Alternative Investments in the Fintech Era:

The Risk and Return of Non-fungible Token (NFT)*

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Abstract

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JEL Classifications: C43, D44, G11, G12, Z11

Keywords: Non-Fungible Tokens, NFT, Fintech, Ethereum, Blockchain, Alternative investments, Risk and return

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* We have no financial relationship with entities that could benefit from our findings. All data are publicly available. We appreciate helpful comments from Lauren Cohen. Any errors are ours.

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1. Introduction

The interest in non-fungible tokens (NFTs) has been exploding in recent years. The public pays momentous attention to NFTs, especially after the sale of Beeple's artwork "*Everydays: the First 5000 Days*" for $69 million on March 12, 2021. NFTs represent ownership over digital assets created by individuals or corporations based on the technique powered by blockchains. Today, NFTs are utilized as a representative of items in various forms and put into use in different fields. For example, Twitter CEO Jack Dorsey tokenized his first-ever tweet in 2006 and sold it for nearly $3 million on March 6, 2021.[1] An NFT could also prove the ownership of a photo (e.g., "Disaster girl"), a video (e.g., "Charlie bit my finger"), or even the documents relating to the Nobel Prize-winning research.[2] Many well-known corporations, such as Louis Vuitton, Warner Music Group, Marvel Entertainment, also begin to set foot in the crypto world. The usage of NFTs has evolved from niche blockchain communities into daily business sectors.[3] Up to this point, the future potential of NFTs is far beyond imagination. However, little is known about how these digital tokens interact with other financial assets. To provide the first evidence, we utilize one of the earliest and largest NFT collections, the CryptoPunks, to construct an NFT index and shed light on what factors determine the pricing of these NFTs.

The CryptoPunks was released by *Larva Labs* in June 2017. This experimental project ushered in the inspiration for the ERC-721 that powers most crypto art and collectibles on the Ethereum blockchain nowadays.[4] The invention of CryptoPunks thus has an iconic role in the development of NFTs over time. In a nutshell, CryptoPunks represent crypto images, consisting of 10,000 tokens with

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[1] Twitter CEO Jack Dorsey sold a digitally signed copy of his first tweet - "just setting up my twttr" from 2006 for nearly $3 million on March 6, 2021 (https://www.reuters.com/article/us-twitter-dorsey-nft-idUSKBN2BE2KJ).

[2] The photograph "Disaster girl," featuring a young girl smiling as the fire roared behind her, was sold for $495,000 on April 17, 2021 (https://www.nytimes.com/2021/04/29/arts/disaster-girl-meme-nft.html). The video "Charlie bit my finger," one of the most viewed videos on YouTube, was auctioned off as an NFT for over $760,000 on May 22, 2021 (https://edition.cnn.com/2021/05/22/us/charlie-bit-my-finger-nft-trnd/index.html). The University of California, Berkeley, auctioned off an NFT based on the Nobel Prize-winning research by James Allison for more than $50,000 on June 8, 2021 (https://news.berkeley.edu/story_jump/uc-berkeleys-nobel-nft-auction-set-for-noon-pdt-on-june-7/).

[3] In April 2021, Warner Music Group (WMG) released that it has established a global partnership with Genies, the world's largest avatar technology company, to develop avatars and digital wearable NFTs for WMG's artists. In June, 2021, Marvel Entertainment also announced a new collaboration with Orbis Blockchain Technologies Limited to launch a variety of Marvel NFTs for Marvel fans and collectors around the world. In August 2021, the first series of official Marvel NFT collectible was released. In the same month, Louis Vuitton launched an NFT video game, called as "Louis: The Game" to celebrate its founder's 200th birthday.

[4] For more details regarding the background of NFTs and the Ethereum blockchain, see Section 2.1.

proof-of-ownership stored on the Ethereum blockchain, and each token is one of a kind. Most CryptoPunk tokens are featured with a male or female face, but there are also some special types, such as alien, ape, and zombie.[5] In most cases, the value of CryptoPunks increases with their rareness. One of the most expensive tokens in the collection, *CryptoPunk#7804*, featuring an alien with a cap and smoking a pipe, was sold for about $7.5 million on March 11, 2021. Although the prototype of NFTs is said to be "*Etheria*," launched in October 2015, just three months after the release of Ethereum, it did not raise much attention by that time.[6] Currently, the popularity of *Etheria* or other NFT collections is still far behind that of the CryptoPunks. According to NonFungible.com and OpenSea, the CryptoPunks is the most extensive NFT collection by total sales volume in either USD or Ethereum's native currency (ETH) up to date.[7] The CryptoPunks arguably has become one of the most popular alternative-investment-vessels in this Fintech era. We, therefore, focus on transactions of the CryptoPunks to proxy for the overall pricing of NFTs.

People typically sell their alternative assets, such as artworks or collections, through dealers or traditional auction markets.[8] However, several features make alternative asset classes in NFT markets different from these markets. NFT markets operate as the peer-to-peer version of auction markets (e.g., OpenSea or Rarible) empowered by blockchain technology. In NFT markets, there are no central entities or intermediaries in trades, allowing NFT owners or collectors to make a deal with their counterparts directly.[9] As long as both parties have an Ethereum wallet (e.g., MetaMask), they can trade at an agreed price anytime, thereby increasing public access to NFTs and reducing deadweight loss in illiquid asset markets.[10] Conceptually, NFTs can be traded just like any financial assets on

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[5] For more details regarding the CryptoPunks, see Section 3.1.

[6] See https://twitter.com/etheria_feed/status/1370825688647884802?lang=en.

[7] According to NonFungible.com (https://nonfungible.com/), the largest NFT collection by total sales volume (in USD) was the CryptoPunks, amounting to nearly $911 million as recorded on August 30, 2021. Similarly, the top NFT collection, ranked by total sales volume (in ETH) on OpenSea was the CryptoPunks. OpenSea (https://opensea.io/) is the world's first and largest digital marketplace for crypto collectibles and NFTs.

[8] Throughout this paper, we use the terms "alternative assets" or "unique assets" interchangeably to refer to creative works and collectibles, including paintings, sculptures, coins, stamps, wine, etc.

[9] For example, the users in OpenSea can create and list an NFT for sale with a fixed price or through two types of auctions (i.e., an English auction and a Dutch auction), and prospective buyers can bid or make an offer for an NFT at auction. Another special feature of auctions in OpenSea is that sellers can accept a bid below the reserve price during or after the auction. See https://support.opensea.io/hc/en-us for greater details.

[10] See https://ethereum.org/en/wallets/.

blockchain-based platforms. Although there is no low- or high-price estimate available in NFT markets, anyone can review historical transactions for a given NFT, including bids, offers, sales prices, trading dates, changes of ownership, or even the information about the parties involved in transactions. Such trackable records considerably reduce efforts and costs to verify whether an NFT is a duplicate or an original work. These features also permit us to analyze NFTs at the transaction level.

We begin our analysis by constructing our NFT index using hedonic regression models that account for hedonic characteristics and network factors. Our database consists of 13,712 transactions recorded on *Larva Labs* over the period running from June 2017 to May 2021. Accordingly, we compile a 48-month NFT index. We find that NFT prices highly depend on a token's scarceness and subjective preference for aesthetics. In the meantime, NFT prices are more likely to surge when there are more active transactions and attention to its native blockchain. We also document that the boom and bust of NFT index values are sensitive to economic conditions, regulation policies set by relevant parties, and public skepticism, at least in the early stage.

We then compare the risk-return characteristics between NFTs and other asset classes. The movements of the NFT index are positively correlated with those of its native cryptocurrency exchange rate (i.e., ETH/USD) and stock indices, implying that most investors are more likely to bid up their investment in NFTs when aggregate wealth increases. On top of that, the negative correlation of returns between NFTs and common hedging vehicles (i.e., VIX index, gold, and bonds) indicates that NFTs resemble risky investments in this regard. In general, NFTs provide superior investment returns than all the other asset classes. During our sample period, the geometric (arithmetic) average of monthly returns on NFTs is 16.99% (27.76%), corresponding to the returns of 5.02%, 1.66%, 0.65%, and 0.71% for ETH, stocks, bonds, and gold, respectively. But the standard deviation of NFT returns is among the highest (i.e., 58.77%), which is around 13 times higher than that of stock returns. The Sharpe ratio is thus higher for the NFT index than for the other indices but only comparable with the NASDAQ index. This finding suggests that investing in NFTs usually comes with extremely high volatility.

As previous research documents that economic conditions affect the demand for alternative investments, we decompose the sample period into two subperiods by the outbreak of COVID-19. We find that NFTs continue to outperform other asset classes in terms of geometric average monthly returns both before and after the pandemic outbreak. Specifically, the returns on NFTs rise from 6.10% in the pre-COVID-19 period to 44.11% in the post-COVID-19 period. This evidence is consistent with the notion that the search for yield in a low interest rate environment encourages the growth of alternative asset markets (e.g., Korteweg, Kräussl, and Verwijmeren, 2016). Nevertheless, the standard deviation of NFT returns also rushes to a stunning 74.57% in the later period.

Finally, we investigate whether the returns on NFTs comove with common stock factors used in conventional asset-pricing models, such as the CAPM, Fama-French three-factor, Carhart four-factor, and Fama-French five-factor models. The abnormal returns vary from 26.31% to 30.70% per month, depending on the models. In the meantime, we observe that most equity factors are unlikely to explain the variations of NFT index values. Consistent with the findings in Liu and Tsyvinski (2021), our results suggest that the on-blockchain digital assets, such as cryptocurrencies and NFTs, share few similarities with traditional asset classes.

Our study contributes to the literature in two ways. First, we expand the studies on alternative investments by exploiting the most valuable NFT collection on the blockchain. We add to the literature by providing novel evidence about the nature of on-blockchain alternative assets by comparing the risk-return characteristics of NFTs to those of traditional financial assets. The existing studies on alternative investments mainly focus on unique asset classes with physical objects, such as paintings (Mei and Moses, 2002; Beggs and Graddy, 2009), real estate (Case and Shiller, 1989), collectible stamps (Dimson and Spaenjers, 2011), or wine (Dimson, Rousseau, and Spaenjers, 2015), traded through dealers or auction houses. To the best of our knowledge, our paper is the first study providing empirical evidence about the pricing of NFTs and the analysis of their risk-return profile.

Second, this paper also contributes to a burgeoning literature on blockchain-based technologies, such as cryptocurrencies and ICOs (e.g., Catalini and Gans, 2018; Cong and He, 2019; Griffin and Shams, 2020; Howell, Niessner, and Yermack, 2020; Cong, He, and Li, 2021; Liu and Tsyvinski, 2021;

Liu, Tsyvinski, and Wu, 2021). We complement this literature by showing that investors evaluate the price of NFTs more unconventionally, and none of the existing asset pricing models can fully explain returns on NFTs. Our results suggest that NFTs are more like a medium for efficiently trading illiquid assets than fiat money as most cryptocurrencies.

