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A Bayesian approach for the determinants of bitcoin returns

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Abstract

This paper examines the effect of thirty-one variables on bitcoin returns over the period 2015-2021. We use a Bayesian LASSO model that accounts for stochastic volatility and leverage effect. We examine the impact of economic, financial and technological variables as well as uncertainty and attention indicators on bitcoin returns. Furthermore, we consider two recently proposed indicators (Central Bank Digital Currency (CBDC)) for uncertainty and attention. Our findings suggest that sentiment and technological factors have the most profound effect on bitcoin returns. Regarding economic/financial variables, stock market returns and volatility indices have the greatest impact on bitcoin returns.

Keywords: bitcoin, cryptocurrency, LASSO, Bayesian, CBDC.

JEL Codes: G12, G15, C11, D80

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1 Introduction

Disentangling the factors that affect the price of bitcoin is an issue of major interest among both researchers and investors, since its introduction by Nakamoto (2009). A large part of the related literature focuses on economic and financial variables that could determine the price of bitcoin. One of the first papers is that of Wijk (2013) where an Error Correction Model is used to analyse the relationship between bitcoin, stock markets, exchange rates and the price of oil. The effect of stock market returns on bitcoin is also examined by Dyhrberg (2016a,b) and Wang et al. (2016).[1] In addition, Dyhrberg (2016a), Dyhrberg (2016b) identify the effect of exchange rates on bitcoin returns. Other economic and financial variables that could impact bitcoin returns are the policy uncertainty (Demir et al. (2018)) and Federal funds interest rate (Dyhrberg (2016a) and Li and Wang (2017)).

A second group of variables that are known to affect bitcoin returns is that of fundamentals (supply and demand). The total amount of bitcoins in circulation is nearly fixed and publicly known.[2] As a result, supply forces have a smaller impact on bitcoin returns than demand forces, de la Horra et al. (2019). An explanation for the (almost) constant amount of bitcoins stems the difficulty to generate new bitcoins. Specifically, the quantity of bitcoin supply depends on 'mining', which is the process of validating transactions on the network. The verified transactions are stored in a database called blockchain. The amount of electricity and computational power which is required for mining hinder the mining process, causing the total amount of bitcoin to remain nearly fixed. The latter motivates the discussion for the third group of factors that could potentially determine bitcoin returns, the group of technology related factors. This group, which draws the least attention, contains variables that measure the difficulty and the computational power required to complete the mining process. The difficulty of mining is usually measured by two proxies. The first one, the hash rate, measures the computational power in the network. A higher hash rate indicates a more secure network and more users validating transactions. In addition, the higher the hash rate, the higher the chance that a user creates a new block in the blockchain and obtain bitcoin. The second proxy, called network difficulty, measures the computational power and the number of hashes required to verify a transaction. Network difficulty is adjusted, based on hash rate and the total number of users, to maintain the time required to verify a transaction approximately at ten minutes.

The last group of variables that is associated with bitcoin returns, consists of variables that proxy the attractiveness of bitcoin as an asset. The variables included in this group measure information demand based on internet sources such as Wikipedia, Google Searches and Twitter which are found to have both positive and negative effect on bitcoin returns (see among others Panagiotidis et al. (2019) and Li and

[1] Bitcoin is also affected by stock market volatility (Akyildirim et al., 2021).
[2] This is the reason that bitcoin can not function as money, according to Loi (2018).

Wang (2017)).

Despite bitcoin existing for almost fifteen years and numerous studies attempting to disentangle between its determinants, there is still a lively discussion on the drivers of bitcoin returns and the related literature often provides contradicting results. For example, according to Dyhrberg (2016a,b) the Financial Times Stock Exchange (FTSE) is related both positively and negatively with bitcoin returns. Similarly, Wang et al. (2016) and Zhu et al. (2017) show that the Dow Jones Industrial Average (DJ) affects bitcoin returns both positively and negatively. The difficulty in identifying the mechanisms that drive bitcoin returns stems both from its unconventional features compared to traditional currencies and assets and the complex technology behind its creation and circulation. As a result, the findings provided in the literature often rely on the methodological approach and the selection of the potential determinants of bitcoin returns.

The aim of the paper is to provide further insight into the potential determinants of bitcoin returns. Specifically, we examine thirty-one variables from all four groups previously discussed. Studies in this strand of the literature either focus on one category of factors or do not pay attention to others. For example, Panagiotidis et al. (2019) examine up to forty-one drivers of bitcoin returns but do not take into account any technology-related factors. In this study, we consider all kinds of variables examined in previous studies, these include technology-related factors, supply and demand factors, stock market returns and volatility indices, commodities returns, exchange rates, federal funds interest rates, uncertainty indices and attention indices. Furthermore, we employ the recently proposed Central Bank Digital Currency (CBDC) uncertainty and attention indices constructed by Wang et al. (2022). The CBDC is a digital currency issued by a central bank. Although the concept of CBDC predates the creation of bitcoin, CBDC in its present form is heavily inspired by bitcoin and other similar blockchain-based cryptocurrencies.

To carry out the analysis, we employ the Least Absolute Shrinkage and Selection Operator (LASSO) framework, put forward by Tibshirani (1996). The LASSO approach has been employed previously in the similar studies. Panagiotidis et al. (2018) use a LASSO model via penalized maximum likelihood to examined a wide range of predictors. This model does not account for the time-varying nature of volatility of bitcoin returns caused by the use of bitcoin as a speculative asset (Fry and Cheah (2016), Blau (2017) and Lee et al. (2020)).[3] Ciner et al. (2022) employ a quantile regression LASSO model to examine potential drivers of bitcoin, ethereum and ripple returns during the COVID-19 period.[4] This model also ignores the volatility dynamics of bitcoin returns. In this paper, we employ a Bayesian LASSO model that

[3]For studies that examine the bitcoin volatility dynamics see among others (Urquhart and Zhang (2019), Walther et al. (2019) and Panagiotidis et al. (2022).

