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The relationship between Bitcoin, gold and foreign exchange returns: The case of Turkey *

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Abstract. This study focuses on the dollar, euro, gold, bitcoin and the impact of bubbles in financial investment instruments on bitcoin returns in the context of Turkey. The causal relationships (using the Toda-Yamamato causality test) between the returns of these financial instruments were also determined. In performing this assessment, the sup augmented Dickey-Fuller (SADF) and generalised SADF (GSADF) tests were employed to determine the existence of bubbles based on the period from 1 August 2018 to 23 March 2018. The volatility of bitcoin was tested by autoregressive conditional variant models. As aresult, it was shown that the observed bubbles in gold's, the euro's and the dollar's returns reduced the volatility of bitcoin's returns. Then, it was shown that the dollar's, the euro's and gold's returns affected bitcoin's returns.

Keywords. Speculative bubbles, Bitcoin, Investment instruments, Autoregressive conditional heteroskedasticity models, Toda-Yamamato causality.

JEL. G10, C58, E44.

1. Introduction

A bubble is the rapid increase in the price of an asset unrelated to the asset's actual value because of an economic entity's speculative activity, leading to a crisis (Diba & Grosman, 1998; Garber, 2000). Situations that can lead to bubbles occur when the price of an asset exceeds its core value, which occurs when the expected value of the cash flows that the related asset can generate are not considered. In addition, bubbles occur when the processing direction of high-value assets subject to commercial transactions is changed regardless of the normal market conditions during expansion and contraction periods of the economy (Phillips & Yu, 2011: 459-460). Recently, bitcoin bubbles have been characterised in such terms.

Introduced in 2008 by a group of programmers, bitcoin is a virtual currency that is derived from mathematical encryption and was designed as an alternative to government-supported currencies. The 2008 crisis and its subsequent effects were the inspiration for this currency's emergence. The weaknesses and deficiencies of the existing financial system became more evident with the 2008 financial crisis, and many countries' currencies started to depreciate. The generation of a virtual currency not connected to a central authority is considered to be an alternative to the existing financial infrastructure based on banking, credit cards and other payment networks. Initially, bitcoin prices were predicted to be relatively stable due to the structure of the digital 'mining' processes (Cheah & Fry, 2015:32). The question of whether bitcoin and other virtual currencies are a speculative investment or a currency is still being discussed. Money must be a tool for exchange, a means of preserving value and a unit of account. In this context, bitcoin functions as money as a means of investment and saving, but the fact that

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bitcoin is not subject to legal regulations and is not controlled by a central authority distinguishes it from traditional money (Wandhöfer, 2017: 248, Bariviera *et al.,* 2017:82). Since bitcoin was first introduced by Nakamoto (2008), there has been considerable interest among policy makers, investors and economists. In this context, many studies have been done on the cryptocurrency market.

For example, Kristoufek (2013) examined the factors affecting bitcoin prices and stated that bitcoin was not speculative. The prevalence of its use in trade, its supply quantity and its price level were used as factors affecting the price of bitcoin. He stated that bitcoin is still not financially safe in view of the extreme decreases and increases it has experienced. MacDonell (2014) identified a bitcoin bubble in 2013 in a study on crypto currencies. This bubble came about because the number of trustable bitcoin platforms waslow, and bitcoin was traded on the black market. In addition, bitcoin's high price volatility was related to speculation in the market. Using robust econometric methods, Cheung *et al.,* (2015), explored the presence of bubbles in the bitcoin market and stated that there were bubbles between 2010 and 2013. This suggested that the Mt. Gox market could collapse due to the bubbles. Cheah & Fry (2015) investigated the existence of a short-term relationship between bitcoin and exchange rates and speculative bubbles in bitcoin's returns. The result of the study showed that bitcoin had grown speculatively and hada tendency to form bubbles. Dyhberg (2015) exploited the asymmetric GARCH model in his study and investigated the financial properties of bitcoin. They suggested that bitcoin can be attractive to risky investors and that bitcoin has similarities to gold and the dollar in some respects. It was also observed that bitcoin's value is more sensitive against the British pound/dollar parity than the euro/dollar parity.

Atik *et al.,* (2015) investigated the relationship between the euro, pound, Japanese yen, Canadian dollar, Australian dollar and Swiss franc cross-currency exchange rates and the bitcoin daily exchange rates through the Johansen cointegration and Granger causality tests from the period between June of 2009 and February of 2015. As a result of the study, it was concluded that there is a long-term relationship between the variables and that only the yen is a Granger-cause of bitcoin. Baek & Elbeck (2015) used the daily return series of bitcoin and the S&P 500 index as a data set. In this study, they tried to determine whether bitcoin was speculative or not. They found that the bitcoin market was 26 times more volatile than the S&P 500, and they concluded that bitcoin was indeed speculative. Hencic & Gourieroux (2015) used a bitcoin price series consisting of 150 observations between 20 February 2013 and 20 July 2013 as a data set. According to the model they created, there were speculative bubbles in prices, and the bitcoin market was subject to a very high number of speculative transactions.

Szetela *et al.,* (2016) explored the relationship between bitcoin and the dollar, euro, pound, Chinese yuan and Polish zloty using the GARCH volatility model. It was determined that there was a relationship between bitcoin and the dollar, euro and yuan in the study. Koçoğlu *et al.,* (2016) selected eight different cryptocurrency markets including Bitfinex, Bitstamp, Mt.Gox, BTC-e, OkCoin, Kraken, ANX and Coinfloor. They investigated the relationship between the selected cryptocurrency markets and the dollar, euro, pound, yen, yuan and gold prices through a Pearson correlation matrix and the Johansen cointegration and Granger causality tests. When the results of the Pearson correlation matrix wereexamined, the researchers concluded that bitcoin had no significant relationship with the other currencies in the study.In addition, they determined that there was a long-term relationship between the Bitfinex, Bitstamp and the Budget cryptocurrency markets. Bhattacahjee (2016) compared the fluctuations in the dollar, euro and ruble currencies with bitcoin fluctuations. According to the study results, bitcoin fluctuated much more than other currencies. Astudy by Hepkorucu & Genç (2017) examined bitcoin prices through Fourier and standard augmented Dickey-Fuller (ADF) methods, and the bitcoin prices were found to be non-stationary according to both methods. According to both methods, they found that the variable was not stable. Moreover, they suggested that the price of bitcoin should be determined by the shocks entering the market.

Balcılar *et al.,* (2017) examined the causality relationship between bitcoin's transaction volume, returns and volatility. The study took into account the period between 19 December 2011 and 25 April 2016, and the researchers reached the conclusion that bitcoin's transaction volume in bear and bull markets could be used without anticipating the yields. Dulupçu *et al.,* (2017) asserted that bitcoin's price increases over time were due to speculative transactions in direct proportion to their popularity, rather from bitcoin's actual value. To determine this they used variance decomposition analysis and Granger causality testing. The analysis concluded that there is a one-way causality relationship between bitcoin's popularity and its price, where bitcoin's popularity determined its price. İçellioğlu & Öztürk (2018) investigated the relationship between bitcoin and the dollar, euro, yen, pound and yuan through the Engle-Granger and Johansen cointegration tests and the Granger causality test. As a result of the study, it was observed that there was no long-run relationship or causality between the variables.

