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THE CAUSAL RELATIONSHIP BETWEEN CRYPTOCURRENCIES AND OTHER MAJOR WORLD ECONOMIC ASSETS: A GRANGER CAUSALITY TEST

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Abstract

This study examines the causal relationship between cryptocurrencies and other major world economic assets, such as gold, stocks, oil, and bonds, using both Granger causality and correlation analyses. The study focuses on the period between 2018 and 2022, using a vector autoregressive model (VAR) to analyze data on cryptocurrencies and other major world economic assets, which collectively represent over 90% of the market during the observed period. Results show that correlation clearly identifies causal interdependency between cryptocurrencies and other major world economic assets and that the variation in cryptocurrencies increasingly explains other major world economic assets. The results reveal that there is Granger causality between the cryptocurrencies (Tether, USD Coin, and Binance USD) and the other major world economic assets (BOND, SP500, and GOLD). Additionally, the study finds evidence that market inefficiency in the cryptocurrency market increased between 2018 and 2022. The findings suggest that the properties of the cryptocurrency market are highly dynamic and that researchers should be hesitant to generalize the market properties observed during idiosyncratic periods. The relevant information is swiftly reflected in asset prices when investors are more interested in a news event, increasing volatility. Strong evidence suggests that volatility spill overs increase sharply at this time. The structure of these markets frequently changes, and a large number of cryptocurrencies appear and disappear every day.

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1. INTRODUCTION

Cryptocurrency is a digital and technology-based financial system that uses virtual money for investment purposes. It is issued by individuals or institutions rather than by governments and is not typically used for everyday transactions. Bitcoin, the first cryptocurrency, remains the most widely traded to date. Cryptocurrency is bought and sold on private exchanges, often yielding high returns, and is considered an investment asset (Bouri et al., 2020). As cryptocurrency gains popularity as a financial asset, portfolio managers have begun to include it in their short and long-term investment decisions. Therefore, it is crucial to estimate its price accurately. To manage the risk associated with fluctuations in spot prices, investors may use futures markets. In addition to providing a means of hedging, futures markets also play a role in determining future prices, which can influence investors' investment decisions. The prices formed in futures markets offer insight into future market conditions and are closely linked to spot markets. Futures markets are primarily used for hedging but can also be used for speculation and arbitrage.

The relationship between cryptocurrency returns and stock market volatility is a subject of ongoing research and debate among academics. Studies such as Akyildirim et al. (2020) have found evidence of a correlation between the two markets, while others, such as Hachicha and Hachicha (2021), have posited that various international stock market indices move in conjunction with the cryptocurrency market. Still, some studies have found no evidence of correlation, such as Corbet et al. (2018) and Gil-Alana et al. (2020). Lahiani et al. (2021) suggested that the BSE 30 index has predictive power over the cryptocurrency market; however, Handika et al. (2019) argued that the Asian stock market does not follow the cryptocurrency market.

The cryptocurrency market has often been described as inefficient, with some researchers finding evidence of bidirectional Granger causality between Bitcoin and altcoin returns. This suggests that lags of one variable can help to predict another variable, indicating market inefficiency. For example, if the price returns of Bitcoin Granger cause the price returns of Ethereum, this means that lags of Bitcoin return have non-zero coefficients in a reduced form vector autoregressive (VAR) equation, indicating that the market is not fully efficient and there is information that can be exploited to make profitable trades (Corbet et al., 2020). To further explore the asymmetric causal relationships between Bitcoin and other assets, Erdas and Caglar (2018) conducted a series of measurements using a variety of variables, including gold, Brent oil, U.S. dollars, S&P 500 Index, and the Borsa Istanbul (BIST) 100 Index (a capitalization-weighted index composed of the top 100 National Market companies except for investment trusts). Their results imply that the Bitcoin market actively interacts with major asset markets, and its long-term equilibrium, as a nascent market, gradually synchronizes with that of other investment assets. In addition, Kurt and Kula (2021) investigated the causality relationship among Brent oil, Bitcoin, and Ethereum by applying the Granger causality test. As a result of the study, a bidirectional causality relationship was determined between Brent oil and Ethereum. However, a one-way causality relationship between Brent oil and Bitcoin was discovered.

The use of gold started with the manufacturing of precious jewelry, which is still a big division of current gold forms circulated in the economy. Gold was then moved to be a value carrier in the barter system all the way to the current money system, where it started in the production of coinage. Afterward, countries used it for bills and gold certificates (which matured into gold coins) in their systems during the 19th century, which helped emphasize the gold standard money and then the gold standard system during that period of time (Toraman et al., 2011; Bilal et al., 2013). Standard & Poor's 500 (S&P 500) is a stock market index that uses the market capitalizations of the 500 largest publicly traded companies in the United States to measure their performance (Investopedia, 2021). Bonds are debt instruments. Governments, businesses, and the general public can all issue and hold bonds. Regular interest payments are made, and after the bond's maturity date, the nominal value is distributed. Bond markets have drawn investors' attention because of their phenomenal growth and significant capacity as a hedge and safe haven (Karim et al., 2022). Cryptocurrencies (Haq et al., 2021; Arif et al., 2021) and bonds (Kurka, 2019) have both reported significant hedge and safe-haven attributes within their respective markets. Furthermore, the empirical findings of Le et al. (2021) demonstrate connectedness and spill-over in the time and frequency domains between cryptocurrencies, bonds, and fintech. GOLD, S&P 500, OIL, and BOND are used as a proxies for different asset classes, such as precious metals, stock market indices, crude oil, and the bond market. These assets have their own characteristics and may have different correlations and volatility; they also have different drivers that affect their prices. These terms commonly refer to different types of financial assets or commodities. In summary, other major world economic assets include a wide variety of financial assets, such as stocks, bonds, real estate, commodities, and various types of current and non-current assets that are used by individuals and institutions to store and grow wealth, raise capital, and support business operations.

In conclusion, the relationship between the cryptocurrency market and traditional stock markets remains a topic of debate among researchers, with mixed evidence having been found. The nature of the relationship may vary depending on the specific stock market indices and geographical regions being analyzed (Corbet et al., 2018; Handika et al., 2019; Gil-Alana et al., 2020; Akyildirim et al., 2020; Hachicha & Hachicha, 2021; Lahiani et al., 2021). This study builds upon previous research by Le Tran and Leirvik (2020), which indicated that cryptocurrency markets are enhancing at an unprecedented rate, with volume increasing and volatility decreasing. This calls for additional research in the near future, not only on the topic of market efficiency, but also on other aspects such as price-return volatility, liquidity, and the relationship to other assets. Market efficiency is a term used in finance to describe the degree to which current market prices accurately reflect all available information regarding the true worth of underlying assets. In an efficient market, all information supplied to any investor has been integrated into the market price, making it difficult for investors to outperform the market consistently. However, market efficiency is not stable and can be frequently altered by market conditions and crises. Market efficiency is important for investors to understand as it can impact investment strategies and the ability to generate returns. Market efficiency is the degree to which current prices accurately represent all pertinent and available information regarding the true worth of the underlying assets. A truly efficient market precludes the prospect of defeating the market because all information supplied to any investor has been integrated into the market price. According to existing finance research, market efficiency is a changing phenomenon frequently altered by market conditions and crises rather than a stable reality (Fernandes et al., 2022). After the pandemic declaration, the market efficiency behavior of the most popularly traded cryptocurrencies significantly changed (El Montasser et al., 2022). Meanwhile, cryptocurrency market efficiency has also been showed to vary with time (Noda, 2020).

