MODELING, FORECASTING THE CRYPTOCURRENCY MARKET VOLATILITY AND VALUE AT RISK DYNAMICS OF BITCOIN[*]

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ABSTRACT

Bitcoin volatility was investigated with various symmetric and asymmetric models in the study. In addition, value at risk (VaR) was calculated by using the Kupiec LR test and the error prediction performances of the models were compared. As a result of the work, the long memory of volatility in Bitcoin returns was found. It means the cryptocurrency market is not efficient. According to the FIAPARCH asymmetric model, it was determined that positive information shocks reaching the Bitcoin market increased volatility more than negative information shocks. Comparing the error prediction performance of the models by calculating VaR, the HYGARCH model prediction results were found to be superior to other models included in the study. Thus, it was determined that the most suitable model in predicting the volatility, namely the risk of Bitcoin in short and long positions for those who consider investing in Bitcoin, is the asymmetric model HYGARCH.

Keywords: Bitcoin Volatility, Cryptocurrency Market, Long Memory, Value at Risk

JEL Classification: C53, G17, G32

KRİPTOPARA PİYASA VOLATİLİTESİNİN MODELLENMESİ, TAHMİNİ VE BİTCOİN'İN RİSKE MARUZ DEĞER DİNAMİKLERİ

ÖZ

Bu çalışmada Bitcoin volatilitesi, çeşitli simetrik ve asimetrik modeller yardımıyla araştırılmaktadır. Bunun yanında Kupiec LR testi yardımıyla riske maruz değer (RMD) hesaplanarak modellerin hata öngörü performansları karşılaştırılmaktadır. Çalışma sonucunda Bitcoin getiri volatilitesinde uzun hafızanın varlığı tespit edilmiştir. Bu durum, kripto para piyasasının etkin olmadığı anlamına gelmektedir. Ayrıca FIAPARCH asimetrik model

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sonucuna göre Bitcoin piyasasına ulaşan pozitif bilgi şoklarının negatif bilgi şoklarına kıyasla volatiliteyi daha çok artırdığı belirlenmiştir. RMD hesaplanarak modellerin hata öngörü performansları karşılaştırıldığında, HYGARCH model tahmin sonuçlarının çalışma kapsamındaki diğer modellerden daha üstün olduğu belirlenmiştir. Böylece Bitcoin'e yatırım yapmayı düşünenlerin kısa ve uzun pozisyonlar için Bitcoin'in volatilitesini yani riskini tahmin etmede en uygun modelin asimetrik bir model olan HYGARCH modeli olduğu tespit edilmiştir.

Anahtar Kelimeler: Bitcoin Volatilitesi, Kripto Para Piyasası, Uzun Hafıza, Riske Maruz Değer

JEL Sınıflandırması: C53, G17, G32

1. INTRODUCTION

As one of the most important financial innovations in recent years, crypto (digital, virtual) currencies have attracted the interest of the public as well as investors and financial institutions. The first and the most important one in terms of market capitalization is Bitcoin. It was first introduced in 2008 as "a peer-to-peer electronic cash system" by a mysterious person or group using the nickname Satoshi Nakamoto, whose identity has not been known yet. In the related article, electronic currency is defined as "a chain of digital signatures" (Nakamoto 2008, 2). In the center of Bitcoin, there is a global ledger or balance sheet called blockchain (Kelly 2014, 10). Blockchain technology is based on the logic of creating a chain from these blocks by sealing the data that are desired to be stored in "blocks". Thus, transactions are recorded chronologically on the blockchain and data cannot be changed retrospectively (Aksoy 2018, 27-28).

The most important feature of Bitcoin is its "decentralized" structure, which cannot be controlled by central authorities such as governments or banks. Bitcoin offers a system based on the proof of encryption that enables transactions directly between parties to be peer-to-peer rather than through financial institutions that serve as a third party and have to be trusted (trust-based). Briefly, it is based on trust in the system instead of individuals or institutions (Nakamoto 2008, 1). As in all cryptocurrencies, there are no underlying assets and government support for Bitcoins, and interest and dividends are not paid for Bitcoin. Instead, they are created by a process called "mining" (Byström and Krygier 2018, 5). The success of Bitcoin led to the invention of many alternative digital currencies called altcoins (Charles and Darné 2019, 24). Aksoy (2018) stated that there are more than 1,600 altcoins in the market, in April 2020, the number of crypto currency units reached 5.394 (coinmarketcap.com). This clearly shows the dramatic increase in cryptocurrencies.

