Asset Pricing of NFTs

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1. Introduction

The market for non-fungible token (NFTs) has been one of the most rapidly growing crypto segments. The NFT market has reached almost 25 billion USD in sales volume in 2021 from less than 100 million USD in 2020. Despite this backdrop and numerous organizations that focus on NFT pricing services, there has been limited – publicly available – research on asset pricing frameworks. Transparency on how these assets should be priced is important for all involved stakeholders and for efficient markets to develop. With this article we hope to provide more transparency and put forward a framework about how to conceptually think about NFT pricing and implement asset pricing models. NFTs present a relatively difficult pricing problem and there are various idiosyncrasies to the NFT market that have to be taken into account. The numerous difficulties in the data exercise include the unique nature of NFTs, limited data availability due to the relative illiquidity, high dimensionality of features relative to the available data, and the volatile non-stationary nature of NFT prices. Given these data issues appropriate considerations would need to be taken into account to create sufficiently unbiased estimates.

2. Value of NFTs

NFTs can represent a variety of different assets where there is thus no one-size-fits-all for NFTs. As a result, the value of a NFT will differ per category and asset pricing would need to differ per category. However, we would argue that we could present a generalizable framework to think about value and pricing of NFTs.

Why would NFTs have value? First of all, they are a store of value for the underlying digital asset that they hold. NFTs represent verifiable and authentic ownership of an asset, and can thus be seen as the store of value of that asset. This asset can be both digital and non-digital where it would rather represent pure proof of ownership/authenticity whereas for the digital

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one it could “hold” the asset itself as well. Numerous benefits of holding assets on NFTs could be argued to include instant verifiability of authenticity, verifiability of ownership of (digital) asset, programmable features, transparency, permissionless, and integration with smart contracts and the broader Web3 ecosystem. The NFT value is thus linked to the value and utility of the asset in question which can be an art piece, collectible, etc. The question thus becomes related to the value of the asset and one would need specific asset valuation for this. In the case of most NFTs the main argument is non-fungibility and thus uniqueness. Throughout human history people have valued scarcity and originality where the pricing is more subjective based on forces of supply and demand.

Since NFTs are argued to represent unique assets, the valuation can be different based on the individual. Some investors will value an asset differently as preferences differ among people. As argued by Lovo and Spaenjers (2018) a unique asset – such as an art piece – will be valued differently by the diverse set of potential owners depending on their private utility function. Although there can exist a shared generalized appraisal of value among participants, the true potential value of a unique asset can be argued to be in the eye of the ultimate buyer.

3. Data Considerations and Difficulties

Financial markets generally provide a challenging environment for quantitative models and NFT data poses additional difficulties. More specifically, limited trading data due to the illiquidity of NFTs, changing distribution of the trading sample, NFT prices representing volatile non-stationary processes, and the curse of dimensionality because of the large feature set relative to the available data.

The majority of NFTs is relatively illiquid with only a limited trading history available for extensive analysis. This illiquid and heterogeneous nature of NFTs presents a challenge to the estimation of expected prices. There is a chicken-and-egg problem in a sense that historical time series samples are required in order to properly fit a pricing model. However, to estimate price time series one would need some model to generate the point-in-time pricing estimates. The curse of dimensionality - which is considered as one of the key problems within financial data science - becomes even worse due to this illiquidity. With NFTs that can contain up to 15 or more different trait categories – with each multiple traits – it presents a data exercise with high feature dimensionality relative (especially to the amount of data that is available). You would need to handle both the unstructured nature and the curse of dimensionality of the trait data. When increasing the amount of features, the data becomes more sparse across the different dimensions.

Financial markets are dynamic throughout time and NFT markets are not different in this regard. This implies, in statistical terms, that the price process is non-stationary as the joint probability distribution changes throughout time. This dynamic character is caused by structural changes in the market, (temporarily) changing trading behavior of participants or time series patterns such as short-term trends and seasonality. Furthermore, NFT markets are driven by human interactions which make them subject to sentiment and erratic movements. The NFT market environment makes handling spurious relationships more important and the limited data problem increases the risk of overfit. As a result of this uncertainty, NFT data is characterized by heavy-tailed distributions with low-frequency difficult-to-predict and large-impact crisis events.