2. Background and related literature

In this section, we first outline the foundation of the Ethereum blockchain and its extensions. We then discuss how non-fungible tokens (NFTs) could be an alternative investment vehicle by connecting the literature on blockchains and unique asset classes.

2.1 The Ethereum blockchain and non-fungible tokens

The concept of blockchains and relevant extensions has been around since the 1990s (Buterin, 2013). Yet, it was not effectively implemented until Satoshi Nakamoto proposed a peer-to-peer electronic cash system based on cryptographic proof, replacing a trusted third party to verify every transaction (Nakamoto, 2008). In 2009, Bitcoin came to existence and henceforth triggered the worldwide craze for cryptocurrencies as well as other blockchain applications. Bitcoin is by far the most valuable and traded cryptocurrency, but the Bitcoin blockchain is restricted to currency transactions due to the limitations of its structure (Porat, Pratap, Shah, and Adkar, 2017). In 2013, Vitalik Buterin put forward a more advanced framework of blockchain, Ethereum, which enables more complex and customized applications rather than serves as a platform just for digital currency (Buterin, 2013; Chevet, 2018; Kim, Ma, Murali, Mason, Miller, and Bailey, 2018). In 2015, Ethereum was officially released, and its native cryptocurrency, the Ether or ETH, is also born. ETH is now the second-largest cryptocurrency by market capitalization.

The advance in blockchain technology brings about revolutionary progress in the financial ecosystem. The introduction of cryptocurrencies, such as Bitcoin, ETH, or Tether, has disrupted traditional banking industries in many dimensions. Another popular application is for entrepreneurial financing. For instance, startups are able to raise capital through initial coin offerings (ICOs), which are similar to the function of initial public offerings (IPOs) or venture capital (VC). In an ICO, startups auction off a certain quantity of crypto tokens to prospective investors in exchange for funding. Entrepreneurs promise that these tokens will be the only medium to purchase their products (Catalini and Gans, 2018). In this sense, crypto tokens issued through ICOs serve as proof of the ownership rights for future claims. Overall, the above blockchain-based tokens are also best known as examples of "fungible tokens."[11]

More specifically, within the same group of fungible tokens, one token is identical to all the other tokens by property and value. Take ETH as an example. The value of one ETH is always equal to another ETH. In the Ethereum universe, most transactions rely on "smart contracts," which are computer programs stored on a blockchain, and these contracts are implemented when certain conditions are satisfied.[12] To some extent, smart contracts, serving as a third-party mediator, can mitigate informational asymmetry and improve welfare and consumer surplus through enhanced entry and competition (Cong and He, 2019). Several standards have been established as part of smart contracts to facilitate composability and interoperability. The primary standard on the Ethereum blockchain is known as the ERC-20 (Ethereum Request for Comments 20), which has been introduced as the technical foundation for all smart contracts for fungible token implementations (e.g., ETH).[13]

In June 2017, the debut of CryptoPunks inspired the standard - the ERC-721 (Ethereum Request for Comments 721). It cultivated a more novel type of digital tokens, widely known as "non-fungible token" or "NFT."[14] Unlike fungible tokens, NFTs can represent the ownership of more unique asset classes, such as digital artwork, a domain name, an essay, to name but a few.[15] The ERC-721 smart contracts improve the efficiency of trading unique tokens because every NFT is identified by a unique

[11] Alternatively, Howell et al. (2020) define three types of digital assets: coins (e.g., Bitcoin and ETH), security tokens (e.g., the representation for real estate ownership), and utility tokens (e.g., the rights for an ICO issuer's product). However, these categories are not mutually exclusive. That is, one token might belong to more than one type.

[12] Smart contracts can define rules, like a regular contract, and automatically enforce them via the code, which cannot be manipulated by anyone.

[13] The ERC-20, proposed by Fabian Vogelsteller in November 2015, defines a common list of rules that all fungible Ethereum tokens should adhere to. See https://ethereum.org/en/developers/docs/standards/tokens/erc-20/.

[14] The ERC-721, proposed by William Entriken, Dieter Shirley, Jacob Evans, Nastassia Sachs in January 2018, is a Non-Fungible Token Standard that implements an API for tokens within smart contracts. Specifically, the ERC-721 sets up a standard for NFT of which token type is unique and can have different value than another token from the same smart contract. See https://ethereum.org/en/developers/docs/standards/tokens/erc-721/.

[15] See Chohan (2021), Fairfield and Trautman (2021), and Fairfield (2021) for greater details regarding NFTs.

token identity (ID) inside such a contract. This token ID shall not change for the contract's life (Entriken, Shirley, Evans, and Sachs, 2018). It is worth noting that most NFTs are created on the Ethereum platforms since the improvement of Ethereum blockchain allows for more diverse applications compared to other blockchains. Nevertheless, the existing literature mainly focuses on cryptocurrencies and ICOs. The literature is void on this type of digital tokens. In this paper, we fill this gap by uncovering the pricing and investment performance of NFTs.

2.2 Alternative investments over time and NFTs

Over the past decades, numerous financial instruments, such as stocks, bonds, futures, or options, are created to satisfy the needs for fundraising, investments, hedging, speculating, and risk-sharing. Meanwhile, the growth of individual wealth leads to the boom in alternative asset markets for artworks, wine, stamps, or other collectibles (Goetzmann, 1993; Dimson and Spaenjers, 2011; Goetzmann, Renneboog, and Spaenjers, 2011; Dimson et al., 2015; Korteweg et al., 2016). Some investors treat alternative asset classes as an investment or a portfolio diversifier, and several funds are even created to cater to this increasing demand (Renneboog and Spaenjers, 2013; Kräussl, Lehnert, and Rinne, 2017; Lovo and Spaenjers, 2018).

An extensive body of research has been devoted to understanding how these alternative assets are different from traditional investment vessels. Unlike financial assets, the characteristics of unique assets are difficult to identify and quantify in terms of monetary units. For instance, stock prices may be predicted by or at least related to financial indicators, while the prices of artworks may exhibit random behavior. As Baumol (1986) suggests that the inventory of a particular stock is made up of a large number of homogeneous securities, they are all perfect substitutes for one another. On the contrary, the value of two identical artworks could vary greatly, if they are created by different artists or sold at different markets.[16] Thus, alternative asset classes are also known as heterogeneous goods

[16] For example, Pesando (1993) finds that there is a substantial price variation in the sale of identical prints, and prices paid by buyers are systematically higher at certain auction houses. Alternative assets are usually sold through dealers or traditional auction markets. In practice, English auction houses (e.g., Sotheby's and Christie's) validate the authenticity of an item up for sale and appraise its market value. They provide a price range estimate to potential buyers, and the lower range estimate is usually set at or above a seller's reserve price (Beggs and Graddy, 2009). On the day of a public sale, an auctioneer helps call out for higher bidding prices, and the item goes to the bidder who makes the highest bid. However, if the bid is below the reserve price, the item is "bought-in," meaning that it is left unsold and the ownership remains

or imperfect substitutes (Stein, 1977). It is also crucial to know how much a collector initially paid for an artist or a gallery in the primary sale to thoroughly analyze the investment returns on unique assets, as Whitaker and Kräussl (2020) suggested. Hence, traditional asset pricing models might not apply to the valuation of such assets.

Existing studies have attempted to measure the investment performance of alternative assets and compare it with several types of financial instruments. Empirical evidence shows that unique asset classes underperform stocks in terms of returns but outperform bonds most of the time (Mei and Moses, 2002; Mandel, 2009; Dimson et al., 2015). Nevertheless, the returns on unique assets are usually accompanied by much higher risk measured by their volatilities, making them less attractive to investors. One strand of theoretical literature suggests that possessing unique assets provides the owners with some nonfinancial utility. In particular, Mandel (2009) proposes that art has a dual nature as an investment vehicle and a conspicuous consumption good. Hence, the return can be decomposed into the utility derived from the ownership and capital gains from the resales.[17] Lovo and Spaenjers (2018) further advance that, in art auction markets, each bidder's valuation of a given work is a function of the expected stream of "emotional dividends" until resale and the expected resale revenues. The concept of emotional dividends is proposed as artworks themselves do not generate any cash flows during the holding period. This special feature contrasts sharply with the design of existing financial instruments and helps to explain why investors are willing to accept lower financial returns generated from alternative assets.

We extend this line of research by exploring on-blockchain unique assets, NFTs, and examine whether their risk-return characteristics resemble those of existing artworks and collectibles. Given that NFTs have grown dramatically and become unneglectable with respect to their market capitalization and extensive applications, NFTs undoubtedly deserve more academic attention at this moment. Moreover, NFT markets provide a gateway for us to keep track of all transaction records for

unchanged. To that end, auction houses have little incentive to hold sales for an item with the insufficient public interest (Goetzmann, 1993). Hence, a successful auction hinges on the pricing and marketing strategy developed by these agents.

[17] The concept of "conspicuous consumption" was first illustrated by Veblen (1899), it refer to the consumption of costly goods or services for reputability, mainly in the leisure class.

each token from the very beginning. We study one representative NFT collection, the CryptoPunks, with 10,000 unique tokens issued on the same date and identifiable characteristics. This unique dataset allows us to adopt a hedonic regression model to construct an index that reflects the price level in NFT markets. We illustrate more in the next section on the data of this NFT collection.

3. Data and sample

3.1 Non-fungible tokens: the CryptoPunks

The CryptoPunks is the earliest and largest NFT project in terms of total sales in USD. In 2017, the CryptoPunks were developed and released by two Canadian software developers, Matt Hall and John Watkinson, the founders of New York-based software company *Larva Labs*. In brief, the CryptoPunks are 24x24 pixel crypto art images, including 10,000 unique tokens with proof of ownership stored on the Ethereum blockchain. Each of CryptoPunk tokens has a unique identification number, running from 0 through 9999. Overall, CryptoPunk tokens can be categorized into five major types (i.e., Alien, Ape, Zombie, Female, and Male), which largely account for the differences in token appearance. There are only 9, 24, and 88 tokens for the type of Alien, Ape, and Zombie, respectively, in the whole collection.[18] Furthermore, there are 87 extra attributes, which serve as accessories for each type, and each CryptoPunk token is featured with from 0 to 7 attributes.[19] Thus, we choose to utilize CryptoPunk tokens to proxy for the overall NFT price level not only due to its size and popularity but also because we can identify every characteristic attached to each token. We collect archived data on trading dates, sales prices, and token characteristics of the CryptoPunks from *Larva Labs'* website (https://www.larvalabs.com/). The sample consists of 13,712 transactions, including 5,630 unique tokens from June 2017 through May 2021.

