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Bitcoin's Effect on Selected Crypto Assets: Quantitative Evidence

(Research Article)

Bitcoin'in Seçili Kripto Varlıklar Üzerindeki Etkisi: Kantitatif Kanıtlar

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ABSTRACT

The main objective of the study is to systematically investigate the effects of Bitcoin on specific crypto assets. In this context, a sample of 135 observations between 2020W01 and 2022W33 for seven crypto assets with the highest value in the financial markets, including Ethereum, Tether, USD Coin, BNB, XRP, and Cardano, has been included in the study sample. These crypto assets, along with Bitcoin, constitute almost 95% of the total crypto asset portfolio. This situation increases the importance of representing a broad universe in the study and contributes to the academic literature. To examine the effects of Bitcoin on the selected crypto assets, a Multivariate Dynamic VAR Model has been used. The model assumes causality among variables. Variables that do not meet this assumption have been excluded from the study sample. The results of the study demonstrate that Bitcoin exhibits significant and one-way effects on all cryptocurrencies. However, the impact of other crypto assets on Bitcoin has been negligible. In this context, it is emphasized that investment decisions obtained from two-way evaluations may be risky and misleading. In order to reduce investment risks for crypto assets to more acceptable levels, the use of comprehensive analysis methods is recommended.

Anahtar Kelimeler:
Bitcoin, Kripto Varlıklar, Nedensellik, Çok Değişkenli Dinamik VAR Modeli, Etki Tepkisi ve Varyans Ayrıştırma Fonksiyonları, Korelasyon ve Kovaryans Matris

ÖZET

Çalışmanın temel amacı, Bitcoin'in belirli kripto varlıklar üzerindeki etkilerini sistemli bir biçimde araştırmaktır. Bu bağlamda, finansal piyasalarda değeri en yüksek olan Ethereum, Tether, USD Coin, BNB, XRP ve Cardano gibi yedi kripto varlığın 2020W01 ile 2022W33 arasındaki 135 gözlemleri çalışma örneklemine dahil edilmiştir. Bu kripto varlıklar, Bitcoin ile birlikte toplam kripto varlık portföyünün neredeyse %95'ini oluşturmaktadır. Bu durum, çalışmanın geniş bir evreni temsil etmesinden kaynaklanan önemini artırmakta ve akademik literatüre katkı sağlamaktadır. Bitcoin'in seçilen kripto varlıklar üzerindeki etkilerini incelemek için, Çok Değişkenli Dinamik VAR Modeli kullanılmıştır. Model, değişkenler arasında nedensellik olduğunu kabul eder. Bu varsayımı sağlamayan değişkenler çalışma örneğinden çıkarılmıştır. Çalışmanın sonuçları, Bitcoin'in tüm kripto para birimleri üzerinde anlamlı ve tek yönlü etkiler gösterdiğini ortaya koymaktadır. Ancak, diğer kripto varlıkların Bitcoin'e etkisi, göz ardı edilebilecek kadar küçük olmuştur. Bu bağlamda, iki yönlü değerlendirmelerden elde edilen yatırım kararlarının riskli ve yanıltıcı olabileceği vurgulanmaktadır. Kripto varlıklara yönelik yatırım risklerini daha kabuledilebilir boyutlara indirebilmek maksadıyla, kapsamlı analiz yöntemlerinin kullanılması önerilmektedir.

1. INTRODUCTION

Money is expected to express a common value and facilitate commercial activities by performing the function of exchange. While discussions on the monetary function of crypto assets continue, they are increasingly recognized as a form of money in the literature. However, it is important to note that crypto assets do not yet fully meet all the functions of money under current market conditions. In practice, crypto assets are predominantly utilized as investment tools (Gandal & Halaburda, 2016).

Bitcoin (BTC), the first and most prominent cryptocurrency, was created by Satoshi Nakamoto in 2009. As a decentralized digital currency, Bitcoin uses blockchain technology to secure transactions and is used globally for value storage and digital payments. Its limited supply and secure transaction capabilities have earned it the title of digital gold (Nakamoto, 2008; Antonopoulos, 2014).

Ethereum (ETH), launched in 2015 by Vitalik Buterin, is a blockchain platform that supports smart contracts and decentralized applications (dApps). Ether (ETH), the native cryptocurrency of Ethereum, facilitates transactions within its ecosystem and various applications, making Ethereum a crucial platform for decentralized finance (DeFi) and innovative blockchain-based projects (Buterin, 2013; Antonopoulos & Wood, 2018).

Binance Coin (BNB), introduced in 2017 by Changpeng Zhao, is the native token of the Binance cryptocurrency exchange. BNB is used to pay trading fees on Binance, facilitate transactions on Binance Smart Chain (BSC), and access various services within the Binance ecosystem. Binance Coin’s integration into the exchange's operations and broader ecosystem highlights its importance in the cryptocurrency market (Binance, n.d.; Binance Research, n.d.).

Ripple (XRP), created by Chris Larsen and Jed McCaleb in 2012, is a digital payment protocol designed for efficient and low-cost international money transfers. XRP serves as the native cryptocurrency of the Ripple network, aiming to improve cross-border transactions and financial institution interoperability (Ripple Labs Inc., n.d.).

Cardano (ADA), launched in 2017 by Charles Hoskinson, is a blockchain platform developed based on scientific research, supporting smart contracts and decentralized applications. ADA, the native cryptocurrency of Cardano, plays a key role in its ecosystem, which focuses on creating a secure and scalable blockchain environment (Cardano Foundation, n.d.).

Tether (USDT) and USD Coin (USDC) are stablecoins pegged to fiat currencies, such as the US dollar. Tether is used to provide liquidity in the cryptocurrency markets and minimize value fluctuations, while USD Coin aims to offer transparency and regulatory compliance through its fiat-pegged value (Tether Limited, 2021; Centre Consortium, n.d.).

Theoretically, the value of money is determined by its supply, indicating an inverse relationship between supply and value. This principle applies to all commodities, including crypto assets. Unlike traditional money, which is controlled by authorities, crypto assets are governed by algorithms and blockchain technology rather than central authorities (Ciaian et al., 2016a, b; Bouoiyour & Selmi, 2015).

