The Impact of Celebrity Ownership on NFT Collection Value

by

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An honors thesis submitted in partial fulfillment of the requirements

for the degree of

Bachelor of Science

Undergraduate College

Leonard N. Stern School of Business

New York University

May 2022

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Acknowledgements

I would like to start off by thanking my thesis advisor, Professor David Yermack. He offered so much wisdom, guidance, and accountability over the past year. His curiosity was infectious and motivated me during particularly frustrating moments of this project. Despite a busy schedule, Professor Yermack was always willing to schedule meetings and offer guidance consistently. I truly could not have asked for a better advisor for this project.

I would also like to thank Professor Mary Billings for a wonderful honors seminar. Being able to hear from distinguished guest speakers was an amazing opportunity to learn firsthand from some of the most renowned Stern faculty across a wide variety of fields. I appreciated her willingness to receive feedback and her flexibility in accommodating everyone's own personal intellectual interests.

Lastly, I want to thank my friends and family who have had to endure my unending rambling about NFTs for the past year. I am so grateful to have a community that supports me and challenges me to step outside my comfort zone.

Abstract

Celebrity endorsements are a widely used tool in marketing. However, the existing academic research on the impact of celebrity endorsements on business value is mixed. In this paper, I look at the effectiveness of celebrity purchases as endorsements in the context of the NFT art market. I analyze the impact of 58 celebrity purchases on NFT art collection value. Using sales price averages and frequencies as proxies for value, I test whether the occurrence of a celebrity transaction is linked to a change in collection-wide value. I also test whether this change in value only occurs for NFTs with similar visual traits in a collection. While my tests are inconclusive, I find that the Ethereum markets and visual traits are important factors of collection value. This provides promising avenues for future research in the NFT art market.

I Introduction

Non-Fungible Tokens, or NFTs, are currently the focal point of cultural discussions on the future of artwork and ownership. The term non-fungible refers to uniqueness, lacking the ability to be interchanged with another item. NFTs are unlike cryptocurrencies, which are issued in large quantities that are indistinguishable from one another – all their tokens are the same. NFTs start with a unique digital asset like a video or picture file, which is then "minted" as a token, creating a digital certificate of authenticity and ownership recorded on a blockchain. These tokens can then be bought and sold, transferring ownership of the asset. The tokens act as hash pointers to digital assets, and it is the tokens themselves that are recorded on a blockchain.

This paper focuses on NFT art collections and aims to uncover the relationship between celebrities owning NFT artwork and a collection's value. Given that public proof of ownership on a blockchain is established during an NFT transaction, I hypothesize that celebrity purchases, acting as endorsements, increase collection value. I also hypothesize that this increase in value will be greater for NFT art pieces that are the most visibly similar to ones purchased by celebrities. In my tests, I use sales price averages and frequency as a proxy for collection value. Ultimately, my tests are inconclusive in proving or rejecting my hypotheses. However, I find that the Ethereum market and visible traits are important factors that play into NFT value, which provide avenues for future research in this market.

II NFTs and Art

While NFT technology has many applications, it is most visible in the world of art. NFT art transactions most commonly occur using the Ethereum blockchain. This is because Ethereum is one of the first and the most prominent blockchain networks designed for smart contract functionality.[1] The transactions on the Ethereum network use Ether, or ETH, as currency, meaning that transactions that are recorded on the blockchain require both the buyer and seller to have Ethereum wallets. These wallets are used to hold ETH as well as NFTs themselves. However, if a buyer and seller wish to have the purchase price of their artwork hidden, a private sale can be arranged. Private sales involve transferring the NFT from one wallet to another, with a payment method like a wire transfer. Nonetheless, all transactions and transfers are recorded on the Ethereum blockchain, which is visible to anyone.

Subsequently, NFTs are able to establish an immutable record of provenance, a term used to refer to the ownership history of an art piece.[2] For tangible artwork, provenance is a key component of an art valuation.[3] Longtime artists Beeple and Pak have sold their digital artwork as NFTs for millions of dollars and have partnered with the two main auction houses, Christie's and Sotheby's, to sell their work.[4] These artists tend to sell their artwork in large, one-off transactions. However, there is another form of NFT art that is more mainstream: large collections of similar characters that have slightly different physical traits. The variety of traits within a certain collection creates a level of scarcity, which is a determinant of value. Notable collections include CryptoPunks, a collection of 10,000 pixelated avatars and The Bored Ape Yacht Club, a collection of 10,000 digital apes.[5]

Originally gaining popularity among crypto enthusiasts, NFT artwork has moved from niche crypto circles into the limelight, with some of the world's largest celebrities purchasing and even creating their own NFT artwork. These names include Steve Aoki (DJ), Jimmy Fallon

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[1] https://www.theverge.com/22310188/nft-explainer-what-is-blockchain-crypto-art-faq
[2] https://www.nationalgallery.org.uk/paintings/glossary/provenance
[3] https://www.jstor.org/stable/refuseserq.54.4.21?seq=1
[4] https://www.barrons.com/articles/paks-nft-artwork-the-merge-sells-for-91-8-million-01638918205
[5] https://www.techtimes.com/articles/265404/20210915/top-5-popular-nft-collections-september-2021-cryptopunks-meebits.htm