Baur *et al.,* (2018) examined the relationship between gold, the dollar and bitcoin. According to the GARCH model, bitcoin returns were observed to be independent of other asset returns. In addition, the weekly fluctuation of the dollar/pound exchange rate indicated a slight or even negative relationship. Güleç *et al.,* (2018) found that bitcoin prices hada rising trend and high volatility in their studies, which used the Johansen cointegration and Granger causality tests on monthly data from March 2012 to May 2018. Ceylan *et al.,* (2018) investigated the existence of financial bubbles in bitcoin and ethereum with the generalised sup augmented Dickey-Fuller (GSADF) test. In the study, the bitcoin database was based on the period from 1 January 2015 to 31 March 2018, and the ether database was based on daily data from the period between 2 October 2016 and 31 March 2018. They determined that there were bubbles in the bitcoin and ethercurrencies and that the bubbles were short lived. In addition, their study found that the existence and history of the currencies' respective bubbles suggests that the bubbles were caused by speculative factors.

Karaağaç & Altınırmak (2018) reviewed the daily prices of the bitcoin, ethereum, Ripple XRP, bitcoincash, Ada, litecoin, NEM, NEO, lumens and mIOTA cryptocurrencies for the period between 15 December 2017 and 17 January 2018. The Johansen cointegration and Granger causality tests were used in the study. As a result, they found that Adais the Granger-cause of NEO, bitcoin is the Granger-cause of bitcoincash, litecoin is the Granger-cause of bitcoin cash, NEM is Granger-cause of bitcoincash and XRP is the Granger-cause of bitcoin. In addition, a two-way Granger causality was found between NEO and ether and between NEO and litecoin. NEM was identified as lumens' Granger-cause. The study stated that the price movements of the mentioned variables affect each other in the short term.

There are three main objectives of this study. First of all, this study aims to investigate the existence of bubbles in euro, dollar and bitcoin variables and then determine the effects of volatility in these variables on the bitcoin return using volatility models. In addition, this study examines whether a causal link between these variables exists. The distinguishing characteristics and contribution of this study compared to other studies on the subject can be summarised as follows:

- This study investigates the presence of bubbles for gold, bitcoin, the euro and the dollar, and it examines and emphasises the effect of the detected bubbles on bitcoin.
- It investigates the relationship between gold, the euro and the dollar and bitcoin using two different methods. The volatility models and causality analysis have been employed in this study to investigate relationship amaong the return of financial instruments and currencies which are gold, dollar, euro and bitcoin.

- There have been no studies towards the stated research goals in the context of Turkey. Therefore, this study aims to eliminate this deficiency in the literature.

The rest of this paper is organised as follows. Section 2 presents a description of the data. Section 3 outlines the models to be compared. Section 4 presents the empirical results obtained from the model comparison. Finally Section 5 summarises this paper's conclusions.

2. Data set

We analysed the period from 1 August 2011 to 23 March 2018. The daily data were collected from [Retrieved from], Central Bank of Trinidad and Tobago and the World Gold Council databases for a total of 1,724 full observations. The details of the data variables are shown in Table 1.

Table 1. *Variables*

Variable	Description
GOLD	Gold Prices Per Troy Ounce ($)
BITCOIN	Bitcoin Prices ($)
DOLLAR	TL/$Purchase Price
EURO	TL/€ Purchase Price

In our research, we have taken into the consideration daily logarithmic rate of return for bitcoin, gold, the dollar and the euro. The returns were obtained as follows;

$$R = \ln(\frac{X_t}{X_{t-1}}) \quad (1)$$

where x_t refers to the asset price in the period *t*. Here, the return variables are defined as RGOLD, RBITCOIN, REURO and RDOLLAR.

Table 2. *Descriptive statistics*

	RGOLD	REURO	RDOLLAR	RBITCOIN
Average	-0.0001	0.0003	0.0004	0.0038
Median	0.0000	0.0000	0.0000	0.0028
Maximum	0.0483	0.0393	0.0389	0.4996
Minimum	-0.0959	-0.0381	-0.0389	-0.4437
Std. deviation	0.0103	0.0064	0.0064	0.0569
Kurtosis	10.5559	7.6954	6.3620	14.2089
Jarque-Bera	4211.408	1585.164	826.5531	9070.296
Prob. value	0.0000***	0.0000***	0.0000***	0.0000***

*, **, and *** represent statistical significance at the levels of 0.10, 0.05, and 0.01

It can be observed that all average return variables, excluding gold, are positive (see Table 2). It was found that the highest return belonged to bitcoin, and the lowest return belonged to gold. Maximum and minimum values indicate that the peak values in bitcoin's return are wider. According to these results, it can be said that the bitcoin variable had the highest return and the highest risk.

3. Methodology

The sup augmented Dickey-Fuller (SADF) test (Phillips, Wu & Yu, 2011) is a repeatable right-tailed unit root test for detecting speculative bubbles (Philips, Shi & Yu, 2014). The test is formulated as follows (Phillips, Shi & Yu, 2013):

$$x_t = \mu_x + \delta x_{t-1} + \sum_{j=1}^{J} \emptyset_j \Delta x_{t-j} + \varepsilon_{x,t} \, , \varepsilon_{x,t} \sim NID(0, \sigma_x^2) \quad (2)$$

In the SADF and GSADF unit root tests, the test hypotheses are defined as follows: $H_0 = \delta = 1 \, , H_1 = \delta > 1$.

The model is repeatedly estimated using recursive sub-clusters of replicate observations at each pass in replicate regressions (Philips, Wu & Yu, 2011). In the case where there are multiple speculative bubbles in the analysis data period, the SADF test statistic loses meaning. In such a case, the GSADF test, developed by Philips, Shi & Yu (2015; PSY), is used. Unlike the SADF test, the sub-clusters are much more comprehensive in the GSADF test (Phillips, Shi & Yu, 2015: 10). While the GSADF test is calculated, the simple regression equation from which the standard ADF test is derived using recursive flexible forecasting windows. Thus, considering the analysis of the long-run time series and the structural breaks can provide more consistent and accurate results in situations where more than one speculative bubble may be encountered during aperiod.

According to the PSY approach, the basic hypothesis is that the price P_t follows a random walk with an asymptotically negligible shift. The equation for the random walk process is as follows:

$$P = dT^{-\eta} + \theta P_{t-1} + \varepsilon_t, \theta = 1 \tag{3}$$

According to the above equation, d is constant, T and$\eta > 1/2$ the number of observations and ε_t is an independent and identically distributed error term. If $\theta > 1$, then the hypothesis that there are bubbles at prices is accepted.

