Cultural Price Premium: Evidence from Cryptopunks [*]

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Abstract

Do investors value the cultural traits in alternative investments? We study CryptoPunks, a pioneer non-fungible token (NFT) project that features the punk subculture, and document price premiums in token prices — punk tokens are 3.4 ETH, equivalent to 5.7% on average, more expensive than tokens without punk attributes. The punk premium only appeared after NFT gained massive public attention when Beeple sold for 69.3 million dollars on March 11, 2021. To rule out alternative mechanisms, we show that punk tokens are not overpriced and do not experience more speculation than non-punk tokens. Also, the punk premium is not affected after we control token rarity and beauty; punk premium is even stronger if the punk feature is rarer. Our findings suggest that investors derive utility by owning digital arts with conspicuous cultural traits that help them distinguish from others.

JEL Classification: *C43, D44, G10, Z11*

Keywords*: Non-fungible Token, Blockchain, Culture, Conspicuous Consumption*

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1 Introduction

Do investors value cultural traits in digital art investment? We study the transaction records of CryptoPunks, the earliest non-fungible token project launched in June 2017 by the Larva Labs studio, and test whether investors appreciate punk attributes. We document punk premium — that token prices with the punk trait exhibit a 5.7% higher value per transaction compared to tokens without punk attributes, spanning from their initial transaction on June 23, 2017, to December 19, 2022. Due to the infrequent trading of each token, we explore various specifications of token prices, including the average token price, the price at the first trade, the price at the last trade, and prices quoted in US dollars. The punk price premiums are robust regardless of how token prices are defined.

CryptoPunks offers two distinct advantages that make it an ideal context for testing the cultural importance of art investments. Firstly, the Larva Labs studio has deployed its own marketplace with smart contracts to facilitate Cryptopunks' transactions. Thus, all transactions are directly recorded on the Ethereum blockchain, providing researchers with complete visibility into the transaction history.[1] Secondly, there is almost no difference in production cost between punk and non-punk tokens. In traditional art markets, painting pieces with unique cultural traits might be fundamentally different from other regular art pieces. For example, artists might spend more time or employ advanced techniques to achieve artistic excellence.[2] In the case of CryptoPunks, this omitted variable concern is heavily mitigated since there is no inherent difficulty difference between drawing red hair and black hair using computer-generated art. Additionally, all tokens are minted simultaneously, and the attribute table is pre-determined by the NFT issuer, ensuring no skill enhancement discrepancies across tokens.

[1]For certain ERC-721 tokens, some marketplaces, e.g., Opensea, allow bundling transactions in which multiple tokens appear in one record. Thus, it becomes challenging to identify the individual price of each token from on-chain data.

[2]Yayoi Kusama delivered her symbolic dots in the middle stage of her career. The dotted style has been regarded as a way to deliver thrive. It is unfair to compare her art pieces with and without dots as they were created at different times in the artist's career.

In order to quantify the cultural attributes inherent in the CryptoPunk tokens, we obtain the attribute table of each token (the metadata) of Cryptopunks. This dataset provides comprehensive information about the characteristics and visual attributes assigned to each token, including elements such as hairstyle and facial appearance. That said, we collect band performance photos from the top 10 punk bands, sourced from a reputable music site, and manually compare and match the attributes listed in the CryptoPunk metadata with the visual elements observed in the selected band performance photos. By leveraging this comparative approach, we develop three measures to capture the punk culture represented by the CryptoPunk tokens. The first measure, *PunkLook*, a binary variable indicating whether a token concerns any punk features or not. The second measure involves counting the number of punk attributes presented in a token, while the third measure quantifies the intensity of punk cultures associated with each individual CryptoPunk token (see Section 2.4 for detailed variables construction).

We first show the punk premium is robust to different definitions of token prices and the definition of punk measure. On average, punk tokens are 3.4 ETH, 5.7%, and $9,346 USD higher than non-punk tokens in each trade. To mitigate sampling frequency differences, we compute the average normalized token prices, resulting in a recorded punk premium of 3.7 ETH, 6.4%, and $10,766 USD. Furthermore, the punk premium extends the intensive margin, in which an additional punk feature is traded at higher prices of 0.84 ETH.

We further analyze the punk premium over time; the punk premium is particularly large when the attention to non-fungible tokens has risen since the NFT art boom in March 2021. Initially, the punk premium was negligible prior to June 2020 but steadily increased in significance as the popularity of NFTs grew. We argue that investors derive greater utility from owning a token with more punk features, thus, are willing to pay a higher price to purchase it from other token holders. The rise of punk premium after massive NFT attention suggests owning a punk token brings more utility for token holders, particularly as the public recognizes CyptoPunks as the pioneer NFT collection. As illustrated in Figure 1, we observe that punk tokens command a higher price of approximately 5% since NFT garnered widespread attention, and this premium continues to persist over the sampling period. As a result, the rise of willingness to pay for punk tokens also demonstrates that investors might not appreciate these punk features on their own, but rather enjoy showing the punk's rebellious culture — an analogy of crypto spirit against regulated finance — to a wider prospective investor audience interested in non-fungible tokens.

We counduct a series of robustness checks. First, we exclude suspicious transactions to mitigate the potential effects of wash trading and price manipulation. Second, the punk premium is also robust to transaction order: the cultural premium remains approximately 4% irrespective of the order in which transactions occur. Third, we use token prices in USD to estimate the punk premium. Punk tokens are 6.1%, corresponding to 9,346 US dollars, more expensive than non-punk tokens. The percentage price premium is quite similar to one obtained using ETH prices.

Next, we examine alternative explanations for the punk premium. Could the punk premium be attributed to speculation? We find no evidence that punk traits lead to an increased frequency of trading in punk tokens. Specifically, punk tokens are traded 0.154 times less than non-punk tokens, corresponding to 3.1% of the trading frequency observed for non-punk tokens. Further, it takes 8.3% longer time period for a punk token to be sold to a new investor. Despite incorporating liquidity controls, the punk premium remains quite similar.

Furthermore, could punk tokens be temporarily overpriced? We test whether punk tokens exhibit price reversals and yield lower investment returns. In the dataset, punk tokens generate higher investment returns than non-punk tokens, if there is anything. The daily return of punk tokens is not statistically different from non-punk tokens. The results remain robust even after controlling for token liquidity and token prices. Hence, during our sample period, there is no evidence of punk features being overpriced.

Alternatively, we conduct additional tests to determine if an omitted variable could potentially account for the punk premium. For example, punk traits might carry undisclosed information that manifests as punk features and contributes to higher prices. First, we test whether the creator intentionally use punk traits to create scarcity and differentiate these tokens from others. We construct two token rarity measures: (1) ATR, which represents the average rarity score, and (2) MTR denoting the minimal rarity score.[3] After controlling for the rarity, the punk premium drops from 3.64 ETH to 3.15 ETH when controlling for the total number of attributes, and further drops to 2.86 ETH when incorporating the token rarity score. Only 21% punk premium can be explained by the rarity. We further add the interaction term of rarity score with the punk feature and show that rare punk attributes enjoy a higher punk premium.

Second, we test whether punk traits deliver greater aesthetic utilities that appeals 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 classify attributes that enhance the token's visual attractiveness, namely a smooth facial appearance and a sense of tidiness, as the indicators of aesthetic utility. The punk premium is robust to the beauty controls. Moreover, investors exhibit greater tolerance of visual flaws if these tokens possess punk features.

Our paper contributes to the following two strands of literature. First, our work contributes to the recent rising study on non-fungible token prices. Numerous studies have been conducted. For example, Goldberg, Kugler, and Schär (2021) and Dowling (2022a) investigate the pricing of virtual real estate in Decentraland. Kireyev and Lin (2021) propose a structural model to capture the pricing of CrytoKitties. Kong and Lin (2022) construct an NFT price index for CryptoPunks using the hedonic regression models. Borri, Liu, and Tsyvinski (2022) study NFT investment returns with asset pricing framework, while Nadini et al. (2021) show that visual features serve as reliable predictors using simple machine learning algorithms. The majority of NFTs are traded using cryptocurrencies and are facilitated by blockchain technology. Thus, several studies investigated the spillover ef-

[3] See Section 4.3 for more detailed explanation.

fects from the cryptocurrency prices to the NFT market (see, e.g., Dowling, 2022b; Ghosh et al., 2023).[4] Our paper demonstrates the significance of cultural traits in determining non-fungible token prices.

Second, our study adds to the existing literature on the asset pricing of alternative investments. Unlike equities and bonds, conventional modeling assumes that fungible assets can be approximated by a random walk with drift (Borri, Liu, and Tsyvinski, 2022), while Lovo and Spaenjers (2018) argue that the return variance in non-fungible assets, such as artworks, do not necessarily converge to zero due to the uncertain distribution of bidders (see, e.g., Goetzmann, Renneboog, and Spaenjers, 2011; and Sagi, 2021). 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. Our paper highlights the mechanism whereby punk features serve as a form of conspicuous consumption.New buyers are happy to pay a premium for punk culture after the NFT investment concept gains traction in the market.

The remainder of this paper is organized as follows. Section 2 provides a detailed description of the CryptoPunk project and punk culture variables construction. Section 3 presents a series of empirical findings of cultural premium on token pricing. Section 4 rules out alternative explanations, as our findings are not driven by over-speculation, investment performance, token rarity, or aesthetic appeal. Section 5 concludes the paper.

[4] 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).

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.[5] The collection comprises 24x24 pixelated art images designed by two software engineers, Matt Hall and John Watkinson, the founders of the software company *Larva Labs studio*. Drawing inspiration from the London Punk scenes of the 1970s, this crypto art project was officially launched in June 2017.[6] In particular, the whole series consists of 10,000 unique tokens with proof of ownership stored on the Ethereum blockchain (Kong and Lin, 2022), with each token corresponding to a unique art image. We obtain the token's detailed characteristics and transaction records from *Larva Labs*' website, and then apply Python programming to extract the relevant data for our analysis. Our data sample consists of 20,679 token transaction data, including 6,833 unique tokens sold from June 2017 to December 2022.[7]

2.2 Prices and Returns

The transaction prices of CryptoPunks are quoted in either ETH or USD, obtained from the real-time ETH prices on the official website of Larva Labs. We begin by analyzing the trading and return data of CryptoPunks. Panel A of Table 1 shows that the average price of CryptoPunk tokens during our sampling period is approximately 40.36 ETH, which is equivalent to an average of $110,065 USD. In terms of investment performance, the average daily returns of CryptoPunks, measured in both ETH and USD, stand at 2.1 basis points (bps)

[5]OpenSea is one of the largest NFT marketplaces that allows participants to create, purchase, sell, and auction NFTs. At the time of this writing, the total sales volume of the CryptoPunks has surpassed 1 million ETH. See `https://opensea.io/collection/cryptopunks/` for details. Meanwhile, this renowned digital art project has also gained prominence through its inclusion in numerous international auctions at prestigious institutions such as Christie's and Sotheby's.

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

[7]In Figure IA1, we plot the number of CryptoPunk tokens traded over time. This figure illustrates a noticeable increase in the number of transactions during the period of heightened attention to NFTs, particularly in March 2021. This surge in trading activity aligns with the broader trend of increased interest and participation in the NFT market during that time.

and 2.4 bps, respectively. At the same time, it is worth noting that investing in CryptoPunks entails a high daily standard deviation of about 8.4 bps and 8.7 bps, respectively.

