Modeling the Cryptocurrency Market Using a VAR Approach: Analyzes, Estimates, and Predictions

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Abstract: *Blockchain technology along with virtual currencies represent a widely debated topic which in the context of the current economic climate shows a growing interest. As digitalization intensifies, it is very likely that in the future a significant part of the workforce will conduct activity in industries that use Blockchain technology. Given their novelty, Blockchain and cryptocurrencies have the potential to impact most industries and moreover to act as a link between distinct industries. Virtual currencies and the technology behind them are two extremely popular topics of the 21st century. As to how they will integrate into the current political and economic framework, researchers' views are divided. There are perspectives that suggest that these technologies will revolutionize the future, putting an end to central banking systems and traditional ways of trading. However, one fact is obvious. The emergence of these technologies seems to change the way we think and use financial resources. The paper aims to conduct an analysis regarding the interdependence between five of the most traded cryptocurrencies in terms of prices (Bitcoin, Binance, Dogecoin, Ethereum and Ripple).*

Keywords: cryptocurrencies, Granger causality, VAR, time series modeling

JEL: C22, C30, E42, E49

1. Introduction

Blockchain and cryptocurrencies are innovative technologies of the FinTech industry that have rapidly infiltrated the financial markets, shaping the power of the global economy. Cryptocurrencies represent a type of virtual currency based on cryptographic principles and benefit from decentralized management. Transaction management is provided by Blockchain technology. This refers to the existence of a distributed ledger, in which all transactions are recorded in structures called blocks, added one by one to a database and being linearly connected.

The interest in Blockchain technology has intensified in recent years, as is becoming a new foundation of transactions around the world in the age of globalization. Blockchain technology is conceptualized as a continuous, complete, distributed and unchangeable database (Yoo, 2017). Among the benefits provided by Blockchain technology are the reduction of trading costs, the elimination of third parties from the trading process, as well as the reduction of the time allocated to trading (Staples et al., 2017).

The paper aims to conduct an analysis regarding the interdependence between five of the most traded cryptocurrencies in terms of prices. The five considered digital currencies are Bitcoin, Binance, Dogecoin, Ethereum and Ripple.

2. Literature review

Beneki et al. (2019) examine the interdependence of the two most traded cryptocurrencies, namely Bitcoin and Ethereum. Their approach is driven by a VAR model and by evaluating the impulse response functions. Thus, the response of each currency to the volatility of the other currency is analyzed. Researchers point to a delayed response in the price of Bitcoin to a shock affecting Ethereum's returns.

Improving the level of digitalization in Romania in the public sector and stimulating entrepreneurs to launch various start-ups represents a challenge for the coming years in an increasing creative economy. A well-developed IT&C sector of a country will significantly contribute to reducing the costs of digitization in the current Fourth Industrial Revolution, characterized by continuous change in comparison with other countries that do not have many specialists in the field (Veith and Savin, 2019).

Yousaf and Ali (2020) analyze the interdependence between Bitcoin, Ethereum and Litecoin cryptocurrencies taking into account two important periods: the pre-pandemic period and the Covid-19 pandemic period. During the Covid-19 pandemic, in the short run, they note that Bitcoin's profitability can make a significant contribution to predicting Ethereum's profitability. An opposite situation characterizes the period before the outbreak of the pandemic, when Ethereum could serve as a benchmark in predicting the profitability of Bitcoin. A two-way relationship is reported in the pre-pandemic period for the Ethereum and Litecoin cryptocurrencies.

Blandin et al. (2020) reveal that in recent years the interest shown to cryptocurrencies has increased considerably. Specifically, they indicate an increase in the number of unique users of digital currencies by 189% in 2020 compared to 2019. The report by Exton and Doige (2018) explores the factors that determine European and American citizens to use or not virtual currencies.

