Antun Fagarazzi [a]

JEL Classification: G15, C58, G11
Original scientific paper
https://doi.org/10.32910/ep.76.6.4

Granger Causation between Bitcoin Prices and Prices of Older Cryptocurrencies

Abstract

This paper analyses the relationship between Bitcoin (BTC) values and the values of older cryptocurrencies. Daily closing price data of Bitcoin (BTC), Litecoin (LTC), Namecoin (NMC), Peercoin (PPC), Ripple (XRP), Dogecoin (DOGE), Primecoin (XPM) and Nxt (NXT) for the period from December 16, 2013 to December 14, 2024 was used to perform Granger causality in two ways. The results show linear and nonlinear Granger causality in both directions between most cryptocurrencies, BTC-LTC, BTC-XRP and BTC-DOGE relationships. On the other hand, BTC does not have a causal influence on NMC, PPC and XPM in the linear model. In contrast, in the nonlinear model, BTC Granger causes NMC. These insights are crucial for understanding the complex cryptocurrency market price dynamics, aiding investors and analysts in making more informed decisions based on historical data and predictive relationships.

Keywords: Bitcoin, cryptocurrencies, Granger causality

[a] A. Fagarazzi, univ. mag. oec., Ph.D. student, Faculty of Economics and Business, Open University of Catalonia (e-mail: afagarazzi1@gmail.com).
The paper was received on 16.12.2024. It was accepted for publication on 16.05.2025.

1. INTRODUCTION

Yermack (2013) has examined the fundamental features of Bitcoin from an economic standpoint, including its role as a transaction unit, storage value, and exchange facility. The author mentioned that several factors, including geopolitics, the government, cybercrime, worldwide socioeconomic events, and others, affect Bitcoin values. Most scholars have compared Bitcoin to gold (Grinberg, 2012; Dyhrberg, 2016a, 2016b; Zhu et al., 2017). Klein et al. (2018) examined the structure, correlation, and portfolio components of Bitcoin, gold, and other assets. They contend that it moves similarly to other precious metals and offers asymmetric returns during market shocks. They also contended that since it cannot hedge, it cannot be considered a safe haven. Barber et al. (2012) conclude that Bitcoin can be regarded as decentralised money if it functions properly. Since the launch of Bitcoin in 2009, the global cryptocurrency markets have expanded quickly. The global proliferation of these digital currencies is because they are often brought up by financial, governmental, and print media outlets (Glaser et al., 2014). Therefore, since Bitcoin and other cryptocurrencies experienced significant growth during this period, reaching a peak of USD 19,497 on December 17, 2017, they can be regarded as alternative investment assets. The returns on cryptocurrencies are far riskier and more volatile than those on traditional currencies and stocks. Cryptocurrencies have a role in portfolio management and financial markets as asset returns (Dyhrberg, 2016a; Wu & Pandey, 2014). The study of cryptocurrency interconnection and volatility co-movements is one of the key concerns for investors to understand cryptocurrency markets better and create more knowledge to make an appropriate decision in improbability and risks (Gkillas & Katsiampa, 2018). Multiple previous studies have investigated interconnections among cryptocurrencies (Corbet et al., 2018; Ciaian et al., 2018; Stosic et al., 2018; Aslanidis et al., 2019; Canh et al., 2019; Katsiampa et al., 2019; Tu & Xue, 2019; Shi et al., 2020; Kim et al., 2021; Nguyen et al., 2023).

The research problem is a lack of understanding of the long-term relationships between Bitcoin and a diverse group of cryptocurrencies over more than 10 years. Older cryptocurrencies such as Namecoin, Peercoin, Primecoin and NXT have historically been underrepresented in linear and nonlinear analysis, leaving a gap in understanding their long-term influence and bidirectional relationships with Bitcoin.

The objective of this research is to conduct a detailed analysis of a comprehensive dataset spanning over a decade, encompassing both primary and historically significant older cryptocurrencies. By employing linear and nonlinear analyses, the study aims to explore the bidirectional causality between Bitcoin and other cryptocurrencies, providing insights into their interconnections.

This study is important for academics, education, regulators, investors, risk managers, decision-makers, market analysts and public awareness in general. Grasping price relationships is essential for adequate portfolio diversification and managing risk. When Bitcoin significantly impacts the value of established cryptocurrencies, investors can enhance their strategies by monitoring Bitcoin's price fluctuations. Recognising systemic risks and the impacts of price contagion allows for improved regulatory actions and efforts to stabilise the market, especially during turbulent times. The examination offers perspectives on market efficiency, the uptake of cryptocurrencies, and the influence of established coins, adding to the body of financial and economic research. For market analysts, this information is essential for creating forecasting models and discovering arbitrage possibilities. It addresses a deficiency in the existing literature by examining lesser-known relationships, providing a broader insight into the crypto ecosystem. Outcomes might inform the creation of innovative applications, tools, and financial products that utilise the interconnections between cryptocurrencies. Understanding these connections can encourage well-informed choices and enhance comprehension of cryptocurrency markets. For the broader public, understanding the idea of Granger causality between Bitcoin and other cryptocurrencies can improve financial knowledge, protect against possible market manipulations, and increase awareness of new technologies.

2. LITERATURE REVIEW

Ciaian et al. (2018) used the Autoregressive Distributed Lag (ARDL) model to study the connectivity between cryptocurrencies. They found a correlation between the returns of Bitcoin and other cryptocurrencies. The study referenced earlier is relevant to this research since it explores the connections between Bitcoin and various other cryptocurrencies. Grasping these relationships is essential for performing Granger causality tests. Using the Dynamic Conditional Correlation (DCC) model, Corbet et al. (2018) observed correlations and interlinkages among cryptocurrencies and discovered interconnections. However, they only have three cryptocurrencies—Bitcoin, Litecoin, and Ripple—in their collection. Stosic et al. (2018) found that most of the eigenvalues in the cross-correlation matrix spectrum do not correspond to random matrix theory's universal predictions. However, a handful of the most significant eigenvalues do. The minimum spanning tree of Bitcoin cross-correlations reveals different yet unexpectedly persistent community structures.