(talk show host), Post Malone (singer), Stephen Curry (NBA player), and Mark Cuban (investor). This form of art is drawing attention from celebrities in a wide variety of categories. These celebrities often use concierge services like Moonpay to purchase NFT artwork.[6] Concierge services eliminate the need for a buyer to purchase cryptocurrency and submit a successful bid for a given art piece. Once these celebrities successfully purchase an NFT, they are usually quick to promote their purchase on social media, most commonly on Twitter. Many have been participating in a recent Twitter trend of uploading pictures of their NFT art as their profile photos.[7]

III Jimmy Fallon and the Bored Ape Yacht Club

On November 8, 2021 Jimmy Fallon, the popular television host of "The Tonight Show Starring Jimmy Fallon" purchased Bored Ape #599 from the Bored Ape Yacht Club NFT collection. Bored Ape #599 has the following traits and rarities: Bored Mouth (23%), Blue Background (12%), Cream Fur (6%), Heart Sunglasses (4%), Navy Striped Tee (3%), and Sea Captain's Hat (3%). Fallon purchased his NFT using Moonpay, who purchased the asset about 10 minutes before it was transferred into his wallet. This transaction occurred on Opensea, the most widely used NFT art marketplace.[8]

On November 12, 2021 Fallon posted a photo of his newly acquired Bored Ape #599 on his Twitter page along with the caption "Permission to come a bored? @BoredApeYC #NewProfilePic." Through this, Fallon publicly endorsed the Bored Ape Yacht Club to his 50

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[6] https://www.moonpay.com/business/nfts
[7] https://www.coindesk.com/business/2022/01/20/twitter-launches-nft-profile-picture-verification/
[8] https://www.benzinga.com/markets/cryptocurrency/21/11/24052185/jimmy-fallon-buys-a-bored-ape-yacht-club-nft-here-are-the-details

million twitter followers and presumably increased the awareness and popularity of the NFT collection.[9]

Witnessing this, I wondered whether celebrities like Jimmy Fallon, who have massive fan bases, could generate value for an NFT collection given their ownership of a single NFT and their endorsement. To explore this, I looked at a one day window of sales averages of the entire Bored Ape Yacht Club collection before and after the date and time of Jimmy Fallon's tweet. 24 hours before Fallon's tweet, the average sales value of the collection was $169,366.10. 24 hours after, the average sales value was $232,506.22, which is a difference of $63,140.12 (Graph 1).

It made sense to me that a significant piece of an NFT's collection value may involve the high profile celebrities that are owners within a collection. The most notable NFT collections that celebrities gravitate to are often the ones with the most visible and active communities. As a result, an NFT art piece in one of these collections can represent a sense of belonging to an exclusive community. [10] This may help explain the trend of NFT owners setting their Twitter profile pictures to pictures of their NFTs.

IV Celebrity Endorsements

A. Previous Literature on Celebrity Endorsements

A celebrity endorsement of a product or service is a common advertising strategy for businesses to build brand awareness, recognition, and increase a potential customer's willingness to buy. With the advent of novel advertising methods like social media, this practice has only increased in popularity. Companies use celebrities in advertising because of the assumption that

[9] https://twitter.com/jimmyfallon/status/1459164143626424321
[10] https://www.coindesk.com/tech/2021/09/03/the-value-of-nfts-is-belonging/

their customer base will purchase products associated with those celebrities (Fowles, 1996). This is an example of meaning transfer, where the image of a celebrity becomes a part of a product's identity (McCracken, 1989).

The body of research on celebrity endorsement advertising is extensive and covers a wide range of psychological factors, geographic markets, and product categories. There is also research on the effectiveness of celebrity endorsement marketing. This particular subset of literature yields mixed conclusions on whether these endorsements are effective from a business perspective.

There are numerous studies that indicate the positive impact of a celebrity endorser and a business' brand or performance. Spry et. al. (2011) found that even a low credibility celebrity endorsement can build brand equity, which is the "incremental value added by a brand name to a product". The authors describe credibility as "attractiveness, expertise and trustworthiness". While this is a qualitative measure of endorsement effectiveness, Agrawal and Kamukura (1995) conduct a study that analyzes excess returns in relation to celebrity endorsement. Excess returns should measure the perceived business impact of a given endorsement announcement. This event study finds that, on average, firms only record a gain of .44% excess returns in their market value because of announcing contracts with celebrities. While this shows a positive impact in market value, this is a rather small effect.

However, there are many other studies that find no impact on business value from celebrity endorsements. Ding et. al. (2009) conducted an event study of 101 US company announcements regarding celebrity endorsements between 1996 and 2008 measuring abnormal returns. The study chooses the same window as Agrawal and Kamakura (1995). The researchers found that the market "anticipates the net discounted cash flow to be close to zero, implying that benefits of a celebrity endorsement match their costs". Likewise, Fizel et al. (2008) analyzed 148 non-mega-star athlete endorsement announcements and found an insignificant impact on a firm's market value.