Considering the unique nature of digital art, factors such as holding periods and the frequency of trades also provide valuable insights into the pricing dynamics of artworks (Lovo and Spaenjers, 2018). We plot the distributions of CryptoPunks' selling prices denominated in ETH, as well as the holding periods and frequency of trades in Figure IA2. Specifically, Panel A plots the distribution of CryptoPunk prices represented as the natural logarithm of one plus ETH, we observe a price spectrum ranging from 0.06 to 5.34, with less than 20% of the token transactions occurring below 1 ETH. The majority price, however, fall within the range of 2.5 to 5. Panel B shows the number of days until the next available sales, and that token owners, on average, tend to resell their tokens after approximately 61 days in our sampling period. Panel C plots the number of transactions per token. Among the 6,833 tokens with transaction records, we find an average of 2.76 trades per token, with a median of 2 trades. Meanwhile, we note that only about 40 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 mentioned earlier, each CryptoPunk token is characterized by a unique facial appearance formed by distinct combinations of attributes. We acquired the 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 is featured with a maximum of seven distinct traits selected from a list of 87 unique attributes. These attributes can be further categorized into nine mutually exclusive dimensions: Hair, Eyes, Facial Hair, Neck Accessory, Month Prop, Mouth, Blemishes, Ears, and Nose. Therefore, the design of each token can be featured with one attribute in each dimension, allowing for a maximum of seven attributes and ensuring their distinctiveness. In addition to the attribute dimensions, CryptoPunks can also be categorized into different types, including humans and special types, such as aliens, apes, and zombies.[8] 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 11 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 40.06 ETH, while the average price of the special-type tokens is 83.43 ETH during the sampling periods.

2.4 Measures of Punk Culture

Punk culture emerged in the 1970s and has continued to thrive over the decades. While the term "punk" was initially used to describe underground artists who were viewed as rebelling against mainstream society, punk culture has evolved and transcended mere rebellion and fashion, even leaving a significant impact on the entertainment industry (Dunn, 2008). Drawing inspiration from this influential movement, the design of CryptoPunks incorporates elements of punk attire, appearance, and attributes, with the aim of capturing the non-conformist spirit of the Web3 movement.

To construct a meaningful measure of punk culture for each CryptoPunk token, we conducted research on the top 10 renowned punk bands[9] from a reputable music site, namely UDiscoverMusic (UDM). This official site is operated by the Universal Music Group, one of the leading global music companies with an extensive record label history spanning across more than 60 countries. By referring to UDM's list of renowned punk bands, we identify

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

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

four performance photos for each band, and manually match the attire, appearance, and accessories from these band photos with the attributes of each CryptoPunks (see Table IA1 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, *PunkLook*, is a binary variable that is coded as 1 if the CryptoPunk token shares at least one punk characteristic with the punk bands' photos, and 0 otherwise. The second measure, *PunkCount*, counts the number of attributes designated as punk characteristics in the punk bands' photos. Our final measure, *PunkScore*, measures the intensity of punk culture encapsulated by each CryptoPunk token. To calculate this score, we first assign a score to each attribute based on the ratio of punk bands exhibiting the same attributes. The punk score of a token is then derived by summing up the scores assigned to each of its attributes. This measure captures the cumulative representation of punk culture within each token.

Panel B of Table 1 reports the summary statistics of punk culture measures. Considering the inspiration drawn from the 1970s London Punk scenes for the CryptoPunk project, it is unsurprising to observe a substantial proportion of the tokens exhibiting discernible punk characteristics. Out of the 10,000 tokens, 7,970 tokens are identified as punk tokens, and in particular, 5,448 of them have recorded at least one transaction during the sampling period. Furthermore, the median value of *PunkCount* is 1, suggesting that 50 percent of the tokens possess at least one punk attribute. In addition, the median value of *PunkScore* 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 is significantly positively correlated but not perfectly correlated. We find that the correlation coefficients of *PunkLook* and *PunkScore* with respect to *PunkCount* are 71% and 80%, respectively.

[Insert Table 1 here]

3 Punk Premium

3.1 Prices

To examine the potential association between cultural traits and the value appreciation of NFT art collectibles from an economic perspective, we undertake a systematic and rigorous analysis using the real price of Ethereum at transaction- and token-level regressions. In all cases, the model is estimated using Ordinary Least Squares (OLS).

For transaction-level regressions, we estimate β_1 from the following regression.

$$Prc_{i,t}^{ETH} = \beta_1 Punk_i + \beta_2 Attribute_i + \gamma + \epsilon_{i,t} \quad (1)$$

where $Prc_{i,t}^{ETH}$ is the real price of Ethereum for the CryptoPunk token i traded at time t. $Punk_i$ is the measure of punk culture that takes three distinct values *PunkLook*, *PunkCount*, and *PunkScore* as discussed in Section 2.4. $Attribute_i$ indicates the skin tone of each CryptoPunk i and takes seven sets of attribute dummies: *Ape*, *Alien*, *Zombie*, *Albino*, *Light*, *Medium*, and *Dark*.[10] We control for each token's skin tone, as prior studies have long argued the existence of consumer discrimination in collectibles. For instance, Nardinelli and Simon (1990) find that the race of baseball player cards affects consumers' willingness to pay, and similarly, Burge and Zillante (2017) also highlight the impact of race on collectible prices. The recent study by Nguyen (2022), documents that digital art, such as CryptoPunk tokens with lighter skin, trade at a higher price even after controlling for token rarity and market conditions. This underscores the significance of controlling the token's skin tone. In addition, we control the time when the token is sold, and all standard errors are clustered at the token level.

To mitigate the possibility of over-sampling, we further calculate the average normalized

[10] Among the 9,879 human-type tokens, we find 1,018 tokens feature with albino skin tone, 2,284 tokens feature with dark skin tone, 3,006 tokens feature with light skin tone, and 3,031 tokens feature with medium skin tone. In all cases, we use medium skin tone as the base variable in the regression analysis to avoid multicollinearity. The details of skin tone classification can be found: `https://rarity.tools/cryptopunks`.

price for each token and perform the following regression.

$$Prc_i^{ETH} = \beta_1 Punk_i + \beta_2 Attribute_i + \gamma + \epsilon_i \tag{2}$$

where Prc_i^{ETH} is the average normalized real price in ETH of each CryptoPunk token during the sampling period. Intuitively, we transform the token prices to bring the price of different tokens to a common scale.

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

In Panel A of Table 2, we find a positive association between the CryptoPunk tokens that share visual aesthetics with punk culture and the real price in ETH, and this result indicates that "punk" tokens command a price premium of 3.37 ETH (*s.e.*=0.503) in the marketplace, which is approximately 5.7% more expensive than non-punk tokens during the sampling period. When quantifying the extent of punk culture on each token, we find the coefficients in Panel B of Table 2 are statistically significant to the real price in ETH, and that the token embedded with an additional unit of the punk attribute can be traded for an extra 1.49 ETH (*s.e.*=0.266) in the market. Moreover, the results in Panel C of Table 2 show that the degree of punk culture is also significantly and positively associated with the selling price in ETH, implying that the CryptoPunk token enjoys a price premium if the attribute is readily found among the top 10 punk rock bands. For example, chokers and crazy hairstyles are commonly found in the band performance photos. Furthermore, the results in Columns (3) and (4) provide consistent evidence that including attribute fixed effect does not alter the economic and statistical significance of the positive relationship between punk measures and the real price in ETH.

To mitigate the concerns that token transactions might be concentrated on specific subgroups, we calculate the average normalized token price for each CryptoPunk token during the sampling period and re-estimate the baseline model using E.q.(2). Specifically, we first calculate a monthly average token price and subtract the token price from its individual price, and then we aggregate the normalized token price at the token level to address the potential scale variations in our sample. Consistent with the findings in Columns (1) to (4), we continue to find robust positive relationships between the real price in ETH and tokens that are featured with punk culture, and specifically, "punk" tokens are, on average, traded with an extra 3.74 ETH (*s.e.*=0.507) as reported in Column (5) of Table 2. Collectively, these findings provide evidence that investors value cultural traits when investing in the digital art market. In the following subsections, we perform a battery of robustness tests to consolidate the existence of punk premium when determining the price of digital artwork.

[Insert Table 2 here]

3.2 Tokens with No Transaction Data

While the willingness to purchase art pieces can be subjective and varied among individuals (Mei and Moses, 2002), we only documented 6,833 tokens with available transaction records during the sampling period. However, one could argue that the remaining tokens without transaction records might carry valuable information for assessing the value of the digital artwork. For example, tokens without transaction records might be characterized by certain attributes that are not widely popular in the marketplace.[11] Therefore, it is crucial to examine whether the punk premium still exists when accounting for the non-traded

[11]The absence of transaction records for certain tokens might be because these tokens represent niche or specialized themes that appeal to specific audiences. Another possibility is that, some tokens might not receive the same level of market exposure. For example, we searched Sotheby's website, one of the largest auction houses for fine art and jewels, and only eight CryptoPunk tokens were listed, three of which are without transaction records.

tokens in the analysis. With that being said, we re-examine our baseline models E.q.(1) and E.q.(2) but imputed tokens with no transaction with a zero price so that we have the full sample of 10,000 tokens. Table IA2 reports the findings with the full sample of the CryptoPunk tokens. We continue to find that tokens that exhibit punk culture is sold with an extra 2.21 ETH (*s.e.* = 0.391) on average. This result implies that even after accounting for the unsold tokens, the coefficient of punk measures remains positively associated with the real price in ETH and that the punk tokens tend to trade at a premium.

3.3 Extensive Margin versus Intensive Margin

As discussed, the launch of CryptoPunks delivers the spirit of punk culture to collectors through its pixelated art images and distinctive attributes. One would be interested in whether collectors still value the punk culture after conditional on tokens that exhibit punk characteristics. To explore this argument further, we conduct intensive effect analyses on punk tokens. Among the 6,833 tokens with transaction records, 5,448 tokens are classified as punk tokens. We re-estimate the coefficients for both E.q.(1) and E.q.(2) while conditioning on punk tokens. The results reveal that more punk features predict higher punk premiums, but the statistical significance and magnitude are smaller.

Table IA3 reports the results from our intensive effect analyses. Specifically, we find that each additional unit of punk characteristics predicts a price increase of 0.84 ETH (*s.e.*=0.426), which accounts for approximately 56% of the full-sample estimate of 1.49 ETH (*s.e.*=0.266). This suggests that the effect of punk characteristics on price is attenuated when considering the intensity of these attributes. Furthermore, we find that the coefficient of the punk score is 5.36 ETH (*s.e.*=0.982) higher, while the effect is about 7% smaller than the full sample estimate of 5.75 ETH (*s.e.*=0.740). In addition, we also obtain similar findings using the average normalized token price and also including tokens that have not been sold in the marketplace. Collectively, the results suggest that the intensity of punk characteristics plays a significant role in determining the value and pricing of the tokens, indicating that investors are willing to pay additional prices for more pronounced punk attributes.

3.4 Dynamic of Punk Premium

In the previous sections, we discovered that punk tokens command a price premium in the marketplace, suggesting that investors place a higher value on tokens that exhibit cultural elements associated with punk culture. While it is worth noting that the CryptoPunks project was not widely recognized by the general public only until the increased attention and media coverage surrounding NFTs in 2021. The heightened interest in the NFT market has likely contributed to a greater awareness of this project as more individuals become aware of the unique characteristics and artistic value of these assets. Therefore, it is of interest to track the dynamic nature of the punk premium over time.

We begin by tracking the public attention of NFTs, and specifically, Da, Engelberg, and Gao (2011) find that the search frequency data on Google provides a useful measure to capture the attention of retail investors (see also, Kong and Lin, 2022; and Liu and Tsyvinski, 2021). Building on this concept, we utilize the Search Volume Index (SVI) provided by Google Trends to search for the topic of "non-fungible tokens" from June 2017 to December 2022 to proxy for worldwide attention. As shown in Figure IA3, we discover three major events in our sample: (1) the launch of CryptoPunks; (2) the NFT art boom; and (3) the free claim of the Sewer Pass. We observed that the launch of CryptoPunks initially garnered limited attention back in 2017. However, public attention surrounding NFTs began to surge in December 2020, reaching its peak in March 2021. This notable increase in attention can be attributed to the landmark sale of the digital artwork titled "*Everdays: the First 5000 Days*" by artist Beeple, in which the project was sold for a stunning $69.3 million USD. This transaction record has attracted significant interest in the burgeoning NFT market. Subsequently, attention towards NFTs declined until January 2022, when Yuga Lab announced the free claim of the Sewer Pass NFT collection.

To track the punk premium over time, we regress each token's last selling price in each month with different definitions of punk measures in Section 2.4. Then we 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 to non-fungible tokens perceived the highest attention in March 2021. In the right panel, we quote the punk premium in the percentage of token prices, and we also find similar results that punk token prices are 5% more expensive than non-punk tokens. Overall, we observe that the effects of punk premium persist over the sampling period.

