The Economics of Non-Fungible Tokens*

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Abstract

We construct a comprehensive dataset on a near universe of non-fungible token (NFT) transactions, create indices for the NFT market and its components, and analyze their properties. The NFT market return is significantly exposed to the cryptocurrency market, but the majority of the return variations remain unexplained. NFT market returns have low exposures to other cryptocurrency factors and factors from traditional asset markets. In the time-series, volatility and the NFT valuation ratio significantly predict NFT market returns. In the cross-section, NFT returns exhibit size and return reversal effects.

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1 Introduction

Non-fungible tokens (NFTs) are blockchain-based assets representing ownership of unique digital or physical items. There is a range of views on what NFTs may represent. On the one hand, NFTs are thought to be a key element of the metaverse and Web3.0 [1] and a revolution in how digital assets are marketed and monetized[2]. On the other hand, the critics regard them as a fad fueled by celebrities[3] and a way to launder money and avoid taxes[4]. NFTs share many similarities with cryptocurrencies, with a key difference: they are not mutually interchangeable, or not fungible.

We construct a comprehensive dataset for the overall NFT market, major NFT categories, and prominent NFT collections. We aggregate transactions from the major exchanges and extensively cross-validate them with the direct blockchain data in order to establish the quality and reliability of the dataset. The data spans from the beginning of 2018 to the end of 2021. The extent and comprehensiveness of our data allows both the overall and the granular view of the NFT market from studying the market performance at the daily frequency to detailed analysis at the collection and category level. The data cover not just the digital art and media categories but also a variety of other key objects such as those related to virtual worlds. This is important as many commentators argue that the main future applications of the NFTs are in their potential of becoming the cornerstone for the metaverse.

Given the comprehensive data that we assemble, a natural way to construct an overall index of the NFT market is to use the repeat sales method (e.g., Bailey et al. (1963)). The repeat sales method has been applied to many different markets where individual properties are heterogeneous and individual trades infrequent, such as the real estate market (e.g., Case and Shiller (1987); Case and Shiller (1989)). The repeat sales method is particularly suitable for the NFT market because individual NFTs significantly differ from each other even within a given collection and also are traded infrequently, making alternative methods such as median price and hedonic models problematic.

The repeat sales regressions show that the NFT market index accounts for 28.5 percent of the variation in the NFT returns, implying that there is an important common component in the NFT market that is captured by our NFT market index. For five prominent NFT collections, the explanatory power of the collection-specific indices is much higher and ranges from 55 percent for CryptoKitties to 89 percent for Bored Ape. The average NFT market return is 2.5 percent per week,

[1] For example, see https://www.forbes.com/sites/josephdeacetis/2022/02/08/the-rise-of-the-metaverse-where-crypto-nft-and-luxury-brands-merge.

[2] For example, see https://fortune.com/2022/02/15/steve-aoki-nft-music-royalties/.

[3] For example, see https://time.com/nextadvisor/investing/cryptocurrency/are-nfts-good-investment/.

[4] For example, see https://fortune.com/2022/02/11/are-nfts-being-used-to-launder-money-crypto-regulation-art-tech-martin-cheek/.

with a weekly standard deviation of about 19 percent. The average weekly NFT market return is more than twice as high in magnitude as that of the cryptocurrency market return (1.1 percent per week), and an order of magnitude larger than that of the stock market return (0.3 percent per week). The NFT market return has large skewness of about 1.1 and large kurtosis of about 8, both of which are larger than those of the coin market return.

We then examine the relationship between the NFT market and factors from other asset markets. We first study its relationship with the cryptocurrency market because both markets are based on blockchain technology. Moreover, NFTs are commonly traded using cryptocurrencies instead of fiat money. We test the NFT market exposure to the cryptocurrency factors, including the cryptocurrency market, size, momentum, and value factors (see Liu et al. (2021a; 2021b)). The NFT market excess return is positively and significantly exposed to the coin market excess return at the 1-percent level – a one percent increase in the coin market excess return is associated with a 0.789 percent increase in the NFT market excess return. The explanatory power of the regression as measured by R-squared is about 20 percent, implying that the majority of the NFT market variation is not captured by the cryptocurrency market despite the fact that the NFTs are commonly traded in cryptocurrencies. Moreover, the NFT market excess return is not significantly exposed to the cryptocurrency size, momentum, and value factors.

We continue to examine the exposure of the NFT market to traditional assets such as equity, commodity, and currency. We find that the NFT market excess return is significantly exposed to the aggregate stock market return, although the explanatory power of the equity excess returns is low and the significance disappears after controlling for the cryptocurrency market returns. Furthermore, the alphas controlling for the equity factor models are quantitatively similar to the average excess returns of the NFT market.

We then study how the NFT market returns comove with the related cryptocurrencies, where the NFT-related cryptocurrencies are coins used to buy NFTs. The returns of the NFT-related cryptocurrencies significantly exposed to the NFT market returns, even controlling for the cryptocurrency market returns. Moreover, we find that the NFT market excess returns positively and significantly predict future cumulative excess returns of NFT-related cryptocurrency returns. At the two-week horizon, a one percent increase in the NFT market excess return is associated with a 0.330 percent increase in the cumulative NFT-related cryptocurrency index returns.

Next, we examine the return predictability of the NFT market. We start with the index level time-series return predictability. We first examine whether NFT market volatility can predict future NFT market returns. We find that the NFT market volatility negatively predicts future cumulative NFT market excess returns. The economic magnitude of the return predictability is large. For example, a one-standard deviation increase in the NFT market volatility measure is associated with a 14.8 percent decrease in the cumulative excess returns of the NFT market at the eight-week horizon, with a corresponding R-squared of 8.4 percent.

We then construct a valuation ratio for the NFT market – the logged index-to-transaction ratio – and find that it negatively and significantly predicts future cumulative NFT market returns. For example, a one-standard-deviation increase in the logged index-to-transaction ratio is associated with a 19.1 percent decrease in the cumulative excess return of the NFT market at the five-week horizon, with a corresponding R-squared of 20.6 percent. The return predictability of the logged index-to-transaction ratio is not subsumed by the NFT volatility measure. The lagged NFT market volatility and the logged index-to-transaction ratio together account for up to 30 percent of the variation of future cumulative NFT market excess returns at the eight-week horizon as measured by R-squared.

Additionally, we examine attention, past returns, and volume as NFT market return predictors. We measure attention to the NFT market and to the cryptocurrency market using Google searches. We show that neither the attention to the NFT market nor the attention to the cryptocurrency market significantly predict future NFT market returns. The past returns of NFTs also do not significantly predict future cumulative NFT market returns at any horizon. The return predictability of volume is largely subsumed by the volatility measure and the valuation ratio.

Lastly, we study the cross-sectional predictability of individual NFT returns of a set of candidate factors. The size effect is one of the earliest return predictor found in the equity market (e.g., Banz (1981)). We find a size effect in the NFT market. We show that doubling the logged NFT purchase price is associated with a 0.4 percent decrease in weekly return, or 20.8 percent annually. Furthermore, we study whether the returns of NFTs are related to their past returns. We show that NFTs with high average weekly returns in their previous repeat sales underperform their respective NFT market index. This reversal effect is consistent with the long-term reversal effect documented in the equity market as in De Bondt and Thaler (1985). As argued in Fama and French (1993) and Asness et al. (2013), the long-run reversal effect is linked to the value effect.

Literature. There is a small literature analyzing various aspects of NFTs. Goldberg et al. (2021) and Dowling (2022) study land pricing in Decentraland. Kireyev and Lin (2021) develop a structural model of valuation for CryptoKitties. Kong and Lin (2021) study the CryptoPunks, a popular NFT collection, using hedonic models. Scharnowski et al. (2021) study fan tokens which can also be thought of as a form of NFTs. Nadini et al. (2021) collect the data from all of the NFT transactions on OpenSea upto March 2021. They report some statistical properties of the market, build a network of trades, and use some of the network and market features to predict prices using machine learning. One limitation of their data is that the NFT market has dramatically expanded since that time. Goetzmann and Nozari (2022) use both the data from Nadini et al. (2021) to construct weekly repeated sales indices and the data from SuperRare to construct monthly repeated sales indices of NFTs and examine their properties. They also provide a number of insights related to the detailed structure of the supply and demand for the market. Our paper, while sharing the focus on the NFT market and its properties with the literature, builds on the comprehensive dataset that covers the near universe of the NFT transactions and allows a comprehensive view of the market and the high-resolution view of its components.

The NFTs are developed using blockchain technology. The study of blockchain technology, as well as its cryptocurrency application, consists of a growing body of research. Liu and Tsyvinski (2021), and Liu et al. (2021a; 2021b) comprehensively study the valuations of the cryptocurrency market in the aggregate time-series and the cross-section. Makarov and Schoar (2020) and Borri and Shakhnov (2018) find that there is dispersion of Bitcoin prices in different exchange platforms at the same moment and Borri and Shakhnov (2022) propose a risk-based explanation of this stylized fact. Hu et al. (2019) show that cryptocurrency returns tend to be positively exposed to Bitcoin returns and Borri and Santucci de Magistris (2021) find that Bitcoin returns reflect a compensation for higher-order moments and tail risk. Shams (2020) studies the correlation structure of cryptocurrencies. Griffin and Shams (2020) suggest potential manipulations in the cryptocurrency market. Benetton et al. (2021) study electricity consumption of cryptocurrency mining. Benetton and Compiani (2021) focus on investor's cryptocurrency beliefs. A number of papers develop models of blockchain and cryptocurrencies (see, e.g., Abadi and Brunnermeier (2018); Cong and He (2019); Easley et al. (2019); Schilling and Uhlig (2019); Biais et al. (2020); Sockin and Xiong (2020); Cong et al. (2021); Huberman et al. (2021); Routledge and Zetlin-Jones (2021)).

2 Data

We construct a comprehensive dataset for the overall NFT market, major NFT categories, and prominent NFT collections. We aggregate the data from the major exchanges – Cryptokitties, Gods Unchained, Decentraland, OpenSea, and Atomic – and cross-validate them with the direct blockchain data in order to establish the quality and reliability of the dataset. Our dataset includes only transactions representing the transfer of ownership of NFTs, while we exclude transactions corresponding to the minting of NFTs or auction bids. For our baseline analysis, we use weekly data. We divide each year into 52 weeks. The first week of the year consists of the first seven days of the year. The first 51 weeks of the year consist of seven days each and the last week of the year consists of the last eight days of the year. If an NFT is traded more than once in a week, we take the average price. We require the trades to be in USD, ETH, WETH, or MANA. The data spans from the beginning of 2018 to the end of 2021. Importantly, our data covers the dramatic increase in the number of transactions on all major NFT exchanges starting from about March 2021. For our baseline specification, we convert all transaction prices to U.S. dollars. In some of the specifications, we also construct indices using cryptocurrency denominated price series. We also present results based on the daily index in the Appendix.

Because transactions related to transfers of ownership of NFTs are registered on the blockchain, it is possible to directly refer to the blockchain to track these transactions. In order to establish a high-quality and reliable dataset, we cross-validate our data by verifying, for random subsamples of our dataset, the information from the exchanges using the information available from the blockchain. This is possible as the records obtained from the exchanges contain information such as the transaction hash, block number and address of the parties involve in a transaction. Specifically, for each record in the random sample, we confirm that the NFT name, identifier and transaction price correspond between our dataset and the information on the blockchain. This cross-validation ensures the quality and reliability of the data we use in the construction of the NFT market index.

To construct a repeat sales index, we link each consecutive sale of an NFT together. If an NFT is not traded, or only traded once in our sample, the NFT then does not enter into the construction of our index. Some NFTs had multiple resales over the years. We consider each resale pair as a unique observation in our dataset. In total, there are about 1.3 million repeat sales in our sample. Our data has continuous observations since 2018, which allow us to construct NFT indices at the daily and weekly level. We denote the first price from each price pair as purchase price, and the second price as the sale price. Sales prices capture the price change for the same NFT, while holding its characteristics constant.

Figure A.2 in the Appendix presents the number of repeat sale observations and the volume of total transactions. Panel A plots the number of repeat sale observations by sale for each week. The number of observations is low at the beginning of the sample. The number of observations starts to increase in 2020, reaching more than 5,000 observations per week by the end of 2020. In 2021, the number of observations increased dramatically, passing 40,000 observations in a single week. Figure A.3 in the Appendix presents the number of repeat sale observations by sale for the full sample against that for the CryptoKitties sample. Before 2019, the vast majority of the sample is from the CryptoKitties. The share of CryptoKitties gradually decreases over time. In the recent sample, the majority of the sample is non-CryptoKitties.

Furthermore, Panel B of Figure A.2 plots the volume of total transactions for each week, where the volume measure includes all repeat sales transactions in the week. The transaction volume of the NFT market is relatively low until late 2020 when the volume of the market passes one million dollars per week. In 2021, the volume of the NFT market rapidly increased, passing 200 million dollars per week.

