

## Modeling the Volatility of Bitcoin Returns Using Egarch Method

### Bitcoin Getiri Volatilitesinin Egarch Yöntemi İle Modellenmesi

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*Abstract: The development process in financial markets give rise to the emergence of various financial instruments and cryptocurrencies, which are the newest tools of this process, are trying to integrate into the system. Even though the use of crypto-currencies for investment and speculation has increased, limited information on the market leads to high level of volatility in price and return. Therefore, this study aims to analyze the volatility dynamics of the returns of Bitcoin, which is the cryptocurrency with the largest market volume, using the weekly data set for 2013:04-2020:09 period. In this context, Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model is employed to investigate the asymmetric volatility, which refers to the asymmetric effects of positive and negative shocks. The results of the analysis show that the leverage effect applies to Bitcoin returns. In other words, the asymmetric effect between good and bad news is revealed. Moreover, the fact that the parameter of the volatility resistance has a high value reflects that the asymmetric past period shocks have a significant effect on the current period conditional variance.*

*Keywords: Bitcoin, Asymmetric Effect, Volatility, EGARCH Model*

*JEL Classification: C58, F65, G23*

*Öz: Finansal piyasalardaki gelişim süreci çeşitli finansal araçların ortaya çıkmasına neden olmakta ve bu sürecin en yeni aracı olan kripto paralar ise sisteme entegre olmaya çalışmaktadırlar. Kripto paraların yatırım ve spekülasyon amacıyla artan kullanımı her ne kadar ivme kazansa da piyasa hakkında oldukça az bilgiye sahip olunması fiyat ve getiri dalgalanmalarının yüksek hızda seyretmesine yol açmaktadır. Dolayısıyla bu çalışma, en büyük piyasa hacmine sahip kripto para olan Bitcoin getirilerinin volatilité dinamiklerini 2013:04-2020:09 dönemine ilişkin haftalık veri setini kullanarak incelemeyi amaçlamaktadır. Bu kapsamda, asimetrik oynaklığı, bir diğer ifadeyle pozitif ve negatif şokların asimetrik etkilerini araştırabilmek için Üstel Genelleştirilmiş Otoregresif Şartlı Değişen Varyans (EGARCH) Modeli kullanılmıştır. Analiz sonuçları, Bitcoin getirilerinde kaldıraç etkisinin geçerli olduğunu, bir diğer ifadeyle iyi ve kötü haberler arasındaki asimetrik etkinin kendini gösterdiğini ortaya koymuştur. Dahası, oynaklık direncine ait parametrenin oldukça yüksek değer olması, asimetrik geçmiş dönem şoklarının cari dönem şartlı varyansı üzerinde anlamlı bir etkisinin olduğunu yansıtmıştır.*

*Anahtar Kelimeler: Bitcoin, Asimetrik Etki, Dalgalanma, EGARCH Modeli*

*JEL Classification: C58, F65, G23*

## 1. Introduction

To date, various payment methods and instruments have been developed for the use in trading goods and services. Varying between the barter economy to the use of precious metals such as gold and silver and the coin, many different exchange instruments have been used in exchanging throughout history. The common point of these exchange instruments is that they are all based on a mechanism transferring the power of purchase between the parties. Moreover, in addition to being used as a means of exchange, the currencies increasing the

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exchange as a store of value have turned into a fundamental condition of wealth accumulation and investment in the next period.

The financial payment mechanisms, which have rapidly improved and facilitated the international commercial relations, have then turned into virtual-digital transactions together with the globalization in order to ensure the ability to move fast and adapt to the technology. Especially the fact that international money transfers have reached high amounts made it gradually more difficult to physically transfer the money and similar payment instruments. At this point, the virtual-digital payment systems limiting the physical transfer of the money during the international payments but making the payment easier and faster have emerged.

The virtual-digital payment systems, which are getting more frequently used in commercial relations between the countries or large-scale companies, have been extended in the way integrating the consumers into the system and the use of virtual-digital payment instruments named debit card and credit card and used instead of physical money has become gradually more popular. On the other hand, this rapid change has brought certain requests for an alternative to the money together with it. Some of the most important requests are the demand for rapid systems that cannot be followed, alternative systems requested by those desiring to stay away from the currencies provided by the states, and the desire of gaining a higher risk and higher profit through the speculative transactions. Furthermore, the individuals' demand for making illegal payments and avoiding risks arising from the excessive volatility of national currencies and exchange rates, which are also supporting the requests against the classical value and payment instruments.

From this aspect, the crypto-currencies drawing more interest throughout the world in recent years and the virtual-digital money applications traded in this parallel draw attention of both users and the researchers interested in such applications. The crypto-currency markets, which draw special interest especially and incorporate risk factors in recent years, attract the investors. High level of revenue and risks they incorporate further attract the investors to these currencies and the speculative trading transactions also increase the interest in these markets (Katsiampa, 2018). The crypto-currencies offering chance to gain a faster and higher level of revenue when compared to the classical financial instruments have become an important investment instrument especially for the investors, who do not want to be followed in financial markets. Thus, the crypto-currencies offering significant monthly, weekly, daily, and even hourly premium chance have found more approval when compared to the conventional markets and the trading volumes in these markets are constantly increasing.

