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EFFECT OF MONETARY POLICY DECISIONS AND ANNOUNCEMENTS ON THE PRICE OF CRYPTOCURRENCIES: AN ELASTIC-NET WITH ARIMA RESIDUALS APPROACH

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Abstract

Research purpose. This study analysed the three cryptocurrencies with the largest market capitalization: Bitcoin, Ether (cryptocurrency built upon the Ethereum project's blockchain technology), and Binance coin, which account for 60% of the total cryptocurrency market capitalization. The purpose of this research was to measure the impact of monetary policy on the price of these cryptocurrencies using an adjusted R squared.

Design / Methodology / Approach. As dependent variables, we used interest rates controlled by the European Central Bank and the Federal Reserve and reports from the European Central Bank and the Federal Open Market Committee. A robust Elastic Net Regression with Autoregressive Integrated Moving Average (ARIMA) residuals machine learning approach was applied to obtain robust regression coefficients and corresponding standard errors. To ascertain the robustness of the model, a technique known as rolling window cross-validation was employed.

Findings. The results of this study show that monetary policy decisions and announcements significantly impact the price of cryptocurrencies. The impact on cryptocurrencies is likely to be significant both in the period of economic stability (2018-2020) and in the period of economic shocks (2020-2022). This relationship is likely to be indirect, acting through investor sentiment.

Originality / Value / Practical implications. The results of this study may be useful to monetary policymakers, as they reveal the link between their actions and the price of cryptocurrencies. Our model will also be useful for mutual fund managers and private investors, as they can anticipate the price dynamics of cryptocurrencies when assessing monetary policy frameworks.

Keywords: cryptocurrency, monetary policy, elastic net, ARIMA.

JEL codes: E42, E52, E58, G02, G15.

Introduction

The advent of blockchain technology has given rise to cryptocurrencies as a significant financial asset class. This development has sparked interest in understanding how these digital currencies react to external influences, particularly the monetary policy decisions enacted by central banks. Despite their decentralized nature, cryptocurrencies, especially Bitcoin, have attracted substantial academic interest, leading to an exploration of their relationship with conventional monetary policy mechanisms (Smith & Kumar, 2018). The remarkable growth in cryptocurrency valuation, highlighted by the total market capitalization surpassing $2 trillion in 2021, underscores the importance of investigating the drivers behind such exponential growth (U.S. Currency Education Program, n.d.).

In the face of global economic uncertainties, such as the Coronavirus 2019 (COVID-19) pandemic and geopolitical tensions, cryptocurrency markets have exhibited significant volatility. This has prompted questions about the impact of central bank actions and announcements on cryptocurrency prices (Kizildag et al., 2020). While cryptocurrencies are often been viewed as operating independently of

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central authorities, recent research suggests they may be influenced by monetary policy interventions (Smith & Kumar, 2018).

The objective of the study is to empirically examine the impact of monetary policy decisions and announcements on cryptocurrency prices using an adjusted R squared. The central hypothesis posits that cryptocurrencies, due to their inherent decentralization and independence from central banks, should not exhibit significant reactions to monetary policy actions. However, initial analysis indicates a potential correlation between monetary policy measures, particularly those of the European Central Bank (ECB) and the Federal Reserve (FED), and the prices of leading cryptocurrencies such as Bitcoin (BTC), Ether a cryptocurrency constructed on the blockchain technology of the Ethereum project (ETH), and Binance Coin (BNB).

To accomplish these objectives, this study employs Elastic Net Regression with Autoregressive Integrated Moving Average (ARIMA) residuals, which was applied to data from November 8, 2017, to November 18, 2022. This approach enables the investigation of the impact of ECB and FED announcements and policies on cryptocurrency prices while addressing multicollinearity and autocorrelation in the data.

Contrary to the initial hypothesis, the findings reveal a discernible relationship between monetary policy decisions and announcements by the ECB and FED and the prices of selected cryptocurrencies. Notable correlations are found between certain types of monetary policy measures and fluctuations in cryptocurrency prices. These results suggest that, despite their decentralized nature, cryptocurrencies are not entirely insulated from the effects of traditional monetary policy mechanisms.

Literature Review

In this section, we delve into two key strands of literature pertinent to our investigation. The initial focus pertains to the multifaceted dimensions intrinsic to cryptocurrencies. This encompasses an examination of the efficacy of the cryptocurrency market (Bariviera, 2017; Nadarajah & Chu, 2017; Tiwari et al., 2018; Urquhart, 2016; Vidal-Tomás & Ibañez, 2018; Wei, 2018), the segregation of cryptocurrencies from other financial and speculative instruments (Bhanja et al., 2023; Bhuiyan et al., 2021; Corbet et al., 2018; Harb et al., 2022), patterns of price and volatility clustering (Baig et al., 2019; Hu et al., 2019; Li et al., 2020; Ma & Tanizaki, 2022; Urquhart, 2017; Zhang et al., 2018), the emergence and consequences of price bubbles (Cheah & Fry, 2015; Choi & Jarrow, 2022; Hayes, 2018; Moosa, 2020; Su et al., 2018), regulatory frameworks surrounding cryptocurrencies (Corbet et al., 2019; Monrat et al., 2019; Pieters & Vivanco, 2017; Schaupp et al., 2022), and the prevalence of fraudulent activities (Bartoletti et al., 2020; Nghiem et al., 2021; Shayegan et al., 2022).

