Alternative Investments in the Fintech Era:

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

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Abstract

Our study highlights the NFT rarity as a key determinant of price premium in the cross-section. Moreover, well-connected investors, who establish their central positions in the NFT network through early adoption and active trading, enjoy pricing advantages. We also find that experienced investors pay lower prices for NFTs. As an investment class, NFTs exhibit a high-return and high-risk profile when compared to traditional assets, especially in a low-interest-rate environment, and outperform most other alternative assets, such as luxury goods, private equity, and artwork. Overall, we provide novel and comprehensive analyses of NFTs, a digital alternative investment in the Fintech era.

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

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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 NFT markets 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 documents relating to 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 utilizes one of the earliest, largest, and most representative NFT collections, the CryptoPunks, to explore determinants of the NFT prices in the cross-section.

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[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. In August 2022, Automobili Lamborghini also launched a new series of monthly NFT collections featuring Lamborghini's iconic vehicles.

We also construct an NFT index and shed novel light on the risk and return of this digital alternative investment.

There are two major reasons why we mainly focus on CryptoPunks. First, there is a valid concern that the time period for NFT markets 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 Bordeaux red 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 establishing the robustness, we also consider other well-known NFT collections, such as Bored Ape Yacht Club, Meebits, Azuki,

[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

and CloneX, 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. In most cases, the value of CryptoPunks increases with their rarity. 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.[6] 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.[7] 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.[8]

Investors typically sell their alternative assets, such as artworks or collections, through dealers or traditional auction markets.[9] Several features make NFT markets different from conventional auction markets. NFT marketplaces operate as the peer-to-peer version of auction platforms (e.g., OpenSea or Rarible) empowered by blockchain technology. In the NFT market, there are no central entities or intermediaries in trades, allowing NFT owners or collectors to make a deal with their counterparts directly.[10] As long as both parties have an Ethereum wallet

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[6] 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.
[7] See https://twitter.com/etheria_feed/status/1370825688647884802?lang=en.
[8] 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.
[9] 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.
[10] 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

(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.[11] 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 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 exploring the determinants of NFT prices using hedonic regression models that account for NFT characteristics and other relevant variables. Our database consists of 23,206 transactions recorded on *Larva Labs* over the period running from June 2017 to December 2022. We find that NFT prices highly depend on a token's rarity. Specifically, the rarity of CryptoPunks comes in three forms. The first one is the type of CryptoPunks. Most CryptoPunks are featured with a male or female face, but the rare types, i.e., Alien, Ape, and Zombie, are usually traded at much higher prices. The second one is the number of attributes each CryptoPunks has. CryptoPunks can have from zero to seven attributes, and only a few rare CryptoPunks have either zero or seven attributes. The third one is the type of the attributes. There are 87 unique attributes in total, and some attributes are very rare. For example, only 44 out of 10,000 CryptoPunks have the attribute "Beanie," thereby making these tokens the most expensive ones.

Next, we investigate the relationship between an investor's characteristics and the NFT trading prices, with a focus on network analysis. Previous studies show that entities occupying central positions in a network tend to perform better (e.g., Hochberg, Ljungqvist, and Lu (2007);

price during or after the auction. See https://support.opensea.io/hc/en-us for greater details.

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

Fracassi (2017)). Based on these studies, we conjecture that the centrality of an NFT investor in the CryptoPunk network would be related to the NFT price she pays or receives. We include centrality measures separately for buyers and sellers in our hedonic regressions and find that more central buyers pay lower prices for NFTs. But the effect of seller centrality is relatively mixed. Moreover, we also find that early adopters or active investors, in terms of transaction counts, transaction amount, and portfolio diversity, are more likely to emerge as central nodes within the network. In addition, buyer experience, as measured by transaction frequency and investment diversity, plays a role in the prices that buyers are willing to pay for NFTs.

We then move on to compile a 67-month NFT index based on the hedonic regression to document its risk and return profile as an alternative investment asset. We find that NFTs generally offer higher returns compared to other asset classes, such as stocks, bonds, wine, artworks, etc. In particular, NFT returns rise dramatically during the low-interest-rate period. This finding is consistent with the notion that searching for yield in a low interest rate environment boosts the growth of alternative asset markets (e.g., Korteweg, Kräussl, and Verwijmeren, 2016). Investing in NFTs, however, carries a substantial level of risk, making its Sharpe ratio less impressive. We also find that wealth creation and emotional dividends serve as key drivers for the aggregate demand for NFTs. Finally, we investigate whether the returns on NFTs comove with common stock factors used in conventional asset-pricing models and find that most equity factors are unlikely to explain the variations in NFT index values. Our results suggest that NFTs share few similarities with traditional asset classes, in line with the finding of Liu and Tsyvinski (2021) on cryptocurrencies.

Our study contributes to the literature in several ways. First, we expand the studies on alternative investments by exploiting the most valuable NFT collections on the blockchain. We show how the rarity of NFT affects the prices in the cross-section and link the prices to the network and investor characteristics. Moreover, 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. We complement these studies by providing a comprehensive comparison of the risk-return profiles between NFTs, an on-blockchain asset, and various asset classes.

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; Makarov and Schoar, 2020; Cong, He, and Li, 2021; Liu and Tsyvinski, 2021; Liu, Tsyvinski, and Wu, 2022).[12] Recent studies show that there is a limited correlation as well as spillover between cryptocurrency and NFT markets (e.g., Dowling, 2022a). Dowling (2022b) presents evidence of the inefficiency in land pricing within the Decentraland, one of the largest blockchain virtual worlds. Ante (2022) further shows that the pricing of Bitcoin and ETH is related to the growth of sales and wallet numbers in NFT markets. Our paper, however, does not focus on the relationship between the prices of cryptocurrencies and NFTs. We focus on how NFT rarity, investor network centrality, and investor experience are related to NFT prices.[13] Our results also show that none of the existing asset pricing models can fully explain the time-series returns on NFTs. These findings suggest that NFTs are more like a medium for efficiently trading illiquid assets than fiat money as most cryptocurrencies.

Finally, we complement the literature on network centrality by expanding its scope to the NFT space. While existing studies mainly focus on how network connections affect firm outcomes and investment decisions (e.g., Hochberg et al., 2007; Fracassi, 2017; Rossi et al., 2018), limited attention has been paid to the relationship between network centrality and crypto

[12] See Makarov and Schoar (2022b) for a detailed review of cryptocurrencies and decentralized finance studies.
[13] Nguyen (2022) extends our findings and shows that CryptoPunks with lighter skin tones are traded at higher prices than the ones with dark skin, suggesting that investor preferences may also affect NFT prices.

assets. One notable exception is Makarov and Schoar (2022a) who study the Bitcoin network and find that the major exchanges (e.g., Binance, Huobi, and Coinbase) are the most central participants within the network, implying the network's vulnerability to systemic risk. However, we find that the CryptoPunk network seems to be dominated by individual investors. Our result shows that NFT buyers who occupy central positions within the network tend to pay lower prices for their NFT transactions. Meanwhile, these central positions are often acquired through early adoption and active trading.

Our paper also differs from a follow-up paper by Borri, Liu, and Tsyvinski (2022) in three significant ways.[14] First, Borri et al. (2022) adopt repeat-sales regression (RSR) models to construct their NFT index. A major drawback of the RSR method is that it requires an NFT to be traded at least twice. In unique asset markets, investors may sell their assets only when the prices go up due to the disposition effect as pointed out by (Goetzmann, 1993). Therefore, the RSR method is often criticized for introducing selection biases. Although Borri et al. (2022) claim to use a comprehensive dataset covering a near universe of NFT transactions, about 40% of the transactions (i.e., nearly 83% of unique NFTs in their sample) are only traded once and thus dropped in the construction of their index. In other words, their RSR index gives a lot of weight to the actively traded NFTs, not to mention that most NFTs are created and traded in or after 2021. In contrast, we include all historical transactions of the CryptoPunks, which is created in June 2017, in our hedonic regression models. This setting allows us to not only probe deeper into the boom and bust of the NFT market but also investigate the drivers of NFT prices more thoroughly, which the RSR models cannot achieve.

Second, Borri et al. (2022) focus on time-series analyses of NFT returns and draw a similar conclusion to ours that NFT return is not significantly exposed to most equity factors. They

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[14] Borri et al. (2022) uploaded their draft to SSRN on March 18, 2022, while we uploaded ours to SSRN on September 1, 2021, more than six months ahead of their work.

also find that other asset pricing factors (i.e., cryptocurrency factors, currency factors, volatility, and investor attention) cannot explain the variations in NFT market returns well. Given that the NFT market has not yet reached its steady state, these tests, however, are up for debate. In our study, we put more emphasis on cross-sectional analyses and compare the risk-return profiles of different asset classes, such as stocks, bonds, cryptocurrencies, artwork, and real estate. We provide novel evidence that the pricing of NFTs is associated with the NFT rarity and investor network centrality and experience. We also find that the demand for NFTs is largely driven by the wealth effect of the cryptocurrency market. Furthermore, NFTs are different from financial instruments because NFTs have unique characteristics, allowing buyers to derive non-financial utility from the ownership (e.g., social status and private enjoyment).

Last, it is debatable whether it is appropriate to estimate an RSR index at such a high-frequency level because most NFTs have a rather low turnover of resales. For example, we find that the median (average) length of CryptoPunk holding periods is 120 days (402 days). Therefore, the weekly returns on NFTs in Borri et al. (2022) may be largely driven by speculative trading. It is also worth noting that their RSR model, including the full sample, only explains about 28.5% of the price movements. Although we construct our NFT index at the monthly level, our hedonic regressions have an adjusted R^2 of over 90% across all specifications.

2. Background and related literature

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

2.1 The Ethereum blockchain and non-fungible tokens

The concept of blockchains and relevant extensions has been around since the 1990s (Buterin, 2013). Yet, it was not effectively implemented until Satoshi Nakamoto proposed a peer-to-peer electronic cash system based on cryptographic proof, replacing a trusted third party to verify every transaction (Nakamoto, 2008). In 2009, Bitcoin came 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 et al., 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 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,"

[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.

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, 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 relatively small on this type of digital token. In this paper, we provide a thorough analysis of the pricing and investment performance of NFTs.

2.2 Alternative investments over time and NFTs

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[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.

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).

[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.

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 non-financial 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 that 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 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, i.e., NFTs, and investigating the determinants of their prices. We also explore whether their risk-return characteristics resemble those of existing traditional and alternative investments (e.g., stocks,

[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.

bonds, and artworks). Our contribution is unique as most research only focuses on the relationship between cryptocurrency and NFT markets (e.g., Ante, 2022; Dowling, 2022a). Moreover, while the concurrent studies explore the NFT market from the investor side (e.g., Oh, Rosen, and Zhang, 2022), we examine the determinants of NFT prices in the cross-sectional setting. In addition, Nadini et al. (2021) study the networks of NFT trades between traders and/or collections. Our findings complement their study by showing that experienced or central NFT buyers within the network possess competitive advantages and pay lower prices for NFTs.

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 details of this NFT collection in the next section.

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 the New York-based

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

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 CryptoPunk has a unique identification number, running from 0 through 9999. Overall, 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 zero to seven 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 23,206 transactions, including 6,847 unique tokens from June 2017 through December 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 6,847 tokens sold in primary sales, implying that initial owners still hold 3,153 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

[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.

sales than those in secondary sales. In other words, the buyers in primary sales usually have higher underlying profits from the resales of CryptoPunks.

[Insert Table 1]

Before we study the investment performance of NFTs, it is important to understand the trading behavior of NFT collectors. Figure 1 shows the distribution of holding periods (in months) from the first purchase to the resale of the CryptoPunks, where the average holding period is about 402 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 2, 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 & 2]

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

3.2 Network effects 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

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

growth, active address growth, transaction count growth, and payment count growth, are important factors for the valuation of cryptocurrency (Liu and Tsyvinski, 2021).

Similarly, NFT prices could be driven by the networks of users (i.e., collectors or investors) in NFT markets (e.g., Ante, 2022). 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 CoinGecko.

We further investigate how network centrality affects NFT prices. Studying network centrality can provide insights into the potential for network effects, where the actions of one investor or group of investors can impact the behavior and decisions of others within a network (e.g., Makarov and Schoar, 2022a). To keep it simple, we focus on the buyers and sellers within the CryptoPunk network. We construct four common measures of centrality, i.e., degree, betweenness, closeness, and eigenvector centrality, to identify important nodes (investors) within a network. First, *Degree* is simply the number of connections an investor has in a network. Investors with a high degree of centrality can be thought of as important hubs within the network because they are well-connected to many other investors. Second, *Closeness* measures how central an investor is in terms of the distance to other investors in the network. Investors with high closeness centrality are located in the middle of a network and can spread information quickly and efficiently because they have direct connections to many other

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

investors.

