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Analysis of the Causal Relationships Among Seven Major Cryptocurrencies

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**Abstract**

This study focuses on the correlation and causation between seven major cryptocurrencies. The study also discusses the difference between correlation and causation, emphasizing that the Pearson correlation coefficient only indicates the existence of a relationship between variables and does not imply causation. The study also used the Granger causality test to identify potential causal relationships between variables, although it does not provide conclusive statements. Liang's quantitative causal analysis takes a more explicit approach, not only identifying causal relationships between variables but also quantifying the degree of those relationships. The results of Liang’s method show that the returns of Ether (ETH) significantly affect the returns of other cryptocurrencies such as Cardano (ADA), Binance (BNB), Bitcoin (BTC), Litecoin (LTC) and Ripple (XRP). This study suggests that investors can benefit from considering trends in other cryptocurrencies to gain a more informed, comprehensive, and effective understanding of cryptocurrency market dynamics.

**Introduction**

Today, with the rapid development of the Internet, the financial and economic areas have undergone tremendous changes. In particular, the emerging cryptocurrency, as a secure transaction currency based on complex cryptography, is away from the constraints of governments and traditional financial institutions and is not limited to specific national or regional restrictions and is widely circulated globally. Even though only a decade or so has passed since cryptocurrencies were issued, they have grown at an exceptionally fast pace, with huge price fluctuations that have had a huge impact on investors. It can be said that the emergence of cryptocurrencies has caused huge challenges and impacts on the traditional financial market.

Against the backdrop of the absence of financial regulation and the failure of global governance, cryptocurrencies show high volatility, speculation, and risk. On the one hand, cryptocurrencies are likely to become new alternatives in the financial market with gradually increasing value. On the other hand, cryptocurrencies are extremely risky. This discourages cautious investors but provides great opportunities for speculators (Smutny et al., 2021). During the COVID-19 pandemic, Bitcoin experienced significant volatility. Bitcoin initially plummeted, but quickly rebounded, exceeding its pre-pandemic value, and hitting an all-time high. However, Bitcoin's surge was followed by a sharp decline, sparking interest in cryptocurrencies (Demir et al., 2020). Bitcoin, first introduced by Satoshi Nakamoto in 2008, was the first cryptocurrency. With the development of the market, in addition to Bitcoin, a variety of cryptocurrencies such as Ether (ETH), Cardano (ADA), Litecoin (LTC), Ripple (XRP), and others have emerged. As of the second quarter of 2020, more than 7,000 cryptocurrencies are actively traded and have a total market capitalization of more than $300 billion. (Wu et al.) As the cryptocurrency market continues to expand and diversify, the interactions and impacts of these currencies have become a hot topic of research and discussion.

**Literature review**

With the rise and development of cryptocurrencies, the currency market has undergone radical changes. Governments, scholars, and industry have begun to pay more attention to the research and analysis of cryptocurrencies. There is a huge amount of research on cryptocurrencies, including their fundamentals, main features, development and evolution, payment methods, policy regulation and relationship with traditional currencies and commodity futures.

Regarding the advantages and disadvantages of cryptocurrencies, scholars have not yet formed a unified opinion on the trade-offs. Most scholars believe that there are huge risks behind the fast growth rate of cryptocurrencies, especially for Bitcoin. Nolasco Braaten & Vaughn argue that Bitcoin is a breeding ground of criminal behavior and is not trustworthy, and even less worth investing in. Huber & Sornette argues that the price of Bitcoin is too volatile, and that the price of Bitcoin in the cryptocurrency market is completely divorced from its own value, creating a huge bubble and a series of side effects and crises, etc. However, many people take a neutral view of cryptocurrencies. They recognize the high risks, but also see the potential for high returns. These people believe that with the right guidance and strict regulation, cryptocurrencies can greatly contribute to innovation and growth in the financial markets. For example, Ertz & Boily believes that cryptocurrency expands the boundaries of technology and opens up a new world of global emerging technology system and industrial ecology. Zachariadis, Hileman, & Scott argue that cryptocurrencies and blockchain are likely to become the supporting technology for a new generation of financial infrastructure, which will have a profound impact on the global financial market.