It is still unclear how Bitcoin should be classified financially (currency, commodity, payment contract, investment instrument, etc.). Dyhrberg (2016a) stated that Bitcoin is somewhere between currency and commodity. Since its creation, experts, traders and regulators have constantly criticized the applicability of Bitcoin as an independent currency due to excessive volatility in prices (Bouoiyour and Selmi 2016, 1). Commodity Futures Trading Commission, one of the regulatory agencies in the U.S., officially declared digital currency as a commodity such as crude oil or gold (Klein et al. 2018, 106). Bozkuş Kahyaoğlu (2017) described Bitcoin as a means of saving. Although Bitcoin is still considered to be mysterious and not well understood by many stakeholders (Dyhrberg 2016b, 139), significant developments regarding Bitcoin continue. Futures Bitcoin transactions were initiated on December 10, 2017, in Chicago Options Exchange and on December 17, 2017, in Chicago Trade Exchange (Baur and Dimpfl 2018, 804). The establishment of the first Bitcoin ATM in the world in a cafe in Vancouver, Canada was one of the important and interesting developments regarding Bitcoin (Vigna and Casey 2017, 367). Due to the recent global pandemic (nCOVID-19), controversy continues in favor of the use of cryptocurrencies rather than the use of traditional coins and banknotes.

Increases and fluctuations in Bitcoin prices in recent years have attracted attention to this direction. Especially the increases in the price of Bitcoin in the last five years have provided an example of super (exponential) growth that is not commonly seen in any financial field other than the cryptocurrency markets (Pichl and Kaizoji 2017, 475). The price of a Bitcoin, traded at $ 1,000 at the beginning of 2017, tremendously increased to $ 15,000 in December 2017. However, some events contributed to the Bitcoin volatility to increase. The monetary restrictions of the Chinese government on July 1, 2017, increased Bitcoin prices excessively due to the increasing demand, and the ban on trading with digital currency in August 2017 also decreased Bitcoin prices excessively (Aksoy 2018, 71).

The fluctuations in prices ironically attract the interest of the sellers more than the price increase (Vigna and Casey 2017, 160). Volatility modeling is of primary importance in portfolio optimization applications, hedging and pricing of derivative securities (Catania et al. 2018, 4). However, in markets where there is no central structure and regulation, there is an additional layer of uncertainty regarding pricing and implementation (Klein et al. 2018, 105). Therefore, it is important to investigate the volatility structure of cryptocurrencies. In this study, Bitcoin volatility, the biggest cryptocurrency in terms of market capitalization, was estimated with symmetric and asymmetric models consisting of FIGARCH, FIAPARCH and HYGARCH. In addition, the error prediction performances of the models were compared by calculating the value at risk with the Kupiec LR test. Thus, the most appropriate model for predicting Bitcoin volatility, namely the risk, for short or long positions of potential investors who consider investing in Bitcoin was presented.

2. LITERATURE REVIEW

There exists a wide and up-to-date literature on cryptocurrency. Due to the significant changes in prices, the volatility of cryptocurrencies has been investigated from different perspectives. Chaim and Laurini (2018), Charles and Darné (2019) investigated jumps in volatility in their studies. In addition, Dyhrberg (2016a), Byström and Krygier (2018) examined the factors that caused volatility in Bitcoin prices (or volatility estimation with other variables) in their studies. Studies on modeling the volatility structure of cryptocurrencies are given below.

Bouoiyour and Selmi (2016) investigated whether it was the beginning of a mature market or a quiet period before the confusion regarding the crypto market. To address this question, they analyzed the behavior of Bitcoin price in two main periods as 01.12.2010-31.12.2014 and 01.01.2015-20.07.2016 in comparison with GARCH type models. Three important findings were reached. It was found that Bitcoin price seemed very variable in the first period and conditional variance tended to follow an "explosive" process. In addition, as of January 2015, the volatility of the Bitcoin price became less permanent, that is it was far from turning to a long memory process. For both periods examined, Bitcoin price dynamics were affected by negative shocks (bad news) rather than positive shocks (good news). Considering all these findings together, it was concluded that the Bitcoin market was far from being mature, although the low volatility rate was reached.

Bouri et al. (2016) examined the relationship between price returns and volatility changes in the Bitcoin market in various currencies (American Dollars, Australian Dollars, Canadian Dollars, British Pounds, Euros and Japanese Yen). The study was divided into two periods considering the Bitcoin price collapse in December 2013. According to the findings of the study; while there was no evidence of an asymmetric return-volatility relationship in the Bitcoin market for the whole sample period, it was determined that there was a significant inverse relationship between volatility and past shocks before the December 2013 price collapse, but then there was no significant relationship. This showed that before the price collapse in December 2013, positive shocks increased conditional volatility more than negative shocks. The authors explained this finding, which was the opposite of expectations, as a safe-haven effect, similar to the gold investment. Moreover, only the results of the pre-collision period showed a significant negative relationship between the US stock market uncertainty (VIX) and Bitcoin volatility.