We first analyze the transactions of CryptoPunk tokens for each type and each year. Panel A of Table 1 shows that more than half of the primary or secondary sales are made between 2020 and 2021, suggesting that the NFT adoption is growing dramatically. Overall, we have 5,630 tokens sold in primary sales, implying that initial owners still hold 4,370 unique tokens during our sample period.

[18] The rarest type is Alien, followed by Ape, Zombie, Female, and Male. See https://www.larvalabs.com/ for details.
[19] In Appendix B, we summarize the number of CryptoPunk attributes featured in the whole collection.

The most-traded type is Male, followed by Female and Zombie. Panel B of Table 1 provides a breakdown of sales prices according to the types of CryptoPunk tokens. We find that, as the type of a CryptoPunk token is scarcer, that token is more expensive. This finding indicates that collectors, on average, are willing to pay a higher price premium for scarcity. Meanwhile, sales prices, especially for the rarest types (i.e., Alien, Ape, and Zombie), are much lower in primary sales than those in secondary sales. In other words, the buyers in primary sales usually have lucrative profits from the resales of CryptoPunk tokens.

[Insert Table 1]

Before we study the investment performance of NFTs, it is important to understand the trading behavior of NFT collectors. Figure 1 shows the distribution of holding periods (in months) from the first purchase to the resale for the CryptoPunks investment. We find that about half of collectors resold their tokens within six months, while approximately 40% of collectors kept the tokens for more than one year, including 15.29% for holding more than 42 months. We also examine the turnover of transactions for each CryptoPunk during our sample period. In Figure A1, we find that 51.31% of CryptoPunks are never resold in NFT markets after the primary sales, and less than 7.5% of CryptoPunks are resold more than five times. These findings suggest that some collectors treat NFTs as opportunistic investments to reap quick financial profits, but others consider NFTs to be collectibles or artworks to gain emotional dividends.

[Insert Figure 1]

3.2 Network factors in NFT markets

The theoretical works on crypto tokens suggest that the network effects are essential for the success of digital platforms and initial coin offerings (e.g., Catalini and Gans, 2018; Sockin and Xiong, 2020). Further analysis reveals that cryptocurrency adoptions, such as wallet users growth, active address growth, transaction count growth, and payment count growth, are important factors for the valuation of cryptocurrency (Liu and Tsyvinski, 2021).

Similarly, NFT prices could be driven by the networks of users (i.e., collectors or investors) in NFT markets (e.g., Ante, 2021). Hence, we utilize five measures to proxy for the NFT network effects: (1) the growth of active wallets ($\Delta NumWallets$), (2) the growth of unique buyers ($\Delta NumBuyers$), (3) the growth of unique sellers ($\Delta NumSellers$), (4) the growth of transactions for sales ($\Delta NumSales$), and (5) the growth of sales volume in USD ($\Delta SalesUSD$). We obtain daily data on the statistics of NFT markets from Nonfungible.com.[20] Given that NFTs are mostly sold via the platforms supported by Ethereum and denominated in ETH, we employ two additional proxies for the networks pertaining to Ethereum. The first proxy, $\Delta ETHUSD$, is the daily growth of ETH/USD exchange rates; the second proxy, $\Delta ETHVol$, is the daily growth of ETH trading volume. Daily data on ETH are from Yahoo! Finance.

3.3 Worldwide attention to Ethereum

Prior research shows that investor attention affects asset prices (e.g., Peng and Xiong, 2006; Barber and Odean, 2008; Da, Engelberg, and Gao, 2011; Huang, Huang, and Lin, 2019). In a similar vein, NFT prices could be stimulated when the public is more aware of NFTs and other blockchain applications (e.g., Ether, Bitcoin, or Dogecoin). Thus, we also consider how public attention to blockchains influences the prices of CryptoPunks.

Similar to the methodology of Liu and Tsyvinski (2021), we utilize Google search frequency (i.e., Search Volume Index, SVI) of the search topic of "Ethereum" to capture worldwide attention paid towards NFTs because most NFTs are traded on the Ethereum blockchain.[21] The SVI values are downloaded from Google Trends.[22] As shown in Figure A2, the average sales prices per month positively comove with the trend of Google searches related to "Ethereum." Since Google Trends does not provide daily SVI for a time period over one year, we construct adjusted SVI (*Adj. SVI*) on a daily basis to capture the attention of individual investors in a more timely fashion. Specifically, we obtain daily SVI in a given month and rescale the index values using monthly SVI over the period from

[20] The data are downloaded from Nonfungible.com (https://nonfungible.com/).

[21] In our paper, the SVI captures the trend of searching for the topics related to "Ethereum." For example, Google users not only search for the term "Ethereum" but also look for one of the following keywords: "Bitcoin", "Mining", "Ether", "Cryptocurrency", "Ripple", "Litecoin", "Non-fungible token", etc.

[22] The index values of SVI represent Google search interest relative to the highest point for the given region in a given period. If the value of SVI is 100, it indicates the peak popularity for the term in a given period. If the value of SVI is 50, it means that the term is half as popular in a given period. A score of 0 means there was not enough data for this term.

January 2016 through May 2021 to construct our proxy, *Adj. SVI*, for the attention to Ethereum (see Appendix A for additional details).

Table 2 reports the correlations between the network factors and worldwide attention we use in this study. Unsurprisingly, the five measures of NFT network factors positively and strongly correlate with each other, with correlations ranging from 0.26 to 0.95, as shown in columns (1) to (5). This finding suggests that when there are more users in NFT markets, the trading activity becomes more active in terms of the number of sales and market capitalization in USD. In columns (6) to (8) of Table 2, we also find that worldwide attention to Ethereum, measured by *Adj. SVI*, is positively correlated with $\Delta ETHUSD$ and $\Delta ETHVol$, consistent with the notion that increasing investor attention to Ethereum induces a higher ETH/USD exchange rate and trading volume. NFT network factors are also positively correlated to the proxies for the network effects of Ethereum, though to a lesser extent. The finding implies that the growth of NFT markets is not entirely driven by the adoption of their native cryptocurrency, ETH.[23]

[Insert Table 2]

4. Methodology

The existing studies typically use two methods for constructing a price index of illiquid asset classes, i.e., the repeat-sales regression (RSR) models (e.g., Case and Shiller, 1989; Pesando, 1993; Lovo and Spaenjers, 2018) and hedonic regression models (e.g., Campbell, Giglio, and Pathak, 2011; Renneboog and Spaenjers, 2013; Dimson et al., 2015). One major empirical issue for the RSR method is that it requires an item to be traded at least twice. This requirement tends to result in a much smaller sample because some unique assets are never resold in markets. Furthermore, the RSR model also suffers from a spurious negative autocorrelation in the estimated return series and an overestimate of the variance of the series (Goetzmann, 1993; Mei and Moses, 2002).

In contrast, the hedonic regression model includes all available transaction data and formulate the

[23] Dowling (2021) shows that the media coverage regarding NFTs could impact NFT prices. However, he simply looks at the raw returns without considering the characteristics for each token and the network effects in NFT markets.

prices of infrequently traded assets in markets by relating transaction prices to the assets' characteristics (Rosen, 1974). Given that we can access historical transactions and identify characteristics of each CryptoPunk token, we adopt the hedonic regression model rather than the RSR method to construct our NFT index.

4.1. Hedonic regression model

To construct an overall price index of the NFTs, we begin by developing a hedonic regression model while controlling for observable characteristics of each CryptoPunk token and the network factors discussed in Section 3. Formally, we utilize the following hedonic regression model using ordinary least squares with the natural logarithm of CryptoPunk token prices in USD as the dependent variable.

$$\ln P_{i,t} = \alpha + \sum_{j=1}^{J} \beta_j X_{j,i} + \sum_{n=1}^{N} \gamma_n Network_{n,t} + \sum_{t=1}^{T} \delta_t T_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $P_{i,t}$ represents the sales price of a CryptoPunk token i sold on date t, α is the regression intercept, $X_{j,i}$ indexes the characteristic j of the token i has, $Network_{n,t}$ denotes the network factor n in NFT markets or the Ethereum blockchain on date t, and $T_{i,t}$ is the time dummy that equals one if the token i is sold in period t. The coefficients β_j reflect the attribution of a relative shadow price to each of the j characteristics, while the coefficients γ_n capture the attribution of a relative shadow price to each of the n network factors. The anti-logs of the coefficients of δ_t are used to construct an NFT index that controls for time variation in the quality of tokens sold. The value of the hedonic NFT index (π_t) in year-month t is estimated as:

$$\pi_t \equiv \exp(\widehat{\delta_t}) \tag{2}$$

In the model, the time dummy coefficient is set to 0 for the initial and left-out period (i.e., June 2017). Thus, an estimated return (r_t) in year-month t is equal to:

$$r_t \equiv \frac{\pi_t}{\pi_{t-1}} - 1 \tag{3}$$

In addition, we add a wide range of CryptoPunk characteristics, including four type dummies (i.e., *Alien*, *Ape*, *Zombie*, and *Female*) and 86 attribute dummies for each token, in the model. We also consider whether a transaction is a primary sale (*PrimarySale*) and control for the changes in the number unique wallets ($\Delta NumWallets$), the number of buyers ($\Delta NumBuyers$), the number of sellers ($\Delta NumSellers$), the number of sales ($\Delta NumSales$), the sales volume in USD ($\Delta SalesUSD$), ETHUSD exchange rate ($\Delta ETHUSD$), the ETH trading volume ($\Delta ETHVol$) as well as worldwide attention to Ethereum (*Adj. SVI*).

4.2. *Hedonic regression results*

To construct our NFT index, we first estimate Eq. (1) using ordinary least squares with the natural logarithm of CryptoPunk token prices in USD as the dependent variable. The results are presented in Table 3. Column (1) shows that the magnitude of coefficients on the type dummies monotonically increases with the level of types' scarcity, suggesting that the rarer a CryptoPunk token is, the higher its sales price is. The coefficient on *PrimarySale* indicates that sales prices in the first sales, on average, are lower than those in the secondary sales. We also examine how the adoption of NFTs, proxied by $\Delta NumWallets$, influences sales prices. In columns (2), however, the coefficient on $\Delta NumWallets$ is not significant. To better understand the result, we further decompose the participants in NFT markets into buy-side and sell-side and calculate the growth rates of each side, proxied by $\Delta NumBuyers$ and $\Delta NumSellers$, respectively. As illustrated in column (3) of Table 3, the growth of NFT buyers (sellers) is positively (negatively) correlated with the prices of CryptoPunk tokens. The finding is consistent with the intuition that greater demand for NFTs helps push up sales prices, while more supply drags down the prices.