To the best of our knowledge, there is a lack of experimental research that addresses the research gap in the relationship between cryptocurrencies and other major world economic assets in the stock market. To address this gap, this study aims to answer the following research questions:

a. Is there a relationship between cryptocurrencies and other major world economic assets?

b. Is there a causal relationship between cryptocurrencies and other major world economic assets?
c. How does the evaluated performance of the cryptocurrency market prediction compare to those of other major world economic assets?

By providing insights into these questions, this study seeks to contribute to the understanding of the relationship between cryptocurrencies and other major world economic assets. This study aims to investigate the causal relationship between cryptocurrency and other major world economic assets by applying various statistical and advanced econometric techniques. The research employs both information-theoretic and linear autoregressive approaches to examine the connections between cryptocurrency and other major world economic assets. The results indicate strong interconnections between cryptocurrency and other major world economic assets and suggest that the cryptocurrency market actively exchanges information with other real markets. However, the data reveal an asymmetry in the streaming of information, with other major world economic assets having a greater influence on cryptocurrency than vice versa. The findings also suggest that the nascent cryptocurrency market may be influenced by other major world economic asset markets with more trading activity and less uncertainty. The remainder of the paper describes the data and methodology used in the study, presents the results, discusses the implications of the findings, and provides the conclusion.

2. MATERIALS AND METHODOLOGY

The vector autoregressive (VAR) model is a statistical method used to analyze the dynamic relationship between multiple time series variables. Generally, the VAR model will be used to produce three types of output: 1) Orthogonal impulse response functions. These visualize how a shock to one variable affects other variables over time; 2) Granger causality tests. These tests can be used to determine whether lags of one variable are helpful for predicting another variable, which can indicate the presence of a causal relationship between the variables; and 3) Forecast error variance decompositions. These decompositions can be used to quantify the relative contribution of each variable to the overall forecast error variance of a VAR model. Using these three types of output, the analysis aims to provide a comprehensive understanding of the dynamic relationship between cryptocurrencies and other major world economic assets.

This study focuses the analysis solely on Granger causality, testing the specific aspects of interest. Granger causality testing is a technique used to assess whether past values of one variable can help predict another variable. It allows for the evaluation of potential causal relationships between variables in a time series context. Granger causality does not necessarily imply a direct cause-and-effect relationship; it indicates that past values of one variable contain useful information for predicting another variable. Therefore, it will not be necessary to calculate Impulse Response Functions or Forecast Error Variance Decomposition. The analysis will center around testing for causality between specific variable pairs based on lagged relationships. These tests can be used to determine whether lags of one variable are helpful for predicting another variable, in turn indicating the presence of a causal relationship between the variables.

2.1 Data Acquisition

This study used cryptocurrency and other major world economic assets data obtained from the yfinance library in Python. This data consisted of Yahoo! Finance data for ten different cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), USD Coin (USDC), Binance Coin (BNB), Ripple (XRP), Binance USD (BUSD), Dogecoin (DOGE), Cardano (ADA), and Polygon (MATIC), and four other major world economic assets: GOLD, OIL, SP500, and BOND. The data covered the period from January 1, 2018 to December 31, 2022 and included variables such as date, open, high, low, close, adjusted closing price (adj close), and volume. In addition, the study included the adjusted closing price (adj close) of the cryptocurrencies and other financial assets in the analysis. This accounts for various corporate actions and events that can affect the asset's price. Calculating the adjusted closing price for cryptocurrencies and other major world economic assets is essential for maintaining the accuracy and consistency of historical price data. It helps investors, analysts, and traders make informed decisions and perform various financial analyses by accounting for corporate actions and events that can distort the asset's price. The assets included in this analysis were chosen because they represent a significant portion of the cryptocurrency market and have a long price history. These assets were selected in order to provide a representative sample that reflects the diversity of the market, including a range of market capitalizations from roughly 3 to 500 billion USD. Some cryptocurrencies with large market capitalizations, such as Cardano and Terra (LUNA), were not included as they are relatively new assets and do not have a sufficient price history for analysis. By focusing on a group of assets that collectively represent a significant portion of the market and have a long price history, the analysis aims to provide a comprehensive understanding of the dynamic relationship between cryptocurrencies and other major world economic assets. The data sources were selected due to their widespread use in previous research and the extensive availability of data. The date parameters were chosen in order to maximize the number of observations available, given the differing launch dates and data availability for the selected cryptocurrencies. By using daily data, the study aims to capture both short-term and long-term dynamics in the relationship between cryptocurrencies and other major world economic assets.

2.2 Data Pre-Processing

It is important to note that cryptocurrencies and other major world economic assets are highly different assets with different characteristics and uses. The other major world economic assets have a long history as a store of value and a medium of exchange and are widely accepted and recognized. In contrast, cryptocurrencies are a relatively new and highly volatile asset with a limited track record and adoption. This is reflected in the differences in price and volatility between the two group assets. It is also worth mentioning that the market for cryptocurrencies is much smaller and less liquid than the market for other major world economic assets, which can contribute to its volatility. As a result, it is necessary for investors to carefully consider the risks and potential rewards of investing in cryptocurrencies and to thoroughly research the asset before making any investment decisions.

The variables were calculated as the log of the ratio of the current price to the previous price as $\log(\frac{P_t}{P_{t-1}})$. This analysis began by collecting data and applying the appropriate transformations to ensure that the time series data were stationary. The augmented Dickey-Fuller test was used to determine the order of integration of the time series variables, determining that taking the difference in natural logs of the variables results in stationarity. All of the variables were found to be stationary, meaning that they are integrated of order 1 and require one difference to become stationary. Next, a structural form vector autoregressive (VAR) model was estimated in order to allow for contemporaneous linkages between cryptocurrency returns. This approach is based on the findings of Ciaian and Rajcaniova (2018), who showed that the returns on Bitcoin and altcoins are interdependent, with Bitcoin returns having a positive and statistically significant impact on altcoin returns in the short term. To account for this interdependence, the VAR model was estimated in a reduced form, using Cholesky decomposition and a recursive model. The selected order of the variables in the model is BTC, ETH, ADA, USDT, USDC, BNB, XRP, BUSD, DOGE, MATIC, GOLD, OIL, SP500, and BOND. The results of the analysis were found to be robust to different orders of the variables. The previous day information was used to replace the Not a Number (NaN) values in the data. Following a series of essential pre-processing steps, made the data fit for further analysis. A normal or Gaussian distribution is required to draw the most extreme information from our data. A typicality test was then performed based on the invalid and interchange speculative instincts to corroborate the data, as shown in Table 1.

