Часопис из области економије, менаџмента и информатике
БизИнфо (Блаце)
www.bizinfo.edu.rs
Journal of Economics, Management and Informatics
BizInfo (BLACE)

Application of the VAR model in examining the determinants of returns of selected cryptocurrencies

Primena VAR modela u ispitivanju determinanti prinosa odabranih kriptovaluta

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Article info

Original scientific paper/ Originalan naučni rad

Received/ Rukopis je primljen:
2 November, 2022
Revised/ Korigovan:
4 December, 2022
Accepted/ Prihvaćen:
26 January, 2023

DOI:
https://doi.org/10.5937/bizinfo2301045S

UDC/ UDK:
004.735.5:336.744

Abstract

The increase in the value of cryptocurrencies, market capitalization, and volume of trading on crypto exchanges resulted in a significant increase in the interest of researchers in this decentralized financial system. The two most popular cryptocurrencies today - bitcoin and ethereum - have captured the greatest attention of researchers. Given that cryptocurrency trading is similar to stock trading, the author's assumption is that their returns are determined by the price of gold and the volatility index – VIX, representing this paper's research hypothesis. Testing through vector autoregression (VAR) models, Granger causality tests, and impulse response function (IRF) shows that gold returns do not impact, unlike the VIX volatility index and Ethereum, indicating a significant relationship between cryptocurrencies bitcoin and US stock markets. On the other hand, Bitcoin returns and the volatility index cause ethereum returns, while gold returns do not.
***Keywords**: Bitcoin, Ethereum, vector autoregression model, Granger causality test, Impulse response function*

Sažetak

Porast vrednosti kriptovaluta, tržišne kapitalizacije i obima trgovanja na kriptoberzama, rezultirali su značajnm povećanjem interesovanja istraživača za ovaj decentralizovani finansijski sistem. Najveću pažnju istaraživača zauzele su dve najpopularnije kriptovalute danas – bitkoin i itirijum. S obzirom na to da je trgovanje kriptovalutama slično trgovanju akcijama, pretpostavka autora je da su njihovi prinosi determinisani cenom zlata i indeksom volatilnosti – VIX, što predstavlja istraživačku hipotezu ovog rada. Testiranjem putem modela vektorske autoregresije (VAR), Grejndžerovim testovima kauzalnosti i funkcijom impulsivnog odziva (IRF), pokazalo se da prinosi zlata nemaju uzročno-posledičan efekat na prinose bitkoina, za razliku od indeksa volatilnosti VIX i itirijuma, što ukazuje na značajnu povezanost kriptovalute bitkoin i tržišta akcija u SAD. S druge strane prinosi bitkoina i indeks volatilnosti uzrokuju prinose itirijuma, dok prinosi zlata ne.
***Ključne reči:** bitkoin, itirijum, vektorski autoregresivni model, Grejndžerov test kauzalnosti, funkcija impulsivnog odziva*

1. Introduction

The last decade has been characterized by significant growth in the cryptocurrency market. Anonymity, low transaction costs, resulting from the absence of intermediaries, increase in the possibility of paying with cryptocurrencies, including illegal purchases, make cryptocurrencies very alluring to prospective users. Prices in the cryptocurrency market are characterized by high volatility. However, regardless of the concerns of economists and financial institutions regarding this risk, since participants in this market can, in a short time, achieve high profits, this new means of exchange is, first of all, traded for speculative purposes. Kirillova and Emelyanova (2021, p. 93) define speculation as the transaction's conclusion whose aim is to derive profit from changes in the derivative on the market.

Bitcoin is a decentralized system with thousands of computers around the world networked via "blockchains"

