Cultural Value in Digital Art: Evidence from CryptoPunks [*]

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Abstract

Do collectors value the culture in artwork? We formalize a stylized auction model that connects the owner's subjective valuation of artwork to its optimal price offering strategy, bids from potential buyers, and transaction prices of artwork. We test our hypothesis with a detailed on-chain auction history of CryptoPunks, a pioneering non-fungible token project featuring punk culture. Tokens with punk features are 3.6 ETH more expensive, equivalent to a 5.6% premium. Consistent with model predictions, punk token owners seek higher returns in the offer prices and receive more bids before they agree to sell; thus, punk tokens are less frequently traded.

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1 Introduction

Unlike traditional investments, art pieces do not command cash flow but deliver non-pecuniary value beloved by a group of collectors. Oxford Dictionary defines art as a product that involves creative or imaginative talent generally expressive of technical proficiency, beauty, emotional power, or conceptual ideas. Many scholars attempt to explore the motivations behind art collection, seeking to understand the unique appeal and economic implications of art as an alternative asset (Mandel, 2009; Renneboog and Spaenjers, 2013; Korteweg, Kräussl, and Verwijmeren, 2016; Lovo and Spaenjers, 2018). Central to these studies is the idea that art pieces deliver collectors with social status, pleasure, and monetary returns. More importantly, this social status is deeply rooted in the cultural significance of art, which reflects heritage and identity. Our paper provides empirical evidence to prove that investors value the culture embedded in art products and that cultural attributes explain art transaction prices and investors' behaviors.

How can we test whether investors value the culture from art auction data? We write down a simple auction model of an art piece marketplace to connect the owner's subjective valuations to transaction prices and the behaviors of owners and bidders. In the market, the artwork owner can make a "take it or leave it" offer to sell; meanwhile, potential buyers can place bids and the owner can decide to accept a bid or refuse to sell. Our model delivers five empirically testable predictions — art pieces with a higher seller's valuation: first, shall be traded at a higher price; second, the price disparity increases when the popularity of the artwork increases; third, they have a longer holding period and are traded less frequently; fourth, the seller would list the art piece at a higher price; fifth, the bidder needs to place more bids until the highest bid can reach the seller's reserve price.

Then, we test these predictions with transaction records of CryptoPunks, the earliest non-fungible token project launched in June 2017 by Larva Labs studio, and test whether investors appreciate punk attributes. CryptoPunks offers three distinct advantages, making it an ideal context to test our hypothesis: First, CryptoPunks, as indicated by the

project, aims to deliver the punk culture — a spirit of rebellion against authority, echos blockchain's decentralized nature of anti-regulation and censorship resistance. Larva Labs predetermined an attribute table creating a quasi-experimental environment where each token is randomly assigned with none or some punk attributes. Second, Larva Labs studio has deployed its own marketplace with smart contracts to facilitate CryptoPunk transactions. Thus, the details of art pieces' pedigree (e.g., bids and offers) are recorded on the decentralized Ethereum blockchain, ensuring complete visibility and impartiality of buyers' and sellers' behaviors (Li, Ma, and Renneboog, 2024). In contrast to traditional auction markets, where only the final transaction prices are observed—specifically, the highest bid price that exceeds the seller's reserve price—the complete history of the bidding process is not available. Moreover, prior studies on artwork valuation might suffer from sample selection issues, as the historical artwork data were mainly sourced from renowned auction houses such as Christie's and Sotheby's, leading to a "backward-filled" data bias towards high-end pieces (Mei and Moses, 2002). Additionally, gallery sales and direct purchases from artists tend to occur privately and are not publicly recorded. Third, unlike traditional artworks[1], non-fungible tokens are designed and created in the same batch by combining various attributes. There is no reason to believe punk tokens deliver more artistic proficiency than non-punk tokens. Additionally, all tokens were minted simultaneously, and the issuer predetermined the attribute table, further ensuring no discrepancies in skill enhancement across tokens.

Before testing our hypothesis, we need to measure each token's punk exposure. CryptoPunks' attribute table provides comprehensive information about each token's characteristics and visual attributes, including hairstyle, facial appearance, and so on. To classify whether these attributes deliver punk culture, we collect performance photos of the top 10 punk

[1]Artists might spend more time or employ advanced techniques in traditional artwork to achieve artistic excellence. Yayoi Kusama delivered her symbolic dots in the middle stage of her career. The dotted style has been regarded as a way to provide a sense of thriving. Painting with dots and without dots can deliver different technical proficiency.

bands from the reputable music site UDiscoverMusic. Then, we manually compare and match the attributes listed in the CryptoPunks' metadata with the visual elements observed in the selected band performance photos. We develop three measures to capture the punk culture represented by the CryptoPunk tokens. The first measure, *Punk Look*, is a binary variable indicating whether a token contains any punk features or not. The second measure, *Punk Count*, involves counting the number of punk attributes present in a token, while the third measure, *Punk Score*, quantifies the intensity of punk culture associated with each individual CryptoPunk token (see Section 2.4 for detailed variable construction).

Our findings show that punk tokens are traded at higher prices than non-punk tokens, and the punk premium is robust to various definitions of prices and punk measures. On average, punk tokens are 3.6 ETH, 5.6%, and $8,973 USD higher than non-punk tokens in each trade, spanning from their initial transaction on June 23, 2017 to December 19, 2022. To mitigate differences in sampling frequency, we compute the standardized average token prices, resulting in a premium of 4.4 ETH, 6.0%, and $10,967 USD. Furthermore, we analyze the punk premium over time and reveal that the premium is particularly large when attention to NFTs has increased, especially during the NFT art boom in March 2021. We contend that the rise of the punk premium after massive attention to NFTs suggests owning a punk token brings more utility for token holders, particularly as the public recognizes CryptoPunks as the pioneering NFT collection. As illustrated in Figure 1, we observe that punk tokens command a higher price of approximately 5% since NFTs have garnered widespread attention, and this premium continues to persist over the sampling period.

Subsequently, we find that punk tokens experience less frequent transactions and prolonged holding periods compared to their non-punk counterparts. The number of trades decreases monotonically as the punk attributes increase, with a decline from 3.53 trades for tokens with zero attributes to 3.02 trades for tokens with three or more attributes. Moreover, punk tokens with three or more attributes exhibit an approximately 8% longer holding period than non-punk tokens.

Lastly, upon closer examination of the detailed bids and offers data, punk token owners demand 6.23 ($s.e.$=2.44) times higher investment returns, and the presence of one extra punk attribute is associated with a decrease of 1.1 percentage points in trades executed through the offer mechanism. Meanwhile, punk tokens attract 0.13 more bids ($s.e.$=0.03) per transaction, and one extra punk attribute attracts 1.8% more unique bidders participating in each trade. Furthermore, each additional punk attribute increases the likelihood of receiving bids within six months after the token has been sold by 2 percentage points.

Our paper argues that the punk premium reflects investors' valuation of the culture embedded in the art pieces. We then rule out the alternative explanations for the observed premium. First, we exclude token transactions deemed suspicious to mitigate the potential effects of wash trading and price manipulation. The results show negligible deviations from our baseline findings, indicating that wash trading is unlikely to be the underlying cause of the punk premium. Further, we examine the possibility of over-speculation driving the premium. Our results provide no evidence that punk traits are associated with a higher trading frequency of punk tokens. Moreover, we find that punk tokens do not experience price reversals; instead, they tend to yield higher investment returns compared to their non-punk counterparts, if anything. The daily returns of punk tokens are not statistically different from those of non-punk tokens. This finding remains robust even after controlling for token liquidity and prices. Hence, during our sample period, there is no evidence of punk features being overpriced.

Lastly, we conduct additional tests to determine if an omitted variable might explain the punk premium. For example, punk traits might contain undisclosed information that manifests in their features and contributes to higher prices. We test whether the creator intentionally used punk traits to create scarcity and distinguish these tokens from others. We construct two measures of token rarity: (1) ATR, representing the average rarity score, and (2) MTR denoting the minimal rarity score.[2] After controlling for rarity, the punk pre-

[2]See Section 5.3 for a detailed explanation.

mium drops from 3.86 ETH to 3.35 ETH when controlling for the total number of attributes, and further drops to 3.03 ETH when incorporating the token rarity score. Only 21% of the punk premium can be explained by rarity. We also incorporate the interaction term between the rarity score and punk features, revealing that rare punk traits command a higher punk premium. Subsequently, we test whether punk traits deliver greater aesthetic utility to investors, thus driving up token prices. To assess this, we analyze the presence of visually appealing attributes among the token attributes. In particular, we categorize attributes that enhance the token's visual appeal, such as smooth facial appearance and a sense of neatness, as indicators of aesthetic utility. We continue to find that the punk premium remains robust after considering the beauty controls.

Literature Review. Our paper contributes to the following three strands of literature. First, our work relates to the growing research on the art auction market. Previous studies have pointed out that artworks' heterogeneity and the infrequency of trading pose challenges to analyzing asset price formation (Mei and Moses, 2002; Renneboog and Spaenjers, 2013; Whitaker and Kräussl, 2020). Unlike traditional equities and bonds, conventional modeling assumes that fungible assets can be approximated by a random walk with drift (Borri, Liu, and Tsyvinski, 2023), while Lovo and Spaenjers (2018) argue that the return variance in non-fungible assets, such as artworks, does not necessarily converge to zero due to the uncertain distribution of bidders (see, e.g., Goetzmann, Renneboog, and Spaenjers, 2011; and Sagi, 2021). Our study provides a unique opportunity to empirically test the auction model that incorporates the diverse behaviors of market participants and accounts for high price volatility, which is not fully captured in prior literature (Athey and Haile, 2002; Bajari and Hortacsu, 2005). In addition, Dimson and Spaenjers (2014) argue that these alternative investments often entail higher risk and even a lower realized return. However, investors might still choose to purchase collectibles because they derive aesthetic utility from owning them (Mandel, 2014). Our paper highlights the mechanism whereby punk features serve as a form of conspicuous consumption. Investors are willing to pay a premium for punk

culture, especially when the concept of NFT investment gains traction in the market.

Secondly, this study relies on a much more comprehensive data sample for analyzing art pieces than prior works. This includes not only transaction details but also the complete histories of all the bidders and sellers, which could be very difficult or impossible to obtain from large auction houses. In addition, the study of one community, CryptoPunks, enables us to control for artwork heterogeneity to minimize the effects such as artistic excellence, artwork condition, and provenance that have been largely documented as common limitations in the extant literature (Dimson, Rousseau, and Spaenjers, 2015; Mei and Moses, 2002; Li, Ma, and Renneboog, 2024). Therefore, having access to the full histories allows us to gain a more complete picture of the art market microstructure. We show that owners who value punk culture expect a much greater return before they are willing to sell the artwork and are less likely to accept bids, while bidders who value punk culture place more bids within each transaction.

Lastly, our paper is also related to the growing studies of non-fungible token prices. Numerous studies have explored the pricing dynamics of various NFT projects, including virtual real estate in Decentraland (Dowling, 2022a; Goldberg, Kugler, and Schär, 2021), CryptoKitties (Kireyev and Lin, 2021), and CryptoPunks (Kong and Lin, 2023). Specifically, Kong and Lin (2023) focus on CryptoPunks and construct a collection-level price index using the hedonic regression model to proxy for the NFT market index. Similarly, Borri, Liu, and Tsyvinski (2023) construct an NFT index by collecting transaction records and characteristics from a range of NFTs and study NFT investment performance with an asset pricing framework. Nadini et al. (2021) show that sale history and visual features serve as reliable predictors using simple machine learning algorithms. Meanwhile, most NFTs are traded using cryptocurrencies. Several studies have also investigated the spillover effects from the cryptocurrency prices to the NFT market (Dowling, 2022b; Ghosh et al., 2023).[3]

[3]Extensive studies have been conducted on cryptocurrency markets from various perspectives (see, e.g., Cong, Li, and Wang, 2021; Cong et al., 2023; Howell, Niessner, and Yermack, 2020; Liu and Tsyvinski, 2021; Makarov and Schoar, 2020; Sockin and Xiong, 2023, and Tang and You, 2021).

The remainder of this paper is organized as follows. Section 2 describes the CryptoPunks project and the construction of punk culture variables. Section 3 provides a simple framework and develops testable hypotheses. Section 4 tests the empirical predictions derived from the framework. Section 5 rules out alternative explanations, as our findings are not driven by price manipulation, over-speculation, investment performance, token rarity, or aesthetic appeal. Section 6 concludes the paper.

2 Data

2.1 A Brief Description of CryptoPunks

According to OpenSea, CryptoPunks is renowned as one of the most iconic and extensive collections of non-fungible tokens (NFTs) in terms of total sales volume.[4] The collection consists of 24×24 pixel art images, designed by two software engineers, Matt Hall and John Watkinson, founders of Larva Labs studio. Inspired by the 1970s London Punk scene, this crypto art project was officially launched in June 2017.[5] The series includes 10,000 unique tokens, each linked to a distinct art image and authenticated on the Ethereum blockchain (Kong and Lin, 2023). We obtain detailed characteristics and transaction data of these tokens from Larva Labs' website for our research.

2.2 Prices and Returns

The transaction prices of CryptoPunks are expressed in either ETH or USD, using real-time ETH prices from Larva Labs' official website. Our final dataset comprises 22,840 token transactions, including 6,823 unique tokens sold from June 2017 to December 2022.[6] We

[4]OpenSea is one of the largest NFT marketplaces that allows participants to create, purchase, sell, and auction NFTs. As of this writing, CryptoPunks' sales have exceeded 1 million ETH (see `https://opensea.io/collection/cryptopunks/` for details). Moreover, the collection's acclaim extends to the global auction stage, with features in renowned institutions like Christie's and Sotheby's.

[5]see `https://www.christies.com/features/10-things-to-know-about-CryptoPunks-11569-1.aspx/`

[6]The detailed data construction is described in Appendix I. Moreover, Figure IA1, plots the number of CryptoPunk tokens traded over time. This figure illustrates a noticeable uptick in the number of transactions during the period of heightened attention to NFTs, particularly in March 2021. This surge in trading mirrors the overarching trend of amplified engagement and participation within the NFT marketplace during this timeframe.

begin by analyzing the trading and return data of CryptoPunks. Panel A of Table 1 shows that the average transaction price for CryptoPunk tokens during our sampling period is approximately 38.91 ETH, corresponding to an average of approximately $102,468 USD. Regarding investment performance, the average daily returns of CryptoPunks, measured in both ETH and USD, stand at 2.35 basis points (bps) and 2.68 bps, respectively. At the same time, the investments in CryptoPunks entail a high daily standard deviation of about 9.40 bps and 9.77 bps, respectively.

Considering the unique nature of art pieces, factors such as holding period and trade frequency offer critical insights into the pricing dynamics of artworks (Lovo and Spaenjers, 2018). We plot the distributions of CryptoPunks' selling prices denominated in ETH, alongside their holding periods and trade frequencies in Figure IA2. Specifically, Panel A plots the distribution of CryptoPunk prices in its natural logarithm form, we observe a price spectrum ranging from 0.04 to 6.07, with approximately 16% of the token transactions occurring below 1 ETH. The majority of prices, however, fall within the range of 2.5 to 5. Panel B shows the number of days until the next available sale, it is found that token owners, on average, tend to resell their tokens after approximately 36 days in our sampling period. Panel C plots the number of transactions per token. Among the 6,823 tokens with transaction records, we find an average of 3.35 trades per token, with a median of 3 trades. Additionally, we note that only about 124 unique tokens have been traded more than 10 times, suggesting that most of the CryptoPunk tokens have a moderate level of trading activity.

