Non-fungible Tokens (NFTs) as Alternative Investments: Evidence from the Solana Monkey Business Collection

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Abstract

Employing Solana Monkey Business tokens' transaction level data from August 16, 2021, to March 8, 2022, an NFT Index was compiled. This index attempts to unravel the risk-return relationship of Solana NFTs as an investment vehicle. It is found that the NFT Index rendered an average arithmetic daily return (standard deviation) of 9.58% (54.48%) over the sample period. This risk-return profile translates to the highest risk-adjusted performance amongst stocks, bonds and commodities indices. Moreover, given that the daily return of the NFT index yields close-to-zero correlations with other asset classes, the role of the proposed asset class is explored in portfolio settings. Positive portfolio weights were found for the NFT Index using different portfolio optimization techniques. This advocates in favor of the diversification potential that this novel asset class can provide to investment portfolios.

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Introduction

Non-fungible Tokens (NFTs) have attracted attention from many stakeholders. Businesses from the fashion industry to real estate developers are in search of applications in their fields of expertise. For instance, Gucci, the high-end Italian-based fashion house, launched its NFT collection in collaboration with Superplastic in February 2022. This utility token grants exclusive access to virtual and in real life (IRL) experiences, products, and events. NFTs from this collection were minted at 1.5 ETH (Ethereum native token) and now trade on Open Sea at a floor of 5.48 ETH[1]. TechCrunch founder, Micheal Arrington sold a flat in Kyiv, Ukraine, in the first-ever NFT Real Estate Auction. Consumer adoption and interest have been on a steep increase since mid-February 2021, peaking at the beginning of 2022, according to Google Trends. On March 12, 2021, the artwork by Beeple´s "*Everydays: the First 5000 Days*" sold for $69 million. This transaction marked the widespread interest not only by NFT enthusiasts but also by investors and the general public.

Collectibles in the NFT space are defined by Pandell (2021) as digital assets that can take forms such as photographs, music, or video clips, among others. Although any user could copy and reproduce them, the ownership of the original asset is secured, powered by the cryptographic characteristics of blockchain technologies. Crypto Punks, The Bored Ape Yacht Clubs (BAYCs), Solana Monkey Business (SMB) and DeGods feature amongst the most popular digital collections both in the Etherium and Solana networks.

Aiming at understanding what non-fungible tokens are, it is of essence to define what fungibility is. "Fungibility is the ability of a good or asset to be interchanged with other individual goods or assets of the same type. Fungible assets simplify the exchange and trade processes, as fungibility implies equal value between the assets." (Frankenfield, 2021). Cryptocurrencies, such as BTC, ETH, SOL, and fiat currencies are all fungible. In contrast, NFTs as per their name, are not fungible. "They are tokens that represent unique assets with characteristics that are particular to them. They cannot be interchanged or replaced by another equivalent token. NFTs can take the form of digital work, virtual land, a domain name or even equipment in a video game."

[1] Information retrieved on March 20, 2022, directly from opeansea.io.

(NonFungible.com, 2022). In short, NFTs give the holders a claim on a digital asset. The main advantage of NFTs is that they are powered by blockchain technology which records all transactions on an immutable, decentralized public ledger.

NFTs have been evolving rapidly in the last 2 years as market players comprehend their full, yet untapped potential. The wide variety of uses and applications that firms, enterprises and, governments can give to NFTs range from tokenization of assets to issuance of copyrights powered by blockchain technology. Due to its rapid adoption rate, price appreciation, and frenzy in social media, NFTs and more specifically Solana NFTs have caught the eye of investors to be employed as an alternative investment vehicle.

Since the launch of the SMB Gen2 collection on August 3, 2021, at a mint price of 2 SOL, it has become a blue-chip token in the Solana environment. On March 24, 2022, the SMB collection had a daily volume of 10010.788 SOL (103322.75 USD) with only less than 10% of the total supply listed at a floor price of 170 SOL[2], namely the minimum price at which an SMB was listed was 170 SOL. Gen2 SMB is a collection of 5000 unique 24x24 pixels randomly generated Monkeys featuring 6 layers with over 99 possible traits (SolanaMonkey.Business, 2021). Figure 1 is a copy of SMB #1355, the rarest trait combination in the whole collection featuring a crown an orange jacket and it being a skeleton. SMB #1355 last changed hands on October 1, 2021, for a price of 13027 SOL (2106205.36 USD[3]). Furthermore, with a total volume of 180 million USD as of April 21, 2022, SMB ranks 24th in volume relative to all NFT collections including those from the Ethereum environment, and 1st relative to all other Solana NFT collections[4].

The share of alternative investments in investors', mutual funds' and pension funds' portfolios has increased in recent years. Perqin (2022) expects AUM to grow from $13.32tn today to $23.21tn in 2026 per their 2022 Global Alternatives Report. Although NFTs' share in the alternative investment asset class might not be ranking high, through recent developments such as securitization and incorporation of utility features the status quo could change (Chapell et al.,

[2] Information retrieved from solanafloor.com on April 20, 2022.
[3] Trading on October 1, 2021, at day closing at 161.68 USD (yahoofinance.com)
[4] Information retrieved from https://www.cryptoslam.io/nfts on April 21, 2022.

2010). Moreover, as has happened with other novel asset classes that typically lack investor confidence and trustworthiness, with time and through further research, the current knowledge gaps could be narrowed, fostering its widespread adoption.

Figure 1: SMB #1355

This paper aims to explain the risk-return relationship of Solana NFTs as an alternative investment, compare and contrast the returns with indices of other asset classes and finally to describe and model their performance in a portfolio setting. This will be achieved by compiling an NFT Index over a period of 208 days starting on August 16, 2021, to March 8, 2022, which will in turn be compared to other conventional financial markets indices. Employing transaction-level data of the Solana Monkey Business (SMB) and network factors, a hedonic regression model with over 7000 transactions is to be constructed. In addition, a Repeated Sales method is used to construct an alternate NFT Index. The incorporation of both methods follows previous literature´s trend when compiling price indices (Kong & Lin, 2022). To explore the role of NFTs as an investment vehicle in a portfolio, the traditional mean-variance model and modern portfolio theory is to be employed. This analysis will shed light on the risk-return relationship of the complied NFT Index.

The main contributions of this paper to existing literature are the analysis of a blockchain that so far has limited to no research, the Solana Blockchain. Moreover, through the employment of transaction-level data and hedonic regression analysis, results shed light on different dimensions of NFTs. First, present Solana NFTs as an alternative investment vehicle and narrow the knowledge gap for non-NFT-expert investors interested in allocating part of their portfolio into this novel asset class. Second, investigate the risk-return relationship of NFTs relative to other traditional financial instruments by using modern portfolio theory. Third, complement existing literature on alternative investments, which are mainly focalized in unique asset subclasses. Amongst the most prominent are, paintings (Mei and Moses, 2002; Beggs and Graddy, 2009), real estate (Case and Shiller, 1989), collectible stamps (Dimson & Spaenjers, 2011), and wine (Dimson, Rousseau, and Spaenjers, 2015). Fourth, findings will contribute to novel literature niched in blockchain technologies such as ICOs and cryptocurrencies (Ante et al., 2018; Blémus et al., 2019; Damsgaard, 2022; Joo et al., 2019; Kehr et al., 2021). Finally, unravel the pricing mechanisms of NFTs, given their illiquidity and heterogenous characteristics, exploring its potential pricing drivers and contrasting the relation of traditional stock factors with the complied NFT Index returns.

The remainder of this paper is structured as follows. First, an exhaustive literature review is presented, featuring topics ranging from blockchain, alternative investments, hedonic pricing modeling, repeated sales technique, and indices performance. Next, the methodology and data are reported. Later, both a comprehensive comparative analysis between the presented NFT Index and other major market indices is reported. Thereafter, the risk-return profile and its performance, both as a standalone asset class and in a portfolio setting, is investigated. Finally, the conclusion and limitations of this paper are rendered.

Background and Literature Review

In this section, background information relating to the Solana Blockchain and its implications in terms of innovation and application to NFTs, and smart contracts is to be provided. Next, a detailed overview of previous research on alternative investments is reported. Aided by this extensive literature, NFTs are proposed as a subclass for investments. Finally, an outline of Modern Portfolio Theory is provided aiming at connecting NFTs as investment vehicles for investors' exposure to new blockchain-powered applications.

Blockchain Technologies and Cryptocurrencies

The blockchain as a technology is not novel, as it has been around for several decades. It relays on a cryptographic primitive that allows users to store information in a decentralized, public, immutable secure ledger (Buterin, 2013). In the aftermath of the global financial crisis in 2009, Satoshi Nakamoto published the white paper for the implementation of a peer-to-peer electronic cash system based on cryptographic proof, replacing a trusted third party to verify every transaction (Nakamoto, 2008). Followed by the launch of Bitcoin in 2009, its native cryptocurrency has grown to an all-time-high market capitalization of over 1.2 trillion in November 2021[5]. Although relative to other crypto assets, Bitcoin is by far the most valuable, it is restricted to currency transactions given its structural design (Porat et *al.*, 2017). In 2015, with the launch of Ethereum, an advanced blockchain framework that accommodates for complex and customizable applications, widespread interest from different stakeholders was sparked (Buterin, 2013; Chavet, 2018; Kim et *al.*, 2018). The implementation of the turing complete[6] language has allowed Ethereum to gain popularity and traction as smart contracts and dApps turned into tools for businesses and organizations employed as enhancers of innovation and disruption.

Cryptocurrencies are defined as transferable digital assets secured by cryptography, unlike fiat currency accounts in banks they are not anyone´s liabilities (White, 2015). Cryptocurrencies can be both native tokens of blockchains such as Ether (ETH) for the Ethereum network, Bitcoin (BTC)

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[5] Information retrieved from coingecko.com.
[6] "… by being Turing Complete, Ethereum has the capability to understand and implement any future agreement, even those that have not been thought of yet." Binance Academy (July, 2022)

for the Bitcoin network, or Solana (SOL) for the Solana network or they can be tokens built on top of a blockchain (i.e., Dogecoin (DOGE) or Basic Attention Token (BAT)). Lie and Aleh (2021), found that cryptocurrency returns are driven and can be predicted by cryptocurrency market-specific factors. They find strong time-series momentum effects and investor attention as a strong forecast element for future returns. Moreover, the constructed index rendered a mean daily return of 0.46% with a standard deviation of 5.46%, these two measures of performance, are higher than equity markets. Moreover, the probability of losses of more than 20% results in 0.48% on a daily frequency. Bouri et *al.* (2017) and Corbet et *al.* (2017) provide empirical evidence suggesting that cryptocurrencies show unusually high volatility compared to traditional assets. Further, they warn about their "speculative nature". However, Brauneis and Mestel (2019) investigate their portfolio performance under the Markowitz mean-variance framework. They conclude that the 1/N-portfolio outperforms single cryptocurrencies and more than 75% of the mean-variance optimal portfolios. Employing cryptocurrencies as a mean of diversification for stock during the Covid-19 crisis is explored by Goodwell and Goutte (2021). Results from their research advocate for the diversification of Tether, a stable coin, as a safe haven for equities. In addition, Bitcoin, Ethereum, and Litecoin are found to be poor diversifiers of equity. Other studies focused on portfolio performance in the inclusion of cryptocurrencies conjecture that the use of cryptocurrencies expands the efficient frontier providing investors with higher utility levels (Chuen et *al., 2017)*. However, high correlations between the most prominent cryptocurrencies and stock markets have been found in most recent periods (Bouri et *al.*, 2020).

The Solana Environment and NFTs

The Solana Environment, launched in 2017 by compression algorithms expert, Anatoly Yakovenko, is open source and touring complete allowing developers to create DApps. Relying on proof-of-history (PoH), Solana is set to be the fastest network in the cryptocurrency market with over 50,000 transactions per second (fps) at its highest future capacity (Hiemstra, 2021). Furthermore, given its low transaction costs relative to Ethereum, Solana and its native token SOL, have great prospects and upside potential. In addition, given the scalability features embedded in the Solana blockchain's design, it makes it a suitable candidate to capture the increasing demand for processing power which are innate to smart contracts and NFTs. Smart contracts act as decentralized mediators, they enforce a set of predetermined rules by the involved parties. For instance, transfer funds from one wallet to another when conditions have been met. As defined by Cong and He (2019) "smart contracts are digital contracts allowing terms contingent on the decentralized consensus that is tamper-proof and typically self-enforcing through automated execution.". Thus, smart contracts are the building blocks of non-fungible tokens (NFTs).

Ethereum Request for Comments 721(ECR-721) tokens dominated the NFT space due to the improvement in trading that came with the smart contract in which a unique token is linked to a unique token identity (ID). Nonetheless, in recent months the Solana NFT environment, which employs Solana Program Library (SPL) tokens has grown to be the second largest following Etherium in volume[7].

Related literature on NFTs' utility and features is limited, nevertheless, Fairfield (2021), analyzes the legal fundamentals of NFTs and elucidates to NFTs to be recognized as personal property rather than as contracts as per its nomenclature. Chohan (2021) explores the value drivers for NFTs. In this report, scarcity and ownership are identified as key elements for the value of this asset class. Finally, Weijers and Turton (2021) propose environmentally smart contracts, a new kind of smart contract for non-fungible tokens to solve the prudential-moral dilemma facing digital artists. That is artists can reap the full benefits of employing NFTs while not contributing to environmental degradation that come from energy-intensive PoW consensus mechanisms.

