Constructing a NFT Price Index and Applications

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Abstract—We are witnessing the emergence of a new digital art market, the art market 3.0. Blockchain technology has taken on a new sector which is still not well known, Non-Fungible tokens (NFT). In this paper we propose a new methodology to build a NFT Price Index that represents this new market on the whole. In addition, this index will allow us to have a look on the dynamics and performances of NFT markets, and to diagnose them.

I. INTRODUCTION

Last year has been the year of the democratization of NFTs. The number of owners (figure 1) and the number of transactions (figure 2) on Ethereum have been exponentially increasing since January 2021. Moreover, the increasing interest of famous brand names for them also suggests that their adoption keeps growing. Online marketplaces like Opensea (https://opensea.io) or LooksRare (https://looksrare.org) have become focal points for trading these new assets.

Fig. 1: Cumulative number of wallet that have ever owned an ETH ERC-721 or ERC-1155 NFT [1].

NFTs or Non-Fungible Tokens are transferable assets secured by a blockchain. A blockchain is an ordered list of blocks that are linked together using cryptography. Blocks contain data about transactions, and are validated and added to the chain through a consensus protocol. Blockchain are used as public transaction ledgers of most cryptocurrencies. For instance bitcoin or ethereum respectively with the network Bitcoin [2] or Ethereum [3]. The need for consensus of blockchain solves the double-spending problem using a cryptographic proof instead of a trusted central authority.

Designed as a medium of exchange, cryptocurrencies are transferable assets as well. Because they are defined by their value, cryptocurrencies are perfectly fungible assets, for example a coin can be substituted to another. In opposition to cryptocurrencies, NFTs are uniquely identified by an id and a set of properties, and cannot be interchangeable or divisible. A NFT is thus the perfect way to represent anything unique on blockchains. They can be used for several purposes, but are often considered as digital art due to their properties. As art, most collectors acquire NFTs for aesthetic reasons, acquiring a social status or as a mean of investment [4].

Fig. 2: Cumulative number of NFT traded volumes in USD [1].

NFTs are created or minted by the execution of a smart contract setting in stone the creation of tokens. Several NFTs can be minted from the same contract, a collection is defined as a set of tokens minted from the same contract. Tokens minted from the same contract collect remain however perfectly identifiable and may differ from each others by their id and their properties or traits. To illustrate this, we represent figures 3 and 4 respectively the tokens CryptoPunk #1463 and CryptoPunk #1466 of the Ethereum collection CryptoPunk.

Besides exceptional trade volumes, sales of NFTs have reached record prices, sometimes up to several tens of millions of dollars [5, 6]. Record breaking sales thus suggest a price explosion, but the dynamics of NFT markets are more complex. Indeed, if some top collections are steadily becoming more and more popular and expensive, e.g. the Ethereum CyberPunks and Bored Ape Yacht Club, prices of most collections vary widely. For this reason, it is difficult to have a global vision of the NFT market. In this work, we undertake the hedonic model to build a price index from...
thousands of NFT transaction records. Subsequent applications presented in this study include:

- the detection of price explosion periods through statistical tests
- the computation of the correlation matrix between the NFT returns with the return of the cryptocurrencies market
- the detection of undervalued and overvalued assets

The hedonic regression framework is a well known model in Economics. Hedonic models decompose an item into its core characteristics and study the contribution of each of them to its value. These models are commonly used in Real Estate Economics \[7, 8\]. A hedonic index is an index computed from a fitted hedonic regression model, \[9\] reviews in the different methodologies that can be used. Hedonic indices are often used as proxies of price indices, such as consumer price indices (CPI). A price index represents the aggregate price of a basket of items, and tracks how the prices of these items, taken as a whole, change over time. The hedonic methodology is particularly appraised because it can be applied to illiquid markets. Moreover, it can even handle the removal, replacement and addition of items over time. For all these reasons, several previous studies have applied it to diagnose art markets \[4, 10, 11\]. Some works also used the hedonic model to price NFTs, but focused on a single collection: CryptoKitties \[12\], CryptoPunks \[13\] or Decentraland \[14\]. To the best of our knowledge, our article is the first proposal of a global NFT price index.