Finally, we introduce additional network factors, which can directly affect the sales prices of CryptoPunk tokens, including $\Delta NumSales$, $\Delta SalesUSD$, $\Delta ETHUSD$, $\Delta ETHVol$, and *Adj. SVI,* in the hedonic model.[24] We find that the sales prices become higher when there is an increase in the number of transactions and NFT market size, as proxied by $\Delta NumSales$ and $\Delta SalesUSD$, respectively. Similarly, worldwide attention to Ethereum (*Adj. SVI*) could lift the value of CryptoPunk tokens. However, the growth of ETH/USD is negatively correlated with the sales prices, indicating that NFT collectors, to

[24] The results are qualitatively similar when we replace $\Delta ETHUSD$ and $\Delta ETHVol$ with the daily growth of Bitcoin/USD exchange rates and Bitcoin trading volume, respectively.

some degree, evaluate CryptoPunk tokens based on USD. More importantly, an adjusted R^2 of over 90% suggests that our hedonic model captures a significant amount of variance in the prices of CryptoPunk tokens in a simple linear setting. As the adjusted R^2 in column (4) of Table 3 is higher than the explanatory power of the models in the first three columns, we use this specification as the baseline model throughout the analysis. We obtain similar results as presented in Appendix C when we estimate our NFT index with the sales prices denominated in ETH. Hence, our findings are robust to alternative currencies for the construction of our NFT index.

[Insert Table 3]

4.3. Hedonic NFT index

In this section, we construct an NFT index using Eq. (2) with the resulting estimates on the time dummies from the hedonic regression model, and the price level of the NFT index is set to one in June 2017 when the CryptoPunks was launched. We calculate returns on NFTs using Eq. (3). Table 4 reports our NFT index values and returns per month. We also provide a graphical snapshot of the results to visually check the relationship between the index values and returns in Figure 2.

As can be observed, there are three apparent bull markets in NFTs, i.e., from November 2017 to January 2018, January 2019 to May 2019, and the period after the outbreak of the COVID-19 as of March 2020. The first two bull markets are mostly due to the boom in media coverage and the adoption of NFTs.[25] The post-COVID-19 period is the strongest and the longest of the three bull markets. This bull market coincided with a series of aggressive measures by central banks across the world to stabilize the financial markets. For example, the U.S. Federal Reserve cut the interest rate to zero and announced a massive quantitative easing (QE) program in March 2020 to boost the U.S. economy.[26] Our evidence so far suggests that the need for investment opportunities or perhaps speculating targets stimulate NFT prices' growth. Consistent with prior studies, investors tend to search for higher yield assets in an environment of low interest rates, leading to higher investments in alternative asset markets

[25] For instance, *CryptoKitties*, the world's first game built on the Ethereum blockchain, was released in November 2017, leading to a mania for "crypto-pets" (https://www.bbc.com/news/technology-42237162).
[26] See https://edition.cnn.com/2020/03/15/economy/federal-reserve/index.html.

(Korteweg et al., 2016; Kräussl et al., 2017).

Our NFT index also identifies three major bear markets in NFTs, i.e., from August 2017 to October 2017, from February 2018 to May 2018, and from July 2019 to September 2019. The price plummets in 2017 and 2018 were related to tighter regulations and security concerns for cryptocurrencies. In late 2017, the authorities in several countries started to express their concerns about the adoption of cryptocurrencies. For example, China and South Korean governments shut down cryptocurrency exchanges, leading to a drastic slump in Bitcoin and ETH.[27] Meanwhile, the world's major advertising providers (i.e., Google and Facebook) even banned cryptocurrency advertisements.

The bear market in 2019 was associated with arising skepticism and scandals of cryptocurrencies. In particular, Donald Trump, the former U.S. president, criticized that the value of Bitcoin and other cryptocurrencies was based on thin air on July 12, 2019. He further commented via Twitter that "*Unregulated Crypto Assets can facilitate unlawful behavior, including drug trade and other illegal activity*." Afterward, NFT markets took another tumble, suggesting that the values of NFTs are vulnerable to market suspicion.[28]

[Insert Table 4 & Figure 2]

Overall, the findings in this section show that NFT prices are closely tied to the adoption of blockchain technology and public awareness of its applications. Nevertheless, it appears to be the economic environment that fosters the rapid appreciation of NFT values.

4.4. The price impact of CryptoPunk attributes

We also investigate how CryptoPunk characteristics affect sales prices. Following the methodology of Renneboog and Spaenjers (2013), we calculate the price impact of each attribute dummy as the exponent of the estimated coefficient minus one. For brevity, Table 5 only reports the top/bottom 10 attributes favored by CryptoPunk collectors. We find that CryptoPunk tokens with an attribute "Beanie,"

[27] See https://www.bbc.com/news/business-42915437.
[28] See https://www.cnbc.com/2019/07/15/bitcoin-price-falls-below-10000-as-president-trump-slams-crypto.html.

on average, can increase the value by almost fivefold, and the tokens with the attributes "Pilot Helmet" and "Tiara" are also double priced. In contrast, tokens with certain characteristics, such as "Stringy Hair," "Bandana," or "Frumpy Hair," are traded at a large discount.

Overall, CryptoPunk collectors are willing to pay a price premium for a specific set of characteristics, while tokens with unfavorable characteristics are sold with discounts. Unsurprisingly, the top 10 attributes are the rarest among all attributes. But they are not only priced according to their scarcity as some of the bottom 10 attributes are also rare. In other words, aesthetic preferences also play an essential role in determining NFT prices.

[Insert Table 5]

5. Investment performance of NFTs

5.1 NFT index versus major market indices

In the previous section, we have constructed the NFT price index. In this section, we compare the performance of NFTs with that of cryptocurrencies (i.e., *ETH/USD Index*), stocks (i.e., *NASDAQ Index*, *S&P 500 Index*, or *Dow Jones Index*), market volatilities (i.e., *VIX Index*), bonds (i.e., *Bond Index*), and commodities (i.e., *Gold Index*).[29] We measure the year-month values for each market index as the average of daily data in a given month. We further set index values to unity in June 2017 to compare the variation of indices more conveniently. Appendix A provides variable definitions in greater detail.

To illustrate the relationship between the NFT index and major market indices, we first present a snapshot of the data. In Figure 3, we plot our NFT index and five-selected market indices. The NFT index is much more volatile than all the other market indices, while the NFT index positively comoves with *ETH/USD Index*. We postulate that investors somewhat peg the values of NFTs to USD when making their investment decisions. In addition, the NFT index seems to have a negative correlation with *Bond Index* from June 2020 to May 2021, indicating that investors might invest in NFTs as a substitute for the U.S. bonds.

[29] Data on major market indices are obtained from Yahoo! Finance and Investing.com.

Turning to the U.S. stock market, proxied by *NASDAQ Index*, it seems to have little impact on the prices of NFTs. Yet, some may argue that NFTs are traded around the world. The pricing of NFTs might be associated with stock markets in regions beyond the U.S. To address this concern, we also compare our NFT index with stock performances in the U.K., Germany, Japan, China, and Hong Kong, as measured by *FTSE Index*, *DAX Index*, *Nikkei Index*, *SSE Index*, and *Hang Seng Index*, respectively. As can be observed in Figure 4, the results are similar.

[Insert Figure 3 & Figure 4]

We then analyze the correlations of returns on NFTs, stocks, market volatilities, bonds, and commodities. We present the results in Table 6. The return on the NFT index is positively correlated to the ETH return but negatively correlated with the U.S. bond return. Although the correlations between the returns on other financial assets and the NFT index are not statistically significant, the result suggests some implications. For instance, NFT returns are positively associated with stock market returns, consistent with the notion that the demand for alternative investments increases with the growth of aggregate financial wealth (e.g., Goetzmann, 1993; Dimson and Spaenjers, 2011; Dimson et al., 2015).

[Insert Table 6]

We present summary statistics for monthly returns on different assets during our sample period in Table 7. Given that returns on an asset might be serially correlated, we calculate monthly returns in two ways, i.e., arithmetic mean and geometric mean. During our sample period, the average of NFT returns is 27.76% (16.99%) per month based on the arithmetic (geometric) estimation method, while the returns on ETH, stocks, and bonds are only 8.92% (5.02%), 1.77% (1.66%), and 1.50% (0.65%), respectively. Collectively, we find that our NFT index substantially outperforms all asset classes in terms of average monthly returns in both methods. But investing in NFTs is accompanied by much higher risk, with a standard deviation of 58.77%. The corresponding numbers are 30.35% and 4.63% for ETH and stocks, respectively. Hence, we analyze the risk-return relationship for different assets by measuring their Sharpe ratios, using one-month T-bill returns as the risk-free rate. As shown in the last two columns of Table 7, the performance of NFTs and stocks seems to be comparable if we use geometric average monthly returns.

[Insert Table 7]

Although the Sharpe ratio is widely adopted as a benchmark of reward-to-variability (Sharpe, 1966), it also receives some criticism. For example, the Sharpe ratio does not distinguish between good and bad volatilities. Hence, extremely high returns are penalized by increasing a portfolio's standard deviation (e.g., Goetzmann, Ingersoll, Spiegel, and Welch, 2007). To address this problem, we employ other indicators (e.g., Jensen's alpha ($\hat{\alpha}$) and the Treynor ratio) to evaluate the risk-return profile of different asset classes. In particular, Sortino and van der Meer (1991) propose an alternative measure of investment performance, i.e., the Sortino ratio, by only considering the downside risk. They argue that only returns that fall below the minimal acceptable return (MAR) incur the risk. The farther the returns fall below the MAR, the greater the risk. Sortino, van der Meer, and Plantinga (1999) further modify the Sortino ratio and only take the returns above the MAR into account when assessing the expected return (i.e., the numerator of the upside potential ratio). As shown in Appendix D, NFT significantly outperforms all the other asset classes when judged by these alternative risk-reward measures that take the upswing and downswing of asset returns into account.

5.2 Investment performance during pre- and post-COVID 19 periods

In Section 4.3, we document a disproportional surge in the NFT index after the outbreak of the COVID-19 as of March 2020. One may wonder whether NFTs still outperform other financial assets in a different environment. Or is there a bubble in NFT markets after the pandemic? To answer these questions, we divide our sample period into two and investigate the investment performance of NFTs in the subperiods. Specifically, we define the pre-COVID-19 period from June 2017 to February 2020 and the post-COVID-19 period from March 2020 to May 2021. In Table 8, we compare the (geometric) average monthly returns, standard deviations, and Sharpe ratios during these subperiods. We find that the risk-return characteristics of all asset classes between these subperiods change significantly. Compared with the overall (geometric) average returns on NFTs (i.e., 16.99%) in Table 7, the returns on NFTs drop to 6.10% in the pre-COVID-19 period but surge to 44.11% after the pandemic. The standard deviation rises sharply from 44.35% to 74.57%. Despite that, NFTs, on average, generate the highest monthly return, which is about 5 to 18 times higher than stocks in the subperiods. With respect to the Sharpe ratio, NFTs underperform stocks in the pre-COVID-19 period but outperform them in the later period. Collectively, we find consistent results as in Table 7, NFT investors are compensated by substantial higher financial returns for bearing high volatility.