From this perspective, the present study aims to investigate the volatility dynamics of the revenues of Bitcoin, which is the crypto-currency having the highest market volume, with EGARCH method using the weekly dataset for 2013:04-2020:09 period. For this purpose, this paper was designed as five sections. Following the introduction section, the second section summarizes the literature on crypto-currencies. Explaining the methodological information required for econometric analyses, the third section is followed by the fourth section representing the analysis results. In the fifth and last section, a general conclusion is presented.

## **2. Theoretical Background and Literature Review**

Together with the globalization, the acceleration of financial transactions arising from the advancement of technology and the increase of the use of Internet and mobile in any field led to a change and transformation in the financial life. From this aspect, the crypto-currencies and payment mechanisms based on the virtual-digital transactions are considered among the value transfer and accumulation instruments originating from the changing and advancing economic activities. From this perspective, the crypto-currencies serve for the purpose of financial freedom by developing new investment instruments. Although traded in accordance with the basic principles of the economy, they are considered different from the conventional currencies in terms of creation and transfer of the money.

The conventional money creation is based on physically printing the money by Central Banks in parallel with the requests of countries. The Central Banks, which are accepted to be independent, are responsible for the monetary policies as the authority that is responsible for coining and printing money. On the other hand, the currencies called crypto-currencies refer to the currencies created completely in virtual-digital media and independently from the power of specific authority. From this aspect, the crypto-currencies fulfill all the functions of money such as value storage and transfer. Thus, from the aspect of method and form, they have the same frame and instruments with conventional currencies. Many authors define them as a commodity and value-oriented hybrid currency (Baur et al., 2016: 1-2).

According to the definition made by European Central Bank, the crypto-currency refers to the digital representative of the values, which can be used as an alternative to the money, other than the currencies circulated by a central bank, credit institution or e-currency institution. Based on this definition, the absence of the institutions authorized for monetization in the process implies that the crypto-currencies are independent of any state or governmental institution. Moreover, besides the fact that no central authority is necessary for

creating them, the crypto-currencies do not require any commercial bank or electronic money transfer institution for the transfer or storage (Doğan, 2018; 235).

The crypto-currencies, which are also known as coded currencies, are created through the codes based on a specific transaction. The code created enables the trading and transaction of that currency. Thus, the main characteristic distinguishing the conventional currencies and crypto-currencies is the money creation and trading activities in virtual-digital media (Alpago, 2018: 414; Gandal and Halaburda, 2014: 4).

Since it is the first and most widely traded one, Bitcoin has an important place among the crypto-currencies. Especially since year 2008, when it has been effectively integrated into the real economy, its market share has constantly increased. The fact that it has reached at higher trading volumes in a short period when compared to the currencies circulating for a century and it is being rapidly traded throughout the world further increases the interest in Bitcoin (Fanusie, Robinson, 2018; 9). A paper written by Satoshi Nakamoto (2009), who is the inventor of Bitcoin, also plays an important role in this gradually increasing interest in Bitcoin. In that paper, Nakamoto emphasizes that the Bitcoin system is a peer-to-peer digital payment system and he clearly explained the Bitcoin payment method's way of functioning.

The interest in crypto-currencies and the positive advancements in this new market derivative have also significantly influenced the advancement of all the crypto-currencies, also the Bitcoin, and made Bitcoin an important instrument of financial market. Thus, the revenue of Bitcoin peaked to 1358% in 2017. In the light of these developments, the financial institutions such as the Chicago Market Exchange (CME) group and Chicago Board of Options Exchange (CBOE) accepted Bitcoin as one of the new market derivatives. The transformation of Bitcoin into a financial phenomenon didn't take a long time but, in 2018, a significant collapse occurred in its value through the immediate speculative transactions. However, all these events didn't decrease the interest in Bitcoin but rather the amount of Bitcoin gradually increased (Huynh, 2019: 1).

The interest in cryptocurrencies, which are represented specifically by Bitcoin here, caused academic groups to carry out different studies on the crypto-currencies and made Bitcoin more popular. The studies generally focused on Bitcoin-oriented price and financial revenues. In a study carried out by Dong and Dong (2014), the role of Bitcoin as a financial instrument and currency was emphasized by making use of the daily data for 2011-2013 period. Moreover, despite the high level of risk it involves, the authors stated that it couldn't provide its investors with high revenues but the investors had to content themselves with low

revenues. Furthermore, it was also concluded that the investors have preferred Bitcoin for long-term investment and making use of arbitrage mechanism.

In the study carried out by Baek and Elbeck (2015), it was aimed to examine the relationship between Bitcoin's price volatility and revenue by using monthly data for 2010-2014 period. In order to investigate this relationship, the authors analyzed various variables such as Bitcoin revenues, consumer price index, real private consumption expenses, industrial production index, SP 500 index, exchange rates, and unemployment rates. The analysis results revealed that the price volatility of Bitcoin has not been influenced by the basic economic factors involved in the analyses, that the aforementioned volatility originates from consumer and seller, and that the progression courses very speculatively.

The study of Ciaian et al. (2016) is the first study investigating the effects of conventional determinants of the rate of exchange based on demand and supply of exchange on the price creation of Bitcoin. In this study based on the monthly data for the period between 2009 and 2015, it was concluded that the market forces and Bitcoin's attractiveness play an important role in the price of Bitcoin.

