Is Love Blind?

AI-Powered Trading with Emotional Dividends*

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Abstract

We leverage the non-fungible tokens (NFTs) setting to assess the valuation of emotional dividends (LOVE), a long-standing empirical challenge in private-value markets such as art, antiques, and collectibles. Having created and validated our proxy, we use deep learning algorithms and discover that contemporaneous price fluctuations, collection features, and ownership wealth significantly contribute to the formation of LOVE. Understanding the drivers of LOVE, we employ AI-powered algorithms to estimate the prices of NFTs. While AI models accurately predict NFT prices, the performance is decreasing in LOVE. Finally, we demonstrate that LOVE-driven trading leads to significant financial losses over the long term, suggesting that some traders trade off wealth for emotional utility. Our study provides novel economic insights into the factors behind emotional dividends and their role in the pricing of private-value assets. It also highlights the challenges AI-powered trading faces in markets with too much LOVE.

JEL classification: G15, G18, G29, K29, K42, O16.
Keywords: AI, deep learning, private-value assets, emotional dividends, algo-trading, NFTs.

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'Hardly any of them [clients] regard their collectibles as pure investments – there is more to it than that. Some also want to create a positive impact, but more often regard collectibles as... something they feel proud about. Collectibles symbolize their passion and interests."[1]

– Michael Strobaek, Global CIO of Credit Suisse.

1 Introduction

Private-value assets—ranging from masterpieces of art and real estate to rare stamps, ancient coins, and vintage wine—have emerged as popular investment asset classes in recent years. Conservative estimates suggest that the value of collectibles owned by private individuals is around USD 1.2 trillion.[2] A survey conducted by Credit Suisse wealth management services involving 55 ultra-high-net-worth individuals (UHNWIs) across various regions has found that 44% allocate 2%–5% of their wealth to this type of assets, 31% allocate more than 5%, while only 13% have no exposure at all.[3] While some investors invest in these assets to diversify their portfolios (e.g., Dimson and Spaenjers (2011); Whitaker and Kräussl (2020)), others use them to symbolize their passion and interests (Hechler-Fayd'herbe and di Torcello (2020)).

Nevertheless, estimating the price of these assets is quite challenging. First, their prices are highly influenced by the satisfaction derived from ownership, known as emotional dividends, which are contingent on the owner's characteristics and financial status that are difficult to observe and quantify (e.g., Han (2013); Lovo and Spaenjers (2018); Goetzmann et al. (2021)). Second, these types of assets often change hands over extended periods—e.g., famous paintings could have exchanged hands over hundreds of years, and, data on traded assets is often scarce and infrequent, leading to significant biases in estimated prices.[4] Therefore, understanding the impact of emotional dividends on the price formation of these type of assets is a long-standing open empirical question (e.g., Goetzmann (1993); Spaenjers et al. (2015)).

[1] Excerpt from *Collectibles: An Integral Part of Wealth*, October 2020, Deloitte and Credit Suisse.

[2] We use the terms "private-value assets" and "collectibles" interchangeably hereafter.

[3] The Survey is based on responses from 620 private bankers and wealth advisors managing more than USD 3.3 trillion of wealth for UHNWI clients. The survey ran during October and November 2019 (See here).

[4] To illustrate the issue, consider the Mona Lisa, da Vinci's masterpiece painted between 1503 and 1517 and sold to King Francis I for 4,000 gold ducats in 1518. The art has never been traded since it was first displayed at the Louvre in Paris in 1797, creating large price estimations among art experts if the museum decides to put it on auction. Mona Lisa estimates vary widely—insurance issued in 1962 set it at $100 million, equivalent to $1 billion in today's value (see here).

Against this background, our study draws two complementary research goals. First, we aim to understand the price formation of private-value assets, particularly the role of emotional dividends in these markets. Since no proxy for emotional dividends has ever been produced in the literature, we devote much of our study to tackling this challenge. Second, given the increasing accessibility to AI technology and its potential repercussions in financial markets (e.g., Babina et al. (2023), Dou et al. (2024), Kim et al. (2024)), we explore the efficacy of AI-driven trading in a market dominated by emotional traders. It is widely recognized that machines can generate superior performance compared to humans due to their ability to make inferences from non-linear data and process millions of parameters (e.g., Bao et al. (2020); Amiram et al. (2022); Chen et al. (2022)); however, their performance in an environment with emotionally driven trading is unknown.

To achieve these goals, we exploit the non-fungible token (NFT) market, a novel digital asset powered by blockchain technology that has attracted the attention of entrepreneurs, artists, investors, and collectors worldwide. The NFT market first drew significant attention in 2017 with the launch of CryptoKitties, a game that utilized blockchain technology to allow users to buy, collect, breed, and sell virtual cats. The game pioneered using blockchain to authenticate unique digital assets to verify ownership and originality. In 2021, the NFT market's value soared—over \$40 billion according to industry estimates, transitioning from a niche interest focused on digital art and gaming to achieving mainstream recognition.[5] In a landmark event, Beeple's digital artwork "Everydays: The First 5000 Days" was sold for over \$69 million in March 2021. Popular collections like CryptoPunks and the Bored Ape Yacht Club have become symbols of the NFT wave, with assets fetching millions and offering additional perks like exclusive club memberships or crypto airdrops.[6] Celebrities, including Justin Bieber, who reportedly spent over \$1.3 million on a Bored Ape NFT, have further propelled the market's popularity, highlighting its broad appeal across various digital domains.[7] Such celebrity involvement highlights emotional interests in NFTs. Perhaps more importantly, it suggests NFTs work and behave just as regular private-value assets.[8]

[5] See here.

[6] See these collections here and here, respectively.

[7] See here.

[8] Determinants of NFT value differ significantly from traditional financial assets like stocks and bonds. Notably, NFTs don't generate cash flows for their owners, meaning there are no direct financial gains and taxable events

For instance, the sale of CryptoPunk 5822, a 24x24 pixel art image of an alien wearing a bandana, for approximately $24 million in February 2022, prompts a critical inquiry into why such a seemingly simple digital asset commands such a high price.[9]

[Figure 1 here]

A potential explanation, reflected in the extant private-value literature (e.g., Spaenjers et al., 2015; Lovo and Spaenjers, 2018; Chambers et al., 2020), is that NFT investors may derive non-financial utility, such as emotional dividends or personal enjoyment, from holding these assets, offsetting the risks they undertake.[10] However, the formation of emotional dividends cannot be easily estimated in traditional private-value assets, such as artworks, fine wine, and collectibles, due to their irregular features and limited accessibility to transaction data (Mei and Moses, 2005; Pesando, 1993). In contrast, the NFT market provides a suitable setting where trading occurs more frequently, and asset characteristics and owner attributes are readily observable.

We start our empirical examination by developing a proxy for emotional dividends. We adopt hedonic regression models, a popular choice for the valuation of private value assets, which link the prices of illiquid assets to their asset characteristics (e.g., Campbell et al. (2011)). We construct our proxy for emotional dividends, hereafter referred to as “LOVE,” representing the non-financial component of the pricing of private-value assets, as the difference between the predicted and actual prices of a given NFT.[11] In other words, our proxy is derived from the residuals of the hedonic regression model.[12] LOVE varies widely in our setting—a standard deviation 23.5 times larger than its mean across all NFT collections. LOVE also evolves over time, increasing during the market boom of 2021 and falling during market crises such as the Luna-Terra crash, in May 2022.[13]

until the NFTs are resold (Beale et al., 2023; Cong et al., 2023; De Simone et al., 2024). Additionally, the risk associated with investing in NFTs is notably higher compared to traditional investments (Kong and Lin, 2022). Although private-value assets often pose liquidity risks due to extended durations for matching buyers and sellers, the emergence of blockchain technology has substantially improved accessibility to NFTs, with transaction histories publicly and securely stored on blockchains.

[9] This curiosity initially motivated our study.

[10] Similar to private-value assets, most NFTs are unique and limited in supply.

[11] We use “emotional dividends” to represent the concept while “LOVE” to describe the proxy from this point on in the paper.

[12] We acknowledge that our method generates a noisy proxy since the residuals may include other non-financial components besides emotional dividends.

[13] The Luna-Terra crash refers to the dramatic collapse of the Terra (LUNA) cryptocurrency and its stablecoin counterpart, TerraUSD (UST). The crash erased billions of dollars in market value and impacted many investors

We then validate our emotional dividends proxy in two scenarios. First, LOVE should be increasing in public attention to the NFT market (e.g., hype). Second, because NFT values are sensitive to the trends or hype within their own communities, celebrity endorsements—such as Justin Bieber's example discussed earlier—are expected to affect LOVE positively. We find empirical support for both conjectures. LOVE highly correlates with public attention, measured by the Google search index, and significantly increases when a celebrity joins the NFT community. These results increase our confidence that our proxy captures a substantial portion of the emotional value embedded in NFT prices.

Having validated our proxy, we are equipped to explore the determinants of LOVE. Although data availability is an advantage of the blockchain setting, linear models often poorly explain private-value assets' performance (e.g., Kong and Lin (2022); Borri et al. (2023)). Therefore, we employ machine and deep learning algorithms to extract non-linear and high-dimensional information from NFT trading. Following the procedure in the machine learning literature (e.g., Gu et al., 2020; Leippold et al., 2022), we construct predictors for NFT prices discussed in the extant literature. In particular, we consider the association of factors forming LOVE in the NFT setting along three dimensions.

The first dimension relates to asset-specific characteristics, which typically take precedence in evaluating illiquid assets (Goetzmann et al., 2021). Consistent with this notion, NFT attributes are important determinants for the pricing of NFTs (Nadini et al., 2021; Nguyen, 2022; Horky et al., 2022; Chandra, 2022). Especially for NFTs with rare features, investors are more willing to pay higher prices for them (Kong and Lin, 2022). Another important feature is royalty or creator fees set by NFT creators (Falk et al., 2022). In addition, we also consider the collection's age and recent price fluctuations (e.g., maximum price and floor price).

The second dimension relates to investor features. The literature on private-value assets indicates that the utility derived from ownership varies with the owner's identity, emphasizing the role of investor attributes in asset pricing. For instance, in the art market, an investor's experience can influence her trading behavior and, thus, auction results (Bruno et al., 2018). Accordingly, our study investigates the transaction history of NFT investors and constructs proxies for investor experience (Oh et al., 2022). We identify sellers and buyers in each transaction

and projects within the cryptocurrency ecosystem.

and examine their characteristics. Specifically, we estimate experience based on the investor's past trading activities, such as investment duration and diversity in a given wallet.

The last dimension relates to market conditions. Previous studies have documented that the variations in cryptocurrency prices and the networking within the NFT market impact NFT prices (Ante, 2022; Dowling, 2022). Hence, we also construct several measures to capture the crypto market dynamics, including the returns on ETH prices, gas prices, and the frequency of Google searches for the topic related to "non-fungible token." We focus on Ether prices because the largest NFT collections run on the Ethereum blockchain.

Our machine and deep learning exercises yield interesting results. First, our findings indicate that contemporaneous price fluctuations (e.g., 30-day highs and lows), the age of NFT collections, NFT rarity, and wealth effects play significant roles in explaining the formation of emotional dividends. Second, the best-performing models—random forests, gradient-boosted regression trees, and neural networks—suggest that deep learning is essential when studying the formation of LOVE, confirming the limitations of linear and non-learning models in pricing private-value assets. Overall, we provide novel empirical insights into the long-standing price-value assets literature, especially regarding the determinants of LOVE and its impact on the price formation of these assets.

We now address our second main research goal: evaluating the performance of AI-based algorithms in markets with emotionally driven traders.

Unlike traditional financial assets, NFTs consist solely of images and contain no other fundamental information. In this unique setting, an image-based AI model appears to be helpful for NFTs valuation. Therefore, we adopt residual network (ResNet), an enhanced deep-learning algorithm for image recognition developed by He et al. (2016). The ResNet, built upon a convolutional neural network, typically demonstrates robust performance and avoids issues, such as gradient exploding or gradient vanishing, even with deeper networks (Seo et al., 2021). This AI model has been widely adopted in various research areas, including medical, engineering, and biological fields (e.g., Wen et al., 2018; Praveen et al., 2022).

We employ deep residual learning techniques to predict NFT prices for the subsequent period. Specifically, we employ ResNet with 18 layers and pre-trained weights from the ImageNet dataset.[14] We train the model using images of the top 1% most valuable NFTs up to month t (i.e., training images) to forecast NFT prices. In particular, we evaluate high-value NFTs using three different benchmarks: sales prices, predicted prices, and LOVE. We then create a feature extractor based on the trained model to learn important features for predicting NFT sales in the following three months (i.e., testing images). The feature extractor transforms raw data into a suitable feature vector capable of detecting patterns in the input (Shibata et al., 2018; Sarki et al., 2020). The resulting scores allow us to investigate how similar each testing image is to a group of training images.

[Figure 2 here]

Our AI-based algorithm accurately predicts NFT values in terms of sales and predicted prices. Specifically, NFTs with high similarity to high-value NFTs during the training period are usually priced higher. However, the algorithm fails to capture the variations in NFT sales or predicted prices if the predictions are made based on NFTs containing high levels of LOVE. This finding suggests that investor preferences for certain NFTs may not be financially based, distorting the price predictions.

Finally, we test the relationship between LOVE and future financial outcomes. We discover that LOVE is negatively correlated with future financial gains. In terms of economic significance, a one standard deviation increase in LOVE is associated with a $6,000 decrease in financial gains, approximately 47% of the average level of proceeds in our sample. This finding indicates that personal enjoyment (e.g., passion and interests) plays a crucial role in determining the pricing of private-value assets. In other words, in these markets, from the perspective of financial gains, "love is blind," especially for assets with high emotional value in the eyes of the beholder.

Our study contributes to the existing literature in at least three ways. First, our study offers insights into the implications of tokenization, a central piece in development by central banks and financial intermediaries (e.g., Han et al., 2019; Lee et al., 2020; Durfee et al., 2023; Cong et al., 2023) that holds the potential to reshape the future of finance (e.g., Harvey et al., 2021; Harvey and Rabetti, 2024).[15] Specifically, we add to the rapidly growing body of literature on NFTs (e.g., Ante, 2022; Dowling, 2022; Nadini et al., 2021; Oh et al., 2022; Vasan et al., 2022)

[14] See the ImageNet website (https://image-net.org/) for greater details.

[15] See also Amiram et al., 2024; Cong et al., 2023, 2024; Lyandres et al., 2022; Rabetti, 2023.

by assessing the emotional component associated with the price formation of these tokenized assets.

Additionally, our findings complement the literature on private-value assets in a few ways. First, we address the long-standing empirical challenge of estimating the value of emotional dividends. As NFTs resemble private-value assets due to their uniqueness and illiquidity, the insights obtained from our findings may apply to other private-value markets, such as the art market and the real estate market. Second, private-value assets invariably focus on sell-side activities because tracking sellers' identities is easier than tracking buyers (Agarwal et al., 2019). By contrast, we take advantage of on-chain data and study both seller and buyer attributes. Hence, we provide a more complete picture of the trading dynamics of private-value assets. Finally, extant literature has consistently illustrated that the risk-return characteristics of private-value assets, such as real estate, stamps, and wine, are notably less appealing than those of stocks (e.g., Dimson et al., 2015; Chambers et al., 2021). Our study suggests that certain private-value assets (i.e., NFTs) might present superior risk-return profiles compared to stocks, especially when accounting for the emotional components in the price formation of these assets.

