum_{j=1}^{p} \gamma' Crypto\ return_{t-j} + \delta' Z_{t-1} + \mu_t. \quad (2)$$

Our primary dependent variable is NFT attention, which represents the weekly time series measuring the frequency of Google searches with the topic "non-fungible token" together with the term "NFT" at the worldwide level. We also use the weekly search volume for the topic "Cryptopunk" and "Decentraland", two of the most popular NFTs. Google search data are being increasingly utilized in financial and cryptocurrency literature to measure investor attention. For instance, Urquhart (2018) [8] and Lin (2021) [10] use Google data to gauge investors' interest in Bitcoin and several different cryptocurrencies. One of the main benefits of Google searches is that, under a single topic, its algorithms can cover various languages and group different searches with the same meaning [17].

In Equations (1) and (2), α is a vector of constants, β is a vector of coefficients on the first endogenous variable (the weekly NTFs Google attention), and γ is a vector of coefficients on the second endogenous variable (either weekly Bitcoin price returns or weekly Ethereum price returns). The vector Z_t represents the exogenous control variables, and δ is the vector of coefficients on these control variables. Finally, μ_t is a vector of independent white noise innovations. In Equations (1) and (2), the value p denotes the number of lags. We determine the optimal number lags using several information criteria, including the Akaike information criterion (AIC), Hannan–Quinn information criterion (HQIC), Schwarz-Bayesian information criteria (SBIC), and final prediction error (FPE).

Next, we use the wavelet coherence technique to investigate co-movement between cryptocurrency returns and NFT levels of attention. Wavelet coherence analysis enables investigation of any detectable co-movement between two-time series (bivariate wavelets) in the domains of time and frequency, whereas standard time series modeling does not. Nonstationary signals can also be analyzed with wavelet coherence. Recent studies by Dowling (2021b), Goodell and Goutte (2021), and Qiao et al. (2020) [2,13,14] employed wavelet coherence for cryptocurrency analyses.

We use cross-wavelets in keeping with Torrence and Compo (1998) [18]. The cross-wavelet transform explores the simultaneity of two signals in the frequency and the time domains, and the wavelet coherence analysis clarifies the correlation of this cross transform. The cross wavelet transform of two times-series is defined by the complex conjugate of their cross wavelet transform, $W_x(a,b)$ and $W_y(a,b)$, as:

$$W_{xy}(a,b) = W_x(a,b) * W_y(a,b), \quad (3)$$

where a is associated with the location and b to the scale. $W_x(a,b)$ and $W_y(a,b)$ are the wavelet transformations of the times series x (either Bitcoin or Ether returns) and y (NFT attention), respectively. The value of $W_{xy}(a,b)$ indicates the strength of the correlation between the two examined series.

Then, $R^2(a,b)$ returns the magnitude-squared wavelet coherence, which measures the correlation between signals x and y in the time-frequency plane. Torrence and Webster (1999) [19] define the wavelet squared coherence as follows:

$$R^2(a,b) = \frac{\left|S\left(b^{-1}W_{xy}(a,b)\right)\right|^2}{S\left(b^{-1}W_x(a,b)\right)^2 S\left(b^{-1}W_y(a,b)\right)^2}, \tag{4}$$

where S refers to a smoothing process over time and scale. $R^2(a,b)$ is a value between 0 and 1 that captures the co-movement between the time series x and y. The higher the value of $R^2(a,b)$, the higher the co-movement between the two variables. Wavelet squared coherence is restricted to positive values as opposed to the classical correlation of two time series. This means determining whether the co-movement between the variables is positive or negative is not possible. Thus, we use the phase difference of Torrence and Compo (1998) [18] to separate out the positive and negative co-movements. The phase difference is required to present lead-lag relationships as a function of frequency. It gives a graphical presentation of the wavelet squared coherence analysis considering the causal relationships between the two-time series. The phase difference can be provided by

$$\Phi_{xy} = \arctan\left(\frac{Im\left\{S\left(b^{-1}W_{xy}(a,b)\right)\right\}}{Re\left\{S\left(b^{-1}W_{xy}(a,b)\right)\right\}}\right), \tag{5}$$

where Im and Re are the imaginary and real operators, respectively. To indicate the direction of influence, we incorporate phase positions in the wavelet analysis.