### II. Methods

We will use the following notations:

- \( C \) is the set of collections
- \( A \) is the set of assets
- \( \{0, 1, ..., T\} \) is the set of sale dates
- \( I(a, b) \triangleq \{a, a + 1, ..., b - 1, b\} \)
- \( I(b) \triangleq I(0, b) \)

#### A. Definitions

An asset \( a \) is defined by a collection \( C^a \), a token id \( i^a \) and a dictionary of traits \( \mathcal{P}^a \). \( \mathcal{P}^a \) is a set of (trait, value) characterizing \( a \) within its collection. \( \mathcal{P}^a \) is usually used to quantify the scarcity of \( a \) w.r.t. other assets of \( C^a \), and, then, to price \( a \). Intuitively the scarcer an asset is, the more expensive it should be. It is therefore straightforward to deal with frequencies of traits within a collection when it comes to build a pricing model. Given an asset \( a \), a couple \((p, v) \in \mathcal{P}^a\), the frequency of the value \( v \) for the trait \( p \) is defined as follows:

\[
f^a_{(p,v)} \triangleq \frac{1}{|C^a|} \sum_{a' \in C^a} \sum_{(p',v') \in \mathcal{P}^a'} 1_{p'=p} 1_{v'=v}
\]

\((1)\)

Since the number of traits may differ from an asset to another, even within the same collection, we construct three aggregate quantities: the minimum frequency \( f_{\text{min}}^a \) (equation \(2\)), the average frequency \( f_{\text{avg}}^a \) (equation \(3\)), and the maximum frequency \( f_{\text{max}}^a \) (equation \(4\)). All these quantities are set equal to 1 if \( \mathcal{P}^a \) is empty.

\[
f_{\text{min}}^a \triangleq \min_{(p,v) \in \mathcal{P}^a} f^a_{(p,v)}
\]

\((2)\)

\[
f_{\text{avg}}^a \triangleq \frac{1}{|\mathcal{P}^a|} \sum_{(p,v) \in \mathcal{P}^a} f^a_{(p,v)}
\]

\((3)\)

\[
f_{\text{max}}^a \triangleq \max_{(p,v) \in \mathcal{P}^a} f^a_{(p,v)}
\]

\((4)\)

A sale is defined by an asset \( a \), a date \( t \) and a price \( P_t^a \) in USD equivalent.

#### B. Pricing model

The pricing model that we develop in this section is the result of three empiric observations:

- as mentioned in the introduction, the price of an asset is impacted by the popularity and hype around its collection,
- assets within the same collection may differ from each others by their traits, the scarcer the traits of an asset are, the more appreciated it is in its collection,
- the NFT market seems to experience periods during which prices of NFT are globally impacted positively or negatively.

We finally come up with the multiplicative pricing model of equation \((5)\).

\[
P_t^a = P \times f(C^a) \times g(a) \times h(t) \times \epsilon(a,t)
\]

\((5)\)

where:

- \( P \in \mathbb{R}^{+*} \) defines a scale price,
- \( f : C \to \mathbb{R}^{+*} \) impacts the price of an asset according to its collection,
- \( g : A \to \mathbb{R}^{+*} \) impacts the price of an asset according to the scarcity of its traits within its collection,
- \( h : \{0, 1, ..., T\} \to \mathbb{R}^{+*} \) impacts the prices according to the global state of the NFT market,
• \( \epsilon : \{0, 1, ..., T\} \times \mathcal{A} \rightarrow \mathbb{R}^{++} \) is a noise term explaining price fluctuations.

We model \( f, g, h \) and \( \epsilon \) as follows:

\[
  f : C \rightarrow \exp \sum_{C'} \alpha_{C'C} \mathbf{1}_{C'C} = C
\]

\( g : a \rightarrow \exp \left( \beta_{\text{min}} f_{\text{min}}^a + \beta_{\text{avg}} f_{\text{avg}}^a + \beta_{\text{max}} f_{\text{max}}^a \right) \)

\[
  h : t \rightarrow \exp \sum_{t' = 0}^{T} \gamma_{t'} 1_{t' = t} + \chi(t, a)
\]

\[
  \epsilon : (a, t) \rightarrow \exp \left( \chi_a(t, t) \right)
\]

where \( \chi(a, t) \) \( \overset{i.i.d.}{\sim} \) \text{Normal}(0, \sigma^2).

