Anatomizing the returns of non-fungible tokens: Evidence from the CryptoPunks

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Abstract

We use transaction data on CryptoPunks to anatomize the factors affecting the returns of non-fungible tokens (NFTs). Our results show that trading volume in the short period before a trader buys (sells) CryptoPunk relates negatively (positively) to the returns on NFTs, suggesting that when market trading volume is at a high level, NFT owners are better off on the sell side, and investors interested in NFTs should avoid joining the herd. Turnover of a token tends to harm its returns. Finally, both traders' willingness to purchase and trading experience have a positive impact on NFT returns within short-term investment horizons.

Keywords: CryptoPunks; NFTs; Non-fungible tokens; COVID-19; Ethereum

JEL classification: C14; C22; G14; G15

1. Introduction

Non-fungible tokens (NFTs) are blockchain-based crypto assets that represent the unique ownership of an intangible digital item. NFT markets trading digital artwork saw unprecedented outperformance in early 2021 thanks to the COVID-19 pandemic. Notable examples include artist Beeple's digital work, *Everydays: The First 5000 Days*, which sold for $69 million at Christie's, and Jack Dorsey's first tweet on Twitter, which auctioned for $2.91 million through the Valuables platform. Despite the unbelievable and controversial nature of these transactions, NFTs do bring a new dimension and an intriguing topic of discussion to cryptocurrency markets, as well as offering a realizable channel of wealth for their enthusiasts.

This study contributes to the literature by using transaction data on CryptoPunks to investigate the factors affecting returns on NFTs. We find that trading volume in the short period before a trader buys (sells) CryptoPunk relates negatively (positively) to returns on NFTs. The turnover of a token tends to harm its returns. Finally, traders' willingness to purchase and trading experience positively affect the returns on NFTs within short-term investment horizons.

Arising from the success of the NFT markets, a growing body of literature has focused on related issues. For example, Kong and Lin (2021) explore the pricing and risk-return profile of the CryptoPunks project (the largest single traded market in NFTs). They find that although NFTs offer higher returns than do traditional financial assets, investment in them is accompanied by extremely high volatility. Furthermore, the pricing of NFTs is driven primarily by the scarcity of tokens and the aesthetic preferences of investors. Mazur (2021) investigates the risk and return characteristics of various NFT-based startups listed on the Binance exchange. His results show that in addition to high first-day returns, NFTs yield prodigious long-term returns on both a raw and a risk-adjusted basis and generate significantly positive alpha. Moreover, Vidal-Tomás (2022) demonstrates that the NFT categories with play-to-earn and metaverse properties have positive long-term performance. These results also support Dowling's (2022a) finding that the pricing behavior of the NFT market is inefficient in the early stage of market development.

Other recent studies have investigated the connectedness or interrelationship between NFTs and other major asset classes. Specifically, Ante (2021a) shows that the Bitcoin/Ether (larger) market affects the growth and development of the NFT (smaller) market, while Ante (2021b) further finds that the NFT submarkets are cointegrated and that there exist various casual short-term connections between them. Using three popular NFT collections (Decentraland, CryptoPunks, and Axie Infinity), Dowling (2022b) documents co-movement between NFTs and Ethereum markets. Additionally, Aharon and Demir (2021) find that NFTs are independent of shocks to other asset classes, while Vidal-Tomás (2022) shows that metaverse and play-to-earn tokens are unconnected with the cryptocurrency market, suggesting that NFTs have diversification benefits for market uncertainty caused by infectious disease. Umar et al. (2022) further document that NFTs absorbed risk during the COVID-19 pandemic only for a short investment horizon of less than two weeks.

In contrast to previous studies focusing on pricing and return characteristics (e.g., Dowling, 2022a; Kong and Lin, 2021; Mazur, 2021), we explore factors that might affect the returns on the NFT market by using detailed transaction data from the largest NFT project, CryptoPunks, from June 2017 to December 2021. Our study is crucial due to at least the following facts. First, the Global Google Trends shown in Figure 1 reveal that "NFT" has surpassed "Crypto" according to search volume as of January 2022, highlighting that NFTs have become the new center of attention in the cryptocurrency industry (see Vidal-Tomás, 2022) as well as potentially becoming a new asset class for the young generation. Second, NFTs are relevant to the fast development of Web 3.0 because NFTs with digital scarcity allows users of this new network to exchange everything in their virtual reality world, for example, in the metaverse.

