Alternative Investments in the Fintech Era:

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

De-Rong Kong† **Tse-Chun Lin**‡

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Abstract

We study one of the earliest and most representative NFT collections and find that NFTs have higher returns than traditional financial assets. However, investing in NFTs comes along with high volatility, leading to a comparable Sharpe ratio to the NASDAQ index. NFT prices surge when there is a drastic increase in demand for alternative investments and a search for yield in a low interest rate environment. The pricing of NFT also largely depends on a token's scarceness and investors' aesthetic preference. Overall, we provide the first comprehensive analysis that NFTs serve as a novel investment vessel in this Fintech era.

JEL Classifications: C43, D44, G11, G12, Z11
Keywords: Non-Fungible Tokens, NFT, Fintech, Ethereum, Blockchain, Alternative investments, Risk and return

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† Department of Finance, National Taiwan University. E-mail address: d06723004@ntu.edu.tw.
‡ Faculty of Business and Economics, The University of Hong Kong. E-mail address: tsechunlin@hku.hk.

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Abstract

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1. Introduction

The markets for unique assets, such as real estate, fine arts, wine, and collectible stamps, have been established to accommodate the need for alternative investments. Investors increasingly turn to these asset classes to diversify their portfolios from traditional investments such as stocks, bonds, mutual funds, etc. Among the alternative assets, the interest in non-fungible tokens (NFTs) has been exploding since 2021. Unlike the other alternative assets, NFTs represent ownership over unique assets based on the technique powered by blockchains so investors usually do not own a physical item. According to data tracker DappRadar, sales volume in the NFT market has surpassed over $30 billion since the middle of 2022.[1] Nevertheless, the literature on this crypto innovation as an alternative investment class is rather limited.

Today, NFTs are utilized as a representative of items in various forms and put into use in different fields. For example, an NFT proves the ownership of a photo, a video, a piece of music, or even the documents relating to the Nobel Prize-winning research.[2] 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. Many well-known companies, such as Louis Vuitton, Warner Music Group, and Marvel Entertainment, have also begun to set foot in the crypto world. Obviously, 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. Our paper provides the first evidence by utilizing one of the earliest,

[1] See DappRadar (https://dappradar.com/nft/marketplaces).
[2] 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.

largest, and most representative NFT collections, the CryptoPunks, to construct an NFT index and sheds light on the risk and return of this alternative investment and what factors determine the pricing of NFTs.

There are two major reasons why we mainly focus on CryptoPunks. First, there is a concern that the time period for the NFT market is too short to derive meaningful conclusions for its return and risk profiles, given that the majority of NFTs were created in or after 2021. The CryptoPunks, in contrast, were released by *Larva Labs* in June 2017, which provides the longest transaction data. This experimental project ushered in the inspiration for the token standard, the ERC-721, that powers most crypto art and collectibles on the Ethereum blockchain nowadays.[4] The invention of CryptoPunks thus has an important role in the development of NFTs over time. Cuy Sheffield, head of the crypto at Visa, also mentions that CryptoPunks have become a "cultural icon for the crypto community."[5] Hence, the time series of CryptoPunks transaction data also epitomizes the development of the NFT market.

The second reason is that NFTs, like arts, wine, and stamps, have almost unlimited variations, which makes it less practical for investment purposes to consider all transactions. Based on the same reason, it is common to rely on one representative collection of data (e.g., fine arts from Sotheby's or Christie's auction houses) to estimate a price index of illiquid assets in the alternative investment literature. For example, Dimson, Rousseau, and Spaenjers (2015) construct a wine index based on transactions for five red Bordeaux wines because these high-end wines have established a reputation long before most other wines and have been popular alternative investments among wealthy groups. In sum, by considering only the CryptoPunks, we mitigate concerns that our findings are influenced by outliers in the short time series and the nature of different NFT collections. That being said, for a robustness check, we also

[4] For more details regarding the background of NFTs and the Ethereum blockchain, see Section 2.1.
[5] See https://www.cnbc.com/2021/08/23/visa-buys-cryptopunk-nft-for-150000.html

consider other well-known NFT collections, such as Bored Ape Yacht Club, Meebits, and Decentraland, and find very similar results.

In a nutshell, CryptoPunks represent crypto images, consisting of 10,000 tokens with proof-of-ownership stored on the Ethereum blockchain, and each token is one of a kind. Most CryptoPunks are featured with a male or female face, but there are also some special types, such as alien, ape, and zombie.[6] In most cases, the value of CryptoPunks increases with their rareness. One of the most expensive tokens in the collection, CryptoPunk #5822, featuring an alien wearing a bandana, was sold for approximately $24 million on February 13th, 2022.[7] 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.[8] Currently, the popularity of *Etheria* and most NFT collections are not comparable to that of the CryptoPunks. According to NonFungible.com and OpenSea, the CryptoPunks is among the most extensive NFT collections by total sales volume in either USD or Ethereum's native currency (ETH) up to date.[9]

People typically sell their alternative assets, such as artworks or collections, through dealers or traditional auction markets.[10] 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

[6] For more details regarding the CryptoPunks, see Section 3.1.
[7] Deepak Thapliyal, the CEO of blockchain firm "Chain," purchased CryptoPunk #5822 for 8,000ETH, which was about $24 million, on February 13th, 2022. See https://www.investing.com/news/cryptocurrency-news/would-you-spend-23-million-on-a-jpeg-2763804.
[8] See https://twitter.com/etheria_feed/status/1370825688647884802?lang=en.
[9] 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.
[10] 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.

collectors to make a deal with their counterparts directly.[11] 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.[12] Conceptually, NFTs can be traded just like any financial assets on 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 22,405 transactions recorded on *Larva Labs* over the period running from June 2017 to June 2022. Accordingly, we compile a 61-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 negatively affected by the competition in the NFT market and the volatility of ETH/USD rates. 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.

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

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[11] 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.

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

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 13.92% (26.77%), corresponding to the returns of 2.50%, 1.01%, –0.61%, and 0.63% for ETH, stocks, bonds, and gold, respectively. But the standard deviation of NFT returns is among the highest (i.e., 65.57%), which is around 14 times higher than that of stock returns. The Sharpe ratio is thus higher for the NFT index than for most indices but comparable with the NASDAQ index and S&P 500 index. This finding suggests that investing in NFTs can generate high returns, but it also comes with 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 shift in monetary policy worldwide. 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 6.07% in the high-interest-rate period to 34.10% in the low-interest-rate period. This evidence is consistent with the notion that the search for yield in a low interest rate environment boosts 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 82.71% 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 25.16% to 32.18% 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.[13] Consistent with the

[13] A follow-up paper by Borri, Liu, and Tsyvinski (2022) uses larger NFT data and draws a similar conclusion to ours that NFTs' return is exposed to the cryptocurrency market but not so much to factors from traditional asset markets.

findings of 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, and the results are similar when we expand our sample by including other popular collections. 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 et al., 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, our 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).[14] 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

[14] See Makarov and Schoar (2022) for a detailed review of cryptocurrencies and decentralized finance studies.

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 into 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 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."[15]

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.[16] 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).[17]

In June 2017, the debut of CryptoPunks inspired the standard - the ERC-721 (Ethereum Request for Comments 721). It cultivates a more novel type of digital token, widely known as the "non-fungible token" or "NFT."[18] Unlike fungible tokens, NFTs can represent the ownership of more unique asset classes, such as digital artwork, a domain name, and an essay, to name but a few.[19] The ERC-721 smart contracts improve the efficiency of trading unique tokens because every NFT is identified by a unique token identity (ID) inside such a contract. This token ID shall not change for the contract's life (Entriken, Shirley, Evans, and Sachs,

[15] 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.

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

[17] 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/.

[18] 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/.

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

2018). It is worth noting that most NFTs are created on the Ethereum platforms since the improvement of the 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 token. 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, or other collectibles (Goetzmann, 1993; Goetzmann, Renneboog, and Spaenjers, 2011; Dimson et al., 2015; Korteweg et al., 2016). Some investors treat the alternative asset class 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). For instance, Dimson and Spaenjers (2011) study transactions for British stamps and find that there is a positive correlation between equity returns and stamp returns, supporting the existence of a wealth effect. They also document that stamps can hedge against expected inflation.

An extensive body of research has been devoted to understanding how 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 in different markets.[20] Thus, alternative asset classes are also known as heterogeneous goods or imperfect substitutes (Stein, 1977).

