

The Non-Fungible Token (NFT) Market and Its Relationship with Bitcoin and Ethereum

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Abstract: Non-fungible tokens (NFTs) are transferrable rights to digital assets, such as art, in-game items, collectables, or music. The phenomenon and its markets have grown significantly since early 2021. We investigate the interrelationships between NFT sales, NFT users (unique active blockchain wallets), and the pricing of Bitcoin (BTC) and Ether (ETH). Using daily data between January 2018 and April 2021, we show that a Bitcoin price shock triggers an increase in NFT sales. Also, Ether price shocks reduce the number of active NFT wallets. The results suggest that (larger) cryptocurrency markets affect the growth and development of the (smaller) NFT market, but there is no reverse effect.

Keywords: NFTs; non-fungible tokens; cryptocurrency; blockchain



Citation: Ante, L. The Non-Fungible Token (NFT) Market and Its Relationship with Bitcoin and Ethereum. *FinTech* **2022**, *1*, 216–224. <https://doi.org/10.3390/fintech1030017>

Academic Editors: David Roubaud and Paolo Giudici

Received: 20 March 2022

Accepted: 27 June 2022

Published: 29 June 2022

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1. Introduction

Prominent examples of non-fungible tokens (NFTs), such as the artist Beeple selling a piece of digital art for \$69 million [1] or Twitter CEO Jack Dorsey auctioning off his first-ever tweet for \$2.9 million [2], show that NFTs have received mainstream attention and represent a popular application in FinTech and the cryptocurrency ecosystem [3]. NFTs are unique certificates of authenticity on blockchains that are usually issued by the creators of the underlying assets. These assets can be digital or physical in nature. Fungible goods such as money or trade goods can be exchanged for goods of the same kind. By contrast, non-fungible items cannot be exchanged for a similar good because their value exceeds the actual material value. Examples from the analogue world include items of artistic or historical significance, or rare trading cards—all of which have a long history of trading in auctions and other marketplaces. In the digital world, it has so far been difficult to trade and auction non-fungible goods, as their authenticity was hard to verify. NFTs now pave the way for the digitization and trade of unique values on the internet.

Within less than half a year (by 16 May 2021), hundreds of thousands of NFTs worth over \$800 million were traded [4]. Most of these referred to digital art, collectibles, music, in-game items, or metaverses (i.e., digital land or assets). Like cryptocurrency and other types of tokens, NFTs rely on blockchain technology and smart contracts as their digital infrastructure [5]; however, they significantly differ from traditional cryptocurrencies such as Bitcoin or Ethereum in other respects. NFTs serve not as a currency, a commodity or a technology, but as an asset [6].

Besides the common technological infrastructure, NFT marketplaces such as OpenSea or Rarible furthermore use cryptocurrency, most commonly Ether (ETH), as a payment and trading option, evidencing a close relationship between the cryptocurrency market and the NFT market [7]. If users typically require cryptocurrency to buy NFTs, it is reasonable to assume that the cryptocurrency market has an impact on the smaller NFT market. Dowling [5] accordingly writes that anyone who is active in the NFT market recognizes the strong overlap between participants in these two markets. Accessing and using cryptocurrencies is a complex task; therefore, those who have mastered it are more likely to also participate in the NFT market.

The academic literature has studied the link between different cryptocurrencies and found significant interdependencies, as positive time-varying conditional correlations exist [8]; Bitcoin leads in importance for return and volatility spillover, e.g., [9,10]. Bouri et al. [11] identify spillover effects between Bitcoin and other asset classes (stocks, commodities, forex, and bonds), whereas Bitcoin is more often a receiver than transmitter of volatility spillover. In addition, studies exist on the extent to which macroeconomic variables affect cryptocurrency markets. One example is the study by Wang et al. [12], who found that there is no spillover effect from economic policy uncertainty to Bitcoin. While it is still unclear whether NFTs represent a distinct market or asset class, it is relevant to understand how comparatively larger cryptocurrency markets relate to and/or affect comparatively smaller NFT markets.