The subsequent and predominant thread of related scholarship centres on the interplay between monetary policy and cryptocurrency markets. Within this domain, Panagiotidis et al. (2018) scrutinized the significance of various drivers of Bitcoin returns employing the Least Absolute Shrinkage and Selection Operator (LASSO) framework. Factors such as stock market returns, exchange rates, gold, and oil returns, as well as interest rates set by the FED and the ECB, alongside internet trends, were assessed. The findings underscored the pivotal roles of search intensity and gold returns in influencing Bitcoin returns. Corbet et al. (2020) explored the response of digital assets, encompassing cryptocurrencies, tokens, and decentralized applications, to announcements regarding interest rates and quantitative stimulus measures from the FED. Their analysis revealed that mined digital assets exhibit heightened sensitivity to volatility spillovers and feedback stemming from monetary policy. Panagiotidis et al. (2019) assessed the impact of various factors, including stock market returns, exchange rates, gold and oil returns, FED and ECB interest rates, and internet trends, on bitcoin returns, employing Vector Autoregression (VAR) and Factor-Augmented Vector Autoregressive (FAVAR) models. Notably, the study uncovered significant interactions between bitcoins and traditional stock markets, with relatively weaker linkages observed with currency markets and monetary policy. Corbet et al. (2017) utilized the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model of order (1,1) model to explore the effects of alterations in international monetary policy on bitcoin returns, highlighting the pronounced impact of interest rate-based monetary policy decisions made by the US Federal Open Market Committee (FOMC) on bitcoin return volatility.

Furthermore, Lyócsa et al. (2020) employed quantum regression to investigate the influence of news and sentiment regarding bitcoin regulation, hacking incidents involving bitcoin exchanges, and scheduled macroeconomic news releases on bitcoin volatility. The analysis delineated a robust reaction of bitcoin volatility to news related to bitcoin regulation and positive investor sentiment concerning regulatory measures. Conversely, most scheduled US macroeconomic news releases were found to exert negligible effects on bitcoin volatility. Nguyen et al. (2019) delved into the asymmetric effects of monetary policy on cryptocurrency returns under differing monetary regimes, highlighting the substantial response of major cryptocurrencies, including bitcoin, to China's monetary tightening.

Nelson (2018) deliberated on the financial and monetary policy risks posed by digital currencies, suggesting minimal risks to monetary policy due to the improbable scenario of digital currencies supplanting fiat currencies. Yang (2020) used a smooth transition autoregressive model with exogenous variables (STARX) to investigate the non-linear relationship between bitcoin and the Taiwanese stock market, contingent upon Taiwan's monetary policy threshold. The study discerned a threshold effect and affirmed the existence of a non-linear relationship between the Taiwanese stock market and Bitcoin. Zhou (2021) utilized the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) framework to examine the evolution of bitcoin exchange rates from 2011 to 2018 and its correlation with global financial markets. The findings highlighted the influence of fundamental factors, bitcoin-specific events, regulatory pronouncements, and news reports on bitcoin volatility, alongside its role as a hedge during periods of low global financial uncertainty. Marmora (2022) investigated the impact of monetary policy announcements on local demand for bitcoins across 26 developing countries, revealing a notable increase in both local attention to bitcoins and local bitcoin trading volumes following such announcements. Additionally, Mnif & Jarboui (2022) assessed the effects of FED monetary policy on the dynamics of Islamic and conventional cryptocurrencies during the COVID-19 pandemic, utilizing novel methodologies to detect market bubbles and examining the impact of FOMC announcements on both conventional and Islamic Sharia-compliant cryptocurrencies. Their findings indicated a significant positive effect of FOMC announcements on conventional cryptocurrency markets in the immediate aftermath of the event, followed by a subsequent negative effect.

This comprehensive review of academic literature underscores the thorough exploration of cryptocurrencies from diverse perspectives and methodologies. While significant attention has been devoted to examining the nexus between monetary policy and cryptocurrencies, there remains a need for more holistic investigations. Many existing studies focus on partial aspects of monetary policy, often intertwined with other macroeconomic factors, thus necessitating a comprehensive understanding. Moreover, the literature predominantly relies on data up to 2018, overlooking subsequent developments such as the economic upheavals triggered by the COVID-19 pandemic and subsequent geopolitical events. Addressing these gaps, our study offers a focused analysis of the impact of monetary policy on cryptocurrency prices, disentangled from other economic factors, and leveraging robust methodologies. Spanning the period from 2017 to 2022, our investigation encompasses a phase marked by significant market capitalization and economic volatility. In this section, we discuss in more detail three literature strands relevant to our work.

Research Methodology

In this section, we provide details about sample characteristics as well as model architecture and rationale for the research methodology. The three cryptocurrencies chosen for the study are BTC, ETH, and BNB, that is, their relationship to the US dollar. They have been chosen as representatives of the cryptocurrency market. The procedure to select the representatives was elementary. The threshold was established at 60% of the market capitalization, and the cryptocurrencies that represent the entire market had to have a market capitalization of at least 60% of the total market capitalization. Based on this criterion, the first three cryptocurrencies were sufficient. In this study, when we refer to a cryptocurrency as being ‘first’, ‘second’, or ‘fifth’, we are referring to their respective rankings based on market capitalization. Market capitalization is a measure of the total value of all available coins of a particular cryptocurrency. BTC, being the first cryptocurrency ever created and the most widely adopted, has the highest market capitalization, hence it is referred to as the ‘first’ cryptocurrency. ETH, known for its smart contract functionality, holds the second-largest market capitalization, making it the

'second' cryptocurrency. BNB, despite being fifth in terms of market capitalization, was chosen over the third and fourth-ranked cryptocurrencies. The reason for this selection is that the third and fourth cryptocurrencies, Tether and USD Coin, are Stablecoins. Stablecoins have their value pegged to a specific asset or a pool of assets, usually a fiat currency like the US dollar. This makes their response to monetary policy identical to that of the US dollar, and therefore they were not suitable for this study. It's important to note that these rankings are dynamic and can change as the market values of these cryptocurrencies fluctuate. The rankings used in this study were accurate as of the 1st of November 2022, according to data from CoinMarketCap (CoinMarketCap, n.d.).