We obtain similar results when the NFT index is constructed with CryptoPunk token prices denominated in ETH, as reported in Panel A of Appendix E. It is noteworthy that NFT performance in the pre-COVID-19 period shows qualitatively similar patterns when we consider the sales prices in ETH, while the average of monthly returns on NFTs during the post-COVID-19 period reduces to only about half of that in Table 8 (i.e., 44.11% versus 23.22%). This finding provides an interesting implication that NFTs could be a hybrid investment in both unique assets and ETH.

[Insert Table 8]

The results in this section collectively indicate that there is a risk-return tradeoff in NFT investments. We also find that NFT markets grow much faster than other asset markets after a series of economic stimuli, implying that investors treat NFTs as alternative investments when they have more surplus funds and search for higher yields.

5.3 Equity factor loadings

We then examine whether the common stock factors help to explain the movement of NFT index values. For the equity risk factors, we employ the capital asset pricing model (CAPM), Fama-French three-factor, Carhart four-factor, and Fama-French five-factor models.[30] As reported in Table 9, the alphas for all factor models are statistically significant.[31] The magnitudes of the alphas range from 26.32% to 30.70% per month, comparable to the average return of 27.76% in Table 7. Concerning market betas, the coefficients on *MKTRF* are neither statistically significant nor stable across all

[30] The equity risk factors are defined as in Fama and French (1993), Carhart (1997) , and Fama and French (2015).
[31] We obtain similar results as shown in Panel B of Appendix E when NFT index values are constructed with CryptoPunk token prices denominated in ETH.

specifications. In particular, the CAPM beta is about 0.95, while the betas are all negative for the three-factor, four-factor, and four-factor models.

It is noteworthy that the exposures to most factors are not statistically significant except for the factor *CMA*. The mild exposure to the *CMA* factor is negative and statistically significant at the 10% level, suggesting that the returns on NFTs may comove more with high-investment rather than low-investment firms. This result can be interpreted as investors treating NFTs as an alternative investment for technological innovation.

[Insert Table 9]

5.4 *Transaction costs in Ethereum*

Although it is common to measure the returns on traditional financial assets as gross of transaction costs, the existing literature documents that the transaction costs associated with buying and selling illiquid assets could be material (e.g., Pesando, 1993; Dimson and Spaenjers, 2011). Therefore, artworks and real estate, for example, are better for long-term investments such that costs can be spread over many years (Case and Shiller, 1989; Mei and Moses, 2002).

On the Ethereum platform, NFT buyers or sellers have to pay an extra trading cost (i.e., gas fee) because every transaction requires computational resources to execute. This fee system aims to prevent hostile infinite loops or other computational wastage (Buterin, 2013).[32] On the platform, "gas" is the fundamental unit of computation. Specifically, gas is a reference to the computation required to successfully process a transaction by a miner, and Ethereum users are charged for this computation.[33] Gas fee is calculated as follows:

$$Gas\ fee\ =\ Gas\ price \times Gas\ used \tag{4}$$

where $Gas\ price$ denotes the cost per unit of gas for the transaction.[34] $Gas\ used$ indicates the exact units of gas used for a given transaction, and $Gas\ fee$ is paid in Ethereum's native currency, Ether

[32] Each transaction is required to set a limit to how many computational steps of code execution it can use. Generally, one computational step costs one gas, but some operations consume higher amounts of gas because they are more computationally expensive. See https://ethereum.org/en/whitepaper/ for details.
[33] See https://ethereum.org/en/developers/docs/transactions/.
[34] Gas price is measured in Gwei, and each Gwei is equal to 0.000000001 ETH (10^{-9} ETH).

(ETH). Gas price depends on the demand for Ethereum network requests, so it is volatile within a day. That is, high transaction activities in Ethereum usually induce higher gas prices. We gather data on gas fees of CryptoPunks' sales from Etherscan (https://etherscan.io/) and examine about 9,000 transactions over our sample period. In untabulated results, we find that gas fees, on average, account for 0.23% of the sales prices. The number gradually decreases from 0.67% in 2017 to 0.06% in 2021. Given that gas fees are trivial for most transactions, we ignore gas fees in the analysis.

In addition to gas fees, some platforms levy a service fee on sellers once their NFTs are sold. For example, OpenSea charges NFT sellers 2.5% of sales prices for processing transactions. To address whether such costs materially impact our results, we adjust NFT returns from Table 4 with service fees (i.e., 2.5%). As shown in Appendix F, NFTs continue to dominate other asset classes by yielding the highest financial returns. Concerning the overall performance, the Sharpe ratios of NFTs are comparable to those of stocks due to the high volatility of NFT prices. Thus, our conclusion is unlikely to be changed by transaction costs.

6. Conclusion

The arrival of on-blockchain digital assets, such as cryptocurrencies and ICO tokens, has already impacted the financial ecosystem in just a few years. A burgeoning stream of the literature has been devoted to understanding the risk-return characteristics of cryptocurrencies, such as Bitcoin, ETH, or Ripple. Today, the boom of NFTs is expected to disrupt the industries more extensively and profoundly in the foreseeable future. Nevertheless, little is known about the pricing and investment performance of this type of digital tokens. In this paper, we fill this gap.

We construct an overall price index based on hedonic regression models and observe that token scarceness and subjective judgments of aesthetics are crucial determinants for explaining a large portion of price premiums. The adoption of blockchain technology and the variation of cryptocurrencies also affect the valuation of NFTs, but to a lesser extent. We document that the average of monthly returns on NFTs is 27.76% (16.99%) based on the arithmetic (geometric) estimation method, outperforming most traditional financial assets. But the standard deviation of NFT returns is among the highest, i.e., 58.77%. There is also evidence that NFTs have become one of the popular alternative investment vessels, especially when conventional financial assets generate relatively low yields. Building on the existing insights, we argue that NFTs provide investors not only financial returns from resales but also emotional dividends from possession. Consequently, investors are more willing to accept such extremely high volatility about NFT investments.

Our findings collectively do not suggest that NFTs are superior to certain traditional financial assets (e.g., small and high-tech stocks) because the pricing of an NFT involves more complex valuations. It could also take more time to search for trading counterparts. Also, armed with the caveat that the authorities worldwide might take part in meddling the applications derived from blockchain technology, NFT returns could be more unpredictable. Finally, we acknowledge the limitation of this study that our NFT index based on the sales of CryptoPunk tokens might not serve as a representative indicator in NFT markets. Indeed, total transactions of the CryptoPunks only account for part of NFT projects from all genres. Yet, the CryptoPunks is among the pioneer and symbolic icons for the development of NFTs. The insights gained from this research framework outweigh its limitations.

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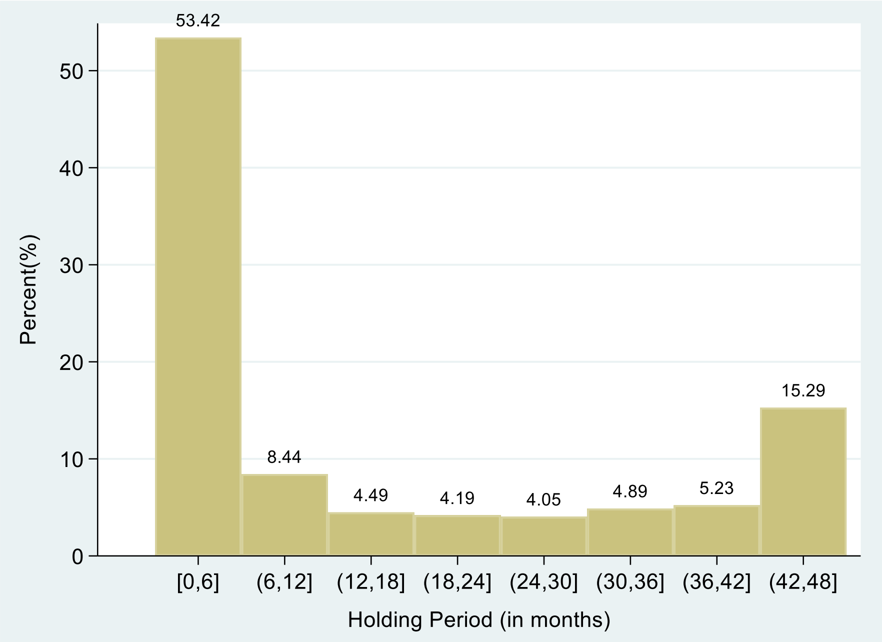

Figure 1. Distribution of holding periods (in months).
The figure shows that the distribution of holding periods (in months) from the first purchase to the resale for each CryptoPunk collector. The sample period is from June 2017 through May 2021.

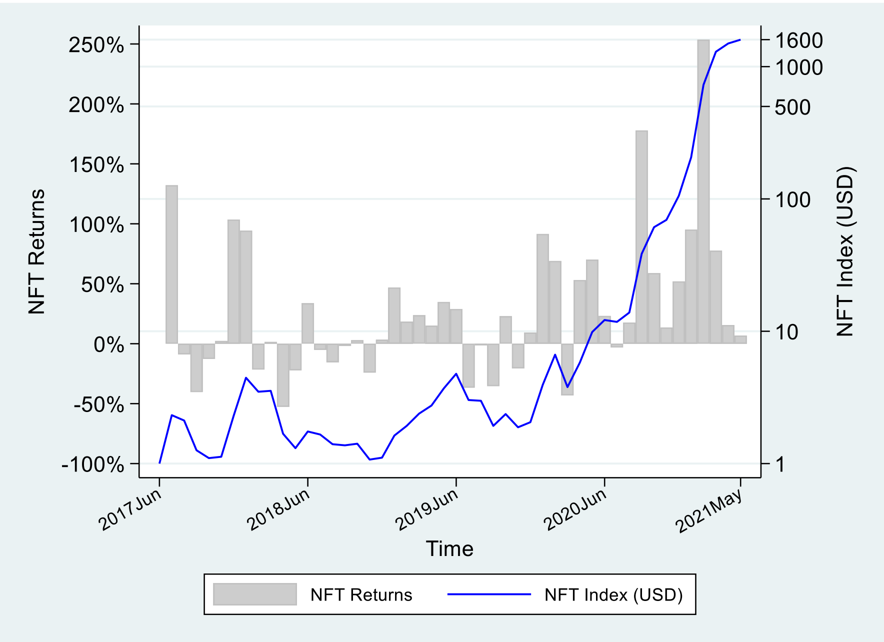

Figure 2. NFT index and returns.
The line in this figure shows our NFT index in USD (against the right-hand axis), and the index is set to unity in June 2017. NFT index is estimated using the hedonic regression model in column (4) of Table 3. The bars represent the month-over-month growth of the NFT index (against the left-hand axis).