Finally, our study contributes to the emerging literature examining the impact of artificial intelligence in the financial markets (e.g., Calvano and Pastorello (2020); Cao et al. (2021); Asker et al. (2021); Cao et al. (2023); Bertomeu et al. (2023); Bagattini and Guagliano (2023)). Babina et al. (2023) demonstrates that AI-investing firms experience higher growth in sales, employment, and market valuations, primarily through increased product innovation. Dou et al. (2024) proposes that informed AI speculators can autonomously learn to employ collusive trading strategies, negatively affecting price informativeness and market liquidity. Kim et al. (2024) suggests that Generative AI tools may change how markets process firms' disclosures, especially for investors with information processing constraints. We contribute to this emerging literature by demonstrating that the performance of AI-powered trading strategies deteriorates in markets dominated by emotional traders.

This study is structured as follows. Section 2 lays out the institutional background. Section 3 describes our data. Section 4 outlines the research design. Section 5 presents and discusses the results on emotional dividend proxy creation, validation, and determinants. Section 6 develops, tests, and evaluates the performance of AI algorithms. Section 7 concludes.

2 Institutional Background

2.1 Private-value assets

Over the last decades, the accumulation of individual wealth has spurred the expansion of private-value asset markets, encompassing real estate, artworks, wine, and various collectibles (Goetzmann et al., 2011; Korteweg et al., 2016). Not surprisingly, some investors view private-value assets as a means of diversifying their portfolios (Renneboog and Spaenjers, 2013; Kräussl et al., 2017; Lovo and Spaenjers, 2018). Such demand has led to the creation of numerous funds catering to this trend. For example, Masterworks, a privately-held startup, provides individual investors with a platform to own fractional shares of high-priced investments in blue-chip art.[16]

A large literature has been devoted to understanding the determinants of private-value assets.[17] For instance, it has been found that the demand for art tends to increase with financial wealth—say, measured by stock returns (Goetzmann, 1993; Renneboog and Spaenjers, 2013). In line with this finding, Dimson and Spaenjers (2011) finds a positive correlation between equity and British stamp returns, suggesting the existence of a wealth effect. Similarly, Dimson et al. (2015) shows that the effects of both wealth growth and aging are associated with wine prices. Unlike most financial assets, private-value assets have characteristics that are challenging to quantify in a general sense. The shares of a specific stock serve as perfect substitutes, whereas two identical artworks might have significantly different values if created by different artists or sold in distinct markets (e.g., Baumol, 1986; Pesando, 1993). Therefore, private-value assets are often referred to as heterogeneous goods or imperfect substitutes (Stein, 1977).

Previous studies have documented that the investment performance of private-value assets appears to be less attractive than that of traditional financial assets. In particular, private-value assets typically entail high idiosyncratic risk but lower financial returns, compared to stocks (Mei and Moses (2002); Dimson et al. (2015)). An interesting question to explore further is why investors are still interested in such high-risk but low-return investments. A possible explanation may be the underlying non-monetary benefits or emotional values attached to private-value assets.

[16] See here.

[17] Goetzmann et al. (2021) provide a comprehensive review of the literature on private-value assets.

2.2 Non-fungible tokens (NFTs)

The emergence of blockchain technology represents a monumental shift in the financial ecosystem, catalyzing transformative changes across various industries (Harvey et al., 2021; Makarov and Schoar, 2022; Harvey and Rabetti, 2024). Blockchain technology has revolutionized the concept of trust in financial transactions. Blockchain networks use cryptographic techniques and consensus mechanisms to ensure the immutability and transparency of transaction records. This eliminates the need for third-party validation and minimizes the risk of fraud or manipulation, thereby enhancing trust and security in financial transactions.

In essence, blockchain technology introduces decentralized and secure ledger systems, fundamentally altering how transactions are recorded and verified (Cong et al., 2021). One of the most prominent disruptions brought about by blockchain technology is the rise of cryptocurrencies, such as Bitcoin, Ethereum, and Tether. These digital currencies operate on decentralized blockchain networks, enabling peer-to-peer transactions without intermediaries like banks or financial institutions (e.g., Cong et al., 2021). As a result, individuals can now conduct cross-border transactions efficiently and at lower costs, circumventing the traditional banking infrastructure (Han et al., 2019; Chiu and Koeppl, 2019; Harvey and Rabetti, 2024).[18]

In 2013, Vitalik Buterin introduced Ethereum, a groundbreaking blockchain platform capable of facilitating more advanced and customized applications beyond simple digital currency transactions (e.g., Buterin, 2013; Chevet, 2018; Kim et al., 2018). Ethereum was formally launched in 2015, alongside its native cryptocurrency, Ether (ETH), and has become the second-largest cryptocurrency by market capitalization. Within the Ethereum ecosystem, most transactions hinge upon "smart contracts," computer programs stored on a blockchain, automating the execution of predefined actions once certain conditions are met. Smart contracts, acting as intermediaries, can partially alleviate informational disparities and enhance the welfare and consumer surplus by fostering increased market entry and competition (Cong and He, 2019). This has streamlined processes like contract management, asset transfer, and settlement, reducing the need for intermediaries and minimizing transaction costs.

[18] In particular, the advent of Bitcoin in 2009 marked a pivotal moment, further igniting widespread global interest in cryptocurrencies and the broader potential of blockchain technology (Nakamoto, 2008). While Bitcoin remains the dominant and most heavily traded cryptocurrency, its blockchain architecture primarily serves currency transactions due to inherent structural limitations (Porat et al., 2017).

Ethereum blockchain's principal standard is ERC-20 (Ethereum Request for Comments 20), which serves as the technical bedrock for all smart contracts governing fungible token implementations (such as ETH). Nevertheless, the disruptive potential of blockchain technology extends far beyond the realm of cryptocurrencies.[19] In addition to cryptocurrencies, blockchain technology has facilitated the emergence of non-fungible tokens (NFTs), representing unique digital assets stored on blockchain networks. NFTs have revolutionized how digital content is bought, sold, and owned, enabling creators to tokenize their works of art, collectibles, and other digital assets. This has created new opportunities for artists, content creators, and collectors to monetize and trade digital content transparently and securely (Bamakan et al., 2022).

Unlike fungible tokens, NFTs represent unique digital assets, ranging from artworks, videos, and music to domain names and beyond. A recent work by Oh et al. (2023) describes NFTs as digital Veblen goods. This unique feature has ignited substantial interest in studying their legal and intellectual property positions. A body of literature categorizes NFTs as intellectual properties (e.g., Fairfield, 2022; Bamakan et al., 2022; Gans, 2024), reflecting the growing recognition of their distinctive nature within legal frameworks. Concurrently, another stream of studies focuses on the price determinants of NFTs (e.g., Ante, 2022; Dowling, 2022; Horky et al., 2022; Huang and Goetzmann, 2023). For example, Kong and Lin (2022) investigates NFT determinants and demonstrates their risk-return profile compared to other investment vehicles. Additionally, Borri et al. (2023) highlights that existing asset pricing models inadequately explain NFT return variations. These endeavors collectively contribute to understanding the multifaceted dynamics of NFTs, encompassing intellectual property concerns and their associated risks and returns.

3 Data and sample

We focus on blue-chip NFT collections throughout our analysis to ensure that our results are not disproportionately affected by price manipulation.[20] We obtain archived data on NFT

[19] For example, decentralized finance (DeFi) platforms leverage blockchain technology to offer a wide range of financial services, including lending, borrowing, trading, and asset management, without the need for traditional financial intermediaries. These platforms operate on decentralized networks, enabling users to access financial services in a permissionless and censorship-resistant manner, regardless of their geographical location or financial status.

[20] We focus 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.

transactions from the Etherscan and Larva Labs (https://www.larvalabs.com/), which provide transaction history, such as dates, sale prices, wallet addresses, etc. Our sample covers the period from June 2017 to December 2022. Table 1 reports the details of NFT collections we include in our study. In particular, the CryptoPunks is the earliest collection in our sample, followed by the CryptoSkulls and Bored Ape Yacht Club. The highest (lowest) creator or royalty fee is 7.5% (0%) charged by the CryptoSkulls (the CryptoPunks), while most collections charge a 5% creator fee. Figure 3 illustrates the distribution of NFT sales over time. Notably, we can observe a substantial surge in NFT sales during mid-2021, followed by a decline after June 2022.

[Table 1 & Figure 3 here]

Our data on daily Ether prices and the statistics of the NFT market come from CoinGecko and NonFungible.com. We download data on Google search frequency of the search topic of "non-fungible token" to capture worldwide attention paid to NFTs.[21] The search index values range from 0 to 100, and a higher value indicates a higher proportion of all queries. We also obtain rarity scores for each collection from Rarity.Tools.[22] For each NFT collection, Rarity.Tools assigns a rarity score to each trait of an NFT, and these scores are summed to establish the NFT's overall rarity score, ranging from 0 to 1. We obtain data on gas price per transaction and trading activities for each wallet from Etherscan.

3.1 Summary Statistics

Table 2 reports summary statistics for the main variables used in our empirical analysis.[23] Our sample consists of 239,711 transactions with a mean NFT price of $0.036 million and an average age of 0.796 years (or 290.54 days). NFTs are typically traded 1.547 times before their next transaction. In general, sellers exhibit more experience than buyers. On average, sellers have traded 321 unique NFTs across 45 types with an experience of 0.49 years, while buyers have traded 212 unique NFTs across 33 types with an experience of 0.398 years.

[21] In our paper, the Google search index captures the trend of searching for the topics related to "non-fungible token." For example, Google users not only search for the term "non-fungible token" but also look for one of the following keywords: "OpenSea", "metaverse nft", "ape nft", "MetaMask", "nft price", etc.

[22] See Rarity.Tools (here) for additional details.

[23] Appendix 1 provides variable definitions in greater detail.

In Table 3, we investigate the correlations of these variables. The result shows that older NFTs are associated with higher creator fees. When there are more active wallets or investors, overall NFT sales in terms of transaction counts and value also increase. Regarding investor attributes (buyers and sellers), we discover that more experienced investors usually invest in a wider range of NFTs from various collections.

[Table 2 & 3 here]

4 Methodology

4.1 Emotional dividends

Previous studies have highlighted the distinctive valuation of private-value assets, such as artworks, wine, stamps, and real estate, in contrast to traditional financial assets like stocks and bonds (Baumol, 1986; Dimson and Spaenjers, 2011; Dimson et al., 2015; Case and Shiller, 1989). Private-value assets offer owners not only the potential for financial gains but also non-financial utility, often referred to as emotional dividends. The concept of emotional dividends, introduced by Lovo and Spaenjers (2018), captures the personal enjoyment derived from ownership. For example, artworks exhibit a dual nature, serving as both an investment vehicle and a conspicuous consumption good (Mandel, 2009). Spaenjers et al. (2015) specifically describe the valuation of artwork as the sum of the present value of emotional dividends and the expected auction proceeds. In a similar vein, we decompose an NFT investor's utility derived from the ownership into financial and non-financial components:

$$P_{i,t} = PV(Expected\ Resale\ Revenue)_{i,t'} + PV(Emotional\ Dividends)_{i,t,\rightarrow t'} + \epsilon \quad (1)$$

where t is the time of purchase, and $t^{'}$ is the optimal time of resale, $Expected\ Resale\ Revenue_{i,t'}$ is estimated as the difference between the predicted and actual prices $(\hat{P}_{i,t'} - P_{i,t})$ of NFT i. However, the non-financial component is typically unobservable. In this framework, we assume that emotional dividends constitute the unexplained components of pricing. Like most private-value assets, NFTs are traded less frequently, compared to financial assets. Hence, we adopt hedonic regression models, which link the prices of illiquid assets to their asset characteristics (e.g., Campbell et al., 2011; Renneboog and Spaenjers, 2013; Dimson et al., 2015). To estimate predicted prices ($\hat{P}_{i,t'}$) for each NFT, we run hedonic regressions as follows:

$$lnP_{i,t} = \alpha + \sum_{j=1}^{J} \beta_j X_{j,i} + \sum_{t=1}^{T} \delta_t T_{i,t} + \epsilon_{i,t} \tag{2}$$

where $P_{i,t}$ represents the price of NFT i on date t, α is the regression intercept, $X_{j,i}$ indexes the characteristic j of NFT i, and $T_{i,t}$ is the time dummy that equals one if the token i is sold in the year-month of date t.

Yet, it is challenging to empirically determine the optimal time of resale for each individual. To simplify, we use the price premium paid by an NFT investor—i.e., the value above the predicted price on the purchase date—as our proxy for emotional dividends. Therefore, we calculate the predicted price ($\hat{P}_{i,t}$) in the same month as date t , and the residual from Eq. (2) serves as our proxy for the emotional dividends from NFT ownership. Specifically, we define an individual's emotional dividends for NFT i on date t as:

$$LOVE_{i,t} = P_{i,t} - \hat{P}_{i,t} \tag{3}$$

4.2 Machine and deep learning models

Our analysis relies on a machine learning software package, Scikit-learn (Pedregosa et al., 2011). There are two main advantages of using machine learning algorithms. First, machine learning techniques can generalize from data through identifying and extracting complex patterns and trends. This feature is what traditional empirical methods cannot achieve, thus failing to explain nonlinear relationships among variables. Second, machine learning algorithms allow us to estimate the relative importance of features or variables in a particular model. Hence, we are able to gain a better understanding of the contribution of features to the predictive power across different models.

We begin our exercise with penalized linear models, such as lasso, and elastic net. We also consider partial least squares, which employ dimension reduction techniques. Nevertheless, when more variables are considered, nonlinear models outperform linear specifications. Thus, we further adopt tree-based models and neural network models to evaluate what variables are important to emotional dividends.

Following the standard procedure in the machine learning studies, we begin our analysis by dividing our sample into three subsamples: the training sample, the validation sample, and the testing sample (see Gu et al., 2020; Leippold et al., 2022; Easley et al., 2021).[24] We utilize the validation sample to tune the hyperparameters and the training sample to estimate the model parameters subject to the pre-specified hyperparameters for the machine learning models. The purpose of validation is to simulate an out-of-sample model test (Gu et al., 2020). Finally, we use the testing sample to evaluate the predictive performance of a model.

4.2.1 Penalized linear models: lasso, and elastic net

A simple linear model performs well when the number of variables is small. One major issue with ordinary least squares (OLS) is overfitting, especially when dealing with a large set of predictors. To address this problem, a common approach is to incorporate a penalty term into linear regressions, a method known as penalized regressions. In our study, we specifically consider Lasso and elastic net regressions as our chosen penalized linear models, designed to minimize out-of-sample prediction error by implementing shrinking operation that can produce coefficients that are exactly zero (Tibshirani, 1996).

4.2.2 Dimension reduction: PLS

Partial Least Squares (PLS) can be used to reduce the dimensionality of the data by creating a compact set of uncorrelated variables, known as latent variables or components, that capture the essential information in the original data. This technique can help reduce noise and prevent overfitting in modeling. PLS is especially effective at dealing with multicollinearity when independent variables in a regression model exhibit high correlations.

[24] We cross-sectionally rank all features and map these ranks into the [-1,1] interval (Kelly et al., 2019).

4.2.3 Gradient boosted regression trees

Gradient boosted regression trees (GBRT) are an ensemble learning method that combines the predictions of multiple decision trees to create a more accurate and robust predictive model. GBRT uses decision trees as base learners. These trees are typically shallow (with a limited number of nodes or depth) to prevent overfitting. GBRT has various hyperparameters that can be tuned to control the model's performance, such as the learning rate, the number of trees (iterations), tree depth, and the minimum number of samples required to split an internal node.

4.2.4 Random forests

Random forest (RF) is one of the most robust and widely used algorithms among machine learning methods (Varian, 2014; Easley et al., 2021). Random forest belongs to the ensemble learning category, where multiple models are trained and combined to make predictions. Specifically, a random forest contains multiple decision trees, which are built on different subsets of the training sample and features. Decision trees are simple models that recursively split the feature space into regions, based on feature values, in order to predict the target variable. Each split is chosen to maximize the purity of the resulting regions. This machine learning technique leverages averaging to enhance predictive accuracy while mitigating overfitting.

