Akademik Araştırmalar ve Çalışmalar Dergisi 2021, 13(24), 290-309
Journal of Academic Researches and Studies 2021, 13(24), 290-309
https://doi.org/10.20990/kilisiibfakademik.731233

Makale Türü: Konferans Bildirisi
Paper Type: Conference Paper

Geliş tarihi/Recceived: 03.05.2020
Kabul tarihi/Accepted: 31.12.2020

Determination Price Volatility of Bitcoin with Autoregressive Conditional Heteroscedasticiy Models[1]

Bitcoin'in Fiyat Oynaklığının Otoregressif Koşullu Değişen Varyans Modellemeleri ile Belirlenmesi

İbrahim Sezer BELLİLER[2], Zerife YILDIRIM[3]

Abstract

Purpose: The purpose of this research is to analyze the price movements of bitcoin, which has become a new phenomenon in financial markets since 2009, the first year of its release, and can be defined as virtual money or crypto money, to be seen as a financial investment tool.
Design/Methodology: In the study, volatility, return behavior and reliability as a financial investment tool are examined with autoregressive Conditional Variable Variance modeling. In this context, symmetrical and asymmetrical ARCH models were used.
Findings: As a result of the analysis; it has been found that it has an asymmetric effect in the first period for the bitcoin return series examined with symmetric and asymmetric ARCH models. In addition, it has been determined that shocks occurring in the bitcoin return series according to the half-life criteria are exposed to the volatility effect for more than 30 days in each period. It has been determined that bitcoin, which is examined by periods, has higher volatility in its first years.
Limitations: The volatility of bitcoin, which has become a new phenomenon in financial markets today, can be defined as virtual money or crypto money, has been analyzed.
Originality/Value: In fact, there are many virtual currencies or cryptocurrencies traded in the market. However, among many virtual currencies, bitcoin is the most known and the most market volume. Analyzing the price movements of bitcoin, which has started to be seen as a financial investment tool, is of great importance in the framework of reliability. The examination made in this respect constitutes the original value of the research.
Keywords: Bitcoin, Cryptocurrency, Volatility, Symmetric and Asymmetric ARCH Models

Öz

Amaç: Bu araştırmanın amacı, ilk çıkış yılı olan 2009'dan günümüze finansal piyasalarda yeni bir fenomen haline gelen, sanal para veya kripto para olarak tanımlanabilen bitcoinin, finansal bir yatırım aracı olarak görülmesi yönündeki fiyat hareketlerinin analiz edilmesidir.
Tasarım/Yöntem: Çalışmada, Otoregresif Koşullu Değişen Varyans modellemeleri ile oynaklık, getiri davranışı ve finansal bir yatırım aracı olarak güvenilirliği incelenmektedir. Bu kapsamda simetrik ve asimetrik etkili ARCH modellemeleri kullanılmıştır.
Bulgular: Analizler sonucunda; simetrik ve asimetrik etkili ARCH modellemeleri ile incelenen bitcoin getiri serisi için ilk dönemde asimetrik etkiye sahip olduğu bulunmuştur. Ayrıca half-life ölçütüne göre bitcoin getiri serisinde meydana gelen şoklar her dönemde 30 günden daha fazla oynaklık kalıcılığı etkisine maruz kaldığı tespit edilmiştir. Dönemler itibariyle incelenen bitcoinin ilk yıllarında daha yüksek oynaklığa sahip olduğu tespit edilmiştir.

Sınırlılıklar: Günümüzde finansal piyasalarda yeni bir fenomen haline gelen, sanal para veya kripto para olarak tanımlanabilen bitcoinin oynaklığı analiz edilmiştir.
Özgünlük/Değer: Aslında piyasada ticareti yapılan çok sayıda sanal para veya diğer adıyla kripto para bulunmaktadır. Ancak birçok sanal para biriminin arasında en çok bilineni ve piyasa hacmi en fazla olanı olarak bitcoin karşımıza çıkmaktadır. Finansal bir yatırım aracı olarak görülmeye başlanan bitcoin'in fiyat hareketlerinin analiz edilmesi güvenilirlik çerçevesinde büyük öneme sahiptir. Bu yönden yapılan inceleme araştırmanın özgün değerini oluşturmaktadır.
Anahtar Kelimeler: Bitcoin, Kriptopara, Oynaklık, Simetrik ve Asimetrik ARCH Modelleri

[1] This study was presented at the "Gap Summit-I International Gap Business Sciences and Economy Congress" held in Şanlıurfa on May 4-6, 2018. The abstract text has been published in the congress summary booklet.
[2] Research Assistant, Harran University, Faculty of Economics and Administrative Sciences, Department of Econometrics sezerbelliler@gmail.com, ORCID: 0000 0001 8141 6347
[3] Assist. Prof. Dr., Harran University, Faculty of Economics and Administrative Sciences, Department of Econometrics zerifeyildirim@gmail.com, ORCID: 0000 0002 2478 2823

1. INTRODUCTION

The rapid development of the computer age and the increase in the volume of online shopping has given rise to virtual currencies as a new concept. Virtual currencies maintain their characteristic to be a controversial concept since their emergence in the market due to the fact that they are not connected with a central bank, contrary to national currencies, and not guaranteed by any institution or organization.

Bitcoin is the first currency which emerged as a virtual currency. The simple definition of bitcoin is given as follows: “The digital version of the most known and accepted currencies such as dollar and euro” (De Martino, 2018).

Bitcoin was announced by its founder or founders in 2008 with an article and defined as given: “It is an end-to-end electronic cash flow transaction that allows digital payments to be transferred directly from one side to another without going through a financial institution” (Nakamoto, 2008).

Because of the fact that bitcoin transfer is not limited for countries which are included in the monitoring list or imposed an embargo, its speed and flexibility are higher in comparison to other currencies regulated by banks (Dyhrberg, 2016).

Bitcoin is based on the idea of a peer-to-peer exchange without a third party involvement and accordingly, it has brought about many discussions since the day it was released in the market. The fluctuations that occur in the price of bitcoin has given rise to differences of opinion among experts, investors and regulatory bodies regarding the definition of bitcoin as an independent currency. Furthermore, the characteristic of bitcoin as a financial asset has started to be stressed as a research topic recently. Glasser et al. (2014) revealed that bitcoin is demanded as a speculative asset rather than being traded as a currency.

The main purpose of the present study was to determine price volatility and price movements of bitcoin with the modelling family of Autoregressive Conditional Heteroscedasticity (ARCH) which is the main method of time series econometrics. The study aimed to determine the price dynamics more accurately by analyzing the volatility modelling and price movements in the form of three different data sets. The data sets were created by receiving the daily closing price of bitcoin (Unit/Dollar) from blockchain. The first data set covered the period that starts from the year 2010 to the mid-2013. This data set represented the period which bitcoin had followed a smooth course before reaching to three digit numbers. The second data set covered the period that bitcoin had reached to three digit numbers and had more tendencies to increase from mid-2013 to the first quarter of 2017. Lastly, the third data set covered the period from the first quarter of 2017 to April 2018, in other words, the period that the unit price of bitcoin expressed with thousands of dollars and had the highest relative volatility.

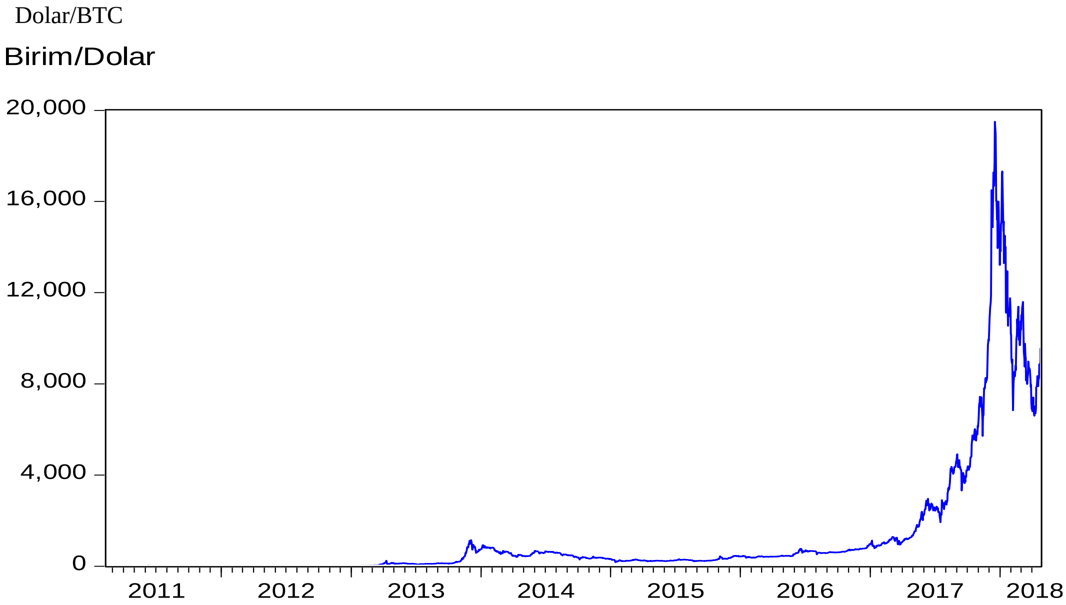
As a result, the study aimed to determine the risk level of cryptocurrency for investors by determining price dynamics and volatility. Within this framework, the points that investors who want to add bitcoin in their investment portfolio should take into consideration were emphasized and the results obtained in the light of the analysis were explained and suggestions were provided.