The variables $r_1$andr_2 are the start and end points of the sample, and the regression model is as follows:

$$\Delta P_t = \alpha_{r1,r2} + \beta_{r1,r2} P_{t-1} + \sum_{i=1}^{k} \gamma_{r1,r2} + \varepsilon_t, \varepsilon_t \sim i.i.d\ (0, \sigma_{r1,r2^2}) \tag{4}$$

Here, $\Delta P_t = P_t - P_{t-1}$, and k is the lag length. The standard ADF statistic is calculated as $ADF_{r1,r2} = \beta_{r1,r2}/se(\beta_{r1,r2})$ (Ceylan 2018: 209-210). The SADF and GSADF tests can be expressed by expanding the sub-sample's starting r_1 and ending r_2 points of the repeated right-tailed ADF test as follows:

$$sup_{r\epsilon[r_0,1]} ADF_r \rightarrow sup_{r\epsilon[r_0,1]} \frac{\int_0^r \widetilde{W} dW}{\left(\int_0^r \widetilde{W}^2\right)^{1/2}}, \tag{5}$$

$$GSADF(r_0) = sup_{r2\in[0,r2-r0]}^{r1\in[r0,1]} \left\{ADF_{r1,r2}\right\} \tag{6}$$

Here, $ADF_r \rightarrow \frac{\int_0^r \widetilde{W} dW}{\left(\int_0^r \widetilde{W}^2\right)^{1/2}}$, W is the standard Brownian process and $\widetilde{W}(r) = W(r) - \frac{1}{r}\int_0^1 W$refers to the descending Brownian process. The asymptotic critical values of the test statistic are obtained from Monte Carlo simulations. If the basic hypothesis is rejected, it is decided that bubbles exist.

After detecting the presence of the bubbles, backward SADF (BSADF) statistical sequences are used to determine the periods of the existing bubbles. BSADF sequences are obtained by right-tailed ADF tests on backward-extending samples.

The BSADF statistic, with the ADF statistic sequence $\left\{ADF_{r1,r2}\right\}_{r1\in[0,r2-r0]}$ is calculated for sub-samples ranging from the start 0 to r_2-r_1 with the constant end point r_2 as follows:

$$BSADF_{r2}(r_0) = sup_{r1\epsilon[0,r2-r_0]} \left\{ADF_{r1,r2}\right\} \tag{7}$$

The obtained BSADF statistics are determined by comparing the series with the right-tailed critical value sequence of each statistic, which is then calculated by Monte Carlo simulation (Çağlı & Mandacı, 2017:66).

Volatility modelling first began with Engle's (1982) autoregressive conditional heteroskedasticity model (ARCH). Bollerslev (1986) developed the generalized autoregressive conditional heteroskedasticity (GARCH) model to eliminate the variance deficiencies of the ARCH model. In the GARCH model, the conditional variance (*ht*) at time *t* depends not only on the error of the past values of the error terms but also on the conditional variances of the past. The variance of error terms is affected both by their own past values and by their conditional variance values. When the lag length *q* of the error squares and the lag length of the autoregressive part are expressed by *p*, $\omega > 0$, $\alpha_i \geq 0, \beta_j \geq 0, \sum_{j=1}^{p} \beta_j + \sum_{i=1}^{q} \alpha_i < 1$, which is a general GARCH (*p*, *q*) process for these conditions, then GARCH(*p*,*q*),

$$h_t = \omega + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad (8)$$

One of the most important deficiencies of the GARCH model is the assumption that volatility responds to positive and negative shocks symmetrically. However, it is possible that this assumption is not valid, for example, when volatility responds asymmetrically to shocks. While some GARCH models are inadequate in modelling the leverage effect in financial time series, Nelson (1991) developed exponential GARCH (EGARCH) models in order to eliminate this deficit.

$$\log(h_t) = \omega + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}|}{\sqrt{h_{t-i}}} + \sum_{i=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \quad (9)$$

Equation (9) shows a general EGARCH (*p*, *q*) model. In this model, β_j is the GARCH effect, α_i is the ARCH effect and γ_i is theleverage effect.

The existence of a causal relationship between return variables was also investigated in this study. The Toda-Yamamato (1995) causality test was used in this regard. The main reason for choosing this test is that it enables causality to be determined by the Modified Wald (MWald) test by predicting a vector autoregressive regression (VAR) model in which the variables have level values even if they are not stable. This test consists of two parts. In the first part, the VAR (k+d_{max}) model is estimated, and the maximum integration degree (d_{max}) of the existing series in the VAR model and the optimal lag length (k) of the VAR model in which the level values exist are determined. In the second part, the coefficients of the k lag lengths in the estimated VAR ($k + d_{max}$) model are summed to zero, and the proposed null hypothesis is tested by the MWald test to determine the direction of causality (Toda & Yamamoto, 1995).

The Toda-Yamamoto causality models in equations (10), (11), (12) and (13) were used to investigate the existence of acausality relationship between the return variables and to determine the direction of the relationship. It should be noted here that in the causality study, the maximum integration degree (d_{max}) of the variables must be smaller than the lag length (k).

$$RBITCOIN_t = a_0 + \sum_{i=1}^{k} a_{1i} RBITCOIN_{t-i} + \sum_{j=1}^{k+d_{max}} a_{2i} RBITCOIN_{t-i} + \sum_{j=1}^{k} \delta_{1i} RGOLD_{t-i} + \sum_{j=1}^{k+d_{max}} \delta_{2i} RGOLD_{t-i} + \sum_{j=1}^{k} \delta_{3i} RDOLLAR_{t-i} + \sum_{j=1}^{k+d_{max}} \delta_{4i} RDOLAR_{t-i} + \sum_{j=1}^{k} \delta_{5i} REURO_{t-i} + \sum_{j=1}^{k+d_{max}} \delta_{6i} REURO_{t-i} + v_{t1} \quad (10)$$

$$REURO_t = \emptyset_0 + \sum_{i=1}^{k} \emptyset_{1i} REURO_{t-i} + \sum_{j=1}^{k+d_{max}} \emptyset_{2i} REURO_{t-i} + \sum_{j=1}^{k} \mu_{1i} RGOLD_{t-i} + \sum_{j=1}^{k+d_{max}} \mu_{2i} RGOLD_{t-i} + \sum_{j=1}^{k} \mu_{3i} RDOLLAR_{t-i} +$$

$$\sum_{j=1}^{k+d_{max}} \mu_{4i} RDOLLAR_{t-i} + \sum_{j=1}^{k} \mu_{5i} RBITCOIN_{t-i} + \sum_{j=1}^{k+d_{max}} \mu_{6i} RBITCOIN_{t-i} + \upsilon_{t2} \quad (11)$$

$$RDOLLAR_t = \gamma_0 + \sum_{i=1}^{k} \gamma_{1i} RDOLLAR_{t-i} + \sum_{j=1}^{k+d_{max}} \gamma_{2i} RDOLLAR_{t-i} + \sum_{j=1}^{k} \varpi_{1i} REURO_{t-i} + \sum_{j=1}^{k+d_{max}} \varpi_{2i} REURO_{t-i} + \sum_{j=1}^{k} \varpi_{3i} RBTCOIN_{t-i} + \sum_{j=1}^{k+d_{max}} \varpi_{4i} RBITCOIN_{t-i} + \sum_{j=1}^{k} \varpi_{5i} RGOLD_{t-i} + \sum_{j=1}^{k+d_{max}} \varpi_{6i} RGOLD_{t-i} + \nu_{t3} \quad (12)$$