[Insert Figure 1 here]

3.5 Robustness Checks and Miscellaneous Discussion

3.5.1 Wash Trading and Price Manipulation

Given the majority of NFT transactions in the marketplace occur using cryptocurrencies, the NFT market is presumably not immune to fraudulent practices.[12] One particular concern is the potential for wash trading of non-fungible tokens — investors sell and purchase the same financial asset (i.e., NFTs in this case) amongst themselves to artificially create trading activities without actually transferring the ownership, and these fake transactions might contaminate our punk premium estimation (Cong et al., 2022b; Cumming, Johan, and Li, 2011; and Imisiker and Tas, 2018).

To alleviate the concerns of suspicious transactions pumping the prices, we define NFT transactions as wash trading if the token experiences high-frequency trades between two or more wallets, and that the original owner maintains control over these wallets.[13] That being said. we have identified 42 tokens associated with suspicious transactions during the

[12] Cong et al. (2022a) find that the transactions in NFTs experience a notable increase during the fiscal year-end, and that crypto investors might engage in legal tax planning with tax-loss harvesting as an alternative to non-compliance.

[13] For example, we identify that some transaction records of CryptoPunk #9620 are suspicious transactions that are considered wash trading. On July 16, 2021, the token was sold with 0 ETH from 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 within 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`

sampling period, and thus we remove 208 token-transaction observations (which accounted for 1.01% of total transactions of CryptoPunks) and re-estimate the punk premium in Table IA4. The results in Columns (3) and (4) of Table IA4 show that the punk premium is 3.64 ETH, corresponding to 6.4% at the transaction level in E.q.(1). Similarly, the punk premium is 3.71 ETH and 6.3% at the token level in E.q.(2). It is worth noting that the coefficients in Table IA4 exhibit minimal variation compared to our baseline estimation, indicating that wash trading does not drive our punk premium.

3.5.2 Punk Premium by Transaction Order

Although CryptoPunks has become one of the prominent projects in the NFT space, this project was not widely known by the general public back in 2017. Specifically, this project initially served as a proof of concept for utilizing blockchain technology in creating and owning digital assets (Wang et al., 2021). Therefore, the initial sales of CryptoPunks likely appealed to collectors who were particularly enthusiastic about the punk culture and those presumably interested in the potential of blockchain-based digital art. If this argument holds true, we should expect CryptoPunk tokens that exhibit punk culture to be significantly and positively associated with the initial sales price. In addition, we also examine whether the punk tokens continue to outperform non-punk tokens throughout the sampling period. As discussed in Section 3.4, the NFT ecosystem has become integrated and has gained considerable market visibility in recent years, with media and celebrity endorsements.[14] The involvement of influential individuals could bring substantial attention to the NFT community, resonating with a wide range of collectors to recognize these digital collectibles. Therefore, we argue that the increasing attention further popularizes CryptoPunks, attracting more collectors with a specific interest in the punk culture to engage in this community.

Table IA5 reports the results using the first and the last transaction prices of the Cryp-

[14] For example, Jack Dorsey, the co-founder of Twitter, sold his first-ever tweet as an NFT for a stunning $2.9 million on March 6. 2021. See
https://www.reuters.com/article/us-twitter-dorsey-nft-idCAKBN2BE2KJ

toPunk tokens in Panel A and B, respectively. The findings provide supporting evidence that punk tokens are traded at a premium in the first transaction and even in the last transaction. More specifically, the effect is higher at 2.45 ETH (*s.e.*=0.808) in the first price and 3.98 ETH (*s.e.*=1.110) in the last price, and these results also indicate that the punk premium is more pronounced when the community gains greater market awareness.

Furthermore, we plot the punk premium relationship based on the transaction orders in Figure 2. In the left panel, we use the punk premium in raw ETH and document punk premium increases from the first transaction till the third transaction, and this premium remains relatively stable throughout the sample. In the right panel, we quote the punk premium in the percentage of token prices; the coefficient is quite stable regardless of the transaction order: punk token prices are 4% higher than non-punk tokens, the coefficient of punk feature count stays around 0.02, and the coefficient of punk score starts from 0.06 for the first transaction and stabilizes around 0.09. The punk premium appears proportionate to the punk price and stable regardless of the transaction order.

[Insert Figure 2 here]

3.5.3 Token Price in US Dollar

As part of the Ethereum blockchain ecosystem, the transactions of CryptoPunk tokens are denominated in ETH. Investors who are interested in acquiring CryptoPunks are required to utilize ETH as the medium of exchange within the marketplace.[15] However, due to the nature of cryptocurrency, the price of ETH price exhibited considerable volatility during our sampling period. It started at $217 USD on June 23, 2017, peaked above $1,386 USD in October 2017, plummeted below $85 USD in December 2018, and rocketed over $4,600 USD in November 2021. Although investors transact with ETH, they might make NFT investment decisions based on the dollar prices in their mental accounts. Therefore, we

[15] Most of the NFTs are primarily purchased on secondary marketplaces, such as OpenSea and Blur. While CryptoPunks also has its own marketplace, allowing investors to buy, sell, and bid on the tokens by simply connecting a Web3 wallet. See the FAQ section for detailed explanations `https://cryptopunks.app/`

conduct additional analyses by re-estimating the β_1 in Eq.(1) and Eq.(2) using the selling price in US dollars in Table IA6. The results show that, on average, punk tokens are traded at an additional \$9,436 (*s.e.*=1,412.590) USD compared to non-punk tokens. Similarly, at the token level, the punk premium is estimated to be 10,766 (*s.e.*=1,449.574).

The results in Table IA6 provide consistent evidence with our previous findings, in which the positive punk premium estimate is not influenced by the volatile prices of ETH or the appreciation of ETH during our sampling period. This strengthens the robustness of the punk premium estimation, as it remains significant even after considering real-time US dollar prices of NFTs.

4 Alternative Mechanisms

Punk premium indicates that investors value the punk subculture and are willing to pay a higher price for punk attributes embedded in non-fungible tokens. In this section, we further discuss multiple alternative hypotheses and evaluate how these hypotheses affect our punk premium estimation.

4.1 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, for example, Aharon and Demir, 2022; Ante, 2022; Borri, Liu, and Tsyvinski, 2022; Horky, Rachel, and Fidrmuc, 2022; and Vidal-Tomás, 2022). Dowling (2022a), and among others, conclude that the pricing mechanism in the NFT market is still far from efficient, and susceptible to pricing manipulation, fraudulent behaviors, and speculative trades, thus leading to price bubbles (Wang, 2022). That being said, it would be intriguing to examine whether the punk premium is driven by over-speculation behavior in the NFT market. Specifically, if speculative trades indeed drive the premium, one would expect punk tokens to have a greater chance of being sold in the market. Thus we examine this argument using logistic regression:

$$SALE_i = \beta_1 Punk_i + \beta_2 Attributes_i + \epsilon_i$$

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 IA7 show that the coefficients are insignificant across punk measures, indicating that there is no evidence that punk tokens are statistically different from non-punk tokens in terms of the probability of being sold in the market. As a robustness check, we also perform the test using the Probit regression model, and the results in Panel B of Table IA7 yield similar findings.

To gain a complete picture of the trading behavior between punk and non-punk tokens, it is important to understand how collectors curate their collections, and in particular, we further examine the liquidity aspect of these tokens by considering the tokens' number of trades and the holding periods between two consecutive trades, the results are reported in Table 3.

[Insert Table 3 here]

Panel A of Table 3 reveals a negative association between tokens exhibiting punk characteristics and the number of trades, indicating that punk tokens, on average, trade less frequently in the marketplace. The results are consistent across different punk measures and even when considering attribute dummies in Columns (4) to (6). Furthermore, the results remain robust after transforming the dependent variable into the natural logarithm form, suggesting that punk tokens are traded approximately 3% less than non-punk tokens. Meanwhile, the results in Panel C of Table 3 show that punk tokens tend to have longer holding periods, which suggests that collectors hold punk tokens for an extended period before engaging in the next trading activities. The holding period is roughly 10% longer compared to the non-punk tokens.

Collectively, the findings reported in Table 3 provide contrasting evidence regarding the role of speculative trades in driving the punk premium as reported in Section 3. Our findings do not support the notion that punk tokens are systematically subject to over-speculation. Instead, punk tokens are traded less frequently during the sampling period and are held for a longer duration than non-punk tokens.

Despite the fact that punk tokens do not appear to be over-speculated in our sampling period, one could also argue that the presence of punk premium is due to the illiquidity nature of these tokens. Therefore, we formally test whether token liquidity affects the punk premium estimation by including the liquidity measures as the control variable. Table 4 reports the results of punk premium after controlling for the liquidity measures.

Panel A of Table 4 presents the results after controlling for token's holding period at the transaction level. We find that punk tokens continue to trade at a premium of 3.96 (*s.e.* = 0.629) ETH after controlling for token liquidity. In addition, the point estimates of different punk measures are also statistically significant at the 1 percent level, suggesting that punk premium is not likely to be driven by the extended holding period of punk tokens. Consistent with the art trading model proposed by Lovo and Spaenjers (2018), we also find that the holding period is negatively correlated with the value of the artwork (see also, Borri, Liu, and Tsyvinski, 2022; and Dimson and Spaenjers, 2011). Meanwhile, Panel B of Table 4 controls the number of trades at the token level. We find that the punk premium continues to hold after controlling for the number of trades, and that the punk token is traded with an extra 3.03 (*s.e.*=0.567) ETH. Furthermore, the estimated coefficients of different punk measures are all significant at the 1 percent level.

Taken together, we find no evidence that that estimated punk premium is due to over-speculation, but instead, the results show that punk tokens are actually less traded and investors tend to hold these tokens for an extended period compared to non-punk tokens. More importantly, even after accounting for token liquidity measures in our sample, the punk premium still exists, implying that investors' trading behavior does not drive our results.

[Insert Table 4 here]

4.2 Investment Returns

The rising recognition of the revolutionary potential of Web3 leads one to believe that NFT as a digital asset class has come of age. NFTs possess the ability to represent the ownership of distinct assets powered by blockchain technology, often taking the form of digital art collectibles (Kong and Lin, 2022). This unique characteristic has captured the attention of investors seeking to diversify their investment portfolios by including NFTs as alternative assets. However, unlike traditional financial instruments such as equities and bonds, investors also derive enjoyment from the intrinsic value of the artworks, which is a mixture of pecuniary and non-pecuniary payoffs to ownerships that makes it challenging to determine their value (Mandel, 2009; Korteweg, Kräussl, and Verwijmeren, 2016). In this section, we seek to examine whether the estimated punk premium in Section 3 is temporary and over-priced due to increased demand for alternative investments Kong and Lin (2022). If so, we would expect the NFT token prices to experience a reversal and deliver lower returns.

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.

$$Ret_{i,t}^{ETH} = \beta_1 Punk_i + \gamma + \epsilon_{i,t} \tag{3}$$

In Column (1) of Table 5, the coefficients of various punk measures exhibit no significant relationship with token's daily return at the transaction level. This suggests that punk tokens do not necessary deliver lower returns. Similar findings are observed in the token-level regression, as well as using the token's daily return form the first to the last price 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) propose that buyers and sellers in the art markets tend to be of very different types, and that the average total return will be lower for longer time periods between purchase and resale. We formally test this argument by including the holding period as the control variable using the following specification:

$$Ret_{i,t}^{ETH} = \beta_1 Punk_i + \beta_2 Ln(1 + HoldingPeriod)_{i,t} + \epsilon_{i,t} \tag{4}$$

The results in Columns (2) and (7) of Table 5 show that even controlling for the holding period, the investment returns do not differentiate by the punk culture measures. Meanwhile, the estimated coefficient of the time period between purchase and resale is significantly negative, which is consistent with Lovo and Spaenjers (2018) model. As a robustness check, we further test the daily return calculated using USD, and the results in Table IA8 still hold.

$$Ret_{i,t}^{USD} = \beta_1 Punk_i + \beta_2 Log(Holding\_Period)_{i,t} + \epsilon_{i,t} \tag{5}$$

Overall, we find no evidence that punk premium is temporary and over-price due to the increased attention as an alternative investment, but instead, the punk premium identified in Section 3 suggests that investors do value the cultural traits and thus, investors who enjoy more from the intrinsic value of punk culture are willing to pay a higher price.

