# Exploring the Diversification Benefits of NFT Sectors

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**Exploring the Diversification Benefits of Non-Fungible Tokens**

Abstract:

This study investigates the evolving diversification benefits of adding Non-Fungible Token (NFT) sector indices to a portfolio consisting of traditional assets. Focusing on two investor types with contrasting risk appetites, this research examines the diversification potential before and after the 2020 Bullrun. Contrary to prior findings, results indicate that the diversification benefits of NFTs have increased over time, benefiting investors across the risk spectrum. Additionally, the study highlights the varying diversification potential of different NFT sectors. The findings challenge the notion that NFTs' diversification advantages have diminished, revealing the importance of considering NFTs as a diverse market rather than a singular asset type. This study paves the way for further investigation into the drivers of diversification benefits in different market conditions and NFT subcategories.

Keywords:

Non-Fungible Tokens, NFTs, Diversification, Bayes-Stein, Markowitz

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# Table of Contents:

# 1. Introduction

The rapid evolution of financial technologies and digital assets continue to reshape the global economic landscape. One of the most significant developments in recent years is the emergence of Non-Fungible Tokens (NFTs), unique digital assets that are stored on the blockchain which have emerged as a new asset class. The success of a variety of projects such as CryptoPunks, Decentraland, Sandbox and Axie Infinity paved the way for a unique, rapidly growing market with a global market capitalization of $443 billion by the first quarter of 2023 (Bao & Roubaud, 2022, Urquhart, 2021). This meteoric rise has paralleled an influx of institutional investment totalling approximately $16.1 billion in the past three years. Thus, financial research began to examine the role this new asset class has in the portfolio.

The low correlation of NFTs with traditional financial assets such as stock markets led to the view that NFTs can be an effective means of diversifying one's portfolio (Aharon and Demir 2022). This has attracted investors to diversify their portfolios with NFTs (Ko, Son, Lee, Jang & Lee, 2022). However, the COVID-19 pandemic saw an increase in positive co-movements between cryptocurrencies and stock indices, raising questions regarding the long-term diversification benefits of NFTs (Goodell & Goutte, 2021). The most recent studies have investigated this question through the use of 'blue chip' NFTs as proxies for the market. Blue Chip NFTs are considered the most liquid and prominent NFTs within the market, analogous to blue-chip stocks in the traditional financial markets (Ko et al. 2022). However, given the evolution of the NFT ecosystem has encapsulated various different industries such as finance and gaming, previous researchers fail to effectively represent the diverse range of assets and sectors within the NFT ecosystem. Furthermore, the short and highly turbulent history of this market has caused great challenges in estimating the inputs for portfolio models in the literature.

A review of the literature highlights the inherent empirical challenges within research into the portfolio characteristics of NFTs and cryptocurrencies. This is encapsulated within data limitations, estimation risk in the input parameters and ambiguity in correlations. José Almeida and Tiago Cruz Gonçalves (2023) provides a systematic literature review on the development of research into the portfolio diversification and hedging properties of cryptocurrency investments. The early literature found evidence that traditional portfolios with stocks, currencies and commodities benefited from increased diversification and returns (Ma, Ahmad, Liu & Wang, 2020). However, as first highlighted by Platanakis and Urquhart (2019), high estimation error in portfolios with cryptocurrencies was indicative of major difficulties within portfolio theory research. More recent studies have challenged the diversification benefits of these new assets, arguing for its deterioration in light of the increased, positive co-movements between cryptocurrencies and stock indices during the COVID-19 pandemic (Goodell & Goutte 2021). Despite this, a lack of data availability led Goodell and Goutte's study to solely focus on the diversification benefits of Bitcoin, Litecoin, Ethereum and Tether leading to problematic findings regarding the cryptocurrency sector as a whole. This was addressed in a study which examined the diversification benefits of 9 different cryptocurrency asset categories (CCACs) rather than individual assets. It was found that most cryptocurrency asset categories provide diversification benefits to investors both pre and post COVID-19, especially for less risk averse investors (Huang, Han, Newton, Platanakis, Stafylas & Sutcliffe, 2022). This study also provided a valuable extension to the literature through controlling for estimation risk in the input parameters which has been a prominent issue within the research into cryptocurrencies.

Research into the portfolio characteristics of NFTs is a much newer frontier within the literature. Hyungjin Ko and Others (2022) provided one of the first studies of portfolio analysis using traditional assets and NFTs. They examined the diversification effect of NFTs on portfolio investing in traditional assets by analyzing correlation, volatility transmission, co-movements and portfolio performances. This found diversification benefits of NFTs due to low correlations to traditional assets and improving risk-adjusted portfolio performances. However, estimation error primarily caused by extreme fluctuations in NFT return was a major issue in the study. Imran Yousaf and Yarovaya (2022) expanded upon this previous study through the addition of Decentralised Finance (DeFi) assets to their portfolio analysis and assessing the hedging properties of NFTs. Based on daily data from five NFTs, five defi assets and four other assets (gold, Bitcoin, WTI, and S&P 500), it was found that hedging risks of other assets through NFTs and defi assets was lower cost. However, the recency of the NFT market has led to limited data availability for these studies causing research to solely focus on a limited number of 'blue chip' projects which may indicate problematic findings. Furthermore, in light of the increased co-movements of crypto and equity markets, a study found that NFTs actually absorbed risk during the outbreak of COVID-19 (Aharon and Demir, 2022). However, they failed to consider the bull run within the NFT market wherein strong co-movement between this market and Ethereum was found, potentially negating these findings

In this study we aim to expand upon the literature surrounding NFT assets in the portfolio through examining the evolution of the diversification benefits of NFT sectors using estimation and portfolio techniques to control for estimation error. This is unique as we directly investigate the impact the 2020 bullrun had on NFT correlations and diversification benefits, whilst building indices to act as proxies for different sectors of the NFT market. This contributes to the literature through taking a broader approach of examining the diversification benefits of NFT categories rather than individual assets, whilst examining the evolution of these benefits into pre- and post-bull run. In contrast to previous studies such as Aharon and Demir (2022) and others, we construct indices representing different sectors of the NFT market rather than constructing portfolios with individual assets, highlighting a key advantage relative to previous studies. This introduces a novel dataset that, to the best of our knowledge, represents the most comprehensive collection of NFT price data ever assembled in academia. Furthermore, this study builds the existing literature by employing a rigorous methodology akin to that of Huang and others (2022) to control for estimation error which includes short selling constraints and the Bayes-Stein Model. This approach for controlling estimation error in input parameters has not been previously applied in research examining the portfolio characteristics of NFTs. Finally, this is the first study to examine the relationship between risk-averseness and NFT portfolio selection over two time periods of differing volatility; pre-bullrun and post-bullrun.

On the basis of prior research suggesting that the diversification benefits of NFTs has potentially diminished following the 2020-2021 bullrun given the increased co-movements of cryptocurrencies and equities, we formulate the hypothesis: the diversification advantages of incorporating NFTs into a portfolio consisting of stocks, bonds, commodities, and cryptocurrencies have decreased when comparing the periods before and after the 2020 bitcoin halving. We study our hypothesis through two investors with contrasting risk appetites. Wherein both seek to maximize their portfolio utility through optimizing for the risk-return tradeoff to accommodate their given risk-averseness. The hypothesis is tested for both investors for the both periods. We describe the two periods under scrutiny as "Pre and Post Bullrun" wherein the Post Bullrun period represents the 2020-2021 Bullrun onwards. The findings of this paper suggest that, contrary to previous findings, the diversification benefits of NFTs have increased rather than decreased during the 2020 bullrun. Additionally, NFT sectors were found to benefit investors across the risk spectrum in the Post Bullrun period.

The rest of the paper is as follows: Section 2 presents a description of our data set, and Section 3 presents our theory and methodology. Section 4 contains our empirical results, and our analysis. Section 5 has our discussion and Section 6, concludes the study and provides suggestions for future research.

## 2. Data

The data used in this study is collected from the official websites of Standard & Poor's (www.spglobal.com), Yahoo Finance's (www.finance.yahoo.com) and Coinmarketcap (www.coinmarketcap.com). The data consists of daily price data for the S&P 500 index, S&P Goldman Sachs Commodities Index (GSCI), S&P US Aggregate Bond Index and the S&P Cryptocurrency Broad Digital Market Index. Additionally, we used the US 10-Year Treasury from Yahoo Finance as a proxy for the risk-free rate. Lastly, we used NFT sector capitalisation-weighted indices which we constructed ourselves using the daily price data of 105 NFT tokens.

We chose to observe index instruments instead of individual asset instruments partly because diversification oriented investors tend to invest in indices rather than individual securities but indices also act as effective proxies for their given market. The S&P 500, for example, tracks the performance of the 500 largest companies in America and is commonly used as a proxy for the market portfolio. The GSCI serves as a measure for commodity performance over time. The US Aggregate Bond index is designed to measure the performance of U.S. dollar denominated investment-grade debt.

The Cryptocurrency Broad Digital Market Index follows the performance of cryptocurrency assets that meet minimum liquidity and market capitalisation requirements. We chose to use data from a cryptocurrency index rather than solely focusing on Bitcoin and Ethereum, as has been the approach of previous researchers (Ko et al., 2022). Whilst Bitcoin and Ethereum are the two most prominent cryptocurrencies in terms of market capitalization, numerous alternative cryptocurrencies, commonly referred to as "Altcoins" in the literature, have emerged in recent years (Ciaian, Rajcaniovar & Kancs, 2018). By observing the S&P Cryptocurrency Broad Digital Market Index, our study examines a wider array of cryptocurrencies, allowing for a more comprehensive understanding of the cryptocurrency landscape and its relationship to NFTs in the portfolio.

Whilst utilizing the US 10-Year Treasury yield as a risk-free rate proxy has its merits, such as being a widely recognized market standard and offering stability and comparability, it also has some disadvantages. These drawbacks include not being entirely risk-free, potential duration mismatches, and unaccounted currency risks. However, the benefits generally outweigh the limitations, making it a widely accepted and practical choice for a risk-free rate proxy in financial analysis (Hull, 2012).

NFT token data is hand collected from Coinmarketcap's NFT Token Index by Market Capitalization. Tokens can be seen as the underlying representation of ownership to a certain NFT asset, similar that of stocks for companies. We chose to only collect the data of NFT tokens with a market capitalization over $10 million. This allows us to focus on the most liquid NFT tokens with significant market presence. Finally, we categorize the NFT tokens into three subcategories. We obtain 105 NFT tokens in total, divided into six NFT categories. These categories are Finance (2), Social (6), Utility (3), Infrastructure (29), MetaGaming (46) and Marketplace (19). The specific NFT assets that form the basis of each category are detailed in Appendix A. The definitions for each NFT category, along with the constraints for categorization, can be found in Appendix B.