In a GARCH-based study carried out by Dyhrberg (2016), the author has focused on the financial revenues of Bitcoin. In the first step of analysis, it was determined that the Bitcoin revenues have advantages such as being an exchange instrument such investment instruments like gold and exchange, as well as protection against the currency risk. According to the results of asymmetric GARCH analysis, it was determined that Bitcoin might play an effective role especially in the risk management and be an ideal investment for the investors aiming to avoid risk arising from market shocks. The authors claimed that Bitcoin gained an important place in portfolio management and financial markets thanks to such effects of it.

In a study carried out by Balcilar et al. (2017), the relationship between Bitcoin revenue and trading volume was investigated by using the daily data for the period between 2011 and 2016. Although the results of analysis based on the causality test revealed that the trading volume could significantly estimate the revenues, it was also emphasized that the investors should consider that they might be negatively affected by the market volatilities, especially in bear and bull stages of markets.

The study carried out by Bouri et al. (2017) examining the Bitcoin revenues from the aspects of protection against risks and being a reliable investment instrument is based on the daily and weekly data for the period between 2011 and 2015. The results of dynamic conditional correlation revealed that, when compared to the large exchange market indices,

oil, gold, and USD indices, Bitcoin offers a weak protection and it might be more suitable for the purpose of portfolio diversification.

Chu et al. (2017) used GARCH modeling for determining the volatility by making use of daily data of 7 most popular cryptocurrencies, including Bitcoin, for the period between 2014 and 2017. As a result of separate models applied to each crypto-currency, it was determined that all the crypto-currencies showed excessive volatility. It was also emphasized that this might be compatible especially with technology markets. Moreover, it was stressed that the increase in regulations and policies related with the cryptocurrency markets and the enlargement of markets because of the increase in the number of investors would regulate the markets and the volatility levels might become more stable.

In a study carried out by Anavatan and Kayacan (2019), the daily data of the period between 2011 and 2018 were used for calculating the Bitcoin revenues. According to the results of the analysis performed using stochastic volatility and leveraged stochastic volatility model, it was determined that, although no significant leverage effect was found on the Bitcoin revenues, the price volatility is permanent and unpredictable. Thus, the authors emphasized that, because of the risks arising from those volatilities, it is impossible to use Bitcoin as an investment instrument or a currency

Studying on the relationship between revenues and trading volumes of Bitcoin and some other crypto-currencies, Briere et al. (2015), Georgoula et al. (2015), Bariviera (2017), Kasper (2017), Li and Wang (2017), Ji et al. (2018), Kautmos (2018), Brauneis and Mestel (2018), Yi et al. (2018), Catania and Sandholdt (2019), and Huynh (2019) reported positive relationships, whereas Blau (2017), Gandal et al. (2018), and Cheah et al. (2018) reported negative ones.

There also are studies investigating the speculative volatilities, balloons, and revenue-based spillover effect of crypto-currencies and Bitcoin. Among them, Yermack (2013), MacDonell (2014), Cheah and Fry (2015), Cheung et al. (2015), Dwyer (2015), Harvey and Tapper (2015), Hencic ve Gourieroux (2015), Frascaroli and Pinto (2016), Chengyuan (2017), Baur and Dimpfl (2018), Hultman (2018), Shi (2018), Urquhart (2018), and Katsiampa et al. (2019) are the prominent ones.

### **3. Data Set, Methodology and Econometric Model**

The main purpose of this study is to investigate the volatility dynamics of Bitcoin returns, the crypto which has the largest market value among other cryptocurrencies, using weekly data set for the period 2013:04-2020:09. For this purpose, EGARCH model is employed to examine the asymmetric volatility effect, in other words, asymmetric effects of positive and

negative shocks. The main reason for choosing the mentioned time period is the availability of the data set. In order to calculate the weekly returns of Bitcoin, the data set consisting of weekly closing prices for Bitcoin are used. The data set are available at <https://coinmarketcap.com> and the prices for Bitcoin are expressed in US dollars. In light of the explanations above, the weekly return series of Bitcoin can be defined as follows:

$$R_t = \ln(P_t) - \ln(P_{t-1}) \quad (1)$$

where  $R_t$  indicates Bitcoin returns on day  $t$ ,  $\ln(P_t)$  shows the natural logarithm of the closing price of Bitcoin on day  $t$  and  $\ln(P_{t-1})$  represents the natural logarithm of the closing price of Bitcoin on day  $t-1$ .

One of the most important deficiencies of GARCH models is the assumption that volatility is symmetrical in response to positive and negative shocks and therefore GARCH process fails to identify the asymmetric linkages in variance structure. However, there can be some other situations where such an assumption is not valid, in other words, where volatility is asymmetrical in response to shocks (Özden, 2008: 344; Songül, 2010: 18). For this reason, instead of GARCH models that are insufficient in modelling leverage effects, EGARCH models introduced by Nelson (1991) are applied to determine the asymmetric effects of the shocks in Bitcoin market. In general, EGARCH models are widely used to examine the asymmetric or leverage effects in stock, currency or cryptocurrency markets. Besides, EGARCH models are generally employed when asymmetric effects of good and bad news on stock or cryptocurrency markets are wanted to determine and they are also preferred since they are highly flexible models in terms of coefficient constraints. Therefore, it can be said that EGARCH analysis where the asymmetry effects in the volatility structure are taken into account is an econometric technique in which the conditional variance is modeled based on both magnitudes and signs of lagged error terms.