In Figure A.1 in the Appendix, we plot the average trading gap between the purchase transaction and the sell transaction of the repeat sales within a week. The average trading gap between the purchase transaction and the sell transaction gradually increases between 2018 and 2020, reaching more than 20 weeks in mid- to late-2020. As a reference, the trading gap has decreased quickly since 2021 to less than 10 weeks.

We also investigate the properties of the NFT market at two higher-resolution levels. First, we classify major NFTs into several categories: Art & Media, Avatars, Games, Virtual World, and Other. Second, we study a number of popular NFT collections. The NFT collections we study include CryptoKitties, CryptoPunks, Bored Ape Yacht Club, Sup Ducks, and Decentraland.

We obtain the stock market factors for the Fama-French 3-factor, Carhart 4-factor, and Fama-French 5-factor models from the Kenneth French website. The commodity and currency indices are from Bloomberg. Individual stock returns are from CRSP. Individual cryptocurrency returns are from Cryptocompare.

3 Index Construction and Summary

Repeat sales regression method is heavily used and relied on in markets where individual asset properties are heterogeneous and when assets trade infrequently. The real estate market is the classic example of such a market and in fact the repeat sales regression method is originally developed to study the real estate market (e.g., Bailey et al. (1963); Case and Shiller (1987; 1989); Goetzmann (1992)). As argued by Shiller (2008), there are important advantages in the repeat sales method relative to earlier methods such as median price and hedonic models (e.g., Yeates (1965); Noland (1979)). Modern real estate indices such as the S&P/Case-Shiller index and the Federal Housing Finance Agency index are largely based on the repeat sales method. The repeat sales method is also central in the analysis of the more specialized markets such as the art market (e.g., Goetzmann (1993); Mei and Moses (2002); Goetzmann et al. (2011)) and the collectible wine market (e.g., Dimson et al. (2015))

Given the constructed comprehensive dataset, a natural way to study both the overall performance of the market and to have a high-resolution view of its components is to construct the repeated sale indices. We use all repeat sales to construct our NFT indices. In our baseline specification, we construct the indices based on the repeat sales regression method of Bailey et al. (1963). We also present results based on the three-stage repeat sales regression method of Case and Shiller (1987; 1989) and find qualitatively similar results.

3.1 Why Repeat Sales Method?

We first briefly discuss the repeat sales regression (RSR) method and the way we apply it to the NFT market. We assume that the difference in logged prices for two sales of an NFT is equal to the difference in the corresponding logged NFT market index, together with a random error term that captures the idiosyncratic component of the specific NFT. There are T time periods and sales can occur in any of the periods from 0 to T. We denote t as the subscript for the time period. In our baseline specification, a time period is a week. For a pair of sales of a given NFT i, prices and the NFT market index are assumed to be related as in the following equation:

$$\frac{P_{it'}}{P_{it}} = \frac{B_{t'}}{B_t} U_{itt'}$$

where P_{it} is the transaction price of NFT i at time period t. For a pair of sales, t is the time at the purchasing transaction and t' is the time at the sale transaction, and $t' > t$. B_t is the general NFT market price index at time t and $U_{itt'}$ is the multiplicative error term for the price pair as discussed above. The model can then be converted to the logged scale, which is the basis of the estimation:

$$r_{it't} = p_{it'} - p_{it} = b_{t'} - b_t + u_{itt'}$$

where p, b, and u are the logged versions of the corresponding terms above. The model is estimated using linear regression method and the estimated logged NFT market index is converted into a price index by taking the exponential. The returns of the NFT market are then calculated as the growth rate of the NFT market index. By construction, only NFTs that have been sold at least twice are used in the calculation of the index, and the remaining observations with only a single transaction are dropped.

In the repeat sales model of Bailey et al. (1963), the error term $u_{itt'}$ is assumed to be independent and identically normally distributed. Therefore, the estimation of the repeat sales index based on Bailey et al. (1963) requires only one step.

The repeat sales model of Case and Shiller (1987; 1989) assume that the error term is heteroscedastic. In particular, they argue that the time length between the purchasing transaction and the sale transaction should increase the variance of the differences of logged prices. Hence, the repeat sales model of Case and Shiller (1987; 1989) further requires the estimation of the variance of the logged error terms as a function of the time length between the purchasing transaction and the sale transaction. Overall, the repeat sales model of Case and Shiller (1987; 1989) is a three-stage procedure.

Now, we turn to the comparison of the repeat sales method to potential alternative methods in constructing the NFT market index. The alternative methods we consider include the methods based on cross-sectional sample moment and the hedonic models. The repeat sales method uses the purchase and sale prices of individual assets to estimate the fluctuation in the value of a representative asset. The main benefit of using the RSR method is that the resulting index is based upon price relatives of the same asset, thus controlling for all different qualities of the asset.

A naive way to construct a price index for the NFTs is to use some cross-sectional sample moments, such as the median price or the minimum/floor price. The most severe problem of a price index based on some cross-sectional sample moments is that it requires some form of homogeneity for the underlying assets, which is a strong assumption in the housing and art markets and a particularly strong assumption in the NFT market. The NFT market consists of many forms of underlying assets, including avatars (e.g., Cryptokitties), games (e.g., Gods Unchained), collectibles (e.g., Cryptopunks, Bored Ape), and virtual lands (e.g., Decentraland). Constructing an NFT market index based on some cross-sectional sample moments will likely result in spurious movements, making the construction of an overall NFT market index based on this method impossible. Even within a single collection, the properties of the individual items can differ dramatically. For example, it is known that the Cryptopunks with certain features are highly valued in the market, relative to the average Cryptopunks. The sales of these valuable Cryptopunks thus may result in large spurious movements in the Cryptopunk index based on the cross-sectional sample moments. Not surprisingly, the idea of constructing price indices based on some cross-sectional sample moments is largely discarded in the academic literature for constructing either housing price indices or art price indices (e.g., Shiller (2008); Nagaraja et al. (2014)).

As an illustration, we plot the median sale price and the minimum/floor sale price for the full sample and for the Cryptopunk sample in Figure A.4 in the Appendix. Panels A and B show the median price indices for the full sample and the Cryptopunk sample. We see that the median price indices for both the full sample and the Cryptopunk sample exhibit large fluctuations. Panels C and D show the minimum/floor price indices for the full sample and the Cryptopunk sample. The indices are even less stable than the median price indices because minimum/floor prices are heavily driven by outliers of the sample.

Another method that is proposed in the literature to construct price indices is the hedonic model. The problem with hedonic models is that there are too many possible variables that might be included, and the choice of the variables can be somewhat arbitrary. As pointed out by Shiller (2008), one could potentially vary the list of included variables until one found the results one wanted. This issue is particularly severe in the NFT market because of the vastly different nature of the collections of NFTs. In the real estate market, at least everyone would agree that the square footage of the properties should be included in the hedonic models. However, such variables are not immediately obvious in the NFT market. Moreover, as pointed out in Shiller (1994), the repeat sales regression is in its essence a hedonic regression where there is an indicator variable for each unique asset and none of the other hedonic variables is included. In other words, the repeat sales regression method is equivalent to taking each sale of NFT as an observation for the dependent variable and using the complete sets of time indicators and NFT indicators as independent variables. Therefore, any NFT that is only sold once is automatically dropped in this hedonic regression with complete sets of time and NFT indicators and has no effect on the estimation results. One can think of the repeat sales method as a hedonic model that eliminates any discretion in choosing hedonic variables.

One may argue that the indices based on the cross-sectional sample moments and hedonic models can incorporate information about single sales. However, as pointed out by Shiller (2008), indices that incorporate both new and existing sales can be highly problematic due to changes in the composition of sales. This issue is particularly severe in the NFT market. We plot the number of first-time sales as a fraction of the number of all sales over time in Figure A.5 in the Appendix. The fraction of the number of first-time sales relative to the number of total sales hovers around 80 percent in the sample, suggesting that the composition of the sample is changing in the market. This change in composition supports the view that it is a potentially important advantage of the repeat sales method the fact that it does not use new NFT prices. It is important to note also that, in contrast to, for example, the art market, the number of the repeat sale transactions we observe is very large and thus do not restrain the construction of the index.

Table 1: **Repeat Sales Regression R-Squared**

This table reports the explanatory power and number of observations in the repeat sales regressions. The results based on the full sample as well as each of the five collections are shown in the table. The five collections include CryptoKitties, CryptoPunks, Bored Ape Yacht Club, Sup Ducks, and Decentraland.

	Full Sample	CryptoKitties	CryptoPunks
R-squared	0.285	0.554	0.659
Observations	1,286,314	63,233	7,054
	Bored Ape	**Sup Ducks**	**Decentraland**
R-squared	0.893	0.863	0.486
Observations	10,272	3,022	11,477

3.2 Repeat Sales Index in NFT Market

We now apply the repeat sales method to construct the NFT market index. In our baseline specification, we use the repeat sales method from Bailey et al. (1963). We also compare the baseline specification to the three-stage repeat sales method from Case and Shiller (1987; 1989) that we refer to as the heteroscedasticity adjusted index, and show that the two methods generate similar indices. To mitigate the influence of outliers and potential data errors, we winsorize the returns of the individual NFTs at the 99-percent level each week. We further remove NFTs with a buy price less than one dollar.

Table 2 presents the R-squareds from the repeat sales regressions. We report the results for the full sample as well as for each of the five collections discussed above. For the full sample, the explanatory power of the index for the repeated sales returns is 28.5 percent as measured by the R-squared of the repeat sales regression. This result suggests that an important fraction of the variation in the returns of NFTs is captured by the index. For the five collections, the explanatory powers are much higher. For example, the explanatory power for CryptoKitties is 55.4 percent and that for CryptoPunks is 65.9 percent.

We plot the resulted repeat sales indices for the full sample in Figure 1.[5] Figure 1 shows the NFT market index based on the repeat sales method from Bailey et al. (1963). The index gradually declined from 2018 to 2020. The index started to increase in 2020, and jumped up in 2021, reaching about ten times its level at the beginning of the sample at one point.

Panel A of Figure A.6 in the Appendix plots the NFT index constructed using transactions denominated in U.S. dollar against the NFT index constructed using transactions denominated in their original cryptocurrency units. The NFT index constructed using transactions denominated by cryptocurrency only experienced a mild decline from 2018 to 2020. The index also exhibited an increase in level in 2021, but the magnitude of the increase is about a third of that of the baseline index. This result shows that some of the fluctuations in the NFT index result from the overall cryptocurrency price movements. In particular, the large run-up in the NFT price index in 2021 is both due to the increase in the NFT market and the underlying cryptocurrency market. The correlation of the logged changes in the two indices is 63.7 percent, suggesting that the a large fraction of the NFT market fluctuation is distinct from that of the cryptocurrency market. Furthermore, Panel B of Figure A.6 in the Appendix plots the NFT index constructed based on the baseline repeat sales method against the heteroscedasticity adjusted index. The two indices track each other closely for the entire sample period. Figure A.7 in the Appendix presents the index at the daily level.

We further compare the overall NFT index to the indices for each of the five collections we considered. Figure A.8 in the Appendix presents the results. Panel A of Figure A.8 shows the baseline NFT market index alone. Panels B–F show the baseline NFT market index alongside the repeat sales indices for each of the five collections. The beginnings of the sub-indices are normalized to one.

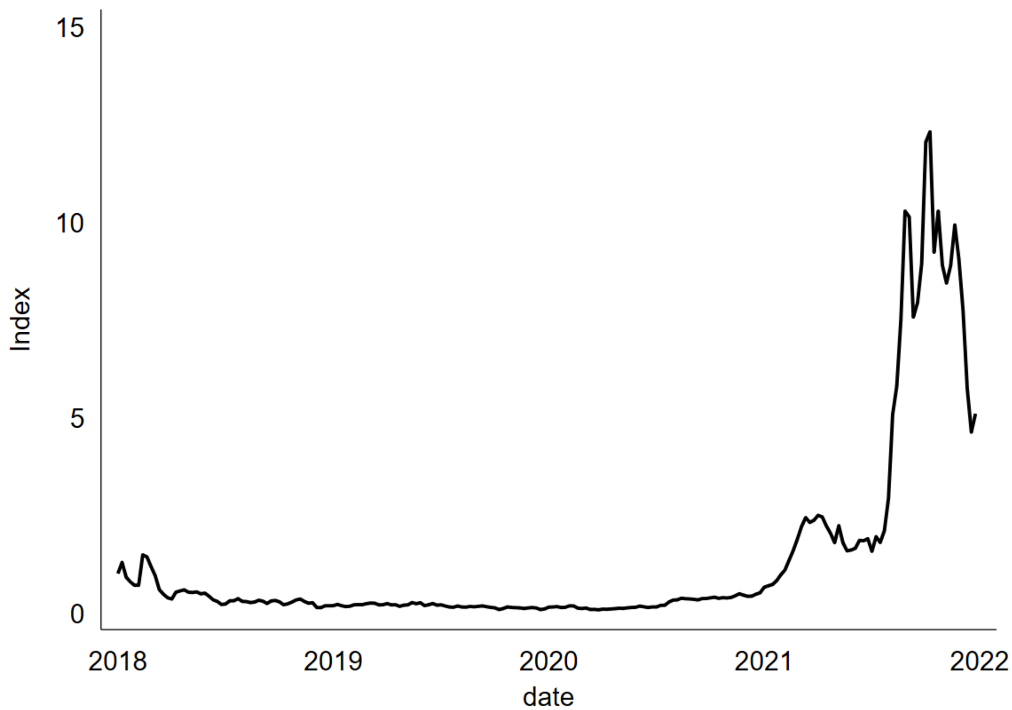
The result for each of the five sub-indices shows that there is a large run-up in the NFT market in 2021. The magnitude of the run-ups for Cryptokitties , Sup Ducks, and Decentraland is of similar magnitude as the overall NFT market. The increases in index levels for the other collections are

[5]We present the daily NFT index based on daily repeat sales regression in the Appendix.

an order of magnitude larger than that of the overall NFT market. For example, the index level of CryptoPunks goes up to more than 1000 times, and the index level of Bored Ape Yacht Club goes up to more than 100 times, relative to their inceptions. In Figure A.9 of the Appendix, we further report the index for each of the five categories: Art & Media, Avatars, Games, Virtual World, and Other.