2.3 Cryptopunks Metadata

As previously noted, each CryptoPunk token is characterized by a unique facial appearance shaped by various combinations of attributes. We acquired metadata for CryptoPunks, which describes each token's essential properties — the mapping from non-fungible tokens to the actual digital art pieces. Specifically, each CryptoPunk token can feature up to seven distinct traits from a list of 87 unique attributes. These attributes can be further categorized into nine mutually exclusive dimensions: Hair, Eyes, Facial Hair, Neck Accessory,

Mouth Prop, Mouth, Blemishes, Ears, and Nose. Consequently, a token's design may incorporate one or zero attributes in each dimension, allowing for a maximum of seven attributes, thereby ensuring their distinctiveness. Besides attribute dimensions, CryptoPunks are also categorized into different types, including humans, aliens, apes, and zombies.[7] Among the human-type tokens, we further observe four skin tones: albino, medium, light, and dark, with each accounting for approximately 30% of the human-type tokens except for albino, which represents 10.3% of the human-type tokens. Thus, in total, we have eleven mutually exclusive dimensions that define the characteristics of CryptoPunks. We collected archived token data from the *Larva Labs'* website, which provides comprehensive information about the attributes of each token. Panel C of Table 1 presents the summary statistics related to skin tone. The results indicate that human-type tokens account for 98.8% of the entire series, with an average price of 37.99 ETH, while the average price of the special-type tokens (i.e., aliens, apes, and zombies) is 97.05 ETH during the sampling period.

2.4 Measures of Punk Culture

Punk culture emerged in the 1970s and has continued to thrive over the decades. Originally, the term "punk" referred to underground artists rebelling against mainstream society. However, punk culture has since evolved beyond mere rebellion and fashion, profoundly influencing the entertainment industry (Dunn, 2008). Inspired by this movement, the design of CryptoPunks incorporates elements of punk attire, appearance, and attributes, intending to capture the non-conformist spirit of the Web3 movement.

To construct a meaningful measure of punk culture for each CryptoPunk token, we researched the top 10 renowned punk bands[8] from a reputable music site, UDiscoverMusic (UDM). This official site is operated by the Universal Music Group, one of the leading global

[7]There are only 9, 24, and 88 tokens for the types of aliens, apes, and zombies, respectively. See `https://www.larvalabs.com/cryptopunks/`

[8]The top 10 hardcore punk bands are Misfits, Germs, Bad Religion, The Minutemen, Hüsker Dü, Circle Jerks, Bad Brains, Minor Threat, Black Flag, and Dead Kennedys. See `https://www.udiscovermusic.com/stories/top-10-hardcore-punk-bands/` for details.

music companies with an extensive record label history spanning more than 60 countries. By referring to UDM's list of renowned punk bands, we identified four performance photos for each band and manually matched the attire, appearance, and accessories from these band photos with the attributes of each CryptoPunk (see Table IA2 of the Appendix).

In the context of our analysis, we have devised three measures to capture the essence of punk culture in relation to the CryptoPunk tokens. The first culture measure indicates whether a particular token exhibits the visual aesthetics associated with punk culture. Specifically, *Punk Look*, is a binary variable coded as 1 if the CryptoPunk token shares at least one punk characteristic found in the punk bands' photos, and 0 otherwise. The second measure, *Punk Count*, counts the number of attributes in the CryptoPunk tokens designated as punk characteristics based on the punk bands' photos. Our final measure, *Punk Score*, quantifies the intensity of punk culture encapsulated by each CryptoPunk token. This score is calculated by assigning a weight to each attribute based on the frequency of punk bands exhibiting the same attribute. The punk score of a token is then derived by summing up the scores assigned to each attribute. This measure captures the cumulative representation of punk culture within each token.

Panel B of Table 1 reports the summary statistics of the punk culture measures. Reflecting the influence of the 1970s London Punk scene on this NFT project, a substantial portion of the tokens display prominent punk characteristics. Among the 10,000 tokens, 7,970 are identified as punk tokens, and 5,440 of these have at least one transaction recorded during the sampling period. Furthermore, the median value of *Punk Count* is 1, suggesting that 50 percent of the tokens possess at least one punk attribute. In addition, the median value of *Punk Score* is 0.4, suggesting that the top 10 punk bands undeniably share common attributes in terms of their attire and appearance. Overall, the computation of punk culture measures shows a significant positive correlation, though not perfectly correlated. We find that the correlation coefficients of *Punk Look* and *Punk Score* with respect to *Punk Count* are 71% and 80%, respectively.

[Insert Table 1 here]

3 Conceptual Framework

We model NFT as positional goods, a concept wherein the value of these digital assets is highly influenced by their relative status compared to things owned by others (Frank, 1985; Truyts, 2010; Charness, Masclet, and Villeval, 2014). Specifically, the value of NFTs is not only derived from their inherent characteristics but also from their comparative ranking against analogous items held by others. Moreover, blockchain technology enables NFT visibility and can be verified as "conspicuous" goods. For simplicity, we posit that NFT owners gain flow utility from owning the token depending on the NFT quality, following Bagwell and Bernheim (1996). Much anecdotal evidence demonstrates that NFT collectors often use these assets to signal their identities or to gain recognition within the Web3 community. For example, Jay-Z, a rapper and billionaire, owns CryptoPunk #6095, and Alexis Ohanian, the co-founder of Reddit, bought CryptoPunk #2950 as a gift for Serena Williams.

We propose a simple framework to connect NFT investors' subjective valuation V (i.e., the reserve price) to the NFT transaction prices, seller's price listing, and the bidders' behavior. Consider a token holder with an exogenous subjective valuation of V. If investors value punk culture, we expect that punk traits positively contribute to the subjective valuation of an NFT, that is, $V_{Punk} > V_{Non-Punk}$.

3.1 NFT Market Structure

A continuum of buyers is characterized by a subjective valuation that follows $W \sim U(0,1)$. To simplify our analysis, we assume the seller is myopic — the seller only maximizes the utility in the current period, to avoid complicated intertemporal choices. With this assumption, we can simply consider a static model, and the probability of being traded captures the NFT trading frequency. We consider the NFT trading mechanism through auction to be the following: potential buyers arrive and choose from the following two options:

Mechanism 1: The Seller Makes Offer

First, the buyer can let the seller make a "take it or leave it" offer every period, and the potential buyer can decide whether to accept the offer. There is one potential buyer for each period. β denotes the time discount factor. The potential buyer decides whether to take it; if the buyer accepts the offer, then the transaction occurs.

The optimal pricing offering strategy is P_{Offer}, where $(1 - P_{Offer})$ is the probability of being sold, and the premium is $P_{Offer} - V$. U_{Offer} is the utility before making the offer. The maximization problem follows:

$$U_{Offer} = \max_{P_{Offer}} (1 - P_{Offer})(P_{Offer} - V) + P_{Offer}\beta U_{Offer}$$

The optimal price offering strategy is $P_{Offer} = \frac{1+V+\beta U_{Offer}}{2}$. Then, we solve for U_{Offer} by its definition $U_{Offer} = \frac{(1+V+\beta U_{Offer})^2}{4} - V$.[9]

$$P_{Offer} = \frac{1 - \sqrt{(1-\beta)(1-\beta V)}}{\beta}$$

Mechanism 2: The Buyer Places Bids

Without loss of generality, we assume that bidders can also make unsolicited bids according to their true subjective valuation and only one bidder arrives in every period.[10] We denote U_{Bid} as the utility without knowing the bid. The seller accepts the bids following a cutoff strategy. The seller agrees to sell if and only if the bid is higher than P_{Bid}; otherwise, the seller refuses to sell. We can pin down P_{Bid} through the following two conditions:

The first condition is that the seller should be indifferent between *accept* and *reject* when a bidder places the bid of P_{Bid}.

$$P_{Bid} - V = \beta U_{Bid}$$

[9]Then, we can solve U_{Offer} as follows:$U_{Offer} = \frac{2-\beta(1+V)-2\sqrt{(1-\beta)(1-\beta V)}}{\beta^2}$. Then, we can plug the utility to obtain the best offer price.

[10]If the seller chooses not to sell, the bidder gets zero utility. Thus, any bidder is willing to bid up to his or her true subjective valuation.

The second condition follows from the definition of utility:

$$U_{Bid} = \underbrace{(1 - P_{Bid})}_{\text{Probability of Acceptance}} \underbrace{(\frac{1 + P_{Bid}}{2} - V)}_{\text{Expected Surplus}} + \underbrace{P_{Bid}}_{\text{Probability of Rejection}} \beta U_{Bid}$$

Then, we can express the reserve price P_{Bid} as a function of discount factor β and subjective valuation V as follows:[11]

$$P_{Bid} = \frac{1 - \sqrt{(1-\beta)(1+\beta-2\beta V)}}{\beta}$$

In equilibrium, the seller chooses to place an offer P_{Offer} and would accept the bid if it is higher than P_{Bid}. Not surprisingly, the offer price P_{Offer} is higher than the reserve price P_{Bid}.

Proposition: Optimal offer and bid reserve prices are monotonically increasing functions of the subjective valuation V, that is $\frac{dP_{Bid}}{dV} > 0$ and $\frac{dP_{Offer}}{dV} > 0$.[12]

Corollary 1: The probabilities of transaction occurrence monotonically decrease with V.

The potential buyer accepts an offer if the subjective valuation is higher than P_{Offer}; symmetrically, the seller can accept a bid if and only if the bid is higher than P_{Bid}. By the proposition, a seller with a higher subjective valuation of V sets a higher bar for the potential buyer, and the trade is less likely to happen.

Then, we consider an extension case where the popularity of the art piece increases. As more bidders appear, it is equivalent that discount rate β increases as the seller expects a

[11] We can combine these two conditions to solve the reserve price P_{Bid}.

$$P_{Bid} - V = \beta \frac{1}{1 - P_{Bid}\beta}(1 - P_{Bid})(\frac{1 + P_{Bid}}{2} - V)$$

$$\frac{\beta}{2}P_{Bid}^2 - P_{Bid} + (1-\beta)V + \frac{\beta}{2} = 0$$

[12] Proof: We take the derivative of the offer price with respect to V: $\frac{dP_{Offer}}{dV} = \sqrt{1-\beta}(1+\beta-2\beta V)^{-\frac{1}{2}} > 0$ Similarly, we compute the derivative of the minimum reserve price with respect to V: $\frac{dP_{Bid}}{dV} = \frac{1}{2}\sqrt{1-\beta}(1-\beta V)^{-\frac{1}{2}} > 0$.

shorter horizon to meet a new potential buyer due to heightened interest in the collection.

Corollary 2: The price response to the subjective value $\frac{dP}{dV}$ is monotonically increasing in the discount factor β (the number of potential buyers).[13]

Corollary 2 shows that bidder arrival frequency would leverage the price gap between two art pieces with different subjective valuations. The artwork owner with a higher subjective valuation would be more reluctant to sell the art piece as they can find more potential buyers when the popularity increases. Thus, we expect the price of more valuable art pieces to become relatively more expensive with increased interest in the art collection, that is, prices would diverge as the collection becomes more popular.

3.2 Empirical Predictions

Our stylized model connects the offer and bid prices P_{Offer} and P_{Bid} with the seller's subjective valuation V. We can derive five testable empirical predictions from the proposition and its corollaries by comparing art pieces with different subjective values.

Prediction 1. *Tokens with higher subjective valuations are sold at higher prices.*

Our model reveals that the sale of an NFT is facilitated either through an offer price (P_{Offer}) or a bid price (P_{Bid}). The first-order conditions for both P_{Offer} and P_{Bid} are positive, implying that the actual transaction price is always higher for NFT holders who attribute greater subjective value to their tokens (Amaldoss and Jain, 2005; Tian, Bearden, and Hunter, 2001; Tereyağoğlu and Veeraraghavan, 2012), and this outcome prevails regardless of which sale mechanism is used.

[13]Proof: We compute the $\frac{dP_{Offer}}{dV}$ and $\frac{dP_{Bid}}{dV}$ as the following:

$$\frac{dP_{Bid}}{dVd\beta} = \frac{1}{4}\frac{1}{1-\beta V}\frac{1-V}{\sqrt{(1-\beta)(1-\beta V)}} > 0$$

$$\frac{dP_{Offer}}{dVd\beta} = \frac{1}{2}\frac{1}{1+\beta-2\beta V}\frac{\beta+2V(1-\beta)}{\sqrt{(1-\beta)(1+\beta-2\beta V)}} > 0$$

Prediction 2. *Token price differences would widen with increased interest in purchasing the artworks.*

Our second prediction posits that as the popularity of an artwork increases, so does the number of potential bidders in the market. Consequently, the price gap identified in Prediction 1 is expected to widen, as sellers anticipate that potential buyers whose subjective valuations closely match their own can be readily found in the market. That said, owners with higher subjective valuations tend to set a higher price as the popularity of artwork increases.

Prediction 3. *Tokens with higher subjective valuations experience lower trading frequency and longer holding periods.*

The third prediction concerns that sellers with higher subjective valuations are more inclined to wait for an optimal match and engage in fewer transactions. This is underscored by the relationships $\frac{\partial Prob_{Offer}}{\partial V} < 0$ and $\frac{\partial Prob_{Bid}}{\partial V} < 0$, indicating that as the subjective valuation increases, the probability of transactions, whether through offers or bids, decreases. Therefore, NFT holders are expected to retain their tokens until they encounter a bidder whose valuation aligns with or exceeds their own.

Prediction 4. *Tokens with higher subjective valuation are offered at a higher price and less likely to be accepted by bidders.*

Our fourth prediction sheds light on the trading behavior of NFT owners, particularly those who place a high subjective value on their tokens. Such owners are predisposed to set higher listing prices. This tendency, however, reduces the likelihood of these higher sale prices being accepted by buyers, as indicated by the negative relationship between the probability of an offer being accepted and the subjective value ($\frac{\partial Prob_{Offer}}{\partial V} < 0$) and the positive relationship between the offer price and the subjective value ($\frac{\partial P_{Offer}}{\partial V} > 0$).

Prediction 5. *Tokens with higher subjective valuation are expected to receive more bids per transaction.*

Finally, Prediction 5 focuses on the trading behavior of NFT buyers. It posits that tokens with higher subjective value are expected to attract more bids. The idea is that sellers who place a higher subjective value on their tokens will likely set a higher price, thereby creating a higher threshold for potential buyers. In addition, our model shows that the probability of a transaction occurring decreases with an increase in subjective valuation. This inverse relationship suggests that while token transactions with high subjective valuations are less likely to happen, these tokens tend to receive more bids as buyers compete for the reserve prices set by the sellers.

4 Empirical Tests

In this section, we hypothesize that investors recognize the value of punk features when investing in Cyptopunks $V_{punk} > V_{non-punk}$ and test five predictions with Cryptopunk's full history of transaction prices, bids, and offers.

4.1 Punk Premium

Prediction 1 states that CryptoPunk tokens with punk attributes should command a price premium if investors value punk culture in these token images. We estimate the punk premium using the transaction prices recorded on Ethereum.

For transaction-level regressions, β_1 captures the punk premium with the following regression:

$$Prc_{i,t}^{ETH} = \beta_1 Punk_i + \beta_2 TokenClass_i + \gamma_t + \epsilon_{i,t} \tag{4.1}$$

where $Prc_{i,t}^{ETH}$ denotes the price quoted in Ether for CryptoPunk token i at time t. $Punk_i$ is the measure of punk culture that takes three distinct values: *Punk Look*, *Punk Count*, and *Punk Score* as outlined in Section 2.4. $TokenClass_i$ indicates the general appearance of each CryptoPunk i and comprises seven sets of dummies: *Ape*, *Alien*, *Zombie*, *Albino*, *Light*,

Medium, and *Dark*, and are distinct from the 87 unique attribute tables.[14] γ_t represents the month dummies indicate when the transaction occurs. Standard errors are clustered at the token level.

To mitigate the possibility of over-sampling, we further calculate the standardized average transaction price for each token and perform the following regression.

$$Prc_i^{ETH} = \beta_1 Punk_i + \beta_2 TokenClass_i + \epsilon_i \tag{4.2}$$

where Prc_i^{ETH} denotes the standardized average transaction price in Ethereum for each CryptoPunk token. This measure is constructed by first calculating a monthly average token price and subtracting the individual token price from the average price. Subsequently, we aggregate the subtracted prices at the token level to address the potential scale variations in our sample.

Table 2 reports the baseline regression results of punk premium at both the transaction and token levels using different measures of punk culture in Panels A, B, and C, respectively. Specifically, Column (1) reports the transaction-level regressions without including the TokenClass fixed effect, while Column (3) further includes the TokenClass fixed effects in the transaction-level regressions. Column (5) reports token-level regressions with the TokenClass fixed effect. Additionally, in Columns (2), (4), and (6), the dependent variable is transformed into the natural logarithm of prices in ETH.