There is a lot of literature studying the risk of cryptocurrencies, in contrast, there are relatively few studies in the literature related to the causality analysis of cryptocurrencies. Lu et al study the causal relationship between cryptocurrencies and emerging stock markets using Granger causality qualitative test and Liang causality quantitative analysis. The qualitative Granger causality test shows that there is no causal relationship between the two. But Liang causality analysis identifies and quantifies the magnitude of unidirectional short-term causality from cryptocurrency markets to emerging stock markets and the inverse unidirectional long-term causality on a strictly physical basis. Rehman and Apergis et al. investigate the causality between cryptocurrencies and commodity futures by using the new approach of nonparametric quantitative causality analysis. The results show that there is a significant causal relationship from cryptocurrencies to commodity futures in terms of mean and volatility.

 In recent years, the trend of cryptocurrencies can be seen that they influence and correlate with each other, but it seems that there is less literature on the causal relationships between cryptocurrencies. Therefore, this study uses the Granger causality test and Liang causality analysis to investigate the causal relationship between the rate of return of seven major cryptocurrencies, which are BTC - Bitcoin, ETH - Ethereum, USDT - Tether, BNB - Binance Coin, XRP - Ripple. ADA - Cardano and LTC - Litecoin. And this study compares the strengths and weaknesses of the two methods.

**Data and Methodology:**

In this paper, the daily closing price data of seven cryptocurrencies, including BTC, ETH, USDT, BNB, XRP, ADA, and LTC, are selected from Yahoo Finance, and the time period is from January 1, 2018, to January 2, 2024. In order to eliminate the effect of heteroskedasticity, this paper takes the logarithm of the daily closing price data and makes the difference, that is, the difference between the daily closing price data and the daily closing price data.

where is the daily closing price and is the rate of return. In this paper, I focus on the the daily returns of seven major cryptocurrencies to study the causal relationship between them.

The descriptive statistics of the yield rates of seven major cryptocurrencies are shown in Table 1. The Jarque–Bera test is a goodness-of-fit test of whether sample data have skewness and kurtosis matching a normal distribution. Normally distributed data should have a skewness of 0, a kurtosis of 0, and their Jarque-Bera (J-B) statistic should also be close to 0.

For skewness, the rate of return of BTC, ETH, ADA, and LTC both have skewness greater than 0, which means a right-skewed distribution. the rate of return of USDT, BNB, and XRP have a skewness less than 0, which means a left-skewed distribution. For kurtosis, the kurtosis of the yield rates of these cryptocurrencies is greater than 0, which means the data distribution is more concentrated near the center and the tails are thicker. The J-B statistics of the yield rates of the seven cryptocurrencies are significantly greater than 0, indicating that the yield rates of these cryptocurrencies do not follow a normal distribution.

Table1: Descriptive Statistics

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |
| mean | 0.000501 | 0.000446 | -0.000002 | 0.001625 | -0.000628 | -0.000115 | -0.000572 |
| sd | 0.036769 | 0.047390 | 0.003591 | 0.052897 | 0.056841 | 0.055560 | 0.050368 ​ |
| min | -0.464730 | -0.550732 | -0.052570 | -0.543084 | -0.550503 | -0.503638 | -0.449062 |
| max | 0.171821 | 0.230695 | 0.053393 | 0.529218 | 0.548555 | 0.321796 | 0.290594 |
| skew | -1.063515 | -1.033042 | 0.360031 | 0.280669 | 0.325104 | -0.023625 | -0.549900 |
| kurtosis | 0.142963 | 0.113260 | 0.515147 | 0.189853 | 0.168649 | 6.024482 | 8.302385 |
| jbtest | 19113.63 | 912128.09 | 242783.1 | 33003.92 | 26060.28 | 3322.652 | 6418.933 |
| jbpvalue | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |

A non-smooth time series may show trends or seasonal variations over time, which can affect the analysis of the data. The ADF (Augmented Dickey-Fuller) unit root test is a statistical method used to determine whether a time series is smooth or not. The ADF test works as follows: Null hypothesis (H0): The time series has a unit root, i.e. it is non-stationary. Alternative hypothesis (H1): The time series does not have a unit root, i.e. it is smooth.

Here I use the ADF unit root test to test the smoothness of the yield rates of seven cryptocurrencies, and the results are shown in Table 2. We can see that the test statistics are less than the critical values at the significant levels of 1%, 5%, and 10%. So, the null is rejected. The ADF test shows that the yield series of seven cryptocurrencies are smooth, and the causal analysis can be continued to the next step.