Aslanidis et al. (2019) found that positive correlations exist across cryptocurrencies, albeit these change over time. Correlations with Monero are more stable over time. The link between cryptocurrency and traditional financial assets is minimal. Beneki et al. (2019) have examined volatility spillovers and hedging features within the BEKK-GARCH model framework, but they have only looked at two cryptocurrencies: Bitcoin and Ethereum. According to their research, there are positive shocks to Ethereum's volatility in addition to unidirectional volatility—transmission from Ethereum returns to Bitcoin returns—lasting no more than ten days before waning over two weeks. Cheikh et al. (2019) examined the asymmetric effects of cryptocurrencies using the Smooth-Transition-GARCH model. For practically all leading digital currencies, they have seen strong evidence of reversed asymmetry impact, meaning that good news affects cryptocurrency volatility more than bad news. In order to qualify as a haven, they have further said that the asymmetric effect of digital currencies is comparable to that of gold. After analysing the co-movement and volatility dynamics of two cryptocurrencies, Bitcoin and Ether, using bivariate Diagonal-BEKK, Katsiampa (2019) concluded that the cryptocurrency markets are interconnected. Essential news will likely affect these currencies, and Ether can be used as a hedge against Bitcoin. Since there is little research on cryptocurrencies in a tiny region, scholarly perspectives must pay close attention to this topic. Shi et al. (2020) found that Bitcoin and Litecoin price volatility readings show a considerable positive association. Ethereum's volatility levels are positively correlated with Ripple and Stellar. Ripple and Dash have a favourable association in terms of volatility. These findings are robust when considering various correlation networks. The evidence suggests that Bitcoin mainly correlates with Litecoin, while Ethereum is linked to other cryptocurrencies. The analysis conducted by Nguyen et al. (2023) demonstrates that alterations in the volatility-driven network framework can help pinpoint significant events that have, in turn, influenced the cryptocurrency market. Furthermore, their findings indicate that frameworks mirror investors' sentiments, encompassing feelings such as fear and greed. By employing metrics like PageRank, they uncovered that certain smaller coins exert an unexpectedly significant impact on the market. In contrast, the largest cryptocurrencies, like BTC and ETH, appear less influential. These studies collectively demonstrate that significant relationships exist between cryptocurrencies regarding price movements, volatility, and market influences. This is particularly relevant for this research, as understanding the strength and direction of these interactions provides a foundation for conducting Granger causality analysis to determine whether past values of one cryptocurrency can predict future values of another.

Canh et al. (2019) used DCC MGARCH to simulate seven leading cryptocurrencies while considering structural breaks and spillover effects simultaneously. According to their empirical findings, all cryptocurrencies exhibit structural fractures, and there are positive, highly significant correlations between them that indicate spillover effects. The constraint of diversification advantages within Bitcoin marketplaces was their primary discovery. In the BEKK-MGARCH model framework, Tu & Xue (2019) investigated bifurcation features between two cryptocurrencies (such as Bitcoin and Litecoin) from 2013 to 2018. They discovered that the shock's transmission direction prior to bifurcation was flipped following bifurcation and that there was a unidirectional influence from Bitcoin returns to Litecoin returns. A study by Kim et al. (2021) utilised a Granger non-causality test in quantiles to explore causal relationships among cryptocurrencies further. The findings demonstrate that no quantile uncorrelated cryptocurrency was identified through the Granger non-causality test in quantiles. Strong bidirectional causal relationships are observed exclusively between Ripple and other cryptocurrencies across the quantile range [0.05, 0.95]. Notable causal connections among cryptocurrency returns are present at higher quantile levels. These studies reflect earlier investigations into Granger causality concerning cryptocurrencies. Nevertheless, this research will broaden the scope over an extended timeframe and include nonlinear relationships, concentrating on less-explored cryptocurrencies to enhance the understanding of their interactions.

Table 1 presents a structured overview of the literature review in tabular form.

Table 1 – Relevant Literature Review

Author(s)	*Time of nalysis*	*Methodology*	*Data frequency*	*Key findings*	*Crypto-currencies analysed*
Caporale & Zekokh (2019)	*July 18, 2010 to April 30, 2018*	*Markov-Switching GARCH models*	*Daily*	*Cryptocurrencies exhibit high volatility and leverage effects*	*Ethereum, Ripple, Litecoin, Bitcoin*
Corbet et al. (2018)	*Between early 2013 and early 2016*	*Dynamic Conditional Correlation (DCC) model*	*Daily*	*Bitcoin, Ripple and Litecoin are interconnected. Bitcoin price can affect the levels of Ripple and Litecoin*	*Bitcoin, Litecoin, Ripple*
Ciaian et al. (2018)	*From 2013 to 2016*	*Autoregressive Distributed Lag (ARDL) model*	*Daily*	*There is a correlation between the returns of Bitcoin and other cryptocurrencies*	*6 major altcoins and 10 minor altcoins.*
Tu & Xue (2019)	*April 28, 2013 to July 31, 2017, and August 1, 2017 to July 31, 2018*	*Granger causality test and a BEKK-MGARCH model*	*Daily*	*Return and volatility spillovers run in one direction only, i.e., from Bitcoin to Litecoin, before the bifurcation.*	*Bitcoin, Litecoin*
Canh et al. (2019)	*August 5, 2014 to December 31, 2018*	*MGARCH, DCC-MGARCH, Granger test*	*Daily*	*There are causality effects among prominent cryptocurrencies, especially in BTC, LTC, XRP, XLM, XMR, DAS and BCN.* *The results from DCC- MGARCH reveal significant positive and strong correlations (correlations between six out of seven cryptocurrencies are larger than 0.6), implying that the cryptocurrency market lacks the diversified feature.*	*20 cryptocurrencies* *with the largest market capitalisation (as of 31st Dec 2018).*