2.2. Data

We collected Google search activity for the keywords "NFT + non-fungible token" (the plus sign means that results can include searches containing the words "NFT" or "non-fungible token"), "Cryptopunk", "Decentraland", "Bitcoin", and "Ethereum" from Google Trends (https://trends.google.com/, accessed on 9 August 2021) between 1 December 2017 and 30 July 2021. The Google search index ranges between 0 and 100. Average weekly NFT sales in USD are available from nonfungible.com (https://nonfungible.com, accessed on 9 August 2021). This data source has been previously used in NFT research (see, for example, [2,4]). We also collected weekly Bitcoin and Ethereum prices between the exact same dates from coinmarketcap.com (https://coinmarketcap.com, accessed on 9 August 2021). This data source has been widely used in cryptocurrency research (see, e.g., [20–22]). VIX index, S&P 500 index, and gold prices are from Yahoo Finance (https://finance.yahoo.com, accessed on 9 August 2021).

Table 1 provides descriptive statistics for the final sample. The results show that the weekly average Google search volume for the topic "non-fungible token + NFT" is 7.93. The weekly average search volume for "Cryptopunk" is 3.93, and the average search volume for "Decentraland" is 7.63. The average weekly return and standard deviation for Bitcoin were 0.76% and 11.91%, respectively. The average weekly return and standard deviation for Ether were 1.02% and 15.00%, respectively. We employ augmented Dickey-Fuller tests (ADF) to examine the stationarity of time-series variables. This analysis is essential as non-stationary data could lead to spurious regression results. The results reported in Table 1 show that, for some series, we cannot reject the null hypothesis of non-stationarity. In particular, we find that unit-roots are present in most Google search indexes. To normalize and detrend these series, we use the first differences of Google search queries in all empirical models in the subsequent sections. In the case of the Bitcoin and Ether returns series, the null hypothesis of a unit root is discarded. Likewise, the series we use as control variables are all stationary according to the ADF test.

Table 1. Descriptive statistics of key variables.

	Observations	Mean	Media	SD	Min	Max	Skewness	Kurtosis	ADF Test
NFT attention	193	7.93	1.00	19.81	0.00	100.00	3.18	12.66	−1.52
CryptoPunk attention	193	3.93	0.00	11.38	0.00	100.00	4.78	32.69	−0.43
Decentraland attention	193	7.63	3.00	13.66	0.00	100.00	3.63	19.53	−3.95 ***
Bitcoin return	193	0.76	0.75	11.91	−53.94	31.51	−0.53	5.17	−13.98 ***
Ether return	193	1.02	1.18	15.00	−65.97	49.89	−0.46	5.54	−12.62 ***
VIX return	193	0.16	−1.68	17.00	−46.09	85.37	0.96	6.41	−15.43 ***
Gold return	193	0.14	0.20	2.08	−9.90	10.10	−0.11	8.31	−17.17 ***
S&P 500 return	193	0.27	0.59	2.86	−16.23	11.42	−1.30	11.39	−15.19 ***
Bitcoin attention	193	16.27	10.00	14.04	6.00	83.00	2.16	7.85	−3.58 ***
Ethereum attention	193	14.03	6.00	17.92	2.00	100.00	2.38	9.37	−2.24
CryptoPunk return	191	4.87	1.32	63.88	−177.31	208.32	0.06	3.44	−21.98 ***
Decentraland return	179	2.76	−0.97	67.62	−227.13	207.45	0.06	4.65	−18.97 ***

Note: This table reports summary statistics for the dependent, independent, and control variables used in this study. The last column shows augmented Dickey-Fuller (ADF) tests to examine the stationarity of time-series data. All variables are defined in Appendix A. *** indicate that the Dickey-Fuller test statistic is significantly larger than the critical value at the 1%.

