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Abstract

We aim to identify the determinants of non-fungible tokens (NFTs) returns. The ten most popular NFTs based on their price, trading volume, and market capitalisation are examined. Twenty-three potential drivers of the returns of each NFT are considered. We employ a Bayesian LASSO model which takes into account stochastic volatility and leverage effect. The results indicate that NFTs returns are primarily driven by volatility and ethereum returns. We find a weak connection between NFTs returns and conventional assets, such as stock, oil, and gold markets.

Keywords: Non-fungible tokens, cryptocurrency, LASSO, Bayesian, volatility.

JEL Codes: C11, C22, G12, G15.

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1 Introduction

The success of cryptocurrencies has given birth to several digital assets over the last few years. Non-fungible tokens (NFTs) have become a popular class of digital assets. NFTs are digital tokens declaring ownership of a digital property (among others, videos, images, and audio files). Similar to cryptocurrencies, NFTs are built on a blockchain (mostly ethereum). However, while the coins of a given cryptocurrency are indistinguishable from one another, each token of an NFT is unique. The uniqueness and rarity of an NFT make it appealing to investors and can cause increases in its value.

As the attention of investors towards NFTs increases, so does the attention of researchers. One strand of the literature focuses on the connection between NFTs and other assets. Dowling (2022b) and Corbet et al. (2023) examine the volatility transmissions between NFTs, cryptocurrencies and other Decentralised Finance (DeFi) assets. Dowling (2022b) examines the volatility spillovers between four NFTs and two cryptocurrencies and argues that there are low volatility spillovers between NFTs and cryptocurrencies. However, evidence from a wavelet coherence analysis suggests a co-movement between the markets. Corbet et al. (2023) employ DCC-GARCH models and spillovers analysis of returns and volatilities of five conventional and five DeFi oriented cryptocurrencies and argue that conventional cryptocurrencies do not influence the formation of bubbles in the DeFi focused cryptocurrencies. Yousaf and Yarovaya (2022b) investigate the connectedness of NFTs, DeFi and conventional assets in both a static and a dynamic framework and find that NFTs are still de-coupled from commodity and stock markets. Yousaf and Yarovaya (2022c) focus on the linkages between three alternative NFTs and find evidence of time-varying connectedness, which is higher during extreme bullish market conditions.[1] Similarly, Aharon and Demir (2022) and Umar et al. (2022) examine the effect of COVID-19 on the interlinkages between NFTs and other assets using a time-varying vector autoregressive and a squared wavelet coherence approach, respectively. The results suggest that in a short-run horizon (less than two weeks) NFTs absorbed the risk due to the Covid-19 pandemic. Regarding pricing efficiency, Dowling (2022a) argues that there is pricing inefficiency in NFTs and that prices are steadily on the rise. Finally, Yousaf and Yarovaya (2022a) find no herding behaviour in the NFT markets.

NFTs form a different class of DeFi assets compared to cryptocurrencies and a distinct class of assets in general. For example, despite their volatile nature and the presence of bubbles, they exhibit an anti-herding behaviour. Disentangling between the forces that drive NFTs returns is a crucial task for several reasons. First, NFTs can ab-

[1] Liu and Tsyvinski (2020) and Liu et al. (2022) also argue that cryptocurrency returns have low exposure to traditional asset markets.

sorb risks even during stressful periods and thus can have substantial implications in the construction of a diversified portfolio. Second, it can aid in the discussion regarding the regulation of NFT and DeFi markets in general. Third, it can help explore the behaviour of individual investors. Similar to cryptocurrencies, NFTs are traded mostly by individuals and less by institutional investors. Since individuals mostly rely on the internet and social media as sources of information and often base their investment decisions on sentiment, it is important to understand how individuals can affect the returns of an asset.

Despite the ongoing discussion, it remains obscure what drives the returns of NFTs. The existing studies focus on the relationship between NFTs and specific variables such as cryptocurrencies or stock market returns. This could lead to misleading conclusions since the omission of certain variables could affect the results. This paper aims to identify the determinants of NFTs returns through an extended list of potential determinants. To capture the features of NFTs as best we can, we consider ten NFTs based on alternative characteristics such their price, trading volume, and market capitalisation. We consider more than twenty potential determinants of the examined NFTs, including the volatility of returns, trading volume, attention indices, stock market returns and volatility indices, exchange rates and oil and gold prices for each NFT. The empirical analysis is carried out independently for each of the ten NFTs, using the Least Absolute Shrinkage and Selection Operators (LASSO). We consider three alternative cases based on the estimation approach and the choice of the dependent variable. In the first case, we consider a LASSO model where the dependent variable is the NFT returns. This model is estimated using penalised Maximum Likelihood. The main drawback in this case is that the model does not account for the time-varying volatility of the NFT returns. To account for the volatility dynamics of each NFT, in the second case, we re-estimate the same model but use the fitted residuals from a Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model as the dependent variable instead of the NFT returns. Although we account for the presence of heteroscedasticity in this case, NFT returns do not enter directly into the LASSO model as the dependent variable. In the last case, we account for both issues that afflict the two previous approaches. Specifically, we employ a Bayesian LASSO model that accounts for stochastic volatility and where the NFT returns are used as the dependent variable. This is the main model of this paper.

