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JEL: G10, G15, F30
Preliminary communication
https://doi.org/10.51680/ev.37.2.7

Received: November 23, 2023
Revision received: March 28, 2024
Accepted for publishing: May 17, 2024

CAN THE MAJOR CRYPTOCURRENCIES BE USED AS A PORTFOLIO DIVERSIFIER?: ANALYSIS OF THE RELATIONSHIP BETWEEN BITCOIN, ETHEREUM, AND GLOBAL FINANCIAL ASSET CLASSES

Abstract

Purpose: It can be stated that in today's competitive conditions, where portfolio management is very important, it has become necessary to examine the relationship between global financial assets and major cryptocurrencies, such as Bitcoin and Ethereum. This paper aims to investigate the cointegration and causality relationships between Bitcoin, Ethereum, and global financial assets such as gold, oil, the S&P Global 100, the Dow Jones Commodity, and the US Dollar Indices, and to determine the diversification role of Bitcoin and Ethereum comparatively for the period between April 2016 and January 2024.

Methodology: The ADF Unit Root, Johansen Cointegration, Granger Causality, Rolling Window Causality tests, and Variance Decomposition Analysis methods were used in the analysis process.

Results: Based on the findings obtained from the paper, it was determined that Bitcoin and Ethereum have no cointegration with selected financial asset classes. Granger causality analysis results indicated that there were unidirectional causalities from Bitcoin and Ethereum prices to Dow Jones Commodity Index prices. In addition to the results of the Rolling Window causality tests, it was also determined that there are some causalities between Bitcoin, Ethereum, and other variables, especially after the 2021-2022 period.

Conclusion: It can be concluded that Bitcoin and Ethereum are effective portfolio diversifiers throughout the entire period; however, the diversification effects of Bitcoin and Ethereum weakened towards the end of the review period. Therefore, it can be said that Bitcoin and Ethereum act similarly in the global investment portfolio.

Keywords: Bitcoin, Ethereum, global financial asset classes, diversifier, causality

1. Introduction

The authority of central banks to control the amount of banknotes in the market can lead to negative economic conditions such as inflation. The Central Bank of the USA reduced the interest rates to stimulate the US economy in 2008, which unexpectedly led to significant losses. The effects of the 2008 global crisis that emerged in the same year spread all over the world; a large number of companies from various sectors were driven into bankruptcy, which indirectly accelerated the beginning of a new currency era (Bhuiyan et al., 2021, pp. 1-2). Cryptocurrencies that emerged with these developments differ from traditional currencies because they are not issued or controlled by any government.

Bitcoin has dominated the cryptocurrency market from its inception to the present; it is a form of virtual money with an intrinsic value of zero, issued through computer code in electronic wallets, cannot be converted into anything, and does not have support of any Central Bank or any government. Bitcoin's value cannot be evaluated as a convertible material asset like gold or a currency like the dollar. It is determined by the mutual interaction of demand and supply. Since its inception in 2008, Bitcoin has gained significant international recognition due to the potential of its underlying technology to develop applications beyond currency. A new currency called Bitcoin facilitates person-to-person business transactions worldwide without the need for any intermediaries, reducing trade barriers and increasing efficiency. However, Bitcoin has always been approached with concern due to many reasons such as its highly volatile structure, speculative behavior, coding with mathematical formulas, inelastic money supply, and lack of legal security (Bouoiyour & Selmi, 2015, p. 3). Cryptocurrencies, which have become widespread with the emergence of Bitcoin, are experiencing increasing competition day by day, with new types of assets entering the market after this year. Several cryptocurrencies have been developed since then, but Bitcoin has dominated the market at all times. For instance, by mid-September 2023, Bitcoin achieved a value of over $500 billion, more than half of the total market value of cryptocurrencies, while Ethereum ranked second with approximately $190 billion (CoinMarketCap, 2023).

Developments in the cryptocurrency market have led to an increase in academic studies aimed at understanding the financial structure of Bitcoin as a currency, investment instrument, and commodity. The biggest obstacle to Bitcoin's ability to serve as a unit of account, a medium of exchange, and a means of savings—key functions it must fulfill to be accepted as a currency—is the high volatility of its prices. However, it has not reached widespread use as a currency. If Bitcoin becomes more widely used as a currency, it will compete with other fiat currencies, affecting the value of the fiat currency and ultimately central bank monetary policies. On the other hand, it can be stated that if it is used as an investment, it can compete with many other assets such as government bonds, stocks and commodities (Baur et al., 2018a, pp. 187-188).

The evaluation of Bitcoin as a new investable asset class has led to the investigation of its relationship with other financial assets and other cryptocurrencies and its adequacy as a safe haven, hedging tool and diversification tool as a financial asset. Some features distinguish assets that offer hedging, safe haven, and diversification benefits. Hedging is the situation where an asset is, on average, unrelated or negatively related to another asset or portfolio. Such an asset cannot effectively mitigate losses during periods of market pressure or financial turmoil because it may be negatively correlated, on average, with a positive correlation during such periods and a negative correlation during normal times. A diversifier is a situation where an asset has an imperfect but, on average, positive correlation with another asset or portfolio. Like the hedging feature, the diversification feature does not specifically reduce losses in extremely adverse market conditions. However, a safe haven is a situation where an asset is negatively correlated or uncorrelated with another asset or portfolio during periods of market pressure and financial turmoil. An asset with such a feature establishes a non-positive relationship with the portfolio in extremely negative market conditions and creates a safe haven for investors (Baur & Lucey, 2010, p. 219). Volatility movements in the price of Bitcoin and Ethereum, appetite for profit as a result of price changes, and curiosity factors have made them financial assets that attract the attention of investors. As major cryptocurrencies like Bitcoin and Ethereum began to provide depth in the financial markets, it became necessary to reveal the relationship between major cryptocurrencies and other investment instruments. Studies continue to discuss whether cryptocurrencies can be considered as an investment instrument, a diversification instrument in portfolios, a hedging instrument, and whether they are a currency.

It can be stated that it has become necessary for rational investors who prioritize the efficiency of their investments to examine the relationship between the major cryptocurrencies Bitcoin, Ethereum, and other global financial asset classes in today's competitive conditions, where portfolio management is very important. In this context, this paper aims to examine the cointegration and causality relationships between Bitcoin, Ethereum, and global financial asset classes such as gold, oil, the Dow Jones commodity, the S&P100 stock, and the US dollar indices. The research findings aimed to make recommendations to investors, financial advisors, policymakers, portfolio managers, and especially Bitcoin and Ethereum investors in determining investment horizons. The study seeks to answer the following questions: Are there cointegration and causality relationships between major cryptocurrencies—specifically Bitcoin and Ethereum—and global financial asset classes? Additionally, do major cryptocurrencies exhibit diversifying features relative to other assets, and can they serve as portfolio diversifiers throughout the selected period?