3. Results

Table 2 shows the estimated results for VAR models. Columns 1 and 2 report the results when we use Google searches for the topic “non-fungible token” together with the term “NFT”. Columns 3 and 4 present the results for the key term “Cryptopunk”. Columns 5 and 6 present the results for the term “Decentraland”. In column 1, we find that past Bitcoin returns significantly influence search queries for NFT at lag 1 and 4, respectively, indicating that an increase in returns will lead to a rise in search queries in the following weeks. We also employ Granger causality tests to investigate the causal relationships between Bitcoin returns and attention to NFTs. We present Granger causality tests for each VAR model at the bottom of Table 2. The Granger causality test indicates that past Bitcoin returns provide significant information about future NFT search queries. In column 2, the estimation results reveal that past NFT search queries do not significantly influence Bitcoin returns as the coefficients are statistically insignificant. The Granger causality test also supports this finding, failing to reject the null hypothesis that NFT search queries does not cause Bitcoin returns. We find similar results when we analyze the dynamic relationship between Bitcoin returns and search queries for specific NFTs. Furthermore, these results remain even after controlling for other economic factors such as CBOE Volatility Index (VIX) returns, gold returns, and S&P 500 returns. Thus, these results support the hypotheses suggesting that an increase in Bitcoin returns will lead to greater attention to other crypto assets such as NFTs.

Table 3 shows the estimated results for VAR models when we use Ether returns. Although NFTs are normally registered on an Ethereum blockchain, we do not find any significant relationship between Ether returns and attention to NFTs when we use VAR models. Furthermore, Granger causality tests also show no meaningful causal relationships between Ether returns and NFT attention.

Table 2. Dynamic relationships among NFT attention and Bitcoin returns.

	ΔNFT + Non-Fungible Tokens	**Bitcoin Return**	**ΔCryptoPunk**	**Bitcoin Return**	**ΔDecentraland**	**Bitcoin Return**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ΔNFT attention t-1	0.1341 *	0.1829	−0.2068 *	0.0677	−0.2799 ***	−0.0327
	(1.8302)	(0.8562)	(1.8806)	(0.3778)	(3.8149)	(0.2673)
ΔNFT attention t-2	0.3235 ***	−0.1923	−0.1756	0.0870	−0.1820 **	0.0425
	(4.5670)	(0.9313)	(1.5079)	(0.4587)	(2.3972)	(0.3361)
ΔNFT attention t-3	−0.1944 ***	−0.1244	0.2142 *	0.2004	−0.1005	0.2011
	(2.6200)	(0.5749)	(1.8522)	(1.0642)	(1.3672)	(1.6426)
ΔNFT attention t-4	−0.1223 *	0.3184	−0.0509	0.0440	−0.0467	−0.1380
	(1.7283)	(1.5428)	(0.4595)	(0.2442)	(0.6327)	(1.1215)
Bitcoin return t-1	0.0556 **	0.0069	0.0603	0.0128	0.1087 **	0.0432
	(2.1739)	(0.0930)	(1.3078)	(0.1709)	(2.3429)	(0.5586)
Bitcoin return t-2	−0.0286	−0.0070	0.1322 ***	−0.0295	0.1045 **	−0.0065
	(1.0645)	(0.0899)	(2.7199)	(0.3723)	(2.1046)	(0.0781)
Bitcoin return t-3	0.0070	0.0938	0.0131	0.0823	−0.0371	0.0807
	(0.2813)	(1.2892)	(0.2912)	(1.1219)	(0.7938)	(1.0368)
Bitcoin return t-4	0.0637 **	−0.0107	0.0026	−0.0097	0.0518	−0.0181
	(2.5245)	(0.1456)	(0.0577)	(0.1313)	(1.0692)	(0.2238)
Exogenous Controls:						
VIX return t-1	0.0011	−0.0027	0.0008	−0.0069	−0.0668	−0.0001
	(0.0417)	(0.0357)	(0.0172)	(0.0921)	(1.4132)	(0.0015)
Gold return t-1	−0.3016 **	−0.8107 *	−0.3271	−0.8532 *	0.0857	−0.6342
	(2.0328)	(1.8741)	(1.2189)	(1.9527)	(0.3402)	(1.5114)
S&P 500 return t-1	0.0429	0.1559	−0.1134	0.1776	−0.3700	0.1548
	(0.2677)	(0.3339)	(0.3939)	(0.3789)	(1.3214)	(0.3319)
ΔBitcoin attention t-1	−0.0325	−0.0646	0.0112	−0.0874	−0.0083	−0.2024
	(0.5749)	(0.3926)	(0.1166)	(0.5598)	(0.0869)	(1.2687)
NFT return t-1			0.0038	0.0082	−0.0073	0.0043
			(0.4614)	(0.6073)	(0.9768)	(0.3418)
Constant	0.1017	0.6930	0.5000	0.6854	0.0071	1.0141
	(0.3600)	(0.8416)	(0.9770)	(0.8224)	(0.0147)	(1.2506)
Observations	189	189	187	187	178	178
R2	0.212	0.0476	0.1244	0.0446	0.1495	0.0693
H0: Bitcoin return does not Granger-cause NFT attention	14.585 ***		9.1201 *		11.795 **	
Prob > chi2	0.006		0.058		0.019	
H0: NFT attention does not Granger-cause Bitcoin return	2.9402		1.2094		5.777	
Prob > chi2	0.568		0.877		0.216	