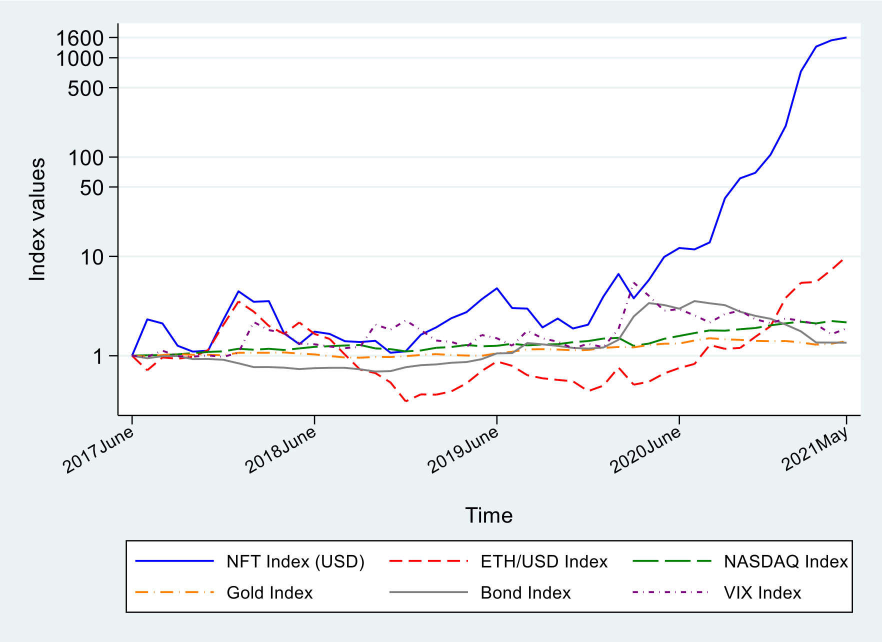

Figure 3. NFT index and major market indices.

This figure shows the NFT index and major market indices over the period from June 2017 through May 2021. NFT index is estimated using the hedonic regression model in column (4) of Table 3. Data on market indices are downloaded from Yahoo! Finance and Investing.com. Appendix A provides variable definitions in greater detail. All indices are set to unity in June 2017.

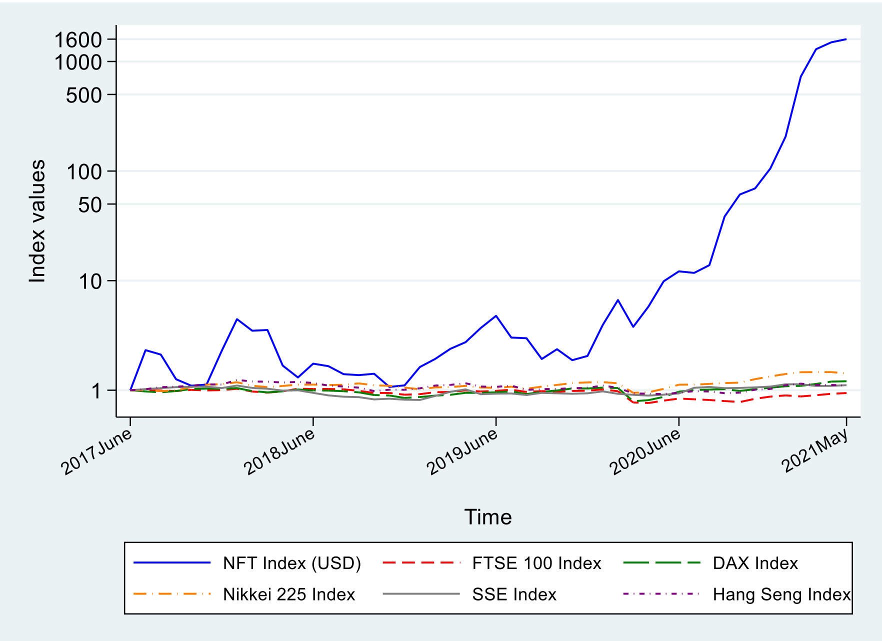

Figure 4. NFT index and stock market indices worldwide.

This figure shows the NFT index and stock market indices worldwide (except for the U.S.) over the period from June 2017 through May 2021. NFT index is estimated using the hedonic regression model in column (4) of Table 3. Data on stock market indices are downloaded from Investing.com. Appendix A provides variable definitions in greater detail. All indices are set to unity in June 2017.

Table 1. Summary statistics

This table reports summary statistics for the transactions used in the empirical analysis. Historical transactions were obtained from *Larva Labs*. The sample period is between June 2017 and May 2021. Panel A reports the number of transactions for different transaction types and CryptoPunk types. Panel B reports the average sales price for each CryptoPunk type denominated in USD thousands.

Panel A. Number of observations for each transaction type and each CryptoPunk type

Year	Transaction type		CryptoPunk type					Total
	Primary Sales	Secondary Sales	Alien	Ape	Female	Male	Zombie	
2017	1,108	178	6	14	475	767	24	1,286
2018	736	163	1	6	309	574	9	899
2019	701	367	0	0	296	769	3	1,068
2020	1,132	3,195	0	6	1,085	3,207	29	4,327
2021	1,953	4,179	3	5	2,080	4,018	26	6,132
2017-2021	**5,630**	**8,082**	**10**	**31**	**4,245**	**9,335**	**91**	**13,712**

Panel B. Summary statistics of sales prices for each CryptoPunk type (in USD thousands)

CryptoPunk type				Average prices by transaction type	
	N	Mean	STD	Primary Sales	Secondary Sales
Alien	10	1,593.97	3,161.13	3.98	5,303.96
Ape	31	162.70	411.19	53.38	295.45
Female	4,245	27.82	44.38	21.59	33.09
Male	9,335	21.33	40.93	15.91	24.75
Zombie	91	147.13	308.28	115.25	178.31

Table 2. Correlation of Network Factors

This table reports the pairwise correlation matrix of the network factors in NFT markets and Ethereum. Appendix A provides variable definitions in greater detail. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. The data frequency is daily.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) ΔNumWallets	1							
(2) ΔNumBuyers	0.9559***	1						
(3) ΔNumSellers	0.9044***	0.8041***	1					
(4) ΔNumSales	0.8371***	0.8711***	0.7858***	1				
(5) ΔSalesUSD	0.3754***	0.3711***	0.2678***	0.2809***	1			
(6) ΔETHUSD	0.0431*	0.0619**	0.0029	0.0389	0.0813***	1		
(7) ΔETHVol	0.0787***	0.1003***	0.0423	0.0769***	0.0541**	0.1256***	1	
(8) Adj. SVI	0.0254	0.0291	0.0188	0.0097	0.0151	0.0527**	0.0883***	1

Table 3. Hedonic regression results

This table reports estimates from our hedonic regression model using ordinary least squares. The dependent variable is the natural logarithm of CryptoPunk token prices (in USD). Data on CryptoPunk characteristics are obtained from *Larva Labs*. Attribute dummies are included as specified. Appendix A provides variable definitions in greater detail. Standard errors (in parentheses) are clustered at the token level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Var.	$\ln P_{i,t}$			
	(1)	(2)	(3)	(4)
Alien	4.1671***	4.1673***	4.1758***	4.1530***
	(0.2377)	(0.2377)	(0.2377)	(0.2368)
Ape	2.7236***	2.7260***	2.7339***	2.7028***
	(0.4235)	(0.4219)	(0.4218)	(0.4199)
Zombie	2.3015***	2.3104***	2.3074***	2.3177***
	(0.1401)	(0.1433)	(0.1430)	(0.1415)
Female	0.1311***	0.1288***	0.1283***	0.1270***
	(0.0268)	(0.0268)	(0.0267)	(0.0267)
PrimarySale	–0.0947***	–0.0930***	–0.0934***	–0.0924***
	(0.0152)	(0.0151)	(0.0151)	(0.0151)
Δ*NumWallets*		0.0024		
		(0.0227)		
Δ*NumBuyers*			0.0697***	–0.0164
			(0.0264)	(0.0554)
Δ*NumSellers*			–0.0723**	–0.0938**
			(0.0351)	(0.0397)
Δ*NumSales*				0.0502*
				(0.0278)
Δ*SalesUSD*				0.0098*
				(0.0050)
Δ*ETHUSD*				–0.6150***
				(0.1140)
Δ*ETHVol*				–0.0333
				(0.0219)
Adj. SVI				0.0056***
				(0.0018)
Constant	3.3209***	3.3517***	3.4005***	3.3058***
	(0.1108)	(0.1166)	(0.1077)	(0.1092)
Observations	13,698	13,637	13,637	13,547
Adj. R^2	0.9366	0.9365	0.9365	0.9371
Year-Month dummies	Yes	Yes	Yes	Yes
Attribute dummies	Yes	Yes	Yes	Yes

Table 4. Monthly NFT index and returns

This table reports the index values of our NFT index from June 2017 through May 2021. The NFT index is estimated by using the hedonic regression model in column (4) of Table 3.

Year-Month	NFT Index	Return	Year-Month	NFT Index	Return
2017-06	1.000		2019-06	4.775	28.98%
2017-07	2.322	132.22%	2019-07	3.023	–36.69%
2017-08	2.115	–8.92%	2019-08	2.983	–1.32%
2017-09	1.260	–40.41%	2019-09	1.927	–35.41%
2017-10	1.100	–12.72%	2019-10	2.368	22.91%
2017-11	1.126	2.35%	2019-11	1.881	–20.58%
2017-12	2.292	103.55%	2019-12	2.055	9.30%
2018-01	4.454	94.35%	2020-01	3.938	91.57%
2018-02	3.491	–21.63%	2020-02	6.657	69.07%
2018-03	3.546	1.58%	2020-03	3.786	–43.13%
2018-04	1.680	–52.63%	2020-04	5.799	53.15%
2018-05	1.308	–22.16%	2020-05	9.866	70.16%
2018-06	1.748	33.70%	2020-06	12.160	23.25%
2018-07	1.658	–5.17%	2020-07	11.772	–3.19%
2018-08	1.401	–15.47%	2020-08	13.849	17.64%
2018-09	1.374	–1.96%	2020-09	38.491	177.94%
2018-10	1.413	2.87%	2020-10	61.157	58.89%
2018-11	1.072	–24.15%	2020-11	69.454	13.57%
2018-12	1.108	3.36%	2020-12	105.575	52.01%
2019-01	1.628	46.93%	2021-01	206.122	95.24%
2019-02	1.928	18.43%	2021-02	728.954	253.65%
2019-03	2.386	23.75%	2021-03	1295.122	77.67%
2019-04	2.745	15.05%	2021-04	1496.688	15.56%
2019-05	3.702	34.85%	2021-05	1598.770	6.82%