We chose to exclude the Finance, Social, and Utility categories from the data set, as these indices consisted of an insufficient number of assets, thereby undermining the primary objective of an index. The exclusion of these indices results in a more reliable and valid assessment of the Infrastructure, MetaGamingand Marketplace sectors. This decision not only ensures that the data set remains relevant and comprehensive but also mitigates the risk of drawing misleading conclusions from an inadequate representation of certain market segments. Our final NFT data set consists of 94 NFT tokens in total.

In evaluating the diversification benefits of NFTs, previous researchers have considered two distinct asset classes: the price fluctuations of NFT tokens and the price changes in secondary sales of the NFTs themselves. Our analysis focuses on the price dynamics of NFT tokens, which are traded on cryptocurrency exchanges and gathered from Coinmarketcap. We chose not to examine the secondary sales of NFTs, as this data is harder to obtain, lacks standardization compared to token prices and is characterized by low liquidity (Yousaf &

Yarovaya, 2022). By focusing on the token prices of NFT tokens, we gain a comprehensive understanding of the NFT market and the performance of its various subcategories.

Our dataset comprises daily data from June 1, 2017, to March 3, 2022, with a total of 1,440 observations for each series. The rationale behind selecting June 1 as the starting date is that the first NFT project, CryptoPunks, was launched in June 2017. All indices and prices are expressed in US dollars.

# 3. Theory and Methodology

In this section, we present key theoretical concepts and the methodology used in this paper. First, we establish the core hypothesis of the paper and offer a summary of the variable construction we utilize. Secondly, we detail the empirical strategy employed and the assessment evaluation metrics applied in this research. Finally, we discuss the robustness tests applied throughout this study.

## 3.1 Hypothesis Development

The aim of this research paper is to investigate the potential diversification benefits of integrating NFT sector indices into a diverse investment portfolio, encompassing assets such as stocks, bonds, commodities, and cryptocurrencies, within a mean-variance framework.

According to the Modern Portfolio Theory and the mean-variance framework, a perfectly diversified portfolio contains only systematic risk and by including various assets in a portfolio, investors can minimize the idiosyncratic risk associated with each asset (Abdelsalam, Barake & Kulaib, 2020). Accordingly, the efficacy of diversification typically hinges on the correlations among assets in a portfolio where higher correlations leads to reduced diversification.

As mentioned previously, the literature on NFTs as a diversification instrument has demonstrated their effectiveness in diversifying portfolios with traditional assets, owing to their low correlation with equities, bonds, and commodities (Ko et al., 2022). Moreover, prior research indicates that cryptocurrencies and NFTs share a higher correlation relative to traditional assets, as both are built on similar blockchain technology and are influenced by the overall sentiment and trends in the cryptocurrency market (Yousaf & Yarovaya, 2022). Nonetheless, NFTs continue to display significant diversification advantages in relation to cryptocurrencies (Alawadhi & Alshamali, 2022). Concurrently, researchers discovered that cryptocurrencies became more correlated with equities following the COVID-19 pandemic, coinciding with the 2020 crypto bull market (Huang et al. 2022). In accordance with the cryptomarket, NFTs also underwent a bull market during 2020 and 2021. Consequently, earlier research suggests that the diversification benefits of NFTs as an aggregate asset class have decreased during and following the bull market due to a potential increase in correlation. However, it remains uncertain whether this pattern holds for the entire NFT market or if specific NFT categories within the market have displayed varying correlation with alternative asset classes, thereby demonstrating varying diversification advantages. Taking these developments into account, the primary hypothesis of the study is proposed:

- The diversification advantages of incorporating NFTs into a portfolio consisting of stocks, bonds, commodities, and cryptocurrencies have decreased when comparing the periods before and after the 2020 bitcoin halving.

Prior research suggests that bitcoin halving events have been instrumental in triggering cryptocurrency bull markets (El Mahdy, 2021). The halvings are an inherent aspect of the Bitcoin protocol, designed to restrict the issuance of new bitcoins over time. The occurrence of bitcoin halvings has historically aligned with the inception of cryptocurrency bull runs, as the market anticipates a decrease in supply. This anticipation prompts the market to purchase bitcoin before the halving event, leading to a surge in prices. Although the 2020 cryptocurrency and NFT bull market didn't transpire overnight, we argue that the 2020 bitcoin halving event serves as an optimal cutoff point for our study.

As a result, we choose to characterize the pre-bull run phase as the time preceding the most recent bitcoin halving, which took place on May 11, 2020. We test our hypothesis by comparing the diversification benefits of incorporating NFT category indices to a portfolio of traditional assets and cryptocurrencies before and after the bitcoin halving in 2020, taking into account two types of investor profiles: one with an aggressive risk appetite and another with a more conservative risk appetite. We define the post-bull run phase as the period following the 2020 bitcoin halving event accordingly:

- Pre bull run: The period between June 1, 2017 and May 10, 2020.
- Post bull run: The period between May 11, 2020 and March 3, 2023.

## 3.2 Methodology

In this section, we present the empirical approach and methodology employed in this paper. To explore our hypothesis, we construct two distinct portfolios containing equities, bonds, commodities, cryptocurrencies and NFT category indices. The assets included in our portfolios are as follows:

- Equity Index: S&P 500.
- Bonds Index: S&P US Aggregate Bond Index.
- Commodity Index: S&P GSCI.
- Cryptocurrency Index: S&P Cryptocurrency Broad Digital Market Index.
- NFT Indices: Marketplace NFT Index, MetaGaming NFT Index & Infrastructure NFT Index.

Based on these instruments, we construct two distinct portfolios:

- **Core Portfolio:** S&P 500, S&P US Aggregate Bond Index, S&P GSCI, S&P Cryptocurrency Broad Digital Market Index, Marketplace NFT Index, Infrastructure NFT Index and MetaGaming NFT Index.
- **Benchmark Portfolio:** S&P 500, Marketplace NFT Index, Infrastructure NFT Index and MetaGaming NFT Index.

These portfolios are created for the same type of investor which follows a Markowitz mean-variance approach, looking to maximize their expected utility through optimizing for the trade-off between expected return and volatility in their portfolio returns. The main objective of these distinct portfolios is to investigate the diversification effect of NFTs in relation to equities as well as a broader set of asset selections within a portfolio.

### 3.2.1 Bayes-Stein Model

We employ the Bayes-Stein model to estimate the input parameters for the asset selection in our portfolio. This model is designed to address estimation risk which is a prominent issue within the literature of portfolio selection involving cryptocurrencies and NFTs (Platanakis and Urquhart, 2019). This has also been used in previous research to address estimation risk and produce better out-of-sample portfolio performance (Huang et al. 2022). The logic behind this model is that asset allocation is highly sensitive to its input parameter, specifically expected returns. As a result, the expected returns of the assets in this study are shrunk towards their global mean, addressing extreme outliers by diminishing their significance in expected return computations. This is done by finding the adjusted Bayes-Stein vector of mean returns $\mu_{BS}$ which can be used as an estimate for the expected returns input of the portfolio selection model.

To finds $\mu_{BS}$, we first compute the initial mean returns vector $\mu_{ML}$ and the global mean return $\mu_g$. The shrinkage factor $g_{mv}$ is used to balance the weighted sum of these two components. First we compute the initial mean returns vector $\mu_{ML}$ for each asset:

$$\mu_{ML} = R * 252$$

where $R$ is the matrix of daily excess returns for all assets and *252* is the number of trading days in a year to annualize the mean returns. Secondly, we compute the global mean return $\mu_g$ for all assets:

$$\mu_g = mean(\mu_{ML})$$

Thirdly, we compute the covariance matrix (Σ) for the excess returns and the inverse covariance matrix:

$$\Sigma \ = \ cov(R) \ * \ 252$$

$$\Sigma^{-1} \ = \ inv(\Sigma)$$

Then, we calculate the global minimum variance portfolio weights $w_{gmv}$:

$$w_{gmv} \ = \frac{\Sigma^\wedge(-1)}{1' * \Sigma^\wedge(-1) *}$$

where 1 is a column vector of ones with the same length as the number of assets. Finally, compute the adjusted Bayes-Stein mean returns vector $\mu_{BS}$ using the shrinkage factor $g_{mv}$:

$$\mu_{BS} \ = \ g_{mv} * w_{gmv} + \ (1 \ - \ g_{mv}) \ * \ \mu_{ML}$$

where $g_{mv}$ is the chosen shrinkage factor, ranging from 0 to 1. This is then used as estimates to input into our portfolio optimisation function.

### 3.2.2 Markowitz Portfolio Optimization

We employ a Markowitz mean-variance portfolio selection model for our portfolio optimization. This model aims to maximize an investor's utility through optimizing for the expected returns and risk tradeoff to achieve the highest return for a given risk level or the lowest risk for a desired return. The optimization problem can be formulated as:

$$max\, U \ = \ x^T \mu_{BS} - \ \frac{\lambda}{2} x^T H_t^{BS} x_{st}$$

$$\text{subject to: } \sum N_i = \ 1 \ \ x_i \ = \ 1, \ \ x_i \geq 0 \ \forall \ i \in \{1, 2, ..., N\},$$

where: λ is the risk aversion coefficient which represents the investor's aversion to risk, $x^T$ is the N×1 vector of asset weights, $\mu_{BS}$ is the vector of expected returns, $H_t^{BS}$ is the covariance matrix of asset returns and $x_{st}$ is the $N$×1 vector of asset weights at the solution. The constraints ensure that the portfolio weights sum up to 1 and that there is a non-negativity constraint, meaning no short sales are allowed. We also chose to analyze the portfolios in a setting where short selling is allowed (see Appendix C). Additionally, the risk aversion coefficient allows for a further analysis on the diversification benefits of NFT in relation to the investors risk profile.

## 3.3 Evaluation Metrics

In this section, we outline our evaluation metrics for assessing the constructed portfolios. The first two metrics, Sharpe ratio and portfolio standard deviation, are employed since investors within the mean-variance framework typically aim to maximize risk-adjusted portfolio returns and view standard deviation as a risk measure. Furthermore, we examine the kurtosis and skewness of the portfolios.

### 3.3.1 Standard Deviation

Within the mean-variance framework, investors assess volatility using the standard deviation. In this study, we evaluate a portfolio's volatility by calculating the sample standard deviation, defined as follows:

$$\sigma_p = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(r_i - \bar{r})^2}$$

Here, N represents the sample size, $r_i$ is the portfolio return at time i, and $\bar{r}$ denotes the mean return of the portfolio. In order to interpret this metric more effectively, we annualise the portfolio standard deviation:

$$\sigma_a = \sqrt{252} \times \sigma_p$$

### 3.3.2 Sharpe Ratio

The Sharpe ratio serves as a metric for evaluating a portfolio's risk-adjusted return. It quantifies the risk premium a portfolio earns relative to the risk taken. To calculate the Sharpe Ratio, we take the average excess return and divide it by the portfolio standard deviation:

$$\text{Sharpe Ratio} = \frac{(r_p - r_f)}{\sigma_p}$$

Where $r_p$ is the portfolio return, $r_f$ represents the risk-free rate and $\sigma_p$ the standard deviation of the portfolio.