Note: This table presents the parameter estimates from vector autoregressive (VAR) models for Bitcoin returns and NFT attention. The key independent variable is the first differences (Δ) of NTF attention from Google search activity for the keywords "NFT + non-fungible token", "Cryptopunk", "Decentraland". t values are in parentheses. All variables are defined in Appendix A. ***, **, and * indicate that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Table 3. Dynamic relationships among NFT attention and Ether returns.

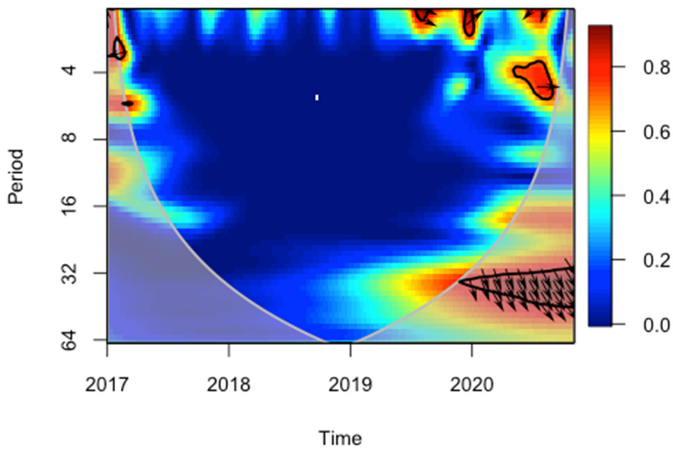
	ΔNFT + Non-Fungible Tokens	**Ether Return**	**ΔCryptoPunk**	**Ether Return**	**ΔDecentraland**	**Ether Return**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ΔNFT attention t-1	0.1768 **	0.2538	−0.1129	−0.1201	−0.2507 ***	−0.0253
	(2.4669)	(0.9336)	(1.0393)	(0.4997)	(3.4229)	(0.1546)
ΔNFT attention t-2	0.3163 ***	−0.5096 *	−0.1087	0.2110	−0.1649 **	−0.0143
	(4.4703)	(1.8990)	(0.9621)	(0.8440)	(2.1956)	(0.0849)
ΔNFT attention t-3	−0.1626 **	−0.0936	0.3096 ***	0.0424	−0.0625	0.3265 **
	(2.3019)	(0.3495)	(2.7317)	(0.1692)	(0.8868)	(2.0698)
ΔNFT attention t-4	−0.1381 *	0.5839 **	0.0021	0.0637	−0.0343	−0.1064
	(1.9423)	(2.1656)	(0.0190)	(0.2650)	(0.4703)	(0.6514)
Ether return t-1	0.0341	0.1175	0.0086	0.1257	0.0536	0.1082
	(1.6196)	(1.4728)	(0.2341)	(1.5474)	(1.4360)	(1.2954)
Ether return t-2	−0.0317	0.0422	0.0484	0.0024	0.0485	−0.0165
	(1.5223)	(0.5339)	(1.2928)	(0.0285)	(1.2779)	(0.1936)
Ether return t-3	−0.0050	0.0135	−0.0072	0.0173	−0.0281	0.0032
	(0.2593)	(0.1834)	(0.2081)	(0.2271)	(0.8033)	(0.0409)
Ether return t-4	0.0287	−0.0166	−0.0192	−0.0029	−0.0267	0.0000
	(1.4527)	(0.2217)	(0.5486)	(0.0373)	(0.7481)	(0.0004)
Exogenous Controls:						
VIX return t-1	0.0037	0.0147	0.0092	0.0185	−0.0433	0.0219
	(0.1427)	(0.1497)	(0.2017)	(0.1842)	(0.9078)	(0.2049)
Gold return t-1	−0.2884 **	−0.6605	−0.3151	−0.7557	0.1009	−0.3971
	(1.9685)	(1.1886)	(1.2265)	(1.3294)	(0.3981)	(0.7001)
S&P 500 return t-1	0.0787	0.1536	0.0033	0.2078	−0.1986	0.1819
	(0.4857)	(0.2498)	(0.0116)	(0.3313)	(0.7087)	(0.2900)
ΔEthereum attention t-1	−0.1333 ***	−0.1152	0.3334 ***	−0.1137	0.0239	−0.1033
	(2.6990)	(0.6149)	(3.8449)	(0.5923)	(0.2823)	(0.5457)
NFT return t-1			−0.1129	−0.1201	−0.0057	0.0130
			(1.0393)	(0.4997)	(0.7523)	(0.7693)
Constant	0.1340	0.7301	0.5101	0.8031	0.0644	1.3120
	(0.4745)	(0.6818)	(1.0325)	(0.7345)	(0.1303)	(1.1872)
Observations	189	189	187	187	178	178
R2	0.2095	0.0499	0.18	0.0273	0.1212	0.0477
H0: Ether return does not Granger-cause NFT attention	7.5409		2.1153		4.8831	
Prob > chi2	0.11		0.715		0.3	
H0: NFT attention does not Granger-cause Ether return	6.5483		1.4026		6.1733	
Prob > chi2	0.162		0.844		0.187	