The security of traditional money is backed by legal authorities and laws, whereas crypto assets rely on blockchain technology for security and encryption. Crypto assets can be stored in user-specific virtual wallets, allowing transfers between users via these wallets and networks. Despite being used in commercial activities in various countries, the absence of legal backing for crypto assets introduces both security concerns and opportunities for innovation (Ciaian et al., 2018).

The characteristics, benefits, and drawbacks of crypto assets include;

- The lack of legal authority backing creates security concerns and complicates the monitoring of illegal transactions,
- Encrypted algorithms ensure minimal human error,
- Asset transfers incur minimal fees compared to traditional intermediaries,
- The absence of legal authority prevents intervention and seizure risks but also makes it impossible to recover lost assets (Çakracıoğlu, 2016; Conti et al., 2017),
- Supply is exclusively achieved through crypto mining,
- Limited supply intervention reduces inflationary pressures,
- The lack of central bank intervention might encourage speculative activities,
- Many countries do not legally recognize crypto assets, complicating taxation (Conti et al., 2017).

The high energy cost and technological demands of cryptocurrency mining create monopolies, limiting access for ordinary entrepreneurs (Wright & De Filippi, 2015).

The purpose of this study is to investigate the impact of Bitcoin on other selected cryptocurrencies. Bitcoin was chosen as the independent variable due to its significant market presence, constituting approximately 49% of all assets traded by volume and market capitalization. The study also examines seven of the most valuable cryptocurrencies, which together represent about 95% of the total crypto asset portfolio. This research contributes to the literature by providing insights into nearly the entire cryptocurrency market. Data for this study were sourced from "Invest.com" (https:///en.investing.com/crypto/currencies, Access date: 22.08.2023).

The impact of Bitcoin on the selected variables was assessed using time series analysis techniques based on the VAR Model. The VAR Model assumes causal relationships between variables, and the study also explored these relationships (Granger, 1980). USDT and USDC were excluded from the VAR Model due to the lack of a causal relationship with Bitcoin.

The introduction covers the concept of money and its functions, discusses why crypto assets are not yet considered money, and reviews their literature, production, security, and transparency mechanisms. It outlines the dynamics and concerns in user and investor preferences, and summarizes the scope, limitations, data set, research methods, and results of the study. The second part reviews the literature, while the third part presents the methodology and empirical findings. The conclusion discusses the findings and offers opinions and recommendations (Sunbul, 2022).

2. LITERATURE

Bitcoin is the beginning of the literature (Nakamoto, 2008) and it is the crypto asset with the highest trading volume and value in the market. It is seen that the production and security protocols in other altcoins imitate Bitcoin (Böhme et al., 2015; Dilek, 2018; Algan et al., 2020). The use of crypto assets as an investment tool rather than an exchange tool has made it spread globally in a short time (Dirican & Canöz, 2017). When the crypto asset market is examined, it is seen that the assets take on highly variable values (Dyhrberg, 2016; Charles & Derne, 2018). While this increases speculative transactions, it also weakens confidence in crypto assets.

In recent years, many empirical studies have been conducted investigating the relationships between crypto assets. It is known that these studies are also used in investment decisions (Şak, 2021). Studies have shown that there is causality and cointegration between almost all crypto assets. Sunbul (2023a) stated that it would be beneficial to examine the nature of crypto assets with different methods other than causality and cointegration.

When the selected literature is examined; Polat & Gemici (2018), researched the relationship between Bitcoin and four different altcoins with Toda-Yamamoto Causality and Johansen Cointegration Methods, Karaağaç & Altınırmak (2018), the relationship between 10 different crypto assets with Johansen Cointegration and Granger Causality Methods, Akçalı & Şişanoğlu (2019), the relationship between Bitcoin, Ethereum, Litecoin, Nem, Ripple, Dash, Stellar and Monero with Yamamoto Causality Method, Salihoğlu & Han (2019), the relationship between Ripple, Ethereum, and Litecoin with Hacker Hatemi Symmetric and Hatemi J Asymmetric Causality Methods, Dastgir et al., (2019) short-term investigated the relationship between Google Trends and Bitcoin with the Granger Causality Methods, Konuskan et al., (2019) the relationship between Bitcoin, Ethereum, and Ripple with Johansen Cointegration Methods.

It is seen that few methods are used in the literature apart from causality and cointegration methods (Sunbul, 2023a). When some of these are examined;

Wei (2018), in Granger Causality Analysis, based on the VAR Model, found that Tether exports caused an increase in Bitcoin transaction volume but did not change its price. Dönmez et al., (2021) used the daily observation values of Bitcoin, Ethereum, Litecoin, and Ripple crypto assets from 03.08.2017 to 17.03.2020, and examined the relationships between the variables with the VAR Model. As a result of the study, they determined that Bitcoin's self-explanatory power decreased over time, while its effect on other variables in the model increased over time. In the same study, investors were advised to diversify their asset baskets and choose independent crypto assets. Özaydın (2021) investigated the relationships between the variables with the help of the VAR Model, using the daily observation values of ETH, BNB, ADA, XRP, and DXY crypto assets from February 2018 to October 2021. As a result of the study, which touched on the dominant power of BTC in terms of transaction volume and market value, it was concluded that the impact of Bitcoin on other altcoins has increased remarkably over time. Emir (2023) investigated the effects of Bitcoin on other coins by using the TVP-VAR Model with data from Bitcoin, Ethereum, Binance Coin, Ripple, Cardano, and Dogecoin between 09.11.2017 and 22.08.2022. As a result of the study, they found that Bitcoin also affected other cryptocurrencies from the beginning of the sample until 2021. However, after 2021, differences have been observed in the severity and direction of the said effect.

Sathyanarayana & Gargesa (2019) investigated the effect of USD, GBP, Euro, Yen, and CHF currencies on Bitcoin with the help of the VAR Model. They used data from the Strosess and Yahoo Finance databases from 2013M9 to 2018M3. As a result of the study, they revealed that the USD, GBP, and JP currencies contributed significantly to the volatility in Bitcoin. According to the impulse response function result, it was determined that Bitcoin was affected by the shocks it experienced, was only affected by the USD for a while, but then the effect continued with insignificant fluctuations. On the other hand, it has been seen that the effect of other currencies on Bitcoin was negligible.