$$RGOLD_t = \tau_0 + \sum_{i=1}^{k} \tau_{1i} RGOLD_{t-i} + \sum_{j=1}^{k+d_{max}} \tau_{2i} RGOLD_{t-i} + \sum_{j=1}^{k} \eta_{1i} REURO_{t-i} + \sum_{j=1}^{k+d_{max}} \eta_{2i} REURO_{t-i} + \sum_{j=1}^{k} \eta_{3i} RDOLLAR_{t-i} + \sum_{j=1}^{k+d_{max}} \eta_{4i} RDOLLAR_{t-i} + \sum_{j=1}^{k} \eta_{5i} RBITCOIN_{t-i} + \sum_{j=1}^{k+d_{max}} \eta_{6i} RBITCOIN_{t-i} + \nu_{t4} \quad (13)$$

4. Results

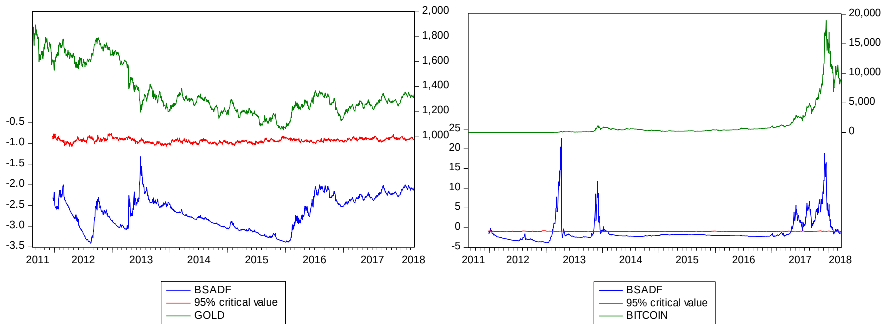
The aim of this study is to investigate the existence of bubbles in bitcoin, gold, the dollar and the euro. The SADF and GSADF methods used in this study are presented in Table 2.

Table 2. *SADF and GSADF test results for financial assets*

	SADF	GSADF		SADF	GSADF
BITCOIN	22.5869***	18.7981***	DOLLAR	0.9409**	1.8574**
90% critical value	1.1066	2.0008	90% critical value	1.1066	2.0008
95% critical value	0.6947	1.6034	95% critical value	0.6947	1.6034
99% critical value	0.4958	1.3979	99% critical value	0.4958	1.3979
	SADF	GSADF		SADF	GSADF
GOLD	-1.3215	0.8212	EURO	1.3491***	1.8667**
90% critical value	1.1066	2.0008	90% critical value	1.1066	2.0008
95% critical value	0.6947	1.6034	95% critical value	0.6947	1.6034
99% critical value	0.4958	1.3979	99% critical value	0.4958	1.3979

Note: Critical values for both tests were obtained from Monte Carlo simulation with 1000 replications. The sample volume is 1724. The minimum volume is 92. *, **, and *** represent statistical significance at the levels of 0.10, 0.05, and 0.01.

Table 2 shows that excluding gold, the assets exceeded the right-tailed critical values of 5% for the dollar variable and 1% for the euro and bitcoin variables. This means that the existence of bubbles is rejected and that the existence of bubbles in the euro and dollar is confirmed. For each observation, 1,000 replications of a Monte Carlo simulation's 95% critical value results and SADF test statistics were also compared to identify bubbles periods.



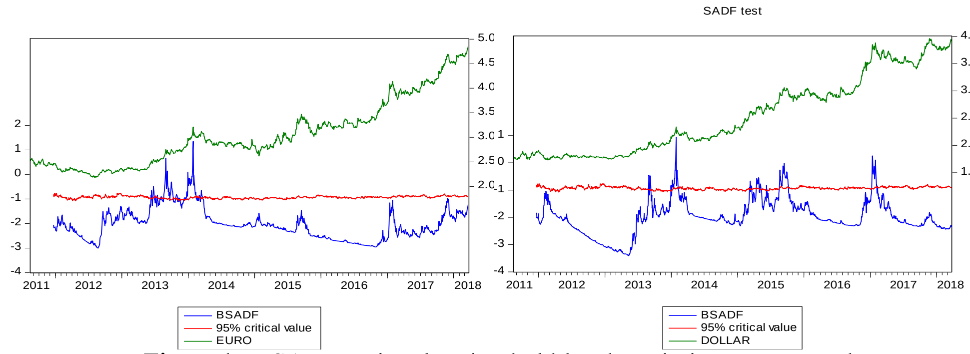


Figure 1. *BSADF series showing bubbles dates in investment tools*

Figure 1 presents the BSADF sequences, which represent bubble periods for the bitcoin, gold, dollar and euro variables. This shows the bubble dates observed in the prices of the investment instruments. The SADF test results show the presence of bubbles in the considered variables except for gold. The bubble dates were determined via the graph obtained from the SADF test. Accordingly, bubble dates can be specified if the corresponding variable is above the 95% critical value. The periods above the critical value indicate bubbles dates. Since bubbles were not observed in gold, the bubble dates of other variables except for gold are reported in Table 3in detail.

Table 3. *Bubble dates*

EURO		DOLLAR		BITCOIN	
Start of Bubbles	End of Bubbles	Start of Bubbles	End of Bubbles	Start of Bubbles	End of Bubbles
10/5/2013	15/7/2013	12/8/2013	3/09/2013	15/1/2013	25/3/2013
5/8/2013	28/10/2013	30/12/2013	18/2/2014	12/3/2013	26/4/2013
13/12/2013	14/3/2013	4/3/2015	13/3/2015	23/10/2013	3/2/2014
		14/4/2015	20/5/2015	3/5/2017	30/1/2018
		10/6/2015	16/6/2015	23/2/2018	28/2/2018
		19/8/2015-	19/10/2015		
		26/12/2016	9/2/2017		

The longest period of the bubble effect occurred in the bitcoin variable between 3 June 2017 and 30 January 2018. It can be seen that the results from the Figure 1 and Table 3and the year 2013 and 2015wasfull of bubbles for the euro and dollar, respectively. As seen in Table 3 and Figure 1, bitcoin was continuously in a bubble starting from April of 2017 until the end of February 2018.

The stationary assumption was verified by the ADF and Philips-Perron (PP) unit root tests. The test results presented in Table 4 show that in all cases, the ADF and PP tests were able to reject the null hypothesis of the appearance of a unit root, proving all of the included variables were stationary.