Table 1 Gaussian Distribution of the Data

Variables	Statistics	p-value	Null and Alternative Hypothesis Intuition
BTC	517.277	0.000	Non-Gaussian data (reject null hypothesis)
ETH	158.153	0.000	Non-Gaussian data (reject null hypothesis)
ADA	161.899	0.000	Non-Gaussian data (reject null hypothesis)
USDT	1331.390	0.000	Non-Gaussian data (reject null hypothesis)
USDC	1040.314	0.000	Non-Gaussian data (reject null hypothesis)
BNB	632.327	0.000	Non-Gaussian data (reject null hypothesis)
XRP	191.204	0.000	Non-Gaussian data (reject null hypothesis)
BUSD	1182.629	0.000	Non-Gaussian data (reject null hypothesis)
DOGE	341.999	0.000	Non-Gaussian data (reject null hypothesis)
MATIC	114.542	0.000	Non-Gaussian data (reject null hypothesis)
GOLD	123.735	0.000	Non-Gaussian data (reject null hypothesis)
OIL	278.141	0.000	Non-Gaussian data (reject null hypothesis)
SP500	179.150	0.000	Non-Gaussian data (reject null hypothesis)
BOND	129.668	0.000	Non-Gaussian data (reject null hypothesis)

These two disseminations helped to improve understanding of how knowledge is shared. The kurtosis of this batch of data was -0.95. This data set was deemed to be light-tailed because its esteem was less than 0. Each tail contains the same amount of information as the primary body. Direct skewness refers to the proportion between -1 and -0.5 or between 0.5 and 1. The daily return price was computed utilizing the adjusted closing price (see Figure 1 and 2). The conventional log return approach was almost used in the daily returns calculation (Mahendra et al., 2021). The day-to-day adjusted closing price was used to calculate the daily return (R_t) for all of the chosen variables and was computed employing the day-to-day adjusted

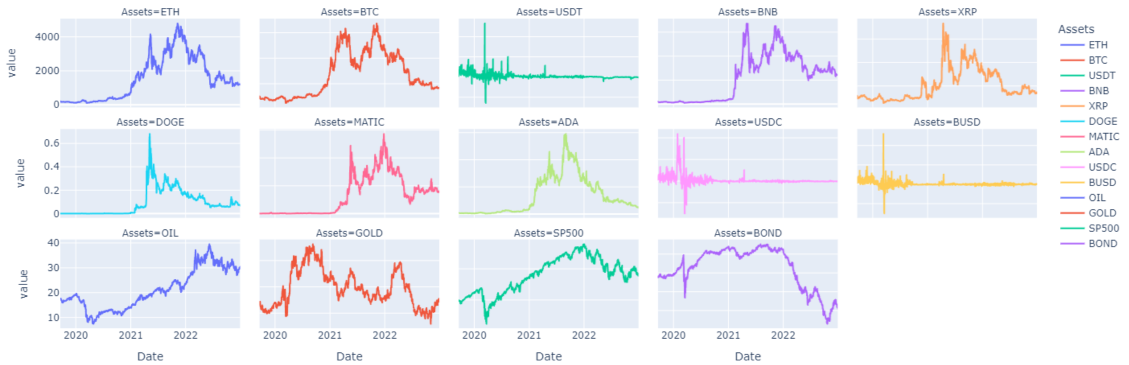

Figure 1 Daily Price of Cryptocurrencies and Other Major World Economic Assets

closing price and the characteristic $R_{ti} = \ln(P_t/P_{t-1})$; where R_{ti} is the daily return of the fetched record *i*; P_t is the record's respect at time *t*; and P_{t-1} is the adjusted closing regard of the fetched list at time *t-1*, as shown in Figure 2.

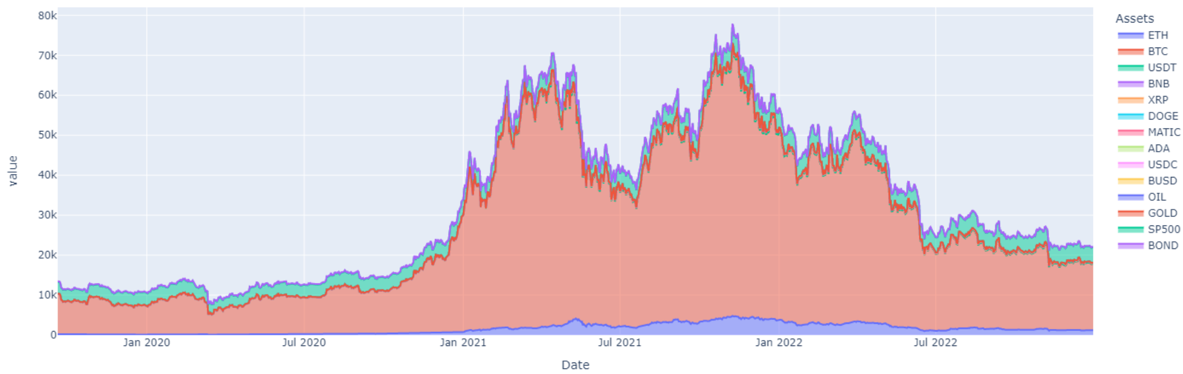

Figure 2 Daily Log Returns

2.3 Descriptive Statistics

Table 2 provides summary statistics for each data set. BTC, ETH, ADA, USDT, USDC, BNB, XRP, BUSD, DOGE, MATIC, OIL, GOLD, SP500, and BOND all have positive median log returns, with ADA having the greatest median and BTC having the highest mean log returns. All cryptocurrency log returns had kurtosis values greater than 3, which denotes heavy tails when compared to a normal distribution.

The risk and return characteristics of other major world economic assets and the selected cryptocurrencies were explained with the help of descriptive statistics, while volatility was displayed through box and whisker analyses (Corbet et al., 2018; Sifat et al., 2019). Initially, the variables for ETH, BTC, USDT, BNB, XRP, DOGE, MATIC, ADA, USDC, and BUSD were denominated in cryptocurrency, while OIL, GOLD, SP500, and BOND were denominated in other major world economic assets. The normal probability plots also showed that the data were far from normally distributed.