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– interconnected chains of independent databases (blocks) containing information about digital transactions. This system is created by the mining process and enables payment between two users without going through a central authority, such as a bank (Casino et al., 2019; Abdelmaboud et al., 2022). In order for a transaction to be carried out, it must be confirmed that the sender has the appropriate number of coins and that there is no double-spending. Therefore, any transaction intention must be announced on the network of the corresponding cryptocurrency. Information about this transaction is automatically broadcast to all users on the network, and this means that every user has insight into transactions. The essence of bitcoin trading is like any other type of trading - buy for less and sell for more money. Compared to 2013, when the market capitalization of Bitcoin was about one billion dollars, in November 2021 it was over $1,218.8 trillion in November 2021 (CoinMarketCop, 2021). After the success of BTC, other cryptocurrencies appeared, so that, as of January 2021, there are 7,346 of them in the global market. Ethereum (ETH), which originated as an idea in 2013 and took off in mid-2015, is the second cryptocurrency after Bitcoin, with a November 2021 market cap of more than $546.8 billion. Considering the market capitalization and trading volume of cryptocurrencies, it is not surprising that the number of startup companies dealing with the same is growing day by day. Today, there is almost no major bank or financial institution in the world that does not consider the possibility of implementing Blockchain technologies, and even some central banks are considering the possibility of introducing national cryptocurrencies (China, Russia) (Đorđević, 2018).

Taking into account the onset of the global pandemic of the COVID-19 virus and the high volatility and sudden fluctuations in the prices of financial assets and commodities on the world market, the subject of this research is the determination of potential factors that determine returns on the cryptocurrency market, using the vector autoregressive model (VAR). Since bitcoin and ethereum have the largest trading volume in Serbia, the aim of the research is to analyze the relationship between the returns of BTC, ETH, gold, and the volatility index VIX. In order to answer the research aim, the paper is structured as follows: after the introductory presentation, in the next part of the paper, a brief overview of the relevant literature is given and the research hypothesis is set. In the third part, data and methodology are presented. After that, the results follow in the fourth part. In the conclusion, key conclusions, limitations, and recommendations for future researchers of this topic are presented.

2. Literature review and research hypothesis

Understanding the origin, behavior, and mechanism behind cryptocurrencies is the subject of a number of recent research dealing with issues of cryptocurrencies and capital markets (Inaba, 2020; Chen, 2021; Ilk et al., 2021; Katsiampa, 2020; Malladi and Dheeriya, 2021; Tomal, 2021). Based on the relevant literature bitcoins are similar to financial securities and, it is worthwhile to include data on other financial variables for comparison. Basher et al. (2012), within a vector autoregressive model with error correction, found interdependence between exchange rates and the prices of oil and stocks. Noga (2017) deals with the role of money and artificial currencies. Conti et al. (2018), as well as Tschorsch and Scheuermann (2016), reviewed the technical aspects of BTC, blockchain, security, network, and privacy. With the advent of cryptocurrencies, researchers have expanded the universe of investment instruments to include cryptocurrencies. Van Wijk (2013) concluded that realistic expectations of the underlying financial variants can help investors build expectations for investing in Bitcoin. Golez and Koudijs (2018) point to the great interest in the financial literature when it comes to the predictability of financial asset returns. The results of certain studies indicate partial predictability of stock returns (Cochrane, 2008; van Binsbergen and Koijen, 2010). Van Wijk (2013) pointed to the connection between the US economy and most of the variables that affect the price of BTC. According to Engle (2002) and Bouri et al. (2017; 2020; 2021), bitcoin can be useful as an effective diversifier in many cases. On the other hand, the findings of the study by Ciaian et al. (2016) indicate that global macro-financial developments cannot drive the price of BTC. Other studies suggested that cryptocurrency price volatility is a result of market sentiment, which can be united with significative “memory” (Cheah and Fry, 2015; Katsiampa, 2017). Based on these studies, the “memory” of cryptocurrency price shocks is the semi-important cryptocurrency price determinant. According to the results of the Dyhrberg (2016a) study, bitcoin could be useful for risk-averse investors, as a negative shocks absorber, and then, in his next study, the aforementioned author (Dyhrberg, 2016b) concludes that bitcoin can serve as a hedge against the market-specific risk. In their paper, Malladi and Dheeriya (2021), concluded that global stock market returns, as well as gold returns, are not a significant determinant of bitcoin returns, unlike Ripple (XRP) returns, which can significantly affect bitcoin prices. Chen (2021) established that: a) in the short term, bitcoin's past values are a significant determinant of its current price; b) bitcoin prices are significantly influenced, either positively or negatively, by exchange means and financial expectations, and; c) the price of bitcoin, in the short term, is not determined by blockchain technology. Estrada (2017) concluded that there is a statistically significant two-way Granger causality between realized volatility of BTC and VIX.