Table 4. *Unit root test results for level values [I(0)]*

Variables	Tests	Constant	Constant and Trend
RGOLD	ADF	-42.1795***	-42.1937***
	PP	-42.2223***	-42.2449***
REURO	ADF	-38.6512***	-38.7808***
	PP	-38.7877***	-38.8548***
RDOLLAR	ADF	-40.0904***	-40.1340***
	PP	-40.1536***	-40.1728***
RBITCOIN	ADF	-40.4898***	-40.4857***
	PP	-40.8083***	-40.8009***

Note: The number of lags is determined by the Schwarz Information Criteria (SIC) for the ADF unit root test and the Newey-West expansion band for the Philips-Perron unit root test. In the ADF unit root test, the maximum number of lags was taken as 28. *, **, and *** represent statistical significance at the levels of 0.10, 0.05, and 0.01.

For the adopted order of model *p* and *q*, selected by the smallest value of the corrected Akaike information criterion, the ARMA model parameters were estimated, and the results are presented in Table 5. The Lagrange multiplier test was used to detect ARCH effects in the residuals. The highly significant *p*-value (<0.0001) points to rejecting the null hypothesis, which indicates the existence of an autocorrelation in the residuals.

Table 5. *ARMA (4,2) model*

Dependent Variable: RBITCOIN				
Variable	Coefficient	Std.Error	t-statistics	p-value
Constant	0.0003	0.0015	2.5074	0.0123**
AR(1)	-0.8126	0.1075	-7.5533	0.0000***
AR(2)	-0.6328	9.0941	-6.7183	0.0000***
AR(3)	0.0815	0.0148	5.4799	0.0000***
AR(4)	0.0873	0.0166	5.2450	0.0000***
MA(1)	0.8406	0.1075	7.8137	0.0000***
MA(2)	0.6900	0.0969	7.1137	0.0000***
SIGMAQ	0.0032	4.56E-05	70.4651	0.0000***
	R^2 = 0.0692	$\bar{R}^2 = 0.0610$	F = 8.3580***	
	AIC= -2.8994	SIC= -2.8709	HQ=-2.8889	
Jarque-Bera test: 7900.344 [0.0000***]		ARCH-LM test: 178.256 [0.0000***]		

Notes: *, **, and *** represent statistical significance at the levels of 0.10, 0.05, and 0.01. Values in square brackets are probability values.

Different GARCH models were estimated to determine the effect of gold's return on bitcoin's return in the study. Based on the smallest value of the information criteria, EGARCH(5,5) was chosen as the model that best fit the data. The results of model[1] are presented in Table 6.

Table 6. *Influence of Gold's return on Bitcoin's return-EGARCH (5,5) model estimation result*

Mean Equation				
	Coefficient	Std. Error	t-statistics	p-value
Constant	0.0282	0.0006	4.0889	0.0000***
AR(1)	0.8351	0.0384	21.7260	0.0000***
AR(2)	0.1033	0.0355	2.9082	0.0036***
AR(3)	-0.0229	0.0194	-1.1803	0.2379
AR(4)	0.0372	0.0149	2.4884	0.0128
MA(1)	-0.8555	0.0370	-23.1188	0.0000***
MA(2)	-0.0694	0.0315	-2.1996	0.0278**
Variance Equation				
	Coefficient	Std. Error	t-statistics	p-value
α_0	-2.7774	0.0946	-29.3303	0.0000***
α_1	0.4207	0.0020	208.8189	0.0000***
α_2	0.4808	0.0025	185.5920	0.0000***
α_3	0.3274	0.0021	150.5009	0.0000***
α_4	0.5031	0.0009	511.2066	0.0000***
α_5	0.3004	0.0132	22.6893	0.0000***
γ_1	0.0181	0.0090	2.0069	0.0448**
β_1	-0.2251	0.0052	-43.1825	0.0000***
β_2	0.2977	0.0033	88.007	0.0000***
β_3	-0.4182	0.0008	-488.9887	0.0000***
β_4	0.2185	0.0080	26.9932	0.0000***
β_5	0.9073	0.0001	8318.789	0.0000***
RGOLD	5.8070	0.6887	8.4315	0.0000***
GED Parameter	0.8533	0.0326	26.1498	0.0000***
R^2 = 0.0030	$\bar{R}^2 = -0.0010$			
AIC= -3.6415	SIC= -3.5722		HQ=-3.6158	
Jarque-Bera test: 6843.261 [0.0000***]			ARCH-LM test: 6.8041[0.703]	

Notes: *, **, and *** represent statistical significance at the levels of 0.10, 0.05, and 0.01. Values in square brackets are probability values.

The increase in gold's return had a positive and significant effect on bitcoin's return. The asymmetry effect of γ_1 was obtained positively, and positive news was

[1]It was found that the EGARCH (5,5) model was the most suitable model in terms of Akaike (AIC) and Schwarz (SIC) information criteria, log-odds value and the significance levels of coefficients from alternate ARCH models.

more influential on the volatility of gold than negative news (see Table 6). Different GARCH models were estimated to observe the effect of the euro bubbles and the euro on bitcoin's return, and then we decided on a suitable model[2] (see Table 7).

Table 7. *Influence of the bubble at the Euro exchange and the Euro's return on Bitcoin's return-GARCH (1,6) model estimation result*

	Mean Equation			
	Coefficient	Std. Error	t-statistics	p-value
Constant	0.0035	0.0008	4.0188	0.0000***
$BUBBLE_{Euro}$	-0.005	0.0026	-2.0071	0.0447**
AR(1)	0.8735	0.0760	11.4893	0.0000***
AR(2)	0.0654	0.0700	0.9341	0.3502
AR(3)	-0.0087	0.0152	-0.5712	0.5679
AR(4)	0.0290	0.0140	2.0605	0.0393**
MA(1)	-0.8800	0.0753	-11.6843	0.0000***
MA(2)	-0.0419	0.0692	-0.6059	0.5445
	Variance Equation			
	Coefficient	Std. Error	t-statistics	p-value
α_0	-1.7135	0.2922	-5.8635	0.0000***
α_1	0.4893	0.0761	6.4296	0.0000***
α_2	0.3545	0.0457	7.7466	0.0000***
α_3	0.3388	0.0451	7.5060	0.0000***
α_4	0.2708	0.0474	5.7128	0.0425***
α_5	-0.1494	0.0736	-2.0287	0.0000***
γ_1	0.0386	0.0096	4.0121	0.0000***
β_1	-0.0874	0.0090	-9.6160	0.0000***
β_2	-0.0278	0.0100	-2.7844	0.0000***
β_3	0.0293	0.0096	2.4726	0.0000***
β_4	0.9582	0.0091	104.3201	0.0134**
REURO	-5.3354	2.1263	-2.5091	0.0121**
GED Parametresi	0.8284	0.0333	24.8551	0.0000***
R^2 = 0.0509	$\bar{R}^2 = 0.0424$			
AIC= -3.6358	SIC= -3.5696		HQ=-3.6113	
Jarque-Bera test: 9899.129 [0.0000***]			ARCH-LM test: 4.6825[0.9678]	

Notes: *, **, and *** represent statistical significance at the levels of 0.10, 0.05, and 0.01. Values in square brackets are probability values.