4.2.5 Neural networks

Another popular machine learning model is neural networks (NN), which consist of interconnected nodes (neurons) organized into layers, including input, hidden, and output layers. In our analysis, we consider NN structure with one, three, and five hidden layers.[25] Neural network (NN) models have become a central part of modern machine learning and artificial intelligence due to their ability to learn complex patterns and representations from data. In the NN models, the introduction of activation functions enables neural networks to capture complex, non-linear relationships within the data.

[25] Following Gu et al., 2020, our shallowest neural network, NN1, has a single hidden layer of 32 neurons; NN3 has three hidden layers with 32, 16, and 8 neurons, respectively; and NN5 has five hidden layers with 32, 16, 8, 4, and 2 neurons, respectively.

4.3 Feature importance: Mean decreased accuracy

Following the machine learning literature, we measure the relative importance of a feature by computing its mean decreased accuracy (MDA) as our proxy for feature importance (Easley et al., 2021; Gu et al., 2020; Leippold et al., 2022). In our paper, we compute feature importances using both the training and testing samples. Specifically, MDA is defined as the reduction in the R^2 score of a model when a feature's value is randomly shuffled while keeping the other features intact. This approach helps us identify which features contribute most to the generalization power of a given model. Specifically, for each feature i in the dataset, we calculate the difference between the baseline performance and the performance after shuffling feature i. This difference represents the importance of feature i. The model repeats the permutation process multiple times and aggregate the importance scores to get a more stable estimate. Finally, we obtain a mean of feature importance over repetitions, denoted by MDA.

5 Empirical results

5.1 Hedonic regression results

For each NFT collection, we regress NFT prices on observable token characteristics (i.e., a rich set of NFT type and attribute dummies) and year-month dummies. Our measure of emotional dividend is the residuals from our hedonic regression model. Table 4 reports the hedonic regression results. We find that our hedonic models capture a large portion of NFT price variations, with R-squared values ranging from 0.449 to 0.976.[26] In Column 8, the low R-squared value for the Moonbirds is likely due to the shorter sample period and smaller sample size.

We utilize predicted NFT price estimated from the hedonic regressions to proxy for an individual's expected resale price on date t. As discussed in Section 4.1, we measure the emotional dividend ($LOVE$) for an NFT as the difference between the actual purchase price and predicted price (i.e., the residuals from our hedonic regression model). On average, emotional dividends

[26]Prior studies on alternative investments, such as art and stamps, have the R-squared of 0.64-0.83 (Beggs and Graddy, 2009; Dimson and Spaenjers, 2011).

account for 13.13% of the sales prices during the sample period. Panel A of Figure 4 shows the scatter plot of emotional dividends by NFT collection. As can be seen, emotional dividends remained at a low level before 2020 due to the early-stage adoption of NFTs. Subsequently, these dividends began to surge notably in 2021 as public attention towards NFTs grew. However, there was a significant drop in mid-2022, largely due to the Terra LUNA crash.

To better understand the dynamics between emotional dividends and market attention toward NFTs, we aggregate emotional dividends for each NFT by weighting them based on the monthly dollar volume traded for each collection. Similarly, we construct a weighted NFT price level based on the monthly dollar volumes. We use the relative interest in the Google search for the topic "non-fungible token" as a proxy for market attention toward NFTs. In Panel B of Figure 4, we observe that NFT prices largely co-move with emotional dividends. In unreported results, the correlation between dollar-weighted prices and emotional dividends is about 0.838. In Panel C, we observe that emotional dividends tend to comove with Google searches. In unreported tests, the correlation between dollar-volume-weighted emotional dividends and the relative interest in Google searches is 0.807, suggesting that our proxy for emotional dividends is associated with the hype for NFTs.

[Table 4 & Figure 4 here]

5.2 Celebrity endorsements

In this section, we further investigate whether our proxy for emotional dividends captures trends or hype caused by celebrity endorsements. A recent study by White and Wilkoff (2023) documents a relationship between celebrity endorsements and the ex-ante success of initial coin offerings. Anecdotally, a celebrity's involvement in an NFT project typically sparks excitement in the NFT market. For instance, Stephen Curry, a renowned NBA basketball player, purchased Bored Ape #7990 in August 2021, leading to a substantial increase in the collection's popularity. In this context, NFT investors are more likely to derive higher emotional dividends from holding NFTs with celebrity endorsements. Hence, we expect that NFT transactions are associated with higher emotional dividends following celebrity involvement in an NFT project.

To capture the effect of celebrity endorsements, we manually compile a list of celebrities who have made NFT purchases. For simplicity, we focus our analysis on the CryptoPunks and Bored Ape Yacht Club when identifying transactions involving celebrities. Appendix 2 reports the list of NFT purchases involving celebrities used in our analysis. Figure 5 illustrates the changes in sales prices and emotional dividends before and after celebrity endorsements. In Panel A, we observe a significant increase in average sales prices following endorsements by celebrities. Similarly, on average, most investors experience positive emotional dividends when acquiring NFTs after endorsements, while such dividends typically remain zero or negative without such endorsements, as demonstrated in Panel B.

To formally test the relationship between celebrity endorsement and emotional dividends, we compare the difference in means of emotional dividends during the periods before and after celebrity endorsements. In particular, we construct a dummy variable, Endorsement, that equals one if a transaction occurs within ten days following a celebrity's involvement in an NFT collection, and zero otherwise. The results are reported in Table 5. As shown in Panel A, emotional dividends, on average, are significantly higher and more volatile compared to those before the endorsements. In terms of the economic impact, celebrity endorsements correlate with an increase of $25,000 in NFT prices. In Panels B and C, we repeat the analysis considering only the CryptoPunks and Bored Ape Yacht Club, respectively. We find similar results, further confirming that our proxy for emotional dividends effectively captures sentiment in the NFT market.

[Table 5 & Figure 5 here]

5.3 Model performance

We first assess the performance of each model using three common performance metrics, i.e., the out-of-sample R^2 (R^2_{oos}), mean squared error (MSE) and mean absolute error (MAE). To estimate these performance metrics, we first fit each model to the training sample and then make predictions using the testing sample. R^2_{oos} evaluates how well a model explains the variance in the target variables, while MSE and MAE measure the accuracy of the predictions. Appendix 3 summarizes the hyperparameter tuning approaches employed for the machine learning models.

Table 6 presents the results across the different models. In terms of the out-of-sample R^2, nonlinear models, including random forest, GBRT, and neural networks, exhibit superior predictability compared to linear models, such as Lasso, ENet, and PLS. It is noteworthy that tree-based models outperform the other models across all performance metrics. In particular, the RF model achieves an R^2_{oos} of 23.06% as the best-performing model in explaining emotional dividends. We further find that the predictive performance of the NN models improves when more hidden layers are considered. The out-of-sample R^2 increases from 3.36% for NN1 to 11.01% for NN5, suggesting that deep learning prevails over shallow learning in explaining the variation in emotional dividends.

[Table 6 here]

5.4 Feature importance

We now investigate feature importance using mean decreased accuracy (MDA) as our benchmark to compare the relative importance of the features in each model. Appendix 4 shows the feature importance for the training sample. Notably, the feature importances for penalized linear models, such as Lasso and ENet, are highly skewed toward the top-3 variables: MaxPrice, minPrice, and ETHRet_30d. The dimension reduction model, i.e., PLS, also closely agrees with these top variables. For tree-based models, such as RF and GBRT, the top-5 most influential features are MaxPrice, Rarity_pct, minPrice, NFTAge, and ETHRet_30d, which consist of four asset characteristics and one market variable. In contrast to linear models, neural network models extract predictive information from a broader range of variables.

[Table 7 here]

To facilitate comparison across different models, we rank the importance of features and report the rankings instead of raw MDA values within each model, as shown in Table 7 (Bui et al., 2023; Chen et al., 2024).[27] In the last column of Table 7, we calculate an overall ranking by averaging the rankings of features for all models. Five out of the top-7 predictors are

[27] Appendix 5 reports the raw values of MDA for the training sample.

linked to asset characteristics, while the remaining are associated with market variables. This finding highlights the significant contribution of asset characteristics to emotional dividends. It's also noteworthy that our investor attributes seem to have a lesser impact on the variations in emotional dividends. One caveat is that features with low importance in an ineffective model could be highly influential in a good model. Hence, we restrict our attention to the best-performing models, i.e., RF, GBRT, and NN5. The top-5 most influential variables are MaxPrice, Rarity_pct, NFTAge, ETHRet_30d, and minPrice.

Alternatively, we estimate feature importance for the testing sample as shown in Appendix 6. We observe that the patterns of relative importance are largely similar when using either the training or testing sample. Likewise, we report the rankings of feature importance in Table 8.[28] When considering RF, GBRT, and NN5, the five most influential predictors are MaxPrice, NFTAge, minPrice, Rarity_pct, and ETHRet_30d. This finding, again, confirms the significant role of asset characteristics in shaping emotional dividends, which represent non-financial utility.

[Table 8 here]

Taken together, our results suggest that emotional dividends are more likely driven by recent price fluctuations (30-day highs and lows), the age of a specific NFT collection, NFT rarity, and the return on ETH. The evidence supports our assertion that earlier NFT collections gain value due to their historical importance.

6 AI-powered trading

In contrast to traditional financial assets, NFTs are comprised solely of images devoid of fundamental information. Given this unique characteristic, AI image-based models become indispensable for NFT evaluations. Thus, we employ the residual network (ResNet), an advanced deep-learning algorithm specialized in image recognition, initially introduced by He et al. (2016). ResNet, which is constructed upon a convolutional neural network (CNN), is renowned for its robust performance and its ability to mitigate issues such as gradient exploding or vanishing, even when applied to deeper networks (Seo et al., 2021).

[28] Appendix 7 reports the raw values of MDA for the testing sample.

Currently, ResNet has found widespread adoption across various fields of research, spanning medical, ecological, engineering, and biological domains (e.g., Wen et al., 2018; Praveen et al., 2022; Miao et al., 2019). Notably, previous studies have leveraged CNN models, including ResNet, for diverse applications such as brain tumor detection, COVID-19 diagnosis, and breast cancer identification, among others (e.g., Haq et al., 2022; Kundu et al., 2021; Shen et al., 2019; Reguant et al., 2021).

6.1 Deep residual learning for image recognition

In this section, we employ deep residual learning techniques to predict NFT prices for the subsequent period. Specifically, we employ ResNet with 18 layers and pre-trained weights from the ImageNet dataset.[29] We train the model using images of the top 1% most valuable NFTs up to month t (i.e., training images) to forecast NFT prices. In particular, we evaluate high-value NFTs using three different benchmarks: sales prices, predicted prices, and emotional dividends. We then create a feature extractor based on the trained model to learn important visual features for predicting NFT sales in the following three months (i.e., testing images). The feature extractor transforms raw data into a suitable feature vector capable of detecting patterns in the input (Shibata et al., 2018).

For each image in the test data, the model examines how similar it is to each image in the training set by comparing their "features," which are numerical representations of the images' characteristics. We calculate a visual similarity score for each pair of testing image and training image. The similarity score is estimated as follows:

$$Similarity\ score = \frac{dot(test\ feature,\ train\ feature)}{\parallel test\ feature \parallel \cdot \parallel train\ feature \parallel} \tag{4}$$

where *Similarity score* is the cosine similarity between the feature vectors of the testing image and the training image. *dot(test feature,train feature)* represents the dot product between the feature vectors of the test image and the training image. $\parallel$ *test feature* $\parallel$ represents the Euclidean norm (magnitude) of the feature vector of the test image. $\parallel$ *train feature* $\parallel$ represents the Euclidean norm (magnitude) of the feature vector of the training image. Finally, we combine

[29] See the ImageNet website (here) for greater details.

the similarity scores to get an overall similarity score for each testing image. The resulting scores allow us to investigate how similar each testing image is to a group of training images. For example, our training image, CryptoPunk 6721, was sold in September 2021. We predict whether NFTs sold between October 2021 and December 2021 are high-value NFTs based on their similarity scores.

To examine whether the predictions from the ResNet models can forecast NFT prices, we categorize NFT sales during the testing period into three groups based on the similarity scores.[30] The results are reported in Table 9.[31] In Panels A and B, we observe that the ResNet models can accurately predict NFT values in terms of sales prices and predicted prices. Specifically, NFTs with high similarity to high-value NFTs during the training period are usually priced higher. However, the ResNet models fail to capture the variations in NFT sales or predicted prices if the predictions are made based on NFTs containing high emotional dividends, as shown in Panel C. This finding suggests that investor preferences for certain NFTs may be irrational, thereby distorting the predictions.

[Table 9 here]

We have shown that our ResNet models can forecast the NFT price level in the subsequent period. Next, we assess the economic magnitudes of return predictability by sorting NFTs into tertiles based on the ResNet model's forecast of visual similarity scores. Nevertheless, like most private-value assets, NFTs are infrequently traded, posing challenges in calculating and comparing returns across different periods. For effective portfolio performance evaluation, we standardize NFT returns on a monthly basis by converting holding period returns into monthly returns. Subsequently, we group NFTs into three portfolios based on their similarity scores for each testing period and estimate portfolio returns with equal weighting.

[Table 10 here]

[30] For this test, we only included the CryptoPunks in our sample. We will incorporate additional data for the updated version.

[31] To account for the rarity effect, we exclude NFTs that are considered rare in the test set. For example, CryptoPunks with Alien, Ape, and Zombie types are much rarer than other types, so they are typically priced much higher.

The average monthly returns over different holding periods are reported in Table 10.[32] We observe that investors, on average, can earn higher financial returns by investing in NFTs that closely resemble high-valued NFTs from the previous month. In Panel C, however, we find that while emotional traders may achieve higher returns in the short term, trading strategies centered on NFTs with significant emotional value tend to underperform over longer horizons. Similar to those previously reported, the ResNet model can better capture the variations in NFT returns in the absence of emotional dividends.

6.2 Emotional dividends and financial gains

As discussed in Section 4.1, the utility derived from possessing private-value assets can be twofold. First, there is the potential for financial gains through resale. These assets may appreciate over time, providing a lucrative opportunity for owners to realize profits when they decide to sell. This financial aspect often serves as a primary driver for investment in private-value assets, attracting individuals with the promise of monetary returns. Apart from financial gains, private value assets also offer non-financial benefits through emotional dividends. Emotional dividends represent the personal enjoyment from possessing and interacting with these assets (Lovo and Spaenjers, 2018). The sentimental value associated with possessions, such as rare artwork or vintage wine, can provide personal satisfaction to their owners.

Having shown what determinants are important drivers for emotional dividends, we further explore the relationship between our proxy for emotional dividends, "LOVE," and realized financial proceeds. In essence, comprehending the dynamic between emotional dividends and financial gains allows us to understand better the motivations behind the acquisition and valuation of such assets. We perform a regression analysis to investigate the relationship between our LOVE and future financial gains. To mitigate the influence of outliers, we winsorize LOVE and financial gains at the 1st and 99th percentiles.

The results are reported in Table 11. We find that emotional dividends negatively predict future financial gains across all columns. In terms of economic magnitude, a one standard deviation increase in emotional dividends is associated with a $6,000 decrease in financial gains, about 47% of the average level of proceeds in our sample. This finding suggests that personal

[32] To mitigate the influence of outliers, we winsorize NFT returns at the 1st and 99th percentiles.

enjoyment plays a crucial role in determining the pricing of private-value assets. Regarding control variables, longer holding periods, recent price levels within a given collection, higher ETH returns, and more Google searches are positively correlated with future returns on NFTs. Surprisingly, NFT rarity is found to negatively predict future financial gains, implying that higher prices of rare NFTs mainly come from investors' private enjoyment.

[Table 11 here]

Overall, emotional utility derived from private value assets surpasses financial considerations, suggesting that, from a financial perspective, "love is blind" in this market.