Equivalently,

\[
  \log P_t^a = \log P + \sum_{C'} \alpha_{C'C} \mathbf{1}_{C'C} = C + \beta_{\text{min}} f_{\text{min}}^a + \beta_{\text{avg}} f_{\text{avg}}^a + \beta_{\text{max}} f_{\text{max}}^a + \sum_{t' = 0}^{T} \gamma_{t'} 1_{t' = t} + \chi(t, a)
\]

The model of equation (10) is also known as the \textit{time dummy variable} version of the hedonic regression model [9]. Hedonic coefficients \( P, \alpha \) and \( \beta \) are inferred only once using all dates \( \{0, 1, ..., T\} \), this approach is called the \textit{multi-period pooled regression} [9].

C. Price Index Construction

Since we used the time dummy variable method to train our pricing model, the hedonic index \( I \) is defined as follows [9]:

\[
  \frac{I_{t+1}}{I_t} = \frac{\exp \gamma_{t+1}}{\exp \gamma_t}
\]

As a result,

\[
  I_t = A \prod_{t' = 0}^{t-1} \left( 1 + \left( \frac{I_{t'+1}}{I_{t'}} - 1 \right) \right)
\]

\[
  = A \prod_{t' = 0}^{t-1} \left( 1 + \frac{\exp \gamma_{t'+1}}{\exp \gamma_{t'}} - 1 \right)
\]

\[
  = A \prod_{t' = 0}^{t-1} \frac{\exp \gamma_{t'+1}}{\exp \gamma_{t'}}
\]

\[
  = A \exp(\gamma_t - \gamma_0)
\]

Thus, the return of \( I \) between \( t \) and \( t + 1 \) is \( \frac{\exp \gamma_{t+1}}{\exp \gamma_t} - 1 \).

The construction of \( I \) can be justified as follows, if \( I \) is proportional to the geometric mean of prices over all assets of \( \mathcal{A} \), then:

\[
  I_{t+1} = \frac{\prod_{a \in \mathcal{A}} (P_{t+1}^a)_{\mathcal{A}}}{\prod_{a \in \mathcal{A}} (P_t^a)_{\mathcal{A}}}
\]

\[
  = \frac{\exp \gamma_{t+1} \prod_{a \in \mathcal{A}} \exp (\chi(a, t+1) - \chi(a, t))}{\exp \gamma_t \prod_{a \in \mathcal{A}} \exp (\chi(a, t+1) - \chi(a, t))}
\]

\[
  = \frac{\exp \gamma_{t+1} \prod_{a \in \mathcal{A}} \chi(a, t+1) - \chi(a, t)}{\exp \gamma_t \prod_{a \in \mathcal{A}} \chi(a, t+1) - \chi(a, t)}
\]

Since \( \chi(a, t+1) - \chi(a, t) \overset{i.i.d.}{\sim} \text{Normal}(0, \sigma^2) \), according to the strong law of large numbers:

\[
  \frac{1}{|\mathcal{A}|} \sum_{a \in \mathcal{A}} \chi(a, t+1) - \chi(a, t) \rightarrow 0, \quad \text{a.s.}
\]

Thus,

\[
  \exp \left( \frac{1}{|\mathcal{A}|} \sum_{a \in \mathcal{A}} \chi(a, t+1) - \chi(a, t) \right) \rightarrow 1, \quad \text{a.s.}
\]

D. Bubble Detection

A bubble is often defined as a period of explosive or mildly explosive behavior in the price dynamic [15]. In particular, autoregressive dynamics can be observed during speculative bubbles. For this reason, unit root tests are useful for making a market diagnosis, e.g. for detecting market excesses or mispricing. Augmented Dickey-Fuller (ADF) tests are usually used to determine whether a series \( y \) is stationary or not, but they can also be used to detect explosive behaviors. Under the null hypothesis \( H_0 \), the process is autoregressive and has an unit root. Under the alternative hypothesis \( H_1 \), the process has an explosive root. Hypothesis \( H_0 \) is wide and must be specified in order to derive an asymptotic distribution and the critical values useful for the ADF test. To this end, Phillips et al. assume that the process \( y \) is a random walk with an unit root and an asymptotically negligible drift [16], i.e.:

\[
  y(t+1) = d(T+1)^{-\eta} + \theta y(t) + \epsilon(t)
\]

where \( \theta = 1, \eta > 1/2 \) and \( \epsilon(t) \overset{i.i.d.}{\sim} \text{Normal}(0, \sigma^2) \).