There are few prior studies on the financial aspects of NFT markets. Nadini et al. [7] map the NFT ecosystem based on sales and traded volume across different projects, stakeholders and other relevant characteristics. Similarly, Ante [13] analyzes major NFT submarkets on the Ethereum blockchain and identifies co-movements between them. Dowling [14] examines the pricing behavior of a particular NFT project, Decentraland, which enables the trading of digital plots of land in a blockchain-based multiverse. In another study, Dowling [6] uses wavelet coherence analysis to identify any co-movement between the cryptocurrency and the NFT markets. He examines three major NFT submarkets (Decentraland, CryptoPunks and AxieInfinity), as well as the prices of Bitcoin and Ether. Aharon and Demir [15] find that NFTs are mainly independent of shocks from other asset classes. Similarly, Umar et al. [16] identify a clear independence of NFTs from other asset classes. These results suggest that cryptocurrency pricing behavior can but must not help to understand NFT pricing patterns. Building on this, the aim of the present study is to investigate how the markets for NFTs and cryptocurrencies are related. Explicitly, we formulate the following two research questions: (1) *Do causal relationships between NFT and cryptocurrency markets exist?* and (2) *if this is the case, how strong are these relationships?* For this purpose, we use NFT sales and NFT wallets as proxies for the NFT market, and the prices of Bitcoin and Ether as representative for the cryptocurrency market (i.e., the two largest and arguably most significant cryptocurrencies). The clarification of this question contributes to the extent to which NFTs represent or develop into an independent asset class, or whether NFTs (at the time under consideration) are only an aspect of cryptocurrency markets. Answering this question can assist stakeholders in their strategic behavior and planning by (a) clarifying the extent to which cryptocurrency markets serve as explanatory factors for NFT markets; or (b) NFT markets may even contribute to the growth or price development of cryptocurrency markets.

We extract macro data on the Ethereum-based NFT market, more specifically the trading volume of all NFTs in USD and the number of blockchain wallets participating in the NFT market (sellers and buyers), and analyze how these relate to the pricing of Bitcoin and Ethereum using a cointegrated vector autoregressive (VAR) model, i.e., a vector error correction model (VECM). This allows us to identify to what extent these markets influence each other, or co-move. Furthermore, we are able to quantify effects and unveil their directions using impulse response functions.

Our data on overall trading volume and users should permit a better understanding of the NFT phenomenon, with the existing research focusing on pricing aspects of NFT (sub)markets [6,14]. We aim to clarify what impact changes in the prices of Bitcoin and Ethereum have on the NFT market, which in turn helps to understand the impact or spillover effect of the (larger) cryptocurrency markets on the (smaller) NFT market. It seems likely that Bitcoin, as the market leader, drives the NFT market, as it does or did with respect to other cryptocurrencies [17]. We also hope to determine whether demand shocks in the NFT market affect the pricing of cryptocurrencies. The results contribute to lessons learned on the co-movement and spillover of blockchain-based markets or assets [10,18], and the use of on-chain data to assess blockchain-based markets and their efficiency [19].

The data set and methodology are described below, followed by a presentation of the results and concluding remarks.

2. Data and Methodology

Our data set comprises 1231 daily observations (1 January 2018 to 16 May 2021) on the volume of NFT sales in USD, the number of blockchain wallets holding or interacting with NFTs on a particular day, and the prices of Ether (ETH) and Bitcoin (BTC) in USD. The first two metrics are collected from NonFungible Corporation (nonfungible.com) and cover data on the Ethereum blockchain only, which (historically) accounts for a majority of the NFT market. Price data (daily close) are collected from the cryptocurrency exchange Bitfinex (bitfinex.com)—for daily data, the source of cryptocurrency pricing is not too sensitive to major cryptocurrency exchanges or data aggregators. In line with Dowling (2021a), as cryptocurrency reference markets we use ETH, the most relevant currency for issuing and trading NFTs, and BTC, the largest and most significant cryptocurrency.