LASSO models have been used as feature selection tools in the cryptocurrency literature (mainly on bitcoin returns) since they reduce the number of independent variables without losing valuable information. Panagiotidis et al. (2018) use the penalised Maximum Likelihood estimator to study the determinants of bitcoin returns. Ciner et al. (2022) employ an adaptive LASSO quantile regression approach to identify informative variables for bitcoin returns during the Covid-19 period. Both of these studies ignore the time-varying nature of the volatility of bitcoin returns. Panagiotidis et al. (2024) employ a Bayesian LASSO model with stochastic volatility, similar to the one we consider in this paper, to assess the effect of alternative variables on bitcoin returns. The Bayesian approach offers three main advantages compared to the traditional frequentist approaches. First, it takes into account the time-varying volatility of returns through stochastic volatility. The latter needs to be accounted for since Wang (2022) showed that NFTs act as volatility spillover receivers. Second, it accounts for overfitting issues caused by the large number of variables in the model. Third, the use of shrinkage priors allows the model to eliminate insignificant variables compared to other estimators and improves the model's ability to exclude non-significant variables. To the best of our knowledge, this is the first study that employs a LASSO model to study NFT returns.

Using the Bayesian LASSO, we can assess the impact of alternative variables on NFTs returns and refine the findings of the related literature. In particular, we find that NFTs returns are mainly driven by their volatility and the returns of ethereum and bitcoin. We find that ethereum has a stronger impact than bitcoin, a finding which is in line with the findings of Corbet et al. (2023). In addition, we find a weak connection between NFTs and commodity and stock markets, as in Yousaf and Yarovaya (2022b). Finally, we conclude that internet attention affects only specific NFTs and that this effect is negative. Our findings are useful for researchers studying the behaviour of NFTs and investors seeking diversification opportunities.

The rest of the paper proceeds as follows: Section 2 describes the data and the methodology. Section 3 discusses the main results. The last session concludes.

2 Data

We consider ten alternative NFTs based on price, trading volume, and market capitalisation. At the moment this study is being conducted, the NTFs with the highest price are Unisocks, XMON, Illuvrium, and NFTX, the most traded are Decentrland, Gala, The Sandbox, and STEPN and the NFTs with the biggest market capitalisation are ApeCoin, Flow, Decentraland, and The Sandbox. Since each NFT is analysed separately, each sample period is based on the availability of the data and the time each NFT was created. We collect NFT daily prices from coinmarketcap.com and calculate the returns as the logarithmic differences of the prices. Table 1 provides some descriptive statistics for the returns of the ten NFTs. We observe negative returns on average for the four NFTs with the biggest capitalisation and the presence of excess kurtosis in all NFTs. The last column of the Table presents the statistics from the ADF test. In all cases, the null hypothesis of a unit root is rejected at the 1% significance level. Figure A1 plots the returns of the ten NFTs considered in the analysis.

For each of the ten examined NFTs, we consider twenty-three potential drivers including the trading volume and the volatility of returns (calculated as the squared returns, as in Balcilar et al., 2017).[2] We proxy NFT attractiveness using three attention indices, the number of Google searches for each NFT and the number of comments on two subreddit communities, the subbreddit dedicated to each NFT (e.g. r/decentraland) and the subreddit r/NFT. Given that blockchain market assets are traded mostly by individuals who look for information on the internet, we seek to understand how attention and sentiment affect investors' decisions. In addition, we examine the role of two cryptocurrencies (bitcoin and ethereum) since both NFTs and cryptocurrencies are based on blockchain technology.

To examine the effect of stock markets on NFTs returns, we employ seven stock market indices (S&P500, NASDAQ, Dow Jones, FTSE 100, EURO STOXX 50, NIKKEI 225 and the Shanghai composite index) which cover most major economies from different geographic regions. We also consider two volatility indices (the CBOE Market Volatility Index and the EURO STOXX 50 Volatility Index). In addition, we consider two commodities: oil and gold. These are assets that can act as safe havens and they allow us to investigate whether these commodities can act as a hedge against NFTs. In particular, for crude oil we consider both the Brent and the West Texas Intermediate (WTI) prices. Finally, we include an economic factor whose impact on NFTs has not been addressed in the literature: exchange rates. We consider four pairs of currencies traded in the foreign exchange market: the euro, British sterling, Japanese yen and Chinese yuan. The exchange rates are expressed as the price of domestic currency to one US dollar, implying that an increase in the exchange rate denotes an appreciation. Table A1 presents the variables used that could be considered as determinants of NFTs returns, along with their data sources. Non-stationary variables are transformed to logarithmic differences and all time series are standardised by subtracting the mean and dividing by the standard deviation. Standardisation is necessary for the LASSO framework to be able to rank the importance of statistically significant coefficients. All data are in daily frequency and no aggregation or imputation is required.

We do not include in the analysis the attention index constructed by Wang (2022) since it is only available on a weekly frequency. However, as a robustness check, we

[2]As robustness test, we use two alternative measures of volatility, the absolute returns and the Garman-Klass volatility. In both cases the results remain qualitatively the same. These results are available upon request.

impute the index and include it as an additional determinant of NFTs returns. These results which are not reported here, are available upon request.

Table 1: Descriptive statistics of the NFTs returns.

	Mean	Maximum	Minimum	SD	Skewness	Kurtosis	ADF stat.
Unisocks	0.005	0.550	-0.439	0.106	1.064	7.078	-10.759
XMON	0.003	0.701	-0.459	0.086	0.949	8.472	-12.874
Illuvrium	0.003	0.748	-0.431	0.100	1.081	9.354	-9.138
NFTX	0.003	0.826	-0.893	0.147	0.394	5.311	-7.915
Decentraland	-0.003	0.322	-0.467	0.080	-0.698	5.529	-11.863
Gala	0.002	0.935	-0.630	0.083	1.697	21.414	-14.674
The Sandbox	-0.003	0.345	-0.363	0.069	0.461	4.752	-14.299
STEPN	0.004	1.331	-0.520	0.118	3.277	26.916	-11.036
Apecoin	-0.001	0.320	-0.244	0.068	0.529	2.615	-12.927
Flow	-0.001	0.591	-0.372	0.102	0.901	5.614	-12.639

Notes: i) SD is the standard deviation. ii) In the implementation of the ADF test we assume only a constant in the test equation and for the selection of the lag-length we use the Schwarz information criterion. The null hypothesis of a unit root is rejected at the 1% significance level for all NFTs.