2. Literature review

According to Van Wijk (2013), the Dow Jones index makes contributes significantly to Bitcoin prices in both the short and long term, as well as the euro-dollar parity and oil prices in the long term. Briere et al. (2015) investigated the portfolio performances that included traditional assets and alternative investments, with or without Bitcoin. They applied correlation analysis, some portfolio performance measurement techniques, and spanning tests. They found that Bitcoin has a low correlation with other assets, offering diversification benefits to investors. As a result, it can be said that Bitcoin improves the risk-return balance of well-diversified portfolios. Georgoula et al. (2015) reported that time series analyses conducted to determine the relationship of Bitcoin prices with important variables, e.g. the S&P 500 index, revealed a negative relation and a good diversification alternative. Dyhrberg (2016) investigated the suitability of adding Bitcoin to a portfolio as a risk-hedging tool and argued that Bitcoin has certain characteristics of gold in terms of its risk-hedging ability. She concluded that Bitcoin should be seen as a hedging tool in a portfolio that includes the dollar and stocks. As a result of their analysis of three commodity indices (S&P GSCI general commodity, energy commodity, and non-energy commodity indices) and Bitcoin, including Bitcoin's 2013 price collapse, Bouri, Jalkh, Molnár, and Roubaud (2017) found that before 2013 Bitcoin experienced a significant decline in relation to two indices. They stated that it had the feature of a risk-hedging tool and a safe haven, but after 2013, it only offered a diversification feature. However, they argued that it was only diversifying for the non-energy commodity index throughout the entire period. The study of Bouri et al. (2017) stated that Bitcoin can be used for diversification purposes for many asset classes consisting of stocks, bonds, currencies, and commodities, but it is a weak hedging tool. Bouoiyour and Selmi (2017) determined that Bitcoin and Ethereum have a negative relationship with oil, S&P 500, and US bonds, and that cryptocurrencies are good diversifiers. Baur et al. (2018b) found that there was no relationship between assets, including gold, paper banknotes, and commodities, and Bitcoin. Güleç et al. (2018) researched the relationship between Bitcoin and stock markets, interest rates, exchange rates, and commodity markets in Turkey. According to the analyses, a relationship was found between Bitcoin prices and interest rates, but no significant relationship was found with other variables. Henriques and Sadorsky (2018) examined the consequences of replacing gold in a portfolio with Bitcoin, using some of the GARCH models for their analysis. They concluded that the performance of portfolios that include Bitcoin is higher than the others, so Bitcoin is a good diversifier. It is essential to say that the weight of Bitcoin is considerably lower. Öztürk et al. (2018) researched the relationship between Bitcoin and some asset groups with cointegration analysis to determine whether Bitcoin may be used as a new hedging tool. As a result of the study, they found that Bitcoin moves only with gold prices and is independent of other assets. This finding indicates that Bitcoin can be a good portfolio diversification instrument. Baumöhl (2019) concluded that Bitcoin and other cryptocurrencies provide diversification benefits for Euro, Yuan, Swiss Franc, Yen and Canadian Dollar investors. Giudici and Abu-Hashish (2019) stated that the correlation between conventional assets and Bitcoin is low; Bitcoin can be used for diversification purposes in portfolios created with gold, oil, S&P 500, Euro, and Yuan. Kajtazi and Moro (2019) investigated the effects of including Bitcoin in US, European, and Chinese asset portfolios. Analysis results showed that performance increased in portfolios where Bitcoin was included, and this was due to an increase in returns rather than a decrease in volatility. Although Bitcoin has speculative features, it has been stated that it may be a good portfolio diversifier. Kliber et al. (2019) investigated which Bitcoin has hedging, safe haven, and diversification features against the stock index of five countries. Their analysis concluded that Bitcoin is a safe haven in Venezuela, a diversifier in Japan and China, and a weak hedging tool in Sweden and Estonia. Akhtaruzzaman et al. (2020) examined the effect of Bitcoin's diversification on global industry portfolios and bond indexes. They applied the VARMA DCC-GARCH method. According to the results, lower correlations were found between the variables so it can be said that Bitcoin is a hedge instrument. Bouri et al. (2020) examined the safe haven and hedging properties of cryptocurrencies during a decline in ten stocks. They argued that cryptocurrencies are valuable digital assets, but there is significant heterogeneity among them. They stated that Bitcoin is a safe haven against all US stocks, while some cryptocurrencies can be used as hedging tools for several sectors. Charfeddine et al. (2020) examined the diversification and hedging properties of Bitcoin and Ethereum against S&P500, gold, and oil prices. They concluded that cryptocurrencies are suitable for financial diversification, risk protection features remain weak, and the relationship between cryptocurrencies and traditional assets is affected by external shocks. Das et al. (2020) compared the qualities of Bitcoin as a safe haven and a hedging tool with gold, commodities and the US dollar. As a result of their analysis, they stated that the hedging and safe haven features of each asset differ for different economic conditions and market situations; therefore, it is not possible to achieve both features under all conditions with a single asset. Dutta et al. (2020) found that both Bitcoin and gold can be safe havens for hedging or diversification purposes during oil price volatility. Kang et al. (2020) investigated the relationship between gold futures, the US dollar, US stocks (S&P 500), and treasury bills in a portfolio, and Bitcoin. Asymmetric Granger causality was found between Bitcoin and gold, indicating a relationship between the two. The findings suggest that Bitcoin can be used as a safe haven by investors to reduce risk and provide diversification benefits in portfolio risk management. Bakry et al. (2021) examined the diversifier effect of Bitcoin with different portfolio choices. They applied the Sharpe ratio for portfolio optimization. The results of the paper showed that Bitcoin acts as a diversifier and hedge for risk-seeking investors, especially in relation to safe havens. Huang et al. (2021) analysed the diversification effect of Bitcoin in the periods before and after COVID-19. They determined that Bitcoin contributes to diversification benefits to traditional assets among different major economies but the pandemic has altered the diversification role of Bitcoin in the markets, with the exception of the United States of America. Qarni and Gulzar (2021) examined the diversification effect of Bitcoin against currency market portfolios. They applied the spillover index and frequency connectedness methods. According to the results, there was a low level of integration and asymmetric volatility spillover between Bitcoin and other currency pairs. Bitcoin is found to provide significant diversification benefits to other currency portfolios, especially euro portfolios. Maghyereh and Abdoh (2022) examined the volatility connectedness between Bitcoin and traditional financial assets during the COVID-19 period. The findings of the analysis indicated that the volatility dynamics were negative and weak before the pandemic and positive during the pandemic. The volatility connectedness of bitcoin-gold and bitcoin-foreign exchange pairs is significant in the short term, but bitcoin-oil and bitcoin-stock pairs are significant in the intermediate term. Bhuiyan et al. (2023) investigated the performance of Bitcoin with stock markets advanced economies and its diversification potential by wavelet analysis in the 2014-2022 period. The results indicated that Bitcoin is a diversifier against gold in all indices; Bitcoin showed a low increase with all indices, with the exception of gold, especially in the short term. Bouri et al. (2023) investigated the relationship between Bitcoin and US stock markets in the 2017-2021 period. The results showed that Bitcoin prices have significant predictability for US stock volatility. Hanif et al. (2023) investigated the connectedness between cryptocurrencies (Bitcoin and Ethereum), stock markets, and gold and oil prices by using time-frequency models in the 2020-2022 period. They concluded that cryptocurrencies, stock markets and commodities are highly interconnected in terms of volatility. Özbek (2023) examined the relationship between Bitcoin and BIST100, and S&P500 indexes to assess Bitcoin's features as a diversification or hedging instrument from 2020 to 2022. The results indicated no relationship between Bitcoin and the BIST100 index over the whole period, while a relationship was observed between Bitcoin and the S&P500 index in three-fifths of the period. It can be said that Bitcoin is a good diversifier but it loses this feature towards the end of the period for S&P500 investors.

