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A COMPARISON OF ARCH MODELS: THE DETERMINANTS OF BITCOIN'S PRICE

The aim of this study is to determine the number of transactions among the currencies, which will eventually become a part of our lives, cannot be physically held, can move quickly, and emerge as a new shopping and investment tool in the changing world order, as of the year (2023) when this study was conducted. The study focuses on the analysis of the variables that affect the most popular currency, Bitcoin. Although the analysis of variables that influence Bitcoin was determined as the primary aim of the study, the study also attempted to reach a general conclusion about the variables affected by the cryptocurrencies. Since there is no other cryptocurrency that is traded as much as Bitcoin, Bitcoin is thought to be a good model for the analysis of cryptocurrencies.

The method used in the study was autoregressive conditional heteroskedastic (ARCH) models. It is believed that the most suitable models for the Bitcoin variable, whose value changes every second, are ARCH and its derivatives. Other models selected from the ARCH models were also added to the analysis as a method. The models used in the study can be listed as follows: linear ARC, generalized ARC (GARCH), exponential GARCH and threshold GARCH. A statistical model called autoregressive conditional heteroscedasticity (ARCH) is used to study the volatility of time series. Through the provision of a volatility model that more closely mimics actual markets, ARCH modeling is utilized in the financial sector to quantify risk. According to ARCH modeling, periods of high volatility are followed by even higher volatility, and periods of low volatility are followed by even lower volatility.

In this study, 5 different variables were selected using literature to analyze the variables affecting Bitcoin returns using ARCH models. The dependent variable in the study is the price of Bitcoin. The remaining variables were included in the models as independent variables. These variables are actually variables that are accepted and selected as the best among a set of variables. In other words, 15 variables were first added to the study using the literature. After this, a correlation analysis was carried out. As a result of the correlation analysis, the variables with the highest correlation with the price of Bitcoin, which is the dependent variable, and the lowest correlation with each other were retained in the model. These variables are Bitcoin Price, Crude Oil Spot Price, Euro-Dollar Parity, Gold Spot Price and NASDAQ Composite Index.

The study period is between 2020 and 2023 and it was studied using daily data. Days with no data were removed from the daily period from 2020 to 2023 and loss of information was prevented. After removing missing observations, this study examined the remaining 837 observations.

During the research, while running the models created using different methods, it was found that the model that gives the best result is the GARCH model. In other words, when modeling the variables affecting bitcoin (cryptocurrency from the perspective of the population), it was seen that the GARCH model gave the best results when comparing linear ARCH, generalized ARCH (GARCH), exponential GARCH, and threshold GARCH of the ARCH model.

Comparing the output of the GARCH model with other ARCH models not included in this study can be a recommendation for the future study.

Keywords: Autoregressive Conditionally Heteroscedastic, GARCH, Threshold GARCH, Exponential GARCH, Cryptocurrency, Bitcoin, Digital Money, Time-Series Analysis, Comparative Analysis, Financial Analysis

JEL classifacation: ***C01, C58, C32, G10***

Метою цього дослідження є визначення кількості транзакцій між валютами, які останнім часом входять у наше життя, не можуть бути фізично утримані, можуть використовуватися лише в цифровому вигляді, можуть швидко рухатися та з'являються як новий інструмент для покупок та інвестицій у мінливому світі станом на рік (2023), коли було проведено це дослідження. Дослідження зосереджено на аналізі змінних, які впливають на найпопулярнішу валюту, біткойн. Хоча основною метою дослідження було визначено аналіз змінних, що впливають на біткойн, дослідження також намагалося дійти загального висновку щодо змінних, на які впливають криптовалюти. Оскільки немає іншої криптовалюти, якою торгують так багато, як біткойн, біткойн вважається хорошою моделлю для аналізу криптовалюти.

Методом, використаним у дослідженні, були авторегресійні умовні гетероскедастичні (ARCH) моделі. Вважається, що найбільш придатними моделями для змінної біткойна, дані якої змінюються щосекунди, є ARCH та її похідні. Інші моделі, вибрані з моделей ARCH, також були додані до аналізу як метод. Моделі, використані у дослідженні, можна перерахувати наступним чином: лінійний ARCH, узагальнений ARCH (GARCH), експоненціальний GARCH і пороговий GARCH. Статистична модель під назвою авторегресійна умовна гетероскедастичність (ARCH) використовується для вивчення волатильності часових рядів. Завдяки наданню моделі волатильності, яка більше імітує реальні ринки, моделювання ARCH використовується у фінансовому секторі для кількісної оцінки ризику. Відповідно до моделювання ARCH, періоди високої волатильності супроводжуються ще більш високою волатильністю, тоді як періоди низької волатильності супроводжуються ще більш низькою волатильністю.