Urom et al., (2020) analyzed the stock, gold, and crude oil data of twelve developed countries using the Bayesian time-varying autoregressive parameter vector (TVP-VAR) Model to investigate the behavior of Bitcoin from different market conditions. As a result of the study, they have seen that the volatility in Bitcoin changed over time. In addition, it has been determined that there were changes in the same direction in Bitcoin in parallel with the increase in stock and crude oil prices in the market. An inverse dependency from Bitcoin to the crude oil exchange was only detected in the Finland, Holland, and US markets. Its dependence on other markets was negligible.

Bourghelle et al., (2022) examined the relationship between variables using data on fluctuations in Bitcoin crypto assets and investor behavior from 2018 to 2021. The consumer market sentiment index, which is also conceptualized as the fear and greed index, was used to determine the investor behavior variable. The variables were examined with the help of Linear and Non-Linear VAR Models. As a result of the study, they revealed that Bitcoin was highly affected by the collective mood of consumers, especially during the COVID-19 outbreak.

Omri (2023) investigated the difference between the stock market indices of fifteen developing and fifteen developed countries, using data from 2017M3 to 2021M12 in terms of the predictability of Bitcoin. In the study conducted using the VAR Model, no significant difference was found between developed and developing countries. In addition, Qatar's QE Index, South Korea's Kospi Composite Index, Saudi Arabia's Tasi Index, Japan's Nikkei 225 Index, Tunisia's Tunindex Index, and Switzerland's Securities Index have been the most influential markets in Bitcoin returns.

Although many empirical studies have been done in the literature to understand the nature of crypto assets, a solid theory that can explain the pricing mechanism has not yet been developed (Sathyanarayana & Gargesa, 2019). The reason for this is that crypto-assets do not have dynamics such as profit share, cash flow, or earnings generation, as in other securities used in the market. The main factor determining the value of crypto assets is that it is a popular investment vehicle. The main reason why both investors and sovereign countries are worried about crypto-assets is the lack of legal authority over these assets.

3. METHODOLOGY AND EMPIRICAL APPLICATIONS

The purpose of the study is to investigate the impact of Bitcoin crypto assets on other selected crypto assets. Bitcoin was chosen as the independent variable because it constitutes approximately 49% of all assets traded in the market in terms of trading volume and market capitalization. Additionally, each of the seven most valuable crypto assets traded in financial markets was selected as the dependent variable. Together with Bitcoin, these selected crypto assets make up about 95% of the entire crypto asset portfolio. In this regard, the study contributes to the literature by representing almost all crypto assets. The data used in the study were obtained from the "Invest.com" webpage (https:///en.investing.com/crypto/curregency, Access date: 22.08.2023).

3.1. Methodology

The impact of Bitcoin on the chosen variables was assessed using time series analysis techniques based on the VAR Model. The causal relationship between Bitcoin and other factors was also examined because the VAR Model analysis assumes a causal relationship between the variables (Granger, 1980).

Time series can contain complex processes and components. This can make it difficult to understand the relationships between variables. In the literature, many different methods have been proposed for the solution of these relations, and studies are continuing on different methods in academia. Each analysis method developed may also have some limitations and assumptions. In this study, a multivariate data set was used and the variables provided stationarity at different degrees. Answers were sought to questions such as in which direction, how much, how many periods the Bitcoin crypto asset affects other variables, the strength of the relationship, and the correlation between the variables. All these factors, the nature of the variables used, and descriptive statistical research have shown that the best answer to the study questions can be found with the Multivariate Dynamic VAR (MDVAR) Model. The model can be easily applied to integrated (stationary) series of different degrees and the statistics produced are reliable. Although the MDVAR model is flexible in terms of stationarity levels, it works on the assumption that there is a causal relationship between the series. Due to the said constraint, the variable to be included in the model was decided by Granger Causality Analysis before the MVAR Model was created and the VDAR Model assumption was provided according to the stationarity conditions of the series.

Granger Causality Analysis uses the least squares estimator to investigate causality in time series. It also calculates the predictive power of the model with the help of the minimum mean squares error coefficient (Granger & Newbold, 1986). In Granger Causality Analysis, the time series must be stationary (Granger, 1980). Series can be stationary at the I(0) level and I(1) difference (Sunbul & Benli, 2021). The equation obtained for a bivariate model in Granger Causality Analysis is presented below (Sunbul, 2023b).

$$\mathcal{Y} = \sum_{i=1}^{m} \partial i \mathcal{Y}(t-i) + \sum_{j=1}^{m} \varphi j \mathcal{X}(t-j) + u(2t) \tag{1}$$

$$\mathcal{X} = \sum_{i=1}^{m} \alpha i \mathcal{Y}(t-i) + \sum_{j=1}^{m} \beta j \mathcal{X}(t-j) + u(1t) \tag{2}$$

It is assumed that the error terms (u(2t) and u(1t)) in the model are independent of each other. It is represented by the lag length (m).

Example equations for the Multivariate VAR Model are as follows (Hacioglu, 2019)

$$\mathcal{Y}_{1,t} = \mathcal{C}_1 + \mathcal{A}_{1,1}\mathcal{Y}_{1,t-1} + \mathcal{A}_{1,2}\mathcal{Y}_{2,t-1} + \mathcal{E}_{1,t} \tag{3}$$

$$\mathcal{Y}_{2,t} = \mathcal{C}_2 + \mathcal{A}_{2,1}\mathcal{Y}_{1,t-1} + \mathcal{A}_{2,2}\mathcal{Y}_{2,t-1} + \mathcal{E}_{2,t} \tag{4}$$

In the estimated model, it is desired that the error terms (Ɛ_(1,t)) and (Ɛ_(2,t)) are I(0) level stationary. Information criteria and unit root analyses are utilized to determine the lag length. It is assumed that there is a causal relationship between the variables in the estimated model. Direct interpretation of the VAR model is statistically quite challenging. A more accurate approach is to interpret the Impulse Response Function, Variance Decomposition, correlation coefficients, and covariance matrix using the model parameters (Sunbul, 2022).

3.2. Empirical Applications

In this section, the basic statistical data of the variables used are given, and in this context, the stationarity of the time series is investigated by evaluating the time path graphs of the original series. The causality relationship between the variables was investigated for the variables that met all the assumptions. In the research, the answers to the research questions are sought with the help of the variables that have a causal relationship with the Bitcoin crypto asset and the parameters obtained by estimating a model based on the VAR Model.