EGARCH model introduced by Nelson (1991) can be described as follow:

$$\ln(\sigma_t^2) = \omega + \sum_{k=1}^p \beta_k \ln(\sigma_{t-k}^2) + \sum_{i=1}^q \alpha_i \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \sum_{s=1}^r \gamma_s \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (2)$$

Considering the regression equation numbered (2), since the model takes into account the logarithm of variances and positive or negative shocks is exponential, it is guaranteed that the conditional variance will be positive. In addition, the equation also points out that there are no restrictions on the parameters,  $\omega$ ,  $\alpha$ ,  $\beta$  and  $\gamma$ . In the regression equation numbered (2),  $\sigma_t^2$  represents the following period predicted variance depends on past period information and it

is called as the conditional variance.  $\alpha$  refers to the effects of the past period shocks on the current period conditional variance.  $\beta$  indicating the volatility resistance points out the persistence of past period shocks on the current period conditional variance. In general, leverage effect refers to the impact of good or bad news on future volatility. If  $\gamma$  parameter, the leverage effect, is equal to zero ( $\gamma_s = 0$ ), a symmetrical relationship is valid between the variables. Therefore, an asymmetric linkage occurs when  $\gamma$  is not equal to zero ( $\gamma_s \neq 0$ ). If  $\gamma$  is positive, the effect of shocks on conditional variance is expected to be  $\alpha + \gamma$  and If  $\gamma$  is negative, in other words the leverage effect exists, the effect of shocks on conditional variance is expected to be  $-\alpha + \gamma$  (Enders, 2015: 156 ; Korap, 2010: 106). Finally,  $\varepsilon$  represents the white-noise error term, *i.i.d.*

#### 4. The Results of the Econometric Analysis

The main motivation of this paper is to examine the volatility dynamics of Bitcoin returns, the crypto which has the largest market value among other cryptocurrencies, using weekly data set for the period 2013:04-2020:09. In this context, in order to investigate the asymmetric effects of positive and negative shocks, briefly asymmetric volatility, EGARCH model is applied. The descriptive statistics of the weekly logarithmic returns of Bitcoin are examined and presented in Figure 1.

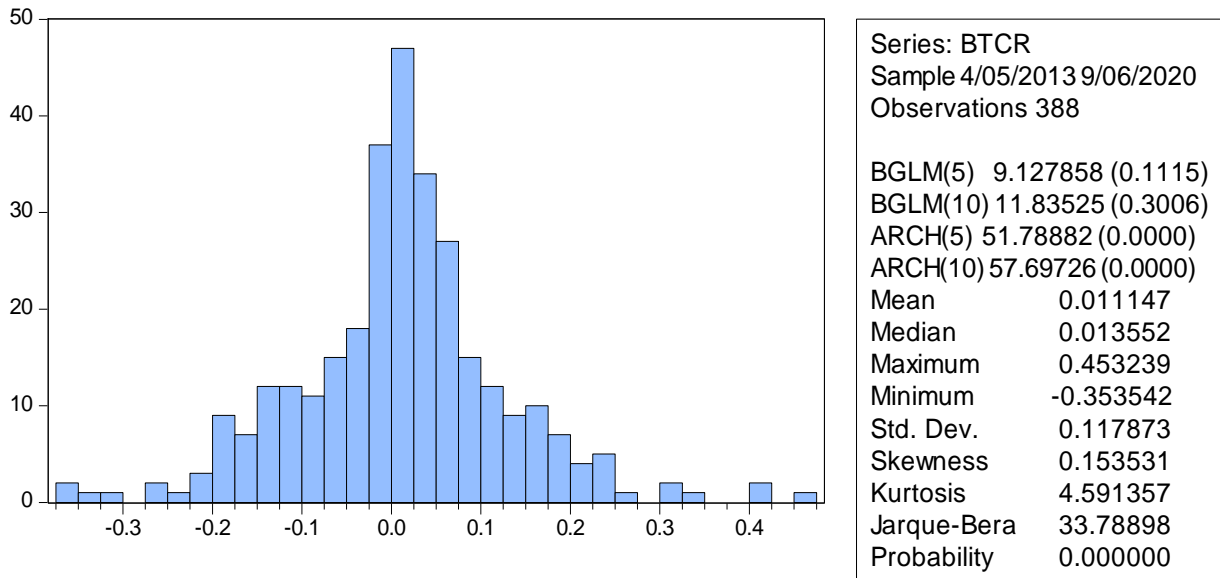


Figure 1. The Descriptive Statistics of the Weekly Logarithmic Returns of Bitcoin

Figure 1 shows that the weekly average closing price return is positive and 1.114% and the standard error is 11.787%. Besides, it is seen that the maximum and minimum return values range from 45.323% to -35.354%. In addition, it can be said that the return values have



a leptokurtic distribution as result of high kurtosis value and that the series shows the right-skewed distribution depending on the positive skewness value. The Jarque-Bera test confirms that the return series do not have the conditions of normal distribution. Furthermore, to check whether there is autocorrelation in the residuals of the return series Breusch-Godfrey LM Test is applied and it is concluded that there is no autocorrelation in the return series. In addition, the results of the analysis reveal the existence of the ARCH effect in the return series of Bitcoin. This result reflects that EGARCH method can be applied to test conditional heteroskedasticity process. As well as these results, Figure 2, where Bitcoin return series is presented, shows that the return values do not exhibit a steady trend, in other words, volatility is high at certain periods. In addition, volatility clusters have been observed in certain periods.