4. Model Considerations

Most conventional pricing models tend to be based on structured hypotheses under specific functional forms and distributional assumptions. While the assumptions and functional restrictions improve model interpretability, parameter estimation, and the ability to apply statistical tests, they also carry considerable model misspecification risk. More specifically, they can fail to properly model the complex non-linear and dynamic relationships that we observe in markets. More advanced numerical approaches – such as machine learning algorithms – tend to be computationally capable of identifying patterns whether they are spurious or not. While it can be beneficial to have a flexible model, more complex models have the tendency to overfit. Overfitting is all the more problematic when the number of features is high and the curse of dimensionality kicks in. Given the various data issues and dangers of overfit, it becomes important to use models where there is room for significant model understanding and it is important that one has a fundamental understanding of the causality of the relationships that one assumes in the model.

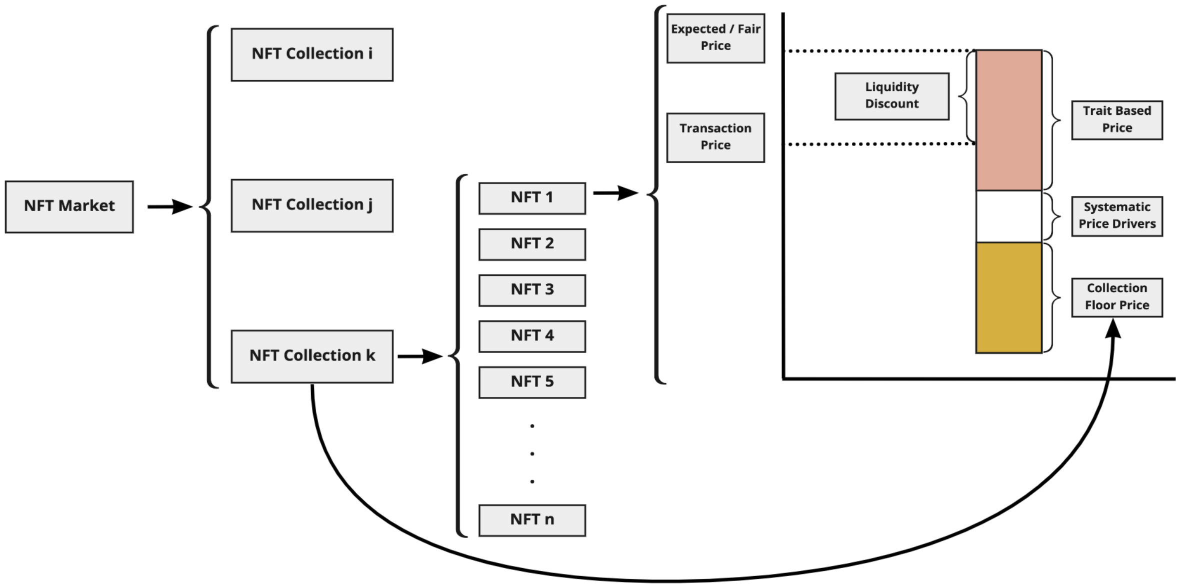
What is more important than model selection, is appropriate feature selection where one has a good fundamental understanding of the relationships. Given the relatively small data environment and the curse of dimensionality in NFT data, it is important to apply methodologies that are suitable for sparse feature settings. Dimensionality reduction should be the very first step of any NFT asset pricing model development process. Dimension reduction by feature selection, feature transformation or a combination of both can help to alleviate this problem. In the selection of features it helps to read up on past research on NFT pricing, perform extensive exploratory analysis and run some basic models to explore the dynamics of some variables.