It can be seen in the literature that there are many studies examining the interaction between Bitcoin and other investment instruments and the diversifying role of Bitcoin. However, in these studies, the existence of the relationship between Bitcoin and investment instruments, the existence and direction of the causality relationship, and the difference in the study results regarding the diversifying role of Bitcoin were the motivations for research presented in this paper. Comparative analysis of the findings in terms of Bitcoin and Ethereum, as well as the use of two different methods in causality analysis, such as the Granger and Rolling Window Causality test, aimed at determining whether the causality relations between the variables and diversifier effects differ during the review period, distinguish the paper from similar ones and it can be stated that the paper will contribute to the literature in this direction.

3. Data

The relationship between global financial asset classes and Bitcoin and/or Ethereum was examined in the study. Gold prices, the US dollar index, WTI crude oil prices, Dow Jones Commodity, and S&P Global 100 were used as financial asset classes. The data set consists of daily data for the period from April 2016 to January 2024. Spot gold price (dollar/ounce) shows the gold price in dollars per ounce. Logarithmic transformation was applied to the data used in the study. The variables used in the study, their abbreviations, and the sources they were obtained from are given in Table 1.

Table 1 Variables used in the study

Variable	Abbreviation	Source
Bitcoin Prices	BTC	Coinmarketcap
Ethereum Prices	ETH	Coinmarketcap
Gold Prices	GLD	World Gold Council[1]
US Dollar Index	USDX	Investing[2]
Oil Prices	WTI	US Energy Information Administration[3]
Dow-Jones Commodity Index	DJCI	Investing
S&P Global100 Index	SP100	Investing

Source: Author

Time-dependent oscillation graphs of the variables used in the study are given in Figure 1.

1 World Gold Council, https://www.gold.org

2 Investing, https://tr.investing.com

3 US Energy Information Administration, https://www.eia.gov

Figure 1 Time-dependent oscillation graphs of variables

Source: Author's calculations

As can be seen in Figure 1, Bitcoin and Ethereum prices started to increase in 2017. Prices, which decreased towards the end of 2018, started to increase again after 2019 and peaked. The fact that Bitcoin and Ethereum were unusual investment tools when they were first introduced contributed to their initial lack of demand. However, sharp price increases that occurred later along with the increasing demand caused it to be seen as an important investment tool by investors. The developments in the course of other global financial asset classes discussed in the study as alternatives to Bitcoin and Ethereum are also shown in Figure 1. There are sharp decreases in stock indices, oil prices, and the dollar index. Sharp increases in gold, Bitcoin, and Ethereum prices are noteworthy, especially during the COVID-19 pandemic period.

4. Research method and findings

The presence of unit roots in econometric analysis shows that a time series is not stationary. Since non-stationary time series will cause spurious regression problems in the analyses, stationarity testing must be done and non-stationary series must be made stationary (Gujarati, 1999, p. 713). Unit root tests commonly used in stationarity testing of time series are Augmented Dickey and Fuller - ADF (1979), Phillips (1987) and Perron (1988) - PP, and Kwiatkowski, Phillips, Schmidt, and Shin (1992) - KPSS. In the study, the stationarity of the time series was tested using the ADF unit root test. Distribution theory supporting the ADF test assumes that the error terms are statistically independent and have a constant variance. The regression equation used for the ADF unit root test is equation (1) (Mushtaq, 2011, pp. 10-11). The fact that the ADF-t statistical values obtained as a result of the ADF unit root test are greater than the MacKinnon critical values in absolute terms indicates that the time series are stationary. Otherwise, the time series must be differentiated to ensure their stationarity:

$$\Delta Y_t = \beta_0 + \beta_1(t\text{-}T/2) + \beta_2 Y_{t-1} \sum_{i=1}^{m} \Delta Y_{t-i} + u_t \ . \quad (1)$$

Determining whether the time series are stationary at the same level is a prerequisite for investigating cointegration, i.e. the long-term relationship, between these series. Long-term relationships between time series can be investigated with the cointegration test developed by Johansen and Juselius (1990). The Johansen cointegration test is a maximum likelihood approach applied to determine the presence of cointegration vectors in time series. Additionally, this method is based on linear vector autoregression (VAR) (Balke & Fomby, 1997, p. 636). The regression equations used for the Johansen cointegration test are equations (2) and (3):

$$\Delta X_t = \Gamma_1 \, \Delta X_{t-1} + \cdots + \Gamma_{k-1} \, \Delta X_{t-n} + \prod \Delta X_{t-n} + \varepsilon_t \quad (2)$$

$$\Gamma_i = -1 + \prod_1 + \cdots + \prod_i \qquad \text{i:1……n} \quad (3)$$

VAR (Vector Autoregression) models based on the appropriate lag length must first be established in order to apply the Johansen cointegration test (Johansen and Juselius, 1990, p. 170). Trace and maximum eigenvalue statistics obtained by the cointegration test show whether there is a cointegration between the variables. In case there is a cointegration vector that indicates the presence of a long-term relation between time series, a VECM (Vector Error Correction Model) model should be established and it should be examined whether there is a short-term relationship.

Statistically, causality refers to the ability to estimate future values of a time series variable based on the influence of its past values or those of another related time series variable (Işığıçok, 1994, p. 94). Causality in the sense of Granger means that if past values of variable X improve the prediction accuracy of variable Y, then X is said to Granger-cause Y. If a cointegration relationship exists between the variables, a VECM-based Granger causality analysis is applied; if there is no cointegration relationship, a VAR-based Granger causality analysis is used. Granger causality analysis expresses the direction of relationships between time series. The regression equations used for the Granger causality test are equations (4) and (5):

$$X_t = \sum_{i-1}^{n} \alpha_i Y_{t-i} + \sum_{i-1}^{n} \beta_i X_{t-i} + U_{1t} \quad (4)$$

$$Y_t = \sum_{i-1}^{n} \gamma_i X_{t-i} + \sum_{i-1}^{n} \theta_i X_{t-i} + U_{2t} \quad (5)$$

The Granger causality test is an analysis method in which one-way or two-way relationships between variables are investigated without distinguishing between dependent and independent variables (Tarı, 2015, p. 436).

The rolling window causality test developed by Balcilar et al. (2010) is important in terms of showing the change in the causality relationship in different periods. The null hypothesis based on the causality relationship predicts that there is no Granger causality between the variables. According to the test results, the Bootstrap-p value must be below the 5% or 10% critical value for the null hypothesis to be rejected and the alternative hypothesis to be accepted (Balcilar et al., 2010, p. 1403). In this context, rolling window causality test results will be evaluated in terms of determining the mutual causality relationships between the dependent variables and each independent variable.

Variance decomposition analysis shows the severity of the error variance estimated for the mobility caused by each of the independent variables at different time horizons beyond the selected period (Ahad, 2017, p. 820). After determining the significant causality relationships between variables with the Granger causality test, variance decomposition analysis is applied to examine the effect level of these causalities.

In the analysis of this paper, the relationship and the causality between Bitcoin, Ethereum, and global financial asset classes was examined for the period between April 2016 and January 2024. The econometric models are as follows:

Model 1:

$$LBTC_t = \alpha_t + \beta_1 LDJC_t + \beta_2 LGLD_t + \beta_3 LSPG100_t + \beta_4 LUSDX_t + \beta_5 LWT_t + \varepsilon_t, \quad (6)$$

Model 2:

$$LETH_t = \alpha_t + \beta_1 LDJC_t + \beta_2 LGLD_t + \beta_3 LSPG100_t + \beta_4 LUSDX_t + \beta_5 LWT_t + \varepsilon_t, \quad (7)$$

where α_t is the constant coefficient, β_t is the slope coefficient, t are the periods, and ε_t is the error term in equations 6 and 7.