Dyhrberg (2016a) examined Bitcoin's financial asset capability using GARCH models. The results of the analysis showed that Bitcoin has many similarities with gold and dollar, and according to the general result of the study, it was stated that Bitcoin is somewhere between money and commodity due to its decentralized structure and limited market size.

Chu et al. (2017) analyzed the seven most popular cryptocurrencies with 12 GARCH models. In addition, the value at risk was used in the study. The results of the study demonstrated that IGARCH and GJRGARCH models provided the best fit.

Katsiampa (2017) investigated the conditional variance model describing Bitcoin price volatility throughout the entire Bitcoin period as of its inception. The results indicated that the best model was the AR-CGARCH model, which emphasized the importance of including both short and long term component of conditional variance.

Baur and Dimpfl (2018) analyzed the asymmetric volatility effects for the 20 largest cryptocurrencies in terms of market capitalization. The Threshold GARCH (TGARCH) model and Quantile regression based asymmetric volatility indicator were used. As a result of the study, it was found that there was a different asymmetric effect compared to stock markets, and positive shocks increased volatility more than negative shocks in related cryptocurrencies. However, weaker evidence was obtained about the results of the largest cryptocurrencies including Bitcoin and Ethereum. This unexpected result in financial assets was explained by trading activities of uninformed noise traders for positive shocks and knowledgeable investors for negative shocks. This result reported that retail investors, generally considered to be uninformed or complex, were particularly active in these markets. In addition, the results were supported by both analysis methods.

Byström and Krygier (2018) focused on the relationship between the volatility in the Bitcoin market and other traditional markets. A significant correlation was found between Bitcoin volatility and Google search volume. In addition, since the internet search activity was thought to be predominantly created by retail investors and the general public, it was concluded that Bitcoin volatility was caused by retail investors rather than institutional investors.

Catania et al. (2018) aimed to predict the effect of long memory and the asymmetric response of the series to the past values in the volatility process. According to the findings of the study, it was determined that more complex volatility models, considering leverage and time-varying distortion, could increase the volatility estimates in different prediction periods from 1% to 6% compared to more standard alternatives.

Chaim and Laurini (2018) investigated Bitcoin daily returns and volatility dynamics. The results pointed two high volatility periods. The first was from the end of 2013 to the beginning of 2014, and the second was in 2017 due to increased interest (peak in December 2017).

Klein et al. (2018), analyses were divided into three sections. First, the volatility behavior of cryptocurrencies compared to stock indices and commodities was investigated. Second, hedging and safe haven capabilities of cryptocurrencies compared to gold were investigated with a dynamic correlation analysis. Finally, a portfolio analysis emphasizing the behavior of gold and Bitcoin in troubled times was applied. According to the results, there were differences in the structures of Bitcoin and gold in terms of conditional variance properties. Second, while gold played an important role in troubled times in financial markets with flight-to-quality, Bitcoin was just the opposite. It was concluded that Bitcoin and gold had different characteristics, mainly as links to assets and stock markets. While the asymmetry effect was significant for Bitcoin, it was not for gold. Also, although the long memory parameter was significant for Bitcoin and gold, it was more prominent for gold than Bitcoin.

Phillip et al. (2018) investigated the general characteristics of cryptocurrencies. As a result of the study, it was determined that cryptocurrencies showed long memory, leverage, stochastic volatility and fat tail features.

Ardia et al. (2019) investigated the presence of regime switching within the GARCH volatility dynamics of Bitcoin logarithmic returns. In addition, the Markov-Switching GARCH (MSGARCH) method was compared to the traditional single regime GARCH specifications in the Value at Risk (VaR) estimate. As a result, regime changes were determined in the GARCH dynamics of Bitcoin. For an asymmetric GARCH model with a skewed and fat-tailed conditional variance, two regime features provided the best fit within the sample. The inverse leverage effect was observed in all volatility regimes. MSGARCH specifications were found to perform better than single regime models for VaR estimation.

Charles and Darné (2019) aimed to predict bitcoin volatility, as well as to identify jumps in volatility and analyze the effects of jumps on volatility modeling. After predicting the models, it was stated that the AR(1)-CGARCH model seemed to be the best specification, and asymmetry parameters were not statistically significant for all asymmetric models. In the analysis with the robust QML predictor, it was concluded that the six GARCH type models included in the study were not suitable for modeling Bitcoin returns. Therefore, it was stated that it would be interesting to extend the study with long memory and Markov-Switching multiple fractional models.

