The Relationship Between BITCOIN and Other Financial Instruments: An Examination With VAR Models[1]

Semih Yılmazer *semihy@yildiz.edu.tr*
Faculty of Economics and Administrative Sciences
Department of Business Administration/Division of Accounting and Finance
Yildiz Technical University, Istanbul, 34220, Turkey

Aslı Aybars *asli.aybars@marmara.edu.tr*
Faculty of Business Administration
Department of Business Administration/Division of Finance
Marmara University, Istanbul, 34730, Turkey

Gözde Bozkurt *gozdebozkurt@beykent.edu.tr*
Faculty of Economics and Administrative Sciences
Department of Economics /Division of Economics
Beykent University, Istanbul, 34433, Turkey

Abstract

Bitcoin has become one of the most popular financial assets in the world because it has an unregulated nature and does not require any central authority. However, there has been an ongoing debate about Bitcoin classification. Whatever classification Bitcoin is subject to, it has become a significant component of investors' portfolios. Accordingly, the returns of this instrument are an important matter of concern for both practitioners and academicians. In this study, we aim to analyze the effect of other financial assets on Bitcoin returns to figure out whether there is a hedging opportunity or not. In this manner, we used Vector Autoregression (VAR) model to test whether the associated variables; namely, gold, euro, and S&P 500 influence Bitcoin returns. The results of the study revealed that Bitcoin returns had no relationship with other financial assets in the long term. In other words, it was determined that financial assets did not affect Bitcoin prices. It was also found that Bitcoin had a deterministic process rather than a stochastic one. Hence, it is thought that Bitcoin should be examined by using VAR models instead of financial models such as ARMA, ARCH, and GARCH.

Keywords: Cryptocurrencies, Vector Autoregression, Bitcoin Returns, Bitcoin Volatility.

1. INTRODUCTION

Bitcoin is one of the most important financial innovations that has marked the last decade. The distinguishing feature of bitcoin is that it is part of a completely private monetary system, not depending on trust in any central bank but relying on trust in the community or the network of bitcoin that confirms transactions (Dowd and Hutchinson, 2015). Because of its unregulated nature, it has been very popular (Blau, 2018). In fact, there are more than two thousand cryptocurrencies and the number of these currencies is supposed to increase, but none of them has reached the popularity, volume, and market capitalization of bitcoin. In addition, almost all digital currency values are dependent on bitcoin prices.

After Bitcoin gaining popularity, it was started to be seen as a new kind of investment (Corbet et al., 2018). However, there is no consensus both in the literature and among finance professionals

[1] An earlier version of this manuscript was presented at the 23rd International Finance Symposium, Antalya, Turkey, 2019

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

about the classification of Bitcoin. Some previous studies claim that it has some common feature with currencies (Dyhrberg, 2016; Polasik et al., 2015), while others put forward that it is a speculative asset and has some unique features that differentiate it from other financial instruments (Baur et al., 2018; Glaser et al., 2014; Klein et al., 2018). Also, the hedging capacity of Bitcoin has questioned by scholars in recent years. Similar to debates about the investment category of Bitcoin, previous studies also find different results for using Bitcoin as a hedging tool. Some studies conclude that involving Bitcoin in financial portfolios can help to mitigate risks (Demir et al., 2018; Guesmi et al., 2019; Katsiampa, 2017). On the other hand, it is also thought that market shocks affect all financial instruments as well as Bitcoin (Klein et al., 2018)

Although number of studies in the literature related to Bitcoin investment has significantly increased in the last decade, we think that there are still research areas which is not sufficiently discussed or shed light upon. In this manner, we contribute to the literature from various aspects. First, our paper is different from previous studies in terms of methodological approach. We employ Vector Autoregressive (VAR) and variance decomposition models to reveal the presence of causality between variables. Second, we include three common financial instruments which are S&P 500 index, gold, and Euro which represent equities, commodities and currencies, respectively in the model. Besides, we analyze our variables in a weekly basis to be able to diminish the effects of temporary and instant shocks. Also weekly analysis provides a benchmark since Bitcoin is traded in all day including weekends despite the fact that other financial instruments are not traded in weekends.

The research question of this study is: Does Bitcoin returns have a causal relationship with other financial assets? In this regard, both the effect of other financial assets on Bitcoin returns and the effect of Bitcoin returns on other financial assets are investigated in the study. In other words, the relationship between the returns of Bitcoin and other financial assets are analyzed to find out if there is a causality between Bitcoin and other financial instruments included in the study.

The structure of the paper is as follows. In the second section, a comprehensive literature review has been conducted. In this manner, the concept and history of Bitcoin has been explained. Additionally, some debates about the characteristics of Bitcoin have been mentioned. The last part of the section focuses on the previous studies investigating the relationship between Bitcoin and other financial assets. In the third section, information about the data and methodology utilized has been provided. Also, the results of the empirical analysis have been assessed. In the last section, the results are discussed and compared with previous studies. Also, the limitations of the study have been mentioned and some suggestions about future studies have been given.

2. THEORETICAL BACKROUND

2.1 The Concept and History of Bitcoin

Bitcoin is the first and most popular digital currency in the world. Nakamoto (2008) has firstly used the concept of ‘Bitcoin’ in his paper entitled as ‘Bitcoin: A Peer-to-Peer Electronic Cash System’. Nakamoto (2008) describes the system and provides technical information about how it can be created or utilized in monetary transactions. He also criticizes the current system in terms of having high transaction costs due to the large number of intermediaries involved in the process. With Bitcoin or any other cryptocurrency, it is aimed to allow members of a network to send or receive money directly between each other without any need for third parties like central banks (Raskin and Yermack, 2018). As opposed to the traditional system, in which there is a trust in financial intermediaries, this system is based on networks and cryptography (Cretarola et al., 2020). Furthermore, Bitcoin has an exchange rate varying according to supply and demand conditions (European Central Bank, 2012).

Bitcoin transactions have started in January 2009. The first bitcoin transaction has been carried out by Hal Finney, who downloaded the Bitcoin Client and received 10 Bitcoins from Nakamoto (Chohan, 2017). Since 2010, Bitcoin has also been used to buy products. Laszlo Hanyecz, the first person to use bitcoin as a medium of exchange has purchased two pizzas by paying 10,000

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

Bitcoins (Polasik et al., 2015). However, today there are more than ten thousand venues accepting bitcoin for payments. According to a website named cryptoglobe.com, more than half of these venues are general shopping stores, ATMs, and lodging services. In fact, virtual currencies have been issued on online game platforms since the late 1980s (Raskin and Yermack, 2018). However, Bitcoin differs from these currencies in terms of its use on various platforms and products.