Table 2 Summary Statistics

Varia-bles	N	Mean	Std.	Min	25%	50%	75%	Max
BTC	1198	27124.05018	17377.71573	4970.788086	9938.704834	20976.89063	41786.94922	67566.82813
ETH	1198	1559.231907	1289.486429	110.605873	265.263855	1326.047485	2586.884277	4812.087402
ADA	1198	0.682357	0.702133	0.023961	0.093128	0.437699	1.187174	2.968239
USDT	1198	1.000974	0.002994	0.974248	1.000035	1.000349	1.001147	1.053585
USDC	1198	1.001051	0.004251	0.970124	0.999923	1.000112	1.000656	1.044029
BNB	1198	221.867436	191.897162	9.38605	21.258883	261.841476	373.282211	675.684082
XRP	1198	0.520989	0.338391	0.139635	0.251386	0.384429	0.750234	1.839236
BUSD	1198	1.000709	0.002945	0.970006	0.999896	1.000165	1.000938	1.052356
DOGE	1198	0.0932	0.11074	0.001537	0.00266	0.061494	0.144667	0.684777
MATIC	1198	0.66143	0.694577	0.008096	0.019678	0.494137	1.146044	2.876757
GOLD	1198	19.742115	3.493745	12.973227	16.9	19.245938	22.256943	28.171627
OIL	1198	21.084758	7.96027	7.46	14.13	19.24	28.2625	39.610001
SP500	1198	3794.485704	571.442282	2237.399902	3298.459961	3861.13501	4276.919922	4796.560059
BOND	1198	101.385592	5.457653	86.467445	98.751062	103.585526	105.789989	107.699585

2.4 Data Set Correlation Checking

The Pearson and Kendall correlations between the retrieved log returns for the OIL and ETH, OIL and BNB, OIL and MATIC, SP500 and ETH, SP500 and BTC, SP500 and BNB, SP500 and XRP, SP500 and DOGE, SP500 and MATIC, and SP500 and ADA that had significant Pearson and Kendall correlations greater than or exceeding 0.50 are shown in Figure 3. Autocorrelation or serial relationships might be a serious problem while analyzing reliable data if they are unable to be detected.

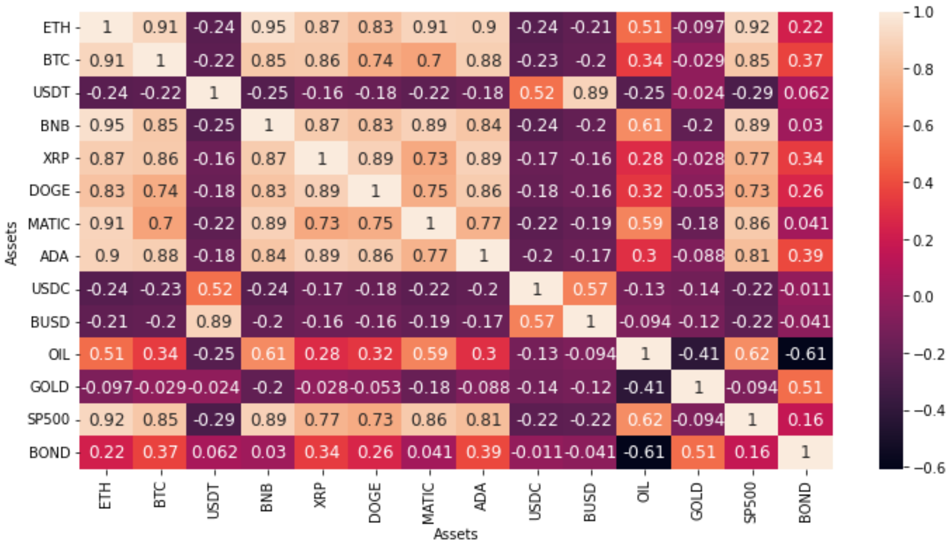

Figure 3 Pearson and Kendall Correlations

The autocorrelation of +1, which is an idealized positive relationship that demonstrates how an increase in one-time arrangements cause a proportionate increase in the other time arrangements, is shown in Figure 4. To stabilize the arrangement, it is necessary to make a change and counter it. Even if the autocorrelation is small, there could still be a nonlinear link between a time arrangement and a relaxed version of it.

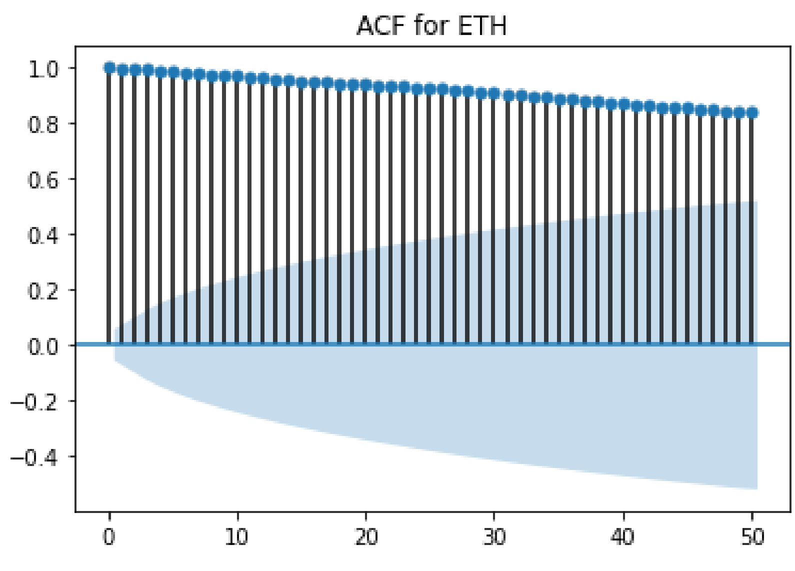

Figure 4 The Autocorrelation Graph of ETH, an Example of an ACF Graph for a Cryptocurrency and other Major World Economic Asset

2.5 Train and Test Data

The following 15 observations were predicted using the VAR model after it was fitted to the X train. These predictions were contrasted with the actual test data results. The time series data preparation process had several steps for consideration as a data mining process.

2.6 Cross-Check ADF Test and KPSS Test

The data set verified with the ADF test and KPSS test followed the steps below:

a) Stationary Data

1) Unit root test

The null hypothesis was that the series had both a stochastic trend and a unit root. The augmented Dicky-Fuller (ADF) test method (Dickey & Fuller, 1981) was used to conduct the unit root test in this study. The augmented Dickey-Fuller (ADF) test model is used to assess whether time series data are stationary and is one of the unit root tests (Mudassir et al., 2020; Mahendra et al., 2021):

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta y_{t-1} + w_t \qquad (1)$$

where y is the examined variable and w_t represents random error. Lagged first differences of dependent variables fix serial correlation. This paper chose the optimal number of lags (p) using log likelihood (Berger & Wolpert, 1988), the Hannan-Quinn criterion (Hannan & Quinn, 1979), and the Akaike information criterion (Akaike, 1998). The null hypothesis was given by $\gamma = 0$. The series may need to be more active. Three-step ADF tests were used to determine unit root tests for scenarios: (1) without a trend and constant and (2) without a trend or constant (Pfaff, 2008). Unit root test results are shown in Table 3. The Akaike information criterion (AIC) recommends lag lengths in parentheses. Additional tests like Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Dickey-Fuller Generalized Least Squares (DF-GLS) were performed to ensure series stationarity (Elliott et al., 1992; Kwiatkowski et al.,1992; MacKinnon, 1996; Phillips & Perron, 1988). PP, DF-GLS, and KPSS unit root tests have null hypotheses for unit root processes and stationary series, respectively. Time series

Table 3 Augmented Dickey-Fuller (ADF) Test and Alternative Unit Root Tests

Assets	Augmented ADF	p-value	Rejection of the Null Hypothesis
BTC	-1.410941	0.577020	NOT stationary
ETH	-1.530435	0.518405	NOT stationary
ADA	-1.581866	0.492696	NOT stationary
USDT	-3.710145	0.003973	stationary
USDC	-5.609568	0.000001	stationary
BNB	-1.529082	0.519079	NOT stationary
XRP	-2.349436	0.156519	NOT stationary
BUSD	-3.634024	0.005143	stationary
DOGE	-2.144042	0.227178	NOT stationary
MATIC	-1.518644	0.524269	NOT stationary
GOLD	-1.958067	0.305256	NOT stationary
OIL	-1.015019	0.747747	NOT stationary
SP500	-1.661572	0.451012	NOT stationary
BOND	-0.263050	0.930577	NOT stationary

Note. Examination of whether a trend exists in the data at the level.

stationarity is a statistical consistency. Stationary time series have constant statistical features.

