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Does The NFT Market Interact With Major Financial Markets?

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ABSTRACT

Non-fungible tokens are digital certificates of ownership representing digital or physical assets such as photos, artworks, videos, tickets, etc. As NFTs are becoming increasingly popular and the market size is exploding, the debate over whether the NFT market is an effective and efficient financial market has been contentious. This study investigates the correlation between the NFT market and major financial markets. Using 508 NFTs' volume and price in 221 days, we construct three versions of NFT market index to track the NFT market volatility. Furthermore, by using an autoregressive moving average model with exogenous variables, the study found a strong positive relationship between all NFT market indices and the cryptocurrency and stock markets. Moreover, based on the sentiment analysis of public user-generated content on NFT on Twitter, we found that negative opinions are positively associated with the NFT market index fluctuation rate.

Keywords

NFT market index; financial markets; sentiment analysis; ARMAX

INTRODUCTION

Non-fungible tokens (NFTs) have gathered worldwide attention over the past several years. NFTs are cryptographic assets that use blockchain technology to represent ownership of digital goods (Kanellopoulos, Gutt, & Li, 2021). Many famous artists, actors, and athletes have minted their own NFTs and started selling their digital goods on the online digital marketplace. While NFTs are becoming increasingly popular and trade globally, the highly volatile poses a risk for consumers, investors and businesses. As more people are creating, buying, selling, and swapping NFTs, one of the biggest challenges is the valuation of NFTs. Several existing studies have compared NFT assets with other financial assets to measure the correlation between NFT asset class with other asset classes (Aharon & Demir, 2022; Ante, 2022; Dowling, 2022; Umar, Gubareva, Teplova, & Tran, 2022). Dowling (2022) found low spillover between cryptocurrencies and NFTs. Umar et al. (2022) indicated that the co-movements between NFTs and other assets only could hold in the short-term horizon. Aharon and Demir (2022) indicated that there might be increased connectedness between NFT prices and general market shocks. In addition, the debate over NFTs on various social media platforms such as Twitter, WeChat, and Reddit is intense and controversial. Some proponents believe that the NFT market will continue to bloom (Kapoor et al., 2022; Luo, Wang, & Jiang, 2019). Others believe NFTs are bubbles that will eventually burst (Jones, 2021; Meyns & Dalipi, 2022).

Thus, the debates and challenges call for further research about valuation of NFTs and what potential factors affect the NFTs in the marketplace (He et al., 2023). After conducting extensive literature search, we found a few published studies in the literature about the relationship among NFT markets, cryptocurrency, stock, bond, gold and social media opinions. Thus, this study fills the gap by examining the relationship between the NFT market and other financial markets, which include cryptocurrency, stock, bond, gold, as well as social media opinions. The results lead to better understanding of the potential risks to consumers, investors and organizations and contribute to the literature on NFTs.

METHODOLOGY

Data sources

Prior research shows that NFTs could be seen as an alternative investment in the Fintech Era. To examine the relationship between the NFT market and primary market indices, we cover four types of market indices, including stock market (S&P500 index, FTSE index, N225 index, Shanghai SE Composite index, and HSI index), bond market (USA 7day bonds and Barclays Bloomberg global treasury index), commodity market (Gold index and WTI index), and cryptocurrency market (Bitcoin/USD index and Bitcoin/Ether index). The cryptocurrency data is collected from Investing.com and others are collected from Wind.com. 508 NFTs' floor price, trading volume and total trading amounts were collected from Jan. 1st to Nov. 31st in 2022 on the website nftpricefloor.com (see Table 1). Moreover, research on crypto tokens suggests that network effects are essential for the success of digital platforms and initial coin offerings. But they do not specifically explain the impact of positive and negative opinions on NFTs. To fill the gap, we include the sentiment data from the public user-generated content in our model. Specifically, the Twitter platform was chosen to examine public opinion on NFTs as it currently has 6% of worldwide social media users. The Tweepy library was employed to extract data from Twitter through Jan. 1st to Nov. 31st in 2022 by using "NFT" as the search keywords and filtering the language by English. Totally, 168542 tweets are observed after cleaning. Each tweet is classified by using the TextBlob library to either positive or negative tweet based on the sentiment.

	Min	Max	Mean	Median	Std
Total amount/USD	4250877.13	1156306613.60	70731867.85	15943390.57	130550517.83
Floor Price /USD	5351.26	40821.37	14848.15	10499.27	8531.04

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
Number of NFT	273	288	288	342	362	385	399	416	425	499	502
trading volume	7752716875.47	3873697065.87	1503196271.28	2217878026.22	3670419739.01	444969515.07	295837939.69	245694965.32	226151278.91	252521149.67	324768658.94

Table 1. Descriptive statistics of the collected data

NFT Market Index

To compare the NFT market with other financial market indices, we constructed three NFT market index following conventions (shown below in Figure 1). Index1 is an arithmetic average price weighted index, index2 is value-weighted index, while index3 is an equal-weighted index. All the indices are continuous in trading days and contain all the available NFTs.