Table 5. Rankings of CryptoPunk attributes

This table presents the top/bottom 10 attributes favored by CryptoPunk collectors. The coefficient estimates on attribute dummies are based on the hedonic regression model in column (4) of Table 3. Following Renneboog and Spaenjers (2013), the price impact for each attribute dummy is calculated as the exponent of the estimated coefficient minus one. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Top 10	Attributes	Coefficient	Price Impact	Bottom 10	Attributes	Coefficient	Price Impact
1	Beanie	1.7685***	486.22%	1	Stringy Hair	–0.1851***	–16.90%
2	Pilot Helmet	1.1989***	231.64%	2	Bandana	–0.1575***	–14.57%
3	Tiara	1.1833***	226.52%	3	Frumpy Hair	–0.1460***	–13.58%
4	Choker	1.0279***	179.53%	4	Mohawk	–0.1360***	–12.71%
5	Orange Side	1.0195***	177.18%	5	Peak Spike	–0.1288***	–12.09%
6	Buck Teeth	0.8973***	145.29%	6	Headband	–0.1266***	–11.89%
7	Welding Goggles	0.8783***	140.68%	7	Shaved Head	–0.1172***	–11.06%
8	Pigtails	0.7556***	112.88%	8	Messy Hair	–0.1022***	–9.72%
9	Pink With Hat	0.6430***	90.22%	9	Knitted Cap	–0.0963**	–9.18%
10	Top Hat	0.6329***	88.31%	10	Wild Hair	–0.0789**	–7.58%

Table 6. Correlation matrix of returns on NFT index and market indices

This table reports the pairwise correlations of the returns on NFTs and different market indices. The data frequency is monthly. Appendix A provides variable definitions in greater detail. ∗∗∗, ∗∗, and ∗ correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) NFT Index	1							
(2) ETH/USD Index	0.4129***	1						
(3) NASDAQ Index	0.2353	0.3993***	1					
(4) S&P 500 Index	0.2229	0.4221***	0.9379***	1				
(5) Dow Jones Index	0.2133	0.4140***	0.8495***	0.9707***	1			
(6) VIX Index	–0.1404	–0.2235	–0.7637***	–0.8649***	–0.8492***	1		
(7) Bond Index	–0.2710*	–0.2315	–0.4567***	–0.6140***	–0.6945***	0.5579***	1	
(8) Gold Index	–0.1615	0.2245	0.1892	0.1419	0.097	–0.0561	0.3509**	1

Table 7. Distribution of returns on NFTs and major market indices

This table reports the distribution of monthly returns for NFTs and different market indices over the period from June 2017 through May 2021. For each index, we examine the arithmetic and geometric average returns per month, the standard deviation, highest/lowest returns recorded return, and the ex post Sharpe ratios. Sharpe ratio is calculated as the difference between index return and one-month T-bill return, divided by the standard deviation of index returns. One-month T-bill returns are obtained from Kenneth R. French's website. Appendix A provides variable definitions in greater detail.

	Mean returns per month		Dispersion of monthly returns			Sharpe ratio	
	Arithmetic	Geometric	Std. dev.	Min	Max	Arithmetic	Geometric
NFT Index	27.76%	16.99%	58.77%	–52.63%	253.65%	47.06%	28.74%
ETH/USD Index	8.92%	5.02%	30.35%	–35.52%	93.00%	29.05%	16.22%
NASDAQ Index	1.77%	1.66%	4.63%	–17.02%	11.54%	35.99%	33.75%
S&P 500 Index	1.24%	1.15%	4.00%	–18.52%	6.90%	28.29%	26.22%
Dow Jones Index	1.11%	1.02%	4.16%	–20.02%	7.21%	24.15%	21.95%
VIX Index	5.55%	1.35%	37.39%	–29.19%	192.96%	14.57%	3.34%
Bond Index	1.50%	0.65%	14.64%	–22.72%	71.46%	9.55%	3.72%
Gold Index	0.76%	0.71%	3.02%	–4.88%	7.16%	21.60%	20.19%
One-month T-bill	0.10%	0.10%	0.07%	0.00%	0.21%	–	–

Table 8. Performance of NFTs and different asset classes: Subperiod analysis

This table reports investment performance of NFTs and different asset classes over the pre-COVID-19 and post-COVID-19 period, respectively. We define the pre-COVID-19 period as the period over June 2017-February 2020, and the post-COVID-19 period as the year-month after March 2020. Mean returns are the geometric average of monthly returns over the subperiod. Sharpe ratio is calculated as the difference between index return and one-month T-bill return, divided by the standard deviation of index returns. One-month T-bill returns are obtained from Kenneth R. French's website.

	Pre-COVID-19 period			Post-COVID-19 period		
	Mean Returns (per month)	Std. dev.	Sharpe ratio	Mean Returns (per month)	Std. dev.	Sharpe ratio
NFT Index	6.10%	44.35%	13.43%	44.11%	74.57%	59.14%
ETH/USD Index	–0.85%	29.23%	–3.41%	18.74%	29.38%	63.76%
NASDAQ Index	1.30%	3.26%	35.59%	2.42%	6.76%	35.68%
S&P 500 Index	0.93%	2.67%	29.42%	1.62%	6.01%	26.70%
Dow Jones Index	0.91%	2.79%	27.46%	1.24%	6.28%	19.58%
VIX Index	1.95%	27.84%	6.50%	0.09%	53.60%	0.15%
Bond Index	1.16%	7.51%	13.55%	–0.45%	24.06%	–1.94%
Gold Index	0.64%	2.69%	18.31%	0.87%	3.74%	23.01%
One-month T-bill	0.15%	0.04%	–	0.01%	0.03%	–

Table 9. NFT returns loadings to equity factors

This table reports the factor loadings of NFT returns on different equity factor models. The factor models include the CAPM, the Fama-French 3-factor model, the Carhart 4-factor model, the Fama-French 5-factor model. The factors are *MKTRF*, *SMB* (small minus big), *HML* (high minus low B/M), *MOM* (momentum), *RMW* (robust minus weak operating profitability (*OP*)), and *CMA* (conservative minus aggressive investment (*Inv*)). *MKTRF* is the excess return on the value-weight return of all CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ. The data frequency is monthly, and returns are in percentage. The t-statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	CAPM	3-factor	4-factor	5-factor
(In percentage)	(1)	(2)	(3)	(4)
ALPHA	26.3169***	28.7273***	28.9802***	30.7026***
	(2.9310)	(3.1079)	(3.0982)	(3.3114)
MKTRF	0.9467	–0.1749	–0.4690	–1.0158
	(0.5517)	(–0.0913)	(–0.2275)	(–0.4720)
SMB		2.9636	2.6128	2.0183
		(0.8819)	(0.7469)	(0.4821)
HML		1.6945	1.1161	4.7449
		(0.6498)	(0.3741)	(1.3910)
RMW				–1.7883
				(–0.2802)
CMA				–9.3491*
				(–1.7231)
MOM			–1.1798	
			(–0.4123)	
Observations	47	47	47	47
R^2	0.0067	0.0491	0.0530	0.1136

Appendix

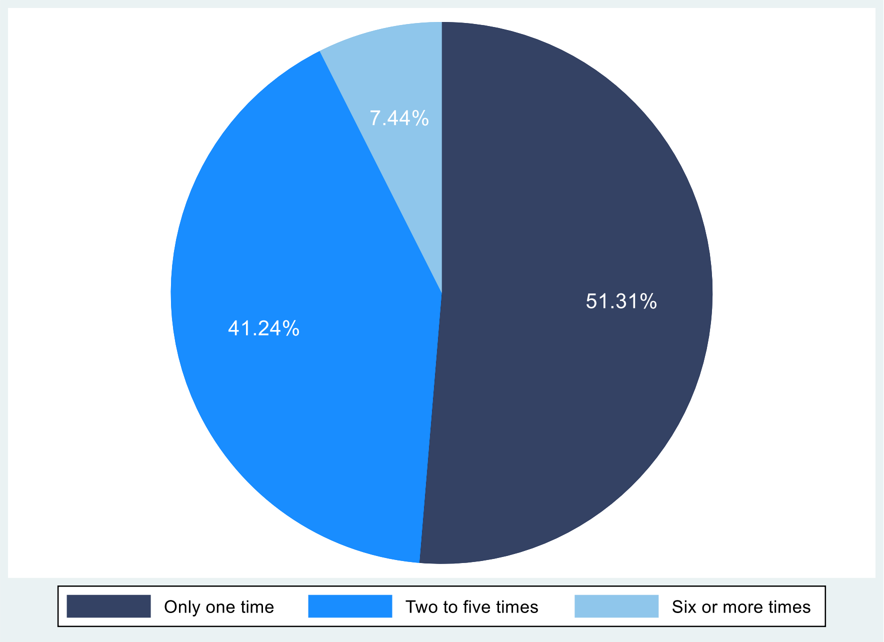

Figure A1. The turnover of CryptoPunk transactions.
The figure shows that the distribution of the number of transactions for each CryptoPunk over the sample period from June 2017 through May 2021.

Figure A2. Monthly sales prices of CryptoPunks and Google SVI.
The solid line represents the average monthly sales price of CryptoPunks in USD (against the left-hand axis). The dash line represents Google search volume index (SVI) with the search topic related to "Ethereum" (against the right-hand axis). The SVI values are obtained from Google Trends.

