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RESEARCH ON THE LINKAGE OF DIGITAL MONEY MARKET: EMPIRICAL ANALYSIS BASED ON GRANGER CAUSALITY TEST AND VARIANCE DECOMPOSITION

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ABSTRACT
Based on the close price data of the main nine currency pairs in the digital money market in the period between 2018 and 2020, the linkage relationship between the nine currency pairs' price changes has been empirically studied. The impact of BTCUSDT and ETHUSDT on the volatility of other currencies is analyzed using Pearson correlation coefficient, Granger causality test and variance decomposition. The results show that the price change of BTCUSDT is the reason for the price change of all other currencies. The fluctuation change of BTCUSDT can be explained by its own fluctuation. The fluctuation of other currencies has little contribution on the fluctuation of BTCUSDT. Among the contributions made on the overall market volatility, BTC's impact on market volatility is higher than ETH's impact on market volatility. XRP volatility can be explained by its own volatility, and its currency trend is quite different from that of other currencies.

Key Words: Digital Currency (Cryptocurrency); Bitcoin; Blockchain; co-movement

JEL Classifications: E42, F31, G12, G15, G29

1. INTRODUCTION
Linkage research between financial assets is one of the key research directions in the financial market (Patel et al., 2022). With regards to quantitative analysis, we can find the correlation between two or more assets (Edmister, 1972), and with qualitative analysis, we can study the logical relationship between two or more assets (Ragin, 1998). As such, quantitative analysis is helpful to verify the logical relationship between the assets and to draw practical conclusions (Edmister, 1972 and Wenjuan and Jinghai, 2017).

For secondary market investors, finding a correlation between the assets means that one asset can be copied to some extent by another or several assets (Harvey and Siddique, 2000). The investors can then make a profit using strategies such as statistical arbitrage in the market, based on the correlation (Hogan et al., 2004). Besides, the study of the interaction and the linkage between markets can help us analyze the market more rationally, that is, to understand the operation of the market and the relationship behind the various assets in the market.

Since 2009, digital currency and Blockchain have developed rapidly and are considered the main driving forces of future financial innovation (Prasad, 2021). Dozens of large-scale exchanges specializing in digital currency trading have been established. The 24-hour trading volume of OKEX, HUOBI, BITFINEX, and OKEX, which is the greater authoritative exchange, is about $7 billion[1]. In addition, some large exchanges in traditional financial markets have begun to trade in digital currencies. CBOE (Chicago Board of Exchange), the largest Options Exchange in the US, launched the Bitcoin futures contract in December 2017 (Bouri et al., 2018). NASDAQ, Wall Street's second-largest stock exchange, has launched the Bitcoin Index (BLX) and ETH index (ELX) on February 28, 2019[2]. The market information shows that the digital money market is attracting increasing attention from the Chinese and foreign capital and large financial institutions. Unlike traditional financial markets and according to Baur et al., 2018, many investors mainly adopt fundamental analysis,

[1] https://cointelegraph.com/news/volumes-on-most-major-cryptocurrency-exchanges-are-fake-or-inflated-study
[2] https://www.bitcoinhistory.com/2019/02/28/28-february-2019/

and institutional investors in the digital money market make decisions mainly through technical analysis to predict if the price of Bitcoin will rise or fall. This phenomenon is mainly due to the following reasons: First, the fundamental information of digital currency is limited and mostly at the technical level of the blockchain. This is highly technical and

cannot be well understood by investors. This makes it difficult to distinguish the fundamental information from different currencies; Second, the future trend of digital currency is not yet clear, its value is difficult to estimate, and it mostly depends on market sentiment; Third, digital currencies are rich in currency types but lack corresponding market regulation. Many newly issued currencies are not strictly qualified for listing, and information disclosure is less; and finally, lack of regulation leads to easy control by a dealer, and price movements are irrational.

In conclusion, due to the lack of basic valuation analysis and market regulation, the price fluctuation of digital money market is very large. Bitcoin peaked in December 2017 to $20,000, and to $3826 in February 2019, down by 80%[3]. Another example is that Bitcoin exceeded to $ 60,000 on March 13, 2021 and in May 19, 2021, prices are trading at $30,000, down by 100%[4] . Bitcoin is arround $ 61,000 on March 17, 2024[5], and we also see the fluctuation of Ethereum prices.

The correlation and linkage between stock and stock, stock and bond, commodity and commodity and a series of financial investment objectives, all these topics have been studied by many scholars, but few studies have been done on digital money market. In this context and according to Sensoy et al., (2021) what is the relationship between the prices of different digital currencies? What is the linkage and transmission mechanism of the digital money market? In this paper, we will explore these issues.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature. Section 3 focuses on the research model, including elaboration of VAR model and GRANGER model; Section 4 presents the sample and discusses our empirical results and analysis. Some concluding remarks are made in Section 5.