The following hypothesis was used in order to conduct the augmented Dickey-Fuller (ADF) test.

H_o: The characteristics of time series data include a unit root, trend, and non-stationarity.

H_1: Time series data have stationarity.

The null hypothesis was rejected, demonstrating that the data were stationary. The null hypothesis is deemed false and is thus rejected by the test when the p-value is less than 0.05 and the test result has a strong negative ADF test statistic. It is essential to ensure that the data follow a normal or Gaussian distribution if one wants to derive the most insight from the available information. In order to verify that this is the case, a normality test can be carried out using the null and alternative hypotheses as guides.

Because the p-values were frequently higher than the 0.05 alpha level, the null hypothesis cannot be disproved. Eleven time series were therefore not stationary.

b) KPSS Test (Kwiatkowski-Phillips-Schmidt-Shin test) for Stationarity

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is a statistical test used to determine if a time series is stationary or non-stationary. The test assumes the null hypothesis that the time series is stationary, meaning that it has a constant mean and variance over time and does not exhibit a trend or cyclical behavior. The alternative hypothesis is that the time series is non-stationary, meaning that it has a unit root and exhibits a trend or cyclical behavior. The results of the KPSS test are presented in Table 4. The test can be used to identify the order of integration of the time series and to determine if the time series is suitable for further analysis.

Table 4 KPSS Statistic and Alternative Unit Root Tests

Variables	KPSS Statistic	p-value	Reject the null hypothesis
BTC	2.109474738620508	0.01	NOT stationary
ETH	2.7977853713354044	0.01	NOT stationary
ADA	1.8635233040346755	0.01	NOT stationary
USDT	2.5905650739081634	0.01	NOT stationary
USDC	1.152694282554201	0.01	NOT stationary
BNB	3.2240233594590157	0.01	NOT stationary
XRP	1.6671936096457058	0.01	NOT stationary
BUSD	1.6504749465630901	0.01	NOT stationary
DOGE	1.6931989832249126	0.01	NOT stationary
MATIC	2.9739296232124324	0.01	NOT stationary
GOLD	0.828289936274542	0.01	NOT stationary
OIL	4.084256766709523	0.01	NOT stationary
SP500	3.4606197771026954	0.01	NOT stationary
BOND	1.7352546794950356	0.01	NOT stationary

The null hypothesis was rejected if the p-value was less than the 0.05 alpha level. Table 4 shows that the p-values of the fourteen-time series were all less than 0.05; thus, the null hypotheses of the fourteen-time series were rejected. This means that there is evidence to indicate that the time series are not stationary. In the analysis, the technique of first differencing was employed on the training set to achieve stationarity for the time series data. Stationarity is a key property in time series analysis, indicating that the statistical characteristics of a series, such as mean, variance, and autocorrelation, remain constant over time. Differencing is a fundamental step in time series analysis to achieve stationarity. It involves iteratively transforming a non-stationary series to eliminate trends and irregular patterns. The goal is to simplify the data and make it amenable to accurate modeling and forecasting techniques. The decision to use first differencing is based on the outcomes of statistical tests, indicating the need for stationarity to ensure reliable analysis.

c) Transformation

First differencing was used on the training set to ensure stationarity of all series. A time series can become stationary by differentiating it. A time series is considered stationary if its statistical properties, such as mean, variance, and autocorrelation, do not change over time. A non-stationary time series can be made stationary by differencing, which involves subtracting the value of the time series at the previous time step from the current value. However, this is an iterative process, where after first differencing, the series may still be non-stationary. A second difference or log transformation can be applied to standardize the series in such cases. It was concluded that the fourteen-time series data were not stationary after comparing the results of the ADF test and KPSS test. By using the difference method, the time series were altered to achieve stationarity.

e) ADF Test Again

The ADF test was repeated to determine that the data were stationary after transformation. The p-values from the augmented Dickey-Fuller test, were all below the 0.05 cut-off, providing proof of stationarity. This means that the null hypothesis, which suggests that the data contains a unit root, can be rejected. The time series data for BTC, ETH, ADA, USDT, USDC, BNB, XRP, BUSD, DOGE, MATIC, OIL, GOLD, SP500, and BOND also support this conclusion, as they all have p-values less than 0.05. The high negative ADF test statistic and the significance levels of 1%, 5%, and 10% further confirm that the data is stationary and does not contain a unit root (Miglietti et al., 2020).

f) KPSS Test Again

The null hypotheses were rejected as the post-transformation p-values were all significantly higher than the 0.05 alpha level. As a result, the present data is static. Part of the KPSS null hypothesis was not able to be disproved.

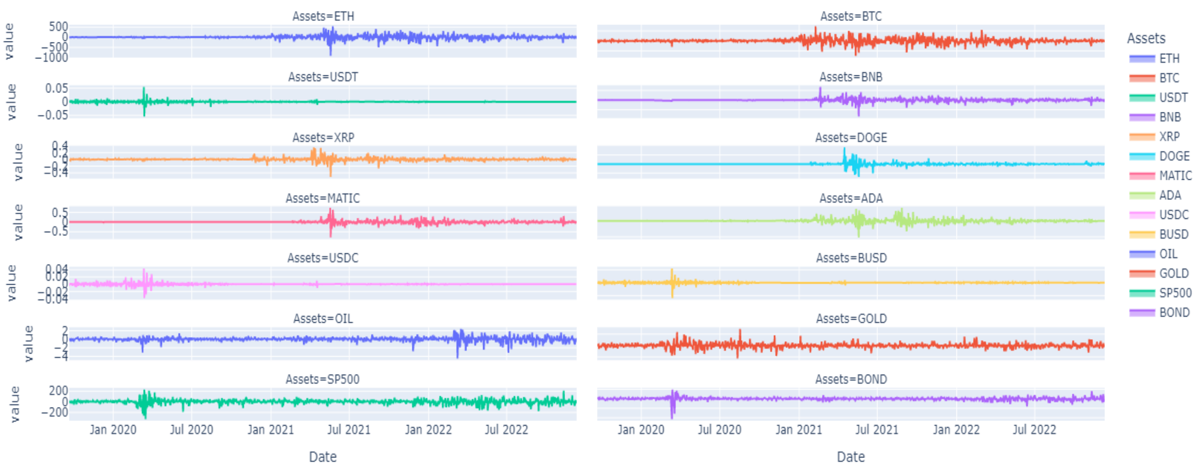

Figure 5 Data Stationarity

A representation of an explanation of data stationarity is provided in Figure 5. None of the data being displayed has a recognizable trend, either rising or declining. Stationarity is the absence of a trend within a time series.