Figure 1 shows the extreme increase in the trading volume of NFTs since early 2021. For example, on the single day of 3 May 2021, over \$100 million worth of NFTs were traded, and the daily average trading volume of the year to date is much higher than in previous years (\$6.13 million, compared to \$0.18 million in 2020, \$0.07 million in 2019, and \$0.10 million in 2018).

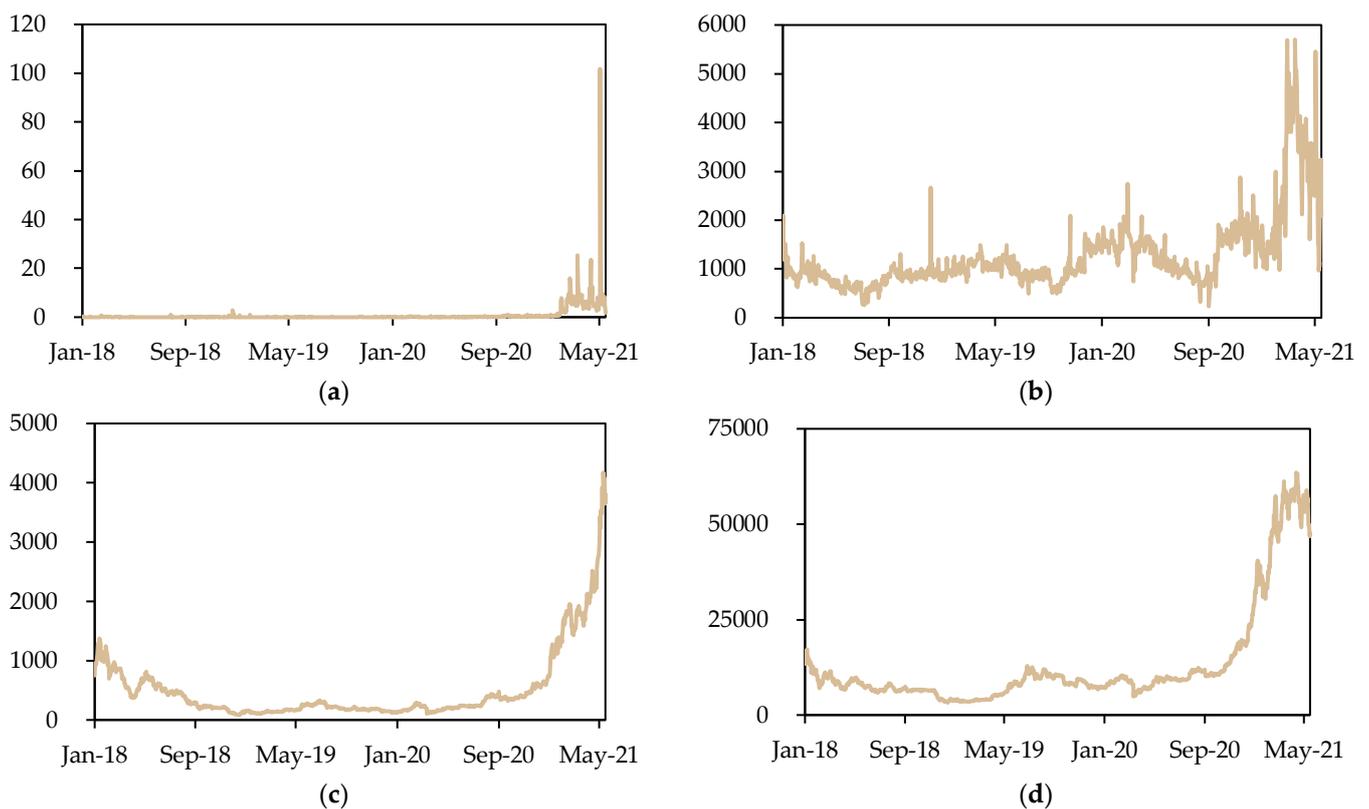


Figure 1. NFT and cryptocurrency market data: (a) Ethereum-based NFT sales in million USD between Jan 2018 and May 2021; (b) number of active NFT wallets on the Ethereum blockchain between Jan 2018 and May 2021; (c) ETH price in USD between Jan 2018 and May 2021; and (d) BTC price in USD between Jan 2018 and May 2021. (a) NFT sales in million USD. (b) Number of active NFT wallets. (c) ETH price in USD. (d) BTC price in USD.