The first section of the study defined the concepts of virtual currency and bitcoin; the second section addressed bitcoin as a currency and an investment tool and reviewed the literature, the third section presented the method to be employed in the study, the fourth section evaluated the implementation and results, and finally, the fifth section provided the results and the discussion. Also contribution and originality of this paper that bitcoin price volatility examined by different period would give point of view researchers and investors.

2. BITCOIN AS A CURRENCY OR AN INVESTMENT TOOL AND LITERATURE

In order to analyze the price movements of bitcoin from the moment that it entered the market, the price graph should be examined as the first step.

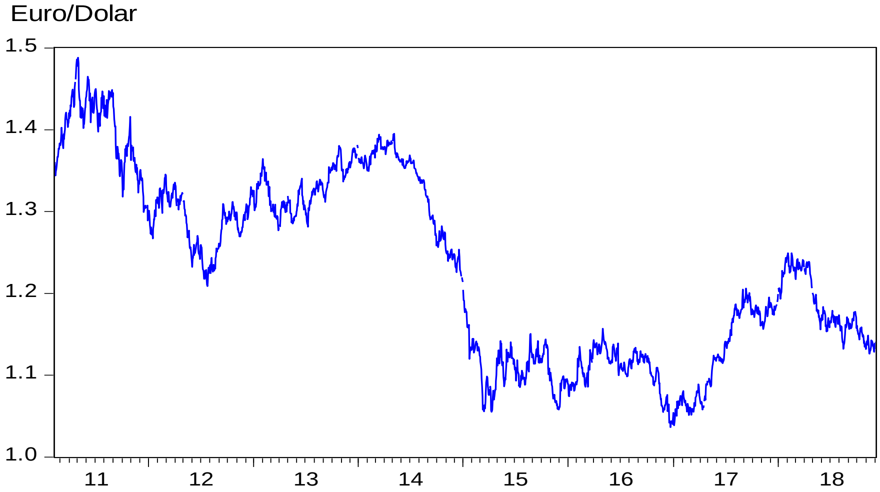
Figure 1: Bitcoin Daily Price Movement (12.02.2011- 26.04.2018)



Source: https://www.coindesk.com/price/bitcoin

It is evident that bitcoin has been on increase since the day it started to be mining. A unit of bitcoin did not even have the value of a half dollar in 2009, yet today it has a value of thousands of dollars. In Figure 1, 2011 is the date that the price movements of bitcoin have started to be examined, as it is the date that the price of bitcoin was higher than one dollar. However, it is not sufficient to address this increase separately. The price movements of bitcoin should be predictable and decrease in mean deviation to be accepted as a currency or as an investment tool.

Figure 2: Daily Euro Dolar Parity (12.02.2011- 04.12.2018)

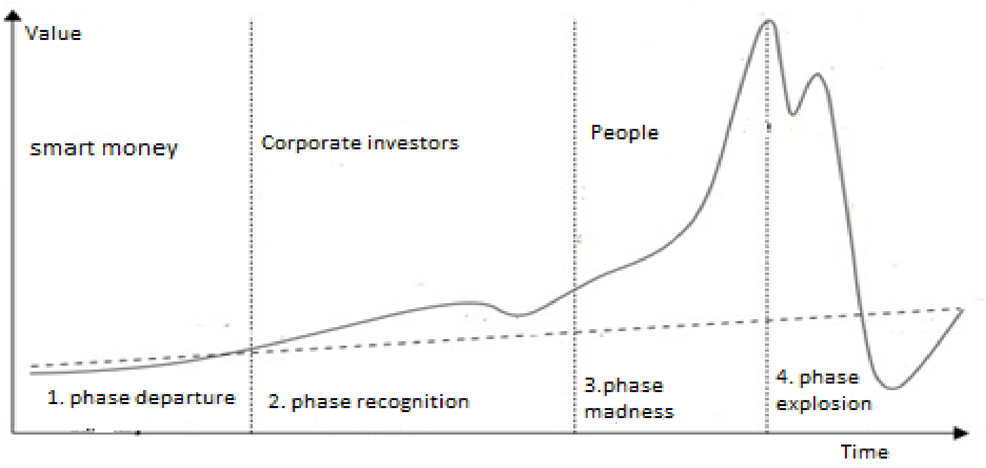


Source: Quandll, 2018

The euro-dollar parity graph presented in Figure 2 has a more balanced structure in comparison to the bitcoin price graph. As the visual analysis demonstrates, the price movements of bitcoin have a very different structure than the most-known currencies. In the contemporary global market, observing the consistent price movements associated with other investment tools of virtual currencies that have a history shorter than 10 years.

Figure 3 illustrates the financial bubble chart of Rodrigue. The price movements of bitcoin show considerable similarities with the financial bubble graph. The experts who considered bitcoin as a financial bubble associate the price movements of bitcoin with the financial bubble chart of Rodrigue (2011). Due to the fact that the concept of crypto money is a relatively new concept, it is difficult to compare the price movements of bitcoin with stocks or currencies such as euro or dollar. Therefore, given the fact that price movements of bitcoin include statistically significant information, analyzing them with a univariate time series method will be a more appropriate approach.

Figure 3: Phases of Financial Bubble



Source: Rodrigue, 2011

Volatility plays major role in risk modelling and price analysing of complex financial derivative products. Conditional variance analysis of financial time series data has received a growing interest in literature. Therefore, investigation volatility effects in bitcoin price as a financial time series organised primary issue of this study.

2.1. Literature

Bitcoin took its place in the world financial news as a fixture in late 2013 and early 2014. The "virtual currency", which was started to be used by computer enthusiasts, rapidly increased exchange rates and the value of a bitcoin increased many times against currencies. Although Bitcoin is considered as a medium of exchange, like money, its use has displayed high volatility levels by showing different prices in different exchanges. When the discussions in the literature are examined, there are various results on the use of bitcoin. Firstly, Nakamoto (2008) stated that it is an end-to-end electronic cash flow process that allows digital payments to be transferred directly from one side to another without going through a financial institution. According to Yermack (2013) in the future studies; Pricing with bitcoin in consumer goods is very difficult and requires a very zero decimal pricing. Again, bitcoin faces daily hacking and theft risks. It is not used to refer to consumer loan or loan agreements as futures. Bitcoin looks more like an investment transaction that behaves more speculatively than a trading currency. It is not used to refer to consumer loan or loan agreements as futures. Bitcoin looks more like an investment transaction that behaves more speculatively than a trading currency. Also "Is bitcoin a real currency?" with his work named has been at the center of these discussions.

Christopher (2013) analyzed the operation and functioning dimensions of bitcoin within the framework of anti-money laundering laws of the USA and emphasized the role of bitcoin as a money laundry tool and also potential crimes and difficulties that can arise in the practice of law due to the use of bitcoin. Atik et al. (2015) investigated the impact of bitcoin on foreign exchange rates and determined that there is a one-way causality from Japanese Yen to Euro, and these two currencies are affected from each other.

Szetela, Mentel and Gedek (2016) in their work, according to the results of the ARMA process, Bitcoin acts independently from other currencies in the analysis. The conditional variance of Bitcoin modeled with the GARCH process is affected by the Euro, Dollar and Yuan returns.

Dyrhberg (2016) determined that bitcoin has a place in the market between gold and American Dollar as a medium of exchange. The given study indicated that according to Asymmetric

Garch model results, including bitcoin in the portfolio could be useful in terms of risk management, and it is ideal for investors who avoid risks to protect themselves from the negative shocks that can occur in the market. Similar to the present study, Bouri et al. (2016) conducted a study on the change in price volatility of bitcoin based on the instant breakswhich happened in bitcoin price in 2013. As a result of the research study, they found out that positive shocks that occur in bitcoin return before the breaks in 2013 affected volatility more than negative shocks. Kocoglu et al. (2016) evaluated the development of bitcoin as a virtual currency and its use as an investment tool. As a result, they stressed that bitcoin is a risky investment tool and could not prove its significance as the currencies of developed countries.

In Katsiampa (2017), Volatility forecast for Bitcoin: Making a comparison of GARCH models and exploration of GARCH-type models to determine bitcoin price volatility. As a result of the analysis in terms of compliance with the data, it was concluded that the suitable model is AR-CGARCH.

Baur et al. (2018), Bitcoin: Is it a medium of exchange or a speculative asset? According to the study, not affiliated with any government or authority and the independent commodity trading in the virtual environment is the currency. Analysis of bitcoin data traded in their accounts shows that bitcoin is not actually an alternative currency and exchange tool, it has shown that it is mostly used as a speculative investment tool.

Çütçü and Kılıç (2018) investigated the medium and long-term relationship between the dollar rate and bitcoin prices. In this context, Maki cointegration test, one of the new generations econometric analysis, was used and found a cointegration relationship between the dollar rate and bitcoin prices in the medium and long term. In addition, according to the Hacker-Hatemi-J Bootstrap causality test, they found a one-way causality relationship from dollar rate to bitcoin prices. According to the analysis results of this study, the change in dollar exchange rates significantly affects the prices of Bitcoin in the medium and long term.