Note: This table presents the parameter estimates from vector autoregressive (VAR) models for Ether returns and NFT attention. The key independent variable is the first differences (Δ) of NTF attention from Google search activity for the keywords "NFT + non-fungible token", "Cryptopunk", "Decentraland". t values are in parentheses. All variables are defined in Appendix A. ***, **, and * indicate that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

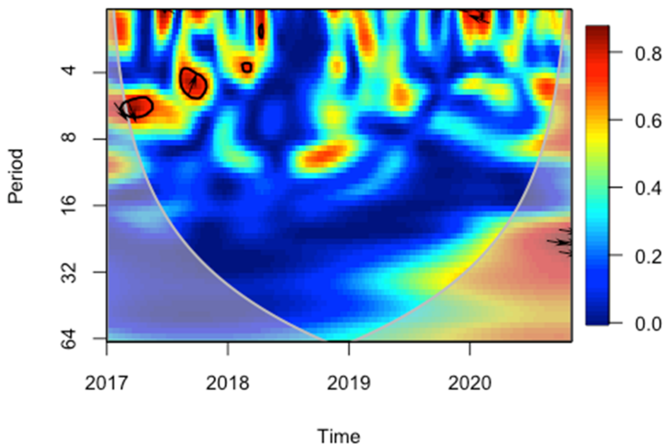
We now turn to our set of results based on a wavelet coherence approach. Figure 1 illustrates the co-movement and phase difference between Bitcoin returns and attention to NFT. Figure 2 shows the results for the co-movement and phase difference between Ether returns and attention to NFT. The horizontal axis depicts time, and the vertical axis shows frequency in all the figures (the lower the frequency, the higher the period). The warmer end of the color spectrum (red) stands for regions with significant interrelation, with the cooler end (blue) signifying lower dependence between the series. Cold regions beyond the significant areas represent time and frequencies without any dependence in the series. The arrows in the wavelet coherence plots represent the lead/lag phase relations between the examined series. Arrows pointing to the right (left) indicate time series that are in-phase (out of phase) or positively (negatively) correlated. An upward-pointing arrow suggests that the first time series leads the second. If it points downward, it indicates the reverse in that the second one leads the first.