The figure also shows that the number of wallets on the Ethereum blockchain holding NFTs has increased significantly. For example, in March 2021, over 5700 different wallets held NFTs. The two metrics clearly illustrate the increasing relevance of NFTs, both in terms of market volume and the number of users, as proxied by the number of blockchain

wallets. The two cryptocurrencies also peaked in 2021, at \$63,537 (BTC) and \$4172 (ETH), having traded significantly lower prior to that. Descriptive statistics on the raw series, the log series, and the log differences are presented in Table A1.

In order to investigate the relationship between the NFT market and the cryptocurrencies, we propose a VAR framework, which can be used to structurally analyze the dependencies between several variables. Here, we model vectors of variables as depending on their own lags and the lags of other variables. With our four variables, the VAR model takes the following form:

$$\begin{bmatrix} NFT\ sales_t \\ NFT\ wallets_t \\ BTC\ price_t \\ ETH\ price_t \end{bmatrix} = a_0 + A_1 \begin{bmatrix} NFT\ sales_{t-1} \\ NFT\ wallets_{t-1} \\ BTC\ price_{t-1} \\ ETH\ price_{t-1} \end{bmatrix} + \dots + A_4 \begin{bmatrix} NFT\ sales_{t-4} \\ NFT\ wallets_{t-4} \\ BTC\ price_{t-4} \\ ETH\ price_{t-4} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \end{bmatrix} \tag{1}$$

where a_0 is a vector of intercept terms, and A_1 to A_4 are coefficients of a 4×4 matrix. The optimal number of lags—4 in our case—is identified by the *Akaike information criterion (AIC)*. All four time series are non-stationary in their logarithmic form and all log differences are stationary (cf. Table A2), making VAR a suitable method. Yet the Johansen test of cointegration [20] indicates one cointegrating relationship (cf. Table A3), thus making the VECM—the cointegrated VAR—our choice of model.

3. Results

In the following, we present two postestimation statistics to interpret the results of the cointegrated VAR. Table 1 lists short-run Granger causality test statistics that indicate whether a change in one variable precedes a change in another variable. The statistics are calculated for each combination of our dependent and independent variables. For example, the first line of results refers to the test of whether all coefficients on four lags of NFT wallets as a potential predictor of NFT sales are zero. Since the p -value exceeds the significance threshold of 10%, we cannot confirm that NFT wallets Granger-cause NFT sales. NFT sales are, however, Granger-caused by the BTC price.

Table 1. The table shows short-run Granger causality test statistics for the VECM model.

Dependent Variable	Independent Variable	F-Statistic	p-Value
NFT sales	NFT wallets	3.92	0.270
	BTC price	10.32	0.016 **
	ETH price	4.68	0.197
NFT wallets	NFT sales	6.25	0.100
	BTC price	1.22	0.747
	ETH price	13.09	0.004 ***
BTC price	NFT sales	1.89	0.596
	NFT wallets	11.86	0.603
	ETH price	5.53	0.137
ETH price	NFT sales	5.23	0.156
	NFT wallets	2.14	0.544
	BTC price	6.81	0.078 *

*** $p < 0.01$; ** $p < 0.5$; * $p < 0.1$.

Furthermore, NFT wallets are Granger-caused by the ETH price. BTC is not Granger-caused by any of the other variables, while ETH is Granger-caused by the BTC price. Accordingly, we find that NFT markets are influenced by cryptocurrency pricing, though Granger causality tells us nothing about the direction of these influences.

In order to understand that direction of influence, impulse response functions are shown in Figure 2. They depict how a standard deviation shock to one variable affects

another variable over a period of 30 days. One impulse is placed in each row and one response in each column.