[4]This model, proposed by Belloni and Chernozhukov (2011) is also used by Nguyen et al. (2020) to examine tail risk dependency among cryptocurrency markets.

has three advantages compared to the models used in the two aforementioned papers. First, it accounts for time-varying volatility of bitcoin returns via stochastic volatility. Second, depending on their sign, shocks can have different effect on the future volatility of bitcoin returns. That is the model allows for leverage effect. Third, the Bayesian framework accounts for over-fitting issues through the usage of shrinkage priors by eliminating the weakly related parameters faster than its frequentist counterparts. As a result, it enhances the ability of the LASSO model to exclude non-significant variables through coefficients' shrinkage.

Before we proceed with the main Bayesian model, we consider a reexamination of the two LASSO models used in the Panagiotidis et al. (2018) and Ciner et al. (2022). In all cases, we employ the same set of predictors as the ones used in the two studies. Based on Panagiotidis et al. (2018) we estimate a LASSO model with the Maximum Likelihood (ML) method **(model 1a)**. Since the model does not take into account bitcoin volatility, we consider a sub-case where we fit an exponential GARCH (EGARCH) model to the bitcoin returns (as a filter) and use the the standardised residuals as the dependent variable in the LASSO model **(model 1b)**. The model is estimated using the ML method as Model 1a. This is the only case where we do not use the bitcoin returns as the dependent variable. The EGARCH model is selected as the filter from a variety of GARCH models based on information criteria. An advantage of the EGARCH specification is that it can capture the inverse leverage effect which is present in bitcoin returns. Next, we consider the quantile regression LASSO model **(model 2)** used by Ciner et al. (2022). This study focuses on the effect of exchange traded funds on bitcoin returns during the recent pandemic. As a result, the set of examined predictors has noteworthy differences from the one we used in this paper. Once we reexamine the two frequentist models, we proceed with the main model, the Bayesian LASSO with stochastic volatility **(model 3)**, that provides full uncertainty quantification in a probabilistic framework rather than relying on asymptotic results.

The rest of the paper proceeds as follows: Section 2 describes the methodology. Section 3 presents the data. Section 4 discusses the main findings. The last one concludes.

2 Methodology

We consider three main cases. In the first case, we estimate a frequentist LASSO with the ML method and we consider two sub-cases regarding the dependent variable. In the first sub-case **(model 1a)**, we use the bitcoin returns as the dependent variable and in the second sub-case **(model 1b)**, we consider the standardised residuals obtained from an EGARCH model fitted to bitcoin returns. Model 1b is the only model where we the dependent variable is not bitcoin returns. In the second case, we consider the quantile regression adaptive LASSO. Apart from the median (50^{th}), we examine the 10^{th} and 90^{th}

quantiles to investigate the predictors in bullish and bearish markets. In the last case **(model 3)**, we estimate the LASSO model using a Bayesian method that takes into account the stochastic volatility of bitcoin returns. Table 1 provides a summary of the different models employed in the analysis.

Table 1: Description of methods used in the analysis.

Mnemonic	**Method**	**Dependent variable**
Model 1a	penalized maximum likelihood	bitcoin returns
Model 1b	penalized maximum likelihood	standardised residuals from an EGARCH model fitted to bitcoin returns
Model 2	quantile regression	bitcoin returns
Model 3	bayesian estimation	bitcoin returns

Notes: i) In all models we consider the same set of potential predictors. ii) In model 2, we examine the 10^{th}, 50^{th} and 90^{th} quantiles. iii) Model 3, is the only model that accounts for stochastic volatility and leverage effect.

Next, we describe the Bayesian model, since models and 1 and 2 are described in Panagiotidis et al. (2018) and Ciner et al. (2022), respectively (for a more detailed discussion on LASSO estimation using frequentist inference see also Tibshirani, 1996; Belloni and Chernozhukov, 2011; Zou, 2006). Let y_t, $t = 1, \ldots, T$ be the vector of bitcoin returns. 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 x_t is the $T \times k$ matrix of the k covariates and β is the $k \times 1$ vector of estimated coefficients. The stochastic volatility parameters μ, ϕ and σ, denote the level, persistence and standard deviation of the log-variance process, h_t, respectively. Furthermore, $\varepsilon_t \sim t_\nu(0, 1)$, $\eta_t \sim N(0, 1)$ and $\text{corr}(\varepsilon_t, \eta_t) = \rho$, where $N(a, b)$ stands for the Normal distribution with mean a and variance b and t_ν stands for the Student's-t distribution with ν degrees of freedom, mean a and variance b. This framework combines Student's-t errors and leverage effect (when $\rho \neq 0$).

We now specify the prior distributions. 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 $\beta \sim N_k, (b_\beta, B_\beta$. Small (large) values for the diagonal of B_β yield shrinkage (uninformative) priors. Here, we assume that $\beta \sim N_k(0, I)$ which yields the special case of Bayesian LASSO, proposed by Park and Casella (2008). For the log-variance, we also consider a normal distribution, $h_t \sim N(\mu, \sigma^2/(1 - \phi)^2)$. Furthermore, to ensure stationarity in the log-variance process, we require that $\phi \in (-1, 1)$. To this end, regarding ϕ, we consider $\phi \sim B(5, 1.5)$ (beta distribution). For the parameter μ, we assume normal prior, that is $\mu \sim N(0, 100)$. With regard to the prior distribution of the standard deviation of h_t, σ, we follow