The sample of the research consists of seven crypto assets with the highest market size and trading volume. These are BTC, ETH, USDT, USDC, BNB, XRP, and ADA crypto assets. Descriptive information and statistics regarding the said assets are presented in Table 1.

Table 1. Descriptive Information and Statistics

Sequence no	Crypto-currency type	Symbol of Money	Unit price (USD)	Market value	Transaction volume (24 hours)
1	Bitcoin	BTC	21,275	$406.21B	$28.11B
2	Ethereum	ETH	1,572.32	$191.28B	$17.64B
3	Tether	USDT	0.9999	$67.55B	$47.67B
4	USD Coin	USDC	1	$52.45B	$5.45B
5	BNB	BNB	296.5	$47.61B	$1.44B
6	XRP	XRP	0.33576	$16.54B	$872.80M
7	Cardano	ADA	0.4524	$15.24B	$704.71M

It was determined that there were 6,669 cryptocurrencies registered in the system on the date of access.
Source: *https://tr.investing.com/crypto/currencies, (Accessed on 22.08.2023).*

When Table 1 is examined, it is seen that BTC ranks first in terms of both market value and transaction volume. Descriptive statistics for the dataset are presented in Table 2.

Table 2. Descriptive Statistics

	BTC	ETH	USDT	USDC	BNB	XRP	ADA
Min	5,183.00	123.00	0.998	0.997	10.01	0.146	0.0258
Median	32,247.00	1,696.00	1.000	1.000	259.2	0.463	0.5535
Mean	30,421.00	1,728.00	1.001	1.000	233.60	0.571	0.7996
Max	64,397.00	4,644.00	1.008	1.002	649.50	1.651	28.464

Table 2 presents descriptive statistics for various cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), USD Coin (USDC), Binance Coin (BNB), Ripple (XRP), and Cardano (ADA). The table includes minimum, median, mean, and maximum values for each cryptocurrency.

For Bitcoin (BTC), the minimum value is 5,183.00 USD, and the maximum value is 64,397.00 USD. The median and mean values are 32,247.00 USD and 30,421.00 USD, respectively. This indicates a broad price range with the average value close to the median.

For Ethereum (ETH), the minimum value is 123.00 USD, and the maximum value is 4,644.00 USD. The median value is 1,696.00 USD, and the mean value is 1,728.00 USD. Ethereum exhibits a narrower price range compared to Bitcoin, with median and mean values being relatively close.

Tether (USDT) and USD Coin (USDC) are stable cryptocurrencies, so their minimum, median, and mean values are very close to each other. Tether has a maximum value of 1.008 USD and a minimum value of 0.998 USD. USDC has a maximum value of 1.002 USD and a minimum value of 0.997 USD. These values reflect the stability of these coins.

For Binance Coin (BNB), the minimum value is 10.01 USD, and the maximum value is 649.5 USD. The median value is 259.2 USD, and the mean value is 233.6 USD. Binance Coin shows a wide price range with median and mean values being relatively close.

For Ripple (XRP), the minimum value is 0.146 USD, and the maximum value is 1.651 USD. The median value is 0.463 USD, and the mean value is 0.571 USD. Ripple also exhibits a broad price range, with the mean value slightly exceeding the median.

For Cardano (ADA), the minimum value is 0.0258 USD, and the maximum value is 28.464 USD. The median value is 0.5535 USD, and the mean value is 0.7996 USD. Cardano has a very wide price range and a high mean value compared to its median.

These statistics provide insights into the price volatility and range for each cryptocurrency. Stablecoins, such as Tether and USD Coin, maintain relatively constant values, while other cryptocurrencies show significant variability in their price ranges.

The time path graphs obtained with the original observation values of the data set are presented in Figure 1.

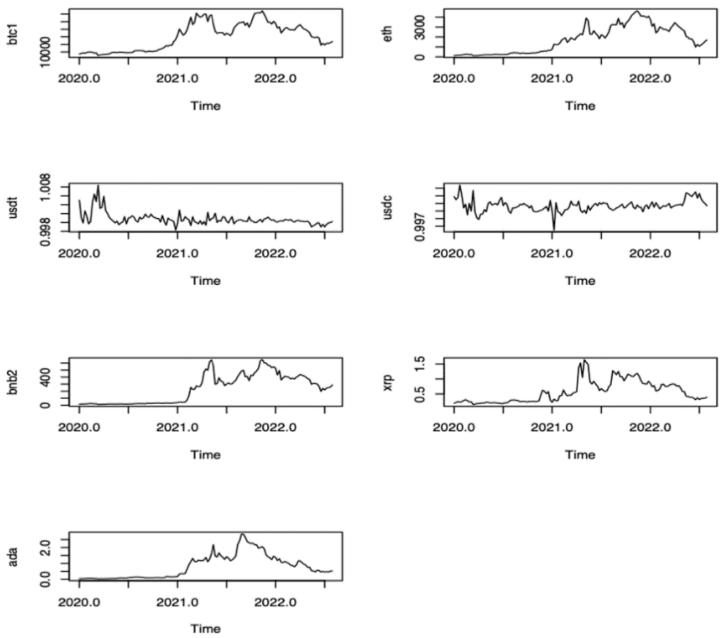


Figure 1. Time Path Charts

When Figure 1 is examined, it can be said that all variables except USDT and USDC follow a similar course. It is seen that these variables followed a horizontal course until the beginning of 2021, tended to increase from the beginning of 2021 until the third quarter, and continued to increase until the end of the year after the downward trend in the middle of 2021. USDT and USDC, on the other hand, seem to be following a calm course despite minor fluctuations.

The stability control of the seven variables in the data set was done with the PP Unit Root Test. null hypothesis for testing;

- H0= Series is non-stationary, ie contains unit root (H0 cannot be rejected for p> 0'***', 0.001'**', 0.01'*', 0.05'.').

The result of stationary test is presented in Table 3.

Table 3. Stationarity Test Results

Variables	***P-value***		**Results**
	***I* (0)**	***I* (1)**	
BTC1	0.9	0.01	*I*(1) for H0 reject
ETH	0.8	0.01	*I*(1) for H0 reject
USDT	0.01	-	*I*(0) for H0 reject
USDC	0.01	-	*I*(0) for H0 reject
BNB2	0.7	0.01	*I*(1) for H0 reject
XRP	0.4	0.01	*I*(1) for H0 reject
ADA	0.9	0.01	*I*(1) for H0 reject

Reference Value: *0'***', 0.001'**', 0.01'*', 0.05'.'*

When Table 3 is examined, it is seen that BTC, ETH, BNB, XRP, and ADA variables are stationary at the I(1) difference, while USDT and USDC variables are stationary at the I(0) level. The original and difference observation values of the variables are presented in Figure 2.