2.7 Econometric Techniques

This section briefly defines the econometric approaches employed in this paper. Mean causality was first investigated by employing linear Granger causality (Granger, 1969) in a vector autoregressive (VAR) system to explore informational linkages between pairs of markets. Given any pair of stationary data (X_t and Y_t), the variable X_t Granger causes Y_t linearly, given that X_t lags provide meaningful information for explaining current Y_t values. In a VAR system, bivariate Granger causality is stated as follows:

$$Y_t = \mu_1 + \sum_{i=1}^{k} a_j Y_t + \sum_{i=1}^{k} b_i X_t + \varepsilon_t \qquad (2)$$

and

$$Y_t = \mu_2 + \sum_{i=1}^{k} c_i Y_{t-i} + V_t \qquad (3)$$

where a, b, and c are the model coefficients; μ_1 and μ_2 are univariate white noise; i is the model lag; and k is the maximum lag; μ_1 and μ_2 are constants. For instance, Y_t represents the most recent sample, while Y_{t-1} represents Y_t. Y_{t-1} is stratigraphically one sampling gap lower than sample Y_t. The estimation accuracy of this climatic element using the unconstrained and limited models is compared to determine the Granger causality relationship between variable Y and variable X. According to the null hypothesis of non-causality,

$$H_0: B_1 = B_2 = \cdots = B_k = 0 \qquad (4)$$

This stage uses a statistical process to determine causality between variables X and Y. The first step is determining if the null hypothesis can be rejected based on the p-value. The next step is comparing the explanatory power of a model that includes variable X to one that does not, which suggests causality. Before performing a Granger causality test, it is important to ensure that the time series being analyzed is stationary to avoid inaccurate results (Stock et al., 1990). This can be done through a unit root test process; if the series has a unit root, it is non-stationary (Dickey & Fuller, 1981). Non-stationary data can be made stationary by taking the first difference or using the Toda-Yamamoto method (Toda & Yamamoto, 1995). The optimal lag number is then selected by using the Akaike information criterion: AIC (Akaike, 1998).

2.8 VAR Model (Vector Autoregressive Model)

The input time series data must be stationary for the VAR model to work. It is frequently possible to make non-stationary data stationary using techniques such as first-differencing. To determine the appropriate order (P) of the VAR model for the study data, various lag values were considered, while metrics like the Akaike information criterion (AIC) were used to identify the lowest value. Based on this analysis, the optimal lag value for fitting the model to the training data was selected. The input time series data must be stationary for the VAR model to work. It is frequently possible to make non-stationary data stationary using techniques such as first-differencing.

Table 5 VAR Model

Lag	AIC	BIC	FPE	HQIC
1	-36.42210236	-35.51676769	1.52E-16	-36.08072997
2	-36.67651011	-34.92500074	1.18E-16	-36.01604497
3	-36.83838724	-34.23954606	1.00E-16	-35.85836623
4	-36.85360763	-33.40627494	9.89E-17	-35.55356654
5	-36.92868174	-32.63169524	9.18E-17	-35.30815534
6	-37.11406719	-31.96626198	7.64E-17	-35.17258914
7	-37.06911113	-31.06931967	8.01E-17	-34.80621403
8	-37.06964384	-30.21669597	8.03E-17	-34.4848592
9	-37.034115	-29.32683792	8.35E-17	-34.12697324
10	-36.97324266	-28.41046093	8.91E-17	-33.74327312
11	-36.95773915	-27.53827467	9.10E-17	-33.40447009
12	-36.90853658	-26.63120861	9.62E-17	-33.03149516
13	-36.879513	-25.74313812	9.99E-17	-32.67822527
14	-36.83467949	-24.8380716	1.05E-16	-32.30867041
15	-36.73396682	-23.87593712	1.18E-16	-31.88276025

Summary of Regression Results
==================================

Model:	VAR
Method:	OLS
Date:	Tue, 10, Jan, 2023
Time:	03:28:46

No. of Equations:	14.0000	BIC:	-31.9663
Nobs:	1171.00	HQIC:	-35.1726
Log likelihood:	-341.792	FPE:	7.64048e-17
AIC:	-37.1141	Det(Omega_mle):	2.86459e-17

Concerning the process of selecting the appropriate lag order for performing a Granger causality test, it is noted that there is no set rule for determining the lag order and that it is often a matter of trial and error. However, it is advised to use the Akaike information criterion (AIC) to select the lag order with the smallest value. It is also stated that in the current example, the lag order chosen is 6, as seen in Table 5. When performing a Granger causality test within the context of a Vector Autoregressive (VAR) model, choosing the appropriate lag order is a crucial step. The lag order determines the number of past periods of each variable included as a predictor when assessing whether one variable causes another. One widely-used approach for selecting the lag order is to employ statistical information criteria, with the Akaike Information Criterion (AIC) being a popular choice. The AIC aims to balance the model's goodness of fit with its complexity (number of parameters). This analysis penalizes models with more parameters, favoring simpler models that explain the data well. In the context of the current analysis, the lag order was chosen based on the AIC. The AIC values are calculated for different lag orders, and the lag order with the smallest AIC is selected. This process aims to balance capturing the system's dynamics with avoiding overfitting. Table 5 shows that the chosen lag order is 6. This implies that the model considers each variable's previous six time periods when assessing Granger causality between them. The decision to use a lag order of 6 is supported by the AIC, which indicates that this choice provides a favorable trade-off between model complexity and goodness of fit. In summary, selecting the lag order involves considering statistical criteria, such as the AIC, to ensure the model captures relevant temporal relationships while avoiding unnecessary complexity. The chosen lag order significantly impacts the results and interpretation of the Granger causality tests, making this step an important aspect of the analysis process.

2.9 Durbin-Watson Statistical Checking

The Durbin-Watson test evaluates autocorrelation in regression analysis residuals. To determine if the residuals still contain any patterns, serial correlation of the residuals is performed (errors). If any correlation is left in the residuals, then there is some pattern in the time series that is remains to be explained by the model. In this case, the typical course of action is to either increase the order of the model, induce further predictors into the system, or find a different algorithm to model the time series. The Durbin-Watson (DW) statistic is a test for autocorrelation in a statistical model or regression analysis residuals. The Durbin-Watson statistic has a constant value between 0 and 4. A value of 2.0 indicates that no autocorrelation was discovered in the sample. Values greater than 0 but less than 2 indicate positive autocorrelation, while values ranging from 2 to 4 indicate negative autocorrelation. The associated results are: ETH (1.99), BTC (1.98), USDT (2.1), BNB (2.01), XRP (1.97), DOGE (1.94), MATIC (2.03), ADA (1.99), USDC (2.06), BUSD (2.1), OIL (1.99), GOLD (2.0), SP500 (2.0), and BOND (1.99). The values, all ranging between 1.94 and 2.10, mean that there is no autocorrelation detected in the residuals; therefore, the forecast can proceed accordingly.