Another unique feature of Bitcoin is that it has a futures market which makes it different from other cryptocurrencies. Bitcoin futures have started to be traded in The Chicago Mercantile Exchange (CME) since December 2017. Also, CBOE Futures Exchange (CFE) began trading CBOE bitcoin futures on 10th December 2017 under the ticker symbol "XBT". However, CFE stopped to offer new Bitcoin futures contracts in the March 2019. On the other hand, Bitcoin futures was launched by CME, the world's largest futures exchange on 17th December 2017 under the ticker symbol “BTC” which equals to 5 Bitcoins.

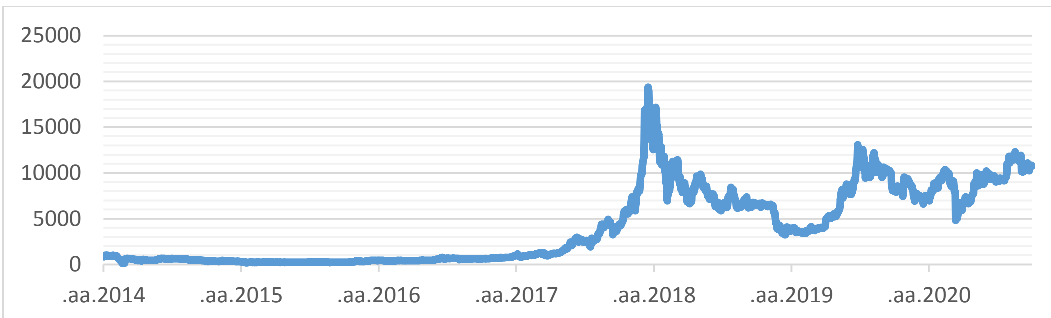

FIGURE 1: The Price of Bitcoin.

Figure 1 shows the data with respect to the historical prices of bitcoin between January 2014 and September 2020. The value of bitcoin has started to increase sharply since March 2017 until December 2017 from $1,200 to $19,350. Although, the price of bitcoin has been decreasing rapidly for 2018, it is observed that it has started to rise again in the first half of 2019. With the second half of 2019, the price of Bitcoin started to follow a fluctuating course. As of September 30, bitcoin is traded at about $10,700.

2.2 Is Bitcoin an Asset or a Commodity?

Regulators and researchers want to define bitcoin in an economic manner because of its advantages (Dyhrberg, 2016). Bitcoin has similarities with fiat currencies because its value is not dependent on any commodity or valuable metal (Polasik et al., 2015). Thus, some studies claim that bitcoin is a currency, while others think it is a commodity or a speculative investment. Baur et. al. (2018), claim that Bitcoin is used for investment purposes rather than commercial transactions. Due to the volatility of the cryptocurrencies, some researchers may question the notion of Bitcoin as a currency (Blau, 2018). According to Brière et al. (2015), the Bitcoin rate of return shows that it is significantly different from those of other commodities such as gold and oil, or assets like hedge funds. Klein et al. (2018) also state that Bitcoin is completely different from gold. Consistent with previous studies, Baur et al. (2018) finds that Bitcoin differs from both gold and traditional currencies as its risk-return characteristics and volatility process are not similar to any other financial instrument.

There are also some studies examining how bitcoin investors use Bitcoin. Glaser et al. (2014) state that new users think that bitcoin is an asset rather than a currency. In addition, Yermack (2015) claims that Bitcoin should be more stable to become reliable, be recognized as a currency, and be used as a store of value and a unit of account in markets.

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

Although Bitcoin is very popular in finance literature, few studies have concentrated on the volatility of Bitcoin. However, to examine Bitcoin volatility is very important because Bitcoin has become one of the most important investment tools in recent years (Katsiampa, 2017). According to the author, Bitcoin is different from any other asset and including it as part of a portfolio can be beneficial for risk management. The study of Guesmi et al. (2019), another research investigating hedging opportunities of Bitcoin, finds that portfolio risk is reduced if Bitcoin is included in a portfolio made up with gold, oil, and emerging stocks. Demir et al. (2018) also state that Bitcoin can be used as a hedging tool against uncertainty since it has a negative relationship with Economic Policy Uncertainty (EPU) index. However, the empirical findings of the study of Klein et al. (2018) show that Bitcoin cannot be used for hedging against equity investments as Bitcoin prices decrease together with market shocks.

According to Bouri et al. (2017), Bitcoin had a safe-haven property before the price crash in 2013, but this situation changed after the crash. It is also stated that adding Bitcoin to US Equity portfolios is effective in reducing risk. Findings of Dyhrberg (2016) show that Bitcoin reactions are significant to federal funds rate which makes it a currency; but it has some mutual features with gold as both of them react symmetrically after good or bad news. Hence, Bitcoin is an investment tool with characteristics that range between those of currencies and commodities.

2.3 The Relationship between Bitcoin and Other Financial Assets

Various studies compare Bitcoin and other financial assets such as currencies, stock indices, fund rates, commodities, and so on. The results of studies generally demonstrate that Bitcoin is not affected from traditional assets. However, few studies claim that there is a relationship between these assets. Ji et al. (2018) find that there is a weak relation between Bitcoin and some investment tools such as equities, gold, and dollar. They also state that the price movements of Bitcoin are relatively independent. Similarly, Zeng et al. (2020) conclude that the relationship between Bitcoin and other assets is weak. However, their findings show that the influence of negative returns on Bitcoin is relatively high. Evidence in the study of Corbet et al. (2018) indicates that Bitcoin and other cryptocurrencies are strongly connected to each other but they are isolated from conventional assets. Kurihara and Fukushima (2018) examine Bitcoin volatility by separating short-term and long-term volatility and find that its volatility is dependent on the length of the period. The authors also conclude that Bitcoin prices are not influenced by stock prices or exchange rates. On the contrary to the literature, Park et al. (2021) reveal that there are interactions between Bitcoin and other financial instruments. In particular, it is concluded that the impact of exchange rates on Bitcoin is stronger when compared to other financial assets. Similarly Bouri et al. (2018) point out that Bitcoin is not independent from other asset classes and especially commodities influence Bitcoin. Erdas and Caglar (2018) find a unidirectional relationship between Bitcoin and S&P 500 index. On the other hand, their results show that oil, gold, dollar, and BIST 100 index have no relationship with Bitcoin.