In the domain of monetary policy, central banks traditionally establish and disclose their determinations on weekdays. This temporal selection aligns with the operational hours of financial markets, thereby facilitating prompt responses to any modifications in policy.

In contrast, the cryptocurrency market operates continuously, spanning 24/7 and encompassing weekends. Nevertheless, the noticeable impact of monetary policy determinations on cryptocurrency prices primarily materializes during weekdays. Consequently, for methodological rigour in a research endeavour, it is advisable to concentrate solely on weekdays when examining the consequences of monetary policy determinations on cryptocurrency valuations. This methodological approach serves to maintain the integrity of the study's findings by ensuring that the data utilized is highly relevant and enlightening.

The study sample period is from 7 November 2017 to 18 November 2022. This study period was chosen for a couple of reasons. First, due to data availability, the ETH and BNB data are only available from 7 November 2017, so to maintain the integrity of the study, we also started collecting the BTC data from the same date. The second reason is the abundance of studies on this topic for the period up to 2018 and the lack of studies from 2018 onwards, so there was no additional motivation to conduct the study using earlier data. The study used a one-day closing price.

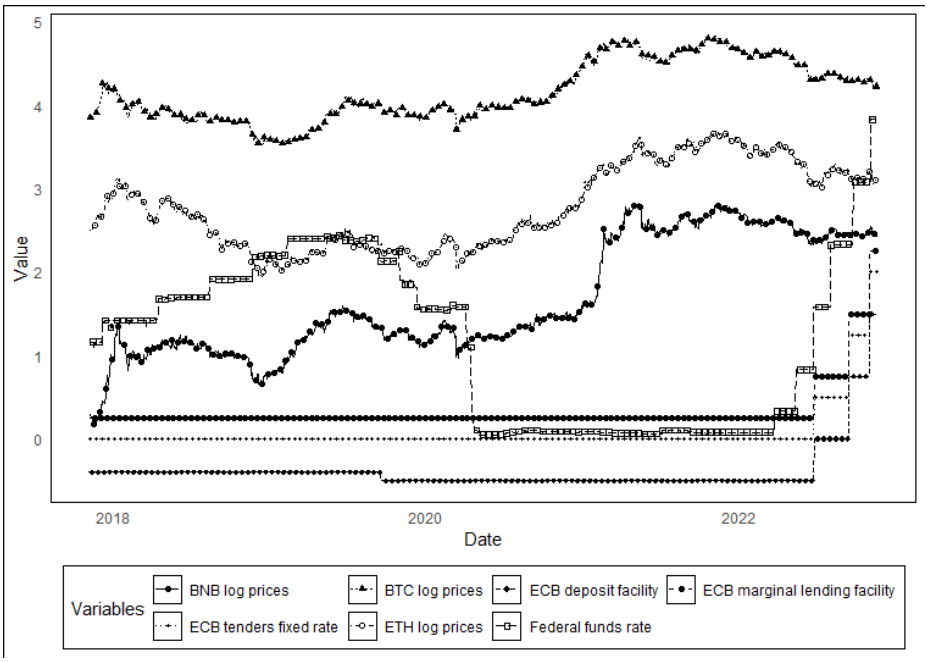


Fig. 1. Logarithmically Transformed BTC, ETH, BNB Prices, and Central Bank Interest Rates (Source: Prepared by the authors)

The central banks of the US and the Eurozone, the FED (n.d.), and the ECB were chosen as the monetary policy proxies, that is the interest rates controlled by these banks and the announcements made by FOMC and ECB Governing Council. The Federal Funds Rate (FFR) was chosen as the FED's interest rate, and although the FED does not directly set it, it is very effective in setting the boundaries within

which the FFR should be set by using the interest rate paid on reserve and the overnight repurchase agreement rate. This single interest rate, instead of the other three rates set by the FED, was chosen to make the research model as simple as possible without reducing its efficiency. The FFR is the key interest rate that the FED tries to influence, so by choosing the FFR, we simplify and make the model more efficient. The ECB unfortunately does not have a single interest rate that it tries to regulate, but it sets 3 main interest rates, all of which are included in the research model, that is the Deposit facility, the Fixed-rate tenders Fixed rate, and the Marginal lending facility. The variables under investigation are visually depicted in Figure 1. It is imperative to underscore that the cryptocurrency prices exhibited are not the raw prices, but rather, they have been subjected to a logarithmic transformation (base 10). The rationale behind the use of a logarithmic transformation was to ensure a consistent scale between the prices of the cryptocurrencies and the interest rates, thereby facilitating a more coherent visual comparison. This approach aids in maintaining the integrity of the data representation, particularly when dealing with variables that span different orders of magnitude. Furthermore, it is crucial to emphasize that the logarithmic transformation was employed solely for data visualization. However, in the subsequent stages of the research, the original, untransformed prices were utilized. This approach ensures a balance between clear data representation and the preservation of the original data characteristics in the analysis.