In their study in which dual long memory was tested in the Bitcoin and Ethereum markets accompanied by structural breaks, Mensi et al. (2019) examined the volatility structure with different GARCH type models. As a result of the study, it was indicated that the FIGARCH model, including structural breaks, had superior prediction performance compared to FIAPARCH and HYGARCH models. In addition, the markets that were mentioned contradicted the market efficiency and random walking hypothesis due to its dual long memory feature.

When the literature was examined, it was seen that GARCH and its derivative methods were generally preferred, but a fractional method (FIAPARCH) was used only in the study of Klein et al. (2018) and Mensi et al. (2019). Thus, our study will be able to present a different perspective to the literature with this aspect.

3. MODEL

The main purpose of this study is to revise the volatility persistence of the leading crypto instrument Bitcoin, which is traded in the crypto money markets, with the daily returns of Bitcoin. At the same time, VaR performances of the models that are used to predict the volatility structure of Bitcoin are tried to be determined. Today, the determination of the value at risk as well as the returns of investment instruments is gaining importance. Thus, the value at risk of Bitcoin is tried to be achieved in terms of long memory models for both policy makers and investors.

Autocorrelation functions of time series can provide information about the rate of shock disappearance. The speed of disappearance of information shocks also helps to make inferences about the memory of the shock. For this reason, it is emphasized that GARCH and its derivative models may be inadequate in volatility modeling of fractional structured financial time series that have similarities with past observations and have long memory characteristics.

The standard GARCH model assumes that the conditional variance is stationary. Therefore, it is emphasized that one unit shock to the variance of the financial asset disappears at an exponential rate. However, with the models they developed, Baillie et al. (1996), Bollerslev and Mikelsen (1996), and Tse (1998) assumed that the information shock to the conditional variance of the financial asset is gradually eliminated, not at an exponential rate. The standard FIGARCH(p,d,q) model developed by Baillie et al. (1996) is given in Equation 1.

$$[1-(\beta(L)]\sigma_t^2 = \omega + [1-\beta(L)-\varphi(L)(1-L)^d]\varepsilon_t^2 \tag{1}$$

In Equation 1, “L” represents the lag operator, and “d” represents the fractional integration term indicating the persistence of the shock in conditional variance. Parameter “d” helps to model long shock characteristics. Parameter “d” can take values between 0 and 1 and shows that the shock disappears at hyperbolic speed in conditional variance. Baillie et al. (1996) stated that if the “d” parameter in the FIGARCH equation is 0, the process is a stationary GARCH process, while if the “d” parameter is 1, the model will converge to IGARCH model.

Although evidence of long memory has been investigated in the volatility structures of financial assets, one of the important conditions observed is the leverage effect. It was emphasized by Nelson (1991) that the information shocks that cause volatility in the returns of financial assets are not symmetric, and that good or bad news has a different effect on return volatility. Bollerslev and Mikkelsen (1996) proposed the FIEGARCH model and pointed out that the information shocks that the FIGARCH model considers symmetrically can be asymmetric. Tse (1998) expanded the FIGARCH model and added the function $(|\varepsilon_t| - \gamma\varepsilon_t)^\delta$ to the equation and proposed the FIAPARCH model. The equation of the FIAPARCH model proposed by Tse (1998) is in Equation 2.

$$\sigma_t^{\delta} = \omega + \{1 - [1 - \beta(L)]^{-1}\varphi(L)(1-L)^d\}(|\varepsilon_t| - \gamma\varepsilon_t)^{\delta} \quad (2)$$

In Equation 2, "δ" represents the power parameter, and "γ" represents the leverage parameter. If $\gamma < 0$, it is interpreted that positive information shocks reaching the related asset cause more return volatility in the financial asset than negative information shocks. Also, if $\delta = 2$, $\gamma = 0$, the FIAPARCH model converges to the FIGARCH model. Evaluated from this point of view, models such as FIEGARCH and FIAPARCH are superior to the FIGARCH model since they also consider the asymmetry effect in information shocks (Balıbey and Türkyılmaz 2014).

The HYGARCH model of Davidson (2004) characterizes the slow decay of shocks in hyperbola form for the long memory properties in conditional volatility. The HYGARCH(1,d,1) is defined as:

$$\sigma_t^2 = \omega[1 - \beta(L)^{-1} + \{1 - [1 - \beta(L)^{-1}\varphi(L)(1+k)[(1-L)^d - 1]\}\varepsilon_t^2 \quad (3)$$

Where $k \geq 0$ and $d \geq 0$. Parameter k measures stationary properties. For $0<k<1$, the HYGARCH process is stationary while, for $k>1$, the process is non-stationary (Charles and Darné, 2014).