Figure 1 confirms the co-movement for Bitcoin returns and NFT attention. In panel A of Figure 1, we see much co-movement between Bitcoin returns and search queries for the topic "non-fungible token" together with the term "NFT". This co-movement is evident at the 1–4-week cycle at the end of 2020 and early 2021. Panel B of Figure 1 shows the co-movement and phase difference between Bitcoin returns and search queries for the term "Cryptopunk". There is also consistent evidence of short-term (1–8 week) positive correlation cycles for Bitcoin returns and attention to the CryptoPunk collection of NFTs. When we consider search queries for the term "Decentraland", panel C of Figure 1 shows clear evidence of co-movement with Bitcoin returns across our sample period at the 1–4-week cycle and at the larger 8–16-week cycle as well. Figure 1 also suggests a positive correlation between Bitcoin returns and NFT attention, which is the most common arrow direction. Regarding the lead/lag relation between variables, the evidence depicted in the charts is inconclusive.

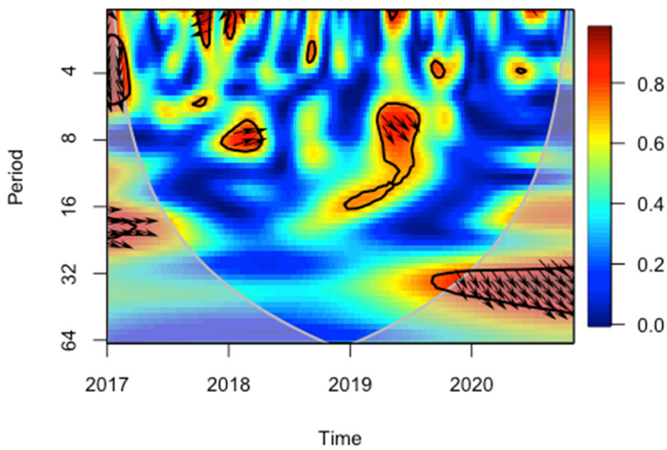
In contrast with the results obtained using VAR models, the wavelet coherence analysis depicted in Figure 2 illustrates the existence of co-movement between Ether returns and NFT attention. This co-movement is particularly evident across the period at the 1–4-week cycle and a larger 8–16-week cycle that dominates the chart of co-movement between Ether and Decentraland. Panel C of Figure 2 shows several red regions with significant interrelation, and the arrows pointing to the right indicate a positive correlation between Ether returns and Decentraland attention.