Panel A of Table 2 shows that tokens with "punk" attributes are priced, on average, 3.64 ETH higher (*s.e.*=0.567) than their non-punk counterparts, which is approximately 5.6% relatively more expensive. After controlling for TokenClass dummies, the punk premium

[14] We control for each token's skin tone, as prior studies, such as Nardinelli and Simon (1990) and Burge and Zillante (2017) have long argued the presence of consumer discrimination in collectibles. A recent study, Nguyen (2022), documents that digital art, such as CryptoPunk tokens with lighter skin tones, command higher prices even when controlling for token rarity and market conditions. Among the 9,879 human-type tokens, we find 1,018 tokens feature albino, 2,284 tokens feature dark, 3,006 tokens feature light, and 3,031 tokens feature medium skin tones. In all cases, we use medium skin tone as the base variable in the regression analysis to avoid multi-collinearity. Further details on skin tone classification are available at `https://rarity.tools/cryptopunks`.

becomes 3.86 ETH, equivalent to 6.1% more expensive than a non-punk token. The TokenClass fixed effect does not alter the economic and statistical significance of the punk premium. Panel B documents that one additional punk attribute leads to 1.89 ETH (equivalent to 3.7%) higher in the transaction price. Similarly, according to Panel C, one standard deviation increase in punk culture intensity leads to 2.38 ETH (0.357×6.675) higher in the transaction price. Different specifications point to the same conclusion that the CryptoPunk tokens enjoy a price premium if their attributes can be readily found among the top 10 punk rock bands, such as chokers or unique hairstyles commonly observed in band performance photos. In addition, punk premium estimated from the token-level regressions Eq.(4.2) in Columns (5) and (6) are slightly higher than the transaction-level estimates. The punk token price is 4.36 ETH higher than tokens without punk features, which corresponds to a 6.0% price difference. One additional punk feature increases the token price by 1.90 ETH, and one standard deviation increase in punk intensity corresponds to a 2.57 ETH higher transaction price.

[Insert Table 2 here]

Regardless of the specifications, all regressions demonstrate that tokens that present punk features are traded at a premium in the NFT market. The collective findings support our initial prediction that punk tokens, perceived to have a higher subjective valuation, are traded at a premium in the market.

4.2 Beeple, NFT Popularity and Punk Premium

Then, we test the second prediction by exploiting the NFT popularity shock triggered by the landmark sale of the digital artwork titled "*Everdays: the First 5000 Days*" by artist Beeple. This digital artwork was sold for a stunning $69.3 million USD at Christie's, and this transaction record has attracted significant interest in the burgeoning NFT market. Cryptopunks, as the first NFT project, inevitably benefits from the publicity of this auction sale.

Figure IA3 reports the Search Volume Index (SVI) provided by Google Trends to track the search interest for the term "non-fungible tokens" from June 2017 to December 2022 to proxy for worldwide attention.[15] We discover two major events in our sample: (1) the launch of CryptoPunks and (2) the NFT art explosion. We observed that the launch of CryptoPunks initially garnered limited attention back in 2017.

To track the punk premium over time, we regress the last selling price of each token in each month against different definitions of punk measures as outlined in Section 2.4. We then plot the estimated coefficients of punk measures in Figure 1. In the left panel, we estimate the punk premium using the real price in ETH and document that the punk premium indeed rose sharply after the attention toward non-fungible tokens reached its peak after Beeple's high-profile sale in March 2021. The right panel, which expresses the punk premium as a percentage of token prices, provides similar findings, indicating that punk token prices are approximately 5% more expensive than non-punk counterparts. We notice the punk premium appears to stabilize thereafter, suggesting that the price differences are not driven by some transactions by hold over time but that the market has established a distinct value for punk tokens, recognizing their unique attributes and cultural significance within the NFT space.

[Insert Figure 1 here]

4.3 Punk Culture and NFT Liquidity

Prediction 3 of the model states that tokens that perceived a greater subjective valuation are expected to be less liquid, as evidenced by trading probability being negatively correlated with V in both the offer and bid mechanisms. In this section, we explore the relationship between NFT liquidity and punk features at both the token and transaction levels. Our first measure, *Numtrade* is defined as the total number of transactions for each

[15] Prior studies, such as Da, Engelberg, and Gao (2011); Kong and Lin (2023); and Liu and Tsyvinski (2021), find that the search frequency data on Google provides a useful measure to capture the attention of retail investors.

token during the sampling period. Additionally, we consider *Holding Period* to be the number of days required for a new transaction to occur. Panel A of Figure 2 shows that the average number of trades across *Punk Count* decreases monotonically, from 3.53 trades for non-punk tokens to 3.02 trades for tokens with three or more attributes. This trend persists when *Numtrade* is transformed into its natural logarithmic form. Furthermore, we observe that, on average, punk tokens experience longer holding periods before the next transaction, with tokens possessing three or more attributes taking approximately 8% longer time than non-punk tokens.

We then depict the relationship between the liquidity measures and *Punk Score* through a locally weighted polynomial regression, as reported in Panel B of Figure 2. A downward sloping trend between *Numtrade* and *Ln*(1 + *Numtrade*) suggests that the increase in the intensity of punk culture is associated with reduced trading frequency. At the same time, *Holding Period* is positively associated with punk culture. In addition, we perform an OLS regression for each plot in Panel B; the coefficients are denoted in the corresponding corners. The estimated coefficient for *Punk Score* on *Numtrade* is -0.283 (*s.e.* = 0.084), suggesting that a one standard deviation increase in punk intensity is associated with a decrement of 0.101 (-0.283 $\times$ 0.357) in trade numbers. Similarly, a one standard deviation increase in punk intensity is related to a 5% longer time to find the next buyer to trade with. Collectively, these findings corroborate Prediction 3, positing that punk tokens, which bear a higher subjective value, are distinguished by less frequent transactions and protracted holding periods.

[Insert Figure 2 here]

4.4 Unraveling the NFT Market Structure: Bid and Offer Data

Predictions 4 and 5 explain why tokens are traded at a higher price but with lower liquidity. Tokens with a higher subjective value are anticipated to command a higher sale price; that said, a seller's higher price expectation decreases the likelihood of their token

being matched by potential buyers. Additionally, bidders are willing to bid up to the true subjective valuation; thus, we expect more bids until the highest bid meets the seller's reserve price for the next transaction to happen. We investigate on-chain bids and offer data to examine our predictions with the following regressions.

$$Y_{i,t}^{Seller} = \beta_1 Punk_i + \beta_2 TokenClass_i + \gamma_t + \zeta_j + \epsilon_{i,t} \tag{4.3}$$

$$Y_{i,t}^{Bidder} = \beta_1 Punk_i + \beta_2 TokenClass_i + \gamma_t + \zeta_j + \epsilon_{i,t} \tag{4.4}$$

where $Y_{i,t}^{Seller}$ are vectors of variables used to examine Prediction 4 from sellers' perspective. Specifically, we test whether the owner expects a higher selling price by evaluating the owner's minimum offer price return, $OfferRet_{i,t}$, which is calculated by dividing the minimum offer price set by the owner before the next sale by the actual sale price, and then subtract one.[16] Subsequently, we aim to identify the trading mechanisms for each token by assessing the likelihood of market matching, $ThroughOffer$, which equals 1 if the transaction is executed through the offer mechanism, and 0 otherwise. Additionally, conditional on the offer mechanisms, we also examine, $OTSdays$, which represents the duration from the owner's first offer date to the transaction date. This measure provides insights into the efficiency of the offer mechanism in facilitating transactions. The subscript j represents the owner's wallet address. In all cases, we control the skin tone of each token, the time when the token is sold, and also the owner's wallet address (see Appendix I for detailed construction).

In Panel A of Table 3, Column (1) indicates that punk token owners expect returns approximately 6.23 times higher ($s.e.$ = 2.435) than the actual sale price when listing their tokens for sale. This observation is consistent with Prediction 4, which posits that the unique traits of punk tokens enhance their perceived value, leading owners to list these tokens at higher prices. The findings in Columns (4) to (6) support a coherent argument that the el-

[16]The calculation of minimum price offer returns facilitates the comparison of digital asset performance, irrespective of initial price levels.

evated valuation placed by owners lowers the transactions of punk tokens through the offer mechanism, with one additional punk attribute lowering trades through the offer mechanism by 1.1 percentage points. Furthermore, conditional on tokens traded through the offer mechanism, the analysis in Column (7) reveals that punk tokens require approximately 11.3% more time from the first offer to sell compared to their non-punk counterparts.

We then shift our focus to the perspective of bidders in Panel B of Table 3. The dependent variable, $Y_{i,t}^{Bidder}$, in Eq.(4.4) includes a set of variables that can proxy for bidder's behavior (see Appendix I). In particular, we measure the number of bids received within each transaction, the number of unique individuals who place bids, and how readily tokens receive a new bid after a transaction. In all cases, we also control the skin tone of each token, the time when the token is sold, and the owner's wallet address. The result in Column (1) aligns with our framework that punk tokens with a higher subjective valuation attract 0.131 ($s.e.$=0.030) more bids per transaction than their non-punk counterparts. When looking at the bidder wallet address, the result in Column (4) shows that punk tokens, on average, have 2 percentage points more unique bidders place bids than non-punk counterparts. Our further analysis examines whether punk tokens have a higher incidence of bids within six months post-transaction. We construct a dummy variable, *ReceiveBid*, coded as one if a token receives at least one bid within six months after its sale, and 0 otherwise to proxy for the velocity of bid reception. The finding in Column (8) provides supporting evidence to Prediction 5, showing that an additional punk attribute increases the likelihood of receiving bids swiftly by 2 percentage points compared to non-punk counterparts.

[Insert Table 3 here]

5 Alternative Explanations

Punk premium suggests that investors value the punk culture and are willing to pay a higher price for punk attributes embedded in non-fungible tokens.[17] In this section, we further discuss alternative hypotheses and evaluate whether they can possibly explain the punk premium and other empirical facts documented in the previous section.

5.1 Wash Trading and Price Manipulation

Like other cryptocurrency markets, NFT transaction records can also be exposed to price manipulation and wash trading — investors selling and purchasing the same NFT amongst themselves to artificially create fake trading activities.[18] Our findings can be contaminated if suspicious transactions correlate with the punk features and simultaneously affect token prices and liquidity.

We define NFT transactions as wash trading when a token is exchanged back and forth between two or more wallets, and the original owner retains control over these wallets.[19] We have identified 38 tokens associated with suspicious transactions during the sampling period, of which 29 were punk tokens and 9 were non-punk tokens, suggesting that punk tokens are prone to suspicious trades. To mitigate the concerns that suspicious trades might bias our findings, we excluded 300 token-transaction observations, which repre-

[17] As a robustness check, we conducted a series of tests to validate the findings of the punk premium. For example, the decision to purchase art pieces can be inherently subjective and vary among individuals (Mei and Moses, 2002), and that tokens without transaction records might contain valuable information for assessing the value of digital artwork. We find robust evidence supporting the punk premium, even when accounting for unsold tokens (see Table IA4). Another robustness test involves examining whether the order of trades influences our results. We plot the estimated punk premium against trading orders in Figure IA4, and the punk premium remains robust across trading orders.

[18] There is a growing number of literature and industry reports argue that the sale of NFTs are fake and also involve wash trading, see for example, Cong et al. (2022); Sifat, Tariq, and van Donselaar (2024); and von Wachter et al. (2022).

[19] For example, we identified some transaction records of CryptoPunk #9620 as suspicious wash trading transactions. On July 16, 2021, the token was sold with 0 ETH from wallet address A to address B, only to be subsequently transferred back to address A and resold to address B again on the same day, July 19, 2021. Furthermore, the token underwent transactions involving three wallets on December 26, 2021, December 28, 2021, and December 29, 2021. These activities have the potential to convey misleading information to the market. See `https://cryptopunks.app/cryptopunks/details/9620`.

sented 1.31% of the total CryptoPunk transactions, and re-estimate the punk premium in Table IA5. The results in Columns (3) and (4) of Table IA5 show that the punk premium is 3.90 ETH, corresponding to 6.3% at the transaction level in Eq.(4.1). Similarly, the punk premium is 4.34 ETH and 6.1% at the token level in Eq.(4.2). It is worth noting that the coefficients in Table IA5 show minimal variation compared to our baseline estimation, indicating that wash trading does not drive the punk premium.

5.2 Punk Feature and Over-Speculation

The recent surge in the popularity of NFTs has attracted scholars to examine the underlying value of the digital collectibles (see, e.g., Aharon and Demir, 2022; Ante, 2022; Borri, Liu, and Tsyvinski, 2023; Horky, Rachel, and Fidrmuc, 2022; Vidal-Tomás, 2022). Dowling (2022a), among others, conclude that the pricing mechanism in the NFT market is deemed inefficient and vulnerable to pricing manipulation, fraudulent activities, and speculative trades, which could lead to price bubbles (Wang, 2022). That being said, it would be intriguing to examine whether the punk premium is driven by over-speculation behavior within the NFT market. In particular, if speculative trading is driving the premium, one might anticipate that punk tokens are more likely to be sold in the market. To explore this hypothesis, we employ logistic regression analysis:

$$SALE_i = \beta_1 Punk_i + \beta_2 TokenClass_i + \epsilon_i \tag{5.1}$$

where $SALE_i$ is a dummy variable coded one if the CryptoPunk token i has been traded at least once during the sampling period, and 0 otherwise.

The results in Panel A of Table IA6 show that the coefficients related to punk measures are not statistically significant. This suggests that punk tokens do not differ from non-punk tokens regarding the likelihood of sale in the market. As a robustness check, we conduct the test using the probit regression model, with results in Panel B of Table IA6 corroborating the initial findings. These results, along with those in Section 4.3, suggest that speculative trades are unlikely to drive punk premium. This interpretation is supported by the evidence

that punk tokens experience fewer trades and longer holding periods, whereas speculative bubbles are typically characterized by trading frenzies for a quick profit, with concurrent rise and drop in prices and volume (DeFusco, Nathanson, and Zwick, 2022). Recent studies have also highlighted that speculators often concentrate on particular styles within an asset class, such as modernist postwar and contemporary art in the art market (Penasse and Renneboog, 2022), and houses in the Los Angeles area (Bayer et al., 2020). Additionally, we test whether token liquidity affects the punk premium estimation by including liquidity metrics as the control variable. The results in Table 4 show that the punk tokens are traded at 4.14 ETH (*s.e.* = 0.678) more expensive than non-punk counterparts after controlling for the liquidity measures.

[Insert Table 4 here]

Meanwhile, anecdotal evidence suggests that speculative assets are often overvalued and underperform relative to non-speculative assets (see e.g., Conrad, Kapadia, and Xing, 2014; Liu et al., 2020). If punk tokens exhibit a preference for speculation, they should attract more attention than their non-punk counterparts, leading to increased buying pressure and higher prices. In other words, if the estimated punk premium in Section 4 is temporary and overpriced due to increased demand from investors, we would expect a subsequent downturn in NFT token prices, resulting in lower returns (Penasse and Renneboog, 2022).

To formally test this idea, we run the following regression to examine the relationship between the daily returns on investments in CryptoPunks across different definitions of punk culture measures.[20]

$$Ret_{i,t}^{ETH} = \beta_1 Punk_i + \gamma_t + \epsilon_{i,t} \tag{5.2}$$

In Column (1) of Table 5, the coefficients of various punk measures exhibit no significant relationship with the daily return of tokens at the transaction level. This suggests that punk

[20]Following prior studies in art investments, we calculate the investment returns using geometric return that enables long-term performance evaluation and facilitates comparison of different art investments (see, e.g., Li, Ma, and Renneboog, 2024).

tokens do not necessarily deliver lower returns. Similar findings are observed in the token-level regressions and also in the analysis of the token's daily return from initial to final price, as presented in Column (6). These results indicate that investors also take into account the intrinsic value of the artworks when curating alternative investments (Mei and Moses, 2002; Renneboog and Spaenjers, 2013; Dimson and Spaenjers, 2014).