Applying the questionnaire method, the research focuses on assessing the opinion of one thousand respondents in fifteen countries on the future of cryptocurrencies and their use. Their findings highlight the following aspects: many respondents (66%) are familiar with the notion of "cryptocurrency", but only 9% of the interviewed individuals stated that they own cryptocurrencies. More than a third of respondents (35%) believe that the future of online payments will be mediated by cryptocurrencies. Comparing cryptocurrencies with other investment opportunities, most respondents (65%) believe that real estate, for example, is a less risky investment option.

Liu, Rahman and Serletis (2020) analyze the spillover effect of cryptocurrency market shocks on traditional financial assets. Inducing a shock equal to a standard deviation on the profitability of cryptocurrencies does not imply a significant effect on traditional financial assets, with one exception, namely the bond market.

Hossain and Ismail (2021) indicate the existence of a significant reciprocal influence of cryptocurrencies. They identify strong, positive correlations in terms of the price movement corresponding to digital assets.

An analysis performed by Popescu et al. (2019) reveals that in Romania, the IT sector is one of the first industries to use integrated solutions. Romania is aligning to the trend that characterizes the situation at European level, that of choosing cashless payments to the detriment of cash payments. In this regard, many software providers have started to launch more and more solutions to facilitate payments between the parties (Leoveanu, 2019).

3. Research methodology

The autoregressive vector (VAR) model is an extension of the univariate autoregressive model to multivariate time series. The VAR model is a system with multiple equations in which all included variables are treated as endogenous (dependent). VAR model is one of the most widely used and flexible models for multivariate time series analysis.

In the case of a VAR model with two variables we will allow the evolution of the variable x to be influenced by previous values (lags) of x, as well as by current and previous values of y. We will also assume that y is influenced by its lags, as well as by current or previous values of x. The VAR methodology involves the structural modeling of endogenous variables in the system as a function of lags, past values, all endogenous variables in the system.

A VAR (p) model can be represented as follows:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + BX_t + \varepsilon_t \qquad [2.1]$$

where:

Yt represents a K-dimensional vector of endogenous variables

Xt represents the D-dimensional vector of exogenous variables

A1,A2,A3…,Ap,B represents the matrix of the coefficients to be estimated

εt represents the vector of innovations. It can be contemporaneously correlated, but it does not correlate with the values corresponding to the previous periods or with the variables on the right side of the equation.

The analysis that will performed must complete the following stages:

Step 1. Testing the time series stationarity

The development of a VAR model requires the use of stationary time series. Therefore, the ADF test will be applied to identify the unit root. If the series are concluded to be non-stationary, differentiation will be performed.

Step 2. Selecting the optimal number of lags

The optimal number of lags will be selected after running a VAR model, using Lag length criteria. Based on the Akaike, Schwartz and Hannan-Quinn criteria, the optimal number of lags will be identified.

Step 3. Estimation of the VAR model

The third stage of the research will consist in estimating the Autoregressive Vector model.

Step 4. Analysis of impulse response functions

The impulse response function (IRF) is a function that identifies the effect that a magnitude shock has on a standard deviation from the ε_t innovation on the past and present values of the variables affected by the shock. The shock response function (IRF) describes the effect of a shock administered to a variable on the future values of each variable in the system. FRS follows the trajectory of this effect over time, at different horizons. For example, the FRS can describe, in relative terms (the unit of measurement commonly being the standard deviation), the response of prices to a shock on the monetary base after a month, two months, etc. The main information provided by the IRF refers to the response sign (positive or negative) and the persistence of the effects of various shocks.

