



Can we price beauty? Aesthetics and digital art markets

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ABSTRACT

What is the relation between the aesthetic value of art and its market price? We address this question in the context of digital art markets by employing data from the popular CryptoPunks NFT art collection. We quantify the visual attractiveness of NFTs using four aesthetic measures that are associated with emotional effects in the cultural economics literature. Using a hedonic pricing model, we identify aesthetics as a driver of prices in digital art markets. Our results indicate that investors prefer NFTs with higher levels of colorfulness and texture complexity and lower levels of saturation and brightness.

1. Introduction

Blockchain-based non-fungible tokens (NFTs) have transformed art markets. In contrast to traditional art that is typically sold via auctions, NFT-based digital art is traded in organized online marketplaces that are characterized by higher liquidity, continuous operation and easy access to creators and collectors. These distinct features of digital art have generated substantial interest from investors, while a new strand of economic research has been developing around understanding the determinants of NFT art prices (e.g., Horky et al., 2022; Schaar and Kampakis, 2022; Nguyen, 2022). We contribute to the literature by studying the relation between the visual attractiveness of digital art and its market price. This is important as art is associated with emotional dividends to the owner that may affect its market value (Throsby, 1994; Candela et al., 2013).

A long-standing challenge in art pricing is posed by the subjective nature of aesthetics. To address this, we employ quantitative aesthetic measures to capture aspects of NFT art, such as colorfulness, brightness and color intensity. This is in the spirit of recent studies in the cultural economics literature that associate such measures with emotional effects and art auction prices (e.g., Pownall and Graddy, 2016; Stepanova, 2019; Ma et al., 2022; Garay et al., 2022). We add to this literature by providing fresh evidence on the impact of aesthetics on digital art markets. We also explore for the first time the price effects of the texture

complexity of art, as measured by the texture range.

Our empirical analysis applies a hedonic pricing model to the CryptoPunks collection, which is the dominant NFT art project in terms of market size and trading volume. Launched in mid-2017 by Larva Labs, CryptoPunks consist of 10,000 pixel-art images of fictional characters, each corresponding to a NFT operating on the Ethereum blockchain. Our results establish several links between aesthetics and CryptoPunk prices. We find that more colorful or more visually complex NFTs are associated with higher prices, while brighter or more saturated NFTs are associated with lower prices.

Our results extend previous studies that explore the relation between CryptoPunk prices and various characteristics of the underlying portraits, such as gender (Schaar and Kampakis, 2022), skin tone (Nguyen, 2022) and rarity (Dobrynskaya and Bianchi, 2023). Our paper is also related to the work of Borri et al. (2023) that extracts visual characteristics from several NFT collections using neural networks and finds that they can partly explain prices. We differ from that paper by focusing on specific aesthetic features of art, such as colorfulness and complexity, and by identifying which of these features matter for NFT investors.

2. Data & methodology

Our dataset consists of images and prices of CryptoPunks traded between June 2017 and March 2023, as reported in Nonfungible.com

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and OpenSea.io, the latter being the largest NFT marketplace over this period. After removing missing observations, we end up with 21,886 sales that involve 6,938 CryptoPunks in total.

We assess the aesthetics of digital art through four quantitative measures.¹ The first is the number of hues and captures the colorfulness of a CryptoPunk. More colorful images have a higher hue count while a low hue count can signify simplicity (Ke et al., 2006). We examine the effect of colorfulness on digital art prices based on evidence from traditional art auctions that more diverse colors may lead to higher prices (e.g., Stepanova, 2019). The second aesthetic measure we adopt is the brightness of the image. This is computed as an arithmetic average of the brightness across all pixels of the CryptoPunk. In the traditional art pricing literature, brighter or lighter colors tend to be linked to lower prices (e.g., Pownall and Graddy, 2016; Garay et al., 2022).

The third measure we employ is the saturation of the NFT. This captures the intensity of the colors and may affect the attractiveness of the artwork. Previous results on the price effects of saturation vary based on the underlying art collection. For instance, Pownall and Graddy (2016) report a positive relation between prices and saturation in their sample. Garay et al. (2022) find an inverse U-shaped relation between the two, with very intense colors negatively affecting prices. Finally, Ma et al. (2022) report no link between color intensity and prices.

Our final measure of aesthetic value is the range of texture in the artwork, which captures visual complexity (Haas et al., 2015). This helps us assess whether digital art investors prefer simpler/smooth or more complex designs. While the art pricing literature has not considered the effects of texture complexity on the art markets, there is experimental evidence that more complex patterns in images are more attractive to the viewer (e.g., see Friedenber and Liby, 2016, and the references therein). For illustration purposes, Fig. 1 presents examples of CryptoPunks with low and high levels of colorfulness, brightness, saturation and texture complexity, respectively.