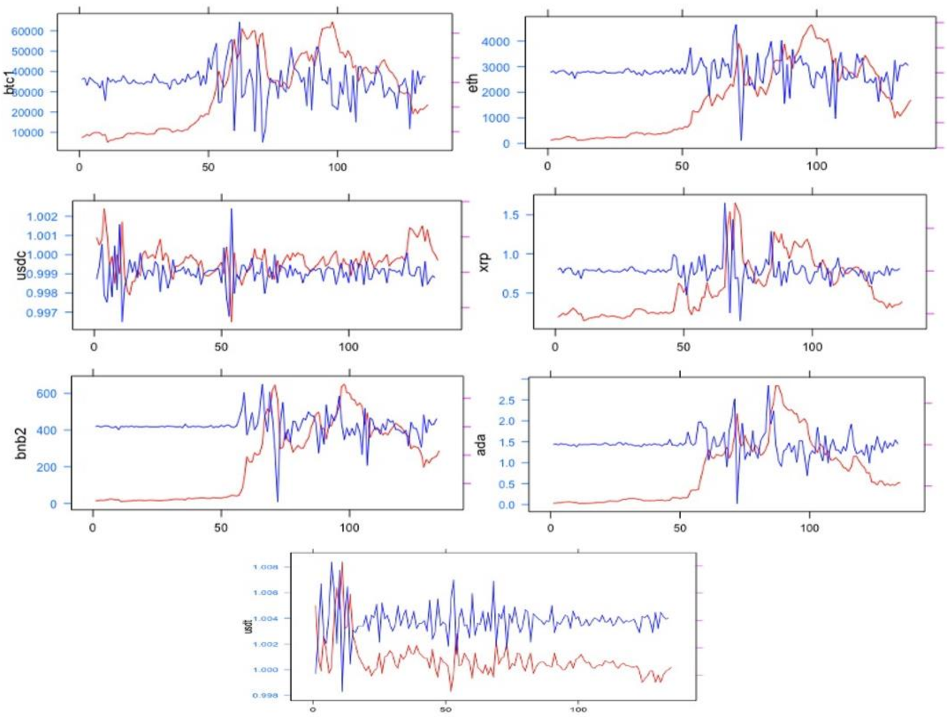


Figure 2. Graph of Original and Difference Series

The red graphs in Figure 2 represent the original series, and the blue graphs represent the difference series.

When Table 4 is examined, it is seen that BTC is the cause of all other variables except USDC and USDT at different lag lengths. According to these results, BTC, ETH, BNB, XRP, and ADA variables were used for the VAR Model.

The implementation process of the VAR Model;

- A temporary VAR model should be estimated and optimal lag lengths should be determined based on the smallest values of the information criteria.
- The best VAR Model should be determined considering the optimum delay length.
- It is expected to give hypothetical results in some specification tests to determine that the best-predicted model is theoretically valid and its results are consistent. If the results are not suitable, the lag length of the model should be changed, and the tests should be started all over again.
- With the help of the VAR Model, which has been determined to be valid and reliable as a result of all tests, the Covariance and Correlation Matrix, Impact Response Function, and Variance Decomposition Functions have been calculated within the scope of this study, and statistical results such as in which direction, how long and in what time BTC affect the dependent variables in the model can be obtained.

The optimum lag length can be decided by several different information criterion statistics. The information criteria statistics calculated in this study are presented in Table 4.

Table 4. Calculated Statistics for Optimal Lag

Kriter	1	2	3	4	5	6	7
AIC(n)	24.84	24.87	24.64	24.45	24.19	24.02	**23.33**
HQ(n)	25.16	25.42	25.42	25.46	25.42	25.48	**25.01**
SC(n)	**25.63**	26.22	26.55	26.92	27.22	27.61	27.47

In Table 4, lag lengths were determined according to the information criteria of Schwarz (SIC), Hannan-Quinn (HQ), and Akaike (AIC) (Schwarz, 1978; Hannan & Quinn, 1979; Akaike, 1974). According to the table, it is concluded that the optimal delay for the best model can be seven.

The VAR Model was estimated with seven lags. The inverse square root values of the characteristic polynomials calculated for the predicted model are expected to be within the unit circle. The null hypothesis for the validity of the model (Sunbul, 2022);

- H0= Model not valid, (H0 cannot be rejected for p>0'***', 0.001'**', 0.01'*', 0.05'.').

Characteristic Polynomial Inverse Root Values of the estimated model and model statistics are presented in Table 5.

Table 5. Characteristic Polynomial Inverse Root Values and Validity Statistics of the Model

0.94 / 0.94 / 0.939 / 0.939 / 0.923 / 0.923 / 0.909 / 0.909 / 0.909 / 0.909 / 0.908 / 0.908 / 0.894 / 0.894 0.885 / 0.885 / 0.881 / 0.881 / 0.875 / 0.875 / 0.869 / 0.869 / 0.869 / 0.869 / 0.86 / 0.86 / 0.856 / 0.856 / 0.769 / 0.769 / 0.689 / 0.689 / 0.489 / 0.448 / 0.448

Dependent Variables	Optimal Lags	Forecast	Standard Error	*t*-value	*P*-value
XRP	3	7,815.79	4,080.16	1.92	0.05**.**
BNB	4	-29.27	14.56	-2.01	0.04 *
BTC	5	0.28	0.16	1.67	0.09**.**
ETH	7	-6.91	2.45	-2.82	0.00 **
ADA	7	5,975.97	3,193.83	1.87	0.06**.**

Reference Value: *0'***', 0.001'**', 0.01'*', 0.05'.'*

Table 5 shows that all of the Characteristic Polynomial Inverse Root Values are less than 1. It can be concluded that in the model estimated with seven lags, the p-values are smaller than the reference value, so the model is valid for all variables. So H0 can be rejected for all variables.

The Portmanteau (Breusch, 1978) Test was used for the validity and reliability of the model, and the Jarque-Bera, Skewness, and Kurtosis Tests (Jarque & Bera, 1987) were used to check whether the residuals were normally distributed.