Panel **A**. Wavelet coherence: NFT attention and Bitcoin returns

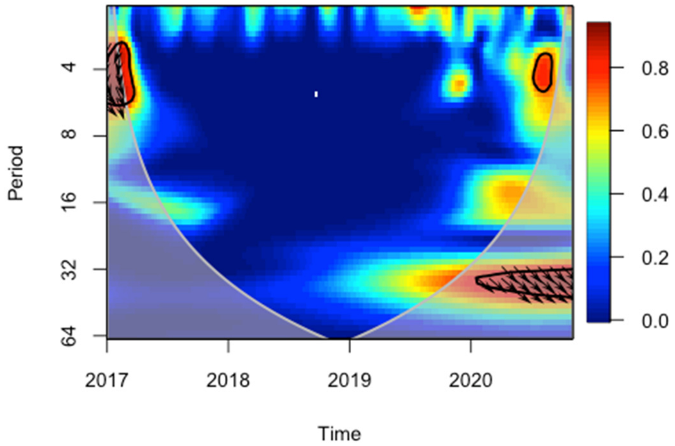


Panel **B**. Wavelet coherence: CryptoPunk attention and Bitcoin returns

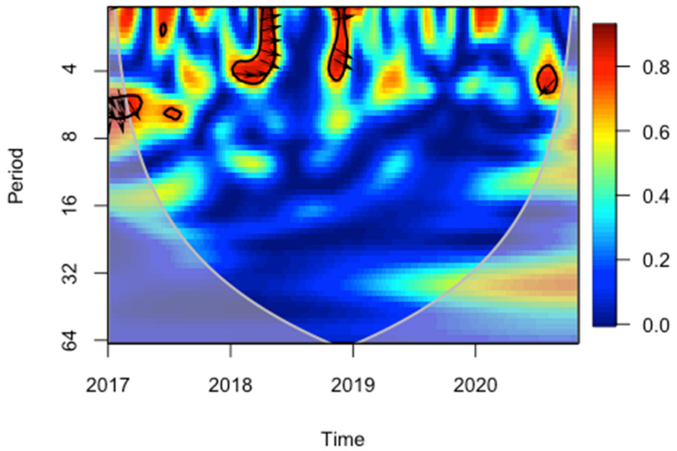


Panel **C**. Wavelet coherence: Decentraland attention and Bitcoin returns

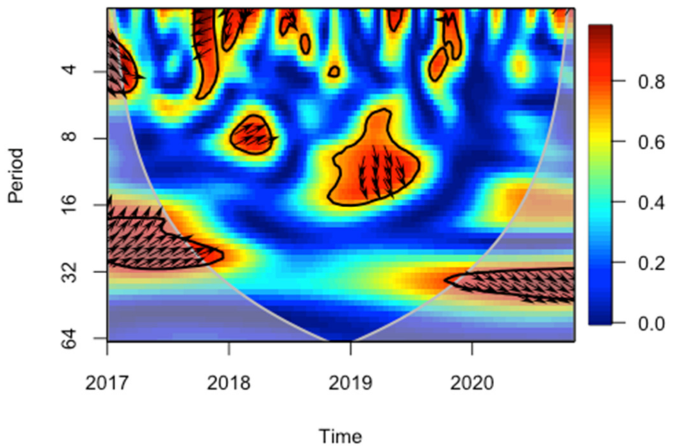
Figure 1. This figure represents the wavelet coherence analysis for Bitcoin returns and NFT levels of attention (Panel **A**), Bitcoin returns and CryptoPunk attention (Panel **B**), and Bitcoin returns and Decentraland attention (Panel **C**). Correlation is shown by the colour—hotter colours (cool blue to hot red) indicate higher absolute correlations. For the arrows, $\rightarrow$ shows positive correlation, $\leftarrow$ shows negative correlation, $\nearrow$ and $\swarrow$ show Bitcoin leads the NFT, and $\searrow$ and $\nwarrow$ show the NFT leads Bitcoin. We use weekly Bitcoin returns and Google search activity between 1 December 2017 and 30 July 2021.



Panel **A**. Wavelet coherence: NFT attention and Ether returns



Panel **B**. Wavelet coherence: CryptoPunk attention and Ether returns



Panel **C**. Wavelet coherence: Decentraland attention and Ether returns

Figure 2. This figure represents the wavelet coherence analysis for Ether returns and NFT levels of attention (Panel **A**), Ether returns and CryptoPunk attention (Panel **B**), and Ether returns and Decentraland attention (Panel **C**). Correlation is shown by the colour—hotter colours (cool blue to hot red) indicate higher absolute correlations. For the arrows, $\rightarrow$ shows positive correlation, $\leftarrow$ shows negative correlation, $\nearrow$ and $\swarrow$ show Ether leads the NFT, and $\searrow$ and $\nwarrow$ show the NFT leads Ether. We use weekly Ether returns and Google search activity between 1 December 2017 and 30 July 2021.