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 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.[21] Lovo and Spaenjers (2018) further advance that, in 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 unique assets (e.g., paintings or jewelry) themselves do not generate any cash flows during the holding period, but owners can utilize these assets to signal their social status or obtain social recognition (Bagwell and Bernheim, 1996). For instance, some conspicuous consumptions allow consumers to associate and/or dissociate themselves from different groups of consumers (Han, Nunes, and Drèze, 2010). This special feature

[20] 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 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.

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

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. Hence, traditional asset pricing models might not apply to the valuation of such 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 become unneglectable concerning their market capitalization and extensive applications, NFTs undoubtedly deserve more academic attention at this moment. However, it is crucial to know how much an investor initially paid for unique assets in the primary sale to thoroughly analyze the investment returns on these assets, as Whitaker and Kräussl (2020) suggest. Fortunately, NFT markets provide a gateway for us to keep track of all transaction records for each token from the very beginning.[22] 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 one of the earliest and the most valuable NFT projects 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 CryptoPunks has a unique identification number, running from 0 through 9999. Overall,

[22] This feature also allows researchers to track investors' performance. For example, Oh, Rosen, and Zhang (2022) show that experienced NFT investors outperform inexperienced ones through greater participation in primary market sales.

CryptoPunks 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.[23] Furthermore, there are 87 extra attributes, which serve as accessories for each type, and each CryptoPunk is featured with from 0 to 7 attributes.[24] Most CryptoPunks have two or three attributes, while only eight tokens have no attribute and one token has seven attributes. Thus, we choose to utilize CryptoPunks 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 22,405 transactions, including 6,759 unique tokens from June 2017 through June 2022.

We first analyze the transactions of CryptoPunks 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 6,759 tokens sold in primary sales, implying that initial owners still hold 3,241 unique tokens during our sample period. 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 CryptoPunks. We find that the scarcer the type of CryptoPunk, the more expensive it is. 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 higher underlying profit from the resales of CryptoPunks.

[Insert Table 1]

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

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 of the CryptoPunks, where the average holding period is about 397 days or 13 months. We find that about 60% of collectors resold their tokens within six months, while approximately 30% of collectors kept the tokens for more than one year, including 18.58% for holding more than three years. We also examine the turnover of transactions for each CryptoPunk during our sample period. In Figure A1, we find that 55.30% of CryptoPunks are never resold in NFT markets after the primary sales, and only 16.67% 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]

To address any concerns about how representativeness of CryptoPunks for the NFT market, we obtain trading data on other well-known collections, (i.e., Bored Ape Yacht Club, Meebits, Decentraland, SuperRare, and Sorare) from Etherscan and include them in our analysis and find similar results (see Section 6 for additional details).[25]

3.2 Network factors in NFT markets

The theoretical works on crypto tokens suggest that 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 user 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)

[25] Etherscan is a blockchain explorer for the Ethereum. Etherscan covers trading data in various NFT marketplaces, such as OpenSea, SuperRare, LooksRare, Rarible, etc.

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 (Δ*NumWallets*), (2) the growth of unique buyers (Δ*NumBuyers*), (3) the growth of unique sellers (Δ*NumSellers*), (4) the growth of transactions for sales (Δ*NumSales*), and (5) the growth of sales volume in USD (Δ*SalesUSD*). We obtain daily data on the statistics of NFT markets from Nonfungible.com.[26] 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, Δ*ETHUSD*, is the daily growth of ETH/USD exchange rates; the second proxy, Δ*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 stablecoins). 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.[27] The SVI values are downloaded from Google Trends.[28] 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 over one year, we construct adjusted SVI

[26] The data are downloaded from Nonfungible.com (https://nonfungible.com/).
[27] 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.
[28] 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 is not enough data for this term.

(*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 January 2016 through June 2022 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 0.38 to 0.96, 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 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.[29]

[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; Goetzmann et al., 2011) and hedonic regression models (e.g., Campbell, Giglio, and Pathak, 2011; Renneboog and Spaenjers, 2013; Dimson et al., 2015). The RSR method relies on price relatives of the same asset to construct the price index (Mei and Moses, 2005). One major empirical issue, however, is that this methodology requires an asset to be traded at least

[29] 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.

twice. Given that some unique assets are never resold in markets, this requirement usually results in a much smaller sample. Moreover, it introduces selection biases because the sales of unique assets may depend on whether asset values have increased, which is known as the disposition effect (Korteweg et al., 2016). For example, Twitter CEO Jack Dorsey's first-ever tweet in 2006 was sold for nearly $3 million on March 6, 2021.[30] Subsequently, the buyer put this NFT up for resale but he ended up refusing to sell it because the highest bid was only 2.2 ETH, which was equivalent to about $6,800.[31] 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 thus generates more reliable estimates of the price index. In addition, the hedonic regression model formulates the prices of infrequently traded assets by relating transaction prices to asset characteristics, which allows us to shed more light on what attributes are more value-relevant (Rosen, 1974). Given that we can access historical transactions and identify characteristics of each CryptoPunk, we adopt the hedonic regression model rather than the RSR method to construct our NFT index. Nevertheless, we also construct the NFT index using the RSR method as a robustness check in Section 6.

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 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 prices in USD as the dependent variable.

[30] 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).
[31] See https://www.theguardian.com/technology/2022/apr/14/twitter-nft-jack-dorsey-sina-estavi.

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

where $P_{i,t}$ represents the sales price of a CryptoPunk i sold on date t, α is the regression intercept, $X_{j,i}$ indexes the characteristic j of the CryptoPunk 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:

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

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:

$$r_t \equiv \frac{\pi_t}{\pi_{t-1}} - 1 \quad (3)$$

In addition, we add a wide range of CryptoPunk characteristics, including four type dummies (i.e., *Alien*, *Ape*, *Zombie*, and *Female*), 86 attribute dummies, and the number of attributes identified for each token (i.e., *_0_Attributes*, *_1_Attributes*, *_2_Attributes*, etc.), in the model. We also consider whether a transaction is a primary sale (*PrimarySale*) and control for the changes in the number of unique wallets (Δ*NumWallets*), the number of buyers (Δ*NumBuyers*), the number of sellers (Δ*NumSellers*), the number of sales (Δ*NumSales*), the sales volume in USD (Δ*SalesUSD*), ETHUSD exchange rate (Δ*ETHUSD*), the ETH trading volume (Δ*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 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 is, the higher its sales price is. Similarly, the CryptoPunks with zero or seven attributes are also worthier because these characteristics are rare in the collection. 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 Δ*NumWallets*, influences sales prices. In columns (2), however, the coefficient on Δ*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 Δ*NumBuyers* and Δ*NumSellers*, respectively. As illustrated in column (3) of Table 3, the growth of NFT buyers (sellers) is positively (negatively) correlated with the prices of CryptoPunks. 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 CryptoPunks, including Δ*NumSales*, Δ*SalesUSD*, Δ*ETHUSD*, Δ*ETHVol*, and *Adj. SVI,* in the hedonic model.[32] We find that the sales prices become higher when there is an increase in NFT market size, as proxied by Δ*SalesUSD*. Moreover, the growth of ETH/USD and ETH trading volume is negatively correlated with the sales prices, indicating that investors, to some degree, evaluate NFTs based on USD and avoid transacting any NFTs when the cryptocurrency market is more volatile. More importantly, an adjusted R^2 of over 90% suggests that our hedonic model captures a significant amount of variance in the prices of CryptoPunks 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

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

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 collection 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.

[Insert Table 4 & Figure 2]

We define a bull (bear) market as the period with a cumulative increase (decline) in NFT returns for more than 50% within three months. As can be observed, there are three apparent bull markets in NFTs, i.e., from November 2017 to January 2018, January 2019 to June 2019, and April 2020 to October 2021. The first two bull markets are mostly due to the boom in media coverage and the adoption of NFTs.[33] The latest 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 after the outbreak of COVID-19. 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.[34] In the same

[33] 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).
[34] See https://edition.cnn.com/2020/03/15/economy/federal-reserve/index.html.

month, the central banks in the UK and Canada also lowered their interest rates to nearly zero. Our evidence so far suggests that the need for investment opportunities or perhaps speculating targets stimulates 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 (Korteweg et al., 2016; Kräussl et al., 2017).