The null hypothesis for validity and reliability;

- H0= Model not significant, (H0 cannot be rejected for p>0'***', 0.001'**', 0.01'*', 0.05'.'),

  The null hypothesis for the normality test;

- H0= Residuals are not normally distributed in the model (H0 cannot be rejected for p> 0 '***', 0.001'**', 0.01'*', 0.05'),

Validity, reliability, and normality test statistics are presented in Table 6.

Table 6. Validity, Reliability, and Normality Test Statistics

Validity and Reliability Test					
Test Methods		χ^2	**df**	***p*-value**	**Result**
Portmanteau Test (asymptotic)	393		225	0.000	H0 Red
Normality Test					
JB-Test (multivariate)	65		0	0.000	H0 Red
Skewness only (multivariate)	11		5	0.060	H0 Red
Kurtosis only (multivariate)	54		5	0.000	H0 Red

The model estimated according to Table 6 is valid and reliable, and the residuals have a normal distribution.

Structural problems and unexpected breaks related to the predicted model can also be examined qualitatively. The CUSUM Test chart can be examined in time series and comments can be made according to the mentioned findings. The test was first proposed by Brown et al. (1975), and Ploberger & Kramer (1992) extended the test by adding OLS residues to the test. The test produces results at a significance level of 0.05, allowing for qualitative inferences about breaks. The CUSUM Test plot obtained for the predicted model is presented in Figure 3.

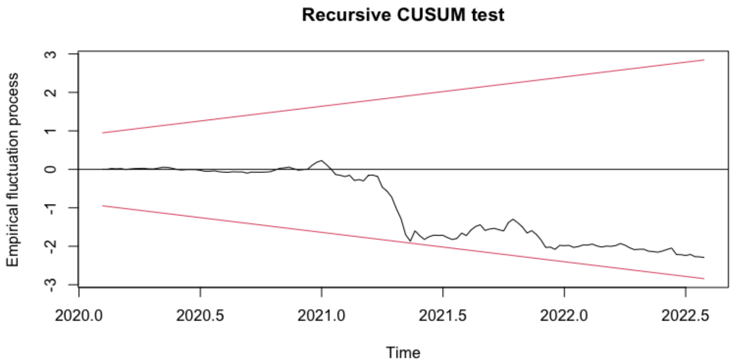


Figure 3. Graph of CUSUM Test

In the model estimated according to Figure 3, there is no unusual break at the 0.05 significance level.

In the previous part of the study, the stationarity of the variables was checked and the non-stationary series was made stationary by applying the difference operation. The causality relationship between the stationary series and BTC was investigated and it was seen that there was a causal relationship between all variables except for two variables (USDC and USDT). A five-variable VAR Model was estimated with causality detected in BTC and ETH, BNB, XRP, and ADA variables. Some validity, reliability, and normal distribution tests of residuals were performed for the predicted model and a VAR Model with seven lags and five variables was Estimated.

In the continuation of the research, the relations between the variables were examined with the help of the proven model. In this context, the relationships between BTC and other variables included in the model were evaluated according to statistical values obtained by calculating Covariance and Correlation matrices, Impact Response, and Variance Decomposition functions. The VAR Model evaluates all the variables included in the model separately as both dependent and independent variables and allows the calculation of the common data of all variables. However, for this study, only BTC was considered as the independent variable and the others as the dependent variable, and one-way statistics were interpreted.

Covariance gives information about the tendency of dependent and independent variables to act together. In other words, it contains information about the direction and strength of the random change in the dependent variable caused by a one-unit change in the independent variable. Covariance Matrix statistics for residuals in the estimated VAR Model are presented in Table7.

Table 7. Covariance Matrix of Residuals

Variables	BTC	ETH	BNB	XRP	ADA
BTC	10,160.543	612,206.0	85,443.20	166.10	244.07
ETH	612,206	59,317.2	6,423.25	12.75	18.49
BNB	85,443	6,423.3	1,180.44	1.94	2.39
XRP	166	12.8	1.94	0.01	0.00
ADA	244	18.5	2.39	0.00	0.01

According to its matrix in Table 7, BTC is the independent variable. It is seen that a one-unit change in BTC causes all variables in the model to change in the same direction. However, when the dependent variables are evaluated one by one, a very high effect on BTC itself is observed. It is possible to observe a similar effect on ETH. Although the trend of BTC to move with the XRP and ADA variables is not as high as ETH and BNB, there is still a very strong relationship.

The correlation matrix contains information about the direction and severity of the relationship between the dependent variable and the independent variable (Hacıoglu, 2019). Correlation Matrix statistics for residuals in the predicted VAR Model are presented in Table 8.

Table 8. Correlation Matrix of Residuals

Variables	BTC	ETH	BNB	XRP	ADA
BTC	1.000	0.789	0.780	0.514	0.613
ETH	0.789	1.000	0.768	0.517	0.608
BNB	0.780	0.768	1.000	0.558	0.558
XRP	0.514	0.517	0.558	1.000	0.673
ADA	0.613	0.608	0.558	0.673	1.000

According to Table 8, it is seen that BTC has a very strong correlation in the same direction with 78% with ETH and BNB, 51% with XRP and 61% with ADA.

The impulse response function reveals the effect of a one-unit shock applied to the independent variable and its effect on the dependent variable. It also answers questions such as the impact, direction, severity and duration of the shock. Impact Response Function statistics for the predicted VAR Model are presented in Table 9.