### 3.3.3 Kurtosis

Kurtosis quantifies a dataset's distribution shape, assessing its "peakedness" or "flatness" compared to a normal distribution. It's useful in evaluating portfolio risk as it indicates tail risk, which represents the probability of extreme events affecting portfolio performance. The kurtosis is measured by the following:

$$Kurtosis = E\left[\left(\frac{X-\mu}{\sigma}\right)^4\right] - 3$$

Where $E$ indicates the expected value of the expression inside the brackets, $X$ represents the values of the variable, μ is the mean of the values and σ is the standard deviation of the values and 3 is subtracted to provide excess kurtosis, which measures kurtosis relative to a normal distribution.

### 3.3.4 Skewness

Skewness measures the degree of asymmetry in a distribution. Positive skewness implies a longer right tail, whereas negative skewness signifies a longer left tail in the distribution. It measures portfolio risk since it can help identify whether assets are more likely to experience non-normal returns, which could signal higher risk due to unforeseen losses or gains. The formula for skewness is:

$$Skewness = E\left[\left(\frac{X-\mu}{\sigma}\right)^3\right]$$

Where $E$ indicates the expected value of the expression inside the brackets, $X$ represents the values of the variable, μ is the mean of the values and σ is the standard deviation of the values.

## 3.4 Variable Construction

This section describes the variable construction and definitions used in this study. First of all, the portfolio construction and evaluation metrics were conducted using the daily asset returns. The daily return for asset i was computed by:

$$r_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$$

where $P_{i,t}$ represents the price of asset $i$ at day $t$.

The foundation of our empirical methodology is an analysis of NFT sectors rather than individual assets. Thus, we constructed Capitalization-Weighted Indices (CWI) to represent each sector. This index methodology entails that each asset in the given index is weighted relative to its total market capitalisation. Based upon this, the daily return for each index *a* was computed by:

$$r_{a,t} = \sum_{i} w_{i,t} \cdot y_{i.t}$$

$$\text{Where } w_{i,t} = \frac{Market\ cap\ of\ asset\ i\ at\ t}{Total\ market\ cap\ a\ t}$$

Where $w_{i,t}$ represents the weighting of asset *i* at day *t* in the index given its market cap at that day relative to the total of the sector at that given day. And $y_{i.t}$ is the return of asset *i* at day *t*.

As mentioned previously, 10 year Treasury bills were used as the risk-free rate in this study. Wherein the daily yield was the risk-free rate for the corresponding asset return. In order to evaluate the portfolio performance within the pre- and post- bullrun time period, the arithmetic average of the daily risk-free rate in the corresponding time period was used. The risk-free rate for period i is therefore computed as such:

$$rf = \frac{1}{N}\Sigma_{i=1}^{N} r_i$$

Where *N* is the number of observations, $r_i$ is the daily risk free rate at day *i*, and *rf* is the mean of the daily risk free rates.

As a result, the risk-free rate differs for each period and represents the economic climate of that time. The following rates were computed for the pre and post- bullrun time period:

| | Risk-free rate |
|---|---|
| **Pre Bullrun** | 2,31% |
| **Post Bullrun** | 1,92% |

## 3.5 Robustness Check: Rolling Window Out-of-Sample Test

In this section, we discuss the rolling window out-of-sample test utilized in our study to assess the robustness of our results. Rolling window out-of-sample analysis is a widely recognized method for assessing the robustness of portfolio optimization strategies, and has been employed by various researchers, including Chekhlov, Uryasev & Zabarankin (2000) as well as Huang et al. (2022).

We conduct a rolling window out-of-sample test to evaluate the performance of our portfolios during two different periods, pre-bull run, and post-bull run. The rolling window out-of-sample test allows us to estimate how the portfolio would have performed if the weights were applied to new data that was not used in the initial optimization.

We introduce a new portfolio, the Traditional Portfolio, alongside the Core Portfolio, effectively replacing the Benchmark Portfolio for this specific test. The assets in the Traditional Portfolio are identical to those in the Core Portfolio, excluding NFT indices. The rationale behind the Traditional Portfolio is to compare its performance with that of portfolios containing NFT indices, in order to assess whether the inclusion of NFTs provides additional diversification benefits within an already diversified portfolio.

To implement the rolling window out-of-sample test, we define a function in R Studio that takes two inputs: the asset returns data for the given period and the 252-day window length. The function first splits the data into in-sample and out-of-sample portions. For each day in the out-of-sample period, the function firstly calculates the optimal portfolio weights based on the in-sample data using Markowitz Portfolio Optimization. Secondly, the function applies these calculated weights to the next day's data in the out-of-sample period to compute the out-of-sample returns. The rolling window then moves forward one day, recalculating the weights based on the new in-sample data and repeating the process. This implies that weights are updated based on the most recent in-sample data, enhancing the robustness of the out-of-sample test. The formula for the out-of-sample return on day i is as follows:

$$R_i = \Sigma (w_j * r_j)$$

where $R_i$ is the out-of-sample return for day $i$, $w_j$ represents the weight of asset $j$ in the portfolio and $r_j$ is the return of asset $j$ on day $i$.

In-sample data comprises 33% of the entire dataset, corresponding to the 252-day window, which is used for portfolio optimization. The rest of the data is reserved for the out-of-sample period, during which the performance of the optimized portfolio is evaluated.

Finally, we determine the portfolios' performance by calculating mean return, standard deviation, skewness, kurtosis, and Sharpe ratio.

# 4. Results

In this section the empirical findings will be presented along with a critical analysis and evaluation of the results and its economic insights. The discussion will also take into account the findings of previous literature to further understand the wider implications of the results. This section will first present and discuss the descriptive statistics followed by a presentation of the main results. Lastly, the results from the robustness analysis are discussed.

## 4.1 Descriptive Statistics

### 4.1.1 Summary Statistics

Table 1 exhibits the development of the performance metrics for each asset for the periods examined. This is primarily in relation to each asset's risk and return profile. In regards to expected returns, it can be seen that all NFT-related assets carried the highest expected returns throughout all periods. Further, it can be seen that the performance evolution of these asset types were quite ambiguous. The performance of the NFT infrastructure and marketplace indices decreased into the post-bullrun period whereas the metagaming index increased significantly in return performance. This major increase in performance paralleled that of commodities that shifted from the lowest performing asset to amongst the highest, possibly due to the significant rise in inflation and energy prices. In contrast, bonds saw a decrease in negative returns which can be attributed to increases in interest rates amongst central banks in the Post-Bull Run period.

Comparing the standard deviation of each asset class between the pre-bull run and post-bull run periods can provide insight into the evolution of volatility. Before the bull run, NFT Metagaming had the highest SD (165,7446%), followed by cryptocurrency (84,5797%) and NFT infrastructure (125,1121%). These asset classes are typically considered to be more volatile, which the high SDs reflect. In contrast, bonds had by far the lowest SD at 3,2937%, followed by the S&P 500 with an SD of 21,9966%. After the bull run, the asset classes' SDs showed mixed results. For example, the SDs for the S&P 500 and bonds decreased whilst they increased commodities and cryptocurrency. Meanwhile, the SDs for NFT infrastructure and NFT meta-gaming remained relatively high, indicating continued high volatility in these asset classes. Overall, the development of the standard deviation for each asset class suggests that the bull run had varying impacts on asset class volatility. While some asset classes experienced a reduction in volatility, others experienced an increase, and some remained volatile throughout.

The Sharpe ratio of the assets reflects the development of risk and return over the two periods. Before the bull run, all NFT-based assets had the highest sharpe ratios, indicating that these assets had higher risk-adjusted returns compared to the other asset classes. In contrast, the Commodity index had negative Sharpe ratios highlighting that the risk-adjusted return for the portfolio is lower than the risk-free rate during this period. This could also be explained by heightened market volatility as the period includes significant market events, such as the

US-China trade war and the early stages of the COVID-19 pandemic, which could have contributed to the negative Sharpe ratio. After the bull run, the Sharpe ratios of commodities, and NFT Metagaming increased significantly to become the two highest amongst the assets. Meanwhile the Sharpe ratios for bonds, NFT infrastructure halved. This suggests that the commodities saw a sharp spike in performance which could be attributed to the macro environment of high inflationary pressure on these asset types.

Finally, skewness and kurtosis statistics display some fascinating insights. Pre Bullrun, solely the NFT-related assets displayed a positive skew. Furthermore, all instruments outside of NFTInfra and Cryptocurrency exhibited extremely high kurtosis, indicating that the distributions of return were peaked and had fat tails compared to a normal distribution. This suggests that most NFT assets had a higher likelihood of extreme positive returns whereas the S&P 500, Bond and Commodity assets exhibited high likelihoods of extreme negative returns. The Post-Bull run period, however, shows a major decrease in the kurtosis for all assets, outside of crypto which remained analogous, with little changes to the skewness. This indicates a reduction in the potential for extreme returns, suggesting the assets may have become less risky. This is significant for NFTs as it highlights a potential stagnation in its tail risk.