B. The Uniqueness of the NFT Art Market

Unlike other markets, celebrity endorsements in the NFT art space often involve a celebrity making a public purchasing decision, without any publicly known payment from collection creators. Because of the transparency that is provided by marketplaces and blockchains, it is fairly simple for anyone who has access to the internet to identify and become aware of a celebrity purchase. Additionally, NFT owners, including celebrities, are displaying their highest value NFTs as their profile pictures on social media. Hence, instead of receiving payment for their endorsement, these celebrities at least appear to promote and purchase their NFT artwork for free. Drawing on Ohanian's (1991) research on source credibility in celebrity endorsement advertising, the trustworthiness of a celebrity impacts purchasing decisions in a significant way. The appearance of a celebrity promoting and purchasing an NFT collection without payment should bolster trustworthiness. Hence, the impact of this kind of celebrity endorsement should be higher on a purchasing decision in the NFT space, where the consumer is unaware of any payment between an NFT collection creator and a celebrity.

V Research Question

A. Hypothesis

Jimmy Fallon's impact on the Bored Ape Yacht Club's sales price average and the nature of NFT celebrity endorsements having proof of ownership provide indications that there may be an impact of celebrity transactions on the market. This leads me to believe that the celebrity ownership of NFT artwork has an impact on other works within the respective collection. And, I presume that the most dramatic impact would be seen in NFTs that have similar traits. Ultimately, this thesis will focus on answering the following question: Does having a celebrity owner in the provenance of an NFT result in an increase in collection value?

B. Importance

As a result of the number of celebrity owners in the NFT art space, collection creators, in building marketing strategies, are figuring out how to engage with celebrities in a way that increases a collection's value. And because many collection creators choose to collect royalty payments from every sale within their collection, they have a strong incentive to maintain a high level of volume in their collection even after the initial sales. My research should assist these creators in pinpointing a key piece of their marketing strategy in this new and rapidly expanding market.

There is also a need, more broadly speaking, of rationalizing value in the NFT art space. Many observers of the market are struggling to reason why an individual would purchase a single NFT in a massive collection of similar characters for sometimes millions of dollars. This research can contribute to understanding what motivates people to purchase NFT art. Additionally, from an investor perspective, this research can supplement the creation of an investment strategy that leverages the buying behavior of influencers.

The existing literature on the NFT art space mostly involves research on understanding market dynamics of efficiency, pricing[11], and market size[12]. Additionally, there is a growing body of research that attempts to classify NFTs within a property and security law framework[13]. Due to the fact that the space has only existed for the past few years, there is little data available on NFT art transactions and subsequently the current research is still focused around making sense of the market. There is preliminary research on understanding scarcity and understanding whether NFT traits is a good predictor of price[6], which can supplement my research well. But, there does not seem to be research on the effect that celebrities have on the NFT market.

VI Research Method

To test the impact of provenance on NFT collection value, I used sales price averages and frequencies as a proxy for collection value in ordinary least squares regressions. Frequency of sales can measure liquidity, and sales averages measure average prices of NFTs in the collection. Higher liquidity and higher sales averages add value to NFT owners and collection creators, as owners are able to sell more easily at a higher price and this consequently allows collection creators to increase royalty revenue.

As a proxy for provenance, I used a sample of 58 celebrity transactions. These celebrities all have sizable followings on social media and receive considerable media attention. These transactions are included into the regressions using a dummy variable to indicate the occurrence of a celebrity purchase. Other dependent variables in the regressions include the USD prices of ETH, trait count, and NFT rarity. The price of ETH should account for the connection between

[11] https://www.sciencedirect.com/science/article/pii/S154461232100177X
[12] https://www.nature.com/articles/s41598-021-00053-8.pdf
[13] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3821102

the NFT Market and cryptocurrency markets. Trait counts measure the number of observable traits each NFT has in the context of a given collection. NFT rarity is an average rarity score based on the rarities of each trait it has within a collection. These rarity scores are from *raritysniper.com*, a website that calculates rarities of visible traits within different collections. Trait counts and NFT rarity should incorporate some of the effects that scarcity may have on an NFT collection's value.

$$Y_{\text{Sales Average}} = \alpha + \text{Dummy Var}_{\text{celeb}} + \text{ETH Price}_{\text{USD}} + \text{Trait Count} + \text{Rarity} + \varepsilon$$

$$Y_{\text{Sales Frequency}} = \alpha + \text{Dummy Var}_{\text{celeb}} + \text{ETH Price}_{\text{USD}} + \text{Trait Count} + \text{Rarity} + \varepsilon$$

To factor in the impact of physical traits, I ran regressions not only on entire collections, but also on portfolios of NFTs in the collection with similar traits. For each NFT in the transaction dataset, the portfolios were constructed by compiling NFTs in the same collection that shared the rarest three traits. Then sales averages and frequencies were calculated for each transaction's portfolio. These regressions test if the value being created by celebrity transactions only apply to NFTs with similar visible traits in the same collection.