3 Methodology

To study the determinants of NFTs returns, we consider three alternative approaches. In the first approach, we use the NFT returns as the dependent variable of the model and estimate the LASSO model using a penalised Maximum Likelihood estimator as in Tibshirani et al. (2012) (model I). In the second approach, first, we fit the NFT returns to a GARCH model and then, use the model's standardised residuals as the dependent variable in the LASSO model. We consider four alternative GARCH specifications, the standard GARCH(1,1) (Bollerslev, 1986), the EGARCH(1,1) (Nelson, 1991), the GJR-GARCH(1,1) (Glosten et al., 1993) and the Asymmetric Power ARCH (APARCH(1,1)) (Ding et al., 1993). For each NFT, we select the optimal GARCH specification based on the Akaike (1974) and the Schwarz (1978) information criteria. In this approach, the LASSO model is estimated using the penalised Maximum Likelihood method (model II) as in the previous case, however, NFTs returns are not used directly as the dependent variable. Rather than that, we use the standardised residuals from the GARCH model as the dependent variable in the LASSO model to account for the volatility dynamics of NFTs returns. In the third case, we consider a Bayesian LASSO model (model III). This model accounts both for stochastic volatility and uses the NFTs returns as the dependent variable. Furthermore, the Bayesian model provides more accurate forecasts compared to the frequentist counterparts, (Panagiotidis et al., 2024). In all three cases, the set of independent variables remains the same for each NFT.

In what follows, we describe the Bayesian LASSO used in the analysis. That is, we discuss the model, the selection of prior distributions and the Markov-Chain Monte Carlo (MCMC) algorithms used to obtain the posterior distributions of the model's parameters. We discuss only the Bayesian LASSO since this is the main focus of the paper (for a more detailed discussion on LASSO estimation using frequentist inference see also Tibshirani, 1996; Zou, 2006; Belloni and Chernozhukov, 2011; Tibshirani et al., 2012).

Let y_t, $t = 1, \ldots, T$ be the dependent variable and x_t a the $T \times k$ matrix of the k predictors. Following Omori et al. (2007) and Nakajima (2012) we employ the following model:

$$y_t = x_t\beta + \exp(h_t/2)\varepsilon_t, \tag{1}$$

$$h_{t+1} = \mu + \phi(h_t - \mu) + \sigma\eta_t, \tag{2}$$

where β is the $k \times 1$ vector of estimated coefficients and we the residuals are assumed to follow a Student's-t distribution with ν degrees of freedom, zero mean and unit variance. That is $\varepsilon_t \sim t_\nu(0, 1)$, where we consider ν as an unknown parameter. The log-variance process h_t, is described by the level μ, the persistence ϕ and the standard deviation σ, parameters. Furthermore, we assume that η_t follow a Normal distribution with zero mean and unit standard deviation, $\eta_t \sim N(0, 1)$. We impose no restrictions regarding the correlation between ε_t and η_t. More formally, we assume that $\text{corr}(\varepsilon_t, \eta_t) = \rho$, where ρ is a parameter to be estimated. If ρ is not zero, then we conclude that that the leverage effect is present in the NFTs returns.

We select the prior distributions based on the literature. As in Park and Casella (2008), we assume that $\beta \sim N_k(0, I)$, where I is a properly sized identity matrix. One could yield shrinkage or uninformative priors by multiplying the identity matrix with a small or large value, respectively.[3] The log-variance is also assumed to follow a normal distribution, $h_t \sim N(\mu, \sigma^2/(1-\phi)^2)$, where, to ensure stationarity of the log-variance process, we require that $\phi \in (-1, 1)$. For the requirement to hold, we consider $\phi \sim B(5, 1.5)$ (beta distribution). For the parameter μ, we assume a normal prior, that is $\mu \sim N(0, 100)$. Following Frühwirth-Schnatter and Wagner (2010) and Kastner and Frühwirth-Schnatter (2014), we choose for the prior distribution of the standard deviation σ, of the stochastic volatility, the half normal distribution with scale parameter

[3] In the general case, β is assumed to follow a k-dimensional normal distribution with vector mean b_β and variance-covariance matrix B_β, that is $\beta \sim N_k, (b_\beta, B_\beta$. However, this would differentiate the model from the Bayesian LASSO proposed by Park and Casella (2008).

equal to one. This is identical to the generalised gamma distribution with scale parameters $d = 1$ and $p = 2$ and shape parameter $a = \sqrt{2}$, $\sigma \sim GG(\sqrt{2}, 1, 2)$. This selection of half normal (or generalised gamma) distribution allows σ to get as close to zero as possible, thus being less informative and improve the estimates. Based on Geweke (1993), we consider the exponential distribution for ν, such that $(\nu - 2) \sim E(0.1)$. Finally, as in Omori et al. (2007), we set $(\rho+1)/2 \sim B(4, 4)$. To summarise, the prior distributions take the following form:

$$
\begin{aligned}
\beta &\sim N(0, I) \\
h_t &\sim N(\mu, \sigma^2/(1-\phi)^2) \\
(\phi+1)/2 &\sim B(5, 1.5) \\
\mu &\sim N(0, 1000) \\
\sigma &\sim GG(\sqrt{2}, 1, 2) \\
(\rho+1)/2 &\sim B(4, 4) \\
(\nu - 2) &\sim E(0.1)
\end{aligned}
$$