7 Conclusion

Our study investigates the formation of emotional dividends in the non-fungible tokens (NFTs) setting. We construct, validate, and explore the implications of a proxy for emotional dividends, "LOVE," representing the non-financial aspect of NFTs pricing. Our findings have important practical implications for the pricing of private-value assets (e.g., art, collectibles, and vintage wine). First, we propose a proxy for emotional dividends, tackling a long-standing empirical challenge (e.g., Goetzmann (1993); Spaenjers et al. (2015)). Second, we surface novel insights on the determinants of LOVE and their impact on forming private-value asset prices. Finally, we demonstrate that while financial considerations generally influence decisions in financial markets, they appear to be second-order in private-value assets markets.

Our study also provides timely insights into the growing interest in the implications of artificial intelligence to financial markets (e.g., Asker et al. (2021); Cao et al. (2021); Babina et al. (2023); Dou et al. (2024); Kim et al. (2024)). We demonstrate that, while AI-powered algorithms excel in predicting NFT values, their performance is decreasing in LOVE. Furthermore, an economic analysis unveils a negative correlation between LOVE and future financial outcomes, indicating that private-value asset owners may trade off wealth for personal emotional considerations. Altogether, we document evidence suggesting that financially driven AI models may face performance challenges in markets dominated by emotional traders.

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Figure 1. The Market for Crypto Punks
This figure depicts the 12 largest sales and 12 most recent transactions (as of March 30, 2024) for the Crypto Punks NFT collection. Source: https://cryptopunks.app/.

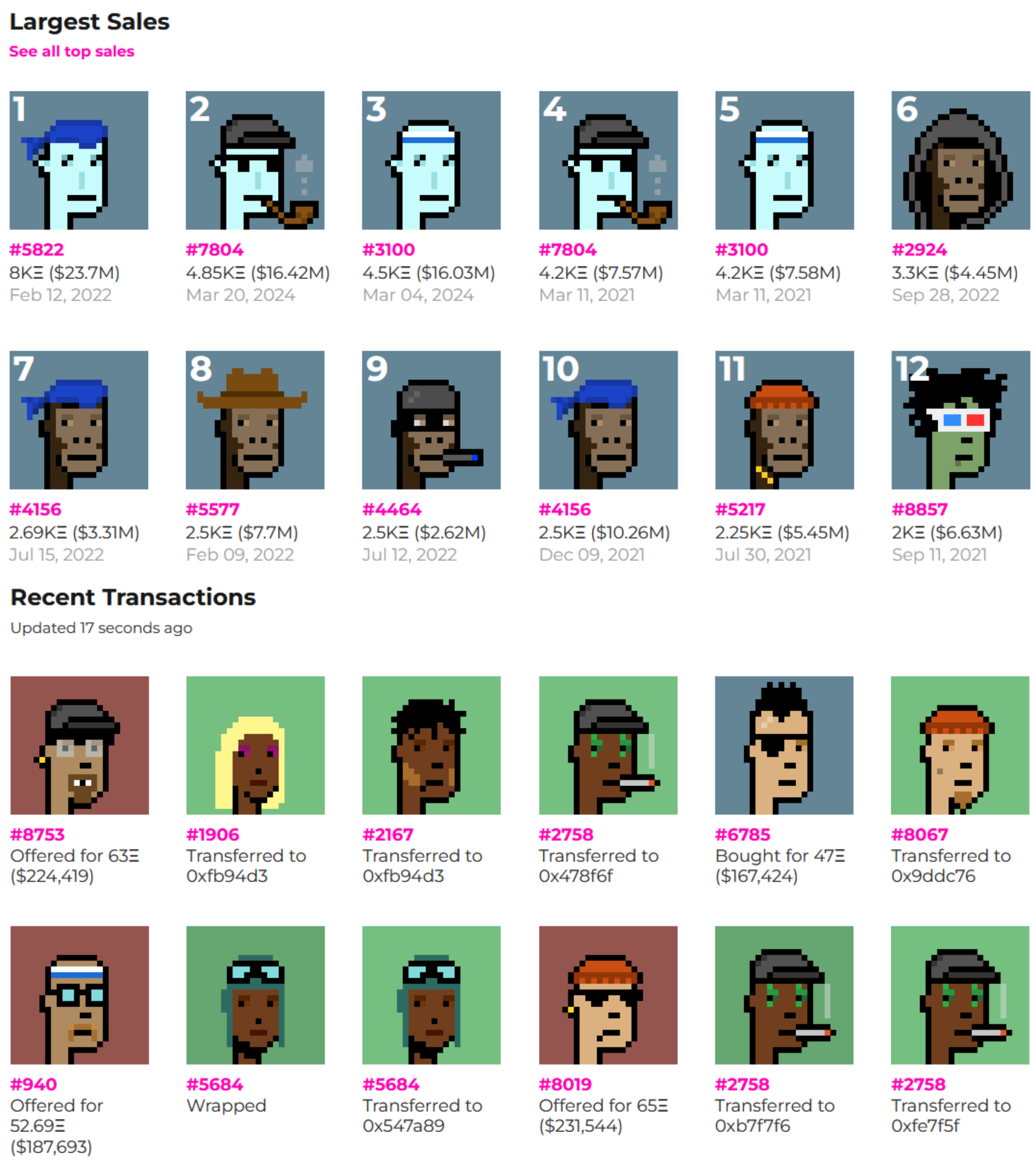


Figure 2. Similarity scores predicted by the ResNet model

This table shows the aggregated similarity scores, as well as sales dates and prices during the testing period, for selected CryptoPunks. We estimate the similarity score for each pair of using Equation 4. The ResNet with 18 layers is employed to predict these similarity scores.

Training image	Testing images		
			
# 6721	# 9612	#1177	# 9848
Similarity score	*0.9935*	*0.9906*	*0.9776*
Sales date	*Nov 11, 2021*	*Oct 1, 2021*	*Oct 10, 2021*
Sales price	*$1.19 million*	*$992,996*	*$1.35 million*

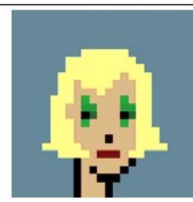
Training image	Testing images		
			
# 9052	# 596	# 1261	# 1411
Similarity score	*0.9914*	*0.9904*	*0.9710*
Sales date	*Oct 5, 2021*	*Nov 7, 2021*	*Nov 9, 2021*
Sales price	*$474,624*	*$569,449*	*$450,889*

Figure 3. Distribution of NFT Sales
This figure depicts the evolution of our sample. The bars represent the monthly number of NFT transactions. The sample period is from June 2017 through December 2022.

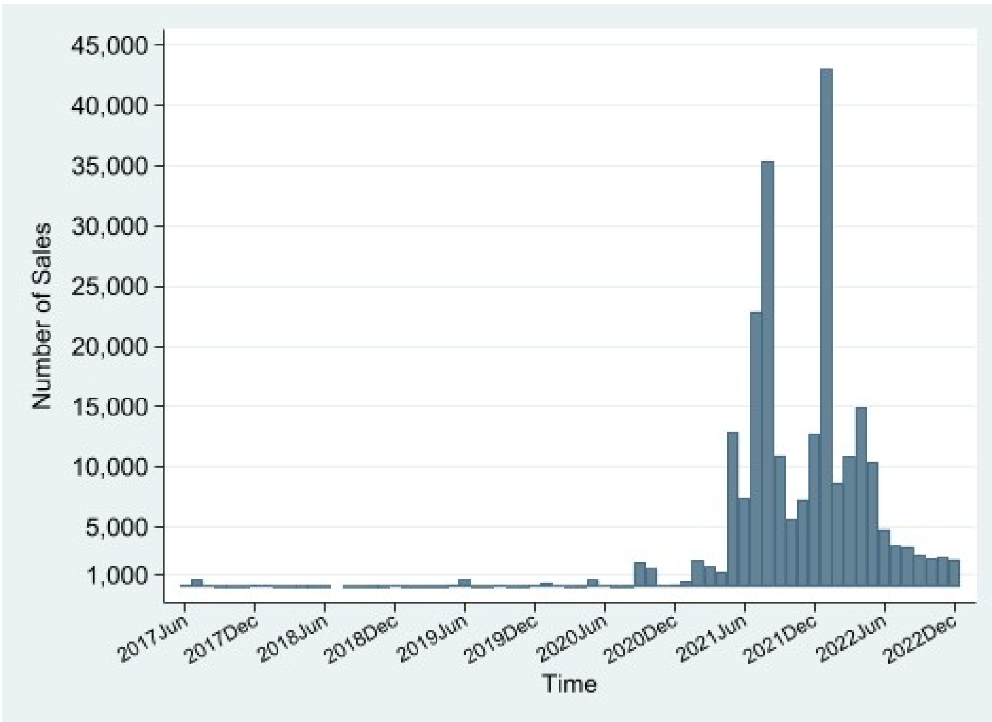
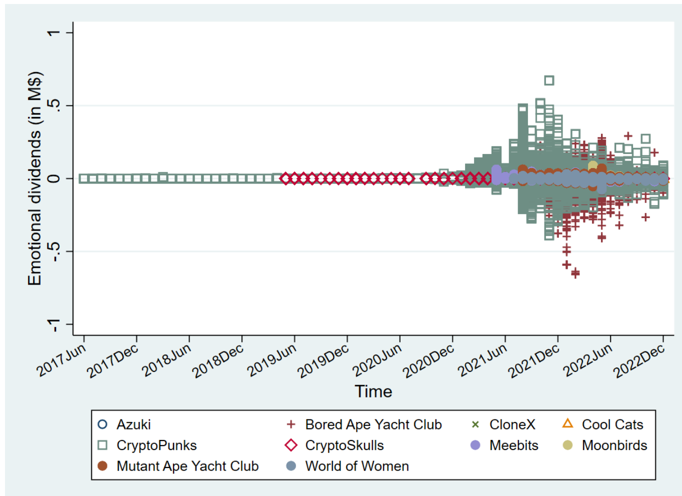
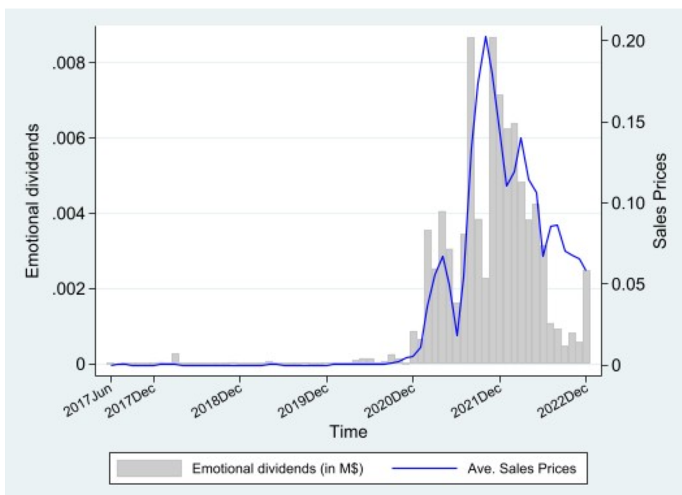


Figure 4. Emotional dividends
This figure shows the distribution of emotional dividends (LOVE) by NFT collection (Panel A), as well as dollar-volume-weighted emotional dividends with weighted sales prices (Panel B) and Google search (Panel C) during our sample period.

A Emotional dividends by NFT collection



B. Emotional dividends and sales prices



C. Emotional dividends and Google search

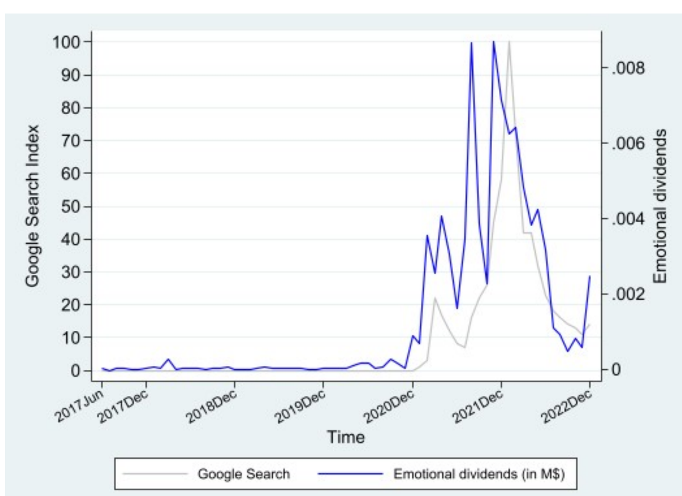
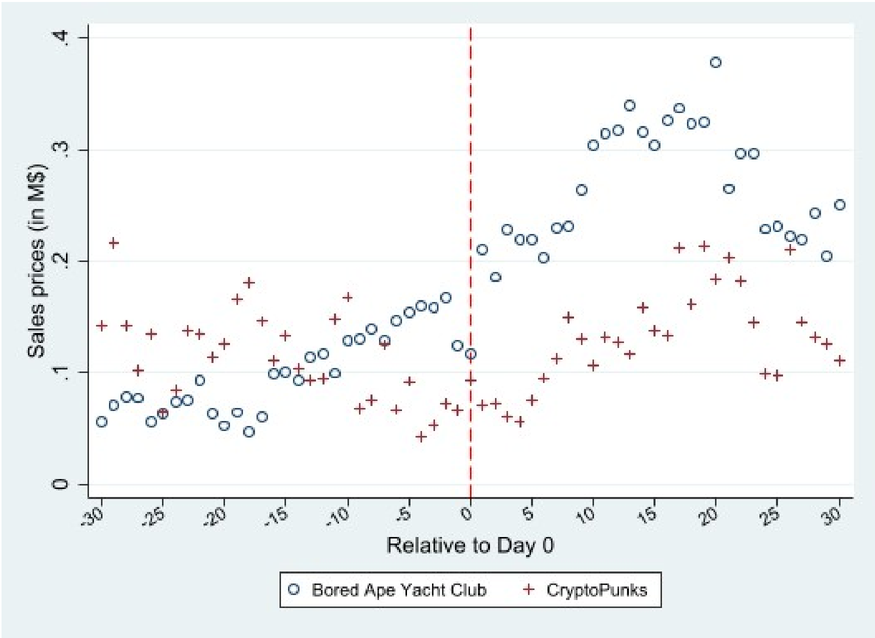


Figure 5. Celebrity endorsements

This figure depicts the sales prices (Panel A) and emotional dividends (Panel B) before and after celebrity endorsements. The x-axis represents the number of days relative to a celebrity endorsement. Each node represents the average sales prices and emotional dividends based on all transactions made on a given day. To avoid any confounding effects, we drop the transactions with more than one endorsement within 30 days. The sale prices and emotional dividends are in millions of US dollars.

A Celebrity endorsements and sales prices



B. Celebrity endorsements and emotional dividends

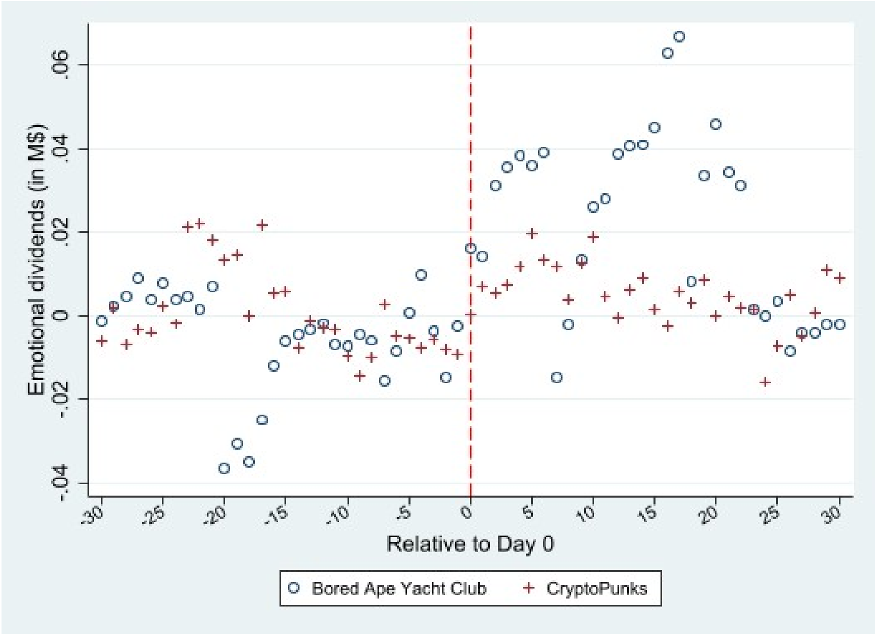


Figure 6. Justin Bieber spends $1.3 million. This figure depicts Justin Bieber's Instagram post related to his NFT purchase. Source: https://www.instagram.com/justinbieber/p/CZZhdyzFITO/.