Frühwirth-Schnatter and Wagner (2010) and Kastner and Frühwirth-Schnatter (2014) and consider the half normal distribution with scale parameter 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. The assumption of the Student's-t errors in the log-variance process, brews up the requirement for the a-priori specification of ν, the number of degrees of freedom. As in Geweke (1993), the exponential distribution is chosen, such that $(\nu - 2) \sim E(0.1)$. Finally, as in Omori et al. (2007), we set $(\rho + 1)/2 \sim B(4, 4)$. Summarising, the priors 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 method of Kastner and Frühwirth-Schnatter (2014).[5] 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, Rue (2001) and McCausland et al. (2011). Kastner and Frühwirth-Schnatter (2014) consider neither a Student's-t distribution nor a leverage effect. To address the estimation issues caused by the assumption of Student's-t distribution, we represent the Student's-t distribution as a scale mixture of normal distributions which requires the addition of Gibbs and independence Metropolis-Hastings steps for the MCMC algorithm as in Kastner (2015). In addition, to handle the increased complexity in the estimation of the posterior distributions, caused by the inclusion of leverage effect in the model, we add repeated ancillarity-sufficiency interweaving strategies, Yu and Meng (2011) steps in the sampling scheme as in Hosszejni and Kastner (2019). The posterior sample is built from 25000 after a burn-in 25000 draws. We consider two robustness checks to further validate our findings. In the first one, we re-estimate the model by increasing the number of burn-in and pos-

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

terior draws to 50000. In the second, we set the number of burn-in 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.

3 Data

This study considers thirty-one potential drivers of bitcoin returns. The complete list of examined variables along with the mnemonics and sources is reported in Table A1. We download from coinmarketcap.com daily bitcoin prices over the period 4/1/2015 to 1/5/2021. The bitcoin returns are calculated as the first logarithmic differences of the closing prices. The sampling period is determined by the availability of the data. Specifically, the two CBDC indices cover the period 2015-2021. For the most part of the sample (January 2015 to October 2020) bitcoin prices are gradually prices with a sudden spike in the prices during the last month of 2017. From November 2020 there is an outburst in bitcoin prices which lasts until the end of our sampling period.

We consider six stock market indices from U.S. (S&P500, NASDAQ and Dow Jones), U.K. (FTSE), Japan (Nikkei 225) and China (SSEC) and three stock market volatility indices (VSTOXX, VXD and VIX). In addition, we consider four pairs of currencies trading in the foreign exchange market (EUR/USD, GPB/USD, CNY/USD and JPY/USD), obtained from finance.yahoo.com. Regarding the commodity prices, we examine the effect of oil (WTI and Brent prices) and gold on bitcoin. Interest rates are obtained from Federal Funds and ECB. In terms of uncertainty, we use economic policy uncertainty (EPU) indices for the U.S., Europe, China and a global index. These indices are available on monthly frequency. Furthermore, we consider the Daily Infectious Disease Equity Market Volatility Tracker (IDEMV) which is a newspaper index that captures stock market uncertainty caused by the recent pandemic. The last uncertainty index, CBDCU, tracks uncertainty around the growing area of CBDC.

To proxy bitcoin attractiveness, we use the amount of search queries on Wikipedia and the CBDCA index which captures the attention around the adoption of CBDC. We choose not to include any data from Google Trends since the Search Volume Index provided by Google Trends is different even if the same parameters (keyword, location and date) are used. To measure bitcoin supply, we use total number of bitcoins in circulation. Similarly, as a measure of bitcoin demand, we employ the number of daily confirmed transactions and unique addresses used. Finally, we utilise two variables that proxy the mining difficulty, the first one (hash rate) is the computational power on the network and the second (network difficulty) indicates the difficulty of creating a new block in the blockchain.

Table A2 reports the summary statistics and the ADF test statistic. We perform the necessary transformations so that all variables are stationary. Furthermore, the variables that are only available on a lower frequency (i.e. policy uncertainty indices) are linearly interpolated. As a robustness check we use the Catmull-Rom Spline interpolation method. The results remain qualitatively the same and are available upon request.

4 Results

4.1 ML estimation

In this section we discuss the main findings of the four models. Table 3 reports the variables with statistically significant coefficients in a decreasing order, for each examined model. The numbers in parentheses denote the value of the estimated coefficient. We begin with the LASSO model that uses penalised maximum likelihood, that is **model 1a**. This model is also used in Panagiotidis et al. (2018). Using this model 1a, we find nine variables that are statistically significant. These are reported in the first column of 3. Stock market returns seem to have the greatest impact on bitcoin returns since four out of the nine significant variables are stock market indices. Furthermore the factors with the greatest positive and negative impact are the NASDAQ and Nikkei 225 indices, respectively.[6] Bitcoin returns are also positive affected by a technology factor, the hash rate. This means that as the computational power on the network increases, bitcoin returns also increase. Considering stock market volatility, the only index with a significant covariate is the VSTOXX volatility index. According to the results of the base model, a rise in the price of gold causes a rise in bitcoin returns while oil prices and bitcoin are unrelated. Finally, while both demand proxies have a substantial effect on bitcoin returns, the coefficient of the supply variables is not significantly different from zero. The top graph in Figure A1 presents the estimated coefficients as functions of the shrinkage value. As the shrinkage value increases, we observe that bitcoin returns are negatively affected by the S&P500 and the global EPU indices.

The downside of model 1a is that it doesn't take into account the volatility dynamics of bitcoin returns. To overcome this issue, in **model 1b**, we first fit an EGARCH model to bitcoin returns. The EGARCH model is selected from a group of candidate GARCH model as the most based on four alternative information criteria. Table 2 presents the results for the goodness-of-fit analysis of the examined GARCH model. We consider the GARCH, threshold GARCH (TGARCH), GJRGARCH, EGARCH, asymmetric power GARCH (APGARCH) and the nonlinear asymmetric GARCH (NAGARCH) models. All information criteria indicate the EGARCH model as the most appropriate. Once we fit the EGARCH model

[6] FTSE impacts bitcoin returns positively and more than Nikkei 225 (in terms of absolute value). In general, for model 1a, the variables with a negative effect on bitcoin returns (Nikkei 225 and JPY/USD exchange rate) have smaller coefficients (in absolute value).

to bitcoin returns, we extract the standardised residuals and then re-estimate the LASSO model as in model 1a using the obtained fitted residuals as the dependent variable.