Table2: ADF Test

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | variable | statistic | pct1level | pct5level | pct10level | results |
| BTC.Dickey-Fuller | BTC | -12.53171 | -3.436111 | -2.863972 | -2.568116 | stationary |
| ETH.Dickey-Fuller | ETH | -12.23892 | -3.436111 | -2.863972 | -2.568116 | stationary |
| USDT.Dickey-Fuller | USDT | -16.15378 | -3.436111 | -2.863972 | -2.568116 | stationary |
| BNB.Dickey-Fuller | BNB | -12.02447 | -3.436111 | -2.863972 | -2.568116 | stationary |
| XRP.Dickey-Fuller | XRP | -13.19189 | -3.436111 | -2.863972 | -2.568116 | stationary |
| ADA.Dickey-Fuller | ADA | -11.83000 | -3.436111 | -2.863972 | -2.568116 | stationary |
| LTC.Dickey-Fuller | LTC | -13.11165 | -3.436111 | -2.863972 | -2.568116 | stationary |

The trend of the seven cryptocurrencies' returns from January 1, 2018, to January 2, 2024, is shown in Figure 1. It can be seen from the figures that the seven cryptocurrencies' returns show basically similar trends. This similarity implies a potential correlation between the seven cryptocurrency yields.

A graph with colorful lines and numbers

Description automatically generated

Figure1: Trend Analysis of Seven Cryptocurrency Yields

In order to further investigate the correlation between the seven cryptocurrency yields, I use the Pearson correlation coefficient to measure the degree of correlation between the seven cryptocurrencies, and the results are shown in Figure 2. From Figure 2, it can be seen that the correlation between the seven cryptocurrency yields is basically positive. That is, when the price of one cryptocurrency changes, the price of the other six cryptocurrencies will also change in the same direction. However, Pearson's correlation coefficient is a probabilistic description, which is generally not conclusive and cannot reveal the internal relationship (Vinod, 2017). Therefore, to study the relationship between cryptocurrencies more deeply, it is necessary to utilize the causality approach to explore the causal relationship between the seven cryptocurrencies.

A screen shot of a chart

Description automatically generated

Figure2: Correlation coefficients between seven cryptocurrency yields

**Granger's test of causality**

The Granger causality test is usually used to analyze whether there is a causal relationship between the variables and to detect the degree of interconnection and mutual influence between the variables (Stern, 2011). If the past information of variables and is included, the prediction of variable is better than the prediction of by the past information of alone. In other words, if variable helps to explain future changes in variable , then variable is considered to be the Granger cause of variable .

First, the following two regression models are estimated: unrestricted regression model () and restricted regression model (), which are shown as:

Where denotes the constant term, and are the lag orders of variables and respectively, and is white noise. The residual sum of squares of the above two regression models, and , are used to calculate the F-statistic, and their expressions are as follows:

where is the sample size. The original hypothesis of the qualitative test of Granger causality is: , i.e., to test whether is valid. If , then is not significant for 0, the original hypothesis should be rejected, stating that is the Granger cause of the change in . Conversely, the original hypothesis should not be rejected.

The specific steps of Granger causality qualitative test are as follows: firstly, calculate the optimal lag order of Granger causality qualitative test by using AIC information criterion, and then calculate the F-statistic and its p-value. If the p-value of F-statistic is greater than or equal to the p-value from the F-distribution, then the null hypothesis that X does not Granger-cause Y is rejected. Table 3 shows the results of the Granger causality test for the returns of the seven cryptocurrencies. We can see that six results show the causal relationship. For example, ADA and BNB are causally related to each other; XRP is not the Granger cause of the change of BTC, but XPR is the Granger cause of the change of ETH. However, the Granger causality test does not quantify the degree of these causal relationships.