Most of the studies also examine Bitcoin volatility to figure out whether Bitcoin can be a diversifier for diminishing portfolio risks. According to Bouri et al. (2017), Bitcoin is an effective instrument for portfolio diversification although it has a hedging capacity and a safe haven feature. Kokkinaki et al. (2018) examine the relationship between bitcoin volatility and various exchange rates and it has been determined that raw annualized volatility of Bitcoin is higher than common currency volatilities. However, when the trade volume of Bitcoin is considered, the Bitcoin volatility is found to be significantly stabilized.

3. DATA AND METHODOLOGY

3.1 Data

We obtained weekly price data of all variables examined in the study from investing.com. The reason of choosing weekly data rather than daily is that Bitcoin is traded on all days of the week while other financial assets are traded only on week days. Accordingly, since we attempt to provide a simple benchmark to determine the effects of financial assets on Bitcoin returns, weekly

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

data is utilized. Our sample period was between March 1st, 2016 and April 24th, 2019. Our data consisted of 169 observations for each asset.

Variables in the study were selected according to the literature examining Bitcoin volatility and returns. As a currency, Euro is one of the mostly analyzed variables to determine Bitcoin hedging opportunities and to find out the effect of Bitcoin in diminishing portfolio risk (Eom et al., 2019; Guesmi et al., 2019; Kokkinaki et al., 2018). In addition, commodities are also included in studies about Bitcoin volatility or the hedging possibility of Bitcoin. Baur et al. (2018) have used both the spot and future price of Gold to determine the relationship with Bitcoin and to classify Bitcoin as a financial asset. Klein et al. (2018) have also used Gold price as a variable to evaluate the performance of a portfolio, which includes Bitcoin. The studies related to Bitcoin volatilities analyze not only currencies or commodities but also equity indices such as FTSE 100, MSCI indexes, and S&P 500 index (Baur et al., 2018; Klein et al., 2018). In line with literature, we selected Euro as a proxy of currencies, spot price of Gold as a commodity, and S&P 500 index to analyze the relationship with equities.

3.2 Methodology

The complexity of the relationships examined in econometric studies has necessitated the use of simultaneous equations. Since the macroeconomic variables can interact, it is difficult to separate the data as being only endogenous or exogenous. For this reason, Vector Autoregressive (VAR) Model is frequently used in practice (Tarı and Bozkurt, 2006). It has advantages because of its potential to display the dynamic characteristics of the economy and its feature of not bringing any restrictions from a specific structural model (Keating, 1990). Since the autoregressive formulation is flexible, a large number of real data sets can be described statistically and many economic hypotheses can be embedded in a general statistical framework. Especially, the concept of integration, cointegration, and common trends can be defined through VAR formulation (Johansen, 1995).

Since all variables are considered to be endogenous and the effect of each variable on other variables is estimated simultaneously, a variable can increase the predictability of the model by its own impact on both the dependent variable and other predictor variables. Thus, variables contribute directly and indirectly via the system of estimated equations (Kumar et al., 1995). VAR models are a linear function of both variables' own and other variables' lagged values in the system. In VAR modeling, series are preferred to be stationary.

VAR Model

The VAR model developed by Sims (1980) is based on the Granger causality test model. If there are two endogenous variables in the model, these variables are associated with both their own and lagged values until a certain period (Ertek, 2000). The general representation of the standard VAR model with two variables is given in equations 3.1 and 3.2.

$$X_t = \alpha + \sum_{j=1}^{m} \beta_j X_{t-j} + \sum_{j=1}^{m} \delta_j Y_{t-j} + \varepsilon_{1t} \qquad (t = 1,2,\ldots\ldots,T) \qquad \textbf{(3.1)}$$

$$Y_t = \alpha + \sum_{j=1}^{m} \theta_j Y_{t-j} + \sum_{j=1}^{m} \gamma_j X_{t-j} + \varepsilon_{2t} \qquad \textbf{(3.2)}$$

The lagged values of Y impact X variable; and the lagged values of X impact Y variable. In this model, since only the lagged variables are present on the right side of the equations, the values to be found by the least squares method will be consistent. The first-order structural VAR (1) model for the two variables is provided in equations 3.3 and 3.4.

$$X_t = \alpha_0 + \beta_1 X_{t-1} + \delta_0 Y_t + \delta_1 Y_{t-1} + \varepsilon_{1t} \qquad \textbf{(3.3)}$$

$$Y_t = \alpha_1 + \theta_1 Y_{t-1} + \gamma_0 X_t + \gamma_1 X_{t-1} + \varepsilon_{2t} \qquad \textbf{(3.4)}$$

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

In the equations given above, it is assumed that the variables X_t and Y_t are weakly stationary, and ε_{1t} and ε_{2t} are not correlated with each other, which is shown below:

$$\Sigma = \begin{bmatrix} var(\varepsilon_{1t}) & cov(\varepsilon_{1t}, \varepsilon_{2t}) \\ cov(\varepsilon_{1t}, \varepsilon_{2t}) & var(\varepsilon_{2t}) \end{bmatrix} \qquad \textbf{\textit{(3.5)}}$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix} \qquad \textbf{\textit{(3.6)}}$$

These structural VAR equations can be converted to the standard VAR equation using matrices. Matrix illustrations of equations 3.3 and 3.4 are given below.

$$\begin{bmatrix} 1 & \delta_0 \\ \gamma_0 & 1 \end{bmatrix} \begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} + \begin{bmatrix} \beta_1 & \delta_1 \\ \gamma_1 & \theta_1 \end{bmatrix} \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \qquad \textbf{\textit{(3.7)}}$$

The closed form expression is as follows:

$$Bx_t = \Gamma_0 + \Gamma_1 x_{t-1} + \varepsilon_t \qquad \textbf{\textit{(3.8)}}$$

$$B = \begin{bmatrix} 1 & \delta_0 \\ \gamma_0 & 1 \end{bmatrix}, \; x_t = \begin{bmatrix} X_t \\ Y_t \end{bmatrix}, \quad \Gamma_0 = \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix}, \quad \Gamma_1 = \begin{bmatrix} \beta_1 & \delta_1 \\ \gamma_1 & \theta_1 \end{bmatrix}, \quad \varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \qquad \textbf{\textit{(3.9)}}$$

In Equation 3.9, standard VAR equations are obtained by multiplying both sides of the equation by $\boldsymbol{B^{-1}}$ (Enders, 1995). The closed form is shown below:

$$x_t = A_0 + A_1 x_{t-1} + e_t \qquad \textbf{\textit{(3.10)}}$$

In the standard VAR model, Akaike (AIC), Schwarz (SC), Hannan-Quinn (HQ), Final Prediction Error (FPE) and Likelihood Ratio (LR) are used to determine the optimal lag length. The correct determination of the lag length in VAR models is crucial because there may be degree of freedom loss in cases of excessive lag length and inconsistency problems in cases of low lag length. It is possible to use different lag lengths in the equations established for each variable. In practice, however, it is preferred to use the same lag length in order not to disturb the symmetry of the equation and to use the least squares technique effectively. Thus, the least squares estimators are ensured to be consistent and asymptotically effective. However, because of the fact that unreliable t-statistics are obtained due to multiple linear connections, the econometric significance of the parameters in VAR models is not clear. Therefore, impulse-response functions and moving average equations are used in the interpretation of the predicted VAR model. Both methods are considered to be useful tools for examining the relationship between economic variables (Enders, 1995).