Additionally, *Betweenness* measures an investor's position on the shortest paths between other investors in a network. Investors with high betweenness centrality play an important role in the flow of information within the network because they act as intermediaries or bridges between different clusters of investors. Finally, *Eigenvector* measures an investor's centrality based on the centrality of its neighbors. Investors with high eigenvector centrality tend to be more influential because they are connected to other influential investors within the network. In other words, an investor's importance in the network depends not only on how many connections they have but also on the importance of the investors to whom they are connected.

We first provide a graphic illustration of the CryptoPunk network by using a directed graph with a distinction between the "seller" and "buyer" of an edge. Figure 3 plots a visual representation of the CryptoPunk network, which consists of 7,426 nodes and 18,567 edges over the period from 2017 to 2022. We find that there are several key investors within the network. To get a closer look at the structure of the CryptoPunk network, we restrict to the top 50 buyers/sellers by transaction counts. Figure 4 displays a subset of the CryptoPunk network, including only the top 50 traders by transaction counts from buy- and sell-sides. This network comprises 75 nodes and 275 edges, and it is dominated by active investors, consistent with our findings in Figure 3.

[Insert Figures 3 & 4]

Panel A of Table 2 highlights the top 10 central traders in the CryptoPunk network. We observe that these central investors appear to be individual investors, such as the trader "punksOTC" who exhibits the highest centrality across all measures. By comparison, the Bitcoin network is mostly dominated by exchanges, such as Binance, Huobi, and Coinbase (Makarov and Schoar, 2022a). This finding suggests that NFT markets may exhibit a higher level of "democratic" participation, compared with cryptocurrency markets. In Panel B, we also investigate the correlations between centrality measures and find that these measures, except for closeness, exhibit a high correlation.

[Insert Table 2]

3.3 Investor experience

We also collect CryptoPunk investors' past transaction records of other NFTs from the Etherscan and use this data to quantify investor experience: *NFTtxn*, *NFTValues*, *NewType*, and *NewNFT*. *NFTtxn* represents the number of NFT trades made by a wallet address to date, while *NFTValues* represents the transaction amount (in USD) invested by a wallet address to date. To capture the breadth and variety of an investor's NFT portfolio, *NewType* and *NewNFT* are measured as the number of different NFT types and new NFTs collected by a wallet address to date, respectively. Together, our proxies provide insight into an investor's investment strategy and engagement with NFT markets.

Panel A of Table 3 reports the summary statistics of buyer and seller experience. Our results show that sellers, on average, spend more money on NFTs, as well as trade more frequently and diversely than buyers, suggesting that sellers are usually more experienced. In Panel B, our proxies for investor experience are shown to be highly correlated, suggesting that investors who possess one of these attributes are likely to possess the others as well. That is, investors who have more experience tend to invest in a wider variety of NFTs or collections.

[Insert Table 3]

3.4 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 A1, 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 (*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 December 2022 to construct our proxy, *Adj. SVI*, for the attention to Ethereum (see Appendix A for additional details).

4. Empirical results

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 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

[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.

disposition effect (Korteweg et al., 2016). For example, former Twitter CEO Jack Dorsey's first-ever tweet in 2006 was sold for nearly $3 million on March 6, 2021.[29] 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.[30] Furthermore, the RSR model also suffers from a spurious negative autocorrelation in the estimated return series and an overestimation 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 the 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 7.

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 control variables 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.

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

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, $Control_{n,t}$ denotes the control

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

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

variable *n* related to NFT or Ethereum 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 variables. The anti-logs of the coefficients of δ_t are used to construct an NFT index that controls for time variation in the quality of tokens sold. The value of the hedonic NFT index (π_t) in year-month t is estimated as:

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

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

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

In addition, we add a wide range of CryptoPunk characteristics, including four type dummies (i.e., *Alien*, *Ape*, *Zombie*, and *Female*), 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 begin our analysis, we 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 4. 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 public sales, on average, are lower than those in the secondary sales. In column (2), we also add dummies for other attributes because certain attributes have a significant impact on the prices. We next examine how the adoption of NFTs, proxied by Δ*NumWallets*, influences sales prices. As shown in column (3), the coefficient on Δ*NumWallets*, however, 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 (4) of Table 4, 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 variables, 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.[31] We find that the sales prices become higher when there is an increase in NFT market size, 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 (5) of Table 4 is higher than the explanatory power of the models in the first four 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

[31] 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.

for the construction of our NFT index.

[Insert Table 4]

Apart from macroeconomic factors, the characteristics of unique assets impact their pricing. 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, Appendix D 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 investors are willing to pay a price premium for a specific set of characteristics, while tokens with unfavorable characteristics might be sold with discounts. Unsurprisingly, most of the top 10 attributes are the rarest among all attributes. But rarity is not the only pricing factor as some of the bottom 10 attributes are also rarely seen. In particular, we find that some characteristics, such as "Hoodie" and "3D Glasses," are much more valuable than others, but they are not necessarily rare. A CryptoPunk with a "Hoodie" attribute can, on average, increase its price by 148%.[32] In other words, aesthetic preferences also play an essential role in determining NFT prices.

4.3. *Network centrality*

Previous studies show that personal connections facilitate the flow of information within a network, thereby influencing investment decisions, M&A deals, and other corporate policies

[32] As a comparison of the economic magnitude, Renneboog and Spaenjers (2013) show that if a painting is auctioned off through the Sotheby's auction house in New York City, its price can go up by roughly 105% on average, while a signature only increases the price by about 31%.

(e.g., Larcker, So, and Wang, 2013; El-Khatib, Fogel, and Jandik, 2015). For instance, Fracassi (2017) finds that central companies within the network invest in a less idiosyncratic way and achieve better economic performance. In the context of delegated investment management, fund managers who have better connections tend to have higher risk-adjusted returns, take on higher portfolio risk, and attract greater investor flows (Rossi et al., 2018). Moreover, using the percentage of investments that successfully exit through an IPO or a sale to another company, Hochberg et al. (2007) find that VC companies with superior networks have much better fund performance.

Compared with conventional assets, unique assets can be more susceptible to information asymmetry. The heterogeneity of such assets, coupled with infrequent trading, poses a significant challenge even for an art expert when evaluating artworks (Mei and Moses, 2005). Meanwhile, it is difficult to identify the buyers and sellers in these alternative asset markets, not to mention evaluating the impact of network structure on the prices. However, in the case of NFT markets, we can track NFT buyers, and sellers, as well as their past transactions. Thus, this feature allows us to analyze the network centrality of NFT investors and its correlation with the prices they buy or sell for the NFTs, highlighting the advantage of blockchain data.

Based on Hochberg et al. (2007), we conjecture that the centrality of an NFT investor in the CryptoPunk network would be related to the price he/she pays or receives for an NFT transaction. To test this conjecture, we include centrality measures separately for buyers and sellers in our hedonic regression model. Table 5 shows that more central buyers pay lower prices for NFTs across all columns, whereas the effect of seller centrality is relatively mixed. We find that central sellers appear to sell NFTs at a premium as reported in columns (2) and (4). These results collectively suggest that buyers with higher centrality exert a greater influence within the CryptoPunk network than their counterparties.

[Insert Table 5]

One may wonder what determines an investor's centrality within the CryptoPunk network. Intuitively, investors who actively engage in trading tend to establish connections with other participants and become central nodes within the network. It is also possible that most central investors are early adopters so they acquire CryptoPunks at lower costs. As prior literature suggests, first movers have the ability to gain competitive advantages over their peers and capitalize on their superior information (e.g., Lieberman and Montgomery, 1988; Michael, 2003; Carow, Heron, and Saxton, 2004).

Accordingly, we explore the determinants of an investor's centrality by regressing our proxy for network centrality on investor characteristics. Apart from our proxies for investor experience, we construct two proxies to capture whether an investor is an early adopter. First, *WalletAge* is the natural logarithm of one plus the number of years since the first transaction was made by a wallet address on the Ethereum blockchain. Second, *Adoption_index* captures how early an investor adopts the CryptoPunks. Specifically, we aggregate the number of days between the purchase and release dates of each CryptoPunk that an investor has bought on a monthly basis. We then scale the days based on the cumulative number of transactions made by the investor during that month. To create an index, we further normalize the variable values, resulting in an index value ranging between zero and one. A lower value indicates earlier adoption.

Table 6 reports the results with *Eigenvector* as our dependent variable.[33] The results are similar when we adopt other measures of centrality. Consistent with our conjecture, we observe that early adopters or active investors, in terms of transaction counts, transaction amount, and portfolio diversity, emerge as central nodes within the network. Our findings highlight the

[33] *Eigenvector* is shown to exhibit a greater resilience to manipulation, compared with other centrality measures (Makarov and Schoar, 2022a).

importance of early adoption and frequent transaction in shaping network dynamics and economic outcomes of NFT markets.

[Insert Table 6]

4.4. *Investor experience*

In this subsection, we explore the potential impact of investor experience on NFT prices. We employ four measures to capture the investor trading behavior: *NFTtxn*, *NFTValues*, *NewType*, and *NewNFT*. Specifically, we use *NFTtxn* and *NFTValues* to evaluate how frequently and substantially an investor engages in NFT markets, respectively. On the other hand, *NewType* and *NewNFT* reflect the diversity of an investor's NFT portfolio.

We first take the natural logarithm of our proxies for investor experience because they exhibit a highly skewed distribution. We then include our experience measures separately for buyers and sellers in our hedonic model. The results are presented in Table 7. In columns (1) and (2), we observe that buyers who engage in more frequent trading but devote less wealth are more likely to spend less on NFTs. Furthermore, those buyers who invest in a wide range of NFTs tend to pay lower prices, as shown in columns (3) and (4). It is worth noting that seller experience, despite being found to be higher in Table 3, does not appear to have a significant impact on prices. In sum, our findings indicate that buyer experience, as measured by transaction frequency and investment diversity, plays a role in determining the prices buyers are willing to pay for NFTs.

[Insert Table 7]

5. Additional analyses: Generative collections

As a robustness check, we include additional nine NFT collections in our sample to examine the impact of an NFT's rarity on its price. Our analysis focuses specifically on generative collections (GCs), as defined by Oh et al. (2022). GCs are NFT collections in which the associated digital artwork shares a common theme, and each NFT represents a unique variation of that theme. Unlike the CryptoKitties, generative collections typically have a finite supply of NFTs. By limiting our sample to GCs, we can investigate how NFT rarity affects sales prices. Lastly, we restrict our attention to NFT collections stored on the Ethereum blockchain.

5.1 Generative collections

In this subsection, we provide a brief overview of additional GCs and highlight some of their unique features that contribute to their rarity and value. Panel A of Table 8 contains details about the NFT collections we selected, which are recognized widely or traded actively. Possessing these NFTs not only provides proof of ownership of the digital assets, but it may also grant their owners access to exclusive member communities or events.

Among the earliest NFT collections, the CryptoSkulls is widely believed to be the second-ever 10,000 supply NFT profile pictures (PFPs), following CryptoPunks. Each CryptoSkull has unique features, such as varying background colors, eye shapes, or hairstyles. The collection also provides a uniqueness index, indicating the rarity of each token. Additionally, we include Meebits in our GC sample, which is another NFT project created by Larva Labs. There are 20,000 unique Meebits in the collection. Similar to the CryptoPunks, Meebits can be categorized into seven major types (i.e., Dissected, Elephant, Human, Pig, Robot, Skeleton, and Visitor) and adorned with additional attributes.

We also consider two well-known collections created by Yuga Labs. The first is the Bored Ape Yacht Club (BAYC), which consists of 10,000 Bored Apes that serve as membership cards for the Yacht Club. Bored Apes with rare fur colors or special attributes tend to be more expensive. The second collection is the Mutant Ape Yacht Club (MAYC), which comprises up to 20,000 Mutant Apes. Mutant Apes can be created by minting a Mutant Ape in a public sale or by exposing an existing Bored Ape to a vial of Mutant Serum. There are three tiers of Mutant

Serum vials: M1, M2, and Mega Mutant, with M1 serums being the most common.