[Insert Table5 here]

4.3 Attribute Count and Rarity

While punk traits are primarily associated with punk culture, one could argue that they might correlate with other attributes of the tokens, and enumerating all possible omitted variables is impossible; however, we formally investigate two prominent factors extensively discussed in the alternative investment literature.

First, we hypothesize that Larva Labs studio (the creator of CryptoPunks) used punk features to establish rarity and differentiate certain punk tokens from others, with the intention of enhancing their visual appeal and investment value. The rationale behind this hypothesis is grounded in prior studies in the field of alternative assets, which suggests that rarity plays a pivotal role in driving price appreciation (see, for example, Koford and Tschoegl, 1998; Hughes, 2022). The underlying psychology is that individuals are inclined to engage in conspicuous consumption of rarer items due to their exclusivity, which can be perceived as a symbol of social prestige within the Web3 community.

Anecdotal evidence also suggests that some 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.[16] This unprecedented high record has sparked curiosity in investigating whether the token rarity design of CryptoPunks' tokens could account for the results presented in Section 3.

In the context of CryptoPunks, there are various approaches to quantifying token rarity. The simplest metric is the count of attributes assigned to each token. In the metadata of CryptoPunks, the creator has assigned a varying number of attributes to each token, ranging from zero to seven.[17] Tokens that possess a greater number of designed components tend to garner more investor attention and stand our more prominently from other tokens.

In addition, we seek to incorporate the frequency of occurrence for each attribute. Tokens that possess attributes with lower occurrence rates within the token collection may 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 into 11 dimensions, ensuring that each trait t is exclusively assigned to single dimension d ($d \in 1, 2, ..., 11$).

[16] 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 12^{th}, 2012. See `https://cryptopunks.app/cryptopunks/details/5822`.

[17] 8 tokens are not assigned to any attribute in the metadata. Token #8348 has seven attributes: Buck Teeth, Top Hat, Big Beard, Classic Shades, Mole, Cigarette, and Earring.

To measure the rarity of each attribute, we compute the trait rarity (TR_t) for each trait t based on its occurrence frequency within the collection Here, m represents the number of tokens sharing the same trait t, and M corresponds to the total token supply 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, the $Rarity_d = TR_t$. However, if the token i does not have any trait tagged under 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 dimensional rarity established, we can proceed to compute the average rarity score (ATR_i) and minimal rarity score (MTR_i) for each token i:

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

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

The ATR_i is the negative average dimensional rarity 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 to ensure rare token gets a higher rarity score.[18]

Among the 10,000 tokens, we find that punk tokens have a higher rarity score, averaging -0.544, compared to the non-punk tokens, which have an average score of -0.571. More specifically, the higher value suggests that punk tokens are rarer in the marketplace. Additionally, there is a positive correlation of 23% between the *PunkLook* variable and the token

[18]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.

rarity measure. 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:

$$Prc_{i,t}^{ETH} = \beta_1 Punk_i + \beta_2 Rarity_i + \beta_3 Attributes_i + \epsilon_{i,t}$$

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

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

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 2.86 (*s.e.*=0.478) — 3.14 (*s.e.*=0.496) ETH even after controlling for token rarity. In Columns (6) and (7) of Table 6, we introduce interaction terms of rarity measures (i.e., *ATR* and *MTR*) with *PunkLook* to examine whether investors are willing to pay a premium for rarer punk traits. The coefficients of the interaction terms in Columns (6) and (7) of Table 6 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 IA9 and Table IA10 also provide consistent evidence that rarer punk traits command a higher price premium.

To mitigate the potential of over-sampling, we also conduct our analysis at the token level in Panel B of Table 6. The results at the token level consistently support the findings reported at the transaction level. Collectively, the results in Table 6 provide further evidence of the punk premium, even after controlling for token rarity design. The coefficient estimates are relatively close to the unconditional premium as presented in Table 2. These findings confirm that the punk premium cannot be solely attributed to the token rarity design.

[Insert Table 6 here]

4.4 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 applied to various fields of research. 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). Central to these studies is that when the available information is limited, facial cues can provide a wealth of information for making economic decisions.[19] In the digital art market, the available information set, such as access to historical transaction and trait information, can differ across the NFT platforms (Fang, Nie, and Zheng, 2023). This suggests that investors might suffer from information asymmetry and rely on NFTs' aesthetic qualities, and possibly through their attributes in determining the value of the NFTs (Kong and Lin, 2022). Therefore, it is of interest to examine whether punk features are considered attractive to the public, and if that follows, it would be intriguing to see whether punk features can provide a visual appreciation for investors.

We construct two metrics that capture the imperfect presentation of the CryptoPunks, namely blemishes, and untidiness. Prior studies find that visual perfect presentation is linked to physical attractiveness. For example, Jaeger et al. (2018) find that people are particularly sensitive to skin blemishes because they could potentially indicate poor health and the presence of an infectious disease. Similarly, recent studies have also indicated that a tidy appearance is considered to be a desired trait for perfect presentation (Choi et al., 2020). Table IA11 of the Appendix shows definitions of untidy and blemished features. We have characterized ten attributes as visual flaws, five of which share both punk features and visual flaws.

[19] For example, Pan, Wang, and Weisbach (2015) examine the impact of CEOs' appearances on shareholder value creation. They find that more attractive CEOs are perceived to have certain attributes and abilities to generate more value for shareholders when the information about the CEOs' abilities is absent.

Our analysis begins by examining whether beauty premium exists between punk and non-punk tokens. Among the 1,385 non-punk tokens with transaction records, we find that 401 tokens with visual flaws have an average price of 31.49 ETH, while the remaining 984 tokens achieve an average price of 36.04 ETH. Thus, a beauty premium of 4.55 ETH emerges among the non-punk tokens, with approximately 28.9 percent of the tokens exhibiting flaws. Turning our attention to the 5,448 punk tokens with transaction records, we find that 1,752 tokens with visual flaws hit an average price of 36.45 ETH, while the remaining 3,696 tokens attain an average price of 39.08 ETH. Interestingly, the proportion of flawed tokens in the punk category is approximately 32.2 percent, which is not much different from that in the non-punk tokens. The beauty premium for punk tokens is 2.63 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 visual disorder inherent in punk tokens may also partially deliver the rebellious spirit against mainstream aesthetic norms. Therefore, this deviation from traditional notions of beauty contributes to a lower beauty premium among punk tokens in comparison to their non-punk counterparts.

We also conduct a formal examination to test whether visual flaws in tokens affect the punk premium estimation by including the visual flaw measure as the control variable. The results in Table 7 indeed demonstrates the presence of a beauty premium in CryptoPunks; that is, we find that visual flaws lead to a reduction in token price by 3.33 (*s.e.*=0.497) ETH. We also employ token-level regression and validate the consistency of the beauty premium as reported in Panel B of Table 7.

[Insert Table 7]

Meanwhile, the punk subculture was supposed to rebel against mainstream aestheticism. We interact the punk feature with the perfect-looking dummy (defined as no blemishes and no untidiness features), and the coefficient of the interaction term is negative. Table 8 shows that even controlling for the visual presentation measures, we continue to find that punk tokens are traded at a higher price, with an extra 5.48 ($s.e$=0.672) ETH compared to non-punk tokens. Collectively, our findings imply that investors value both punk features and good-looking NFTs. However, the punk token prices would worry less about visual flaws for punk tokens.

[Insert Table 8]

5 Conclusion

In this paper, we document a punk culture price premium among NFT collection Cryptopunks — tokens with punk traits consistently trade at higher prices than non-punk tokens. Given that non-fungible tokens do not generate cash flow nor incur any difference in production costs, the observed price disparity must stem from the flow utility gap among tokens assigned with distinct visual attributes.

Why are investors willing to pay more for punk attributes? Our findings suggest that public attention plays a crucial role. Specifically, investors derive more utility from owning tokens with punk features, mainly when these features are rare in the collection. In addition to serving as an investment, digital art also enables investors to signal their identity within the Web3 community, such as through the possession of punk tokens. The blockchain technology also allows for transparent verification of token ownership, making the ownership of non-fungible tokens a form of conspicuous consumption. The flow utility component of cultural traits is of great importance in the asset prices of alternative investments and is worth further investigation.

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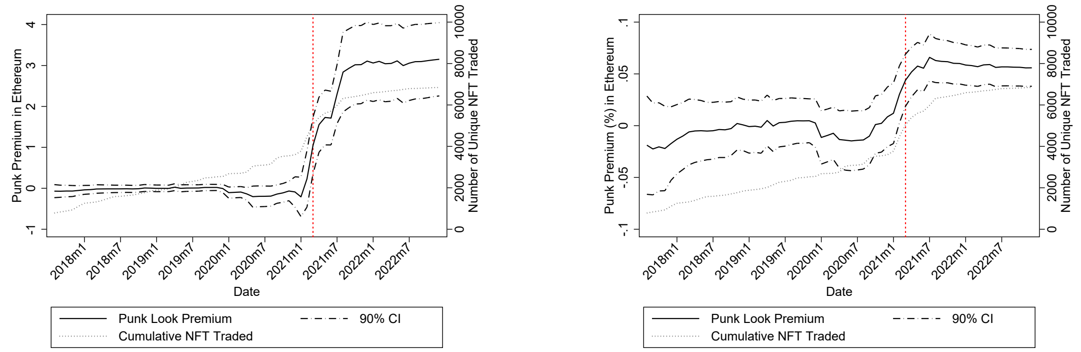
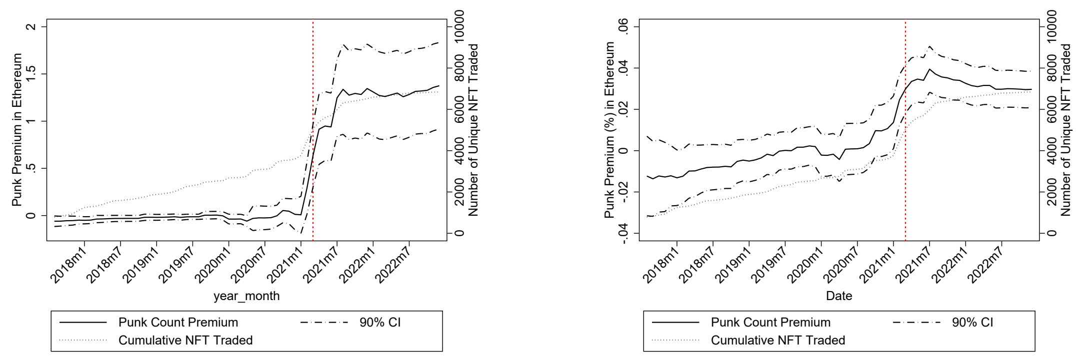
Figures and Tables