Figure 1: **NFT Market Indices**

This figure presents the NFT market Index, which plots the NFT index constructed based on the baseline repeat sales method. The beginning of the indices is normalized to one.



Next, we report the basic summary statistics for the overall NFT market. We calculate the returns of the overall NFT market as the growth rate of the corresponding indices. We report the returns based on the baseline method outlined above and the one based on the heteroscedasticity adjusted index.

Table 2 reports these summary statistics. Based on the NFT index, the average weekly return of the NFT market is 2.5 percent. The average weekly return of the NFT market using the heteroscedasticity adjusted NFT index is also 2.5 percent. The weekly standard deviation of the

NFT market is 19.2 percent based on the standard NFT index and is 19.5 percent based on the heteroscedasticity adjusted index. The magnitude of the average return of the NFT market is more than twice as large as that of the cryptocurrency market (1.1 percent per week) in the sample period, and is an order of magnitude higher than that of the stock market (0.3 percent per week). The volatility of the NFT market is much higher than those of the coin market (10.3 percent per week) and stock market (2.5 percent per week). The skewness and the kurtosis of the NFT market are highly positive. These moments are much higher than those of the coin market. The annualized Sharpe ratios of the NFT market are 0.939 based on the baseline NFT index and 0.925 based on the heteroscedasticity adjusted NFT index, which is higher than those of the coin market at 0.799 and is similar to the stock market at 0.931 during the period. We further examine the average weekly returns of the NFT market by each quarter in Panel B of Table 2. The results are similar based on the two indices.

Table 2: **NFT Market Return Summary**

This table presents the summary statistics of the NFT market returns. Panel A reports the overall summary statistics of the weekly NFT market returns alongside those of weekly coin market excess returns and weekly stock market excess returns of the same period. Panel B reports the quarter-by-quarter average weekly NFT market returns for the sample period. NFTH index is the heteroscedasticity adjusted NFT index. CMKTRF is the cryptocurrency market excess return. MKTRF is the stock market excess return.

Panel A	Mean	SD	Median	Skewness	Kurtosis	10%	90%	SR (annual)
NFT Index	0.025	0.192	0.024	1.098	7.732	-0.195	0.237	0.939
NFTH Index	0.025	0.195	0.021	1.062	7.198	-0.197	0.254	0.925
CMKTRF	0.011	0.103	0.005	0.083	4.119	-0.122	0.129	0.799
MKTRF	0.003	0.025	0.007	-1.164	7.243	-0.025	0.026	0.931

Panel B	NFT Index	NFTH Index		NFT Index	NFTH Index
2018Q1	-2.69%	-2.60%	2020Q1	0.01%	0.26%
2018Q2	-3.03%	-2.72%	2020Q2	6.11%	6.15%
2018Q3	4.36%	4.42%	2020Q3	8.02%	8.17%
2018Q4	-1.63%	-1.41%	2020Q4	2.87%	2.93%
2019Q1	1.76%	1.76%	2021Q1	12.91%	12.91%
2019Q2	1.06%	1.31%	2021Q2	-1.09%	-1.19%
2019Q3	-1.97%	-1.85%	2021Q3	15.38%	15.22%
2019Q4	-0.13%	-0.14%	2021Q4	-2.81%	-2.90%

4 Exposures of NFT Market

In this section, we examine the relationship between NFT market returns and the cryptocurrency market, as well as its relationship with the traditional asset markets such as equity, commodity, and currency.

4.1 Exposures to Cryptocurrency Market Factors

We first investigate the NFT exposures to cryptocurrencies. Liu et al. (2021b) show that three factors – cryptocurrency market, size, and momentum – are important drivers of the cross-section of the expected returns in the cryptocurrency market. Furthermore, Liu et al. (2021a) find that the price-to-new address ratio negatively predicts cryptocurrency returns in the cross-section, which they refer to as the cryptocurrency value effect. Therefore, we test the exposures of the NFT market to these common factors in the cryptocurrency market.

Table 3 presents the results about the exposures of the NFT market to the cryptocurrency factors. Column (1) of Table 3 reports the exposure of NFT market returns to the cryptocurrency market factor (CMKTRF) by regressing the NFT market excess returns on the cryptocurrency market factor. The point estimate on CMKTRF is positive and significant at the 1-percent level, showing that the NFT market is significantly exposed to the cryptocurrency market returns. A one percent increase in the coin market excess return is associated with a 0.789 percent increase in the NFT market excess return. The alpha adjusting for the coin market excess return is insignificant at 1.2 percent per week, dropping from the sample average return of 2.5 percent per week. The R-squared of the regression is 21.3 percent, which shows that the majority of the variation in NFT market returns is not captured by the cryptocurrency market, although about half of the run-up of the NFT index is attributable to the increase in cryptocurrency valuation during the period. This result echoes the finding in Figure 1, and show that the majority of the NFT market fluctuations is distinct from that of the cryptocurrency market. Columns (2) to (4) report the results using the cryptocurrency market factor alongside cryptocurrency size, momentum, and value factors. The NFT market excess return is not significantly exposed to these factors, while its exposure to the cryptocurrency market factor remains significant at the 1-percent level in all the specifications. The explanatory power as measured by R-squareds remains similar to the specification using only the cryptocurrency market factor.

4.2 Exposures to Traditional Asset Market Factors

We next study the exposures of the NFT market to traditional asset markets, such as equity, commodity, and currency. For each asset market, we use the common factors documented in the literature to capture the expected returns of the market.

Table 3: **Exposures of NFT Market to Cryptocurrency Factors**

This table reports the exposures of NFT market returns to cryptocurrency factors. $R^{NFT} - R^f$ is the NFT market excess returns. CMKTRF, CSIZE, CMOM, and CVALUE are the cryptocurrency market, size, momentum, and value factors. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

	(1) $R^{NFT} - R^f$	(2) $R^{NFT} - R^f$	(3) $R^{NFT} - R^f$	(4) $R^{NFT} - R^f$
CMKTRF	0.789***	0.788***	0.851***	0.853***
	(7.349)	(7.314)	(7.407)	(7.396)
CSIZE		-0.009		-0.012
		(-0.477)		(-0.649)
CMOM		-0.024		-0.018
		(-0.298)		(-0.219)
CVALUE			-0.275	-0.288
			(-1.495)	(-1.547)
α	0.012	0.013	0.017	0.018
	(1.111)	(1.171)	(1.443)	(1.519)
R-squared	0.213	0.215	0.222	0.225

We report the results in Table 4. Panel A shows results using equity factors, while Panel B shows results using commodity factors and currency factors. For the equity factors, we use the CAPM model, the Fama-French 3-factor model as in Fama and French (1993), the Carhart 4-factor model as in Carhart (1997), and the Fama-French 5-factor model as in Fama and French (2015). Column (1) of Panel A in Table 4 shows the result using the CAPM model. The point estimate on the market excess return is positive and significant, which is consistent with the result that the cryptocurrency market is positively and significantly exposed to the market excess return in the recent sample (Liu et al. (2021a)). The point estimate suggests that a one percent increase in market excess returns is associated with a 1.359 percent increase in NFT market excess returns. Columns (2) to (5) show results using the market excess return alongside the other equity factors, including size, value, momentum, investment, and profitability. The NFT market excess return is not significantly exposed to these factors at the 5-percent level, except the value premium. The alphas adjusting for these equity factors are similar to the sample average of NFT market excess returns. Moreover, in Table A.3 of the Appendix, we show that, controlling for the cryptocurrency market returns, the exposure to the stock market excess return is no longer significant.

Table 4: **Exposures of NFT Market to Traditional Asset Market Factors**

This table reports the exposures of NFT market returns to equity, commodity, and currency factors. $R^{NFT} - R^f$ is the NFT market excess returns. Panel A reports results for the equity factors, Panel B reports results for the commodity factors and the currency factors. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

Panel A	(1) $R^{NFT} - R^f$	(2) $R^{NFT} - R^f$	(3) $R^{NFT} - R^f$	(4) $R^{NFT} - R^f$	(5) $R^{NFT} - R^f$
MKTRF	1.359**	1.368**	1.417**	1.472**	1.480**
	(2.537)	(2.498)	(2.592)	(2.565)	(2.585)
SMB		-0.074	0.083	-0.425	-0.146
		(-0.082)	(0.092)	(-0.399)	(-0.134)
HML		1.356**	2.142***	1.388	2.049*
		(2.212)	(2.705)	(1.518)	(1.965)
MOM			1.037		0.912
			(1.560)		(1.311)
RMW				-1.107	-0.675
				(-0.776)	(-0.462)
CMA				1.296	0.860
				(0.694)	(0.454)
α	0.021	0.023*	0.024*	0.024*	0.024*
	(1.561)	(1.722)	(1.817)	(1.761)	(1.812)
R-squared	0.030	0.056	0.067	0.061	0.069

Panel B	(1) $R^{NFT} - R^f$	(2) $R^{NFT} - R^f$	(3) $R^{NFT} - R^f$	(4) $R^{NFT} - R^f$
Gold	0.906			
	(1.325)			
BBG Commodity		1.861***		
		(2.895)		
Dollar			-1.821	
			(-1.077)	
Carry				2.707
				(1.583)
α	0.023*	0.024*	0.025*	0.025*
	(1.757)	(1.815)	(1.869)	(1.855)
R-squared	0.008	0.039	0.006	0.012

Panel B of Table 4 shows results controlling for commodity factors and currency factors. For the commodity factors, we use the return of Gold and the return of the BBG commodity index. For the currency factors, we use the dollar and carry factors (Lustig et al. (2011)). The NFT market return is significantly exposed to the BBG commodity factor at the 1-percent level. The point estimates on the return of the BBG commodity index is 1.861. That is, a one percent increase in BGG commodity index is associated with a 1.861 percent increase in the NFT market index. The magnitudes of the alphas adjusting for the commodity factors are similar to the sample average of the NFT index return. On the other hand, the NFT market return is not significantly exposed to the currency factors, as shown in Columns (3) and (4) of Panel B. Moreover, in Table A.3 of the Appendix, we show that, controlling for the cryptocurrency market returns, the exposure to the BBG Commodity return is no longer significant.

4.3 NFT-Related Cryptocurrencies and NFT Market

In this subsection, we turn to the NFT-related cryptocurrencies. There are a number of companies that issue both cryptocurrencies and NFTs. For example, Decentraland is a virtual reality company that makes its digital land, estates, and avatars NFTs, which can be traded among users. At the same time, Decentraland also issues its own cryptocurrency, called MANA. Another example is Axie Infinity, which is a blockchain gaming company. Axie Infinity makes its avatars NFTs and issues its own cryptocurrency, called AXS. We construct a value-weighted return index for the NFT-related cryptocurrencies. The list of NFT-related cryptocurrencies is documented in Table A.6 in the Appendix.

Table 5 shows the results relating NFT-related cryptocurrency and the NFT market. Panel A of Table 5 examines the contemporaneous relationship between NFT-related cryptocurrency and NFT market. We regress NFT-related cryptocurrency excess returns on NFT market excess returns. The point estimate is statistically significant at the 1-percent level at 0.333. That is, a one percent increase in NFT market excess return is associated with a 0.33 percent increase in the excess returns of NFT-related cryptocurrencies. When the cryptocurrency market factor is included, the point estimate to the NFT market excess return is statistically significant at the 5-percent level. The point estimate drops by more than a half from 0.333 to 0.146.

Panel B of Table 5 studies the lead-lag relationship between the NFT market returns and the NFT-related cryptocurrency index returns. We use the NFT market excess returns to predict future cumulative excess returns of the NFT-related cryptocurrency index, controlling for the cryptocurrency market excess returns. The NFT market returns positively predict future cumulative NFT-related cryptocurrency index returns from one-week to two-week ahead. The return predictability is significant at the 5-percent level at these horizons. The economic magnitude of the predictability is large. For example, a one percent increase in the NFT market returns is associated with a 0.330 percent increase in cumulative NFT-related cryptocurrency index returns at the two-week horizon.