Another collection we consider is the Cool Cats, which features 9,999 cat characters issued in July 2021. Each Cool Cat has its tier of rarity, which ranges from one to eight levels. Additionally, each character is adorned with a unique combination of faces, hats, and shirts. Also launched in the same month is World of Women (WoW), illustrated by Yam Karkai. WoW comprises 10,000 PFPs, with their rarity primarily determined by the Skin Tone, together with a distinct sequence of other attributes.

We also include CloneX, a collection of 20,000 avatars created by an artist, Takashi Murakami, in collaboration with RTFKT in December 2021. All avatar traits were generated randomly and revealed after the public sale. CloneX primarily comes in eight different forms, including Alien, Angel, Demon, Human, and more.

In early 2022, the other two popular NFT collections, Azuki and Moonbirds, are released. Azuki includes four major types: Blue, Human, Red, and Spirit. The most common type is Human, while the rarest is Spirit. Additionally, each Azuki character features unique accessories. Similarly, Moonbirds can be classified based on their body type, with a total of 17 categories, and each category is further distinguished by various attributes, such as beak shapes, eye shapes, headwear, feather colors, etc.

5.2 Hedonic regression results: GC sample

Like CryptoPunks, many NFTs can be classified into several types and enriched with additional attributes. However, each collection has a distinct set of types, making it challenging to capture the rarity effect by simply including type dummies. To address this issue, we rank the NFT types within each collection and create two rarity dummies: *ExtremeRare* and *SuperRare*. *ExtremeRare* (*SuperRare*) is a dummy variable that equals one if the NFT type belongs to the top 1% (10%) of a collection and zero otherwise. We repeat the analysis in Table

4 to check whether NFT rarity affects sales prices in our GC sample. In Panel B of Table 8, we show that the price impact of *ExtremeRare* on NFT prices is greater than that of *SuperRare,* thus confirming the existence of a rarity effect in NFT markets.

[Insert Table 8]

Nevertheless, as discussed in Section 4.2, other attributes or attribute counts can also impact NFT prices. Thus, we consider an overall rarity score provided by Rarity.Tools. For each NFT collection, Rarity.Tools assigns a rarity score to each trait of an NFT, and the scores for all traits are then summed to determine the overall rarity score of the NFT. Accordingly, we construct three rarity dummies based on the ranking of the scores. *Rarity_1_pct* is a dummy variable that equals one if the rarity ranking of an NFT is within the top 1% of a collection and zero otherwise. Similarly, *Rarity_10_pct (Rarity_20_pct)* is a dummy variable that equals one if the rarity ranking of an NFT is within the top 10% (20%) of a collection and zero otherwise. These rarity dummy variables are mutually exclusive. In Appendix I, we provide evidence that NFT prices increase with the level of NFT rarity.

6. Investment performance of NFTs

In this section, we construct an NFT index using Eq. (2) with the resulting estimates on the time dummies from the hedonic regression model in column (5) of Table 4. The price level of the NFT index is set to one in June 2017 when the CryptoPunks was launched. We focus on the CryptoPunks because it is the most representative and earliest NFT collection. The results, however, are similar when we consider other collections.

6.1 Hedonic NFT index

We calculate returns on NFTs using Eq. (3). Table 9 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 5.

[Insert Table 9 & Figure 5]

We define a bull (bear) market as a 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.[34] 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.[35] In the same 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.[36] Meanwhile, the world's major advertising providers (i.e., Google and Facebook) even banned

[34] 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).
[35] See https://edition.cnn.com/2020/03/15/economy/federal-reserve/index.html.
[36] See https://www.bbc.com/news/business-42915437.

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.[37] The third bear market was mainly due to tightening monetary policy and the Terra LUNA crash, caused by the failure of Terra's algorithmic stablecoin (UST) and its linked coin LUNA.[38] A series of events led to 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 blockchain technology and public awareness of its applications. Nevertheless, it appears to be the economic environment that fosters the rapid appreciation of NFT values. Figure A2 shows a comparable pattern when generative collections are used. Hence, our results are robust to different sample choices for constructing the NFT index.

6.2 NFT index versus major market indices

In the previous section, we construct 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*).[39] 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.

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[37] See https://www.cnbc.com/2019/07/15/bitcoin-price-falls-below-10000-as-president-trump-slams-crypto.html.
[38] See https://www.forbes.com/sites/lawrencewintermeyer/2022/05/25/from-hero-to-zero-how-terra-was-toppled-in-cryptos-darkest-hour/?sh=613f4944389e.
[39] Data on major market indices are obtained from Yahoo! Finance and Investing.com.

To illustrate the relationship between the NFT index and major market indices, we first present a snapshot of the data. In Figure 6, 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 an environment with a low interest rate.

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*. As can be observed in Figure A3, the results are similar.

[Insert Figure 6]

We then analyze the correlations of returns on NFTs, ETH, stocks, market volatilities, bonds, and commodities. We present the results in Table 10. 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 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 10]

We present summary statistics for monthly returns on different assets during our sample period in Table 11. Given that returns on an asset might be serially correlated, we calculate monthly returns in two ways, i.e., arithmetic mean and geometric mean. Panel A compares the investment performance of NFTs with traditional investments. During our sample period, the average of NFT returns is 24.97% (12.85%) per month based on the arithmetic (geometric) estimation method, while the returns on ETH, stocks, and bonds are only 5.60% (2.13%), 0.97% (0.85%), and 0.05% (–0.76%), respectively. Collectively, we find that our NFT index substantially outperforms traditional 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 63.92%, and the corresponding numbers are 28.30% and 4.92% 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, the performances of NFTs and stocks are comparable if we use geometric average monthly returns.

[Insert Table 11]

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 E, 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 investment performance of NFTs with other alternative assets, such as luxury goods, private equity, real estate, artwork, and fine wines. We utilize *Global Luxury Index* and *Private Equity Index* (both from S&P Dow Jones Indices) to proxy for the investment performance of luxury goods and private equity, respectively. We use Case-Shiller U.S. National Home Price Index to proxy for the price level of real estate (*Home Price Index*), one of the largest illiquid investments. We obtain data on the All Art Index and the Liv-ex Fine Wine 1000 from Art Market Research (AMR) and the London International Vintners Exchange (Liv-ex) to capture the price level of artworks (*Art Index*) and fine wines (*Wine index*), respectively. See Appendix A for more details.

As shown in Panel B of Table 11, we find that the average monthly return of real estate (fine wine) is 0.65% (0.65%) with a standard deviation of 0.81% (1.14%), yielding a higher Sharpe ratio than that of NFTs. Figure 7 shows that the price level of real estate and fine wines increases over time, but the growth rate of these assets is much lower than that of NFTs. Our findings suggest that real estate and fine wines are low-risk and low-return investments relative to NFTs.

[Insert Figure 7]

We also compare NFT returns with the other cryptocurrency returns as shown in Appendix F. Other well-known cryptocurrencies, including Bitcoin, Cardano, Dogecoin, and Litecoin also outperform traditional investments but still underperform NFTs according to their risk-return profiles. As expected, stablecoins (e.g., Tether and USD Coin) have low volatilities but low returns (relative to NFTs). NFTs may resemble Solana and meme coins, such as Shiba Inu.

However, Solana and Shiba Inu were issued in 2020, so their performance might not be directly comparable to CryptoPunks.

6.3 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 securities, agency securities, and mortgage-backed securities holdings on the Federal Reserve's balance sheet.[40] As shown in Figure A4, the NFT price level rises with the size of U.S. quantitative easing, and the correlation estimate between the NFT index and the QE proxy is 0.686 at the 1% significant level (untabulated).

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, as well as the period from March 2022 to December 2022. The low-interest-rate period is defined as the period between March 2020 and February 2022. In the later subperiod, the Federal Reserve kept its benchmark interest rate at around zero. In Table 12, 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., 12.85%) in Table 11, the returns on NFTs drop to 2.13% in the high-interest-rate period but surge to 34.36% after the QE. The standard deviation rises sharply from 43.21% to 83.70%. Despite that, NFTs, on average, generate the highest monthly return, which is about 5 to 30 times higher than stocks in the subperiods. With

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

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 policy 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 H.

[Insert Table 12]

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.

6.4 Why investors are interested in NFTs?

After exploring the determinants of NFT prices and comparing the investment performance across various asset classes, our attention turns to understanding the drivers of NFT demand. Specifically, we investigate the impact of the wealth effect and emotional dividends on NFT demand, using the returns on NFTs as a proxy.

Since 2021, there has been a growing public interest in the crypto market. As shown in Figure A5, the market capitalization of the top three cryptocurrencies, i.e., Bitcoin (BTC), Ethereum (ETH), and Tether (USDT), grew substantially around early 2021, and this coincided the expansion of NFT markets. This pattern indicates that the growth in the wealth of blockchain communities may induce the demand for NFTs.

The previous literature also documents that the prices of unique assets respond to a wealth effect from the stock market (Goetzmann, 1993; Mei and Moses, 2002). Therefore, we utilize the returns on ETH/USD and the NASDAQ index as proxies for the wealth effect, as the increase in cryptocurrency and stock prices could be reasonable indicators of the growth in personal wealth for blockchain tech-savvy investors. We focus on ETH because the NFT collections in our sample are on the Ethereum blockchain. In addition, some individuals may perceive NFTs as a form of conspicuous consumption, similar to fine art or luxuries, to signal their social status (Bagwell and Bernheim, 1996; Mandel, 2009). As a result, we utilize the returns on the Global Luxury Index as a measure of conspicuous consumption growth to compare the relation between NFTs and other luxury goods.

One unique feature of NFTs is that they offer owners access to exclusive member communities, creating a sense of social identity among them. This identity can be further reinforced if a celebrity is involved. Specifically, when a celebrity uses NFTs as the profile picture on social media platforms, it often sparks excitement within the NFT community, resulting in emotional dividends or non-financial utility. For instance, NBA player Stephen Curry purchased the Bored Ape #7990 in August 2021, drawing public attention to the Bored Apes and causing hype within the NFT community. Figure A6 shows that the average sale price for Bored Apes doubled in the following few months.

To capture this phenomenon within the CryptoPunk community, we construct a dummy variable, Celebrity, that equals one if a celebrity purchases a CryptoPunk in a given month and zero otherwise. Notable celebrities who have acquired CryptoPunks include Chain CEO Deepak Thapliyal, American rapper Jay-Z, American entrepreneur Gary Vaynerchuk, etc.

The results are presented in Appendix J. Our findings indicate that the wealth effect of cryptocurrency and stock markets account for about 28% and 8% of NFT demand, respectively. Conspicuous consumption and emotional dividends also play a role, albeit to a lesser extent, as suggested by the adjusted R-squared. Nevertheless, when considering all drivers in our regression in a horse race, the growth of ETH prices and emotional dividends appear to be more relevant.

6.5 *Equity factor loadings*

We further 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 Appendix G, the alphas for all factor models are statistically significant.[42] The magnitudes of the alphas range from 23.40% to 29.89% per month, comparable to the average return of 24.97% in Table 11. 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.

6.6 *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

[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 H when NFT index values are constructed with CryptoPunk prices denominated in ETH.
[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.

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.

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 11 with service fees (i.e., 2.5%). In unreported results, NFTs continue to dominate other asset classes by yielding the highest financial returns, that is, 10.02%. Concerning the overall performance, the Sharpe ratio of NFTs is 15.93%, which is comparable to those of stocks due to the high volatility of NFT prices. Thus, our conclusion is unlikely to be changed by transaction costs.

7. An alternative way to construct the NFT index

7.1 Repeat-sales regression (RSR) model

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[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).

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 sale date s_i may be expressed as

$$r_i = \ln\left(\frac{P_{i,s}}{P_{i,b}}\right) = \sum_{t=b+1}^{s} r_{i,t} = \sum_{t=b+1}^{s} \mu_t + \sum_{t=b+1}^{s} \varepsilon_{i,t} \quad (5)$$

Specifically, the log-price relatives are regressed on a set of dummy variables, one for each observation of the log-price index. 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).

7.2 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 without identifying token characteristics 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 240,122 individual transactions to 155,535 repeated sales.[47] We then construct the NFT index with the RSR model using the OLS 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_{OLS}. 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 8 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 31.56% (23.33%) over the period from July 2017 to December 2022. In particular, the value of the RSR index (π_{OLS}) increases significantly more than that of the hedonic index (π) after the middle of 2021 due to the issuance of new NFT collections. Taken together, the correlation between the indices is 0.784, further confirming that our findings are robust to both sample selection and methodology for estimating NFT indices.

[Insert Figure 8]

8. 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 industries more

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[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.