The rest of this study is structured as follows. Section 2 describes the empirical data and methodology. Section 3 presents the descriptive statistics and estimation results. Section 4 concludes this study.

2. Data and methodology

2.1 Data description

In this study, we use CryptoPunks for our empirical analysis because it is one of the earliest and largest NFT projects (e.g., Dowling, 2021; Kong and Lin, 2021) as well as a leading blue chip in the current NFT market. Specifically, there are 10,000 unique generated characters with proof of ownership stored on the Ethereum blockchain. CryptoPunks can be briefly classified into five types based on their attributes: Alien, Ape, Zombie, Female, and Male (in order of rarity). The market statistics[1] show that CryptoPunks (those available) have a floor price of 70 ETH ($220,949), and the total value of all sales during the lifetime of this project has reached $2.07 billion as of February 16, 2022, which further highlights the importance and popularity of the project. Our empirical period of June 2017 to December 2021 saw a total of 13,189 transactions. The data are freely available from the website of Larva Labs (www.larvalabs.com/).

2.2 The empirical model

For a given transaction *i*, the return of the trader (i.e., the CryptoPunk's owner) can be expressed as follows:

$$PunkRet_i = \frac{P_{i,S} - P_{i,B}}{P_{i,B}} \times \frac{365}{Nday_i} \tag{1}$$

[1] According to nonfungible.com as of February 16, 2022: nonfungible.com/market/history

where $PunkRet_i$ denotes the annualized return of the punk of transaction i from buying at price $P_{i,B}$ on day $Date_{i,B}$ to selling at price $P_{i,S}$ on day $Date_{i,S}$. Both $P_{i,B}$ and $P_{i,S}$ are denominated in U.S. dollars; $Nday_i$ denotes the investment horizon and can be defined as the number of holding days for transaction *i* from buying to selling (i.e., $Nday_i = Date_{i,S} - Date_{i,B} + 1$).

We use a transaction history sample recorded by Larva Labs to illustrate our empirical data structure, as well as the variables defined in the previous paragraph. Take the transaction of address 0x944f9f*** in Figure 2 for example. This user bought the CryptoPunk (#2382) on September 6, 2021 for $391,198 (i.e., $P_{i,B}$) and then sold it to address 0x6f6ab4*** on September 9, 2021 for $356,222 (i.e., $P_{i,S}$). In this transaction, the user with address 0x944f9f*** held the CryptoPunk for 4 days (i.e., $Nday_i$). Thus, the corresponding annualized return (i.e., $PunkRet_i$) for this transaction was -8.1584 ($= \frac{356{,}222-391{,}198}{391{,}198} \times \frac{365}{4}$).

[Insert Figure 2 about here]

We use the following empirical model to anatomize the return on the NFT market:

$$PunkRet_i = \alpha + \beta_1 BVol7_i + \beta_2 SVol7_i + \beta_3 BOD_i + \beta_4 MarketRet_i + \beta_5 Punknum_i + \beta_6 Experience_i + \theta X + \varepsilon_i \quad (2)$$

where $BVol7_i$ ($SVol7_i$) denotes the trading volume of the entire CryptoPunk market within the seven days prior to the date (i.e., $Date_{i,B}$ ($Date_{i,S}$)) that the punk of transaction *i* was bought (sold). This allows us to discuss the effect of the overall market liquidity/activity on the return on CryptoPunks. BOD_i denotes the difference between the number of bids and the number of offers within the duration of the period in which transaction *i* is completed. For example, for the transaction from address 0x944f9f*** to address 0x6f6ab4*** in Figure 2, there were 2 bids and 7 offers between September 6, 2021 and September 9, 2021. Thus, $BOD_i = 2 - 7 = -5$. The BOD_i can be linked to traders' willingness or interest in buying the punk and is expected to have a coefficient with a positive sign. $MarketRet_i$ denotes the annualized NFT market return with the same duration as transaction *i*. In this study, we use the average asset sale USD value available at nonfungible.com as a proxy for the overall NFT market price. $Punknum_i$ denotes the number of times the punk associated with transaction *i* has ever been traded. We use $Punknum_i$ as a measure for turnover, which allows us to explore its relationship with the return of CryptoPunks. $Experience_i$ denotes the number of trades the seller (owner) associated with transaction *i* has ever made. We use $Experience_i$ to examine whether the trading experience increases CryptoPunks' returns on the basis of Ivković et al.'s (2008) and Fjesme's (2020) documentation that as retail investors gain more trading experience, their ability to turn portfolio concentration into excess returns improves. Hence, we expect a positive relationship between $Experience$ and $PunkRet$. Last, X denotes the vector of dummy variables for controlling the year and the type of CryptoPunks.