**Table 1**

Summary Statistics pre- and post- Bullrun for each asset based upon annualized daily returns.

| **Pre Bull Run** | **Expected Returns** | **Std. Dev** | **Sharpe Ratio** | **Skewness** | **Kurtosis** | **Observations** |
|---|---|---|---|---|---|---|
| S&P500_Returns | 8,7978% | 21,9966% | 0,3135 | −0,6182 | 22,2557 | 739 |
| Commodity_Returns | −7,3963% | 23,7614% | -0,3913 | −1,2594 | 16,8061 | 739 |
| Bond_Returns | 4,5114% | 3,2937% | 0,7923 | −0,9036 | 13,0895 | 739 |
| Crypto_Returns | 65,6973% | 84,5797% | 0,7543 | −0,1657 | 5,6325 | 739 |
| NFTInfra_Returns | 119,9336% | 125,1121% | 0,9434 | 0,0761 | 7,0313 | 739 |
| NFTMetaGaming_Returns | 145,2018% | 165,7446% | 0,8646 | 6,1432 | 80,2548 | 739 |
| NFTMarketplace_Returns | 156,0388% | 148,9446% | 1,03486 | 2,6981 | 27,4660 | 739 |
| **Post Bull Run** | **Expected Returns** | **Std. Dev** | **Sharpe Ratio** | **Skewness** | **Kurtosis** | **Observations** |
| S&P500_Returns | 13,78080% | 19,2418% | 0,6174 | −0,3678 | 4,7743 | 700 |
| Commodity_Returns | 29,5596% | 24,4854% | 1,1296 | −0,6943 | 6,5538 | 700 |
| Bond_Returns | −3,5388% | 4,7068% | -1,1559 | 0,0564 | 5,9637 | 700 |
| Crypto_Returns | 62,0100% | 68,7666% | 0,8741 | −0,3308 | 5,4418 | 700 |
| NFTInfra_Returns | 40,7664% | 96,3746% | 0,4033 | 0,0601 | 6,9915 | 700 |
| NFTMetaGaming_Returns | 254,9844% | 112,3844% | 2,2519 | 0,8267 | 8,4333 | 700 |
| NFTMarketplace_Returns | 132,0372% | 104,7268% | 1,2426 | 0,1066 | 7,3696 | 700 |

### 4.1.2 Correlation

Figure 1 represents the 6-month rolling correlation for each instrument with the S&P 500. In general, one can see that the 2020 COVID-19 crash and subsequent bull run had a significant effect on increasing the correlation of assets to equities. Particularly cryptocurrencies and NFTs.

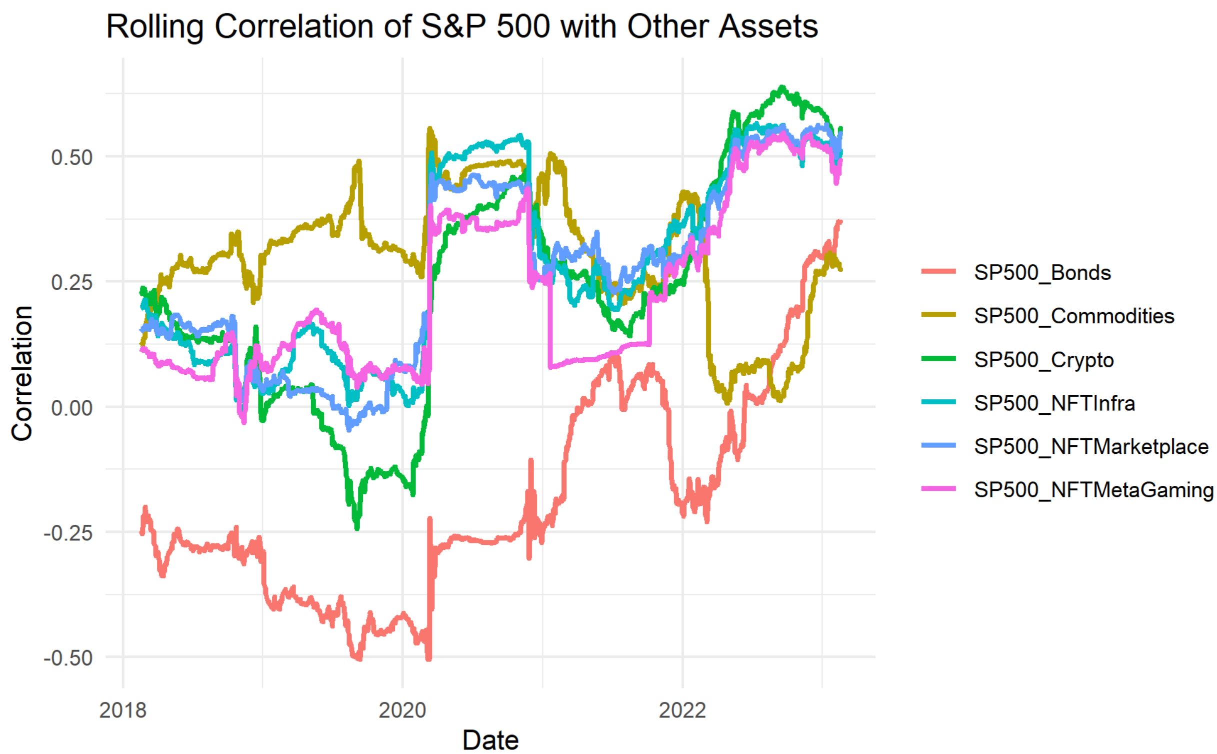
Initially, bonds exhibited a negative correlation with the S&P 500. This trend persisted until the stock market turnaround in March 2020. At this point, bond correlation dramatically surged from -0,5 to -0,25 within a few days. Bond correlation with the stock market has generally continued to increase over time thereafter, reaching positive levels as of the middle of 2022. Suggesting a decrease in the effectiveness of using them as a hedge against equity.

Examining the correlation between cryptocurrencies and the S&P 500, it is evident that the COVID-19 market crash and subsequent bull run in 2020, caused an increase in the correlation between the asset class and equities. After the crash, the correlation experienced a sharp increase, moving from -0,2 to 0,5 throughout 2020. Highlighting an extreme shift in the correlation between cryptocurrencies and equities.

All NFT indices display similar patterns to cryptocurrencies when observing their correlation with the S&P 500 index over time. Individually, the NFT indices appear to perform very similarly to one another, with the NFT MetaGaming Index exhibiting more extreme drops in correlation during the end of 2020 and 2021 period. This could be attributed to the

Overall, it is clear that the general trend indicates that correlation has increased over time, with the March 2020 COVID crash collectively influencing the assets' correlation with the S&P 500 positively, increasing their respective correlations with the stock market. Undoubtedly, the 2020 bull market and the Bitcoin halving played significant roles in the increased correlation of crypto and NFT indices, from around -0,12 and approximately 0,1 to 0,55 and 0,5 respectively, when comparing March 2020 to early 2023. Thus arguably diminishing the potential diversification benefits of adding NFT assets to the portfolio.

**Figure 1**
This figure illustrates the 6-month rolling correlation of assets with the S&P 500 over the examined time period. The assets include the S&P Cryptocurrency Broad Digital Market Index (represented by a light green line), the S&P GSCI Commodity Index (represented by a yellow line), the S&P US Aggregate Bond Index (represented by a red line), the NFT MetaGaming Index (represented by a purple line), the NFT Marketplace Index (represented by a blue line), and finally, the NFT Infrastructure Index (represented by a green line).




### 4.1.3 Efficient Frontiers

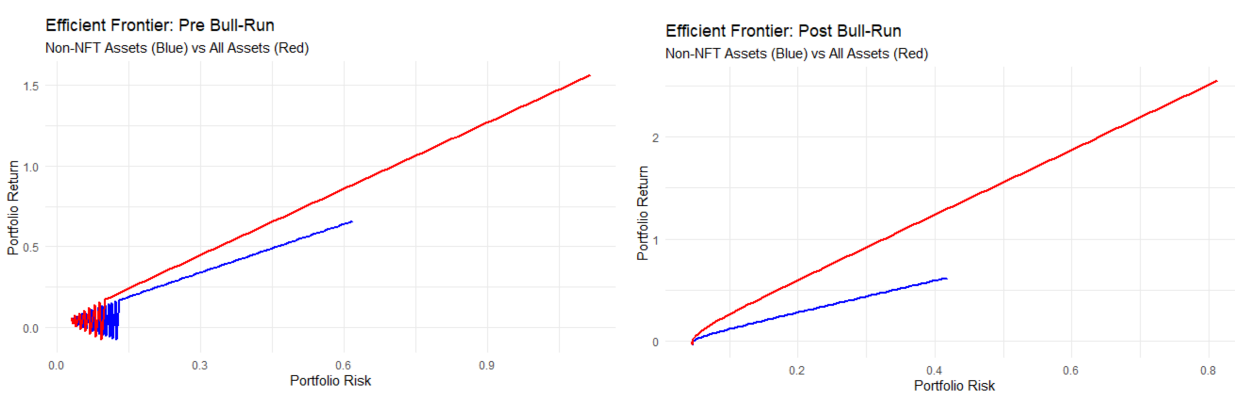
Figure 2 displays the efficient frontier for two distinct bundles of assets during the Pre and Post Bullrun period respectively. The efficient frontiers plot the highest expected return for a given level of risk possible for a portfolio consisting of each bundle of assets. The weightings allocated to each asset on the efficient frontier will vary based upon level of risk.

For the Pre-Bullrun period, both frontiers start at the same place and exhibit volatility in regards to the most efficient portfolio at a given level of risk. This could imply a number of things. First, small changes in weights have large effects upon the portfolio's risk and return. Wherein, the risk profiles of the assets in both vary significantly and are potentially highly correlated causing the efficient frontier to appear volatile. Since this volatility is more significant in the NFT bundle, it may suggest a lack of diversification benefits for risk-averse investors as their portfolio performance may become more unpredictable with the addition of NFT assets. Another possible reason for this abnormality in the efficient frontier may be errors in the estimation of returns and covariances. Given the high estimation risk found in NFT assets and the bundles containing a minimal number of assets, this holds strong explanatory power and further highlights the necessity to control estimation risks later in our study.

The efficient frontiers in the Post-Bullrun period exhibit much smoother slopes compared to the previous period. Typically this would signify a decrease in the correlation amongst the assets. However, as seen in Figure 1, this likely is not the case as correlations have increased. Thus implying a shift in asset behaviors and the estimation of the input parameters where the assets for each bundle behaved in a more stable and predictable manner in this period allowing for more accurate estimations for the returns and covariances. The summary statistics support this interpretation as one can see a significant decrease in the risk metrics for the majority of assets in the Post Bullrun period.

The efficient frontiers for both periods share a number of characteristics which imply that NFT assets offer diversification benefits. First, the portfolios where NFT assets are included outperform in both periods, excluding the lower levels of risk in the Pre-Bullrun period. This implies that an investor, generally regardless of their risk aversion, would benefit from the inclusion of NFTs in their portfolio. Despite this, it can be seen that the addition of NFTs to portfolios benefit risk-seeking investors to a greater extent. Through addition of NFT assets, the efficient frontier slopes upward and extends further along the risk axis as investors are able to take increasing risk. These results suggest that the hypothesis is incorrect as the diversification benefits for investors seem to actually become more established in the following period. Offering benefits to investors of all risk attitudes, albeit primarily risk-tolerant ones.

**Figure 2**
Efficient frontiers for the bundle of assets including NFTs (Red Line) and excluding NFTs (Blue Line), Pre and Post bull run.




## 4.2 Portfolio Weighting & Performance

In this section, we present the empirical results of our portfolio analysis using the Bayes-Stein model. We evaluate the risk-adjusted performance of our Core and Benchmark portfolios before and after a bull run for two levels of investor risk aversion ($\lambda$ = 1 and 5) to represent the most aggressive and conservative investor risk appetites. We conduct tests on five levels of risk aversion in total (including λ = 2, 3, and 4, which are displayed in Appendix D), and choose to focus our evaluation on the investors with the highest and lowest risk appetites. The evaluation is based on five metrics: expected return, standard deviation, Sharpe ratio, skewness, and kurtosis.