[47] Panel A of Table 7 shows the repeated sales by NFT collection used in the RSR model.

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.

Our paper sheds light on the determinants of NFT prices. First, NFT rarity is a key determinant for explaining a large portion of price premiums, and this relationship holds across different samples. Furthermore, we find that early adopters or active investors, in terms of transaction counts, transaction amount, and portfolio diversity, emerge as central nodes within the network and enjoy pricing advantages over NFT valuation. Finally, we construct an overall price index based on hedonic regression models. We document that the returns on NFTs outperform those on most traditional and alternative assets, but the standard deviation of NFT returns is among the highest. We find similar results when considering other NFT collections 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 traditional financial assets because the pricing of an NFT involves more complex valuations. Additionally, it takes more time to search for trading counterparts in NFT markets. 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.

Our paper also raises questions regarding the implications of NFTs on the financial ecosystem. In contrast to other alternative assets (e.g., real estate or artworks), NFTs can be traded more effectively and efficiently. Obviously, NFTs have emerged as a new form of digital alternative investment, and our study provides insights into NFT evaluation. Future research can build on our findings in several ways. For instance, exploring NFTs via the lens of securitization, tokenization, taxation, and crowdfunding would be all important and relevant directions.

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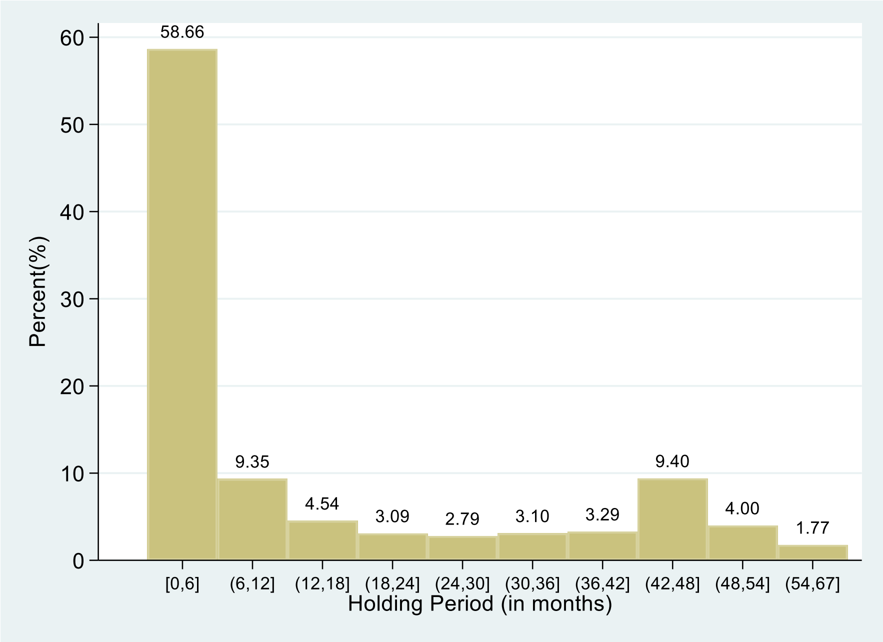

Figure 1. Distribution of holding periods (in months).
The figure shows the distribution of holding periods (in months) from the first purchase to the resale for each CryptoPunk collector. The sample period is from June 2017 through December 2022.

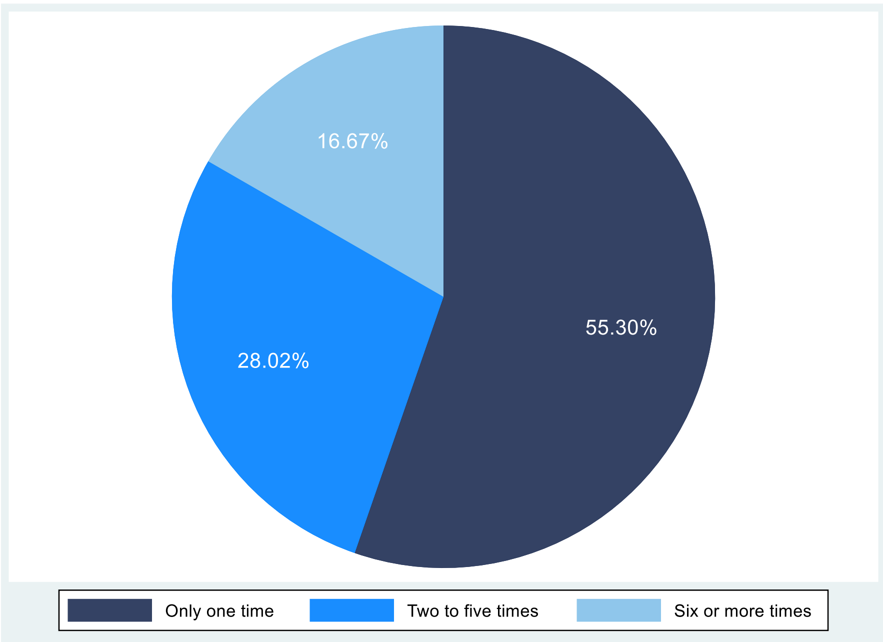

Figure 2. The turnover of CryptoPunk transactions.
The figure shows the distribution of the number of transactions for each CryptoPunk over the sample period from June 2017 through December 2022.

Figure 3. The CryptoPunk network.

The figure plots a visual representation of the CryptoPunk network. The sample period is from June 2017 through December 2022. The resulting network consists of 7,426 nodes and 18,567 edges.

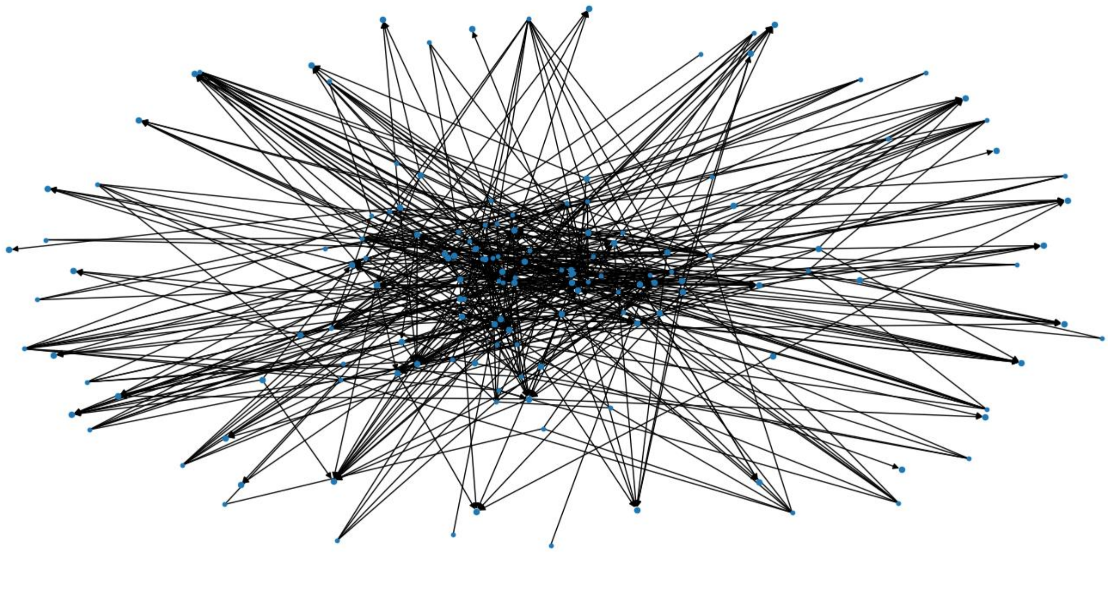

Figure 4. The CryptoPunk network: the top 50 traders.

The figure plots a subset of the CryptoPunk network, which we only include the top 50 traders by transaction counts. The resulting network consists of 75 nodes and 275 edges.

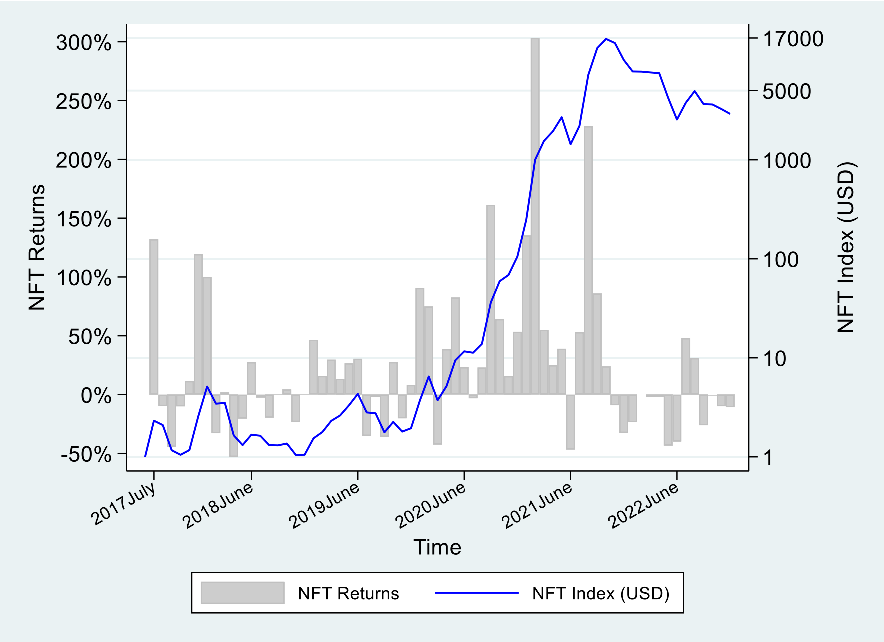

Figure 5. NFT index and returns.
The line in this figure shows our NFT index in USD (against the right-hand axis), and the index is set to unity in June 2017. The NFT index is estimated using the hedonic regression model in column (5) of Table 4. The bars represent the month-over-month growth of the NFT index (against the left-hand axis).

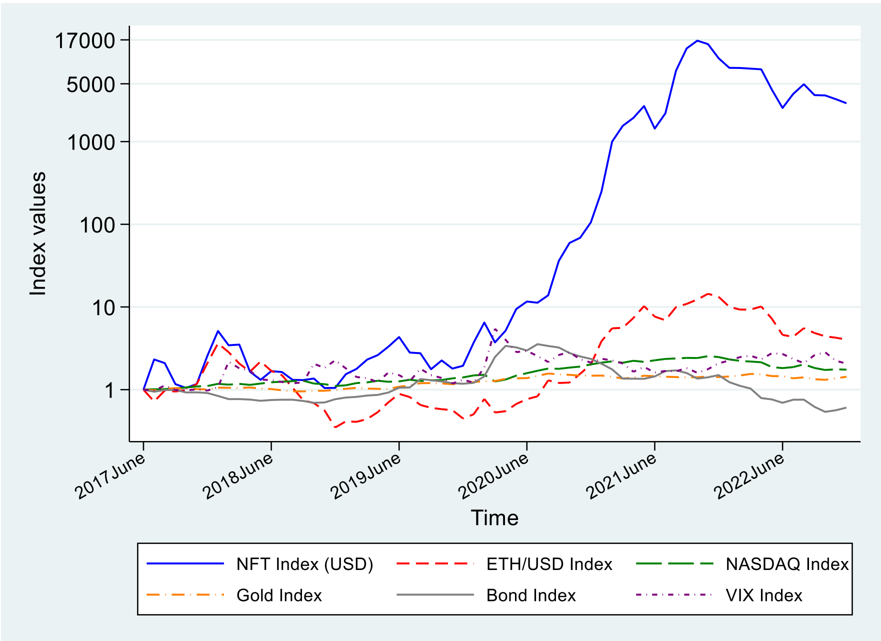

Figure 6. NFT index and major market indices.
This figure shows the NFT index and major market indices over the period from June 2017 through December 2022. The NFT index is estimated using the hedonic regression model in column (5) of Table 4. Data on market indices are downloaded from CoinGecko and Investing.com. Appendix A provides variable definitions in greater detail. All indices are set to unity in June 2017.