Our NFT index also identifies three major bear markets in NFTs, i.e., from February 2018 to May 2018, from July 2019 to September 2019, and from November 2021 to June 2022. The price plummets in early 2018 were related to tighter regulations and security concerns for crypto assets because 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.[35] 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 about 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.[36] The third bear market was mainly due to tightening monetary policy and the Terra crash, caused by the failure of Terra's algorithmic stablecoin – UST and its linked coin LUNA.[37] A series of events led to a panic selling in both cryptocurrency and NFT markets.

Overall, the findings in this section show that NFT prices are closely tied to the adoption of

[35] See https://www.bbc.com/news/business-42915437.
[36] See https://www.cnbc.com/2019/07/15/bitcoin-price-falls-below-10000-as-president-trump-slams-crypto.html.
[37] See https://www.forbes.com/sites/lawrencewintermeyer/2022/05/25/from-hero-to-zero-how-terra-was-toppled-in-cryptos-darkest-hour/?sh=613f4944389e.

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

Apart from macroeconomic factors, the characteristics of unique assets impact their pricing. For example, on March 11th, 2021, CryptoPunk #7804, featuring an alien with a cap and smoking a pipe, was sold for about $7.5 million because of its rare traits. Hence, we 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 CryptoPunks with the attribute "Beanie," 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 "Knitted Cap," "Front Beard Dark," or "Cap Forward," are traded at a discount.

Overall, CryptoPunk collectors are willing to pay a price premium for a specific set of characteristics, while tokens with unfavorable characteristics might be 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. We now 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*).[38] 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 peg the values of NFTs to USD when making their investment decisions. In addition, the NFT index has a negative correlation with *Bond Index* from June 2020 to June 2022, indicating that investors invest in NFTs as a substitute for U.S. bonds in a low interest rate environment.

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, ETH, stocks, market volatilities, bonds, and commodities. We present the results in Table 6. As expected, the returns on NFTs are highly correlated to the ETH returns at the 1% significant level. Additionally, we find that NFT returns are positively associated with stock market returns, proxied by the *NASDAQ Index*, *S&P 500*

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

Index, and *Dow Jones Index*, 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 26.77% (13.92%) per month based on the arithmetic (geometric) estimation method, while the returns on ETH, stocks, and bonds are only 6.18% (2.50%), 1.12% (1.01%), and 0.22% (–0.61%), 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 65.57%, and the corresponding numbers are 29.14% and 4.80% 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 performances of NFTs and stocks are 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, NFTs significantly outperform all the other asset classes when judged by these alternative risk-reward measures that take the upswing and downswing of asset returns into account.

The above asset classes we analyze are frequently traded, so their characteristics to some degree may be different from those of NFTs (e.g., illiquidity). Therefore, we further compare the performance of NFTs with one of the largest illiquid investments, real estate, proxied by the *Case-Shiller U.S. National Home Price Index*. The index is a composite of single-family home price indices for the nine U.S. Census divisions, capturing changes in housing market prices.[39] Although housing prices increase over time as shown in Figure 5, the growth rate of price level for real estate is much slower than that of NFTs. In unreported results, we find that the average monthly return of real estate is 0.79% with a standard deviation of 0.70% during our sample period, suggesting that real estate is a low-risk and low-return investment relative to NFTs.

[Insert Figure 5]

5.2 Investment performance during the high- and low-interest-rate periods

In Section 4.3, we document a disproportional surge in the NFT index after the outbreak of COVID-19 as of March 2020, when the Federal Reserve started to implement quantitative easing (QE). To get a better sense of the impact of the QE, we follow the methodology of Yang and Zhou (2017) to construct the proxy for U.S. quantitative easing as the size of U.S. Treasury

[39] For more information regarding the index, please visit Standard & Poor's.

securities, agency securities, and mortgage-backed securities holdings on the Federal Reserve's balance sheet.[40] As shown in Figure A3, the NFT price level rises with the size of U.S. quantitative easing, and the correlation estimate (untabulated) between the NFT index and the QE proxy is 0.696 at the 1% significant level.

One may wonder whether NFTs still outperform other financial assets in a different environment. To answer this question, we divide our sample period into two and investigate the investment performance of NFTs in the subperiods. Specifically, we define the high-interest-rate period from June 2017 to February 2020 and the low-interest-rate period from March 2020 to February 2022. In the later subperiod, the Federal Reserve kept its benchmark interest rate at around zero. 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 NFTs and ETH between these subperiods change significantly. Compared with the overall average returns on NFTs (i.e., 13.92%) in Table 7, the returns on NFTs drop to 6.07% in the high-interest-rate period but surge to 34.10% after the QE. The standard deviation rises sharply from 45.91% to 82.71%. Despite that, NFTs, on average, generate the highest monthly return, which is about 5 to 20 times higher than stocks in the subperiods. With respect to the Sharpe ratio, NFTs underperform stocks in the high-interest-rate period but outperform them in the later period. Our findings are consistent with the notion that a lax monetary decreases risk aversion and uncertainty so investors tend to engage in risky investments and search for yield (Bekaert, Hoerova, and Duca, 2013).

We obtain similar results when the NFT index is constructed with CryptoPunk prices denominated in ETH, as reported in Panel A of Appendix E. It is noteworthy that NFT performance in the high-interest-rate period shows qualitatively similar patterns when we consider the sales prices in ETH, while the average of monthly returns on NFTs during the low-

[40] The data is from the Federal Reserve Economic Data (FRED) database (https://fred.stlouisfed.org/).

interest-rate period reduces to only about 60% of that in Table 8 (i.e., 34.10% versus 20.88%). 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. Although NFTs entail illiquid and tail risks, investors are compensated with higher financial returns. 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.[41] As reported in Table 9, the alphas for all factor models are statistically significant.[42] The magnitudes of the alphas range from 25.16% to 32.18% per month, comparable to the average return of 26.77% in Table 7. Concerning market betas, the coefficients on *MKTRF* are positive but not statistically significant across all specifications.

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 5% 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]

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

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).[43] 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.[44] The 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.[45] $Gas\ used$ indicates the exact units of gas used for a given transaction, and $Gas\ fee$ is paid in Ethereum's native currency, Ether (ETH). The gas price depends on the demand for Ethereum network requests, so it is volatile within a day. Hence, 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 17,000 transactions over our sample period. In untabulated results, we find that gas fees, on average, account for 0.13% of the sales prices. The number gradually decreases from 0.62% in 2017 to 0.01% in 2022. Given that gas fees are trivial for most transactions, we ignore gas fees in the analysis.

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43 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.

44 See https://ethereum.org/en/developers/docs/transactions/.

45 Gas price is measured in Gwei, and each Gwei is equal to 0.000000001 ETH (10^{-9} ETH).

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. An alternative way to construct the NFT index

6.1 Repeat-sales regression (RSR) model

Despite the drawbacks of the repeat-sales regression (RSR) model discussed in Section 4, we alternatively construct our NFT index using the RSR method as a robustness check. The RSR model was originally utilized to estimate real estate price indexes (Bailey, Muth, and Nourse, 1963; Case and Shiller, 1987). The RSR model is particularly useful when asset characteristics are unobservable or difficult to measure so this methodology is popular for the estimation of some illiquid asset indices.

Following previous literature (e.g., Goetzmann, 1993; Mei and Moses, 2005), we assume that the continuously compounded return ($r_{i,t}$) for a certain asset i in period t may be represented by μ_t, the return of a price index of assets and an error term:

$$r_{i,t} = \mu_t + \varepsilon_{i,t} \qquad \varepsilon_{i,t} \sim N(O, \sigma_i^2) \text{ and i.i.d.} \quad (4)$$

where μ_t is the average return in period t of assets in the portfolio, and $\varepsilon_{i,t}$, is an idiosyncratic return that is particular to an asset. In the RSR model, the observed data consist of purchase and sales price pairs, $P_{i,b}$ and $P_{i,s}$, of the individual assets, as well as the dates of purchase (b_i) and sale (s_i), where $b_i < s_i$. Hence, the logged price relative to asset i, held between its purchase date b_i and its sales date s_i may be expressed as

$$r_i = \ln\left(\frac{P_{i,s}}{P_{i,b}}\right) = \sum_{t=b+1}^{s} r_{i,t}$$

$$= \sum_{t=b+1}^{s} \mu_t + \sum_{t=b+1}^{s} \varepsilon_{i,t} \tag{5}$$

Let $\mathbf{r}$ represent the N-dimensional vector of logged price relatives for N repeated sales observations. As Goetzmann (1992) suggests, the RSR model using ordinary least squares (OLS) regression usually overweight (underweights) those that contain relatively less (more) information about the fluctuations of the μ series. Therefore, we employ generalized least-squares (GLS) regression techniques to estimate the following equation:

$$\hat{\boldsymbol{\mu}} = (\mathbf{X}'\boldsymbol{\Omega}^{-1}\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{\Omega}^{-1}\mathbf{r} \tag{6}$$

is the maximum-likelihood estimate of μ, where $\mathbf{X}$ is an $N \times T$ matrix that contains a row of dummy variables for each asset in the sample and a column for each holding interval; $\boldsymbol{\Omega}$ is a weighting matrix that weights could be set as the times between sales as suggested by Goetzmann (1993). For example, the dummy variables are zero except that the dummy is –1, corresponding to the first period when an asset was sold, while the dummy is +1, corresponding to the second period when an asset was sold (Case and Shiller, 1989).