Table 2: GARCH model selection based on information criteria.

Criterion / Model	GARCH	TGARCH	GJRGARCH	EGARCH	APGARCH	NAGARCH
AIC	-3.832	-3.839	-3.832	**-3.841**	-3.837	-3.835
BIC	-3.815	-3.819	-3.812	**-3.821**	-3.814	-3.815
SIC	-3.832	-3.839	-3.832	**-3.841**	-3.837	-3.835
HQ	-3.826	-3.832	-3.825	**-3.834**	-3.828	-3.828

Notes: i) AIC, BIC, SIC, HQ is the information criterion proposed by the Akaike (1974), Schwarz (1978) (Bayesian), Shibata (1976) and Hannan and Quinn (1979), respectively. ii) For each criterion, the minimum value is shown in bold.

The results from the second LASSO model are reported in the second column of 3 where the variables are ranked based on the value of their coefficients.[7] The number of statistically significant regressors is increased to twenty-three compared to the first case. The coefficients of the variables that were significant in model 1a are also significant in this case and retain their sign. Stock market returns continue to have the greatest positive effect on bitcoin returns since the NASDAQ and FTSE indices have the greatest positive impact and the Nikkei 225 index the most negative impact on bitcoin returns. Another stock market index with significant coefficient is the Shanghai stock exchange composite index (SSEC). Furthermore, all stock market indices affect bitcoin returns. However, the effect is different between VXD and VSTOXX (positive) and VIX (negative). In addition, model 1b provides more evidence of the positive relationship between commodity markets and bitcoin returns.

An important difference between the two ML models is that model 1b identifies uncertainty as a driver of bitcoin returns. China's EPU index has a substantial positive impact on bitcoin returns.[8] The effect CBDCU and IDEMV is positive and negative, respectively. Another difference between models 1a and 1b is that in the latter, both factors associated with the attractiveness of bitcoin (WIKI and CBDCA) are positive and significant. In addition, according to the results obtained from model 1b, an increase in two exchange rate pairs, EURO/USD and CNY/USD, yields an increase in bitcoin returns while an increase in JPY/USD yields a decrease. The last difference we observe is that ECB's deposit facility rate has a negative relationship with bitcoin returns. The lower graph in Figure A1 plots the estimated coefficients as functions of the shrinkage value, for model 1b. Similar to the first case, for larger values of the shrinkage parameter, the S&P500 index has a substantial negative effect on bitcoin returns.

4.2 Quantile regression adaptive LASSO

This section discusses the findings from the quantile regression. The quantile regression adaptive LASSO, **model 2**, is used by Ciner et al. (2022) to analyse the impact of exchange traded funds on bitcoin

[7] Variables with insignificant coefficients are not included.

[8] In fact, all variables associated with China affect bitcoin positively.

returns during the recent pandemic. Similar to model 1a, model 2 also ignores the volatility dynamics of bitcoin returns.

We consider the 10^{th}, 50^{th} and 90^{th} quantiles. For each of the three quantiles, the variables with statistically significant coefficients are reported in the third, fourth and fifth column of Table 3. At the 50^{th} quantile, we identify fourteen variables that affect significantly bitcoin returns. All country specific EPU indices are significant and positive (the CEPU index has the greatest positive coefficient). However, the global EPU index appears to have a negative effect on bitcoin returns. Both gold and oil (BRENT) affect bitcoin returns. The number of daily confirmed addresses which is used as proxy for bitcoin demand has also a positive effect on bitcoin returns. Regarding stock markets, we find that two U.S. stock market indices, NASDAQ and the Dow Jones, have significant and positive coefficients while Japanese index (Nikkei 225) is significant but negative. Finally, while all stock market volatility indices have a significant effect on bitcoin returns, the sign of the effect differs.

We proceed with the examination of the results at the 10^{th} quantile which is often used to reflect bearish markets. The results are reported in the third column of Table 3. Out of the ten covariates with statistically significant coefficients, only two are negative, the number of Wikipedia searches and the CBOE Volatility Index. It is notable that this is the only case where the effect (in absolute value) of the negative coefficients is greater compared to the effect of positive coefficients. Even the second most negative coefficient (VIX) is greater (in absolute value) than the most positive significant coefficient (VXD). Furthermore, both are stock market volatility indices which suggest that although stock market volatility has a strong impact on bitcoin returns, the sign of the impact depends on the examined index. Regarding the remaining variables with positive coefficients, we observe differences compared to the results from the median. First, the hash rate is now significant. Second, only the Brent oil price (and not the gold price) has an effect on bitcoin returns. Third, the only significant EPU index is the European. However, the CBDCU index is now positive and significant. Finally, this is the only case where all significant stock market indices are positively related to bitcoin returns. These are the NASDAQ, FTSE and SSEC index.

The final quantile we examine is the 90^{th} quantile. The variables with significant coefficients are presented in the fifth column of table 3. The results reveal that bitcoin returns are positively related with attention, reflected by the number of Wikipedia searches and demand, reflected by the number of unique addresses used and the number of confirmed transactions per day. All three variables have positive and significant coefficients. Contrary to the demand, supply forces, measured through the total number of bitcoins in circulation have a negative effect on bitcoin returns. Furthermore, we observe that the coefficient of hash rate is positive and significant, indicating that bitcoin returns increase together with the probability of adding a new block in the blockchain (and creating a new bitcoin). Considering EPU, we observe that while country-specific EPU indices are not significant, the global EPU index is positively related with bitcoin returns. There is one more uncertainty index that affects bitcoin returns, the IDEMV index. The index, which is a proxy for stock market uncertainty caused by the pandemic, has a negative effect on the pandemic.