Variance Decomposition

Coefficients are interpreted by making variance decomposition regarding error terms with moving averages method, in which the change in any of the endogenous variables within the system is divided into separate shocks that affect all endogenous variables. Thus, information can be obtained about the dynamic structure of the system. The main purpose of the variance decomposition analysis is to determine the effect that will occur in the forecast error variance due to each random shock (Kutlar, 2000).

In the methods used to determine the indirect and direct effect between the variables in the system, the reasons of the shocks that are seen in all variables are indicated as percentages. If all of the changes in any variable are caused by the shock in itself, this indicates that the related

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

variable acts endogenously. On the other hand, if it is caused by other variables within the system, it means that the related variable acts endogenously (Lütkepohl, 2005).

Impulse Response Function
Another method used in the assessment of the coefficients obtained in the VAR model estimation is impulse-response analysis. The responses of the variables in the system are measured through this method. The impulse-response functions provide information about the effects on the present and future values of the variables for a standard deviation of shock in any of the error terms. In addition, the direction and extent of these effects are examined with tables and graphs. After determining the most effective variable on a macroeconomic magnitude by using variance decomposition technique, the usability of this variable as a policy tool is determined by the effect-response functions (Tarı, 2010).

Based on the matrix form representation of Equation 3.10, how the effect-response functions are obtained is represented as follows [36].

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} + \begin{bmatrix} \beta_1 & \delta_1 \\ \gamma_1 & \theta_1 \end{bmatrix} \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \qquad \textbf{\textit{(3.11)}}$$

A vector of errors is obtained by adding differences from the mean to the given matrix form.

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \bar{X} \\ \bar{Y} \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} \beta_1 & \delta_1 \\ \gamma_1 & \theta_1 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t-j} \\ \varepsilon_{2t-j} \end{bmatrix} \qquad \textbf{\textit{(3.12)}}$$

$$\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = [1/(1 - b_{12}b_{21})] + \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} + \begin{bmatrix} \varepsilon_{xt} \\ \varepsilon_{yt} \end{bmatrix} \qquad \textbf{\textit{(3.13)}}$$

The revised form of the matrix equation 3.12 with the moving average, in which the vector of errors is obtained, is shown below.

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \bar{X} \\ \bar{Y} \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} \emptyset_{11}(j) & \emptyset_{12}(j) \\ \emptyset_{21}(j) & \emptyset_{22}(j) \end{bmatrix} + \begin{bmatrix} \varepsilon_{xt-j} \\ \varepsilon_{yt-j} \end{bmatrix} \qquad \textbf{\textit{(3.14)}}$$

In the method, the effects of $\emptyset$ coeffcients and ε_{xt} and ε_{zt} shocks on X_t and Y_t series are revealed. These coefficients represent the impulse-response functions. Graphs which show how series react to different shocks are obtained by functions.

4. FINDINGS
The characteristics of the time series that were utilized in the analyses were examined through Eviews. The series, whose characteristics were determined, and the analyses that were applied are provided below.

Figure 2 displays the logarithmic levels of the series that are being investigated. In order to deal with the non-stationarity problem of the variances, logarithmic transformation was applied.

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

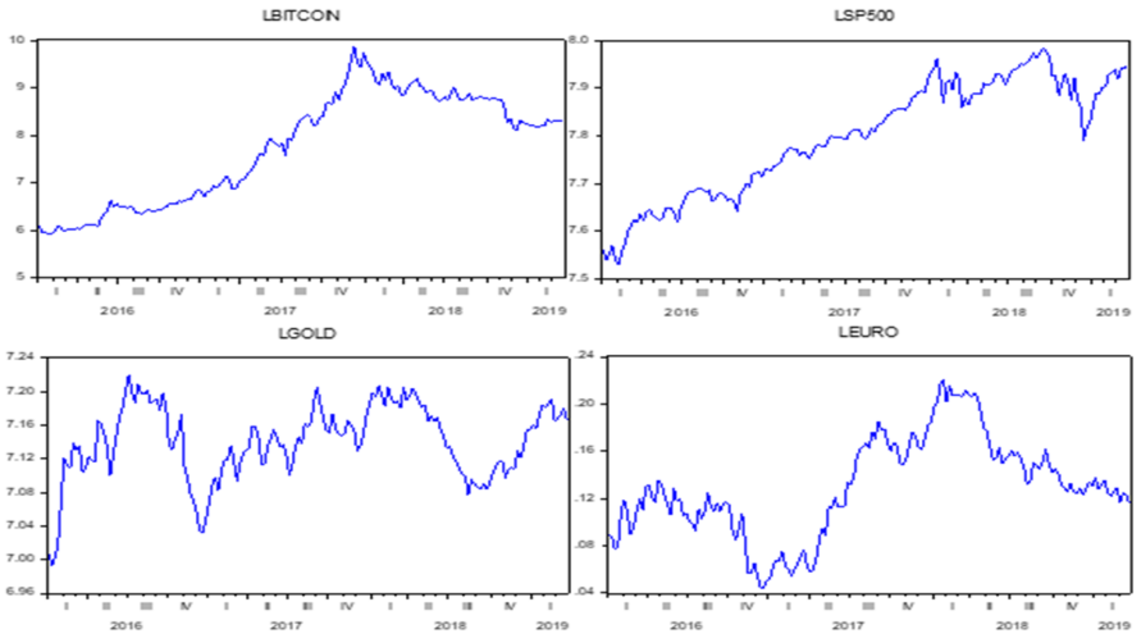

FIGURE 2: Level- Time Graphs of Series.

When the graphs shown in Figure 1 are examined, it can be seen that the means of the series is changing over time, in other words it is not distributed around a fixed average. By examining the graphs of the series, it is possible to state that they are not stationary on a level basis. However, as utilizing only the graphical analysis can give misleading results, Augmented Dickey-Fuller (ADF) unit root test developed by Dickey and Fuller (1979) was applied. The results are shown in Table 1.