6.2 NFT index using the repeat-sales method

One advantage of the repeat-sales method (RSR) methodology is that it controls for the heterogeneity of unique assets by using their price relatives across different periods (Goetzmann, 1993). This feature allows us to include different NFT collections (i.e., Bored Ape Yacht Club, Meebits, Decentraland, Sorare, and SuperRare) in our RSR model.[46] To construct an RSR index, we require that (i) each NFT is traded at least twice during the sample period, and (ii) the repeated sales of a given NFT in the same months are discarded. These restrictions drastically reduce the observations from 108,038 individual transactions to 27,174

[46] One caveat is that most NFTs are launched after 2020 so the resulting index values in earlier years still rely on the repeated sales of the CryptoPunks.

repeated sales.[47] We then construct the NFT index with the RSR model using the GLS method to check the quantitative robustness of our baseline results. Finally, NFT index values are the anti-logs of resulting coefficients. We denote the NFT index from the RSR model by π_{GLS}. The price level is set to one in July 2017 instead of June 2017 because there is no dummy variable corresponding to the primary sale.

Figure 6 plots the NFT indices using different methodologies. We find that NFT indices have a similar trend over time regardless of the models we employ. In untabulated results, the average monthly return on the NFT index from the RSR model (hedonic-regression model) is 27.21% (25.04%) with a standard deviation of 63.43% (64.73%) over the period from July 2017 to June 2022. The correlation between the hedonic returns and the repeat-sales returns is 0.92. Collectively, we confirm that our findings are robust to both sample selection and methodology for estimating NFT indices.

[Insert Figure 6]

7. 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 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. In particular, NFTs might be the most important assets in the metaverse which could potentially become one of the largest digital-economy forms. Nevertheless, little is known about the pricing and investment performance of this type of digital token. In this paper, we fill this gap.

We construct an overall price index based on hedonic regression models and observe that

[47] Appendix G shows the repeated sales by NFT collection used in the RSR model.

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, though to a lesser extent. We document that the average monthly return on NFTs is 13.92% (26.77%) based on the geometric (arithmetic) estimation method, outperforming most traditional financial assets. But the standard deviation of NFT returns is among the highest, i.e., 65.57%, generating a Sharp ratio close to stocks. There is also evidence that NFTs have become one of the popular alternative investment vessels, especially when monetary policy becomes loose, leading to a demand for risky and alternative investments. We find similar results when considering other NFT data and an RSR model for estimating the NFT index.

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 in 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. Additionally, it takes more time to search for trading counterparts in the NFT market. Also, armed with the caveat that the authorities worldwide might take part in meddling with the applications derived from blockchain technology, NFT returns could be more unpredictable. Finally, we focus on widely known NFT collections to construct the NFT index so our index series can be seen as the upper bound of the NFT price level.

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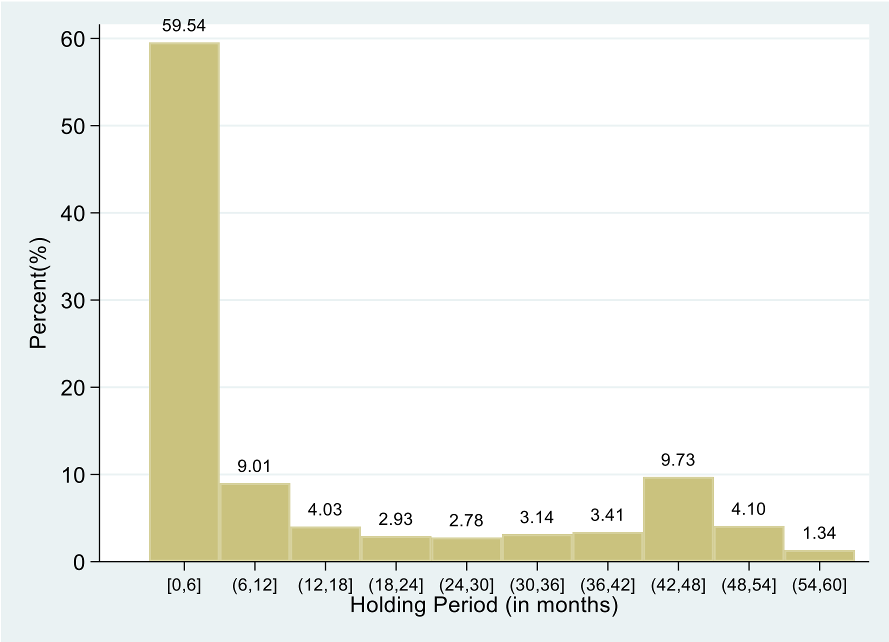

Figure 1. Distribution of holding periods (in months).
The figure shows the distribution of holding periods (in months) from the first purchase to the resale for each CryptoPunk collector. The sample period is from June 2017 through June 2022.

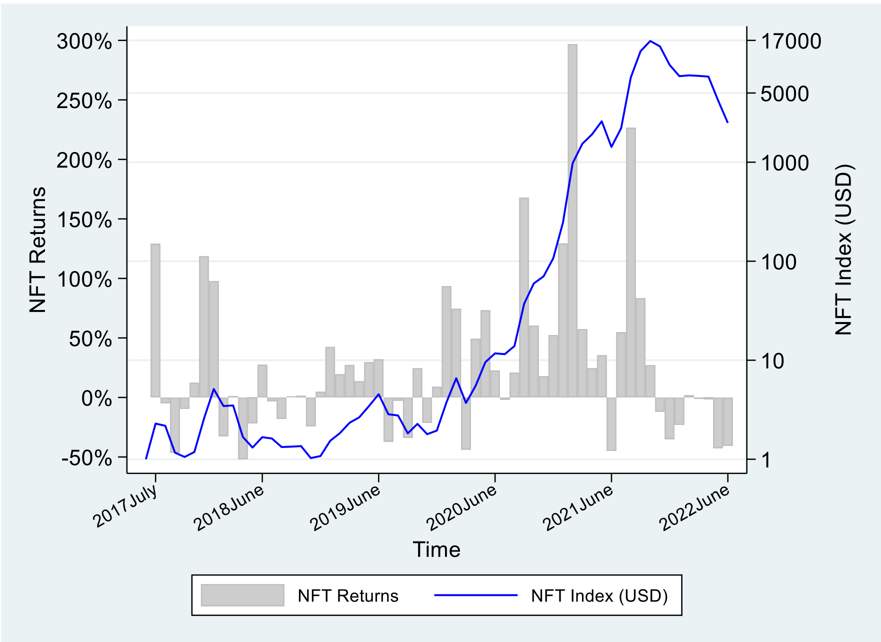

Figure 2. NFT index and returns.
The line in this figure shows our NFT index in USD (against the right-hand axis), and the index is set to unity in June 2017. NFT index is estimated using the hedonic regression model in column (4) of Table 3. The bars represent the month-over-month growth of the NFT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