У цьому дослідженні було відібрано 5 різних змінних за допомогою літератури для аналізу змінних, що впливають на прибуток біткойнів за допомогою моделей ARCH. Залежною змінною в дослідженні є ціна біткойна. Решта змінних були включені в моделі як незалежні змінні. Ці змінні насправді є змінними, які прийняті та обрані як найкращі серед набору змінних. Іншими словами, 15 змінних спочатку були додані до дослідження за допомогою літератури. Після цього було проведено кореляційний аналіз. У результаті кореляційного аналізу в моделі були збережені змінні з найвищою кореляцією з ціною біткойна, яка є залежною змінною, і найменшою кореляцією між собою. Ці змінні: ціна біткойна, спотова ціна сирої нафти, паритет євро-долар, спотова ціна золота та зведений індекс NASDAQ

Період дослідження – між 2020 і 2023 роками, і воно вивчалося за щоденними даними. З щоденного періоду між 2020 і 2023 роками було видалено дні без даних. Коли відсутні спостереження були видалені, решта 837 спостережень були вивчені у цьому дослідженні.

У ході дослідження під час запуску моделей, створених за допомогою певних методів, було виявлено, що найкращий результат дає модель GARCH. Іншими словами, під час моделювання змінних, що впливають на біткойн (криптовалюти з точки зору населення), було видно, що модель GARCH дала найкращі результати, коли порівнювали лінійну ARCH, узагальнену ARCH (GARCH), експоненціальну GARCH і порогову GARCH моделі ARCH.

Порівняння результатів моделі GARCH з іншими моделями ARCH, не включеними в це дослідження, може бути рекомендацією для майбутнього дослідження.

Ключові слова: авторегресійна умовна гетероскедастика, GARCH, порогова GARCH, експоненціальна GARCH, криптовалюта, біткойн, цифрові гроші, аналіз часових рядів, порівняльний аналіз, фінансовий аналіз

JEL classifacation: *C01, C58, C32, G10*

Introduction and purpose of the study. Since its launch by Nakamoto in 2008, Bitcoin has drawn the attention of both investors and researchers. A decentralized, peer-to-peer payment system called Bitcoin was created to promote safer online transactions without the involvement of a third party [1]. Since Bitcoin is built on the public distributed network known as blockchain, its transaction, issuance and storage are independent of any central bank or server. The academic literature on finance has recently begun to pay more attention to cryptocurrencies, particularly bitcoin. Cryptocurrency is a type of digital asset that serves primarily as a medium of exchange. It uses cryptography to ensure the security of all transactions and the control of all newly created currencies within its own system. Cryptocurrencies could be considered a subcategory of digital currencies [2].

There is a growing body of literature that studies the determinants of Bitcoin return. With a sample size of 838, this study aims to test which of the models estimated in the analysis explains the Bitcoin price better. Autoregressive Conditional Heteroskedasticity models (ARCH/GARCH/EGARCH/TARCH) are used to analyse which of these methods gives a better model output. For this purpose, 4 independent variables are included in the study to explain the Bitcoin price. Based on the correlation analysis, the best 5 variables were selected, and the remaining variables discarded from the further analysis. The selected variables are Bitcoin price (BTC), crude oil spot price (CL), Euro Dollar parity (EUR), gold spot price (XAU)) and NASDAQ Composite index return (IXIC). All variables are obtained from investing.com.

The purpose of the study is to ascertain the number of transactions made digitally by using currencies that will eventually become a part of our lives, that can be used only in digital format, evolve rapidly and emerge as the new tools for investing and purchasing in a changing world. The study focuses on the analysis of the variables that affect the most popular currency, Bitcoin. Although the analysis of the variables affecting Bitcoin was determined as the primary aim of the study, the study also attempted to reach a general conclusion about the variables affected by the cryptocurrencies. Since no other cryptocurrency is exchanged as frequently as Bitcoin, it is considered a good model for studying cryptocurrencies.