The findings of previous studies, which have dealt with the relationship between gold/oil prices and returns, are mixed. Kjærland et al. (2018) and Kristoufek (2015), based on the obtained results, concluded that the dynamics of gold prices do not significantly affect the returns of cryptocurrencies. On the other hand, according to the results of studies by Elsayed et al. (2022) as well as Wu (2021) gold is very sensitive to an uncertainty shock from the cryptocurrency market. Paule-Vianez et al. (2020) concluded that bitcoin, ethereum, and gold can provide positive returns in a situation where there is a decline in market returns.

Taking into account the above, the following hypothesis is defined in this paper:
H1: There is a significant causal effect between the returns of bitcoin, ethereum, gold, and the Volatility Index.

3. Data and methodology

Data from various sources were used for research purposes. Data on daily prices and trading volumes of BTC and ETH were taken from the Cointelegraph (2021) website, gold prices from World Gold Council (2021), and the closing value of the volatility index - VIX (CBOE Volatility Index) from the Yahoo! Finance (2021) website. The VIX Volatility Index is a real-time index that generates a 30-day forward projection of US stock market volatility. Volatility, i.e. the speed of price change, is often considered a way of assessing market sentiment, especially the degree of fear among market participants (Kuepper, 2021). The analysis covers the period from November 9, 2020 to November 9, 2021. During the observed period, the price of BTC increased by 3,880% and ETH by 909%, while the price of gold recorded a decrease of 3.51%.

Data on prices of selected cryptocurrencies are available seven days a week. However, data related to the price of gold and the VIX index are only available on US trading days. Accordingly, VIX days (from CBOE trading days) were used as a basis, while data on prices and trading volumes of selected cryptocurrencies were removed from the data set, resulting in 242 daily price points, for the period between November 9, 2020, and November 9, 2021.

Following Nasir et al. (2019) approach, the logarithmic values of cryptocurrency prices are used to calculate returns as shown:

$$LogReturn = ln\left(\frac{P_1}{P_0}\right) \tag{1}$$

Where: P_1 is the closing value of the cryptocurrency for the current trading day, and P_0 is the closing value of the cryptocurrency for the previous trading day. Due to the robustness of the data, the logarithmic prices of cryptocurrencies were used in the research.

The results shown in Table 1 indicate a pronounced volatility of the returns of the observed cryptocurrencies (for BTC returns range from -14.26 to 21.21, while for ETH returns range from -27.68 to 38.51), compared to gold, where returns range from -4.41 to 2.95.

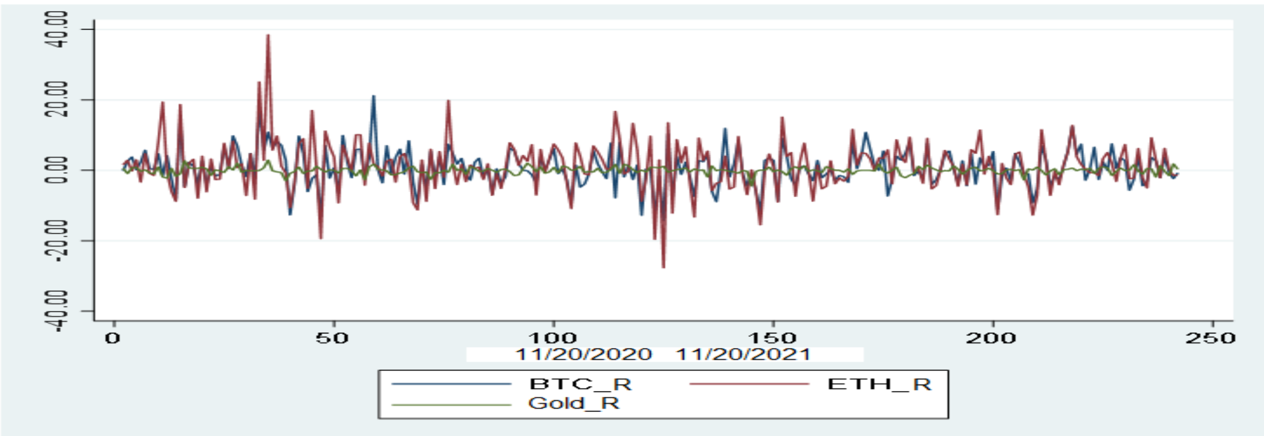
Table 1. Summary of statistics of the variables included in the research, for the period November 9, 2020 – November 9, 2021 (N = 242)