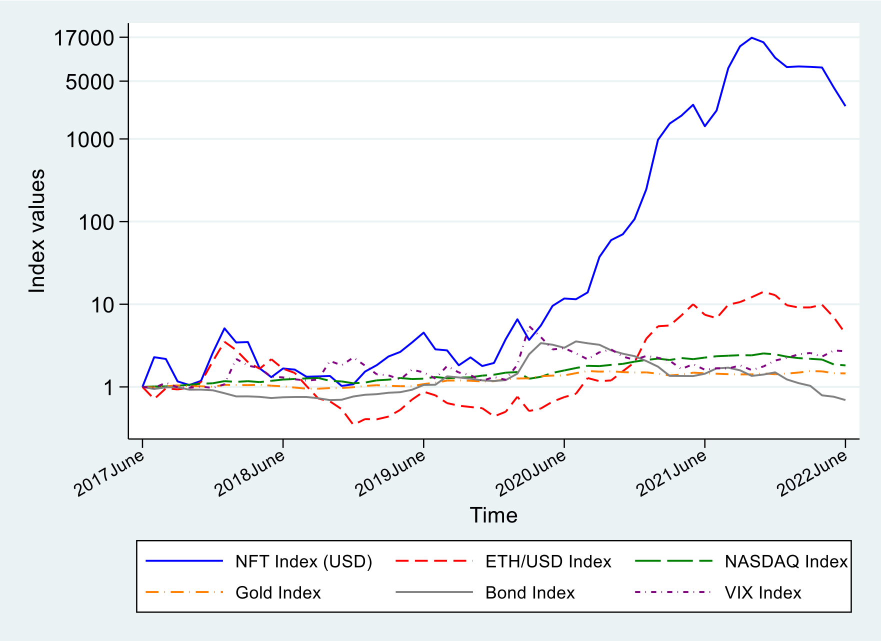

Figure 3. NFT index and major market indices.
This figure shows the NFT index and major market indices over the period from June 2017 through June 2022. NFT index is estimated using the hedonic regression model in column (4) of Table 3. Data on market indices are downloaded from Yahoo! Finance and Investing.com. Appendix A provides variable definitions in greater detail. All indices are set to unity in June 2017.

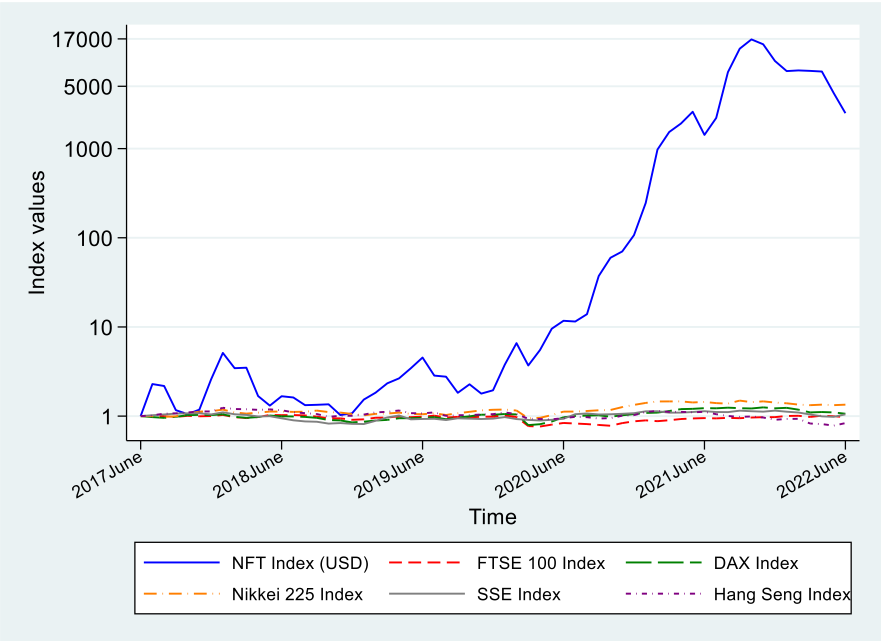

Figure 4. NFT index and stock market indices worldwide.
This figure shows the NFT index and stock market indices worldwide (except for the U.S.) over the period from June 2017 through June 2022. NFT index is estimated using the hedonic regression model in column (4) of Table 3. Data on stock market indices are downloaded from Investing.com. Appendix A provides variable definitions in greater detail. All indices are set to unity in June 2017.

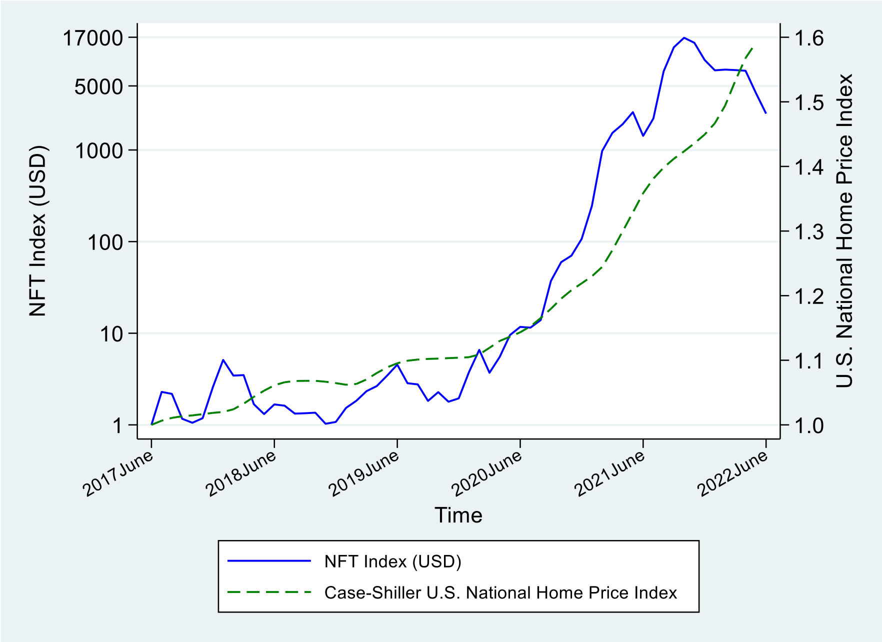

Figure 5. NFT index and Case-Shiller U.S. National Home Price Index.
This figure shows the NFT index and Case-Shiller U.S. national home price index over the period from June 2017 through May 2022 due to data availability. NFT index is estimated using the hedonic regression model in column (4) of Table 3. The index values are set to unity in June 2017. Appendix A provides variable definitions in greater detail. All indices are set to unity in June 2017.

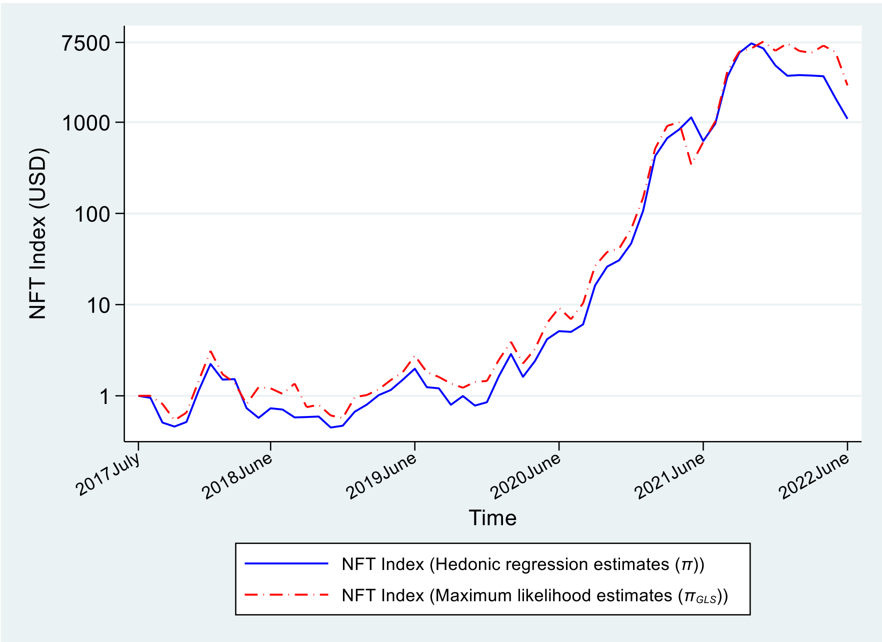

Figure 6. NFT index using repeat-sales regression (RSR) model.
This figure compares the NFT indices estimated using the hedonic regression and RSR models. Appendix A provides variable definitions in greater detail. The indices are set to unity in July 2017.