Baur et al. (2018) stated that Bitcoin follows a different volatility process compared to other assets and it has been found to have a specific risk-return characteristic. In addition, analysis results showed that no relationship could be determined between bitcoin and gold and dollar. Chaim and Laurini (2018), In their studies, they explored the development of bitcoin daily returns and volatility. Not captured properly by traditional conditional volatility models, changing average volatility and created models of discontinuous yield increases.

Katsiampa et al. (2019) they determined the bidirectional volatility spreading effects between three pairs of cryptocurrencies through econometric analysis in their studies. According to the study, a cryptocurrency's own past shocks and its volatility again, it significantly affects its current conditional variance. But the important thing here is as evidence of the bidirectional shock realization effects, between Bitcoin and Ether and between Bitcoin and Litecoin oneway shock from Ether to Litecoin has been found. Finally, it has been shown that positive correlations are predominant, with conditional correlations that change over time.

Gemici and Polat (2019) in this study, the relationship between bitcoin price and bitcoin volume was investigated by symmetric and asymmetric causality tests. According to the standard causality test results, there is a causality relationship between the price and volume. An asymmetric causality relationship was found between the positive and negative shocks of the variables in the analyzes. Also, it has been determined that the relationship between bitcoin price and bitcoin volume is cointegrated.

3. ECONOMETRIC METHODOLOGY

In this section, the econometric time series models are presented that lay the foundation for the price movements of bitcoin which will be analyzed. ARMA models which examine the linear dimension of time series and GARCH-family processes that model the condition of time series to be linear and non-linear on average.

3.1. Autoregressive Moving Average Models (ARMA)

The model which emerges as the combination of AR(p) and MA(q) models is called 'ARMA(p,q) model'. This model is expressed as a linear combination of the lagged values of the y series itself and current and lagged values of the error term.

$$y_t = \phi_1 + y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \theta_2 u_{t-1} + \theta_2 u_{t-2} + \ldots + \theta_q u_{t-q} + u_t \quad (1)$$

The equation is presented in 1. In this equation, the degree of the AR model can be expressed as "p" and the degree of the MA model can be expressed as "q".

3.2. Autoregressive Conditional Heteroscedasticity Models

Granger and Andersen (1978) proposed the model of the conditional heteroscedasticity that can be explained by the past values of its dependent variable in the following equation.

$$y_t = \varepsilon_t y_{t-1} \quad (2)$$

In the equation (2) conditional heteroscedasticity can be expressed as $\sigma^2 y_{t-1}^2$ Engle (1982) eliminated this model which was developed by Granger due to the fact that conditional heteroscedasticity is equal to zero or infinite. The model proposed by Engle (1982) can be expressed as follows.

$$y_t = \varepsilon_t h_t^{1/2} \quad (3)$$

$$h_t = \alpha_0 + \alpha_1 y_{t-1}^2 \quad (4)$$

Engle defined the model in which the variance of the error term is $V(\varepsilon_t) = 1$ as 'Autoregressive Conditional Heteroscedasticity Model' (ARCH). Although the defined model is not purely a bilinear model, it is considerably approximate to one. When the normal distribution assumption is added to the model with ψ_{t-1}, the model can be expressed as follows.

$$y_t | \psi_{t-1} \sim \mathrm{N}(0, h_t) \quad (5)$$

$$h_t = a_0 + a_1 y_{t-1}^2 \quad (6)$$

The variance function of the Autoregressive Conditional Heteroscedasticity Model can be demonstrated with its general lines as follows.

$$h_t = h(y_{t-1}, y_{t-2}, \ldots, y_{t-p}, a) \quad (7)$$

The given "p" in the equation (7) implies the level of the ARCH process and "a" implies the unknown parameter vector.

ARCH regression model states the mean of y_t as linear combination of $x_t\beta$'s internal and external lags. The model includes ψ_{t-1} information set and β unknown vector parameters (Engle, 1982).

3.3. GARCH Model

The fact that the ARCH model is simple it often requires several parameters in practice. For this reason, alternatives models were required (Tsay, 2010). The initial empiric implementations of the ARCH model investigated the relationship between inflation volatility and inflation level. Engle (1982, 1983) needed to calculate the high-level lag q parameter to predict appropriate condition-variance function in the ARCH model. The high lag parameter might violate the parameter limitations of the ARCH model. Bollerslev (1986) and Taylor (1986) by adding the past values of the conditional variance to the obtained conditional variance function, the Generalized Autoregressive Conditional Variable Variance (GARCH) model is given in equation (7) (Bera & Higgins, 1993).

Bollerslev (1986) defines the GARCH model as: Let ε_t denote a real-valued discrete-time stochastic process, and ψ_t the information set (a-field) of all information through time t. The GARCH (p, q) process (Generalized Autoregressive Conditional Heteroscedasticity) is then given by:

$$\varepsilon_t \,|\psi_{t-1} \sim N(0, h_t) \tag{8}$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

$$= a_0 + A(L)\varepsilon_{t-i}^2 + B(L)h_t \tag{9}$$

In the GARCH model, it assumed that $p \geq 0, q > 0, a_0 > 0, a_j \geq 0, j = 1, ..., q, \gamma_i \geq 0,$. For p = 0, the model is reduced to the ARCH model without any doubt. For p = q = 0, the process is expressed as a white noise process. In the ARCH(q) process the conditional variance is defined as a linear function of past sample variances in the model only. On the other hand, the GARCH (p, q) process allows lagged conditional variances as well. When the error terms are left alone in the GARCH (p, q) model, the model is as follows.

$$\varepsilon_t = y_t - x_t' b \tag{10}$$

In the equation (10)'da y_t is the dependent variable, x_t is the vector of explanatory variables and b is the vector of unknown parameters. In the case that all roots of 1- B(Z) = 0 equity lie outside the unit circle the equation (11) be can be rewritten as a distributed lag of past ε_t^2 s.

$$h_t = a_0(1 - B(1))^{-1} + A(L)(1 - B(L))^{-1}\varepsilon_t^2$$

$$= a_0\left(1 - \sum_{i=1}^{p} \beta_i\right)^{-1} + \sum_{i=1}^{\infty} \delta_i \varepsilon_{t-i}^2 \tag{11}$$

The equation (11) can be considered as an infinite-dimensional ARCH (∞) process. In the GARCH (p,q) process which is defined in the equation (8) and (9), the process is stationary only if, $E(\varepsilon_t) = 0$, $var(\varepsilon_t) = \alpha_0(1 - A(1) - B(1))^{-1}$ and $cov(\varepsilon_t, \varepsilon_s) = 1$ for $t \neq s$ and the A(1) + B(1) < 1 condition is fulfilled (Bollerslev, 1986).

4. IMPLEMENTATION

The study covers the period between the years 2011 and 2018. The daily closing prices of bitcoin (Dollar/BTC) were used in the analysis. The analysis process was separated into three periods as 1st Period.

10.02.2011- 02.10.2013, 2nd Period 03.10.2013- 31.12.2016 and 3rd Period 01.01.2017-27.04.2018. In total 2633 observations were performed. The logarithms of the series were calculated to determine the return series. Returns were calculated in the following formulas. Rt = Ln (P_t / P_{t-1}) The main purpose of separating the price movements of bitcoin is to determine the volatility between the periods in a more sensitive figure. As presented by Figure 1, bitcoin shows similarities between the phases of the financial bubble provided in Figure 3. Therefore, performing an analysis by separating the process into periods was found more useful to identify the volatility.

The descriptive statistics that were subjected to an inter-period analysis showed that the 2nd Period had the highest variation coefficient. The variation coefficient that was found later on as 14.04 belongs to the 2nd Period. In the context of variation coefficient, the lowest volatility coefficient -

relatively- belongs to the 3rd period with 11.04. Given the fact that bitcoin returns gained a significant acceleration in the second period, it is possible that it has a more volatile structure in this period. The third period which has the lowest variation coefficient proves that 3rd-period bitcoin returns became more consistent. As a characteristic feature of the daily return series, the normality assumption could not be fulfilled in all periods. The series had high-level extreme kurtosis and the return series of the 2nd and 3rd period have negative skewness.

Table 2: Descriptive Statistics

Variable	**1. Period (10.02.2011-03.10.2013)**	**2. Period (03.10.2013-31.12.2016)**	**3. Period (01.01.2017-27.04.2018)**
Mean	0.004719	0.001863	0.004669
Median	-0.000194	0.001194	0.008075
Maximum	0.515324	0.230735	0.246615
Minimum	-0.478305	-0.268621	-0.225712
Standard Deviation	0.066296	0.038771	0.051551
Variation Coefficient	14.04887	20.811057	11.041122
Skewness	0.779086	-0.173239	-0.298518
Kurtosis	17.50661	11.41256	5.739517
Jarque-Bera	8559.136	3503.205	157.5556
Probability	0.0000	0.0000	0.0000
Number of Observations	965	1186	481

The descriptive statistics that were subjected to an inter-period analysis showed that the 2nd Period had the highest variation coefficient. The variation coefficient that was found later on as 14.04 belongs to the 2nd Period. In the context of variation coefficient, the lowest volatility coefficient -relatively- belongs to the 3rd period with 11.04. Given the fact that bitcoin returns gained a significant acceleration in the second period, it is possible that it has a more volatile structure in this period. The third period which has the lowest variation coefficient proves that 3rd-period bitcoin returns became more consistent. As a characteristic feature of the daily return series, the normality assumption could not be fulfilled in all periods. The series had high-level extreme kurtosis and the return series of the 2nd and 3rd period have negative skewness.