Table 9. Impact Response Function Statistics

Period	BTC	ETH	BNB	XRP	ADA
1	3,187.56	192.06	26.80	0.05	0.07
2	148.33	19.61	0.32	0.00	0.04
3	-606.79	-19.76	0.67	0.01	0.01
4	-13.93	16.57	0.46	-0.01	-0.01
5	-21.55	-9.40	4.08	0.01	0.00
6	352.22	38.61	5.86	0.01	0.01
7	-61.69	-13.13	-6.82	-0.03	-0.01
8	347.98	6.80	7.85	0.01	0.00

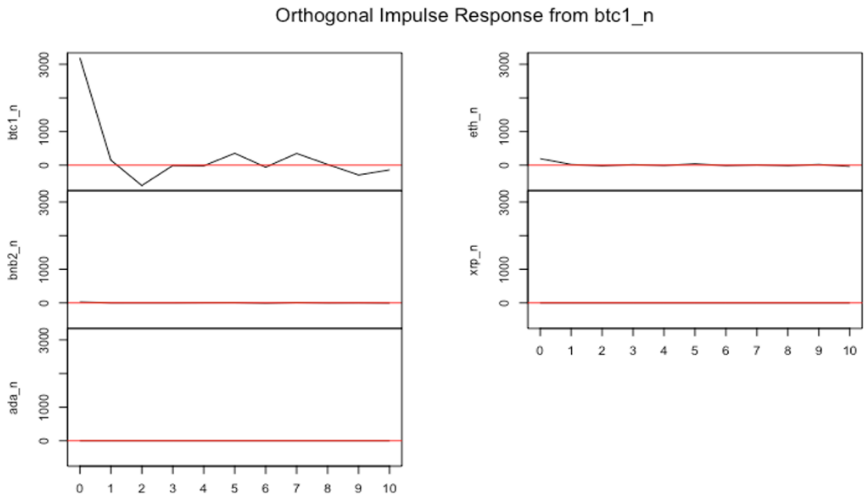
According to Table 9; A one-unit shock to BTC affects itself quite strongly and in the same direction for a week. Although the positive effect continues at the end of the second period, its severity decreases. As of the third period, it is seen that the effect has turned negative quite strongly. It is seen that these positive and negative effects indicate high volatility. Likewise, it can be stated that the volatility in question stems from the dynamics of BTC itself.

While the one-unit shock to BTC created the same significant effect on ETH in the first period, the shock of the said effect continues in the second period but shows a more stable appearance.

The effect of a one-unit shock to BTC on BNB is similar to ETH in the first period, but the effect has decreased with the second period.

On the other hand, while the impact of BTC on XRP and ADA causes minor changes, this effect can be ignored.

As a result, it can be said that any shock to crypto assets lasts for a long time, this situation creates negative effects on the investor and at the same time increases the appetite for speculative initiatives due to volatility. The graph of the statistics calculated with the Impact Response Function is presented in Figure 4.



Figüre 4. Impact-Response Function Graphs

The variance decomposition function expresses the self-explanatory power of the independent variable. Likewise, it contains information about changes in dependent variables. In other words, it reveals how much of the change in the dependent variable for each period, and the change in itself and other variables can be explained. Variance Decomposition Function statistics for the estimated VAR Model are presented in Table 10.

Table 10. Variance Decomposition Function Statistics

Period	BTC	ETH	BNB	XRP	ADA
1	1.000	0.000	0.000	0.000	0.000
2	0.973	0.003	0.017	0.004	0.000
3	0.904	0.008	0.050	0.035	0.000
4	0.872	0.026	0.048	0.042	0.009
5	0.852	0.025	0.060	0.048	0.012
6	0.790	0.023	0.109	0.047	0.029
7	0.753	0.024	0.147	0.045	0.028
8	0.683	0.066	0.138	0.045	0.066
9	0.681	0.066	0.138	0.047	0.066
10	0.639	0.068	0.146	0.078	0.067

When Table 10 is examined, how much of the change in BTC is explanatory? In addition to showing this, it is an important statistic in terms of showing how much it can explain other variables.

When the statistics are examined, BTC reveals itself 100% at the end of the first period. Although this rate decreased over time, it was 64% at the end of ten periods. But, BTC's power to explain other variables was negligible.

The Granger Causality Test was used for the relationship between BTC and other variables. The null hypothesis for testing;

- H0= Independent variable (v2) is not the cause of dependent variable (v1) (H0 cannot be rejected for *p*> 0'***', 0.001'**', 0.01'*', 0.05'.').

The test statistics are causality in Table 11.

Table 11. Causality Test Results

Model	*F*-value	*P*-value	Result
Eth ~ Lags (btc, 1:7)	1.88	0.079.	H0 reject
Usdt ~ Lags (btc, 1:11)	0.76	0.68	H0 accept
Usdc ~ Lags (btc, 1:11)	0.77	0.67	H0 accept
Bnb2 ~ Lags (btc, 1:4)	3.97	0.0046**	H0 reject
Xrp ~ Lags (btc, 1:4)	5.07	0.0008***	H0 reject
Ada ~ Lags (btc, 1:1)	16.8	0.0000***	H0 reject

Reference Value: *0'***', 0.001'**', 0.01'*', 0.05'.'*

The results of the causality test, presented in Table 11, indicate varying relationships between Bitcoin (BTC) and the selected cryptocurrencies, based on the F-values and p-values derived from the models.

For Ethereum (ETH), the F-value is 1.88 with a p-value of 0.079. This p-value is slightly above the conventional significance level of 0.05, leading to the acceptance of the null hypothesis (H0) that there is no causality from Bitcoin to Ethereum. This suggests that Bitcoin does not have a statistically significant causal effect on Ethereum within the examined lag structure (1 to 7 lags).

In the cases of Tether (USDT) and USD Coin (USDC), the p-values are 0.68 and 0.67, respectively, with corresponding F-values of 0.76 and 0.77. Both p-values are significantly above the 0.05 threshold, indicating that the null hypothesis (H0) cannot be rejected for these variables. Hence, Bitcoin does not exhibit a causal effect on USDT and USDC within the specified lag structures (1 to 11 lags for both).

In contrast, Binance Coin (BNB), Ripple (XRP), and Cardano (ADA) exhibit significant causal relationships with Bitcoin. For Binance Coin, the F-value is 3.97 with a p-value of 0.0046, which is below the 0.01 significance level. This indicates a strong causal effect from Bitcoin to Binance Coin, and the null hypothesis (H0) is rejected. Ripple shows an even stronger causality with an F-value of 5.07 and a p-value of 0.0008, leading to the rejection of the null hypothesis (H0) at a significance level of 0.001. Similarly, Cardano presents a robust causal relationship with an F-value of 16.8 and a p-value of 0.0000, also rejecting the null hypothesis (H0) at the 0.001 level. These results suggest that Bitcoin significantly influences the values of Binance Coin, Ripple, and Cardano, indicating a strong directional effect.

Overall, the causality test results highlight that while Bitcoin has a notable impact on some cryptocurrencies, such as Binance Coin, Ripple, and Cardano, it does not have a statistically significant causal relationship with Ethereum, Tether, or USD Coin in the specified lag structures.