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 June 2022. 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	3,193	0	6	1,083	3,207	29	4,325
2021	2,853	9,538	3	8	4,229	8,111	40	12,391
2022	229	2,207	1	1	892	1,538	4	2,436
2017-2022	**6,759**	**15,646**	**11**	**35**	**7,284**	**14,966**	**109**	**22,405**

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

CryptoPunk type	N	Mean	P50	Average prices by transaction type	
				Primary Sales	Secondary Sales
Alien	11	3,603.611	2.690	3.98	9,902.97
Ape	35	920.390	2.447	478.19	1,388.60
Female	7,284	101.513	45.488	58.54	122.59
Male	14,966	96.791	37.061	48.57	116.15
Zombie	109	572.312	18.887	317.42	780.48

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	0.9556***	1						
(3) ΔNumSellers	0.9042***	0.8038***	1					
(4) ΔNumSales	0.8210***	0.8536***	0.7547***	1				
(5) ΔSalesUSD	0.3768***	0.3679***	0.2780***	0.2734***	1			
(6) ΔETHUSD	0.0339	0.0500**	0.0030	0.0388*	0.0699***	1		
(7) ΔETHVol	0.0645***	0.0842***	0.0320	0.0749***	0.0383	0.0775***	1	
(8) Adj. SVI	0.0082	0.0079	0.0027	–0.0135	–0.0298	0.0374	0.0871***	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 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	3.9302***	3.9260***	3.9363***	3.8905***
	(0.2158)	(0.2164)	(0.2174)	(0.2235)
Ape	2.5805***	2.5762***	2.5853***	2.5689***
	(0.4050)	(0.4042)	(0.4039)	(0.4036)
Zombie	2.3613***	2.3705***	2.3670***	2.3675***
	(0.1188)	(0.1207)	(0.1201)	(0.1197)
Female	0.0528***	0.0512***	0.0509***	0.0496***
	(0.0180)	(0.0180)	(0.0179)	(0.0179)
PrimarySale	–0.0567***	–0.0553***	–0.0560***	–0.0558***
	(0.0116)	(0.0117)	(0.0117)	(0.0117)
ΔNumWallets		–0.0096		
		(0.0201)		
ΔNumBuyers			0.0807**	0.0182
			(0.0315)	(0.0344)
ΔNumSellers			–0.0928**	–0.1183***
			(0.0388)	(0.0417)
ΔNumSales				0.0253
				(0.0201)
ΔSalesUSD				0.0289***
				(0.0062)
ΔETHUSD				–0.4817***
				(0.0902)
ΔETHVol				–0.0640***
				(0.0160)
Adj. SVI				–0.0021*
				(0.0012)
_0_Attributes	3.2124***	3.2020***	3.2295***	3.2296***
	(0.3940)	(0.3958)	(0.3841)	(0.3859)
_1_Attributes	0.7948***	0.7985***	0.7975***	0.8005***
	(0.0623)	(0.0623)	(0.0622)	(0.0626)
_2_Attributes	0.1435***	0.1408***	0.1405***	0.1425***
	(0.0345)	(0.0346)	(0.0346)	(0.0348)
_4_Attributes	–0.1138***	–0.1104***	–0.1101***	–0.1093***
	(0.0360)	(0.0361)	(0.0361)	(0.0363)

_5_Attributes	0.1443	0.1503*	0.1505*	0.1454
	(0.0909)	(0.0912)	(0.0913)	(0.0918)
_6_Attributes	1.2606***	1.2717***	1.2804***	1.2406***
	(0.2921)	(0.2927)	(0.2918)	(0.2882)
_7_Attributes	1.7110***	1.7168***	1.7510***	1.6839***
	(0.1779)	(0.1780)	(0.1775)	(0.1791)
Constant	2.8341***	2.8702***	2.9301***	2.9520***
	(0.1292)	(0.1335)	(0.1269)	(0.1284)
Observations	21,828	21,767	21,767	21,677
Adj. R^2	0.9510	0.9508	0.9508	0.9510
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 June 2022. 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	–	2020-01	3.772	93.61%
2017-07	2.291	129.07%	2020-02	6.587	74.61%
2017-08	2.178	–4.90%	2020-03	3.702	–43.79%
2017-09	1.166	–46.47%	2020-04	5.522	49.15%
2017-10	1.054	–9.59%	2020-05	9.559	73.12%
2017-11	1.183	12.25%	2020-06	11.734	22.76%
2017-12	2.587	118.59%	2020-07	11.511	–1.91%
2018-01	5.119	97.86%	2020-08	13.909	20.84%
2018-02	3.449	–32.61%	2020-09	37.262	167.89%
2018-03	3.493	1.25%	2020-10	59.717	60.26%
2018-04	1.680	–51.91%	2020-11	70.268	17.67%
2018-05	1.312	–21.87%	2020-12	107.095	52.41%
2018-06	1.672	27.42%	2021-01	245.761	129.48%
2018-07	1.620	–3.15%	2021-02	975.490	296.93%
2018-08	1.328	–18.03%	2021-03	1,535.360	57.39%
2018-09	1.341	0.99%	2021-04	1,911.742	24.51%
2018-10	1.358	1.28%	2021-05	2,589.085	35.43%
2018-11	1.029	–24.25%	2021-06	1,425.189	–44.95%
2018-12	1.076	4.65%	2021-07	2,205.810	54.77%
2019-01	1.534	42.50%	2021-08	7,202.187	226.51%
2019-02	1.833	19.52%	2021-09	13,202.876	83.32%
2019-03	2.334	27.33%	2021-10	16,772.233	27.03%
2019-04	2.653	13.64%	2021-11	14,781.327	–11.87%
2019-05	3.442	29.75%	2021-12	9,610.389	–34.98%
2019-06	4.540	31.92%	2022-01	7,399.369	–23.01%
2019-07	2.849	–37.25%	2022-02	7,533.839	1.82%
2019-08	2.768	–2.85%	2022-03	7,444.420	–1.19%
2019-09	1.827	–34.00%	2022-04	7,316.446	–1.72%
2019-10	2.277	24.63%	2022-05	4,200.925	–42.58%
2019-11	1.790	–21.37%	2022-06	2,494.741	–40.61%
2019-12	1.948	8.83%			

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	1.8639***	544.91%	1	Knitted Cap	–0.0900**	–8.60%
2	Pilot Helmet	1.3674***	292.51%	2	Front Beard Dark	–0.0460	–4.49%
3	Tiara	1.2663***	254.78%	3	Cap Forward	–0.0288	–2.84%
4	Orange Side	1.1343***	210.90%	4	Stringy Hair	–0.0278	–2.74%
5	Choker	1.0466***	184.80%	5	Mohawk	0.0016	0.16%
6	Welding Goggles	0.9268***	152.64%	6	Frumpy Hair	0.0118	1.19%
7	Hoodie	0.8976***	145.38%	7	Bandana	0.0227	2.30%
8	Buck Teeth	0.8228***	127.68%	8	Mohawk Dark	0.0279	2.83%
9	Pink With Hat	0.7632***	114.51%	9	Headband	0.0344	3.50%
10	3D Glasses	0.7332***	108.17%	10	Mohawk Thin	0.0424	4.33%

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	0.5325***	1						
(3) NASDAQ Index	0.2851**	0.4290***	1					
(4) S&P 500 Index	0.2782**	0.4602***	0.9313***	1				
(5) Dow Jones Index	0.2510*	0.4478***	0.8183***	0.9588***	1			
(6) VIX Index	–0.1191	–0.1860	–0.6658***	–0.7908***	–0.7986***	1		
(7) Bond Index	–0.1719	–0.1532	–0.2302*	–0.4275***	–0.5576***	0.5125***	1	
(8) Gold Index	–0.0971	0.2239*	0.1747	0.1241	0.0719	0.0078	0.3195**	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 June 2022. 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	26.77%	13.92%	65.57%	–51.91%	296.93%	40.70%	21.11%
ETH/USD Index	6.18%	2.50%	29.14%	–36.78%	93.00%	20.92%	8.30%
NASDAQ Index	1.12%	1.01%	4.80%	–17.02%	11.54%	21.64%	19.20%
S&P 500 Index	0.86%	0.78%	3.89%	–18.52%	6.90%	19.84%	17.82%
Dow Jones Index	0.72%	0.64%	3.88%	–20.02%	7.21%	16.38%	14.34%
VIX Index	5.07%	1.67%	33.38%	–29.19%	192.96%	14.95%	4.75%
Bond Index	0.22%	–0.61%	14.07%	–23.24%	71.46%	0.96%	–4.92%
Gold Index	0.67%	0.63%	2.91%	–4.99%	6.60%	20.21%	18.81%
One-month T-bill	0.08%	0.08%	0.08%	0.00%	0.21%	–	–

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

This table reports the investment performance of NFTs and different asset classes over the high-interest-rate and low-interest-rate periods, respectively. We define the high-interest-rate period as the period over June 2017-February 2020, and the low-interest-rate period as the year-month over March 2020-February 2022. 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.