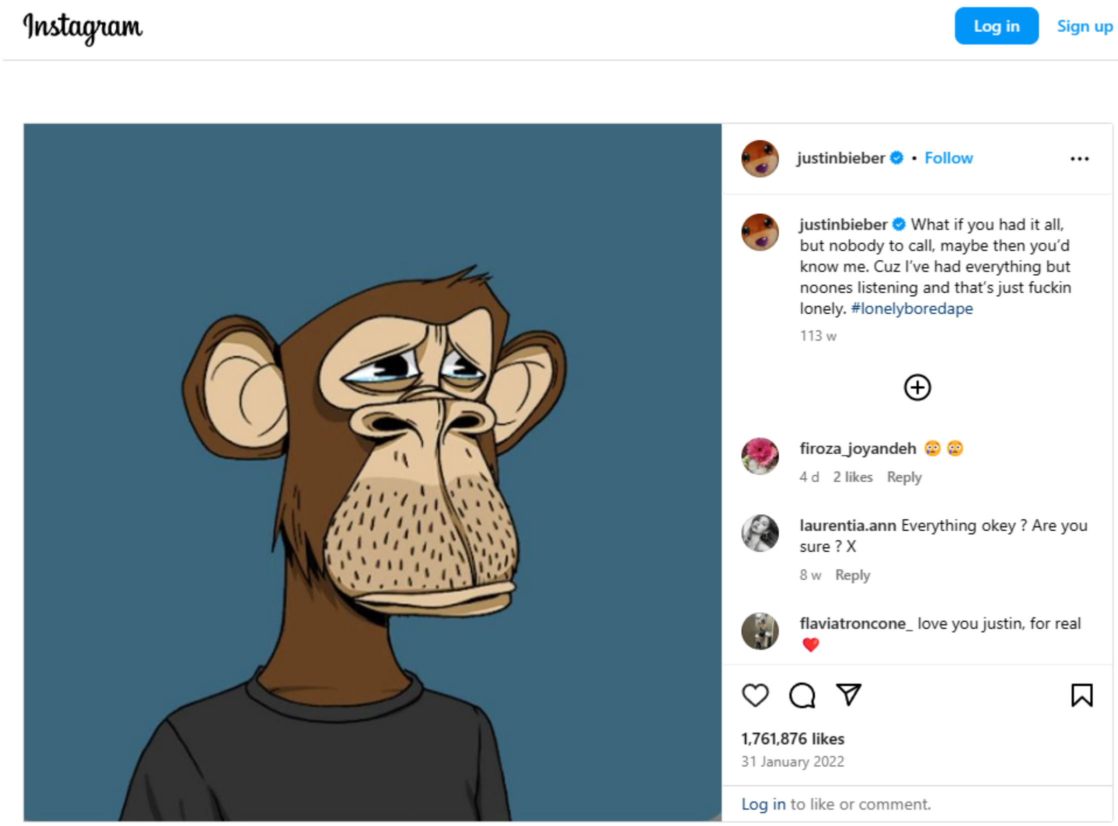


Figure 7. Bored Ape Yacht Club
This figure depicts 24 NFTs for sale in the Bored Ape Yacht Club collection (as of March 30, 2024) via Open Sea, the largest NFT trading platform. Source: https://opensea.io/collection/boredapeyachtclub?tab=items.

Table 1. Sample overview by collection

This table summarizes the information for each collection, as well as the distribution of transactions. The sample period is from June 2017 to December 2022. Our sample includes Azuki, Bored Ape Yacht Club, CloneX, Cool Cats, CryptoPunks, CryptoSkulls, Meebits, Moonbirds, Mutant Ape Yacht Club, and World of Women.

NFT	Supply	Creator fee	Start_Date	Total Txns	Unique Tokens
Azuki	10,000	5.0%	2022/1/12	25,442	8,701
Bored Ape Yacht Club	10,000	2.5%	2021/5/1	27,143	8,761
CloneX	20,000	5.0%	2021/12/12	19,741	9,838
Cool Cats	20,000	5.0%	2021/7/1	30,514	8,310
CryptoPunks	10,000	0.0%	2017/6/23	23,022	6,843
CryptoSkulls	10,000	7.5%	2019/5/18	21,819	7,126
Meebits	20,000	5.0%	2021/5/3	22,722	9,278
Moonbirds	10,000	5.0%	2022/4/16	9,244	5,602
Mutant Ape Yacht Club	19,430	2.5%	2021/8/29	35,460	12,924
World of Women	10,000	4.0%	2021/7/27	24,604	8,995
Total				239,711	86,378

Table 2. Summary statistics

This table presents summary statistics for the key variables used in this paper. The sample period is from June 2017 to December 2022. Appendix 1 provides variable definitions in greater detail.

	N	Mean	P50	Std. dev.
P_USD	239,711	0.036	0.014	0.099
LOVE	239,711	0.002	0.000	0.047
Creatorfee	239,711	0.040	0.050	0.019
NFTAge	239,711	0.796	0.238	1.215
MaxPrice	225,298	0.616	0.207	1.430
minPrice	225,298	0.004	0.000	0.020
TxnRecord	239,711	1.547	1.000	1.807
Rarity_pct	239,710	0.538	0.553	0.285
GaspriceUSD	208,624	0.000	0.000	0.001
GoogleSearch	239,711	38.234	22.000	33.430
ETHRet_30d	239,711	0.022	-0.063	0.289
NumSales_growth	239,650	0.053	0.017	0.349
NumWallets_growth	239,650	0.028	0.015	0.162
NumBuyers_growth	239,650	0.038	0.011	0.211
NumSellers_growth	239,650	0.030	0.027	0.167
SalesUSD_growth	239,650	0.247	0.034	1.109
Buyer_NFTExp	229,023	0.398	0.230	0.578
Buyer_CumNewType	229,023	33.218	12.000	60.661
Buyer_CumNewNFT	229,023	212.081	44.000	561.128
Seller_NFTExp	199,942	0.490	0.326	0.616
Seller_CumNewType	199,942	45.858	21.000	69.662
Seller_CumNewNFT	199,942	321.578	92.000	680.887

Table 3. Correlation matrix of NFT-related variables

This table reports the pairwise correlations of NFT-related variables. Appendix 1 provides variable definitions in greater detail.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Creatorfee	1																	
(2) NFTAge	0.568	1																
(3) MaxPrice	-0.161	-0.154	1															
(4) minPrice	-0.113	0.058	0.058	1														
(5) TxnRecord	-0.007	0.225	0.013	0.117	1													
(6) Rarity_pct	-0.045	-0.047	0.013	0.010	0.132	1												
(7) GaspriceUSD	0.023	0.033	0.036	-0.005	-0.006	-0.012	1											
(8) GoogleSearch	0.325	0.323	-0.022	-0.066	0.012	-0.050	0.157	1										
(9) ETHRet_30d	-0.208	-0.228	0.209	-0.064	-0.047	0.020	-0.005	-0.451	1									
(10) NumSales_growth	0.048	0.124	-0.069	0.042	0.010	-0.007	0.015	0.039	-0.095	1								
(11) NumWallets_growth	0.027	0.081	-0.072	0.050	-0.010	-0.007	0.019	0.015	-0.051	0.799	1							
(12) SalesUSD_growth	-0.080	-0.019	-0.053	0.123	0.000	0.002	0.006	-0.053	0.017	0.524	0.562	1						
(13) Buyer_NFTExp	0.081	0.060	-0.041	0.029	0.017	-0.006	0.003	-0.001	-0.053	-0.012	-0.014	-0.006	1					
(14) Buyer_CumNewType	0.107	0.090	-0.075	0.082	0.048	-0.005	0.038	0.105	-0.134	0.002	-0.006	-0.001	0.313	1				
(15) Buyer_CumNewNFT	0.061	0.011	-0.024	0.038	0.001	-0.010	0.012	0.044	-0.057	-0.004	-0.004	0.000	0.320	0.738	1			
(16) Seller_NFTExp	0.070	0.127	-0.029	0.035	-0.048	-0.013	-0.012	0.015	-0.057	0.008	0.004	0.007	0.039	0.053	0.025	1		
(17) Seller_CumNewType	0.148	0.173	-0.089	0.084	0.017	-0.036	0.008	0.145	-0.152	0.028	0.011	-0.010	0.054	0.121	0.051	0.309	1	
(18) Seller_CumNewNFT	0.100	0.085	-0.044	0.029	-0.075	-0.028	0.003	0.062	-0.064	0.025	0.016	-0.002	0.024	0.052	0.027	0.345	0.714	1

Table 4. Hedonic regression models
This table reports the explanatory power and number of observations in the hedonic regressions. The data on token attributes are obtained from OpenSea. Fixed effects are included as specified.

	Azuki	BoredApe	CloneX	CoolCats	CryptoPunks
	(1)	(2)	(3)	(4)	(5)
Observations	25,442	27,143	19,741	30,514	23,022
R-squared	0.687	0.929	0.654	0.783	0.976
Year-Month dummies	Yes	Yes	Yes	Yes	Yes
Attribute dummies	Yes	Yes	Yes	Yes	Yes
	CryptoSkulls	**Meebits**	**Moonbirds**	**MutantApe**	**World Of Women**
	(6)	(7)	(8)	(9)	(10)
Observations	21,819	22,722	9,244	35,460	24,604
R-squared	0.795	0.701	0.449	0.678	0.772
Year-Month dummies	Yes	Yes	Yes	Yes	Yes
Attribute dummies	Yes	Yes	Yes	Yes	Yes

Table 5. Celebrity endorsements

This table reports the difference in mean before and after celebrity endorsements. Endorsement is a dummy variable that equals one if an NFT transaction occurs within ten days after a celebrity's endorsement for a collection, and zero otherwise. Panel A incorporates NFT transactions from both the CryptoPunks and Bored Ape Yacht Club. Panels B and C focus solely on NFT transactions from the CryptoPunks and Bored Ape Yacht Club, respectively. Standard errors are reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. The CryptoPunks & Bored Ape Yacht Club

Variable	Endorsement=0	Endorsement=1	Diff
LOVE	0.001	0.025	0.0238***
	[0.000]	[0.001]	[0.0012]
$\sigma(LOVE)$	0.035	0.092	0.0569***
	[0.000]	[0.001]	[0.0010]

Panel B. The CryptoPunks

Variable	Endorsement=0	Endorsement=1	Diff
LOVE	0.003	0.022	0.0189***
	[0.001]	[0.002]	[0.0020]
$\sigma(LOVE)$	0.054	0.087	0.0336***
	[0.001]	[0.001]	[0.0017]

Panel C. Bored Ape Yacht Club

Variable	Endorsement=0	Endorsement=1	Diff
LOVE	-0.001	0.031	0.0312***
	[0.000]	[0.002]	[0.0011]
$\sigma(LOVE)$	0.024	0.103	0.0788***
	[0.000]	[0.001]	[0.0008]

Table 6. Performance metrics for machine learning models

This table reports the performance metrics for Lasso, elastic net (ENet), partial least squares (PLS), random forest (RF), gradient boosted regression trees (GBRT), and neural network (with 1, 3, and 5 layers (NN1, NN2, and NN5)) models. We adopt three performance metrics, including the out-of-sample R^2 (R^2_{oos}), mean squared error (MSE), and mean absolute error (MAE).

	Lasso	ENet	PLS	RF	GBRT	NN1	NN3	NN5
R^2_{oos}	0.0154	0.0196	0.0219	0.2306	0.1944	0.0363	0.0434	0.1101
MSE	0.0006	0.0006	0.0006	0.0005	0.0005	0.0006	0.0006	0.0006
MAE	0.0082	0.0082	0.0083	0.0064	0.0061	0.0095	0.0087	0.0085

Table 7. Feature importance for the training sample

This table reports the rankings of feature importance by each model for the training sample. The relative importance of each feature is estimated based on mean decreased accuracy (MDA). A lower value of ranking indicates that a feature is more important in explaining a given model. Appendix 1 provides variable definitions in greater detail.

Variable	Lasso	ENet	PLS	RF	GBRT	NN1	NN3	NN5	Average Ranking
MaxPrice	2	2	3	1	1	1	1	2	1.625
minPrice	1	1	1	3	2	7	4	7	3.250
ETHRet_30d	3	3	2	5	5	5	5	4	4.000
NFTAge	6	5	4	4	3	3	7	5	4.625
GoogleSearch	5	4	5	8	8	4	6	6	5.750
Rarity_pct	7	10	12	2	4	6	3	3	5.875
Creatorfee	8	7	6	14	10	2	2	1	6.250
SalesUSD_growth	4	6	7	12	7	9	8	8	7.625
NumWallets_growth	18	9	8	10	6	8	9	10	9.750
Buyer_CumNewType	12	13	9	13	12	13	10	13	11.875
TxnRecord	9	8	10	18	17	10	14	9	11.875
Buyer_CumNewNFT	13	14	11	6	15	15	15	15	13.000
NumSales_growth	17	18	13	15	9	11	12	12	13.375
GaspriceUSD	10	11	17	7	13	18	17	18	13.875
Buyer_NFTExp	11	12	15	16	11	14	18	14	13.875
Seller_CumNewNFT	16	17	14	11	16	17	11	11	14.125
Seller_NFTExp	14	15	16	9	14	16	13	16	14.125
Seller_CumNewType	15	16	18	17	18	12	16	17	16.125

Table 8. Feature importance for the testing sample

This table reports the rankings of feature importance by each model for the testing sample. The relative importance of each feature is estimated based on mean decreased accuracy (MDA). A lower value of ranking indicates that a feature is more important in explaining a given model. Appendix 1 provides variable definitions in greater detail.

Variable	Lasso	ENet	PLS	RF	GBRT	NN1	NN3	NN5	Average Ranking
MaxPrice	2	2	2	1	1	2	1	2	1.625
minPrice	1	1	1	3	2	7	7	6	3.500
ETHRet_30d	3	3	3	5	5	5	4	5	4.125
NFTAge	6	6	5	2	3	3	6	4	4.375
Creatorfee	9	7	6	7	9	1	2	1	5.250
GoogleSearch	5	4	4	6	8	4	5	7	5.375
Rarity_pct	7	10	12	4	4	6	3	3	6.125
SalesUSD_growth	4	5	7	9	7	8	8	8	7.000
NumWallets_growth	18	8	8	8	6	9	17	10	10.500
Buyer_CumNewType	12	13	9	11	11	13	10	12	11.375
TxnRecord	8	9	10	18	15	10	11	13	11.750
NumSales_growth	17	18	11	13	10	11	9	9	12.250
Buyer_CumNewNFT	13	14	14	14	14	12	12	18	13.875
GaspriceUSD	10	11	18	10	13	17	16	17	14.000
Seller_CumNewNFT	16	17	13	12	18	15	13	11	14.375
Buyer_NFTExp	11	12	17	16	12	16	15	16	14.375
Seller_NFTExp	14	15	16	15	17	18	14	15	15.500
Seller_CumNewType	15	16	15	17	16	14	18	14	15.625

Table 9. Predictive performance using AI-powered trading

This table presents the average NFT prices, sorted based on the similarity scores estimated using the ResNet with 18 layers. We train the ResNet model using images of the top 1% most valuable NFTs up to month t. We evaluate high-value NFTs using three benchmarks: sales prices, predicted prices, and emotional dividends in Panel A, B, and C, respectively. We calculate a similarity score for each pair of training images and testing images and aggregate the similarity scores to get an overall similarity score for each testing image. The resulting scores indicate how similar each testing image is to a group of training images. Finally, we classify NFTs into three groups based on their similarity scores for sales occurring from month t+1 to month t+3 during the testing period. The prices are in millions of US dollars.