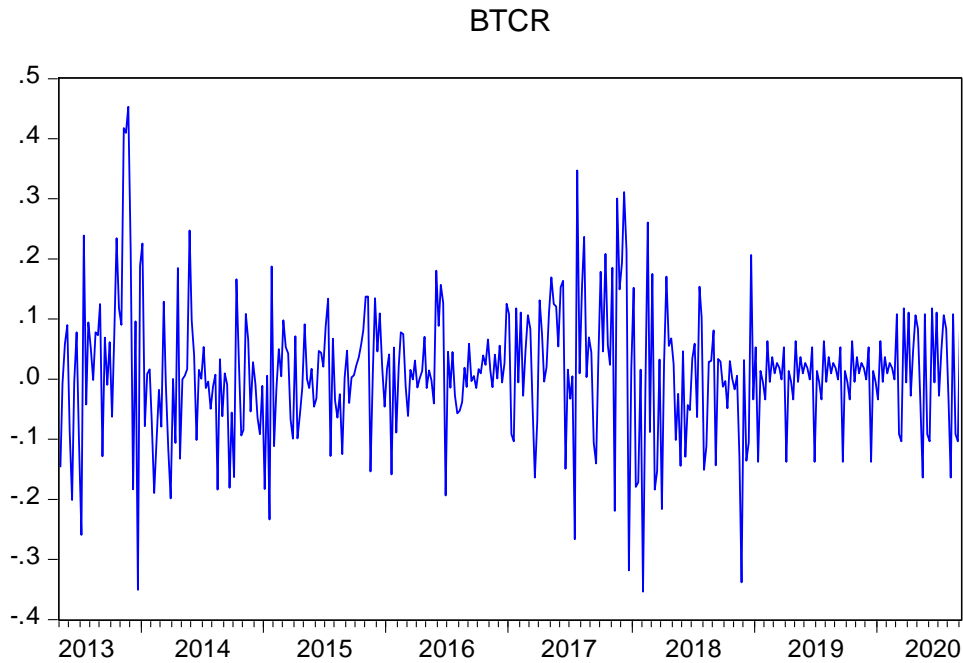


Figure 2. Time-Varying Return Series of Bitcoin

In order to model the volatility of the bitcoin return series with the help of EGARCH analysis, stationary information of the return series is needed. For this purpose, table 1 shows the results of ADF and PP unit root tests belonging to the Bitcoin return series. The findings of ADF and PP unit root tests reveal that the Bitcoin return series is stationary at level and it is significant at % 1.

Table 1. The Results of ADF and PP Unit Root Tests

The Results of ADF Unit Root Test at Level						
Variable	Intercept		Trend & Intercept		None	
BTCR	-8.226(2)	*** [0.000]	-8.155(2)	*** [0.000]	-7.886(2)	*** [0.000]
<b>Critical Values</b>	<b>1%</b>	-3.451	<b>1%</b>	-3.988	<b>1%</b>	-2.572
	<b>5%</b>	-2.870	<b>5%</b>	-3.424	<b>5%</b>	-1.941
	<b>10%</b>	-2.571	<b>10%</b>	-3.135	<b>10%</b>	-1.616

The Results of PP Unit Root Test at Level						
Variable	Intercept		Trend & Intercept		None	
BTCR	-16.338(4)	*** [0.000]	-16.341(4)	*** [0.000]	-16.285(4)	*** [0.000]
Critical Values	1%	-3.451	1%	-3.988	1%	-2.572
	5%	-2.870	5%	-3.424	5%	-1.941
	10%	-2.571	10%	-3.135	10%	-1.616

**Note:** In the ADF test, the values in parenthesis reflect the optimum lag lengths for the variable, which are obtained using the Akaike Information Criteria over a maximum of 15 lag lengths. In the PP test, the values in parenthesis show the optimum lag lengths and these values are obtained by taking the Newey-West criteria into account. In both tests, the values in square brackets point out the probability value of the coefficient. \*\*\* indicates the stationary of the variable at the significance level of 1%.

Following the obtaining of the stationary information of the variable, the optimum ARIMA model should be determined and the conditional mean equation should be estimated. For this purpose, the optimum model is found to be ARMA (3,3) and the results of the analysis of the conditional mean equation are shown in Table 2.

Table 2. The Results of the Analysis of the Conditional Mean Equation

Variable	Coefficient	Statistics of the Model
Constant	0.017 (0.144)	R <sup>2</sup> : 0.086
AR(1)	-0.962 (0.000)***	F-Statistic: 3.886 (0.000)***
AR(2)	-0.987 (0.000)***	Durbin-Watson: 1.944
AR(3)	-0.729 (0.000)***	ARCH(5): 36.779 (0.000)***
MA(1)	1.101 (0.000)***	ARCH(10): 63.969 (0.000)***
MA(2)	-1.229 (0.000)***	AIC Value of ARMA(3,3): -1.477
MA(3)	0.922 (0.000)***	

**Note:** \*\*\* reflects that the coefficient of the variable is significant at 1%. The values in parenthesis point out the probability value of the coefficient.