The model is estimated following the Bayesian MCMC algorithms of Kastner and Frühwirth-Schnatter (2014).[4] The MCMC sampler approximates a mixture representation of the model similar to the one in Kim et al. (1998) and leads to a Gaussian state-space representation. The posterior distribution of h_t is drawn using the Cholesky Factor Algorithm by Rue (2001) and McCausland et al. (2011). Since Kastner and Frühwirth-Schnatter (2014) consider neither a Student's-t distribution nor a leverage effect, additional blocks in the algorithm are required. Specifically, following Kastner (2015), we represent the Student's-t distribution as a scale mixture of normal distributions which leads to the addition of Gibbs (Geman and Geman, 1984) and independence Metropolis-Hastings (Metropolis et al., 1953; Hastings, 1970) steps in the initial algorithm. The repeated ancillarity-sufficiency interweaving strategies Yu and Meng (2011) steps in the sampling scheme are required to handle the increased complexity in the estimation of the posterior distributions which is caused by the assumption of leverage effect in the model (see also Hosszejni and Kastner, 2019).

The first 25000 in the algorithm are discarded as burn-in draws. We build the posterior sample using the next 25000 draws. To validate the results, we consider two robustness checks. In the first one, we re-estimate the model by increasing the number of burn-in and posterior draws to 50000. In the second, we set the number of burn-in

[4] Kastner and Frühwirth-Schnatter (2014) assume that $\varepsilon_t \sim N(0, 1)$ and no leverage effect in the model.

and posterior draws to 50000 but we keep every 10^th draw. The thinning process is used to account for autocorrelation among draws, Korobilis (2017). In both cases, we obtain results similar to the ones reported in the paper. These results are available upon request.

4 Empirical results

4.1 The penalised Maximum Likelihood models

In this section, we discuss first the results obtained from models I and II. That is, the two models are estimated using the penalised Maximum Likelihood methods. Table 2 presents the findings from model I. For each NFT, the values denote the estimated coefficients. Coefficients that are not statistically significant are not reported. For all NFTs, we note three predictors that are always statistically significant. These are the returns' volatility and the trading volume of each NFT and the ethereum returns. In addition, these coefficients are always positive. The only exception is the volatility of returns for Apecoin which has a negative coefficient. The positive effect of ethereum returns on NFTs returns can be explained by the fact that NFTs are mostly created in the ethereum blockchain. Apart from ethereum, bitcoin returns also appear to positively influence most of the NFTs. Regarding the rest of the predictors, we observe that for each NFT, the number of significant coefficients varies. For example, in the case of Unisocks, the model indicates only four significant coefficients while in the case of STEPN, we obtain sixteen statistically significant coefficients. Furthermore, a potential determinant of NFTs can have a different impact on different NFTs. For example, the FTSE has a positive effect on XMON but a negative effect on Illuvrium returns.

Table 2: Coefficients of the independent variables for the Model I.

Variable/NFT	Unisocks	XMON	Illuvrium	NFTX	Decentraland	Gala	The Sandbox	STEPN	Apecoin	Flow
VOL	0.319	0.203	0.232	0.315	0.383	0.578	0.397	0.306	-0.159	0.219
TV	0.022	0.019	0.079	0.025	0.029	0.069	0.136	0.219	0.774	0.119
SVI	–	0.058	0.003	–	0.013	–	0.001	–	-0.326	-0.021
REDDIT	-	-	–	-	–	–	-0.017	0.033	-0.449	0.005
R/NFT	–	-0.017	-0.015	–	–	–	–	-0.05	–	–
BTC	–	–	0.139	0.043	0.238	0.141	0.225	0.16	0.291	0.26
ETH	0.536	0.497	0.614	0.5091	0.391	0.235	0.375	0.406	0.335	0.422
SP500	–	–	–	–	0.061	–	–	–	–	–
DJI	–	-0.01	–	–	–	–07	0.031	–	–	–
NASDAQ	–	0.025	–	–	0.006	0.032	–	-0.023	0.107	–
STOXX	–	–	0.005	–	0.008	–	–	-0.102	-0.018	–
FTSE	0.027	0.032	–1	0.028	0.033	–	–	0.093	–	0.034
NIKKEI	–	–	0.018	–	–	–	–	–	-0.037	0.001
SSEC	–	–	–	-0.009	0.001	–	-0.009	0.024	-0.003	–
CVIX	–	-0.002	-0.031	–	–	–	–	-0.096	–	–
VSTOXX	–	–	–	–	-0.027	-0.022	-0.037	0.125	-0.017	–
EURO	–	-0.103	–	–	–	–	-0.013	–	-0.044	–
GBP	–	0.078	0.017	–	–	–	–	0.024	–	–
JPY	–	–	0.02	–	–	–	0.03	–	0.019	–
CNY	–	–	-0.005	-0.017	–	–	–	-0.067	0.1	–
WTI	–	–	-0.01	0.006	–	–	–	-0.151	-0.063	–
BRENT	–	–	–	–	-0.002	–	–	0.011	–	–
GOLD	–	-0.021	–	–	–	–	-0.025	–	0.011	–

Notes: i) For each NFT a LASSO model is fitted to the data, with the returns as the dependent variable. Each model is estimated using a penalised Maximum Likelihood. ii) The variable REDDIT is not included in the analysis of Unisocks, XMON and Illuvium.

Model I provides some clear results regarding some of the determinants of NFTs, but the effect of some factors such as the stock market indices remains unclear. In addition, model I ignores the volatility dynamics of NFTs returns. To deal with these issues, we proceed with model II which is a two-step procedure. In the first step, we fit alternative GARCH models the NFT returns and select the best model in terms of goodness-of-fit. Table 3 presents the results from the Akaike and Schwarz information criteria. For the majority of the examined NFTs, both criteria indicate the EGARCH model as the most appropriate. According to the information criteria, the most suitable models for Decentraland and Apecoin are the GARCH and APARCH, respectively. In the case of Flow, the Akaike information criterion indicates the GJR-GARCH as the best model while the Schwarz indicates the GARCH model. To select the most appropriate GARCH specification we consider two additional information criteria, the Shibata and the Hannan-Quinn which both favour the selection of the GJR-GARCH model.