Variable	Mean	Median	Min.	Max.	Std. Dev.	Skew.	Kurtosis
BTC	42604.01	43552.00	15314	66021	12977.9	.339	.719
ETH	2276.71	2229.00	451	4604	1068.62	.080	-.765
Gold	1805.48	1799.60	1684	1943.20	52.97	.170	-.523
BTC_R	.71	.43	-14.26	21.21	5.32	.110	1.106
ETH_R	1.22	1.47	-27.68	38.51	7.23	.372	3.953
Gold_R	-.0061	.01	-4.41	2.95	.97	.532	2.17
VIX	19.89	19.37	15.01	37.21	3.45	1.19	2.7

Source: Author's calculation based on Stata 16

The price movements of BTC, ETH, and gold are illustrated in Figure 1. The rapid increase in the price of BTC, recorded between the end of November 2020, and the middle of April 2021, was followed by a sharp decline between the end of April 2021 and the middle of July 2021, which was followed by new growth. In contrast to these developments, the prices of ETH and gold did not register large fluctuations, but compared to ETH, where there was an increase, gold saw a slight decrease in price.

Figure 1. Logarithmic prices of BTC, ETH, and gold during the observed period



Source: Author's calculation based on Stata 16

Figure 2 shows the swings in BTC, ETH, and gold returns. The largest fluctuations were observed with the cryptocurrency ETH (the highest returns were recorded on January 4, 2021 (38.51%), and the lowest on May 19, 2021 (27.68%)).

Figure 2. BTC, ETH, and gold returns during the observed period

Source: Author's calculation based on Stata 16

For a better understanding of the interrelationships between the returns of cryptocurrencies, gold, and the VIX index, as well as the interrelationships between the prices of selected cryptocurrencies and gold, the VAR technique (Vector Autoregression Models) was used. VAR belongs to the group of multidimensional models and has the widest application in the analysis of financial time series. It is an example of a linear model, the advantage of which is that it takes into account the mutual dependencies of the series that are the subject of analysis. Vector autoregressive is a generalization of the one-dimensional AR model to more dimensions. Unlike structural models with simultaneous equations, the VAR model does not require as much knowledge about the forces affecting the variable. The only prior knowledge required is a list of variables that can be assumed to influence each other intertemporally. The variables included in the VAR enter the model in the same way, with each of them having its own equation explaining the lag of the variable of interest and of other variables, and an error term, so the VAR (p) model can be defined as follows:

$$Y_t = \Phi + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \varepsilon_t \qquad (2)$$

Where: $Y_t = (r_{1t}, r_{2t}, \ldots, r_{nt})'$ is an n-dimensional time series, a vector of time series variables; Φ_0 is a constant vector of dimension $n \times 1$, Φ_i is a constant matrix of dimension $n \times n$, i =1, ..., n; $\varepsilon_t = (a_{1t}, a_{2t}, \ldots, a_{nt})'$is a vector of mutually uncorrelated errors of dimensions n x 1, while ε_t represents white noise with $E(\varepsilon_t) = 0$ and covariance matrix Σ, which is positive definite, t is the time dimension operator and n is a number of arrears involved.

4. Empirical Results

4.1. Examining the relationship between the returns of BTC, ETH, gold, and the VIX volatility index

Before conducting the VAR analysis, the existence of a unit root was examined. The stationarity of the variables was first checked by the Dickey-Fuller test and then confirmed by the Phillips-Peron test. Since the statistical significance is $p < 0.05$, it can be concluded that the time series does not have a unit root, that is, it is stationary, which is the basic condition for further analysis. The results are shown in Table 2.