Table 5: **NFT Coins**

This table reports the results regarding the relationship between the NFT market returns and the NFT-related cryptocurrency index returns. Panel A examines the contemporaneous relationship. Panel B uses the NFT market excess returns to predict future cumulative NFT-related cryptocurrency index excess returns. The standard errors are adjusted by Newey-West procedure with $n-1$ lags where n is the number of overlapping periods. The list of NFT-related cryptocurrencies is documented in Table A.6 in the Appendix. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

Panel A: Contemporaneous Relationship

	$R^{Coins}-R^f$	$R^{Coins}-R^f$
$R^{NFT}-R^f$	0.333***	0.146**
	(5.408)	(2.105)
CMKTRF		0.737***
		(6.250)
α	0.017	0.019*
	(1.419)	(1.729)
R-squared	0.125	0.263

Panel B: Lead-Lag Relationship

$R^{Coins}-R^f$	+1	+2	+3	+4	+5	+6
$R^{NFT}-R^f$	0.229***	0.330**	0.328	0.311	0.297	0.391
	(3.077)	(2.553)	(1.585)	(1.239)	(1.064)	(1.042)
CMKTRF	-0.239	-0.012	0.144	0.406	0.743	0.810
	(-1.625)	(-0.053)	(0.404)	(1.139)	(1.359)	(1.200)
R-squared	0.042	0.042	0.028	0.028	0.031	0.027

5 NFT Market Return Predictability

In this section, we explore the return predictability of the NFT market. We first examine the predictability at the index level. We study a set of variables that are shown to predict time-series returns for the traditional asset markets. The variables we include are volatility, valuation ratio, attention, past returns, and volume. We find that the volatility and valuation ratio are strong time-series predictors of the NFT market return, while attention, past returns, and volume have limited power in predicting NFT market returns in the time-series. Then, we examine the cross-sectional return predictability. We show that there is a size effect and a reversal effect in the cross-section of NFT returns.

5.1 Time-Series Return Predictability

We first examine the predictability at the NFT index level and use a set of variables to predict NFT market excess returns in the time-series. The set of variables we study includes volatility, a valuation ratio, attention, past returns, and volume.

Volatility

The trade-off between risks and returns is the cornerstone of asset pricing, and perhaps the most simple and naive way to measure the risk of an asset is volatility. One of the major findings in asset pricing literature is that asset volatility does not generally seem to be positively related to expected returns (e.g., Fama and French (1992)). In fact, it has been shown that some forms of asset volatility tends to negatively predict future asset returns (e.g., Ang et al. (2006); Frazzini and Pedersen (2014)). We test whether the volatility of NFT market returns is related to its expected returns by predicting NFT market returns.

Table 6 presents results of predicting future cumulative NFT market excess returns with its volatility. We measure the volatility of NFT market returns as the sum of the trailing squared NFT market excess returns of the past eight weeks, denoted as Vol. Similar to evidence shown in other asset markets, Table 6 shows that Vol negatively predicts future cumulative NFT market excess returns. We find that Vol negatively and significantly predicts future cumulative NFT market excess returns from the five-week to the eight-week horizons. The economic magnitude of the return predictability is large. For example, a one-standard-deviation increase in Vol is associated with a 14.8 percent decrease in the cumulative excess returns of the NFT market at the eight-week horizon.[6] The corresponding R-squared is 8.4 percent at the eight-week horizon. In Table A.5 of the Appendix, we show that lagged cryptocurrency and stock market volatilites do not significantly predict future cumulative NFT market returns. These results suggest that the NFT market volatility is a strong NFT market return predictor in the time-series.

[6]The standard deviation of Vol is 0.20. Therefore, a one-standard-deviation increase in Vol is associated with a $0.20 \times 0.739 = 14.8\%$ decrease in future cumulative NFT market excess returns at the five-week horizon.

Table 6: **NFT Time-Series Volatility**

This table reports results of predicting NFT market excess returns with lagged NFT market volatility. Vol is constructed as the sum of the trailing squared NFT market excess returns of the past eight weeks. The standard errors are adjusted by Newey-West procedure with $n-1$ lags where n is the number of overlapping periods. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

	+1	+2	+3	+4	+5	+6	+7	+8
Vol	-0.045	-0.119	-0.197	-0.287	-0.368*	-0.483*	-0.606**	-0.739**
	(-0.590)	(-0.875)	(-1.170)	(-1.510)	(-1.690)	(-1.906)	(-2.113)	(-2.346)
R-squared	0.003	0.008	0.015	0.025	0.034	0.049	0.065	0.084

Valuation Ratio

In the equity market, the market-to-fundamental ratios are commonly referred to as valuation ratios and are measured as the ratio of the market value to the book value of equity or market value to some other fundamental value (e.g., price-to-dividend; price-to-earnings). It is shown that valuation ratios tend to negatively forecast equity returns (e.g., Campbell and Shiller (1988a); Campbell and Shiller (1988b); Cochrane (2008)). In the housing market, analogous ratios have been used, such as the price-to-rent (e.g., Meese and Wallace (1994); Geltner and Mei (1995); Campbell et al. (2009)), value-to-loan (e.g., Lamont and Stein (1999)), and the income-to-price ratio (e.g., Malpezzi (1990); Malpezzi (1999)), and these valuation ratios are also shown to negatively predict housing market returns in the future. In the NFT market, the market value of NFT is summarized by our repeat sales index. However, there is no direct measure of fundamental value for the NFTs. To this end, we use the total transaction count to partially capture the idea of the fundamental value of the NFT market, where the transaction count can be thought of as a way to capture the network effect of the NFT market (e.g., Sockin and Xiong (2020); Cong et al. (2021); Liu et al. (2021a)). Therefore, we use the logged index-to-transaction ratio as a measure of the valuation ratio of the NFT market.

We test the NFT market return predictability of the index-to-transaction ratio, and the results are presented in Table 7. Panel A of Table 7 shows results using the logged index-to-transaction ratio as the only predictor. We find that the ratio negatively and significantly predicts future cumulative NFT market excess returns from the one-week to the eight-week horizons. The economic magnitude of the return predictability is large. For example, a one-standard-deviation increase in the logged index-to-transaction ratio is associated with a 19.1 percent decrease in the cumulative excess returns of the NFT market at the five-week horizon.[7] The corresponding R-squared is 20.6 percent at the five-week horizon. These results suggest that the logged index-to-transaction ratio is a strong NFT market return predictor in the time-series.

Furthermore, we jointly test the return predictability of the logged index-to-transaction ratio and lagged volatility, the results of which are documented in Panel B of Table 7. The point estimates on the logged index-to-transaction ratio remain negative and significant from the one-week to eight-week horizons. The absolute values of the point estimates only are similar to those of the standalone regressions. For example, the magnitude of the point estimate only decreases slightly from 0.239 to 0.232 at the five-week ahead horizon. The point estimates on Vol remain negative for all the horizons and are significant from the seven-week to the eight-week horizons. The magnitudes of the point estimates decrease from the standalone regressions. The R-squareds of the joint regression can reach about 30 percent at the eight-week horizon. Overall, although parts of the return predictability of the valuation ratio and Vol overlap, both effects exist in predicting the NFT market returns in the future.

Other Potential Predictors

It has been shown that investor attention can predict asset returns. Da et al. (2011) show that investor attention as proxied by Google searches positively predicts stock returns. Liu and Tsyvinski (2021) find that investor attention proxied by either Google searches or Twitter postings positively predicts cryptocurrency market returns in the time-series.

In this subsection, we test whether investor attention is a return predictor of future NFT market returns. Specifically, we construct the deviation of Google searches for the word "NFT" in a given week compared with the average of those in the preceding eight weeks.[8] We standardize the Google search measure to have a mean of zero and a standard deviation of one. We denote the NFT attention measure as $Google^{NFT}$. Similarly, we construct $Google^{Crypto}$, and $Google^{Bitcoin}$ to proxy for investor attention of cryptocurrency.

Table 8 presents the return predictability results based on investor attention. Panel A of Table 8 contains results of predicting future cumulative NFT market excess returns using $Google^{NFT}$. We find that $Google^{NFT}$ does not significantly predict future cumulative NFT market excess returns from the one-week to eight-week horizons. We further test whether investor attention to cryptocurrency, and Bitcoin can predict NFT market returns in the future. Panels B and C present return predictability results based on $Google^{Crypto}$ and $Google^{Bitcoin}$. We show that

[7] The standard deviation of the logged index-to-transaction ratio is 0.80. Therefore, a one-standard-deviation increase in the logged index-to-transaction ratio is associated with a $0.80 \times 0.239 = 19.1\%$ decrease in future cumulative NFT market excess returns at the five-week horizon.

[8] The word "non-fungible token" was rarely used before 2019, and the only NFT traded before 2019 was Cryptokitties. Therefore, we use Google searches for the word "Cryptokitties" between 2018 and 2019.

$Google^{Crypto}$ and $Google^{Bitcoin}$ also do not statistically significantly predict cumulative NFT market excess returns in the future.

Table 7: **NFT Time-Series Valuation Ratio**

This table reports results of predicting NFT market excess returns with the index-to-transaction ratio. Panel A reports the results of predicting future cumulative NFT market excess returns using the logged index-to-transaction ratio. Panel B reports the predictability results of the logged index-to-transaction ratio controlling for the lagged NFT market volatility as measured by Vol. The standard errors are adjusted by Newey-West procedure with $n-1$ lags where n is the number of overlapping periods. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

Panel A	+1	+2	+3	+4	+5	+6	+7	+8
$\log(Index/Trans)$	-0.061***	-0.120***	-0.164***	-0.203***	-0.239***	-0.271***	-0.309***	-0.339***
	(-3.698)	(-3.589)	(-3.272)	(-3.350)	(-3.591)	(-3.693)	(-3.846)	(-3.772)
R-squared	0.071	0.124	0.152	0.177	0.206	0.228	0.255	0.269

Panel B	+1	+2	+3	+4	+5	+6	+7	+8
$\log(Index/Trans)$	-0.066***	-0.122***	-0.162***	-0.196***	-0.232***	-0.262***	-0.289***	-0.307***
	(-4.156)	(-3.701)	(-3.301)	(-3.361)	(-3.697)	(-3.763)	(-3.647)	(-3.460)
Vol	-0.031	-0.101	-0.176	-0.258	-0.330	-0.440	-0.561*	-0.697**
	(-0.435)	(-0.763)	(-1.043)	(-1.286)	(-1.385)	(-1.573)	(-1.771)	(-2.020)
R-squared	0.084	0.138	0.168	0.198	0.234	0.263	0.285	0.297

The momentum effect is observed in many asset markets, such as equity (e.g., Jegadeesh and Titman (1993); Moskowitz et al. (2012)), bond (e.g., Jostova et al. (2013)), currency (e.g., Menkhoff et al. (2012)), real estate (e.g., Beracha and Skiba (2011)), art (e.g., Pesando (1993)), and cryptocurrency markets (e.g., Liu and Tsyvinski (2021); Liu et al. (2021b)). We test whether the NFT market index exhibits serial dependence in our sample period. We use current NFT market excess returns to predict future cumulative market returns, and report the results in Table 9. Table 9 shows that current NFT market excess returns do not statistically significantly predict future NFT market excess returns at any of the horizons. The R-squareds are small in these regression specifications. There is no evidence of serial dependence in the NFT market returns.

Table 8: **NFT Time-Series Attention**

This table reports results of predicting NFT market excess returns with investor attention. Investor attention measures are constructed as the deviation of Google searches in a given week compared with the average of those in the preceding eight weeks. The measure is standardized to have a mean of zero and a standard deviation of one. The key words are "NFT", "Cryptocurrency", and "Bitcoin" for $Google^{NFT}$, $Google^{Crypto}$, and $Google^{Bitcoin}$. The standard errors are adjusted by Newey-West procedure with $n-1$ lags where n is the number of overlapping periods. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

Panel A	+1	+2	+3	+4	+5	+6	+7	+8
$Google^{NFT}$	0.023	0.019	0.010	0.016	0.018	0.017	0.029	0.021
	(1.558)	(0.688)	(0.247)	(0.353)	(0.346)	(0.288)	(0.464)	(0.289)
R-squared	0.010	0.003	0.001	0.001	0.001	0.001	0.002	0.001
Panel B	+1	+2	+3	+4	+5	+6	+7	+8
$Google^{Crypto}$	0.013	0.005	0.016	0.022	0.032	0.043	0.032	0.018
	(0.830)	(0.177)	(0.380)	(0.375)	(0.410)	(0.457)	(0.305)	(0.155)
R-squared	0.004	0.000	0.002	0.003	0.005	0.008	0.004	0.001
Panel C	+1	+2	+3	+4	+5	+6	+7	+8
$Google^{Bitcoin}$	-0.002	0.001	0.008	0.018	0.041	0.057	0.072	0.076
	(-0.139)	(0.031)	(0.197)	(0.304)	(0.581)	(0.689)	(0.756)	(0.722)
R-squared	0.000	0.000	0.000	0.002	0.007	0.012	0.016	0.016

Table 9: **Serial Dependence**

This table reports results of predicting future NFT market excess returns with current NFT market excess returns. The standard errors are adjusted by Newey-West procedure with $n-1$ lags where n is the number of overlapping periods. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

	+1	+2	+3	+4	+5	+6	+7	+8
$R^{NFT}-R^f$	-0.039	-0.188	-0.273	-0.346	-0.284	-0.152	-0.081	-0.122
	(-0.247)	(-0.614)	(-0.683)	(-0.718)	(-0.554)	(-0.287)	(-0.158)	(-0.240)
R-squared	0.000	0.005	0.007	0.008	0.004	0.001	0.000	0.001

We further construct the detrended volume measure, $Volume$, as the deviation of NFT trading volume in a given week compared with the average of those in the preceding eight weeks. Table 10 presents the results using $Volume$ to predict future cumulative NFT market excess returns. Panel A of Table 10 reports the predictability results using $Volume$ only. We find that $Volume$ positively predicts future cumulative NFT market excess returns. However, the predictability is only statistically significant at the 5-percent level from the one-week to the two-week horizons. The explanatory power as measured by R-squareds is relatively small compared to the logged index-to-transaction ratio in predicting future NFT market excess returns. For example, the R-squared is only 3.3 percent at the two-week horizon using $Volume$ only.