For each NFT, the standardised residuals from the best GARCH model are extracted and used as the dependent variable in the LASSO model. Table 4 reports the estimated coefficients for each LASSO model estimated using the penalised Maximum Likelihood estimator (model II). The results are qualitatively similar with the results from model I. Specifically, we observe that the volatility and the trading volume of each NFT along with the returns of ethereum and bitcoin have a strong positive effect in the NFTs. Furthermore, we observe that an increase in stock market returns has a positive impact on most NFTs (the only exception is STEPN which appears to be unaffected by the movements of the stock market). The effect of market commodities is not clear since in most cases, the coefficients are not statistically significant. In the few cases that these coefficients are statistically significant, the sign of the coefficients changes based on which NFT is examined. Similarly, model II does not provide clear evidence regarding the effect of exchange rates on the NFT markets.

In general, both models I and II indicate a relatively large number of factors that can potentially influence the behaviour of NFTs. However, the increased number of significant coefficients leads to several contradicting results between the two models regarding the sign and significance of the coefficients (e.g. the effect of Dow Jones and FTSE on Gala and Illuvium, respectively). The frequentist approach may fail to quickly identify the insignificant coefficients and shrink them towards zero. To deal with this issue, we consider model III, the Bayesian LASSO model, which we discuss in the next session.

Table 3: GARCH model selection using information criteria.

Variable/Model	GARCH	EGARCH	GJR-GARCH	APARCH
		AIC		
Unisocks	-2.534	**-2.557**	-2.543	-2.544
XMON	-2.463	**-2.474**	-2.463	-2.464
Illuvrium	-2.581	**-2.587**	-2.580	-2.583
NFTX	-1.756	**-1.780**	-1.759	-1.779
Decentraland	**-2.639**	-2.633	-2.630	-2.635
Gala	-1.898	**-1.918**	-1.896	-1.897
The Sandbox	-2.012	**-2.027**	-2.000	-1.995
STEPN	-2.219	**-2.225**	-2.220	-2.218
Apecoin	-1.964	-1.959	-1.962	**-1.994**
Flow	-1.100	-1.098	**-1.104**	-1.102
		SIC		
Unisocks	-2.461	**-2.473**	-2.458	-2.447
XMON	-2.446	**-2.454**	-2.443	-2.441
Illuvrium	-2.543	**-2.544**	-2.536	-2.532
NFTX	-1.723	**-1.741**	-1.720	-1.735
Decentraland	**-2.598**	-2.585	-2.582	-2.581
Gala	-1.861	**-1.875**	-1.852	-1.848
The Sandbox	-1.941	**-1.944**	-1.917	-1.900
STEPN	-2.187	-2.187	-2.182	-2.175
Apecoin	-1.930	-1.920	-1.923	**-1.949**
Flow	**-1.061**	-1.053	-1.058	-1.050

Notes: i) AIC and SIC denote the Akaike and the Schwarz information criteria, respectively. ii) The bold entries signify the model with the best fit according to each information criterion. iii) In the case of Flow, we employ the Shibata and Hannan-Quinn information criteria which both indicate the GJR-GARCH model as the most appropriate.

Table 4: Coefficients of the independent variables for the Model II.

Variable/NFT	Unisocks	XMON	Illuvrium	NFTX	Decentraland	Gala	The Sandbox	STEPN	Apecoin	Flow
VOL	0.225	0.217	0.191	0.225	0.149	0.510	0.029	0.376	–	0.223
TV	0.021	0.018	0.062	0.018	0.017	0.004	0.238	0.069	0.559	0.126
SVI	–	0.056	–	–	0.014	–	–	–	-0.247	-0.029
REDDIT			–		0.006	–	0.008	–	-0.311	0.009
R/NFT	–	-0.023	-0.014	–	–	–	-0.003	–	–	-0.002
BTC	–	–	0.156	0.067	0.228	0.105	0.163	0.204	0.196	0.314
ETH	0.574	0.447	0.599	0.492	0.388	0.273	0.434	0.42	0.475	0.372
SP500	–	–	–	–	0.032	–	–	0.052	–	0.004
DJI	–	–	–	–	–	0.011	–	0.018	0.037	–
NASDAQ	–	0.056	0.046	–	0.033	0.053	–	–	–	0.003
STOXX	–	–	0.005	–	0.020	–	–	–	–	–
FTSE	0.053	0.033	0.006	0.028	–	–	–	–	0.007	0.037
NIKKEI	–	–	0.022	–	–	–	–	–	–	0.005
SSEC	–	–	0.012	–	0.018	–	–	–	-0.050	–
CVIX	–	-0.003	0.008	–	–	–	–	–	–	0.010
VSTOXX	–	–	–	–	-0.018	–	0.010	-0.028	-0.069	–
EURO	0.001	-0.071	–	–	–	–	–	-0.016	–	–
GBP	–	0.045	0.006	0.01	–	0.003	–	–	–	–
JPY	0.012	–	0.017	–	–	–	–	0.017	0.086	–
CNY	-0.018	–	-0.026	-0.030	–	–	-0.023	–	0.061	–
WTI	0.020	–	–	0.017	–	–	-0.061	–	-0.062	–
BRENT	–	–	–	–	–	–	–	–	–	–
GOLD	–	-0.003	–	–	–	–	–	-0.023	–	0.005

Notes: i) For each NFT, a GARCH-type (GARCH, EGARCH, GJR-GARCH or APARCH) model is fitted to the returns, the standardised residuals are obtained, and used as the dependent variable in the LASSO model. ii) The selection of the GARCH-type specification is based on information criteria (see also Table 3). iii) Each LASSO model is estimated using a penalised Maximum Likelihood. iii) The variable REDDIT is not included in the analysis of Unisocks, XMON and Illuvium.