Katsiampa (2019)	*August 7, 2015 to January 15, 2018*	*Augmented Dickey-Fuller and Phillips-Perron unit-root tests, Engle's ARCH-LM test for ARCH effects*	*Daily*	*Bitcoin and Ethereum seem to follow a similar pattern and could be correlated.*	*Bitcoin, Ethereum*
Katsiampa et al. (2019)	*August 7, 2015 to July 10, 2018*	*BEKK model*	*Daily*	*Lagged volatility and lag shocks of these currencies themselves determine their volatility. Additionally, unidirectional shock spillovers between Ethereum and Litecoin and bidirectional shock transmissions between Bitcoin and the other two coins.*	*Bitcoin, Ethereum, Litecoin*
Beneki et al. (2019)	*August 8, 2015 to June 10, 2018*	*BEKK-GARCH model*	*Daily*	*There are positive shocks to Ethereum's volatility in addition to unidirectional volatility—transmission from Ethereum returns to Bitcoin returns—lasting no more than ten days before waning over two weeks.*	*Bitcoin, Ethereum*
Kim et al. (2021)	*July 23, 2017 to November 28, 2019*	*Quantile Granger non-causality test*	*Daily*	*The quantile causality test indicates that cryptocurrency has no independent causal link with others. Ripple and other cryptocurrencies have statistically significant bi-directional causal correlations at the quantile level (0.05, 0.95). Cryptocurrencies have more significant causal correlations at upper quantile levels (0.6-0.8 and 0.8-0.95) compared to lower quantile levels. In high quantiles, the largest cryptocurrencies, such as BTC and ETH, have a more significant causal relationship with smaller ones.*	*Ethereum, Bitcoin, Ripple, Bitcoin Cash, Litecoin, EOS, Bifrost, Export Import Coin, Stellar*
Nguyen et al. (2023)	*February 13, 2019 to April 6, 2021*	*Pearson correlation, Minimum Spanning Tree (MST), graph-based metrics, PageRank, Random Matrix Theory (RMT), Market Component Concept*	*30-minute dataset sourced from the HitBTC exchange*	*Analysis shows that changes in volatility-based network structure can indicate significant events affecting the bitcoin market. These structures represent investors' emotions, including fear and greed. Using metrics like PageRank, authors found that tiny coins have a disproportionate impact on the market, whereas more prominent cryptocurrencies like BTC and ETH appear less significant.*	*34 most active cryptocurrencies*

Stosic et al. (2018)	*August 26, 2016 to January 18, 2018*	*Random matrix theory And minimum spanning trees*	*Daily*	*Most of the eigenvalues in the cross-correlation matrix spectrum do not correspond to random matrix theory's universal predictions, but few of the most significant eigenvalues do. The minimum spanning tree of bitcoin cross-correlations reveals different yet unexpectedly persistent community structures.*	*119 cryptocurrencies*
Shi et al. (2020)	*August 8, 2015, to January 1, 2020*	*MFSVM with the Bayesian estimation procedure*	*Daily*	*Bitcoin and Litecoin price volatility readings show a considerable positive association. Ethereum's volatility levels are positively correlated with Ripple and Stellar. Ripple and Dash have a favourable association in terms of volatility. These findings are robust when considering various correlation networks. The evidence suggests that Bitcoin is mainly correlated with Litecoin, while Ethereum is linked to other cryptocurrencies.*	*Bitcoin, Dash, Ethereum, Litecoin, Ripple, and Stellar*
Aslanidis et al. (2019)	*May 21, 2014 to September 27, 2018*	*generalised DCC class model*	*Daily*	*Positive correlations exist across cryptocurrencies, albeit these change over time. Correlations with Monero are more stable over time. The link between cryptocurrency and traditional financial assets is minimal.*	*Four cryptocurrencies (Bitcoin (BTC), Dash (DASH), Monero (XMR), and Ripple (XRP)), and three traditional financial assets (Standard & Poors 500 Composite (SP500), S&P US Treasury bond 7-10Y index (BOND), and Gold Bullion LBM (GOLD))*