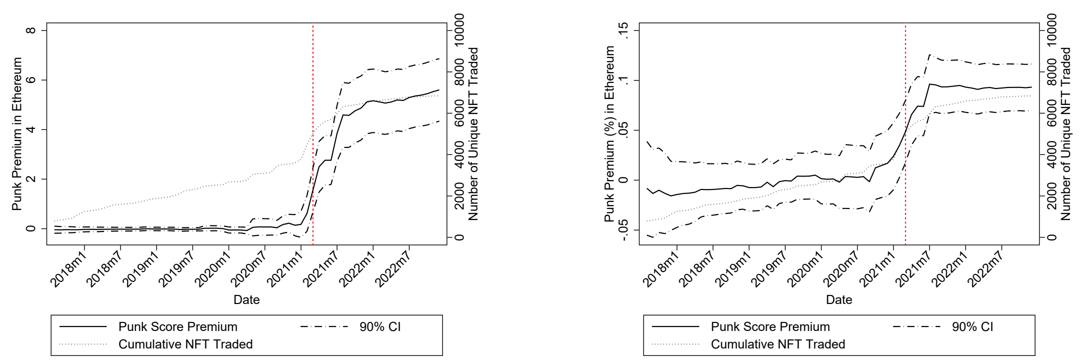
Figure 1. **Dynamic of punk premium**



Panel A. Punk Look Premium



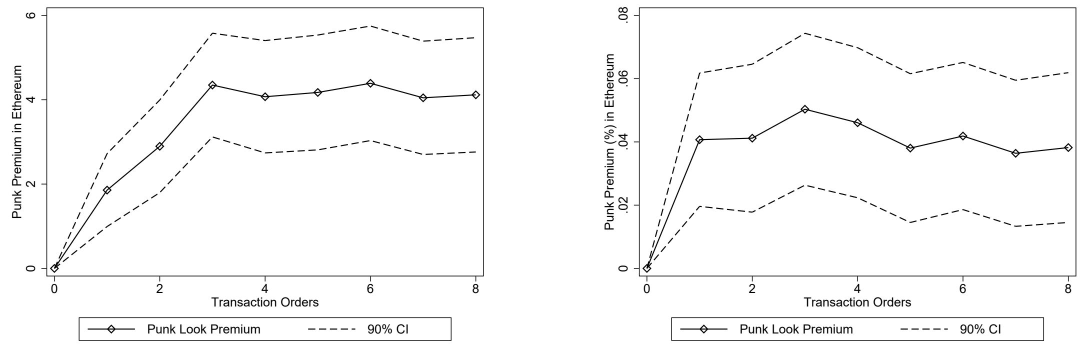
Panel B. Punk Count Premium



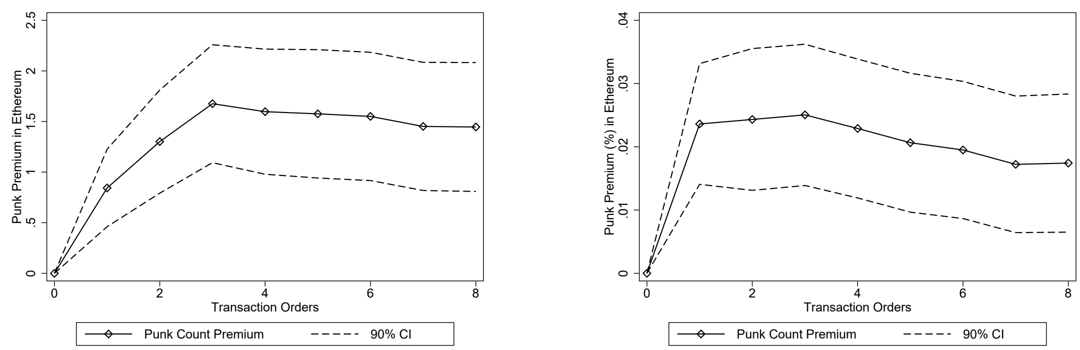
Panel C. Punk Score Premium

Note: This figure plots the dynamics of the punk premium and the cumulative number of tokens sold over time. We first estimate the coefficients of the punk premium by regressing each month's last selling price of the CryptoPunk tokens and punk measures. We also calculate how many unique tokens have been 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 monthly cumulative unique NFT sold. The red vertical dotted line indicates the point at which NFTs received the highest market attention as proxied 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 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.

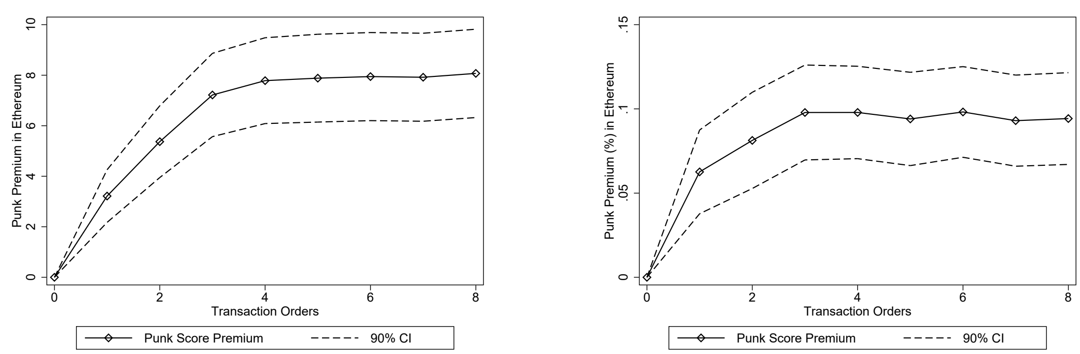
Figure 2. **Punk premium by transaction order**



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 price in Ethereum of the CryptoPunk tokens and the punk measures in each transaction order. CryptoPunk tokens are imputed as zero if 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 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.

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}	40.36	43.27	3.50	24.00	68.00	20,679
Prc_{USD}	111,065.20	145,585.20	1,351.20	54,528.52	168,252.90	20,679
Ret_{ETH}	2.078	8.420	0.167	0.549	1.531	13,149
Ret_{USD}	2.429	8.700	0.209	0.896	2.214	13,149
Numtrade	2.761	1.948	1.000	2.000	4.000	20,679
HoldingPeriod	3.963	1.785	2.565	4.127	5.283	13,897
			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 Skin Tone			
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
Flaw	0.316	0.465	0.000	0.000	1.000	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 were retrieved from Larva Labs. The sampling period is from June 2017 to December 2022. Panel A summarizes the CryptoPunk tokens' transaction and investment performance. Panel B summarizes different aspects of punk measures. Panel C summarizes CryptoPunks' skin tone features. Panel D summarizes additional measures used in Section 4.

Table 2. **Cultural premium in CryptoPunks**

	(1)	(2)	(3)	(4)	(5)	(6)
	$Prc^{ETH}_{i,t}$	$ln(1 + Prc^{ETH}_{i,t})$	$Prc^{ETH}_{i,t}$	$ln(1 + Prc^{ETH}_{i,t})$	Prc^{ETH}_{i}	$ln(1 + Prc^{ETH}_{i})$
	Panel A: Punk Token Indicator					
Punk Look	3.370***	0.057***	3.640***	0.064***	3.738***	0.064***
	(0.503)	(0.010)	(0.480)	(0.009)	(0.507)	(0.010)
Attribute FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.703	0.929	0.721	0.936	0.103	0.154
	Panel B: Punk Attribute Count					
Punk Count	1.488***	0.032***	1.723***	0.037***	1.689***	0.038***
	(0.266)	(0.005)	(0.261)	(0.005)	(0.255)	(0.005)
Attribute FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.703	0.929	0.721	0.936	0.103	0.158
	Panel C: Intensity of Punk Culture					
Punk Score	5.749***	0.091***	5.898***	0.095***	5.836***	0.098***
	(0.740)	(0.014)	(0.726)	(0.013)	(0.722)	(0.013)
Attribute FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.704	0.929	0.722	0.936	0.108	0.158
Observations	20,679	20,679	20,679	20,679	6,833	6,833

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

$$Prc^{ETH}_{i,t} = \beta_1 Punk_i + \beta_2 Attribute_i + \gamma + \epsilon_{i,t}$$

where $Prc^{ETH}_{i,t}$ represents the Ethereum selling price of CryptoPunk i in time t. Prc^{ETH}_{i} 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 ETH price. In Columns (3) and (4), we perform the estimations using the real price in ETH and the natural logarithm price by including $Attribute_i$ to control for the token's skin tone, including dark, medium, light, albino, zombie, ape, and alien. We use medium skin tone as the base variable to avoid multi-collinearity. 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 *PunkLook*, *PunkCount*, and *PunkScore*, 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 ***, **, * for 1%, 5%, and 10%, respectively.

Table 3. **The liquidity of punk tokens**

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Dependent Variable *Numtrade*					
Punk Look	-0.154**			-0.163**		
	(0.066)			(0.066)		
Punk Count		-0.098***			-0.104***	
		(0.028)			(0.028)	
Punk Score			-0.189***			-0.188***
			(0.071)			(0.071)
Attribute FE	No	No	No	Yes	Yes	Yes
Observations	6,833	6,833	6,833	6,833	6,833	6,833
Adjusted-R^2	0.001	0.002	0.001	0.007	0.008	0.007
	Panel B: Dependent Variable Ln(1+*Numtrade*)					
Punk Look	-0.031**			-0.033**		
	(0.015)			(0.015)		
Punk Count		-0.022***			-0.023***	
		(0.006)			(0.006)	
Punk Score			-0.039**			-0.039**
			(0.016)			(0.016)
Attribute FE	No	No	No	Yes	Yes	Yes
Observations	6,833	6,833	6,833	6,833	6,833	6,833
Adjusted-R^2	0.001	0.002	0.001	0.007	0.008	0.007
	Panel C: Dependent Variable *HoldingPeriods*					
Punk Look	0.083**			0.086**		
	(0.035)			(0.034)		
Punk Count		0.042***			0.043***	
		(0.015)			(0.015)	
Punk Score			0.102**			0.098**
			(0.040)			(0.040)
Attribute FE	No	No	No	Yes	Yes	Yes
Year_month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,897	13,897	13,897	13,897	13,897	13,897
Adjusted-R^2	0.082	0.082	0.082	0.085	0.085	0.085

Note: This table investigates whether price premium is driven by over-speculation. In Panel A, the dependent variable is the total number of CryptoPunk tokens i traded over the sampling period. In Panel B, we replace the dependent variable with the natural logarithm of one plus $Numtrade_i$. In Panel C, the dependent variable, $HoldingPeriod_{i,t}$, is defined as the natural logarithm of one plus the number of days between the next transaction of each token i in time t. $Punk_i$ is one of the punk culture measures for CryptoPunk token i, including *Punk Look*, *Punk Count*, and *Punk Score*. $Attribute_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use 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 ***, **, * for 1%, 5%, and 10%, respectively.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Dependent Variable $Prc_{i,t}^{ETH}$					
Punk Look	3.964***			4.287***		
	(0.629)			(0.609)		
Punk Count		1.758***			2.017***	
		(0.349)			(0.345)	
Punk Score			6.963***			7.180***
			(0.981)			(0.970)
Holding Period	-4.147***	-2.953***	-4.046***	-15.719*	-14.713*	-15.556*
	(0.699)	(0.592)	(0.751)	(8.376)	(8.418)	(8.435)
Attribute FE	No	No	No	Yes	Yes	Yes
Year_month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,877	13,877	13,877	13,877	13,877	13,877
Adjusted-R^2	0.654	0.654	0.656	0.678	0.678	0.680
	Panel B: Dependent Variable Prc_{i}^{ETH}					
Punk Look	3.030***			3.550***		
	(0.567)			(0.503)		
Punk Count		1.226***			1.580***	
		(0.270)			(0.254)	
Punk Score			5.362***			5.618***
			(0.753)			(0.718)
Numtrade	-1.181***	-1.175***	-1.169***	-0.995***	-0.985***	-0.986***
	(0.092)	(0.092)	(0.092)	(0.087)	(0.087)	(0.087)
Attribute FE	No	No	No	Yes	Yes	Yes
Observations	6,833	6,833	6,833	6,833	6,833	6,833
Adjusted-R^2	0.018	0.018	0.023	0.113	0.113	0.117

Note: This table examines whether the price premium still holds when controlling for token liquidity. In Panel A, the dependent variable is the ETH price of CryptoPunks i sold in time t. $HoldingPeriod_{i,t}$, is defined as the natural logarithm of one plus the number of days between the next transaction of each token i in time t. In Panel B, the dependent variable is the average token price sold in ETH during the sampling period. *Numtrade* is the total number of CryptoPunk tokens i traded over the sampling period. $Punk_i$ is one of the punk culture measures for CryptoPunk token i, including *Punk Look*, *Punk Count*, and *Punk Score*. $Attribute_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use 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 ***, **, * for 1%, 5%, and 10%, respectively.