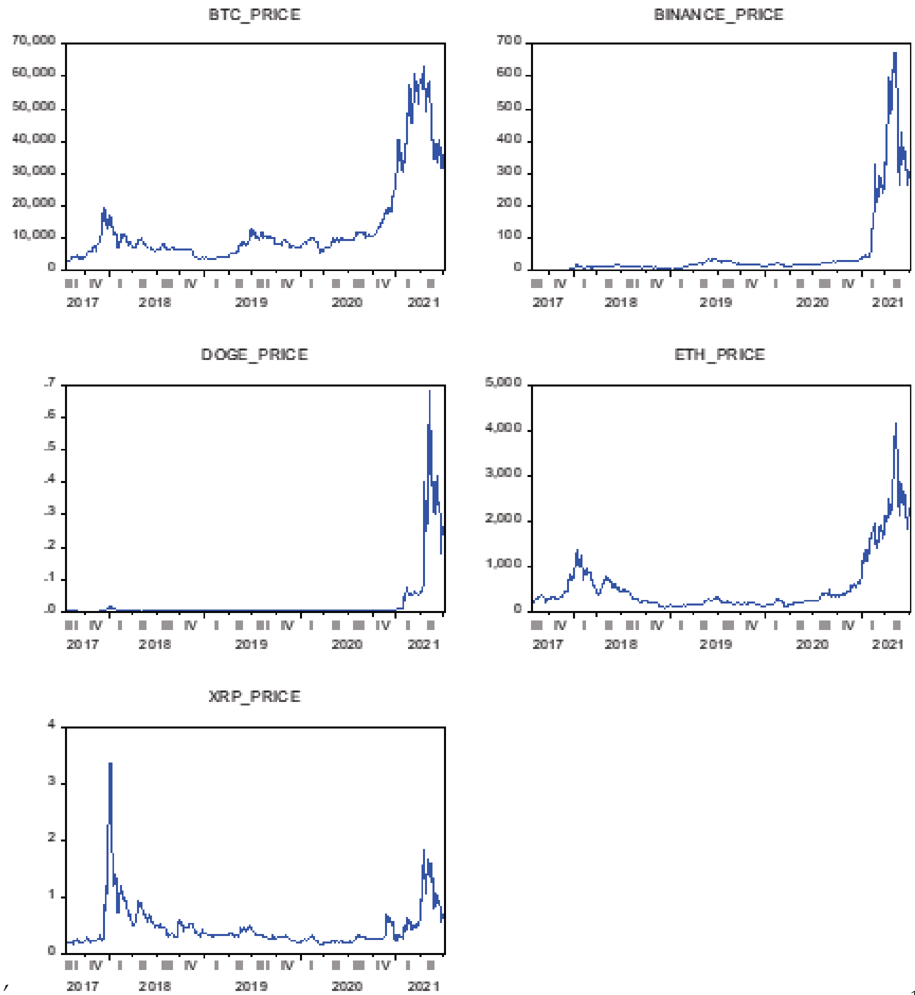
Step 5. The Granger causality test

Granger causality tests indicate which variables are useful for predicting other variables. Specifically, we can say that a variable X Granger-causes on Y if a prediction of Y based on information containing the history of X is better than a prediction that ignores the historical values of X.

Data used within this study represent the daily price recorded by five of the most traded and well-known cryptocurrencies namely: Bitcoin (BTC), Binance (BINANCE), Dogecoin (DOGE), Ethereum (ETH) and Ripple (XRP).

Thus, the analysis undertaken in this paper will be based on the use of time series collected on a daily basis, covering a time span situated between July 26th of 2017 and July 6th of 2021. The total number of observations collected is 1442, the source of data collection being represented by the https://coinmarketcap.com/ website

Figure 1: Price evolution of the five considered cryptocurrencies



Source: Authors' processings

4. Results and discussions

The previous figure shows the price evolution of the five cryptocurrencies considered in the analysis over the time span situated between July 2017 and July 2021. One can note that the prices of Binance and Dogecoin cryptocurrencies had a similar evolution. Starting with the fourth quarter of 2020 prices appreciated considerably but collapsed in the second quarter of 2021. The decline in cryptocurrency prices during this period, however, characterizes all five cryptocurrencies. Similar trends characterize the Ethereum (ETH) and Bitcoin (BTC) prices. Ripple (XRP), however, is a digital asset that has undergone a distinct evolution, so that while most cryptocurrencies have appreciated in terms of prices, XRP has reached quite low values in 2021.