In time series analyses, firstly, the ADF unit root test was applied to ensure that there is no spurious regression between the variables, in other words, to check the stationarity of the series. The Johansen cointegration test was applied to the series that were stationary at their first differences. Then, the Granger causality test was applied to test the existence of causality between asset classes and Bitcoin, and Ethereum. It is aimed to strengthen the findings by reanalyzing the causal relationships between variables in terms of different periods with rolling window causality analysis. The variance decomposition test was applied to determine the extent of the effect of this causality on Bitcoin and Ethereum, if causality was present. ADF unit root test results are given in Table 2.

Table 2 ADF unit root test

Variable	ADF unit root test (trend & constant)			
	Level $t_{statistics}$	p	1.Difference $t_{statistics}$	p
LBTC	-1.985	0.601	-7.895	0.000*
LETH	-1.843	0.675	-7.986	0.000*
LDJCI	-1.902	0.645	-7.730	0.000*
LGLD	-2.622	0.271	-9.950	0.000*
LSPG100	-2.839	0.187	-10.27	0.000*
LUSDX	-2.012	0.586	-8.578	0.000*
LWTI	-2.942	0.154	-7.076	0.000*
Critical values	1% 5% 10%		-2.590 -1.944 -1.614	
* indicates a 1% statistical significance level.				

Source: Author's estimate

According to Table 2, when the first differences of all variables were taken at the 1% significance level, it was determined that t-statistics in absolute terms were greater than the MacKinnon critical values. This finding shows that all-time series are not stationary at I(0), but time series are stationary at I(1) at the 1% significance level. The VAR (Vector Autoregression) model was created by first determining the lag length to investigate the long-term relationship between time series determined to be stationary at the same level. Table 3 presents the lag length criteria and optimal lag lengths for the established models.

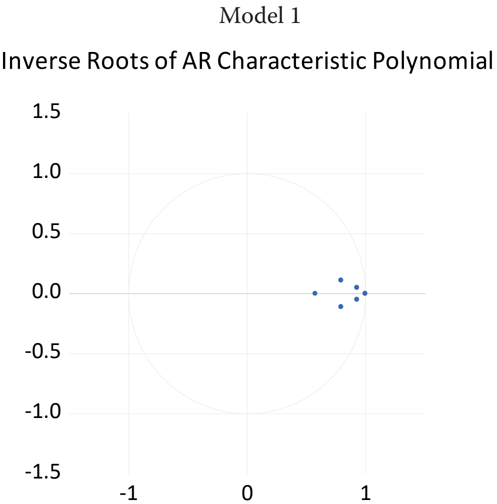
Table 3 Lag length criteria for Model 1 and Model 2

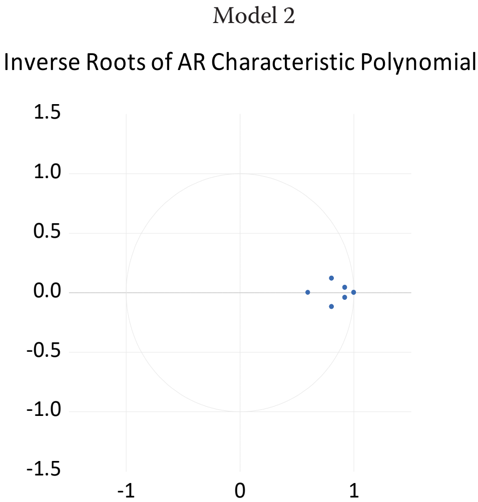
Lag	LogL	LR	FPE	AIC	SC	HQ
Model 1						
0	324.3309	NA	2.466e-11	-7.403045	-7.231811	-7.334131
1	851.4145	968.3628	2.70e-16*	-18.82359*	-17.62496*	-18.34120*
2	884.4094	56.01462*	2.93e-16	-18.75371	-16.52767	-17.85783
Model 2						
0	286.7775	NA	5.88e-11	-6.529709	-6.358476	-6.460795
1	817.0772	974.2716*	6.00e-16*	-18.02505*	-16.82642*	-17.54266*
2	844.4409	46.45458	7.42e-16	-17.82421	-15.59817	-16.92833

* indicates the optimal lag length.
Source: Author's estimate

It was found that various information criteria for the study's models reached their minimum values for lag 1, as shown in Table 3. To determine the optimum lag length of the models, hypothetical tests of the model were carried out based on the appropriate lag length. It was examined whether the inverse roots of the AR-characteristic polynomials were within the unit circle to determine whether the model established according to appropriate lag lengths was stable.

Figure 2 Inverse roots graph of AR-characteristic polynomials of the models





Source: Author's estimate

Figure 2 shows that the inverse roots of the AR-characteristic polynomials are located within the unit circle and the established models are stable.

After determining that the models were stable, LM and White tests were performed to test the autocorrelation and heteroscedasticity problems in the models presented in Table 4, which indicates that there were no autocorrelation and heteroscedasticity problems in the models since the p-probability values of the tests were greater than 0.05.

Table 4 Autocorrelation and heteroscedasticity test results

	Lag length	LM test p-probability	White test p-probability
Model 1	1	0.1966	0.2374
Model 2	1	0.1737	0.3518

Source: Author's estimate

VAR(1) models were established and the VAR model-based Johansen cointegration test was applied. Johansen cointegration test results are presented in Table 5.

Table 5 Johansen cointegration test

Model 1							
		Trace			Maximum eigenvalue		
Cointegration number	Eigenvalue	Trace statistic	0.05 Critical value	p	Max-eigen statistic	0.05 Kritik Değer	p
None	0.267559	82.06125	95.75366	0.2990	28.64622	40.07757	0.5161
At most 1	0.229132	53.41503	69.81889	0.4870	23.94190	33.87687	0.4598
At most 2	0.139737	29.47313	47.85613	0.7454	13.84760	27.58434	0.8330
At most 3	0.090908	15.62554	29.79707	0.7383	8.768437	21.13162	0.8507
At most 4	0.071801	6.857099	15.49471	0.5943	6.854807	14.26460	0.5065
At most 5	2.49E-05	0.002292	3.841465	0.9598	0.00229	3.841465	0.9598
Model 2							
		Trace			Maximum eigenvalue		
Cointegration number	Eigenvalue	Trace statistic	0.05 Critical value	p	Max-eigen statistic	0.05 Kritik Değer	p
None	0.273406	82.30789	95.75366	0.2917	29.38365	40.07757	0.4651
At most 1	0.232287	52.92424	69.81889	0.5085	24.31927	33.87687	0.4325
At most 2	0.153746	28.60497	47.85613	0.7868	15.35806	27.58434	0.7194
At most 3	0.086801	13.24690	29.79707	0.8800	8.353706	21.13162	0.8808
At most 4	0.051576	4.893196	15.49471	0.8201	4.871780	14.26460	0.7579
At most 5	0.000233	0.021417	3.841465	0.8836	0.021417	3.841465	0.8836

Source: Author's estimate

Based on the cointegration analysis results presented in Table 5, it was found that there were no cointegration equalities at a 5% significance level for the established models. Therefore, it can be said there are no long-term relationships between the variables used in the established models.