The subsequent subsections, along with Tables 2 to 3, detail the findings for the portfolio performance and allocations with λ values of 1 and 5 which represent aggressive and conservative investors respectively. Lastly, we explore the results when short selling is permitted.

### 4.2.1 The Aggressive Investor

This section presents the results for the portfolio allocations and performance of a highly aggressive investor, shown in Table 2. The results for each time period are presented and discussed in chronological order.

**Table 2**

Displayed in this table are the portfolio weightings of respective asset along with the annualized Expected Return, Sharpe Ratio, Standard Deviation, Skewness, Kurtosis, and Risk-free rate pertaining to the mean-variance portfolios with a risk aversion level of λ=1. The data encompasses both the core and benchmark portfolios during the respective timeframes of pre and post bull run periods.

**Bayes-Stein Outputs, for aggressive investor ( $\lambda = 1$ )**

| | **Pre-Bull Run** | | **Post-Bull Run** | |
|---|---|---|---|---|
| | **Core Portfolio** | **Benchmark Portfolio** | **Core Portfolio** | **Benchmark Portfolio** |
| S&P500_Returns | 0,0000% | 86,4472% | 0,0000% | 44,1988% |
| Commodity_Returns | 0,0000% | - | 0,0000% | - |
| Bond_Returns | 83,3271% | - | 34,8945% | - |
| Crypto_Returns | 0,0000% | - | 0,0000% | - |
| NFTInfra_Returns | 0,0000% | 0,0000% | 0,0000% | 0,0000% |
| NFTMetaGaming_Returns | 5,4575% | 4,1388% | 65,1056% | 55,8012% |
| NFTMarketplace_Returns | 11,2515% | 9,4139% | 0,0000% | 0,0000% |
| Expected Return | 29,2691% | 28,3045% | 164,7740% | 148,3753% |
| Sharpe Ratio | 1,2669 | 0,9446 | 2,2257 | 2,2196 |
| Standard Deviation | 21,6012% | 27,9505% | 73,1757% | 65,9896% |
| Skewness | 1,4155 | -0,2664 | 0,8198 | 0,6583 |
| Kurtosis | 13,4202 | 13,2039 | 5,4136 | 4,6167 |
| Risk-free rate | 2,3100% | 2,3100% | 1,9200% | 1,9200% |

#### 4.2.1.1 Pre-Bull Run

Table 2 illustrates the strategy of an aggressive investor with the highest relative risk tolerance, aiming to maximize their risk-adjusted return when short selling is prohibited. Bonds, despite offering lower returns, constitute the foundation of the Core Portfolio with an 83,3271% allocation. The findings suggest that the investor would opt to not include the S&P 500, Crypto Index or NFT Infra in the Core Portfolio. Due to its negative Sharpe ratio, commodities are also naturally excluded. The NFT MetaGaming and NFT Marketplace receive allocations of 5,4575% and 11,2515% respectively. The considerable allocation to bonds, in spite of the much higher Sharpe ratios among NFT assets, can be attributed to the substantial risk associated with those assets. Consequently, the investor leverages the diversification effect to minimize volatility while preserving a high return rate due to the elevated returns. This approach results in a high Sharpe ratio of 1,2669 and an expected return of 29,2691%. The returns display positive skewness and with fat tails suggesting that the portfolio is likely to experience extreme movements. It also suggests a high number of positive outliers implying that the portfolio returns are generally below the mean.

In contrast, the Benchmark Portfolio allocation heavily leans towards the S&P 500 assets, with an allocation of 86,4472%. The NFT Infrastructure Index remains excluded, while the NFT MetaGaming and NFT Marketplace receive allocations of 4,1388% and 9,4139% respectively. By excluding conservative assets such as commodities and bonds, the investor is unable to leverage the diversification effect in the same manner by investing in assets with low volatility. As a result, capital is naturally allocated to equities instead. The expected return of the Benchmark Portfolio is 28,3045%, slightly lower than the Core Portfolio, while the standard deviation is higher at 27,9505%, indicating that the assets included in the portfolio are riskier. Consequently, the Sharpe ratio for the Benchmark Portfolio is lower, representing diminished risk-adjusted returns for an aggressive investor seeking to maximize risk-adjusted returns. Skewness is negative, indicating a higher likelihood of returns below the mean.

The results suggest that incorporating NFTs within a portfolio of traditional assets offers diversification benefits. Both the Core and Benchmark Portfolios exhibit high kurtosis, indicating a higher probability of extreme events or outliers. However, the Core Portfolio experiences positive skewness, while the Benchmark Portfolio displays negative skewness, suggesting that the latter is more prone to larger losses during market downturns. The Core Portfolio's significant allocation to bonds, despite the higher Sharpe ratios of NFT assets, demonstrates the effective utilization of diversification effects to minimize volatility. This suggests that incorporating NFT assets can enhance portfolio diversification and reduce overall risk. In contrast, the exclusion of conservative assets like bonds and commodities in the Benchmark Portfolio implies that the aggressive investor cannot leverage diversification effects in the same way, resulting in a higher standard deviation and a lower Sharpe ratio in the Pre-Bull Run period.

#### 4.2.1.2 Post-Bull Run

The corresponding results from the Post-Bull Run period highlight a shift within the market and thus the portfolio weightings and their outputs. Specifically, as seen in the Summary Statistics, commodities had a significant increase in its performance, going from a negative Sharpe ratio to the third highest amongst the assets. As a result, the portfolio allocation within the core portfolio only held commodities and NFT MetaGaming with allocations of 34,8945% and 65,1056% respectively. The sudden shift away from the heavy allocation into bonds can be attributed to its shift towards negative returns causing its benefits towards improving risk-adjusted returns to diminish. Overall, the Core Portfolio had an extremely strong performance with a Sharpe ratio of 2,2257 and expected return of 164,7740%.

The Benchmark Portfolio exhibited a similar shift in allocations during the same period, with 55,8012% of capital allocated to NFT MetaGaming, while the remaining portion was allocated to the S&P 500. The lower volatility of the Benchmark Portfolio compared to the Core Portfolio, while still maintaining high returns, demonstrates that NFTs can offer diversification benefits without adding excessive risk to the portfolio. Both skewness and kurtosis experienced declines in the Benchmark Portfolio.

For both the Core and the Benchmark Portfolio, the standard deviation increased compared to the pre-bull run period, indicating higher volatility and risk. Skewness is positive, suggesting returns are more likely to be above the mean. The kurtosis decreased, implying a more uniform distribution of returns and a more stable investment environment. The results suggest that NFTs, particularly NFT MetaGaming, can provide diversification benefits to a portfolio, especially during periods of market shifts. In the post-bull run period, commodities experienced a significant increase in performance and were included in the Core Portfolio along with NFT MetaGaming. This shows that the inclusion of NFTs, specifically NFT MetaGaming, can enhance the diversification of a portfolio by providing exposure to different sectors and reducing risk. The shift away from bonds, which had negative returns, also suggests that diversification benefits can be achieved through dynamic asset allocation.

#### 4.2.1.3 Relaxing the Short Selling Constraint

Table C.1 in the Appendix presents the Bayes-Stein results for an aggressive investor with no short selling constraints. During the Pre-Bull Run period, NFT indices display a balanced positive allocation, making up about 50% of the portfolio. However, in the Post-Bull Run period, NFT MetaGaming receives a larger share in both the Core and Benchmark Portfolios, while NFT Marketplace increases. Conversely, NFT Infrastructure exhibits negative weights in both portfolios due to its comparative underperformance, as shown in the summary statistics.

In both periods, Bonds reach a maximum positive allocation of 300,0000% in the Core Portfolio, reflecting their attractive low standard deviation and consistent returns. Commodities shift from being shorted in the Pre-Bull Run period to having a positive allocation in the

Post-Bull Run period, while the S&P 500 allocation turns from -4,7892% to fully negative leverage in the Post-Bull Run period.

The Sharpe Ratio is generally lower for both the Core and Benchmark portfolios in the Pre-Bull Run period when short selling is allowed, compared to when it is not allowed. Conversely, the Sharpe Ratio is higher for all portfolios in the Post-Bull Run period with short selling allowed, suggesting that investors can more effectively capture returns by hedging their positions during volatile market conditions, as observed in the Post-Bull Run period.

### 4.2.2 The Conservative Investor

This section presents the results for the portfolio allocations and performance of a highly conservative investor, shown in Table 3. The results for each time period are presented and discussed in chronological order.

**Table 3**

Displayed in this table are the portfolio weightings of respective asset along with the annualized Expected Return, Sharpe Ratio, Standard Deviation, Skewness, Kurtosis, and Risk-free rate pertaining to the mean-variance portfolios with a risk aversion level of λ=5. The data encompasses both the core and benchmark portfolios during the respective timeframes of pre and post bull run periods.

**Bayes-Stein Outputs, for the conservative investor ($\lambda = 5$)**

| | **Pre-Bull Run** | | **Post-Bull Run** | |
|---|---|---|---|---|
| | **Core Portfolio** | **Benchmark Portfolio** | **Core Portfolio** | **Benchmark Portfolio** |
| S&P500_Returns | 0,0000% | 97,3475% | 0,0000% | 91,1765% |
| Commodity_Returns | 0,0000% | - | 0,0000% | - |
| Bond_Returns | 96,6566% | - | 86,8161% | - |
| Crypto_Returns | 0,0000% | - | 0,0000% | - |
| NFTInfra_Returns | 0,0000% | 0,0000% | 0,0000% | 0,0000% |
| NFTMetaGaming_Returns | 1,0783% | 0,8138% | 13,5457% | 8,8235% |
| NFTMarketplace_Returns | 2,2991% | 1,8388% | 0,0000% | 0,0000% |
| Expected Return | 9,5124% | 12,6152% | 30,5445% | 35,0633% |
| Sharpe Ratio | 1,4114 | 0,4811 | 1,8668 | 1,4540 |
| Standard Deviation | 5,3919% | 22,2651% | 15,3429% | 22,8065% |
| Skewness | 0,2688 | -0,6759 | 0,7267 | -0,3333 |
| Kurtosis | 8,8052 | 19,3820 | 4,5762 | 1,6373 |
| Risk-free rate | 2,3100% | 2,3100% | 1,9200% | 1,9200% |

### 4.2.2.1 Pre-Bull Run

The summary statistics table revealed that NFT sectors experienced higher expected returns while also displaying higher volatility compared to traditional assets. Consistent with these observations, the conservative investor naturally allocates heavily towards assets with lower standard deviations during the Pre-Bull Run period in order to minimize their portfolio volatility. However, despite the conservatism, the investor utilizes extreme returns of NFT to optimize their sharpe ratio wherein a small allocation to these assets allows for a significant increase in expected returns. This suggests that NFT assets may provide diversification benefits to highly risk averse investors due to the positively skewed, leptokurtic distributions of returns allowing for small allocations to significantly increase portfolio expected returns.

