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DETERMINANTS OF BITCOIN PRICE MOVEMENTS

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ABSTRACT

Purpose- Investors want to include Bitcoin in their portfolios due to its high returns. However, high returns also come with high risks. For this reason, the volatility prediction of Bitcoin prices is the focus of attention of investors. Because Bitcoin's volatility is used as an important input in portfolio selection and risk management. This means that the models to be used in predicting Bitcoin volatility increases the importance of performance. In this research; A comparative examination of the models applied for Bitcoin shows an effective performance in volatility prediction. It is very important for evaluation. The aim of this study is to model Bitcoin price returns and to examine future return predictions and return directions using historical Bitcoin prices.

Methodology- Many models have been used in studies on financial instruments and price predictions. Models such as linear and nonlinear regression, Random Walk Model, GARCH and ARIMA fall into this category. Nonlinear econometric models such as ARCH and GARCH are used for financial time series with variable volatility. These models assume that the variance is not constant. In this study, first Bitcoin price returns for the period between January 2020 and December 2023 will be modeled with the GARCH model, and then the ARCH-GARCH models will be used for future prediction of returns for the period between January 2024 and June 2024. Finally, the actual values will be compared with the forecasted values. In other words, the primary aim of this study is to use the daily Bitcoin closing price between May 2020 and December 2023 to estimate the returns for the periods of 2024 and compare it with the actual returns.

Findings- The analysis reveals that GARCH Model results showed that in the mean and variance equations, it is seen that all variables are except intercept of the mean equation significant according to the error level of 0.05. Namely, the reaction and persistence parameters are significant accounding to 0.05 in the variance equation. Both the coefficient of the reaction parameter and the coefficient of the persistent parameter are higher than zero (positive). Also, the coefficient of the reaction parameter plus the coefficient of the persistent parameter approximately equals 0.72. That is, it is lower than 1 and higher than zero (positive). The level of persistence is not too high. So, we do not think about non-stationary variance in the model. Reaction parameter's coefficient is 0.13. And persistence parameter's coefficient is 0.58. As we can see, persistent parameter is much higher than reaction parameter. That is, when there is a new shock that creates the persistent parameter, that shock will be in effect for a long time, it will not disappear immediately. That is, a significant part of the shock that occurs in one period flows into the next period. After determining the appropriate mean and variance models, a forecast is made using Automatic ARIMA forecasting for BITCOIN return forecasting. This forecast is made for the first five months of 2024, without adding the actual values of the first five months of 2024 to the data. The program ranks the most appropriate model. The program chose GARCH(3,3) as the most appropriate model in "bitcoin return prediction".

Conclusion- The results of the test applied in the study can be summarized that the unit root test results showed that it was necessary to work with return series. GARCH(1,1) model results show when there is a new shock that creates the persistent parameter, that shock will be in effect for a long time, it will not disappear immediately. That is, a significant part of the shock that occurs in one period flows into the next period. According to GARCH automatic forecasting results, the best GARCH model that models Bitcoin return is the GARCH(3,3) model. According to these model results, although the slopes of the actual and forecasted return series move in the same direction, the model remains weak for forecasting. In future studies, it may be recommended to estimate Bitcoin returns with non-linear models.

Keywords: Bitcoin, ARCH models, GARCH models, forecasting, ARIMA models
JEL Codes: C58, G10, G12

1. INTRODUCTION

Investors want to include Bitcoin in their portfolios due to its high returns. However, high returns also come with high risks. For this reason, the volatility prediction of Bitcoin prices is the focus of attention of investors. Because Bitcoin's volatility is used as an important input in portfolio selection and risk management. This means that the models to be used in predicting Bitcoin volatility increases the importance of performance. In this research; A comparative examination of the models applied for Bitcoin shows an effective performance in volatility prediction. It is very important for evaluation. The aim of this study is to model Bitcoin price returns and to examine future return predictions and return directions using historical Bitcoin prices. In the study, daily returns calculated from the daily closing price of Bitcoin for the period from May 2020 to December 2023 are used. Data are observed from investing.com. Many models have been used in studies on financial instruments and price predictions. Models such as linear and nonlinear regression, Random Walk Model, GARCH and ARIMA fall into this category. Nonlinear econometric models such as ARCH and GARCH are used for financial time series with variable volatility. These models assume that the variance is not constant. In this study, first Bitcoin price returns for the period between January 2020 and December 2023 will be modeled with the GARCH model, and then the ARCH-GARCH models will be used for future prediction of returns for the period between January 2024 and June 2024. Finally, the actual values will be compared with the forecasted values. In other words, the primary aim of this study is to use the daily Bitcoin closing price between May 2020 and December 2023 to estimate the returns for the periods of 2024 and compare it with the actual returns.

2. LITERATURE REVIEW

The study Naimy and Hayek (2018) aims to estimate the the Bitcoin/ USD exchange rate volatility. Then, it is compared some forecasting methods such as GARCH(1,1), EWMA, and EGARCH(1,1). Its results provided an analysis of the characteristics of Bitcoin, which functions differently from typical currencies. The study Shen et al. (2019) is used conventional economic models as well as machine learning model for forecasting bitcoin return's volatility. The aim of the study is to check against the models' performances. The study showed the neural network analysis showed the better performance than the GARCH and the simple MA model. The study The study Loureiro (2023) aims to determine the most accurate model to look into the processes of Bitcoin's price and volatility. It used models such as GARCH, EGARCH and the GARCH model. The study revealed that the EGARCH (1,1) model is the most suitable model among these models. This study also showed the importance of working with a model that is compatible with investors' risk proneness. The study Quan et al. (2023) aims to estimate the volatility of Bitcoin. It used GARCH models, its derivatives, and Box-Jenkins Method. A clustering in shocks is provided for Bitcoin in the GARCH models. In this study, The model Glosten, Jagannathan, and Runkle (GJR)- GARCH(1,1) is also used. The model found when Bitcoin returns experience a positive shock, the volatility of the returns increases. In other words, it creates reverse leverage.