In the framework of this investigation, the phrase "FOMC positive" denotes instances where the FOMC issues favourable news, indicative of dissident decisions aimed at implementing expansionary monetary policies designed to stimulate economic growth. Conversely, "FOMC negative" characterizes scenarios wherein the FOMC makes decisions intended to contract the economy, reflecting a contractionary economic policy. This dichotomy in the impact of FOMC decisions on economic conditions applies analogously to the ECB.

Historical data for BTC, ETH, and BNB was downloaded from https://finance.yahoo.com/, using the Jupyter Lab platform in the Python programming language environment with the yfinance library. Historical FFR data were obtained from (FRED, n.d.) and processed using the Jupyter lab platform in Python. The FOMC announcements were manually edited by reading each message from FED (n.d.). ECB interest rates and ECB governing council messages were manually aggregated by checking each message from ECB Monetary Policy Decisions (n.d.).

The study was carried out using full-time series data, that is, from 7 November 2017 to 18 November 2022, to test how the model performs in a mixed environment, where a stable economic period transitions into a volatile one. We also isolated the stable period and the unstable period, so that each currency pair was subjected to 3 tests: the full period, the stable period before the pandemic, and the unstable period after the pandemic. Therefore, a total of 9 studies were conducted. The breakpoint between the stable and unstable periods was chosen as the date on which the first international case of the disease outside of China was declared, January 2020 (WHO, n.d.). It is imperative to clarify that by "post-Covid," we do not imply the cessation of the pandemic; rather, it denotes the commencement and continuation of the Covid era. The term "post-Covid" in the context of our research signifies the period after the onset of the Covid pandemic and its ongoing presence.

In our analytical framework, untransformed time series data was employed due to our focus on the examination of the variables themselves. This choice was motivated by a specific interest in understanding how monetary policy influences the pricing dynamics of cryptocurrencies, as opposed to assessing their returns. The objective of our research is to clarify the impact of monetary policy on the valuation of cryptocurrencies, with a central emphasis on contributing valuable insights for central banks. The methodological approach employed involves elastic net regression.

It is pertinent to note that elastic net regression was selected, given its inherent lack of the assumption of stationarity. This characteristic allows us to preserve the integrity of the data without violating underlying assumptions. Unlike many researchers who opt for log differences to address stationarity concerns, our focus diverges as our primary concern is the direct influence of monetary policy on cryptocurrency prices, which will be estimated by adjusted R squared. In this context, the primary stakeholders benefiting from our research findings are central banks, as they gain insights into how their monetary policy decisions impact the cryptocurrency market.

Furthermore, attempts were made to assess the model using differenced data, revealing a suboptimal fit and additional issues with residuals. Consequently, the untransformed data approach was retained as the more suitable choice for our research objectives. It is important to acknowledge that the detailed examination of results derived from transformed data is beyond the scope of this research.

In this study, we used regression analysis to identify the relationship between the dependent variable (the price of the cryptocurrencies in question) and the independent target variables (monetary policy measures) with the ARIMA residuals to ensure that the assumptions of the regression will be held. The most common method for estimating linear models is the ordinary least squares (OLS) method. OLS is the most commonly used due to its simplicity, but it gives the best estimates of the regression coefficients and associated robust standard errors only when the model satisfies Gauss-Markov assumptions. In this study, we employed OLS as our baseline model. The findings derived from the application of the OLS model serve as a benchmark for our analysis.

However, in most cases, including the case of this study, compliance with these assumptions is a rather rare phenomenon. In the case of this study, the multicollinearity assumption may be violated when several related dependent variables are used. This is reflected in the above loss function. We can see that as the number of dependent variables approaches n, the loss function approaches infinity. When the multicollinearity assumption is violated, the variance of the OLS estimate will be very large. However, estimators with very large variances produce poor estimates. This phenomenon is called overfitting.

Each regression model has 2 possible errors based on its complexity: i) underfitting and ii) overfitting. To overcome underfitting, we can add new parameters to the model to increase the complexity of the model and thus reduce the high bias. In the case of this study, 4 interest rates are included as dependent variables and 4 dummy variables as proxies for expansionary and contractionary news, so the number of parameters is sufficient, and the model cannot suffer from underfitting. However, as the complexity of the model increases, the expected variance increases, but the bias decreases, this is known as overfitting. In the case of this study, overfitting is certainly possible using the usual OLS methodology. There are two ways to reduce the possibility of overfitting: (i) reducing the complexity of the model, but this would result in a loss of accuracy and would not allow the study of the impact of all the desired factors on the price of cryptocurrencies; and (ii) regularization, which is a technique that restricts, adjusts, or shrinks the estimated coefficient towards zero. In other words, this approach discourages the learning of more complex or flexible models to avoid the risk of overfitting. Regularization is one way to improve the performance of the model by ignoring the less important features without losing the ability to explore all the desired factors. Regularization also reduces validation loss and tries to improve the accuracy of the model. We can see that the OLS approach is not suitable for this study and that regularization should be used.

$$OLS\ loss = \sum_{i=1}^{n}(Y_i - \beta X_i)^2 \quad (1)$$

Where:

$OLS\ loss$ is an OLS loss function;

Y_i is the actual value at the time *I;*

β is the parameter obtained by OLS;

X_i is the value of the dependent variable at the time *I;*

There are three types of regularization: lasso, ridge, and elastic-net, a generalization of both. Elastic-net first emerged as a criticism of lasso (Tibshirani, 1996), which can make variable selection too data-dependent and therefore unstable. The solution was to combine the penalties of ridge regression and lasso to obtain the best results in both worlds. For all of the above reasons, the E-net method (Zou & Hastie, 2005) was chosen for this study. The e-net aims to minimize this loss function:

$$ENET\ loss = \sum_{i=1}^{n}(Y_i - \beta X_i)^2 + \lambda\left(\alpha\sum_{j=1}^{k}|\beta_j| + (1-\alpha)\sum_{j=1}^{k}|\beta_j|^2\right) \quad (2)$$

Where:

$ENET\ loss$ is the Elastic net regression loss function;

α is the mixing parameter for the ridge (α = 0) and the lasso (α = 1) and

λ is the Lasso parameter.