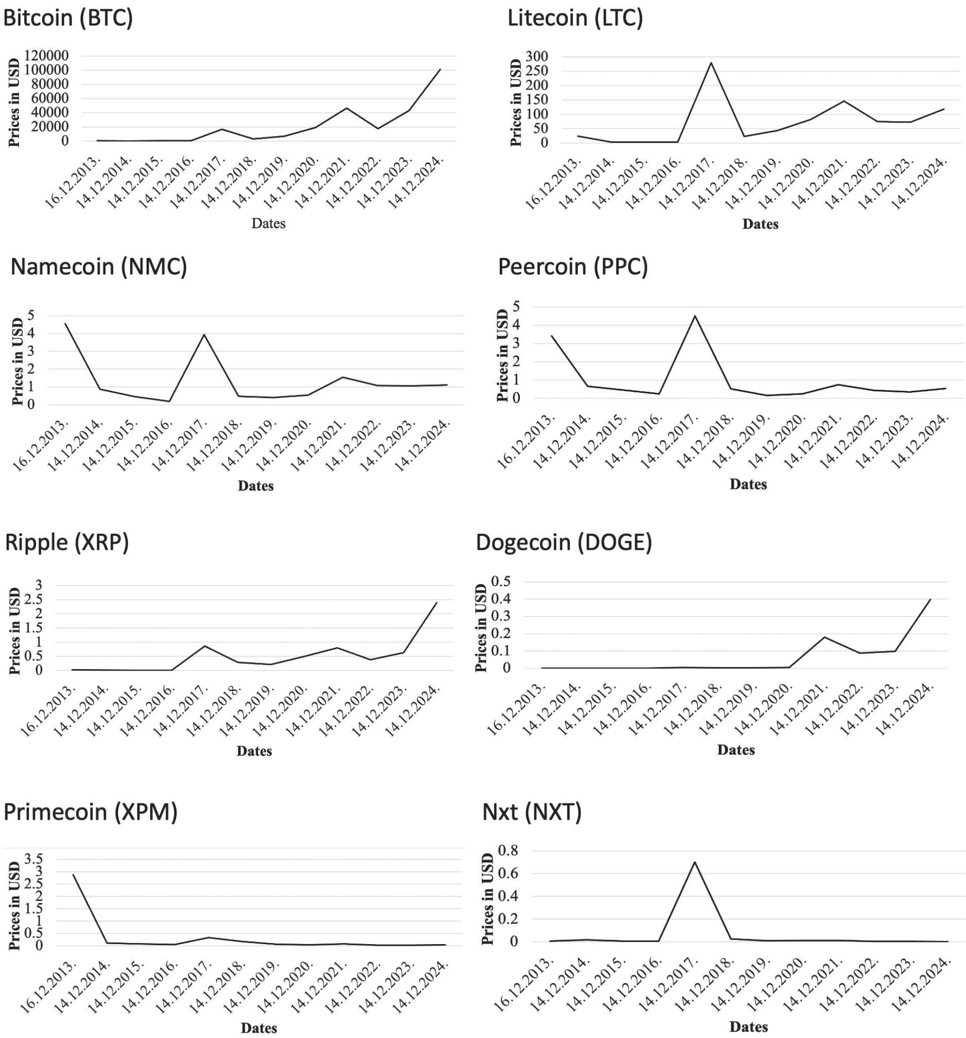
Source: created by author

3. RESEARCH METHODOLOGY AND USED DATA

This research used a quantitative approach, and secondary data were utilised. The cryptocurrency data was gathered from https://coinmarketcap.com/. CoinMarketCap is considered a reliable source for cryptocurrency prices due to its data aggregation from numerous reputable exchanges, providing real-time, accurate market information. Daily closing price data of eight cryptocurrencies in USD was used. Cryptocurrencies included in the sample are Bitcoin (BTC), Litecoin (LTC), Namecoin (NMC), Peercoin (PPC), Ripple (XRP), Dogecoin (DOGE), Primecoin (XPM) and Nxt (NXT). The examination duration ranges from December 16, 2013, to December 14, 2024. The initial dataset contained 4017 observations for each cryptocurrency. There were no missing values or gaps in the dataset, as historical price data for each cryptocurrency was retrieved and consolidated into a single document. Therefore, no imputation or deletion techniques were necessary. After applying the first difference transformation to ensure stationarity, the number of observations was reduced to 4016. All variables are endogenous. Granger causality between Bitcoin and selected cryptocurrencies was performed. Granger causality is a statistical theory of causality based on prediction. Granger causality states that if signal X1 "Granger-causes" (or "G-causes") signal X2, then past values of X1 should provide information that helps predict X2 beyond the information provided by past values of X2 alone, making it a precise tool for examining interdependencies in time series data. It accounts for lagged relationships, essential in financial datasets where past prices can influence future trends. Its mathematical approach uses linear regression based on stochastic process modelling (Granger, 1969). R software was used to conduct the aforementioned statistical analysis.

The price movements of Bitcoin, along with those of earlier cryptocurrencies over time, are presented in Figure 1.

Figure 1. Bitcoin Prices and the Prices of Older Cryptocurrencies by Date.



Note: The x-axis represents dates, while the y-axis represents prices in USD. Each data point is spaced one year apart, starting from December 16, 2013, to December 14, 2024.
Source: CoinMarketCap, https://coinmarketcap.com/

3.1. Linear Granger causality

The linear Granger causality test (1969) determined the linear relationship between Bitcoin and the chosen cryptocurrencies. First, the augmented Dickey-Fuller (ADF) unit root test (1979) is employed to investigate the stationary characteristics of cryptocurrency time series. Sims (1980) suggested the Vector autoregression (VAR) model, which can be utilised for the linear Granger causality test when all-time series are stationary. In this work, the bivariate VAR model is built in the following way:

$$\Delta Y_t = \alpha_1 + \sum_{i=1}^{m} b_{1i}\Delta X_{t-1} + \sum_{j=1}^{m} c_{1j}\Delta Y_{t-1} + \varepsilon_{1t}$$

$$\Delta X_t = \alpha_2 + \sum_{i=1}^{m} b_{2i}\Delta X_{t-1} + \sum_{j=1}^{m} c_{2j}\Delta Y_{t-1} + \varepsilon_{2t}$$

In this equation, α1 and α2 represent the intercept terms, b and c represent the estimated coefficients, and m represents the optimal lag order based on the Schwarz information criterion (SIC). Koehler and Murphree (1988) suggest that the SIC is a superior criterion for this application to the Akaike information criterion (AIC), which would overfit the data. The null hypothesis states that X cannot strictly cause Y in Equation (1) and Y cannot strictly cause X in Equation (2). This is represented by $b_{1i} = 0$ and $c_{2j} = 0$ (i= 1, 2, . . . , m; j= 1, 2, . . . , m).

3.2. Nonlinear Granger causality

Diks and Panchenko (2006) constructed a nonlinear Granger causality test used in this study.

It examines whether past values of one variable provide additional predictive information for another by analysing deviations in joint probability density functions. The null hypothesis states that past values of X do not improve the prediction of Y:

$$H_0 = Y_{t+1} \mid (X_t^q;\ Y_t^p) \sim Y_{t+1} \mid Y_t^p$$

This condition translates into a constraint on the joint probability density function:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y,z)}{f_Y(y)}$$

Diks and Panchenko propose the test statistic:

$$T_n(\varepsilon) = \frac{(n-1)}{n(n-2)} \sum_i (\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i)\hat{f}_Y(Y_i) -$$

$$- \hat{f}_{X,Y}(X_i, Y_i)\hat{f}_{Y,Z}(Y_i, Z_i))$$

where the local density estimator for a d_W-variate random vector W at W_i is given by:

$$\hat{f}_W(W_i) = \frac{(2\varepsilon)^{-d_W}}{n-1} \sum_{j,j\neq \mathrm{i}} I_{ij}^W$$

With $I_{ij}^W = I(\left\|W_i - W_j\right\| < \varepsilon.$. The test is consistent if the bandwidth follows:

$$\varepsilon_n = C_n^{-\beta}, \text{ for } \beta \in (\tfrac{1}{4}, \tfrac{1}{3}).$$

Diks and Panchenko (2006) recommend selecting the bandwidth as follows:

$$\varepsilon_n = \max(C_n^{-\frac{2}{7}}, 1.5),$$

where CC can be determined based on the series' ARCH coefficient, under the null hypothesis, the test is asymptotically normal but may under-reject when the sample size is below 500.

4. EMPIRICAL RESULTS

4.1. Unit Root Test Results

All time series must be stationary before performing a linear and nonlinear Granger causality test to avoid spurious regression. Table 2 shows the results of unit root testing for all series individually utilising the Augmented Dickey-Fuller (ADF) test. According to Koehler and Murphree (1988), using the SIC produces lower-order forecasting models. The appropriate lag length is found using the SIC criterion, shown in brackets. The Augmented Dickey-Fuller (ADF) test is a statistical method used to test the null hypothesis that a time series has a unit root, meaning the series is non-stationary. The ADF test accounts for higher-order autocorrelation by adding lagged differences of the time series as explanatory variables, making it more robust compared to the traditional Dickey-Fuller test. Results of the ADF test with SIC criterion are presented in Table 2.