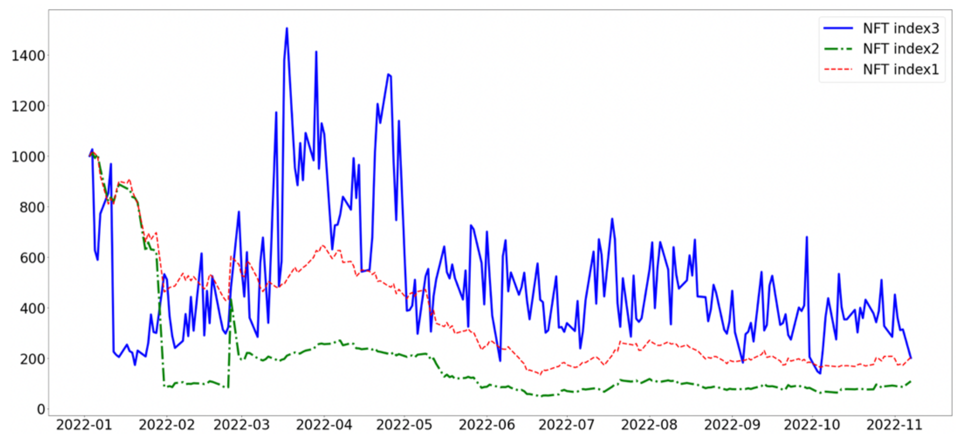

Figure 1. The NFT market indices

As shown in figure1, index3 has the largest volatility, and index1 has the lowest total return. All the indices have downward trend in 2022, and particularly there were large volatiles at the first half of the year. Then we calculated these indices' monthly returns and monthly return volatilities and Sharpe ratios in table 2. As shown in figure 1, index1 has the lowest monthly return and Sharpe ratio, while index2 has the largest return rate and volatility.

Index	Min	Max	Mean	Median	Std	Mean Returns (monthly)	Returns Std (monthly)	Monthly Sharpe Ratio
Index1	133.59	1019.11	370.68	262.11	212.98	-9.21%	32.91%	-32.20%
Index2	46.29	1012.21	189.73	99.71	214.77	2.39%	60.21%	1.64%

Index3	139.01	1505.83	513.55	443.7	262.23	20.65%	85.16%	22.59%

Table 2. Descriptive statistics of the three indices

Methodology approach

To investigate the interactions between the NFT market and major financial markets, the three indices are analyzed using the autoregressive–moving-average model with exogenous variables (ARMAX). We adopted this model to estimate the impact of major financial markets on the NFT market. The ARMAX model with m exogenous variables can be expressed as follows:

$$y_t = \sum_{i=1}^{p} y_{t-i}\,\gamma_i + \sum_{j=0}^{q}\ \sum_{m=0}^{n} x_{t-j,m}\,\beta_{j,m} + \sum_{k=0}^{l} \varepsilon_{t-k}\,\delta_k + \alpha_0$$

Where y_i is the dependent variable, $x_{j,m}$ is the m-th exogenous variable in j lags, and ε_t is the white noise that is generally assumed to be independent, identically distributed variables and satisfy the standard normal distribution. Since the market indices are volatile and not stationary, we use the logged difference variables on all the indices to represent the daily return results. The sentiment variables are the ratio of total sentiment data collected.

EMPIRICAL RESULTS

Model specification

Before identifying the structure of the ARMAX model, we selected the appropriate exogenous variables by testing the collinearity and stationarity. Severe multicollinearity can impair the performance of the model. We calculated the correlation between all independent variables. Since all the correlation values in the matrix between variables are below 0.6, we could reject the multicollinearity problem.

Then we tested the stationarity of the various time series using the ADF test. The indices are non-stationary, but their returns (log differences) are stationary. According to the ADF test result, the two sentiment variables were stationary.

We first identified the orders p and q in the ARMA(p,q) model to determine the model structure. According to the Box-Jenkins' method, one could calculate the series autocorrelation coefficient (AC) and partial autocorrelation coefficient (PAC) to determine the orders p and q of the ARMA models. In this study, we separately determined the ACF and PACF diagram of the three dependent variables – index1, index2 and index3. The PACF of index2 evidently tailed off to zero, and the ACF of index1 evidently presented a cut-off. Since the PAC in the third-order lag was significant not 0 at the level of 1%, q was determined to be 3. Similar to index2, index3 also presented the same ARMA(1,3) structure. For index1, both the ACF and the PACF presented a cut-off, so the model structure of index3 is ARMA(0,0).