I ran these tests varying the windows of time in calculating the sales averages and frequencies for each transaction. These tests yielded similar results to the baseline test of a 1-day window, which is 24 hours before and after a transaction. As a result, I only analyze the 1-day window tests in this paper.

VII Data Collection:

The primary data source is Opensea.io, which is the most popular online marketplace for buying and selling NFT artwork.[14] Opensea maintains an API which is mainly designed for developers to build applications which integrate Opensea's marketplace. I collected 151,504 transactions from Opensea's API across seven of the highest volume NFT collections (Figure 1). To rank these collections, I cross-referenced four NFT collection analytics webpages.

I collected historical transaction data for each NFT in the collection going back to its first sale on Opensea. The data includes the price of sale, time and date of sale, username of buyer, and username of seller. I also collected asset data, detailing the visible traits of each NFT art piece.

The Opensea transaction data listed prices in wei, which is the smallest denomination of Ether. But due to Ether's volatility in relation to fiat currencies, I downloaded a dataset from Gemini, a popular cryptocurrency exchange, that included minute by minute data on the ETH to USD conversion rate. I then merged this with the data from Opensea to get the USD price for every transaction.

In order to create my sample of celebrity transactions, I used various crypto blogs, social media accounts, and news articles to identify a celebrity purchase of an NFT. Then, I used *etherscan.io*, which is an Ethereum blockchain explorer to verify and obtain the timestamp for each transaction/transfer. And, to ensure an apples-to-apples comparison, I selected only the first known transaction for each celebrity wallet in my sample, which includes 58 celebrity transactions.

To create the trait portfolios that I used, I downloaded data from *raritysniper.com*, which is a website that aggregates NFT collection data and computes the rarity of each NFT's traits

[14] https://dappradar.com/nft/marketplaces

within the context of its collection. From this data, I included each NFT's rarity score in my regression equations.

VIII Regression Results:

In both collection-wide and similar trait regressions, there is no clear link between the dummy variable and sales average or frequency. Due to the statistical insignificance of the dummy variable, which indicates a celebrity transaction, the tests fail to reject the null hypothesis of zero impact of celebrity transactions on collection value.

A. Collection-wide Regressions

The collection wide regressions on sales averages showed that the number of traits, rarity, and the USD price of ETH were significant variables with low p-values (Table 1). The number of traits and rarity interestingly have negative coefficients, although small in absolute terms. This suggests a slight negative correlation between sales averages and these two variables. ETH price has a sizable coefficient, +29.16. This indicates that, holding all else equal, the impact of ETH price on sales price average is large.

Likewise, the collection wide regressions on sales frequency showed the number of traits, rarity, and the USD price of ETH were significant variables with low p-values (Table 2). Unlike the other significant variables, the number of traits had a large coefficient, +23.32. It is interesting that the number of traits has a positive coefficient compared to the previous regression on sales averages.

B. Similar Trait Regressions

In the regressions on sales price averages, the USD price of ETH and the number of traits were statistically significant variables (Table 3). Like the regressions on the entire collection, the coefficient for trait count is slightly negative and the one for ETH price is sizable at +26.94.

In the regressions on sales frequency, the rarity, trait count, and ETH price were all significant. The coefficients for rarity and ETH price were slightly negative, indicating a negative relationship with sales frequency. The coefficient for trait count was very large at +41.84.

IX Concluding Remarks:

A. Findings

No conclusions regarding the impact of celebrity transactions can be drawn based on the tests conducted. This is due to the statistical insignificance of the dummy variable in every regression. As a result, the null hypothesis of zero celebrity impact cannot be rejected. However, the tests revealed the importance of both the price of ETH and the traits of NFTs on sales averages and frequency, respectively (Graphs 2 & 3).

The impact of ETH price on average sales prices (in USD) is fairly obvious given the fact that a vast majority of all NFTs are transacted using ETH. There seems to be a slight positive relationship between the prices of NFTs in USD and the price of ETH in USD (Graph 3). This corroborates previous research in Ante (2021) which shows how the ETH markets are correlated with the NFT art market. A decrease in ETH value, or cryptocurrency value in general, leads to a drop in purchasing power, which is evident in NFT markets.

The link between the number of traits and sales frequency is fairly interesting. As evident in Graph 2, there is a positive association between the number of traits and the sales frequency.

However, this association drops significantly once the number of traits exceeds eleven. This may indicate that there are certain visible traits that are seen as valuable in a given collection, and the NFTs that have a higher number of traits have a higher probability of possessing these valuable traits. However, at a certain point the number of traits may become too high, resulting in too convoluted of a product for buyers. Future research is needed to confirm this presumption.

B. Limitations

The main limitation of this research stems from the sample of the celebrity transactions. The sample consisted of 58 transactions from celebrities with various claims to fame. However, 37 of these transactions were from a single collection (Figure 2). Additionally, as seen in Graph 4, most of the transactions occurred in late 2021/early 2022. Ideally, this sample would have more observations and a larger distribution of collections and dates.