Table 1 shows the variables used in the analysis. The dependent variable is Bitcoin price, the other variables are added to the model as independent variables. Independent variables were selected with the help of correlation analysis.

Review of literature. The popular digital currency Bitcoin has been the subject of many studies in the literature. Researches [3] have examined the significance of twenty-one potential drivers of bitcoin returns for the period 2010 to 2017 (2,533 daily observations). Within a LASSO framework, they have studied the effects of factors such as stock market returns, exchange rates, gold and oil returns, FED's and ECB's rates and internet trends on bitcoin returns for alternate time periods. Search intensity and gold returns emerge as the most important variables for bitcoin returns.

Some scholars [4] have applied the Gets reduction method which has a good reputation compared to other competing approaches in terms of the statistical apparatus available for a repeated search to determine the final set of determinants and the consideration of location shifts. They have found that the reduced set of explanatory variables that affects Bitcoin returns is composed of Twitter-based economic uncertainty, gold return, the return of the Euro/USD exchange rate, the return of the US NASDAQ stock exchange index, market capitalization, and Bitcoin mining difficulty. In contrast, the volatility of Bitcoin is affected only by the lag terms of the ARCH effect and the volume of this cryptocurrency.

A study by Adjei (2019) [5] examines the relationship between Bitcoin mining technology variables and Bitcoin returns, using a GARCH-M model. Additionally, it examines the predictive power of the mining technology variables on future Bitcoin

Table 1

Variables and definitions

Variable	Definition
BTC	Bitcoin Price
CL	Crude Oil Spot Price
XAU	Gold Spot Price
EUR	Euro Dollar Parity (Price)
IXIC	NASDAQ Composite Index (Price)

returns. The study finds that mining difficulty and block size are inversely related to Bitcoin returns. Additionally, the results of the study show that the larger the block size, the lower the price of Bitcoin and therefore the lower the expected profit. Also, its results show that mining difficulty and block size are robust predictors of future Bitcoin returns.

A number of authors [6] consider a relatively large set of predictors and investigate the determinants of cryptocurrency returns at different quantiles. Their analysis exclusively focuses on the highly volatile period of COVID-19. One of the drivers behind the innovation of the paper stems from the fact that the authors employ the LASSO penalty within a quantile regression framework to select informative variables. The results show that US government bond indices and small company stock returns (a new predictor introduced in this study) significantly impact the tail behavior of the cryptocurrency returns.

Malladi and Dheeriya (2021) [7] in their study use the Autoregressive-moving-average model with exogenous inputs model (ARMAX), Generalized Autoregressive Conditionally Heteroscedastic (GARCH) model, Vector Autoregression (VAR) model, and Granger causality tests to determine linkages between returns and volatilities of Bitcoin and of Ripple. The study finds that the Bitcoin crash of 2018 could have been explained using these time series methods. It also finds that returns of global stock markets and of gold do not have a causal effect on Bitcoin returns, and that returns on Ripple have a causal effect on Bitcoin prices.

Corbet et al.'s study [8] examines the relationship between news coverage and Bitcoin returns. It constructs a sentiment index based on news stories that follow the announcements of four macroeconomic indicators: GDP, unemployment, Consumer Price Index (CPI) and durable goods. It determines whether each series has a significant impact on Bitcoin returns. While an increase in positive news on unemployment rates and durable goods typically leads to a corresponding increase in equity returns, the opposite is true for Bitcoin.

Some authors [9] investigate factors that affected Bitcoin's price from 2010 and 2018 with the help of the GARCH model. According to the experimental findings, the price of Bitcoin is positively correlated with the DAX, the Nikkei 225, the exchange rates (USD/Euro, USD/GBP, USD/CHF, and Euro/GBP), and negatively correlated with the Fed funds rate, the FTSE 100, and the USD index. The Fed funds rate has the biggest impact on the price of Bitcoin, followed by the exchange rates for the US dollar, the British pound, and the West Texas Intermediate. The decision tree and support vector machine approaches are also used in this study to forecast the price trend of Bitcoin.

By combining trade data with the autoregressive distributed lag model and the nonlinear autoregressive distributed lag model, which both capture the asymmetric effects of explanatory variables, the authors [10] develop a novel empirical approach based on Bitcoin sentiment. This approach avoids relying on opinions of people who are not Bitcoin users. This research shows the non-linearity and asymmetry of this relationship in the short and long runs, as well as the usefulness of estimating Bitcoin sentiment using trade data and reveals a strong impact of the Bitcoin Misery Index (BMI) on short- and long-term Bitcoin returns.