3. Descriptive statistics and empirical results

3.1 Descriptive statistics

Table 1 presents the descriptive statistics of various variables and their corresponding correlation matrix. We find that the annualized return of CryptoPunks ($PunkRet$) has a mean of 42.608 and varies in a wide range between -15.719 and 1069.255. While the average annualized return for CryptoPunks is more than four times that of the entire NFT market, this single NFT market also has a considerably higher standard deviation than does the market. The negative mean of the BOD (-2.706) shows that the number of offers during the transactions is, on average, greater than that of bids. Moreover, the average turnover ($Punknum$) and trading experience ($Experience$) during our sample period are 2.825 and 27.196, respectively. The correlation matrix in the right-hand part of Table 1, on the other hand, provides a better understanding of the relationship between these variables. The results show that the correlation coefficients of $SVol7$, BOD, $MarketRet$, and $Experience$ with $PunkRet$ are positive, while $BVol7$ and $Punknum$ exhibit a negative relation.

[Insert Table 1 about here]

3.2 Empirical results and analysis

Table 2 presents the regression result for the full sample; we winsorize our sample at the 1^{th} and 99^{th} percentiles to mitigate the effect of outliers on the estimation. When year and CryptoPunk type fixed effects are controlled for, our result shows that the estimated coefficients of all variables considered are significant at least at the 5% level. For example, $BVol7$ is negatively correlated with the returns on CryptoPunks, while $SVol7$ has an opposite effect. The practical implication of such results is clear. Namely, when trading volumes are at high levels or the market is actively traded, owners of NFTs are better off on the sell side, and investors who are interested in NFTs should avoid joining the herd. As expected, traders' willingness to buy that is proxied by the BOD has a positive impact on CryptoPunk returns. Moreover, the negative sign for $Punknum$ indicates that the turnover of CryptoPunks tends to harm the return of NFTs. This finding is also in line with the general perception that the more collectable the artwork is, the less liquid it should be. Last, $Experience$ exhibits a positive relation, suggesting that trading experience facilitates investors' ability to turn portfolio concentration into excess returns (Fjesme, 2020), thus increasing their returns obtained from the NFT market.

[Insert Table 2 about here]

To further examine whether the investment horizon affects the relationship between various independent variables and the dependent one, we divided our sample observations into two subsamples according to the number of holding days (i.e., $Nday$) of the transaction data. Table 3 presents related regression results: the left-hand (right-hand) part shows the result for subsample ST (LT) with a short-term (long-term) investment horizon[2]. We find that most of the results in Table 3 are consistent with those in Table 2, with the exception of BOD and $Experience$. Specifically, the coefficients of both BOD and $Experience$ remain significantly positive for subsample ST but become insignificant for subsample LT. These results also show that the effects of willingness to buy and trading experience on the returns of NFTs play a significant role only within short-term investment horizons.

[Insert Table 3 about here]

4. Conclusions

This study anatomizes the returns of the NFT market by using a detailed transaction dataset from CryptoPunks from June 2017 to December 2021. Our results show that this single NFT project has a substantially higher annualized return and volatility than the entire market. The trading volume in the short period before a trader buys (sells) CryptoPunk is negatively (positively) correlated with returns on NFTs, suggesting that when the market trading volume is at a high level, NFT owners are better off on the sell side, and investors interested in NFTs should avoid joining the sheep flock. Moreover, turnover tends to harm the returns of the token. Finally, both traders' willingness to purchase and trading experience have a positive impact on NFT returns within short-term investment horizons.

[2] We choose 30 days (1 month) as the cut-off point between short- and long-term investment horizons to facilitate the balancing of subsample data points.