The bidirectional influence of cryptocurrencies will be subject to a multivariate analysis. The first question we ask in the context of VAR modeling refers to the stationarity of the analyzed time series. Thus, we will investigate the presence of the unit root in the time series considered using the Augmented Dickey-Fuller test. The results of the stationarity test can be consulted in the following table. Applying the stationarity test on the series at level, we note the presence of the unit root (p-values are higher than the significance threshold of 5%). Following the first-order differentiation, the time series become stationary. All five time series are first order integrated integrated I(1).

Table 1: ADF unit root test results

At level		1st difference	
BINANCE_PRICE	0.776	ΔBINANCE_PRICE	0.000***
BTC_PRICE	0.793	ΔBTC_PRICE	0.000***
DOGE_PRICE	0.717	ΔDOGE_PRICE	0.000***
ETH_PRICE	0.901	ΔETH_PRICE	0.000***
XRP_PRICE	0.191	ΔXRP_PRICE	0.000***

Source: Authors' processings

Once the integration order of the five variables has been determined, we will analyze their potential cointegration relationship. The concept of cointegration was first introduced by Granger (1981). It refers to the existence of a long-term relationship between the variables subject to analysis. Before determining whether the considered variables are cointegrated, it is necessary to establish an optimal number of lags that will be included in the Johansen cointegration procedure (1991, 1995). Selecting the optimal number of lags involves estimating a VAR model that includes the original time series at level, not differentiated data. The optimal number of lags specified by the Schwartz, HQ and Akaike information criteria is equal to 2, according to the results specified in the following table.

Table 2: Optimum number of lags to include

Lag	AIC	SC	HQ
0	24.685	24.703	24.703
1	24.573	24.683	24.683
2	24.524*	24.726*	24.726*

Source: Authors' processings

Following the application of the Johansen cointegration procedure, it is found that the existence of a cointegration relationship is not confirmed for the selected variables.

Table 3: Results of the Johansen Cointegration Procedure

No. of Cointegration Equations	Critical Value	Prob. **
None*	69.818	1.000
At most 1*	47.856	0.000
At most 2*	29.797	0.000

Source: Authors' processings

Given the first-order integration of the five variables, but the absence of Johansen cointegration, the analysis will continue with the estimation of a multivariate VAR model which will contain the first-order differentiated variables. The results of the VAR model estimation is highlighted in the following figure.