Panel A. Predictions based on the NFTs with the top 1% sales prices

Similarity	Sales Price	Predicted Price	Emotional Dividend
1 (Low)	0.107	0.096	0.011
2	0.111	0.098	0.013
3 (High)	0.116	0.102	0.015

Panel B. Predictions based on the NFTs with the top 1% predicted prices

Similarity	Sales Price	Predicted Price	Emotional Dividend
1 (Low)	0.106	0.095	0.011
2	0.112	0.098	0.014
3 (High)	0.116	0.103	0.013

Panel C. Predictions based on the NFTs with the top 1% emotional dividend

Similarity	Sales Price	Predicted Price	Emotional Dividend
1 (Low)	0.111	0.099	0.012
2	0.112	0.099	0.013
3 (High)	0.111	0.098	0.014

Table 10. Portfolio performance using visual similarity scores

This table presents the portfolio returns over different holding periods. We form three portfolios for each testing period by sorting NFTs based on their visual similarity scores estimated from the ResNet with 18 layers. Panels A, B, and C report the average portfolio returns using predictions based on the top 1% of NFT sales prices, predicted prices, and emotional dividends, respectively. Given that NFTs are traded at different frequencies, we convert NFT returns to a monthly equivalent for easier comparison of returns over different holding periods. Portfolio returns are equally weighted and standardized on a monthly basis.

Panel A. Portfolio returns based on the top 1% NFT sales prices

	Average monthly return			
	11-60 days	61-120 days	121-180 days	181-360 days
1 (Low)	75.90%	49.90%	62.70%	194.20%
2	100.00%	63.30%	67.90%	215.70%
3 (High)	94.60%	58.50%	80.60%	244.10%
High-Low	18.70%	8.60%	17.90%	49.90%

Panel B. Portfolio returns based on the top 1% NFT predicted prices

	Average monthly return			
	11-60 days	61-120 days	121-180 days	181-360 days
1 (Low)	85.10%	49.50%	62.00%	190.30%
2	86.30%	58.70%	65.20%	218.10%
3 (High)	92.70%	61.30%	81.40%	254.20%
High-Low	7.60%	11.80%	19.40%	63.90%

Panel C. Portfolio returns based on the top 1% NFT emotional dividends

	Average monthly return			
	11-60 days	61-120 days	121-180 days	181-360 days
1 (Low)	73.10%	52.90%	62.70%	211.40%
2	112.80%	48.50%	78.90%	201.10%
3 (High)	94.40%	68.10%	66.80%	240.50%
High-Low	21.30%	15.20%	4.10%	29.10%

Table 11. Emotional dividends and financial gains

This table reports regression estimates of financial gains on emotional dividends and control variables. The dependent variable, financial gains, is defined as the proceeds from the resale less the purchase costs of a given NFT. Emotional dividends and financial gains are denominated in millions of US dollars. To mitigate the influence of outliers, we winsorize emotional dividends and financial gains at the 1st and 99th percentiles. Standard errors are clustered at the token level. Appendix 1 provides variable definitions in greater detail.

	(1)	(2)	(3)	(4)
LOVE	-0.386***	-0.435***	-0.422***	-0.393***
	(0.011)	(0.012)	(0.013)	(0.013)
Rarity_pct		-0.007***	-0.006***	-0.006***
		(0.000)	(0.000)	(0.000)
TxnRecord		0.000***	-0.001***	0.000***
		(0.000)	(0.000)	(0.000)
HoldPeriod		0.032***	0.025***	0.031***
		(0.001)	(0.000)	(0.001)
MaxPrice		0.006***	0.006***	0.005***
		(0.000)	(0.000)	(0.000)
minPrice		0.119***	0.082***	0.119***
		(0.012)	(0.012)	(0.012)
ETHRet_30d		0.028***	0.028***	0.026***
		(0.000)	(0.000)	(0.000)
GoogleSearch		0.001***	0.000***	0.001***
		(0.000)	(0.000)	(0.000)
Creatorfee				-0.389***
				(0.009)
Observations	152,089	149,468	149,468	149,468
Adjusted R-squared	0.187	0.351	0.303	0.293
Controls	No	Yes	Yes	Yes
Collection FE	Yes	Yes	Yes	No
YearMonth FE	Yes	Yes	No	Yes

Appendices for:

Is Love Blind? AI-Powered Trading with Emotional Dividends

De-Rong Kong and Daniel Rabetti (July 2024)

Appendix 1. Definition of Variables

Variable	Definition
Panel A. Asset characteristics	
P_USD	NFT price ($M) on date t.
LOVE	Emotional dividend ($M), the residuals from the hedonic models.
Creatorfee	Collection-level fees paid out to creators when NFTs are resold.
NFTAge	The years since an NFT collection was issued on date t.
MaxPrice	The highest price ($M) within a given NFT collection over the past 30 days.
minPrice	The lowest price ($M) within a given NFT collection over the past 30 days.
TxnRecord	Number of sales records for an NFT before date t.
Rarity_pct	An overall rarity score for an NFT, provided by Rarity.Tools.
Panel B. Market variables	
GaspriceUSD	The cost per unit of gas for a transaction. The unit is converted into USD.
GoogleSearch	Google searches for the topic regarding "non-fungible token."
ETHRet_30d	The growth rate of ETH prices in the past 30 days.
NumSales_growth	The growth of NFT sales on date t.
NumWallets_growth	The growth of unique wallets in the NFT market on date t.
SalesUSD_growth	The growth of NFT sales volume (in USD) on date t.
Panel C. Investor attributes	
HoldPeriod	Number of years between the purchase and sales of an NFT by a buyer.
Buyer_NFTExp	Number of years since the first NFT trade by a buyer up to date t.
Buyer_CumNewType	Number of new NFT types collected by a buyer up to date t.
Buyer_CumNewNFT	Number of new NFT collected by a buyer up to date t.
Seller_NFTExp	Number of years since the first NFT trade by a seller up to date t.
Seller_CumNewType	Number of new NFT types collected by a seller up to date t.
Seller_CumNewNFT	Number of new NFT collected by a seller up to date t.

Appendix 2. Celebrity list

This table reports the celebrity buyers of the NFT projects, the CryptoPunks and Bored Ape Yacht Club. We present the NFT project name, token ID, transaction date, the celebrity name, celebrity description.

NFT	Token ID	Date	Celebrity name	Celebrity description
Bored Ape Yacht Club	1442	2021/8/21	Logan Paul	Influencer & YouTuber
Bored Ape Yacht Club	7990	2021/8/28	Stephen Curry	NBA basketball player
Bored Ape Yacht Club	961	2021/10/29	Post Malone	CEO of VaynerMedia & VeeFriends
Bored Ape Yacht Club	599	2021/11/8	Jimmy Fallon	American television host & producer
Bored Ape Yacht Club	9055	2021/12/31	Eminem	American singer
Bored Ape Yacht Club	5269,6633	2022/1/20	Neymar Júnior	Brazilian football player
Bored Ape Yacht Club	1294	2022/1/22	Paris Hilton	American socialite
Bored Ape Yacht Club	3001	2022/1/29	Justin Bieber	Canadian singer
Bored Ape Yacht Club	4988	2022/3/14	Madonna	American singer
CryptoPunks	1558, 6156	2021/2/17	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends
CryptoPunks	7391,9871	2021/2/17	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends
CryptoPunks	7459	2021/3/6	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends
CryptoPunks	5339	2021/3/14	Alexis Ohanian	Co-founder of Reddit
CryptoPunks	1719	2021/4/14	Tobi Lutke	CEO & Founder of Shopify
CryptoPunks	6095	2021/4/25	Jay-Z (Shawn Carter)	American singer
CryptoPunks	2424	2021/5/24	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends
CryptoPunks	4072	2021/6/17	Alexis Ohanian	Co-founder of Reddit
CryptoPunks	1006, 7936	2021/6/25	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends
CryptoPunks	2950	2021/6/28	Alexis Ohanian	Co-founder of Reddit
CryptoPunks	5955	2021/7/5	Alexis Ohanian	Co-founder of Reddit
CryptoPunks	7873, 8352	2021/7/11	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends
CryptoPunks	3435	2021/7/14	Alexis Ohanian	Co-founder of Reddit
CryptoPunks	3109	2021/7/22	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends
CryptoPunks	2140	2021/7/30	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends
CryptoPunks	6473	2021/7/30	Steve Aoki	American DJ
CryptoPunks	1302	2021/8/7	Alexis Ohanian	Co-founder of Reddit
CryptoPunks	8115	2021/8/21	Alexis Ohanian	Co-founder of Reddit
CryptoPunks	6633	2021/12/24	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends
CryptoPunks	7605	2022/1/17	Deepak Thapliyal	CEO of Chain
CryptoPunks	5822	2022/2/12	Deepak Thapliyal	CEO of Chain
CryptoPunks	5690	2022/6/14	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends
CryptoPunks	3022, 8801	2022/6/18	Gary Vaynerchuk	CEO of VaynerMedia & VeeFriends

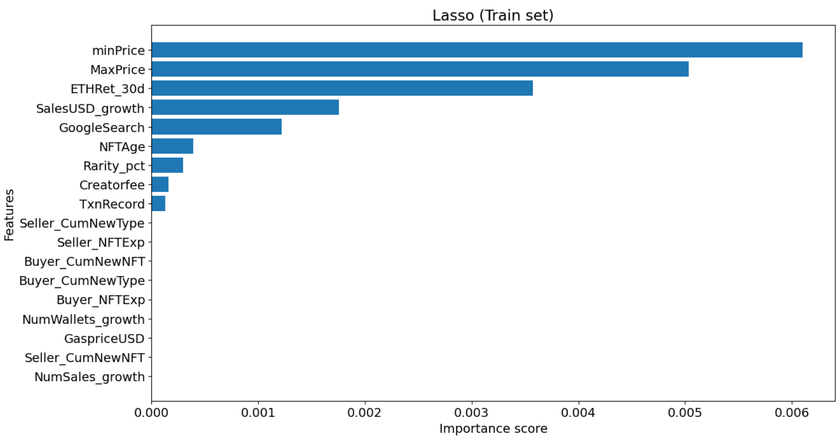
Appendix 3. Hyperparameter tuning

This table describes the hyperparameters that we tune in each machine learning model.

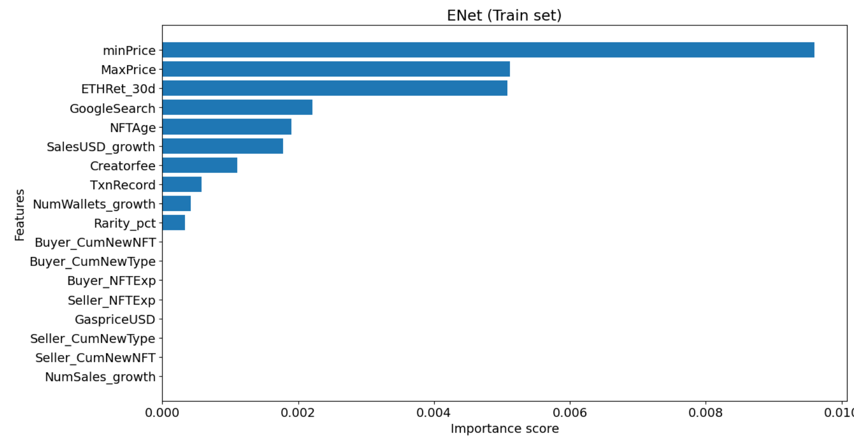
	Lasso model		ENet model		PLS model	
	λ	$[10^{-4}, 10^{-1}]$	ρ	0.5	#Components	$\{2,4,6,8,10\}$
Hyperparameters	Epochs	100	λ	$[10^{-4}, 10^{-1}]$	Epochs	100
			Epochs	100		
	Random Forest		**GBRT**		**NN model**	
	#Trees	$\{100, 300\}$	#Trees	$\{100, 500, 1000\}$	#L1 penalty	$\{10^{-5}, 10^{-3}\}$
Hyperparameters	Max_depth	1~10	Max_depth	$\{1, 2\}$	Learning_rate	$\{10^{-3}, 10^{-2}\}$
	Max_features	$\{4, 6, 8\}$	Learning_rate	$\{0.01, 0.1\}$	Batch_size	$\{1000, 10000\}$
					Epochs	100

Appendix 4. Feature importance using the training sample

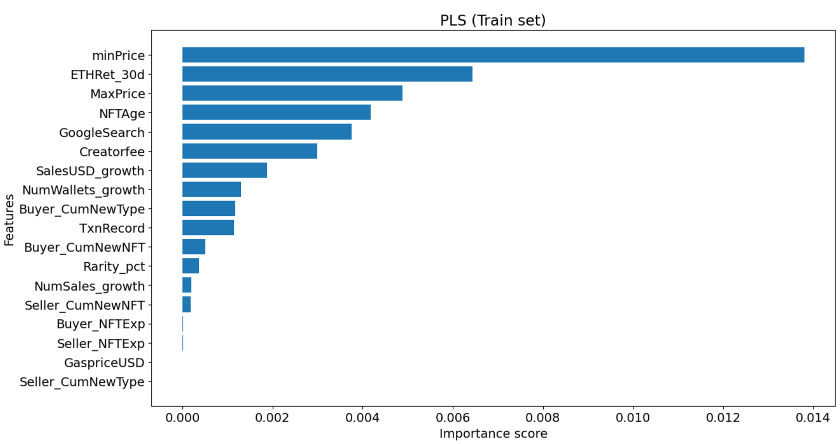
This figure depicts the feature importance score of the variables in each model. Feature importance is measured based on mean decreased accuracy (MDA). Appendix 1 provides variable definitions in greater detail.