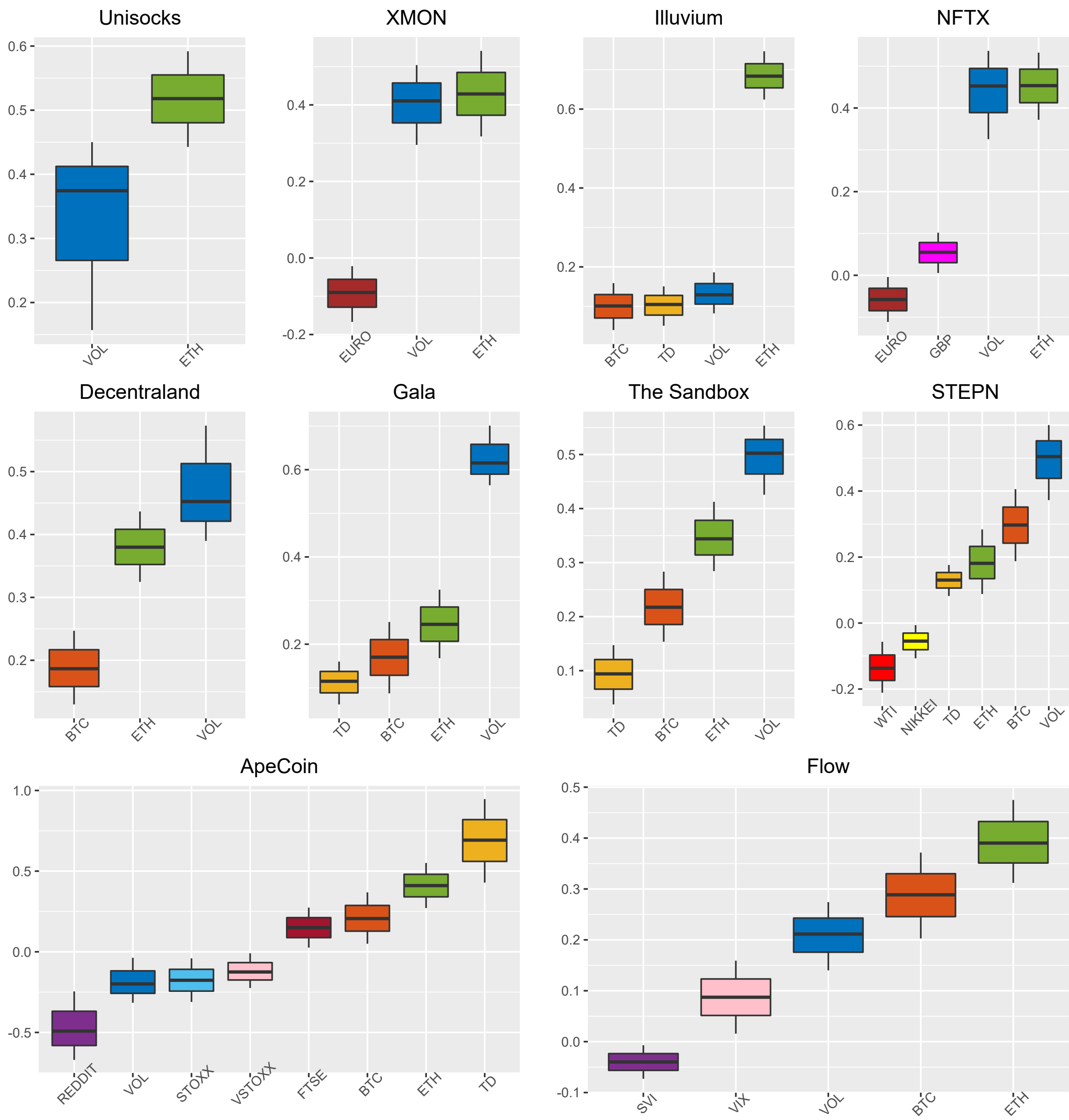
4.2 The Bayesian LASSO with stochastic volatility

In this section, we discuss the findings from model III which accounts both for stochastic volatility and models directly the returns of each NFT. Figure 1 presents the posterior median along with a 95% credible set for the statistically significant coefficients regarding each of the ten NFTs returns. In all cases, NFT returns are positively affected by their respective volatility and ethereum returns (which is in line with the findings of the ML models). The only exception is ApeCoin where the posterior median of volatility is negative. Furthermore, we observe that most NFTs are affected only by a small number of variables. The top row of Figure 1 reports the results regarding the four NFTs with the highest price. Ethereum returns and volatility have the biggest impact on all of them and the effect of both variables is quantitatively similar. However, in the case of Illuvium, there is a substantial difference between the values of the two coefficients. In addition, XMON and NFTX are negatively affected by the EUR/USD exchange rate. These are the only NFTs that are affected by exchange rates (for NFTX, the coefficient of the GBP/USD is also significant but positive). Considering the four most traded NFTs, middle row of Figure 1, the results indicate the most important determinant of NFTs returns is volatility, followed by the returns of ethereum and bitcoin. The coefficient of trading volume is also positive and significant for three out of the four NFTs. In addition, STEPN, the NFT with the lowest trading volume out of the four, is negatively associated with oil prices and the NIKKEI index. The last row of Figure 1 plots the results for ApeCoin and Flow. The two NFTs (together with Decentraland and the Sandbox) are the NFTs with the highest market capitalisation. These two NFTs are the only ones negatively affected by attention indices. Finally, both the returns and the volatility of STOXX 50 index have a negative impact on ApeCoin. The greatest difference between the frequentist and the Bayesian models is that the latter eliminates considerably more coefficients, which can be attributed in the use of shrinkage priors.