The VAR-based Granger causality test was applied to the model to examine the causality relationship and it was not found to have a cointegration relationship. Granger causality test results are presented in Table 6.

Table 6 Granger causality test results

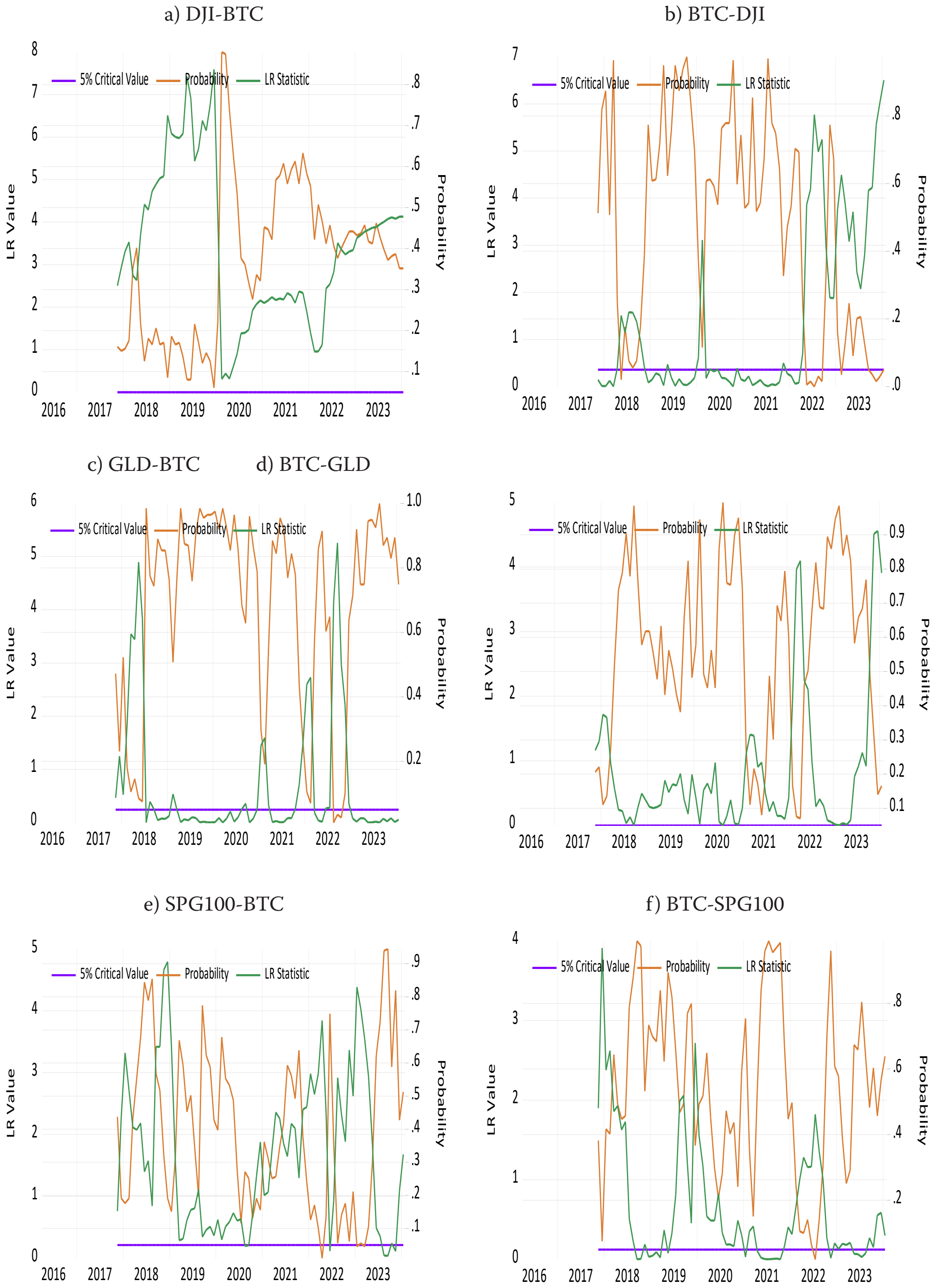
H_0 hypothesis	F-statistics	p-probability
LDJCI →LBTC.	0.34035	0.5611
LBTC →LDJCI.	4.42326	0.0382**
LGLD →LBTC.	1.48726	0.2258
LBTC →LGLD.	1.59241	0.2102
LSPG100 →LBTC.	0.59903	0.4410
LBTC →LSPG100.	2.63308	0.1082
LUSDX →LBTC.	0.26403	0.6086
LBTC →LUSDX.	0.19364	0.6610
LWTI →LBTC.	1.53751	0.2182
LBTC →LWTI.	2.06117	0.1546
LDJCI →LETH.	0.01497	0.9029
LETH →LDJCI.	4.04539	0.0473**
LGLD →LETH.	2.05614	0.1551
LETH →LGLD.	0.18879	0.6650
LSPG100 →LETH.	1.45198	0.2314
LETH →LSPG100.	0.44902	0.5045
LUSDX →LETH.	0.01102	0.9166
LETH →LUSDX.	0.22864	0.6337
LWTI →LETH.	1.10472	0.2960
LETH →LWTI.	3.40931	0.0681

** indicates 5% statistical significance levels.
Source: Author's estimate

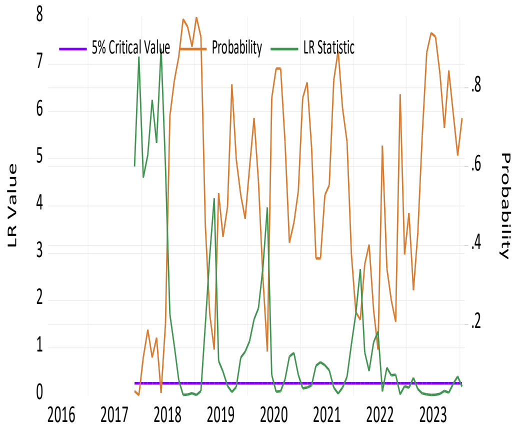
According to Table 6, unidirectional causality relationships have been identified from the LBTC and LETH variables to the LDJCI variable. The results obtained from the Granger causality test indicate that Bitcoin and Ethereum prices Granger-cause the Dow Jones Commodity Index. It can be stated that the change in the Bitcoin and Ethereum prices caused a change in Dow Jones Commodity Index prices. The results obtained from the Granger causality test indicate that there is no causality relationship between Bitcoin, Ethereum, and other variables.

The rolling window causality test (Balcilar et al., 2010) was applied to determine whether there is a causal relationship between the variables in the estimated models for different periods. The results were also compared with classical Granger causality analysis. Figures 3 and 4 show the rolling window causality test results for Model 1 and Model 2, respectively. Bootstrap p (probability)-values of LR statistics were calculated to test the null hypothesis that the dependent variable/independent variable does not Granger-cause the independent variable/dependent variable.