This paper proposes Solana NFTs as an investment vehicle. So far, existing literature investigating the risk-return relationship of NFTs is highly scarce. Borri et *al.* (2022), construct an overall NFT index employing multi-collection transaction level data and the RSR method. They favor the RSR method over a hedonic model as excluding assets that were traded only once decreases the biases for the index as in their sample, on average 80% of transactions are first sales. This is beneficial as they do not include mint transactions which are transactions between buyers and artists. Analogically, in the securities market proceeds from IPOs are not to be included in indices, only price movements following the funding phase. Their overall NFT Index renders a weekly average

[7] Information inferred from Cryptoslam.io.

return and standard deviation of 2.5% and 19.5%, respectively. Moreover, the annualized Sharpe ratio results in 0.939.

Dowling (2022) and Goldberg et *al.* (2022) explore land pricing in Decentraland. Kong and Lin (2021) employ a hedonic regression analysis on CryptoPunks. Nadini et *al.* (2021) report NFT market factors, mainly visual characteristics and network effects which are in turn used to predict prices using machine learning. Goetzmann and Nozari (2022) expand on Nadini et *al.* (2021) by constructing a weekly repeated sales index to examine their fundamentals. The authors report insights relating to market demand and supply. The contribution of this investigation to the existing literature is to present Solana NFTs, which have not been researched before as a potential complementary asset for investors 'portfolios. Moreover, as NFTs will become the cornerstone of the metaverse and Web 3.0 it is crucial to understand the driving mechanisms in their markets (Borri et *al.*, 2022).

Alternative Investments

Traditionally, alternative investments (AI) are defined as any asset class outside of stocks, bonds, and financial market instruments (Erdos, 2010). The increasing need for portfolio diversification together with the expansion of the population of high-net-worth individuals has sparked interest in alternative investments. The Wall Street Journal published in 2010 that 6% of total wealth is held in "passion investments", including but not limited to art, musical instruments, wine, jewelry, and antiques. From this list, art has the highest likelihood of value appreciation (Capgemini, 2010). Departing from this premise, several art funds have been created, yet not many have been successful due to the market conditions specific to the niche market, such as high transaction costs and scarcity of investment-worthy art pieces (Horowitz, 2011). Dimson & Spaenjers (2014), construct indices for several alternative investment vehicles ranging from art pieces, and stamps to violins and find annual arithmetic returns (standard deviation) of the indices to be 7.2% (13.2%), 7.6% (13.5%), and 7.0% (10.1%), respectively.

Wine as an investment vehicle has been formally adopted even in the creation of wine-specialized mutual funds. Namely, the Ascot Wine Management Fine Wine Fund, founded in 1999 by a Bahamian company, reporting returns ranging from 10.9% to 13% *per annum*, and the Orange

Wine Fund, founded in 2001, listed on the Euronext Stock Exchange in Amsterdam (Sanning et *al.,* 2006). Employing investment-grade wine as an asset class in investment portfolios has proven to be isolated to market risk factors whilst yielding monthly returns of up to 0.75% (Sanning et *al.*, 2006). Results stemming from an investigation conducted by Bouri (2015) provide evidence of the ability of fine wine to hedge equity risk during economic downturns. Yet, the *ad hoc* characteristics of wine, storing costs, and aging, represent risks that other asset classes do not portray (Bouri, 2015; Sanning et *al.,* 2006). Moreover, Nahmer (2020) asserts that when accounting for all costs, all portfolios exhibit a worsening in risk-adjusted returns.
The consensus amongst academics is that alternative investments, specifically art and wine seem to yield lower returns compared to equity and debt markets. Studies that include variability over time, conclude that collectibles embody more risk than other financial assets (Burton and Jacobsen, 1999). Pompe (1996) for instance, finds that photographs render 30% yearly returns, net of fees, yet have a 300% standard deviation in year-to-year returns. This phenomenon is attributed to a narrow and niche market. Furthermore, Pensado (1993), suggests that particular kinds of painting fall “in and out of fashion”, thus yielding lower returns.

Yet, there is vast evidence of collectibles having hedging characteristics when combined with investors’ traditional portfolios. Ibbotson and Brinson (1987), when comparing Salomon indices for coins, stamps, Chinese ceramics, and Old Masters paintings with financial assets such as stocks bonds, and treasury bills from 1970 to 1985, find a negative correlation in returns. Cardell et al. (1995) asses that collectibles can have hedging properties against inflation based on the period from 1947 to 1988. On the flip side, Goetzmann (1993) and Chanel (1995) unveil positive correlations between collectibles and financial markets in their research.

Collectibles’ returns have been measured mainly, with two methodologies, Repeated Sales Regression models and Hedonic Regression models. Adopting the right specification requires a deep understanding of the data and its fit with the model specification. In addition, both methods come with certain drawbacks and advantages. The section dedicated to methodology covers the implications and presents a rationale for choosing a hedonic model for this research.

Contributions by Sanning et *al.* (2006) not only shed light on the returns of wine as an alternative investment but also unveil their joint performance with traditional asset classes in investment portfolios. They make use of the Fama and French 3-factor model (Fama and French, 1993) to investigate whether "wine returns compare favorably with historical financial returns on other assets, both in mean value and in volatility or covariance.". Following this motivation, this paper aims at unveiling the risk-return relationship of Solana NFTs, in the context of portfolio optimization and expects to identify drivers that have a direct impact on this novel asset class.

Data and Sample

In the Solana environment, the largest NFT collection by volume is SMB[8]. The SMB Collection consists of 5000 24x24 pixel randomly generated Monkeys with over 99 possible traits spread over 6 layers. Every token in the collection is named with a unique numerical identificatory that runs from 1 to 5000. Each SMB is to be categorized into 9 *Types* (i.e., Solana, Skeleton, Alien, Zombie, Dark, Purple, Red, Orange, and Brown) which determine and account for the visual characteristics of each SMB. Figure 2 is a graphical representation of the sample distribution of the *Type*. In addition, there are 84 attributes distributed over 5 layers, *Clothes*, *Ears*, *Mouth*, *Eyes*, and *Hat* (See Appendix 1 for the distribution). Furthermore, every SMB features 0 to 5 attributes. Appendix 1 renders a full overview of the attributes' distribution of the sample. This paper opts to utilize the SMB collection over the sample period as a proxy for Solana NFT price levels given its observables, heterogenous and identifiable characteristics, and its importance relative to other collections or projects.

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[8] Total daily Volume of 103322.75 USD (Information retrieved from https://www.cryptoslam.io/nfts on April 21, 2022.)

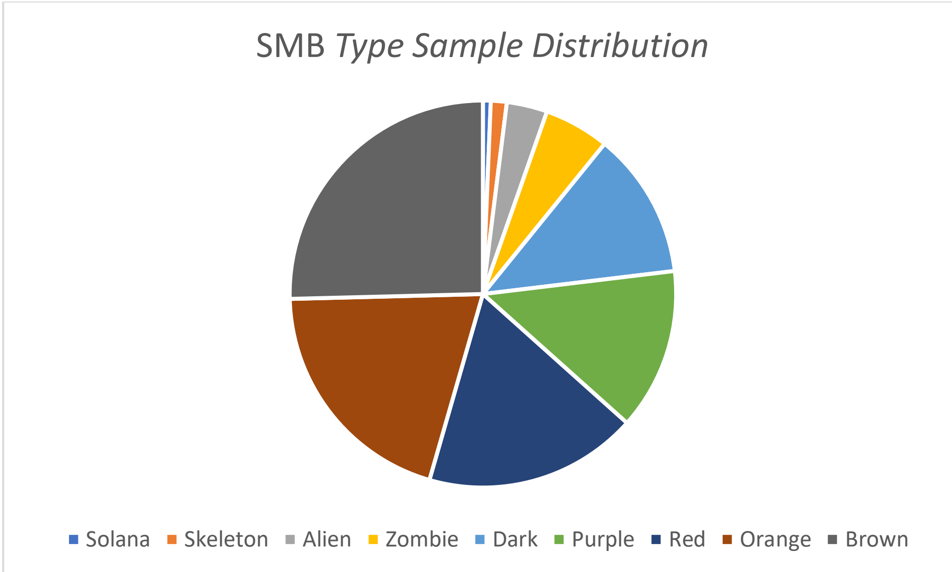

Figure 2: SMB *Type* Sample Distribution

The collection efforts of the transaction level data which consist of 7504 observations over a 208-days sample period ranging from August 16, 2021, to March 8, 2022, were enabled by querying Solana developers, who had the expertise, to retrieve the contract metadata stored on-chain. Ultimately, a member of the Solana Monkey Business Team provided the raw data set. In the sample, a total of 3301 unique SMB tokens were transacted with the distribution as shown in Figure 3.

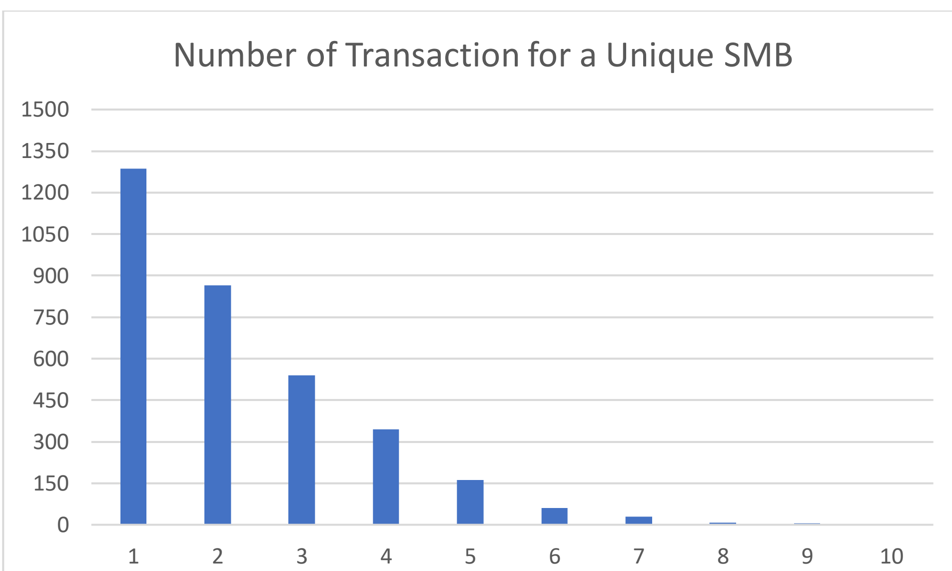

Figure 3: Number of Transactions for Unique SMB

As reported in Figure 3, 1287 SMB were only traded once during the sample, whilst only 1 SMB was traded 10 times. Moreover, given the total supply of SMB of 5000, it is to be assumed that 33.98% of the total supply is still held by original owners, at least until March 8, 2022. Figure 4 yields a frequency distribution table featuring the average price of each NFT in the sample period. The majority of SMB (2264) over the sample period averaged a sales price of between 50 and 200 SOL. In addition, only 3 SMB traded at an average higher than 2500.

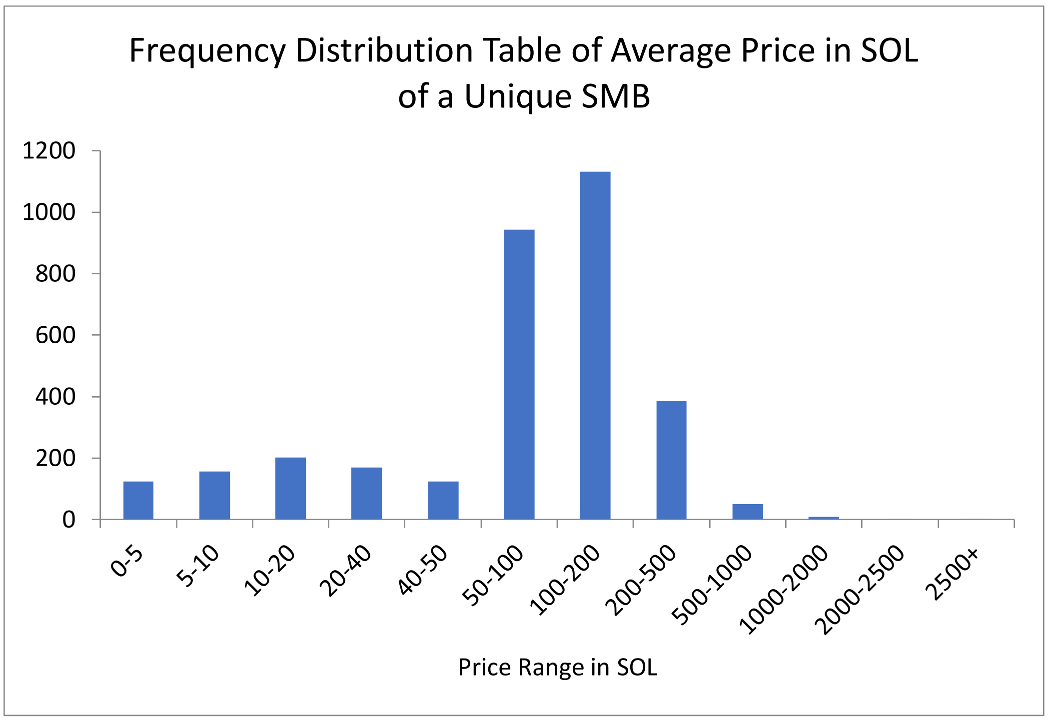

Figure 4: Frequency Distribution Table of Average Prices of Unique SMB

If the transactions are subdivided into the *Type* category, the results suggest that rarer types of SMBs trade on average for higher prices and fewer times. As featured in Table 1, the SMB *Type* is ordered from top to bottom from rarest to most common. Interestingly, the mean price and standard deviation for the dark, orange, and brown *Types* render similar results with a mean price of 107, 106, and 108 SOL and a standard deviation of 93, 96, and 100 SOL, respectively. Moreover, only 49 transactions linked to Solana *Type* SMB took place during the sample with a mean price of 707 SOL and a standard deviation of 886 SOL. Higher moments are useful to understand the sample beyond mean and standard deviation. The sample, across types, renders a price positive skewness and kurtosis, higher than 3 for all *types* except Alien. In addition, the 99^{th} percentile of rarer *Types* results significantly higher than for their more common counterparts.