Figure 4 examined the graph of the return series. The visual analysis of the return series highlighted that the 2nd period has a more volatile structure as it can be also seen in the descriptive statistics. The general observations of the return series revealed that a positive volatility is followed by a positive volatility, and a negative volatility was followed by a negative volatility. In this context, it is revealed that the series have a volatility clustering. Unit root tests examined for the return series and results showed at the following.

Figure 4: Time Path Charts of Return Series

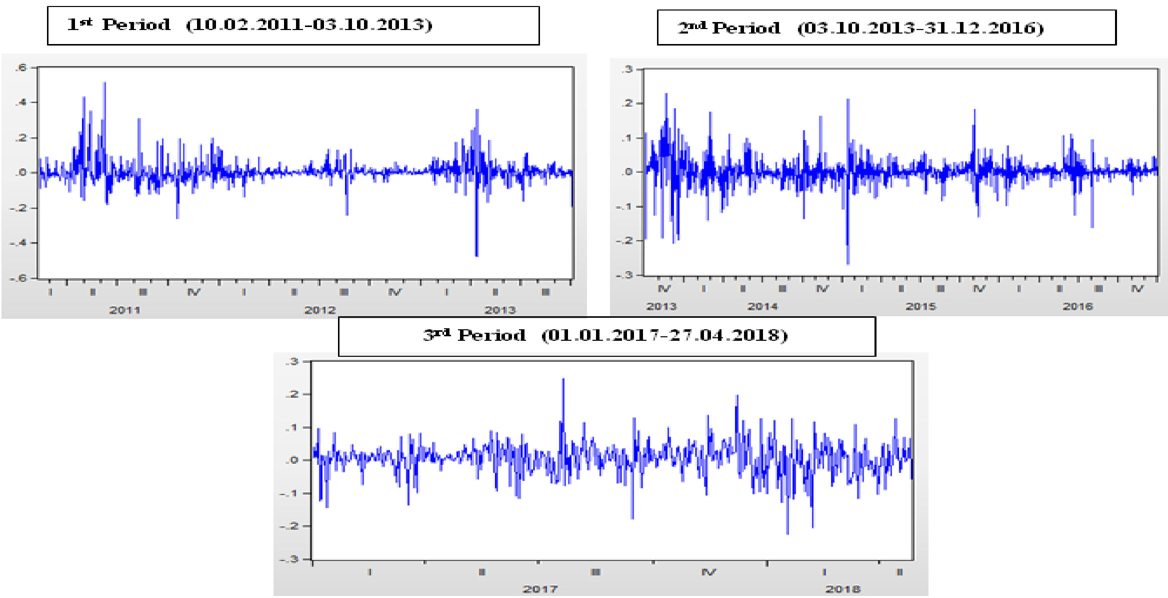


Table 3: Unit Roots Test Results

First Period (10.02.2011- 02.10.2013)							
	Test	**Difference**	**Percent**	**Critical Value**	**t- stat**	**Probability Value**	**Decision**
Intercept	ADF	Level	%1	-3.431	-18.101	0.0000	I(0)
			%5	-2.862			
			%10	-2.567			
	PP	Level	%1	-3.431	-17.892	0.0000	I(0)
			%5	-2.862			
			%10	-2.567			
	Test	**Difference**	**Percent**	**Critical Value**	**t- stat**	**Probability Value**	**Decision**
Trend and Intercept	ADF	Level	%1	-3.960	-12.603	0.0000	I(0)
			%5	-3.410			
			%10	-3.127			
	PP	Level	%1	-3.960	-63.981	0.0000	I(0)
			%5	-3.410			
			%10	3.127			
Second Period (03.10.2013-31.12.2016)							
	Test	**Difference**	**Percent**	**Critical Value**	**t- stat**	**Probability Value**	**Decision**
Intercept	ADF	Level	%1	-3.431	-33.218	0.0000	I(0)
			%5	-2.862			
			%10	-2.567			
	PP	Level	%1	-3.431	-33.9578	0.0000	I(0)
			%5	-2.862			
			%10	-2.567			
	Test	**Difference**	**Percent**	**Critical Value**	**t- stat**	**Probability Value**	**Decision**
Trend and Intercept	ADF	Level	%1	-3.960	-33.217	0.000	I(0)
			%5	-3.410			
			%10	-3.127			
	PP	Level	%1	-3.960	-33.945	0.000	I(0)
			%5	-3.410			
			%10	-3.127			
Third Period (01.01.2017-27.04.2018)							
	Test	**Difference**	**Percent**	**Critical Value**	**t- stat**	**Probability Value**	**Decision**
Intercept	ADF	Level	%1	-3.431	-22.129	0.000	I(0)
			%5	-2.862			
			%10	-2.567			
	PP	Level	%1	-3.431	-22.130	0.000	I(0)
			%5	-2.862			
			%10	-2.567			
	Test	**Difference**	**Percent**	**Critical Value**	**t- stat**	**Probability Value**	**Decision**
Trend and Intercept	ADF	Level	%1	-3.431	-22.126	0.000	I(0)
			%5	-2.862			
			%10	-2.567			
	PP	Level	%1	-3.431	-22.170	0.000	I(0)
			%5	-2.862			
			%10	-2.567			

As can be seen from the unit root results return series are I(0) for all periods. ARMA model trials have been made for return series and the most suitable model has been reported according to the selected information criteria.

Table 4: Selected ARIMA Models

	Models	**AIC***	**BIC**	**LO**	**HQ**
1. PERIOD	ARIMA (3,1,3)	-2.6129	-2.5725	1270.053	-2.5975
	ARIMA (2,1,4)	2.6111	-2.5708	1269.193	-2.5958
	ARIMA (2,1,2)	2.6058	-2.5755	1264.633	-2.5943
	ARIMA (1,1,2)	-2.6003	-2.5751	1260.978	-2.5907
	ARIMA (1,1,1)	-2.5986	-2.5784	1259.135	-2.5909
2. PERIOD	ARIMA (3,1,3)	-3.6902	-3.6559	2196.299	-3.6773
	ARIMA (1,1,3)	-3.6749	-3.6492	2185.247	-3.6652
	ARIMA (1,1,2)	-3.6617	-3.6403	2176.428	-3.6536
	ARIMA (0,1,0)	-3.6597	-3.6512	2172.247	-3.6565
	ARIMA (1,1,1)	-3.6586	-3.6414	2173.550	-3.6521

Table 4 (Continued): Selected ARIMA Models

	Models	AIC*	BIC	LO	HQ
3. PERIOD	ARIMA (6,1,6)	-3.1024	-2.9808	760.1306	-3.0546
	ARIMA (5,1,5)	-3.0874	-2.9832	754.5312	-3.0465
	ARIMA (1,1,0)	-3.0821	-3.0561	744.2621	-3.0719
	ARIMA (1,1,2)	-3.0739	-3.0305	744.2809	-3.05687

* Information criterion which was accepted as a reference in model selection

To select the most appropriate ARIMA models, Akaike, Bayes, Hannan-Quinn information criteria were provided in Table 3. The Akaike Information Criterion was accepted as the reference criterion that directs the model selection process. The ones which are specified with bold fonts are the selected models. For the 1st and 2nd periods the ARIMA (3,1,3) model, and for the 3rd period, the ARIMA (6,1,6) were preferred. Suitability of the selected models depends on some assumptions. Rediulas should not be autocorrelated and heteroskedastic. Autocorrelation and heteroskedasticity tests showed at the following.

Table 5: ARMA Models' Residuals Autocorrelation Test Results

First Period (10.02.2011- 02.10.2013)					
ARMA (3,3)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
AC	0.372	0.127	0.092	0.045	0.004
PAC	0.372	0.075	0.048	0.029	-0.036
Q.Stat.	133.76	283.08	315.77	353.08	388.03
Prob.	0.000	0.000	0.000	0.000	0.000
Second Period (03.10.2013-31.12.2016)					
ARMA (3,3)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
AC	0.350	0.053	0.134	0.046	0.113
PAC	0.350	-0.006	0.044	-0.039	0.057
Q.Stat.	145.41	235.91	316.23	428.53	504.99
Prob.	0.000	0.000	0.000	0.000	0.000
Third Period (01.01.2017-27.04.2018)					
ARMA (6,6)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
AC	0.113	0.110	0.020	0.048	-0.013
PAC	0.113	0.103	0.006	0.034	-0.033
Q.Stat.	6.227	13.229	17.867	24.408	27.832
Prob.	0.013	0.021	0.057	0.225	0.579

Autocorrelation tests results show that return series' residuals autocorrelated even in thirtieth lag. Only last period's autocorrelation have disappeared at the end of twentieth lag. To sum up all the ARMA models' residuals autocorrelated. Heteroskedasticity tests indicate that ARMA model residuals are heteroskedastic even at 36^{th} lag. ARMA models' residuals suffered both autocorrelation and heteroskedasticity so these models inadequate. Heteroskedasticity should be modelled for the further analysis. Therefore, variance component of ARMA models can be nonlinear. Nonlinearity of return series should be examined.