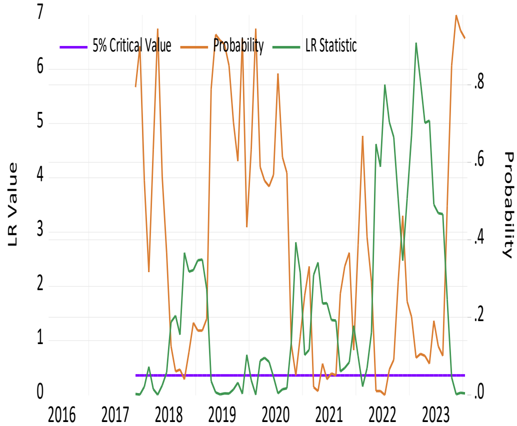
Figure 3 Rolling window causality results of Model 1



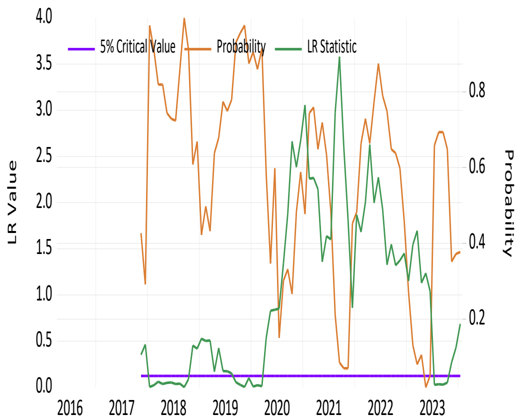
g) USDX-BTC



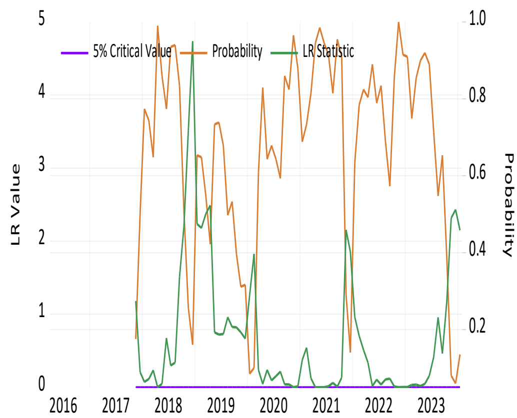
h) BTC-USDX



i) WTI-BTC



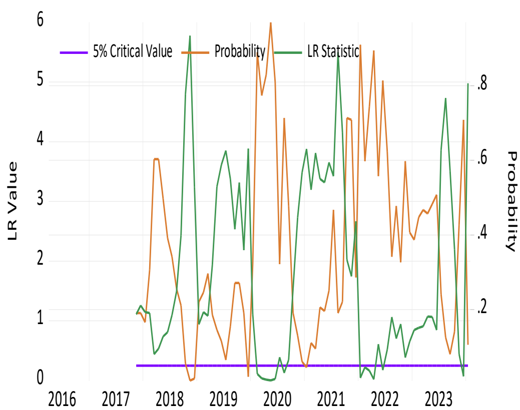
j) BTC-WTI



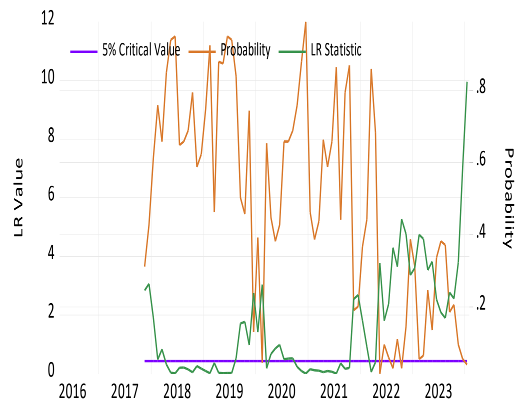
Source: Author's estimate

Figure 4 Rolling window causality results of Model 2

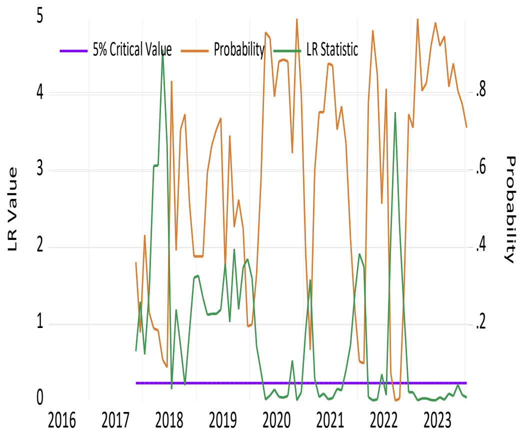
a)DJI-ETH



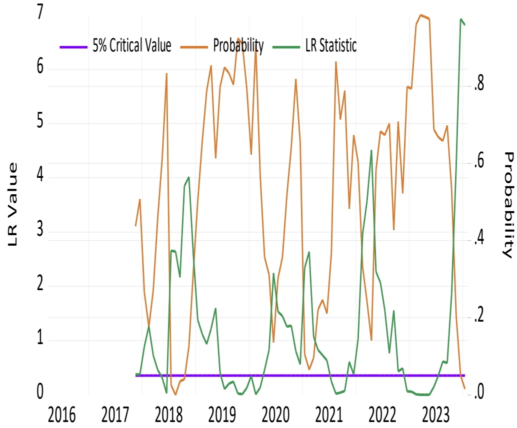
b) ETH-DJI



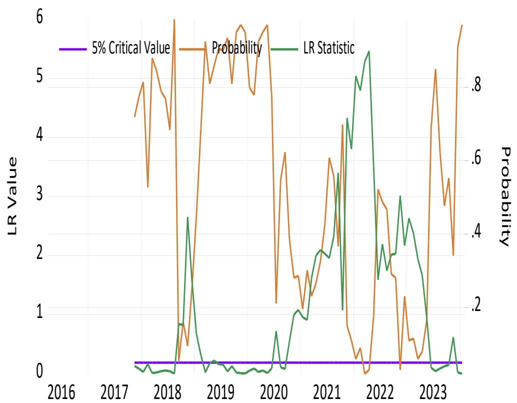
c) GLD-ETH



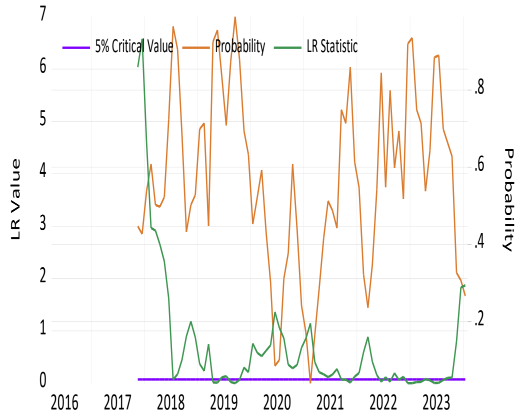
d) ETH-GLD



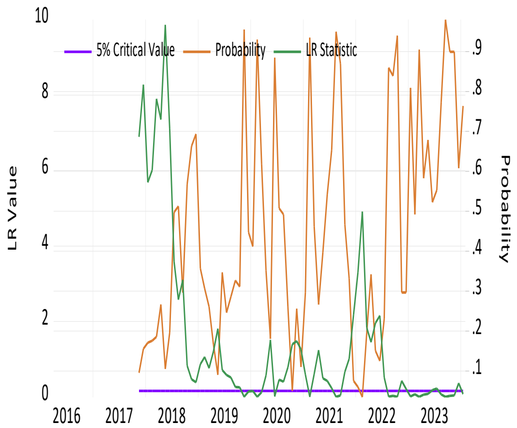
e) SPG100-ETH



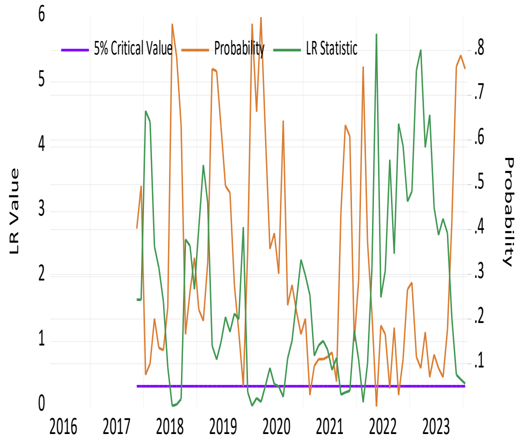
f) ETH-SPG100



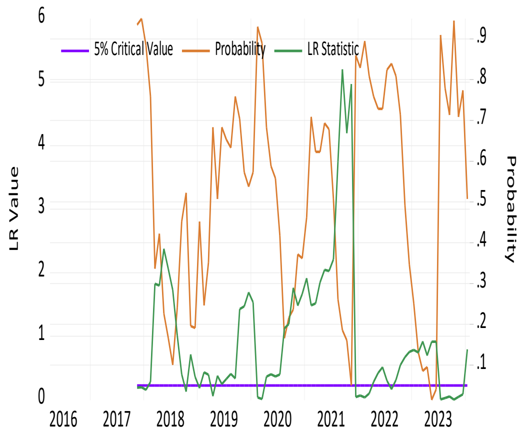
g) USDX-ETH



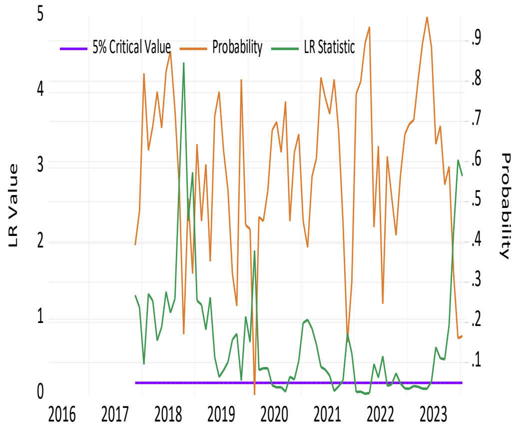
h) ETH-USDX



i) WTI-ETH



j) ETH-WTI



Source: Author's estimate

According to Figure 3, Rolling window causality test results of Model 1, there is a one-way causality between LBTC-LDJCI variables. It means that Bitcoin prices Granger-cause the Dow Jones Commodity Index prices. There are causalities in May 2018, May to September 2022, February and September to December 2023, and January 2024. This finding is in line with the classic Granger causality test. In contrast to the classic Granger causality test, there is a causality between LBTC-LUSDX in October 2018, March, April, June and August 2021, and May-July 2022. It means that Bitcoin prices Granger-cause the US Dolar Index prices. However, unlike the classic Granger causality test, it can be said that there are some weak causalities, too. There is a weak one-way causality between LGLD-LBTC in August-October 2022. There is a weak bidirectional causality between LSPG100-LBTC variables in April 2022, January and March 2023, and LBTC-LSPG100 in July 2022. There is a bidirectional causality between LBTC and LUSDX variables, and a weak causality between LUSDX-LBTC in November and December 2017, and May 2018. Furthermore, there is a weak causality between LWTI-LBTC only in May 2023.

According to Figure 4, Rolling window causality test results of Model 2, it can be stated that there are bidirectional causalities between all variables, although some are weak. There is a causality between LETH-LDJCI variables. It means that Ethereum prices Granger-cause the Dow Jones Commodity Index prices. There are causalities in February 2020, May-October 2022, February, March, November and December 2023, and January 2024. This finding is parallel to the classic Granger causality test. However, unlike the Granger causality test, there is a weak causality between LDJCI-LETH variables at the end of 2018 and 2019. In contrast to the classic Granger causality test, there is a causality between LETH-LGLD in the July-October 2018 period, and in December 2023 and January 2024. It means that Ethereum prices Granger-caused the gold prices in these periods. Also, there is a causality between LETH-LUSDX in November 2019, February 2021, and May, August, and October 2022. Unlike the classic Granger causality test, the rolling window causality test suggests that there are some other weak causalities, too. For example, there is a weak LGLD-LETH causality in September and October 2022, a weak LSPG100-LETH causality in March, April, and November 2022, a weak LETH-LSPG100 causality in February 2021, a weak LWTI-LETH causality in May and June 2023, and a weak LETH-LWTI causality in February 2020.