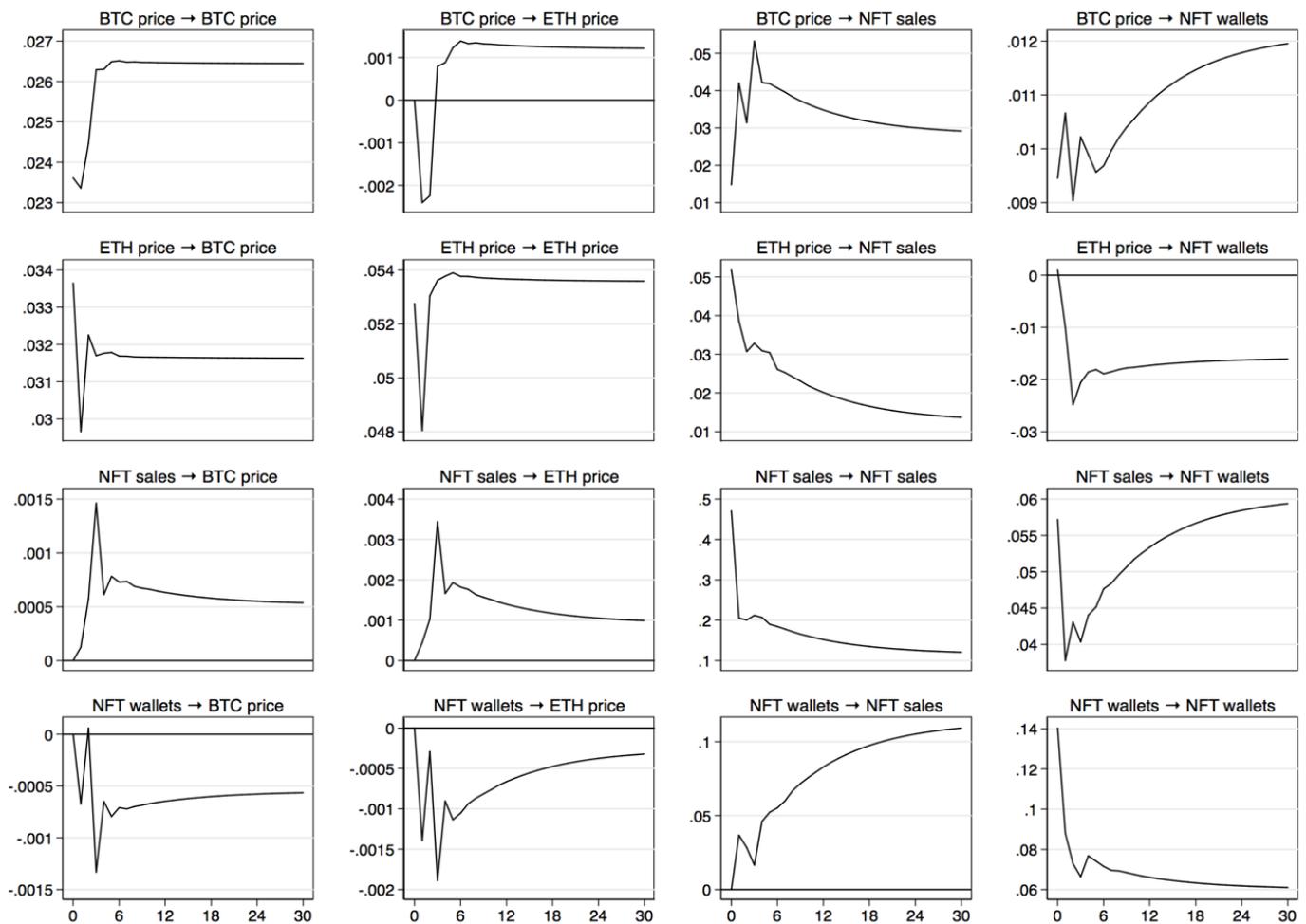


Figure 2. Impulse response functions. Impulse response functions based on the VECM with four lags are shown for a time horizon of 30 days.