We can see that the first part of the e-net loss function is the regular OLS estimation, which has a penalty added. As mentioned above, our study consisted of a total of 9 samples: a full period sample, a pre-COVID-19 pandemic sample, and a post-COVID-19 pandemic sample with each of the currencies under study. Thus, 9 alpha and 9 lambda hyperparameters had to be estimated. These were obtained by cross-validation hyperparameter tuning in JupyterLab using the Python programming language, the sci-kit-learn library, and the GridSearchCV method. The resulting hyperparameter values are presented in Appendix 1.

The regression included four dummy variables that were supposed to represent the ECB Governing Council and FOMC announcements. These variables are ECB expansionary monetary policy announcements (ECB positive), ECB contractionary monetary policy announcements (ECB negative), FED expansionary monetary policy announcements (FED positive), and FED contractionary monetary policy announcements (FED negative). Following Corbet et al., (2020) methodology we denote the 50 days following the announcement, as the announcement period.

The regression parameters were obtained by machine learning in JupyterLab using the Python programming language, sci-kit-learn library. The coefficients obtained will be presented in more detail in the next section, Results.

Following the application of elastic-net regression to our dataset, a robustness check was executed utilizing the residuals of the model. Subsequently, the test results revealed the presence of autocorrelation, heteroskedasticity, and non-normality in the residuals. To address these issues, the ARIMA process was employed. Before the application of the ARIMA process, an Augmented Dickey-Fuller test was conducted to ascertain the stationarity of the residuals. The integration parameter of the ARIMA model was set to zero if the data was found to be stationary. The subsequent implementation involved the utilization of the classical ARIMA process, which will be expounded upon in the forthcoming paragraph.

For the AR(p) part of the ARIMA process formula 3 was used:

$$X_t = c + \sum_{i=1}^{p}\phi_i X_{t-i} + \epsilon_t \quad (3)$$

Where:

X_t is the time series value at time t;

$\phi_i$are the coefficients of the lagged values;

ϵ_t is the difference between the observed and the predicted value at each time point;

c is the mean value of the time series when the values of X_{t-i} are zero.

The AR part of the ARIMA model captures the influence of the previous values on the current value. The larger the value of p, the more past values are taken into account in the model.

For the MA(q) part of the ARIMA process formula 4 was used:

$$X_t = \mu + w_t + \sum_{i=1}^{q} \theta_i w_{t-i} \quad (4)$$

Where:

X_t is the time series value at time t;

q is the number of lag observations included in the model

θ_i are the coefficients of the lagged error terms;

μ is the mean of the series;

w_{t-i} is the error term at time t-1 respectively.

The MA part of the ARIMA model captures the influence of the previous error terms on the current value. The larger the value of q, the more past error terms are taken into account in the model.

The hyperparameters (p,q) were obtained by cross-validation hyperparameter tuning in JupyterLab using the Python programming language, the sci-kit-learn library. The GridSearchCV method upper values for cross-validation were chosen either by using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) or setting the upper limit to 5 in line with Petropoulos et al. (2021).

After performing the ARIMA procedure on the residuals obtained from elastic net regression, a subsequent evaluation of robustness was carried out. This involved subjecting the residuals of the ARIMA model to tests for autocorrelation, heteroskedasticity, and normality. In this process, it was found that there was no autocorrelation in any of the cases, and to a large extent, there was a lack of heteroscedasticity. However, the residuals still exhibited non-normality, which is an important aspect to consider, especially when using the model for forecasting purposes and constructing confidence intervals.

The examination of robustness was finalized through the utilization of the Rolling Window Forecasting Technique, which is a cross-validation technique. This technique was employed in the forecasting process, with the Mean Absolute Scaled Error (MASE) metric serving as the benchmark for evaluating forecast accuracy one step ahead of forecasting as suggested by (Qiang & Shen, 2021). As a result, it was not necessary to compare the performance of our model with the baseline naive forecasting method.

Results

In this section, we will present the results of the study in detail. Table 1 shows the general regression statistics. We can see that the values of the F-statistic range from 40 to 432, which are extremely high. The average value of the F-statistic is 205. Associated with these high F-statistics are extremely low regression p-values, which range from 1.62266860556908E-50 to 0, with a mean value of 1.80297E-51. These statistics show that all regressions are statistically significant, even at the 1% significance level, as the p-values are well below 1%.

We can also see that all the regression equations have high R-squared values ranging from 0.3944 to 0.6976, with a mean value of 0.5468. This shows that the monetary policy factors included in this model explain more than half of the cryptocurrency price movements. We can see that BTC has the highest R-squared values, which could be explained by the fact that BTC is the main cryptocurrency with the highest market capitalization and the most popular crypto unit of investment, and is, therefore, the most responsive to monetary policy decisions. We can also see that the full sample R-squared is the largest except for BNB. This is quite a logical conclusion since a larger amount of data usually means a more accurate model in econometrics. The most inaccurate model based on R-squared data is with the pre-covid sample. The reason for this could be the smallest data sample and rather passive monetary policy.