Table 2. ADF test with SIC

Cryptocurrency	*Level*	*First Difference*
Bitcoin (BTC)	*0.01 *** (2)*	*0.01 *** (1)*
Litecoin (LTC)	*0.06222 * (14)*	*0.01 *** (13)*
Namecoin (NMC)	*0.1712 (21)*	*0.01 *** (20)*
Peercoin (PPC)	*0.05585 * (23)*	*0.01 *** (22)*
Ripple (XRP)	*0.01 *** (33)*	*0.01 *** (32)*
Dogecoin (DOGE)	*0.02925 ** (39)*	*0.01 *** (38)*
Primecoin (XPM)	*0.5166 (21)*	*0.01 *** (20)*
Nxt (NXT)	*0.01 *** (25)*	*0.01 *** (29)*

Note: The symbols *, **, or *** indicate rejection of the null hypothesis at significance levels of 10%, 5%, and 1%, respectively.
Source: Author

H0: non-stationary

The results show that the p-value of every cryptocurrency in the sample is 0.01 * after the first difference. Thus, the null hypothesis is rejected, and the time series data is stationary.

4.2. Linear Granger Causality

Table 3 presents the results of linear Granger causality.

Table 3. Linear Granger Causality Results

Null Hypothesis	*Lag*	*p-value*
BTC does not Granger Cause LTC	*1*	*7.356e-07 ****
LTC does not Granger Cause BTC	*1*	*0.002607 ****
BTC does not Granger Cause NMC	*1*	*0.3932*
NMC does not Granger Cause BTC	*1*	*0.7175*
BTC does not Granger Cause PPC	*1*	*0.1535*
PPC does not Granger Cause BTC	*1*	*0.995*
BTC does not Granger Cause XRP	*18*	*2.894e-11 ****
XRP does not Granger Cause BTC	*18*	*0.00102 ****
BTC does not Granger Cause DOGE	*29*	*< 2.2e-16 ****
DOGE does not Granger Cause BTC	*29*	*< 2.2e-16 ****
BTC does not Granger Cause XPM	*5*	*0.712*
XPM does not Granger Cause BTC	*5*	*0.2695*
BTC does not Granger Cause NXT	*15*	*0.03364 ***
NXT does not Granger Cause BTC	*15*	*0.04648 ***

Note: The symbols *, **, or *** indicate rejection of the null hypothesis at significance levels of 10%, 5%, and 1%, respectively.
Source: author

BTC → LTC: Bitcoin Granger causes Litecoin with a very high significance at lag 1 (F-test: 24.598; p-value: 7.356e-07 ***), indicating that past values of BTC significantly help in predicting future values of LTC.

LTC → BTC: Litecoin Granger causes Bitcoin at lag 1 (F-test: 9.0755; p-value: 0.002607 ***), suggesting that past LTC values also significantly predict future BTC values.

BTC → XRP: At lag 18, Bitcoin exhibits a Granger causal effect on XRP (F-test: 4.9514; p-value: 2.894e-11 ***).

XRP → BTC: A Granger causal relationship from XRP to Bitcoin is detected at lag 18 (F-test: 2.355; p-value: 0.00102 ***).

BTC → DOGE: A significant Granger causality from Bitcoin to Dogecoin is observed at lag 29 (F-test: 5.8094; p-value: < 2.2e-16 ***).

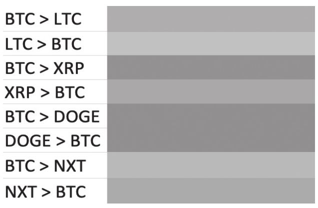
DOGE → BTC: At lag 29, Dogecoin Granger causes Bitcoin (F-test: 6.3747; p-value: < 2.2e-16 ***).

BTC → NXT: Bitcoin Granger causes NXT at lag 15 (F-test: 1.7657; p-value: 0.03364 **), showing a significant relationship in which past BTC values predict future NXT values.

NXT → BTC: NXT's previous values are significant predictors of Bitcoin's future prices at lag 15 (F-test: 1.687; p-value: 0.04648 **).

A heatmap illustrating notable findings of Linear Granger Causality can be seen in Figure 2.

Figure 2. Heatmap Showing Significant Results of Linear Granger Causality



Source: author

4.3. Nonlinear Granger Causality

The nonlinear Granger causality test by Diks and Panchenko (2006) requires careful selection of the bandwidth parameter ε to ensure accurate testing of nonlinear dependencies. According to Diks and Panchenko (2006), the recommended bandwidth is:

$$\varepsilon n = \max(C_n^{-\frac{2}{7}}, 1.5)$$

where C is a parameter determined from the properties of the time series.

In this study, C was set using the ARCH coefficients ($\alpha 1$) obtained from modelling each time series. The ARCH model captures the conditional heteroskedasticity in financial time series, making it suitable for reflecting volatility dynamics. Specifically, the mean of the $\alpha 1$ coefficients from the two series being tested was used as the parameter C:

$$C = \frac{\alpha 1, \mathrm{x} + \alpha 1, \mathrm{y}}{2}$$

This approach leverages the persistence in volatility captured by the ARCH coefficients, aligning the bandwidth parameter with the series' heteroskedastic nature. Using $\alpha 1$ for C ensures consistency between the properties of the time series and the test's sensitivity.

$\alpha 1$ coefficients for cryptocurrencies are shown in Table 4.

Table 4. α1 Coefficients for Cryptocurrencies

Cryptocurrency	α1
Bitcoin (BTC)	*0.999*
Litecoin (LTC)	*0.999*
Namecoin (NMC)	*0.972032*
Peercoin (PPC)	*0.999*
Ripple (XRP)	*0.050183*
Dogecoin (DOGE)	*0.900671*
Primecoin (XPM)	*0.999*
Nxt (NXT)	*0.054887*

Source: author

Table 5 displays bandwidth parameters (C) for different combinations of X and Y, determined as the mean value of the α1 coefficients.