Figure 2: VAR estimation results

	DBTC	DBINANCE	DETH	DXRP	DDOGE
DBTC(-1)	0.123931	0.001340	0.011527	1.69E-06	-1.53E-07
	(0.03608)	(0.00046)	(0.00252)	(2.6E-06)	(5.4E-07)
	[3.43535]	[2.91770]	[4.57082]	[0.63827]	[-0.28432]
DBTC(-2)	-0.004486	0.000178	-0.005357	2.74E-06	-1.06E-06
	(0.03619)	(0.00046)	(0.00253)	(2.7E-06)	(5.4E-07)
	[-0.12396]	[0.38747]	[-2.11740]	[1.03104]	[-1.96106]
DBINANCE(-1)	-4.255825	-0.208152	-0.536699	0.000314	-0.000166
	(2.78572)	(0.03546)	(0.19474)	(0.00020)	(4.2E-05)
	[-1.52773]	[-5.87023]	[-2.75598]	[1.53298]	[-4.00926]
DBINANCE(-2)	9.474079	0.086737	0.386250	0.000437	3.87E-05
	(2.79896)	(0.03563)	(0.19567)	(0.00021)	(4.2E-05)
	[3.38486]	[2.43455]	[1.97403]	[2.12789]	[0.92852]
DETH(-1)	-3.065403	-0.018328	-0.171207	-0.000191	-5.97E-06
	(0.58446)	(0.00744)	(0.04086)	(4.3E-05)	(8.7E-06)
	[-5.24487]	[-2.46367]	[-4.19037]	[-4.44211]	[-0.68601]
DETH(-2)	-0.268470	0.014851	0.154486	-8.12E-05	3.11E-05
	(0.58902)	(0.00750)	(0.04118)	(4.3E-05)	(8.8E-06)
	[-0.45579]	[1.98077]	[3.75181]	[-1.87681]	[3.53825]
DXRP(-1)	-575.5062	-3.753179	-51.19130	0.069469	-0.000561
	(402.258)	(5.12027)	(28.1204)	(0.02955)	(0.00599)
	[-1.43069]	[-0.73300]	[-1.82043]	[2.35108]	[-0.09361]
DXRP(-2)	489.8930	-3.475564	0.842781	0.024056	0.005358
	(401.130)	(5.10591)	(28.0416)	(0.02946)	(0.00598)
	[1.22128]	[-0.68069]	[0.03005]	[0.81643]	[0.89648]
DDOGE(-1)	3153.117	127.2379	333.0770	0.205271	-0.039238
	(1896.22)	(24.1367)	(132.558)	(0.13929)	(0.02825)
	[1.66284]	[5.27155]	[2.51268]	[1.47374]	[-1.38879]
DDOGE(-2)	1979.745	17.69223	-165.7361	0.289126	0.059306
	(1883.61)	(23.9762)	(131.677)	(0.13836)	(0.02807)
	[1.05103]	[0.73791]	[-1.25866]	[2.08967]	[2.11309]
C	21.95162	0.197873	1.386187	0.000359	0.000173
	(21.7429)	(0.27676)	(1.51997)	(0.00160)	(0.00032)
	[1.00960]	[0.71496]	[0.91199]	[0.22459]	[0.53316]

Source: Authors' processings

Based on the results provided by the VAR model, we can appreciate the mutual influence of the five analyzed cryptocurrencies. The estimated positive coefficients indicate a positive influence, while the minus sign denotes the negative impact of the exogenous variables on the endogenous variables. The equation of the model that denotes the evolution of the Bitcoin price according to its previous values taking into account two lags, as well as the prices of the other four cryptocurrencies is given below.

$$\Delta BTC_t = 0.123 * \Delta BTC_{t-1} - 0.004 * \Delta BTC_{t-2} - 4.255 * \Delta BINANCE_{t-1} + 9.474 * \Delta BINANCE_{t-2} - 3.065 * \Delta ETH_{t-1} - 0.268 * \Delta ETH_{t-2} - 575.5 * \Delta XRP_{t-1} + 489.8 * \Delta XRP_{t-2} + 3153.1 * \Delta DOGE_{t-1} + 1979.7 * \Delta DOGE_{t-2} + 21.951 + \varepsilon_{1t} \quad [3.1]$$

The price of Bitcoin at time t is positively influenced by its price in the previous period, by the price of Binance cryptocurrency at time t-2, by the price of Ripple (XRP) at time t-1, but also by the price of Dogecoin at time t-1, respectively t-2. All other coefficients denote the negative impact on the price of Bitcoin at time t.

Table 4: Granger causality test results

Null Hypothesis	**Prob.**
DBTC does not Granger cause DBINANCE	0.004
DBINANCE does not Granger cause DBTC	0.000
DDOGE does not Granger cause DBINANCE	0.000
DBINANCE does not Granger cause DDOGE	0.000
DETH does not Granger cause DBINANCE	0.101
DBINANCE does not Granger cause DETH	0.058
DXRP does not Granger cause DBINANCE	0.805
DBINANCE does not Granger cause DXRP	0.040
DDOGE does not Granger cause DBTC	0.402
DBTC does not Granger cause DDOGE	0.000
DETH does not Granger cause DBTC	0.000
DBTC does not Granger cause DETH	0.000
DXRP does not Granger cause DBTC	0.001
DBTC does not Granger cause DXRP	0.122
DETH does not Granger cause DDOGE	0.000
DDOGE does not Granger cause DETH	0.008
DXRP does not Granger cause DDOGE	0.000
DDOGE does not Granger cause DXRP	0.083
DXRP does not Granger cause DETH	0.492
DETH does not Granger cause DXRP	0.000