Table3: Granger Causality Test

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Null Hypothesis | F- Statistic | Probability | Test Result |
| 1 | BTC is not a Granger cause of changes in ETH | 4.228879 | 0.039860 | Reject |
| 2 | BTC is not a Granger cause of changes in USDT | 1.733888 | 0.188052 | Reject |
| 3 | BTC is not a Granger cause of changes in BNB | 3.116922 | 0.077622 | Reject |
| 4 | BTC is not a Granger cause of changes in XRP | 3.639556 | 0.056552 | Reject |
| 5 | BTC is not a Granger cause of changes in ADA | 0.034180 | 0.853341 | Reject |
| 6 | BTC is not a Granger cause of changes in LTC | 1.086750 | 0.297307 | Reject |
| 7 | ETH is not a Granger cause of changes in BTC | 1.416865 | 0.234049 | Reject |
| 8 | ETH is not a Granger cause of changes in USDT | 4.618131 | 0.031745 | Reject |
| 9 | ETH is not a Granger cause of changes in BNB | 1.016986 | 0.313346 | Reject |
| 10 | ETH is not a Granger cause of changes in XRP | 4.506470 | 0.033878 | Reject |
| 11 | ETH is not a Granger cause of changes in ADA | 0.009176 | 0.923693 | Reject |
| 12 | ETH is not a Granger cause of changes in LTC | 0.370182 | 0.542968 | Reject |
| 13 | USDT is not a Granger cause of changes in BTC | 0.237785 | 0.625858 | Reject |
| 14 | USDT is not a Granger cause of changes in ETH | 0.453678 | 0.500664 | Reject |
| 15 | USDT is not a Granger cause of changes in BNB | 2.437884 | 0.118580 | Reject |
| 16 | USDT is not a Granger cause of changes in XRP | 0.325079 | 0.568629 | Reject |
| 17 | USDT is not a Granger cause of changes in ADA | 0.002899 | 0.957062 | Reject |
| 18 | USDT is not a Granger cause of changes in LTC | 0.462692 | 0.496440 | Reject |
| 19 | BNB is not a Granger cause of changes in BTC | 3.334012 | 0.067997 | Reject |
| 20 | BNB is not a Granger cause of changes in ETH | 5.326040 | 0.021101 | Reject |
| 21 | BNB is not a Granger cause of changes in USDT | 0.606186 | 0.436311 | Reject |
| 22 | BNB is not a Granger cause of changes in XRP | 7.680664 | 0.005628 | Fail to Reject |
| 23 | BNB is not a Granger cause of changes in ADA | 5.234279 | 0.022241 | Reject |
| 24 | BNB is not a Granger cause of changes in LTC | 5.796254 | 0.016142 | Reject |
| 25 | XRP is not a Granger cause of changes in BTC | 5.344692 | 0.020877 | Reject |
| 26 | XRP is not a Granger cause of changes in ETH | 11.104320 | 0.000875 | Fail to Reject |
| 27 | XRP is not a Granger cause of changes in USDT | 3.064623 | 0.080153 | Reject |
| 28 | XRP is not a Granger cause of changes in BNB | 2.775044 | 0.095887 | Reject |
| 29 | XRP is not a Granger cause of changes in ADA | 2.350110 | 0.125418 | Reject |
| 30 | XRP is not a Granger cause of changes in LTC | 8.828271 | 0.002998 | Fail to Reject |
| 31 | ADA is not a Granger cause of changes in BTC | 8.512758 | 0.003562 | Fail to Reject |
| 32 | ADA is not a Granger cause of changes in ETH | 8.454980 | 0.003677 | Fail to Reject |
| 33 | ADA is not a Granger cause of changes in USDT | 5.445709 | 0.019706 | Reject |
| 34 | ADA is not a Granger cause of changes in BNB | 0.065818 | 0.797549 | Reject |
| 35 | ADA is not a Granger cause of changes in XRP | 3.700143 | 0.054537 | Reject |
| 36 | ADA is not a Granger cause of changes in LTC | 6.496202 | 0.010878 | Reject |
| 37 | LTC is not a Granger cause of changes in BTC | 2.114247 | 0.146077 | Reject |
| 38 | LTC is not a Granger cause of changes in ETH | 9.468708 | 0.002115 | Fail to Reject |
| 39 | LTC is not a Granger cause of changes in USDT | 4.638923 | 0.031363 | Reject |
| 40 | LTC is not a Granger cause of changes in BNB | 1.052123 | 0.305131 | Reject |
| 41 | LTC is not a Granger cause of changes in XRP | 4.225567 | 0.039937 | Reject |
| 42 | LTC is not a Granger cause of changes in ADA | 2.442435 | 0.118237 | Reject |

However, Lopez & Weber pointed out the possible problems in the Granger causality test, such as variable transformation may lead to the distortion of the true relationship between the original variables, and its statistical inference may be wrong. The results of Smirnov also showed that the Granger causality test can lead to false causality inference in many cases. In order to draw more accurate conclusions and quantify the magnitude of causality, I re-examine the causality among the seven cryptocurrency yields using a newly developed and rigorous causality inference methodology - Liang's quantitative causality analysis.