To study the impact of aesthetics on NFT prices, we employ a hedonic regression analysis as is common in the traditional and digital art pricing literatures (e.g. Stepanova, 2019; Garay et al., 2022; Nguyen, 2022; Schaar and Kampakis, 2022).² Our model can be expressed as:

$$\log p_{it} = \beta_0 + \sum_{j=1}^4 \beta_j f_{j,i} + \sum_{k=1}^K \gamma_k C_{k,i,t} + \varepsilon_{it}, \quad (1)$$

where $\log p_{it}$ is the natural logarithm of the USD price of the NFT i at time t , $f_{j,i}$ is the natural logarithm of the j -th aesthetic measure for the CryptoPunk i and $C_{k,i,t}$ is our set of controls. We consider three variations of the above model that differ in the specification of controls. First, we account for time-specific effects using month-year dummies that correspond to the time of the sale. The second variation expands the set of controls with market-based variables, i.e., the daily percentage change in the CryptoPunks sales volume and the ETH/USD exchange rate, where ETH is the native cryptocurrency in the Ethereum blockchain.³ These variables respectively reflect changes in the demand for CryptoPunks and ETH. Our third model further controls for the type of the CryptoPunk (Female, Alien, Ape, or Zombie) using dummy variables. Motivated by the findings of Dobrynskaya and Bianchi (2023), we also



Fig. 1. Examples of CryptoPunks with different aesthetic properties.

account for the effects of rarity as captured by the number of unique characteristics (such as spots, hair color, accessories, etc.) and the rarity score of each CryptoPunk, obtained from Rarity.Tools. Table 1 provides descriptive statistics of all variables in this work.

3. Empirical results

Table 2 summarizes the estimation results for the three hedonic pricing models under study. In line with previous studies in the CryptoPunks market (e.g., Nguyen, 2022), we observe high R^2 's due to the large effect of the month-year dummies with the models capturing around 92 % of the variation in logarithmic prices. All considered aesthetic measures have a statistically and economically significant price effect. Consistent with evidence from artwork auctions (e.g., Stepanova, 2019), digital art investors pay a premium for more colorful CryptoPunks. Under the third model specification, a 1 % increase in the hue count is associated with a higher NFT price by 32 basis points (bps).

¹ We are grateful to Haas et al. (2015) for providing the MATLAB code for the computation of the four aesthetic measures we use in this work (<https://peerj.com/articles/1390/>).

² An alternative approach to NFT pricing is the repeat-sales method which can better accommodate heterogeneity or potential omitted-variable bias compared to hedonic models (Borri et al., 2023). We do not employ this method as it requires at least two sales for each asset while 30% of NFTs are sold only once in our sample. Moreover, heterogeneity is less of a concern here as we focus on a largely homogeneous NFT collection.

³ ETH/USD rate is obtained from CoinMarketCap.com. Sales volumes are from DappRadar.com.

Table 1
Descriptive statistics.

	Sample Size	Mean	Median	St. Dev	Min.	Max.
log (USD price)	21,886	9.713	10.864	3.034	-4.948	16.985
Δ ETH/USD (% daily)	1696	0.002	0.001	0.053	-0.423	0.265
Δ Sales (% daily)	1696	1.168	-0.006	6.071	-0.995	159.201
Hue count	6938	2.229	2	0.452	1	4
Brightness	6938	0.425	0.424	0.053	0.262	0.637
Saturation	6938	0.346	0.339	0.061	0.167	0.567
Texture range	6938	0.006	0.006	0.001	0.003	0.033
Rarity	6938	118.810	101.680	161.486	44.490	10,342.680
Number of traits	6938	2.791	3	0.783	0	7
Alien	6938	0.001	0	0.032	0	1
Ape	6938	0.003	0	0.052	0	1
Female	6938	0.359	0	0.480	0	1
Zombie	6938	0.007	0	0.082	0	1

Table 2
Hedonic regression results.

	Dependent Variables: log (USD price)		
	(1)	(2)	(3)
Hue count	0.421*** (0.063)	0.422*** (0.059)	0.317*** (0.047)
Brightness	-0.136** (0.061)	-0.136** (0.059)	-0.132*** (0.049)
Saturation	-0.308*** (0.055)	-0.311** (0.053)	-0.263*** (0.041)
Texture range	0.114*** (0.038)	0.115*** (0.038)	0.123*** (0.037)
Δ ETH/USD (% daily)		0.206 (0.242)	0.311*** (0.110)
Δ Sales (% daily)		0.003** (0.001)	0.001 (0.001)
Rarity			0.001*** (0.000)
Number of traits			0.022** (0.010)
Alien			1.730** (0.716)
Ape			2.430*** (0.275)
Female			0.094*** (0.014)
Zombie			2.020*** (0.143)
Intercept	3.536*** (0.214)	3.540*** (0.212)	3.424*** (0.217)
Month-dummies?	Yes	Yes	Yes
Observations	21,886	21,886	21,886
Adjusted R^2	0.920	0.920	0.927
F-statistic	3442	3351	3419

Note: HAC standard errors are reported in parenthesis. **, *** and **** respectively denote significance at the 10 %, 5 % and 1 % level.

At the same time, a 1 % increase in brightness is linked to a price decrease of 13 bps. This result highlights that darker colors are more attractive in the CryptoPunks market, similar to previous studies on art pricing (e.g., Pownall and Graddy, 2016; Garay et al., 2022).

It appears that investors tend to prefer more muted colors with a 1 % increase in the saturation associated with a lower price by 26 bps. This result contrasts with evidence by Pownall and Graddy (2016) that find

the opposite result in art auctions while it extends the finding of Garay et al. (2022) that high saturation may dampen art prices. Finally, we find that investors in the CryptoPunks market prefer more complex patterns as prices tend to be higher by 12 bps when texture range increases by 1 %. This finding is consistent with Friedenber and Liby (2016) in that visual complexity of an image may be desirable to the viewer. Overall, our results establish aesthetics as a driver of prices in the CryptoPunks market. Future research could explore the relation between aesthetics and prices for other NFT collections.

Data availability

The data used in this work is available for free from online sources, as mentioned in the text.

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