A recent study by Lovo and Spaenjers (2018) proposes that the art market typically involves distinct types of buyers and sellers, leading to a lower average total return over extended holding periods. We test this argument by including the holding period as the control variable using the following specification:

$$Ret_{i,t}^{ETH} = \beta_1 Punk_i + \beta_2 HoldingPeriod_{i,t} + \gamma_t + \epsilon_{i,t} \tag{5.3}$$

The results in Columns (2) and (7) of Table 5 show that controlling for the holding period does not lead to any significant distinction in investment returns based on punk culture measures. Moreover, the estimated coefficient of the period between purchase and resale is significantly negative, aligning with the findings of Lovo and Spaenjers (2018). As a robustness check, we further test the daily return calculated using USD, and the results in Table IA7 remain consistent across different currency evaluations.

$$Ret_{i,t}^{USD} = \beta_1 Punk_i + \beta_2 HoldingPeriod_{i,t} + \gamma_t + \epsilon_{i,t} \tag{5.4}$$

Overall, we find no evidence that punk premium is a transient or inflated phenomenon resulting from heightened interest in alternative assets. Instead, the punk premium identified in Section 4 suggests investors value cultural traits. Thus, investors who derive greater enjoyment from the intrinsic value of punk culture are willing to pay a higher price.

[Insert Table 5 here]

5.3 Attribute Count and Rarity

The last possibility is omitted variable bias. It is possible that investors value something else other than punk culture, but the omitted variable happens to be correlated with the design of punk attribute. For example, since punk traits are primarily associated with punk culture, it is plausible that they might be correlated with other attributes of the tokens. The existing literature, such as Koford and Tschoegl (1998), Kong and Lin (2023), and Mekacher et al. (2022), suggests that rarity is a crucial component in the NFT and other art markets. This section evaluates the relationship between rarity and punk premium.

Our first hypothesis posits that Larva Labs studio (i.e., the creator of CryptoPunks) intentionally incorporated punk features to establish rarity and differentiate certain punk tokens from others, aiming to enhance their visual appeal and investment value. The rationale behind this hypothesis is grounded in prior studies in the field of alternative assets, which emphasizes the significant role of rarity in driving price appreciation (Koford and Tschoegl, 1998; Hughes, 2022). Psychologically, individuals are inclined to engage in conspicuous consumption of rare items as they are perceived as exclusive and can symbolize social prestige within the Web3 community (Stock and Balachander, 2005; Balachander, Liu, and Stock, 2009; Fan, Li, and Jiang, 2019).

Additionally, anecdotal evidence suggests that certain CryptoPunks, considered rare in the market, command higher prices. For instance, CryptoPunk #5822, which deviates from the typical punk tokens, was sold for an astonishing price of approximately $23.7 million USD.[21] This unprecedented high record has sparked curiosity and raised questions about whether the design of rarity in CryptoPunks' tokens might shed light on the results discussed in Section 4.

In assessing the rarity of CryptoPunk tokens, one simple metric is the number of attributes assigned to each token. According to the metadata from CryptoPunks, the number

[21] CryptoPunk #5822, featuring an alien skin tone (0.09% of the entire series) with a bandana (4.81% of the entire series), was traded for approximately $23.7 million on February 12th, 2012. See `https://cryptopunks.app/cryptopunks/details/5822`.

of attributes assigned to each token varies, ranging from none to seven.[22] Tokens with a higher count of distinct features often garner investor attention and stand out more prominently among other tokens.

Furthermore, we incorporate the attribute occurrence frequency into our analysis. This is because tokens that possess attributes with lower occurrence rates within the token collection may also capture more attention from investors. Building on the discussion in Section 2.3, we have classified 89 token attributes (i.e., including type and skin tone) and assigned them to 11 dimensions, ensuring that each trait t is exclusively linked to a single dimension d ($d \in 1, 2, ..., 11$).

To measure the rarity of each attribute, we compute the trait rarity (TR_t) for each trait t by considering how frequently it appears across the entire collection. In this context, m represents the number of tokens that share the same trait t, while M corresponds to the total supply of tokens in the NFT collection. The trait rarity is defined as:

$$TR_t = \frac{m}{M}$$

Next, we aggregate the trait rarity at the token level. If token i possesses a trait t under dimension d, we assign the value of $Rarity_d = TR_t$. However, if token i does not have any trait associated with dimension d, we assign the probability of "no feature" in this dimension, that $Rarity_d = 1 - \sum_{t \in d} TR_t$. We implicitly assume that the absence of a trait is also a "trait" under this dimension. With the establishment of dimensional rarity, we can then proceed to compute the average rarity score (ATR_i) and minimal rarity score (MTR_i) for each token i:

$$ATR_i = -\frac{\sum_{d \in 1,2,...,11} Rarity_d}{11}$$

[22] Among the entire collection, 8 tokens have no attributes, while CryptoPunk #8348 has seven attributes: Buck Teeth, Top Hat, Big Beard, Classic Shades, Mole, Cigarette, and Earring.

$$MTR_i = - \min_{d \in 1,2,...,11} Rarity_d$$

The ATR_i is the negative average dimensional rarity score for each token ranging from -0.652 to -0.303, and MTR_i is the negative trait occurrence probability of the rarest attribute ranging from -0.048 to -0.001. The minus sign is applied to assign higher rarity scores to rare tokens.[23]

Among the 10,000 tokens, the average rarity score for punk tokens is -0.544, which is higher than the average score of -0.571 for non-punk tokens. Figure IA5 plots the kernel density function of the average rarity score, providing a visual representation of the distribution. The figure indicates that punk tokens are rarer in the marketplace. Additionally, there is a positive correlation of 21% between the *Punk Look* variable and the average rarity score. Therefore, we formally test whether token rarity affects the estimation of punk premium by including the rarity measure as the control variable. Table 6 presents the rarity as the control at the transaction level:

$$Prc_{i,t}^{ETH} = \beta_1 Punk_i + \beta_2 Rarity_i + \beta_3 TokenClass_i + \gamma_t + \epsilon_{i,t} \tag{5.5}$$

We also conduct the estimation at the token level to avoid the potential of over-sampling.

$$Prc_{i}^{ETH} = \beta_1 Punk_i + \beta_2 Rarity_i + \beta_3 TokenClass_i + \epsilon_{i} \tag{5.6}$$

The results in Columns (4) and (5) of Table 6 indicate that the punk measures continue to be positively associated with the real price in ETH. This suggests that tokens exhibiting punk characteristics, on average, command a price premium of 3.03 ETH($s.e.$=0.554) to 3.35 ETH($s.e.$=0.569), even when controlling for token rarity. To further explore the relationship

[23]For illustration purposes, we take CryptoPunk #123 as an example. It is a female token (3840/10000) with a medium skin tone (3031/10000). Among the full set of traits, this token is featured with Choker (48/10000), Straight Hair Blonde (144/10000), but without the following attributes: Eyes (3928/10000), Facial Hair (6497/10000), Mouth (7455/10000), Ears (7541/10000), Mouth Prop (8275/10000), Blemishes (9104/10000), and Nose (9788/10000). To compute the measure of *ATR* for this token, we take the average of all these ratios.

between rarity and punk traits, we interact the rarity measures (i.e., *ATR* and *MTR*) with *Punk Look* in Columns (6) and (7) of Table 6. The coefficients of the interaction terms are significantly positive, implying that investors are inclined to pay a considerably higher price for tokens that possess the attribute associated with punk culture and are rare within the collection. Furthermore, we perform additional analyses using various measures of punk culture. The results in Table IA8 and Table IA9 also provide consistent evidence that rarer punk traits command a higher price premium.

To mitigate over-sampling concerns, we also conduct our analysis at the token level in Panel B of Table 6. The token-level results align with those obtained at the transaction level. Collectively, the results in Table 6 provide further evidence of the existence of a punk premium, even when controlling the influence of token rarity. The coefficient estimates are relatively close to the unconditional premium in Table 2. Therefore, these findings affirm that the punk premium cannot be solely attributed to the token rarity design.

[Insert Table 6 here]

5.4 Beauty Premium

Prior studies in psychology find that people often draw trait inferences from the facial appearance of other people (Willis and Todorov, 2006; Todorov, Pakrashi, and Oosterhof, 2009). This concept has been extended to diverse research domains.[24] Central to these studies is that when the available information is limited, facial cues can offer a wealth of information for making economic decisions. In the context of the digital art market, the available information set, including access to historical transaction and trait information, can vary across different NFT platforms (Fang, Nie, and Zheng, 2023). This suggests that investors might suffer from information asymmetry and rely on NFTs' aesthetic qualities, including their attributes, when determining the value of the NFTs (Kong and Lin, 2023).

[24]For instance, people form impressions about an individual's overall disposition and specific traits when evaluating the pace of their career advancement (Hamermesh, 2011), personal lending decisions (Ravina, 2019), and firm valuation (Colombo et al., 2022).

Therefore, it is of interest to examine whether punk features are deemed attractive by the general public and whether punk features can contribute to visual appreciation among investors.

To assess the visual aesthetics of CryptoPunks, we have devised two metrics to quantify the imperfect presentation of the CryptoPunks, specifically focusing on blemishes and untidiness. Prior studies indicate a connection between visual perfection in appearance and physical attractiveness. For example, Jaeger et al. (2018) find that individuals exhibit heightened sensitivity to skin blemishes due to their potential association with poor health and the possibility of contagious diseases. Likewise, recent studies have highlighted that maintaining a neat appearance is often viewed as desirable for achieving visual perfection (Choi et al., 2020). Table IA10 of the Appendix shows definitions of untidiness and blemish features. We have identified ten attributes as visual flaws, five of which are common to both punk features and visual flaws.

We commence our analysis by examining the existence of a beauty premium between punk and non-punk tokens. Out of the 1,383 non-punk tokens with transaction records, we find that 400 tokens exhibiting visual flaws have an average price of 30.59 ETH, whereas the remaining 983 tokens achieve an average price of 35.86 ETH. Therefore, a beauty premium of 5.27 ETH emerges among the non-punk tokens, with approximately 28.9% of the tokens exhibiting flaws. Turning our attention to the 5,440 punk tokens with transaction records, we find that 1,753 tokens with visual flaws achieve an average price of 36.35 ETH, whereas the remaining 3,687 tokens attain an average price of 40.15 ETH. The proportion of punk tokens with visual flaws stands at approximately 32.2%, closely mirroring the rate in non-punk tokens. The beauty premium for punk tokens is 3.80 ETH, which is considerably lower than that observed for non-punk tokens. These findings suggest that the "rebellious" investors who hold punk tokens exhibit a diminished sensitivity toward visual flaws. To some extent, the inherent visual disorder in punk tokens may also partially deliver a rebellious spirit against mainstream aesthetic norms. Therefore, this deviation from tra-

ditional beauty standards contributes to a diminished beauty premium among punk tokens compared to their non-punk counterparts.

Furthermore, we formally examine whether visual flawless in tokens affects the punk premium by including the flawless dummy (defined as the absence of blemishes and untidiness features) as the control variable. The results in Table 7 provide evidence of a beauty premium in CryptoPunks. Specifically, we find that flawless dummy is associated with an increase in token price by 3.68 ETH (*s.e.*=0.540). The findings in token-level regression verify the consistency of the beauty premium as reported in Column (5) of Table 7. In addition, we find that even after controlling for the visual presentation measures, we continue to find that punk tokens are traded at a higher price, with an extra 3.63 ETH (*s.e.*=0.561) compared to non-punk tokens at the transaction level, and 3.98 ETH (*s.e.* = 0.765) at the token level.

[Insert Table 7 here]

6 Conclusion

In this paper, we explore whether investors value the culture delivered in art pieces. We introduce a stylized model of an art marketplace that links investors' subjective valuations to transaction prices and the actions of bidders and sellers. We analyze the detailed trading histories of CryptoPunks and show that art pieces featuring punk cultural ideas are consistently traded at a premium of 5.6% in the market. We attribute this price disparity to the flow utility gap among tokens assigned with distinct visual attributes, given that NFTs neither generate cash flows nor incur any difference in production costs. In addition, punk tokens exhibited lower trading frequency and longer holding periods but received more bids and attracted more unique bidders within each transaction, and punk token owners demanded higher investment returns.

What drives investors to pay a premium for punk conceptual ideas? Our findings suggest that popularity plays a crucial role. Specifically, the punk premium became significant

when interest in NFTs peaked in March 2021, suggesting that investors gain greater utility from owning tokens with punk attributes. Our results are robust when considering various alternative explanations, such as price manipulation, over-speculation, investment performance, token rarity, and aesthetic appeal. Taken together, our findings underscore the importance of the flow utility provided by conceptual ideas in determining the value of alternative investments and are worth further investigation.

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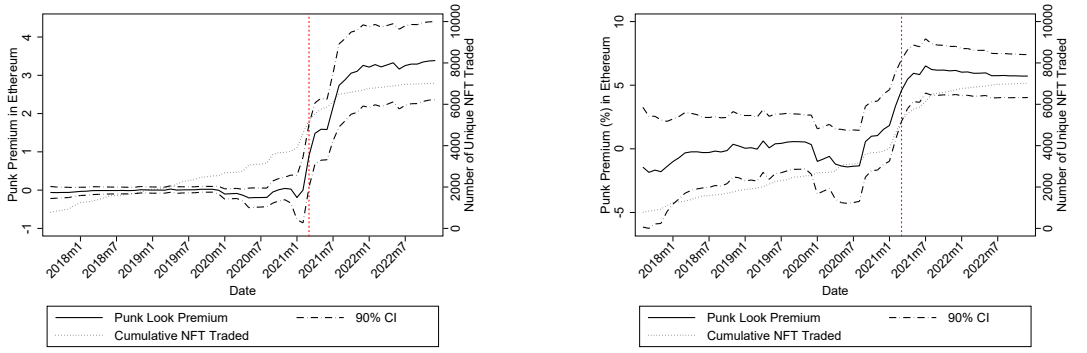
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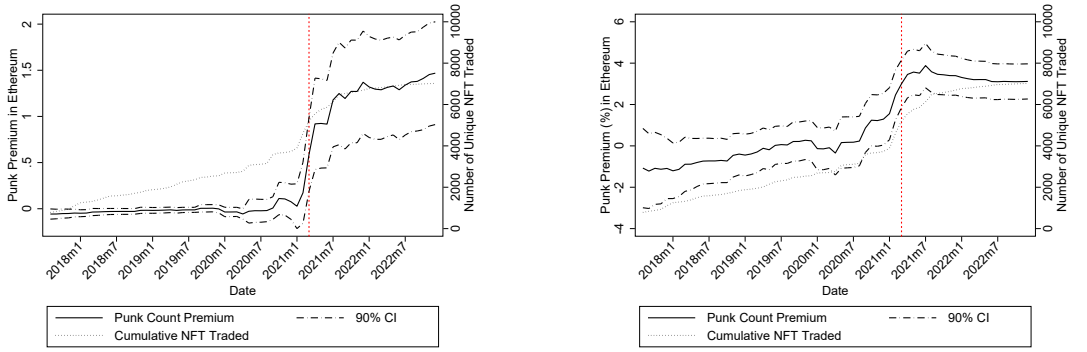
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Figures and Tables