Another major limitation is the sheer number of confounding variables that are present. The regressions have relatively low R-squared values, indicating a lack of prediction power from the variables included in the models. Consequently, there are many more components of collection value apart from the ones accounted for in this paper. Part of this has to do with the complexity of this novel NFT art market, which many would deem as irrational. For instance, many buyers still do not know that purchasing NFT art is not equivalent to purchasing a jpeg image file.[15] Given these conditions, it can be difficult to tease out the components of collection value.

The variables included also suffer from multicollinearity. For instance, a celebrity may choose to purchase a given NFT based on traits or rarity. In fact, we know this occurs by looking

[15] https://hackernoon.com/how-to-explain-nfts-to-people-who-think-theyre-just-jpegs

at examples of Serena Williams[16] and Eminem[17] who purchased NFTs that share a number of visible traits with their real, public personas.

C. *Future Research*

From this research, it is evident that traits and the price of ETH are important factors in collection value. As a result, this paper provides a promising jumping off point for research on the effects visible traits and Ethereum market conditions have on NFT artwork. In tying traits with NFT value, it would be interesting to research the kinds of traits buyers value the most or least. As the amount and type of physical traits associated with each NFT in a given collection is entirely up to the creator, there is a need to make sense of this unstandardized data. In regards to the Ethereum market, there is a lot to be explored in linking ETH prices and volume to the NFT market. And as more blockchains are becoming used for NFT sales, an interesting angle to explore would be whether there is an impact on NFT value depending on which blockchain is used.

Another interesting future research question is why celebrities purchase NFT art. It is fascinating to think about why some of the most renowned celebrities, like Justin Bieber, purchase digital art for amounts exceeding the seven figure mark. Are celebrities' incentives to purchase NFT art different from the majority of buyers? Do these purchases have any impact on the brand or influence of these celebrities? The blogger *Read Max* has begun to map out incentives that certain celebrities who purchased NFT art have based on talent agencies and

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[16] https://mashable.com/article/met-gala-cryptopunk-serena
[17] https://www.prestigeonline.com/my/people-events/people/eminem-buys-bored-ape-yacht-club-nft/

connections to financiers (Figure 3).[18] Continuing this exploration within an academic research context would hopefully help to find an answer to this question.

[18] https://maxread.substack.com/p/mapping-the-celebrity-nft-complex?s=r

Figure 1: *Collected Collection Data from Opensea API Ranked by Volume*

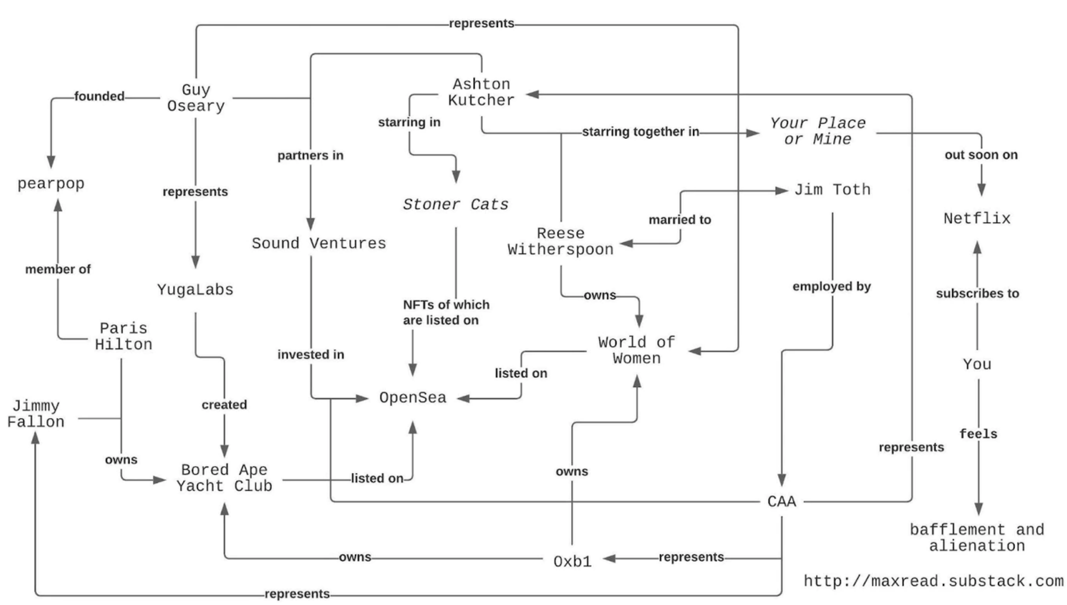
Collection Data Obtained	Volume ($M)
Crypto Punks	1529.65
Bored Ape Yacht Club	1084.57
Mutant Ape Yacht Club	296.90
Meebits	226.85
World of Women	174.95
Hashmasks	92.35
CryptoKitties	55.46

sources: CoinMarketCap.com, Ayzd.com, NonFungible.com, DappRadar.com

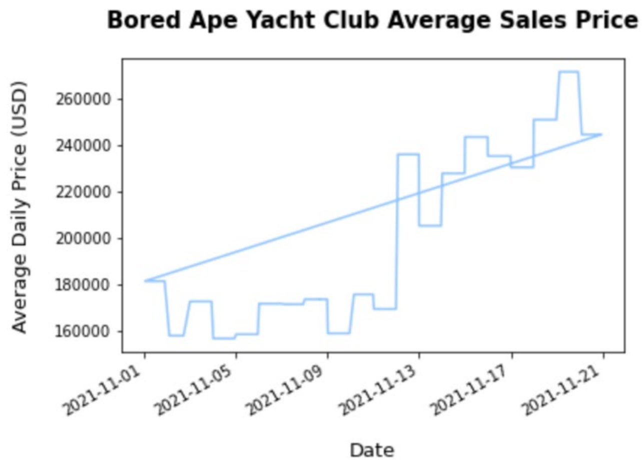
Figure 2: *Celebrity Transaction Sample (58) -- Collection Distribution*