In the core portfolio, 96,6566% was allocated to bonds, 2,2991% to NFT Marketplace and the remaining 1,0783% was allocated to NFT Metagaming. Despite the large allocation to bonds which exhibited the second lowest return amongst the bundle assets in this period, the portfolio was still able to achieve a high return of 9,5124% and Sharpe ratio of 1,4114. Indicating that a small level of exposure allows investors to reap the benefits of high returns without significantly increasing their risk exposure.

The benchmark portfolio highlights the need for risk-averse investors to hedge against the high risk present in NFT assets. Where 97,3475% was allocated to the S&P 500 whilst the rest was invested into MetaGaming and Marketplace. However, due to the exclusion of typically safer assets, the investor was unable to hedge against the risk of NFT assets leading to a significantly less efficient Sharpe ratio to the of the core portfolio of 0,4811. The inability to hedge is further highlighted by the relatively higher standard deviation of the portfolio. In contrast, the benchmark portfolio delivered a higher return of 12,6152% compared to the Core Portfolio. However, the Sharpe Ratio of the benchmark portfolio was lower, owing to its higher standard deviation.

The findings suggest that NFT assets offer diversification benefits to conservative investors through offering exposure to volatile returns. However, these benefits can generally only be leveraged in the presence of effective hedges.

### 4.2.2.2 Post-Bull Run

The results for the conservative investor under the Post-Bullrun period further highlights potentially positive diversification effects for NFTs for risk-averse investors. Wherein the Investor further shifts their portfolio allocation towards NFT assets.

The Core Portfolio in this period continues to have a substantial allocation of 86,8161% in bonds but has moved almost 10% of its allocation to NFT Metagaming. The rest of the portfolio is allocated towards this asset, totaling at 13,5457%. The decreased overall diversification may be somewhat counterintuitive when the allocation should be optimized to align with a risk-averse investor. This is further magnified in the portfolio volatility, being 15,3429%. However, the investor is seeking to maximize their returns through optimizing for the risk-return tradeoff, respective of the risk preferences. Thus suggesting that, certain NFT assets offer optimal risk-adjusted returns and, thus, diversification benefits. The Benchmark Portfolio has a major allocation of 91,1765% in the S&P 500 returns with some exposure to the NFTMetaGaming sector (8,8235%).

The skewness of the Core Portfolio is positive 0,7267, suggesting a distribution of returns that has a longer tail on the right or positive side. Furthermore, one can see that despite the increased allocation to NFTs, specifically Metagaming, the kurtosis has decreased significantly indicating less occurrences of extreme outliers in the portfolio return and thus less risk. On the other hand, the Benchmark Portfolio's negative skewness (-0,3333) suggests a distribution with a longer tail on the left or negative side, indicating a greater likelihood of negative returns.

Ultimately, the findings from the Post-Bullrun suggest that NFT sectors continue to offer diversification benefits, as previously, but with a lower caste in regards to risk. Where the decrease in kurtosis and volatility indicate that the diversification benefits of NFT sectors increase rather than decrease in the Post-Bullrun period.

#### 4.2.2.3 Relaxing the Short Selling Constraint

Table C.2 in the Appendix displays the Bayes-Stein results for a conservative investor without short selling constraints. The conservative investor predominantly allocates their portfolio to bonds (300%), showcasing their appeal for risk-averse investors. Moreover, NFT MetaGaming and NFT Marketplace maintain allocations in both Core and Benchmark portfolios, indicating their potential diversification benefits for conservative investors. We also note that the conservative investor generally opts to short sell NFT Infrastructure, except in the pre-bull run period where the Core Portfolio has a minor allocation.

The overall pattern of portfolio allocations and evaluation metrics stays consistent between the two periods. However, when short selling is allowed, the Benchmark Portfolio appears to outperform the Core Portfolio in both periods in terms of lower standard deviation, which is not the case when short selling is not permitted.

## 4.3 Robustness Check: Rolling Window Out-of-Sample Test

In this section, we evaluate the robustness of the results by using the Rolling Window Out-of-Sample Test. The results of the test are presented in Table. 4 and 5.

**Table 4**

Displayed in this table are the annualized Expected Return, Sharpe Ratio, Standard Deviation, Skewness, Kurtosis, and Risk-free rate pertaining to the Rolling Window Out-of-Sample Test with a risk aversion level of λ=1. The data encompasses both the core and benchmark portfolios during the respective timeframes of pre and post bull run periods.

**Rolling Window Out-of-Sample Test, Bayes-Stein Outputs, for Aggressive Investor ( $\lambda = 1$)**

| | **Pre-Bull Run** | | **Post-Bull Run** | |
|---|---|---|---|---|
| | **Core Portfolio** | **Traditional Portfolio** | **Core Portfolio** | **Traditional Portfolio** |
| Expected Return | -0,3596% | 4,3064% | 159,2743% | -15,7299% |
| Sharpe Ratio | -0,1091 | 0,3083 | 1,5552 | -0,4550 |
| Standard Deviation | 24,2205% | 6,5586% | 101,1894% | 38,7567% |
| Skewness | -4,1116 | -1,9562% | 0,7993 | -1,2724 |
| Kurtosis | 61,8285 | 34,0186 | 11,7896 | 14,6858 |
| Risk-free rate | 2,3100% | 2,3100% | 1,9200% | 1,9200% |

**Table 5**

Displayed in this table are the annualized Expected Return, Sharpe Ratio, Standard Deviation, Skewness, Kurtosis, and Risk-free rate pertaining to the Rolling Window Out-of-Sample Test with a risk aversion level of λ=5. The data encompasses both the core and benchmark portfolios during the respective timeframes of pre and post bull run periods.

**Rolling Window Out-of-Sample Test, Bayes-Stein Outputs, for Conservative Investor ( $\lambda = 5$)**

| | **Pre-Bull Run** | | **Post-Bull Run** | |
|---|---|---|---|---|
| | **Core Portfolio** | **Traditional Portfolio** | **Core Portfolio** | **Traditional Portfolio** |
| Expected Return | 5,7458% | 6,6240% | 26,2304% | -9,9074% |
| Sharpe Ratio | 0,5670 | 1,1318 | 1,0080 | -1,1422 |
| Standard Deviation | 6,1061% | 3,8347 | 24,1358% | 10,3387% |
| Skewness | -3,8590 | -1,0522 | -0,2561 | -1,4739 |
| Kurtosis | 48,8506 | 8,3447 | 12,5560 | 10,3670 |
| Risk-free rate | 2,3100% | 2,3100% | 1,9200% | 1,9200% |

As observed in Tables 4 and 5, we find confirmation regarding the robustness of our findings, with a few observations to consider. Consistent with the full sample outputs, the Core Portfolio demonstrates better out-of-sample performance metrics during the Post-Bull Run period for both aggressive and conservative investors. This indicates the potential benefits of NFTs in diversification, independent of risk appetite, have been maintained or increased in the Post-Bull Run period. These results align with our main findings, where the Core Portfolio and Benchmark Portfolio both allocate relatively higher shares of their capital to the NFT indices in the Post-Bull Run period.

During the Pre-Bull Run period, both aggressive and conservative investors experience higher Sharpe Ratios, higher expected returns, and lower standard deviations in the Traditional Portfolio. This suggests that, irrespective of their risk appetite, investors seeking to maximize their risk-adjusted returns would be better off selecting the Traditional Portfolio in the Pre-Bull Run period, as adding NFTs to the portfolios would only decrease risk-adjusted returns during this time. These findings indicate that NFTs do not offer any diversification benefits in the Pre-Bull Run period. Whereas there are diversification benefits in the Post-Bull Run period for any type of investor seeking to maximize their risk-adjusted Sharpe Ratio. This is consistent yet somewhat ambiguous with the full sample main results, which show that NFT indices receive small allocations in the Pre-Bull Period. Arguably negating the robustness of our results for the Pre-Bullrun period.

The out-of-sample results exhibit high kurtosis across the board for both investor types, implying a leptokurtic distribution. Furthermore, the skewness is also negative, indicating that the distribution of returns is both heavy-tailed and asymmetric, with a longer left tail. In other words, the portfolio is more likely to experience extreme negative returns or losses than positive returns. The difference in kurtosis and skewness between the out-of-sample results and the full sample results suggests that the portfolio optimization process is not optimal in terms of accounting for volatile market conditions, which reduces the robustness of the main results.

Nevertheless, the key findings from the Rolling Window Out-of-Sample Test confirm the robustness of the main results: NFTs offer more diversification benefits in the Post-Bull Run period compared to the Pre-Bull Run period, and investors, regardless of their risk appetite, shift their portfolio allocations to have more exposure to the NFT indices in the Post-Bull Run Period. However, it does also challenge our main results for the Pre-bullrun period which argued that diversification benefits existed with NFTs.

## 5. Discussion

This section discusses the theoretical implications of this paper's findings. First, the results are discussed in relation to the hypothesis along with additional findings. Then a discussion regarding the limitations of the study and possible implications of them are presented.

### 5.1 Diversification Benefits of NFT Categories

The initial hypothesis for this study postulated that the diversification benefits of adding NFTs into a portfolio consisting of traditional assets has decreased over time, specifically following the 2020 Bitcoin halving and subsequent Bullrun. This hypothesis was investigated through the lens of two distinct investors of contrasting risk aversion.

Contrary to this hypothesis, the results suggest that the diversification advantages of NFTs have increased overtime for investors, regardless of their risk appetite. Both periods showed that, despite a wide array of options in the core portfolio, the investor seeking to optimize their risk-adjusted returns would leverage the high, yet efficient, returns of NFT assets through hedging against their risk with large allocations into bonds.

However, the out-of-sample testing found that in the Pre-Bullrun period, portfolios excluding NFT assets performed better than ones including them. Thus challenging the robustness of a large component of our results and thus suggesting a need for further scrutiny towards this area of study. This underperformance in the Pre-Bullrun could be attributed to the volatility and highly leptokurtic distribution of the NFT returns implying that their returns are extremely vulnerable to sudden events that may have occurred in the out of sample testing. This high kurtosis exhibited by the NFT assets may explain the, arguably, false positive result that our main results reveal since the level of outliers may have been so significant that the Bayes Stein Shrinkage towards the global mean for the asset returns may not have effective mitigated the estimation risks for the input parameters. Causing misleading results. This suggests that future research should be even more rigorous in their control of the estimation risks.