**Liang's quantitative analysis of causality**

Completely different from Granger's qualitative test of causality, Liang proposes to assess the causality of a time series based on a rigorous, real physical meaning and in a quantitative way. The magnitude of causality is measured by the rate of information flow. The quantitative information flow causality analysis is based on a rigorous physical meaning. Liang [14] proved that for an n-dimensional dynamical system, the information flow *X* has the following expression:

where is the Wiener process vector, is the vector of drift coefficients (any nonlinear operator), is the matrix of perturbation coefficients (which can be any function of and ), and the information flow from component to component is denoted as:

where denotes except and , denotes the mathematical expectation, and is the marginal probability density function of ,. If it means that is not the cause of . If , then is the cause of and there is a causal relationship between them. And we can use to calculate the exact value of the causal relationship between and . The magnitude of the causal relationship between any nonlinear system can be precisely calculated using .

The above formula is rigorously derived from the information flow principles, but it relies on a model and is therefore difficult to apply to some extent. Therefore, Liang proved under linear assumptions that for two time series and , the maximum likelihood estimation of the rate of information flow from to is , it has the following form:

where denotes the covariance between and , , is the covariance between and , and is obtained by utilizing the forward Eulerian difference approximation with the following expression:

where denotes the time period, in general, the information flow rate calculated by the above equation may or may not be zero. When , it means that is not the cause of and does not cause to change. If , then there is a causal relationship between and . If there is a causal relationship between and , two cases can be distinguished according to the sign of the rate of information flow: when is positive, it means that makes unstable and changeable. However, for the purpose of causal reasoning, the sign is not very important and only its magnitude needs to be considered (Rong & Liang, 2021). The formula is compact in form, involves only a common statistic, the sample covariance, so it is easy to calculate, and it clears up the debate between causality and correlation. That is, causality implies correlation, but correlation is not necessarily causation. In practice, however, the statistical significance of the variables must be tested. The formula has been applied in many different fields and has significant results.

Table4: Liang’s Causality Test Results

| T2 | ADA | BNB | BTC | ETH | LTC | USDT | XRP |
| --- | --- | --- | --- | --- | --- | --- | --- |
| ADA | NA | -0.037 0.027 | -0.004 0.035 | -0.002 0.042 | -0.036 0.038 | 0 0.001 | -0.03 0.032 |
| BNB | -0.004 0.027 | NA | -0.035 0.032 | -0.02 0.033 | -0.02 0.032 | -0.001 0.001 | -0.023 0.023 |
| BTC | -0.062 0.035 | -0.036 0.032 | NA | -0.038 0.052 | -0.041 0.046 | 0 0.001 | -0.039 0.028 |
| ETH | -0.074 0.042 | -0.046 0.033 | -0.065 0.053 | NA | -0.095 0.051 | -0.001 0.002 | -0.064 0.032 |
| LTC | -0.058 0.038 | -0.046 0.032 | -0.029 0.046 | -0.019 0.051 | NA | -0.001 0.001 | -0.057 0.032 |
| USDT | -0.002 0.002 | 0.001 0.002 | -0.001 0.001 | -0.003 0.002 | -0.002 0.001 | NA | -0.002 0.002 |
| XRP | -0.037 0.032 | -0.039 0.023 | -0.032 0.028 | -0.041 0.032 | -0.04 0.032 | 0.001 0.002 | NA |

1): Confidence level at 90% 2): Shading indicates a significant causal relationship

Table4 shows the information flow rates between the seven cryptocurrency yields. As can be seen in Table 4, the absolute information flow rate values vary from 0.032 to 0.095, we can see , , and as well as other shaded parts in the table, are not equal to 0 and their values are negative. This indicates a unidirectional causality between the seven cryptocurrencies. For example, ETH yield is the cause of changes in ADA, BNB, BTC, LTC and XRP yields. BTC yield is the cause of changes in ADA, BNB and XRP yields. XRP yield is the cause of changes in ADA, BNB, BTC, ETH and LTC yields.

**Conclusion**

This study focuses on the discussion of correlation and causation among seven major cryptocurrencies. Pearson's correlation coefficient can only show that there is a correlation between the variables, but it cannot prove that there is a causal relationship between the variables, and correlation is not the same as causation. Granger's causality test is a kind of statistical hypothesis test, which can only determine whether there is a causal relationship between the variables but cannot make a conclusive statement. Liang's quantitative causality analysis can not only determine the causal relationship between variables, but also quantify the degree of the causal relationship between variables. The results of Liang's quantitative causality analysis show that ETH yield is the cause of changes in ADA, BNB, BTC, LTC and XRP yields. When investing in a particular cryptocurrency, investors can probably refer to the trends of other cryptocurrencies in order to obtain clearer, more comprehensive, and more effective information about cryptocurrencies.

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