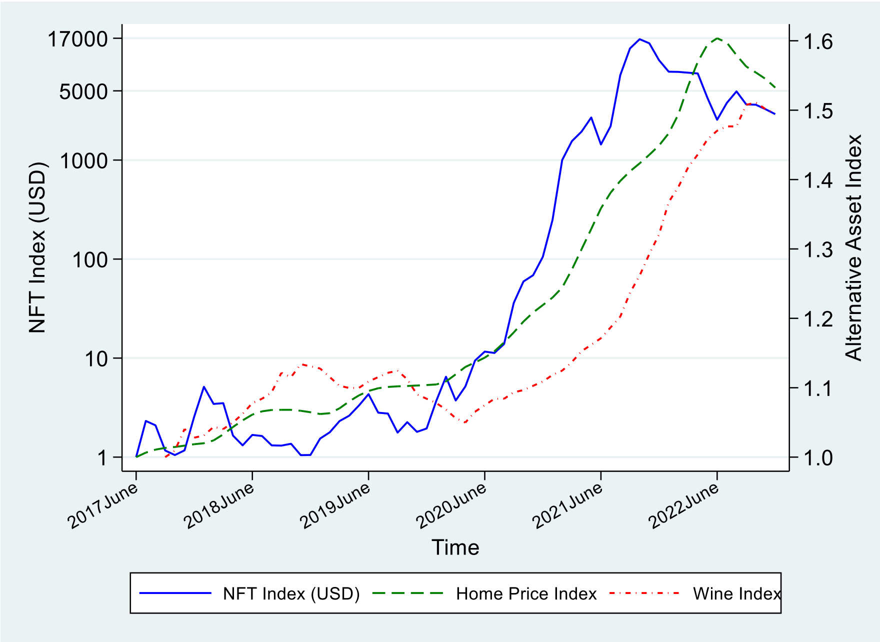

Figure 7. NFT index and alternative asset indices.

This figure shows the NFT index and alternative asset indices over the period from June 2017 through December 2022. The NFT index is estimated using the hedonic regression model in column (5) of Table 4. The NFT and home price index values are set to unity in June 2017. The wine index values are set to unity in September 2017 due to data availability.

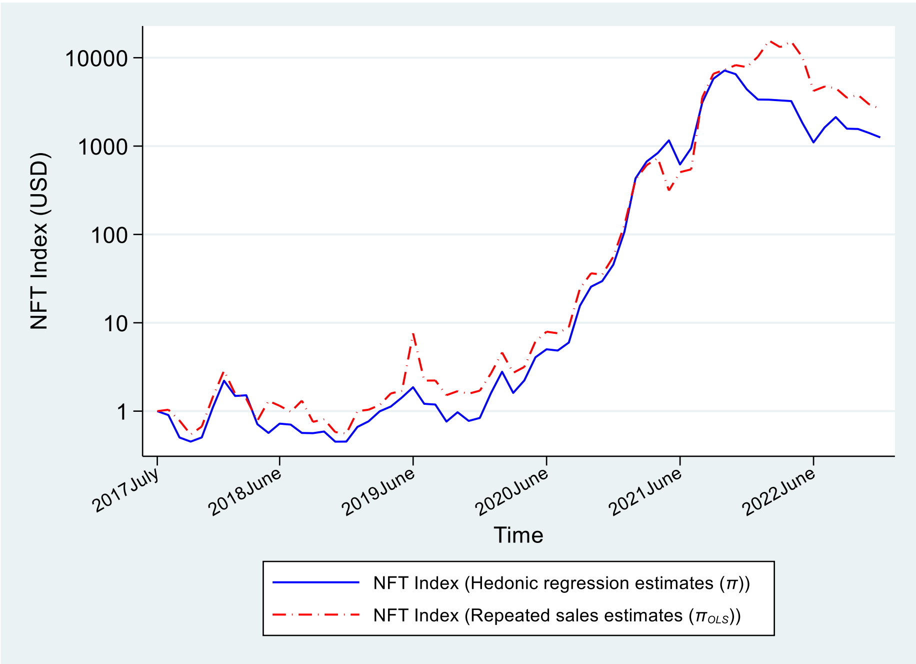

Figure 8. NFT index using the repeat-sales regression (RSR) model.

This figure compares the NFT indices estimated using the hedonic regression and RSR models. The RSR model based on generative collections. 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 December 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 thousand USD.

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	735	164	1	6	309	574	9	899
2019	701	367	0	0	296	769	3	1,068
2020	1,124	2,938	0	6	1,058	2,969	29	4,062
2021	2,847	9,465	3	8	4,196	8,065	40	12,312
2022	317	3,262	1	4	1,194	2,374	6	3,579
2017-2022	**6,832**	**16,374**	**11**	**38**	**7,528**	**15,518**	**111**	**23,206**

Panel B. Summary statistics of sales prices for each CryptoPunk type (in k$)

CryptoPunk type				Average prices by transaction type	
	N	Mean	P50	Primary Sales	Secondary Sales
Alien	11	3,603.611	2.690	3.98	9,902.97
Ape	38	1,120.885	4.224	590.92	1,650.85
Female	7,528	103.529	50.627	59.43	124.54
Male	15,518	99.619	41.715	49.61	118.96
Zombie	111	585.964	19.070	317.42	798.20

Table 2. Network centrality

Panel A reports the top 10 central traders in the CryptoPunk network. For those wallets we cannot find their name tags, we subtract the last six digits of their wallet addresses. Panel B reports the pairwise correlations between centrality measures. *Degree* is the number of connections an investor has in a network. *Closeness* measures how central an investor is in terms of the distance to other investors in the network. *Betweenness* measures an investor's position on the shortest paths between other investors in a network. *Eigenvector* measures an investor's centrality based on the centrality of its neighbors. Appendix A provides variable definitions in greater detail. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. The top 10 central traders

Degree	Closeness	Betweenness	Eigenvector
punksOTC	punksOTC	punksOTC	punksOTC
Pranksy	cb87d7	Pranksy	Pranksy
hemba.eth	d5e9e5	cb87d7	cb87d7
c7c647	subbo.eth	ee0bf9	d5e9e5
cb87d7	4ee9f4	shilpixels.eth	subbo.eth
ee91ec	20a068	Autoglyphs: Deployer	ee0bf9
90b376	3b7845	c7c647	tokenangels.eth
2.punksotc.eth	11232a	3b7845	Carlini8N
ee0bf9	shilpixels.eth	subbo.eth	20a068
vault.punksotc.eth	a1a836	13009d	717e9e

Panel B. Pairwise correlations of centrality measures

Variables	(1)	(2)	(3)	(4)
(1) *Degree*	1			
(2) *Closeness*	0.206***	1		
(3) *Betweenness*	0.709***	0.223***	1	
(4) *Eigenvector*	0.763***	0.377***	0.753***	1

Table 3. Investor experience

Panel A reports summary statistics of investor experience measures. Panel B reports the pairwise correlations between centrality measures. *NFTtxn* represents the number of NFT trades made by a wallet address to date, while *NFTValues* represents the transaction amount of NFT purchases (in USD) made by a wallet address to date. *NewType* and *NewNFT* represent the number of different NFT types and new NFTs traded by a wallet address to date, respectively. Appendix A provides variable definitions in greater detail. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Pairwise correlations of experience measures

Variables	(1)	(2)	(3)	(4)
(1) *NFTtxn*	1			
(2) *NFTValues*	0.641***	1		
(3) *NewType*	0.835***	0.544***	1	
(4) *NewNFT*	0.970***	0.636***	0.838***	1

Panel B. Summary of experience measure

	Buyer			**Seller**		
	N	**Mean**	**P50**	**N**	**Mean**	**P50**
NFTtxn	10,909	205.232	21.000	10,915	328.746	68.000
NFTValues	10,909	186.969	8.890	10,915	286.520	26.795
NewType	10,909	18.058	4.000	10,915	25.915	8.000
NewNFT	10,909	213.350	21.000	10,915	327.624	62.000

Table 4. 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)	(5)
Alien	3.726***	3.926***	3.922***	3.933***	3.915***
	(0.233)	(0.215)	(0.216)	(0.217)	(0.222)
Ape	2.592***	2.605***	2.602***	2.611***	2.610***
	(0.382)	(0.365)	(0.365)	(0.364)	(0.365)
Zombie	2.313***	2.357***	2.365***	2.362***	2.365***
	(0.127)	(0.116)	(0.118)	(0.118)	(0.118)
Female	0.112***	0.042**	0.040**	0.040**	0.040**
	(0.013)	(0.017)	(0.017)	(0.017)	(0.017)
PrimarySale	–0.036***	–0.054***	–0.052***	–0.053***	–0.054***
	(0.013)	(0.011)	(0.011)	(0.011)	(0.011)
ΔNumWallets			–0.006		
			(0.020)		
ΔNumBuyers				0.087***	0.030
				(0.031)	(0.034)
ΔNumSellers				–0.096**	–0.101**
				(0.039)	(0.041)
ΔNumSales					0.018
					(0.020)
ΔSalesUSD					0.022***
					(0.006)
ΔETHUSD					0.316***
					(0.091)
ΔETHVol					–0.004*
					(0.003)
Adj. SVI					–0.003***
					(0.001)
_0_Attributes	2.673***	3.218***	3.209***	3.237***	3.235***
	(0.405)	(0.394)	(0.396)	(0.383)	(0.385)
_1_Attributes	0.569***	0.794***	0.798***	0.796***	0.800***
	(0.053)	(0.060)	(0.060)	(0.060)	(0.060)
_2_Attributes	0.001	0.145***	0.143***	0.142***	0.144***

	(0.013)	(0.033)	(0.033)	(0.033)	(0.033)
_4_Attributes	0.051***	–0.117***	–0.114***	–0.113***	–0.115***
	(0.019)	(0.034)	(0.034)	(0.034)	(0.034)
_5_Attributes	0.530***	0.182**	0.187***	0.188***	0.185***
	(0.039)	(0.071)	(0.071)	(0.071)	(0.071)
_6_Attributes	1.824***	1.254***	1.263***	1.273***	1.264***
	(0.216)	(0.288)	(0.289)	(0.288)	(0.287)
_7_Attributes	3.668***	1.734***	1.739***	1.776***	1.756***
	(0.029)	(0.171)	(0.171)	(0.171)	(0.171)
Observations	22,744	22,744	22,683	22,683	22,683
R-squared	0.944	0.953	0.953	0.953	0.953
Year-Month dummies	Yes	Yes	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes	Yes	Yes
Attribute dummies	No	Yes	Yes	Yes	Yes

Table 5. Hedonic regression results: Network centrality

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). *Degree* is the number of connections a node has in a network. *Closeness* is the reciprocal of the average shortest path distance between a node and all other nodes. *Betweenness* is the sum of the fraction of all-pairs shortest paths that pass through a node. *Eigenvector* is the centrality for a node based on the centrality of its neighbors. In all specifications, we include the same set of control variables used for column (5) of Table 4. Appendix A provides variable definitions in greater detail. Standard errors (in parentheses) are clustered at the firm level. ∗∗∗, ∗∗, and ∗ correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Var.	$\ln P_{i,t}$			
	(1)	(2)	(3)	(4)
Buyer_Degree	–0.660***			
	(0.145)			
Seller_Degree	–0.196*			
	(0.103)			
Buyer_Closeness		–0.758***		
		(0.175)		
Seller_Closeness		0.459**		
		(0.181)		
Buyer_Betweenness			–0.648***	
			(0.250)	
Seller_Betweenness			–0.029	
			(0.306)	
Buyer_Eigenvector				–0.250***
				(0.083)
Seller_Eigenvector				0.319***
				(0.122)
Observations	8,633	8,633	8,633	8,633
R-squared	0.964	0.964	0.964	0.964
Controls	Yes	Yes	Yes	Yes
Year-Month dummies	Yes	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes	Yes
Attribute dummies	Yes	Yes	Yes	Yes

Table 6. The determinants of network centrality

The table reports the OLS regression estimates of network centrality on investor characteristics. The dependent variable is our proxy for network centrality, *Eigenvector*. Investor characteristics include our proxies for investor experience (i.e., *NFTtxn*, *NFTValues*, *NewType*, and *NewNFT*) and early adoption (i.e., *WalletAge* and *Adoption_index*). *WalletAge* is the natural logarithm of one plus the number of years since the first transaction was made by a wallet address. *Adoption_index* captures how early an investor adopts the CryptoPunks, with a value ranging from zero to one. A lower value indicates an earlier adoption. The data frequency in this analysis is on a monthly basis. Appendix A provides variable definitions in greater detail. Standard errors (in parentheses) are clustered at the firm level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Var	*Eigenvector*			
	(1)	(2)	(3)	(4)
Adoption_index	–0.074***	–0.077***	–0.078***	–0.075***
	(0.005)	(0.005)	(0.005)	(0.005)
WalletAge	0.002*	0.004***	0.004***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
NFTtxn	0.003***			
	(0.000)			
NFTValues		0.002***		
		(0.000)		
NewType			0.003***	
			(0.000)	
NewNFT				0.003***
				(0.000)
Observations	6,594	6,594	6,594	6,594
R-squared	0.284	0.275	0.264	0.281
Year-Month dummies	Yes	Yes	Yes	Yes