In bullish markets, at the 90^{th} quantile, stock market volatility is positively associated with bitcoin returns. This is suggested by the positive and significant coefficients of VIX and VXD (the coefficient of VSTOXX is insignificant). The effect of stock market returns is unclear since out of the six indices, the model identifies three significant indices. Two of them, the S&P500 and the Nikkei 225, have a negative effect while the NASDAQ index has a positive effect on bitcoin returns. In addition, in terms of absolute values, the coefficients of Nikkei 225 and NASDAQ are very close (the coefficient of S&P500 has a smaller value compared to the other two variables). Finally, we detect two pairs of exchange rates with a substantial effect on the bitcoin returns. A rise in CNY/USD and the JPY/USD exchange rates yields a rise and a decrease in bitcoin returns, respectively.

4.3 Bayesian LASSO with stochastic volatility and leverage effect

Out of the three models used in the analysis, two of them, models 1a and 2 do not take into account the volatility dynamics of bitcoin returns. Model 1b accounts for conditional volatility (indirectly) via the use of the EGARCH models which is used as a filter. However, in model 1b, bitcoin returns do not enter directly the LASSO model, but the standardised residuals from the EGARCH model are used instead. To overcome the drawbacks of all previous models, we employ the Bayesian LASSO model with stochastic volatility which also allows for possible leverage effect, **model 3**. Furthermore, the Bayesian estimation reduces the risk of over-fitting (due to the large number of independent variables) through parameter shrinkage based on prior information.

The results from the last model are reported in the last column of Table 3. Figure 1 plots the posterior median along with 95% credible interval for the variables with statistically significant coefficients. The results indicate that the most important determinant of bitcoin returns is the CBDC attention index. This result reinforces the view of Goczek and Skliarov (2019) who argue that the popularity of bitcoin is the main driving factor of bitcoin returns.[9] Furthermore, this finding supports the view that public interest in bitcoin and the fear of missing out is closely related to bitcoin price bubbles. The second most important variable that drive bitcoin returns is the hash rate. This result is in line with the findings of Kristoufek (2020) and Li and Wang (2017) which indicate a positive relationship between hash rate and bitcoin returns. The strong relationship between bitcoin returns and hash rate, not an economic-

[9] Wang et al. (2022) show that a positive shock in the CBDCA index yields a rise in bitcoin returns.

related factor, reveals the competitive nature of the bitcoin mining since the greater the computational power the higher the chance of creating a new bitcoin. One could argue that the herding behaviour that occurs in bitcoin investors is also found in bitcoin miners, as indicated by the burst in demand for mining rigs (graphic cards) in the winter of 2017. Furthermore, the negative value of the coefficient mining difficulty (DIF) provides additional validation that the complex digital nature of bitcoin strongly affects bitcoin returns.[10]

The results from model 3 suggest that investors' sentiment and mining difficulty are the principal drivers of bitcoin returns. The economic variables with the greatest impact on bitcoin returns are stock market indices. Specifically, the S&P500, NASDAQ and Nikkei 225 affect the bitcoin prices positively and the Dow Jones and Shanghai stock exchange composite index negatively. The only stock market index that does not affect bitcoin is FTSE.[11] The strong relationship between stock market and bitcoin can by explained by the inclusion of a substantial part of the COVID-19 pandemic in the sample. As shown by Nguyen (2022), stock market returns impact significantly bitcoin returns during periods of high uncertainty (such as the period during the recent pandemic). Similarly, we expect volatility spillover effects from the stock market to bitcoin returns. Specifically, two out of three stock market volatility indices (VIX and VXD) have a positive relationship with bitcoin returns (Akyildirim et al., 2021). VSTOXX is the only stock market volatility index with a negative coefficient. In general, we observe that European stock market impacts bitcoin returns negatively which can by partially explained by the stricter regulation which could favour conventional markets.

The results regarding the relationship of bitcoin returns and exchange rates are ambiguous. The EUR/USD exchange rate affects positively bitcoin returns, implying that an appreciation of the Euro yields an increase in bitcoin returns. On the contrary, an increase the GBP/USD and CNY/USD exchange rates causes a fall in bitcoin returns.[12] The opposite effect of the alternative exchange rates on bitcoin returns can be explained by taking geopolitical factors into account. For instance, the uncertainty caused during the Brexit in the UK could motivate investors to seek alternative safer assets such as bitcoin which can function as risk diversifier (Guesmi et al., 2019). Results regarding the effect of uncertainty on bitcoin returns are also ambiguous. The coefficients of IDEMV and the European EPU indices are positive suggesting that at periods of turbulence bitcoin is considered as a safe haven. However, the U.S. EPU appears to have a negative effect on bitcoin returns. Regarding the CBDCU index, we observe a negative relationship since a decrease in the index denotes a more regulated, central bank oriented