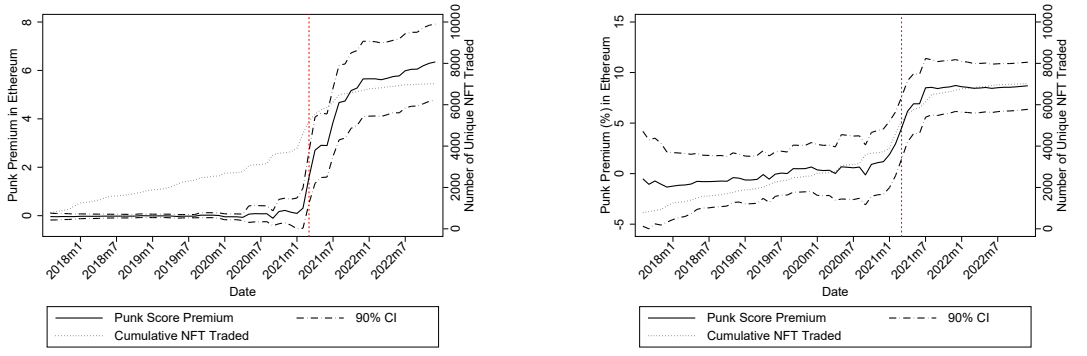
Figure 1. **Dynamic of punk premium**



Panel A. Punk Look Premium



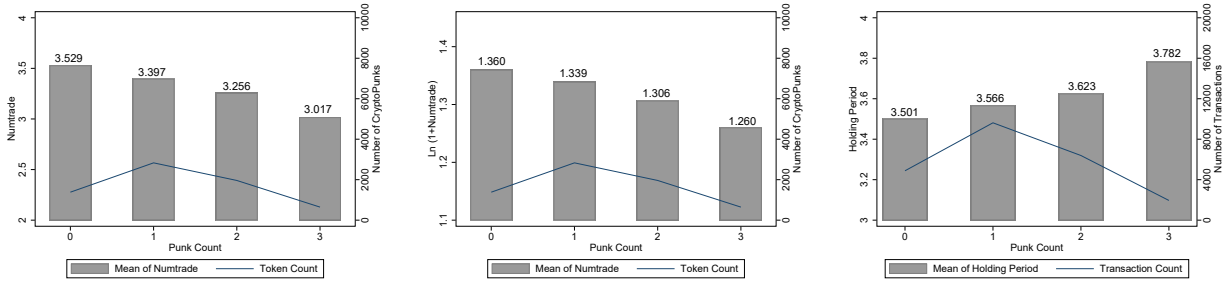
Panel B. Punk Count Premium



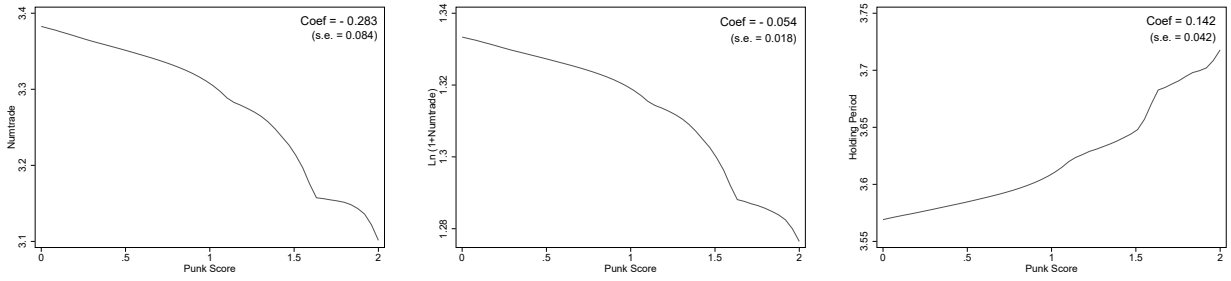
Panel C. Punk Score Premium

Note: This figure plots the evolving trend of the punk premium alongside the cumulative number of tokens sold over time. We first estimate the coefficients of the punk premium by regressing the last selling price of CryptoPunk tokens and punk measures for each month. We also calculate the number of unique tokens sold each month since the release of the CryptoPunks project. The solid line represents the punk premium for each month. The dotted line represents the cumulative unique NFTs sold monthly. The red vertical dotted line indicates the point where NFTs received the highest market attention as measured by Google Trends. The dashed lines represent the 90% confidence intervals. The left column plots the punk premium in Ethereum, while the right column plots the percentage of the punk premium in Ethereum. Panel A plots the *Punk Look* premium, Panel B plots the *Punk Count* premium, and Panel C plots the *Punk Score* premium.

Figure 2. **The liquidity of punk tokens**



Panel A. Punk Attribute Count



Panel B. Intensity of Punk Culture

Note: This figure examines Prediction 2. In Panel A, we present our analysis with *PunkCount*, and our Y-axes for each graph are *Numtrade*, *Ln*(1 + *Numtrade*), and *Holding Period*, respectively. The X-axis represents the number of punk attributes, ranging from 0 to greater than or equal to three attributes. The grey bars indicate the corresponding averages. The Y-axis on the right represents the number of observations. In Panel B, we depict the relationship between the liquidity measures and *Punk Score* through a locally weighted polynomial regression; the definitions for Y-axes are the same. In addition, we perform an OLS regression analysis for each plot in Panel B; the coefficients and standard errors are denoted in the corresponding corners.

Table 1. **Summary statistics**

Variable	Mean	S.D.	25^{th} Percentile	Median	75^{th} Percentile	Observations
	Panel A: CryptoPunks Trading and Return Data					
Prc_{ETH}	38.91	47.11	2.99	22.49	65.30	22,840
Prc_{USD}	102,467.92	148,004.83	1,031,00	45,167.50	140,223.00	22,840
Ret_{ETH}	2.352	9.403	0.178	0.589	1.895	14,319
Ret_{USD}	2.678	9.774	0.191	0.956	2.528	14,319
Numtrade	3.348	2.520	1.000	3.000	5.000	6,823
HoldingPeriod	3.692	1.977	2.079	3.932	5.165	15,148
	Panel B: Punk Culture Measures					
PunkLook	0.797	0.402	1.000	1.000	1.000	10,000
PunkCount	1.286	0.918	1.000	1.000	2.000	10,000
PunkScore	0.417	0.357	0.100	0.400	0.700	10,000
	Panel C: CryptoPunk TokenClass					
Ape	0.002	0.049	0.000	0.000	0.000	10,000
Alien	0.001	0.030	0.000	0.000	0.000	10,000
Zombie	0.009	0.093	0.000	0.000	0.000	10,000
Albino	0.102	0.302	0.000	0.000	0.000	10,000
Dark	0.282	0.450	0.000	0.000	1.000	10,000
Medium	0.303	0.460	0.000	0.000	1.000	10,000
Light	0.301	0.456	0.000	0.000	1.000	10,000
	Panel D: Additional Measures					
ATR	-0.550	0.047	-0.586	-0.553	-0.521	10,000
MTR	-0.025	0.011	-0.030	-0.026	-0.015	10,000
Flawness	0.684	0.465	0.000	1.000	1.000	10,000

Note: This table reports summary statistics of the variables used in the empirical analysis. Historical trading data of CryptoPunks was obtained from Larva Labs studio. The sampling period spans from June 2017 to December 2022. Panel A summarizes the transactions, investment performance, and trading conditions of CryptoPunk tokens. Panel B summarizes the different definitions of punk measures. Panel C summarizes the skin tone features of CryptoPunks. Panel D summarizes the additional measures used in Section 5.

Table 2. **Cultural premium in CryptoPunks**

	(1)	(2)	(3)	(4)	(5)	(6)
	$Prc_{i,t}^{ETH}$	$ln(1+Prc_{i,t}^{ETH})$	$Prc_{i,t}^{ETH}$	$ln(1+Prc_{i,t}^{ETH})$	Prc_{i}^{ETH}	$ln(1+Prc_{i}^{ETH})$
	Panel A: Punk Token Indicator					
Punk Look	3.637***	0.056***	3.858***	0.061***	4.358***	0.060***
	(0.567)	(0.010)	(0.539)	(0.009)	(0.678)	(0.010)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.605	0.923	0.634	0.932	0.109	0.188
	Panel B: Punk Attribute Count					
Punk Count	1.625***	0.032***	1.887***	0.037***	1.903***	0.037***
	(0.324)	(0.005)	(0.316)	(0.005)	(0.330)	(0.005)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.605	0.923	0.635	0.932	0.110	0.192
	Panel C: Intensity of Punk Culture					
Punk Score	6.506***	0.089***	6.675***	0.092***	7.198***	0.096***
	(0.919)	(0.014)	(0.901)	(0.014)	(1.000)	(0.013)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.607	0.923	0.635	0.932	0.114	0.192
Observations	22,840	22,840	22,840	22,840	6,823	6,823

Note: This table shows how CryptoPunk tokens with punk features are associated with their corresponding selling price in ETH. We run the following regressions at transaction and token levels:

$$Prc_{i,t}^{ETH} = \beta_1 Punk_i + \beta_2 TokenClass_i + \gamma_t + \epsilon_{i,t}$$

$$Prc_{i}^{ETH} = \beta_1 Punk_i + \beta_2 TokenClass_i + \epsilon_{i}$$

where $Prc_{i,t}^{ETH}$ represents the selling price of CryptoPunk i in Ethereum at time t. Prc_{i}^{ETH} represents the standardized average transaction price of token i. Columns (1) and (2) involve regression without TokenClass fixed effects, using the transaction price in ETH and the natural logarithm of the ETH price. Columns (3) and (4) perform estimations using the transaction price in ETH and the natural logarithm price, by including $TokenClass_i$ to control for the token's skin tone (i.e., dark, medium, light, albino, zombie, ape, and alien). We use the medium skin tone as the base variable to avoid multicollinearity. Columns (5) and (6) report the results using the standardized average transaction price at the token level. In addition, Panels A, B, and C report the findings across the different definitions of the $Punk_i$ measures, including *Punk Look*, *Punk Count*, and *Punk Score*, respectively. We also control the time of the token sale, and standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Table 3. **Investor Trading Behavior in NFT market structure**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: The Behavior of Seller									
	Dependent Variable *OfferRet*			Dependent Variable *ThroughOffer*			Dependent Variable *OTSdays*		
Punk Look	6.232**			-0.014			0.113***		
	(2.435)			(0.010)			(0.043)		
Punk Count		2.783**			-0.011***			0.048**	
		(1.396)			(0.004)			(0.021)	
Punk Score			6.928*			-0.030***			0.095*
			(3.828)			(0.012)			(0.054)
Year Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.199	0.199	0.199	0.012	0.013	0.013	0.436	0.436	0.436
Observations	7,703	7,703	7,703	6,446	6,446	6,446	6,797	6,797	6,797
Panel B: The Behavior of Bidder									
	Dependent Variable *BidCount*			Dependent Variable *UniqueBidder*			Dependent Variable *ReceiveBid*		
Punk Look	0.131***			0.020*			0.020		
	(0.030)			(0.011)			(0.013)		
Punk Count		0.077***			0.018***			0.020***	
		(0.015)			(0.005)			(0.006)	
Punk Score			0.198***			0.046***			0.039**
			(0.039)			(0.014)			(0.015)
Year Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.325	0.326	0.326	0.195	0.196	0.196	0.267	0.268	0.267
Observations	13,794	13,794	13,794	13,794	13,794	13,794	8,000	8,000	8,000

Note: This table investigates the trading behavior of punk token sellers and buyers of the NFT market. We focus on the seller perspective in Panel A, the dependent variable in Columns (1) to (3), $OfferRet_{i,t}^{ETH}$, is derived by dividing the minimum offer price by the real transaction price before the subsequent transaction and then subtracting one. Similarly, the dependent variable, *ThroughOffer*, in Columns (4) to (6) is a dummy variable coded as one if the transaction occurs through the offer mechanism. The dependent variable in Columns (7) to (9), *OTSdays*, is the natural logarithm of one plus the number of days between the first offer date and the actual transaction date. For Panel B, we examine from the bidder's perspective, *BidCount* is the total number of bids prior to each transaction. *UniqueBidder* is the number of unique bidders within each CryptoPunk transaction. *ReceiveBid*, is assigned a value of one if the token receives at least one bid within the next six months following its sale, and 0 otherwise. *Punk Look*, *Punk Count*, and *Punk Score* represent measures of punk culture for the CryptoPunk token. We control the skin tone of each CryptoPunk token, encompassing categories such as dark, medium, light, albino, zombie, ape, and alien. To prevent multicollinearity, we adopt the medium skin tone as the reference variable. We also include the owner's wallet-fixed effects and time-fixed effects in Columns (1) to (9). Standard errors (in parentheses) are clustered based on the token level. Statistical significance is denoted by ***, **, and * to signify the significance levels of 1%, 5%, and 10%, respectively.

Table 4. **The punk premium with liquidity controls**

	(1)	(2)	(3)	(4)	(5)	(6)
	$Prc_{i,t}^{ETH}$	$ln(1+Prc_{i,t}^{ETH})$	$Prc_{i,t}^{ETH}$	$ln(1+Prc_{i,t}^{ETH})$	Prc_{i}^{ETH}	$ln(1+Prc_{i}^{ETH})$
	Panel A: Punk Token Indicator					
Punk Look	4.141***	0.058***	4.395***	0.061***	4.103***	0.056***
	(0.678)	(0.011)	(0.651)	(0.011)	(0.673)	(0.010)
Holding Period	1.199***	0.013***	1.010***	0.011***		
	(0.138)	(0.002)	(0.126)	(0.002)		
Numtrade					-1.063***	-0.018***
					(0.088)	(0.001)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.567	0.895	0.608	0.905	0.119	0.201
	Panel B: Punk Attribute Count					
Punk Count	1.890***	0.033***	2.176***	0.037***	1.735***	0.034***
	(0.418)	(0.006)	(0.411)	(0.006)	(0.329)	(0.005)
Holding Period	1.188***	0.013***	0.997***	0.010***		
	(0.137)	(0.002)	(0.125)	(0.002)		
Numtrade					-1.051***	-0.018***
					(0.089)	(0.001)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.567	0.896	0.608	0.906	0.118	0.204
	Panel C: Intensity of Punk Culture					
Punk Score	7.526***	0.096***	7.781***	0.098***	6.902***	0.091***
	(1.193)	(0.017)	(1.173)	(0.016)	(0.994)	(0.013)
Holding Period	1.178***	0.013***	0.991***	0.010***		
	(0.137)	(0.002)	(0.125)	(0.002)		
Numtrade					-1.049***	-0.018***
					(0.088)	(0.001)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.568	0.896	0.610	0.906	0.123	0.205
Observations	16,017	16,017	16,017	16,017	6,823	6,823

Note: This table examines whether the price premium still holds when controlling for token liquidity. In Columns (1) and (2), we perform the regression without attribute fixed effects using the real price in ETH and the natural logarithm of one plus the ETH price. In Columns (3) and (4), we perform the estimations using the real price in ETH and the natural logarithm price by including *TokenClass* to control for the token's skin tone (i.e., dark, medium, light, albino, zombie, ape, and alien). We use the medium skin tone as the base variable to avoid multicollinearity. Columns (5) and (6) report the results using the average normalized price at the token level. *Holding Period* is defined as the natural logarithm of one plus the number of days between the transactions for each token i at time t. *Numtrade* is the total number of CryptoPunk tokens i traded over the sampling period. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Table 5. **Investment performance of CryptoPunk tokens with punk features**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$Ret_{i,t}^{ETH}$	$Ret_{i,t}^{ETH}$	$Ret_{i,t}^{ETH}$	Ret_{i}^{ETH}	Ret_{i}^{ETH}	$Ret_FL_{i}^{ETH}$	$Ret_FL_{i}^{ETH}$
	Panel A: Punk Token Indicator						
Punk Look	0.051	0.174	0.200	0.076	0.122	-0.002	0.004
	(0.185)	(0.182)	(0.182)	(0.123)	(0.122)	(0.018)	(0.016)
Holding Period		-1.414***	-1.431***				-0.260***
		(0.070)	(0.072)				(0.018)
Initial Price (ETH)			-0.013***				-0.126***
			(0.002)				(0.009)
Numtrade					0.164***		
					(0.022)		
Adjusted-R^2	0.050	0.118	0.119	0.000	0.010	0.000	0.166
	Panel B: Punk Attribute Count						
Punk Count	0.005	0.088	0.102	0.004	0.031	0.002	0.005
	(0.070)	(0.067)	(0.066)	(0.051)	(0.050)	(0.009)	(0.008)
Holding Period		-1.415***	-1.432***				-0.260***
		(0.070)	(0.072)				(0.018)
Initial Price (ETH)			-0.013***				-0.126***
			(0.002)				(0.009)
Numtrade					0.164***		
					(0.022)		
Adjusted-R^2	0.050	0.118	0.119	0.000	0.010	0.000	0.166
	Panel C: Intensity of Punk Culture						
Punk Score	0.050	0.204	0.223	0.041	0.097	0.045*	0.044**
	(0.196)	(0.186)	(0.186)	(0.155)	(0.154)	(0.024)	(0.022)
Holding Period		-1.414***	-1.431***				-0.260***
		(0.070)	(0.072)				(0.018)
Initial Price (ETH)			-0.012***				-0.126***
			(0.002)				(0.008)
Numtrade					0.164***		
					(0.022)		
Adjusted-R^2	0.050	0.118	0.119	0.000	0.010	0.001	0.167
Observations	14,319	14,319	14,319	4,318	4,318	4,318	4,318