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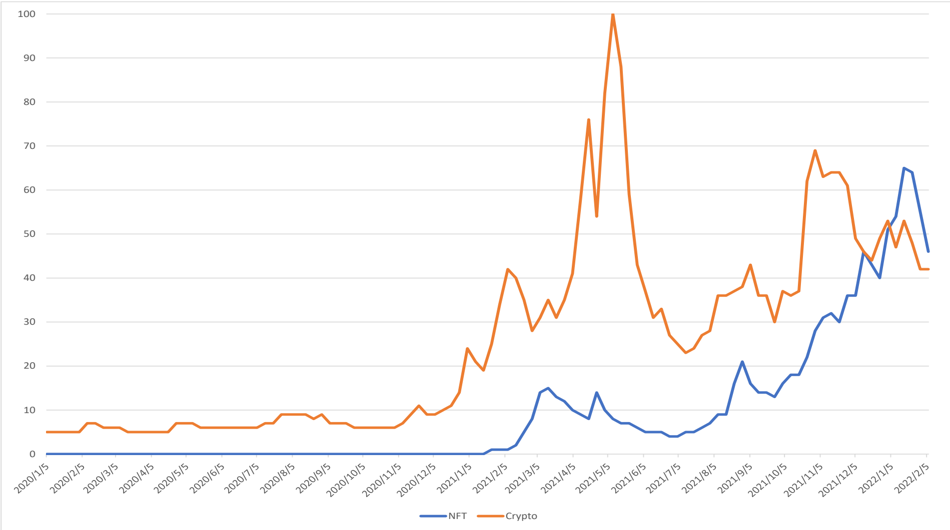

Figure 1. Global Google Trends for the keywords "NFT" and "Crypto"

Transaction History

Type	From	To	Amount	Txn
Sold	0x6f6ab4	0xf605c6	129Ξ ($385,301)	Sep 30, 2021
Offered			129Ξ ($403,542)	Sep 23, 2021
Bid Withdrawn	0xdb1cf6		110Ξ ($343,444)	Sep 23, 2021
Bid	0xdb1cf6		110Ξ ($342,348)	Sep 23, 2021
Bid	0x1649b2		102Ξ ($311,150)	Sep 20, 2021
Offered			119Ξ ($363,008)	Sep 20, 2021
Offered			129Ξ ($468,816)	Sep 16, 2021
Offered			119.50Ξ ($397,639)	Sep 14, 2021
Offered			139.50Ξ ($482,392)	Sep 09, 2021
Sold	0x944f9f	0x6f6ab4	101Ξ ($356,222)	Sep 09, 2021
Bid	0x6f6ab4		101Ξ ($356,222)	Sep 09, 2021
Bid Withdrawn	0x6f6ab4		95Ξ ($330,286)	Sep 09, 2021
Offered			104.90Ξ ($364,706)	Sep 09, 2021
Bid	0x6f6ab4		95Ξ ($330,098)	Sep 08, 2021
Offered			109Ξ ($379,147)	Sep 08, 2021
Offered			119Ξ ($399,578)	Sep 08, 2021
Offered			129Ξ ($449,988)	Sep 08, 2021
Offered			134Ξ ($453,067)	Sep 07, 2021
Offered			139Ξ ($546,630)	Sep 07, 2021
Offered			149Ξ ($582,885)	Sep 06, 2021
Sold	black1ce...	0x944f9f	100Ξ ($391,198)	Sep 06, 2021

Figure 2. A portion of transaction history (CryptoPunk #2382)

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Table 1. Basic statistics and correlation matrix

This table presents descriptive statistics on various variables ($PunkRet$, $BVol7$, $SVol7$, BOD, $MarketRet$, $Punknum$, and $Experience$) and the corresponding correlation matrix. Our sample comprises 13,189 transactions from June 2017 to December 2021.