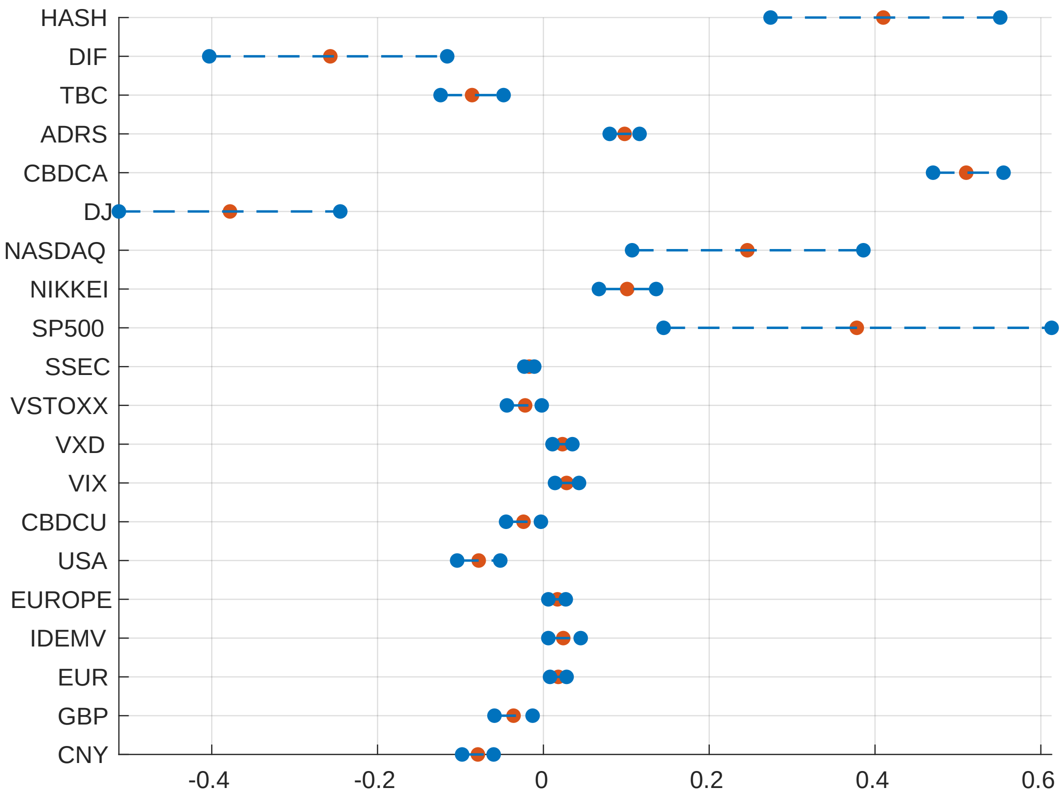
[10] According to model 3 the coefficient mining difficulty (DIF) is negative. However, it is smaller (in absolute value) compared to the coefficient of hash rate.

[11] Dyhrberg (2016b) also argues that FTSE and bitcoin are uncorrelated and Wang et al. (2016) find that in the long-run, Dow Jones and bitcoin are negatively related.

[12] Note that the findings in the existing literature are not clear. For example, Dyhrberg (2016a) and Dyhrberg (2016b) find contradicting results regarding the effect of GBP/USD exchange rate on bitcoin returns.

framework which could provide fewer opportunities for speculative behaviour from retail investors. Finally, similar to the first two models, model 3 identifies the positive impact of demand on bitcoin returns.[13]

Figure 1: Posterior median along with the 95% credible interval of coefficients of independent variables in model III. We report only the coefficients of variables that are statistically significant.



Regarding the leverage parameter ρ, the posterior mean is equal to -0.009, meaning that ϵ_t and η_t are negatively correlated. This finding suggests that a decrease in bitcoin returns would increase the volatility. This contradicts the general consensus that bitcoin returns exhibit an inverse leverage effect (a rise in bitcoin returns yields a rise in volatility). However, regardless of the significance level, the credible interval contains zero, indicating that ϵ_t and η_t are not correlated and thus no leverage effect is present in bitcoin returns.[14] The leverage parameter ρ, is the only stochastic volatility parameter that is not statistically significant. Table A3 reports the posterior median along with the 95% credible set for all parameters in equation (2). Specifically, the posterior median of ϕ approaches one which reveals the high persistence of the variance process. This result reinforces the argument that the assumption of constant volatility is too strict when modelling bitcoin returns and can lead to erroneous conclusions.

[13]Model 3 fails to identify any relationship between bitcoin returns and commodities returns or interest rate.
[14]For example the 95% credible interval is (-0.132, 0.094).

Table 3: Estimated coefficients of independent variables for each model.

Model 1				**Model 2**						**Model 3**	
Model 1a		**Model 1b**		**Q10**		**Q50**		**Q90**			
NASDAQ^{6}	(0.077)	NASDAQ^{6}	(0.085)	VXD^{7}	(0.131)	CEPU^{10}	(0.041)	WIKI^{4}	(0.824)	CBDCA^{4}	(0.510)
ADRS^{3}	(0.050)	FTSE^{6}	(0.074)	NASDAQ^{6}	(0.107)	ADRS^{3}	(0.030)	NASDAQ^{6}	(0.129)	HASH^{1}	(0.408)
FTSE^{6}	(0.050)	ADRS^{3}	(0.067)	HASH^{1}	(0.084)	VXD^{7}	(0.024)	ADRS^{3}	(0.117)	SP500^{6}	(0.377)
VSTOXX^{7}	(0.026)	VXD^{7}	(0.049)	BRENT^{5}	(0.039)	NASDAQ^{6}	(0.019)	VIX^{7}	(0.062)	NASDAQ^{6}	(0.245)
HASH^{1}	(0.025)	HASH^{1}	(0.044)	FTSE^{6}	(0.026)	GOLD^{5}	(0.012)	VLM^{3}	(0.055)	NIKKEI^{6}	(0.100)
VLM^{3}	(0.009)	CEPU^{10}	(0.026)	EEPU^{10}	(0.023)	DJ^{6}	(0.009)	CNY^{8}	(0.040)	ADRS^{3}	(0.098)
GOLD^{5}	(0.001)	VLM^{3}	(0.026)	SSEC^{6}	(0.019)	EEPU^{10}	(0.008)	HASH^{1}	(0.031)	VIX^{7}	(0.028)
JPY^{8}	(-0.018)	VSTOXX^{7}	(0.023)	CBDCU^{5}	(0.013)	VSTOXX^{7}	(0.007)	GEPU^{10}	(0.014)	IDEMV^{10}	(0.024)
NIKKEI^{6}	(-0.024)	WTI^{5}	(0.017)	VIX^{7}	(-0.141)	BRENT^{5}	(0.002)	VXD^{7}	(0.006)	VXD^{7}	(0.022)
		WIKI^{4}	(0.016)	WIKI^{4}	(-0.484)	SP500^{6}	(0.001)	TBC^{2}	(-0.013)	EUR^{8}	(0.018)
		BRENT^{5}	(0.013)			USEPU^{10}	(0.001)	JPY^{8}	(-0.028)	EEPU^{10}	(0.016)
		DIF^{5}	(0.011)			GEPU^{10}	(-0.007)	IDEMV^{10}	(-0.041)	SSEC^{6}	(-0.016)
		CNY^{8}	(0.010)			NIKKEI^{6}	(-0.033)	SP500^{6}	(-0.067)	VSTOXX^{7}	(-0.022)
		EUR^{8}	(0.010)			VIX^{7}	(-0.040)	NIKKEI^{6}	(-0.125)	CBDCU^{5}	(-0.024)
		CBDCA^{4}	(0.010)							GBP^{8}	(-0.036)
		SSEC^{6}	(0.009)							USEPU^{10}	(-0.077)
		GOLD^{5}	(0.008)							CNY^{8}	(-0.079)
		CBDCU^{5}	(0.005)							TBC^{2}	(-0.085)
		IDEMV^{10}	(-0.001)							DIF^{5}	(-0.256)
		ECB DFR^{9}	(-0.003)							DJ^{6}	(-0.378)
		JPY^{8}	(-0.033)								
		VIX^{7}	(-0.052)								
		NIKKEI^{6}	(-0.057)								