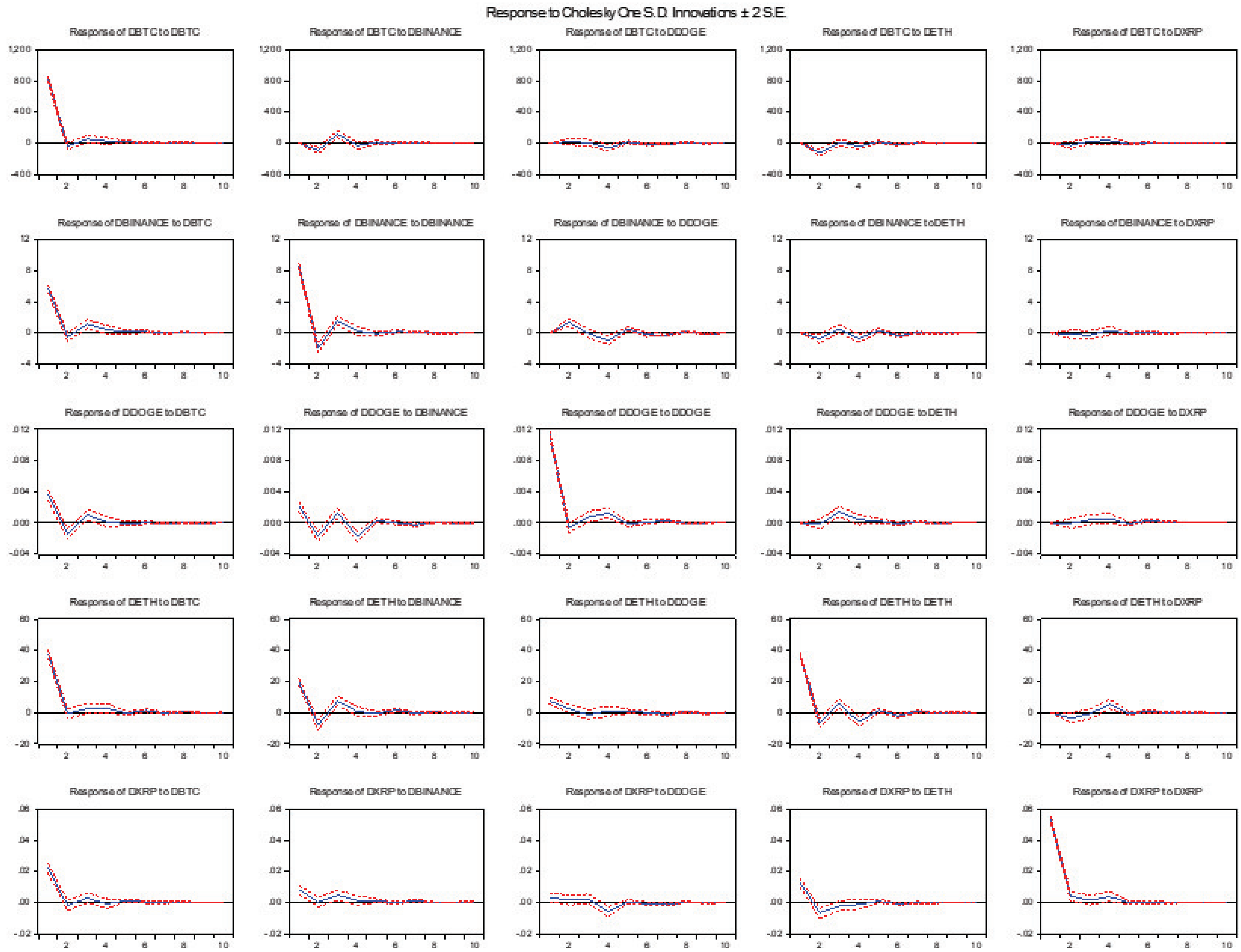
Source: Authors' processings

The causal relationship between two variables can be explored through the method proposed by Granger (1969). Granger's approach is to investigate whether a certain time series can be considered appropriate in predicting another time series. Considering the five cryptocurrencies, the causal relationship between them will be explored one by one. The null hypothesis of the absence of Granger causation is rejected for the majority of cryptocurrencies, given the values highlighted in the Prob column, below the 5% significance threshold. Bidirectional and significant causal relationships are established between the variables DBTC and DBINANCE, DDOGE and DBINANCE, DETH and DBTC, as well as between DETH and DDOGE. On the other hand, there are situations in which causality manifests itself unilaterally. This is the case with Ripple (XRP) and Bitcoin (BTC) cryptocurrencies, given that only the DXRP variable is a Granger cause of the DBTC variable.

Figure 3: Impulse-response functions associated to the five analyzed cryptocurrencies

Source: Authors' processings

Applying the vector autoregressive methodology implies an important stage, that of inter-



preting the impulse response functions, which highlight the evolution of a variable under the action of shocks induced at the level of other variables in the model. Or, in other words, they denote changes in the endogenous variable in response to an external shock. The graphs in the previous figure show the response of each digital currency to a shock produced at the level of each other analyzed cryptocurrency. The variables are expressed using the first order differentiation. Analyzing the graphs of the impulse response curves we conclude that certain cryptocurrencies do not respond significantly to shocks that affect other digital assets. One can note that the response of certain cryptocurrencies to shocks affecting other digital assets is not significant (BTC's response to XRP or DOGECOIN, BINANCE's response to XRP, or DOGECOIN's response to XRP).