Variables	LM Test	Table Critical Value **(5 %)** & Hypothesis	ADF	Table Critical Value **(5 %)** & Hypothesis	Result
LBITCOIN	11.16	χ^2_{12}=21.02	8.85 (0)	Φ_3=6.49	H_0 is rejected
LGOLD	14.76	$H_0: \rho_1 = \ldots = \rho_{12}$	5.83 (0)	$H_0: \beta = \rho = 0$ (DSP)	H_0 cannot be rejected.
LEURO	14.72		1.32 (0)	$H_a: \beta \neq 0, \rho < 0$ (TSP)	H_0 cannot be rejected.
LSP500	9.89		3.94 (0)		H_0 cannot be rejected.
Note: As a testing method, a constant term and trend were used for all variables at level value.					

TABLE 1: Results of Augmented Dickey –Fuller Test (1981).

As can be seen in Table 1, data generation processes of the time series differ. The processes for gold, Euro, and SP500 series were determined to be stochastic, whereas the Bitcoin series were found to be deterministic. In this case, the non-stationary series should be made stationary by differencing. After removing the bitcoin series from deterministic features, the same test was applied for error terms. The results are provided in Table 2.

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

Variables	DF	Table Critical Value **(%5)**	Hypothesis & Decision		Result
$\widehat{\varepsilon_t}$	-4.24	$\tau =$ -1.95	$H_0: \rho = 0$ $H_a: \rho < 0$	H_0 is rejected.	$\widehat{\varepsilon_t} \sim I(0)$
LGOLD	-11.55	τ_μ =-2.89		H_0 cannot be rejected.	$\Delta LGOLD \sim I(0)$
LEURO	-12.93	τ_μ =-2.89		H_0 cannot be rejected.	$\Delta LEURO \sim I(0)$
LSP500	-14.62	τ_μ =-2.89		H_0 cannot be rejected.	$\Delta LSP500 \sim I(0)$

TABLE 2: Dickey-Fuller (1979) Test Results for the First Difference Series.

According to Table 2, when the first differences of the variables were tested, H0 hypothesis was rejected at 5% significance level and it was decided that the series was stationary at the level of I (1) by accepting the alternative hypothesis that there was no unit root. In addition, since the data generation process of the Bitcoin series was deterministic and the error terms examined were stationary, they were used instead of the logarithmic Bitcoin series. Due to the different processes of the series, stationary VAR analysis was applied. First, we attempted to find the appropriate lag length in VAR model. The results are given in Table 3.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1401.905	NA	1.94e-13	-17.92186	-17.84365	-17.89009
1	1497.393	184.8565*	6.99e-14*	-18.94094*	-18.54994*	-18.78213*
2	1501.710	8.135576	8.12e-14	-18.79116	-18.08735	-18.50530
3	1508.852	13.09380	9.10e-14	-18.67759	-17.66098	-18.26469
4	1521.995	23.42011	9.46e-14	-18.64096	-17.31153	-18.10100
5	1531.131	15.81254	1.04e-13	-18.55296	-16.91073	-17.88596
6	1540.372	15.52111	1.14e-13	-18.46631	-16.51128	-17.67226
**: Appropriate Lag Length*						

TABLE 3: Determining the Appropriate Lag Length for VAR Analysis.

Table 3 represents that 1 lag is appropriate according to all information criteria. Therefore, the VAR (1) model was estimated and the results of the econometric assumption tests of the model are given in Table 4 below.

Lag Length	LM Test Statistics	Probability
1	10.84463	0.8190
2	11.30343	0.7904
3	12.36734	0.7183
4	20.34441	0.2051
5	18.80922	0.2787
6	15.72440	0.4724
7	12.18802	0.7309
8	15.45588	0.4915
9	14.71440	0.5456
10	9.780250	0.8778
11	13.42451	0.6415
12	16.75553	0.4016

TABLE 4: LM Autocorrelation Test Results.

The presence of autocorrelation problem in the model residuals was investigated with LM autocorrelation test and the analysis that was performed for 12 lags shows that there was no autocorrelation problem in the residuals. The White Heteroskedasticity test for VAR (1) model was used to determine whether there is heterosckedasticity. According to the test results given in Table 5, it was observed that there was no heteroskedasticity problem in the model.

Chi-Square Test Statistic	Degree of Freedom	Probability
119.9268	100	0.0851

TABLE 5: White Heteroskedasticity Test Results.

The characteristic roots of the estimated VAR model are given in Figure 2. All of the characteristic roots of the system remain within the unit circle which satisfies stability condition for the VAR (1) model. This confirms that the series are stationary and an appropriate mathematical form has been used in this study.

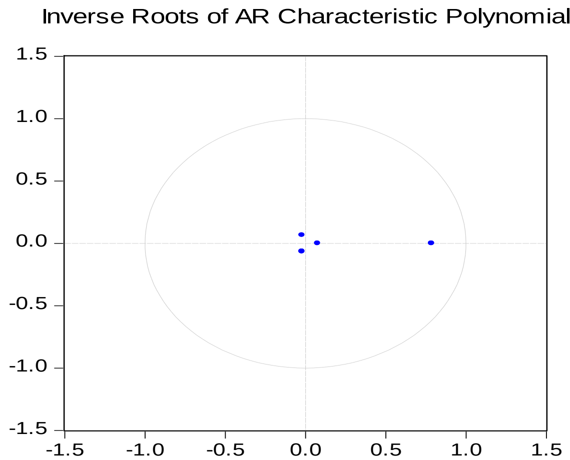

FIGURE 3: Inverse roots of AR characteristic polynomial of the estimated VAR (1) model.

Since the econometric assumptions of the VAR (1) model are satisfied, it is accepted to be the appropriate one and the model is provided as below. In line with the aim of the study, Bitcoin is selected as the dependent variable. Thus, the remaining variables are modelled as independent. Accordingly, the final model is;

$$\hat{\varepsilon}_t = -0.001262 + 0.824931\hat{\varepsilon}_{t-1} + 0.242337\Delta LGOLD_{t-1} - 1.623645\Delta LEURO_{t-1} - 1.171278\Delta LSP500_{t-1}$$

where;

LGOLD is the weekly returns of spot price of gold per ounce. LEURO is the weekly return of Euro in USD. LSP500 is the weekly return of S&P 500 index in USD.