Appendix 2 presents the parameters and statistics of the regression coefficients for BTC, ETH, and BNB, using the full sample data. We can see that the e-net model has shrunk several insignificant coefficients down to zero, which is a good sign, as this is the task of the model to reduce or eliminate insignificant coefficients. Based on the data, we can see that the ECB Marginal Lending Facility rate

could be excluded from the model; as with the three cryptocurrencies, this coefficient is zero, which means that it does not affect cryptocurrency price fluctuations at all. We can also see that ETH and BNB are also unaffected by the deposit facility interest and the ECB negative news, while with ETH the ECB tender fixed interest rate the p-value is 0.376, which means that this coefficient is not significant, even with a 10% significance coefficient, and that the only element of the ECB that has a significant impact is the ECB positive, which is the ECB's expansionary monetary policy messages. Finally, it is worth noting that the FED has a much larger impact than the ECB, as all regression features related to the FED are statistically significant for the cryptocurrencies' price fluctuation, while many features related to the ECB are insignificant.

Appendix 3 shows the regression parameters and statistics for BTC, ETH, and BNB, using the pre-covid sample data. It can be seen that in this case many more parameters are reduced to zero. Six of the eight coefficients are significant for BTC, three for BNB, and only two for ETH. In the case of BTC, only the ECB coefficient parameters, i.e., ECB Tenders Fixed Rate and ECB Marginal Lending Facility, are collapsed, while all the features related to the FED remain significant.

Table 1. Statistics of the regressions (Source: Authors' calculations)

Sample	F statistics	P value	R squared
BTC-USD full sample	432,5	0	0,6976
BTC-USD pre-covid	40,13425072	1,62E-50	0,3944
BTC-USD post-covid	199,7849108	9,2337E-179	0,6188
ETH-USD full sample	298,1591381	5,0336E-288	0,6153
ETH-USD pre-covid	99,60301094	2,8767E-102	0,5514
ETH-USD post-covid	148,409287	6,0818E-148	0,5466
BNB-USD full sample	331,168657	0	0,4863
BNB-USD pre-covid	105,7203298	1,5671E-106	0,4028
BNB-USD post-covid	194,918554	4,3969E-176	0,6085
Average	205,5997932	1,80297E-51	0,546855556

As in the full sample. case, the ECB Marginal Lending Facility is insignificant with all cryptocurrencies, so this rate can also be dropped from the model. In the case of BNB, none of the ECB interest rates are significant, i.e., the parameters for all of them are shrunk to zero. In this case, the remaining coefficients are the FFR, FOMC positive, i.e., FOMC expansionary monetary policy announcements, and ECB negative, i.e., ECB restrictive monetary policy announcements. It is worth noting that in the case of BTC, the ECB negative does not collapse to zero, but the p-value of this parameter is 0.19, which means that it is not statistically significant. In the case of ETH, only two coefficients remain unshrunk, i.e., the FFR and the ECB deposit facility rate. Interestingly, no announcements from these central banks affect the ETH price using the pre-covid sample data.

Appendix 4 shows the parameters and statistics of the regression coefficients for BTC, ETH, and BNB, using post-covid sample data. In this case fewer coefficients are collapsed to zero than in the pre-covid sample, but more than in the full sample. Six of the eight coefficients are significant for BTC, five for BNB, and five for ETH. As in the full sample and the pre-covid sample, the ECB's marginal lending facility is insignificant with all cryptocurrencies, so this rate can be dropped from the model in any case, as it does not add any information. However, in this case, the only significant interest rate with all three currencies is the ECB's deposit facility. The parameters for the other two interest rates are set to zero. This should not be surprising, as the ECB deposit facility is the main interest rate used by European banks to set their commercial interest rates. As in previous samples, the ECB's restrictive policy announcements had no impact on BNB and ETH prices. The impact of the FED is much larger than that of the ECB, as all FED-related regression terms have a statistically significant effect on cryptocurrency price movements using the post-covid and the full sample data, while many ECB-related terms are insignificant.

The results of this study are surprising considering that cryptocurrencies are decentralized financial entities, independent of any government, economic policy maker, or central monetary authority such as

a central bank. After studying the effect of interest rates and monetary policy announcements by the FED and the ECB, we have found a strong relationship between monetary policy and cryptocurrency prices, with high r-squared values as high as 0.69. Despite such a strong statistical relationship, central banks cannot to be claimed to control cryptocurrency prices. The relationship is most likely indirect, working through investor sentiment, i.e., central banks' expansionary monetary policy, which in turn heats the economy and helps it to grow faster, influencing investor sentiment that cryptocurrencies as a unit of investment should also grow in price. In a positive sentiment, investors invest in cryptocurrencies, increasing both their demand and prices. Positive investor sentiment reduces the supply of cryptocurrencies, as many investors choose to hold cryptocurrencies instead of selling them in anticipation of an increase in value. Thus, increased demand and reduced supply further increase the price of cryptocurrencies. With positive investor sentiment toward cryptocurrencies, the price of cryptocurrencies has increased and continues to influence positive investor sentiment. Meanwhile, as central banks pursue restrictive economic policies, the economy freezes, economic growth slows, and investor sentiment turns negative, leading to the expectation that cryptocurrency prices may fall. The supply of cryptocurrencies increases as people are no longer willing to hold them as units of investment, but the demand for cryptocurrencies also decreases as fewer investors are willing to invest their money in cryptocurrencies considering negative sentiment, resulting in a downward price trend. Our study can neither confirm nor deny the hypothesis of a link between monetary policy, investor sentiment, and the price of cryptocurrencies, which is beyond the scope of this study and requires a separate investigation.