Table 6: ARCH-LM Heteroskedasticity Test Performed on the Error Terms of the ARIMA Models

	Number of Lags	Test Statistic	Probability Value
1. PERIOD	1	133.8566	0.000
	2	166.1298	0.000
	4	166.3109	0.000
	12	176.4546	0.000
	24	209.4356	0.000
	36	222.8497	0.000
2. PERIOD	1	145.5468	0.000
	2	157.1399	0.000
	4	159.2385	0.000
	12	192.9329	0.000
	24	216.9208	0.000
	36	236.0558	0.000

Table 6 (Continued): ARCH-LM Heteroskedasticity Test Performed on the Error Terms of the ARIMA Models

	Number of Lags	Test Statistic	Probability Value
3. PERIOD	1	6.2724	0.0123
	2	6.3169	0.0425
	4	7.1608	0.1276
	12	13.9313	0.3051
	24	19.5778	0.7205
	36	23.9165	0.9386

BDS nonlinearity tests indicates that return series has nonlinear components.

Table 7: BDS Test Results

	Dimension	BDS-Stat.	Std-Error	z-stat.	Prob.
1. Period	2	0.0426	0.0040	10.5668	0.0000
	3	0.0800	0.0064	12.4297	0.0000
	4	0.1056	0.0077	13.7218	0.0000
	5	0.1204	0.0080	14.9438	0.0000
	6	0.1269	0.0078	16.2619	0.0000
2. Period	**Dimension**	**BDS-Stat.**	**Std-Error**	**z-stat.**	**Prob.**
	2	0.0398	0.0034	11.6682	0.0000
	3	0.0764	0.0054	14.0487	0.0000
	4	0.0990	0.0065	15.2293	0.0000
	5	0.1118	0.0068	16.4482	0.0000
	6	0.1181	0.0065	17.9509	0.0000
3. Period	**Dimension**	**BDS-Stat.**	**Std-Error**	**z-stat.**	**Prob.**
	2	0.0147	0.0043	3.3862	0.0007
	3	0.0268	0.0069	3.8680	0.0001
	4	0.0389	0.0083	4.6850	0.0000
	5	0.0480	0.0086	5.5342	0.0000
	6	0.0548	0.0084	6.5266	0.0000

There are doubts that the series has a volatility clustering and permanence. In this context, it was thought that the predicted ARIMA processes might have heteroskedasticity and autocorrelation. Also BDS test results show that nonlinearity of residuals should be modelled.

Table 8: Volatiliy Model Results

Periods	Volatility Model	Coefficient							
		a_0	a_1	a_2	a_3	β_1	β_2	β_3	γ_3
1.Period	ARCH (1)	0.0011***	1.3023***						
	ARCH (2)	0.0010***	0.8514***	0.2928***					
	ARCH (3)	0.0007***	0.2526***	0.4438***	0.4483***				
2.Period	ARCH (1)	0.0005***	0.9279***						
	ARCH (2)	0.0004	0.6145	0.3188					
	ARCH (3)	0.0004	0.5725	0.2495	0.0637				
3.Period	ARCH (1)	0.0021	0.1549						
	ARCH (2)	0.0017	0.1682	0.1850					
	ARCH (3)	0.0011	0.2117	0.2454	0.1737				

$$h_t = a_0 + \sum_{t=1}^{q} a_j u_{t-i}^2 \quad . \tag{12}$$

Periods	Volatility Model	Coefficient							
		a_0	a_1	a_2	a_3	β_1	β_2	β_3	γ_3
1.Period	GARCH (1,1)	0.000065***	0.1916***			0.8173***			
	GARCH (1,2)	0.000070***	0.2093***			0.7086***	0.0938		
2.Period	GARCH (1,1)	0.0000373***	0.2184***			0.7861***			
	GARCH (1,2)	0.0000440***	0.27207***			0.4360***	0.2984***		
3.Period	GARCH (1,1)	0.0000861***	0.1992***			0.7906***			
	GARCH (1,2)	0.00011**	0.2623***			0.30454*	0.4207***		

$$h_t = a_0 + \sum_{t=1}^{q} a_j u_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \quad . \tag{13}$$

Table 8 (Continued): Volatiliy Model Results

Periods	Volatility Model	Coefficient							
		a_0	a_1	a_2	a_3	β_1	β_2	β_3	γ_3
1.Period	TGARCH (1,1)	0.0000657***	0.1864***			0.8147***			0.0214
	TGARCH (1,2)	0.0000659***	0.1871***			0.8104***	0.0036		0.0214
2. Period	TGARCH (1,1)	0.0000374***	0.2061***			0.7853***			0.0261
	TGARCH (1,2)	0.0000443***	0.2589***			0.4366***	0.2964***		0.0287
3. Period	TGARCH (1,1)	0.0000722**	0.1933***			0.7735***			0.0671
	TGARCH (1,2)	0.000120**	0.2015***			0.2467*	0.4525***		0.1698**

*: % 10, **: % 5, ***: % 1 represent the statistically significant coefficients according to the significance level.

$$h_t = a_0 + \sum_{t=1}^{q} a_j u_{t-i}^2 + \gamma_i u_{t-i}^2 d_{t-1} \sum_{i=1}^{p} \beta_i h_{t-i} \quad . \tag{14}$$

Periods	Volatility Model	Coefficient							
		a_0	a_1	a_2	a_3	β_1	β_2	β_3	γ_3
1.Period	EGARCH (1,1)	-0.4388***	0.3284***			0.9634***			0.0055
	EGARCH (1,2)	-0.4737***	0.3687***			0.7621***	0.1999		0.0089
	EGARCH (2,1)	-0.4551***	0.4230***	-0.0856		0.9614***			-0.0174
	EGARCH (2,2)	-0.8104***	0.3791***	0.2470***		0.0490	0.8859***		0.0305
	EGARCH (2,3)	-0.9178***	0.2809***	0.4571***		-0.0534	0.3039***	0.6787***	0.0672**
	EGARCH (3,2)	-0.8595***	0.4165***	0.2982***	-0.0621***	-0.0303***	0.9631***		-0.0123**
	EGARCH (3,3)	-1.5519***	0.2821***	0.6011***	0.3271***	-0.3728***	0.3322***	0.9190***	0.0656***
2. Period	EGARCH (1,1)	0.0000374***	0.2061***			0.7853***			0.0261
	EGARCH (1,2)	0.0000443***	0.2589***			0.4366***	0.2964***		0.0287
3. Period	EGARCH (1,1)	0.0000722**	0.1933***			0.7735***			0.0671
	EGARCH (1,2)	0.000120**	0.2015***			0.2467*	0.4525***		0.1698**

Periods	Volatility Model	Coefficient							
		a_0	a_1	a_2	a_3	β_1	β_2	β_3	γ_3
1.Period	PARCH (1,1)	0.0078***	0.1568***			0.8538***			0.4595***
	PARCH (1,2)	0.0088***	0.1769***			0.7112***	0.1221		0.4608***
2. Period	PARCH (1,1)	0.000012	0.2111***			0.7760***			2.3112***
	PARCH (1,2)	0.000025	0.2687***			0.4336***	0.2918***		2.21405***
3. Period	PARCH (1,1)	0.0045	0.1652***			0.8352***			0.7187**
	PARCH (1,2)	0.0077	0.1802***			0.5573**	0.2667		0.5360**

$$\log(h_t) = a_0 + \sum_{t=1}^{q} \beta_j \log(h_{t-j}) + \sum_{i=1}^{p} a_i \left| \frac{u_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{\sqrt{h_{t-k}}} \quad . \tag{15}$$

ARCH, GARCH, TGARCH, EGARCH, PARCH models examined for all periods in Table 8. Some models have insignificant parameters and they are eliminated from heteroskedasticity test. If the problem of heteroskedasticity in models can not be solved. It can be said that ARCH/GARCH models are insufficient in volatility modeling.

$$\sigma_t^d = a_0 + \sum_{i=1}^{q} a_i \left(|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i} \right)^d + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^d \tag{16}$$