Table 1: Transaction Level Summary Statistics

This table reports the summary statistics of the transaction level data collected as the sample. The number of transaction mean price, standrad deviation, skewness and kurtosis in SOL per Type is displayed over the sample period. Also, the 25th, 75th and 99th percentiles are reported.

SMB

Type

	N	Mean	STD	Skewness	Kurtosis	Q1	Q3	99th percentile
Solana	49	707.918	886.016	4.541	25.053	295.000	850.000	4090.080
Skeleton	100	454.870	1289.450	9.374	90.399	128.750	424.750	1080.670
Alien	255	186.796	148.795	1.303	2.462	60.000	259.500	647.760
Zombie	410	169.180	171.465	4.111	28.759	70.000	220.000	888.930
Dark	919	107.372	93.532	2.641	20.879	40.000	160.000	379.100
Purple	1014	110.380	186.289	18.682	453.273	35.000	159.000	367.830
Red	1340	114.643	118.039	5.641	62.169	44.000	164.000	457.080
Orange	1511	106.938	96.943	1.402	3.912	33.500	160.000	397.500
Brown	1906	108.382	100.318	4.999	72.496	42.000	155.000	390.000
Total	7504	123.855	214.778	34.167	1850.950	43.000	169.750	587.850

Hedonic Model

Methodology Hedonic Regression Model

If we are to shed light on the pricing, risk-return relationship, and investment performance, it is crucial to understand the illiquid nature of the discussed asset class, NFTs. Per Bernstein (1987), liquidity in markets is found in two dimensions. The limited change in prices of the same asset and the speed at which market participants can transact. Figure 3 uncovers certain characteristics of illiquidity for this asset class. From its nature, NFTs are illiquid assets, as the speed at which an NFT can be bought or sold is relatively slow and highly dependent on market conditions.

Using transaction-level data to determine prices of illiquid assets has extended precedent both in the housing and art retail markets. The two main methods adopted by academics are the repeated-sales regression (RSR) models (e.g., Case and Shiller, 1989; Pesando, 1993; Lovo and Spaenjers,

2018) and hedonic regression models (e.g., Campbell, Giglio, and Pathak, 2011; Renneboog and Spaenjers, 2013; Dimson et al., 2015)). As asserted by Renneboog and Spaenjers (2013), the RSR method, which uses purchase and sale price pairs to estimate the average return of a portfolio of assets in each time period, poses potential methodological problems in 2 different dimensions. First, given that every unique asset is required to be at least traded twice, the sample size would be reduced significantly. Moreover, Meese and Wallace (1997) suggest that the RSR estimates are subject to great sensitivity from influential observations. Second, through the influence from selection bias, RSR estimators tend to be upward biased (Mei and Moses, 2002), although this problem is overcome as all transactions, from mint to retail, take place in a centralized marketplace. Borri et *al.* (2022) advantageously use these limitations to mitigate biases in the index given the high ratio of first sales in the data set. Finally, the RSR model could suffer from spurious negative autocorrelation in the estimated return series and an overestimation of the variance in the time series (Goetzmann, 1993; Mei and Moses, 2002, Kong & Lin 2021). Still, Pesando (1993), Borri et *al.* (2022), Goetzmann (1993), Mei and Moses (2002), and Pesando and Shum (2008) have already set precedent for using this methodology applied to (digital) art investments.

Hedonic regressions control for quality changes in the transacted goods by attributing implicit prices to their "utility-bearing characteristics" (Rosen, 1974). Central from the hedonic regression model, are the time dummies. All transaction data is pooled, and logarithmic prices are regressed against a set of value determining attributes and time-binary variables. Assuming omitted and unobservable variables are orthogonal to the one included (Meese and Wallace 1997), estimators for time-dummies will absorb constant-quality price trends over the sample period (Renneboog and Spaenjers, 2013). Due to the wholesome and complete incorporation of all available observations in the data set, the hedonic model is adopted for the construction of the NFT Index. Through Kong & Lin (2021) setting a precedent for the use of a hedonic model in application to NFTs' pricing, their methodology is adopted and adapted to this paper's aim.

To construct an overall price index of Solana NFTs the following hedonic regression is used while controlling for observable characteristics as described in the Data section and for network effects.

The following hedonic regression (Equation 1) is estimated by ordinary least squares with the natural logarithm of SMB token price in USD and SOL as the dependent variable.

$$\ln P_{i,t} = \alpha + \sum\nolimits_{j=1}^{J} \beta_j X_{j,i} + \sum\nolimits_{n=1}^{N} \gamma_n Network_{n,t} + \sum\nolimits_{t=1}^{T} \delta_t T_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $P_{i,t}$ represents the sales price of a SMB token *i* sold on date *t, α* is the regression intercept, X indexes the characteristic *j* of the token *i*, $Network_{n,t}$ denotes the network factor *n* in NFT Markets of the Solana blockchain on date *t*, $T_{i,t}$ is the time dummy that equals one if the token *i* is sold in period *t*. The coefficients β_j reflect the attribution of a relative shadow price to each of the *j* characteristics, while the coefficients γ_n capture the attribution of a relative shadow price to each of the *n* network factors. The anti-logs of the coefficients of δ_t are used to construct an NFT Index (π_t) that controls for time variation in the quality of tokens sold. The value of the hedonic NFT Index (π_t) in day *t* is estimated as per Equation 2.

$$\pi_t \equiv \exp\,(\hat{\delta}_t) \tag{2}$$

In the model, the first day is excluded to comply with the perfect multicollinearity requirement of OLS. Thus, the estimated return r_t in day *t* is calculated as per Equation 3.

$$r_t \equiv \frac{\pi_t}{\pi_{t-1}} - 1 \tag{3}$$

Moreover, every possible attribute is included as a dichotomous variable. Amongst these, there are the *types* (i.e., Solana, Zombie, Red, Brown, etc.) and attributes from the five categories (i.e., Hat, Eyes, Mouth, Ears, and Clothes). In addition, we employ the Google-Trends-proved search value index (SVI) for the terms “Solana”, “NFT” and “Solana Monkey Business”. Figure 5 provides a graphical representation of the trends. Note that the Google Trends tool sets the day in which the term was searched the most as 100 and uses that observation as the reference point. Interestingly, the term "NFT" seems to follow the same pattern as the other two but lagged by 4 months. "NFT" peaks in late January 2022 whilst "Solana Monkey Business" and "Solana" peak in September 2021. Literature by Peng and Xiong, (2006), Barber and Odean (2008), Da, et *al.* (2011), and Huang et *al.* (2019) suggest effects of investor attention on asset prices, thus the inclusion of a proxy for investor attention in the form of Google searches is well justified.

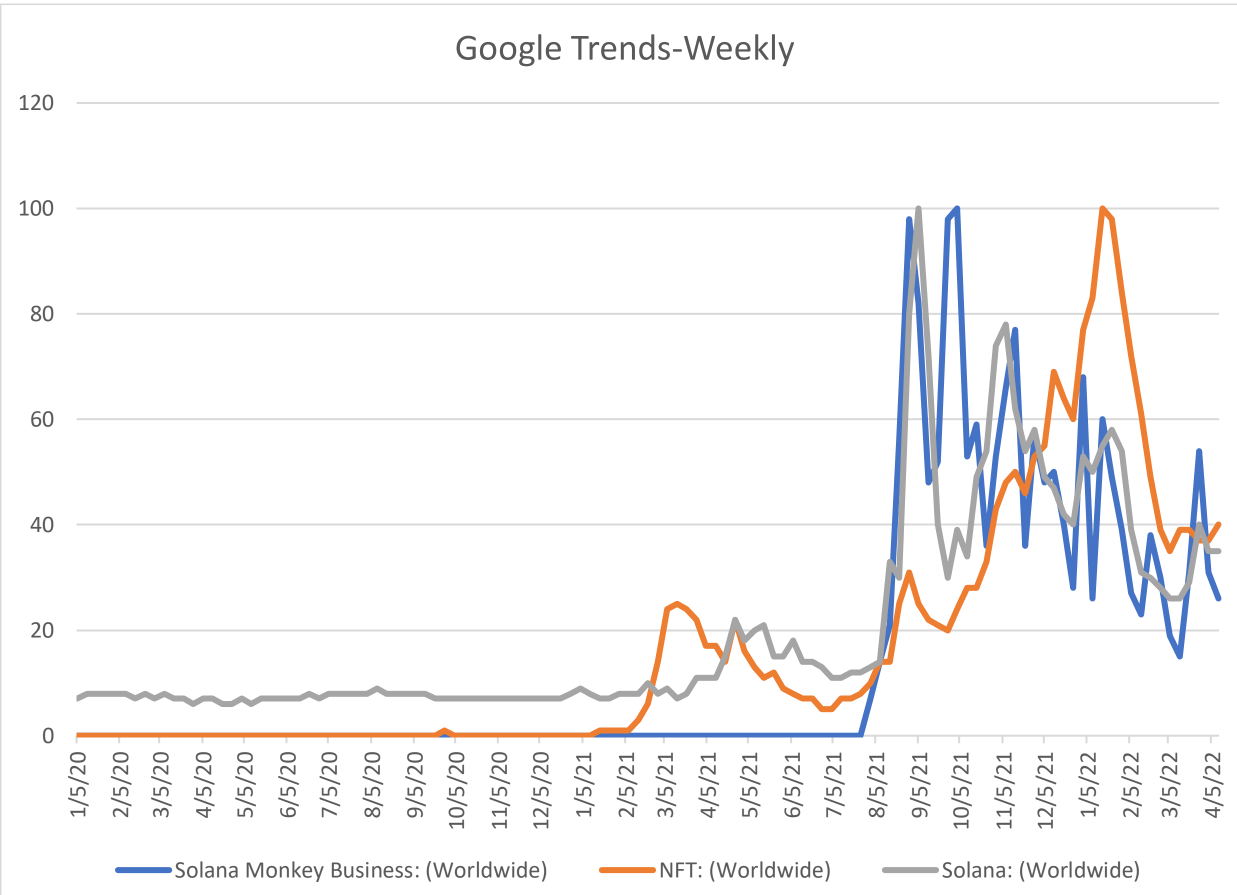

Figure 5: Google Trends SVI for terms; "Solana Monkey Business", "NFT" and "Solana".

Hedonic Regression Results

The NFT Index is constructed estimating Equation 1 by OLS with the natural logarithm of prices in USD and SOL as the dependent variables. Table 2 renders the regression results.

Variables on the *type* of SMB render the price effect that the type of SMB has on the sales price. Moreover, the *type* "Brown", the least rare, was selected as the reference category and the other *types* are ordered from most rare to least rare starting with *Solana* and ending with *Red.* The magnitude of the coefficient decreases monotonically suggesting that rarer types are associated with higher selling prices. Moreover, both in Model 1 and 2 the network effects render significant coefficients. In addition, an increase of 1 dollar in the SOL/USD pair at close leads to a 2.19% increase in the NFT price index, *ceteris paribus*. This suggests that buyers in this ecosystem do not evaluate these tokens based on USD, but rather on the SOL value. This result is contrary to that of Kong & Lin (2022), this can be attributed to differences in investor preferences in the Solana NFT environment, relative to that of the Ethereum NFT ecosystem. These differences stem from investors in the Ethereum NFT market having to buy ETH with the sole purpose to acquire NFTs, whilst it is theorized that Solana NFT investors are mainly SOL investors and builders, who held SOL *a priori* of buying NFTs. In addition, the Ethereum NFT ecosystem at the time had a considerably higher number of collections and projects which attracted demand from new investors. Finally, two SVI variables ("NFT" and "Solana Monkey Business") are paired with positive coefficients in line with previous literature with findings placing network effects as central to the success of digital platforms and Initial coin offerings (ICOs) (Catalini and Gans, 2018; Sockin and Xiong, 2020). Nevertheless, the SVI variable for "Solana" yields a negative coefficient. Given the wide use of the search term "Solana", it is plausible to have an increased amount of noise in that variable coming from other Google users searching for the same term but not referring to the Solana under scrutiny by this paper. However, the benefit of including the variable outweighs omitting it given the tracking behavior of the "Solana" and the "Solana Monkey Business" terms over the time period as reported in Figure 5.

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Table 2. Hedonic Regression Results

This table reports the estimates stemming from the hedonic regression model as per Equation 1. The dependent variables are the natural logarithms from the sales price both in SOL and USD. Data retrieved from the Solana Blockchain and was provided by a SMB Team member. All attribute and time dummies are included but not reported in this table. The SE in parenthesis are clustered at a token level. $***$, $**$, and $*$ correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Var.	$\ln P_{i,t}$ *(SOL)*	$\ln P_{i,t}$ *(USD)*
	(1)	(2)
ClosingSOL/USD on transaction day	0.0154***	0.0219***
	(0.00146)	(0.00146)
AttributesCount	0.0878***	0.0878***
	(0.00669)	(0.00669)
SVI SolanaMonkeyBusiness	0.0322***	0.0359***
	(0.00373)	(0.00373)
SVI NFT	0.0150***	0.0166***
	(0.00254)	(0.00254)
SVI Solana	-0.0115***	-0.0105***
	(0.00257)	(0.00257)
Type		
Solana	2.068***	2.068***
	(0.0483)	(0.0483)
Skeleton	1.452***	1.452***
	(0.0344)	(0.0344)
Alien	0.819***	0.819***
	(0.0221)	(0.0221)
Zombie	0.531***	0.531***
	(0.0182)	(0.0182)
Dark	0.0214	0.0214
	(0.0133)	(0.0133)
Purple	0.0262**	0.0262**
	(0.0130)	(0.0130)
Red	0.00326	0.00326
	(0.0118)	(0.0118)
Orange	-0.0114	-0.0114
	(0.0115)	(0.0115)
Constant	0.0980	3.696***
	(0.496)	(0.496)
Observations	7,504	7,504
R-squared	0.933	0.956
Day dummies	Yes	Yes
Attribute dummies	Yes	Yes

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In terms of the number of attributes, tokens with a higher attribute count result to be sold and bought for higher prices. Both within the sample and in the full collection a higher attribute count is linked with rarity, thus explaining these results.