Note: This table examines whether the punk tokens are overpriced by considering factors such as holding periods, initial trading price, and the number of trades. $Ret_{i,t}^{ETH}$ in Columns (1) to (3) represents the logarithm of one plus the daily return for CryptoPunks i at time t. Ret_{i}^{ETH} in Columns (4) and (5) represents the average normalized logarithm of one plus the daily return for each CryptoPunk token i. $Ret_FL_{i}^{ETH}$ in Columns (6) and (7) represents the average normalized logarithm of one plus daily return between the first and the last transaction price for each CryptoPunk i. $Holding\ Period_{i,t}$ is defined as the natural logarithm of one plus the days between each token transaction i at time t. *Initial Price* is the natural log of the first token selling price. *Numtrade* is the number of trades. $Punk_i$ is one of the punk culture measures for CryptoPunks i, including *Punk Look*, *Punk Count*, and *Punk Score*. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Table 6. **Cultural premium in CryptoPunks with token rarity**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Dependent Variable $Prc_{i,t}^{ETH}$						
Punk Look	3.858***	3.353***	-8.179***	3.351***	3.034***	34.952***	10.693***
	(0.539)	(0.569)	(3.001)	(0.569)	(0.554)	(10.281)	(2.085)
Traits		1.140**	-2.676***	0.323	0.519	0.275	0.482
		(0.517)	(0.940)	(0.789)	(0.517)	(0.787)	(0.518)
Punk Look × Traits			4.609***				
			(1.111)				
ATR				15.900		-30.385*	
				(12.537)		(17.567)	
MTR					505.207***		274.712***
					(28.118)		(52.452)
Punk Look × ATR						55.933***	
						(18.213)	
Punk Look × MTR							283.859***
							(65.060)
TokenClass FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.634	0.635	0.635	0.635	0.647	0.635	0.648
Observations	22,840	22,840	22,840	22,840	22,840	22,840	22,840
	Panel B: Dependent Variable Prc_{i}^{ETH}						
Punk Look	4.358***	4.017***	-9.533**	4.007***	3.540***	32.457***	8.581***
	(0.678)	(0.698)	(3.871)	(0.700)	(0.683)	(12.036)	(2.855)
Traits		0.694	-3.782***	0.190	0.131	0.220	0.100
		(0.514)	(1.293)	(0.915)	(0.516)	(0.910)	(0.518)
Punk Look × Traits			5.447***				
			(1.432)				
ATR				9.849		-33.093	
				(14.644)		(20.539)	
MTR					502.013***		345.671***
					(28.898)		(73.909)
Punk Look × ATR						50.360**	
						(21.159)	
Punk Look × MTR							190.533**
							(88.984)
TokenClass FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.110	0.110	0.113	0.110	0.147	0.111	0.147
Observations	6,823	6,823	6,823	6,823	6,823	6,823	6,823

Note: This table examines whether the token attribute count (*Traits*) and rarity (*ATR* and *MTR*) affect the punk premium. In Panel A, $Prc_{i,t}^{ETH}$ is the ETH selling price of token i at time t, while Prc_{i}^{ETH} in Panel B is the average normalized token price for token i. Column (2) includes controls for token attribute counts. Columns (4) and (5) control for token rarity in terms of the average rarity score (*ATR*) and the minimal rarity score (*MTR*) for each token i. Columns (3), (6), and (7) incorporate interaction terms. $TokenClass_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use the medium skin tone as the base variable to avoid multicollinearity. $Rarity_i$ denotes the rarity score of each CryptoPunk token i. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Table 7. **Cultural premium in CryptoPunks with flawless appearance**

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Dependent Variable $Prc_{i,t}^{ETH}$			Panel B: Dependent Variable Prc_{i}^{ETH}		
Punk Look	3.637***		3.634***	3.835***		3.976***
	(0.567)		(0.561)	(0.765)		(0.765)
Flawless		3.678***	3.676***		4.183***	4.281***
		(0.540)	(0.538)		(0.651)	(0.652)
TokenClass FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R2	0.605	0.606	0.607	0.003	0.005	0.008
Punk Count	1.625***		1.653***	1.475***		1.571***
	(0.324)		(0.323)	(0.357)		(0.358)
Flawless		3.678***	3.725***		4.183***	4.318***
		(0.540)	(0.537)		(0.651)	(0.651)
TokenClass FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R2	0.605	0.606	0.607	0.002	0.005	0.007
Punk Score	6.506***		7.203***	6.921***		7.933***
	(0.919)		(0.933)	(1.043)		(1.070)
Flawless		3.678***	4.331***		4.183***	5.103***
		(0.540)	(0.553)		(0.651)	(0.676)
TokenClass FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R2	0.607	0.606	0.609	0.008	0.005	0.014
Observations	22,840	22,840	22,840	6,823	6,823	6,823

Note: This table examines whether perfect visual presentation (i.e., facial features without blemishes and untidiness) matters to the punk premium. We run the following regression:

$$Prc_{i,t}^{ETH} = \beta_1 Punk_i + \beta_2 Flawless_i + \beta_3 TokenClass_i + \gamma_t + \epsilon_{i,t}$$

where $Prc_{i,t}^{ETH}$ in Panel A represents the selling price of the CryptoPunk token i at time t. In Panel B, Prc_{i}^{ETH} represents the average normalized token price of the CryptoPunk token i. $Punk_i$ is one of the punk culture measures for CryptoPunk token i, including *Punk Look*, *Punk Count*, and *Punk Score*. *Flawless* is an indicator that equals one if the CryptoPunk tokens do not exhibit blemishes and untidiness in their appearance. $Punk_i \times$ *Flawless* is the interaction term of punk measures with the visual appearance of each token. $TokenClass_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use the medium skin tone as the base variable to avoid multicollinearity. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

For Online Publication

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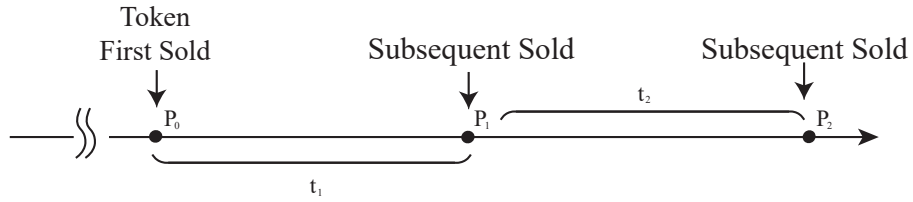
I Appendix

Market Structure of CryptoPunks

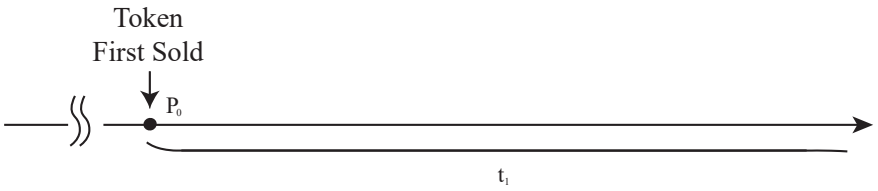
The decentralized nature of blockchain technology offers new paradigms for studying the pricing behavior of digital asset trading. Larva Labs provides a comprehensive set of trading histories accessible to all investors on their website. In addition to transaction records, we can obtain valuable data for each digital art piece, including detailed information on bidding and offer histories, which are challenging to acquire in the traditional art auction market. Specifically, for each CryptoPunk token, the website lists all attributes and the complete transaction history, such as the offer and bid prices set by the owners and bidders, the number of sellers and buyers in the market, and the actual transaction price. We collected data for each CryptoPunk from June 2017 to December 2022. The total number of observations over the sampling period contains 220,922 observations. We then filtered the data to include only trading actions with "Bids", "Offered", and "Sold", and removed any duplicate observations. Additionally, we excluded observations with a price less than 0.01 ETH and also observations with missing data.

Token Transactions

After removing missing and duplicate observations, our final sample consists of 22,840 sales records, with 6,823 tokens sold at least once during the sampling periods. Additionally, we constructed measures to proxy for bidding and offer behaviors. From the seller's perspective, the first measure, $OfferRet$, represents the minimum price return expected by the owner to sell their token. This variable is calculated by identifying the minimum price offered by the seller, excluding the offer price from the first round of transactions because the owner initially acquired the tokens for free. In other words, conditional on those tokens that have been sold in the market, we determine the minimum price offered by the seller, regardless of whether the token will be sold in the market (see the brief illustration below). For example, for tokens with subsequent transactions, we record the minimum price offered by the seller within t_1, and repeat this process for t_2, and so on for further transactions. Meanwhile, for tokens without subsequent transactions, we consider the minimum offer price set by the seller over the entire time horizon. During our sampling period, we excluded 15,137 observations that did not meet the above criteria, resulting in 7,703 observations in Panel A Columns (1) to (3) of Table 3. The second measure, $ThroughOffer$, addresses the mechanism through which the token is traded, either through a bid or an offer. By definition, a transaction occurs if and only if the willingness to sell matches the willingness to pay. We use the full sample and define this measure as through offer if the minimum offer price matches the actual transaction price, and zero otherwise. However, some token transactions are executed immediately following a successful transaction; we cannot ascertain whether the transaction was through a bid or an offer. Therefore, we excluded 6,855 instances that did not match the definition and left 6,446 observations at the token level for Panel A Columns (4) to (6) of Table 3. The third measure, $OTSdays$, measures the duration from the first offer date to the actual sale date. In this case, we dropped transactions that were not traded through the offer mechanism and also excluded the offer price data from the initial trade, resulting in 6,797 observations for Panel A Columns (7) to (9) of Table 3.



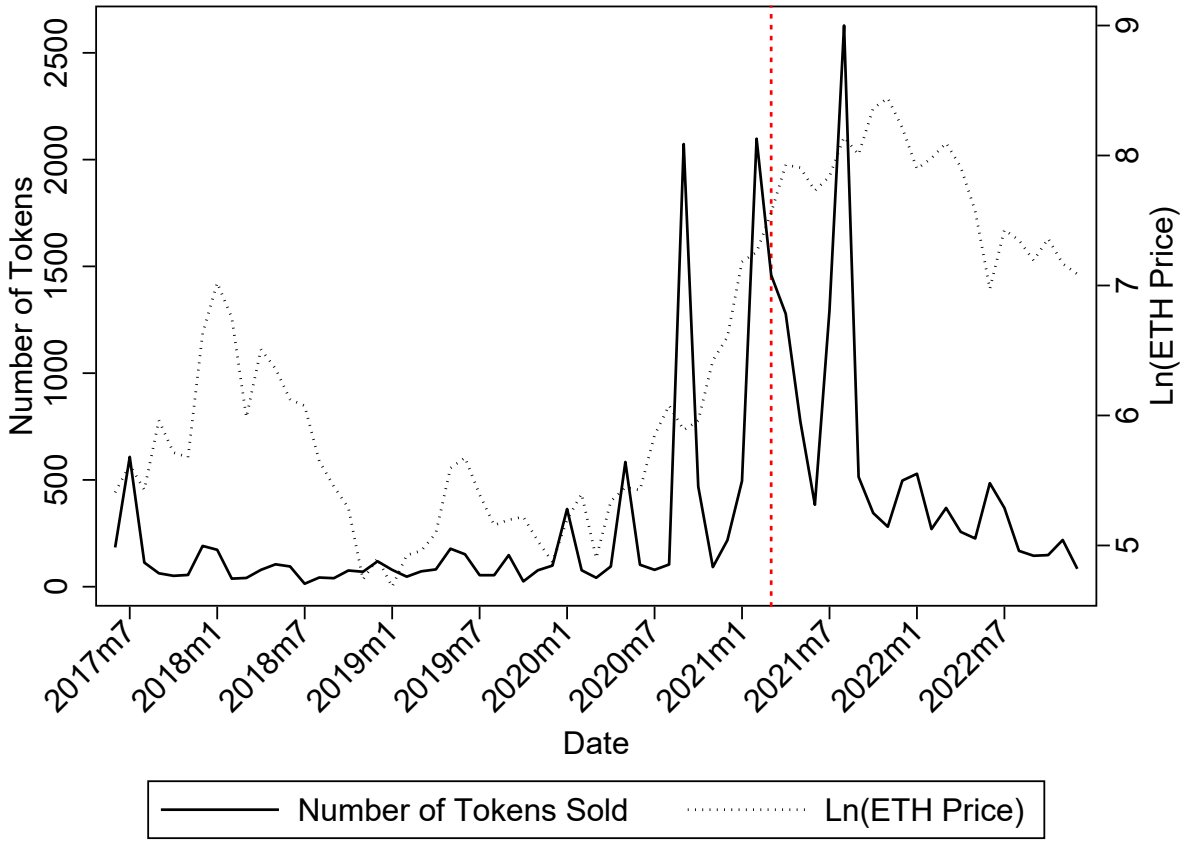
Timeline (Tokens with subsequent transactions)



Timeline (Tokens without subsequent transactions)

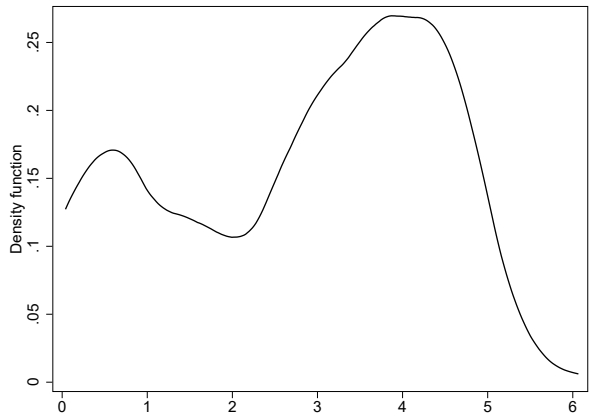
From the perspective of buyers, we devised three measures to capture their behaviors. The first measure, *BidCount*, represents the number of bids placed by buyers for each CryptoPunk in each trading round, starting from when the tokens have traceable ownership in the marketplace. We removed 6,855 observations where the trading mechanisms were unclear, resulting in 15,985 observations for our analysis. After accounting for the owner's wallet address fixed effect, 2,191 singleton observations were excluded, leaving 13,794 observations in Panel B Columns (1) to (6) of Table 3. The variable, *UniqueBidder* quantifies the number of unique buyers by assuming each buyer's wallet address represents an individual buyer, thus maintaining the same number of observations as in Panel A. The third measure, *Receivable*, assesses the readiness of a token to receive bids post-sale in the market. This measure is a dummy variable indicating whether the token received at least one bid in the subsequent 180 days, provided that it is not in the final trading round. For this measure, we excluded observations where the bidding status was unclear and the final trading records for each CryptoPunk, as bids at this stage may not indicate genuine buyer interest. We focused on periods when the token had a positive next bid date and was actively traded under more stable and representative market conditions. This resulted in 9,488 observations, and after controlling for the owner's wallet address fixed effect, the final count was 8,000 observations.

Figure IA1. **Number of CryptoPunk tokens traded over time**

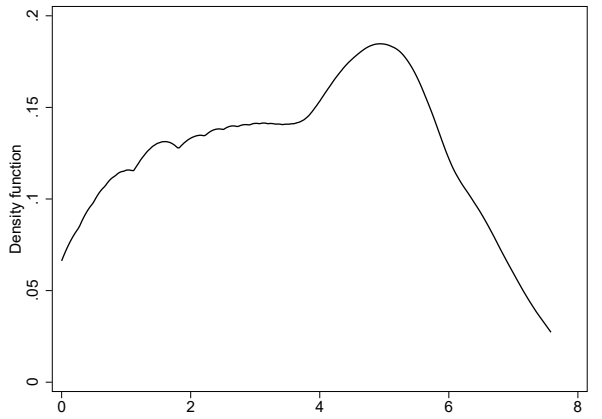


Note: This figure illustrates the time-series relationship between CryptoPunk token transactions and Ethereum price. The solid line represents the number of CryptoPunk tokens traded, while the dotted line represents the natural logarithm of one plus the Ethereum price. The red vertical dotted line indicates the point where NFTs received the highest market attention as measured by Google Trends. The sampling period spans from June 2017 to December 2022.