3. RESULTS

This section takes a look at the Granger causality test, comparing asset forecasting. The Granger causality test is a statistical method used to determine whether one time-series is helpful in forecasting another. It tests the null hypothesis that the coefficients of past values of a second time series do not significantly improve the forecast of the first time series.

3.1 Pairwise Granger Causality Test

The Granger causality test is used to determine the relationship between variables' causes and effects (Wei, 2018). According to this statement, this test can be used to determine the causal trend between two independent variables, X and Y. It is used to determine whether one variable causes changes in another variable or not. It is a statistical method that tests for a lagged relationship between two time-series, where a lagged value of one time-series is used to predict the other time series.

$$\gamma_t = \alpha_0 + \alpha_1\gamma_{t-1} + \alpha_2\gamma_{t-2} + \cdots + \alpha_m\gamma_{t-m} + error_t. \quad (5)$$

$$\gamma_t = \alpha_0 + \alpha_1\gamma_{t-1} + \alpha_2\gamma_{t-2} + \cdots + \alpha_m\gamma_{t-m} + b_p x_{t-p} + \cdots b_q x_{t-q} + error_t. \quad (6)$$

The Granger causality test and how it is used to determine the direction of causality between two variables, X and Y, involves analyzing the relationship between the two variables over time (denoted by "t") and taking into account any error (denoted by "ε"). It checks for causation in both directions (X to Y and Y to X) by applying the test to all possible pairs of the series. The null hypothesis is that there is no causal relationship between X and Y. The Akaike information criterion (AIC) is used to determine the optimal lag length, which is a common methodology used in previous studies (Sifat et al., 2019).

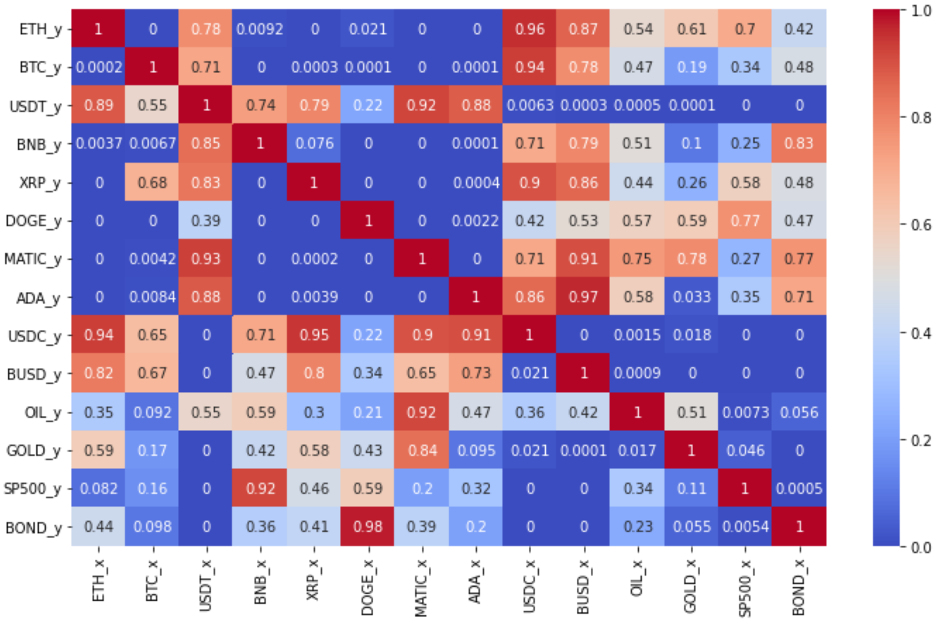

Figure 6 P-Values of Granger Causality Testing Shown via a Heat Map

Figure 6 is presented as a correlation matrix that illustrates the Granger causality between the different time series. It states that all of the time series in the data are found to be causally related to one another. The rows represent the variables that cause changes in other variables (Granger-cause) with a 6 order lag if a given p-value is at or below the significance level (0.05), while the columns represent the variables that are affected by the causal relationship (Granger effect). The columns are the predictor series, and the rows are the reaction (Y) (X). The Granger causality test determines the causal relationship between two time-series. It has often been used in the vector autoregression (VAR) forecasting method; however, it is important to note that the Granger causality test does not test the true cause-and-effect relationship; it only tests if one variable X is casual to Y, based on the correlation.

3.2 Forecasting

This process uses a vector autoregression (VAR) model to forecast time series data. It explains that in order to make accurate forecasts, the VAR model requires a certain number of past observations, known as the lag order. The VAR model requires as many prior values as the chosen lag order indicates as the terms are based on the lags of the time series. The data will be inverted to restore it to its original scale after being previously changed via the difference method. The data must be de-differenced as forecasts are produced at the scale of the model's training data. The base number is increased by adding each successive difference. Finding the cumulative total at an index and adding it to the base number is a simple technique to accomplish this. By including the observation from the previous time step with the difference value, the procedure can be reversed. The final result is the original time series data.

3.3 Evaluation

This section discusses the process of evaluating the performance of different assets in a comparison study. The mean squared error (MSE) of each asset was computed, generating the results shown in Table 6. An 80/20 split of the data was used, with 80% of the total observations (1198) used as training data (958 observations) and the remaining 20% (240 observations) used as test data to forecast the log returns of all assets. Mean squared error (MSE) was used for accuracy, while other comparison measures were used to compare the accuracy of the univariate time series assets.

Root mean square (prediction) error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\gamma_t - \gamma_t)^2}{n}} \quad (7)$$

and

Mean absolute error (MAE) deviation:

$$MAE = \frac{\sum_{t=1}^{n}|\gamma_t - \gamma_t|}{n} \quad (8)$$

This paragraph details the results of the evaluation of the performance of different assets. The root mean squared error (RMSE) and mean absolute error (MAE) were used as metrics to analyze the performance of the methods. It should be mentioned that MAE is not sensitive to outliers, while RMSE takes bias and variance into account, normalizing the units. Table 6 shows the measures of accuracy of forecasting all assets. It was found that among the 14 different univariate time series assets, USDT had the smallest values of accuracy in terms of RMSE and MAE. It is concluded that the proposed USDT, USDC, and BUSD predictions for other major world economic asset price log returns performed better than other univariate time-series assets, including the neural network time-series model. This prediction can help investors and financial policy committees to identify threats and make future financial decisions with predictable cryptocurrency price log-returns information.