The EGARCH (1,6) model shows the effect of the bubbles on the euro and the euro's return on bitcoin's return volatility. The increase in the euro return and the euro bubbles are negative and had significant effects on bitcoin's return. As seen in Table 8, the asymmetry effect of γ_1 was obtained positively, and positive news was more effective than negative news.

The GARCH (5,6) model[3] shows the effect of the dollar's bubbles and the dollar return on the bitcoin return. The increase in the dollar's bubbles had a positive effect on bitcoin's return, while the increase in the dollar's return had negative effects on bitcoin's return. The asymmetry effect of γ_1 was negative (see Table 8). Negative news was more effective on volatility than positive news.

[2] It was found that the EGARCH (1,6) model was the most suitable model in terms of AIC and SIC, log-odds value and the significance levels of coefficients from alternate ARCH models.

[3] It was found that the GARCH (5,6) model was the most suitable model in terms of AIC and SIC, log-odds value and the significance levels of coefficients from alternate ARCH models.

Table 8. *Influence of the bubble at the Dollar exchange and Dollar return on Bitcoin return-GARCH (5,6) model estimation result*

	Mean Equation			
	Coefficient	Std. Error	t-statistics	p-value
Constant	0.0032	0.0007	4.6106	0.0000***
$BUBBLE_{Dolar}$	0.0013	0.0018	0.7073	0.4794
AR(1)	0.9400	0.0563	16.6732	0.0000***
AR(2)	-0.0076	0.0461	-0.1664	0.8678
AR(3)	-0.0267	0.0195	-1.3653	0.1721
AR(4)	0.0337	0.0153	2.1963	0.0281**
MA(1)	-0.9386	0.0600	-15.6248	0.0000***
MA(2)	0.0314	0.0519	0.6043	0.5456
	Variance Equation			
	Coefficient	Std. Error	t-statistics	p-value
α_0	-2.9605	0.0628	-47.0751	0.0000***
α_1	0.5294	0.0116	45.6405	0.0000***
α_2	0.4663	0.0144	32.2087	0.0000***
α_3	0.0837	0.0160	5.2307	0.0000***
α_4	0.5049	0.0165	30.4845	0.0000***
α_5	0.4793	0.0075	63.4288	0.0000***
γ_1	-0.0295	0.0049	-6.0112	0.0000***
β_1	-0.3710	0.0037	-99.5589	0.0000***
β_2	0.7211	0.0006	1144.546	0.0000***
β_3	-0.4230	0.0035	-118.8965	0.0000***
β_4	-0.4621	0.0026	-175.6022	0.0000***
β_5	0.8740	6.68E-05	13078.47	0.0000***
β_6	0.4161	0.0025	162.4466	0.0000***
RDOLLAR	-4.0882	1.2538	-3.2606	0.0011***
GED Parametresi	0.8615	0.0342	25.1897	0.0000***
R^2 = 0.0509	$\bar{R}^2 = 0.0424$			
AIC= -3.6435	SIC= -3.5710		HQ=-3.6167	
Jarque-Bera test: 7773.25 [0.0000***]			ARCH-LM test: 7.4679 [0.8265]	

Notes: *, **, and *** represent statistical significance at the levels of 0.10, 0.05, and 0.01. Values in square brackets are probability values.

Table 9 shows the GARCH (1,6)[4] model estimation results. These results show the effect of the bubbles on the fluctuation of bitcoin's return. The rise in bitcoin bubbles had positive and significant effects on the bitcoin return.

Table 9. *Influence of the bubble at Bitcoin prices on Bitcoin return-GARCH (1,6) model estimation result*

	Mean Equation			
	Coefficient	Std. Error	t-statistics	p-value
Constant	0.0021	0.0006	3.3012	0.0100**
AR(1)	0.9940	0.0460	21.5643	0.0000***
AR(2)	-0.0577	0.0401	-1.4393	0.1501
AR(3)	-0.0144	0.0195	-0.7412	0.4586
AR(4)	0.0257	0.0144	1.7841	0.0744*
MA(1)	-1.0093	0.0570	-17.6933	0.0000***
MA(2)	0.0883	0.0511	1.7292	0.0838*
	Variance Equation			
	Coefficient	Std. Error	t-statistics	p-value
Constant	0.0001	2.66E-05	4.0118	0.0001***
ε_{t-1}^2	0.3271	0.0671	4.8686	0.0000***
GARCH(-1)	0.1465	0.0674	2.1719	0.0299**
GARCH(-2)	0.1625	0.0750	2.1665	0.0303**
GARCH(-3)	0.1324	0.0683	1.9376	0.0527*
GARCH(-4)	0.2029	0.0699	2.9000	0.0037***
GARCH(-5)	0.2552	0.0609	4.1886	0.0000***
GARCH(-6)	-0.2545	0.0707	-3.5992	0.0003***

[4] It was found that GARCH (1,6) model was the most suitable model in terms of AIC and SIC, log-odds value and the significance levels of coefficients from alternate autoregressive conditionally varying variance models.

$BUBBLE_{bitcoin}$	0.0011	0.0003	2.9700	0.0030***
GED Parametresi	0.8158	0.0313	26.024	0.0000***

R^2 = 0.0106 $\bar{R}^2 = 0.0424$

AIC= -3.6320 SIC= -3.5753 HQ=-3.6110

Jarque-Bera test: 11171.83 [0.0000***] ARCH-LM test: 4.0096 [0.9833]

Notes: *, **, and *** represent statistical significance at the levels of 0.10, 0.05, and 0.01. Values in square brackets are probability values.

The findings from the volatility models at this stage of the study are summarised in Table 10.

Table 10. *Summary of findings from volatility models*

Bubbles	Effect on volatility	Variables	Effect on volatility
BITCOIN	+*	RGOLD	+*
DOLAR	-	RDOLLAR	-*
EURO	-*	REURO	-*

Notes: *, **, and *** represent statistical significance at the levels of 0.10, 0.05 and 0.01.

Under the influence of the 2008 crisis, large economies began increasing their monetary aggregates. Bank rates were reduced to zero or negative rates. Thus, the decrease in investment cost increased the propensity for financial actors to take risks, which led to significant increases in financial markets (bubbles) even if the real economy was not exactly the same. This situation continued from the summer of 2013 until the Federal Reserve announced that the they would reduce monetary expansion; then, they continued their movements in a fluctuating market.

Over the past 10 years, the interest rate decisions made by the central banks of major countries such as the US, EU and UK have been decisive in the movements of financial markets. Bitcoin started to develop in such an environment, has benefited from the increasing risk atmosphere and has attracted investors, especially in the last 2 years. Due to the fact that it is not subject to a central authority and is outside of legal bounds, it rapidly increased up to $20,000 and then fell back down to levels below $10,000 with a sharp decline. This fast-paced trend can be likened to the tulip mania of the Netherlands in the first half of the 17th century, the South Sea Bubble in South America in 1720 and the Mississippi Bubble in France in the same year.