Collection	# of Celeb Transactions
Crypto Punks	8
Bored Ape Yacht Club	37
Mutant Ape Yacht Club	7
Meebits	1
World of Women	3
Hashmasks	1
CryptoKitties	1

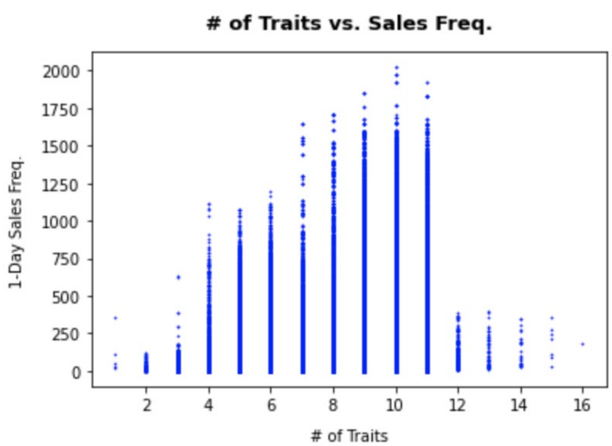
Figure 3: *Max Read Blog Post on the NFT Celebrity Complex*



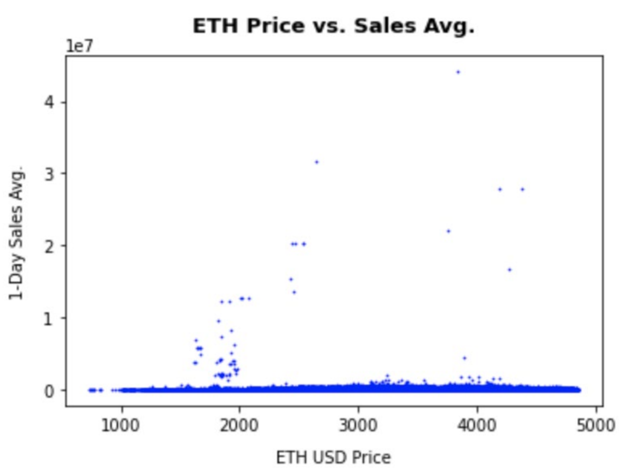
Graph 1: *Increase in Bored Ape Yacht Club Prices after Jimmy Fallon's Purchase*



Graph 2: *Number of Physical Traits and 1-Day Sales Frequency*



Graph 3: *Price of Ethereum and 1-Day Sales Price Average*



Graph 4: *Date Distribution of Celebrity Transaction Sample (58)*

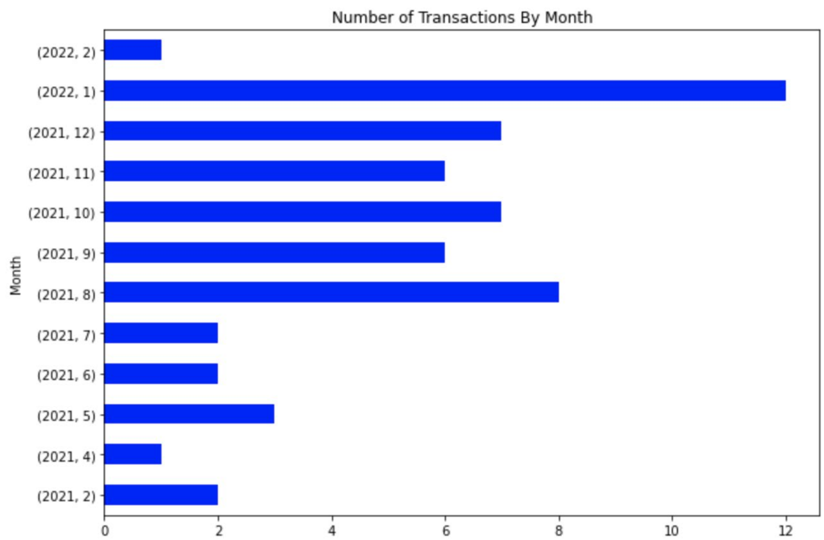


Table 1: *Collection-Wide Regression Result -- Sales Price Average (1-day window)*