Table 2 shows that all parameters except the constant term are statistically significant. In addition, it is provided that the sum of the parameter of the same type is smaller than 1, in other words  $AR(1)+AR(2)+AR(3)<1$  and  $MA(1)+MA(2)+MA(3)<1$ . Furthermore, the findings of the analysis showing no autocorrelation in the model reveal the existence of the ARCH effect in the residuals of the return series.

In general, ARCH and GARCH models are inadequate in determining asymmetry effects in variance structure. In this context, it is necessary to apply EGARCH model proposed by Nelson (1991) in order to determine the asymmetry effects of the shocks on volatility. Table 3 points out the estimation results of ARMA(3,3)-EGARCH(3,3) models for the Bitcoin return series.

Table 3. The Estimation Results of EGARCH Model

Mean Equation		Variance Equation	
Variable	Coefficient	Variable	Coefficient
Constant	0.009 (0.411)	Constant ( $\omega$ )	-3.452 (0.000)***
AR(1)	-1.096 (0.000)***	$\alpha_1$ (Shock Effect)	0.536 (0.000)***
AR(2)	0.182 (0.181)	$\alpha_2$ (Shock Effect)	0.360 (0.000)***

AR(3)	0.401 (0.009) <sup>***</sup>	$\alpha_3$ (Shock Effect)	0.137 (0.000) <sup>***</sup>
MA(1)	1.132 (0.004) <sup>***</sup>	$\gamma$ (Leverage Effect)	-0.172 (0.000) <sup>***</sup>
MA(2)	-0.155 (0.268)	$\beta_1$ (Volatility Persistence)	0.373 (0.000) <sup>***</sup>
MA(3)	-0.366 (0.020) <sup>**</sup>	$\beta_2$ (Volatility Persistence)	-0.655 (0.000) <sup>***</sup>
		$\beta_3$ (Volatility Persistence)	0.782 (0.000) <sup>***</sup>

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**Statistics of the Model**


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R<sup>2</sup>: 0.501

Log Likelihood: 280.918

Durbin-Watson: 1.947

ARCH(5): 2.202 (0.803)

ARCH(10): 6.868 (0.739)

AIC Value of ARMA(3,3): -1.477

AIC Value of EGARCH(3,3): -1.735

**Note:** <sup>\*\*\*</sup> and <sup>\*\*</sup> reflect that the coefficients of the variables are significant at 1% and 5%, respectively. The values in parenthesis point out the probability value of the coefficient. Gaussian error distribution is taken into consideration in the analysis of EGARCH model. In addition, BFGS optimization method and Marquardt step method are used in the estimation process. The models are estimated with a maximum of 500 iterations.

In Table 3, it is observed that the conditions of  $AR(1)+AR(2)+AR(3)<1$  and  $MA(1)+MA(2)+MA(3)<1$  are provided in the mean equation. In addition, it is provided that the condition of the sum of the parameter of the same type is smaller than 1. On the other hand, being positive all of the coefficient of  $\alpha$  parameters reflecting the shock effects means that Bitcoin return volatility is affected by the shocks. In addition, some of the coefficients of the  $\beta$  parameters indicating the volatility persistence are negative and some of them are positive. Negative volatility persistence shows that the volatility shocks of the previous periods have a negative effect on the current period conditional variance and positive volatility persistence reveals that the volatility shocks of the previous periods have a positive effect on the current period conditional variance. However, being positive of the net effect of the volatility shocks of the previous periods indicates that the volatility shocks of the previous period on the current period conditional variance remain last long. When evaluated together with the shock effects and the volatility persistence, it can be said that the shocks increase the volatility persistence. Furthermore, taking a value different than zero of the  $\gamma$  parameter indicating the leverage effect point out that the shocks have an asymmetric effect on the Bitcoin return volatility. Since the coefficient of leverage parameter is negative and statistically significant, it can be claimed that the bad news (negative information shocks) affect Bitcoin return volatility more compared to good news (positive information shocks). In other words, the validity of leverage effect for Bitcoin returns can be noted. Besides, it is observed that there is no autocorrelation and no ARCH effect in the estimated model.

## 5. Conclusion

Although there are many applied studies on the volatility dynamics of price and return of securities in the economics, the insufficiency of studies for the crypto money markets is remarkable. This study, which considers the price volatilities and the specific structure of crypto money markets, aims to examine the volatility dynamics of Bitcoin returns, which is the largest market capitalization of all the crypto money market. For this purpose, EGARCH model is employed to examine the asymmetric volatility effect, in other words, asymmetric effects of positive and negative shocks on conditional variance using weekly data set for the period 2013:04-2020:09.

The findings of the analysis indicating Bitcoin returns are not normally distributed and there exist an ARCH effect (heteroscedasticity) in the return series point out that the conditional variance of the current period Bitcoin returns are affected by the past shocks, and that the volatility shocks of the previous periods can remain last long on the current period conditional variance. In addition, it has been determined that the past period shocks have an asymmetric effect on the current period Bitcoin return volatility and the bad news has been found to affect the volatility of the Bitcoin return more than the good news. This result reflects the existence of leverage effect on Bitcoin returns.