Abramova and Bohre's study [11] details the exploration of the main drivers and barriers to Bitcoin use. We incorporate the multiple advantages and disadvantages of using Bitcoin to create the multidimensional constructs Perceived Benefit and Perceived Risk, drawing on the Technology Acceptance Model and a literature analysis. A theoretical model describing the use of Bitcoin as an online payment system for legal purchases and money transfers is proposed, and empirical testing of the concept is conducted. In the context of decentralized and sharing economy systems, we also consider several conceptual and methodological opportunities for developing theories of technology acceptance.

Research methods and data. In this study, Bitcoin price is modeled with the help of ARCH models to compare the results with the variables that are thought to explain the digital currency Bitcoin price. Using 837 observations as daily data from investing.com, the outputs of two models are analyzed and evaluated between 01.01.2020 and 05.01.2023. Beyond a variety of outcomes, our main focus is on the differences between these models' outputs. In this regard, the article will present the models ARCH, GARCH, EGARCH, TARCH. These models are ARCH models that give statistically significant results in terms of the variables included in the analysis. Several econometric models attempt to capture ARCH, or Autoregressive Conditional Heteroskedasticity, which is now acknowledged as a significant aspect of financial data [12]. Using ARCH class models, this paper provides an extensive empirical study of the mean and conditional variance of the Bitcoin series.

Several parametric specifications of ARCH models have been taken into consideration for the description of the features of financial markets in recent research [13]. The conditional variance is assumed to be a linear function of the previous q-squared innovations in the linear ARCH(q) model, which was first proposed by [14]. In the generalized ARCH or GARCH(p,q) model [15], the conditional variance was proposed to be a linear function of both the prior q-squared innovations and the prior p conditional variances. The exponential GARCH, or EGARCH, model was proposed by Nelson (1991) [16]. The EGARCH model (a member of the family of asymmetric GARCH models) captures the phenomena that negative returns indicate more volatility than positive returns of the same magnitude. The threshold GARCH, or TARCH models proposed by Zakoian in 1990 [17] are two other well-known asymmetric models.

The distribution of the stochastic error ε_t conditional on the actual values of the $\Psi_{t-1} = \{y_{t-1}, x_{t-1}, y_{t-2}, x_{t-2}, \dots\}$ set of variables is characterized by the ARCH model. Engle's (1982) [14] basic ARCH model, in particular,

$$\varepsilon_t|\Psi_{t-1} \sim N(, h_t) \quad (1)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 \quad (2)$$

with $\alpha_0 > 0$ and $\alpha_i \geq 0, i = 1, \dots, q$ to provide that the conditional variance is positive. Observe that h_t clearly a function of the $\Psi_{t-1})$ elements as $\varepsilon_{t-i} = y_{t-i} - x_{t-i}\xi, i = 1, \dots, q, h_t$

Equations (1) and (2) differ from each other not just in that the conditional variance h_t is a function of the conditioning set Ψ_{t-1}, but also in that a specific functional form is stated.

A rather lengthy lag in the conditional variance equation is frequently required in empirical applications of the ARCH model, and to prevent issues with estimations of the negative variance component, a fixed lag structure is typically imposed; see [14], [18]. In this context, expanding the ARCH class of models to support both a larger memory and a more flexible lag structure seems to be of critical practical importance. The Generalized ARCH, or GARCH, model in Bollerslev (1986) [15] frequently offers an alternate and more adaptable lag structure,

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \quad (3)$$

It is expected that the roots of the polynomial β(λ)-1 are outside the unit circle, and all parameters in the infinite-order AR representation $\sigma_t^2 = \phi(L)\varepsilon_t^2 = \left(1 - \beta(L)\right)^{-1} \alpha(L)\varepsilon_t^2$ must be nonnegative to guarantee a well-defined process; for further information, see Nelson and Cao (1991) [19] and Drost and Nijman (1991) [20].