Table 7. Hedonic regression results: Investor experience

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). *NFTtxn* is the cumulative number of NFT trades (i.e., unique transaction hash) for a wallet address until date *t*. *NFTValues* is the cumulative transaction amount of NFT purchases made by a wallet address until date *t*. *NewType* is the cumulative number of different NFT types traded by a wallet address until date *t*. *NewNFT* is the cumulative number of new NFTs traded by a wallet address until date *t*. We take the natural logarithm of our proxies for investor experience because they exhibit a highly skewed distribution. In all specifications, we include the same set of control variables used for column (5) of Table 4. Appendix A provides variable definitions in greater detail. Standard errors (in parentheses) are clustered at the firm level. ∗∗∗, ∗∗, and ∗ correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Var.	$\ln P_{i,t}$			
	(1)	(2)	(3)	(4)
Buyer_NFTtxn	–0.010***			
	(0.003)			
Seller_NFTtxn	–0.004			
	(0.003)			
Buyer_NFTValues		0.007**		
		(0.003)		
Seller_NFTValues		0.000		
		(0.002)		
Buyer_NewType			–0.017***	
			(0.004)	
Seller_NewType			0.000	
			(0.004)	
Buyer_NewNFT				–0.008**
				(0.003)
Seller_NewNFT				–0.004*
				(0.002)
Observations	10,905	10,905	10,905	10,905
R-squared	0.915	0.915	0.915	0.915
Controls	Yes	Yes	Yes	Yes
Year-Month dummies	Yes	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes	Yes
Attribute dummies	Yes	Yes	Yes	Yes

Table 8. Generative collections

Panel A reports the total sales and repeated sales in different NFT collections. The sample period is between June 2017 and December 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. Panel B reports estimates from our hedonic regression model using ordinary least squares with generative collections. The dependent variable is the natural logarithm of CryptoPunk prices (in USD). *ExtremeRare* is a dummy variable that equals one if the NFT type belongs to the top 1% of a collection and zero otherwise. *SuperRare* is a dummy variable that equals one if the NFT type belongs to the top 10% of a collection and zero otherwise. In all specifications, we include the same set of control variables used for column (5) of Table 4. Appendix A provides variable definitions in greater detail. Standard errors (in parentheses) are clustered at the firm level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. The distribution of the sales by NFT collection

NFT	Repeated Sales	Total Sales	Created Date
CryptoPunks	16,374	23,206	June 2017
CryptoSkulls	15,086	21,868	May 2019
Bored Ape Yacht Club	18,480	27,125	May 2021
Meebits	13,698	22,743	May 2021
Cool Cats	22,289	30,513	July 2021
World of Women	15,728	24,598	July 2021
Mutant Ape Yacht Club	22,818	35,645	August 2021
CloneX	10,115	19,747	December 2021
Azuki	17,106	25,440	January 2022
Moonbirds	3,841	9,237	April 2022
Total	**155,535**	**240,122**	

Panel B. Hedonic regression results: Generative collections

Dependent Var.	$\ln P_{i,t}$	
	(1)	(2)
ExtremeRare	1.806***	1.800***
	(0.045)	(0.045)
SuperRare	0.376***	0.374***
	(0.009)	(0.009)
Observations	239,478	239,417
R-squared	0.819	0.820
Controls	No	Yes
Collection FE	Yes	Yes
Year-Month dummies	Yes	Yes
Attribute dummies	Yes	Yes

Table 9. Monthly NFT index and returns

This table reports the index values of our NFT index from June 2017 through December 2022. The NFT index is estimated by using the hedonic regression model in column (5) of Table 4.

Year-Month	NFT Index	Return	Year-Month	NFT Index	Return
2017-06	1.000		2020-04	5.171	38.60%
2017-07	2.320	131.98%	2020-05	9.444	82.63%
2017-08	2.094	–9.73%	2020-06	11.636	23.21%
2017-09	1.167	–44.29%	2020-07	11.263	–3.21%
2017-10	1.049	–10.05%	2020-08	13.859	23.06%
2017-11	1.170	11.47%	2020-09	36.199	161.19%
2017-12	2.566	119.39%	2020-10	59.419	64.14%
2018-01	5.130	99.91%	2020-11	68.740	15.69%
2018-02	3.443	–32.89%	2020-12	105.477	53.44%
2018-03	3.507	1.87%	2021-01	248.184	135.30%
2018-04	1.650	–52.94%	2021-02	1,000.685	303.20%
2018-05	1.314	–20.38%	2021-03	1,551.783	55.07%
2018-06	1.676	27.52%	2021-04	1,938.326	24.91%
2018-07	1.634	–2.49%	2021-05	2,694.398	39.01%
2018-08	1.314	–19.58%	2021-06	1,436.809	–46.67%
2018-09	1.307	–0.56%	2021-07	2,198.499	53.01%
2018-10	1.364	4.38%	2021-08	7,213.936	228.13%
2018-11	1.047	–23.23%	2021-09	13,412.736	85.93%
2018-12	1.050	0.29%	2021-10	16,628.777	23.98%
2019-01	1.539	46.52%	2021-11	15,116.770	–9.09%
2019-02	1.781	15.76%	2021-12	10,198.643	–32.53%
2019-03	2.311	29.74%	2022-01	7,805.392	–23.47%
2019-04	2.619	13.33%	2022-02	7,773.066	–0.41%
2019-05	3.315	26.57%	2022-03	7,630.587	–1.83%
2019-06	4.326	30.50%	2022-04	7,492.666	–1.81%
2019-07	2.810	–35.04%	2022-05	4,244.079	–43.36%
2019-08	2.756	–1.95%	2022-06	2,551.304	–39.89%
2019-09	1.768	–35.85%	2022-07	3,773.243	47.89%
2019-10	2.255	27.55%	2022-08	4,941.825	30.97%
2019-11	1.799	–20.23%	2022-09	3,651.123	–26.12%
2019-12	1.945	8.13%	2022-10	3,621.378	–0.81%
2020-01	3.707	90.58%	2022-11	3,261.753	–9.93%
2020-02	6.484	74.93%	2022-12	2,910.063	–10.78%
2020-03	3.731	–42.46%			

Table 10. 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	0.542***	1						
(3) NASDAQ Index	0.307**	0.440***	1					
(4) S&P 500 Index	0.286**	0.461***	0.933***	1				
(5) Dow Jones Index	0.242*	0.431***	0.803***	0.950***	1			
(6) VIX Index	–0.115	–0.180	–0.648***	–0.773***	–0.783***	1		
(7) Bond Index	–0.155	–0.136	–0.144	–0.327***	–0.456***	0.465***	1	
(8) Gold Index	–0.096	0.231*	0.216*	0.200*	0.158	–0.021	0.341***	1

Table 11. 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 December 2022. Panels A and B compare the investment performance of NFTs with traditional and alternative investments, respectively. In Panel B, the sample period of the wine index begins in September 2017 due to data availability. For each index, we examine the arithmetic and geometric average returns per month, the standard deviation, the 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.

Panel A. NFTs and traditional investments

	Mean returns per month		Dispersion of monthly returns			Sharpe ratio	
	Arithmetic	Geometric	Std. dev.	Min	Max	Arithmetic	Geometric
NFT Index	24.97%	12.85%	63.92%	–52.94%	303.20%	38.92%	19.94%
ETH/USD Index	5.60%	2.13%	28.30%	–37.94%	91.14%	19.43%	7.20%
NASDAQ Index	0.97%	0.85%	4.92%	–17.02%	11.54%	17.79%	15.30%
S&P 500 Index	0.81%	0.72%	3.97%	–18.52%	6.90%	17.85%	15.79%
Dow Jones Index	0.77%	0.69%	3.97%	–20.02%	8.21%	16.93%	14.86%
VIX Index	4.32%	1.11%	32.23%	–29.19%	192.96%	13.11%	3.14%
Bond Index	0.05%	–0.76%	13.77%	–23.24%	71.46%	–0.35%	–6.19%
Gold Index	0.59%	0.55%	3.11%	–5.78%	6.77%	16.00%	14.49%
One-month T-bill	0.10%	0.10%	0.09%	0.00%	0.33%	–	–

Panel B. Alternative investments

	Mean returns per month		Dispersion of monthly returns			Sharpe ratio	
	Arithmetic	Geometric	Std. dev.	Min	Max	Arithmetic	Geometric
Global Luxury Index	0.94%	0.76%	5.85%	–24.62%	12.83%	14.56%	11.52%
Private Equity Index	0.44%	0.25%	5.89%	–29.48%	11.79%	6.07%	2.90%
Home Price Index	0.65%	0.65%	0.81%	–1.14%	2.73%	70.42%	70.03%
Wine Index	0.65%	0.64%	1.14%	–1.96%	3.54%	49.36%	48.81%
Art Index	1.08%	0.59%	10.71%	–15.38%	44.70%	9.32%	4.70%

Table 12. 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 March 2022-December 2022. The low-interest-rate period is defined as the period over March 2020-February 2022. Mean returns are the geometric average of monthly returns over the subperiods. 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	2.13%	43.21%	4.60%	34.36%	83.70%	41.05%
ETH/USD Index	–2.58%	27.42%	–9.93%	10.93%	28.34%	38.55%
NASDAQ Index	0.40%	4.28%	6.04%	1.63%	5.88%	27.57%
S&P 500 Index	0.42%	3.35%	8.11%	1.26%	4.90%	25.53%
Dow Jones Index	0.62%	3.30%	14.34%	0.80%	5.01%	15.86%
VIX Index	1.05%	25.28%	3.58%	1.21%	42.34%	2.82%
Bond Index	–0.56%	8.77%	–8.08%	–1.09%	19.97%	–5.52%
Gold Index	0.48%	3.13%	10.63%	0.67%	3.14%	20.93%
One-month T-bill	0.15%	0.07%	–	0.01%	0.03%	–

Appendix

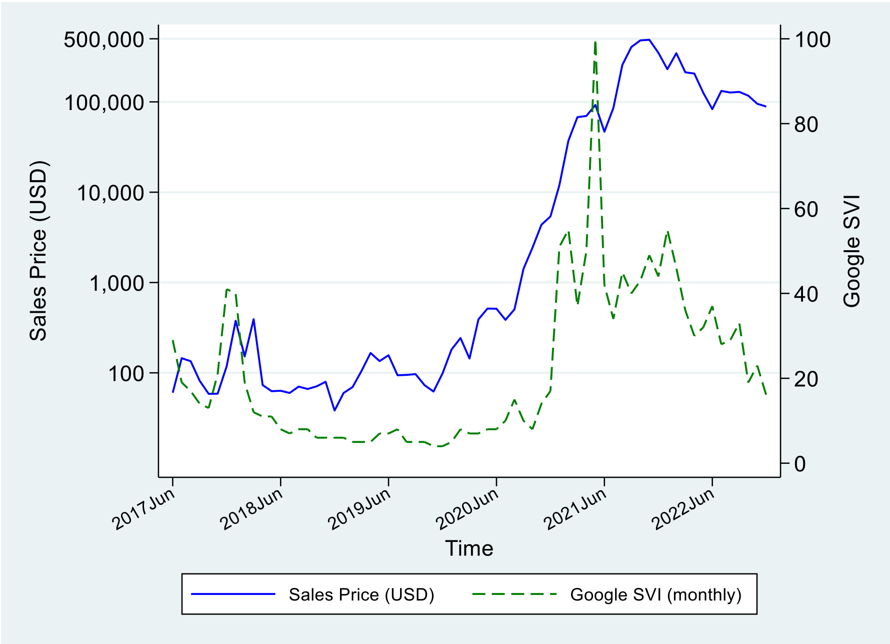

Figure A1. Monthly sales prices of CryptoPunks and Google SVI.
The solid line represents the monthly average sales price of CryptoPunks in USD (against the left-hand axis). The dashed line represents the Google search volume index (SVI) with the search topic related to "Ethereum" (against the right-hand axis). The SVI values are obtained from Google Trends.