Additionally, we test the return predictability of $Volume$ alongside with the logged volume-to-transaction ratio and Vol, and report the results in Panel B of Table 10. Controlling for the logged volume-to-transaction ratio and Vol, the point estimates on $Volume$ are only significant at the 10-percent level at the one-week horizon. The magnitude of the coefficient estimate decreases from 0.054 to 0.039 at the one-week horizon. The magnitudes of the point estimates to the logged volume-to-transaction ratio and Vol remain largely unchanged. In summary, $Volume$ predicts future NFT market excess returns but the predictability is largely subsumed by the logged volume-to-transaction ratio and Vol.

Table 10: **NFT Time-Series Volume**

This table reports results of predicting NFT market excess returns with the detrended volume. $Volume$ is constructed as the deviation of NFT trading volume in a given week compared with the average of those in the preceding eight weeks. Panel A reports the results of predicting future cumulative NFT market excess returns using $Volume$ only. Panel B reports the predictability results of $Volume$ controlling for the logged index-to-transaction ratio and the lagged volatility measure (Vol). The standard errors are adjusted by Newey-West procedure with $n-1$ lags where n is the number of overlapping periods. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

Panel A	+1	+2	+3	+4	+5	+6	+7	+8
$Volume$	0.054***	0.072**	0.090*	0.098	0.081	0.080	0.088	0.076
	(2.901)	(2.040)	(1.727)	(1.455)	(1.019)	(0.903)	(0.900)	(0.727)
R-squared	0.041	0.033	0.035	0.031	0.017	0.015	0.015	0.010

Panel B	+1	+2	+3	+4	+5	+6	+7	+8
$Volume$	0.039*	0.042	0.049	0.044	0.015	0.002	-0.003	-0.025
	(1.863)	(1.216)	(0.993)	(0.734)	(0.210)	(0.024)	(-0.038)	(-0.308)
$\log(Index/Trans)$	-0.059***	-0.115***	-0.153***	-0.189***	-0.230***	-0.261***	-0.289***	-0.312***
	(-3.833)	(-3.579)	(-3.248)	(-3.333)	(-3.724)	(-3.823)	(-3.723)	(-3.540)
Vol	-0.013	-0.081	-0.153	-0.237	-0.323	-0.439	-0.562*	-0.708**
	(-0.177)	(-0.602)	(-0.904)	(-1.203)	(-1.392)	(-1.605)	(-1.810)	(-2.103)
R-squared	0.105	0.149	0.178	0.204	0.235	0.263	0.285	0.298

5.2 Cross-Sectional Return Predictability

We next study the cross-sectional return predictability in the NFT market. A large literature studies the return predictors in the cross-section of asset returns (see, e.g., Feng et al. (2020); Hou et al. (2020) for lists of factor zoo). Size, momentum, and value are among the most studied predictors in asset pricing. The size effect is first documented in Banz (1981), and the momentum effect is first documented in Jegadeesh and Titman (1993). Fama and French (1993) find that the value effect is similar to the long-term reversal effect documented in De Bondt and Thaler (1985). In this subsection, we examine whether these effects exist in the cross-section of NFT returns. We note that other characteristics that have been examined in predicting the cross-section of equity returns, such as volume, volatility, and accounting ratios, are difficult to construct at the individual NFT level because individual NFTs are traded infrequently and the accounting information for the market is not commonly available.

Size Effect

In the equity market, one of the earliest predictors documented in the literature of cross-section returns is market capitalization. The return predictatbility of market capiatlization is known as the size effect (e.g., Banz (1981); Chan and Chen (1988); Fama and French (1992)), which is a phenomenon that small firms tend to outperform large firms in the cross-section of stock returns.

The NFT market also features a large dispersion of prices. We use the market capitalization or the market price of individual NFT to identify potential size effect in the cross-section of NFTs. We apply the same repeat sales regression approach and add an additional term to capture the effect[9]:

$$r_{it't} = p_{it'} - p_{it} = b_{t'} - b_t + \gamma \times (t' - t) \ln P_{i,t} + u_{itt'}$$

where γ is the elasticity of the returns with respect to the logged price of the NFT and the holding period $(t' - t)$. The interpretation of γ is that it gives the expected percentage weekly returns associated with a 1-percent change in the NFT's purchasing price.

We report the results in Table 11. We present the results using the full sample as well as each of the collections. The results are uniform across all categories – expensive NFTs underperform their respective NFT market index. For the full sample, the point estimate is -0.004, suggesting that doubling the logged NFT purchase price is associated with a 0.4 percent decrease in the weekly return, or 20.8 percent annually. The effect is weaker for the CryptoKitties and Bored Ape, and stronger for the other popular collections. Overall, there is a strong size effect in the NFT market. That is, the results suggest that expensive NFTs tend to significantly underperform compared to the less expensive NFTs.

In the art market, a piece of common advice by the art dealers is that clients should buy the best and most expensive artworks they can afford. In other words, it is assumed that the expected returns of expensive masterpieces of the famous artists tend to outperform the less expensive art pieces. However, this common view has been challenged by academic research (e.g., Pesando (1993); Mei and Moses (2002)). It has been shown that, contrary to the advice, masterpieces actually tend to underperform the market. The size effect for the largest NFTs can also be thought of as the masterpiece effect in the NFT market.

[9]The method is similar to Pesando (1993) and Mei and Moses (2002) in the art market.

Table 11: **Size Effect**

This table reports the the point estimate of repeat sale regressions with the additional term to capture the masterpiece/size effect

$$r_{it't} = p_{it'} - p_{it} = b_{t'} - b_t + \gamma\,(t'-t)\ln P_{i,t} + u_{itt'}$$

The standard errors are clustered at the time level. The results are reported using the full sample and each of the five collections. The five collections include CryptoKitties, CryptoPunks, Bored Ape Yacht Club, Sup Ducks, and Decentraland. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

	Full Sample	CryptoKitties	CryptoPunks
$(t'-t)\ln P$	-0.004***	-0.001***	-0.011**
	(-10.553)	(-8.904)	(-2.232)
	Bored Ape	**Sup Ducks**	**Decentraland**
$(t'-t)\ln P$	-0.003	-0.029**	-0.012***
	(-0.976)	(-2.415)	(-21.073)

Past Returns

We next test the relationship between the returns of NFTs and their past returns in the cross-section. Both momentum (e.g., Jegadeesh and Titman (1993); Moskowitz et al. (2012)) and reversal (e.g., De Bondt and Thaler (1985)) effects are documented and heavily studied in the asset pricing literature. In particular, the long-term reversal effect is found to be related to the value effect (e.g., Fama and French (1992); Fama and French (1993); Asness et al. (2013)).

To study the relationship between the returns of NFTs and their past returns in the cross-section, we need at least three transactions for an NFT. Similar to the size specification, we apply the same repeat sales regression approach and add an additional term to capture the effect related to past return:

$$r_{it't} = p_{it'} - p_{it} = b_{t'} - b_t + \gamma\,(t'-t)\,r_{i,b} + u_{itt'}$$

where $r_{i,b}$ is the logged average weekly return of NFT i's previous repeat sale and γ is the elasticity of the returns with respect to logged return of the NFT's previous repeat sale and the holding period $(t'-t)$. The interpretation of γ is that it gives the expected percentage weekly returns associated with a 1-percent change in the average weekly return of the NFT's previous repeat sale.

We report the results in Table 12. We present the results using the full sample as well as each of the collections. The directions of the results are uniform across all categories – NFTs with high average weekly returns in their previous repeat sales underperform their respective NFT market index. For the full sample, the point estimate is −0.014, suggesting that a 10 percent increase in average weekly return in the NFT's previous repeat sale is associated with an about 0.14 percent decrease in the weekly return, or 7.3 percent annually. The effect is weaker for the CryptoKitties collection and stronger for the other four collections. Overall, there is a strong reversal effect in the NFT market. That is, the results suggest that NFTs with high average past returns in their previous repeat sale tend to significantly underperform.

Table 12: **Reversal Effect**

This table reports the the point estimate of repeat sales regression with the additional term to capture the past return effect

$$r_{it't} = p_{it'} - p_{it} = b_{t'} - b_t + \gamma\,(t'-t)\,r_{i,b} + u_{itt'}$$

$r_{i,b}$ is the logged average weekly return of NFT i's previous repeat sale. The results are reported using the full sample and each of the five collections. The five collections include CryptoKitties, CryptoPunks, Bored Ape Yacht Club, Sup Ducks, and Decentraland. The standard errors are clustered at the time level. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

	Full Sample	CryptoKitties	CryptoPunks
$(t'-t)\,r_{i,t}$	-0.014***	-0.004***	-0.108***
	(-6.517)	(-6.970)	(-4.072)
	Bored Ape	**Sup Ducks**	**Decentraland**
$(t'-t)\,r_{i,t}$	-0.027***	-0.051**	-0.020***
	(-3.537)	(-2.150)	(-7.078)

6 Conclusion

In this paper, we construct a comprehensive dataset of the NFT market. This data allows detailed analysis of this market from the finance and asset pricing point of view. We show that NFTs behave differently from both the existing asset classes and from cryptocurrencies but have their own NFT-specific driving forces. We note that while this market is relatively recent, understanding its properties from the finance point of view is important as NFTs may potentially become a cornerstone of the metaverse and Web 3.0.

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Online Appendix

Figure A.1: **Trading Gap**

This figure plots the average trading gap between the two transactions of the repeat sales over time. The data are at the weekly frequency.

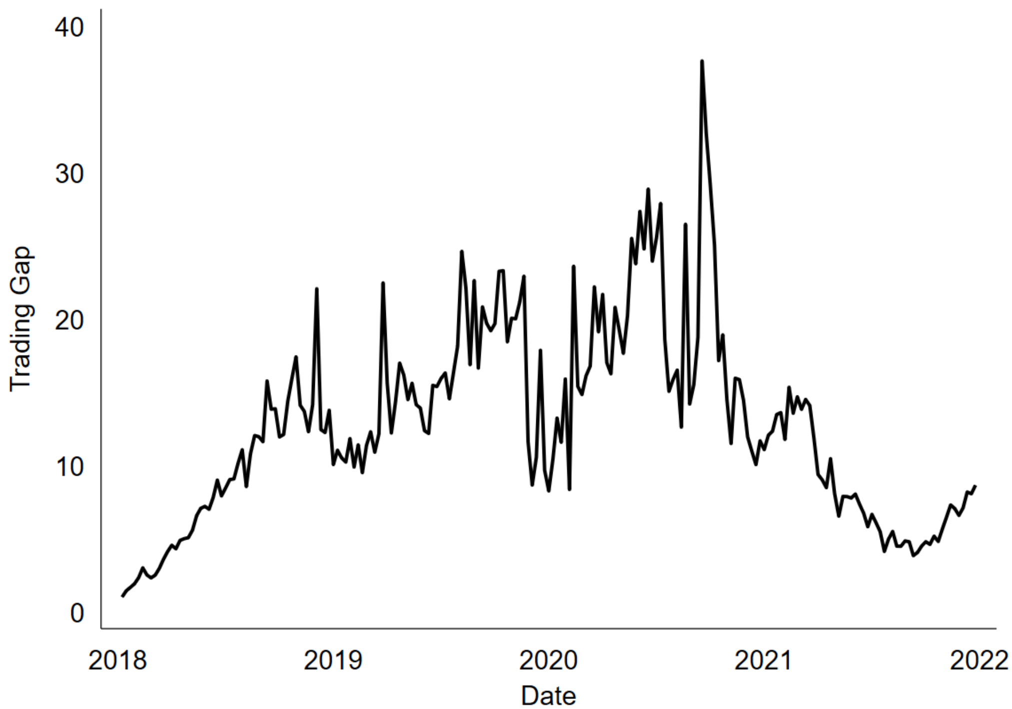
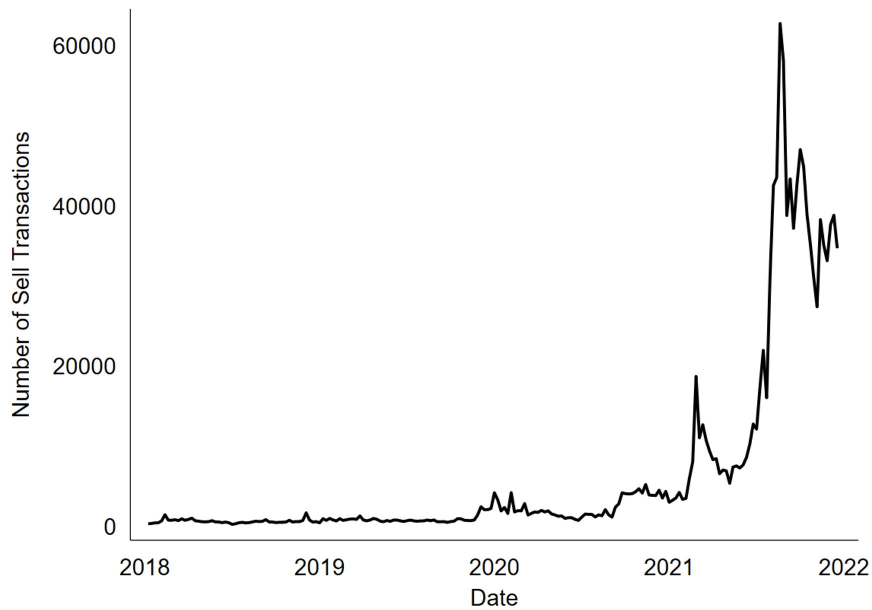