The determination of long memory properties in the volatility structure of the Bitcoin return with symmetric and asymmetric volatility models can be valuable for portfolio investors if the VaR predictions of the investment instrument are performed. In brief, VaR is used to measure the probable loss probabilities of financial assets. Possible losses caused by the invested asset in a certain time horizon and confidence interval are determined by VaR analysis. With one-day forecasting predictions, the risks that the financial asset will be exposed to due to price decreases in different quantities are shown with long position statistics, and the risks of loss due to price increases are shown with short position statistics.

4. DATA AND DESCRIPTIVE STATISTICS

In the study, 1557 daily closing price data of Bitcoin between 07.08.2015-10.11.2019 period were used. In addition, daily price data in the range of 08.2015-08.2019 were included in the analysis in-sample, and 100-day price data between 08.2019-11.2019 were out-of-sample and used to measure the predictive performance of the models. The daily closing price series of Bitcoin were converted into a logarithmic return form with $Ln(P_t/P_{t-1})$. Bitcoin was symbolized as "btc" in analysis. Descriptive statistics for Bitcoin returns are shown in Table 1 below.

When Table 1 was examined, it was found from skewness and excess kurtosis values that all Bitcoin returns were asymmetrically structured and exhibited a fat tail feature. According to Ljung-Box statistics (Q and Q^2) calculated for different lags, it was also understood that the error squares and squared error squares did not have "independently and identically disributed – iid" features. Errors and squared errors at different lags had a high level of correlation with past values. This result proved the volatility clusters seen in Figure 1 below.

Table 1. Descriptive Statistics for Bitcoin Returns

	rbtc
Mean	0,002234
Std. Deviation	0,03939
Skewness	-0,1982**
Excess Kurtosis	4,6600**
J-B Prob.	1419,0**
ARCH(2)	37,56**
ARCH(5)	21,04**
ARCH(10)	11,67**
ADF	-22,098**
Q(5)	4,0115
Q(20)	27,162
Q(50)	57,761
Q^2(5)	140,993**
Q^2(20)	268,026**
Q^2(50)	407,976**
Lo R/S Test Stat. for Return	1,7233
Lo R/S Test Stat. for Sq. Return	3,2542**

Note: ** denotes statistically significant at 5% level.

According to ARCH-LM statistics in Table 1, it was understood that standardized errors had ARCH effect at different lag levels. According to the Lo R/S test results, it was determined that Bitcoin returns did not exhibit long memory behavior, but return volatility had long memory. The fact that the Lo R/S test statistics were greater than the range of [0,809-1,862] at 5% significance level meant the rejection of the hypothesis claiming the series had short memory. In addition, ADF unit root tests of the return series showed that the series were stationary, that is, they did not display random walk. In Figure 1 below, price and return series graphs and autocorrelation functions regarding Bitcoin are shown.