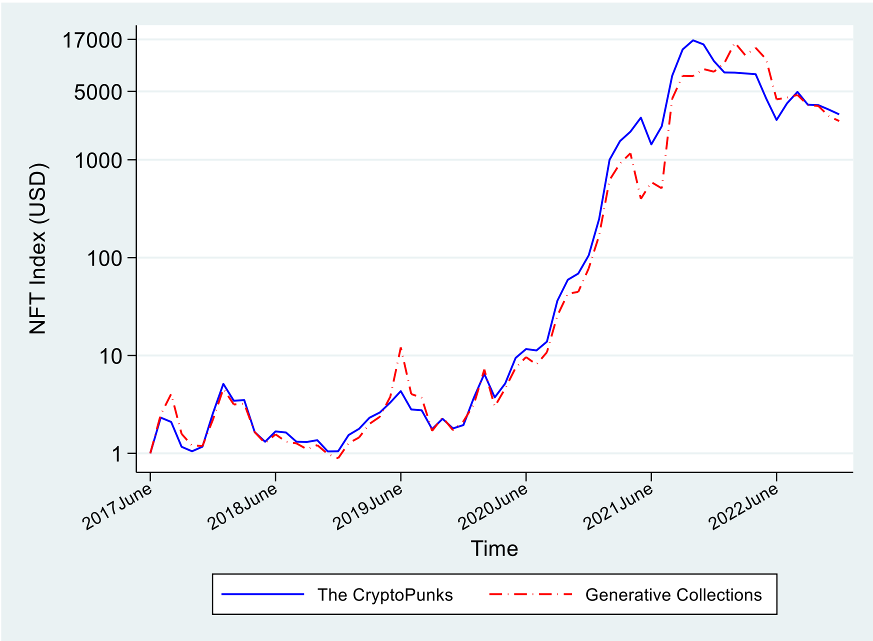

Figure A2. NFT index using generative collections.
This figure compares the NFT indices estimated using the CryptoPunks and generative collections in the hedonic regression models. The NFT index based on generative collections is estimated using the hedonic regression model in column (2) of Panel B in Table 7. The indices are set to unity in June 2017.

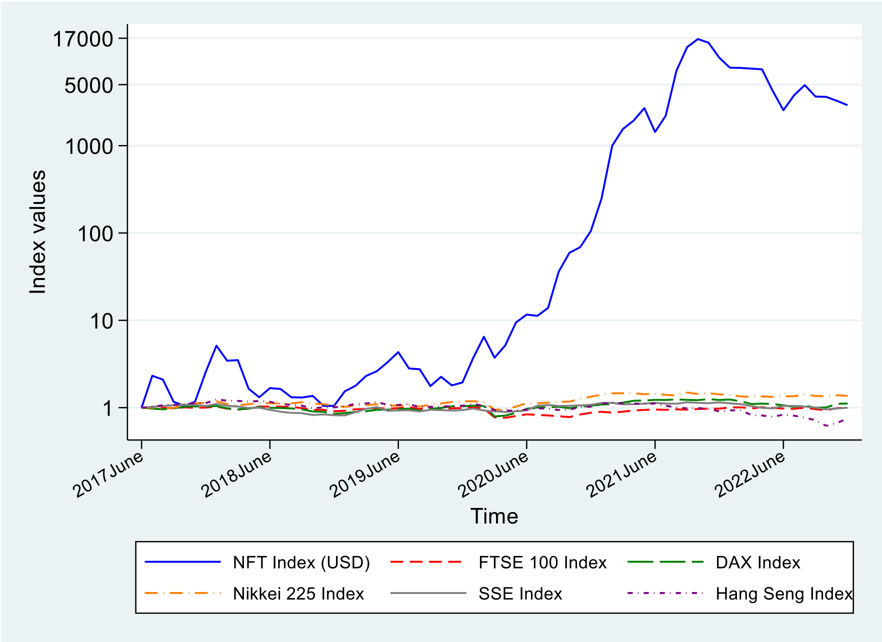

Figure A3. NFT index and stock market indices worldwide.
This figure shows the NFT index and stock market indices worldwide (except for the U.S.) over the period from June 2017 through December 2022. The NFT index is estimated using the hedonic regression model in column (5) of Table 4. Data on stock market indices are downloaded from Investing.com. Appendix A provides variable definitions in greater detail. All indices are set to unity in June 2017.

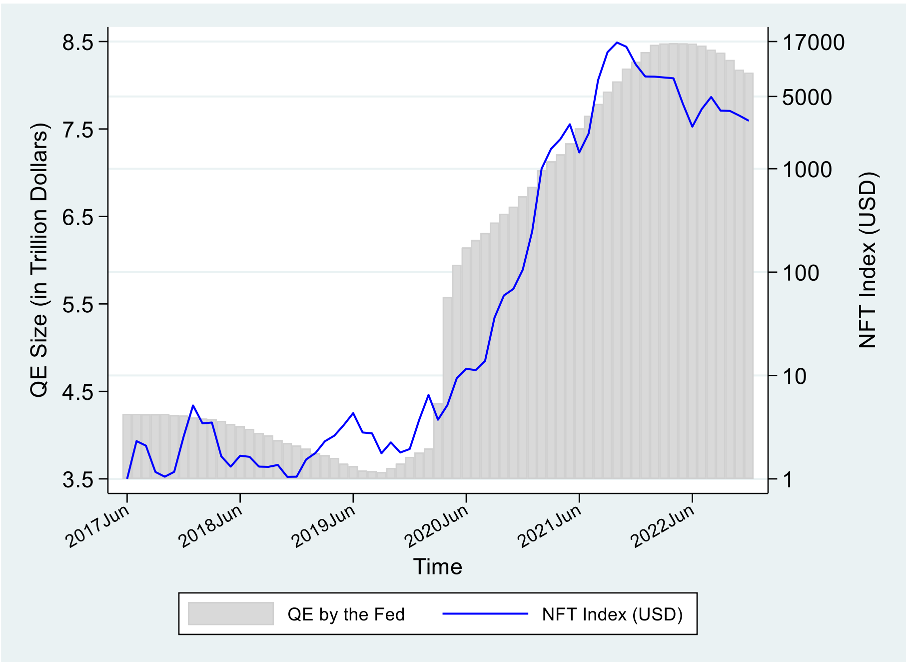

Figure A4. NFT index and the quantitative easing by the Fed.
This figure shows the NFT index and the QE size, which is the proxy for U.S. quantitative easing, over the period from June 2017 through December 2022. The NFT index is estimated using the hedonic regression model in column (5) of Table 4. 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.

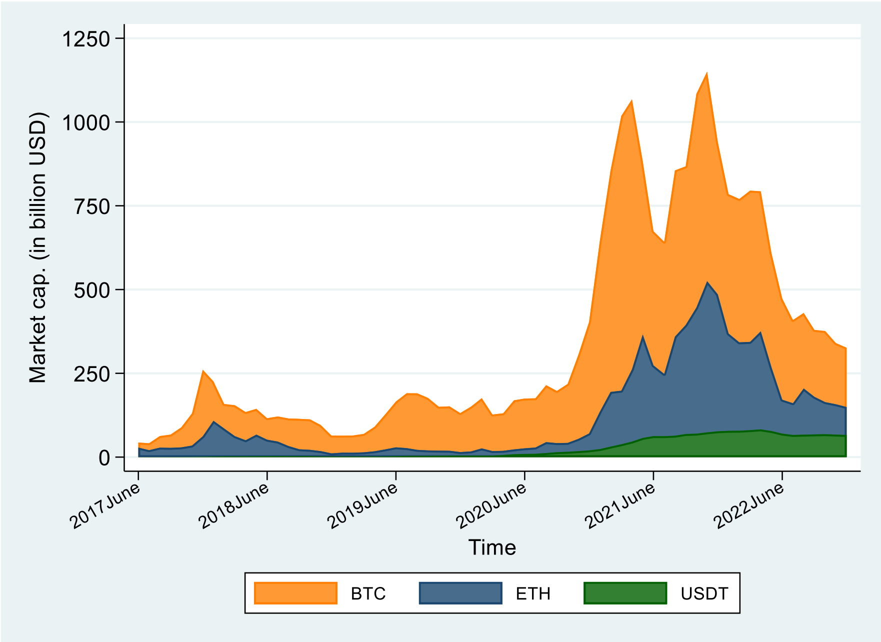

Figure A5. The market capitalization of the major cryptocurrencies
This figure shows the market capitalization of Bitcoin (BTC), Ethereum (ETH), and Tether (USDT) over the period from June 2017 through December 2022.

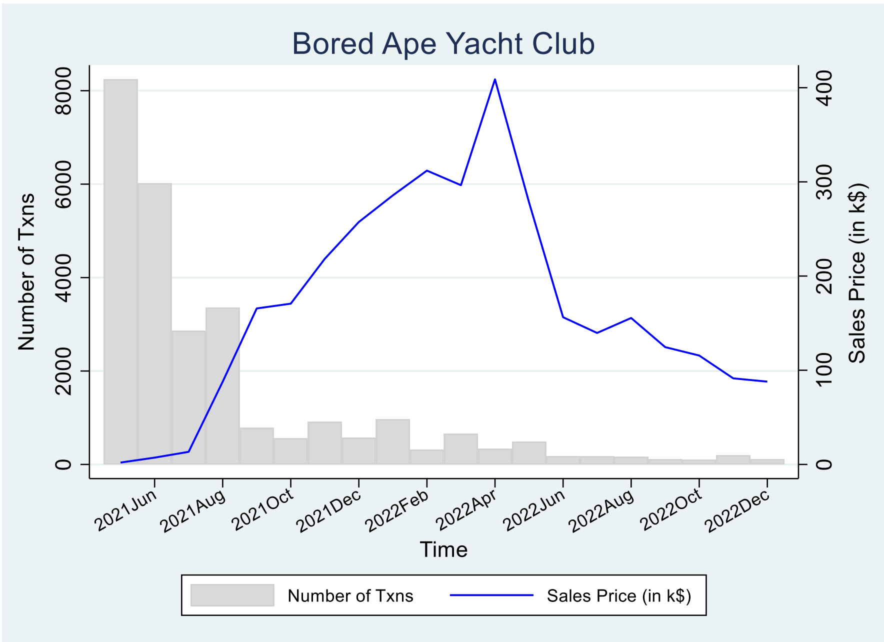

Figure A6. The transactions of the Bored Ape Yacht Club.
This figure shows the number of transactions (against the left-hand axis) and the average sale prices (against the right-hand axis) of the Bored Ape Yacht Club (BAYC) over the period from June 2017 through December 2022. The average sale price is in thousand USD.

Appendix A. Definition of Variables

Variable	Definition	Source
Panel A: NFT 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
Rarity_1_pct	A dummy variable that equals one if the rarity ranking of an NFT is within the top 1% of a collection and zero otherwise. Similarly, *Rarity_10_pct (Rarity_20_pct)* is a dummy variable that equals one if the rarity ranking of an NFT is within the top 10% (20%) of a collection and zero otherwise. These rarity dummy variables are mutually exclusive.	Rarity.Tools
Panel B: Network variables		
Degree	The number of connections a node has in a network.	Larva Labs
Closeness	The reciprocal of the average shortest path distance between a node and all other nodes.	Larva Labs
Betweenness	The sum of the fraction of all-pairs shortest paths that pass through a node.	Larva Labs
Eigenvector	The centrality for a node based on the centrality of its neighbors.	Larva Labs
ΔNumWallets	The growth of unique wallets in the NFT market on date *t*.	NonFungible.com
ΔNumBuyers	The growth of unique buyers in the NFT market on date *t*.	NonFungible.com
ΔNumSellers	The growth of unique sellers in the NFT market on date *t*.	NonFungible.com
ΔNumSales	The growth of NFT sales on date *t*.	NonFungible.com
ΔSalesUSD	The growth of NFT sales volume (in USD) on date *t*.	NonFungible.com
Panel C: Market indices		
ETH/USD Index	The average of daily exchange rates of ETH/USD in month *t*.	CoinGecko
NASDAQ Index	The average of daily NASDAQ index values in month *t*.	Investing.com
S&P 500 Index	The average of daily S&P 500 index values in month *t*.	Investing.com
Dow Jones Index	The average of daily Dow Jones Industrial Average index values in month *t*.	Investing.com
VIX Index	The average of daily CBOE Volatility index values on month *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
Global Luxury Index	The average of daily S&P Global Luxury index values on month *t*. The index tracks the performance of 80 of the largest publicly-traded companies engaged in the production	S&P Dow Jones Indices

	or distribution of luxury goods or the provision of luxury services.	
Private Equity Index	The average of daily S&P Listed Private Equity index values on month *t*. The index tracks the performance of the leading listed private equity companies.	S&P Dow Jones Indices
Home Price Index	The Case-Shiller U.S. National Home Price 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 and FRED
Art Index	The All Art index is constructed by Art Market Research (AMR) using price data from auction sales worldwide. The data frequency is monthly. For more information regarding the index, please visit Art Market Research website.	AMR
Wine index	The Liv-ex Fine Wine 1000 compiled by London International Vintners Exchange (Liv-ex) tracks 1,000 wines from across the world. The data frequency is monthly.	Liv-ex