Figure A.2: **Number of Observations and Volume of Transactions**

This figure plots the number of observations by sale and volume of transactions. The sample is constrained to the repeat sale sample for easy comparison. The first price from each price pair is denoted as purchase price and the second price is denoted as sale price from the perspective of the investor for the time between the two transactions of the repeat sale. The data are at the weekly frequency.



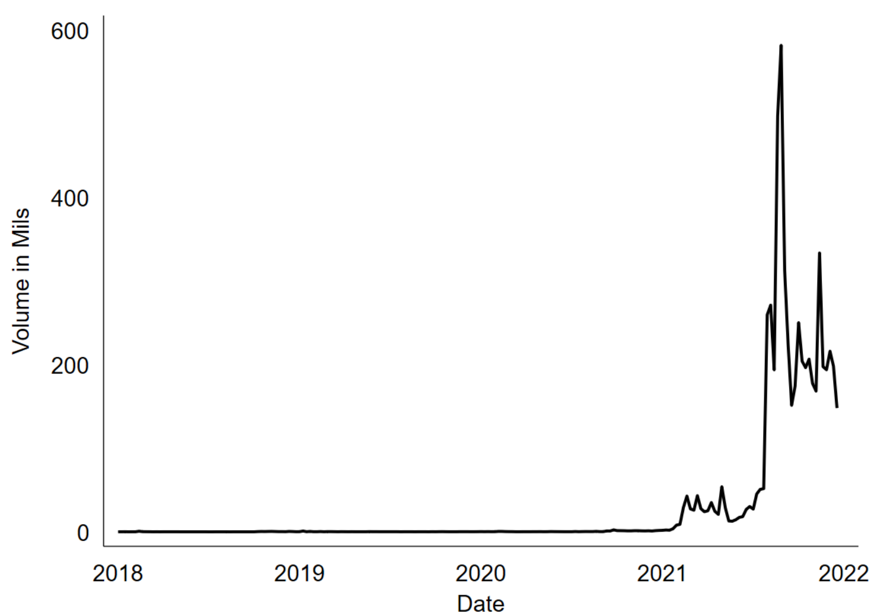


Figure A.3: **Number of Observations – Full Sample vs CryptoKitties**

This figure plots the number of observations by sale for the full sample and for the Cryptokitties sample. The sample is constrained to the repeat sale sample for easy comparison. The data are at the weekly frequency.

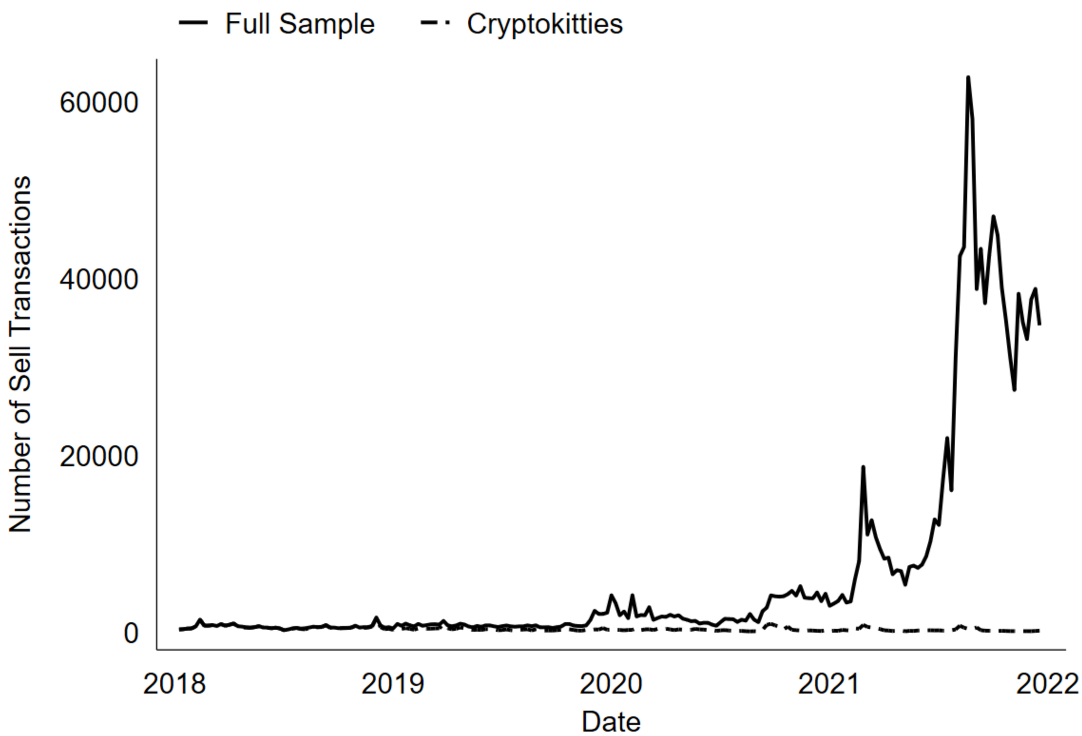


Figure A.4: **Median and Minimum/Floor Price Indices**

This figure plots the median and minimum/floor price indices for the full sample and for the Cryptopunk sample. The sample is constrained to the repeat sale sample for easy comparison. The data are at the weekly frequency.

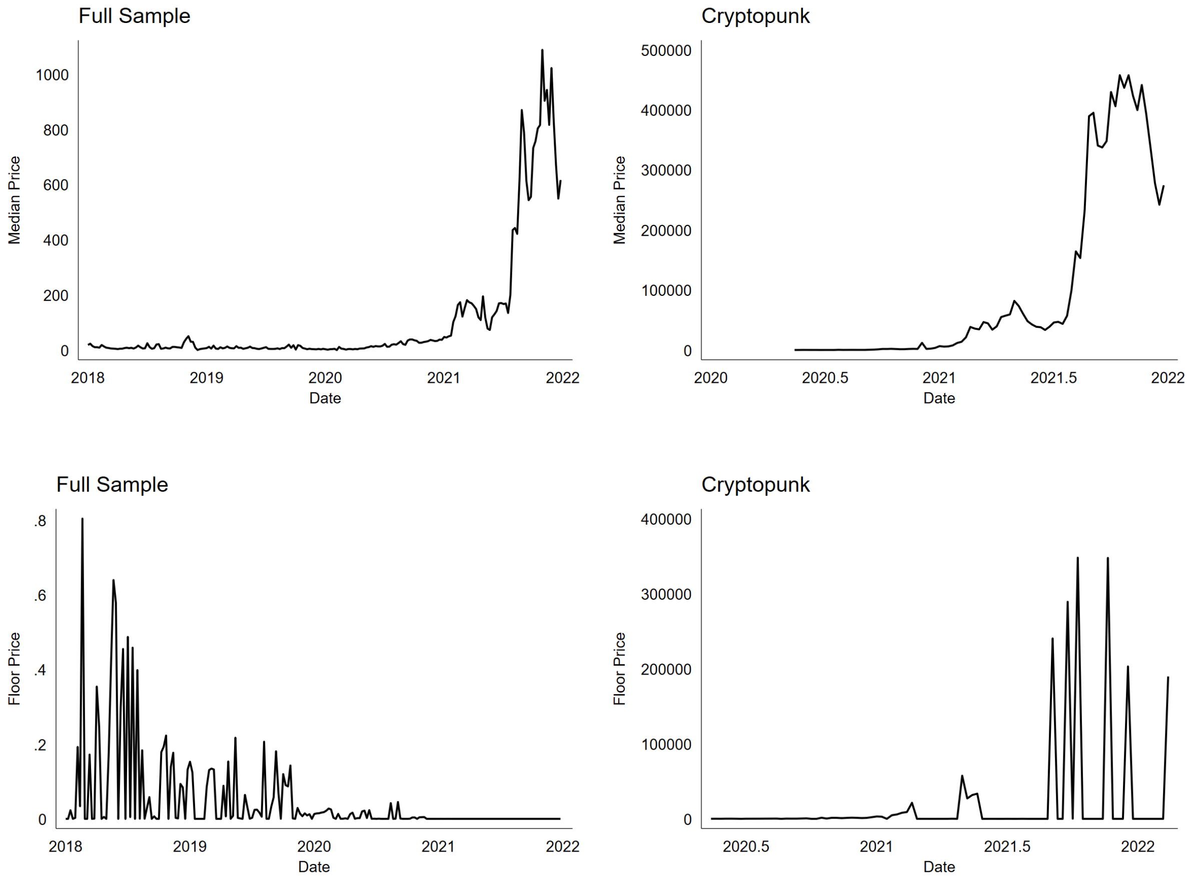


Figure A.5: **Fraction of First Time Sale**

This figure plots fraction of the number of first time sale relative to the number of total sale. The data are at the weekly frequency.

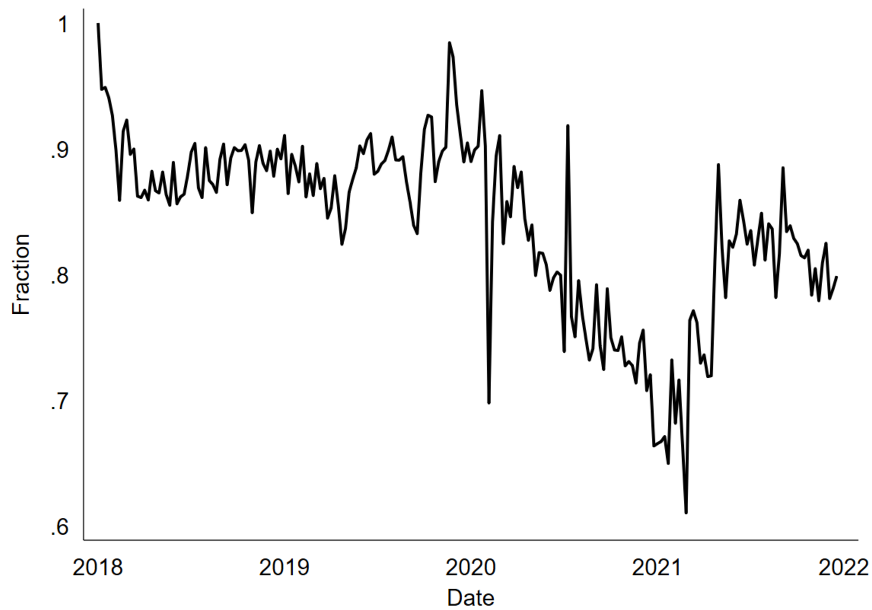
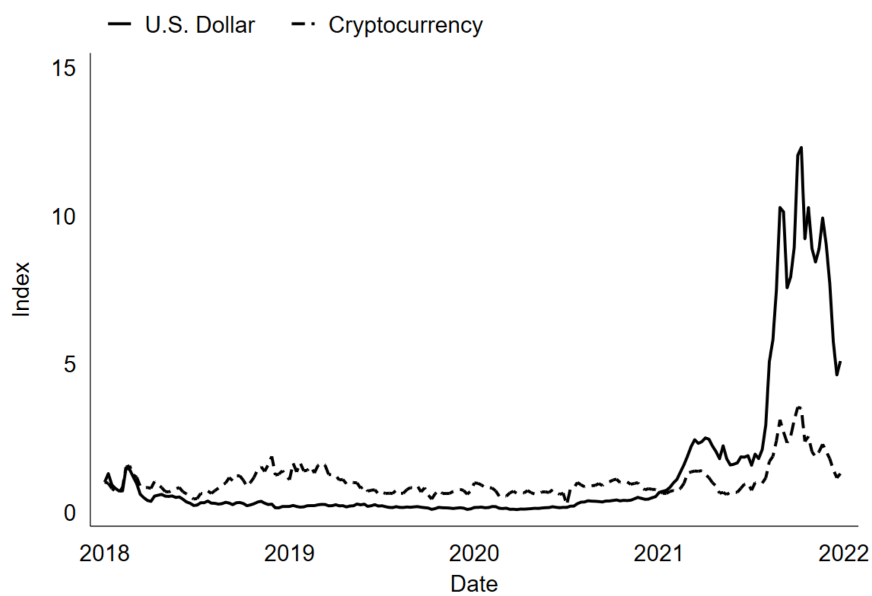


Figure A.6: **Additional NFT Market Indices**

This figure presents the additional NFT indices. Panel A plots the NFT index constructed using transactions denominated in U.S. dollar against the NFT index constructed using transactions denominated in cryptocurrency. Panel B plots NFT indices based on the baseline method and the heteroscedasticity adjusted index. The beginning of the indices is normalized to one.