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              1_day_avg   R-squared:                       0.011
Model:                            OLS   Adj. R-squared:                  0.011
Method:                 Least Squares   F-statistic:                     421.6
Date:                Tue, 03 May 2022   Prob (F-statistic):               0.00
Time:                        10:07:38   Log-Likelihood:            -2.1252e+06
No. Observations:              148722   AIC:                         4.250e+06
Df Residuals:                  148717   BIC:                         4.250e+06
Df Model:                           4
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const           8.814e+04   5328.487     16.542      0.000    7.77e+04    9.86e+04
dummy_variable  1.246e+05    7.1e+04      1.754      0.079   -1.46e+04    2.64e+05
trait_rarity      -1.0183      0.399     -2.552      0.011      -1.800      -0.236
trait_count    -1.728e+04    446.723    -38.671      0.000   -1.82e+04   -1.64e+04
eth_price         29.1646      1.489     19.589      0.000      26.247      32.083
==============================================================================
Omnibus:                   532649.877   Durbin-Watson:                   1.436
Prob(Omnibus):                  0.000   Jarque-Bera (JB):   227833230359.087
Skew:                          73.203   Prob(JB):                         0.00
Kurtosis:                    6064.776   Cond. No.                     2.17e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.17e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Table 2: *Collection-Wide Regression Result -- Sales Frequency (1-day window)*

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             1_day_freq   R-squared:                       0.242
Model:                            OLS   Adj. R-squared:                  0.242
Method:                 Least Squares   F-statistic:                 1.196e+04
Date:                Mon, 02 May 2022   Prob (F-statistic):               0.00
Time:                        17:52:59   Log-Likelihood:            -1.3606e+06
No. Observations:              150107   AIC:                         2.721e+06
Df Residuals:                  150102   BIC:                         2.721e+06
Df Model:                           4
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const           2500.3109     25.815     96.854      0.000    2449.713    2550.908
dummy_variable   -99.5149    318.879     -0.312      0.755    -724.512     525.482
trait_rarity       0.0127      0.002      7.606      0.000       0.009       0.016
trait_count       23.3244      0.125    186.869      0.000      23.080      23.569
eth_price         -1.2151      0.008   -150.819      0.000      -1.231      -1.199
==============================================================================
Omnibus:                    33635.371   Durbin-Watson:                   0.083
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            63251.586
Skew:                           1.410   Prob(JB):                         0.00
Kurtosis:                       4.471   Cond. No.                     1.97e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.97e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Table 3: *Similar Traits Regression Result -- Sales Price Average (1-day window)*

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              1_day_avg   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     36.18
Date:                Thu, 28 Apr 2022   Prob (F-statistic):           2.85e-30
Time:                        09:40:18   Log-Likelihood:            -2.3449e+06
No. Observations:              151142   AIC:                         4.690e+06
Df Residuals:                  151137   BIC:                         4.690e+06
Df Model:                           4
Covariance Type:            nonrobust
======================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
const             9.495e+04   1.81e+04      5.246      0.000    5.95e+04     1.3e+05
dummy_variable    1.619e+05   4.68e+05      0.346      0.729   -7.55e+05    1.08e+06
trait_rarity        -0.7527      1.056     -0.713      0.476      -2.822       1.317
trait_count      -1.726e+04   1507.378    -11.453      0.000   -2.02e+04   -1.43e+04
eth_price           26.9373      5.039      5.346      0.000      17.061      36.814
==============================================================================
Omnibus:                   771577.550   Durbin-Watson:                   1.750
Prob(Omnibus):                  0.000   Jarque-Bera (JB):   24357887492146.523
Skew:                         232.599   Prob(JB):                         0.00
Kurtosis:                   62193.020   Cond. No.                     4.57e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.57e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Table 4: *Similar Traits Regression Result -- Sales Frequency (1-day window)*

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             1_day_freq   R-squared:                       0.242
Model:                            OLS   Adj. R-squared:                  0.242
Method:                 Least Squares   F-statistic:                 1.196e+04
Date:                Mon, 02 May 2022   Prob (F-statistic):               0.00
Time:                        17:52:59   Log-Likelihood:            -1.3606e+06
No. Observations:              150107   AIC:                         2.721e+06
Df Residuals:                  150102   BIC:                         2.721e+06
Df Model:                           4
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const           2500.3109     25.815     96.854      0.000    2449.713    2550.908
dummy_variable   -99.5149    318.879     -0.312      0.755    -724.512     525.482
trait_rarity       0.0127      0.002      7.606      0.000       0.009       0.016
trait_count       23.3244      0.125    186.869      0.000      23.080      23.569
eth_price         -1.2151      0.008   -150.819      0.000      -1.231      -1.199
==============================================================================
Omnibus:                    33635.371   Durbin-Watson:                   0.083
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            63251.586
Skew:                           1.410   Prob(JB):                         0.00
Kurtosis:                       4.471   Cond. No.                     1.97e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.97e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

References

Agrawal, J., & Kamakura, W. A. (1995). The Economic Worth of Celebrity Endorsers: An Event Study Analysis. *Journal of Marketing*, *59*(3), 56. https://doi.org/10.2307/1252119

Ante, Lennart, The non-fungible token (NFT) market and its relationship with Bitcoin and Ethereum (June 6, 2021). https://ssrn.com/abstract=3861106