Both models render high explanatory power with R-squared values of over 93%. Such values advocate the fitness of the model for the data and suggest an extreme capture of price variance throughout the sample. As both models, one denominated in SOL and another in USD yield similar results, Model 2 is to be employed as the bassline specification to construct the NFT Index. Moreover, in the following sections opting to employ the USD-denominated index will eliminate any currency risks that may bias optimal portfolio allocation results.

Hedonic NFT Index

In this section, the NFT Index is reported. Computing the Index values is achieved aided by Equation (2) and time-dummy estimates in the hedonic model. The returns are calculated using Equation (3). The first day in the sample is excluded to avoid perfect multicollinearity. Moreover, the price level is set to one for August 17, 2021. The NFT Index is presented graphically in Figure 6 with the index value on the left y-axis and USD for the SOL/USD pair on the right y-axis and date on the x-axis. Figure 7 features the returns of the NFT index with returns in percentage on the y-axis and date on the x-axis.

The NFT Index denominated in USD seems to reach a higher value for any index level throughout the sample. It is theorized that this phenomenon stems from an amplifying effect of the SOL/USD pairing price. The SOL/USD pair reached a sample all-time high on November 7, 2021, at almost $250, yet by March 11, 2022, the price had decreased to almost $80. During the second half of the SOL/USD bear run, a bull run in the NFT Index is identified. A potential explanation could be the transfer of 1000 SOL from the community funds to the Monke DAO, a decentralized autonomous organization focused on investment into other NFT and web3 projects (@MonkeDao, 2022). Such action undertaken by the SMB community likely boosted confidence and by proxy demand for the SMB collection. Furthermore, the bull run in the NFT Index is likely driven by the network effects as shown in Figure 5, where the term "NFT" peaks at the same time as the start of the bull run. This phenomenon signifies the entry of mainstream investors into the Solana NFT ecosystem.

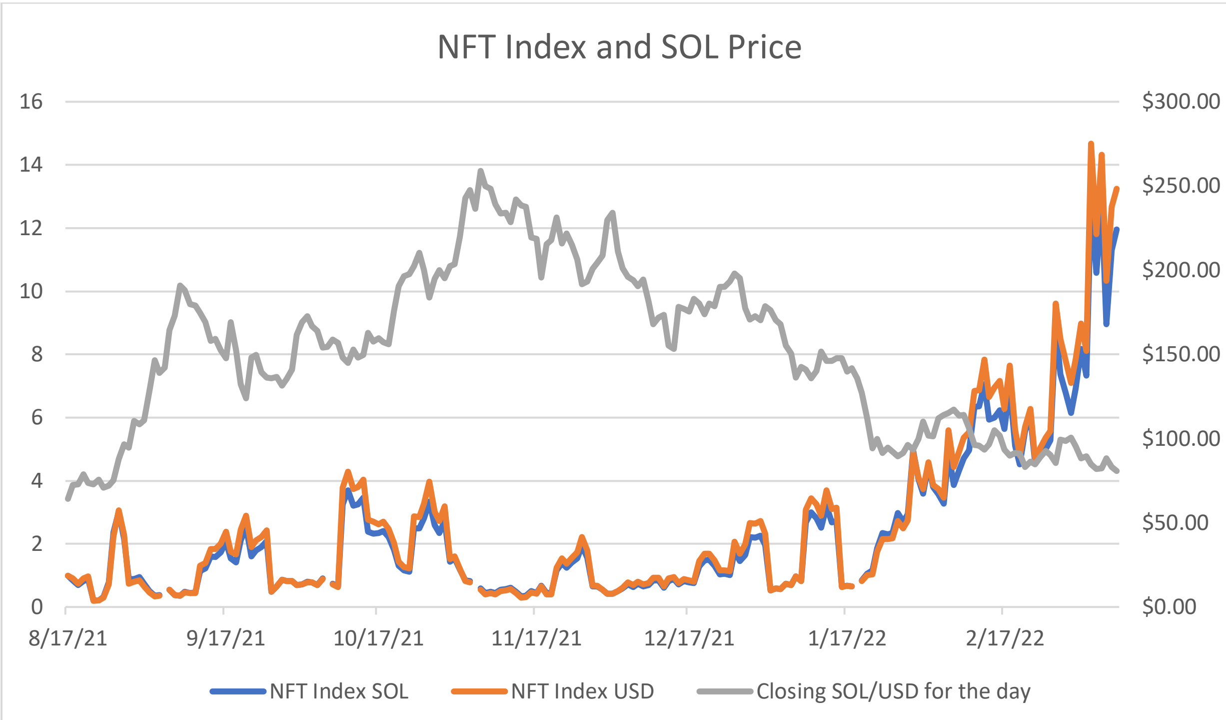

Figure 6: NFT Index in SOL and USD and SOL/USD pair.

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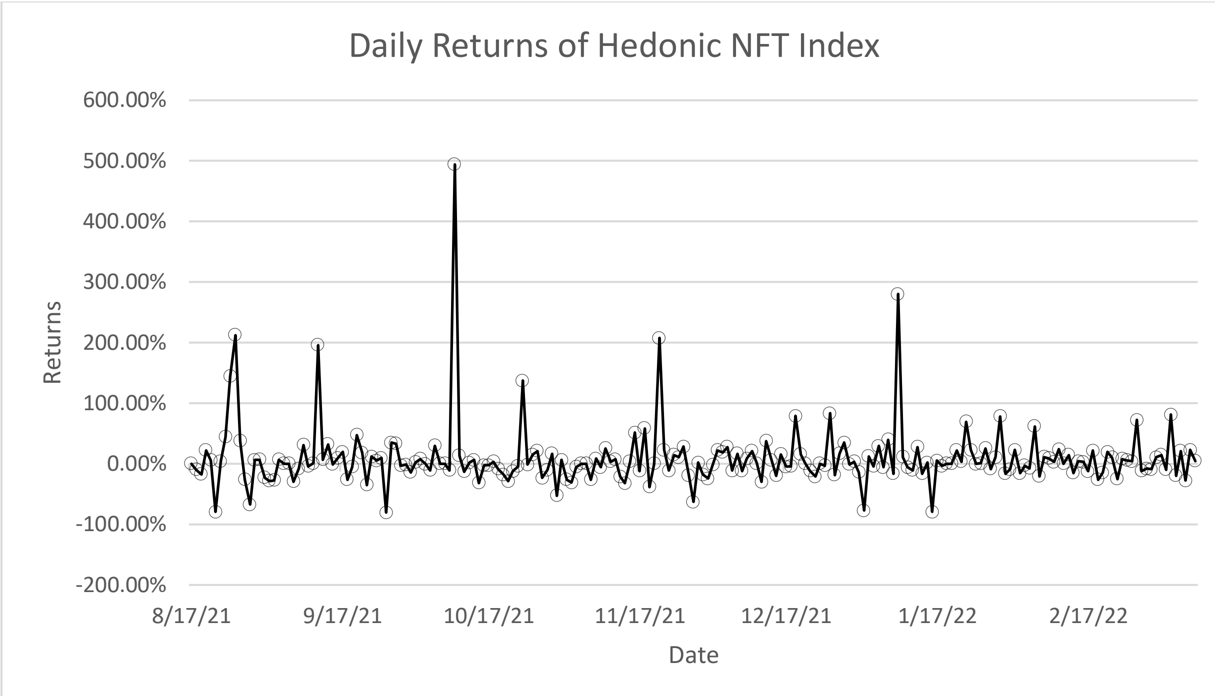

Figure 7: Hedonic NFT Index Daily Returns

As reported in Figure 7 a return of around 500% is captured for the NFT Index on the 10th of October 2021. This sharp increase in return is to be associated with the sale of SMB #1355 the rarest token in the collection. The transaction took place on October 1st, 2021, at a price of around 2 million USD or 13027 SOL, which is 28.56 times higher than the floor price at that time. This transaction placed the SMB collection on the map, as this token became number 12 in the chart for Top Sales by USD Value, where only *CryptoPunks*, the prominent Etherium collection, claimed higher places in the ranking (@IcedKnife, 2021). Interestingly, it is theorized that the market incorporated this new information after 9 days of the transaction, pushing the overall prices to higher levels. These developments shed light on poor market efficiency and high information frictions found in the Solana NFT environment. Cumming and Zhang (2016) found such characteristics in alternative investment markets in emerging markets. Thus, market features of this novel asset class could follow trends portraited by other alternative investment asset classes. Bid and ask prices, which are available to extract from the blockchain could serve as a tool to investigate this matter further. Yet, the investigation of this theory falls outside the scope of this paper.

The Price Impact of SMB Attributes

As suggested by Kong & Lin (2021), observable aesthetic attributes have a direct impact on investors' pricing of NFTs. Aided by the estimates of the hedonic regression of the attribute dummies, the price impact of each attribute is calculated by using the antilog of the coefficient and subtracting one. Table 3 lists the top and bottom attributes that are associated with the highest price impact on transactions.

Table 3. Ranking of SMB Attributes

This Table presents the top (bottom) 10 attributes (dis)favoured by SMB investors/collectors. The coefficent estimates on attribute dummies are based on hedonic regression presented in Table 3 Model 1. Per Renneborg and Spaenjers (2013), the price impact is calculated by using the antilog of the coefficient linked to the attribute and substracting 1. ∗∗∗, ∗∗, and ∗ correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	Attributes	Coeffiecnt	Price impact
Top 10			
1	Diamond	2.531***	1156.61%
2	Crown	2.232***	831.85%
3	SpaceWarriorHair	1.919***	581.41%
4	NinjaBandana	1.809***	510.43%
5	SolanaBackwardsCap	1.768***	485.91%
6	AdmiralHat	0.703***	101.98%
7	BlackKimono	0.665***	94.45%
8	PirateHat	0.472***	60.32%
9	Strawhat	0.404***	49.78%
10	AngelRing	0.390***	47.70%
Bottom 10			
1	OrangeShirt	-0.162***	-14.96%
2	GreenCap	-0.161***	-14.87%
3	GreenShirt	-0.151***	-14.02%
4	RedShirt	-0.151***	-14.02%
5	GreenSmoking	-0.148***	-13.76%
6	PurpleShirt	-0.148***	-13.76%
7	BrownJacket	-0.146***	-13.58%
8	GreenJacket	-0.143***	-13.32%
9	BlueShirt	-0.139***	-12.98%
10	BeigeSmoking	-0.136***	-12.72%

It is found that the attribute *Diamond, is* associated with a price impact of 1156.61%, *ceteris paribus*. On average, tokens with attributes such as *SpaceWarriorHair, NinjaBandana, and SolanaBackwardsCap* can be valued sixfold relative to not having an attribute for that feature. Moreover, the attribute *BeigeSmoking* is linked to a negative price impact of 12.72%. The top and bottom favored attributes all yield significance at a 1% level, suggesting collectors and investors value both rarity in attributes and aesthetic features. Tokens will sell at premiums and discounts. This could be driven both by aesthetic preferences and rarity. Evidence for this is clear, the most favored attribute, *Diamond*, is not the rarest, while the least favored, *BeigeSmoking*, is not the most common, ranking 17 out of 22 under the *Clothes* category.

Repeated Sales Regression Model

Repeated Sales Regression Methodology

Previous literature suggests that constructing the price index employing the Repeated Sales Model could prove useful. Bailey et al. (1963) and Case & Shiller (1987) first presented this approach for estimating real estate price indices. When asset attributes are unobservable, RSR is a powerful specification because it accounts for them by assessing the price change over time for the same asset.

In line with Goetzmann (1993) and Mei and Moses (2005) and following Kong and Lin's (2022) methodology, it is to be assumed that the continuously compounded return ($r_{i,t}$) for a certain asset *i* in period *t* is represented by μ_t, the return of an index of the assets, and error term are defined as per Equation 4.

$$r_{i,t} = \mu_t + \varepsilon_{i,t} \qquad \varepsilon_{i,t} \sim N(0, \sigma_i^2) \text{ and i.i.d.} \tag{4}$$

Where μ_t may be interpreted as the average return in period *t* of assets in portfolio and $\varepsilon_{i,t}$ is the idiosyncratic return that is particular to an asset. The data set was reconfigured such that it matches the RSR format, where there are pairs of purchase and sale price $P_{i,b}$and $P_{i,s}$of an individual asset as well as dates of purchase b_i and sale s_i, where $b_i < s_i$. Henceforth, the logged price relative to asset i, held between the purchase date b_i and the sales date s_i may be expressed as per Equation 5.

$$r_i = ln\left(\frac{P_{i,s}}{P_{i,b}}\right) = \sum_{t=b+1}^{s} r_{i,t} = \sum_{t=b+1}^{s} \mu_t + \sum_{t=b+1}^{s} \varepsilon_{i,t} \tag{5}$$

As proposed by Goetzmann (1992), the RSR model using an OLS specification usually overweights pairs that contain relatively less information about fluctuations of the μ series. In addition, given the low likelihood of the error term being homoscedastic, a generalized least-squares (GLS) regression technique is adopted to estimate μ, as shown in Equation 6 (Case & Shiller, 1987).

$$\hat{\mu} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}r \tag{6}$$

Equation 6 is the maximum likelihood estimate of μ, where X is an N × T matrix, containing a row of dummy variables for each asset in the sample and a column for each holding interval. Ω is a weighting matrix, populated by weights according to the time between the two time points in a pair (Goetzmann, 1993). The dummy variables are zero except that the dummy is -1, corresponding to the first period, namely, to the sale date. The dummy +1 corresponds to the second period when the asset was sold (Case and Shiller, 1989).