However, the impulse response curves associated to DOGECOIN and ETH indicate that the price of these cryptocurrencies is more sensitive to shocks affecting the price of other digital assets. For example, a shock induced by the DBINANCE variable implies an oscillating evolution of the DOGECOIN price over the next five periods. A similar situation is noticed when the problem of inducing a shock at the level of the DBTC variable is raised. The possible shocks in the price of the BINANCE cryptocurrency asset also affect the behavior of Ethereum coin for three consecutive periods.

5. Conclusions

Our study focused on a time horizon situated between July 26th of 2017 and July 6th of 2021, totaling 1442 daily observations which represent prices of the five cryptocurrencies. Prior to modeling the time series, it was necessary to investigate their stationarity. The results of the stationarity test indicated the presence of the unit root, an aspect that required the differentiation of the considered variables. Subsequently, the cointegration of the variables was evaluated using the Johansen cointegration procedure. No long-term relationship has been reported between the prices of the five cryptocurrencies, given the absence of cointegration. Therefore, the vector autoregressive method was chosen in order to assess the prices' interdependence of the five digital currencies. Our results indicated that the price of each cryptocurrency is influenced in a distinct manner by the price of other digital currencies. The price of Bitcoin was found to be negatively influenced by the price of Ethereum, regardless of the specified lag, given that the estimated coefficients were negative. The price of the same currency, but corresponding to the previous period, positively influences the price movement at time t, but an opposite situation is highlighted if we consider the price with a delay of two periods. Granger causality has also been studied to check if the price of each individual currency can be considered a good indicator in predicting the price of other digital currencies. Bidirectional and significant causation has been identified for Bitcoin and Binance, Dogecoin and Binance, but also for Ethereum and Bitcoin. Through impulse response curves, it has been observed that Ethereum and Dogecoin are two virtual currencies more likely to be significantly affected by potential shocks affecting the market of other cryptocurrencies.

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