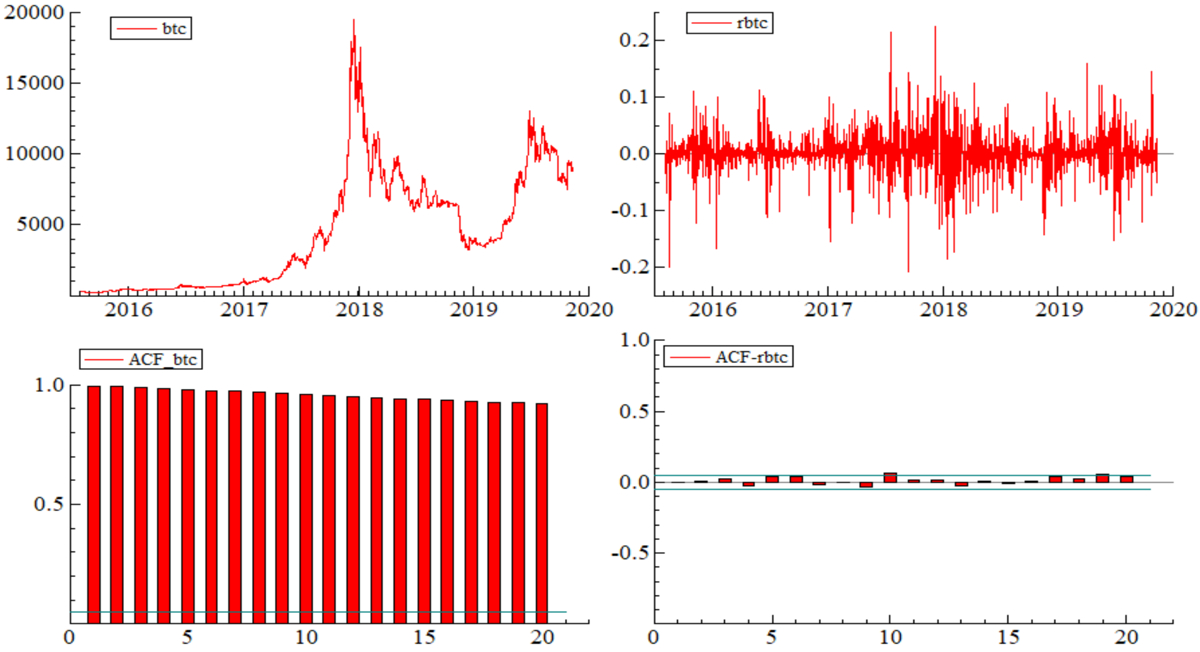

Figure 1. Price and Return Series and Autocorrelation Functions of Bitcoin

When Figure 1 was examined, it was seen that the return series of Bitcoin had a volatility cluster, and the conditional variance did not have an independent structure over time. It could be seen that there was an increase in return volatility as of the end of 2017. Density functions and distribution properties of Bitcoin returns are shown in Figure 2 below.

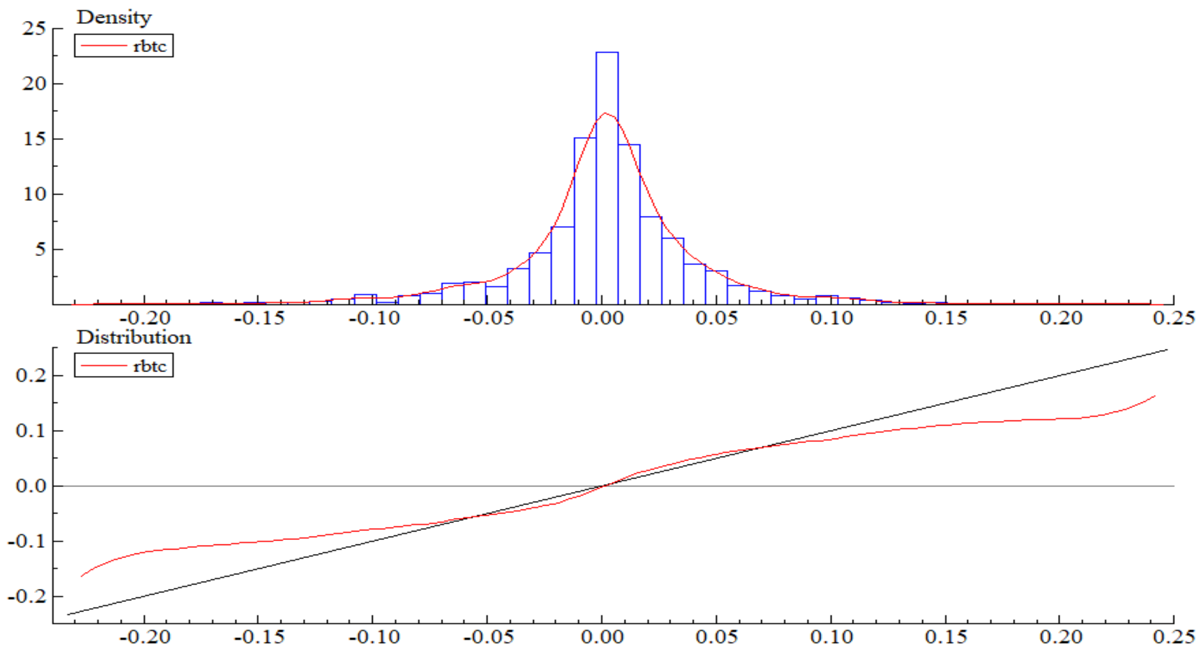

Figure 2. Density Functions and Distribution Properties of Bitcoin Logarithmic Return Series

When Figure 2 was examined, it was seen that the Bitcoin currency had a fat-tailed distribution compared to the normal distribution.

5. EMPIRICAL FINDINGS

To determine the symmetric and asymmetric long memory characteristics of Bitcoin return volatility, FIGARCH, FIAPARCH and HYGARCH models (p,q = 0, 1 and 2) were predicted in different ranges, and according to BIC information criteria FIGARCH(1,d,1), FIAPARCH(1,d,1) and HYGARCH(1,d,1) models were determined. The prediction results for the symmetric and asymmetric models are shown in Table 2 below.

In all of the model results in Table 2, the parameter "d", which represents the presence of long memory in Bitcoin return volatility, was found statistically significant. The long memory parameter, calculated in the range of 0.68-0.82, proved that useful information reaching the btc market created a long-term shock effect, and it was not amortized in a short time. This result is an indication that the crypto money market is not kept under control by central authorities, that the markets are volatile, contrary to the effective market hypothesis.