According to GARCH models, the magnitude but not the sign of the innovation will determine how the news will affect conditional volatility. Empirical research has demonstrated, as mentioned by GARCH, that increases in volatility are adversely connected with changes in financial markets. Nelson (1991) [16] developed the exponential GARCH (EGARCH) model to address these issues. In this model, the conditional variance's logarithm is expressed as follows:

$$ln\sigma_t^2 = \alpha_0 + \alpha_{1a}\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha_{1b}\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - E\left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}\right]\right) + b_1 ln\sigma_{t-1}^2 \quad (4)$$

For $\varepsilon_t \sim N(0, \sigma_t^2)$ the standardised variable $\frac{\varepsilon_t}{\sigma_t}$ follows a standard normal distribution and consequently $E\left[\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right] = \sqrt{\frac{2}{\pi}}$ The paramete $\alpha_{1\alpha}$ captures the leverage effect. For «good news» ($\frac{\varepsilon_{t-1}}{\sigma_{t-1}} > 0$) the impact of the innovation ε_{t-1} is $\alpha_{1b} + \alpha_{1\alpha} \cdot \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ and for «bad news» (($\frac{\varepsilon_{t-1}}{\sigma_{t-1}} < 0$) it is $(\alpha_{1b} + \alpha_{1\alpha}) \cdot \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$. If $\alpha_{1\alpha} = 0$ $ln\sigma_t^2$ responds symmetrically to $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$. To produce a leverage effect, $\alpha_{1\alpha}$ must be negative [21].

In the equities markets, it is frequently noticed that lower moves of the same magnitude are followed by higher volatilities than bigger ones. The leverage effect is a term used to describe this asymmetric effect. The GARCH model would be viewed as insufficient to model the volatility in the presence of such an influence. The models that allow for such asymmetric shocks to volatility are the Threshold ARCH (TARCH) and Exponential ARCH (EGARCH), which were put forth by Glosten et al. (1993) [22] and Nelson (1991) [16], respectively. Following are the details of the TARCH (1, 1) model:

$$r_t = \mu + \alpha r_{t-1} + \varepsilon_t \quad (5)$$

Research findings. In this study, all variables included in the model were included according to their stationarity levels. That is, all the variables in the analysis are stationary. The correlation coefficients between the variables included in the study based on the literature review and found to be statistically significant and the BITCOIN variable under analysis are shown in Table 2.

The table above indicates that there is a not very low correlation between BTC, which was chosen as the dependent variable since it is the subject of the research, and other variables. The correlation coefficient between BTC and the IXIC, that is, NASDAQ index, is greater than with the others. In other words, according to the correlation analysis, the IXIC variable can explain the change in BTC better than the others. When looking at the correlation coefficients of other variables besides BTC, they range from -0.40 to +0.40. The coefficient is neither too high nor too low. In other words, independent variables may be affected by the same events and not be affected. Therefore, a model can be created with these variables.

Summary statistics of the models are shown in Table 3. In this table, when considering the Akaike information criteria, it can be seen that the GARCH(1,1) model gives the best results in estimating the volatility of the ARCH(2) model when considering Schwarz information criteria. On the other hand, the results of this study also revealed high persistence (maintenance of shocks over a long period of time), which is one of the important problems of the ARCH and GARCH models. When considering the persistence results summarized in Table 4, the persistence, which was high for the GARCH and TARCH models, increased greatly with the EGARCH model. In fact,

Table 2

Correlation coefficients*

	BTC	CL	XAU	EUR	IXIC
BTC	1	0.4377	0.2001	0.3724	0.8798
CL	0.4377	1	0.2080	-0.4485	0.4481
XAU	0.2001	0.2080	1	0.2967	0.3766
EUR	0.3724	-0.4485	0.2967	1	0.4228
IXIC	0.8798	0.4481	0.3766	0.4228	1

* Calculated by the author.

Table 3

ARCH Models summary statistics*

	Log likelihood	Akaike criterion	Schwarzcriterion	Persistence
ARCH(1)	-8208.803	19.631	19.671	
ARCH(2)	-8200.772	19.659	19.632	
GARCH(1,1)	-8199.913	19.612	19.657	0.241
GARCH(1,2)	-8202.089	19.620	19.671	0.296
TARCH(1,1)	-8199.890	19.615	19.665	0.241
EGARCH(1,1)	-8216.767	19.653	19.698	0.885

**Calculated by the author. AIC : Akaike Information Criteria, AIC= L-N, N: Number of parameters. SIC: Schwarz Information Criterion, SIC= L-(N/2)*ln(T), T: Number of Observations. The coefficients of the lagged parameters in the persistence conditional variance equation were found by summing.*

the persistence value, which was around 0.20 for GARCH(1,1), GARCH(1,2) and TARCH(1,1) increased to 0.08 for EGARCH(1,1).