4. Discussion and Concluding Remarks

This paper utilizes Google search queries to analyze the drivers of attention to non-fungible tokens (NFTs). We use weekly data between 2017 and 2021 to show that Google search activity for the topic "non-fungible token" and "NFT" is positively associated with major cryptocurrency returns. We arrive at similar conclusions when using Google search activities for specific NFT collections, such as "Cryptopunk" and "Decentraland". Using vector autoregressive (VAR) models, we find that the previous week's Bitcoin returns are significant attention drivers to NFTs. Furthermore, when we use wavelet coherence analysis, we find that investors are more attracted to NFTs after increases in both Bitcoin and Ether returns. Our findings are consistent with the notion that the excitement around cryptocurrencies induced by record-high prices in 2021 could explain the NFT growth in popularity during the same period.

Our paper contributes to the academic literature on NFTs that focuses on the factors that explain the sudden attention of investors in the NFT market. Furthermore, we extend the understanding of the effects of the leading cryptocurrencies on new blockchain developments, such as the NFT market.

The results of this study have practical implications for investors, institutions and governments that are called to understand this burgeoning industry as part of this new digital economy where the crypto markets are the protagonists.

Future research directions need to address the continued evolution of the NFT ecosystem, the effect of the transaction and environmental costs, and the legal framework associated with the use of the crypto technology.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1 defines all the variables we use in this study.

Table A1. Definitions of variables.

Variable Name	Definition
Bitcoin return (%)	Weekly Bitcoin return in percentage is defined as $\left[\ln\left(\frac{bitcoin\ price_t}{bitcoin\ price_{t-1}}\right)\right] * 100$. Bitcoin price on week t is taken from coinmarketcap.com (accessed on 9 August 2021).
Ether return (%)	Weekly Ether return in percentage is defined as $\left[\ln\left(\frac{ether\ price_t}{ether\ price_{t-1}}\right)\right] * 100$. Ether price on week t is taken from coinmarketcap.com (accessed on 9 August 2021).
VIX return (%)	Weekly VIX index return in percentage is defined as $\left[\ln\left(\frac{VIX\ index_t}{VIX\ Index_{t-1}}\right)\right] * 100$. VIX index on week t is taken from Yahoo Finance (accessed on 9 August 2021).
Gold return (%)	Weekly gold return in percentage is defined as $\left[\ln\left(\frac{gold\ price_t}{gold\ price_{t-1}}\right)\right] * 100$. Gold price on week t is taken from Yahoo Finance (accessed on 9 August 2021).

Table A1. *Cont.*

Variable Name	Definition
S&P 500 return (%)	Weekly S&P 500 index return in percentage is defined as $\left[\ln\left(\frac{S\&P500\ index_t}{S\&P500\ index_{t-1}}\right)\right] * 100$. S&P 500 index on week t is taken from Yahoo Finance (accessed on 9 August 2021).
NFT attention	Weekly time series measuring the frequency of Google search volumes for the topics "NFT" and "Non-Fungible Token" at the worldwide level. The Google search index ranges between 0 and 100. Data is taken from Google Trends (accessed on 9 August 2021).
CryptoPunk attention	Weekly time series measuring the frequency of Google search volumes for the topic "CryptoPunk" at the worldwide level. The Google search index ranges between 0 and 100. Data is taken from Google Trends (accessed on 9 August 2021).
Decentraland attention	Weekly time series measuring the frequency of Google search volumes for the topic "Decentraland" at the worldwide level. The Google search index ranges between 0 and 100. Data is taken from Google Trends (accessed on 9 August 2021).
NFT return (%)	Weekly NFT return in percentage is defined as $\left[\ln\left(\frac{NFT\ price_t}{NFT\ price_{t-1}}\right)\right] * 100$. NFT price on week t is either the price of CryptoPunk or Decentraland, depending on the model. Prices are taken from nonfungible.com (accessed on 9 August 2021).
Bitcoin attention	Weekly time series measuring the frequency of Google search volumes for the topic "Bitcoin" at the worldwide level. The Google search index ranges between 0 and 100. Data is taken from Google Trends (accessed on 9 August 2021).
Ethereum attention	Weekly time series measuring the frequency of Google search volumes for the topic "Ethereum" at the worldwide level. The Google search index ranges between 0 and 100. Data is taken from Google Trends (accessed on 9 August 2021).

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