However, the predicted coefficients in VAR models do not provide much information in terms of econometric interpretation. The important information is provided by the impulse-response functions obtained by the moving average equations. Variance Decomposition and Impulse-Response Function were examined in order to see the dynamic response of the variables to shocks.

The results of the variance decomposition for the Bitcoin series in the VAR (1) model are given in Table 6 and can be summarized as follows;

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

When the return of Bitcoin is considered as the dependent variable, it is seen that 99.48% of the change in the first period is determined by the Bitcoin return itself. In the second period, 99.07% of the change is explained by itself while 0.04%, 0.65%, 0.23% of the change are explained by Gold, Euro and S&P500, respectively. In the following periods, it is observed that the rate of explaining the change in Bitcoin by the other series is increasing, but this increase is very limited. Other periods can be evaluated in a similar manner.

According to Table 6, it is also seen that Bitcoin return does not influence other financial assets. As can be seen, in the first period Bitcoin does not determine Euro returns. In the last period only 0.024 % of Euro returns are determined by Bitcoin. Similarly, the impact of Bitcoin returns on S&P index is quite limited. The explanatory levels of Bitcoin returns in the first and last period are 0 % and 0.26 %, respectively. Gold returns are also determined by Bitcoin returns in very low percentage. However, the explanatory level is relatively higher when compared with the effect of Bitcoin returns on other financial assets. To sum up, the explanatory level of Bitcoin returns on financial assets is very minimal. Also, other financial assets explain Bitcoin returns restrictively. However, it is seen that Bitcoin is influenced more by the selected variables in the last periods. Similarly, Bitcoin returns affected the financial assets included in the study more in the last periods when compared to former periods.

BITCOIN Variance Decomposition						EURO Variance Decomposition				
Term	Standard Error	GOLD	EURO	SP500	BITCOIN	Standard Error	GOLD	EURO	SP500	BITCOIN
1	0.109907	0.056386	0.113252	0.346841	99.48352	0.009841	25.22790	74.77210	0.000000	0.000000
2	0.142774	0.041178	0.654507	0.233909	99.07041	0.009879	25.38961	74.40824	0.201181	0.000967
3	0.161359	0.044634	0.789098	0.191371	98.97490	0.009882	25.38466	74.39402	0.212979	0.008342
4	0.172856	0.047415	0.843314	0.172776	98.93650	0.009882	25.38324	74.38987	0.212971	0.013923
5	0.180255	0.048912	0.872859	0.162644	98.91558	0.009882	25.38227	74.38706	0.212964	0.017704
6	0.185117	0.049798	0.890384	0.156637	98.90318	0.009882	25.38161	74.38516	0.212960	0.020273
7	0.188352	0.050350	0.901298	0.152896	98.89546	0.009883	25.38116	74.38386	0.212957	0.022020
8	0.190520	0.050704	0.908304	0.150494	98.89050	0.009883	25.38086	74.38298	0.212955	0.023208
9	0.191980	0.050936	0.912890	0.148922	98.88725	0.009883	25.38065	74.38238	0.212954	0.024016
10	0.192967	0.051090	0.915930	0.147881	98.88510	0.009883	25.38051	74.38198	0.212953	0.024565
GOLD Variance Decomposition						SP500 Variance Decomposition				
Term	Standard Error	GOLD	EURO	SP500	BITCOIN	Standard Error	GOLD	EURO	SP500	BITCOIN
1	0.016541	100.0000	0.000000	0.000000	0.000000	0.017525	4.079182	0.346021	95.57480	0.000000
2	0.016794	97.94268	1.697244	0.113129	0.246947	0.017786	4.370968	1.536283	94.01354	0.079213
3	0.016816	97.69232	1.716759	0.117774	0.473149	0.017792	4.370720	1.535757	93.95375	0.139779
4	0.016829	97.53863	1.715761	0.117681	0.627924	0.017796	4.368959	1.535581	93.91527	0.180187
5	0.016838	97.43441	1.715201	0.117607	0.732779	0.017798	4.367760	1.535488	93.88912	0.207629
6	0.016844	97.36367	1.714834	0.117556	0.803943	0.017800	4.366946	1.535427	93.87135	0.226281
7	0.016848	97.31562	1.714585	0.117521	0.852274	0.017801	4.366392	1.535385	93.85926	0.238960
8	0.016851	97.28298	1.714416	0.117497	0.885110	0.017802	4.366015	1.535357	93.85105	0.247579
9	0.016853	97.26079	1.714301	0.117481	0.907425	0.017803	4.365759	1.535338	93.84546	0.253439
10	0.016854	97.24571	1.714223	0.117470	0.922592	0.017803	4.365585	1.535325	93.84167	0.257423

TABLE 6: Variance Decomposition Results.

Impulse-response analysis is used to examine the response of other variables to a shock occurring in one of the variables in the system. Figure 3 displays the responses of each variable to a one standard deviation shock in Bitcoin, Gold, Euro and SP500, respectively.

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

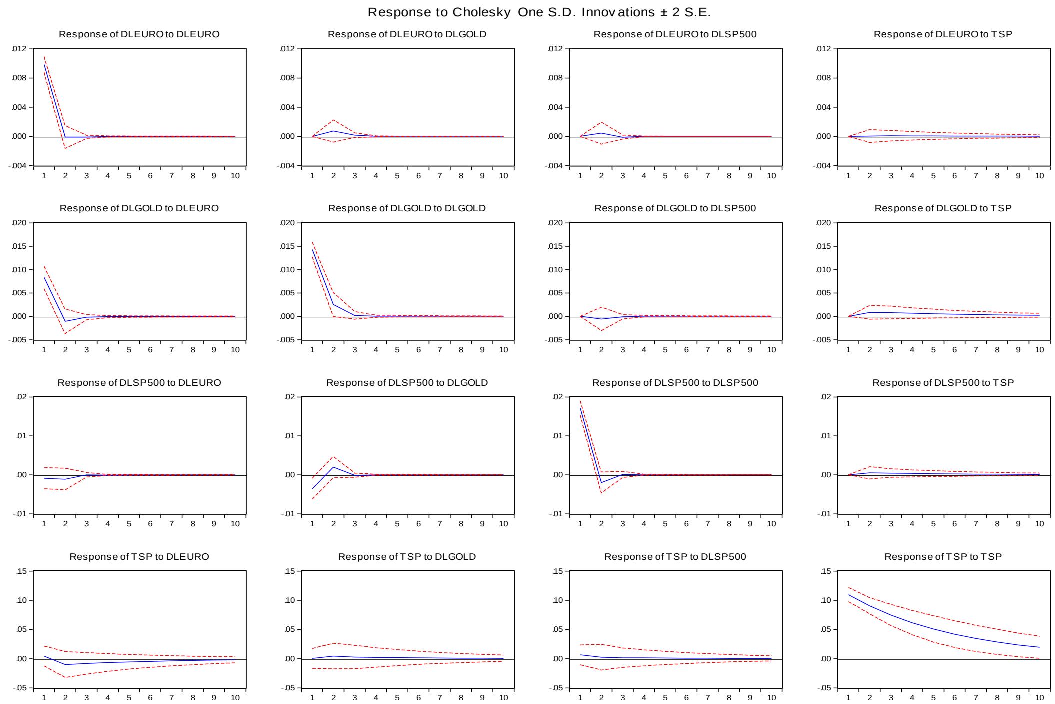

FIGURE 4: Impulse-Response Graphs of Variables Included in Analysis.