	High-interest-rate period			Low-interest-rate period		
	Mean Returns (per month)	Std. dev.	Sharpe ratio	Mean Returns (per month)	Std. dev.	Sharpe ratio
NFT Index	6.07%	45.91%	12.90%	34.10%	82.71%	41.22%
ETH/USD Index	–0.85%	29.23%	–3.41%	10.91%	28.41%	38.38%
NASDAQ Index	1.30%	3.26%	35.57%	1.63%	5.88%	27.57%
S&P 500 Index	0.93%	2.67%	29.39%	1.26%	4.90%	25.53%
Dow Jones Index	0.91%	2.79%	27.44%	0.80%	5.01%	15.86%
VIX Index	1.95%	27.84%	6.50%	1.21%	42.34%	2.82%
Bond Index	1.16%	7.51%	13.55%	–1.09%	19.97%	–5.52%
Gold Index	0.74%	2.73%	21.68%	0.69%	3.07%	22.11%
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, and 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	25.1558***	26.2650***	26.3585***	32.1825***
	(2.9271)	(3.0232)	(2.9695)	(3.6861)
MKTRF	1.7119	1.0884	1.0397	0.2614
	(1.0269)	(0.6095)	(0.5350)	(0.1415)
SMB		2.9694	2.9076	0.0578
		(0.9204)	(0.8593)	(0.0161)
HML		1.0495	0.9872	6.2341**
		(0.5034)	(0.4291)	(2.1740)
RMW				–4.3833
				(–0.9793)
CMA				–11.5236**
				(–2.4340)
MOM			–0.1869	
			(–0.0670)	
Observations	60	60	60	60
R^2	0.0179	0.0431	0.0432	0.1456

Appendix

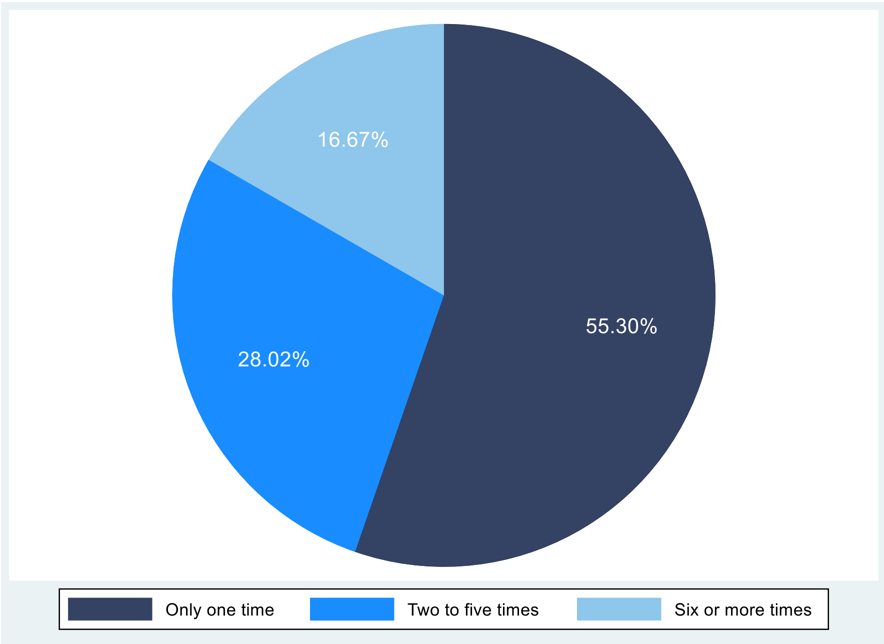

Figure A1. The turnover of CryptoPunk transactions.
The figure shows the distribution of the number of transactions for each CryptoPunk over the sample period from June 2017 through June 2022.

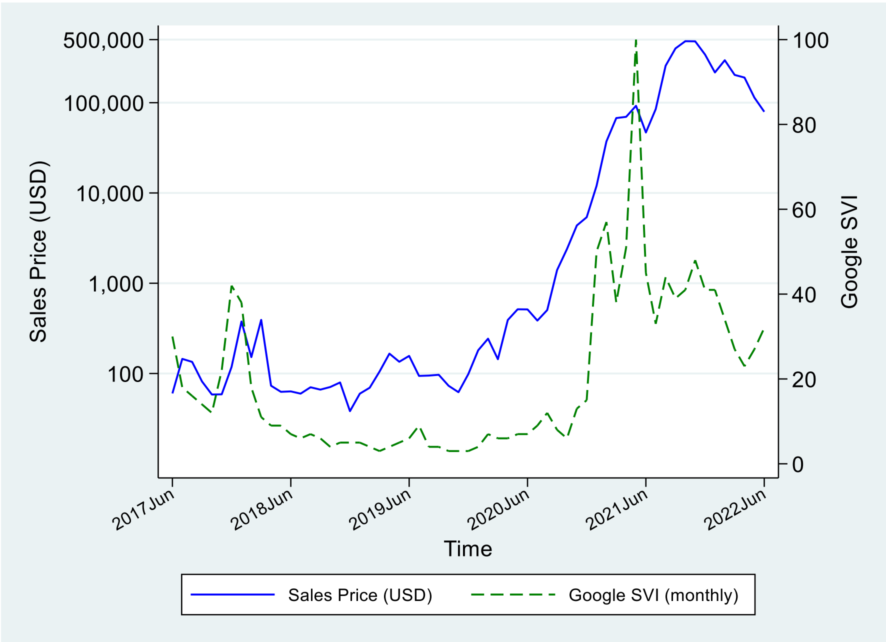

Figure A2. Monthly sales prices of CryptoPunks and Google SVI.
The solid line represents the average monthly sales price of CryptoPunks in USD (against the left-hand axis). The dash line represents the Google search volume index (SVI) with the search topic related to "Ethereum" (against the right-hand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

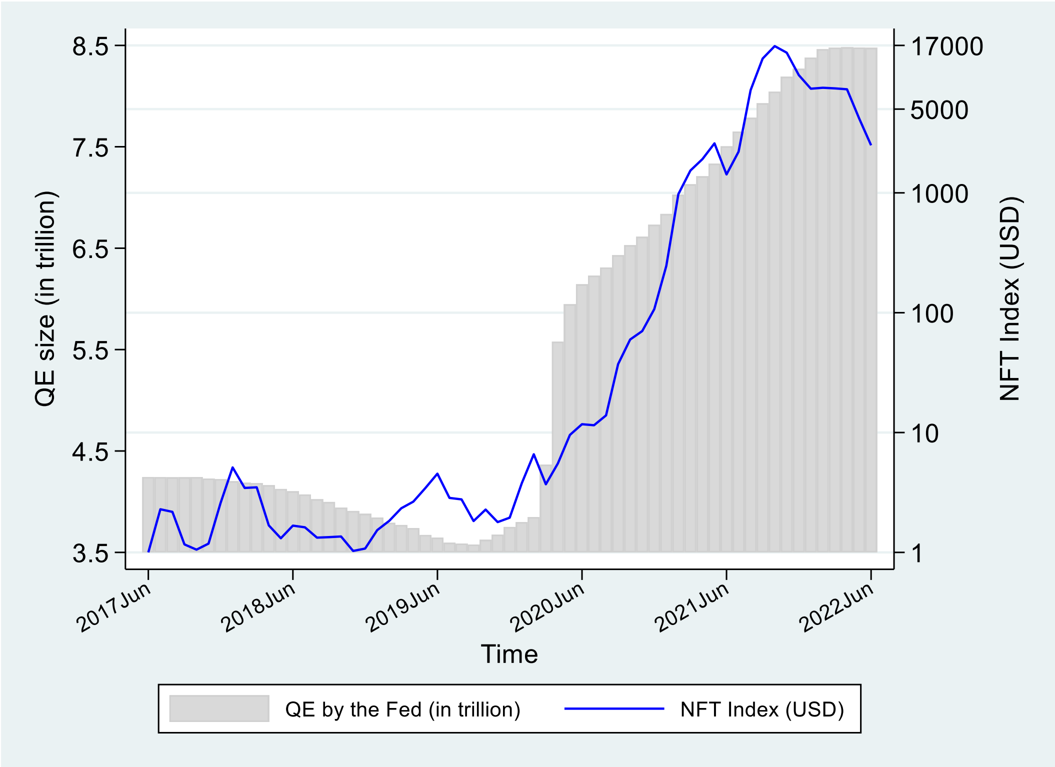

Figure A3. NFT index and the quantitative easing by the Fed.