Table 9: Heteroskedasticity Test Results for Volatility Models

Periods	ARCH (1)	Lag.1	Lag.5	Lag.10	Lag.20	Lag30
	F stat.	3.1191	3.3289	2.6471	2.4706	2.0876
	F stat. Prob.	0.0777	0.0055	0.0035	0.0004	0.0006
	Obs. R^2	3.1155	16.4618	26.0482	47.9669	60.5732
	R^2 Prob.	0.0775	0.0056	0.0037	0.0004	0.0008
	ARCH (2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	2.2235	1.7464	1.4923	1.2895	1.8521
	F stat. Prob.	0.1363	0.1214	0.1369	0.1765	0.0038
1. Period	Obs. R^2	2.2229	8.7071	14.8619	25.6608	54.1369
	R^2 Prob.	0.1360	0.1213	0.1372	0.1773	0.0044
	ARCH (3)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.2573	0.9113	0.9601	1.4580	0.9224
	F stat. Prob.	0.6121	0.4728	0.4769	0.0880	0.5875
	Obs. R^2	0.2577	4.5635	9.6154	28.9113	27.7734
	R^2 Prob.	0.6116	0.4714	0.4749	0.0895	0.5824
	ARCH (1)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	1.5685	2.9972	3.7614	2.3192	2.1892
	F stat. Prob.	0.2107	0.0108	0.0001	0.0009	0.0002
	Obs. R^2	1.5691	14.8731	36.7820	45.3972	63.7633
	R^2 Prob.	0.2103	0.0109	0.0001	0.0010	0.0003
	ARCH (2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.7169	0.9103	2.4628	1.7113	1.7529
2. Period	F stat. Prob.	0.3973	0.4734	0.0065	0.0262	0.0076
	Obs. R^2	0.7176	4.5573	24.3463	33.8434	51.6250
	R^2 Prob.	0.3969	0.4723	0.0067	0.0272	0.0084
	ARCH (3)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.2164	0.6549	2.7679	1.8332	1.7188
	F stat. Prob.	0.6418	0.6577	0.0022	0.0139	0.0096
	Obs. R^2	0.2168	3.2825	27.2919	36.1790	50.6654
	R^2 Prob.	0.6415	0.6565	0.0023	0.0147	0.0106
	ARCH (1)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.0751	2.0989	1.6347	1.4143	1.0316
	F stat. Prob.	0.7841	0.0644	0.0940	0.1101	0.4230
	Obs. R^2	0.0754	10.3966	16.1644	27.8471	30.9529
	R^2 Prob.	0.7836	0.0647	0.0950	0.1131	0.4177
	ARCH (2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.0187	2.3201	1.9538	1.5042	1.1700
3. Period	F stat. Prob.	0.8912	0.0424	0.0366	0.0750	0.2492
	Obs. R^2	0.0188	11.4663	19.1916	29.5054	34.7850
	R^2 Prob.	0.8909	0.0429	0.0379	0.078	0.2505
	ARCH (3)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.0495	1.7048	1.7209	1.1423	0.9720
	F stat. Prob.	0.8240	0.1319	0.0734	0.3024	0.5112
	Obs. R^2	0.0497	8.4792	16.9863	22.7563	29.2808
	R^2 Prob.	0.8236	0.1317	0.0747	0.30009	0.5029
	GARCH (1,1)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.3809	0.5316	0.7339	0.6108	0.6148
	F stat. Prob.	0.5374	0.7524	0.6926	0.9056	0.9471
	Obs. R^2	0.3822	2.6768	7.3967	12.4528	18.9735
	R^2 Prob.	0.5364	0.7496	0.6875	0.8996	0.9406
1. Period	**GARCH (1,2)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.0334	0.1087	0.1386	0.2853	0.4314
	F stat. Prob.	0.8549	0.9904	0.9992	0.9992	0.9969
	Obs. R^2	0.0335	0.5470	1.4008	5.8004	13.1986
	R^2 Prob.	0.8547	0.9903	0.9992	0.9991	0.9966

Table 9 (Continued): Heteroskedasticity Test Results for Volatility Models

2. Period	**GARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	3.8539	1.2715	1.2511	0.8073	0.7389
	F stat. Prob.	0.0499	0.2738	0.2537	0.7067	0.8457
	Obs. R^2	3.8479	6.3556	12.4957	16.2138	22.3404
	R^2 Prob.	0.0498	0.2731	0.2532	0.7033	0.8414
	GARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	1.5674	0.8733	0.9285	0.6260	0.6331
	F stat. Prob.	0.2108	0.4983	0.5057	0.8958	0.9386
	Obs. R^2	1.5680	4.3726	9.2992	12.6135	19.1934
	R^2 Prob.	0.2105	0.4971	0.5040	0.8933	0.9359
3. Period	**GARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.4990	0.7405	0.9045	0.6858	0.6861
	F stat. Prob.	0.4803	0.5934	0.5288	0.8414	0.8953
	Obs. R^2	0.5005	3.7206	9.0829	13.9372	21.0710
	R^2 Prob.	0.4792	0.5903	0.5242	0.8337	0.8857
	GARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.0028	0.2176	0.7579	0.5619	0.5416
	F stat. Prob.	0.9576	0.9550	0.6695	0.9374	0.9784
	Obs. R^2	0.0028	1.0994	7.6349	11.4817	16.7980
	R^2 Prob.	0.9575	0.9542	0.664	0.9328	0.9749
1. Period	**TGARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.0282	0.2392	0.1685	0.5191	0.5976
	F stat. Prob.	0.8667	0.9451	0.9982	0.9595	0.9575
	Obs. R^2	0.0282	1.2041	1.7081	10.5416	18.2709
	R^2 Prob.	0.8665	0.9445	0.9981	0.9573	0.9540
	TGARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.6453	0.2173	0.1664	0.4987	0.6164
	F stat. Prob.	0.4221	1.0939	0.9983	0.9676	0.9476
	Obs. R^2	0.6465	0.9552	1.6861	10.1320	18.8295
	R^2 Prob.	0.4214	0.9546	0.9982	0.9657	0.9435
2. Period	**TGARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	3.2830	1.1265	1.1514	0.7676	0.7176
	F stat. Prob.	0.0703	0.3443	0.3201	0.7548	0.8685
	Obs. R^2	3.2794	5.6345	11.5095	15.4274	21.7088
	R^2 Prob.	0.0702	0.3434	0.3192	0.7514	0.8644
	TGARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	1.2897	0.7900	0.8675	0.6005	0.6206
	F stat. Prob.	0.2563	0.5568	0.5634	0.9147	0.9461
	Obs. R^2	1.2904	3.9571	8.6930	12.1033	18.8225
	R^2 Prob.	0.2560	0.5556	0.5615	0.9125	0.9436
3. Period	**TGARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	1.1552	0.6739	0.7175	0.5353	0.4971
	F stat. Prob.	0.2830	0.6433	0.7081	0.9514	0.9889
	Obs. R^2	1.1573	3.3886	7.2344	10.9501	15.4657
	R^2 Prob.	0.2820	0.6403	0.7031	0.9475	0.9868
	TGARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.1972	0.4723	0.6907	0.5246	0.4972
	F stat. Prob.	0.6572	0.7969	0.7334	0.9564	0.9889
	Obs. R^2	0.1979	2.3800	6.9675	10.7363	15.4686
	R^2 Prob.	0.6564	0.7944	0.7285	0.9528	0.9868
1. Period	**EGARCH (3,2)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.0383	0.3246	0.2792	0.6463	0.5973
	F stat. Prob.	0.8449	0.8983	0.9857	0.8790	0.9582
	Obs. R^2	0.0383	1.6307	2.8169	13.0381	18.1767
	R^2 Prob.	0.8447	0.8975	0.9854	0.8757	0.9556
	EGARCH (3,3)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.3443	0.2581	0.1995	0.3458	0.4998
	F stat. Prob.	0.5575	0.9358	0.9963	0.9968	0.9891
	Obs. R^2	0.3449	1.2970	2.0147	7.0227	15.2582
	R^2 Prob.	0.5570	0.9352	0.9962	0.9966	0.9882

Table 9 (Continued): Heteroskedasticity Test Results for Volatility Models

2. Period	**EGARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	3.1585	1.3868	1.4234	0.8746	0.8136
	F stat. Prob.	0.0758	0.2265	0.1642	0.6206	0.7514
	Obs. R^2	3.1554	6.9285	14.1957	17.5448	24.5503
	R^2 Prob.	0.0757	0.2260	0.1643	0.6174	0.7466
	EGARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.7443	1.0427	1.1454	0.7251	0.6954
	F stat. Prob.	0.3884	0.3909	0.3244	0.8030	0.8901
	Obs. R^2	0.7451	5.2171	11.4505	14.5833	21.0490
	R^2 Prob.	0.3880	0.3900	0.3235	0.7997	0.8863
3. Period	**EGARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	1.5279	1.0063	0.8148	0.6543	0.5816
	F stat. Prob.	0.2170	0.4133	0.6144	0.8705	0.9638
	Obs. R^2	1.5294	5.0418	8.1983	13.3143	17.9883
	R^2 Prob.	0.2162	0.4108	0.6095	0.8635	0.9587
	EGARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.2164	0.5222	0.6737	0.5811	0.5069
	F stat. Prob.	0.6420	0.7595	0.7491	0.9258	0.9871
	Obs. R^2	0.2172	2.6301	6.7991	11.8646	15.7597
	R^2 Prob.	0.6412	0.7568	0.7443	0.9207	0.9847
1. Period	**PARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.0220	0.2410	0.2040	0.4147	0.4608
	F stat. Prob.	0.8821	0.9443	0.9960	0.9894	0.9945
	Obs. R^2	0.0220	1.2113	2.0602	8.4076	14.0861
	R^2 Prob.	0.8819	0.9438	0.9959	0.9888	0.9940
	PARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	0.0118	0.2124	0.1669	0.3653	0.4366
	F stat. Prob.	0.9132	0.9573	0.9983	0.9954	0.9966
	Obs. R^2	0.0119	1.0679	1.6860	7.4139	13.3561
	R^2 Prob.	0.9131	0.9569	0.9982	0.9951	0.9962
2. Period	**PARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	2.3379	0.9533	1.0186	0.7070	0.6833
	F stat. Prob.	0.1265	0.4455	0.4251	0.8220	0.9009
	Obs. R^2	2.3372	4.7716	10.1935	14.2253	20.6858
	R^2 Prob.	0.1263	0.4444	0.4237	0.8189	0.8974
	PARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	1.2484	0.8029	1.1257	0.7318	0.7056
	F stat. Prob.	0.2641	0.5475	0.3390	0.7956	0.8804
	Obs. R^2	1.2492	4.0215	11.2548	14.7172	21.3518
	R^2 Prob.	0.2637	0.5463	0.3380	0.7924	0.8766
3. Period	**PARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	1.9858	0.9482	0.7431	0.6026	0.6033
	F stat. Prob.	0.1594	0.4494	0.6837	0.9115	0.9534
	Obs. R^2	1.9859	4.7535	7.4885	12.2900	18.6309
	R^2 Prob.	0.1588	0.4467	0.6787	0.9057	0.9474
	PARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	F stat.	1.2647	0.6952	0.7459	0.5756	0.6779
	F stat. Prob.	0.2613	0.6273	0.6810	0.9293	0.9024
	Obs. R^2	1.2664	3.4946	7.5162	11.7539	20.8292
	R^2 Prob.	0.2604	0.6242	0.676	0.9243	0.8932
1. Period	**EGARCH (3,2)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	AC	-0.006	0.029	0.008	-0.018	-0.022
	PAC	-0.006	0.029	0.007	-0.018	-0.015
	Q.Stat.	0.0293	1.2686	2.3106	10.996	17.146
	Prob.	0.864	0.938	0.993	0.946	0.971
	EGARCH (3,3)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	AC	0.014	-0.015	-0.018	0.009	-0.016
	PAC	0.014	-0.014	-0.017	0.009	-0.014
	Q.Stat.	0.1830	0.6809	1.1647	3.7260	7.8501
	Prob.	0.669	0.984	1.000	1.000	1.000