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

	(1) $Ret^{ETH}_{i,t}$	(2) $Ret^{ETH}_{i,t}$	(3) $Ret^{ETH}_{i,t}$	(4) Ret^{ETH}_{i}	(5) Ret^{ETH}_{i}	(6) $Ret\_FL^{ETH}_{i}$	(7) $Ret\_FL^{ETH}_{i}$
				Panel A: Punk Token Indicator			
Punk Look	-0.090	0.009	0.033	0.015	0.059	0.006	0.010
	(0.143)	(0.138)	(0.136)	(0.113)	(0.112)	(0.017)	(0.016)
Holding Periods		-1.386***	-1.424***				-0.255***
		(0.075)	(0.077)				(0.018)
Initial Price			-0.239***				-0.131***
			(0.044)				(0.008)
Numtrade					0.218***		
					(0.022)		
Adjusted-R^2	0.047	0.125	0.126	0.000	0.015	0.000	0.164
				Panel B: Punk Attribute Count			
Punk Count	-0.022	0.035	0.049	0.009	0.030	0.007	0.009
	(0.059)	(0.055)	(0.055)	(0.050)	(0.049)	(0.009)	(0.008)
Holding Periods		-1.387***	-1.425***				-0.255***
		(0.075)	(0.077)				(0.018)
Initial Price			-0.240***				-0.132***
			(0.044)				(0.009)
Numtrade					0.218***		
					(0.022)		
Adjusted-R^2	0.047	0.125	0.126	0.000	0.015	0.000	0.164
				Panel C: Intensity of Punk Culture			
Punk Score	-0.067	0.058	0.076	0.032	0.083	0.050**	0.048**
	(0.184)	(0.173)	(0.173)	(0.147)	(0.145)	(0.024)	(0.021)
Holding Periods		-1.386***	-1.425***				-0.255***
		(0.075)	(0.076)				(0.018)
Initial Price			-0.239***				-0.132***
			(0.044)				(0.008)
Numtrade					0.218***		
					(0.022)		
Adjusted-R^2	0.047	0.125	0.126	0.000	0.015	0.001	0.165
Observations	13,149	13,149	13,149	4,293	4,293	4,293	4,293

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. $Ret^{ETH}_{i,t}$ in Columns (1) to (3) represent the logarithm of one plus the daily return for CrytoPunk tokens i in time t. Ret^{ETH}_{i} in Columns (4) and (5) represent the average normalized logarithm of one plus the daily return for each CryptoPunk token i. $Ret\_FL^{ETH}_{i}$ in Columns (6) and (7) represent the average normalized logarithm of one plus daily return between the first and the last transaction price for each CryptoPunk token i. $HoldingPeriod_{i,t}$, is defined as the natural logarithm of one plus the days between each token transaction i in time t. *InitialPrice* 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 CryptoPunk token i, including *Punk Look*, *Punk Count*, and *Punk Score*. *Holding Period* is defined as the natural logarithm of one plus the number of days between the next transaction of each token. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, * 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	3.640***	3.145***	-6.999***	3.140***	2.864***	29.318***	8.948***
	(0.480)	(0.496)	(2.394)	(0.496)	(0.478)	(7.970)	(1.617)
Traits		1.102***	-2.257***	-0.027	0.535	-0.058	0.502
		(0.402)	(0.756)	(0.667)	(0.397)	(0.666)	(0.397)
Punk Look × Traits			4.055***				
			(0.881)				
ATR				22.003**		-16.596	
				(10.774)		(14.467)	
MTR					481.730***		295.309***
					(22.982)		(43.577)
Punk Look × ATR						46.367***	
						(14.207)	
Punk Look × MTR							228.680***
							(51.746)
Attribute FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,679	20,679	20,679	20,679	20,679	20,679	20,679
Adjusted-R^2	0.721	0.721	0.722	0.722	0.735	0.722	0.735
	Panel B: Dependent Variable Prc_{i}^{ETH}						
Punk Look	3.738***	3.378***	-7.548***	3.359***	2.947***	25.566***	6.833***
	(0.507)	(0.518)	(2.556)	(0.519)	(0.504)	(8.481)	(1.899)
Traits		0.733**	-2.878***	-0.278	0.224	-0.254	0.201
		(0.373)	(0.842)	(0.659)	(0.371)	(0.657)	(0.371)
Punk Look × Traits			4.394***				
			(0.943)				
ATR				19.753*		-13.784	
				(10.531)		(15.324)	
MTR					458.090***		337.471***
					(22.294)		(51.917)
Punk Look × ATR						39.312***	
						(15.032)	
Punk Look × MTR							147.110**
							(60.190)
Attribute FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,833	6,833	6,833	6,833	6,833	6,833	6,833
Adjusted-R^2	0.103	0.104	0.107	0.104	0.159	0.105	0.160

Note: This table examines whether token attribute count (i.e., *Traits*) and rarity (i.e., *ATR* and *MTR*) affect the punk premium. The dependent variable is *PunkLook*. In Panel A, $Prc_{i,t}^{ETH}$ is the ETH selling price of token i in 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 average rarity score (*ATR*) and minimal rarity score (*MTR*) for each token i. Columns (3), (6), and (7) include the interaction terms. $Attribute_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use medium skin tone as the base variable to avoid multi-collinearity. $Rarity_i$ is the rarity score of each CryptoPunk token i. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10%, respectively.

Table 7. **Cultural premium in CryptoPunks with visual flaw**

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Dependent Variable $Prc^{ETH}_{i,t}$			Panel B: Dependent Variable Prc^{ETH}_{i}		
Punk Look	3.397***			3.346***		
	(0.497)			(0.570)		
Punk Count		1.526***			1.426***	
		(0.265)			(0.272)	
Punk Score			6.456***			6.434***
			(0.749)			(0.770)
flaw	-3.327***	-3.372***	-3.962***	-3.462***	-3.505***	-4.129***
	(0.473)	(0.472)	(0.483)	(0.495)	(0.493)	(0.505)
Observations	20,679	20,679	20,679	6,833	6,833	6,833
Adjusted-R^2	0.704	0.704	0.706	0.010	0.009	0.017

Note: This table examines whether imperfect visual presentation (i.e., facial features with blemish and untidiness) matters to punk cultural premium. We run the following regression:

$$Prc^{ETH}_{i,t} = \beta_1 Punk_i + \beta_2 Flaw_i + \gamma + \epsilon_{i,t}$$

where $Prc^{ETH}_{i,t}$ in Panel A represents the Ethereum selling price of CryptoPunk token i in time t. In Panel B, Prc^{ETH}_{i} represents the average normalized token price of CryptoPunk token i. $Punk_i$ is one of the punk culture measures for CryptoPunk token i, including *Punk Look*, *Punk Count*, and *Punk Score*. *Flaw* is an indicator that equals one if the CryptoPunk tokens contain imperfect visual presentation, such as blemish and untidiness in their appearance. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10%, respectively.

Table 8. **Cultural premium in CryptoPunks with flawless appearance**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Dependent Variable $Prc^{ETH}_{i,t}$				Panel B: Dependent Variable Prc^{ETH}_{i}			
Punk Look	3.370***		3.397***	5.483***	3.235***		3.346***	4.968***
	(0.503)		(0.497)	(0.672)	(0.572)		(0.570)	(0.905)
Flawless		3.307***	3.327***	5.737***		3.382***	3.462***	5.320***
		(0.476)	(0.473)	(0.754)		(0.495)	(0.495)	(1.005)
Punk Look × Flawless				-3.044***				-2.303**
				(0.941)				(1.153)
Observations	20,679	20,679	20,679	20,679	6,833	6,833	6,833	6,833
Adjusted-R^2	0.703	0.703	0.704	0.705	0.003	0.006	0.010	0.010
Punk Count	1.488***		1.526***	2.969***	1.348***		1.426***	2.849***
	(0.266)		(0.265)	(0.395)	(0.272)		(0.272)	(0.428)
Flawless		3.307***	3.372***	6.110***		3.382***	3.505***	6.278***
		(0.476)	(0.472)	(0.724)		(0.495)	(0.493)	(0.810)
Punk Count × Flawless				-2.152***				-2.109***
				(0.524)				(0.549)
Observations	20,679	20,679	20,679	20,679	6,833	6,833	6,833	6,833
Adjusted-R^2	0.703	0.703	0.704	0.705	0.003	0.006	0.009	0.011
Punk Score	5.749***		6.456***	6.895***	5.615***		6.434***	6.639***
	(0.740)		(0.749)	(0.884)	(0.758)		(0.770)	(0.973)
Flawless		3.307***	3.962***	4.282***		3.382***	4.129***	4.281***
		(0.476)	(0.483)	(0.674)		(0.495)	(0.505)	(0.732)
Punk Score × Flawless				-0.726				-0.335
				(1.405)				(1.467)
Observations	20,679	20,679	20,679	20,679	6,833	6,833	6,833	6,833
Adjusted-R^2	0.704	0.703	0.706	0.706	0.009	0.006	0.017	0.017

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

$$Prc^{ETH}_{i,t} = \beta_1 Punk_i + \beta_2 Flawless_i + \beta_3 Punk_i \times Flawless_i + \gamma + \epsilon_{i,t}$$

where $Prc^{ETH}_{i,t}$ in Panel A represents the Ethereum selling price of CryptoPunk token i in time t. In Panel B, Prc^{ETH}_{i} represents the average normalized token price of 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 contain blemish and untidiness in their appearance. $Punk_i \times Flawless$ is the interaction term of punk measures with the visual appearance of each token. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10%, respectively.

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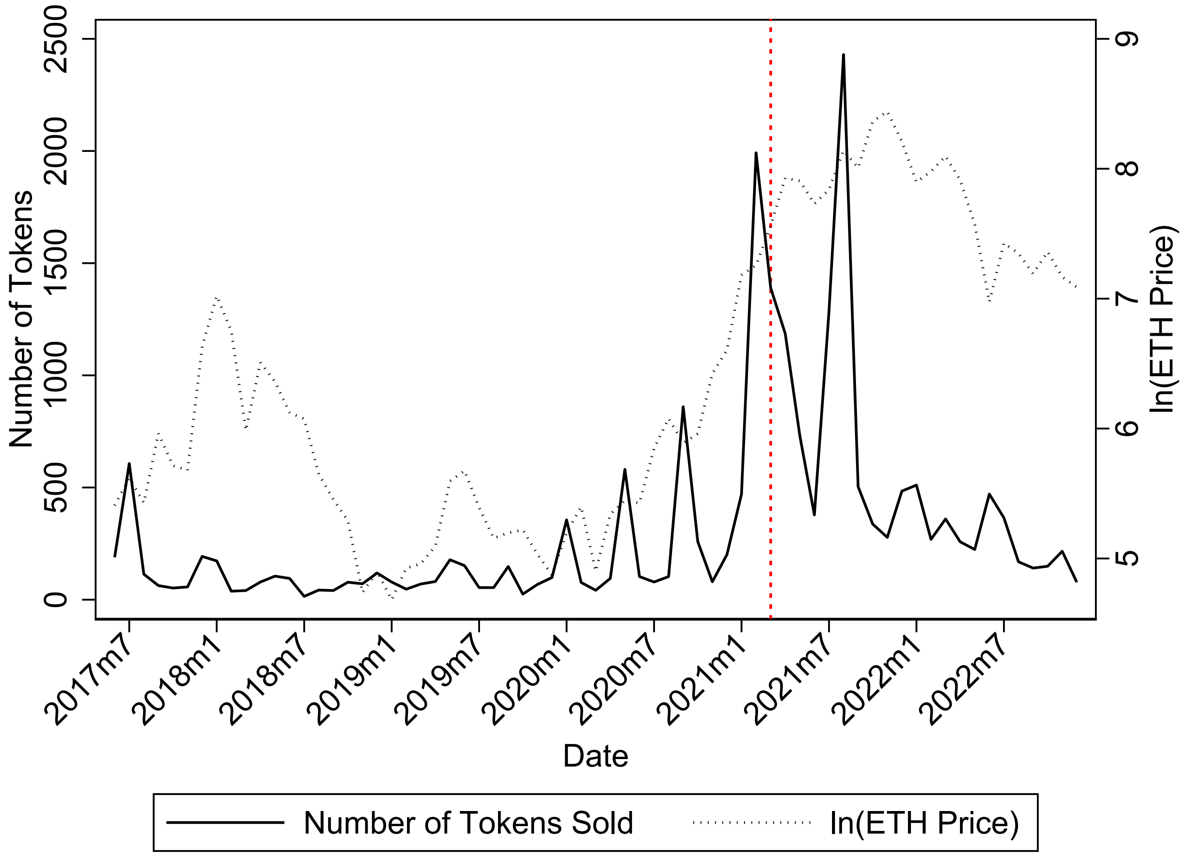
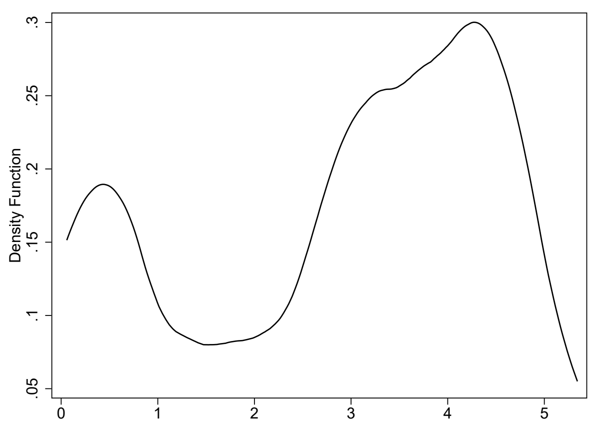
I Appendix