The ADF testing procedure is applied to the regression model of equation (18):

\[
  \Delta y(t) = \mu + \nu y(t-1) + \sum_{i=1}^{k} \psi_i \Delta y(t-i) + \epsilon(t)
\]

where \( \Delta y(t) = y(t) - y(t-1), k \in \mathbb{N} \) is a lag order and \( \epsilon(t) \overset{i.i.d.}{\sim} \text{Normal}(0, \sigma^2) \). The ADF statistic is defined as the t-statistic of the coefficient \( \nu \) of the regression model.
Under the null hypothesis (equation 17), the process $y$ has an unit root, thus $\nu = 0$. Under the alternative hypothesis of an explosive root, $\nu > 0$. For this reason, we use the right-sided version of the ADF test, i.e. if ADF exceeds the critical value : $H_0$ is rejected and $H_1$ accepted, else : $H_0$ is accepted and $H_1$ rejected.

In order to detect local bubbles and not to be fooled by pseudo-stationary behaviors, the ADF test can be performed on continuous sub-sample of $y$. We denote by $ADF_{t_1 \rightarrow t_2}$ the ADF statistic computed on $\{y_{t_1}, y_{t_1+1}, ..., y_{t_2}\}$, Phillips et al. develop in [16] a methodology to detect multiple bubbles. For this purpose, they derive the BSDAF statistic from the ADF statistic (equation 19).

$$BSDAF(t) = \sup_{t' \in (0, t-w)} ADF_{t' \rightarrow t}$$

where $w$ is a hyper-parameter defining the minimum window size on which ADF tests can be performed. The beginning and the end of a bubble, denoted respectively by $t_b$ and $t_e$, are detected as follows:

$$t_b \triangleq \inf \{t \in I(w, T), BSDAF(t) > v_c^e(t) \}$$

$$t_e \triangleq \inf \{t \in (t_b + \delta, T), BSDAF(t) < v_c^e(t) \}$$

where $\delta$ is the minimum duration of a bubble and $v_c^e(t)$ is a critical value defined as the $(1-c)$ quantile of the distribution of the statistic $\sup_{t' \in \{w, ..., t\}} ADF_{0 \rightarrow t'}$. Critical values $v_w(t)$ can be estimated using Monte-Carlo simulations.

### III. DATA

Several blockchains support NFTs including Ethereum, Solana, Flow, Tezos or Polygon. However, most of the NFT trade volume is concentrated on Ethereum (figure 5). For this reason, we decide to focus our work on Ethereum NFT collections, more precisely on NFTs satisfying the standard ERC-721.

We report on table I the inferred parameters $eta$ of our indices, i.e. the hyper-parameter $A$, is set equal to 100. We use the Huber Regressor, a linear regression model that is robust to outliers. We train two models: a model with all collected collections in order to build the NFT price index, and another model with only metaverse-related collections to build the metaverse price index. Collections used for both indices can be found in the appendix (section VII-B). The first value of our indices, i.e. the hyper-parameter $A$, is set equal to 100.

We report in table III the realized return of our indices, ETH, BTC and SOL.

| Coefficient | Value |
|-------------|-------|
| $\beta_{\min}$ | -0.176 |
| $\beta_{\text{avg}}$ | -0.009 |
| $\beta_{\max}$ | -0.025 |

### IV. MATERIALS AND APPLICATIONS

In order to train the model of equation (18) we use the Huber Regressor, a linear regression model that is robust to outliers. We train two models: a model with all collected collections in order to build the NFT price index, and another model with only metaverse-related collections to build the metaverse price index. Collections used for both indices can be found in the appendix (section VII-B). The first value of our indices, i.e. the hyper-parameter $A$, is set equal to 100.

We plot in figures 6 and 7 the 7-day moving averages of the NFT and Metaverse Index respectively. Raw indices can be found in the appendix (section VII-A). We also plot in figures 6 and 7 the Google Trends (GT) signals for the queries "nft" and "metaverse" between the 1st June 2021 and the 16th January 2022. Since the GT signals for $q$ is proportional to the Google search volume for $q$, both GT signals will be used to chart the fad for NFTs and the metaverse.