Table 2. Results of Symmetric and Asymmetric Fractional GARCH Bitcoin Log-Returns

	FIGARCH(1,d,1)-st	FIAPARCH(1,d,1)-st	HYGARCH(1,d,1)-st
	rbtc	rbtc	rbtc
μ	0.002247** (0.000443)	0.002409** (0.0004336)	0.002155*** (0.000418)
ω	0.000008 (0.081347)	-0.025929 (0.033186)	-0.098447 (0.19923)
d_figarch	0.81873*** (0.079035)	0.73731*** (0.087155)	0.67969*** (0.11944)
φ (arch)	0.19895*** (0.063175)	0.268117*** (0.076152)	0.33638*** (0.11659)
β (garch)	0.80779*** (0.046116)	0.789079*** (0.058125)	0.796538*** (0.05336)
γ (asymmetry)	-	-0.23239*** (0.074285)	-
δ (power)	-	2.296362*** (0.21556)	-
Log(α)	-	-	0.34466* (0.18305)
ν	3.31667*** (0.16344)	3.132870*** (0.17672)	2.42645*** (0.17486)
AIC	-4.150912	-4.15980	-4.165226

BIC	-4.129152	-4.130786	-4.139839
Log-Likelihood	3029.94	3038.41	3041.37
$Q^2(10)$	4.3609 [082317]	10.1957 [0.25156]	3.7240 [0.88112]
ARCH(10)	0.42592 [0.9346]	0.98369 [0.4555]	0.36126 [0.9629]
MSE	0.001035	0.001037	0.001035
MAE	0.02149	0.02152	0.02147
RMSE	0.03218	0.03220	0.03217

Note: ***, ** and * represent 1%, 5% and %10 significance levels, respectively.

The significance of the "ν" parameter in all three predicted models showed that standardized errors had fat tail distribution. Ljung-Box (Q^2) and ARCH test results also indicated that standardized errors showed iid properties and errors did not contain heteroscedasticity. The fact that the "γ" parameter, which represents the leverage effect in the FIAPARCH model, was negative and significant could be interpreted as the positive information shocks reaching the btc market had more effects on the return volatility than the negative information shocks. The diagnostic test results of the HYGARCH model, which is based on the modeling of the volatility structure in the hyperbolic structure when compared to the symmetric FIGARCH and asymmetric FIAPARCH model, showed that it was superior to other models. Both the log-likelihood and information criteria (AIC, BIC) and error statistics (MSE, MAE and RMSE) between actual values and predicted values indicated that the HYGARCH model predictions were more robust (fit).

One of the issues that the investors wonder is the determination of the model that will most accurately identify the risks they are exposed to as a result of their investments. For this purpose, the in-sample VaR prediction was made with the Kupiec LR test to determine possible losses and gains with the models established. With Kupiec LR test, error rates for different α values between 0.25% and 5% for both the short and long position were calculated separately for three different models. The analysis results are presented in Table 3.

Tablo 3. In-Sample VaR Calculated by GARCH-Type Models for BTC

FIGARCH(1,d,1)							
Short Position				**Long Position**			
Quantile α	**Success Rate**	**Kupiec LR**	**P-value**	**Quantile α**	**Failure Rate**	**Kupiec LR**	**P-value**
0.9500	0.93686	4.9092	0.026714**	**0.0500**	0.0700	10.9790	0.0009***
0.9750	0.96294	7.5910	0.005865***	**0.0250**	0.0398	11.1410	0.0008***
0.9900	0.98490	3.3098	0.06886	**0.0100**	0.0178	7.3457	0.0067***
0.9950	0.99314	0.91044	0.34000	**0.0050**	0.0089	3.6500	0.0560
0.9975	0.99657	0.45394	0.50047	**0.0025**	0.0041	1.2779	0.2583
FIAPARCH(1,d,1)							
Short Position				**Long Position**			
Quantile α	**Success Rate**	**Kupiec LR**	**P-value**	**Quantile α**	**Failure Rate**	**Kupiec LR**	**P-value**
0.9500	0.9396	3.1189	0.0773	**0.0500**	0.0679	8.9272	0.0028***
0.9750	0.9691	1.9285	0.1649	**0.0250**	0.0363	6.7980	0.0091***
0.9900	0.9876	0.7588	0.3837	**0.0100**	0.0164	5.1585	0.0231**
0.9950	0.9931	0.9104	0.3400	**0.0050**	0.0089	3.6500	0.0560
0.9975	0.9986	0.8887	0.3458	**0.0025**	0.0048	2.4381	0.1184
HYGARCH(1,d,1)							
Short Position				**Long Position**			
Quantile α	**Success Rate**	**Kupiec LR**	**P-value**	**Quantile α**	**Failure Rate**	**Kupiec LR**	**P-value**
0.9500	0.9450	0.7168	0.3971	**0.0500**	0.0576	1.7157	0.1903
0.9750	0.9739	0.0688	0.7929	**0.0250**	0.0253	0.0092	0.9233
0.9900	0.9911	0.1773	0.6737	**0.0100**	0.0096	0.0228	0.8799
0.9950	0.9958	0.2424	0.6224	**0.0050**	0.0034	0.8098	0.3682
0.9975	0.9993	2.7045	0.1000	**0.0025**	0.0020	0.1209	0.7280

Note: *** and ** denote statistically significant at 1% and 5% level, respectively.