Table 2. Unit root tests

Returns	Dickey-Fuller Test statistics	Dickey-Fuller p	Phillips-Perron Test statistics	Phillips-Perron p
BTC_R	-16.175	.0000	-16.165	.0000
ETH_R	-17.082	.0000	-17.021	.0000
GOLD_R	-14.869	.0000	-14.858	.0000
VIX	-4.565	.0001	-4.251	.0005

Source: Author's calculation based on Stata 16

An important factor when identifying the model is determining the optimal length of the delay or lags since it can affect the results of the model. The relevant literature singles out three specific criteria: Akaike (AIC), Hannan-Quinn (HQIC), and Schwartz's information criterion (SBIC), where the differences are reduced to different ways of punishment due to the presence of a larger number of parameters in the model. According to the econometric literature (eg, Acquah, 2012; Lojanica, 2018), the Schwarz Information Criterion has an advantage over other criteria. The results indicate that all three criteria suggest lag length one. Based on this, in the research, lag length 1 will be used as the optimal lag length (Table 3).

Table 3. Choosing the optimal lag length in the VAR model

Lag	AIC	HQIC	SBIC
0	20.345	20.3685	20.4032
1	19.1285*	19.2457*	19.4194*
2	19.2058	19.4168	19.7294

Source: Author's calculation based on Stata 16

The stability of the VAR system implies stationarity. In the literature, the condition of stability is also called the condition of stationarity. If all the inverse roots of the characteristic AR polynomial have modules less than 1 and lie within the unit circle, it is estimated that the VAR model is stable. According to the results, shown in Table 4, all eigenvalues are within the unit circle, because all values in the Module column are less than 1, and it can be concluded that the VAR satisfies the stability condition.

Table 4. Stability of the VAR model

Characteristic value	Module
.8750684	.875068
-.3578609	.357861

Source: Author's calculation based on Stata 16

In the next step, the null hypothesis was tested, according to which there is no autocorrelation in the lag order. The hypothesis was tested using the Lagrange multiplier. Bearing in mind that $p > 0.05$, the null hypothesis cannot be rejected, thus confirming another assumption of the VAR model (Table 5). In addition, the results of the Johansen test (Johansen, 1991) indicate acceptance of the null hypothesis of no cointegration, since the value of the test statistic (36.4474) is less than the critical value (47.21).

Table 5. Lagrange multiplier

Lag	$\chi 2$	df	p
1	16.1013	16	0.45

Source: Author's calculation based on Stata 16

The Granger causality test is used to reveal the direction of causality between variables, as well as to determine those variables that are exogenous to a given set of variables (Marjanović et al., 2021). According to the Granger causality test, only variables that can explain the values of the current variable are included in the VAR model, while other variables should be excluded from the model. The test results, shown in Table 6, indicate causal relationships, that is, changes in the VIX volatility index cause changes in BTC and ETH returns changes in BTC returns cause changes in ETH returns, and changes in ETH returns cause changes in BTC returns.

Table 6. Granger causality test results

H0	$\chi 2$	p
VIX does not cause BTC_R	8.2263	.016
VIX does not cause ETH_R	7.7662	.027
BTC_R does not cause ETH_R	21,056	.0001
ETH_R does not cause BTC_R	11.2662	0.009

Source: Author's calculation based on Stata 16

By forming a VAR model of the appropriate order, and looking at the impact of the variable individually, it can be concluded that the past values of the VIX help explain the current value of the returns of bitcoin and ethereum. Past values of gold returns cannot explain the current values of bitcoin and ethereum returns. In addition, the past values of bitcoin return help explain the current value of ethereum returns, and the past value of ethereum help explain the current value of bitcoin returns. Gold returns should be removed from the BTC_R and ETH_R equations. Table 7 shows the estimated short-term coefficients of the VAR model. The coefficients of determination are low (for the equation BTC_P(t) it is 0.1517, which means that about 15% of the variation in the sample is explained by the model, and for the equation ETH_P(t) it is 0.1190, which means that about 12% of the variation in the sample is explained by the model). However, small values of these coefficients do not necessarily mean that the models are bad, but can only indicate that linear models are not the best choices for describing the behavior of the observed time series. When it comes to interpreting the estimated coefficients, for the equation BTC_R(t), assuming other values remain unchanged if the value of BTC_R(t-1) increases by one unit, BTC_R(t) will increase by 0.40178 units and vice versa. It is positively affected by all variables, except ETH_R previous value. Since in practice the invariance of other values rarely happens, the values for BTC_R(t) are obtained as a consequence of the changes of all other values in its equation. The coefficients of the equation for ETH_R(t) are interpreted analogously.