#### A. Correlation with cryptocurrency markets

In table II we report the correlation coefficients between the daily returns of our indices, ETH, BTC and SOL.

|       | NFT | Metaverse | ETH | SOL | BTC |
|-------|-----|-----------|-----|-----|-----|
| NFT   | 0.09| 0.16      | 0.18| 0.10|     |
| Metaverse |     | 0.30    | 0.17| 0.20|     |
| ETH   |     | 0.59      | 0.82|     |     |
| SOL   |     |           | 0.48|     |     |

### TABLE II: Correlation matrix of daily returns. Correlation coefficients are computed using the data from the 1st June 2021 to the 15th January 2022.

We report in table III the realized return of our indices, ETH, BTC, and SOL between the 1st June 2021 and the 15st January 2022.

![Fig. 5: Daily sale volumes in dollar on four blockchains (data from 17).](image-url)
TABLE III: Realized return computed from prices in USD between the 1st June 2021 and the 15st January 2022.

|          | Return  |
|----------|---------|
| NFT      | 7011%   |
| Metaverse| 1064%   |
| ETH      | 26%     |
| BTC      | 6%      |
| SOI      | 372%    |

TABLE IV: Critical values \( v^c_w(t) \) of SADF with \( t = T = 230 \) and \( w = 40 \).

|          | \( v^c_w(t) \) |
|----------|----------------|
| 90%      | 1.08           |
| 95%      | 1.36           |
| 99%      | 1.97           |

B. Bubble Detection

The minimum length \( w \) to compute an ADF test is fixed equal to 40. We use the methodology of Phillips et al presented in section II-D to detect the start and the end of bubbles. \( c \)-critical values \( v^c_w(t) \) of \( \sup_{t' \in [w, T]} ADF_{0-t'} \) are estimated using Monte-Carlo simulations of \( N_{MC} = 5000 \) random walks with an asymptotically negligible drift (equation (17)) where we set \( \eta = \sigma = d = 1 \). \( v^c_w(t) \) are estimated for \( t \in [w, T) \). We report in particular the 90%, 95% and 99% critical values when \( t = T = 230 \) in table IV. We plot on figures 6 and 7 the \( t \to BSADF(t) \) signals (equation (19)) computed for both indices. We have also plotted the 95% and 99% critical value signal for the statistics \( t \to \sup_{t' \in [w, T]} ADF_{0-t'} \). We recall that an explosive behavior is detected in the price dynamic if the BSADF statistic exceeds the 99% critical value signal.

C. Undervalued and Overvalued Assets

Once the parameters \( P, \alpha, \beta, \gamma \) and \( \sigma \) of equation (10) are inferred after a training phase, any asset \( a \) can be priced at time \( t \in \{0, ..., T\} \) if at least one asset of the same collection has been used during the training phase. According to the model of equation (10), the log-price of \( a \) at time \( t \) follows the distribution \( \text{Normal}(\log P^a_t, \sigma^2) \) where \( \log P^a_t \) is computed as follows:

\[
\log P^a_t = \log P + \alpha C^a + \beta_{\min} f_{\min}^a + \beta_{\avg} f_{\avg}^a + \beta_{\max} f_{\max}^a + \gamma t
\]  

We define the probabilities of being undersold and oversold in equations (23) and (24), respectively.

\[
p_{\text{under}}(P^a_t) \triangleq \frac{1}{2} \left( 1 - \text{erf} \left( \frac{\log(P^a_t) - \log(\bar{P}^a_t)}{\sigma \sqrt{2}} \right) \right)
\]

\[
p_{\text{over}}(P^a_t) \triangleq \frac{1}{2} \left( 1 + \text{erf} \left( \frac{\log(P^a_t) - \log(\bar{P}^a_t)}{\sigma \sqrt{2}} \right) \right)
\]

where \( \text{erf} \) is the Gauss error function. According to the definitions (23) and (24), it is straightforward to derive the following properties:

- \( p_{\text{over}} + p_{\text{under}} = 1 \),
- at \( P^a_t = \bar{P}^a_t \), \( p_{\text{over}}(P^a_t) = p_{\text{under}}(P^a_t) = \frac{1}{2} \),
- \( p_{\text{under}} \) is strictly increasing, \( \lim_{0+} p_{\text{under}} = 1 \) and \( \lim_{\infty} p_{\text{under}} = 0 \).