Table 5. Bandwidth Parameters (C) for Different Combinations of X and Y

Combination	*Bandwidth parameter (C)*
BTC < > LTC	*0.999*
BTC < > NMC	*0.985516*
BTC < > PPC	*0.999*
BTC < > XRP	*0.5245915*
BTC < > DOGE	*0.9498355*
BTC < > XPM	*0.999*
BTC < > NXT	*0.5269435*

Source: author

Table 6. Nonlinear Granger Causality Results

Null Hypothesis	$L_x = L_Y$				
	1	2	3	4	5
BTC does not Granger Cause LTC	**0** *** *6.133*	**0** *** *6.351*	**0** *** *5.954*	**0** *** *5.491*	**0** *** *4.890*
LTC does not Granger Cause BTC	**0** *** *5.261*	**0.00001** *** *4.377*	**0.00015** *** *3.613*	**0.00873** *** *2.377*	**0.01133** ** *2.279*
BTC does not Granger Cause NMC	*0.26036*	**0.04234** ** *1.724*	**0.00324** *** *2.723*	**0.01009** ** *2.323*	**0.00259** *** *2.795*
NMC does not Granger Cause BTC	*0.87741*	*0.99031*	*0.99752*	*0.83178*	*0.44029*
BTC does not Granger Cause PPC	*0.99910*	*0.99920*	*0.97780*	*0.93695*	*0.88659*
PPC does not Granger Cause BTC	*0.93513*	*0.99259*	*0.99907*	*0.99895*	*0.99980*
BTC does not Granger Cause XRP	**0** *** *8.575*	**0** *** *9.176*	**0** *** *8.356*	**0** *** *7.310*	**0** *** *6.717*
XRP does not Granger Cause BTC	**0** *** *7.435*	**0** *** *5.216*	**0** *** *4.604*	**0.00014** *** *3.629*	**0.00008** *** *3.762*
BTC does not Granger Cause DOGE	**0** *** *6.522*	**0** *** *7.385*	**0** *** *7.309*	**0** *** *7.237*	**0** *** *6.779*
DOGE does not Granger Cause BTC	**0** *** *6.044*	**0** *** *4.986*	**0.00014** *** *3.633*	**0.01609** ** *2.142*	**0.06153** * *1.542*
BTC does not Granger Cause XPM	*0.95999*	*0.98549*	*0.73505*	*0.96410*	*0.96104*
XPM does not Granger Cause BTC	*0.97209*	*0.97438*	*0.92120*	*0.94465*	*0.99223*
BTC does not Granger Cause NXT	*0.84170*	*0.15796*	*0.15801*	*0.15810*	*0.15817*
NXT does not Granger Cause BTC	*0.13599*	*0.15851*	*0.15153*	*0.24828*	*0.50000*

Note: The symbols *, **, or *** indicate rejection of the null hypothesis at significance levels of 10%, 5%, and 1%, respectively.
Source: author

The findings indicate a significance at the 1% level across all tested lags, confirming that BTC Granger causes LTC.

Significance is observed at the 1% level for the first four lags, indicating strong evidence that LTC Granger causes BTC. At the fifth lag, the significance remains significant at the 5% level, further supporting the predictive influence of LTC on BTC.

BTC exhibits significant Granger causality on NMC at the 5% level for the second and fourth lags, and even stronger significance at the 1% level for the third and fifth lags.

Statistical significance at the 1% level across all evaluated lags confirms that BTC Granger causes XRP.

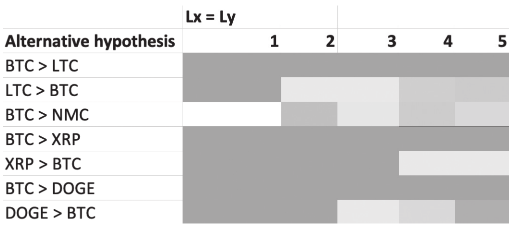
The analysis indicates that XRP Granger causes BTC, with significant p-values at the 1% level across all lags.

BTC Granger causes DOGE, supported by statistically significant p-values at the 1% level across all analysed lags.

DOGE demonstrates notable Granger causality over BTC at the 10% significance level for the fifth lag, with stronger significance at the 5% level for the fourth lag and even greater significance at the 1% level for the first three lags.

A heatmap illustrating notable outcomes of Nonlinear Granger Causality could be displayed in Figure 3.

Figure 3. Heatmap Showing Significant Results of Nonlinear Granger Causality



Source: author

A summary of the findings from both linear and nonlinear Granger causality is shown in Table 6.

Table 7. A Summary of the Results of Linear and Nonlinear Granger Causality

Alternative hypothesis	*Linear Granger causality*	*Nonlinear Granger causality*
BTC > LTC	+	+
LTC > BTC	+	+
BTC > NMC	-	+
NMC > BTC	-	-
BTC > PPC	-	-
PPC > BTC	-	-
BTC > XRP	+	+
XRP > BTC	+	+
BTC > DOGE	+	+
DOGE > BTC	+	+
BTC > XPM	-	-
XPM > BTC	-	-
BTC > NXT	+	-
NXT > BTC	+	-

Note: + represents Granger causality significance, while – Granger causality non-significance
Source: author

5. DISCUSSION

The bidirectional Granger causality observed between Bitcoin and the chosen cryptocurrencies indicates a significant interconnection among the leading digital assets. Market contagion or spillover effects in financial markets might account for this outcome. As stated by Dornbusch et al. (2000), the contagion effect occurs when the interconnections between countries in different markets see a notable rise during or following a crisis. In the realm of cryptocurrencies, this suggests that the fluctuations in Bitcoin's price can affect other cryptocurrencies, and the reverse is also true, emphasising the interdependence of the cryptocurrency market. Bitcoin, as the original and most prominent cryptocurrency, frequently guides the market. The observation that Bitcoin can forecast the movements of other cryptocurrencies supports the notion of market leadership in financial theory. The reciprocal relationship between BTC and LTC, XRP, and DOGE indicates that investors might be engaging in speculative activities, as traders frequently respond to trends and news regarding Bitcoin. For instance, it could involve a collective of market players who engage in trading in the same direction simultaneously (Nofsinger and Sias, 1999), investors who disregard their initial evaluations and choose to trade by conforming to the trend established by the previous transaction (Avery and Zemsky, 1998), mutual imitation (Welch, 2000), an excessive consensus in analyst forecasts (DeBondt and Forbes, 1999), a behaviour that tends to align with the average (Hirshleifer and Teoh, 2003), a type of correlated behaviour (Hwang and Salmon, 2004), a group of investors moving in and out of the same securities in unison (Sias, 2004), among other analogous descriptions. This could be especially significant in the realm of cryptocurrencies, where market actors frequently demonstrate a strong reaction to fluctuations in Bitcoin prices and related news, potentially affecting the behaviour of other cryptocurrencies reciprocally. Litecoin and Ripple are recognised for their technological advancements, including quicker transaction times and improved scalability. The findings of bidirectional causality with Bitcoin may indicate the impact of technological progress and competitive interactions within the cryptocurrency sector. The application of nonlinear Granger causality enhances the analysis by acknowledging that financial markets do not consistently follow linear patterns. Nonlinear causality suggests that the connections between Bitcoin and other cryptocurrencies vary over time, potentially driven by market cycles, investor sentiment, or external shocks (like regulatory events or technological progress). Nonlinear behaviour in cryptocurrency markets is frequently seen due to the significant volatility and speculative characteristics of digital assets, where the intensity and direction of causality may fluctuate in response to outside influences. The declaration of regulatory choices in key markets (such as the U.S. SEC's stance on cryptocurrencies or China's prohibition of crypto mining) frequently impacts the whole market, leading to price fluctuations that cascade throughout the cryptocurrency network, which clarifies the two-way causation noted between Bitcoin and other cryptocurrencies.