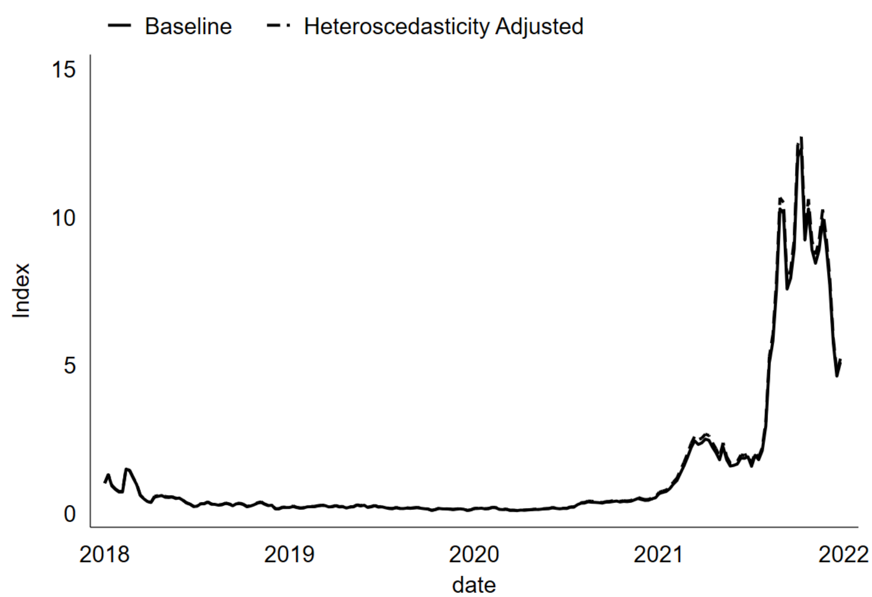


Figure A.7: **Daily Index**

This figure presents the daily indices. The indices include the median price index and the index constructed using the repeat sales method of Bailey et al. (1963).

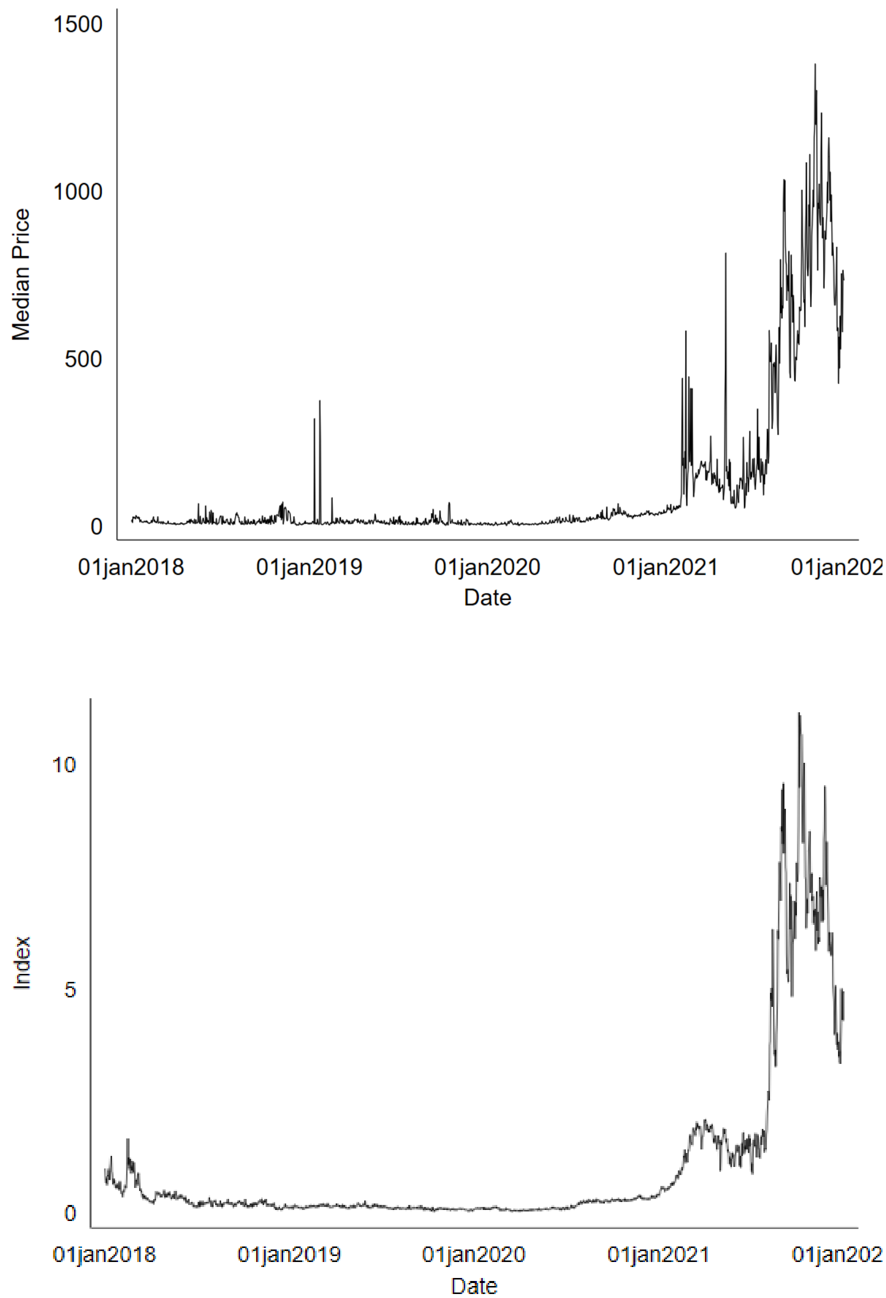


Figure A.8: **Collection Indices**

This figure presents the NFT index for the full sample and for each collection. Each graph plots the NFT index for the full sample against a specific collection – Cryptokitties, CryptoPunks, Bored Ape Yacht Club, Sup Ducks, and Decentraland. The beginnings of the indices are normalized to one.

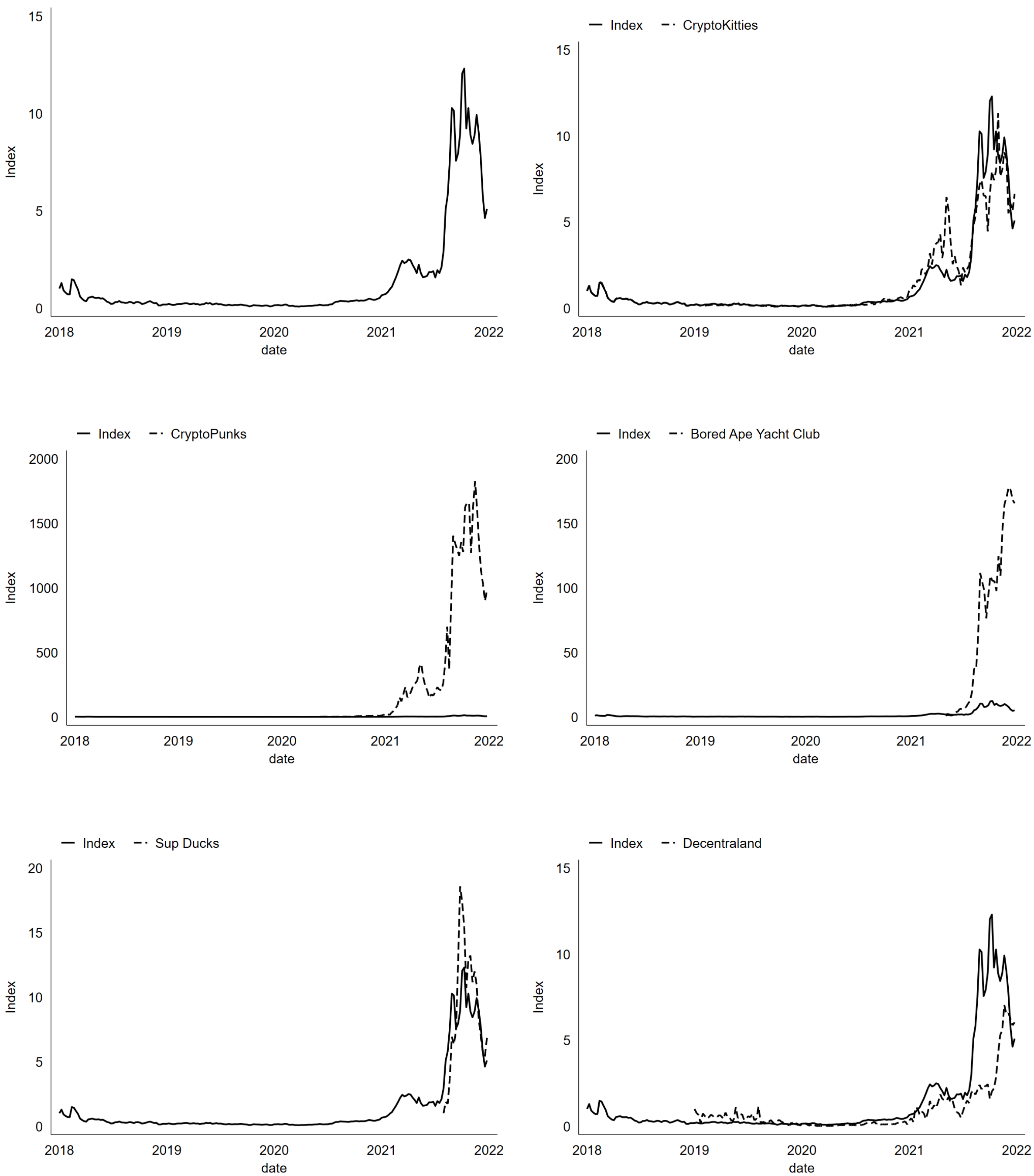


Figure A.9: **Category**

This figure presents the NFT index for the full sample and for each category. The categories include Art & Media, Avatars, Games, Virtual World, and Other. The indices start and are normalized to one at the beginning of 2020.

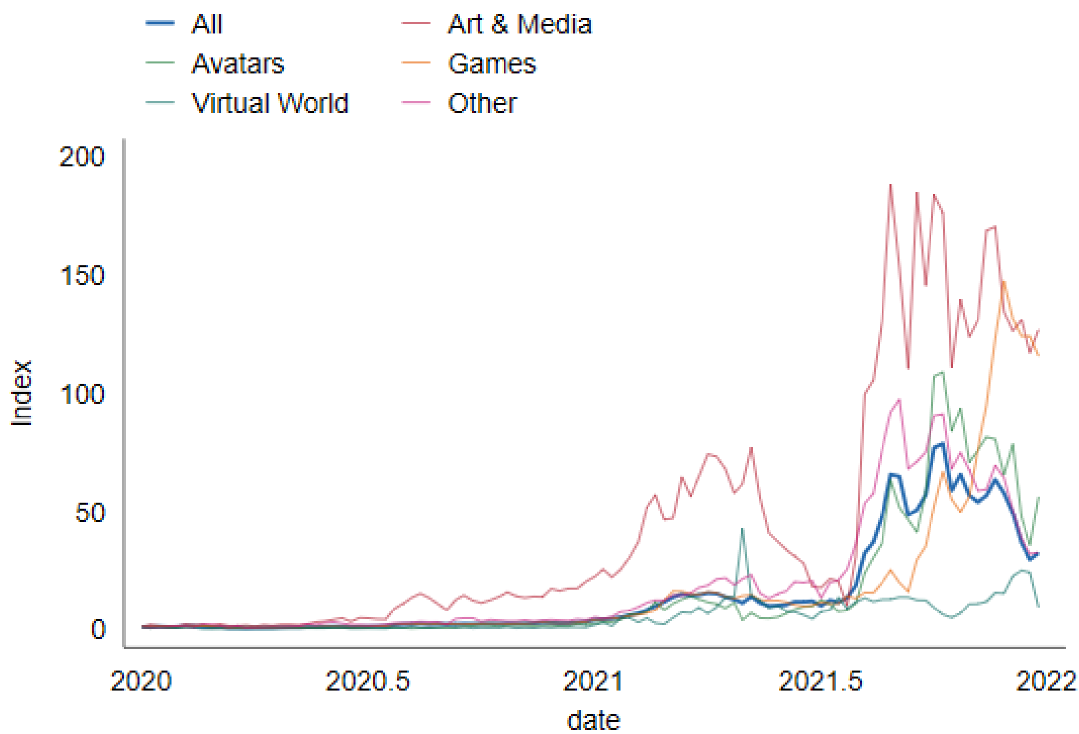


Figure A.10: **Logged Index-to-Transaction Ratio**

This figure plots the logged index-to-transaction count ratio over time. The data are at the weekly frequency.