Appendix A. Definition of Variables

Variable	Definition	Source
Panel A: CryptoPunk characteristics		
Alien	A dummy variable that equals one if the type of a CryptoPunk token is categorized as "Alien" and zero otherwise.	Larva Labs
Ape	A dummy variable that equals one if the type of a CryptoPunk token is categorized as "Ape" and zero otherwise.	Larva Labs
Zombie	A dummy variable that equals one if the type of a CryptoPunk token is categorized as "Zombie" and zero otherwise.	Larva Labs
Female	A dummy variable that equals one if the type of a CryptoPunk token is categorized as "Female" and zero otherwise.	Larva Labs
PrimarySale	A dummy variable that equals one if a CryptoPunk token is sold in a primary sale and zero otherwise.	Larva Labs
Panel B: Network factors		
Δ*NumWallets*	The growth of unique wallets in NFT markets on date *t*.	NonFungible.com
Δ*NumBuyers*	The growth of unique buyers in NFT markets on date *t*.	NonFungible.com
Δ*NumSellers*	The growth of unique sellers in NFT markets on date *t*.	NonFungible.com
Δ*NumSales*	The growth of transactions for sales in NFT markets on date *t*.	NonFungible.com
Δ*SalesUSD*	The growth of USD sales volume in NFT markets on date *t*.	NonFungible.com
Δ*ETHUSD*	The growth of ETH/USD exchange rate on date *t*.	Yahoo! Finance
Δ*ETHVol*	The growth of ETH trading volume on date *t*.	Yahoo! Finance
Adj. SVI	Adjusted Google search volume index (*Adj. SVI*) on date *t*. Index values range between 1 and 100. We reconstruct our daily SVI using daily SVI in a given month and monthly SVI over our sample period. In particular, *Adj. SVI* is computed as $$Adj.SVI_t = SVI_{t,m} \times \frac{SVI_m}{100}$$ where t denotes the date and m indexes the month of date t. A higher value indicates a higher level of worldwide attention to the topics regarding "Ethereum."	Google Trends
Panel C: Market indices		
ETH/USD Index	The average of daily closing exchange rates of ETH/USD in month *t*.	Yahoo! Finance
NASDAQ Index	The average of daily closing NASDAQ index values in month *t*.	Investing.com
S&P 500 Index	The average of daily closing S&P 500 index values in month *t*.	Investing.com
Dow Jones Index	The average of daily closing Dow Jones Industrial Average index values in month *t*.	Investing.com
VIX Index	The average of daily closing CBOE Volatility index values on date *t*.	Investing.com
Bond Index	The inverse of the average of daily closing US 10-Year bond yields in month *t*.	Investing.com
Gold Index	The average of daily closing gold future prices in month *t*.	Investing.com

Appendix B. Distribution of CryptoPunk attributes

This table presents the number of CryptoPunk attributes featured in the whole collection. There are 87 unique attributes in total, and each CryptoPunks token can have from 0 to 7 attribute(s). Data on CryptoPunk attributes are collected from *Larva Labs*.

Attribute	N	Attribute	N	Attribute	N
Beanie	44	Police Cap	203	Crazy Hair	414
Choker	48	Clown Nose	212	Knitted Cap	419
Pilot Helmet	54	Smile	238	Mohawk Dark	429
Tiara	55	Cap Forward	254	Mohawk	441
Orange Side	68	Hoodie	259	Mohawk Thin	441
Buck Teeth	78	Front Beard Dark	260	Frumpy Hair	442
Welding Goggles	86	Frown	261	Wild Hair	447
Pigtails	94	Purple Eye Shadow	262	Messy Hair	460
Pink With Hat	95	Handlebars	263	Eye Patch	461
Top Hat	115	Blue Eye Shadow	266	Stringy Hair	463
Spots	124	Green Eye Shadow	271	Bandana	481
Rosy Cheeks	128	Vape	272	Classic Shades	502
Blonde Short	129	Front Beard	273	Shadow Beard	526
Wild White Hair	136	Chinstrap	282	Regular Shades	527
Cowboy Hat	142	3D Glasses	286	Horned Rim Glasses	535
Wild Blonde	144	Luxurious Beard	286	Big Shades	535
Straight Hair Blonde	144	Mustache	288	Nerd Glasses	572
Big Beard	146	Normal Beard Black	289	Black Lipstick	617
Red Mohawk	147	Normal Beard	292	Mole	644
Half Shaved	147	Eye Mask	293	Purple Lipstick	655
Blonde Bob	147	Goat	295	Hot Lipstick	696
Vampire Hair	147	Do-rag	300	Cigarette	961
Clown Hair Green	148	Shaved Head	300	Earring	2459
Straight Hair Dark	148	Muttonchops	303		
Straight Hair	151	Peak Spike	303		
Silver Chain	156	Pipe	317		
Dark Hair	157	VR	332		
Purple Hair	165	Cap	351		
Gold Chain	169	Small Shades	378		
Medical Mask	175	Clown Eyes Green	382		
Tassle Hat	178	Clown Eyes Blue	384		
Fedora	186	Headband	406		

Appendix C. Hedonic regression results with token prices in ETH

This table reports estimates from our hedonic regression model using ordinary least squares. The dependent variable is the natural logarithm of CryptoPunk token prices (in ETH). The data on CryptoPunk characteristics are obtained from *Larva Labs*. Attribute dummies are included as specified. Appendix A provides variable definitions in greater detail. Standard errors (in parentheses) are clustered at the token level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Var.	$\ln P_{i,t}$ (ETH)			
	(1)	(2)	(3)	(4)
Alien	4.0726***	4.0731***	4.0796***	4.0683***
	(0.2069)	(0.2073)	(0.2070)	(0.2116)
Ape	2.8570***	2.8628***	2.8687***	2.8473***
	(0.2662)	(0.2655)	(0.2651)	(0.2636)
Zombie	2.2826***	2.2942***	2.2917***	2.2963***
	(0.1363)	(0.1393)	(0.1392)	(0.1381)
Female	0.1185***	0.1182***	0.1177***	0.1174***
	(0.0217)	(0.0217)	(0.0217)	(0.0215)
PrimarySale	–0.0833***	–0.0823***	–0.0826***	–0.0820***
	(0.0095)	(0.0095)	(0.0095)	(0.0094)
Δ*NumWallets*		0.0236		
		(0.0158)		
Δ*NumBuyers*			0.0641***	0.0245
			(0.0162)	(0.0262)
Δ*NumSellers*			–0.0464**	–0.0710***
			(0.0205)	(0.0226)
Δ*NumSales*				0.0351**
				(0.0165)
Δ*SalesUSD*				0.0026
				(0.0021)
Δ*ETHUSD*				–0.6191***
				(0.0886)
Δ*ETHVol*				0.0116
				(0.0184)
Adj. SVI				0.0029***
				(0.0007)
Constant	–2.2342***	–2.2123***	–2.1757***	–2.2217***
	(0.0753)	(0.0760)	(0.0738)	(0.0731)
Observations	13,695	13,636	13,636	13,546
Adj. R^2	0.9371	0.9371	0.9372	0.9383
Year-Month dummies	Yes	Yes	Yes	Yes
Attribute dummies	Yes	Yes	Yes	Yes

Appendix D. Different performance measures

This table compares the performance measures for different asset classes over the sample period from June 2017 through May 2021. The $\hat{\beta}$ and Jensen's alpha ($\hat{\alpha}$) are the slope and the intercept estimated based on the market model, $r_i - r_f = \alpha + \beta(r_m - r_f) + \varepsilon$. r_i is the monthly return for a given asset class, and $r_m - r_f$ is the value-weight return on the market portfolio of all CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ minus the one-month Treasury bill rate (r_f). The Treynor (1965) ratio is defined as the ratio of Jensen's alpha ($\hat{\alpha}$) to $\hat{\beta}$. Following Sortino and van der Meer (1991) and Sortino et al. (1999), the Sortino ratio and the upside potential ratio are measured as follows:

$$Sortino\ ratio = \frac{\mathbb{E}[r_i]}{\sqrt{\mathbb{E}[Min^2(r_i - MAR, 0)]}} \qquad Upside\ potential\ ratio = \frac{\mathbb{E}[Max(r_i - MAR, 0)]}{\sqrt{\mathbb{E}[Min^2(r_i - MAR, 0)]}}$$

where $\mathbb{E}[r_i]$ is the expected return, and MAR is the minimal acceptable return, which is set to zero in this analysis.

	$\hat{\beta}$	Jensen's alpha ($\hat{\alpha}$)	Treynor ratio	Sortino ratio	Upside potential ratio
NFT Index	0.947	26.32%	27.80%	109.36%	225.95%
ETH/USD Index	1.693	6.42%	3.79%	37.10%	122.39%
NASDAQ Index	0.631	0.77%	1.22%	54.74%	93.66%
S&P 500 Index	0.591	0.29%	0.50%	38.16%	69.68%
Dow Jones Index	0.594	0.16%	0.27%	31.69%	63.56%
VIX Index	–5.440	13.16%	–2.42%	12.13%	116.96%
Bond Index	–0.824	2.57%	–3.12%	10.89%	82.17%
Gold Index	0.098	0.51%	5.22%	48.07%	107.94%

Appendix E. Investment performance of NFT index (in ETH)

This table reports the summary statistics and the factor loadings of NFT returns. In this table, NFT index values are constructed based on the hedonic regression model in column (4) of Appendix C. Panel A reports investment performance of NFTs over the whole sample period, the pre-COVID-19 period, and post-COVID-19 period, respectively. We define the pre-COVID-19 period as the period over June 2017-February 2020, and the post-COVID-19 period as the year-month after March 2020. Mean returns are the geometric average of monthly returns over a given period. Sharpe ratio is calculated as the difference between index return and one-month T-bill return, divided by the standard deviation of index returns. One-month T-bill returns are obtained from Kenneth R. French's website. Panel B reports the factor loadings of NFT returns on different equity factor models. Standard errors (in parentheses) are clustered at the token level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Summary statistics of NFT returns

	Full sample period		Pre-COVID-19 period		Post-COVID-19 period	
	Mean Returns (per month)	Sharpe ratio	Mean Returns (per month)	Sharpe ratio	Mean Returns (per month)	Sharpe ratio
NFT Index	11.47%	23.65%	6.35%	15.98%	23.22%	37.16%

Panel B: NFT returns loadings to equity factors

	CAPM	3-factor	4-factor	5-factor
(In percentage)	(1)	(2)	(3)	(4)
ALPHA	20.5521***	21.6273***	22.0176***	22.9679***
	(2.8130)	(2.8275)	(2.8588)	(3.0065)
MKTRF	–1.1881	–1.5851	–2.0389	–2.5972
	(–0.8509)	(–1.0000)	(–1.2013)	(–1.4646)
SMB		0.8132	0.2720	0.8177
		(0.2924)	(0.0944)	(0.2371)
HML		0.9272	0.0345	3.0869
		(0.4297)	(0.0141)	(1.0983)
RMW				0.5285
				(0.1005)
CMA				–8.1163*
				(–1.8155)
MOM			–1.8208	
			(–0.7729)	
Observations	47	47	47	47
R^2	0.0158	0.0255	0.0392	0.0995

Appendix F. NFT returns net of transaction costs

This table reports the summary statistics of NFT returns net of 2.5% transaction costs (i.e., service fees) over the whole sample period, the pre-COVID-19 period, and post-COVID-19 period, respectively. We define the pre-COVID-19 period as the period over June 2017-February 2020, and the post-COVID-19 period as the year-month after March 2020. Mean returns are the geometric average of monthly returns over a given period. Sharpe ratio is calculated as the difference between index return and one-month T-bill return, divided by the standard deviation of index returns.

	Full sample period		Pre-COVID-19 period		Post-COVID-19 period	
	Mean Returns (per month)	Sharpe ratio	Mean Returns (per month)	Sharpe ratio	Mean Returns (per month)	Sharpe ratio
NFT Index (USD)	14.07%	24.37%	3.45%	7.64%	40.51%	55.70%
NFT Index (ETH)	8.68%	18.31%	3.69%	9.37%	20.14%	33.05%