5. Appraisal and Market Prices

First question to answer in the asset pricing framework is to precisely define what we would like to model. The appraisal value is different from the market price that one could immediately receive. Kim, Lommers and Baioumy (2022) – who discuss a pricing model for market making in NFTs – argue that investors take into account the floor price, appraisal price, volatility and liquidity to determine the price that one is willing to pay. Due to the uniqueness of NFTs there are high potential search costs to find an appropriate buyer who is willing to pay the appraisal price and due to the high volatility there are high inventory risks for the holder. Given the aforementioned market making risk and search costs, a liquidity discount is charged depending how quickly one would like to sell their NFT. There is a chicken-and-egg problem in the sense that one only observes transaction prices within the market. We do not observe the appraisal value or the (liquidity) discount that has been charged in the trade. One has to account for the fact the some prices might include a relatively large liquidity discount in the case that the sellers had to liquidate their holdings.

6. Pricing Framework

As previously stated, there is no one-size-fits-all. As a result, the asset pricing models would need to differ per category. That being said, we attempt to provide a general framework to think about NFT asset pricing models. We present a framework for NFT pricing models in the figure below. Expected prices could be computed using information from the market, collection, and individual NFT level. The pricing approach is based on a hierarchical structure where market movements influence NFT collections, collections have systematic co-movements with each other, and collection movements influence the individual NFTs. The floor price represents the market price of immediate liquidity of NFTs within a collection. Expected prices within collections could be formed based on the floor price, systematic factors, and idiosyncratic features of the NFT in question. NFTs have fundamental traits or features that distinguish them from others. The main differentiator is whether these features are explicitly provided by the developers or one would need to perform data collection to classify NFTs according to features. Providing traits has been standard practice within generative art collections while it requires more data classification for other NFT categories.



It should be emphasized that the proposed pricing framework is for collection NFTs where there are a number of heterogeneous NFTs within a collection. Prices of NFTs within a collection tend to co-move with each other on the collection level and NFTs within a collection could be directly compared. The relatively large collection size within the NFT space provides us with daily trading and market-based data within the collection. Systematic pricing models would be more difficult to implement on non-collection NFTs, however, one could use a similar principle for non-collection NFTs where the methodology could be tweaked to generate clusters of NFTs with strong systematic co-movements. The "collection" has been de facto used to cluster similar NFTs and this logic could be extended to clusters other than the collection. It should be noted that this would require the development of factors (or clustering) models and data on categories to properly divide the NFTs into these groups.

There is a strong link between the crypto market (and other risky asset classes) and the NFT market – e.g., as shown by Borri, Liu, and Tsyvinski (2022). More specifically, the NFT market systematically co-moves with the crypto market. One could use crypto and NFT market signals to estimate the systematic component with the market. NFT market signals could include overall NFT market return, sentiment, number of NFT launches, leverage within the NFT space, LTV in lending protocols (e.g., default liquidations can affect collections). wallet analytics (long-term versus short-term investors, hot vs cold wallets, etc.). General crypto and NFT market signals can provide a signal about the overall sentiment and trend for NFTs which will affect different NFTs/NFT collections differently.

Similar to other asset classes, there is systematic exposure of NFTs to the broader NFT market. While there is a systematic market co-movement between NFT collections, there can be significant idiosyncratic movements on the collection level. You could cluster NFT collections based on certain characteristics (e.g. factors, theme, etc) and track the effect of crypto/NFT market movements on these clusters. Different NFT collections will be more sensitive to market movement – for example, small size and less established collections react more heavily to market movements (a tendency that we observe in a variety of other asset classes and in crypto as well). You could track the clusters as well (e.g. gaming NFTs) to try to predict movements of collections within this cluster. For example, when Ape NFT market sentiment is in a downward trend then we could expect Ape collections to perform badly and small Ape collections to perform even worse.

Factor models have been popular in traditional finance and relate asset pricing to systematic co-movements to factors. Previous studies have shown that a three factor model captures a large part of systematic returns in crypto. As seen in the principal component analysis of Two Sigma (2021), the first three factors roughly capture 70% of the movement in crypto currencies. One can construct factors on the collection level where one tries to capture systematic co-movements based on exposure to common factors. Examples of such factors can include L1 ecosystem, collection size, collection growth, collection liquidity, collection volatility, price momentum in the collection floor, etc.