Table 9 (Continued): Heteroskedasticity Test Results for Volatility Models

	EGARCH (1,1)	Lag.1	Lag.5	Lag.10	Lag.20	Lag30
2. Period	AC	0.052	-0.013	0.021	-0.005	0.015
	PAC	0.052	-0.007	0.010	-0.008	0.016
	Q.Stat.	3.165	7.2365	15.372	18.490	25.306
	Prob.	0.075	0.204	0.119	0.555	0.710
	EGARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	AC	0.025	-0.007	0.008	-0.004	0.001
	PAC	0.025	-0.003	0.001	-0.007	0.003
	Q.Stat.	0.7474	5.2142	11.692	14.562	20.702
	Prob.	0.387	0.390	0.306	0.801	0.897
3. Period	**EGARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	AC	0.056	0.039	0.0160	0.059	-0.006
	PAC	0.056	0.034	0.011	0.054	-0.010
	Q.Stat.	1.5410	5.5241	9.9517	16.333	20.600
	Prob.	0.214	0.355	0.445	0.696	0.900
	EGARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	AC	0.021	0.041	0.025	0.053	-0.010
	PAC	0.021	0.038	0.020	0.049	-0.010
	Q.Stat.	0.218	2.9679	7.7352	14.171	17.373
	Prob.	0.640	0.705	0.655	0.822	0.968

According to Table 9, for ARCH (1) model we can see that null hypothesis can be rejected at %10 significancy level which is resudials are heteroskedastic at first lag and first period. Residuals are also heteroskedastic in fifth, tenth, twentieth even in thirtieth lag at the first period. ARCH (2) model also suffer from heteroskedasticty. At the second and third periods have same problem according to ARCH (1) and ARCH (2) models. ARCH (3) model's residuals are also heteroskedastic in the second period at tenth, twentieth even in thirtieth lag. Heteroskedasticity test have been done for all models in table 9 but this occupy lots of place. Therefore, autocorrelation results have reported for only selected models.

Table 10: Autocorrelation Test Results for Selected Models

	EGARCH (3,2)	Lag.1	Lag.5	Lag.10	Lag.20	Lag30
1. Period	AC	-0.006	0.029	0.008	-0.018	-0.022
	PAC	-0.006	0.029	0.007	-0.018	-0.015
	Q.Stat.	0.0293	1.2686	2.3106	10.996	17.146
	Prob.	0.864	0.938	0.993	0.946	0.971
	EGARCH (3,3)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	AC	0.014	-0.015	-0.018	0.009	-0.016
	PAC	0.014	-0.014	-0.017	0.009	-0.014
	Q.Stat.	0.1830	0.6809	1.1647	3.7260	7.8501
	Prob.	0.669	0.984	1.000	1.000	1.000
2. Period	**EGARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	AC	0.052	-0.013	0.021	-0.005	0.015
	PAC	0.052	-0.007	0.010	-0.008	0.016
	Q.Stat.	3.165	7.2365	15.372	18.490	25.306
	Prob.	0.075	0.204	0.119	0.555	0.710
	EGARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	AC	0.025	-0.007	0.008	-0.004	0.001
	PAC	0.025	-0.003	0.001	-0.007	0.003
	Q.Stat.	0.7474	5.2142	11.692	14.562	20.702
	Prob.	0.387	0.390	0.306	0.801	0.897
3. Period	**EGARCH (1,1)**	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	AC	0.056	0.039	0.0160	0.059	-0.006
	PAC	0.056	0.034	0.011	0.054	-0.010
	Q.Stat.	1.5410	5.5241	9.9517	16.333	20.600
	Prob.	0.214	0.355	0.445	0.696	0.900
	EGARCH (1,2)	**Lag.1**	**Lag.5**	**Lag.10**	**Lag.20**	**Lag30**
	AC	0.021	0.041	0.025	0.053	-0.010
	PAC	0.021	0.038	0.020	0.049	-0.010
	Q.Stat.	0.218	2.9679	7.7352	14.171	17.373
	Prob.	0.640	0.705	0.655	0.822	0.968

All tests had been done for volatility models in Table 9 and Table 10 Only ARCH (1) and ARCH (2) models have autocorrelation and heteroskedasticity problems for according to selected lags. Other tried models' residuals have not heteroskedasticity and autocorrelation problems. According to determine the most suitable model for volatility modeling Theil Inequality Coefficient (TIC), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values calculated. The best models for return series have been selected both parameter significancy and prediction fitness.

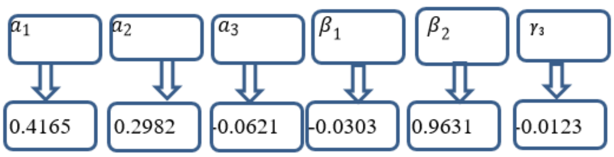
When the calculated TIC coefficients are evaluated in Table 11, smallest theil value is the main criteria for periods. Also small RMSE and MAE criterias important for some situations The EGARCH (3,2) model It has been determined as the most suitable model for the first period. EGARCH (1,2) is the most suitable model for the second period. GARCH (1,1) is the most suitable model for the last period.

Table 11: Results of Volatility Models' Comparison

Periods	Models	TIC	RMSE	MAE
1. Period	ARCH (1)	0.8824	0.4828	0.3101
	ARCH (2)	0.9962	18.0496	8.5107
	ARCH (3)	0.9651	0.0662	0.0371
	GARCH (1,1)	0.9509	0.0662	0.0371
	GARCH (1,2)	0.9553	0.0662	0.0371
	TGARCH (1,1)	0.9567	0.0662	0.0371
	TGARCH (1,2)	0.9353	0.0663	0.0371
	EGARCH (1,1)	0.9765	0.0664	0.0369
	EGARCH (1,2)	0.9788	0.0664	0.0369
	EGARCH (2,1)	0.7994	0.0716	0.0462
	EGARCH (2,2)	0.9785	0.0664	0.0369
	EGARCH (2,3)	0.9662	0.0662	0.0370
	EGARCH (3,2)	0.9626	0.0663	0.0372
	EGARCH (3,3)	0.9626	0.0663	0.0372
	PARCH (1,1)	0.9698	0.0665	0.0369
	PARCH (1,2)	0.9758	0.0663	0.0370
2. Period	ARCH (1)	0.9331	0.0386	0.0233
	ARCH (2)	0.9360	0.0387	0.0234
	ARCH (3)	0.9385	0.0387	0.0233
	GARCH (1,1)	0.9149	0.0386	0.0232
	GARCH (1,2)	0.9149	0.0386	0.0232
	TGARCH (1,1)	0.9163	0.0386	0.0232
	TGARCH (1,2)	0.9161	0.0386	0.0232
	EGARCH (1,1)	0.8698	0.0382	0.0230
	EGARCH (1,2)	0.8670	0.0382	0.0231
	PARCH (1,1)	0.9163	0.0386	0.0232
	PARCH (1,2)	0.9096	0.0387	0.0234
3. Period	ARCH (1)	0.8525	0.0509	0.0359
	ARCH (2)	0.8253	0.0509	0.0357
	ARCH (3)	0.8336	0.0510	0.0362
	GARCH (1,1)	0.8158	0.0506	0.0360
	GARCH (1,2)	0.8345	0.0509	0.0357
	TGARCH (1,1)	0.8398	0.0508	0.0357
	TGARCH (1,2)	0.8444	0.0508	0.0357
	EGARCH (1,1)	0.8462	0.0508	0.0357
	EGARCH (1,2)	0.8470	0.0510	0.0358
	PARCH (1,1)	0.8695	0.0511	0.0361
	PARCH (1,2)	0.8914	0.0514	0.0361

The coefficients for the EGARCH (3, 2) model in the first period were calculated as follows.

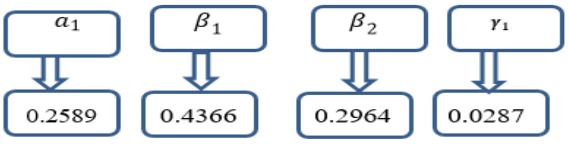
Model 1: Calculated Results in the First Period



Leverage parameter is statistically insignificant for EGARCH (2, 1) model in the first period. There is an asymmetric effect in the first period. So negative shock has more effect than positive shock in this period. We can say that first period of bitcoin volatility dependent of market news.