3. DATA AND METHODOLOGY

In the study, daily returns calculated from the daily closing price of Bitcoin for the period from May 2020 to December 2023 are used. Data are taken from https://www.investing.com. In this study, the GARCH model was used for Bitcoin prices. In other words, the primary aim of this study is to use the daily Bitcoin closing price between May 2020 and December 2023 to estimate the returns for the periods of 2024 and compare it with the actual returns. In the GARCH models developed by Tim Bollerslev (1986), the conditional variance (h_t) at period t depends on the square of the previous values of the error terms and the previous conditional variances. Therefore, the variance of the error terms is affected by both the conditional variance values and the past values. Under these conditions:

$$\omega > 0;\ \alpha_i \geq 0;\ \beta_j \geq 0;\ \sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1 \tag{1}$$

With q as the lag length of the error squares and p as the lag length of the autoregressive part, a general GARCH(p,q) process can be described as follows:

$$h_t = \omega + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 \tag{2}$$

4. FINDINGS

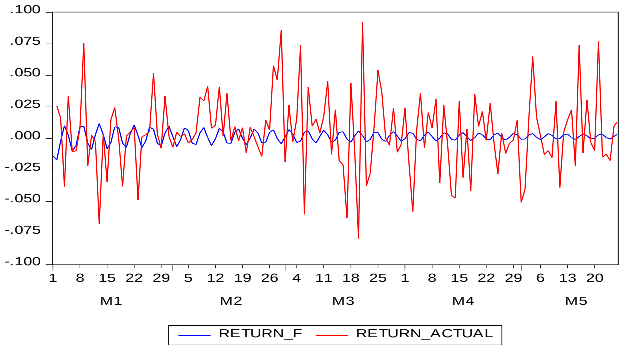
The GARCH model was applied to the Bitcoin prices in this study. Simply put, the main goal of this study is to estimate the returns for the years 2024 and compare them with the actual returns using the daily closing price of Bitcoin between May 2020 and December 2023. In this analysis, the BITCOIN variable is included in the model as logaritmic and first-order difference, that is, as a return series. ARCH-LM test is used to determine whether there is an ARCH effect in the Bitcoin series after the series is stationary. Testing with various ARIMA models, the most suitable model for the series's structure is found. The appropriate ARIMA model is determined as ARIMA(1,1,1). Essentially, variance structure asymmetry effects cannot be adequately determined using ARIMA models. To estimate the asymmetric impacts of the shocks on volatility in this situation, the GARCH model must be applied. The GARCH(1,1) models' estimation results for the Bitcoin return series appear in Table 1.

Table 1: GARCH Model

Mean Equation				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.0010	0.0009	1.0741	0.2827
AR(1)	0.6163	0.0347	17.749	0.0000
MA(1)	-0.9309	0.0154	-60.126	0.0000
Variance Equation				
C	0.0100	0.0020	4.8571	0.0000
RESID(-1)^2	0.1345	0.0219	6.1363	0.0000
GARCH(-1)	0.5845	0.0791	7.3880	0.0000

According to the variance equation, the reaction and persistence parameters are significant at significance level of 0.05. The persistent parameter is significantly higher than the reaction parameter, as can be shown. In other words, a new shock that generates a persistent parameter will not go away quickly; instead, it will remain in effect for an extended period. In other words, a significant amount of the shock that happens in one period flows through into another. After determining the appropriate mean and variance models, a forecast is made using Automatic ARIMA forecasting via the Eviews10 package program for BITCOIN return forecasting. This forecast is made for the first five months of 2024, without adding the actual values of the first five months of 2024 to the data. The program ranks the most appropriate model. The most suitable model for BITCOIN return estimation is found to be ARMA(3,3) with automatic ARIMA forecasting. Comparing the return estimates estimated with ARMA(3,3) with the actual returns is important for this study. It is necessary to compare the forecasted and actual returns. This comparison is shown in Figure 1.

Figure 2: Forecasted and Actual returns



The lines indicated by “RETURN_ACTUAL” and shown in “red” in Figure 1 represent the actual BITCOIN return series for the first five months of 2024, while the lines indicated by “RETURN_F” and shown in “blue” represent the forecasted BITCOIN return series for the first five months of 2024. It is seen that the decreasing-increasing trends of both actual and forecasted returns are the same on a period basis. In other words, both actual and forecasted returns have the same trends in the same periods. This shows that the method used in the study is suitable for estimating BITCOIN in periods when its actual values are unknown.

5. CONCLUSION

The aim of this study is to model Bitcoin price returns and to examine future return predictions and return directions using historical Bitcoin prices. In this study, first Bitcoin price returns for the period between January 2020 and December 2023 will be modeled with the GARCH model, and then the ARCH-GARCH models will be used for future prediction of returns for the period between January 2024 and June 2024. Finally, the actual values will be compared with the forecasted values. Unit root test results showed that it was necessary to work with return series. GARCH(1,1) model results show when there is a new shock that creates the persistent parameter, that shock will be in effect for a long time, it will not disappear immediately. That is, a significant part of the shock that occurs in one period flows into the next period. According to GARCH automatic forecasting results, the best GARCH model that models Bitcoin return is the GARCH(3,3) model. According to these model results, although the slopes of the actual and forecasted return series move in the same direction, the model remains weak for forecasting. In future studies, it may be recommended to estimate Bitcoin returns with non-linear models.

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