The graphs in the fourth line show the responses of the Bitcoin series to other variables. In the gold series, the Bitcoin series reacted positively in the 1st period to a standard deviation shock, while in the subsequent periods it reacted negatively. In the 10th period, it was below the previous level. In the Euro series, the Bitcoin series reacted positively in the 1st period against a standard deviation shock, while in the subsequent periods it reacted negatively. As can be seen, it was below the previous level in the 10th period. In the SP500 series, the Bitcoin series gave a positive response to a standard deviation shock in the 1st period. It also reacted positively in the following periods. In the 10th period it converged to its former balance.

4.1 Johansen Cointegration Test

The Johansen approach utilizes the maximum likelihood estimation to estimate the number of cointegration relationships and the parameters of these relationships, and is made up of VAR estimations which includes the differences and the levels of the non-stationary series and is a function of all endogenous variables' lagged values. Furthermore, this approach reveals the cointegrated relationships between the variables.

According to Trace and Maximum Eigenvalue test statistics below, it is seen that there is no long-term relationship between the examined variables. Thus, it is possible to say that Bitcoin differs from all other financial assets and no evidence has been obtained about the characteristic of Bitcoin having a relationship with other financial instruments.

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. Of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.114735	33.91156	40.17493	0.1850
At most 1	0.053227	13.55963	24.27596	0.5742
At most 2	0.025688	4.425409	12.32090	0.6493

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

At most 3	0.000476	0.079469	4.129906	0.8170

Trace test indicates no cointegration at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

** MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegraion Rank Test (Maximum Eigenvalue)

Hypothesized No. Of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.114735	20.35193	24.15921	0.1510
At most 1	0.053227	9.134224	17.79730	0.5794
At most 2	0.025688	4.345940	11.22480	0.5741
At most 3	0.000476	0.079469	4.129906	0.8170

TABLE 7: Johansen Cointegration Test.

In order to test the forecast accuracy of the estimated VAR model given above, the model was re-estimated for the 16th July 2017 and 06th August 2017 period. The criteria based on the deviation between the estimated and actual values of the model were obtained and the results are given in Table 8.

Variables	RMSE	MAPE
$\hat{\varepsilon_t}$	0.006641	0.005454
$\Delta LGOLD$	0.014232	0.011903
$\Delta LEURO$	0.011104	0.010162
$\Delta LSP500$	0.086846	0.082443
$r = 0.9321$		

TABLE 8: Forecast Results for Estimated Model.

The criteria given in Table 8 are expected to be small and the correlation coefficient is expected to be close to 1 (Guttormsen, 1999). In addition, the finding that the MAPE (Mean Absolute Percentage Error) criterion is below 10% indicates that the estimation is good when evaluating the estimation accuracy of a single model (Temuçin and Temiz, 2016). In this respect, it can be said that the relationship between the predicted and actual values of the model is positive and high. Additionally, it is possible to say that the estimation accuracy within the period of the model is very high when evaluated according to the estimation criteria.

5. CONCLUSION

Digital currencies have become a part of the global financial system. The number of cryptocurrencies is more than two thousand and it has been increasing day by day. However, none of them is as popular as Bitcoin.

Bitcoin is firstly seen in Nakamoto's (2008) paper entitled as 'Bitcoin: A Peer-to-Peer Electronic Cash System'. The author explains how the blockchain system works and gives technical information about Bitcoin mining and trade in money transaction after the mining process. According to Raskin and Yermack (2018), investors or traders transfer money directly without any central bank.

The innovative notion of Bitcoin has attracted investors to use it as a financial instrument. Nevertheless, studies about Bitcoin or any other cryptocurrency have questioned how Bitcoin should be classified and where it can be placed in the financial system. The results are complicated since some studies state that Bitcoin carries the characteristics of both a currency and a commodity (Dyhrberg, 2016; Polasik et al., 2015) whereas some claim that it is a speculative asset as it differs from some currencies and commodities and has high volatility (Baur et al., 2018: Briere et al., 2015). In addition, some studies have examined whether Bitcoin is a hedging tool or not and investigated its diversification capacity for diminishing portfolio risk. The results of these studies are also mixed. On one hand, findings of some studies reveal that Bitcoin can be used as an instrument to reduce portfolio risk and for hedging (Baur et al., 2018; Guesmi et al., 2019; Katsiampa, 2017). On the other hand, Bitcoin cannot be a good diversification tool in terms of decreasing risk in the portfolios according to some other studies (Klein et al., 2018).

The study differs from previous studies in terms of including data generation process in the analysis. In the literature, financial models such as ARCH and GARCH are mostly preferred and the series are generally accepted as stochastic. However, we have used the traditional time series model, in which determining the data creation process may provide more accurate results. Therefore, it is determined that Bitcoin series is deterministic after this process is examined. However, it should not be neglected that the process of the series may change if a different period is chosen or data frequency is changed.

Results in the study reveal that Bitcoin has no relationship with other financial assets in the long term. In other words, Bitcoin returns cannot be affected by other financial instruments. According to variance decomposition results, returns of Bitcoin are mostly explained by itself. The impact of other financial instruments on Bitcoin returns are very limited. Similarly, Bitcoin returns has no effect on Euro, Gold, and S&P 500 returns. Thus, it can be concluded that Bitcoin is a highly speculative asset and its returns cannot be explained with the returns of other financial instruments. In other words, we found that investors should consider Bitcoin’s price movements rather than other financial instruments for their investment decisions since Bitcoin returns are mostly explained itself and not influenced by other assets. It is seen that these results obtained in the study support the studies finding Bticoin is isolated from traditional assets in the related literature (Corbet et al., 2018; Ji et al., 2018; Kurihara and Fukushima 2018; Zeng et al., 2020).