Since cryptocurrencies are often used for investment and speculative gains, it is important to determine the causes of the price and return volatilities. In particular, determining the price and return volatilities of the cryptocurrencies in making long-term investment decisions may be the main determinants of investor behavior. Regardless of the economic purposes, it is of utmost importance that investors who want to invest in the Bitcoin market should closely follow the price movements and follow the impacts of the past period shocks on the current period. Furthermore, monitoring the effects of the past period cumulative shocks on the current period returns may be more important for investor decisions. In addition, determination of shock persistence and of breaking periods may increase the reliability of decisions to be taken. In other words, the determination of bull and bear periods in the cryptocurrency markets, as in the security markets, is of great importance for the sustainable returns. Finally, the behavior of economic agents should be closely monitored in determining the trends in the cryptocurrency markets and considering the good and bad news trends attention should be paid to determining the volatile movements that may occur on the return.

## REFERENCES

- Alpago, H. (2018). “Bitcoin’den Selfcoin’e Kripto Para”, *Uluslararası Bilimsel Araştırmalar Dergisi*, 3(2), 411-428.
- Anavatan, A. and Kayacan, E.Y. (2019). “Are Bitcoin Returns Predictable”, *Journal of Current Researches on Business and Economics*,9(1), 13-22.
- Baek, C. and Elbeck, M. (2015). “Bitcoins as an Investment or Speculative Vehicle? A First Look”, *Applied Economics Letters*, 22(1), 30-34.
- Balcilar, M., Bouri, E., Gupta, R. and Rounbaud, D. (2017). “Can Volume Predict Bitcoin Returns and Volatility A Quantiles-Based Approach”, *Economic Modelling*, 64,74-81.
- Bariviera, A. F. (2017). “The Inefficiency of Bitcoin Revisited: A Dynamic Approach”, *Economics Letters*, 161, 1-4.
- Baur, D.G., Hong, K.J. and Lee, A.D. (2016). “Bitcoin: Currency or Asset?”, [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2736020](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2736020).
- Baur, D. G. and Dimpfl, T. (2018). “Excess Volatility as an Impediment for a Digital Currency”, [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2949754](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2949754).
- Blau, B. M. (2017). “Price Dynamics and Speculative Trading in Bitcoin”, *Research in International Business and Finance*, 41, 493-499.
- Bouri, E., Gil-Alana, L.A., Gupta, R. and Roubaud, D. (2017). “Modelling Long Memory Volatility in The Bitcoin Market: Evidence of Persistence and Structural Breaks”, *International Journal Finance and Economics*, 24(1), 412-426.
- Brauneis, A., and Mestel, R. (2018). “Price Discovery of Cryptocurrencies: Bitcoin and Beyond”, *Economics Letters*, 165, 58-61.
- Briere, M., Oosterlinck, K. and Szafarz, A. (2015). “Virtual Currency, Tangible Return: Portfolio Diversification with Bitcoin”, *Journal of Asset Management*, 16: 365–73.
- Catania, L. and Sandholdt, M. (2019). “Bitcoin at High Frequency”, *Journal of Risk and Financial Management*, 12(36), 1-19.
- Cheah, E.T., Tapas, M., Parhi, M. and Zhang, Z. (2018). “Long Memory Interdependency and Inefficiency in Bitcoin Markets”. *Economics Letters*, 167: 18–25.
- Chengyuan, Q. (2017). “BitCoin in China: Price Discovery and Volatility Transmission”, *SSRN Electronic Journal*, 1–13, <https://ssrn.com/abstract=2934031>.
- Cheung, A., Roca, E. And Su, J. (2015), “Crypto-Currency Bubbles: An Application of the Phillips–Shi–Yu Methodology on Mt. Gox Bitcoin Prices”, *Applied Economics*, 47(23), 2348–2358.
- Chu, J., Chan, S., Nadarajah, S. and Osterrieder, J. (2017). “GARCH Modelling of Cryptocurrencies”, *J. Risk Financial Management*,10(17), 1-15.
- Ciaian, P., Rajcaniova, M. and Kancs, D.A. (2016). “The Economics of Bitcoin Price Formation”, *Applied Economics*, 48(19), 1799-1815.
- Doğan, H. (2018). “İslam Hukuku Açısından Kripto Paralar ve Blockchain Şifreleme Teknolojisi”, *Selçuk Üniversitesi Hukuk Fakültesi Dergisi*, 26(2), 225-253.
- Dwyer, G.P. (2015). “The economics of Bitcoin and similar private digital currencies”, *Journal of Financial Stability*, 17, 81–91.
- Dong, H. and Dong, W. (2014). “Bitcoin: Exchange Rate Parity, Risk Premium, and Arbitrage Stickiness”, *British Journal of Economics, Management & Trade*, 5(1).
- Dyhrberg, A.H. (2016). “Bitcoin, Gold and The Dollar-A GARCH Volatility Analysis”, *Finance Research Letters*, 16, 85-92.
- Enders, W. (2015). *Applied Econometric Time Series*. 4th Ed. The USA: John Wiley & Sons.
- Fanusie, Y.J. and Robinson, T. (2018). “Bitcoin Laundering: An Analysis of Illicit Flows into Digital Currency Services”, *Center on Sanctions and Illicit Finance, Foundation for Defense of Democracies*.
- Frascaroli, B. F. and Pinto, T. C. (2016). “The Innovative Aspects Of Bitcoin, Market Microstructure And Returns Volatility: An Approach Using Mgarch”, <http://www.ufjf.br/encontroeconomiaaplicada/files/2016/05/artigo64MicroeconomiaAplicada.pdf>.
- Gandal, N. and Halaburda, H. (2014). “Competition in the Cryptocurrency Market”, *Bank of Canada Working Paper 2014-33*, 1-32.
- Gandal, N., Hamrick, J.T, Moore, T. and Oberman, T. (2018). “Price Manipulation in the Bitcoin Ecosystem”, *Journal of Monetary Economics*, 95: 86–96.
- Georgoula, I., Pournarakis, D., Bilanakos, C., Sotiropoulos, D. N. and Giaglis, G. M. (2015). “Using Time-Series and Sentiment Analysis to Detect the Determinants of Bitcoin Prices”, [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2607167](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2607167).
- Harvey, C. and Tepper, T. (2015). “Can You Really Beat The Market?”, *Money*, 44(2), 76-79.
- Hencic, A. and Gouriéroux, C. (2015). “Noncausal Autoregressive Model in Application to Bitcoin/USD Exchange Rates.”, In *Econometrics of Risk* (pp. 17-40). Springer International Publishing.