Starting from the end of 2017, bitcoin regulation has reduced the activity of bubbles. The most striking motion-reducing effect in the bubbles of this period can be attributed to bitcoin becoming visible in the term market. Bitcoin is generally priced in dollars; this may be there as on why there is no statistically meaningful relationship with this type of bubbles. On the other hand, the assessment of international bitcoin markets as an investment instrument rather than a currency explains the opposite direction of the bubble in the euro.

In this study, the direction of causality between the return variables was investigated through the Toda-Yamamoto causality test. The analysis results are presented in appendices. A summary of the Toda-Yamamato causality test results is reported in Table 11.

Table 11. *Summary of causality test results*

RGOLD, RDOLLAR, REURO =>RBITCOIN
RBITCOIN,RDOLLAR, RGOLD ≠> REURO
REURO, RBITCOIN, RGOLD =>RDOLLAR
REURO,RDOLLAR, RBITCOIN => RGOLD

Note: => shows causality, ≠> shows no causality.

According to Table 11, it can be said that gold's, the dollar's and the euro's returns are responsible for bitcoin's return. This causality relationship is parallel to the results obtained from the volatility models. In this study, it was also determined that the euro's, bitcoin's and gold's returns were a Granger-cause of the dollar return. In addition, the euro's, dollar's and bitcoin's returns are a Granger-cause of gold's return. According to the results, only bitcoin, the dollar and gold are not a Granger-cause of the euro's returns. In examining the literature, Atik *et al.,* (2015) stated that the dollar's and euro's return movements are not a Granger-cause of bitcoin's return. However, the results of causality in thisstudy contradict the results of these authors. This study sample was limited to February 2015, it is believed that speculative bubbles in the dollar in 2017 and in March 2015 affected this variability. It is very important to recognise that the bubbles are influential in the market and that investors and policy makers take into account the existence of speculative movements.

All the findings obtained from this study do not indicate that bitcoin is a viable financial instrument for Turkey. It is predicted that bitcoin will be considered a financial investment tool in the world economy in the coming periods. In this context, it is suggested that financial investment instruments should be diversified, and the period interval expanded. In this way, new studies will contribute to the literature.

5. Conclusion

In the changing and developing world, economists who think about the nature of money and the new uses of money have carried out a lot of research on this subject. Here, this study examined one crypto currency, bitcoin, as a financial investment tool. Between the period of 1 August 2011 and 23 March 2018, the euro and dollar were taken into consideration with bitcoin. Their relationships and the effect of the bubbles from this period on bitcoin were researched.

The existence of frequent bubbles was confirmed in all investment vehicles except for gold. The findings related to bitcoin's bubbles were similar to those in other studies (Cheung *et al.,* 2015; Cheah & Fry 2015; Ceylan *et al.,* 2018). These other studies stated that the bubbles emerging in bitcoin, the euro and the dollar were caused by speculative factors.

Another significant finding in this study was that the dollar only affected bitcoin's bubbles and that the dollar and euro did not affect bitcoin's return. Gold, dollar and euro returns were found to have a significant effect on the volatility of bitcoin generation. This result shows the existence of are lationship between the dollar and euro and bitcoin's return, and this relationship parallels the findings of Szetela *et al.*, (2016).

Finally, according to the results of the causality analysis between the return variables, bitcoin, the dollar and gold are not Granger-causes for the euro's return. In addition to this result, it was determined that there is a causal link between all variables. This result supports other findings of the study. In other words, it shows that financial investment instruments affect bitcoin

When all the obtained findings are examined together, it can beseen that the bitcoin market and foreign exchange market cause speculative bubbles to occur due to uncertainty and that there is a relationship between the mentioned variables.

Note

An earlier draft of this paper was presented at International Conference on Empirical Economics and Social Science (ICEESS' 18), 27-28 June, 2018, Balıkesir, Turkey

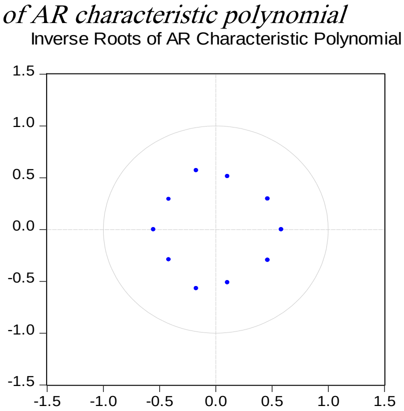
Appendices

Appendix A. *Determining the optimal lag length of VAR system*

Lag	FPE	AIC	SC	HQ
0	3.56e-07	-9.173511	-9.167201	-9.171177*
1	3.56e-07	-9.172143	-9.153212	-9.165140
2	3.57e-07	-9.170280	-9.138728	-9.158609
3	3.56e-07	-9.173099	-9.128927	-9.156761
4	3.55e-07	-9.175237	-9.118444	-9.154230
5	3.54e-07*	-9.178307*	-9.168893*	-9.152632

Note: * Indicates the optimal lag length.

Appendix B. *Inverse roots of AR characteristic polynomial*



Appendix C. *Results of Toda-Yamamoto causality test*

	MWald statistics	P-value
H₀:δ_{1i}=δ_{2i}=δ_{3i}=δ_{4i}=δ_{5i}=δ_{6i}=0	1.9683	0.0143**
H₀: δ_{1i}=δ_{2i}= 0	3.8162	0.0019***
H₀: δ_{3i}=δ_{4i}=0	1.5027	0.0858*
H₀: δ_{5i}=δ_{6i}=0	1.6136	0.0532*
Jarque-Bera test:8040.84***		
Breusch-Godfrey LM test: 2.07118	Breusch-Pagan Godfrey test: 1.8859	
	MWald statistics	P-value
H₀:μ_{1i}=μ_{2i}=μ_{3i}=μ_{4i}=μ_{5i}=μ_{6i}=0	0.8548	0.6160
H₀: μ_{1i}=μ_{2i}= 0	1.4643	0.1984
H₀: μ_{3i}=μ_{4i}= 0	0.4173	0.8369
H₀: μ_{5i}=μ_{6i}=0	0.7977	0.5512
Jarque-Bera test : 1484.08***		
Breusch-Godfrey LM test: 2.04489	Breusch-Pagan Godfrey test : 4.6788	
	MWald statistics	P-value
H₀:γ_{1i}=γ_{2i}=γ_{3i}=γ_{4i}=γ_{5i}=γ_{6i}=0	4.2567	0.0000***
H₀: γ_{1i}=γ_{2i}= 0	2.5886	0.0308**
H₀: γ_{3i}=γ_{4i}= 0	2.2089	0.0258**
H₀: γ_{5i}=γ_{6i}=0	11.9780	0.0000***
Jarque-Bera test istatistiği: 955.6626		
Breusch-Godfrey LM test : 1.2810	Breusch-Pagan Godfrey test: 3.6922	
	MWald statistics	P-value
H₀:η_{1i}=η_{2i}=η_{3i}=η_{4i}=η_{5i}=η_{6i}=0	1.9582	0.0150**
H₀: η_{1i} = η_{2i}= 0	3.6004	0.0030***
H₀: η_{3i}=η_{4i}= 0	2.3997	0.0352**
H₀: η_{5i}=η_{6i}=0	2.4201	0.0339**
Jarque-Bera test: 0.8261		
Breusch-Godfrey LM test: 0.8878	Breusch-Pagan Godfrey test: 6.1496	

Note: The optimal lag length (k) of the VAR model was determined to be 5. Since these return variables are stationary in the level values, dmax is taken as 0. In addition, *, ** and *** are statistically significant in 10%, 5% and 1% respectively.