Aiming at employing the RSR estimation technique, the original data set was reconfigured. From the original sample with over 7504 transactions, 3301 unique assets were identified. Moreover, assets that were sold only once during the sample or more than once per day were dropped. This reduces the sample size from 7504 to 3825 transactions. In addition, the network effect variables as described in the sections above were included as control variables. Finally, after the RSR model is estimated using the GLS method the RSR NFT Index takes form as the antilogs of the coefficients. This is denoted by π_{GLS} . The price level is set to one for the first day in the sample. Figure 8 depicts both the RSR NFT Index and the Hedonic NFT Index.

Repeated Sales Regression Results and Index

Kong and Lin (2022) report both models yielding similar results. Yet, for this sample of transactions and sample period, the index construction with the two different approaches resulted in a different magnitude and daily fluctuations. However, there is a positive trend being followed by these two price indicators. Also as identified by previous literature, coefficients corresponding to day dummies early in the sample tend to be biased as the sample size is relatively smaller.

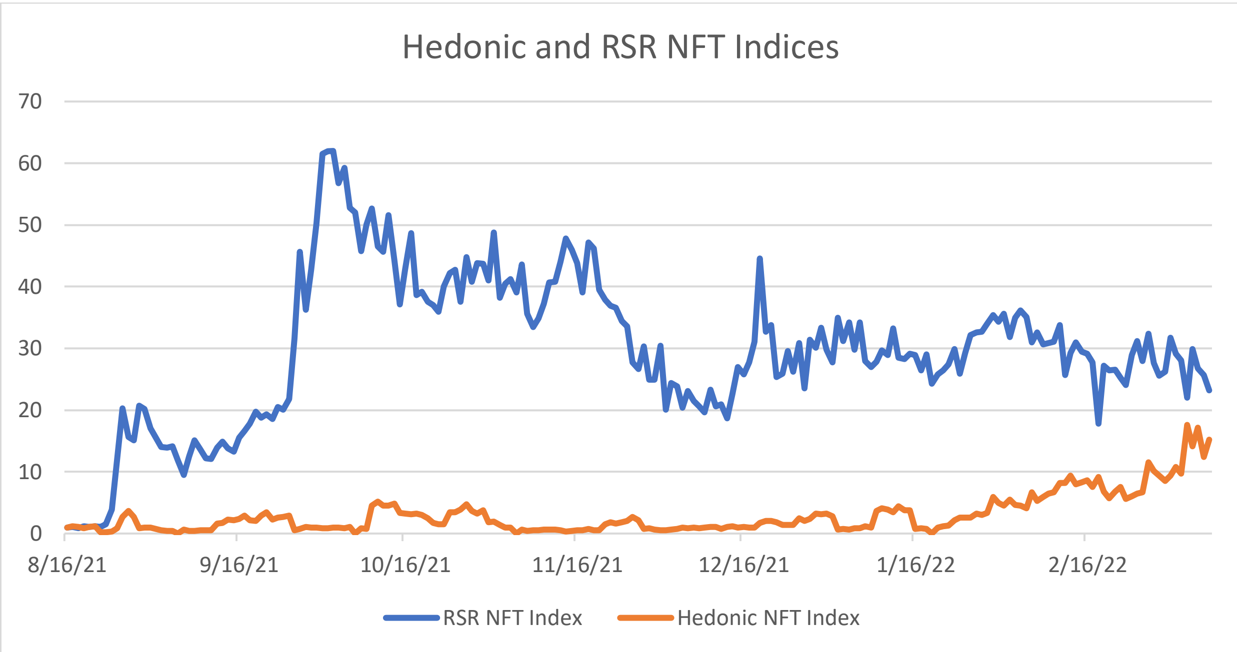

Figure 8: Visual representation of the constructed NFT Indices both with the hedonic and repeated sales models.

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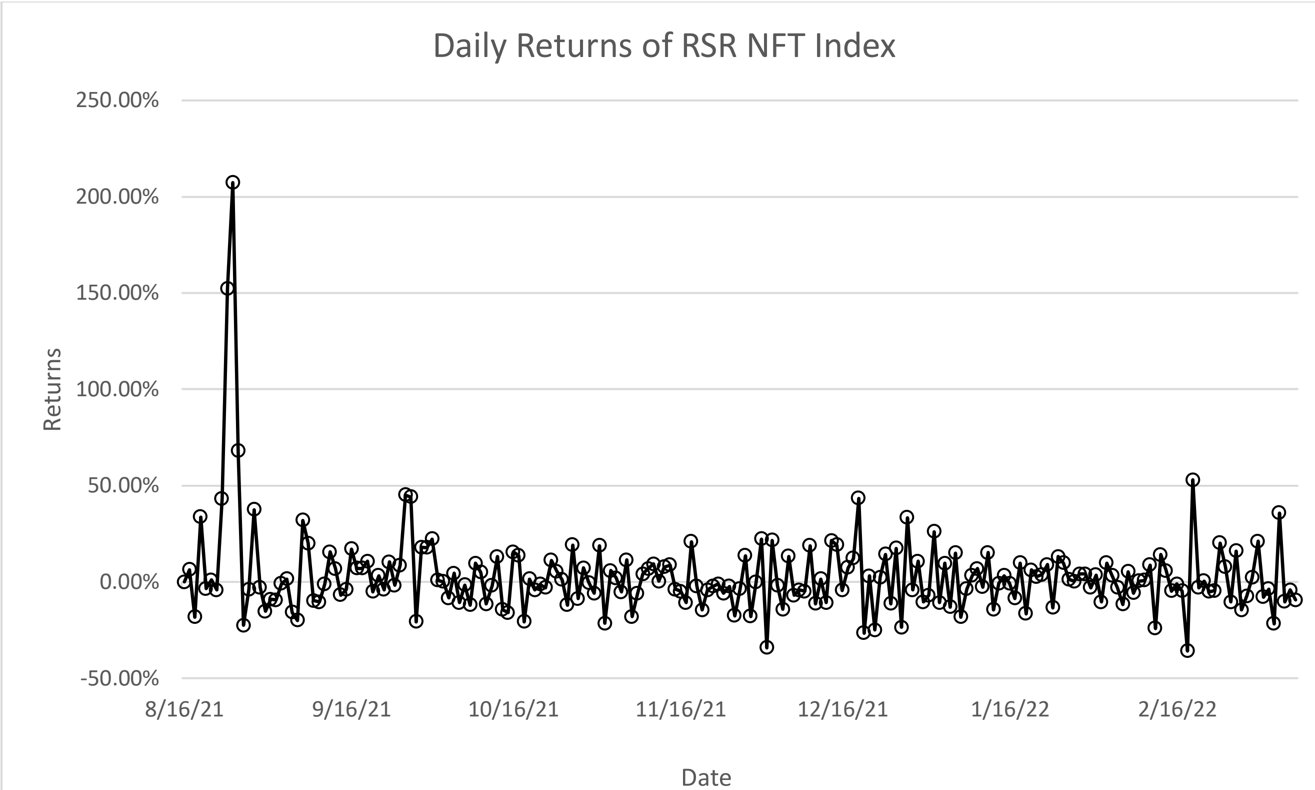

Figure 9: RSR NFT Index Daily Returns

Despite the correlation coefficient of 0.015 between the two indices, they depict a convergent trend starting in 2022 towards a stable value of 20, at least during the sample period. The return is calculated analogically to the hedonic method in line with Equation 3. The RSR NFT Index (Hedonic NFT Index) yields a daily arithmetic average return, standard deviation, skewness, and kurtosis of 3.36% (9.96%), 23.37% (55.55%), 4.71 (4.69), and 35.30 (33.13), respectively. The arithmetic mean in this case renders a forward-looking estimation of the index, whilst the geometric mean indicates the return of holding an asset over a stipulated period. The outcome heterogeneity between the two models raises questions about the reliability of the sample, which is addressed in the next section where both the benefits and drawbacks of the two approaches are presented in full.

The RSR and Hedonic Models as NFT Price Indexing Techniques

This subsection will provide theoretical and practical arguments for the benefits and drawbacks of both the hedonic and repeated sales models. Moreover, it will outline the rationale behind the preference for the hedonic model. There is an extensive body of literature that evaluates the performance of both methods, in terms of specification bias and efficiency (Case, Pollakowski and Wachter, 1991; 1997; Cho, 1996; Clapp, Giacotto and Tirtiroglu, 1991; Gatzlaff and Haurin, 1997; Haurin and Hendershott, 1991; Steele and Goy, 1997).

Case, Pollakowski, and Wachter (1991) claim that a potential bias in hedonic models is to arise if the incorrect functional form or set of explanatory variables is used. Similarly, the RSR model could suffer from biases, for instance, if the subsample of assets traded more than once is not representative of the population. "Repeatedly sold properties may differ from non-transacting or single-sale properties in ways that affect their measured appreciation rates." (Case, Pollakowski, and Wachter,1997). Moreover, if the price of attributes changes over time, then the RSR might lead to biases (Case, Pollakowski, and Wachter, 1991). Contrary to these findings, other researchers did not find a strong indication of selection biases for the RSR technique (Steele and Goy, 1997; Clapp, Giacotto, and Tirtiroglu, 1991).

As suggested by Haurin and Hendershott (1991), data availability is a key driver of the methodology selection process. In housing pricing indices, getting information on asset-specific attributes is highly costly and practically unachievable. This problem is overcome by the RSR method, as it is in its nature to control for these unobservables by comparing the same asset in two transactions at two points in time, with a fundamental assumption. Namely, the quality of the asset does not change over time. For this study, given the nature of the data and the immutability of the assets, both methods would not suffer any biases stemming from these assumptions. First, NFTs are randomly generated assets under certain rules. For SMB all the possible attributes that every unique asset could have, are known and public. Second, once the asset is minted (sold to the first owner by the artist), it cannot undergo any changes. Therefore, the main concern of the hedonic model is the impossibility of controlling for all potential attributes. Yet, this is not present for this data set and NFTs in general provided both the asset-specific attributes and the universe of attributes are known. In addition, the RSR does not violate the constant quality assumption as, by construct, NFTs are immutable and unchangeable in attributes, at least for this collection.

As presented by Steele (1997), Haurin and Hendershott (1991), and Case, Pollakowski, and Wachter (1991) (1997), the RSR's inherent nature is subject to two potential biases that could be present in this study. Namely, sample selection bias and time-changing attribute prices bias. First, we address the implications and effects of the sample selection bias, then the time-changing attribute prices bias.

"The RSR is, by construction, confined to assets selling relatively frequently, and this sample selection will yield a biased index if price changes in the subsample are different from those of all transacting assets." Steele (1997). Under this premise, the model would lead to a biased index if there was a structural difference between assets only sold once, which are excluded from the RSR sample, and those traded more than once. Moreover, due to NFT market characteristics, assets sold at high frequency could signal speculative behavior from investors. Thus, it is hypothesized that investors with speculative behavior might pay a premium on assets that coincidentally are also sold by the same "type" of investor, speculative. Hence, this results in an upward-biased index. Table 4 presents the price summary statistics of the full sample by the number of transactions. NFTs sold only once show the highest standard deviation, as investors are likely less aware of their fair value as they do not have a secondary transaction history relative to assets with higher trading frequency.

Table 4. Price Summary Statistics by Transaction Frequency

Number of Transations	*1*	*2*	*3*	*4*	*5*	*6*
Mean	149.90	123.92	118.36	115.79	115.70	119.81
StdDev	462.23	127.46	106.60	92.51	100.56	75.88
Max	13027.00	1169.00	1200.00	940.00	1200.00	350.00
Min	2.91	1.00	3.00	3.51	3.00	3.51

Number of Transations	*7*	*8*	*9*	*10*	Full Sample
Mean	107.24	92.14	127.16	90.70	123.85
StdDev	70.28	70.94	82.89	63.55	214.78
Max	315.69	287.00	400.00	175.00	13027.00
Min	3.51	4.00	8.00	4.00	1.00

Table 5. SMB Type by Transaction Frequency

This table renders a distribution of the Type of asset that was sold for each frequency of trades in the sample. The attributes are ordered as per the rarity table in descending order.

Transaction frequency	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Solana	37%	20%	24%	8%	10%	0%	0%	0%	0%	0%
Skeleton	39%	36%	12%	8%	5%	0%	0%	0%	0%	0%
Alien	31%	36%	15%	11%	4%	2%	0%	0%	0%	0%
Zombie	22%	30%	21%	13%	9%	3%	0%	0%	2%	0%
Dark	14%	24%	22%	19%	11%	7%	2%	1%	0%	0%
Purple	17%	22%	22%	17%	12%	5%	3%	1%	0%	0%
Red	18%	23%	19%	19%	12%	5%	3%	0%	1%	0%
Orange	15%	22%	24%	22%	7%	4%	4%	2%	1%	0%
Brown	15%	20%	23%	19%	13%	5%	3%	1%	0%	1%
Total	17%	23%	22%	18%	11%	5%	3%	1%	1%	0%

Moreover, Table 5 depicts the distribution of the *Type* of SMB being traded per frequency. For instance, SMBs with rarer *Types* such as *Solana* and *Skeleton* are mostly traded once. Namely, for the full sample, 37% of *Solana Type* SMBs were traded once. In contrast, less rare *Types*, such as *Brown* and *Orange* have a more heterogeneous distribution. There is an indication that assets with rarer attributes are sold less than those with more common features. This points to sample selection biases for the RSR index, as assets that were sold only once were excluded from the subsample used for the RSR. Analogically to Haurin and Hendershott (1991), less rare assets (overrepresented in the RSR) have different price appreciation and depreciation structures relative to their counterparts. Appendix B expands on this by presenting a similar table that portrays the distribution of assets in terms of *Clothes* attributes and their trading frequency. Data from Appendix B provides complementary evidence to support selection bias for the RSR technique. Similarly, assets with rarer attributes are sold relatively less than their less rare counterparts.