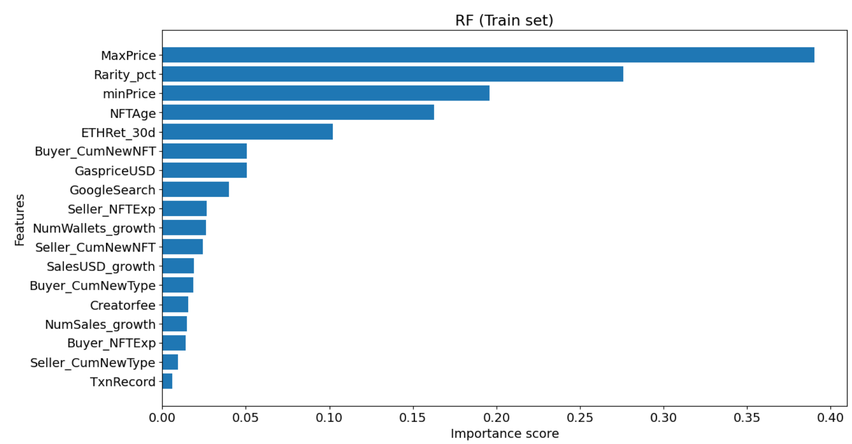
(a) Lasso



(b) ENet



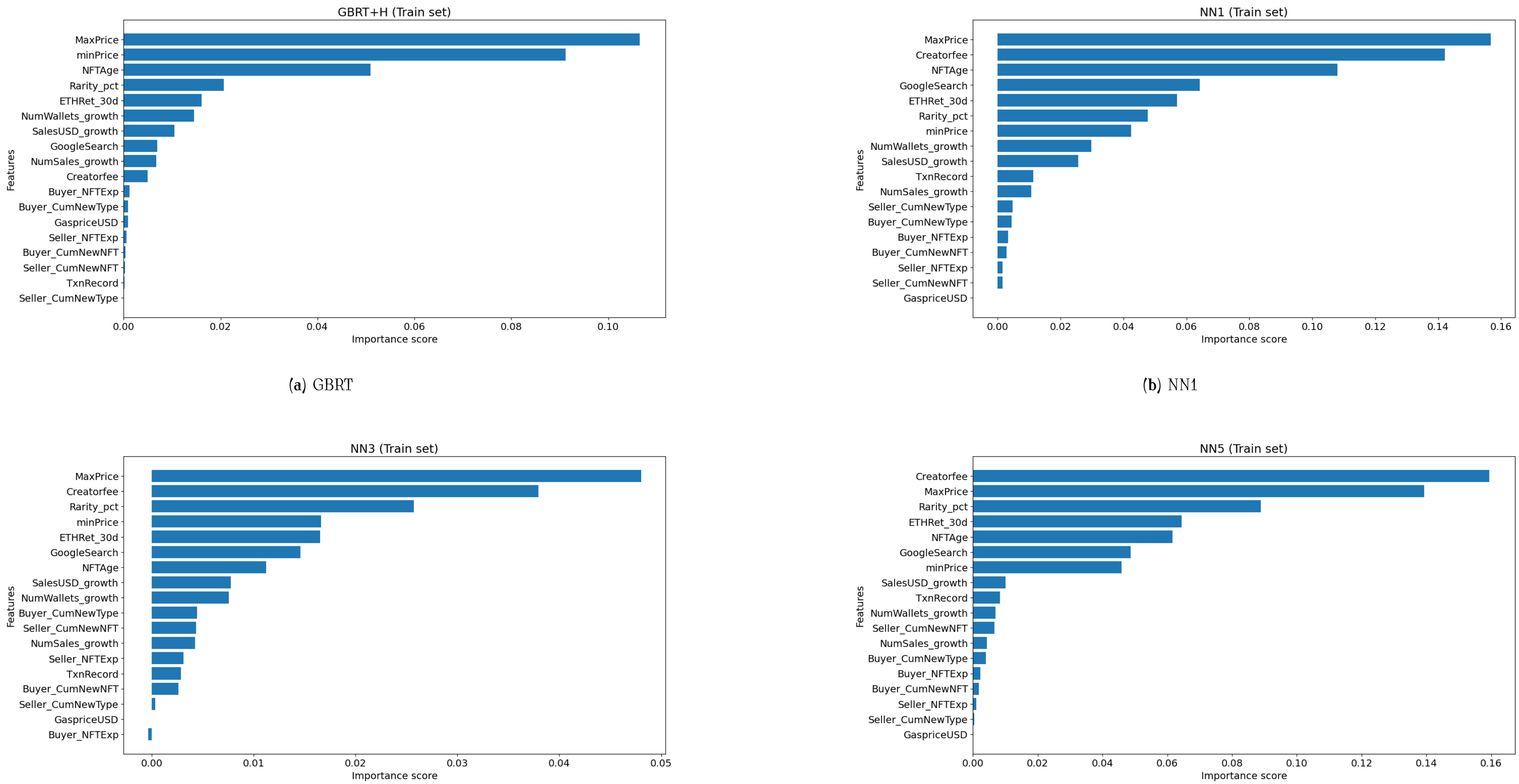
(c) PLS



(d) RF

Appendix 4. - Continuation.

This figure depicts the feature importance score of the variables in each model. Feature importance is measured based on mean decreased accuracy (MDA). Appendix 1 provides variable definitions in greater detail.



(a) GBRT

(b) NN1

(c) NN3

(d) NN5

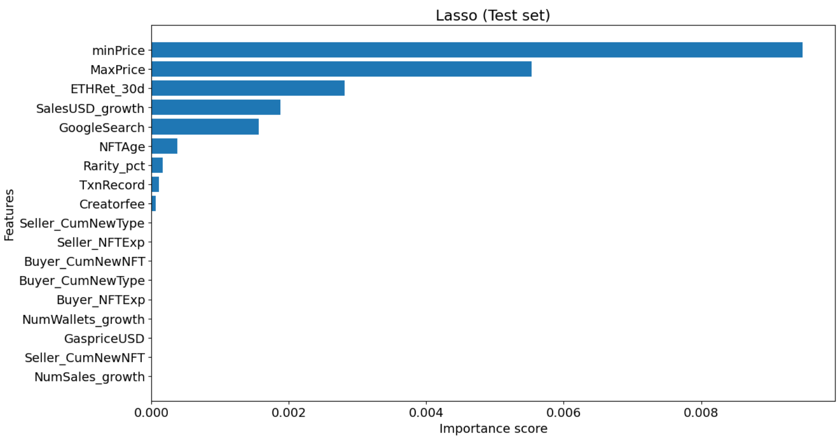
Appendix 5. MDA for the training sample

This table reports the mean decreased accuracy (MDA) of features by model for the training sample. MDA is defined as the reduction in the R^2 score of a model when a feature's value is randomly shuffled while keeping the other features intact. Appendix 1 provides variable definitions in greater detail.

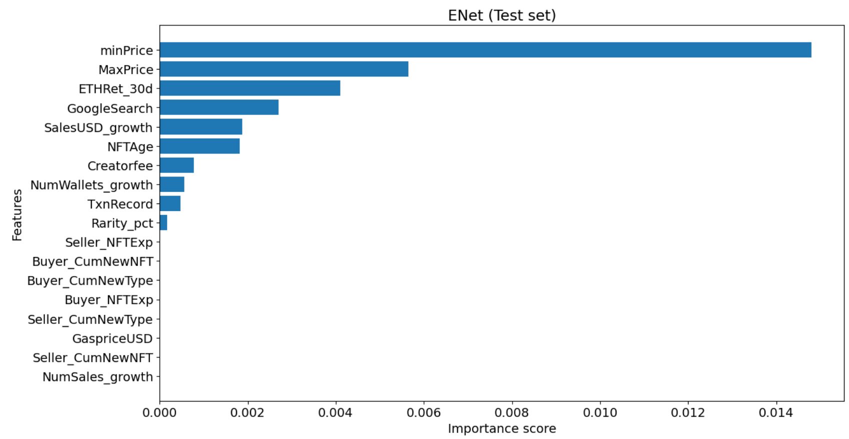
Variable	Lasso	ENet	PLS	RF	GBRT	NN1	NN3	NN5
MaxPrice	0.005	0.005	0.005	0.390	0.107	0.157	0.048	0.139
minPrice	0.006	0.010	0.014	0.196	0.091	0.042	0.017	0.046
ETHRet_30d	0.004	0.005	0.006	0.102	0.016	0.057	0.017	0.064
NFTAge	0.000	0.002	0.004	0.163	0.051	0.108	0.011	0.062
GoogleSearch	0.001	0.002	0.004	0.040	0.007	0.064	0.015	0.049
Rarity_pct	0.000	0.000	0.000	0.276	0.021	0.048	0.026	0.089
Creatorfee	0.000	0.001	0.003	0.015	0.005	0.142	0.038	0.159
SalesUSD_growth	0.002	0.002	0.002	0.019	0.010	0.026	0.008	0.010
NumWallets_growth	0.000	0.000	0.001	0.026	0.015	0.030	0.008	0.007
TxnRecord	0.000	0.001	0.001	0.006	0.000	0.011	0.003	0.008
Buyer_CumNewType	0.000	0.000	0.001	0.019	0.001	0.004	0.004	0.004
Buyer_CumNewNFT	0.000	0.000	0.001	0.050	0.000	0.003	0.003	0.002
NumSales_growth	0.000	0.000	0.000	0.015	0.007	0.011	0.004	0.004
GaspriceUSD	0.000	0.000	0.000	0.050	0.001	0.000	0.000	0.000
Buyer_NFTExp	0.000	0.000	0.000	0.014	0.001	0.003	0.000	0.002
Seller_NFTExp	0.000	0.000	0.000	0.026	0.001	0.002	0.003	0.001
Seller_CumNewNFT	0.000	0.000	0.000	0.024	0.000	0.002	0.004	0.007
Seller_CumNewType	0.000	0.000	0.000	0.009	0.000	0.005	0.000	0.000

Appendix 6. Feature importance using the testing sample

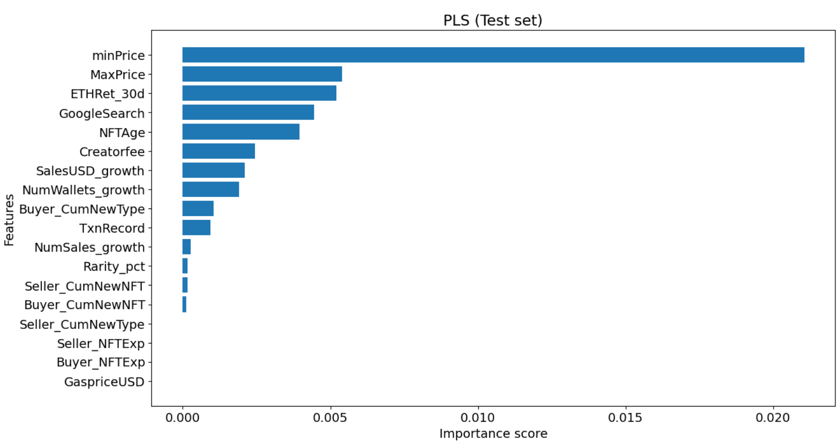
This figure depicts the feature importance score of the variables in each model. Feature importance is measured based on mean decreased accuracy (MDA). Appendix 1 provides variable definitions in greater detail.



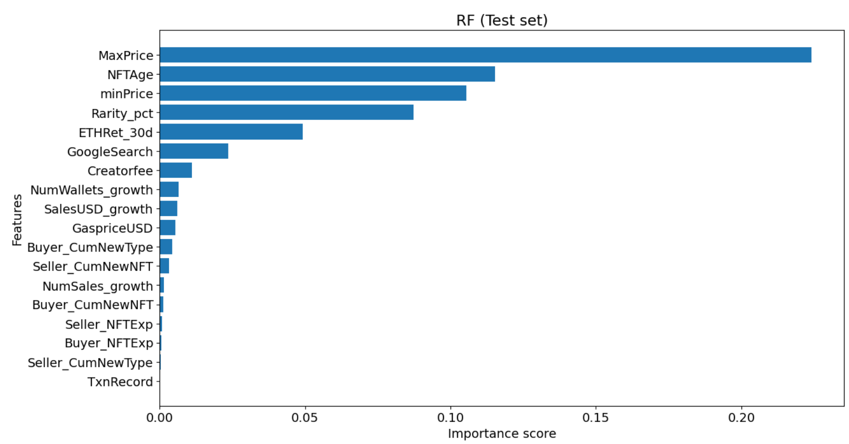
(a) Lasso



(b) ENet



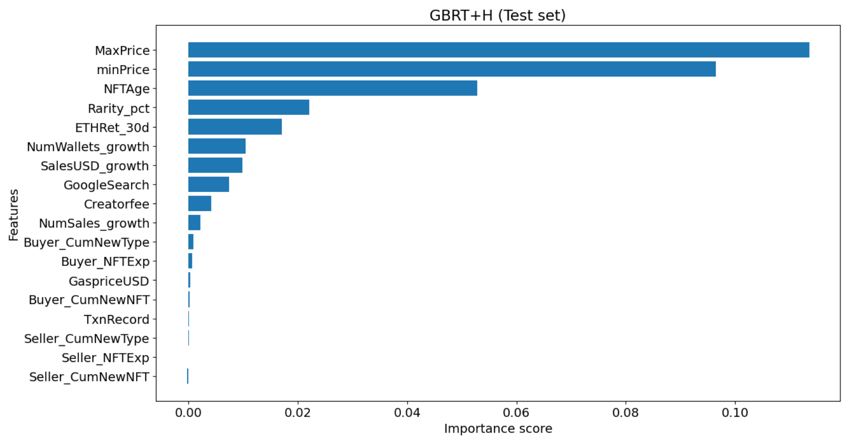
(c) PLS



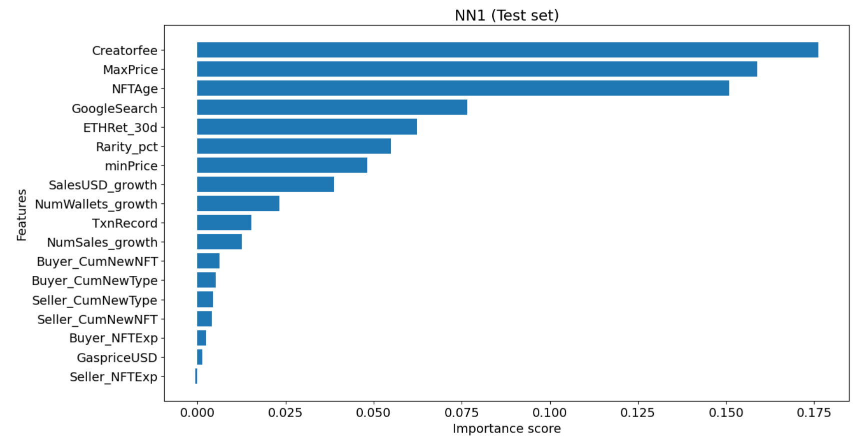
(d) RF

Appendix 6 - Continuation.

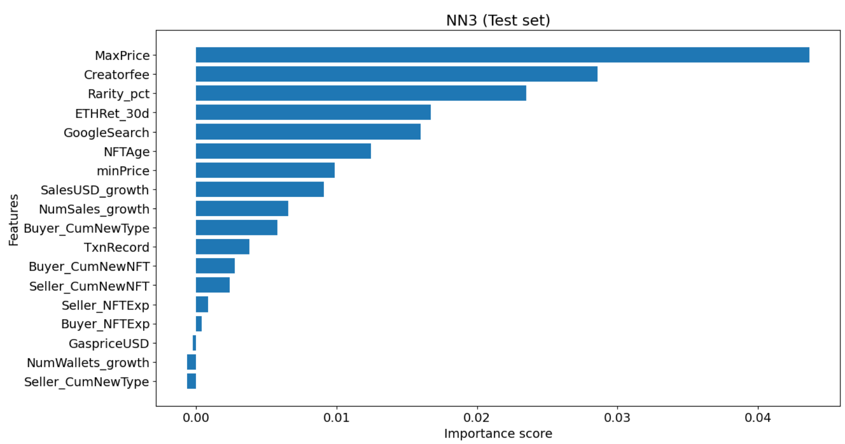
This figure depicts the feature importance score of the variables in each model. Feature importance is measured based on mean decreased accuracy (MDA). Appendix 1 provides variable definitions in greater detail.