Panel D: Other variables

NFTtxn	Natural logarithm of the number of NFT trades (i.e., unique transaction hash) for a wallet address until date *t*.	Etherscan
NFTValues	Natural logarithm of the transaction amount of NFT purchases made by a wallet address until date *t*.	Etherscan
NewType	Natural logarithm of the cumulative number of different NFT types collected by a wallet address until date *t*.	Etherscan
NewNFT	Natural logarithm of the cumulative number of new NFTs collected by a wallet address until date *t*.	Etherscan
WalletAge	Natural logarithm of one plus the number of years since the first transaction made by a wallet address.	Larva Labs
Adoption_index	The purchase dates relative to the release date of the CryptoPunks (i.e., 23 June, 2017), scaled by the total number of transactions made by a wallet address in a given month. To construct an index, we further normalize the variable values. The index value ranges between 0 and 1. A lower value indicates an earlier adoption.	Larva Labs
ΔETHUSD	The growth of ETH/USD exchange rate on date *t*.	CoinGecko
ΔETHVol	The growth of ETH trading volume on date *t*.	CoinGecko
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

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)	(5)
Alien	3.658***	3.822***	3.825***	3.831***	3.826***
	(0.228)	(0.197)	(0.197)	(0.197)	(0.201)
Ape	2.702***	2.697***	2.701***	2.706***	2.704***
	(0.263)	(0.253)	(0.252)	(0.252)	(0.251)
Zombie	2.292***	2.331***	2.344***	2.342***	2.339***
	(0.125)	(0.114)	(0.115)	(0.115)	(0.115)
Female	0.106***	0.035**	0.035**	0.034**	0.035**
	(0.011)	(0.014)	(0.014)	(0.014)	(0.014)
PrimarySale	–0.032***	–0.051***	–0.050***	–0.050***	–0.051***
	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
ΔNumWallets			0.006		
			(0.018)		
ΔNumBuyers				0.049***	–0.001
				(0.019)	(0.024)
ΔNumSellers				–0.043**	–0.055**
				(0.021)	(0.022)
ΔNumSales					0.027*
					(0.015)
ΔSalesUSD					0.009***
					(0.003)
ΔETHUSD					–0.007
					(0.060)
ΔETHVol					–0.002
					(0.002)
Adj. SVI					–0.003***
					(0.001)
_0_Attributes	2.570***	3.073***	3.072***	3.085***	3.087***
	(0.414)	(0.404)	(0.406)	(0.400)	(0.400)
_1_Attributes	0.588***	0.783***	0.781***	0.780***	0.782***
	(0.049)	(0.063)	(0.063)	(0.063)	(0.063)
_2_Attributes	0.001	0.121***	0.123***	0.122***	0.123***

	(0.011)	(0.037)	(0.037)	(0.037)	(0.037)
_4_Attributes	0.057***	–0.082**	–0.083**	–0.083**	–0.083**
	(0.015)	(0.037)	(0.037)	(0.037)	(0.037)
_5_Attributes	0.534***	0.238***	0.235***	0.235***	0.235***
	(0.036)	(0.080)	(0.081)	(0.081)	(0.081)
_6_Attributes	1.812***	1.299***	1.289***	1.294***	1.289***
	(0.207)	(0.285)	(0.288)	(0.287)	(0.288)
_7_Attributes	3.690***	1.903***	1.896***	1.915***	1.898***
	(0.027)	(0.180)	(0.180)	(0.180)	(0.180)
Observations	22,745	22,745	22,686	22,686	22,686
R-squared	0.931	0.949	0.949	0.949	0.949
Year-Month dummies	Yes	Yes	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes	Yes	Yes
Attribute dummies	No	Yes	Yes	Yes	Yes

Appendix D. 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 4. 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	1.839***	529.05%	1	Knitted Cap	–0.093**	–8.93%
2	Pilot Helmet	1.356***	288.01%	2	Front Beard Dark	–0.051	–5.01%
3	Tiara	1.248***	248.27%	3	Cap Forward	–0.035	–3.41%
4	Orange Side	1.099***	200.18%	4	Stringy Hair	–0.028	–2.72%
5	Choker	1.037***	182.04%	5	Mohawk	0.003	0.33%
6	Welding Goggles	0.920***	150.94%	6	Frumpy Hair	0.015	1.51%
7	Hoodie	0.909***	148.15%	7	Mohawk Dark	0.023	2.30%
8	Buck Teeth	0.791***	120.63%	8	Bandana	0.024	2.40%
9	Pink With Hat	0.771***	116.26%	9	Headband	0.041	4.14%
10	3D Glasses	0.739***	109.38%	10	Mohawk Thin	0.044	4.49%

Appendix E. Different performance measures

This table compares the performance measures for different asset classes over the sample period from June 2017 through December 2022. The $\widehat{\boldsymbol{\beta}}$ and Jensen's alpha ($\widehat{\boldsymbol{\alpha}}$) are the slope and the intercept estimated based on the market model, $\boldsymbol{r_i - r_f = \alpha + \beta(r_m - r_f) + \varepsilon}$. $\boldsymbol{r_i}$ is the monthly return for a given asset class, and $\boldsymbol{r_m - r_f}$ 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 ($\boldsymbol{r_f}$). The Treynor (1965) ratio is defined as the ratio of Jensen's alpha ($\widehat{\boldsymbol{\alpha}}$) to $\widehat{\boldsymbol{\beta}}$. Following Sortino and van der Meer (1991) and Sortino et al. (1999), the Sortino ratio and the upside potential ratio are measured as follows:

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

where $\mathbb{E}[\boldsymbol{r_i}]$ is the expected return, and $\boldsymbol{MAR}$ 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	1.741	23.40%	13.44%	70.81%	187.90%
ETH/USD Index	1.420	4.29%	3.02%	14.93%	95.85%
NASDAQ Index	0.515	0.44%	0.85%	25.35%	73.72%
S&P 500 Index	0.464	0.31%	0.68%	24.39%	62.60%
Dow Jones Index	0.472	0.27%	0.58%	22.88%	59.37%
VIX Index	–3.616	7.30%	–2.02%	10.77%	107.74%
Bond Index	–0.192	0.12%	–0.60%	–10.68%	60.96%
Gold Index	0.039	0.46%	12.03%	36.82%	104.03%

Appendix F. Distribution of returns on different cryptocurrencies

This table reports the distribution of monthly returns on different cryptocurrencies. The sample period for Bitcoin, Tether, Litecoin, and Dogecoin is from June 2017 through December 2022. The price data on Cardano and USD Coin, Solana, and Shiba Inu begins in October 2017, October 2018, April 2020, and August 2020, respectively. For each index, we examine the arithmetic and geometric average returns per month, the standard deviation, the 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. Data on cryptocurrency prices is from CoinGecko.

	Mean returns per month		Dispersion of monthly returns			Sharpe ratio	
	Arithmetic	Geometric	Std. dev.	Min	Max	Arithmetic	Geometric
NFT Index	24.97%	12.85%	63.92%	–52.94%	303.20%	38.92%	19.94%
Bitcoin (BTC)	5.20%	2.85%	23.64%	–33.03%	98.95%	21.58%	11.66%
Cardano (ADA)	18.92%	3.84%	108.03%	–52.43%	797.08%	17.43%	3.47%
Dogecoin (DOGE)	17.59%	5.16%	74.78%	–42.01%	385.99%	23.40%	6.77%
Litecoin (LTC)	5.14%	1.01%	36.20%	–40.20%	233.94%	13.93%	2.53%
Tether (USDT)	0.00%	–0.01%	1.04%	–5.55%	5.94%	–9.56%	–10.07%
USD Coin (USDC)	–0.03%	–0.03%	0.28%	–1.22%	1.10%	–44.37%	–44.49%
Solana (SOL)	22.15%	9.55%	64.05%	–44.34%	194.28%	34.43%	14.76%
Shiba Inu (SHIB)	251.87%	45.68%	703.65%	–41.82%	3111.33%	35.78%	6.48%

Appendix G. 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	23.398***	24.307***	24.838***	29.885***
	(2.944)	(3.038)	(3.024)	(3.737)
MKTRF	1.741	1.103	0.884	0.617
	(1.179)	(0.703)	(0.516)	(0.370)
SMB		3.500	3.228	0.314
		(1.153)	(1.020)	(0.091)
HML		0.557	0.336	5.755**
		(0.287)	(0.163)	(2.132)
RMW				–4.009
				(–1.009)
CMA				–10.046**
				(–2.512)
MOM			–0.838	
			(–0.334)	
Observations	66	66	66	66
R^2	0.021	0.048	0.049	0.148

Appendix H. 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 March 2022-December 2022. The low-interest-rate period is defined as the period 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. The t-statistics are reported in parentheses. ∗∗∗, ∗∗, 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	10.22%	21.95%	4.47%	12.18%	21.06%	35.84%

Panel B: NFT returns loadings to equity factors

	CAPM	3-factor	4-factor	5-factor
(In percentage)	(1)	(2)	(3)	(4)
ALPHA	17.172***	17.361***	18.323***	21.620***
	(2.963)	(2.939)	(3.035)	(3.703)
MKTRF	–0.129	–0.262	–0.660	–0.844
	(–0.120)	(–0.226)	(–0.524)	(–0.694)
SMB		0.716	0.224	–1.420
		(0.320)	(0.096)	(–0.563)
HML		0.164	–0.235	4.267**
		(0.115)	(–0.155)	(2.165)
RMW				–2.147
				(–0.740)
CMA				–8.390***
				(–2.874)
MOM			–1.519	
			(–0.822)	
Observations	66	66	66	66
R^2	0.000	0.003	0.013	0.128

Appendix I. Generative collections: Rarity scores

This table reports estimates from our hedonic regression model using ordinary least squares with generative collections. The dependent variable is the natural logarithm of CryptoPunk prices (in USD). We obtain NFT rarity scores from Rarity.Tools. *Rarity_1_pct* is a dummy variable that equals one if the rarity ranking of an NFT is within the top 1% of a collection and zero otherwise. *Rarity_10_pct* is a dummy variable that equals one if the rarity ranking of an NFT is within the top 10% of a collection and zero otherwise. *Rarity_20_pct* is a dummy variable that equals one if the rarity ranking of an NFT is within the top 20% of a collection and zero otherwise. These rarity dummy variables are mutually exclusive. In all specifications, we include the same set of control variables used for column (5) of Table 4. Appendix A provides variable definitions in greater detail. Standard errors (in parentheses) are clustered at the firm level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Var.	ln $P_{i,t}$	
	(1)	(2)
Rarity_1_pct	1.699***	1.693***
	(0.043)	(0.043)
Rarity_10_pct	0.667***	0.666***
	(0.010)	(0.010)
Rarity_20_pct	0.275***	0.274***
	(0.008)	(0.008)
Observations	239,479	239,418
R-squared	0.806	0.807
Sample period	Full	Full
Controls	No	Yes
Collection FE	Yes	Yes
Year-Month dummies	Yes	Yes

Appendix J. The drivers of NFT demand

This table reports regression estimates of NFT returns on different drivers of NFT demand. The dependent variable is the returns on the NFT index. *ΔETH/USD Index* is the return on ETH/USD on month *t*. *ΔNASDAQ Index* is the return on NASDAQ Index on month *t*. *ΔGlobal Luxury Index* is the return on Global Luxury Index on month *t*. *Celebrity* is a dummy variable that equals one if a celebrity purchases a CryptoPunk in a given month and zero otherwise. The NFT index is estimated using the hedonic regression model in column (5) of Table 4. 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.

	(1)	(2)	(3)	(4)	(5)
ΔETH/USD Index	1.225***				1.178***
	(0.237)				(0.255)
ΔNASDAQ Index		3.989**			4.079
		(1.547)			(2.448)
ΔGlobal Luxury Index			2.250*		–2.871
			(1.337)		(2.024)
Celebrity				0.387*	0.443**
				(0.216)	(0.179)
Observations	66	66	66	66	66
Adj. R-squared	0.283	0.080	0.027	0.033	0.339