Barham, R. (2015). The Alert Collector: What is it Worth? A Guide to Art Valuation and Market Resources. Reference & User Services Quarterly, 54(4), 21-25. doi:http://dx.doi.org/10.5860/rusq.54n4.21

Block, F. (2021, December 7). *Pak's NFT Artwork 'The Merge' Sells for $91.8 Million*. Barron's. https://www.barrons.com/articles/paks-nft-artwork-the-merge-sells-for-91-8-million-01638918205

Casey, M. J. (2021, September 3). *The Value of NFTs Is Belonging*. CoinDesk Latest Headlines RSS. https://www.coindesk.com/tech/2021/09/03/the-value-of-nfts-is-belonging/

Clark, M. (2021, March 3). *NFTs, explained*. The Verge. https://www.theverge.com/22310188/nft-explainer-what-is-blockchain-crypto-art-faq

Ding, H., Molchanov, A. E., & Stork, P. A. (2010). The value of celebrity endorsements: A stock market perspective. *Marketing Letters*, *22*(2), 147–163. https://doi.org/10.1007/s11002-010-9117-y

Dowling, M. (2022). Fertile LAND: Pricing non-fungible tokens. *Finance Research Letters*, *44*, 102096. https://doi.org/10.1016/j.frl.2021.102096

Fairfield, Joshua, Tokenized: The Law of Non-Fungible Tokens and Unique Digital Property (April 6, 2021). Indiana Law Journal, Forthcoming, https://ssrn.com/abstract=3821102

Fallon, J. [jimmyfallon]. (2021, November 12). Permission to come a bored? @BoredApeYC #NewProfilePic [Tweet]. Retrieved from https://twitter.com/jimmyfallon/status/1459164143626424321.

Fizel, J., McNeil, C. R., & Smaby, T. (2008). Athlete Endorsement Contracts: The Impact of Conventional Stars. *International Advances in Economic Research*, *14*(2), 247–256. https://doi.org/10.1007/s11294-008-9144-0

Fowles, J. (1996). *Advertising and Popular Culture*. SAGE Publications.

Gavin. (2021, October 12). *How to Explain NFTs to People Who Think They're Just JPEGs*. HackerNoon. Retrieved May 9, 2022, from https://hackernoon.com/how-to-explain-nfts-to-people-who-think-theyre-just-jpegs

Gottsegen, W. (2022, January 20). *Twitter Launches NFT Profile Picture Verification*. CoinDesk Latest Headlines RSS. https://www.coindesk.com/business/2022/01/20/twitter-launches-nft-profile-picture-verification/

Henry, J. (2021, September 15). *Top 5 Most Popular NFT Collections As Of September 2021: From Cryptopunks to Meebits*. Tech Times. https://www.techtimes.com/articles/265404/20210915/top-5-popular-nft-collections-september-2021-cryptopunks-meebits.htm

Katje, C. (2021, November 12). *Jimmy Fallon Buys A Bored Ape Yacht Club NFT: Here Are The Details*. Benzinga. https://www.benzinga.com/markets/cryptocurrency/21/11/24052185/jimmy-fallon-buys-a-bored-ape-yacht-club-nft-here-are-the-details

McCracken, G. (1989). Who Is The Celebrity Endorser? Cultural Foundations of the Endorsement Process. *Journal of Consumer Research*, *16*(3), 310. https://doi.org/10.1086/209217

Nadini, M., Alessandretti, L., Di Giacinto, F., Martino, M., Aiello, L. M., & Baronchelli, A. (2021). Mapping the NFT revolution: market trends, trade networks, and visual features. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-00053-8

NFT (non-fungible tokens) marketplaces. DappRadar. https://dappradar.com/nft/marketplaces.

Ohanian, R. (1991). The impact of celebrity spokespersons' perceived image on consumers' intention to purchase. Journal of Advertising Research, 31(1), 46–54.

Paul, T. (2022, January 6). *Musician Eminem buys a Bored Ape Yacht Club NFT for US $452K*. Prestige Online - Malaysia. https://www.prestigeonline.com/my/people-events/people/eminem-buys-bored-ape-yacht-club-nft/

Read, M. (2022, February 2). *Mapping the celebrity NFT complex*. Mapping the celebrity NFT complex. https://maxread.substack.com/p/mapping-the-celebrity-nft-complex?s=r

Schroeder, S. (2021, October 29). *Alexis Ohanian showed off the NFT he bought for Serena Williams at the Met Gala*. Mashable. Retrieved May 9, 2022, from https://mashable.com/article/met-gala-cryptopunk-serena

Spry, A., Pappu, R., & Bettina Cornwell, T. (2011). Celebrity endorsement, brand credibility and brand equity. *European Journal of Marketing*, *45*(6), 882–909. https://doi.org/10.1108/03090561111119958

The National Gallery, L. (n.d.). *Glossary*. Provenance | Glossary | National Gallery, London. https://www.nationalgallery.org.uk/paintings/glossary/provenance

The NFT checkout experience your users deserve. MoonPay. (n.d.). https://www.moonpay.com/business/nfts