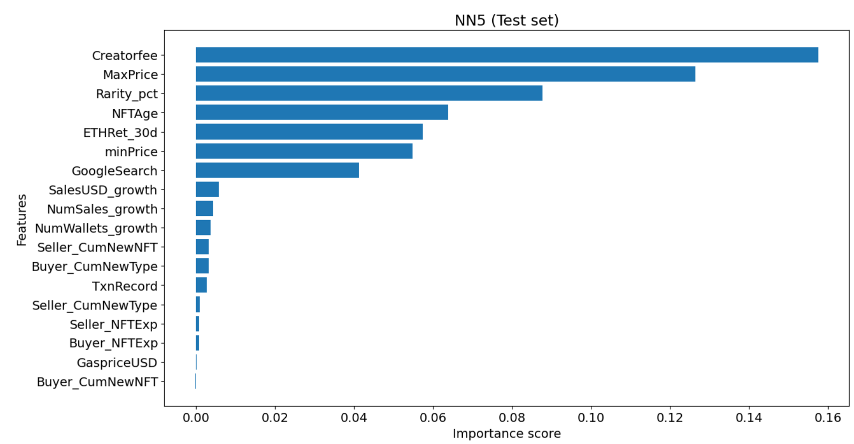
(a) GBRT



(b) NN1



(c) NN3



(d) NN5

Appendix 7. MDA for the testing sample

This table reports the mean decreased accuracy (MDA) of features by model for the testing sample. MDA is defined as the reduction in the R^2 score of a model when a feature's value is randomly shuffled while keeping the other features intact. Appendix 1 provides variable definitions in greater detail.

Variable	Lasso	ENet	PLS	RF	GBRT	NN1	NN3	NN5
MaxPrice	0.006	0.006	0.005	0.224	0.114	0.159	0.044	0.126
minPrice	0.009	0.015	0.021	0.105	0.097	0.048	0.010	0.055
ETHRet_30d	0.003	0.004	0.005	0.049	0.017	0.062	0.017	0.057
NFTAge	0.000	0.002	0.004	0.115	0.053	0.151	0.012	0.064
Creatorfee	0.000	0.001	0.002	0.011	0.004	0.176	0.029	0.157
GoogleSearch	0.002	0.003	0.004	0.024	0.007	0.077	0.016	0.041
Rarity_pct	0.000	0.000	0.000	0.087	0.022	0.055	0.024	0.088
SalesUSD_growth	0.002	0.002	0.002	0.006	0.010	0.039	0.009	0.006
NumWallets_growth	0.000	0.001	0.002	0.007	0.010	0.023	-0.001	0.004
Buyer_CumNewType	0.000	0.000	0.001	0.004	0.001	0.005	0.006	0.003
TxnRecord	0.000	0.000	0.001	0.000	0.000	0.015	0.004	0.003
NumSales_growth	0.000	0.000	0.000	0.002	0.002	0.013	0.007	0.004
Buyer_CumNewNFT	0.000	0.000	0.000	0.001	0.000	0.006	0.003	0.000
GaspriceUSD	0.000	0.000	0.000	0.006	0.000	0.001	0.000	0.000
Seller_CumNewNFT	0.000	0.000	0.000	0.003	0.000	0.004	0.002	0.003
Buyer_NFTExp	0.000	0.000	0.000	0.001	0.001	0.002	0.000	0.001
Seller_NFTExp	0.000	0.000	0.000	0.001	0.000	-0.001	0.001	0.001
Seller_CumNewType	0.000	0.000	0.000	0.000	0.000	0.004	-0.001	0.001

Appendix 8. Top 100 Crypto Punks owners (March, 2024).

#	Account	Magic Eden / ENS	NFTs Owned	last Active	#	Account	Magic Eden / ENS	NFTs Owned	last Active
1	0xb7f7f6c52f2e2	WrappedCryptoPu	846	1 day ago	51	0xb70c1a3242e36		19	1 month ago
2	0xa858ddc0445d8		419	1 month ago	52	0x231d688aa706d		19	2 years ago
3	0xb88f61e6fbda8		221	2 years ago	53	0x7b8440cdd3995		18	
4	0xa25803ab86a32	wilcox.eth	215	1 year ago	54	0x896848ad1a209		18	2 years ago
5	0x2238c8b16c366		160	6 days ago	55	0x9df6a358688cc		18	3 months ago
6	0x69021ae876958	sovpunk.eth	144	6 months ago	56	0x702a39a9d7d84		18	2 years ago
7	0x26f744711ee9e		141	6 years ago	57	0x982cf02280185		18	
8	0x577ebc5de943e		129	23 days ago	58	0x0845fc89c51b2		18	1 year ago
9	0x4084df8bf74ba		98		59	0x2754637ab168f	thecryptopunk.e	17	22 days ago
10	0x269616d549d7e		95	2 days ago	60	0x9ae8912ea6562	snax	17	1 month ago
11	0x31a5ff62a1b2c		93	1 year ago	61	0xdd9d84399a8e8		17	6 years ago
12	0x7174039818a41		89	5 years ago	62	0xd94e9acc4e850	cdb-vault.eth	16	22 days ago
13	0x0232d1083e970	2.punksotc.eth	86	22 hours ago	63	0x3d331379990dd		16	4 months ago
14	0x062c5432107e3		67	1 year ago	64	0x6ccd607e6e2cc		16	
15	0x7760e0243ca9b		66	5 years ago	65	0x2a538000a53f3	0x_NFT	15	1 year ago
16	0x2be665ee27096		63	3 days ago	66	0x030defb961d3f		15	9 months ago
17	0xf5a4ba515dd36	vault.mabu.eth	62	4 months ago	67	0xd5b171571df3b	gpunk.eth	15	1 year ago
18	0xf68e4d63c8ea8	garyvault.eth	62	10 months ago	68	0x51636d9efbfb7		15	2 years ago
19	0xdde8df9a7dc9f	Kenney	58	22 days ago	69	0x53311150764f7	ohana.eth	15	1 year ago
20	0x810fdbc7e5cfe		57	15 days ago	70	0x03205743e7fc5	bimyou.eth	15	5 months ago
21	0x0000000000000		54	1 day ago	71	0x8e7644918b3e2	zoink.eth	14	2 years ago
22	0x530afa101bed3	PB	50	11 months ago	72	0x931e8194d3615	idtgallery.eth	14	
23	0xff36ff458b51d	hodlponkz.eth	49	5 months ago	73	0x9eedbfcffa625		14	
24	0x6301add4fb128	ddaavvee	48	2 months ago	74	0x175b49d39c059	realbuddha.eth	13	1 year ago
25	0x2cc12318de28e		44	1 year ago	75	0x95b2917b823ba		13	1 year ago
26	0x00b278dd68f9d		40	1 year ago	76	0x052564eb0fd8b	pablopunkasso.e	13	25 days ago
27	0x005734d7d408b		39	22 days ago	77	0x7447397496b36		13	6 years ago
28	0xf65c1c4274560		39	29 days ago	78	0xb0dafc466871c	thecitadel.eth	13	2 months ago
29	0x4d8e16a70f384		35	1 month ago	79	0x99466e1f59811		13	2 months ago
30	0xc6a8206756fbc	punks.pixls.eth	35	2 years ago	80	0x9df947cd8a981	jdhvault.eth	12	9 months ago
31	0xb47a70df538b9	niftynaut.eth	32	1 month ago	81	0x090af0d7aaffd		12	
32	0xc47af8f0aeaad		31		82	0x30b1e85b3e134		12	19 days ago
33	0x0cdb1e900885f		31	20 days ago	83	0xb60211811a497		12	2 months ago
34	0xcc2a855946a3c		31	16 hours ago	84	0xe5c4c41194901	Katasterfoes	12	4 days ago
35	0xc24f574d6853f	shilpixels.eth	30	8 days ago	85	0x783ca9833d58a	pjcurly.eth	11	8 days ago
36	0x83e551e481581		29	4 months ago	86	0x4b2a97d536e66		11	
37	0x66c7a7348250f	cx000.eth	28	1 month ago	87	0x6ec30fd91a504	daddykalish.eth	11	21 days ago
38	0x7583534d2f2c3		27	14 days ago	88	0x98cfea4a7632e		11	3 years ago
39	0xbb67d2ab6251a		26	1 year ago	89	0x449c69df8487c		11	1 year ago
40	0x2f2f237d2e655	thebeautyandthe	25	1 month ago	90	0x2a193336b79d9	atscrypto.eth	11	26 days ago
41	0x2c81cee7050c9	ddaavvee.eth	25		91	0xd6a27d42b481f		11	1 year ago
42	0x78f0269f5b1ca	TokenAngels	24	2 months ago	92	0x5163588239afc		10	1 year ago
43	0x3295df41a2f28	Cyrus	23	5 years ago	93	0x79bb5016e87ec		10	
44	0x67954ac510255		22	1 month ago	94	0xe83c750b27083	Snowfro	10	9 months ago
45	0x410b332f56cdd		21	1 month ago	95	0x8be6ad79f67d1		10	3 months ago
46	0x163e10cccfbc5		20		96	0x80845058350b8		10	2 years ago
47	0x8088d74111a23		20	2 years ago	97	0x2503e93fbb53f	spykid.eth	10	1 year ago
48	0x95b9f6e912120		20		98	0x485248150969e	.eth	10	1 year ago
49	0xc98a513970f32		19		99	0x1919db36ca2fa	punksotc.eth	10	6 hours ago
50	0x44fab57dba0e6		19	6 years ago	100	0xa8d31c4546a78		10	1 year ago

Appendix 9. Top 100 NFT Collections by Total Sales Volume in USD (March, 2024).

Rank	Project name	Sales Volume	Units Transacted	Avg Price	Rank	Project name	Sales Volume	Units Transacted	Avg Price
1	Bored Ape Yacht Club	6,310,366,347.34	190,026	33,207.91	51	Lazy Lions	105,684,260.08	45,599	2,317.69
2	Axie Infinity	4,011,616,313.39	22,952,735	174.78	52	3Landers	104,379,036.15	38,161	2,735.23
3	CryptoPunks	3,149,115,379.46	31,487	100,013.19	53	Alien Frens	104,163,976.75	74,061	1,406.46
4	Art Blocks	1,822,271,666.68	466,002	3,910.44	54	Memeland	98,306,380.28	34,965	2,811.57
5	Otherside	1,551,771,445.36	178,906	8,673.67	55	CyberBrokers	96,794,001.36	25,908	3,736.07
6	Loot	1,488,328,941.65	24,804	60,003.59	56	V1 Punks (Wrapped)	88,462,293.25	4,583	19,302.27
7	Azuki	1,440,701,658.98	131,554	10,951.41	57	PROOF Collective	86,876,260.55	4,749	18,293.59
8	Meebits	1,093,710,070.74	49,654	22,026.63	58	Sneaky Vampire Syndicate	85,908,323.78	51,437	1,670.17
9	CloneX	878,779,573.17	45,434	19,341.89	59	Treeverse	84,374,272.50	36,638	2,302.92
10	Moonbirds	712,532,464.23	53,727	13,262.09	60	Autoglyphs	84,335,912.95	1,095	77,019.10
11	Doodles	677,742,689.91	117,920	5,747.48	61	Worldwide Webb	84,063,934.55	37,125	2,264.35
12	The Sandbox	585,025,982.74	189,014	3,095.15	62	MoonCatRescue	82,067,446.62	38,451	2,134.34
13	Pudgy Penguins	498,997,609.10	160,124	3,116.32	63	Sorare	79,090,002.53	430,765	183.60
14	Cool Cats	495,528,429.61	95,923	5,165.90	64	Coolman's Universe	78,948,027.51	44,335	1,780.72
15	Audioglyphs	384,128,988.39	19,846	19,355.49	65	RENGA	76,922,695.02	46,258	1,662.91
16	CyberKongz	344,365,347.11	48,648	7,078.72	66	Jungle Freaks	76,697,647.30	33,740	2,273.20
17	VeeFriends	344,034,594.60	59,940	5,739.65	67	Forgotten Runes Wizard's Cult	75,375,848.62	48,464	1,555.30
18	Ethereum Name Service	308,634,003.16	3,674,031	84.00	68	SuperNormal	73,461,855.88	27,356	2,685.40
19	Nouns	301,283,793.22	2,294	131,335.57	69	Adam Bomb Squad	71,852,930.33	67,059	1,071.49
20	SuperRare	296,830,811.72	41,968	7,072.79	70	KILLABEARS	69,743,611.37	18,972	3,676.13
21	World of Women	277,105,102.89	43,956	6,304.15	71	Rumble Kong League	69,119,929.60	20,205	3,420.93
22	Neo Tokyo	261,564,824.77	14,567	17,955.98	72	The Currency	68,127,718.89	3,987	17,087.46
23	CrypToadz	261,250,401.00	34,208	7,637.11	73	Art Gobblers	67,833,622.93	6,303	10,762.12
24	Wolf Game	238,001,522.94	112,551	2,114.61	74	CryptoSkulls	66,833,475.26	26,905	2,484.05
25	Decentraland	233,208,824.53	109,758	2,124.75	75	CryptoPhunks	66,711,371.43	36,015	1,852.32
26	0n1 Force	191,468,883.29	47,785	4,006.88	76	My Pet Hooligan	66,413,227.99	42,032	1,580.06
27	MekaVerse	184,117,565.65	26,981	6,823.97	77	Galactic Apes	65,696,490.41	38,994	1,684.78
28	FLUF World	183,639,207.17	63,252	2,903.29	78	Pak	64,898,366.61	17,813	3,643.31
29	NFT Worlds	171,638,453.84	43,797	3,918.95	79	CryptoBatz by Ozzy Osbourne	63,989,994.85	26,054	2,456.05
30	PUNKS Comic	170,243,350.78	52,931	3,216.33	80	Lil' Heroes	62,941,765.76	18,611	3,381.97
31	HAPE Prime	166,909,800.28	27,908	5,980.72	81	Crypto Bull Society	62,299,983.30	25,724	2,421.86
32	Creepz	163,471,774.71	60,085	2,720.68	82	Nanoverse	62,005,202.76	18,442	3,362.17
33	Phantom Network (PxN)	160,556,847.01	35,786	4,486.58	83	OnChainMonkey	59,985,692.99	38,271	1,567.39
34	Milady	153,970,027.51	53,078	2,900.83	84	Squid DAO	59,846,881.10	224	267,173.58
35	Foundation	153,198,436.30	61,028	2,510.30	85	Lives of Asuna	58,782,035.74	31,433	1,870.07
36	Pixelmon	148,352,006.06	38,957	3,808.10	86	CryptoKitties	57,643,593.94	2,881,003	20.01
37	Emblem Vault	147,030,275.98	46,002	3,196.17	87	10KTF	57,631,243.10	67,071	859.26
38	mfers	146,797,781.44	51,325	2,860.16	88	Quirkies	55,483,727.04	42,841	1,295.11
39	Karafuru	141,884,148.25	38,402	3,694.71	89	Altered State Machine	55,170,708.56	39,883	1,383.31
40	Prime Ape Planet	131,999,833.98	49,698	2,656.04	90	BYOVerse	54,644,169.33	44,804	1,219.63
41	Invisible Friends	130,290,209.18	16,631	7,834.18	91	Wizards & Dragons Game	54,250,977.79	51,740	1,048.53
42	Creature World	123,845,744.49	40,328	3,070.96	92	MURI	54,013,434.54	27,981	1,930.36
43	Nifty Gateway	123,062,303.76	21,400	5,750.57	93	Degen Toonz	53,134,357.69	39,070	1,359.98
44	goblintown	121,096,683.13	55,717	2,173.42	94	Killer GF	52,977,201.94	20,667	2,563.37
45	Phanta Bear	120,446,921.33	35,502	3,392.68	95	Imaginary Ones	52,335,374.43	30,059	1,741.09
46	The Doge Pound	112,721,012.19	42,008	2,683.32	96	Bored Bunny	51,882,380.06	27,616	1,878.71
47	KaijuKingz	109,736,485.53	23,651	4,639.82	97	Murakami.Flowers	51,559,438.72	11,065	4,659.69
48	DeadFellaz	106,848,278.35	53,765	1,987.32	98	Chain Runners	50,829,038.47	25,527	1,991.19
49	RaidParty	106,272,243.63	48,391	2,196.12	99	Desperate ApeWives	50,368,898.17	27,124	1,856.99
50	Hashmasks	105,911,869.03	38,950	2,719.18	100	ALPACADABRAZ	50,207,534.75	48,276	1,040.01
						TOTAL	35,017,533,485.09	34,767,896	10,881.02