The second source of bias stems from the inability of both models to allow for the specification of time-interactive effects. That is, attributes are priced constantly over the whole sample. As suggested by Case, Pollakowski, and Wachter (1991) and adapted for this paper's purpose, every

NFT is a bundle of separate attributes, which most likely have their indices determined by supply and demand. Intuitively, the price of *SolanaBackwardsCap* could appreciate more rapidly than *NinjaBandana* through the aesthetic preferences of investors entering the market. The RSR and hedonic techniques implicitly assert that all prices for all characteristics move together over time by limiting the time-interactive effects to zero, ultimately leading to biased estimates (Case, Pollakowski, and Wachter, 1991). However, Chen & Harding (2016) postulate that "for assets where a large number of transactions are observed over short periods of time, the time window for estimating the hedonic relationship can be narrowed, making the assumption of constant characteristic prices over that window acceptable." Although the sample period for this paper is short relative to the sample period employed for housing indices, it is to be noted how high-paced and dynamic the NFT environment is. This creates the possibility for changes in attributes' prices highly likely, thus leading to biased estimates for both the hedonic and the RSR techniques.

Lastly, given the nature of the constructed daily index, transactions by day are highly heterogeneous. Hence, days with low informational density probably yield biased coefficients, which in turn lead to a biased index. Kong and Lin (2022), construct the index both with monthly time intervals and with a much longer time period of over 2 years. In contrast due to the novelty of this collection, a daily index is more suitable in terms of data efficiency.

Given the nature of the data, i.e. constant observable attributes and invariable quality of the assets, the hedonic model is preferred as it presents a lower likelihood of biased estimates. Nevertheless, both indices will be employed in the coming sections to add robustness to the results.

Investment Performance of NFTs

This section will evaluate the investment performance of NFTs as investment vehicles through the previously constructed NFT Index, relative to that of other cryptocurrencies *(SOL/USD Index)*, stocks (*NASDAQ Index, S&P500 Index, and Dow Jones Index*), bonds (*Bond Index)* and commodities (*Gold Index).* See Appendix C for a detailed definition of the underlings of these indices.

Aiming at eliminating idiosyncratic risk from the portfolio, two market-wide indices were chosen, namely the *S&P500 Index* and the *Dow Jones Index.* Whilst the *S&P500 Index* encompasses a wide range of firms' equities, the *Dow Jones Index* provides exposure to value (blue chip) stocks. The *NASDAQ Index* is also included as it is technology focused, which is in line with the novel asset class proposed by this paper. The *Bond Index* consists of 10-year US Treasury Bonds and is employed to capture the risk-return relationships in portfolio settings of bonds as an asset class. The *SOL/USD Index* is integrated as it is the native token with which NFTs from the SMB collection can be transacted. Lastly, the *Gold Index*, commonly used as a safe haven for investors, provides limited exposure to the stock market, which is valuable during high volatility and uncertainty periods.

First, the data for the new set of indices was collected for the 208-day period that matches the NFT Index[9]. Next, the value for all indices was set equal to one for August 16, 2021, the first day of the NFT Index. Figure 10 spans from August 16, 2021, to March 10, 2022. It was assumed that during non-trading days for non-crypto assets, the adjusted closing price was equal to the opening price of the next trading day. To illustrate the relationship between the NFT Index and the other indices Figure 10 presents a snapshot of the data. Appendix D presents an extension of Figure 10 by plotting the RSR NFT Index next to the other indices.

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[9] The source of the data is Investing.com and yahoofinance.com

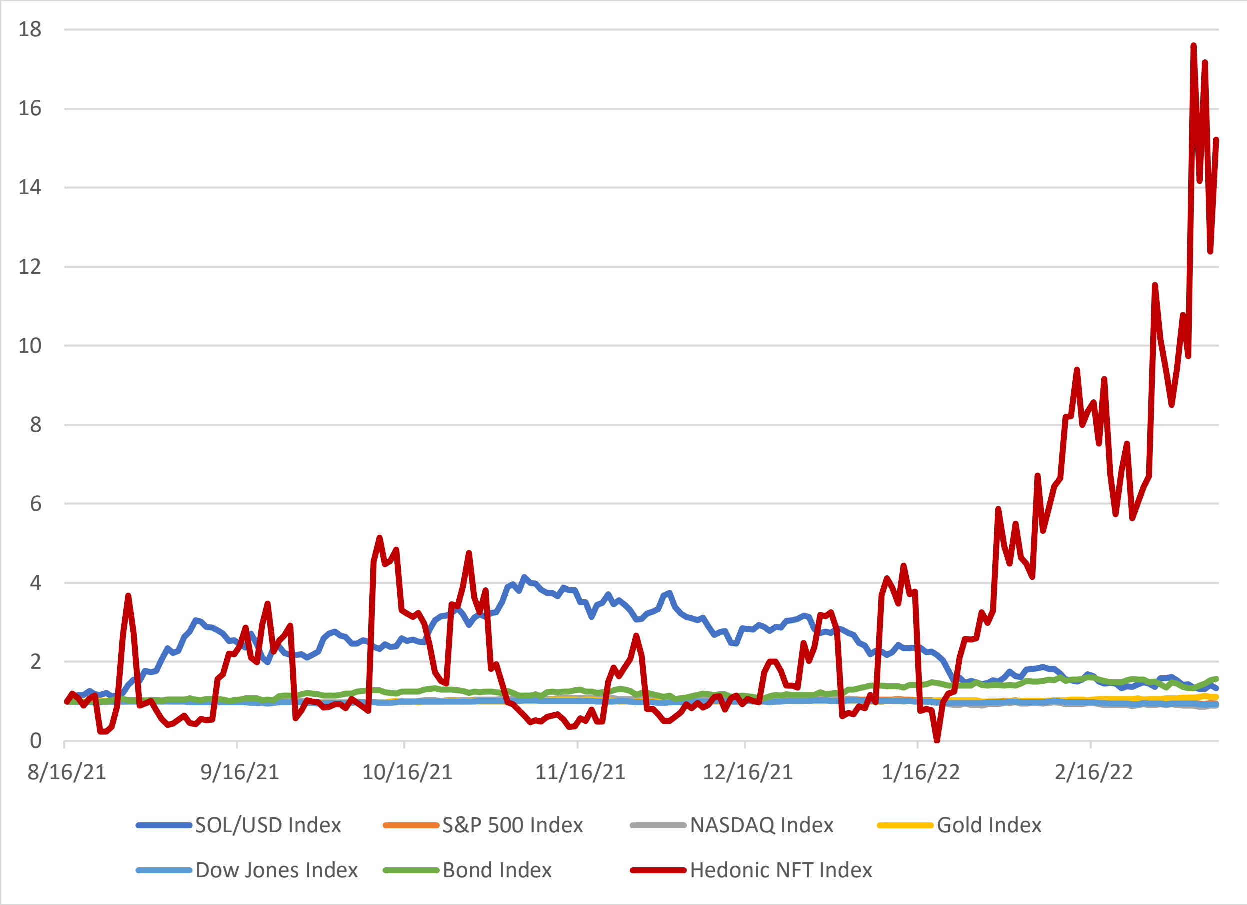

Figure 10: NFT Index and other major market Indices.

The Figure illustrates the indices over the period between August 16, 2021, and March 10, 2022. Go to Appendix C for more detail on definitions of the Indices. Data stems from Investing.com or Yahoofinance.com.

Next, the correlations between cryptocurrencies, commodities, stocks, bonds, and the NFT Index are analyzed. A correlation matrix between the indices is reported in Table 6.

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Table 6. Indices Returns Correlation Table								
This table reports pairwise correlations of the Indices employed in Figure 10. Data frequency is daily. * represents any statistical significance greater than a 5% level.								
	SOL/USD Index (1)	*S&P 500 Index (2)*	*NASDAQ Index (3)*	*Gold Index (4)*	*Dow Jones Index (5)*	*Bond Index (6)*	*Hedonic NFT Index (7)*	*RSR NFT Index (8)*
(1)	1							
(2)	0.3317*	1						
(3)	0.3358*	0.9307*	1					
(4)	-0.0846	-0.2437*	-0.1785*	1				
(5)	0.2915*	0.9214*	0.7581*	-0.3009*	1			
(6)	0.0556	0.1995*	0.1745*	-0.3803*	0.2518*	1		
(7)	-0.2079*	-0.0515	-0.0443	0.0072	-0.0415	-0.0136	1	
(8)	-0.0133	-0.0251	-0.0223	-0.0727	-0.0299	0.0925	0.1598*	1

The Hedonic NFT Index reports insignificant negative weak correlations with all indices except for the *Gold Index* for which a close-to-zero correlation is reported and with the *SOL/USD Index*, which renders a negative but slightly stronger correlation than for all other indices. The correlation between the *Hedonic NFT Index* and the *SOL/USD Index* of -0.2079 indicates that the dollar-denominated Hedonic NFT Index portrays a negative significant relationship with the SOL/USD pair for this sample period. This coefficient suggests that when the *SOL/USD* pair drops, the NFT Index increases. Furthermore, whilst the *Hedonic NFT Index* did not produce significant correlations with any of the equity indices or the debt index, results could shed some light on their relationship or lack thereof. That is, given the near-zero correlation to all equity indices and the debt index, one could hypothesize the diversification power that NFTs could have over investors' portfolios, which mainly consist of bonds and equities.

Table 7 presents the summary statistics of daily returns on the different assets over the sample period. During this period the daily average return for the *Hedonic (RSR) NFT Index* was 9.58% (3.36%), whilst the average daily returns for *SOL/USD, S&P500,* and the *Bond Index were* 0.33%, -0.02%, and 0.26%, respectively. Collectively, both NFT indices outperform all asset classes during the sample period. Yet, investing in this novel asset class is linked with high risks. The *Hedonic (RSR) NFT Index* renders a standard deviation of daily average arithmetic returns of

54.48% (23.37%), a value higher by a factor of over 62 (27) relative to the *S&P500'*s measure of dispersion.

Table 7. Summary Statistics of Returns on NFT and Other Indices

This table renders the distribution of daily arithmetic returns for all indices presented in Figure 10 over the period from August 17, 2021 through March 10, 2022. For each index, the arithmetic average, the standard deviation, highest/lowest returns recorded return, and the ex post Sharpe ratios are computed. Sharpe ratio is calculated as the mean index return minus the one-month T-bill return, divided by the standard deviation of index returns. One-month T-bill returns stem from Kenneth R. French's data library. Appendix C provides variable definitions in greater detail.

	Mean	Standard Deviation	Max	Min	Sharpe Ratio
SOL/USD Index	0.33%	6.21%	19.34%	-15.89%	5.24%
S&P 500 Index	-0.02%	0.86%	2.57%	-2.91%	-2.44%
NASDAQ Index	-0.05%	1.21%	3.59%	-3.74%	-4.18%
Gold Index	0.06%	0.75%	2.36%	-2.68%	7.50%
Dow Jones Index	-0.03%	0.74%	2.52%	-2.28%	-4.26%
Bond Index	0.26%	2.74%	10.05%	-7.14%	9.37%
Hedonic NFT Index	9.58%	54.48%	494.17%	-80.45%	17.58%
RSR NFT Index	3.36%	23.37%	207.32%	-35.89%	14.37%
1-month T-Bill	0.00%	0.00%	0.00%	0.00%	-

Aiming at examining the risk-return relationship of the NFT Index, the sharp ratio is computed and presented in Table 7. Defined as the difference between the average daily return and the risk-free rate, divided by the standard deviation, it measures *ex-post* the number of units of return an asset can yield for every unit of risk (Sharpe, 1998). For this sample period, both NFT Indices have a comparable risk-adjusted profile rendering 17.58% and 14.27%, respectively. Moreover, both the *Gold Index* and *the SOL/USD Index*, present similar results with a sharp ratio of 7.5% and 5.24%, respectively. Across the board, the NFT Indices have the most desirable risk-return relationship. However, alternative measures of risk could be better suited to analyzing returns of volatile assets (Goetzmann et *al.*, 2007). For instance, the Sharpe ratio does not distinguish between volatilities that contribute to positive gains and those that erode them. Hence, Table 8 features other risk and risk-adjusted-performance measurements for the indices. $\hat{\alpha}$and $\hat{\beta}$are, respectively the estimates of the intercept and the slope of Equation (7).

$$r_i - r_f = \alpha + \beta\left(r_m - r_f\right) + \varepsilon_i \tag{7}$$

where r_i is the daily return of a given asset, $r_m - r_f$ is the difference between the daily return of the *S&P500 Index* and the risk-free rate (market premium) and ε_i is the error term. This equation is also known as the market model. The Sortino ratio stems from Equation 8.

$$Sortino\ Ratio = \frac{\mathbb{E}[r_i]}{\sqrt{\mathbb{E}[min^2(r_i - MAR, 0)]}} \tag{8}$$

where $\mathbb{E}[r_i]$ is the daily expected return of asset *i*. MAR stands for the minimum acceptable return and was set to zero.