According to Table 3, the null hypothesis that success/failure rate equals to quantiles (α) in FIGARCH was rejected by the Kupiec LR test for α values of 0.95, 0.9750 for short position, and the null hypothesis was rejected for α values of 0.05, 0.025, 0.01 for long position. Similarly, the null hypothesis was rejected for α values of 0.05, 0.025, 0.01 for long position in FIAPARCH model. Furthermore, the HYGARCH model performed accuracy predictions for the in-sample VaR calculations based on Kupiec LR test than the other GARCH type models. According to the predicted model results, HYGARCH model was superior to FIGARCH and FIAPARCH models.

6. CONCLUSION

Cryptocurrencies have gained an important place in the financial world in a very short period. Bitcoin is the first cryptocurrency to be created and has the largest market capitalization. However, it is not clear how cryptocurrencies should be classified financially (money, commodity, payment contract, investment instrument etc.). Bitcoin was introduced to the public for the first time in 2008 as “a peer-to-peer electronic cash system” by a mysterious person or group who used the name Satoshi Nakamoto. Electronic money is defined as “a chain of digital signatures”. As can be understood from the definition, one of the most important features of Bitcoin is its decentralized structure, which cannot be controlled by central authorities such as governments or banks.

While the formation process of Bitcoin has not been fully understood yet, the high price and excessive volatile structure have begun to attract the attention of investors. Modeling the volatility structure of Bitcoin prices is important for those who consider investing in Bitcoin. In this study, Bitcoin volatility was investigated with various symmetric and asymmetric models. In addition, by using the Kupiec LR test, the value at risk was calculated and the error prediction performances of the models were compared. Three main conclusions of study are described in detail below and compared with other studies in the literature.

The results of FIGARCH, FIAPARCH and HYGARCH showed long memory in the Bitcoin return volatility. There was evidence of the existence of long memory for Bitcoin in the study of Klein et al. (2018) and for different cryptocurrencies in the study of Phillip et al. (2018). In addition, Mensi et al. (2019) identified dual long memories for Bitcoin and Ethereum. However, Bouoiyour and Selmi (2016) stated that the volatility of the Bitcoin price became less permanent as of January 2015, that is, it was far from having the long memory process of Bitcoin.

On the other hand, according to the FIAPARCH asymmetric model, it was determined that positive information shocks reaching the Bitcoin market increased volatility more than negative information shocks. The same evidence was obtained for Bitcoin in the study of Bouri et al. (2016) before the price collapse in December 2013; for 18 cryptocurrencies (weaker evidence for Bitcoin and Ethereum) in the study of Baur and Dimpfl (2018). Ardia et al. (2019) and Mensi et al. (2019) found similar results for Bitcoin. However, Bouoiyour and Selmi (2016) claimed that Bitcoin price dynamics were more affected by negative shocks. In addition, Klein et al. (2018) stated that asymmetry effects were statistically significant, while Charles and Darné (2019) claimed that asymmetry parameters were not statistically significant.

Comparing the error prediction performance of the models by calculating the value at risk, the HYGARCH model prediction results were determined to be superior to other models. Thus, it was determined that the most suitable model to predict the volatility, i.e. value at risk, of the Bitcoin for those considering investing in Bitcoin for short and long positions was the HYGARCH, which is an asymmetric model. In their study, Chu et al. (2017) stated that IGARCH and GJRGARCH models provided the best match for the seven most popular cryptocurrencies. Katsiampi (2017) concluded that the best model for Bitcoin was the AR-CGARCH model. Charles and Darné (2019) also stated that the AR-CGARCH model seemed to be the best specification, but it would be more interesting to expand the study with long memory and Markov-Switching multiple fractional models. Catania et al. (2018) stated that their models considering leverage and time-varying distortion were more compatible, Ardia et al. (2019) found that MSGARCH specifications performed better than single regime models for VaR prediction. Mensi et al. (2019) stated that FIGARCH model, which takes into account the structural breaks, was superior to FIAPARCH and HYGARCH models in predicting volatility.

Those who would like to invest in Bitcoin, one of the most remarkable investment instruments of recent years, will be able to benefit from the findings related to predicting the volatility risk of Bitcoin. In future studies, this study may be developed by including other cryptocurrencies along with Bitcoin and by using multi-regime models.

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