It should be emphasized that the illiquid and heterogeneous nature of NFTs presents not only a challenge to the price estimation of the NFTs themselves but also to the estimation of the collection index. Constructing a NFT collection and market in itself is not an obvious task where the illiquid and heterogeneous nature of the index constitutions presents a challenge to the estimation of the index. Taking inspiration from return estimation within other illiquid asset classes, one could develop a framework for (expected) return estimation throughout time. In financial analysis of the art market there are similar computational issues with respect to estimating returns given limited pricing information due to illiquidity of art and the heterogeneous (non-fungible) nature of art works. As discussed by Agnello (2016) economists have addressed the heterogeneity problem via repeated sales or hedonistic price regression. Numerous papers within the NFT space such as Nadini et al. (2021), Goetzmann and Nozari (2022), and Borri, Liu, and Tsyvinski (2022) have used the repeated sales regression approach. Lommers, Beckers and Jayant (2022) suggest an approach where they try to estimate NFT returns based on liquid proxy portfolios on the collection level.

NFT prices are volatile and one could observe different trading and liquidity regimes. One could assume that these liquidity regimes are strongly correlated to volatility and can create volatility spikes. More specifically, NFT prices experience jump events where the price process reverts to the process mean and collection floor. As discussed by Kim, Lommers and Baioumy (2022) these liquidity events represent the exogenous events causing price jumps on thinly traded markets with fragmented liquidity. These events can involve macro events, cascading liquidations, sentiment-driven momentum episodes, etc. The magnitude of these jump price movements is magnified by the low liquidity. Liquidity shocks often exhibit clustering effects which can be caused due to common exposure to certain fundamental factors and contagion by market-wide events.

Collection-based NFTs have fundamental exposure to the collection they are part of and NFT prices within collections co-move with each other. As shown in the figure above, one could argue that NFT prices could be decomposed in the collection floor price, systematic pricing factors on the NFT level, and NFT-specific fundamental price. The floor price of a collection represents the lower bound at which NFTs within the collection are traded and are a measure for the absolute base price of the collection. The price in excess of the floor could be argued to represent the idiosyncratic utility of the NFT.

Market participants have been mainly using traits or features to compare and value NFTs within collections. The assumption that market participants look at NFT traits in their fundamental valuation seems reasonable given that these are the main heterogeneous elements within collection NFTs. Collection NFTs differentiate themselves in the traits and we would argue that these represent the fundamental characteristics of the NFT in question (each NFT is unique). As previously discussed, these features can be formally provided by the creators of the NFT or one has to try to categorize features in data labeling exercise.

A key attribute that market participants have used as a measure of fundamental value is rarity. There are various rarity measures proposed such as rarity score, Jaccard Index, rarity information content, etc. These rarity scores represent measures based on the assumption that market participants value NFTs based on the relative occurrence of its traits. Numerous authors made the argument that economic agents derive social status with the consumption of rare items, and as a result they put value into acquiring items that others cannot obtain (Koford and Tschoefl (1998). However, certain characteristics can be rare but undesirable while other characteristics can be very popular but not particularly rare. One could extract the de facto valuation or desirability of features from market prices as done by Lommers, Lemahieu and Baioumy (2022). Market prices are, by definition, the representation of preferences and signal desirability. As a result, they argue that the pricing or desirability of NFT traits could be derived from market prices and a function to score the NFT based on its traits could be constructed.

Numerous other NFT specific or systematic pricing elements can affect prices. Prices within the market can thus represent other elements outside of the collection floor price and trait-based price. For systematic price drivers one could think about collection return, collection volatility, and crypto market movements which can impact NFTs within the collection differently. Within equities there is a whole literature on factors (the factor zoo) and one could expect the existence of a variety of factors that can help explain cross-sectional price movements within NFTs as well.

7. References

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