ARMAX model structure

The study adopted the stepwise elimination method of multiple linear regression to find the optimal ARMAX model (Niu & Li, 2022). At first, we included all independent variables and their maximum k-order lag terms. In this model, we set all the independent variables' k to 2. Next we estimated the model and gradually eliminated the term with largest p-value in the t-test of coefficients to optimize the model. The optimal model could be obtained until the coefficients of all terms are significant at the level of 5%. Table 3(a),(b),(c) report the regression results of the three ARMAX models.

Index1	cryptocurrency market			future market	stock market		bond market
var	Btc/Eth	Bitcoin(lag_1)	Btc/Eth(lag_2)	WTI	FTSE	S&P500(lag_2)	7 Bond(lag_2)
coefficient	0.3155**	0.2767**	0.5281***	-0.5059***	0.8226**	0.8912***	1.4457**
std	-0.1347	-0.1209	-0.1352	-0.1711	-0.3639	-0.318	-0.7149
var	sigma2	const	Vars	AIC		BIC	
coefficient	0.0044***	-0.1524***	39 variables	166.38		315.30	

std	-0.0002	-0.0554	7 exogenous variables	134.69	182.09

Table 3(a). ARMAX model result of index1

Index2	stock market	cryptocurrency market					
var	FTSE	Btc/Eth(lag_2)	sigma2	const	vars	AIC	BIC
coefficient	2.9225***	1.2517***	0.0374***	-0.0917**	42 variables	-56.5	82.27
std	-2.4854	0.667	0.01	0.023	2 exogenous variables	-91.98	-78.44

Table 3(b). ARMAX model result of index2

Index3	stock market					cryptocurrency market	bond market	sentiment	
var	SSE	HIS	S&P500 (lag_1)	N225(lag_2)	HSI(lag_2)	Btc/Eth(lag_1)	7 Bond(lag_1)	Negative(lag_1)	
coefficient	3.8875**	-3.3090***	5.3478***	3.7399**	-4.0256***	-1.8740***	9.2919***	1.3087***	
std	-1.7528	-1.018	-1.3422	-1.5095	-1.0829	-0.6656	-3.1065	-0.4019	
var	ar.L1	ma.L1	ma.L2	ma.L3	sigma2	const	vars	AIC	BIC
coefficient	-0.8177***	0.3197*	-0.6692***	-0.3391***	0.0947***	-0.0917***	43 variables	-503.42	-364.65
std	-0.1694	-0.164	-0.1164	-0.0677	-0.0091	-0.0247	8 exogenous variables	-548.02	-535.72

Table 3(c). ARMAX model result of index3

Diagnostic Tests of the ARMAX model

Finally, we did a diagnostic test to evaluate whether the residual series was white noise through the Ljung-Box Q test. The P-values are 2.47, 2.75 and 0.95 in the three models which are higher than 0.05 and showed that there is no autocorrelation in the residual of the model. After that, we could determine the three optimal ARMAX models in the following ways:

$$Index1 = -0.1524 + 0.3155 Btc/Eth + 0.2767 Bitcoin_{t-1} + 0.5281 Btc/Eth_{t-2} - 0.5059 WTI + 0.8226 FTSE + 0.8912 S\&P500_{t-2} + 1.4457 Bond_{t-2}$$

$$Index2 = -0.0917 + 1.2517 Btc/Eth_{t-2} + 2.9225 FTSE$$

$$Index3 = -0.0917 - 0.8177\, Index3_{t-1} + 3.8875 SHZH - 3.3090 HSI + 5.3478 S\&P500_{t-1} + 3.7399 N225_{t-2} - 4.0256 HSI_{t-2} - 1.8740 Btc/Eth_{t-1} + 9.2919 Bond_{t-1} + 1.3087 Negative_{t-1} + 0.3197 MA_{t-1} - 0.6692 MA_{t-2} - 0.3391 MA_{t-3}$$

Just as the equations show, NFT market indices have a relationship with cryptocurrency market, stock market, future market, bond market and social media opinions, but different ways to construct NFT market index lead to different results. Index1, the average-weighted NFT market index, shows strong relationship with cryptocurrency market. Index1 not only relates to current stage Btc/Eth rate of change, but also relates to past stage bitcoin returns and Btc/Eth rate of change. Besides, Index1 shows relationship with stock market index, future market, and bond market. For Index2 which is the price-weighted index, only Btc/Eth in the past two days earlier and FTSE show the colinear relation. For Index3, seven exogenous variables present significant relationship, including four stock market indices (SSE, HSI, S&P500, N225), one cryptocurrency market index, one bond index and negative opinions.