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

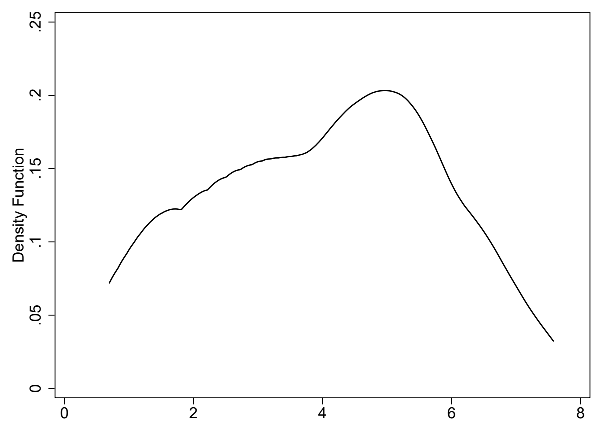


Note: This figure plots the time-series relationship between CryptoPunk token transactions and Ethereum price. The solid line is the number of CryptoPunk tokens traded, and the dotted line is the natural logarithm of one plus the Ethereum price. The sampling period is from June 2017 to December 2022.

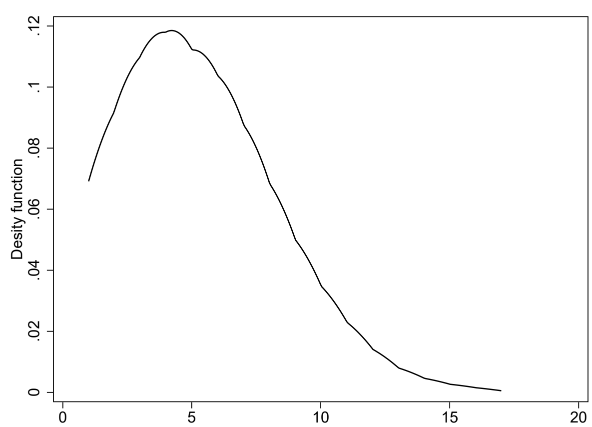
Figure IA2. **The distribution of CryptoPunks price, holding period, and transactions**



Panel A. CrytoPunks Ethereum Prices



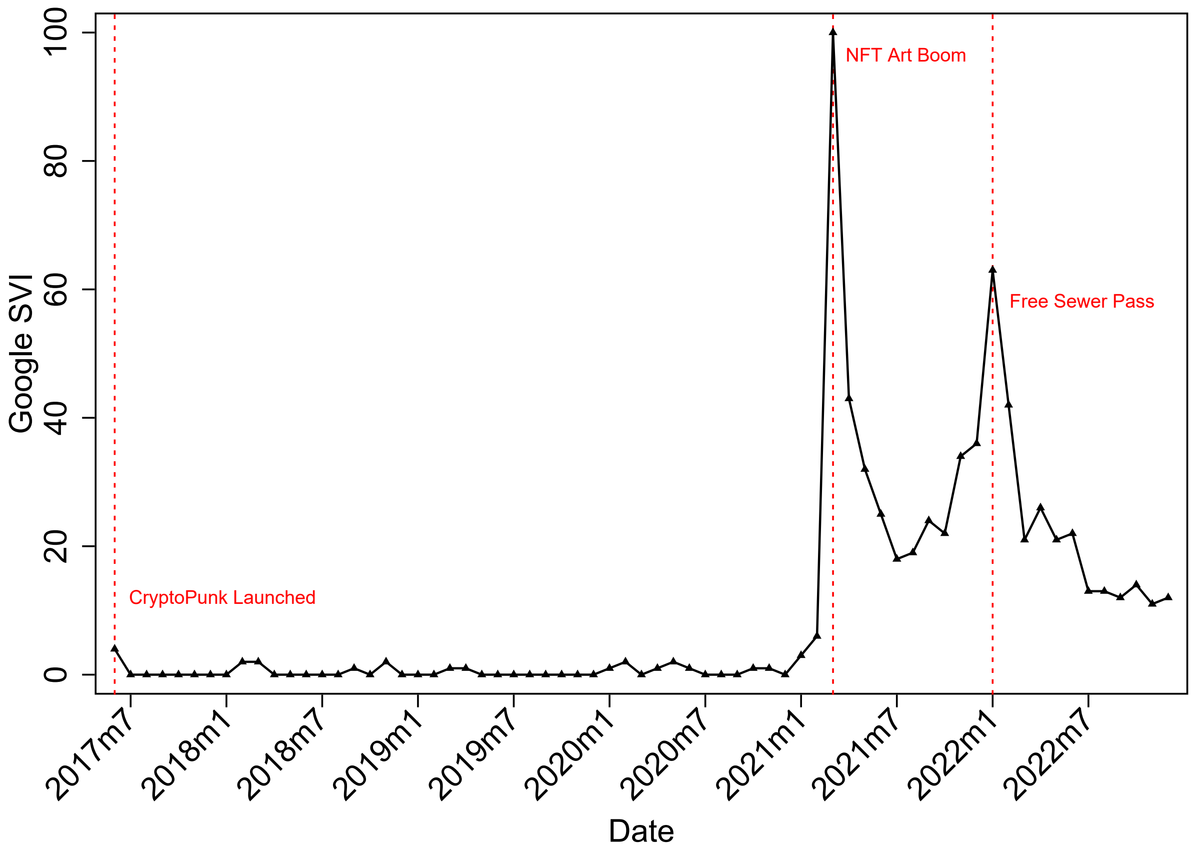
Panel B. CryptoPunks Holding Periods



Panel C. CryptoPunks Transaction Numbers

Note: This figure plots the kernel density functions of 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 plots the search interest on Non-fungible tokens 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 at a Christie's auction, which garnered widespread attention for NFTs. Lastly, the right red vertical dotted line corresponds to the announcements by Yuga Labs regarding the Sewer Pass NFT, which serves as a ticket to access their game and offers the opportunity to win surprise rewards. This announcement has also intensified interest in the NFT market.

Table IA1. **Classification of punk attributes**

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

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

Table IA2. **Cultural premium in CryptoPunks including non-traded tokens**

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Prc_i^{ETH}					
Punk Look	2.210***			2.673***		
	(0.391)			(0.363)		
Punk Count		0.911***			1.184***	
		(0.185)			(0.177)	
Punk Score			3.810***			4.097***
			(0.519)			(0.503)
Attribute FE	No	No	No	Yes	Yes	Yes
Observations	10,000	10,000	10,000	10,000	10,000	10,000
Adjusted-R^2	0.003	0.002	0.006	0.062	0.062	0.065

Note: This table shows how CryptoPunk tokens with punk culture are associated with the corresponding selling price in ETH by including the unsold tokens. We imputed these tokens with 0 ETH and run the following regression.

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

where Prc_i^{ETH} represents the average normalized Ethereum selling price of each CryptoPunk token i. $Attribute_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use 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 ***, **, * for 1%, 5%, and 10%, respectively.

Table IA3. **Intensive effects analysis on punk tokens**

	(1)	(2)	(3)	(4)
	Panel A: Dependent Variable $Prc^{ETH}_{i,t}$			
Punk Count	0.837**		1.114***	
	(0.426)		(0.417)	
Punk Score		5.362***		5.265***
		(0.982)		(0.967)
Attribute FE	No	No	Yes	Yes
Observations	16,318	16,318	16,318	16,318
Adjusted-R^2	0.693	0.695	0.710	0.711
	Panel B: Dependent Variable Prc^{ETH}_{i}			
Punk Count	0.682*		1.001**	
	(0.408)		(0.395)	
Punk Score		5.315***		5.147***
		(0.965)		(0.940)
Attribute FE	No	No	Yes	Yes
Observations	5,448	5,448	5,448	5,448
Adjusted-R^2	0.000	0.006	0.072	0.077
	Panel C: Dependent Variable Prc^{ETH}_{i}			
Punk Count	0.451		0.702***	
	(0.277)		(0.271)	
Punk Score		3.592***		3.575***
		(0.658)		(0.645)
Attribute FE	No	No	Yes	Yes
Observations	7,970	7,970	7,970	7,970
Adjusted-R^2	0.000	0.004	0.046	0.049

Note: This table shows how punk tokens (i.e., $PunkLook = 1$) are associated with the corresponding Ethereum selling price. We run the following regression:

$$Prc^{ETH}_{i,t} = \beta_1 Punk_i + \beta_2 Attribute_i + \gamma + \epsilon_{i,t}$$

where $Prc^{ETH}_{i,t}$ in Panel A represents the Ethereum selling price of CryptoPunk token i in time t. In Panel B, Prc^{ETH}_{i} represents the average (mean) Ethereum selling price of CryptoPunk token i throughout the sampling period. $Punk_i$ is one of the punk culture measures for CryptoPunk token i, including *Punk Count*, and *Punk Score*. $Attribute_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use 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 ***, **, * for 1%, 5%, and 10%, respectively.

Table IA4. **Cultural premium in CryptoPunks without suspicious transactions**

	(1)	(2)	(3)	(4)	(5)	(6)
	$Prc^{ETH}_{i,t}$	$ln(1 + Prc^{ETH}_{i,t})$	$Prc^{ETH}_{i,t}$	$ln(1 + Prc^{ETH}_{i,t})$	Prc^{ETH}_{i}	$ln(1 + Prc^{ETH}_{i})$
	Panel A: Punk Token Indicator					
Punk Look	3.370***	0.057***	3.650***	0.064***	3.705***	0.063***
	(0.508)	(0.010)	(0.484)	(0.009)	(0.509)	(0.010)
Attribute FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.703	0.929	0.721	0.936	0.102	0.158
	Panel B: Intensity of Punk Culture					
Punk Count	1.506***	0.032***	1.741***	0.038***	1.697***	0.037***
	(0.268)	(0.005)	(0.263)	(0.005)	(0.256)	(0.005)
Attribute FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.703	0.929	0.721	0.936	0.102	0.161
	Panel C: Degree of Punk Similarity					
Punk Score	5.773***	0.091***	5.926***	0.095***	5.796***	0.097***
	(0.746)	(0.014)	(0.731)	(0.013)	(0.725)	(0.013)
Attribute FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.704	0.929	0.722	0.936	0.106	0.161
Observation	20,471	20,471	20,471	20,471	6,791	6,791

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:

$$Prc^{ETH}_{i,t} = \beta_1 Punk_i + \beta_2 Attribute_i + \gamma + \epsilon_{i,t}$$

where $Prc^{ETH}_{i,t}$ represents the Ethereum selling price of CryptoPunk i in time t. Prc^{ETH}_{i} 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 ETH price. In Columns (3) and (4), we perform the estimations using the real price in ETH and the natural logarithm price by including $Attribute_i$ to control for the token's skin tone, including dark, medium, light, albino, zombie, ape, and alien. We use medium skin tone as the base variable to avoid multi-collinearity. 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 *PunkLook*, *PunkCount*, and *PunkScore*, 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 ***, **, * for 1%, 5%, and 10%, respectively.