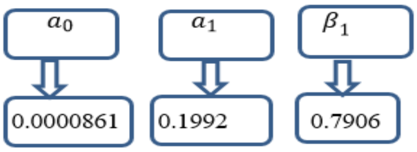
The coefficients for the EGARCH (1, 2) model in the second period were calculated as follows.

Model 2: Calculated Results in the Second Period



Leverage parameter is statistically insignificant for EGARCH (1, 2) model in the second period. There is no asymmetric effect in the second period. So positive and negative shocks have same effect in this period. The effect of the shock on the bitcoin return series last for approximately 85.22 days in the second period.

Model 3: Calculated Results in the Third Period



Last period suits GARCH (1,1) model. The sum of coefficients of GARCH (1,1) parameters is 0,9898. Volatility shocks have temprorary effect on bitcoin return series in last period. Affecting of bitcoin return series schocks has %19.92 of past shocks while %79.06 caused a previous period shocks. (a_1 + β_1) measurement is an indicator of volatility persistence.

HL (halflife) indicator can be calculated with HL= ln(0.5) /ln (a_1 + β_1) formulas. HL measurement shows period of shock and also shows recovery from shock (Topaloğlu, 2020: 33). The effect of the shock on the bitcoin return series last for approximately 67.61 days in the last period.

In the first period there is an asymmetric effect bitcoin return series sensitive to market news. In the second period bitcoin return series have high volatility because a shock has been continued approximately 3 months and there is not any asymmetric affect. In the last period volatility more temporary than second period so the effect of the shock on the bitcoin return series last for approximately 67.61 days.

5. RESULTS AND DISCUSSION

Bitcoin returns have an asymmetric effect in the first period so it is sensitive to market news. Bitcoin returns depend on market news at the first period. As a result of the speculative flows occurred between the dates, 10.02.2011- 02.10.2013, which Bitcoin has started to draw attention for the first time and it is relatively calm than other periods. Second period have not any asymmetric affect, also have the highest volatility persistence. Thus, half-life indicator shows that effect of the shock on the bitcoin return series last for approximately 85.22 days in the second period. In this framework, the observed return series reached very high volatility levels and cause negative impacts on the consistency of the model in the second period. Last period is relatively calm than second period because the effect of the shock on the bitcoin return series last for approximately 67.61 days. There is not any asymmetric affect have been found in the last period. The return behaviours of bitcoin in the given periods caused to the permanence of volatility which was identified in the model. The return volatility of bitcoin was high and close to be non-stationary in ARCH modelling. The given situation may stem from the fact that virtual currency rates are not accepted by many countries and do not have an advanced market. Bitcoin, which is not accepted in many countries and traded in a relatively narrow market in comparison to the acknowledged currencies of developed countries, has become successful in the recent period in terms of having a -relatively- predictable volatility but still a risky asset for investors.

As a result, investors who enjoy risk may follow the recent development in virtual currencies and include bitcoin in their basket with predictable volatilities. The inclusion of bitcoin by investors in their portfolio will reduce the portfolio risk of bitcoin which is not associated with other investment tools.

Ethics Statement: *In this study, no method requiring the permission of the "Ethics Committee" was used*
Author Contributions Statement: *1st author's contribution rate 50%, 2nd author's contribution rate 50%.*
Conflict of Interest: *There is no conflict of interest among the authors.*

Etik Beyan: *Bu çalışmada "Etik Kurul" izini alınmasını gerektiren bir yöntem kullanılmamıştır.*
Yazar Katkı Beyanı:*1. Yazarın katkı oranı %50, 2. Yazarın katkı oranı ise %50' dir.*
Çıkar Beyanı: *Yazarlar arasında çıkar çatışması yoktur.*

REFERENCES

Atik, M., Köse, Y., Yılmaz, B., & Sağlam, F. (2015). Kripto para: Bitcoin ve döviz kurları üzerine etkileri. *Bartın Üniversity İİBF Journal*, *6*(11), 247-262. http://abs.kafkas.edu.tr/upload/357/11_sayi_bartin_univ__iibf_dergisi.pdf

Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar-A replication and extension. *Finance Research Letters*, *25*, 103-110. https://doi.org/10.1016/j.frl.2017.10.012

Baur, D. G., Hong, Ki-H., & Lee, A. D. (2017). Bitcoin: Medium of exchange or speculative assets?. *Journal of International Financial Markets. Institutions and Money*, *54*, 177-189. https://www.sciencedirect.com/science/article/abs/pii/S1042443117300720?casa_token=OhBXjgoI7uEAAAAA:xzpqdhhW0WdtCoeenG60g9axO6SA2geaDKfzQsxQV0EhfkEx_Buq-4CDoRzkDJNyOkOerpn

Bera, A. K., & Higgins, M. L. (1993). ARCH models: Properties, estimation and testing. *Journal of Economic Surveys*, 7(4), 305-366. https://www.onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-6419.1993.tb00170.x

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307-327. https://www.sciencedirect.com/science/article/abs/pii/0304407686900631

Bouri, E., Azzi, G., & Dyhrberg, A. H. (2016). On the return-volatility relationship in the Bitcoin market around the price crash of 2013. *Economics Discussion Papers*, (41), https://ideas.repec.org/p/zbw/ifwedp/201641.html

Brooks, C. (2014). *Introductory econometrics for finance*. Cambridge University Press. https://www.scirp.org/reference/ReferencesPapers.aspx?ReferenceID=2271775

Chaim, P., & Laurini, M. P. (2018). Volatility and return jumpsin bitcoin. *Economics Letters*, *173*, 158-163. https://doi.org/10.1016/j.econlet.2018.10.011

Christopher, C. M. (2013). Whack-A-Mole: Why prosecuting digital currency exchanges won't stop online money laundering. *Social Science Research Network*, http://ssrn.com/abstract=2312787

Coindesk. (2018). *Bitcoin price*. https://www.coindesk.com/price/bitcoin

Cutcu, I., & Kılıc, Y. (2018). Döviz kurları ile Bitcoin fiyatları arasındaki ilişki: Yapısal kırılmalı zaman serisi analizi. *Yönetim ve Ekonomi Araştırmaları Dergisi, 16*(4), 349-366. https://doi.org/10.11611/yead.474993

DeMartino, I. (2018). *The bitcoin guidebook: How to obtain, invest and spend the world?, First decentralized cryptocurrency*. New York; Skyhorse Publishing. (Revised Ed.). https://www.torontopubliclibrary.ca/detail.jsp?R=3371138

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar-A GARCH volatility analysis. *Finance Research Letters, 16*, 85-92. https://www.sciencedirect.com/science/article/abs/pii/S1544612315001038

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, *50*(4), 987-1007. https://ideas.repec.org/a/ecm/emetrp/v50y1982i4p987-1007.html

Gemici, E., & Polat, M. (2019). Relationship between price and volume in the Bitcoin market, *Journal of Risk Finance, Emerald Group Publishing*, *20*(5), 435-444. https://ideas.repec.org/a/eme/jrfpps/jrf-07-2018-0111.html

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M., & Siering, M. (2014). Bitcoin-asset or currency?. *Revealing Users' Hidden Intentions.* https://www.scirp.org/reference/ReferencesPapers.aspx?ReferenceID=2313124

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economic Letters, 158*, 3-6. https://econpapers.repec.org/article/eeeecolet/v_3a158_3ay_3a2017_3ai_3ac_3ap_3a3-6.htm

Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters, 29*, https://doi.org/10.1016/j.frl.2019.03.009

Kocoglu, Ş., Çevik, Y. E., & Tanrıöven, C. (2016). Bitcoin piyasalarının etkinliği, likiditesi ve oynaklığı. *Journal of Business Studies*, *8*(2), 77-97. https://doi.org/10.20491/isarder.2016.170

Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system*. http://bitcoin.org/bitcoin.pdf

Quandll. (2018). *Euro-Dollar*. https://www.quandl.com/data/ECB/EURUSD-EUR-vs-USD-Foreign-Exchange-Reference-Rate

Rodrigue, J. P. (2011). Factors impacting North American freight distribution in view of the Panama canal expansion. *Horne Institut Van*, http://people.hofstra.edu/jeanpaul_rodrigue/downloads/Panama%20Canal%20Study%202011%20Final.pdf

Szetela, B., Mentel G., & Gedek S. (2016). Dependency analysis between Bitcoin and selected global currencies. *Dynamic Econometric Models*, *16*, 133-144. https://ideas.repec.org/a/cpn/umkdem/v16y2016p133-144.html

Topaloglu, E. E. (2020). Borsa İstanbul pay endekslerinin volatilite yapısı ve volatilite yayılımı: GARCH ve MGARCH modelleri ile BIST sınai ve mali endeksleri örneği. dergipark.org.tr/tr/pub/dpusbe/issue/51845/568128

Tsay, R. S. (2010). *Analysis of financial time series*. John Wiley & Sons, Inc. https://www.scirp.org/(S(oyulxb452alnt1aej1nfow45))/reference/referencespapers.aspx?referenceid=2848858

Yermarck, D. (2013). *Is bitcoin a real currency? An economic appraisal*, NBER Working Paper Series, Working Paper 19747, National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w19747/w19747.pdf