This figure shows the NFT index and the QE size, which is the proxy for U.S. quantitative easing, over the period from June 2017 through June 2022. NFT index is estimated using the hedonic regression model in column (4) of Table 3. The index values are set to unity in June 2017. Following Yang and Zhou (2017), the QE proxy is the size of U.S. Treasury securities, agency securities, and mortgage-backed securities holdings on the Federal Reserve's balance sheet.

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 is categorized as "Alien" and zero otherwise.	Larva Labs
Ape	A dummy variable that equals one if the type of a CryptoPunk is categorized as "Ape" and zero otherwise.	Larva Labs
Zombie	A dummy variable that equals one if the type of a CryptoPunk is categorized as "Zombie" and zero otherwise.	Larva Labs
Female	A dummy variable that equals one if the type of a CryptoPunk is categorized as "Female" and zero otherwise.	Larva Labs
PrimarySale	A dummy variable that equals one if a CryptoPunk is sold in a primary sale and zero otherwise.	Larva Labs
_7_Attributes	A dummy variable that equals one if a CryptoPunk has seven attributes and zero otherwise. Similarly, *_0_Attributes* denotes that a CryptoPunk has no attribute. Approximately half of CryptoPunks are featured with three attributes so we treat them as the base or reference category.	Larva Labs
Panel B: Network factors		
ΔNumWallets	The growth of unique wallets in NFT markets on date *t*.	NonFungible.com
ΔNumBuyers	The growth of unique buyers in NFT markets on date *t*.	NonFungible.com
ΔNumSellers	The growth of unique sellers in NFT markets on date *t*.	NonFungible.com
ΔNumSales	The growth of transactions for sales in NFT markets on date *t*.	NonFungible.com
ΔSalesUSD	The growth of USD sales volume in NFT markets on date *t*.	NonFungible.com
ΔETHUSD	The growth of ETH/USD exchange rate on date *t*.	Yahoo! Finance
ΔETHVol	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
Case-Shiller U.S. National Home Price Index	The index values are estimated using the repeat-sales methodology, based on observed changes in home prices. The index is constructed by S&P Dow Jones Indices LLC. For more information regarding the index, please visit Standard & Poor's.	S&P Dow Jones Indices LLC and FRED

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 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	3.8264***	3.8296***	3.8348***	3.8142***
	(0.1992)	(0.1988)	(0.1991)	(0.2040)
Ape	2.6713***	2.6750***	2.6799***	2.6684***
	(0.2797)	(0.2789)	(0.2785)	(0.2780)
Zombie	2.3344***	2.3474***	2.3452***	2.3429***
	(0.1158)	(0.1175)	(0.1173)	(0.1170)
Female	0.0454***	0.0453***	0.0452***	0.0444***
	(0.0142)	(0.0142)	(0.0142)	(0.0142)
PrimarySale	-0.0546***	-0.0534***	-0.0538***	-0.0538***
	(0.0074)	(0.0074)	(0.0074)	(0.0074)
ΔNumWallets		0.0035		
		(0.0182)		
ΔNumBuyers			0.0462**	-0.0095
			(0.0186)	(0.0238)
ΔNumSellers			-0.0422**	-0.0682***
			(0.0210)	(0.0223)
ΔNumSales				0.0313**
				(0.0150)
ΔSalesUSD				0.0152***
				(0.0032)
ΔETHUSD				-0.3741***
				(0.0671)
ΔETHVol				-0.0442***
				(0.0128)
Adj. SVI				-0.0027***
				(0.0005)
_0_Attributes	3.0656***	3.0644***	3.0777***	3.0830***
	(0.4043)	(0.4066)	(0.4007)	(0.4008)
_1_Attributes	0.7840***	0.7825***	0.7820***	0.7852***
	(0.0662)	(0.0662)	(0.0662)	(0.0667)
_2_Attributes	0.1176***	0.1193***	0.1192***	0.1209***
	(0.0389)	(0.0391)	(0.0391)	(0.0394)
_4_Attributes	-0.0788**	-0.0794**	-0.0792**	-0.0783**
	(0.0395)	(0.0396)	(0.0397)	(0.0399)

_5_Attributes	0.2652***	0.2628***	0.2629***	0.2591***
	(0.0842)	(0.0845)	(0.0846)	(0.0850)
_6_Attributes	1.3069***	1.2973***	1.3015***	1.2658***
	(0.2908)	(0.2932)	(0.2929)	(0.2910)
_7_Attributes	1.8792***	1.8715***	1.8893***	1.8422***
	(0.1889)	(0.1893)	(0.1892)	(0.1901)
Constant	-2.6561***	-2.6356***	-2.6063***	-2.5667***
	(0.1059)	(0.1072)	(0.1054)	(0.1052)
Observations	21,827	21,768	21,768	21,678
Adj. R^2	0.9470	0.9468	0.9469	0.9473
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 June 2022. 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	1.7119	25.16%	14.69%	76.76%	198.54%
ETH/USD Index	1.7819	4.51%	2.53%	17.50%	101.45%
NASDAQ Index	0.5772	0.52%	0.91%	30.05%	74.76%
S&P 500 Index	0.5180	0.31%	0.60%	26.20%	61.96%
Dow Jones Index	0.5021	0.19%	0.37%	21.35%	57.00%
VIX Index	–4.1841	8.73%	–2.09%	16.24%	113.13%
Bond Index	–0.3192	0.42%	–1.32%	–8.59%	62.08%
Gold Index	0.0618	0.53%	8.61%	42.48%	100.46%

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 the investment performance of NFTs over the whole sample period, the high-interest-rate period, and low-interest-rate period, respectively. We define the high-interest-rate period as the period over June 2017-February 2020, and the low-interest-rate period as the year-month over March 2020-February 2022. 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		High-interest-rate period		Low-interest-rate period	
	Mean Returns (per month)	Sharpe ratio	Mean Returns (per month)	Sharpe ratio	Mean Returns (per month)	Sharpe ratio
NFT Index	11.13%	23.04%	6.43%	16.08%	20.88%	35.26%

Panel B: NFT returns loadings to equity factors

	CAPM	3-factor	4-factor	5-factor
(In percentage)	(1)	(2)	(3)	(4)
ALPHA	19.0124***	19.3038***	19.9492***	24.1556***
	(3.0043)	(2.9839)	(3.0286)	(3.7769)
MKTRF	–0.5589	–0.7154	–1.0518	–1.4729
	(–0.4553)	(–0.5380)	(–0.7295)	(–1.0889)
SMB		0.7238	0.2969	–1.5608
		(0.3013)	(0.1183)	(–0.5923)
HML		0.3814	–0.0490	4.7006**
		(0.2457)	(–0.0287)	(2.2377)
RMW				–3.2200
				(–0.9821)
CMA				–9.8038***
				(–2.8268)
MOM			–1.2908	
			(–0.6232)	
Observations	60	60	60	60
R^2	0.0036	0.0073	0.0142	0.1421

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 high-interest-rate period, and the low-interest-rate period, respectively. We define the high-interest-rate period as the period over June 2017-February 2020, and the low-interest-rate period as the year-month over March 2020-February 2022. 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		High-interest-rate period		Low-interest-rate period	
	Mean Returns (per month)	Sharpe ratio	Mean Returns (per month)	Sharpe ratio	Mean Returns (per month)	Sharpe ratio
NFT Index (USD)	11.08%	17.19%	3.42%	7.30%	30.75%	38.12%
NFT Index (ETH)	8.35%	17.69%	3.77%	9.51%	17.86%	30.93%

Appendix G. The distribution of the sales by NFT collection

This table reports the total sales and repeated sales in different NFT collections. The sample period is between June 2017 and June 2022. We define a repeated sale as an NFT being sold at least twice and the sales of a given NFT occur in different months.

NFT	Genre	Repeated Sales	Total Sales
Bored Ape Yacht Club	Collectibles	9,655	27,390
CryptoPunks	Collectibles	9,242	22,405
Decentraland	Virtual Worlds	269	13,547
Meebits	Collectibles	6,480	31,613
Sorare	Sports	84	836
SuperRare	Art	1,444	12,247
	Total	**27,174**	**108,038**