The $\hat{\beta}$ for the *Hedonic NFT Index* yields a value of -3.28, which means that a decrease of one percent in the market *(S&P500*) is associated with an increase of 3.28 percent in the *Hedonic NFT Index.* Similarly, the *Hedonic NFT Index* renders a Jensen’s alpha of 9.51%, a value higher by a factor of twenty relative to the *SOL/USD Index.* Once the performance was adjusted with the MAR set equal to 0, both *NFT Indices* outperform all other asset classes.

[Continue to next page]

Table 8. Risk-adjusted Performance Measures for all Indices

This table reports the risk adjusted performance measures for the different indices employed over the sample period from August 17, 2021, through March 10, 2022. Definitions and equations are to be found in text.

	$\hat{\beta}$	Jensen's alpha ($\hat{\alpha}$)	Sortino
SOL/USD Index	2.41	0.38%	8.59%
S&P 500 Index	1.00	0.00%	-3.37%
NASDAQ Index	1.32	-0.02%	-5.58%
Gold Index	-0.21	0.05%	10.85%
Dow Jones Index	0.80	-0.01%	-5.92%
Bond Index	0.64	0.27%	15.10%
Hedonic NFT Index	-3.28	9.51%	55.22%
RSR NFT Index	-0.69	3.34%	39.34%

Performance metrics presented are calculated with daily returns, which provides an indication for one-day investment horizons. These metrics could lead to biasness for investors with investment horizons longer than one day. For instance, if T is the length of the investment horizon, the expected return will grow with proportion of T, whilst the standard deviation by the squared root of T. This leads to a decreased risk for longer investment horizons (Bodie et *al.*, 2011). Moreover, if instead of reporting a daily mean, a monthly mean that stems from monthly data points were presented, Table 7 would show lower levels of risk as the returns would be smoothed out by the time frame. Future research is required when the market matures with time to unravel a more updated and precise understanding of the risk-return relationship of NFTs.

Borri et *al.* (2022) as aforementioned, also compile an NFT Index with a broader data set that includes several collections. They find a 2.5% weekly average return and a 19.2% standard deviation over their sample stretching from 2018 to 2022. Their index underperforms the one presented by this paper, due to the inclusion of the early stages of the NFT environment. Yet, the weekly average returns for the quarters that overlap this paper's sample period, render lower but more commensurable returns to this study's findings. This is attributable to the wide range of NFT collections employed.

The risk-return profile of NFTs is also to be compared with other alternative investment vehicles. Dimson & Spaenjers (2014) assert that the daily average return (standard deviation) for art pieces, stamps to violins is 0.019% (0.034%), 0.02% (0.035%), 0.019% (0.026%), respectively. Whilst their standalone performance is lower compared to the NFT index, they still hold to a certain degree diversification power in portfolio settings due to their low correlation to the major stock indices such as S&P500, a feature that is shared with the NFT Index.

Portfolio Performance

This section is devoted to examining the function of this new asset class in a portfolio setting given its reported characteristics. Namely, its close-to-zero correlation with other asset classes, negative beta values, high alphas, and overall outperformance of other asset classes with risk-adjusted performance metrics. Mayor equity, bonds, and commodity indices, which have exposure to different sectors, were employed to approximate the market portfolio. Optimizing such a portfolio with the inclusion of a novel asset class elucidates its potential role in improving portfolio performance for investors.

Modern portfolio theory first introduced by Markowitz (1952) transformed investors' decision-making. "The important message of the theory was that assets could not be selected only on characteristics that were unique to the security. Rather, an investor had to consider how each security co-moved with all other securities. Furthermore, taking these co-movements into account resulted in an ability to construct a portfolio that had the same expected return and less risk than a portfolio constructed by ignoring the interactions between securities." (Edwin & Gruber, 1997).

Aiming at shedding light on the diversification potential and the portfolio performance that the proposed *Hedonic NFT Index* could have, the following analysis is presented. First, the weights of the minimum-variance portfolio with the asset classes presented above are reported. Next, a Markowitz portfolio optimization is conducted to arrive at the optimal weights for a certain level of risk. Last, the role of the *Hedonic NFT Index* on a portfolio level is evaluated.

The minimum variance portfolio is computed with one single set of inputs, the returns. Let **X** be a 7 by 206 matrix containing the daily returns for 7 different assets (the indices presented above) over a period of 206 days. **N** is a column vector with 1/206 in every entry. **M,** the 7 by 7, variance-covariance matrix is calculated as per Equation 9.

$$\boldsymbol{M = X`XN} \tag{9}$$

The portfolio variance is defined as per Equation 10. Where the 1 by 7 column vector, **W** is the vector with the weights for every asset. Column vector **W** is optimized, such that the portfolio variance $\boldsymbol{\sigma_P^2}$ is minimized.

$$\boldsymbol{\sigma_P^2 = W`MW} \tag{10}$$

The following weights were found for a portfolio comprising all the aforementioned indices and are reported in Table 9.

Table 9. Minimum Variance Portfolio Weights

This table reports the weights found to be minimizing the portfolio variance. The optimization problem did not allow for short selling nor borrowing of the risk-free object. Note that the risk-free rate was found to be 0% for the sample period.

Index	Weight
SOL/USD Index	0.00%
S&P 500 Index	0.00%
NASDAQ Index	0.00%
Gold Index	51.32%
Dow Jones Index	43.99%
Bond Index	4.67%
Hedonic NFT Index	0.02%
Total	100.00%

Most of the allocation of the portfolio goes to the *Gold* and *Dow Jones Indices*, these two indices present the lowest level of risk as presented by Tables 7 and 8, with beta values under 1 and standard deviations of 0.74% and 0.75% respectively. Moreover, a 4.65% allocation goes to the

Bond Index, an asset presenting a negative correlation against the *Gold Index*. This feature decreases risk for the portfolio. The *Hedonic NFT Index* receives a weight of 0.02%. This extremely low, but positive weight could be attributed to its negative correlation with the market, found by its beta value in Table 8. Despite their increased risk level, results suggest that this novel asset class has diversification potential even with minimum variances portfolios. Overall, under the inputs, these weights render a daily portfolio standard deviation of 0.423%. This portfolio allocation is only optimal for investors with a relatively high degree of risk aversion. Thus, it is of essence to transcend towards the mean-variance portfolio optimization proposed by Markowitz to approximate common investors' needs and behavior.

The Markowitz mean-variance portfolio optimization was also performed on the set of assets presented. This method maximizes the Sharpe ratio of the portfolio. This is defined as the excess excepted return over the standard deviation. The expected return for asset *i* is defined as the mean return over the 206-day period. The optimal weights are presented in Table 10.

Table 10. Markowitz Portfolio Weights

This table reports the weights found to maximize the Sharpe ratio of the portfolio given the expected return (mean return of sample). The optimization problem did not allow for short selling nor borrowing. Note that the risk-free rate was found to be 0% for the sample period.

Index	Weight
SOL/USD Index	6.70%
S&P 500 Index	0.00%
NASDAQ Index	0.00%
Gold Index	70.33%
Dow Jones Index	0.00%
Bond Index	21.39%
Hedonic NFT Index	1.59%
Total	100.00%
Sharpe Ratio	23.61%

Whilst the expected daily portfolio return equals 0.259%, the daily standard deviation is 1.096%. Given the negative average returns for the *S&P 500 Index, NASDAQ Index,* and *Dow Jones Index,* these indices get 0% weights as they would decrease portfolio performance. Whilst the *Gold*

Index, with a mean daily return (standard deviation) of 0.06% *(0.75%)* accounts for 70.33% of the portfolio, the *Hedonic NFT Index* secures 1.59% of the portfolio allocation. This finding is rather significant. It provides further proof of the diversification benefits that this novel asset class can provide to mainstream investors.

Although the optimization problem presented above yielded a positive weight for the proposed *NFT Index*, results are to be interpreted with caution. As Black & Litterman (1992) highlighted, portfolio optimization is subject to investors' auxiliary assumptions about assets. In this case, they employ historical returns to proxy future performance, which has proven to be a poor guide for future returns. Lindenberg (2009) suggests that an equilibrium expected return is to be found to minimize the drawbacks of optimization techniques. Findings from Doeswijk, Lam, and Swinkels (2020) which include an annual average Sharpe ratio for the global market portfolio, equities, and bonds to be 0.36 for the years 1960 to 2017 could serve as a guide to calculating an equilibrium expected return for each asset under the assumption that the realized volatility is to remain constant in the long run. That is, the expected return is reverse engineered from the measure of risk found and the equilibrium annual (daily) target Sharpe ratio of 0.36 (0.01884). This method signifies that the relationship between assets, as captured by the variance-covariance matrix will dictate the optimal weights.

Table 11 reports the expected return and optimal weight for each asset in a Sharpe-maximizing portfolio. These optimal weights yield a daily portfolio expected return of 0.027%, yet a standard deviation (Sharpe Ratio) of 0.556% (0.048). The *Hedonic NFT Index's* weight renders 0.48%, about one-third lower than the optimized portfolio in Table 10. Overall, even with a significantly lower expected return, the novel NFT Index seems to have powerful diversification potential. In line with previous literature, the inclusion of blockchain-based asset classes increases risk-adjusted portfolio performance (Ma et *al.,* 2020). However, due to volatility and other risks inherent to the asset class itself, future performance might structurally shift its comovement with other assets.

Table 11. Markowitz Portfolio Weights with Equilibrium Expected returns

This table reports the weights found to maximize the Sharpe ratio of the portfolio given the equilibrium expected returns for each asset. The target Sharpe ratio for each asset was transformed from a yearly to a daily basis by dividing by the square root of 365. The optimization problem did not allow for short selling nor borrowing. Note that the risk-free rate was found to be 0% for the sample period.

Index	Equilibrium Daily Expected Return	Weight
SOL/USD Index	0.117%	3.57%
S&P 500 Index	0.016%	0.00%
NASDAQ Index	0.023%	3.30%
Gold Index	0.014%	55.49%
Dow Jones Index	0.014%	25.91%
Bond Index	0.052%	11.25%
Hedonic NFT Index	1.026%	0.48%
Total	-	100.00%
Portfolio Sharpe Ratio	-	4.80%

Limitations and Further Research

This section will first address the limitations in terms of the data used for the construction of the index. The drawbacks of the methodology, that is, the hedonic and RSR methods, have been discussed and exposed extensively in the previous section and thus will not be covered in this section. Moreover, the extent to which the portfolio performance section can be interpreted will be challenged.

The transaction level data was procured by a member of the SMB development team. At the time of sourcing, the team had only been able to retrieve the sample period from August 16, 2021, to March 10, 2022. This period finds itself right after the mint[10], which is characterized by high daily volumes and increased demand depending on the market conditions. A longer sample period could expose other price movement drivers. In addition, it could shed light on the true risk-reward profile of this novel asset class. Yet, the lack of data points is inherent for novel asset classes. Thus, further research in this field is warranted, as more information becomes available.

[10] Day in which investors can buy the NFTs directly from the supplier.

One fundamental assumption of this paper is that the transaction level data for the SMB collection is representative of the whole Solana NFT market. This assumption could be challenged as the number of collections in the environment is large and highly heterogeneous. Further research could be directed into compiling data from different collections into a single meta NFT Index as presented by Borri et *al.,* (2022). Future empirical investigations should focus on compiling a market-capitalization-weighted index following mainstream financial indicators of several collections in the Solana NFT environment. Such an index will provide a more accurate estimation of the risk-return relationship that this asset class exhibits. Due to data limitations, namely the inclusion of only one collection, no market-capitalization-weighted index was compiled.

The construction of a comprehensive Solana NFT Index, with the inclusion of all known transactions from different collections, comes with one fundamental issue. Namely, stock indices do not factor in proceeds stemming from IPOs. Conversely, accounting for the mint transactions would factor in such proceeds. Such inclusion would lead to issues when comparing the NFT Index to other stock-based indices. Fortunately, this issue was avoided in this paper as mint transactions were not part of the data set. In recent months, NFT collections now incorporate utility and or cashflows to tokens. These newly incorporated characteristics are to be thoroughly investigated as an alternative method for funding through traditional financial instruments by firms.

To compute the sharp-ratio-maximizing weights an expected return for each asset class is to be assumed. For this, researchers and practitioners are to consider the length of historical data, change in structural market conditions, and investment horizon together with the frequency of rebalancing. This type of modeling is subject to an increased number of assumptions that can and should be challenged. Moreover, under the premise of GIGO (garbage in, garbage out) small changes in the inputs can lead to extreme variations in outputs.

The optimization problem executed in this paper suffers from two main sources of biases. The first stems from the limited number of days available, which in this case are 206 daily returns. At least for the *Hedonic NFT Index.* Given the novelty of this asset class and information availability, no improvements to this source can be proposed. However, given the results presented in this section, continuous research on this asset class is essential. The second problem relates to the novelty itself of the asset class. In the past novel asset classes are less understood by investors and might be mispriced in markets. In addition, NFTs had been transacted amongst a niched community until recently. This causes less experienced and sophisticated investors to disrupt market equilibriums and feed in the bull run that was present during the sample period both in NFT and crypto markets.

The data frequency could also pose a challenge in terms of external validity. As the sample period is constrained, weekly and monthly indices would lead to fewer data points. Moreover, time estimators would have smoothed out the price swings that were lived in the market within a single month or week. Yet, employing daily observations leads to "noise" and non-normality in the data. Moreover, it constraints findings to investment horizons of one day. Yet, results could be indicative of longer investment horizons. A longer sample period could prove to be beneficial for comparison with other asset classes.

This topic commands an increased research effort. Due to the lack of regulation, it is the responsibility of community members with a background in research to investigate and publish the underlying factors and drivers of this asset class. As previously exposed, with more time the market will mature and converge into an equilibrium state. Longer sample periods will also allow academics to dive deeper into the risk-return profile of this asset class and how it is to be employed for optimizing investment portfolios.