References

Atik, M., Köse, Y., Yılmaz, B., & Sağlam, F. (2015). Kripto para: Bitcoin ve döviz kurları üzerine etkileri, *Bartın Üniversitesi İ.İ.B.F. Dergisi*, 6(11), 247-261.

Baek, C., & Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A first look, *Applied Economics Letters*, 22(1), 30-34. doi. 10.1080/13504851.2014.916379

Bariviera, A.F., Basgall, M.J., Hasperué, W., & Naiouf, M. (2017). Some stylized facts of the bitcoin market, Phys. A, 484, 82-90. doi. 10.1016/j.physa.2017.04.159

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

Balcılar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict bitcoin returns and volatility? A quantiles-based approach, *Economic Modelling*, 64, 74-81. doi. 10.1016/j.econmod.2017.03.019

Bhattacahjee, S. (2016). A statistical analysis of bitcoin transactions during 2012 to 2013 in terms of premier currencies: Dollar, Euro and Rubles, *Vidwat: The Indian Journal of Management*, 9(1), 8-16.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307-327. doi. 10.1016/0304-4076(86)90063-1

Ceylan, F., Tüzün, O., Ekinci, R., & Kahyaoğlu, H. (2018). Kripto para piyasalarında finansal balonlar (bubbles): Bitcoin ve Etherium, *4th SCF International Conference on "Economic and Social Impacts of Globalization* and *Future of Turkey-EU Relations*, 26-28th April 2018, Nevşehir, pp.207-215.

Cheah, E.T., & Fry, J. (2015). Speculative bubbles in bitcoin markets? An emprical investigation into the fundamental value of bitcoin, *Economics Letters*, 130, 32-36. doi. 10.1016/j.econlet.2015.02.029

Cheung, A., Roca, E., & Su, J. (2015). Crypto-currency bubbles: An application of the Philips-Shi-Yu methodology on Mt. gox bitcoin prices, *Applied Economics*, 47(23), 2348-2358. doi. 10.1080/00036846.2015.1005827

Çağlı, E.Ç., & Mandacı, P.E. (2017). Borsa İstanbul'da rasyonel balon varlığı: sektör endeksleri üzerine bir analiz, *Finans Politik & Ekonomik Yorumlar*, 54(629), 63-76.

Diba, B.T., & Grossman, H.I. (1988). Explosive rational bubbles in stock prices?, *American Economic Reviev*, 78(3), 520-530.

Dulupçu, A., Yiyit, M., & Genç, A.G. (2017). Dijital ekonominin yükselen yüzü: Bitcoin'in değeri ile bilinirliği arasındaki ilişkinin analizi. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi.* 22(15), 2241-2258.

Dyhrberg, A.H. (2015), Bitcoin, gold and the dollar: A GARCH volatility analy- sis, UCD Centre for Economic Research, *Working Paper Series*, No:15/20. [Retrieved from].

Garber, P.M. (2000). *Famous First Bubbles: The Fundamentals of Early Manias*, MIT Press, Cambridge, MA.

Güleç, Ö.F., Çevik, E., & Bahadır, N. (2018). Bitcoin ile finansal göstergeler arasındaki ilişkinin incelenmesi. *Kırklareli Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 7(2), 19-37.

Hencic, A., & Gourieroux, C. (2015). Noncausal autoregressive model in application to bitcoin/USD exchange rates, *In: Econometrics of Risk*, Springer.

Hepkorucu, A., & Genç, S. (2017). Finansal varlık olarak bitcoin'in incelenmesi ve birim kök yapısı üzerine bir uygulama, *Osmaniye Korkut Ata Üniversitesi İktisadi ve İdari Bilimler Fakültesi*, 1(2), 47-58.

İçellioğlu, C.Ş., & Öztürk, M.B.E. (2018). Bitcoin ile seçili döviz kurları arasındaki ilişkinin araştırılması: 2013-2017 Dönemi için Johansen testi ve Granger nedensellik testi, *Maliye ve Finans Yazılan*, 109, 51-70.

Karaağaç, G.A., & Altınırmak, S. (2018). En yüksek piyasa değerine sahip on kripto paranın birbiriyle etkileşimi, *Muhasabe ve Finansman Dergisi*, 79, 123-138.

Kristoufek L. (2013). Bitcoin meets Google trends and Wikipedia: Quantifying the relationship between phenomena of the internet era, *Scientific Reports,* 3, 3415.

Koçoğlu, Ş., Çevik, Y.E., & Tanrıöven, C. (2016). Bitcoin piyasalarının etkinliği, likiditesi, *İşletme Araştırmalan Dergisi*, 8(2), 77-97.

MacDonell, A. (2014). Popping the bitcoin bubble: An application of log-periodic power law modelling to digital currency, *University of Notre Dame Working Paper*, [Retrieved from].

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system, [Retrieved from].

Nelson, D. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica,* 59(2), 347-370. doi. 10.2307/2938260

Philips, P.C.B., & Yu, J. (2011). Dating the timeline of financial bubbles during the suprime crises, *Quantitive Economics,* 2(3), 455-491. doi. 10.3982/QE82

Philips, P.C.B., Shi, S., & Yu, J. (2013). Testing for multiple bubbles: Hıstorical episodes of exuberance and collapse in the S&P 500. *Cowles Foundation Discussion Paper,* No.1914. [Retrieved from].

Philips, P.C.B., Shi, S., & Yu, J. (2014). Specification sensitivity in right-tailed unit root testing for explosive behavior. *Oxford Bulletin of Economics and Statistics*, 76(3), 315-333. doi. 10.1111/obes.12026

Philips, P.C.B., Shi, S., & Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. *International Economic Review*, 56(4), 1043-1078. doi. 10.1111/iere.12132

Philips, P.C.B., Wu, Y., & Yu, J. (2011). Explosive behavior in the 1990s NASDAQ: When did exuberance escalate asset values?. *International Economic Review*, 52(1), 201-226. doi. 10.1111/j.1468-2354.2010.00625.x

Szetela, B., Mentel, G., & Gedek, S. (2016). Dependency analysis between bitcoin and selected global currencies, *Dynamic Econometric Models*, 16, 133-144. doi. 10.12775/DEM.2016.009

Toda, H.Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes, *Journal of Econometrics*, 66(1-2), 225-250. doi. 10.1016/0304-4076(94)01616-8

Wandhöfer, R. (2017). The future of digital retail payments in Europe: A place for digital cash, *Journal of Payments Strategy & Systems*, 11(3), 248-258.