Despite this, the Post-Bull Run results indicated that portfolios including NFTs exhibited significantly better out-of-sample performance metrics to that of solely traditional assets. Implying that the benefits of adding NFT assets into the portfolio have actually increased overtime. Wherein, despite the increased correlation with other assets, the role of the NFT in the portfolio has somewhat shifted away from that of a hedge. Given their extremely high expected returns and more stabilized risk metrics, investors are able to utilize small weightings of this asset to efficiently increase their portfolio return. As a result, investors experienced benefits from the addition of NFTs to their portfolio regardless of their risk-averseness. It should be noted that all investors with a risk averseness above 1 displayed similar weightings and performance. Overall, as seen in the summary statistics, the decrease and stabilization of the risk metrics for NFT assets in the Post Bull run has contributed to their improved diversification benefits.

The corroboration of the summary statistics with the portfolio selection of the NFT sectors may also imply that future research should consider NFTs as a diverse market rather than that of a singular asset type. Despite the fact that all NFT indices generally exhibited the highest risk performances, it is clear that the different NFT sectors behaved differently. NFT infrastructure, for example, was an inefficient asset that showed minimal to no allocations to in the main results as well as an inefficient Sharpe ratio. Whereas NFT Metagaming outperformed all other assets and consistently was a key component of the investor's portfolio. Thus, one can argue that future research needs to consider the heterogeneity present in the NFT market in order to expand upon our contributions, but also find more valid results.

In summary, the findings present evidence that contrasts that of our hypothesis and previous findings in the literature. These results indicate that the diversification benefits of NFT-derived assets have increased during and after the 2020 Bullrun for investors across the risk spectrum. Where, unlike previous findings in the literature, the instability present in the distribution of returns amongst NFTs highlight a lack of diversification advantages for investors in the Pre-Bullrun period. This contradiction in the literature could be the result of our novel dataset which uses NFT indices to consider large aggregations of NFT assets for a given sector rather than, as done in previous research, using a small number of 'blue chip' assets as a proxy for the market.

## 5.2 Limitations

There are three primary limitations that need to be taken into consideration. First of all, our study operates under a restricted scope of data. As a result of the historical data that ranges from 2017 to 2023 and the volatile nature of NFT markets, the findings may not be indicative of future trends. This limitation holds additional merit given the youth of the NFT markets and, thus, lack of trends to base one's forecasting on.

Additionally, the exclusion of additional inputs in the portfolio selection may have diminished the overall reliability of the findings. These inputs include transaction costs or taxes that can have an impact on the actual returns of the portfolio and thus lead to overestimation regarding the benefits of proposed NFT allocations. Additional inputs may include different risk parameters such as skewness and kurtosis allowing for a more comprehensive portfolio selection.

Finally, the third limitation relates to the dependence on the Bayes-Stein shrinkage model for portfolio optimization. While this model has merits, it may not be universally applicable or superior to other portfolio optimization models in every situation. The results of this study may differ if alternative optimization models were employed, which could impact the conclusions drawn about the diversification benefits of NFTs.

## 6. Conclusion

This study examines the evolution of the diversification benefits of NFT sector indices over time. Previous research has examined the relationships between NFTs and other financial assets both in the portfolio. The literature argues that, prior to the COVID Outbreak, NFTs displayed strong diversification benefits which deteriorated following the 2020 Bullrun. However, these studies contained a number of limitations including ineffective proxies for NFT and  lack of estimation risk controls for the input parameters. This study is the first to address such limitations through the creation and addition of NFT sector indices into the dataset as well as the deployal of the Bayes-Stein model with no short sales to mitigate the effects of estimation risks. With this, the study analyzed the performance of portfolios with contrasting risk preferences. Followed by a rolling window out-of-sample test to ensure the robustness of results.

The findings suggest that, contrary to previous findings, the diversification benefits of NFTs have increased rather than decreased during the 2020 bullrun. We also find that, when looking at stronger proxies for the NFT market, the diversification benefits in the prior period are lacking as a result of high riskiness and volatility amongst the assets. Additionally, NFT sectors were found to benefit investors across the risk spectrum in the Post Bullrun period.

To further build upon these findings, it would be recommended that future researchers investigate the drivers behind the diversification benefits of NFTs in different market conditions and also further examine the diversification potential of different NFT subcategories such as art, utility and finance.

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# Appendix A: Data Structure

**Table A.1**
Distribution of Weights in NFT Tokens for the NFT Infrastructure, NFT MetaGaming, and NFT Marketplace Sectors as of March 2023. It is important to note that the indices are continuously re-weighted, and the figures presented here serve as an illustration of how the weightings may vary across the sectors.

| **NFT Infrastructure** | | **NFT MetaGaming** | | **NFT Marketplace** | |
|---|---|---|---|---|---|
| **Token** | **Weight** | **Token** | **Weight** | **Token** | **Weight** |
| Internet Computer ICP | 16.53% | Decentraland MANA | 19.96% | PancakeSwap CAKE | 28.50% |
| Flow FLOW | 11.33% | Axie Infinity AXS | 18.55% | Enjin Coin ENJ | 17.84% |
| Tezos XTZ | 10.75% | The Sandbox SAND | 17.21% | Blur BLUR | 11.82% |
| Stacks STX | 11.73% | Gala GALA | 4.68% | SushiSwap SUSHI | 11.27% |
| Chiliz CHZ | 8.63% | STEPN GMT | 4.26% | iExec RLC RLC | 6.03% |
| ImmutableX IMX | 8.82% | WAX WAXP | 3.23% | APENFT NFT | 5.30% |
| Conflux CFX | 5.00% | Illuvium ILV | 3.37% | LooksRare LOOKS | 3.25% |
| Oasis Network ROSE | 3.46% | Smooth Love Potion SLP | 0.26% | Biswap BSW | 3.09% |
| Render Token RNDR | 3.49% | Cocos-BCX COCOS | 2.13% | Ultra UOS | 0.06% |
| Fetch AI FET | 3.65% | Vulcan Forged PYR PYR | 1.72% | Origin Protocol OGN | 2.58% |
| Nervos Network CKB | 1.88% | MOBOX MBOX | 1.60% | SuperRare RARE | 2.06% |
| DigiByte DGB | 1.69% | CEEK VR CEEK | 1.42% | BakeryToken BAKE | 1.59% |
| Syscoin SYS | 1.31% | Alien Worlds TLM | 1.24% | Ethernity ERN | 1.29% |
| WEMIX WEMIX | 5.04% | Verasity VRA | 1.20% | Rarible RARI | 1.06% |
| LUKSO LYXE | 1.47% | MyNeighborAlice ALICE | 1.26% | Phantasma SOUL | 1.10% |
| Chromia CHR | 1.09% | RACA RACA | 1.20% | Circuits of Value COVAL | 1.29% |
| Efinity Token EFI | 0.53% | Aavegotchi GHST | 1.14% | Splintershards SPS | 1.03% |
| Telos TLOS | 0.48% | Yield Guild Games YGG | 1.04% | NFTX NFTX | 0.43% |
| LTO Network LTO | 0.47% | Mines of Dalarnia DAR | 1.00% | BabySwap BABY | 0.40% |
| Dego Finance DEGO | 0.31% | SuperVerse SUPER | 0.93% | **Total** | **100.00%** |
| VIDT DAO VIDT | 0.30% | Gods Unchained GODS | 0.91% | | |
| FIO Protocol FIO | 0.28% | Star Atlas DAO POLIS | 0.87% | | |
| Boson Protocol BOSON | 0.24% | UFO Gaming UFO | 0.75% | | |
| Proton XPR | 0.25% | Virtua TVK | 0.82% | | |
| Handshake HNS | 0.23% | Battle World BWO | 0.88% | | |
| StreamCoin STRM | 0.47% | Sweat Economy SWEAT | 0.74% | | |

| | |
|---|---|
| Ternoa CAPS | 0.30% |
| pNetwork PNT | 0.16% |
| Blocto Token BLT | 0.11% |
| **Total** | **100.00%** |

| | |
|---|---|
| League of Kingdoms Arena LOKA | 0.67% |
| Wilder World WILD | 0.61% |
| Step App FITFI | 0.48% |
| Star Atlas ATLAS | 0.57% |
| YooShi YOOSHI | 0.56% |
| DEAPcoin DEP | 0.57% |
| Voxies VOXEL | 0.47% |
| DeRace DERC | 0.38% |
| RFOX RFOX | 0.41% |
| RMRK RMRK | 0.40% |
| Nakamoto Games NAKA | 0.32% |
| DeFi Kingdoms JEWEL | 0.33% |
| Somnium Space Cubes CUBE | 0.27% |
| SIDUS SIDUS | 0.23% |
| Dvision Network DVI | 0.26% |
| Aurory AURY | 0.23% |
| VIMworld VEED | 0.22% |
| Altura ALU | 0.31% |
| Victoria VR VR | 0.19% |
| NFT Worlds WRLD | 0.15% |
| **Total** | **100.00%** |

## Appendix B: NFT Categories

In this section, we present the categorization of NFTs into six distinct categories, namely Finance, Social, Utility, Infrastructure, MetaGaming, and Marketplace. By considering each NFT's primary use case or function, we assign them to the most relevant index. When an NFT fits multiple categories, the one that best aligns with its primary purpose is chosen. This classification approach aids in understanding the diverse range of NFTs and their potential roles in investment portfolios.

**Finance**: NFTs in the Finance category are primarily associated with decentralized finance (DeFi) applications, financial services, or assets that are designed to generate returns, offer lending/borrowing services, or enable asset management. To be included in this index, an NFT must have a clear financial use case or be directly tied to a financial service or product.

**Social**: Social NFTs are focused on community-building, networking, and content sharing. These NFTs can represent membership in online clubs or communities, access to exclusive content, or facilitate user interactions. To be part of this index, an NFT should promote social engagement, networking, or community-driven benefits.

**Utility**: Utility NFTs have a specific functional use case, beyond their inherent value as collectibles or investment assets. Examples include NFTs that grant access to software, services, or digital goods. To be included in this index, an NFT must offer some form of utility or function that enhances user experience or provides access to a particular product or service.

**Infrastructure**: Infrastructure NFTs are related to the development and maintenance of the underlying technology or platforms that support the broader NFT ecosystem. These can include NFTs tied to governance tokens, development platforms, or protocols. To qualify for this index, an NFT must be directly connected to the fundamental building blocks of the NFT space or contribute to its technological development.

**MetaGaming**: NFTs in this category are associated with virtual worlds, online games, or digital experiences. They can include virtual land, in-game items, avatars, or characters. To be part of this index, an NFT must be related to a virtual environment, gaming experience, or digital entertainment platform.