Conclusions. To compare the results with the factors hypothesized to explain the price of the digital currency Bitcoin, this study uses ARCH models to model the price of Bitcoin. The results of each model are analyzed and assessed between January 1, 2020, and January 5, 2023 using 837 observations as the daily data from investing.com. Our focus is mostly on the variations in these models' outputs rather than the range of results. From this perspective, the study established the ARCH, GARCH, EGARCH, and TARCH models, respectively.

When considering the Akaike information criteria, it can be seen that the GARCH(1,1) model gives the best results in estimating the volatility of the ARCH(2) model when considering Schwarz information criteria. On the other hand, the results of this study also revealed high persistence (maintenance of shocks over a long period of time), which is one of the important problems of the ARCH and GARCH models. When considering the persistence results summarized in Table 4, the persistence, which was high for the GARCH and TARCH models, increased greatly with the EGARCH model. In fact, the persistence value, which was around 0.20 for GARCH (1,1), GARCH (1,2) and TARCH (1,1) increased to 0.08 for EGARCH (1,1)

Using forecasts of future volatility as data, especially in Bitcoin pricing, highlights the importance of making correct forecasts. According to this study, using the GARCH model, a relatively new model in the ARCH family, to forecast volatility helps achieve more accurate forecasts. According to the study's findings, investors and portfolio managers should consider the GARCH model as a good alternative to other competing volatility forecasting models. However, it should be noted that when different frequency data and different periods are employed, the models that give good results may change. In fact, this can be seen in various studies in the literature.

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A COMPARISON OF ARCH MODELS: THE DETERMINANTS OF BITCOIN'S PRICE

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The aim of this study is to determine the number of transactions among the currencies, which will eventually become a part of our lives, cannot be physically held, can move quickly, and emerge as a new shopping and investment tool in the changing world order, as of the year (2023) when this study was conducted. The study focuses on the analysis of the variables that affect the most popular currency, Bitcoin. Although the analysis of variables that influence Bitcoin was determined as the primary aim of the study, the study also attempted to reach a general conclusion about the variables affected by the cryptocurrencies. Since there is no other cryptocurrency that is traded as much as Bitcoin, Bitcoin is thought to be a good model for the analysis of cryptocurrencies.

The method used in the study was autoregressive conditional heteroskedastic (ARCH) models. It is believed that the most suitable models for the Bitcoin variable, whose value changes every second, are ARCH and its derivatives. Other models selected from the ARCH models were also added to the analysis as a method. The models used in the study can be listed as follows: linear ARC, generalized ARC (GARCH), exponential GARCH and threshold GARCH. A statistical model called autoregressive conditional heteroscedasticity (ARCH) is used to study the volatility of time series. Through the provision of a volatility model that more closely mimics actual markets, ARCH modeling is utilized in the financial sector to quantify risk. According to ARCH modeling, periods of high volatility are followed by even higher volatility, and periods of low volatility are followed by even lower volatility.

In this study, 5 different variables were selected using literature to analyze the variables affecting Bitcoin returns using ARCH models. The dependent variable in the study is the price of Bitcoin. The remaining variables were included in the models as independent variables. These variables are actually variables that are accepted and selected as the best among a set of variables. In other words, 15 variables were first added to the study using the literature. After this, a correlation analysis was carried out. As a result of the correlation analysis, the variables with the highest correlation with the price of Bitcoin, which is the dependent variable, and the lowest correlation with each other were retained in the model. These variables are Bitcoin Price, Crude Oil Spot Price, Euro-Dollar Parity, Gold Spot Price and NASDAQ Composite Index.

The study period is between 2020 and 2023 and it was studied using daily data. Days with no data were removed from the daily period from 2020 to 2023 and loss of information was prevented. After removing missing observations, this study examined the remaining 837 observations.

During the research, while running the models created using different methods, it was found that the model that gives the best result is the GARCH model. In other words, when modeling the variables affecting bitcoin (cryptocurrency from the perspective of the population), it was seen that the GARCH model gave the best results when comparing linear ARCH, generalized ARCH (GARCH), exponential GARCH, and threshold GARCH of the ARCH model.

Comparing the output of the GARCH model with other ARCH models not included in this study can be a recommendation for the future study.

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