The simplest investment strategy could consist in investing at time \( t \) in an asset \( a \) for which the listing price \( P^a_t \) gives a high undersold probability \( p_{\text{under}}(P^a_t) \) below 1/2, and listing it at \( \bar{P}^a_t \). One problem, however, is that equation (22) assumes to have estimated \( \gamma_t \), i.e. the market impact coefficient of today. To deal with it, \( \gamma_t \) can be estimated using earlier in the day transactions, or it can be approximated by a moving average of the market impact coefficients over recent previous days.

V. DISCUSSION

From figures 6 and 7 we detect a strong upward trend for both price indices indicating a global price rise. This increase in prices appears to follow the rising interest for both themes. The NFT price index seems to have experienced several brief explosive periods, while the metaverse price index experienced an unique explosive period beginning in November 2021. This comes a short time after the renaming of Facebook’s parent company to Meta reveiling their interest for the metaverse.

As shown in table IV, the parameters of \( g \) are all non positive. As a consequence, \( g \), and then the price, is strictly
decreasing with the quantities $f_{\text{min}}$, $f_{\text{avg}}$ and $f_{\text{max}}$. It statistically confirms our intuition that scarcer assets are more expensive.

According to table II, returns of both indices are positively correlated with the returns of the top-tier cryptocurrencies BTC, ETH and SOL, but correlation coefficients remain relatively small compared to the ones between BTC, ETH and SOL. From table III we observe that the selected collections have, on the whole, dramatically outperformed these cryptocurrencies. Putting these results together suggests that blue ship NFTs have, taken as a whole, offered both-crypto-and-NFT investors high returns while diversifying their risk.

According to figure 8, only a brief bubble has been detected by the presented methodology. Thus, the NFT price index has globally never experienced any explosive price dynamic, but it doesn’t mean that some collections have not. Indeed, as shown in figure 8, a bubble has been detected in the metaverse index between the 2. November 2021 and the 2. December 2021 following the renaming of Facebook.

Concerning our methodology, two weaknesses have been identified. First, the selection of collections is highly subjective and includes a look-ahead bias. Secondly, hedonic coefficients $\alpha$ and $\beta$ are hold fixed over time, thus, our model can not take into account the time varying popularity of collections to explain price dynamics. Both of these problems could be solved by implementing a quantitative rule to update the collection set on a regular basis, and, by using the adjacent dummy variable method [2], an alternative training procedure for the time dummy variable hedonic model. It could also be interesting in a future work to consider the temporal dependence of the trends according to the collections, or to detect NFT market regimes. Finally, it would also be appropriate to test and compare other bubble detection models.

VI. ACKNOWLEDGEMENT

We would like to thank Opensea for providing us an API key to collect all the necessary data to conduct this study.

VII. CONCLUSION

In this work, we have proposed a methodology to construct price indices for the NFT markets. In contrary to previous works, our indices aggregate transactions from varied collections, this allows us to better represent this new art market 3.0. These indices have allowed us to analyse the dynamics and performances of NFT markets, and to perform diagnostic tests. In particular, we have used statistical tests to detect speculative bubbles. Finally, we have demonstrated that simple intuitive investment strategies could be derived from the pricing model used for the construction of our indices.

REFERENCES

[1] D. Analytics and @thomas_m. Nft market overview. [Online]. Available: https://dune.xyz/thomas_m/NFT-stats
[2] S. Nakamoto, “Bitcoin: A peer-to-peer electronic cash system,” Decentralized Business Review, p. 21260, 2008.
[3] V. Buterin et al., “Ethereum white paper,” GitHub repository, vol. 1, pp. 22–23, 2013.
[4] R. Kräussl, T. Lehnhrt, and N. Martelin, “Is there a bubble in the art market?” Journal of Empirical Finance, vol. 35, pp. 99–109, 2016.
[5] Opensea. Cryptopunk #9998. [Online]. Available: https://opensea.io/assets/0xb47e3cd837dd37dd37e3d6e193ebb9998
[6] ——. Cryptopunk #3100. [Online]. Available: https://opensea.io/assets/0xb47e3cd837dd37dd37e3d6e193ebb3100
[7] S. Herath and G. Maier, “The hedonic price method in real estate and housing market research: a review of the literature,” 2010.
[8] S. Selim, “Determinants of house prices in turkey: A hedonic regression model,” Doğuş Üniversitesi Dergisi, vol. 9, no. 1, pp. 65–76, 2011.
[9] J. Tripplett, “Handbook on hedonic indexes and quality adjustments in price indexes: Special application to information technology products,” 2004.