Table IA5. **Cultural Premium with first and last token price**

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Dependent Variable First Selling Price in Prc_i^{ETH}					
Punk Look	2.445***			2.780***		
	(0.808)			(0.775)		
Punk Count		1.371***			1.601***	
		(0.370)			(0.360)	
Punk Score			2.824***			2.978***
			(1.011)			(0.992)
Attribute FE	No	No	No	Yes	Yes	Yes
Observations	6,833	6,833	6,833	6,833	6,833	6,833
Adjusted-R^2	0.001	0.002	0.001	0.028	0.029	0.028
	Panel B: Dependent Variable Last Selling Price Prc_i^{ETH}					
Punk Look	3.976***			4.553***		
	(1.110)			(1.077)		
Punk Count		1.044**			1.454***	
		(0.509)			(0.500)	
Punk Score			6.338***			6.605***
			(1.423)			(1.406)
Attribute FE	No	No	No	Yes	Yes	Yes
Observations	6,833	6,833	6,833	6,833	6,833	6,833
Adjusted-R^2	0.001	0.000	0.003	0.038	0.037	0.039

Note: This table shows how CryptoPunk tokens with punk features are associated with the first and last selling price of CryptoPunk token in ETH. We run the following regression:

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

where Prc_i^{ETH} in Panel A represents the first Ethereum selling price of CryptoPunk token i. In Panel B, Prc_i^{ETH} represents the last Ethereum selling price of CryptoPunk token i throughout the sampling period. $Punk_i$ is one of the punk culture measures for CryptoPunk token i, including *Punk Look*, *Punk Count*, and *Punk Score*. $Attribute_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use 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 ***, **, * for 1%, 5%, and 10%, respectively.

Table IA6. **Cultural premium in CryptoPunks**

	(1)	(2)	(3)	(4)	(5)	(6)
	$Prc^{USD}_{i,t}$	$ln(1+Prc^{USD}_{i,t})$	$Prc^{USD}_{i,t}$	$ln(1+Prc^{USD}_{i,t})$	Prc^{USD}_{i}	$ln(1+Prc^{USD}_{i})$
	Panel A: Punk Token Indicator					
Punk Look	9,345.900***	0.061***	9,856.338***	0.071***	10,765.899***	0.074***
	(1,412.590)	(0.013)	(1,385.761)	(0.011)	(1,449.574)	(0.014)
Attribute FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.775	0.970	0.782	0.974	0.052	0.177
	Panel B: Intensity of Punk Culture					
Punk Count	3,871.275***	0.036***	4,313.632***	0.044***	4,216.552***	0.046***
	(715.503)	(0.006)	(710.511)	(0.006)	(712.115)	(0.007)
Attribute FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.775	0.970	0.782	0.974	0.051	0.180
	Panel C: Degree of Punk Similarity					
Punk Score	15,425.595***	0.094***	15,664.341***	0.100***	15,475.105***	0.104***
	(2,001.742)	(0.016)	(1,988.973)	(0.016)	(2,032.723)	(0.017)
Attribute FE	No	No	Yes	Yes	Yes	Yes
Adjusted-R^2	0.776	0.970	0.782	0.974	0.055	0.179
Observations	20,679	20,679	20,679	20,679	6,833	6,833

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

$$Prc^{USD}_{i,t} = \beta_1 Punk_i + \beta_2 Attribute_i + \gamma + \epsilon_{i,t}$$

where $Prc^{USD}_{i,t}$ represents the dollar selling price of CryptoPunk i in time t. Prc^{USD}_{i} 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 ETH price. In Columns (3) and (4), we perform the estimations using the real price in ETH and the natural logarithm price by including $Attribute_i$ to control for the token's skin tone, including dark, medium, light, albino, zombie, ape, and alien. We use medium skin tone as the base variable to avoid multi-collinearity. 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 *PunkLook*, *PunkCount*, and *PunkScore*, 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 ***, **, * for 1%, 5%, and 10%, respectively.

Table IA7. **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			0.003		
	(0.053)			(0.053)		
Punk Count		-0.008			-0.011	
		(0.024)			(0.024)	
Punk Score			0.017			0.014
			(0.061)			(0.061)
Attribute dummies	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			0.002		
	(0.032)			(0.032)		
Punk Count		-0.005			-0.007	
		(0.014)			(0.014)	
Punk Score			0.010			0.008
			(0.037)			(0.037)
Attribute dummies	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 model. The punk culture measures include *PunkLook*, *Punk Count*, and *Punk Score*. $Attribute_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use 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 ***, **, * for 1%, 5%, and 10%, respectively.

Table IA8. **Investment performance of CryptoPunk tokens with punk features**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Without Controlling for Holding Period									
	Panel A: Dependent Variable $Ret_{i,t}^{ETH}$			Panel B: Dependent Variable Ret_{i}^{ETH}			Panel C: Dependent Variable Ret_{i}^{ETH}		
Punk Look	-0.037			0.063			0.006		
	(0.149)			(0.123)			(0.023)		
Punk Count		0.005			0.041			0.004	
		(0.063)			(0.056)			(0.012)	
Punk Score			-0.029			0.081			0.056*
			(0.192)			(0.164)			(0.031)
Observations	13,149	13,149	13,149	4,293	4,293	4,293	4,293	4,293	4,293
Adjusted-R^2	0.054	0.054	0.054	0.000	0.000	0.000	0.000	0.000	0.001
Controlling for Holding Period									
	Panel A: Dependent Variable $Ret_{i,t}^{ETH}$			Panel B: Dependent Variable Ret_{i}^{ETH}			Panel C: Dependent Variable Ret_{i}^{ETH}		
Punk Look	0.067			0.076			0.010		
	(0.143)			(0.120)			(0.022)		
Punk Count		0.065			0.047			0.006	
		(0.059)			(0.055)			(0.011)	
Punk Score			0.102			0.098			0.061**
			(0.181)			(0.160)			(0.029)
HoldingPeriod	-1.458***	-1.458***	-1.458***	-0.657***	-0.657***	-0.657***	-0.202***	-0.202***	-0.202***
	(0.076)	(0.076)	(0.076)	(0.051)	(0.051)	(0.051)	(0.013)	(0.013)	(0.013)
Observations	13,149	13,149	13,149	4,293	4,293	4,293	4,293	4,293	4,293
Adjusted-R^2	0.135	0.135	0.135	0.031	0.031	0.031	0.099	0.099	0.100

Note: This table examines whether the punk tokens price are temporarily overpriced and deliver lower returns to investors with and without controlling for token holding periods in Panel A and B, respectively. We run the following regression:

$$Ret_{i,t}^{USD} = \beta_1 Punk_i + \beta_2 Holding\_Period_{i,t} + \gamma + \epsilon_{i,t}$$

where $Ret_{i,t}^{USD}$ in Columns (1) to (3) represent the logarithm of one plus the daily return for CrytoPunk tokens i between the next transaction. Ret_{i}^{USD} in Columns (4) to (6) represent the average (mean) logarithm of one plus the daily return for each CryptoPunk token i. $Ret\_FL_{i}^{USD}$ in Columns (7) to (9) represent the average (mean) logarithm of one plus daily return between the first and the last transaction price for each CryptoPunk token i. $HoldingPeriod_{i,t}$, is defined as the natural logarithm of one plus the number of days between the next transaction of each token i in time t. $Punk_i$ is one of the punk culture measures for CryptoPunk token i, including *Punk Look*, *Punk Count*, and *Punk Score*. *Holding Period* is defined as the natural logarithm of one plus the number of days between the next transaction of each token. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, * 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 Count	1.723***	1.450***	-4.358***	1.434***	1.327***	14.812***	3.149***
	(0.261)	(0.265)	(1.342)	(0.266)	(0.253)	(3.980)	(0.779)
Traits		0.775*	-1.768***	-0.279	0.233	-0.270	0.194
		(0.408)	(0.623)	(0.662)	(0.403)	(0.658)	(0.404)
Punk Count × Traits			1.945***				
			(0.450)				
ATR				20.682*		-13.417	
				(10.765)		(13.835)	
MTR					482.032***		391.759***
					(23.062)		(38.393)
Punk Count × ATR						24.766***	
						(7.309)	
Punk Count × MTR							70.322***
							(25.285)
Attribute FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,679	20,679	20,679	20,679	20,679	20,679	20,679
Adjusted-R^2	0.721	0.722	0.722	0.722	0.736	0.723	0.736
	Panel B: Dependent Variable Prc_{i}^{ETH}						
Punk Count	1.689***	1.544***	-3.330***	1.526***	1.365***	9.944***	2.398***
	(0.255)	(0.268)	(1.262)	(0.269)	(0.259)	(3.554)	(0.787)
Traits		0.394	-1.697***	-0.560	-0.081	-0.511	-0.105
		(0.388)	(0.616)	(0.657)	(0.385)	(0.654)	(0.385)
Punk Count × Traits			1.622***				
			(0.413)				
ATR				18.764*		-3.325	
				(10.544)		(13.068)	
MTR					405.731***		405.731***
					(38.811)		(38.811)
Punk Count × ATR						15.631**	
						(6.560)	
Punk Count × MTR							40.402
							(25.386)
Attribute FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,833	6,833	6,833	6,833	6,833	6,833	6,833
Adjusted-R^2	0.103	0.103	0.107	0.104	0.161	0.105	0.161

Note: This table examines whether token attribute count (i.e., *Traits*) and rarity (i.e., *ATR* and *MTR*) affect the punk premium. The dependent variable is *PunkCount*. In Panel A, $Prc_{i,t}^{ETH}$ is the ETH selling price of token i in 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 average rarity score (*ATR*) and minimal rarity score (*MTR*) for each token i. Columns (3), (6), and (7) include the interaction terms. $Attribute_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use medium skin tone as the base variable to avoid multi-collinearity. $Rarity_i$ is the rarity score of each CryptoPunk token i. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10%, respectively.

Table IA10. **Cultural premium in CryptoPunks with token rarity**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Dependent Variable $Prc_{i,t}^{ETH}$						
Punk Score	5.898***	5.468***	-8.988**	5.746***	6.753***	50.178***	12.028***
	(0.726)	(0.754)	(3.793)	(0.754)	(0.728)	(11.565)	(2.279)
Traits		0.505	-1.651***	-1.217***	-0.360	-1.380**	-0.406
		(0.408)	(0.604)	(0.676)	(0.404)	(0.669)	(0.405)
Punk Score × Traits			4.890***				
			(1.288)				
ATR				32.520***		-1.583	
				(10.717)		(12.984)	
MTR					500.571***		420.849***
					(23.267)		(34.599)
Punk Score × ATR						81.548***	
						(20.967)	
Punk Score × MTR							199.277***
							(72.449)
Attribute FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,679	20,679	20,679	20,679	20,679	20,679	20,679
Adjusted-R^2	0.722	0.722	0.723	0.723	0.737	0.723	0.737
	Panel B: Dependent Variable Prc_{i}^{ETH}						
Punk Score	5.836***	5.728***	-7.061**	5.997***	6.939***	36.765***	9.453***
	(0.722)	(0.768)	(3.468)	(0.766)	(0.750)	(10.134)	(2.322)
Traits		0.122	-1.748***	-1.533**	-0.690*	-1.586**	-0.718*
		(0.387)	(0.578)	(0.670)	(0.386)	(0.668)	(0.669)
Punk Score × Traits			4.291***				
			(1.140)				
ATR				31.280***		6.587	
				(10.406)		(12.122)	
MTR					477.854***		438.759***
					(22.522)		(36.018)
Punk Score × ATR						56.683***	
						(18.487)	
Punk Score × MTR							96.081
							(74.423)
Attribute FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,833	6,833	6,833	6,833	6,833	6,833	6,833
Adjusted-R^2	0.108	0.108	0.111	0.109	0.169	0.111	0.169

Note: This table examines whether token attribute count (i.e., *Traits*) and rarity (i.e., *ATR* and *MTR*) affect the punk premium. The dependent variable is *PunkScore*. In Panel A, $Prc_{i,t}^{ETH}$ is the ETH selling price of token i in 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 average rarity score (*ATR*) and minimal rarity score (*MTR*) for each token i. Columns (3), (6), and (7) include the interaction terms. $Attribute_i$ indicates the skin tone of each CryptoPunk token, including dark, medium, light, albino, zombie, ape, and alien. We use medium skin tone as the base variable to avoid multi-collinearity. $Rarity_i$ is the rarity score of each CryptoPunk token i. Standard errors (in parentheses) are clustered at the token level. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10%, respectively.

Table IA11. **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.