**Marketplace:** Marketplace NFTs pertain to platforms or services that facilitate the buying, selling, or trading of NFTs. These can include NFTs that grant access to premium marketplace features, governance tokens for decentralized marketplaces, or even specific, exclusive auctions. To be included in this index, an NFT must be linked to the facilitation of NFT transactions or the operation of an NFT marketplace.

When categorizing NFTs, we consider the primary use case or function of each NFT, and assign it to the most relevant index accordingly. If an NFT seems to fit multiple categories, we opt for the category that aligns most closely with its primary purpose or function.

# Appendix C: Relaxing the Short-Selling Constraints

In this segment, we showcase the outcomes for investors seeking to maximize their risk adjusted return with aggressive and moderate risk appetite, respectively, in scenarios where short selling is permitted. Note that for all portfolios, we have imposed a constraint of 3x leverage for both positive and negative holdings. In reality, the appropriate level of leverage depends on various factors such as the investor's risk tolerance, investment horizon, and the specific investment strategy employed. First, we reveal the findings for the aggressive investor seeking to maximize risk adjusted returns throughout the pre- and post-bull run periods. Second, we present the corresponding results for the conservative investor seeking to maximize risk adjusted returns.

## C.1 The Aggressive Investor

**Table C.1**

Displayed in this table are the portfolio weightings of respective asset along with the annualized Expected Return, Sharpe Ratio, Standard Deviation, Skewness, Kurtosis, and Risk-free rate pertaining to the mean-variance portfolios with a risk aversion level of λ=1 when the no short selling constraint is removed. The data encompasses both the core and benchmark portfolios during the respective timeframes of pre and post bull run periods.

**Bayes-Stein Outputs, for Aggressive Investor ( $\lambda = 1$) without no short selling constraint**

| | **Pre-Bull Run** | | **Post-Bull Run** | |
|---|---|---|---|---|
| | **Core Portfolio** | **Benchmark Portfolio** | **Core Portfolio** | **Benchmark Portfolio** |
| S&P500_Returns | -4,7892% | 89,8330% | -299,9999% | 119,0354% |
| Commodity_Returns | -248,7880% | - | 28,1657% | - |
| Bond_Returns | 300,0000% | - | 300,0000% | - |
| Crypto_Returns | 4,5055% | - | 20,7280% | - |
| NFTInfra_Returns | 17,1014% | -6,9956% | -163,9038% | -203,0000% |
| NFTMetaGaming_Returns | 13,4451% | 5,1569% | 175,5989% | 164,6289% |
| NFTMarketplace_Returns | 18,5251% | 12,0057% | 39,4111% | 19,3356 |
| Expected Return | 103,4134% | 25,7347% | 402,1898% | 378,9563% |
| Sharpe Ratio | 1,2508 | 0,8324 | 2,6476 | 2,6869 |
| Standard Deviation | 81,1571% | 28,6308% | 151,1867% | 140,3271% |

| | | | | |
|---|---|---|---|---|
| Skewness | 0,7160 | 0,3818 | 1,6268 | 1,2413 |
| Kurtosis | 4,3991 | 12,0467 | 8,8795 | 9,8309 |
| Risk-free rate | 2,3100% | 2,3100% | 1,9200% | 1,9200% |

## C.2 The Conservative Investor

**Table C.2**
Displayed in this table are the portfolio weightings of respective asset along with the annualized Expected Return, Sharpe Ratio, Standard Deviation, Skewness, Kurtosis, and Risk-free rate pertaining to the mean-variance portfolios with a risk aversion level of λ=5 when the no short selling constraint is removed. The data encompasses both the core and benchmark portfolios during the respective timeframes of pre and post bull run periods.

**Bayes-Stein Outputs, for Conservative Investor ( $\lambda = 5$) – without no short selling constraint**

| | **Pre-Bull Run** | | **Post-Bull Run** | |
|---|---|---|---|---|
| | **Core Portfolio** | **Benchmark Portfolio** | **Core Portfolio** | **Benchmark Portfolio** |
| S&P500_Returns | -86,0570% | 98,3781% | -187,2780% | 107,2322% |
| Commodity_Returns | -122,0266% | - | -35,7910% | - |
| Bond_Returns | 300,0000% | - | 300,0000% | - |
| Crypto_Returns | -3,5060% | - | 7,6276% | - |
| NFTInfra_Returns | 5,8074% | -2,1294% | -30,7795% | -41,9293% |
| NFTMetaGaming_Returns | 2,5011% | 1,1236% | 37,3655% | 32,2198% |
| NFTMarketplace_Returns | 3,2811% | 2,6276% | 8,8552% | 2,4774% |
| Expected Return | 28,4018% | 11,83299% | 52,1462% | 83,1108% |
| Sharpe Ratio | 0,6057 | 0,4457 | 1,0926 | 2,4162 |
| Standard Deviation | 43,7449% | 22,2806% | 45,9849% | 33,6090% |
| Skewness | 1,3772 | -0,6202 | 0,4576 | 0,5800 |
| Kurtosis | 11,4447 | 18,3245 | 1,5123 | 4,2346 |
| Risk-free rate | 2,3100% | 2,3100% | 1,9200% | 1,9200% |

## Appendix D: Bayes-Stein Outputs

**Table D.1**

Displayed in this table are the portfolio weightings of respective asset along with the annualized Expected Return, Sharpe Ratio, Standard Deviation, Skewness, Kurtosis, and Risk-free rate pertaining to the mean-variance portfolios with a risk aversion level of λ=2. The data encompasses both the core and benchmark portfolios during the respective timeframes of pre and post bull run periods.

**Bayes-Stein Outputs, for** $\lambda = 2$

| | **Pre-Bull Run** | | **Post-Bull Run** | |
|---|---|---|---|---|
| | **Core Portfolio** | **Benchmark Portfolio** | **Core Portfolio** | **Benchmark Portfolio** |
| S&P500_Returns | 0,0000% | 95,5308% | 0,0000% | 83,3469% |
| Commodity_Returns | 0,0000% | - | 0,0000% | - |
| Bond_Returns | 91,1616% | - | 67,3455% | - |
| Crypto_Returns | 0,0000% | - | 0,0000% | - |
| NFTInfra_Returns | 0,0000% | 0,0000% | 0,0000% | 0,0000% |
| NFTMetaGaming_Returns | 2,7206% | 1,3679% | 32,6544% | 16,6531% |
| NFTMarketplace_Returns | 5,6638% | 1,1013% | 0,0000% | 0,0000% |
| Expected Return | 16,92% | 15,2301% | 80,8806% | 53,9486% |
| Sharpe Ratio | 1,3445 | 0,5862 | 2,1453 | 1,8353 |
| Standard Deviation | 11,17% | 22,7351% | 36,8136% | 28,3579% |
| Skewness | 1,1573 | -0,6849 | 0,8096 | -0,0590 |
| Kurtosis | 12,6187 | 18,6935 | 5,2986 | 1,9571 |
| Risk-free rate | 2,3100% | 2,3100% | 1,9200% | 1,9200% |

**Table D.2**

Displayed in this table are the portfolio weightings of respective asset along with the annualized Expected Return, Sharpe Ratio, Standard Deviation, Skewness, Kurtosis, and Risk-free rate pertaining to the mean-variance portfolios with a risk aversion level of λ=3. The data encompasses both the core and benchmark portfolios during the respective timeframes of pre and post bull run periods.

**Bayes-Stein Outputs, for** $\lambda = 3$

| | **Pre-Bull Run** | | **Post-Bull Run** | |
|---|---|---|---|---|
| | **Core Portfolio** | **Benchmark Portfolio** | **Core Portfolio** | **Benchmark Portfolio** |
| S&P500_Returns | 0,0000% | 95,5531% | 0,0000% | 83,3469% |
| Commodity_Returns | 0,0000% | - | 0,0000% | - |
| Bond_Returns | 94,4397% | - | 78,1625% | - |

| | | | | |
|---|---|---|---|---|
| Crypto_Returns | 0,0000% | - | 0,0000% | - |
| NFTInfra_Returns | 0,0000% | 0,0000% | 0,0000% | 0,0000% |
| NFTMetaGaming_Returns | 1,8082% | 1,3679% | 21,1961% | 16,6531% |
| NFTMarketplace_Returns | 3,7946% | 1,1013% | 0,0000% | 0,0000% |
| Expected Return | 12,8052% | 15,2301% | 52,9161% | 53,9486% |
| Sharpe Ratio | 1,3905 | 0,5862 | 2,0577 | 1,8353 |
| Standard Deviation | 7,8411% | 22,7351% | 24,7913% | 28,3579% |
| Skewness | 0,8513 | -0.6849 | 0,7897 | -0,05901 |
| Kurtosis | 11,2929 | 18.6935 | 5,1077 | 1,9571 |
| Risk-free rate | 2,3100% | 2,3100% | 1,9200% | 1,9200% |

**Table D.3**

Displayed in this table are the portfolio weightings of respective asset along with the annualized Expected Return, Sharpe Ratio, Standard Deviation, Skewness, Kurtosis, and Risk-free rate pertaining to the mean-variance portfolios with a risk aversion level of λ=4. The data encompasses both the core and benchmark portfolios during the respective timeframes of pre and post bull run periods.

**Bayes-Stein Outputs, for $\lambda = 4$**

| | **Pre-Bull Run** | | **Post-Bull Run** | |
|---|---|---|---|---|
| | **Core Portfolio** | **Benchmark Portfolio** | **Core Portfolio** | **Benchmark Portfolio** |
| S&P500_Returns | 0,0000% | 96,6622% | 0,0000% | 88,2404% |
| Commodity_Returns | 0,0000% | - | 0,0000% | - |
| Bond_Returns | 95,7880% | - | 40,3865% | - |
| Crypto_Returns | 0,0000% | - | 0,0000% | - |
| NFTInfra_Returns | 0,0000% | 0,0000% | 0,0000% | 0,0000% |
| NFTMetaGaming_Returns | 1,3520% | 1,0216% | 16,4289% | 1,5144% |
| NFTMarketplace_Returns | 2,8600% | 2,3122% | 0,0000% | 1,1760% |
| Expected Return | 10,75% | 13,5958% | 38,9339% | 42,1453% |
| Sharpe Ratio | 1,3905 | 0,5217 | 1,9643 | 1,6294 |
| Standard Deviation | 6,27% | 22,4149% | 18,8517% | 24,6983% |
| Skewness | 0,5448 | -0,6831 | 0,7615 | -0,2388 |
| Kurtosis | 9,9236 | 19,1857 | 4,8600 | 1,6706 |
| Risk-free rate | 2,3100% | 2,3100% | 1,9200% | 1,9200% |