Table 7. Estimated short-term VAR model coefficients for bitcoin and ethereum returns

Dependent variable		Coef.	Std. err.
BTC_R(t)			
	BTC_R(-1)	.4017811	.1494412
	VIX (-1)	.2696525	.1144149
	ETH_R(-1)	-.2696525	.1144149
ETH_R(t)			
	ETH_R(-1)	-.2972938	.1002312
	VIX (-1)	-.2329288	.1211334
	BTC_R (-1)	.7812863	.0980934
Const. BTC_R	0.016		
Const. ETH_R	0.002		
R-sq BTC_R	0.1517		
R-sq ETH_R	0.1190		

Source: Author's calculation based on Stata 16

4.2. Testing the impact of shocks on variables

The results of the decomposition of the variance of the prediction error after 24 periods (2 years) show that about 93% of the changes in the volatility index occur under the influence of its own variability, the gold returns (about 6%), while the impacts of the ethereum returns (slightly more than 1%) and the bitcoin returns are negligible (less than 1%). About 72% of the fluctuations in bitcoin returns are caused by its own variability, while changes in the volatility index - VIX participate with slightly more than 16.5%, gold returns (about 8%) and ethereum returns (about 4%) in the total variability of bitcoin. On the other hand, the results show that the fluctuations in ethereum returns are mostly influenced by bitcoin (46%), its own variability (about 37.5%), and the volatility index (12%), while the influences of gold returns (just over 4%) are significantly smaller. About 96% of fluctuations in gold returns are due to its own variability, while the effects of bitcoin return (less than 2%), ethereum (slightly more than 1%), and the volatility index (less than 1%) are almost negligible. More detailed results are shown in Table 8.

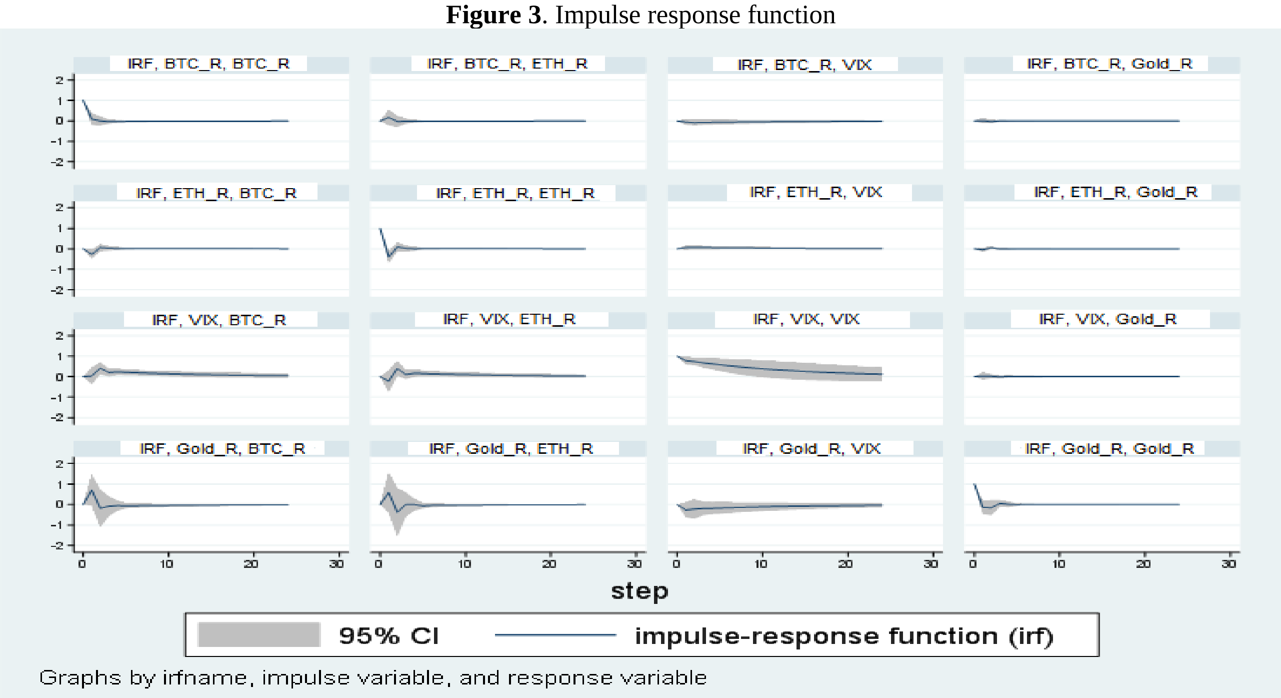
Figure 3 shows the rated impulse response function. The impulse response function shows the impulse responses (after 24 months) to a positive shock of the variable of interest in the value of one standard deviation. In the case of a positive shock in bitcoin returns, there is a positive impact in the initial period (during the first month) on ethereum returns, while there is no impact in the case of the volatility index and gold returns. The growth of ethereum returns, in the initial period, negatively affects the returns of bitcoin. The growth of the volatility index, during the first month, has a positive effect on the returns of bitcoin and a negative on the returns of ethereum. The growth of gold returns, during the initial period, has a positive effect on the growth of bitcoin and ethereum returns, while it has a negative effect on the volatility index. After the initial shock in the first month, during the second month, each of the observed variables reaches its stable values.