The results of this study may be useful for monetary policymakers, as they reveal the link between their actions and the price of cryptocurrencies, which have become an integral part of the economy. The model we have developed will also be useful for investors who allocate part of their investments to cryptocurrencies, as they can predict the dynamics of cryptocurrency prices when assessing the fundamentals of monetary policy. The findings of this study further confirm the results of previous research that both Bitcoin and other cryptocurrencies exhibit a response to monetary policy actions (Nguyen et al., 2019; Yang, 2020; Zhou, 2021).

In this section, we delve deeper into the robustness check. We share the outcomes of robustness checks, focusing on the cross-validation technique known as the rolling window. We also present the Mean Absolute Scaled Error metrics, offering insights into the forecasting performance of our model.

Table 2. MASE Metrics Results (Source: Authors' calculations)

Cryptocurrency	Sample period	MASE
BTC/USD	Full sample	2.19
BTC/USD	Pre-covid	0.98
BTC/USD	Post-covid	1.61
ETH/USD	Full sample	2.67
ETH/USD	Pre-covid	-18.17
ETH/USD	Post-covid	1.74
BNB/USD	Full sample	2.94
BNB/USD	Pre-covid	1.13
BNB/USD	Post-covid	1.87

Table 2 displays the results of the MASE metrics in the context of a rolling window cross-validation forecasting technique, employed as a part of a robustness check. The results are not confidence-inspiring, as the MASE values mostly exceed unity, indicating a significant deviation from optimal performance. In most cases, the model used in this study exhibits inferior forecasting capabilities compared to a baseline naive model. However, there are exceptions, particularly with Bitcoin before the COVID-19 pandemic, where the model outperformed the naive approach.

The use of the MASE metric confirms that, overall, the model shows suboptimal predictive accuracy. This is accompanied by a higher computational resource requirement, highlighting its disadvantage compared to the less computationally demanding naive model.

Conclusions

In this article, we have analysed the three cryptocurrencies with the highest market capitalization, BTC, ETH, and BNB, which represented 60% of the total market capitalization of cryptocurrency. We examined the impact of monetary policy on the price of cryptocurrencies (as distinct from other economic and operational factors). We used the interest rates controlled or influenced by the ECB and the FED as dependent variables, as well as reports from these institutions. In addition, we use a robust e-net machine learning method with ARIMA residuals to obtain robust regression coefficients and the corresponding standard errors. The period of the analysis is from 2017-11-8 to 2022-11-18, thus covering a period of economic instability.

The degree of association between monetary policy actions and cryptocurrency prices was assessed using the adjusted R Square. In most instances, this measure exceeded 50%, indicating a substantial level of influence. Hence, The results of this study show that monetary policy decisions and announcements have a significant impact on the price of cryptocurrencies, i.e. the FFR, which is influenced by the FED, as well as the deposit facility, the fixed rate, and the marginal lending facility, which are set by the ECB's Governing Council, as well as the announcements by these two institutions of complementary programs, such as the quantitative easing programs in the United States and the asset purchase programs in the EU, have a significant impact on the price of the cryptocurrencies under investigation. The impact of the monetary policy decision on cryptocurrency is likely to be significant in both a period of economic stability (2018-2020) and a period of turmoil (2020-2022). This relationship is likely to be indirect, acting through investor sentiment.

In the primary robustness assessment, we conducted residual diagnostics, revealing autocorrelation, heteroskedasticity, and non-normality in the residuals of the elastic net regression. To address these issues, an ARIMA process was employed, successfully mitigating autocorrelation concerns. However, residual heteroskedasticity persisted in some instances, and non-normality remained prevalent in the majority of cases. This persistence is noteworthy and should be considered when engaging in forecast activities and constructing confidence intervals.

For the conclusive robustness check, we employed the rolling window cross-validation technique and MASE as a metric. The findings indicated that, in most instances, the model under consideration did not outperform the naive forecasting model, as reflected by MASE values exceeding one. This outcome underscores the comparative limitations of the model in achieving superior forecasting accuracy.

The results of this study may contribute to monetary policymakers, as they reveal the link between their actions and the price of cryptocurrencies, which have become an integral part of the economy. Our model will also be useful for mutual fund managers and private investors, as they can anticipate the price dynamics of cryptocurrencies when assessing monetary policy frameworks.

A primary limitation of the study pertains to the samples used. The research could benefit from more diverse sample sets. For instance, it would be advantageous to construct three distinct samples: one exclusively employing conventional monetary tools, another solely utilizing interest rates (commonly referred to as conventional monetary tools), and a third sample that combines both unconventional monetary tools and interest rates. This approach could provide a comprehensive understanding of the effects of different monetary tools. Therefore, this presents a promising avenue for future research.