Notes: i) The dependent variable in models 1a, 2 and 3 is the BTC returns. In model 1b the dependent variable is the standardised residuals from an EGARCH(1,1) model on the BTC returns. ii) Variables with statistically insignificant coefficients are not reported. iii) The superscript denotes the category of each variable. 1: technology related factor, 2: supply, 3: demand, 4: attention index, 5: market commodity, 6: stock market index, 7: stock market volatility index, 8: exchange rate, 9: interest rate and 10: uncertainty index.

4.4 Out-of-sample analysis

The results obtained from the four models exhibit partial differences which are theoretically attributed to the different estimation estimation approaches and the assumption of stochastic volatility. To assess the validity of the findings obtained from each model, we compare the ability of each model to correctly perform one-step-ahead forecasts. To carry out this exercise, first we use the 80% of the sample to estimate the models' parameters and then test the performance of the models over the remaining 20% of the sample.[15] To compare the forecasting ability of the models, we employ the Mean Squared Error (MSE) and the Mean Absolute Error (MAE) criteria.

Table 4 reports the MSE and MAE obtained from each model. Both criteria reveal that the most accurate forecast of bitcoin returns is obtained when the Bayesian LASSO model is employed. Regarding the non-Bayesian models, the quantile regression adaptive LASSO provides the best forecasts when the median is used but is substantially outperformed when the estimates from the 10^{th} and the 90^{th} quantiles are used for prediction. Finally, when comparing models 1a and 1b which differ only in the dependent variable, we observe that model 1b is outperformed by the simpler model 1a where bitcoin returns are used as the dependent variable.

Table 4: Forecast MSE and MAE for each LASSO model.

	Model 1		**Model 2**			**Model 3**
	Model 1a	**Model 1b**	**Q10**	**Q50**	**Q90**	
MSE	1.358	1.503	4.519	1.213	2.453	1.196
MAE	0.789	0.843	1.582	0.707	1.250	0.704

Notes: i) A lower value indicates that the model performs a more accurate forecast. ii) The dependent variable in models 1a, 2 and 3 is the BTC returns. In model 1b the dependent variable is the standardised residuals from an EGARCH(1,1) model on the BTC returns.

5 Conclusions

Bitcoin is a digital currency that is used mainly as a speculative asset. Identifying the forces that determine bitcoin returns is subject of discussion among researchers and investors. The related literature suggests that bitcoin is affected not only by economic and financial variables but also by investors' sentiment and technology-related factors. However, most studies on this subject either focus on specific factors or ignore others.

The purpose of this paper is to examine potential determinants of bitcoin returns using the LASSO feature selection method. Our contribution to the existing literature is twofold. The first contribution

[15] To further validate our findings, we consider two alternative training samples, the 50% and 60% of the sample and perform the forecast on the remaining parts of the sample, 50% and 40% of the sample, respectively.

lies in the econometric methodology. The LASSO model has been previously employed in the papers of Panagiotidis et al. (2018) and Ciner et al. (2022). However, both studies ignore the time-varying nature of bitcoin's volatility. In this study, we deal with the issue of time-varying volatility by utilising a Bayesian LASSO with stochastic volatility. The model not only accounts for the volatility dynamics of bitcoin returns but also performs parameter shrinkage based on prior information and shrinks the coefficients of weakly related variables faster than the ML or the OLS estimators. The second contribution regards the set of set of examined variables as potential determinants of bitcoin returns. We consider a wide range of potential factors such as economic and financial variables, sentiment and uncertainty indices and technology-related factors. In addition, we include in the analysis the CBDCA and CBDCU indices which capture the attention and uncertainty towards the adoption and expansion of CBDC.

Using the Bayesian LASSO, we are able to confirm findings from previous papers in the related literature. Based on the results, we conclude that attractiveness and the difficulty of the mining process are the main determinants of bitcoin returns. Furthermore, our findings provide further evidence on the importance of the demand over supply forces. Considering economic variables, we observe that stock market returns are strongly related to bitcoin returns but the nature of the relationship (positive or negative) differs among the examined indices. The latter finding also holds for exchange rates and policy uncertainty. Finally, the analysis does not identify any connection between bitcoin returns and commodities prices or interest rates.