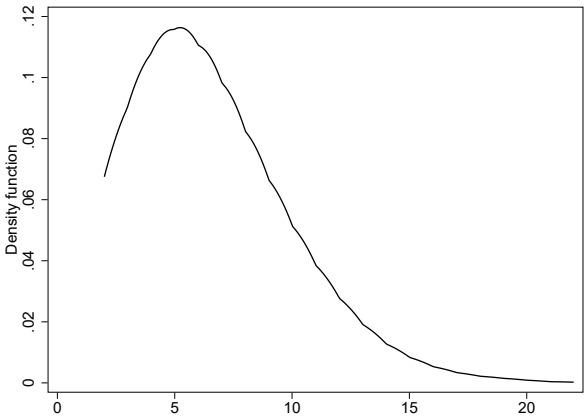
Figure IA2. **The distribution of CryptoPunks price, holding period, and transactions**



Panel A. CrytoPunks Ethereum Prices



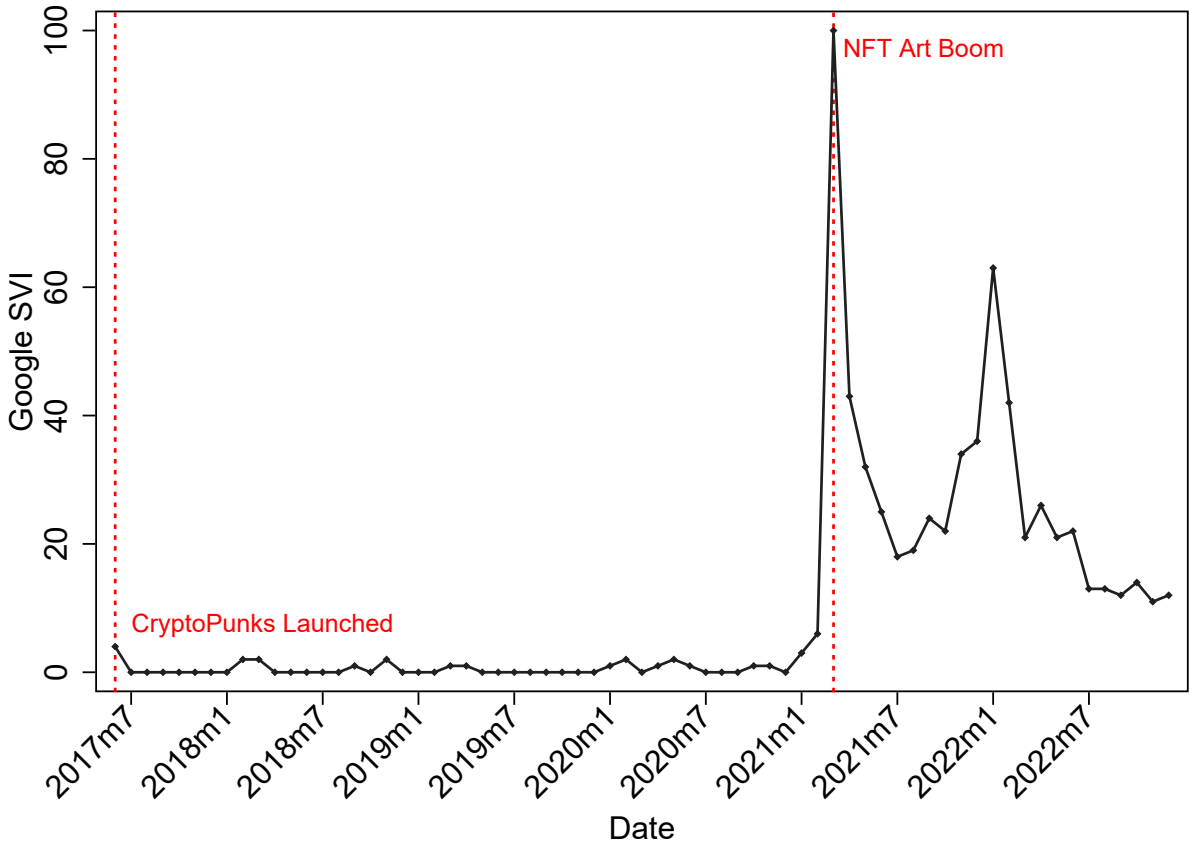
Panel B. CryptoPunks Holding Periods



Panel C. CryptoPunks Transaction Numbers

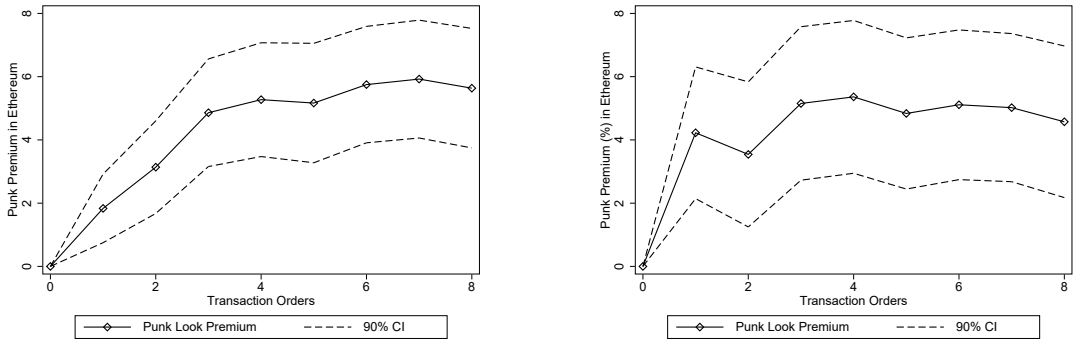
Note: This figure displays the kernel density functions of three variables: the natural logarithm of the CryptoPunks Ethereum Price in Panel A, the natural logarithm of one plus the holding period of the CryptoPunk tokens in Panel B, and the natural logarithm of one plus the number of CryptoPunks transaction numbers in Panel C.

Figure IA3. **Monthly Google SVI of Non-fungible tokens**

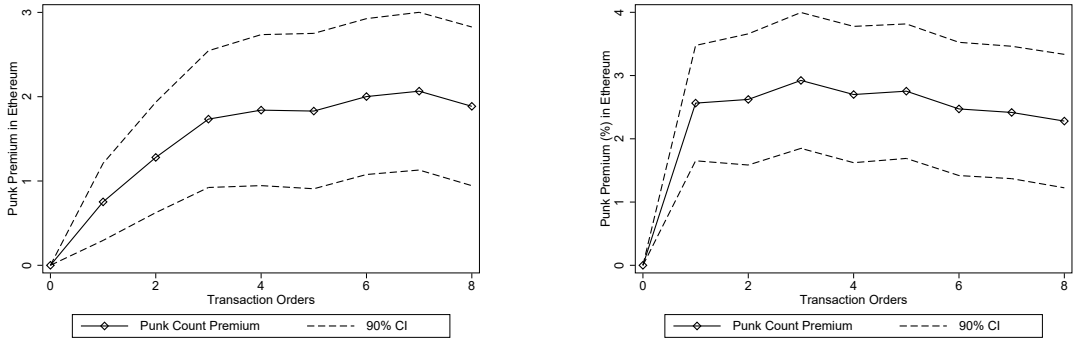


Note: This figure displays the search interest on Non-fungible tokens (NFTs) from Google Trends over the sampling period. It highlights three significant events related to NFTs. The left red vertical dotted line indicates the launch of the CryptoPunk project. The middle red vertical dotted line represents the sale of digital artwork by artist Beeple for $69 million US dollars at a Christie's auction, which garnered widespread attention for NFTs.

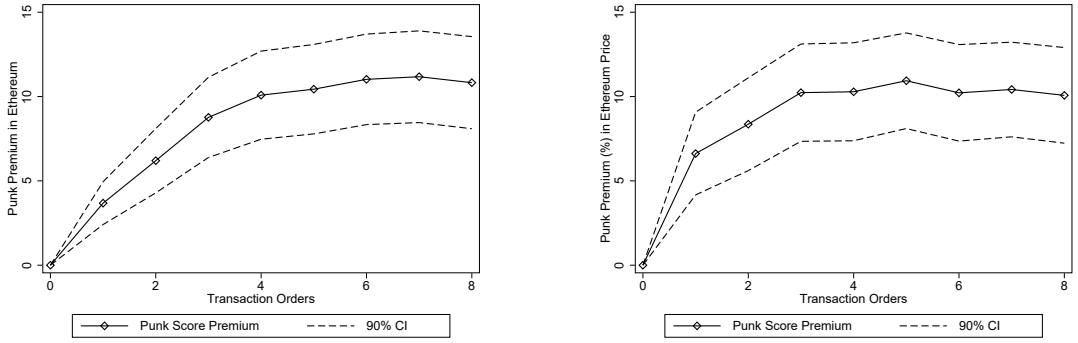
Figure IA4. **Punk premium by transaction order**



Panel A. Punk Look Premium



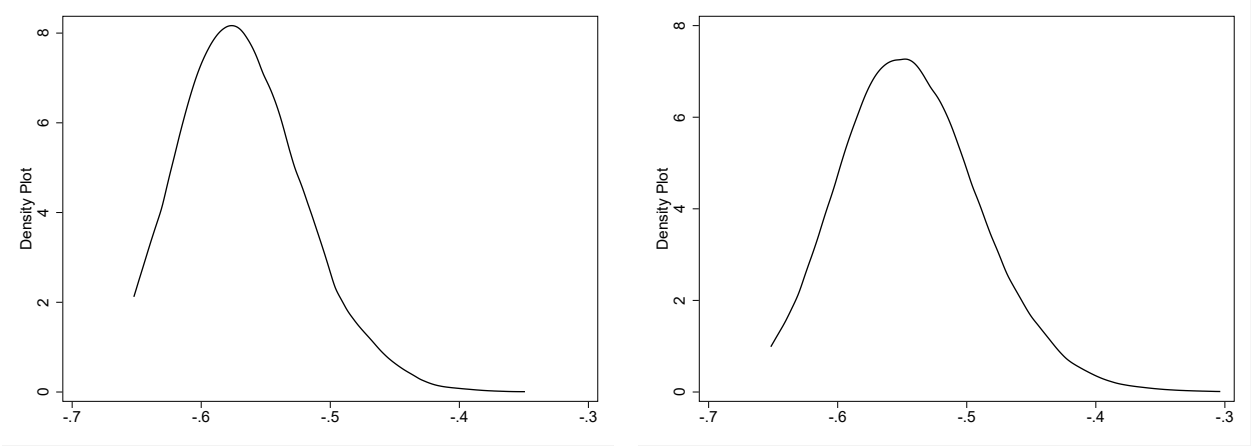
Panel B. Punk Count Premium



Panel C. Punk Score Premium

Note: This figure explores the heterogeneity in punk premium across different transaction orders. We estimate the coefficients for each punk measure by regressing the selling price of CryptoPunks in Ethereum and the punk measures for each transaction order. The selling price of CryptoPunks is imputed as zero if the token is not sold in the market. The solid line represents the punk premium for each transaction order. The dashed lines depict the 90% confidence interval. The left column plots the punk premium in Ethereum, while the right column plots the percentage of the punk premium in Ethereum. Panel A plots the *Punk Look* premium, Panel B plots the *Punk Count* premium, and Panel C plots the *Punk Score* premium.

Figure IA5. **The distribution of average rarity score for punk and non-punk tokens**



Panel A. Non-Punk Tokens

Panel B. Punk Tokens

Note: This figure displays the kernel density functions of the average rarity score for non-punk tokens in Panel A, and in Panel B, it shows the kernel density functions of the average rarity score for punk tokens.

Table IA1. **Variable definitions**

Variable	Definition
Prc^{ETH}	Selling price of CryptoPunk in Ethereum.
Prc^{USD}	Selling price of CryptoPunk in US dollars.
Ret^{ETH}	The logarithm of one plus the Ethereum daily return.
Ret^{USD}	The logarithm of one plus the US dollars daily return.
Numtrade	Total number of trades for each CryptoPunk over the sampling period.
HoldingPeriod	The natural logarithm of one plus the number of days between the next transaction for each CryptoPunk.
PunkLook	Dummy variable that is coded as one if the CryptoPunk token shares at least one punk characteristic found in the punk band's photos and 0 otherwise.
PunkCount	The number of attributes in CryptoPunk *i* designed to resemble punk characteristics based on the punk bands' photos.
PunkScore	The total score of each attribute assigned to the CryptoPunk token. Each attribute score is calculated based on the frequency of punk bands exhibiting the same attributes.
Ape	Dummy variable coded as one if the type of CryptoPunks is categorized as "Ape" and 0 otherwise.
Alien	Dummy variable coded as one if the type of CryptoPunks is categorized as "Alien" and 0 otherwise.
Zombie	Dummy variable coded as one if the type of CryptoPunks is categorized as "Zombie" and 0 otherwise.
Albino	Dummy variable coded as one if the skin tone of CryptoPunks is categorized as "Albino" and 0 otherwise.
Dark	Dummy variable coded as one if the skin tone of CryptoPunks is categorized as "Dark" and 0 otherwise.
Medium	Dummy variable coded as one if the skin tone of CryptoPunks is categorized as "Medium" and 0 otherwise.
Light	Dummy variable coded as one if the skin tone of CryptoPunks is categorized as "Light" and 0 otherwise.
InitialPrice	The natural logarithm of the initial sale price of each CryptoPunk.
ATR	The negative average dimensional rarity score for each CryptoPunk token (see Section 5.3).
MTR	The negative minimum trait rarity score for each CryptoPunk token (see Section 5.3).

Variable	Definition
Flawness	Dummy variable coded as one if CryptoPunk tokens do not exhibit blemishes and untidiness in their appearance, and 0 otherwise (see Section 5.4).
Traits	The total number of attribute counts for each CryptoPunk token, ranging from 0 to 7.
$OfferRet$	The minimum offer price return is calculated by dividing the minimum offer price before the subsequent transaction by the latest transaction price, then subtracting one.
$ThroughOffer$	Dummy variable coded as one if the CryptoPunk token transaction deals through the offer, and 0 otherwise.
OTSdays	The natural logarithm of one plus the number of days between the first offer date and the actual transaction date.
BidCount	The total number of bids received for CryptoPunk token before each transaction.
ReceiveBid	Dummy variable coded as one if CryptoPunk token received at least one bid in the next six months after its sale, and 0 otherwise.
UniqueBidder	The total number of unique bidders who place bids before each transaction.
SALE	Dummy variable coded as one if the CryptoPunk token has been traded in the market, and 0 otherwise.

Table IA2. **Classification of punk attributes**

Attribute	N	Attribute	N	Attribute	N
Panel A: Punk Attributes					
Hair:					
Beanie	44	Hoodie	259	Shaved Head	300
Blonde Short	129	Messy Hair	460	Top Hat	115
Cowboy Hat	142	Mohawk	441	Vampire Hair	147
Crazy Hair	414	Mohawk Dark	429	Wild Blonde	144
Fedora	186	Mohawk Thin	441	Wild Hair	447
Half Shaved	147	Red Mohawk	147	Wild White Hair	136
Eyes:					
Blue Eye Shadow	266	Green Eye Shadow	271	3D Glasses	286
Clown Eyes Blue	384	Purple Eye Shadow	262		
Clown Eyes Green	382	Small Shades	378		
Mouth:					
Black Lipstick	617	Hot Lipstick	696	Purple Lipstick	655
Facial Hair:					
Big Beard	146	Mustache	288	Normal Beard Black	289
Luxurious Beard	286	Normal Beard	292		
Neck Accessory:					
Choker	48	Gold Chain	169	Silver Chain	156
Ears:					
Earring	2459				
Panel B: Non-Punk Attributes					
Hair:					
Bandana	481	Headband	406	Purple Hair	165
Blonde Bob	147	Knitted Cap	419	Straight Hair	151
Cap	351	Orange Side	68	Straight Hair Blonde	144
Cap Forward	254	Peak Spike	303	Straight Hair Dark	148
Clown Hair Green	148	Pigtails	94	Stringy Hair	463
Dark Hair	157	Pilot Helmet	54	Tassle Hat	178
Do-rag	300	Pink With Hat	95	Tiara	55
Frumpy Hair	442	Police Cap	203		
Eyes:					
Big Shades	535	Eye Patch	461	Regular Shades	527
Classic Shades	502	Horned Rim Glasses	535	VR	332
Eye Mask	293	Nerd Glasses	572	Welding Goggles	86
Mouth:					
Buck Teeth	78	Frown	261	Smile	238
Blemishes:					

Continued on next page

Table IA2. **Classification of punk attributes** (Continued)

Panel B: Non-Punk Attributes					
Mole	644	Rosy Cheeks	128	Spots	124
Mouth Prop:					
Cigarette	961	Pipe	317	Vape	272
Medical Mask	175				
Facial Hair:					
Chinstrap	282	Goat	295	Shadow Beard	526
Front Beard	273	Handlebars	263		
Front Beard Dark	260	Muttonchops	303		
Nose:					
Clown Nose	212				

Note: This table presents a comprehensive classification of the punk attributes derived from the performance photos of the top 10 punk rock bands. Panel A displays attributes that are identified as punk features, whereas Panel B presents attributes that are not considered punk features.