Variable	Mean	Std.	Median	Max.	Min.	Correlation Matrix (1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $PunkRet$	42.608	110.104	12.751	1069.255	-15.719	1.000						
(2) $BVol7$	344.549	322.802	230.000	1265.000	0.000	-0.142	1.000					
(3) $SVol7$	384.853	335.881	239.000	1265.000	1.000	0.118	0.350	1.000				
(4) BOD	-2.706	4.363	-1.000	16.000	-56.000	0.056	-0.056	0.054	1.000			
(5) $MarketRet$	10.211	23.246	2.955	368.060	-61.743	0.322	-0.186	0.215	0.028	1.000		
(6) $Punknum$	2.825	2.144	2.000	19.000	1.000	-0.103	0.225	0.090	-0.013	-0.008	1.000	
(7) $Experience$	27.196	65.415	6.000	536.500	1.000	0.000	-0.028	0.013	0.018	0.016	-0.062	1.000

Table 2. The regression result for the full sample

This table presents the result for the full sample using the following regression model:

$$PunkRet_i = \alpha + \beta_1 BVol7_i + \beta_2 SVol7_i + \beta_3 BOD_i + \beta_4 MarketRet_i + \beta_5 Punknum_i + \beta_6 Experience_i + \theta X + \varepsilon_i$$

where $BVol7_i$ ($SVol7_i$) denotes the trading volume of the entire CryptoPunk market within the seven days prior to the date that the punk of transaction *i* was bought (sold). BOD_i denotes the difference between the number of bids and the number of offers within the duration of the period in which transaction *i* was completed. $MarketRet_i$ denotes the annualized NFT market return with the same duration as transaction *i*. $Punknum_i$ denotes the number of times the punk associated with transaction *i* has ever been traded. $Experience_i$ denotes the number of trades the seller (owner) associated with transaction *i* has ever made. X denotes the vector of year and CryptoPunk type dummy variables. ** and *** denote significance at the 5% and 1% levels, respectively.

Variable	Estimate	S.E.	*p*-value
$BVol7$	-0.0247***	0.0029	0.0000
$SVol7$	0.0391***	0.0027	0.0000
BOD	0.5928***	0.1831	0.0012
$MarketRet$	0.6426***	0.0387	0.0000
$Punknum$	-0.9654**	0.3882	0.0129
$Experience$	0.0255**	0.0121	0.0360
$Constant$	-87.25	88.09	0.3219
Adjusted R^2		0.3656	
Year FE		YES	
Type FE		YES	
No. of obs.		12,818	

Table 3. Regression results for two subsamples

This table presents the results for two subsamples using the following regression model:

$$PunkRet_i = \alpha + \beta_1 BVol7_i + \beta_2 SVol7_i + \beta_3 BOD_i + \beta_4 MarketRet_i + \beta_5 Punknum_i + \beta_6 Experience_i + \theta X + \varepsilon_i$$

where $BVol7_i$ ($SVol7_i$) denotes the trading volume of the entire CryptoPunk market within the seven days prior to the date that the punk of transaction *i* was bought (sold). BOD_i denotes the difference between the number of bids and the number of offers within the duration of the period in which transaction *i* was completed. $MarketRet_i$ denotes the annualized NFT market return with the same duration as transaction *i*. $Punknum_i$ denotes the number of times the punk associated with transaction *i* has ever been traded. $Experience_i$ denotes the number of trades the seller (owner) associated with transaction data *i* has ever made. X denotes the vector of year and CryptoPunk type dummy variables. *** denotes significance at the 1% level.

	Subsample *ST* ($Nday \leq 30$)			Subsample *LT* ($Nday > 30$)		
Variable	Estimate	S.E.	*p*-value	Estimate	S.E.	*p*-value
$BVol7$	-0.0106^{***}	0.0022	0.0000	-0.0584^{***}	0.0054	0.0000
$SVol7$	0.0319^{***}	0.0021	0.0000	0.0171^{***}	0.0047	0.0002
BOD	1.2774^{***}	0.1828	0.0000	0.0662	0.2691	0.8058
$MarketRet$	0.1000^{***}	0.0276	0.0003	1.1508^{***}	0.0691	0.0000
$Punknum$	-0.6149^{***}	0.2379	0.0010	-2.3830^{***}	0.7922	0.0026
$Experience$	0.0193^{***}	0.0070	0.0058	-0.0372	0.0282	0.1874
$Constant$	102.89^{***}	24.25	0.0000	-135.20	112.08	0.2277
Adjusted R^2		0.1104			0.4214	
Year FE		Yes			Yes	
Type FE		Yes			Yes	
No. of obs.		6,220			6,598	