[10] R. Kärrssl and N. v. Eslund, “Constructing the true art market index: A novel 2-step hedonic approach and its application to the german art market,” CFS working paper. Tech. Rep., 2008.

[11] D. Witkowska, “An application of hedonic regression to evaluate prices of polish paintings,” *International Advances in Economic Research*, vol. 20, no. 3, pp. 281–293, 2014.

[12] P. Kireyev and R. Lin, “Infinite but rare: Valuation and pricing in marketplaces for blockchain-based nonfungible tokens,” 2021.

[13] D.-R. Kong and T.-C. Lin, “Limit theory for moderate deviations from a unit root,” *Journal of Econometrics*, vol. 136, no. 1, pp. 115–130, 2007.

[14] M. Goldberg, P. Kugler, and F. Schärf, “The economics of blockchain-based virtual worlds: A hedonic regression model for virtual land,” Available at SSRN 3932189, 2021.

[15] P. C. Phillips, S. Shi, and J. Yu, “Testing for multiple bubbles,” 2012.

[16] P. C. Phillips, S. Shi, and J. Yu, “Testing for multiple bubbles,” 2012.

[17] Cryptoslam. [Online]. Available: https://cryptoslam.io

[18] Google trends. [Online]. Available: https://trends.google.com/trends/explore?date=2021-01-23%202022-01-23&q=nft

[19] BoredApeYachtClub 0x75E95ba5997Eb235F40eCF8347cDb11F18ff640B

[20] CryptoBullSociety 0x469823c7B84264D1BAfBcD6010e9cdf1cac305a3

[21] CryptoPunks 0xb47e3cd837dDF8e4c57F05d70Ab865de6e193BBB

[22] Metaverse 0x79986aF15539de2db9A5086382daEdA917A9CF0C

[23] MyPetHooligan 0x09233d553058c2F42ba751C87816a8E9FaE7Ef10

[24] NFT Worlds 0xBD4455dA5929D5639EE098ABFaa3241e9ae111Af

[25] VeeFriends 0xa3AEe8BcE55BEeA1951EF834b99f3Ac60d1ABeeB

[26] Fig. 11: Metaverse Index.

APPENDIX

A. Raw signals

| Index | Collection | Ethereum Contact |
|-------|------------|------------------|
| NFT   | CryptoFrenies | 0x49907029e80dE1cBB3A46fD44247BF8BA8B5f12F |
|      | CryptoBullSociety | 0x469823c7B84264D1BAfBcD6010e9cdf1cac305a3 |
|      | CryptoKings | 0x75E95ba5997Eb235F40eCF8347cDb11F18ff640B |
|      | CryptoPunks | 0xb47e3cd837dDF8e4c57F05d70Ab865de6e193BBB |
|      | Decentraland | 0xF87E31492Faf9A91B02Ee0dEAAd50d51d56D5d4d |

TABLE V: Composition of the indices.

| Index                    | Collection               | Ethereum Contact            |
|--------------------------|--------------------------|-----------------------------|
| NFT                      | CryptoBullSociety        | 0x469823c7B84264D1BAfBcD6010e9cdf1cac305a3 |
|                          | CryptoKings              | 0x75E95ba5997Eb235F40eCF8347cDb11F18ff640B |
|                          | CryptoPunks              | 0xb47e3cd837dDF8e4c57F05d70Ab865de6e193BBB |
|                          | Decentraland             | 0xF87E31492Faf9A91B02Ee0dEAAd50d51d56D5d4d |
|                          | Metaverse                | 0x79986aF15539de2db9A5086382daEdA917A9CF0C |

Fig. 10: NFT Index.