4. CONCLUSION AND DISCUSSION

In this study, the effects of Bitcoin (BTC) crypto assets on other selected crypto assets were investigated. The sample of the study consists of the seven most traded crypto assets in the market (USDC, USDT, ETH, BNB, XRP, and ADA) together with BTC. The chosen variables make up 95% of the entire crypto market in terms of both transaction and value. Therefore, it can be said that the results obtained are of interest to the general crypto-asset market. In this study, the Decomposition of Variance, Impulse-Response Function, correlation and covariance coefficients, and the relationships between the variables in the sample were examined based on the MDVAR Model.

The VAR Model assumes that variables are in a causal relationship with each other. For this reason, in model estimation, a series of time series analyses were made first and the best possible data set was tried to be reached. For analysis in time series; The stationarity of the data was researched with the PP Unit Root Test, and the stationarity was obtained by taking the difference of the non-stationary series. Granger Causality Analysis was performed to determine the variables associated with BTC. USDT and USDC, which are not related to Bitcoin, were not included in the VAR Model. As a result, Variance Decomposition, Impact Response Function, Correlation, and Covariance Matrices were calculated with the help of the MDVAR Model consisting of BTC, ETH, BNB, XRP, and ADA variables, and the relationships between the variables were interpreted as follows.

Covariance refers to the tendency of dependent and independent variables to act together. In other words, it contains information about the direction and strength of the random change in the dependent variable caused by a one-unit change in the independent variable. It was seen that a unit change in BTC caused a change in all variables in the model in the same direction. When the said change is evaluated separately in terms of dependent variables; It is concluded that BTC itself is highly affected by the lagged changes. It is also possible to see this change in ETC and BNB. However, a very low change effect is observed in other variables.

Correlation contains information about the direction and severity of the relationship between the dependent variable and the independent variable. According to the results of the analysis, there is a very strong correlation of 78% between BTC and ETH and BNB, 51% between BTC and XRP, and 61% between BTC and ADA. As a result, all variables are moving strongly with BTC.

The Impulse-Response Function expresses how much the other variables in the model will respond to a one-unit shock applied to the independent variable. This method also answers questions such as the direction, severity, and duration of the impact of the shock. To the one unit shock in BTC, at the end of the first period, BTC's reaction was 30 times stronger and in the same direction. However, at the end of the third period, the said effect turns from positive to negative. Volatility seems to have maintained its intensity for eleven periods. From this point of view, it can be interpreted that BTC is a very unstable asset, has a structure that is open to volatility and speculative initiatives, and does not give confidence to its investors. In addition, the one-unit shock applied to BTC showed a significant reaction in the same direction in ETH in the first period, but its effect seems to have decreased with the second period. BNB's response to the single-unit shock to BTC is extremely low. On the other hand, the impact of BTC on XRP and ADA variables causes minor changes. As a result, it can be said that any shock to crypto assets lasts for a long time, this situation creates negative effects on the investor and also increases the appetite for speculative initiatives due to volatility.

The variance decomposition function reveals its power to explain the change in the independent variable and the change in the dependent variable. In other words, to what extent can the independent variable explain the change in the dependent variable? BTC can explain the entire change in BTC (100%) in the first period, and this situation continues strongly until the tenth period (64%). However, the power to explain other variables is considered to be negligible.

One of the strongest and most traded variables in the securities portfolio is the BTC crypto asset. It may not be the right investment choice for investors seeking stability due to excessive volatility. BTC seems to be mostly associated with ETH. However, ETH's shock permeability is more limited than BTC. The very high correlation of all variables in the model with BTC may be due to the investor's reflex to keep a certain portion of all assets in the portfolio pool. In other words, the investor who wants to minimize the risk can demand from other crypto assets while demanding from BTC. The use of crypto assets as money is still a very remote possibility. Considering the behavior of market actors, crypto assets will continue to be seen only as an investment tool for many years. Although the impact of BTC on other crypto assets in investment decisions gives healthy results, investment decisions for BTC, based on other crypto assets, will be misleading. Its highly volatile nature indicates that distrust in crypto assets will continue. In-depth analyses of different economic variables can be suggested to reduce the investment risks for crypto assets to more acceptable levels.

4.1. Comparison with Existing Literature

Our findings are in line with many studies in the literature. For instance, Wei (2018) found that Tether exports caused an increase in Bitcoin transaction volume but did not change its price, indicating that Bitcoin's market movements can significantly influence other assets. Similarly, Dönmez et al., (2021) concluded that Bitcoin's self-explanatory power decreased over time while its effect on other variables in the model increased, which corroborates our findings that BTC has a strong influence on other major cryptocurrencies such as ETH and BNB.

Moreover, Özaydın (2021) noted that the impact of Bitcoin on other altcoins has increased remarkably over time, which parallels our observation of BTC's substantial effect on ETH, BNB, XRP, and ADA. Emir (2023) also reported significant changes in the relationship dynamics between Bitcoin and other crypto assets over time, reflecting our findings on the impulse-response function where BTC's influence varied in strength and direction.

Sathyanarayana & Gargesa (2019) highlighted the significant contribution of major fiat currencies to Bitcoin's volatility, which aligns with our results that indicate BTC's instability and susceptibility to external shocks. This volatility was also observed by Bourghelle et al., (2022) during the COVID-19 outbreak, underscoring BTC's sensitivity to broader market sentiments.

Omri (2023) identified no significant difference in Bitcoin's predictability between developed and developing countries, suggesting a universal behavioral pattern of BTC across different markets, which is consistent with our results showing BTC's predominant influence within the crypto market.

Urom et al., (2020) observed that Bitcoin's volatility changed over time and exhibited an inverse dependency on crude oil prices in certain markets, which complements our findings of BTC's high volatility and its speculative nature, further highlighting the need for investors to consider broader economic variables when making investment decisions involving crypto assets.

4.2. Conclusion

Overall, our study reinforces the existing literature by demonstrating Bitcoin's predominant role and significant influence on other major cryptocurrencies. The findings suggest that while Bitcoin can drive the crypto market, its inherent volatility and susceptibility to speculative activities make it a risky investment. Investors should approach BTC with caution, acknowledging its potential for substantial returns but also its propensity for dramatic value fluctuations. Future research should continue exploring the interactions between crypto assets and various economic indicators to provide more robust investment strategies and risk management practices for market participants.

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