The aim is to determine the extent to which Bitcoin and Ethereum prices are affected by their shocks and the shocks of the independent variables considered, with variance decomposition analysis. Figures 5 and 6 show the variance decomposition analysis results of Models 1 and 2, respectively.

Figure 5 Variance decomposition analysis results of Model 1

Period	S.E.	LBTC	LDJCI	LGLD	LSPG100	LUSDX	LWTI
1	0.206486	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.284327	99.42769	0.003313	0.072994	0.452112	0.011219	0.032676
3	0.340685	98.60005	0.004028	0.229966	1.076226	0.015626	0.074107
4	0.385914	97.71978	0.036723	0.449988	1.678233	0.012957	0.102318
5	0.424013	96.82484	0.139050	0.712505	2.200199	0.013047	0.110361
6	0.457061	95.89656	0.335423	1.000408	2.637590	0.027420	0.102594
7	0.486321	94.90566	0.634068	1.300614	3.003450	0.065588	0.090625
8	0.512635	93.82938	1.029537	1.603669	3.314158	0.133860	0.089400
9	0.536593	92.65640	1.506909	1.903069	3.584380	0.235369	0.113876
10	0.558620	91.38650	2.046001	2.194575	3.825744	0.370630	0.176550
Cholesky ordering:		LBTC	LDJCI	LGLD	LSPG100	LUSDX	LWTI

Source: Author's estimate

Figure 6 Variance decomposition analysis results of Model 2

Period	S.E.	LETH	LDJCI	LGLD	LSPG100	LUSDX	LWTI
1	0.315431	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.433453	99.61692	0.017539	0.051308	0.144783	0.001536	0.167914
3	0.517965	98.99865	0.021069	0.164671	0.368777	0.001119	0.445716
4	0.585009	98.29333	0.016517	0.328236	0.613065	0.003565	0.745288
5	0.640724	97.55949	0.025946	0.529114	0.855263	0.017188	1.012999
6	0.688219	96.81239	0.069802	0.755851	1.089985	0.050070	1.221901
7	0.729341	96.04911	0.160352	0.999267	1.319002	0.108416	1.363853
8	0.765311	95.26115	0.300908	1.252477	1.546573	0.196126	1.442764
9	0.797004	94.44030	0.487543	1.510568	1.777340	0.314975	1.469270
10	0.825082	93.58096	0.711548	1.770177	2.015452	0.465048	1.456813
Cholesky ordering:		LETH	LDJCI	LGLD	LSPG100	LUSDX	LWTI

Source: Author's estimate

Examination of Figure 5 reveals that Bitcoin prices are influenced by approximately 91% of changes in their lagged values, with 3.8% attributed to the SPG100 index, 2.2% to gold prices, 2.0% to the DJCI index, 0.4% to the USDX index, and 0.2% to oil prices. Initially, Bitcoin prices were entirely influenced by their shocks, but this rate decreased to approximately 91% with a 10-period delay. In contrast, Figure 6 shows that Ethereum prices are affected by about 94% of changes in their lagged values, with 2.0% attributed to the SPG100 index, 1.8% to gold prices, 1.5% to oil prices, 0.7% to the DJCI index, and 0.5% to the USDX index. Like Bitcoin, Ethereum prices were initially fully affected by their shocks, but this rate decreased to around 89% after a 10-period delay.