Table IA3. **Cultural premium in CryptoPunks**

	(1)	(2)	(3)	(4)	(5)	(6)
	$Prc_{i,t}^{USD}$	$ln(1+Prc_{i,t}^{USD})$	$Prc_{i,t}^{USD}$	$ln(1+Prc_{i,t}^{USD})$	Prc_{i}^{USD}	$ln(1+Prc_{i}^{USD})$
	Panel A: Punk Token Indicator					
Punk Look	8,973.011***	0.054***	9,437.135***	0.061***	10,966.528***	0.060***
	(1,528.808)	(0.013)	(1,496.102)	(0.011)	(1,889.034)	(0.013)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.681	0.966	0.695	0.970	0.063	0.234
	Panel A: Punk Token Indicator					
Punk Count	3,795.622***	0.035***	4,346.933***	0.042***	4,366.220***	0.043***
	(824.439)	(0.006)	(816.407)	(0.006)	(897.563)	(0.006)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.682	0.966	0.695	0.971	0.063	0.238
	Panel A: Punk Token Indicator					
Punk Score	16,339.467***	0.088***	16,701.438***	0.094***	17,917.458***	0.095***
	(2,352.027)	(0.017)	(2,339.243)	(0.016)	(2,727.552)	(0.017)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.683	0.966	0.696	0.971	0.068	0.236
Observations	22,840	22,840	22,840	22,840	6,823	6,823

Note: This table shows how CryptoPunk tokens with punk features are associated with the corresponding selling price in USD. We run the following regression:

$$Prc_{i,t}^{USD} = \beta_1 Punk_i + \beta_2 TokenClass_i + \gamma_t + \epsilon_{i,t}$$

where $Prc_{i,t}^{USD}$ represents the dollar selling price of CryptoPunk i at time t. Prc_{i}^{USD} represents the average normalized token price of token i. In Columns (1) and (2), we perform the regression without attribute fixed effect using the real price in USD and the natural logarithm of one plus US dollar price. In Columns (3) and (4), we perform the estimations using the real price in USD and the natural logarithm price by including $TokenClass_i$ to control for the token's skin tone (i.e., dark, medium, light, albino, zombie, ape, and alien). We use the medium skin tone as the base variable to avoid multicollinearity. Columns (5) and (6) report the results using the average normalized price at the token level. In addition, Panels A, B, and C report the findings across the different definitions of $Punk_i$ measures, including *Punk Look*, *Punk Count*, and *Punk Score*, respectively. We also control the time when the token is sold, and standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Table IA4. **Cultural premium in CryptoPunks including non-traded tokens**

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable Prc_i^{ETH}					
Punk Look	2.617***			3.182***		
	(0.522)			(0.491)		
Punk Count		0.994***			1.341***	
		(0.243)			(0.229)	
Punk Score			4.693***			5.042***
			(0.712)			(0.698)
TokenClass FE	No	No	No	Yes	Yes	Yes
Adjusted-R^2	0.002	0.001	0.005	0.060	0.060	0.063
Observations	10,000	10,000	10,000	10,000	10,000	10,000

Note: This table illustrates the association between CryptoPunk tokens that exhibit punk culture characteristics and their corresponding selling price in ETH, including the valuation of unsold tokens. For these unsold tokens, a value of 0 ETH was assigned, and we performed the following regression.

$$Prc_i^{ETH} = \beta_1 Punk_i + \beta_2 TokenClass_i + \epsilon_{i,t}$$

where Prc_i^{ETH} represents the average normalized Ethereum selling price of each CryptoPunk token i. $TokenClass_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use the medium skin tone as the base variable to avoid multi-collinearity. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Table IA5. **Cultural premium in CryptoPunks without suspicious transactions**

	(1)	(2)	(3)	(4)	(5)	(6)
	$Prc_{i,t}^{ETH}$	$ln(1+Prc_{i,t}^{ETH})$	$Prc_{i,t}^{ETH}$	$ln(1+Prc_{i,t}^{ETH})$	Prc_{i}^{ETH}	$ln(1+Prc_{i}^{ETH})$
	Panel A: Punk Token Indicator					
Punk Look	3.658***	0.057***	3.899***	0.063***	4.336***	0.061***
	(0.574)	(0.010)	(0.546)	(0.009)	(0.681)	(0.010)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.605	0.923	0.633	0.932	0.109	0.189
	Panel B: Punk Attribute Count					
Punk Count	1.654***	0.033***	1.917***	0.038***	1.922***	0.038***
	(0.328)	(0.005)	(0.319)	(0.005)	(0.331)	(0.005)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.605	0.923	0.634	0.932	0.109	0.192
	Panel C: Intensity of Punk Culture					
Punk Score	6.560***	0.089***	6.744***	0.093***	7.174***	0.096***
	(0.929)	(0.014)	(0.910)	(0.014)	(1.003)	(0.013)
TokenClass FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.606	0.924	0.634	0.932	0.113	0.192
Observations	22,540	22,540	22,540	22,540	6,785	6,785

Note: This table shows how CryptoPunk tokens with punk features are associated with the corresponding selling price in ETH after removing suspicious transactions. We run the following regression:

$$Prc_{i,t}^{ETH} = \beta_1 Punk_i + \beta_2 TokenClass_i + \gamma_t + \epsilon_{i,t}$$

where $Prc_{i,t}^{ETH}$ represents the selling price of CryptoPunk i in Ethereum at time t. Prc_{i}^{ETH} represents the average normalized token price of token i. In Columns (1) and (2), we perform the regression without attribute fixed effect using the real price in ETH and the natural logarithm of one plus ETH price. In Columns (3) and (4), we perform the estimations using the real price in ETH and the natural logarithm price by including $TokenClass_i$ to control for the token's skin tone, including dark, medium, light, albino, zombie, ape, and alien. We use the medium skin tone as the base variable to avoid multicollinearity. Columns (5) and (6) report the results using the average normalized price at the token level. In addition, Panel A, B, and C report the findings across the different definitions of $Punk_i$ measures, including *Punk Look*, *Punk Count*, and *Punk Score*, respectively. We also control the time when the token is sold, and standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Table IA6. **Whether CryptoPunks with punk features are more likely to be sold**

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Logit regression *SALE*					
Punk Look	0.006			0.000		
	(0.053)			(0.053)		
Punk Count		-0.008			-0.013	
		(0.023)			(0.024)	
Punk Count			0.017			0.013
			(0.061)			(0.061)
TokenClass FE	No	No	No	Yes	Yes	Yes
Observations	10,000	10,000	10,000	10,000	10,000	10,000
	Panel B: Probit regression *SALE*					
Punk Look	0.004			-0.000		
	(0.032)			(0.032)		
Punk Count		-0.005			-0.008	
		(0.014)			(0.014)	
Punk Count			0.010			0.007
			(0.037)			(0.037)
TokenClass FE	No	No	No	Yes	Yes	Yes
Observations	10,000	10,000	10,000	10,000	10,000	10,000

Note: This table examines whether CryptoPunk tokens with punk culture are more likely to be sold in the market. In Panel A, the dependent variable in the logit model is *SALE*, which is coded one if the CryptoPunk tokens have been traded in the market, and 0 otherwise. In Panel B, we also perform a robustness check using the probit regression model. The punk culture measures include *Punk Look*, *Punk Count*, and *Punk Score*. $TokenClass_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use the medium skin tone as the base variable to avoid multicollinearity. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Table IA7. **Investment performance of CryptoPunk tokens with punk features**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$Ret_{i,t}^{USD}$	$Ret_{i,t}^{USD}$	$Ret_{i,t}^{USD}$	Ret_{i}^{USD}	Ret_{i}^{USD}	$Ret_FL_{i}^{USD}$	$Ret_FL_{i}^{USD}$
	Panel A: Punk Token Indicator						
Punk Look	0.057	0.184	0.206	0.074	0.123	-0.021	-0.007
	(0.189)	(0.186)	(0.186)	(0.129)	(0.127)	(0.024)	(0.021)
Holding Period		-1.465***	-1.479***				-0.293***
		(0.074)	(0.075)				(0.016)
Initial Price (USD)			-0.000***				-0.000***
			(0.000)				(0.000)
Numtrade					0.179***		
					(0.022)		
Adjusted-R^2	0.050	0.118	0.118	0.000	0.011	0.000	0.245
	Panel B: Punk Attribute Count						
Punk Count	-0.001	0.084	0.095	0.005	0.034	-0.004	0.001
	(0.071)	(0.068)	(0.067)	(0.053)	(0.052)	(0.012)	(0.011)
Holding Period		-1.466***	-1.479***				-0.293***
		(0.073)	(0.075)				(0.016)
Initial Price (USD)			-0.000***				-0.000***
			(0.000)				(0.000)
Numtrade					0.178***		
					(0.022)		
Adjusted-R^2	0.050	0.118	0.118	0.000	0.011	0.000	0.245
	Panel C: Intensity of Punk Culture						
Punk Score	0.037	0.197	0.214	0.057	0.118	0.053*	0.065**
	(0.204)	(0.194)	(0.193)	(0.167)	(0.166)	(0.032)	(0.027)
Holding Period		-1.465***	-1.479***				-0.293***
		(0.073)	(0.075)				(0.016)
Initial Price (USD)			-0.000***				-0.000***
			(0.000)				(0.000)
Numtrade					0.179***		
					(0.022)		
Adjusted-R^2	0.050	0.118	0.118	0.000	0.011	0.001	0.246
Observations	14,319	14,319	14,319	4,318	4,318	4,318	4,318

Note: This table examines whether the punk tokens are overpriced by considering factors such as holding periods, initial trading price, and the number of trades. $Ret_{i,t}^{USD}$ in Columns (1) to (3) represents the logarithm of one plus the daily return for CrytoPunks i at time t. Ret_{i}^{USD} in Columns (4) and (5) represents the average normalized logarithm of one plus the daily return for each CryptoPunks i. $Ret_FL_{i}^{USD}$ in Columns (6) and (7) represents the average normalized logarithm of one plus daily return between the first and the last transaction price for each CryptoPunks i. $Holding\ Period_{i,t}$, is defined as the natural logarithm of one plus the days between each token transaction i at time t. *Initial Price* is the natural log of the first token selling price in USD. *Numtrade* is the number of trades. $Punk_i$ is one of the punk culture measures for CryptoPunk token i, including *Punk Look*, *Punk Count*, and *Punk Score*. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10%, respectively.

Table IA8. **Cultural premium in CryptoPunks with token rarity**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Dependent Variable $Prc_{i,t}^{ETH}$						
Punk Count	1.887***	1.622***	-5.797***	1.612***	1.482***	19.424***	3.512***
	(0.316)	(0.309)	(2.017)	(0.310)	(0.298)	(5.995)	(0.972)
Traits		0.762	-2.489***	0.017	0.169	0.021	0.129
		(0.511)	(0.862)	(0.776)	(0.511)	(0.770)	(0.510)
Punk Count × Traits			2.495***				
			(0.691)				
ATR				14.584		-30.382*	
				(12.536)		(18.205)	
MTR					505.468***		406.734***
					(28.227)		(47.057)
Punk Count × ATR						32.915***	
						(10.958)	
Punk Count × MTR							77.534**
							(31.242)
TokenClass FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.634	0.635	0.636	0.635	0.647	0.636	0.647
Observations	22,840	22,840	22,840	22,840	22,840	22,840	22,840
	Panel B: Dependent Variable Prc_{i}^{ETH}						
Punk Count	1.903***	1.786***	-4.406**	1.778***	1.586***	13.045**	2.463**
	(0.330)	(0.344)	(1.973)	(0.346)	(0.336)	(5.397)	(1.039)
Traits		0.317	-2.339**	-0.127	-0.208	-0.063	-0.228
		(0.532)	(0.921)	(0.912)	(0.533)	(0.910)	(0.533)
Punk Count × Traits			2.060***				
			(0.651)				
ATR				8.735		-20.800	
				(14.668)		(18.802)	
MTR					502.705***		457.841***
					(29.048)		(51.643)
Punk Count × ATR						20.921**	
						(9.940)	
Punk Count × MTR							34.260
							(33.150)
TokenClass FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.110	0.110	0.113	0.110	0.146	0.111	0.146
Observations	6,823	6,823	6,823	6,823	6,823	6,823	6,823

Note: This table examines whether the token attribute count (*Traits*) and rarity (*ATR* and *MTR*) affect the punk premium. In Panel A, $Prc_{i,t}^{ETH}$ is the ETH selling price of token i at time t, while Prc_{i}^{ETH} in Panel B is the average normalized token price for token i. Column (2) controls for token attribute counts. Columns (4) and (5) control for token rarity in terms of the average rarity score (*ATR*) and the minimal rarity score (*MTR*) for each token i. Columns (3), (6), and (7) incorporate interaction terms. $TokenClass_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use the medium skin tone as the base variable to avoid multicollinearity. $Rarity_i$ denotes the rarity score of each CryptoPunk token i. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Table IA9. **Cultural premium in CryptoPunks with token rarity**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Dependent Variable $Prc_{i,t}^{ETH}$						
Punk Score	6.675***	6.327***	-11.979**	6.584***	7.604***	62.629***	14.154***
	(0.901)	(0.907)	(5.844)	(0.906)	(0.893)	(18.186)	(2.991)
Traits		0.412	-2.298***	-1.107	-0.515	-1.334*	-0.571
		(0.508)	(0.847)	(0.786)	(0.512)	(0.775)	(0.513)
Punk Score × Traits			6.203***				
			(2.028)				
ATR				28.643**		-13.440	
				(12.432)		(16.827)	
MTR					525.743***		429.001***
					(28.624)		(42.659)
Punk Score × ATR						102.713***	
						(32.843)	
Punk Score × MTR							244.356***
							(93.564)
TokenClass FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.636	0.636	0.637	0.636	0.649	0.637	0.649
Observations	22,840	22,840	22,840	22,840	22,840	22,840	22,840
	Panel B: Dependent Variable Prc_{i}^{ETH}						
Punk Score	7.198***	7.307***	-8.069	7.517***	8.634***	43.297***	11.308***
	(1.000)	(1.069)	(5.643)	(1.057)	(1.054)	(16.282)	(3.358)
Traits		-0.124	-2.371***	-1.411	-1.023*	-1.478	-1.053*
		(0.532)	(0.872)	(0.918)	(0.536)	(0.915)	(0.540)
Punk Score × Traits			5.157***				
			(1.865)				
ATR				24.337*		-4.271	
				(14.353)		(17.717)	
MTR					526.504***		484.800***
					(29.235)		(50.784)
Punk Score × ATR						65.912**	
						(29.643)	
Punk Score × MTR							102.060
							(104.501)
TokenClass FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	0.114	0.114	0.117	0.114	0.154	0.116	0.154
Observations	6,823	6,823	6,823	6,823	6,823	6,823	6,823

Note: This table examines whether the token attribute count (*Traits*) and rarity (*ATR* and *MTR*) affect the punk premium. In Panel A, $Prc_{i,t}^{ETH}$ is the ETH selling price of token i at time t, while Prc_{i}^{ETH} in Panel B is the average normalized token price for token i. Column (2) controls for token attribute counts. Columns (4) and (5) control for token rarity in terms of the average rarity score (*ATR*) and the minimal rarity score (*MTR*) for each token i. Columns (3), (6), and (7) incorporate interaction terms. $TokenClass_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use the medium skin tone as the base variable to avoid multicollinearity. $Rarity_i$ denotes the rarity score of each CryptoPunk token i. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10%, respectively.

Table IA10. **Classification of visual imperfect presentation attributes**

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

Note: This table provides a comprehensive classification of visual attributes associated with imperfect presentations. Following previous research on physical attractiveness, facial characteristics such as blemishes and untidiness are considered undesirable traits. To validate the classification, we also employ the trait information from *rarity.tool*. Panel A presents attributes that are categorized as flaw presentations, while Panel B presents attributes that are considered flawless.