- Hultman, H. (2018). “An Empirical Study on Bitcoin Using Garch and Stochastic Volatility Models”, Lund University Department of Economics, <https://lup.lub.lu.se/student-papers/search/publication/8958504>.
- Ji, Q., Bouri, E., Gupta, R. and Roubaud, D. (2018). “Network Causality Structures among Bitcoin and Other Financial Assets: A Directed Acyclic Graph Approach”, *The Quarterly Review of Economics and Finance*, 70: 203–13.
- Kasper, J. (2017). “Evolution of Bitcoin: Volatility Comparisons with Least Developed Countries Currencies”, *SSRN Electronic Journal*, 1–22, <https://ssrn.com/abstract=3052207>.
- Katsiampa, P., (2018). “An Empirical Investigation of Volatility Dynamics in the Cryptocurrency Market”, [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3202317](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3202317).
- Katsiampa, P., Corbet, S. and Lucey, B., (2019). “Volatility Spillover Effects in Leading Cryptocurrencies: A BEKK-MGARCH Analysis”, *Finance Research Letters*, 29(1), 68-74.
- Korap, L. (2010). “An Econometric Essay for the Asymmetric Volatility Content of the Portfolio Flows: EGARCH Evidence from the Turkish Economy”. *Sosyal Bilimler Dergisi*, 4, 103-109.
- Koutmos, D. (2018). “Bitcoin Returns and Transaction Activity”, *Economics Letters*, 167, 81-85.
- Li, X. and Wang, C.A. (2017). “The Technology and Economic Determinants of Cryptocurrency Exchange Rates: The case of Bitcoin”, *Decision Support Systems*, 95: 49–60.
- MacDonell, A. (2014). “Popping the Bitcoin Bubble: An Application of Log-Periodic Power Law Modeling to Digital Currency.”, University of Notre Dame working paper, [https://economics.nd.edu/assets/134206/mac\\_donell\\_popping\\_the\\_bitcoin\\_bubble\\_an\\_application\\_of\\_log\\_periodic\\_power\\_law\\_modeling\\_to\\_digital\\_currency.pdf](https://economics.nd.edu/assets/134206/mac_donell_popping_the_bitcoin_bubble_an_application_of_log_periodic_power_law_modeling_to_digital_currency.pdf).
- Nakamoto, S. (2009). “Bitcoin: A Peer-to-Peer Electronic Cash System”, <https://bitcoin.org/bitcoin.pdf>.
- Nelson, D. B. (1991). “Conditional Heteroskedasticity in Asset Returns: A New Approach”, *Econometrica*, 59, 347-370.
- Özden, Ü. H. (2008). “İMKB Bileşik 100 Endeksi Getiri Volatilitésinin Analizi”, *İstanbul Ticaret Üniversitesi Sosyal Bilimler Dergisi*, 7(13), 339-350.
- Shi, S. (2018). “The Impact of Futures Trading on Intraday Spot Volatility and Liquidity: Evidence from Bitcoin Market”. *SSRN Electronic Journal*, 1–14, <https://ssrn.com/abstract=3094647>.
- Songül, H. (2010). *Otoregresif Koşullu Değişen Varyans Modelleri: Döviz Kurları Üzerine Uygulama*, Türkiye Cumhuriyet Merkez Bankası Uzmanlık Yeterlilik Tezi, Ankara.
- Urquhart, A. (2018). “What Causes the Attention of Bitcoin”, *SSRN Electronic Journal*, 1–12, <https://ssrn.com/abstract=3097153>.
- Yermack, D., 2013. “Is Bitcoin a Real Currency? An Economic Appraisal”, *SSRN Electronic Journal*, 1-23. [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2361599](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2361599).
- Yi, S.Z.X. and Wang, G.J. (2018). “Volatility Connectedness in the Cryptocurrency Market: Is Bitcoin A Dominant Cryptocurrency”, *International Review of Financial Analysis* 60: 98–114.