Table 8. Variance decomposition of the prediction error of volatility index, bitcoin, ethereum, and gold returns

Impuls - VIX				
Period	Response			
	VIX	BTC_R	ETH_R	Gold_R
3	.94492	.110104	.102591	.005958
6	.933869	.131595	.10869	.006299
12	.92834	.154205	.116623	.006343
24	.926497	.165237	.119656	.006368
Impuls - BTC_R				
Period	Response			
	VIX	BTC_R	ETH_R	Zlato_R
3	.000357	.769765	.469883	.017973
6	.00032	.748843	.466422	.018056
12	.000309	.727159	.462204	.018055
24	.000305	.716589	.460067	.018055
Impuls - ETH_P				
Period	Response			
	VIX	BTC_R	ETH_R	Zlato_R
3	.009789	.04034	.382967	.014472
6	.012879	.039878	.38029	.014633
12	.014398	.039271	.377023	.014655
24	.014904	.038971	.375365	.014655
Impuls - Gold_R				
Period	Response			
	VIX	BTC_R	ETH_R	Gold_R
3	.044934	.07973	.044559	.961597
6	.052931	.079685	.044597	.960991
12	.056952	.079365	.044803	.960946
24	.058293	.079204	.044911	.960922

Source: Author's calculation based on Stata 16

Figure 3. Impulse response function



Source: Author's calculation based on Stata 16

4. Conclusion

The aim of the paper was to determine the causal relationships between the returns of bitcoin, ethereum and gold, and the volatility index, using the VAR model. The obtained results indicate a significant positive correlation between bitcoin returns and the volatility index, as well as a significant negative correlation between bitcoin returns and ethereum returns. On the other hand, ethereum returns are positively correlated with bitcoin returns and negatively correlated with the volatility index. Similarly, Estrada (2017) found a statistically significant causal relationship between BTC volatility and VIX.

The results also indicated that gold returns do not have a significant impact on bitcoin and ethereum returns, which is in line with the research results of Malladi and Dheeriya (2021), whose results indicate that gold returns do not have a significant impact on bitcoin returns. Lawuobahsumo et al. (2022), investigating the correlation between commodity returns (wheat, gold, platinum, and crude oil) and bitcoin returns, found that, although scarce, this relationship, during periods of economic, health and financial turbulence, shows a growing trend. The increased interdependence of returns, during busy market periods, the aforementioned author state, can be explained as a consequence of the effects of contagion of one market by another. The statistically insignificant effect of gold returns on bitcoin and ethereum returns can be attributed to the difference between the drivers of bitcoin and ethereum returns and other commodities.

The cryptocurrency market is still under-researched, and even trying to draw conclusions about the drivers of sudden changes in cryptocurrency prices and returns, based on commodity markets, can be difficult. The obtained research results can improve the understanding of the interdependence between observed cryptocurrencies, and can have important implications for both users and investors of cryptocurrencies. This paper also has certain limitations, primarily related to the number of variables included in the research (bitcoin, ethereum, gold, and volatility index). In this sense, future research could be expanded by including other currencies (for example Ripple), or, for example, the stock market, based on the methodology applied in the current work, or by applying other econometric methods.

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