Unlike with the VAR, impulse response functions of a VECM need not return to their mean value, as series are cointegrated in the long run. We find that one-time standard deviation shock increases in the prices of BTC and ETH have positive effects on NFT sales. The effects level off at around 0.03% for BTC and at around 0.015% for ETH. Bitcoin price shocks have a clear positive effect on the number of active NFT wallets. Surprisingly, the reverse effect applies to the ETH price. As expected, NFT sales and the number of NFT wallets are positively related. A 1% price shock of BTC has a negative short-term effect on the price of ETH. After about 5 days, the trend reverses, settling at a permanent effect of around 0.001%. An ETH price shock has a positive effect on the price of BTC (0.032%). Due to the existence of a long run equilibrium relationship between series, impulse response functions must be interpreted with caution for VECM models. They are helpful in interpreting the basic relationships between the variables, mapping short-run effects, and complementing the above results of the short-run Granger causalities.

4. Concluding Remarks

This paper has analyzed the interplay between the cryptocurrency market and the NFT market, contributing to the emerging literature on the latter. In line with Dowling's [6] conjecture, we find that BTC and ETH pricing affects the NFT market, while the NFT market does not significantly influence the pricing of cryptocurrencies. It thus appears

that the smaller NFT market is driven by the cryptocurrency market. This is plausible, as cryptocurrencies are the common currency for buying and trading NFTs. A drop in cryptocurrency value means lower purchasing power, which is likely to depress the NFT market. Conversely, when cryptocurrencies appreciate, investors tend to look for new or alternative investment opportunities. This is especially plausible in the context of ETH, the standard denomination of NFTs. While the impulse response function indicates such a relationship between NFT sales and ETH, we do not find a significant Granger causality between these metrics—yet we do for BTC.

Our results contribute to research on spillover effects between blockchain-based markets of different sizes. For initial coin offerings (ICOs)—another market that is much smaller than cryptocurrency markets—Masiak et al. [21] have shown that shocks in cryptocurrency pricing have positive effects on market volume. Like NFTs, ICOs also typically rely on cryptocurrency for payment. Similarly, stablecoin markets are driven by the demand for cryptocurrency [22,23]. The question thus arises as to what extent insights, issues, and challenges from other blockchain-based markets can be transferred to the NFT market. This includes issues related to quality signaling in the context of token pricing or valuation [24], investment returns [25], or legal challenges [26]. While this study focuses only on NFTs and cryptocurrency markets, there are several other factors or markets that can influence NFTs. This includes topics such as market sentiment, social media, transaction fees, blockchain infrastructures, uncertainty, volatility, policy, or different asset classes. Studies such as Aharon and Demir [25] or Umar et al. [16] provide first empirical evidence in this regard. However, there is still a great deal of research potential. One particularly promising research approach could be to create a comparative analysis of other submarkets. On the one hand, this could be done using a methodology that is similar to the one chosen in this article but including additional variables (e.g., stablecoin activity, ICO activity, etc.); on the other hand, the comparison could be done on the basis of a meta-analysis.

In this study, sales and wallets were chosen as proxies for economic significance and activity of NFTs. The results suggest that these are appropriate metrics, which also suggests the use of similar metrics in other blockchain-specific articles, e.g., [27–29]). Nevertheless, it must be noted that there are a variety of other NFT-specific metrics whose inclusion could lead to differentiated or different results. Likewise, “only” BTC and ETH were considered; accordingly, this is both a limitation and an option for future research, as the same metrics could be tested for NFT subsectors or fully new metrics could be identified, derived, and tested. Similarly, alternative econometric methods of spillover detection, such as correlation networks, e.g., [30], represent a way to validate or extend the results of this study.

A potential limitation of this study, and at the same time an exciting challenge for future research, is the topic of NFT wash trading. This is an issue that poses significant challenges to blockchain-based pseudo-anonymous markets and cryptocurrency markets [31,32]. In principle, an owner or creator can trade her own NFT transparently but anonymously by transferring it between two different addresses/wallets on the public blockchain infrastructure. This way, demand can be suggested, faked, or inflated with the goal to attract future buyers. The legality of any such behavior is currently unclear. If it were to take place, this could—besides the evident investor protection challenges—bias the statistics on NFT sales and wallets and their interpretation used in this study. Accordingly, future research might analyze (large) NFT sales, the blockchain addresses involved, and transaction patterns, in order to identify any wash trading. The study of von Wachter et al. [33] represents a helpful basis.