Our work could be extended by increasing the number of examined factors or considering the time-varying effect of the variables on bitcoin returns since Bayesian methods are suitable for estimating time-varying models.

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A Supplementary tables and figures

Table A1: Data sources. Sample period: 4/1/2015 - 1/5/2021 (2310 observations).

	Variable	Source
	Bitcoin price [BTC]	1
Technology	Hash Rate [HASH]	2
	Network Difficulty [DIF]	2
Supply	Total number of bitcoins in circulation [TBC]	2
Demand	Confirmed transactions per day [VLM]	2
	Unique addresses used [ADRS]	2
Attention	Number of Wikipedia searches [WIKI]	3
	CBDC Attention Index [CBDCA]	4
Commodities	Brent oil price (in USD per barrel) [BRENT]	5
	West Texas Intermediate oil price (1 barrel) [WTI]	6
	Gold price (in USD per troy ounce) [GOLD]	6
Stock market	Dow Jones NYSE index [DJ]	7
	NASDAQ index [NASDAQ]	7
	S&P500 [SP500]	6
	FTSE100 index [FTSE]	8
	Nikkei225 index [NIKKEI]	7
	Shanghai Composite Index [SSEC]	7
Volatility	VSTOXX Volatility EUR Price Index [VSTOXX]	7
	CBOE DJIA Volatility Index [VXD]	6
	CBOE Market Volatility Index [VIX]	6
Exchange rate	EUR/USD exchange rate [EUR]	6
	GBP/USD exchange rate [GBP]	6
	CNY/USD exchange rate [CNY]	6
	JPY/USD exchange rate [JPY]	6
Interest rate	Fed Funds effective rate [EFFR]	6
	ECB deposit facility rate [ECB DFR]	6
Uncertainty	CBDC Uncertainty Index [CBDCU]	4
	US policy uncertainty index [USEPU]	9
	Europe policy uncertainty index [EEPU]	9
	China policy uncertainty index [CEPU]	9
	Global Economic Policy Uncertainty index [GEPU]	9
	Infectious Disease Volatility Tracker [IDEMV]	9

Notes: i) The codes in brackets are used to denote the variables in the main text. ii) 1: coinmarketcap.com, 2: blockchain.com, 3: R package 'wikipediatrend', 4: sites.google.com/view/cryptocurrency-indices/the-indices/cbdc-indices, 5: eia.gov, 6: fred.stlouisfed.org, 7: finance.yahoo.com, 8: wsj.com, 9: policyuncertainty.com

Table A2: Summary statistics and ADF statistic of the variables.

Variable	Mean	Max.	Min.	St. Dev.	ADF stat.
BTC	7422	63503	178.1	10955	1.535
HASH	443.3×10^5	172.1×10^6	282.5×10^3	505.1×10^5	-1.498
DIF	613.7×10^9	235.8×10^9	406.4×10^8	703.6×10^10	-1.615
TBC	167.2×10^5	186.9×10^5	136.8×10^5	141.1×10^4	-2.290
VLM	252.3×10^2	439.5×10^2	769.1×10^1	754.5×10^2	-2.548
ADRS	489.0×10^3	978.2×10^3	161.5×10^3	155.9×10^3	-2.834
WIKI	100.1×10^2	923.4×10^3	0.000	271.2×10^2	-11.638***
CBDCA	99.89	106.0	99.44	0.716	0.444
BRENT	54.93	86.07	9.120	12.775	-1.912
WTI	51.06	77.41	-36.98	11.021	-2.605
GOLD	1373	2061.5	1050.6	233.0	-2.222
DJ	23097	34200	15660	4471	-3.102
NASDAQ	7296	14138	4266	2397	-1.008
NIKKEI	20949	30467	14952	3031	-2.206
SP500	2651	4211	1829	534.8	-2.212
FTSE	6883	7877	4993	570.0	-2.428
SSEC	3172	5166	2464	387.5	-2.488
VSTOXX	37.22	47.30	25.19	3.605	-2.254
VXD	15.63	48.98	8.880	4.694	-4.144***
VIX	17.69	82.69	9.140	8.074	-4.712***
CBDCU	99.91	105.8	99.11	0.780	-1.324
USEPU	120.1	503.0	46.39	84.77	-4.479***
EEPU	226.2	433.2	131.7	55.49	-5.820***
CEPU	247.3	661.8	60.20	127.3	-6.611***
GEBU	207.8	430.0	101.3	71.91	-4.664***
IDEMV	4.914	112.9	0.000	11.26	-3.663**
EUR	1.135	1.249	1.038	0.045	-2.834
GBP	1.346	1.588	1.149	0.097	-1.882
CNY	6.674	7.154	6.197	0.265	-1.490
JPY	111.1	125.5	100.1	5.467	-2.741
EFFR	0.935	2.450	0.040	0.832	-0.492
ECB DFR	-0.392	-0.200	-0.500	0.094	-1.963

Notes: In the implementation of the ADF test we assume a trend in the test equation and for the selection of the lag-length we use the Schwarz information criterion. *, ** and *** denote the rejection of the ADF test at the 10, 5 and 1% significance level.

Table A3: Posterior draws of the stochastic volatility parameters.

Parameter	2.5%	50%	97.5%
μ	-0.870	-0.380	-0.036
ϕ	0.999	1.000	1.000
σ	0.003	0.007	0.014
ρ	-0.132	-0.009	0.094

Notes: i) The value of ϕ at the 50 and the 97.5 percentile is equal to one due to rounding.

Figure A1: Magnitude of the regression coefficients with respect to the shrinkage value for models 1a (top) and 1b (bottom).