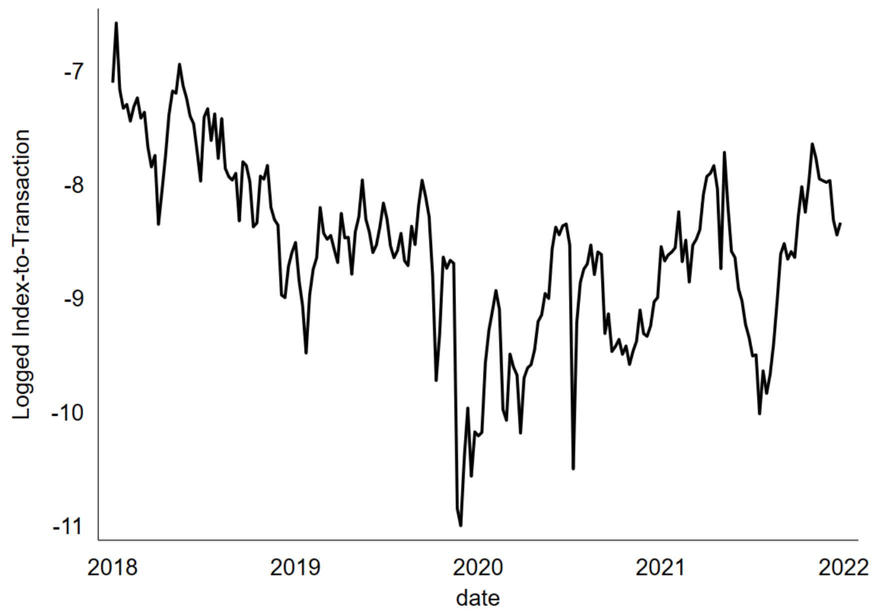
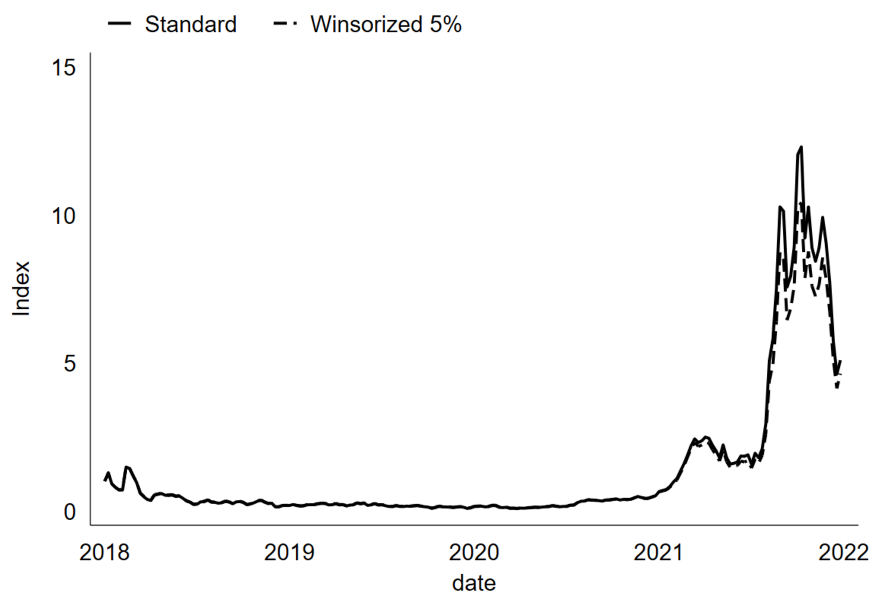


Figure A.11: **Winsorized at 5% and 10% level**

This figure plots the baseline index against several alternative ways of construction of the indices.



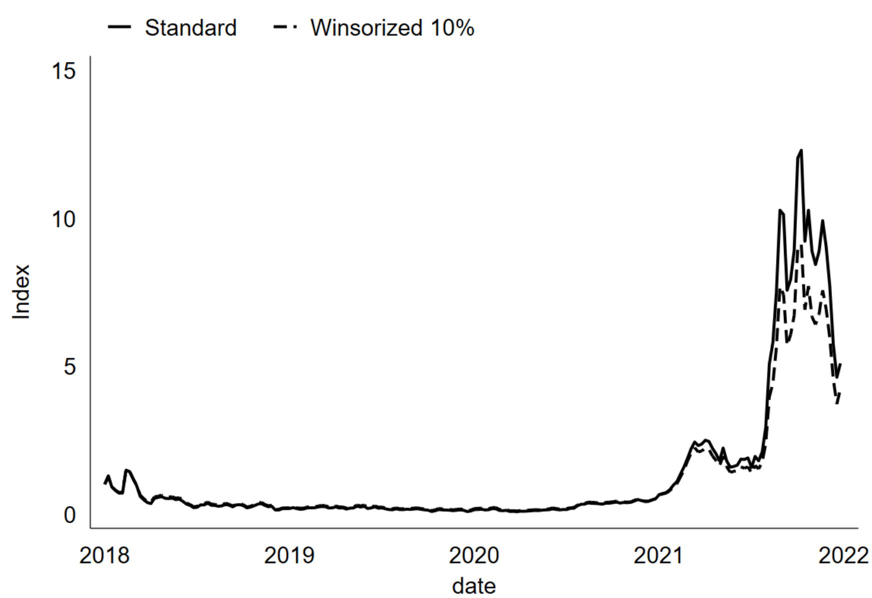


Table A.1: **Distribution of Total Transactions of NFTs**

This table reports the distribution of the total number of transactions of an unique NFT.

Total Transaction	Number	Percentage
1	5,772,644	83.24
2	920,311	13.27
3	179,895	2.59
4	41,244	0.59
5	11,581	0.17
6	4,039	0.06
7	1,721	0.02
8	828	0.01
9	570	0.01
10	397	0.01
11	306	0.00
12	247	0.00
13	201	0.00
14	178	0.00
15	120	0.00
16	86	0.00
17	80	0.00
18	69	0.00
19	66	0.00
20	57	0.00
>20	447	0.00
Total	6,935,087	100.00

Table A.2: **Collection Exposure to NFT Market**

This table reports the exposures of excess returns of each NFT collection to the NFT market excess returns. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

	$R^{kitties} - R^f$	$R^{punks} - R^f$	$R^{boredape} - R^f$	$R^{supducks} - R^f$	$R^{decentraland} - R^f$
$R^{NFT} - R^f$	0.696***	0.732***	0.746***	0.982***	0.711***
	(8.768)	(3.304)	(3.973)	(3.926)	(2.647)
Constant	0.004	0.050	0.127***	0.066	-0.004
	(0.253)	(1.441)	(3.425)	(1.212)	(-0.085)
Observations	207	84	34	21	155
R-squared	0.273	0.117	0.330	0.448	0.044

Table A.3: **Exposures of NFT Market to Traditional Asset Market Factors – Controlling Coin Market Returns**

This table reports the exposures of NFT market returns to equity, commodity, and currency factors, controlling for the coin market excess returns. $R^{NFT} - R^f$ is the NFT market excess returns. Panel A reports results for the equity factors, Panel B reports results for the commodity factors and the currency factors. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

Panel A	(1)	(2)	(3)	(4)	(5)
	$R^{NFT} - R^f$	$R^{NFT} - R^f$	$R^{NFT} - R^f$	$R^{NFT} - R^f$	$R^{NFT} - R^f$
CMKTRF	0.772***	0.768***	0.758***	0.774***	0.767***
	(7.048)	(7.019)	(6.868)	(7.031)	(6.895)
MKTRF	0.367	0.485	0.514	0.643	0.648
	(0.790)	(1.025)	(1.081)	(1.292)	(1.298)
SMB		-0.734	-0.665	-0.767	-0.671
		(-0.975)	(-0.875)	(-0.859)	(-0.734)
HML		1.277**	1.590**	0.962	1.180
		(2.521)	(2.403)	(1.264)	(1.344)
MOM			0.411		0.294
			(0.737)		(0.502)
RMW				-0.306	-0.166
				(-0.256)	(-0.135)
CMA				1.631	1.470
				(1.031)	(0.910)
α	0.011	0.013	0.014	0.012	0.013
	(1.018)	(1.160)	(1.214)	(1.068)	(1.097)
R-squared	0.216	0.241	0.243	0.245	0.246

Panel B	(1)	(2)	(3)	(4)
	$R^{NFT} - R^f$	$R^{NFT} - R^f$	$R^{NFT} - R^f$	$R^{NFT} - R^f$
CMKTRF	0.808***	0.775***	0.796***	0.773***
	(7.314)	(6.790)	(7.340)	(7.148)
Gold	-0.441			
	(-0.761)			
BBG Commodity		0.209		
		(0.360)		
Dollar			0.753	
			(0.522)	
Carry				1.627
				(1.134)
α	0.013	0.012	0.012	0.012
	(1.148)	(1.112)	(1.089)	(1.100)
R-squared	0.216	0.214	0.215	0.219

Table A.4: **NFT-Related Stocks**

This table reports the results of regressing excess returns of NFT-related stocks on the NFT market excess returns. The lists of NFT-related stocks is documented in Table A.6 in the Appendix. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

	$R^{NFT\ Stock} - R^f$	$R^{NFT\ Stock} - R^f$	$R^{NFT\ Stock} - R^f$
$R^{NFT} - R^f$	0.015	0.004	-0.005
	(0.852)	(0.170)	(-0.533)
CMKTRF		0.056	-0.010
		(1.547)	(-0.669)
MKTRF			0.961***
			(16.918)
Constant	0.005	0.004	0.001
	(1.544)	(1.320)	(0.459)
R-squared	0.004	0.017	0.597

Table A.5: **NFT Time-Series Volatility – Additional**

This table reports results of predicting NFT market excess returns with lagged NFT market volatility, controlling for lagged cryptocurrency market and stock market volatilities. Vol is constructed as the sum of the trailing squared NFT market excess returns of the past eight weeks. The standard errors are adjusted by Newey-West procedure with $n-1$ lags where n is the number of overlapping periods. The data frequency is at the weekly level. *, **, and *** represent significance at the 1%, 5%, and 10% levels.

	+1	+2	+3	+4	+5	+6	+7	+8
Vol	-0.022	-0.161	-0.308*	-0.485**	-0.652**	-0.802**	-0.965**	-1.118**
	(-0.292)	(-1.162)	(-1.835)	(-2.230)	(-2.357)	(-2.397)	(-2.462)	(-2.538)
Vol^{crypto}	0.208	0.604	0.974*	1.278*	1.383	1.279	1.134	0.960
	(0.980)	(1.597)	(1.749)	(1.789)	(1.598)	(1.246)	(0.984)	(0.775)
Vol^{stock}	-0.563	-1.398	-2.077	-1.555	-0.280	1.740	4.558	7.527
	(-0.325)	(-0.486)	(-0.498)	(-0.293)	(-0.043)	(0.223)	(0.510)	(0.771)
R-squared	0.005	0.024	0.049	0.079	0.100	0.112	0.127	0.142

Table A.6: **List**

This table reports the lists of related cryptocurrencies and stocks used in the paper.

NFT Cryptocurrencies	NFT Stocks
Polygon (matic)	FUNKO INC-CLASS A
Decentraland (mana)	PLBY GROUP INC
Sand (sand)	EBAY INC
WAX Economic Token (wax)	MATTEL INC
Axie Infinity Shard (axs)	CLOUDFLARE INC - CLASS A
Enjin Coin (enj)	COINBASE GLOBAL INC -CLASS A
Yield Guild Games Token (ygg)	CLEANSPARK INC
Illuvium (ilv)	SILVERGATE CAPITAL CORP-CL A
Rarible (rari)	DOLPHIN ENTERTAINMENT INC
NETVRK (ntvrk)	WISEKEY INTERNATIONAL HOLDIN
Gods Unchained (gods)	GAMESTOP CORP-CLASS A

Table A.7: **Correlation Between Different Versions of Measure**

This table reports correlations between the baseline index and alternative ways of construction of the indices.

	Winsorize 5%	Winsorize 10%	No Cryptokitties	Crypto Price
r^{NFT}	0.998	0.993	0.951	0.637