Model III accounts for the leverage effect by allowing the two error terms, ε_t and η_t to be correlated. However, in all cases, the results suggest that the two error terms are uncorrelated. This implies that there is no leverage effect in NFTS returns, as opposed to cryptocurrencies returns, where we observe the presence of inverse leverage effect (see also Panagiotidis et al., 2022). This finding supports the view of Horky et al. (2022) who argue that NFTs should not be viewed as simple derivatives of cryptocurrencies and Borri et al. (2022) who argue that NFTs have their own driving forces. Furthermore, in all cases, the value of the persistence parameter ϕ, approaches the unit which further supports the selection of a model that accounts for stochastic volatility.

To validate the findings from model III, we re-estimate the model by adding the NFT attention index, constructed by Wang (2022), as an additional explanatory variable. Since the index is available only on a weekly frequency, we impute the missing data. The results remain qualitatively the same as the ones obtained from the main model and the added variable is insignificant in most of the cases. More specifically, the new variable affects significantly only the returns of Decentraland and the Sandbox NFTs and in both cases, the effect is negative. This is in line with the results from the main model that suggest that attention is not one of the main determinants of NFTs returns and that attention and NFTs returns are negatively related.

Figure 1: Posterior estimation, median and 95% credible set, of the statistically significant coefficients (model III).



5 Conclusions

The popularity of NFTs has increased. Similar to cryptocurrencies, NFTs are built on blockchains. Yet, it is unclear whether they are affected by the same mechanisms as cryptocurrencies and what determines their returns. This paper examines the potential determinants of ten alternative NFTs returns. Our contribution to the literature is twofold. First, we differentiate from the existing literature which examines the relationship between NFTs and a specific type of variables such as stock market returns or cryptocurrencies. Here, we consider an extended set of potential drivers of NFTs including volatility of returns, trading volume, attention indices, cryptocurrencies, stock market returns and volatility, commodities returns, and exchange rates. Using a variety of alternative variables we can better assess which variables that truly affect the returns of NFTs. Second, we conduct the analysis using a Bayesian LASSO model that takes into account the volatility dynamics of NFTs returns and allows for faster elimination of insignificant variables, compared to frequentist counterparts, through the use of shrinkage priors. While the volatility dynamics of NFTs are studied in the literature, they are overlooked when the focus is on NFTs returns. The Bayesian LASSO takes into account the time varying volatility of NFTs returns and accounts for potential over-parameterisation issues caused by the increased number of variables.

The results indicate that cryptocurrencies, especially ethereum, and volatility of returns have the biggest impact on NFTs returns. In particular, the NFTs with the highest price are primarily driven by Ethereum returns while the NFTs with the biggest trading volume are driven by volatility. The stronger effect of Ethereum on NFTs compared to bitcoin can be explained by the fact that most NFTs reside on ethereum's blockchain. Furthermore, stock markets, exchange rates, and market commodities appear to have a feeble impact on a few of the examined NFTs. Finally, attention indices are significant only in the cases of ApeCoin and Flow. In both cases, as attention rises, returns decrease. Our study validates findings from previous studies and also provides new results regarding the drivers of NFTs returns. These findings can be useful to investors who seek to diversify their portfolio and mitigate potential risks since most of the analysed NFTs are associated with neither stock market returns nor exchange rates. Specifically, we find that euro impacts only two NFTs and in both cases, the effect is negative. Another, implication of this research is that NFTs market is not driven by popularity. Due to their individuality, NFTs are viewed as art and safe haven during turbulent times rather than speculative assets.

Our research can be expanded in various ways. First, one could further extend the set of potential regressors such as technological factors that could affect NFTs returns.

Second, the interrelationship between NFTs could be taken into account by including NFTs returns as explanatory variables. Third, the long-run relationships of NFTs and their determinants could be examined using cointegration analysis.

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A Supplementary tables and figures

Table A1: Variables and Data sources for the independent variables

Variable	Source
Returns volatility [VOL]	
Trading volume [TV]	CoinMarketCap
Search volume index [SVI]	Google Trends
Number of comments in subreddit [REDDIT]	Subreddit Stats
Number of comments in subreddit r/NFT [R/NFT]	Subreddit Stats
Bitcoin price [BTC]	CoinMarketCap
Ethereum price [ETH]	CoinMarketCap
Brent oil price (in USD per barrel) [BRENT]	FRED St. Louis
West Texas Intermediate oil price (1 barrel) [WTI]	FRED St. Louis
Gold price (in USD per troy ounce) [GOLD]	investing.com
S&P500 [SP500]	FRED St. Louis
Dow Jones NYSE index [DJI]	FRED St. Louis
NASDAQ index [NASDAQ]	FRED St. Louis
EURO STOXX 50 index [STOXX]	wsj.com
FTSE 100 index [FTSE]	wsj.com
NIKKEI 225 index [NIKKEI]	wsj.com
Shanghai Composite Index [SSEC]	wsj.com
CBOE Market Volatility Index [VIX]	FRED St. Louis
EURO STOXX 50 Volatility Index [VSTOXX]	wsj.com
EUR/USD exchange rate [EURO]	FRED St. Louis
GBP/USD exchange rate [GBP]	FRED St. Louis
JPY/USD exchange rate [JPY]	FRED St. Louis
CNY/USD exchange rate [CNY]	FRED St. Louis

Notes: i) The mnemonics in brackets are used to denote the variables in the Tables and Figures. ii) Volatility of returns is based on authors' calculations. iii) Volatility of returns, trading volume, search volume index, number of comments on subreddit are different for each examined NFT. iv) Due to data unavailability, we do not include REDDIT in the analysis of NFTX, Unisocks, and XMON.