Adding to previous research (Corbet et al., 2018; Ciaian et al., 2018; Stosic et al., 2018; Aslanidis et al., 2019; Canh et al., 2019; Katsiampa et al., 2019; Tu & Xue, 2019; Shi et al., 2020; Kim et al., 2021; Nguyen et al., 2023), the results demonstrate that while there are numerous linear causal relationships, a considerable number of relationships are only significant under nonlinear conditions. This highlights the complex dynamics of the cryptocurrency market, where factors such as market volatility, investor sentiment, and extreme price movements may influence causality. For example, Bitcoin's relationship with cryptocurrencies like Litecoin, Ripple, and Dogecoin is found to be significant in both linear and nonlinear models, suggesting stable and dynamic interdependencies. In contrast, some cryptocurrencies like Namecoin and Primecoin show nonlinear relationships or no causal links, likely due to their smaller market presence. These findings suggest that while Granger causality offers insights into the interdependence of cryptocurrencies, understanding the full scope of these relationships requires consideration of both linear and nonlinear models, especially in volatile market conditions.

5.1. Theoretical Contributions

The value of this study, in addition to covering a broader timeframe and investigating older cryptocurrencies, lies in its enhancement of causal analysis in the cryptocurrency sector. Utilising both linear and nonlinear Granger causality tests, the research provides a more nuanced understanding of the relationships between various cryptocurrencies, including those that have not been thoroughly examined in earlier studies. This methodology yields more accurate insights into the directional connections between Bitcoin and lesser-known cryptocurrencies such as Namecoin, Peercoin, and Primecoin, offering fresh perspectives on their significance within the market. Furthermore, by incorporating a more varied selection of cryptocurrencies, the study broadens the range of previous research, enriching the overall comprehension of how smaller and older cryptocurrencies interact with major players like Bitcoin and Litecoin.

5.2. Practical Implications

Regulators can utilise observed Granger causality to gain a deeper insight into how price fluctuations in one cryptocurrency (such as Bitcoin) influence the prices of other cryptocurrencies. This enables them to more effectively detect potential risks within the system, serving as a practical tool to avert financial disturbances. Drawing on the interconnections identified, regulatory agencies can develop strategies to more effectively handle the fluctuations that may emerge from the connections between significant cryptocurrencies (such as Bitcoin) and lesser-known, higher-risk currencies. These strategies can help mitigate the potential for market disruption. If it is determined that Bitcoin significantly impacts the volatility of other currencies, regulators may introduce mechanisms to track those currencies, facilitating prompt reactions to market disruptions and supporting overall market stability.

Investors can leverage these findings to gain insights into the correlations between various cryptocurrency pairs, allowing them to diversify their investments more effectively. For instance, if there is a significant causal link between Bitcoin and Litecoin, traders can utilise this knowledge to mitigate risk in their portfolios by investing in cryptocurrencies that have no causal link with Bitcoin. Investors can leverage their understanding of the causal links between Bitcoin and other cryptocurrencies to formulate hedging strategies, thereby minimising the risk of significant losses stemming from Bitcoin's volatility. This can be essential for hedging strategies in fluctuating market environments. Market players can enhance their judgment on the timing and selection of cryptocurrencies for purchase or sale by understanding the identified correlations. This enables them to make well-informed choices based on Granger causality, minimising the uncertainty surrounding market fluctuations.

6. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

The dataset size (4017 observations) is relatively large, with linear and nonlinear Granger causality analysis ensuring the robustness of the results. The nonlinear Granger causality test was employed to capture complex dependencies; however, its effectiveness depends on the accurate selection of test parameters, particularly the bandwidth parameter (ε), which was set based on the mean of the ARCH coefficients ($\alpha 1$) from the time series being tested. This approach helps account for volatility persistence, a critical feature of financial time series. Nevertheless, the choice of lags ($Lx = Ly = 1, 2, \ldots, 5$) and bandwidth may still influence the results, especially if they fail to fully capture the intricate relationships between cryptocurrencies or external market shocks. While the method of Granger causality remains valuable for detecting temporal relationships, it has limitations in accounting for structural breaks, which are prevalent in the cryptocurrency market.

Future research could explore the impact of external factors, such as regulatory changes or market sentiment, on the causal relationships between Bitcoin and other cryptocurrencies. Additionally, investigating the dynamic interactions between a more extensive set of cryptocurrencies, including emerging altcoins, could provide further insights into the evolving structure of the cryptocurrency market.

7. CONCLUSION

The results show linear and nonlinear Granger causality in both directions between most cryptocurrencies, BTC-LTC, BTC-XRP and BTC-DOGE relationships. On the other hand, BTC does not Granger cause NMC, PPC and XPM in the linear model. On the other hand, BTC does not have a causal influence on NMC, PPC and XPM in the linear model. In contrast, in the nonlinear model, BTC Granger causes NMC. This suggests that the nonlinear analysis reveals additional connections that the linear approach does not detect, indicating more complex dynamics among specific cryptocurrencies. These insights are crucial for understanding the complex market price dynamics within the cryptocurrency sector, aiding investors and analysts in making more informed decisions based on historical data and predictive relationships.