5. Conclusion

This paper aims to reveal the cointegration and causality relationships between major cryptocurrencies, Bitcoin and Ethereum, and global financial asset classes, the diversifying feature of cryptocurrencies for other assets, as well as to make recommendations to investors, financial advisors, policymakers, and especially Bitcoin and Ethereum investors, in line with the findings. The findings relate to asset allocation, hedging, risk management, financial stability, investment decisions, and portfolio diversification. This paper aims to fill a gap in the literature by conducting a comparative analysis of the major cryptocurrencies Bitcoin and Ethereum, and examining whether the diversification effect remains consistent throughout the review period. Although cryptocurrencies are considered highly speculative, they have been included in the investment asset class, especially in recent years. In this way, the relationship between two important cryptocurrencies and global financial assets was comparatively analyzed, and depending on whether there was a relationship or not, the study aimed to determine whether they would provide diversification benefits in the portfolios created with these assets. In this paper, Johansen cointegration, Granger causality, rolling window causality, and variance decomposition analyses were applied to reveal the relationships between selected global financial asset classes and Bitcoin and Ethereum, as well as the diversification features of these cryptocurrencies.

The results of the research study indicate that there are no cointegration relationships between Bitcoin and Ethereum and selected global financial asset classes. One of the main reasons for the lack of relationship may be that Bitcoin and Ethereum exhibit high variance, while the other variables have low variance. Another reason may be because financial asset classes other than Bitcoin and Ethereum depend on a certain central authority and are traded under certain rules. Because of that, cyrptocurrencies represent virtual assets created without any authority, as stated. When we look at volatility movements in the markets in recent years, it appears that the low transaction volume of cryptocurrencies, compared to other traditional investment instruments, contributes to the lack of relationship between Bitcoin, Ethereum and these instruments. This finding is compatible with similar studies in the literature (Bouri et al. (2017), Baur et al. (2018b), Güleç et al. (2018), Giudici & Abu-Hashish (2019) and Özbek (2023)). However, this finding is opposite to a similar study in the literature by Van Wijk (2013). Granger causality analysis results indicated that there are no significant causality relationships between the variables, with the exception of significant unidirectional causalities from Bitcoin and Ethereum prices to the Dow Jones Commodity Index. The causalities between asset classes, except Bitcoin, Ethereum, and DJCI. This finding aligns with the findings in the literature ((Bouri et al. (2017a), and Kang et al. (2020)). As of December 2017, cryptocurrencies, especially Bitcoin, started to be traded in the futures market of the US Chicago Commodity Exchange, revealing that cryptocurrencies can be considered as commodities. Because of that, there may be a causality relationship between Bitcoin, Ethereum, and the commodity index. Hence, it can be stated that Bitcoin and Ethereum are not good diversifiers for a portfolio containing the Dow Jones Commodity Index, but they are good diversifiers for a portfolio containing gold, oil, the S&P100 stock, and the US dollar investments. The unidirectional causality obtained from Bitcoin and Ethereum prices to Dow Jones Commodity Index prices shows that the major cryptocurrency prices have a significant impact on Dow Jones Commodity Index prices. That is why Bitcoin and Ethereum cannot be used as diversification instruments within a portfolio containing the Dow Jones Commodity Index. Therefore, because the Bitcoin and Ethereum markets and the global financial system have no long-term relationship and causality relationships, with the exception of the Dow Jones Commodity Index, it can be stated that these major cryptocurrencies act separately from selected global financial asset classes, other than the Dow Jones Commodity Index, throughout most of the review period. It includes a suggestion for investors to include Bitcoin or Ethereum in a portfolio created from selected global financial assets so that they can have a better diversified, and hence better risk-balanced, portfolio. These findings are parallel to Briere et al. (2015), Georgoula et al. (2015), Bouoijour and Selmi (2017), Baumöhl (2019), Kajtazi and Mono (2019), Kang et al. (2020), Charfeddine et al. (2020), Dutta et al. (2020), Qarni and Gulzar (2021), Bhuiyan et al. (2023), Bouri et al. (2023), and Hanif et al. (2023). However, a causality relationship found between most of the selected financial assets and Bitcoin and Ethereum, especially after 2021-2022, obtained as a result of rolling window causality analysis, suggests that there is a loss in the diversification feature of Bitcoin and Ethereum. Given that this period coincides with negative developments in the economy after the COVID-19 period, which is a global epidemic disease, it can be stated that the negative atmosphere in the cryptocurrency markets has spread to other global investment instruments. However, the significant increases observed in the transaction volume of Bitcoin and Ethereum in recent years, similar to other assets, can be seen as an element contributing to the causality observed between Bitcoin, Ethereum, and selected global financial assets. Similarly, in their studies, Huang et al. (2021), Maghyereh and Abdoh (2022), Hanif et al. (2023), and Özbek (2023) concluded that there was a loss in Bitcoin's diversification ability after COVID-19. Variance decomposition analysis indicates that Bitcoin prices are affected by approximately 91% of changes in their lagged values, while 9% is attributed to the selected global financial asset prices. Ethereum prices are affected by approximately 94% of the changes in their lagged values, and 6% are attributed to the selected global financial asset prices. These findings indicate that compared to Ethereum, Bitcoin prices are more affected by these global financial asset classes; however, it can be stated that the level of influence is low for both Bitcoin and Ethereum. Bitcoin and Ethereum can provide diversification benefits to portfolios as a result of their inclusion in investment portfolios, with the finding that Bitcoin and Ethereum act separately from selected global financial assets. It can be said that Bitcoin and Ethereum act similarly in the global investment portfolio. However, it can be concluded that investors should be more careful when including these assets in their portfolios, especially during periods of sharp declines in Bitcoin and Ethereum markets, such as after crisis periods that can affect the whole world, and the effect may spread to other assets during these periods.

In addition, policymakers should take into account Bitcoin, Ethereum, which has millions of users, and the cryptocurrency market in this context, in terms of economic reforms and cryptocurrency regulations. Our findings are important to investors, financial advisors, Bitcoin and Ethereum investors, and policymakers for making decisions regarding asset allocation, hedging, risk management, financial stability, investment decisions, and portfolio diversification. The findings serve as a reminder to those who manage portfolios that they plan to include Bitcoin and Ethereum in their investment portfolios as a diversification instrument to keep abreast of global geopolitical conditions and other global economic events when trading investment instruments. This paper is serves as a valuable reference for investors and portfolio managers in determining investment horizons, managing risks, and aiming for profitable opportunities.

The interaction between the two major cryptocurrencies, Bitcoin and Ethereum, and global gold, oil prices, the US Dollar Index, the Dow Jones Commodity Index, and the S&P Global 100 Index was analyzed in this paper. The interaction between selected financial investment instruments and other cryptocurrencies can be examined in further research to determine whether the findings also apply to other cryptocurrencies. Within the scope of the study, it was concluded that Bitcoin and Ethereum are generally good diversifiers for selected financial investment instruments. It is recommended to examine the interaction between Bitcoin, Ethereum, and other cryptocurrencies and different investment instruments in further research to determine whether Bitcoin and Ethereum are good diversifiers for other investment instruments within the scope of the paper.

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