Conclusion

The impact of blockchain-based assets such as NFTs has been on the rise as many investors turn to increase their portfolio allocations of alternative investments. Understanding the value drivers, risks, and returns have become ever more critical. This paper has contributed to the literature on alternative investments, crypto-related assets, and indexing of illiquid assets. Moreover, the results exposed could have implications for policy and regulation, as efficient legislation comes from a deep knowledge of the matter at hand and its effect on citizens.

First, aided by transaction-level data sourced from the SMB development team, a hedonic indexing model was presented. This technique reveals that NFT investors attach a monetary value to specific attributes. Furthermore, this value is driven both by rarity and aesthetic preference. The *Hedonic NFT Index* renders an average arithmetic daily return (standard deviation) of 9.58% (54.48%) for the sample period. Moreover, the constructed Solana NFTs outperform their peers relative to other alternative investment vehicles, at least for the sample period.

Following previous research by Kong & Lin (2022), the NFT index was also estimated employing the RSR method, which requires significantly less information density. The resulting *RSR NFT Index* with an average arithmetic daily return (standard deviation) of 3.36% (23.37%) is likely to suffer from selection bias, as SMBs that are sold once, thus are excluded from the sample, are heterogenous in attributes and rarity to those sold more than once. This leads to biases in the index. Moreover, given the nature of the data, namely the universe of and actual attributes, is known, all possible sources of variation can be controlled for with the hedonic method. In addition, it also allows for controlling for network effects. Hence, the Hedonic NFT Index was preferred to conduct the investment performance analyses.

Having compiled an NFT Index, its risk-return profile was compared with other major market indices from other asset classes: stocks, bonds, gold, and cryptocurrencies. It was found that the risk-adjusted return for the novel asset class outperforms all other asset classes. Moreover, the NFT Index renders a close-to-zero correlation with the market indices, providing indicative evidence of its diversification potential.

There different portfolio optimizations were performed. Optimal portfolio weights corresponding to the *Hedonic NFT Index* was 0.02% for the minimum-variance portfolio. The Sharpe-maximizing portfolio, more in line with the risk aversion levels of investors set the weight for the *Hedonic NFT Index* at 1.59% and renders a daily return (standard deviation) of 0.259% (1.096%). Nevertheless, the expected return of the individual assets could have been subject to biases, as it was calculated from the limited sample period. Thus, a new optimal portfolio allocation was found for a portfolio for which the assets' expected returns were reverse engineered from a target long-term Sharpe ratio proposed by Doeswijk, Lam, and Swinkels (2020). Such a portfolio yields a daily return (standard deviation) of 0.027% (0.556%), resulting in a Sharpe ratio of 0.048.

Results from the optimization problems suggest that although NFTs as an investment vehicle has a return standard deviation 63 times higher than that of the S&P500, they possess diversification power in investment portfolio settings. This diversification potential is driven by the low correlations with the market. However, these correlations are subject to change as the NFT market evolves with time and new participants enter it. For instance, regulatory risk could prove to be

Future research is essential to understand the price drivers of NFTs. Once these are known, an increased number of investors will be drawn to these high-yield assets. While this NFT Index might not be representative of the whole NFT market, it does shed light on the risk-return relationship and investment performance of the Solana NFT environment.

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Appendix

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Appendix A. Distribution of SMB Attributes

This table yields the number of SMB attributes featured in the sample. The is a total of 84 unique atributes and every SMB can have from 0 to 5. The data was provided by the SMB Team. Note that N represents number of transactions.

Attribute	*N*	Attribute	*N*	Attribute	*N*
Clothes		Cigarette	980	Protagonist Black Hat	96
Diamond	3	***Eyes***		Green Top Hat	105
Black Kimono	17	Solana Vipers	27	Green Punk Hair	109
Roman Armor	49	Laser Eyes	94	Firefighter Hat	114
Orange Jacket	66	VR Glasses	135	Sombrero	114
Pirate Vest	82	Vipers	147	Flower	121
Sailor Vest	95	3D Glasses	178	Military Helmet	124
Poncho	169	Purple Glasses	198	Mining Hat	137
Green Jacket	202	Gold Glasses	208	Black Cap	141
Orange Kimono	246	Cool Glasses	255	Green Beret	156
Green Smoking	247	Yellow Glasses	306	Black Backwards Cap	163
Black Smoking	259	Green Glasses	329	Viking Helmet	170
Biker Vest	267	***Hat***		Cowboy Hat	172
Military Vest	294	Crown	1	Black Top Hat	177
Cop Vest	306	Space Warrior Hair	8	Thief Hat	179
Brown Jacket	308	Ninja Bandana	9	Pink Headset	201
White Shirt	451	Admiral Hat	10	Purple Backwards Cap	205
Beige Smoking	561	Solana Backwards Cap	14	White Headset	209
Blue Shirt	565	Strawhat	39	Cop Hat	213
Red Shirt	567	Pirate Hat	42	Blue Cap	216
Green Shirt	578	Red Cap	46	Orange Cap	221
Orange Shirt	591	Red Punk Hair	50	Green Backwards Cap	229
Purple Shirt	616	Angel Ring	54	Green Cap	236
Ears		Red Beret	66	Orange Backwards Cap	290
Gold Earring	311	Sailor Cap	72	Blue Backwards Cap	294
Silver Earring	1373	Pirate Bandana	78	White Fedora 1	314
Mouth		Roman Helmet	80	Black Fedora 1	316
Pipe	182	Blue Punk Hair	90	White Fedora 2	338
Mask	324	Protagonist White Hat	92	Black Fedora 2	395
Vape	498	Horns	95		

Appendix B. Clothes Attribute by Transaction Frequency

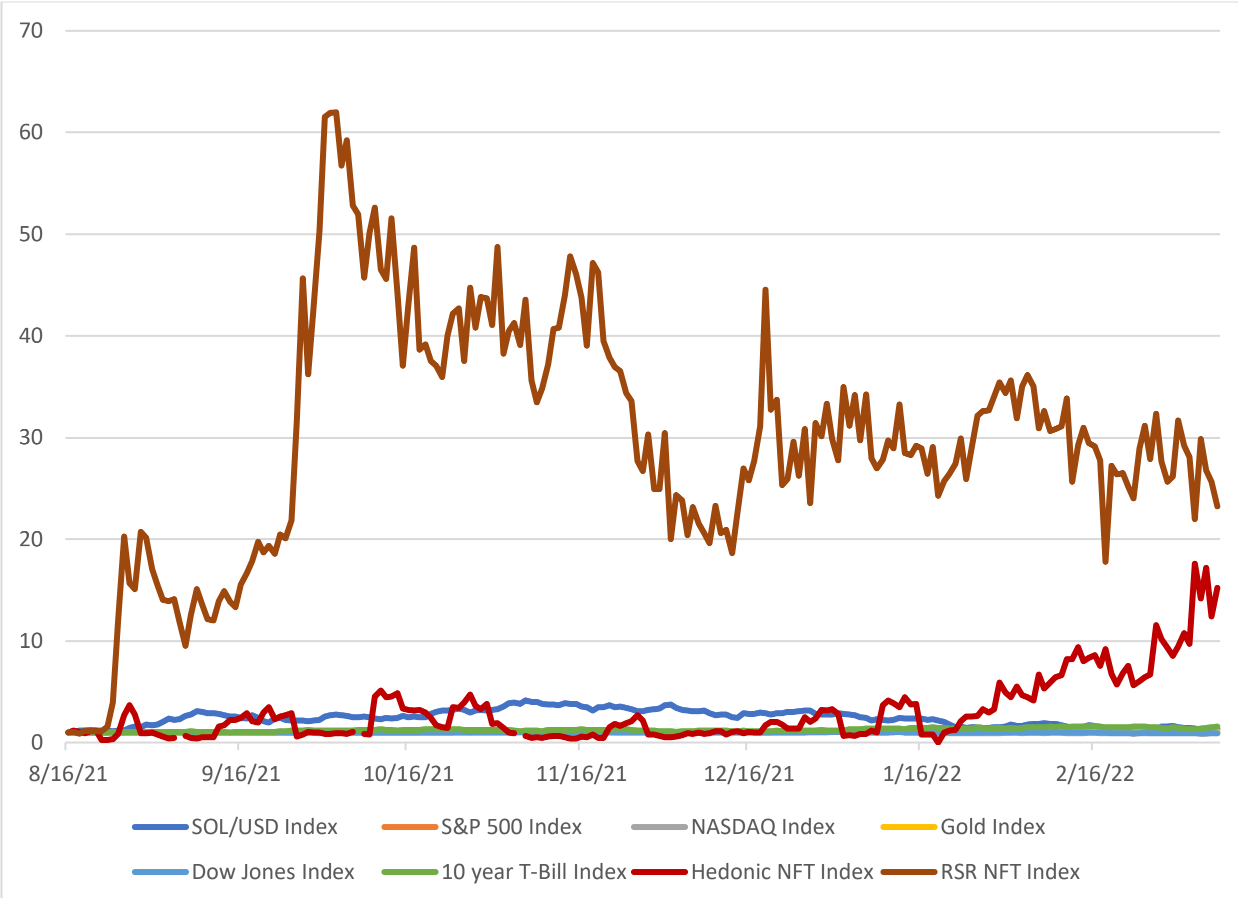
This table depicts the distribution of each clothes attributes for different transaction frequencies. The attributes are ordered as per the rarity table in descending order.

Number of Transactions	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Diamond	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Black Kimono	35.29%	47.06%	17.65%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Roman Armor	24.49%	36.73%	30.61%	8.16%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Orange Jacket	16.67%	30.30%	27.27%	18.18%	7.58%	0.00%	0.00%	0.00%	0.00%	0.00%
Pirate Vest	23.17%	24.39%	14.63%	24.39%	6.10%	7.32%	0.00%	0.00%	0.00%	0.00%
Sailor Vest	21.05%	27.37%	28.42%	0.00%	10.53%	12.63%	0.00%	0.00%	0.00%	0.00%
Poncho	20.12%	33.14%	15.98%	14.20%	8.88%	3.55%	4.14%	0.00%	0.00%	0.00%
Green Jacket	23.76%	25.74%	14.85%	17.82%	14.85%	2.97%	0.00%	0.00%	0.00%	0.00%
Orange Kimono	17.48%	21.14%	19.51%	21.14%	10.16%	4.88%	5.69%	0.00%	0.00%	0.00%
Green Smoking	17.00%	27.53%	14.57%	12.96%	14.17%	4.86%	5.67%	3.24%	0.00%	0.00%
Black Smoking	20.85%	24.71%	24.32%	15.44%	9.65%	2.32%	2.70%	0.00%	0.00%	0.00%
Military Vest	18.37%	21.77%	23.47%	13.61%	13.61%	4.08%	2.38%	2.72%	0.00%	0.00%
Brown Jacket	14.61%	18.83%	27.27%	14.29%	16.23%	3.90%	2.27%	2.60%	0.00%	0.00%
Biker Vest	22.85%	22.47%	17.98%	14.98%	16.85%	2.25%	2.62%	0.00%	0.00%	0.00%
Cop Vest	16.01%	31.37%	21.57%	16.99%	9.80%	1.96%	2.29%	0.00%	0.00%	0.00%
White Shirt	15.74%	19.96%	25.28%	24.83%	7.76%	1.33%	3.10%	0.00%	2.00%	0.00%
Blue Shirt	13.63%	26.19%	25.49%	21.24%	7.08%	6.37%	0.00%	0.00%	0.00%	0.00%
Orange Shirt	14.89%	23.01%	15.74%	18.95%	11.00%	10.15%	4.74%	0.00%	1.52%	0.00%
Green Shirt	14.71%	20.42%	15.57%	22.15%	18.17%	2.08%	2.42%	1.38%	3.11%	0.00%
Red Shirt	17.28%	20.81%	25.40%	23.28%	2.65%	5.29%	2.47%	2.82%	0.00%	0.00%
Purple Shirt	15.10%	19.48%	19.97%	18.18%	12.99%	7.79%	2.27%	2.60%	0.00%	1.62%
Beige Smoking	17.47%	24.24%	21.93%	21.39%	8.91%	1.07%	4.99%	0.00%	0.00%	0.00%
None	18.55%	20.93%	24.87%	15.34%	10.36%	6.84%	2.18%	0.00%	0.93%	0.00%
Total	17.15%	23.05%	21.59%	18.39%	10.73%	4.80%	2.71%	0.85%	0.60%	0.13%

Appendix C. Indices Definitions and Sources

This appenidx features the definitions and the sources for the market indices employed. The historical returns matching the sample period were employed. For non-blockchain based assets, non trading days prices were set to be equal to the opening price of the next trading day.

Index Name	Description	Source
SOL/USD Index	The average of daily closing exchange rates of SOL/USD in day t.	Investing.com
S&P 500 Index	The average of daily closing S&P 500 index values in day t.	Investing.com
NASDAQ Index	The average of daily closing NASDAQ index values in day t.	Investing.com
Gold Index	The average of daily closing gold future prices in day t.	Investing.com
Dow Jones Index	The average of daily closing Dow Jones Industrial Average index values in day t.	Investing.com
Bond Index	The inverse of the average of daily closing US 10-Year bond yields in day t.	Investing.com
1-month T-Bill	Interest rate of the 1-month US T-Bill	Keneth French Data Library



Appendix D: NFT Indices and other major market Indices.

The Figure illustrates the indices over the period between 16 August 2021, and 10 March 2022. Go to Appendix C for more detail on definitions of the Indices. Data stems from Investing.com or Yahoofinance.com.