In the final determined models, all NFT market indices have a strong relationship with cryptocurrency and stock markets, and most of them are positively related. What's more, Index2 and Index3 show positive relationship with bond market index. In a word, NFTs have some similar financial characteristics with stock, cryptocurrency and bond assets. However, only index1 is negatively related to future market, meaning NFTs and future investment could be very different varieties. Contrary to expectations, index3 is positively related to negative opinions rather than positive opinions as shown in Figure 2. This confirms the prior findings that negative opinions generally spread faster than positive opinions (Fang & Ben-Miled, 2017). Positive opinions were not tested significantly in our 2-stage lag model. As negative opinions still play the mass media function to attract public attention, negative opinions are positively related to the NFT market index fluctuation rate.

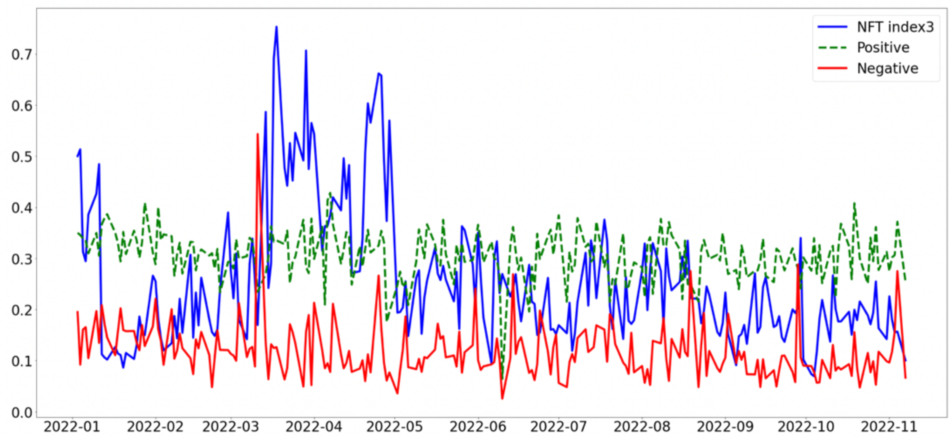

Figure 2. The relationship of NFT index3 returns and sentiment

CONCLUSION

This study is one of the earliest studies that constructs and tests the ARMAX model to estimate the impact of major financial markets on NFT markets and provides new insights for studying NFT markets and enriching existing NFT literature. We analyzed the correlations of returns on NFTs, cryptocurrency market, stock market, bond market, and as expected, the returns on NFT are highly correlated with these major financial markets. The result means that the demand for alternative investments increases with growth of aggregate financial wealth, which is not in line with previous empirical finding (Aharon & Demir, 2022) who claim that NFT markets are relatively independent of other financial markets. Also, our findings suggest that in 2022 when the world economy is in an increasingly gloomy and uncertain time, the NFT market is inevitably influenced by the economic ecology.

Moreover, our work provides empirical evidence to understand how the price changes in the NFT marketplace with the influence of investor sentiment. The volume-weighted NFT index is positively related to negative opinions which is quite on the contrary to earlier research (Yang, Liu, Chen, & Hawkes, 2018).There are three ways to explain the anomaly. First of all, Yu and Yuan (2011) suggested that market is less rational during high-sentiment periods due to higher participation by noise traders in such periods. Thus, even the opinions about NFTs are negative, many investors hunting for novelty just jumped into the market. Secondly, the NFT market does not have short selling which could eliminate sentiment-driven mispricing. Stambaugh et al. (2012) concluded that overpricing is more prevalent when market-wide sentiment is high but with a short selling obstacle. Thirdly, according to classic investment theory, rational investors are risk-aversion, but during high-sentiment periods, irrationality makes noise traders behave as if they are less risk averse than rational investors (Baker & Wurgler, 2007). As a result, this approach could help them survive or even come to dominate financial markets (Guidolin & Ricci, 2020). We believe that these theories help explain the anomaly in the NFT market of 2022. Building on existing insights, the interesting results we found can enlighten further study of the relationship among NFT markets, major financial market and investor sentiment.

For practitioners, our NFT market index provides insight to guide their future investment and decision making on NFTs. Additionally, our model and results could be a reference for future investment in the NFT market. We suggest that managers pay attention to the diversity of the NFT market and don't take the NFT market as an isolated investment.

Our work has several limitations. First, our data covers a period of 221 trading days and as a result the effect we are observing could be temporary. Besides, we only analyze some selected NFTs with continuous transactions instead of the entire NFT collections. in the future we should collect the trading data for a long period to do analysis in different situations. Second, we did not look at other factors such as market manipulation in pricing, fraud, and sentiments from other channels and how they affect the price change of the NFT market.

Overall, our study contributes to emerging literature related to NFTs and leads to a better understanding of the relationship among NFT markets, cryptocurrency market, stock market and investors' sentiment. Our findings show that all NFT market indices have a strong relationship with cryptocurrency market and stock market and most of them are positively related. Future research needs to be focused on empirical and longitudinal research of potential factors that lead to NFT prices and values change as well as the use cases of NFTs in various industries.

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