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Appendices

Appendix 1. E-Net Regression Hyper-Parameters (Source: Authors' calculations)

Sample	Alpha	Lambda
BTC-USD full sample	0,9	0,1
BTC-USD pre-covid19	1	0,1
BTC-USD post-covid19	1	0,1
ETH-USD full sample	1	0,1
ETH-USD pre-covid19	1	0,2
ETH-USD post-covid19	1	0,1
BNB-USD full sample	0,5	1
BNB-USD pre-covid19	1	0,1
BNB-USD post-covid19	1	0,1

Appendix 2. Full Sample E-net Regression Coefficient Parameters and Statistics (Source: Authors' calculations)

(BTC)

Feature	Coefficient	Standard error	T-stat	p-value
Federal funds rate	-15348,86037	485,4355686	-31,6187386	2,5603E-163
ECB deposit facility	-11347,13822	9428,853073	-3,87411310	0,000112331
ECB tenders fixed rate	30518,26505	8611,487887	6,217935893	6,77065E-10
ECB Marginal lending facility	0			
FOMC negative	1898,391571	675,8808039	2,818421006	0,004899014
FOMC positive	12879,45887	750,2715782	16,54783939	5,65237E-56
ECB negative	3299,962518	730,6488209	4,46609218	8,65572E-06
ECB positive	-16870,83894	746,7507301	-23,3675895	3,7894E-101

(ETH)

Feature	Coefficient	Standard error	T-stat	P-value
Federal funds rate	-1059,443023	38,81430757	-27,2951674	4,1171E-130
ECB deposit facility	0			
ECB tenders fixed rate	1488,0341	753,9093277	-0,88534869	0,376131946
ECB Marginal lending facility	0			
FOMC negative	575,0716739	54,04186899	10,64122475	2,04505E-25
FOMC positive	924,8192362	59,98998359	15,41622753	2,2067E-49
ECB negative	0			
ECB positive	-1151,167558	59,7084647	-19,2798050	4,56638E-73

(BNB)

Feature	Coefficient	Standard error	T-stat	P-value
Federal funds rate	-135,3551923	5,746497976	-23,5543791	1,7305E-102
ECB deposit facility	0			
ECB tenders fixed rate	173,4219846	111,6170479	-5,54299133	3,59505E-08
ECB Marginal lending facility	0			

FOMC negative	24,48951922	8,000954035	11,05122318	3,34661E-27
FOMC positive	57,37405437	8,881578492	18,68080156	3,45332E-69
ECB negative	0			
ECB positive	-84,50197322	8,839899333	-21,3341147	7,41539E-87

Appendix 3. Pre-Covid Sample E-net Regression Coefficient Parameters and Statistics (Source: Authors' calculations)

(BTC)

Feature	Coefficient	Standard error	T-stat	p-value
Federal funds rate	-5303,496772	301,950521	-17,5641252	2,7761E-55
ECB deposit facility	44069,61666	4269,451664	10,32207884	5,64584E-23
ECB tenders fixed rate	0			
ECB Marginal lending facility	0			
FOMC negative	-883,6057367	259,9656858	-3,39893218	0,000724889
FOMC positive	3947,598215	322,9077875	12,22515643	1,30013E-30
ECB negative	356,8595659	272,2056021	1,310992732	0,19040044
ECB positive	2288,359013	469,4694193	4,874351596	1,42567E-06

(ETH)

Feature	Coefficient	Standard error	T-stat	p-value
Federal funds rate	-406,4245313	21,38363267	-25,1903829	4,8732E-94
ECB deposit facility	1695,954066	302,3554514	13,47958921	4,8243E-36
ECB tenders fixed rate	0			
ECB Marginal lending facility	0			
FOMC negative	0			
FOMC positive	0			
ECB negative	0			
ECB positive	0			

(BNB)

Feature	Coefficient	Standard error	T-stat	p-value
Federal funds rate	3,6668722	0,646782703	10,83517684	5,9125E-25
ECB deposit facility	0			
ECB tenders fixed rate	0			
ECB Marginal lending facility	0			
FOMC negative	0			
FOMC positive	4,2245675	0,691673493	14,95361377	9,463E-43
ECB negative	-0,8659431	0,583068625	-9,74277054	8,129E-21
ECB positive	0			

Appendix 4. Post-Covid Sample E-Net Regression Coefficient Parameters and Statistics (Source: Authors' calculations)

(BTC)

Feature	Coefficient	Standard error	T-stat	p-value
Federal funds rate	-19293,7651	852,252753	-22,6385483	1,5864E-86
ECB deposit facility	21381,57622	2007,991496	10,64824042	1,0056E-24
ECB tenders fixed rate	0			
ECB Marginal lending facility	0			
FOMC negative	6325,578009	1104,958556	5,724719695	1,5087E-08
FOMC positive	16265,47092	1092,291622	14,89114316	4,9545E-44
ECB negative	5246,008547	1154,962815	4,542144975	6,5054E-06
ECB positive	-19262,9244	1005,476162	-19,1580120	1,1095E-66

(ETH)

Feature	Coefficient	Standard error	T-stat	p-value
Federal funds rate	-1326,1551	69,70359062	-19,0256353	6,04178E-66
ECB deposit facility	1760,620499	164,2285305	10,72055199	5,12216E-25

ECB tenders fixed rate	0			
ECB Marginal lending facility	0			
FOMC negative	1126,742216	90,37175718	12,46785778	1,66212E-32
FOMC positive	1375,225137	89,33576075	15,39389294	1,45669E-46
ECB negative	0			
ECB positive	-1207,832254	82,23534455	-14,6875076	5,10321E-43

(BNB)

Feature	**Coefficient**	**Standard error**	**T-stat**	**p-value**
Federal funds rate	-179,691342	9,614653594	-18,6893205	4,3992E-64
ECB deposit facility	252,388048	22,65307162	13,56242902	1,4563E-37
ECB tenders fixed rate	0			
ECB Marginal lending facility	0			
FOMC negative	187,2013339	12,46554349	15,01750277	1,1562E-44
FOMC positive	254,7097712	12,322642	20,67006176	3,3728E-75
ECB negative	0			
ECB positive	-191,145826	11,34323704	-16,8510827	3,9461E-54