References

Aslanidis, N., Bariviera, A. F., & Martínez-Ibañez, O. (2019). An analysis of cryptocurrencies conditional cross correlations. *Finance Research Letters, 31*, 130-137.

Avery, C., & Zemsky, P. (1998). Multidimensional uncertainty and herd behavior in financial markets. *American economic review*, 724-748.

Barber, S., Boyen, X., Shi, E., & Uzun, E. (2012). Bitter to better—how to make bitcoin a better currency. In *Financial cryptography and data security: 16th international conference,* 399–414.

Beneki, C., Koulis, A., Kyriazis, N. A., & Papadamou, S. (2019). Investigating volatility transmission and hedging properties between Bitcoin and Ethereum. *Research in International Business and Finance, 48*, 219–227.

Canh, N. P., Wongchoti, U., Thanh, S. D., & Thong, N. T. (2019). Systematic risk in cryptocurrency market: Evidence from DCC-MGARCH model. *Finance Research Letters, 29*, 90–100.

Caporale, G. M., & Zekokh, T. (2019). Modelling volatility of cryptocurrencies using Markov-Switching GARCH models. *Research in International Business and Finance, 48*, 143–155.

Cheikh, N. Ben, Zaied, Y. Ben, & Chevallier, J. (2019). Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition GARCH models. *Finance Research Letters, 35*, 1–9.

Ciaian, P., Rajcaniova, M., & Kancs, d. (2018). Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money, 52*, 173–195.

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

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

Diks, C., & Panchenko, V. (2006). A new statistic and practical guidelines for nonparametric Granger causality testing. *Journal of Economic Dynamics and Control, 30* [9–10], 1647-1669.

Dornbusch, R., Park, Y. C., & Claessens, S. (2000). Contagion: Understanding how it spreads. *The World Bank Research Observer*, *15*(2), 177-197.

Dyhrberg, A. H. (2016a). Bitcoin, gold and the dollar: A GARCH volatility analysis. *Finance Research Letters, 16*, 85–92.

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

Gkillas, K., & Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters, 164*, 109–111.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014). Bitcoin: Asset or currency? revealing users' hidden intentions. *22nd European Conference on Information Systems (ECIS)*, January, 1–14.

Granger, C. (1969). Investigate causal relations by econometric models and cross spectral methods. *Econometrica, 37*(3), 424–438.

Grinberg, R. (2012). Bitcoin: An innovative alternative digital currency. *Hastings Science and Technology Law Journal, 4*(1), 159.

Hirshleifer, D., & Hong Teoh, S. (2003). Herd behaviour and cascading in capital markets: A review and synthesis. *European Financial Management*, *9*(1), 25-66.

Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of empirical finance*, *11*(4), 585-616.

Katsiampa, P. (2019). Volatility co-movement between Bitcoin and Ether. *Finance Research Letters, 30*, 221–227.

Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters, 29*, 68–74.

Kim, M. J., Canh, N. P., & Park, S. Y. (2021). Causal relationship among cryptocurrencies: A conditional quantile approach. *Finance Research Letters, 42*, 101879.

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

Koehler, A. B., & Murphree, E. S. (1988). A comparison of the Akaike and Schwarz criteria for selecting model order. *Applied Statistics, 37*(2), 187–195.

Nguyen, A. P. N., Mai, T. T., Bezbradica, M., & Crane, M. (2023). Volatility and returns connectedness in cryptocurrency markets: Insights from graph-based methods. *Physica A: Statistical Mechanics and its Applications, 632*, 129349.

Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of finance*, *54*(6), 2263-2295.

Shi, Y., Tiwari, A. K., Gozgor, G., & Lu, Z. (2020). Correlations among cryptocurrencies: Evidence from multivariate factor stochastic volatility model. *Research in International Business and Finance, 53*, 101231.

Sias, R. W. (2004). Institutional herding. *The review of financial studies*, *17*(1), 165-206.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica, 48*(1), 1–48.

Stosic, D., Stosic, T., Ludermir, T. B., & Stosic, D. (2018). Collective behavior of cryptocurrency price changes. *Physica A, 507*, 499–509.

Tu, Z., & Xue, C. (2019). Effect of bifurcation on the interaction between Bitcoin and Litecoin. *Finance Research Letters, 31*, 382–385.

Welch, I. (2000). Herding among security analysts. *Journal of Financial economics*, *58*(3), 369-396.

Wu, C. Y., & Pandey, V. K. (2014). The value of bitcoin in enhancing the efficiency of an investor's portfolio. *Journal of Financial Planning, 27*(9), 44–52.

Yermack, D. (2013). Is Bitcoin a real currency? *SSRN Electronic Journal*.

Zhu, Y., Dickinson, D., & Li, J. (2017). Analysis on the influence factors of Bitcoin's price based on VEC model. *Financial Innovation, 3*(1), 1–13s

Grangerova kauzalnost između cijena Bitcoina i cijena starijih kriptovaluta

Sažetak

Ovaj rad analizira odnos između vrijednosti Bitcoina (BTC) i vrijednosti starijih kriptovaluta. Podaci o dnevnim cijenama Bitcoina (BTC), Litecoina (LTC), Namecoina (NMC), Peercoina (PPC), Ripplea (XRP), Dogecoina (DOGE), Primecoina (XPM) i Nxta (NXT) za razdoblje od 16. prosinca 2013. do 14. prosinca 2024. korišteni su za izvođenje Grangerove kauzalnosti u oba smjera. Rezultati pokazuju linearnu i nelinearnu Grangerovu kauzalnost u oba smjera između većine kriptovaluta, odnosa BTC-LTC, BTC-XRP i BTC-DOGE. S druge strane, BTC ne uzrokuje prema Grangeru NMC, PPC i XPM u linearnom modelu. S druge strane, BTC nema Grangerov uzročni utjecaj na NMC, PPC i XPM u linearnom modelu. Nasuprot tome, u nelinearnom modelu, BTC Granger uzrokuje NMC. Navedeni rezultati su ključni za razumijevanje složenih dinamika cijena na tržištu kriptovaluta, pomažući ulagačima i analitičarima u donošenju informiranijih odluka na temelju povijesnih podataka i prediktivnih odnosa.

Ključne riječi: Bitcoin, kriptovalute, Grangerova uzročnost