Figure A1: Returns of the ten examined cryptocurrencies.

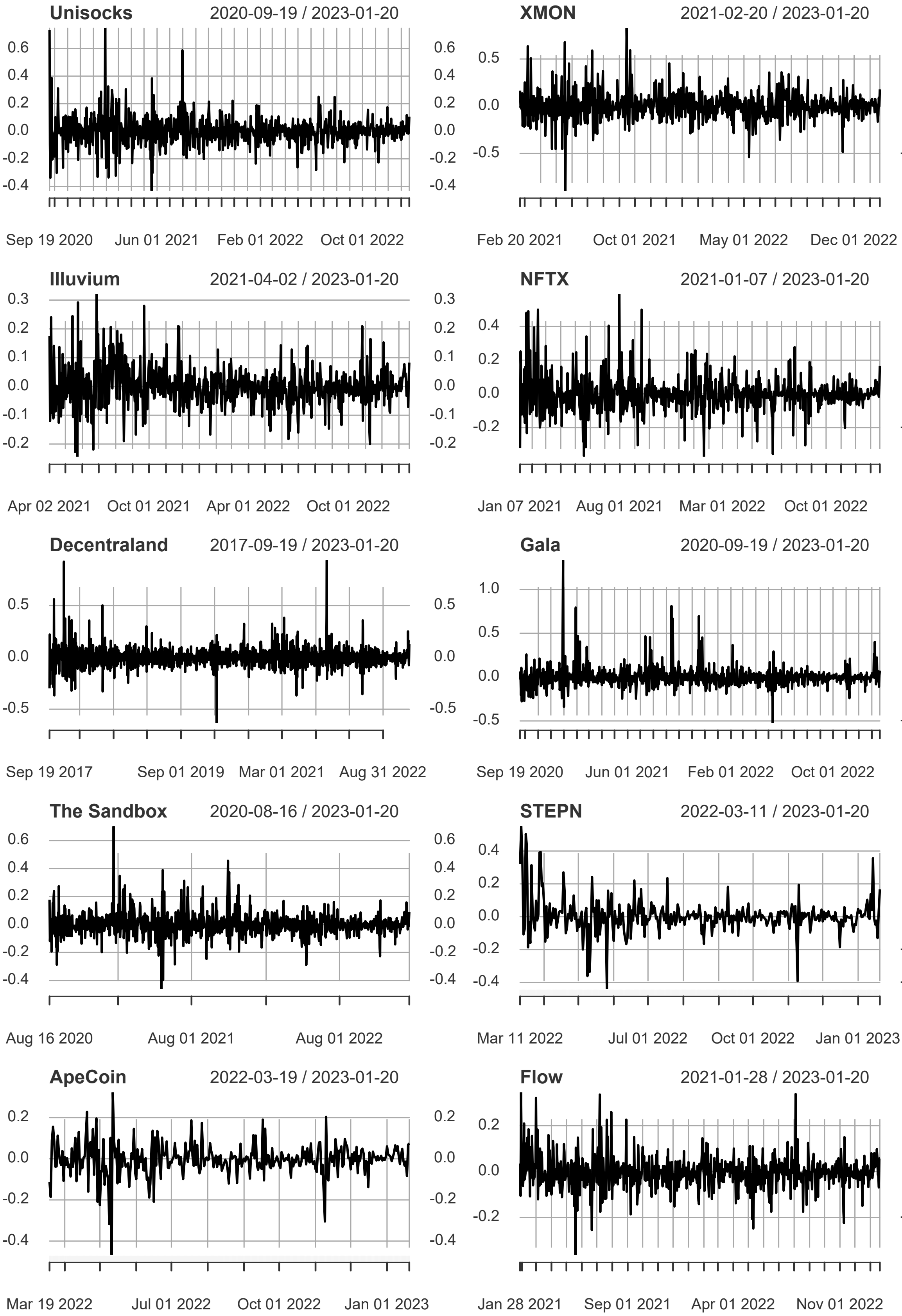
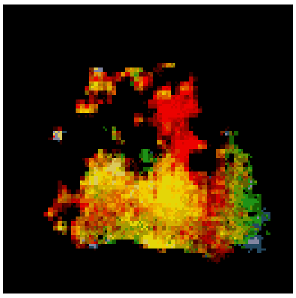


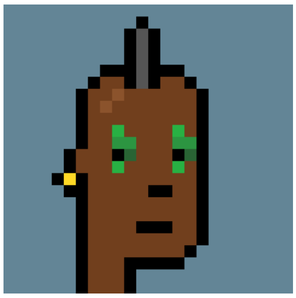
Figure A2: Popular items of the examined NFTs.

(a) Unisocks



(b) XMON

(c) Illuvium



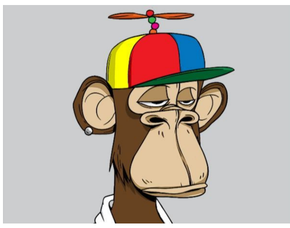
(d) NFTX

(e) Decentraland

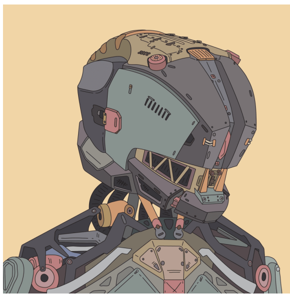
(f) Gala

(g) The Sandbox

(h) STEPN



(i) Apecoin



(j) XMON