Table 6 Evaluation of the Forecasts Using a Wide Range of Metrics

Model	RMSE	MAE
BTC	346.21	251.81
ETH	60.3	53.81
ADA	0.04	0.04
USDT	0.00042	0.0003
USDC	0.00049	0.00031
BNB	40.34	38.07
XRP	0.04	0.03
BUSD	0.00056	0.00046
DOGE	0.02	0.02
MATIC	0.13	0.12
GOLD	0.78	0.70
OIL	2.16	1.98
SP500	102.46	96.15
BOND	0.74	0.57

This study focuses on comparing different methods of predicting the price of cryptocurrencies and other major world economic assets. USDT, USDC, and BUSD should be used to make predictions as it was found that USDT, USDC, and BUSD had the smallest mean squared error (MSE), indicating that these models were the best for prediction. A support vector machine (SVM) was also used to make predictions, finding that there was a time lag between the real data and the predicted data. Nevertheless, the model was able to predict the trend of the cryptocurrencies and other major world economic asset prices, although with some delay. It is suggested that this information could be helpful for cryptocurrency investors to make more informed decisions and potentially earn greater profits.

4. DISCUSSION

The vector autoregression (VAR) model was used in this study to examine the relationship between the variance of cryptocurrency prices and the variance of prices for other significant global economic assets. Data on the prices of cryptocurrencies and other major global economic assets were collected between January 2018 and December 2022. The results of the testing show that there is a relationship between the variance of USDT, USDC, and BUSD and the variance of GOLD, SP500, and BOND prices and that the variance of these stablecoins can be used as a predictor for the variance of other major world economic asset prices. The study also identified other features that can be used to predict GOLD, SP500, and BOND prices, including the variance of GOLD, SP500, and BOND prices, moving average, exponential moving average, and bias. According to Corbet et al. (2018), who analyzed the relationships between three popular cryptocurrencies and various other financial assets in the time and frequency domains, cryptocurrency may offer diversification benefits for investors with short investment horizons, according to their results. They found evidence of the relative isolation of these assets from financial and economic assets. External economic and financial shocks are reflected in the time variation of the linkages.

The Pearson correlation coefficient was used to investigate the relationship between the returns of other major world economic assets and selected cryptocurrencies. In time-series data, the Pearson correlation coefficient is a statistical measure that measures how much two variables change in relation to one another (Pollet & Wilson, 2010). Its value can be between -1 and 1, with -1 denoting a perfect negative correlation, 1 denoting a perfect positive correlation, and 0 denoting no connection. Such analysis can be used to assess the correlation between two variables. This method is useful in understanding how two variables behave with respect to each other over time. This method was used to examine the relationship between the return of other major world economic assets and the selected cryptocurrencies. The results show that certain cryptocurrencies (BTC, ETH, BNB, XRP, DOGE, ADA, and MATIC) have a slight positive correlation with other major world economic assets (OIL, SP500, and BOND), except for Tether (USDT), USD Coin (USDC), and Binance USD (BUSD). These findings are consistent with Wu et al. (2021), whose study explored the effects of economic policy uncertainty (EPU) on Bitcoin, Ethereum, Litecoin, and Ripple returns. The results show that there is a meaningful relationship between changes in the EPU indices and BTC/USD returns. Additionally, GOLD has a negative correlation with all of the cryptocurrencies. A support vector machine (SVM) was also used to make predictions, finding that there was a time lag between the real data and the predicted data but that the model could predict the trend of the cryptocurrency and other major world economic asset prices, although with some delay.

The pairwise Granger causality test was used to determine whether there was a causal relationship between the returns of other major world economic assets and selected cryptocurrencies. This test, proposed by Granger in 1969, is used to examine whether one variable causes change in another variable over time (Granger, 1969). The optimal lag length, which is the number of previous time steps used in the test, is determined using the Akaike information criterion (AIC). It was found that lag 6 has the lowest AIC value; the Granger causality test was conducted accordingly using lag 6. The null hypothesis is that there is no causal relationship between the two variables, and is rejected when the p-value is less than 0.05, while it is accepted when the p-value is greater than 0.05.

The Granger causality test was applied between the return of other major world economic assets and other variables with lag 6. The analysis discovered that there was no causal association between other significant global economic assets and cryptocurrencies as the associated p-values were greater than 0.05; the null hypothesis was therefore not ruled out. This validates the conclusions of Malladi and Dheeriya (2021), who found that large global economic assets do not affect cryptocurrencies and vice versa. In the case of other major world economic assets and Bitcoin, Ethereum, Binance, Ripple, Dogecoin, Cardano, and Polygon, the null hypothesis was not rejected as the p-value was greater than 0.05, indicating that they do not have a causal relationship. However, because the p-value for Tether, USD Coin, and Binance USD was less than 0.05, the null hypothesis was disproved for other significant global economic assets. This means that other major world economic assets are a casual factor for Tether, USD Coin, and Binance USD. These results suggest that there is a one-way causality from Tether, USD Coin, and Binance USD to other major world economic assets (BOND, SP500, and GOLD). These findings are consistent with Jang et al. (2019), who studied the causal relationship between Bitcoin and other investment assets. Unlike the Granger causality test, they discovered that transfer entropy identifies causal interdependence between Bitcoin and other assets, including gold, stocks, and the U.S. dollar. In contrast to research by Bhuyan and Dash (2018), the Granger causality test shows no relationship between gold and stock returns. However, this is not the case for other cryptocurrencies and other major world economic assets except Tether, USD Coin, Binance USD and the price of OIL. Oil-importing countries are especially vulnerable to significant changes in oil prices as they do not have much control over prices, and their oil supply and demand do not match up. A high oil price reduces a firm's profits and people's incomes, leading them to conserve energy and finance green projects by issuing green bonds (Liu et al., 2020; Chen et al., 2020; Ren et al., 2022).

5. CONCLUSION

In summary, this paper collected data on the prices of cryptocurrencies and other major world economic assets between January 2018 and December 2022, using statistical analysis methods to examine the prices of these assets. The study used the Granger causality test to analyze the relationship between the variance of cryptocurrency prices and the variance of other real asset prices. Results showed that Bitcoin (BTC), Ether (ETH), Binance Coin (BNB), Ripple (XRP), Dogecoin (DOGE), Cardano (ADA), and Polygon (MATIC) had a slight positive correlation with OIL, SP500, and BOND assets, which was not the case for Tether (USDT), USD Coin (USDC), and Binance USD (BUSD). Gold had a negative correlation with all cryptocurrencies. However, the analysis reveals that there is Granger causality between the cryptocurrencies (Tether, USD Coin, and Binance USD) and the other major world economic assets (BOND, SP500, and GOLD) as the associated p-values were less than 0.05. This means that other major world economic assets are a Granger cause of changes in these currencies and that the variance of these stablecoins (USDT, USDC, and BUSD) can be used as a predictor for the variance of other major world economic asset prices. It was discovered that there was a time lag between the real data and the predicted data; nevertheless, the model could predict the trend of the cryptocurrency and other major world economic asset prices, although with some delay.

It should be taken into account that the relationship between cryptocurrencies and other major world economic assets can vary over time and may not be the same for all cryptocurrencies. The results of this study are based on a specific period (January 2018 to December 2022) and may not be representative of future trends. Additionally, other factors such as investor sentiment, regulatory environment, and market conditions can also impact the returns of cryptocurrencies and should be considered when making investment decisions. It is also important to note that the results of this study are based on a specific set of assets and may not be generalizable to other assets or markets. Therefore, it is always necessary to do your own research and consult with a professional financial advisor before making any investment decisions.

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