But the study has time and variable limitations. So, examining the relationship with addition of different financial assets such as other indices, other currencies and other commodities may give different results. Additionally, the last three years were investigated in this study. To extend the period for analyses may provide different results. Also, we focused only on the relationship between Bitcoin and other financial assets. Future studies may extend the analysis by examining Bitcoin based on portfolio theories to figure out the impact of Bitcoin investing on the risk and returns of portfolios. Furthermore, investigating Bitcoin returns on daily or monthly basis may contribute to the literature related to Bitcoin and other cryptocurrencies.

6. REFERENCES

Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar–A replication and extension. *Finance research letters,* 25, 103-110.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets?. *Journal of International Financial Markets, Institutions and Money*, 54, 177-189.

Blau, B. M. (2018). Price dynamics and speculative trading in Bitcoin. *Research in International Business and Finance*, 43, 15-21.

Bouri, E., Azzi, G., & Dyhrberg, A. H. (2017). On the return-volatility relationship in the Bitcoin market around the price crash of 2013. *Economics: The Open-Access, Open-Assessment E-Journal*, 11(1), 1-16.

Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics*, 50(55), 5935-5949.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. *Finance Research Letters*, 20, 192-198.

Bozkurt, P., & Tari, R. (2006). Turkiye'de Istikrarsiz Buyumenin Var Modelleri Ile Analizi (1991.1-2004.3). *Istanbul University Econometrics and Statistics e-Journal*, 4(1), 1-16.

Briere, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management*, 16(6), 365-373.

Chohan, U. W., (2017). A History of Bitcoin. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3047875

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28-34.

Cretarola, A., Figà-Talamanca, G., & Patacca, M. (2020). Market attention and Bitcoin price modeling: Theory, estimation and option pricing. *Decisions in Economics and Finance*, 43(1), 187-228.

Demir, E., Gozgor, G., Lau, C. K. M., & Vigne, S. A. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Finance Research Letters*, 26, 145-149.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, 74(366a), 427-431.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: journal of the Econometric Society*, 49(4), 1057-1072.

Dowd, K., & Hutchinson, M. (2015). Bitcoin will bite the dust. *Cato Journal*, 35(2), 357-382.

Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold?. *Finance Research Letters*, 16, 139-144.

Enders, W. (1995). *Applied Econometric Time Series*. New York: Iowa State University. Jonh Wiley&Sons.

Eom, C., Kaizoji, T., Kang, S. H., & Pichl, L. (2019). Bitcoin and investor sentiment: statistical characteristics and predictability. *Physica A: Statistical Mechanics and its Applications*, 514, 511-521.

Erdas, M. L., & Caglar, A. E. (2018). Analysis of the relationships between Bitcoin and exchange rate, commodities and global indexes by asymmetric causality test. *Eastern Journal of European Studies*, 9(2), 27-45.

Ertek, T. (2000). *Ekonometriye Giriş*, (Second Edition). Beta Publication.

European Central Bank (2012). Virtual Currency Schemes. https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemes201210en.pdf

Glaser, F., Zimmarmann, K., Haferhorn, M., Weber, M.C., & Siering, M., (2014). Bitcoin Asset or currency? Revealing users' hidden intentions. In: Twenty Second European Conference on Information Systems, ECIS 2014, Tel Aviv, pp. 1–14. Available at SSRN: https://ssrn.com/abstract=2425247

International Journal of Business Research and Management (IJBRM)
ISSN: 2180-2165, https://www.cscjournals.org/journals/IJBRM/description.php

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis*, 63, 431-437.

Guttormsen, A. G. (1999). Forecasting weekly salmon prices: risk management in fish farming. *Aquaculture Economics & Management*, 3(2), 159-166.

Ji, Q., Bouri, E., Gupta, R., & Roubaud, D. (2018). Network causality structures among Bitcoin and other financial assets: A directed acyclic graph approach. *The Quarterly Review of Economics and Finance*, 70, 203-213.

Johansen, S. (1995). *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford University Press on Demand.

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, 158, 3-6.

Keating, J. W. (1990). Identifying VAR models under rational expectations. *Journal of Monetary Economics*, 25(3), 453-476.

Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the New Gold–A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, 59, 105-116.

Kokkinaki, A., Sapuric, S., & Georgiou, I. (2018, October). The relationship between bitcoin trading volume, volatility, and returns: A study of four seasons. In *European, Mediterranean, and Middle Eastern Conference on Information Systems* (pp. 3-15). Springer, Cham.

Kumar, V., Leone, R. P., & Gaskins, J. N. (1995). Aggregate and disaggregate sector forecasting using consumer confidence measures. *International Journal of Forecasting*, 11(3), 361-377.

Kurihara, Y., & Fukushima, A. (2018). How does price of Bitcoin volatility change?. *International Research in Economics and Finance*, 2(1), 8-14.

Kutlar, A. (2000). *Ekonometrik zaman serileri*. Gazi Publication.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. Unpublished manuscript, retrieved from https://Bitcoin.org/Bitcoin.pdf.

Park, S., Jang, K., & Yang, J. S. (2021). Information flow between bitcoin and other financial assets. *Physica A: Statistical Mechanics and its Applications*, 566, 1-13.

Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R., & Lightfoot, G. (2015). Price fluctuations and the use of bitcoin: An empirical inquiry. *International Journal of Electronic Commerce,* 20(1), 9-49.

Raskin, M., & Yermack, D. (2018). Digital currencies, decentralized ledgers and the future of central banking. In P. Conti-Brown, & M.L. Rosa (Eds.), *Research handbook on central banking*. (pp. 474-486). Edward Elgar Publishing.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 48(1), 1-48.

Tarı, R. (2010). *Ekonometri,* (Extended 6th Edition). Umuttepe Publications.

Temuçin, T., & Temiz, İ. (2016). Türkiye Dış Ticaret İhracat Hacminin Projeksiyonu: Holt-Wınters ve Box-Jenkıns Modellerinin Bir Kıyaslaması. *Suleyman Demirel University The Journal of Faculty of Economics and Administrative Sciences,* 21(3), 937-960.

Yermack, D. (2015). Is Bitcoin a real currency? An economic appraisal. In D. L. K. Chuen (Ed) *Handbook of digital currency* (1st pp. 31-43). Academic Press.

Zeng, T., Yang, M., & Shen, Y. (2020). Fancy Bitcoin and conventional financial assets: Measuring market integration based on connectedness networks. *Economic Modelling*, 90, 209-220.