We agree with Dowling’s [6] main conclusion “that NFTs do appear to be a distinct (and exciting) new asset class”. While the NFT market still seems to depend on the cryptocurrency market, specifically BTC, it may well mature over time. The question is to what extent this relationship will change once traditional marketplaces such as eBay allow trading of NFTs (against fiat currencies or stablecoins) [34], established companies such as Instagram fully appreciate the potential of NFTs [35], or media firms like Fox launch their own NFT ventures [36]. As of now, NFTs on public blockchains are subject to an

increased degree of cyber risk [37], and lack clear and uniform regulation—both topics for future research. In the future, we may see NFT submarkets that are strongly related to cryptocurrency markets, and others that are much more independent. For example, different types of NFTs include collectables, play-to-earn tokens, digital real estate (e.g., digital land), financial claims (e.g., Uniswap v3 positions) or domain names—the literature still lacks a comprehensive classification framework for NFTs. It seems likely that these different forms of NFTs are (or will be) influenced by significantly different factors, due to their clear economic and practical differences. Accordingly, a more detailed analysis of NFT characteristics and submarkets is a promising research avenue. Further development of the NFT market and its relationship to the cryptocurrency market still holds significantly more areas of interest for research. For future research on NFTs in the field of finance, Baals et al. [38] present a very helpful basis: major research topics include diversification benefits, market efficiency, herding behavior, and market correlation.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data used in the study can be obtained from nonfungible.com and bitfinex.com.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. Descriptive statistics. Descriptive statistics for the raw metrics, log-transformed series, and the logarithmic differences of 1231 daily observations.

	Mean	SD	P50	Min	Max	Skewness	Kurtosis
Raw series							
NFT sales	780,199	3,644,778	78,349	14,591	102,000,000	485.80	18.59
NFT wallets	1261	767	1026	233	5701	11.41	2.65
BTC price	13,139	13,458	8818	3281	63,537	7.78	2.43
ETH price	503	606	246	85	4172	12.92	2.90
Log series							
NFT sales	11.73	1.44	11.27	9.59	18.44	5.64	11.73
NFT wallets	7.02	0.47	6.93	5.45	8.65	4.38	7.02
BTC price	5.80	0.83	5.51	4.45	8.34	3.07	5.80
ETH price	9.19	0.68	9.08	8.10	11.06	4.24	9.19
Log differences							
NFT sales	0.0021	0.5452	−0.0107	−3.4753	3.5531	11.0229	−0.0823
NFT wallets	0.0001	0.1637	−0.0037	−1.0603	1.1160	11.2118	0.0688
BTC price	0.0010	0.0413	0.0016	−0.4919	0.1789	21.0601	−1.4379
ETH price	0.0013	0.0533	0.0012	−0.5801	0.2331	15.8410	−1.2076

Table A2. Unit root tests.

	Log Series		Log Differences	
	ADF	<i>p</i> -Value	ADF	<i>p</i> -Value
NFT sales	−1.593	0.4869	−17.219	0.0000 ***
NFT wallets	−2.452	0.1275	−16.536	0.0000 ***
BTC price	−0.011	0.9576	−12.264	0.0000 ***
ETH price	0.084	0.9650	−11.902	0.0000 ***

*** $p < 0.01$.

Table A3. Johansen cointegration test.

Hypothesized Number of Cointegrated Vectors	Eigenvalue	Trace Statistic	5% Critical Value	Maximum Eigenvalue Statistic	5% Critical Value
0		64.48	39.89	30.04	23.80
1	0.0317	24.92	24.31	14.35	17.89
2	0.0124	9.63	12.53	2.13	11.44
3	0.0067	1.42	3.84	0.11	3.84

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