2. LITERATURE REVIEW

2.1. CHINESE SCHOLARS' RESEARCH ON THE DIGITAL MONEY MARKET

The rise of digital money was short, and the concept of Bitcoin was introduced only in 2008 (Nakamoto, 2008), In China, for example when the country's top three digital currency exchanges began charging trading fees. Chinese scholars paid attention to digital money only in recent years. The research direction is also mostly towards the regulation of digital money market, research on digital money and payment relationship, the application of distributed accounting books, the problem of digital money laundering, the development of Blockchain technology and so on.

There are few studies made on digital money market using statistical research methods of traditional financial markets such as Capital Asset Pricing Model (CAPM). Another reason for this paucity is that digital money markets differ from traditional financial markets in many fundamental ways (Raza et al., 2022). The information used to distinguish different digital currencies is mostly the complex technical aspects, such as the selection of consensus mechanisms (POS, POW DPOS, etc.) (Wan et al., 2020). The value of digital money is hard to predict from fundamental information available (Yu et al., 2019). It is thus difficult to find the intrinsic logic of correlations between pairs of coins or currencies (Hayes, 2017).

2.2. CHINESE SCHOLARS' RESEARCH ON MARKET LINKAGE OF THE DIGITAL MONEY MARKET

Although Chinese scholars have little research information on the linkage of the digital money market, they have enough research data available on the linkage of the traditional financial market and the research methods used by scholars that have a strong reference value. Hui and Zhang (2018) used the *GRANGER CAUSALITY TEST* and *VAR-GARCH-BEKK* model to study the relationship between Chinese RMB and domestic interest rates and overseas currencies and interest rates, and obtained the volatility spillover effects between Chinese and overseas markets. Zhichao and Zheng (2016) studied the transmission relationship between China's stock market and commodity futures market by using the Granger causality test model. It was found that the commodity price was affected by downstream demand, but the price fluctuation had a great impact on upstream companies.

Yishan and Yuwei (2018) studied the linkage between China inter-bank bond market and interest rate swap market by establishing two-factor volatility component model-DDC-MIDAS,and found that there is a two-way price guidance between the two markets, and the fluctuation conditions have negative correlation.

2.3. RESEARCH ON THE RELEVANCE AND LINKAGE OF THE DIGITAL CURRENCY

[3] https://www.theguardian.com/technology/2019/jan/11/experience-i-lost-1m-on-bitcoin
[4] https://www.ft.com/content/c4c29bb3-c8ee-454c-a2dd-eac9f644007f
[5] https://coinmarketcap.com/fr/currencies/bitcoin/

MARKET

Contrary to the few studies carried out on the digital markets in China, we have several researches conducted on the digital

markets of Western countries. Unlike Chinese scholars, foreign scholars have conducted more research on the digital money market.

The main research direction is the correlation between price fluctuations of Bitcoin and traditional financial assets. The three directions: the relationship between Bitcoin price and market index (Corbet et al., 2018), correlation between Bitcoin price and gold trend (Baur et al., 2018; Bouri et al., 2017; Dyhrberg, 2016 (A); Dyhrberg, 2016 (B)), and the correlation between Bitcoin price and exchange rate (Li and Wang, 2017) are our research foci. Although the research objective is not limited to the digital money market, the research method has a strong reference value to it. Wing Chan and Le (2018) used Garch, CCC and frequency dependence models to study Bitcoin prices and Euro STOXX, Nikkei, Shanghai A-Share, S&P500, TSX Index data, and found that Bitcoin can hedge different indices at different frequencies.

Bitcoin's monthly earnings hedge all indices. Bitcoin's ability to hedge against daily and weekly gains is weak. Data from UHF shows that Bitcoin can hedge S&P, Euro and Shanghai A-Share index. Efthymia and Konstantinos (2018), Bayramoğlu and Başarır 2019 and Kyriazis, 2020 conducted a dynamic conditional correlation study of the portfolios of Bitcoin, gold, crude oil and equities, performed a variety of portfolios of Bitcoin diversity and diverse portfolios, and estimated the net economic benefits of transaction costs.

It was found that the decrease in overall portfolio risk is due to the low correlation between Bitcoin and other assets but was not affected by the high volatility of Bitcoin. The same results are shown by Ghabri et al., 2021 and Blau, 2017. There are also some scholars such as Sifat et al, 2019; Corelli, 2018; Yhlas, 2018; Ciaian et al., 2018; Urquhart, 2017; Nadarajah and Chu, 2017; Urquhart, 2016 who do research on the price of Bitcoin and other digital currency prices. Many scholars have used different methods to study the relationship between the two most important digital currencies: Bitcoin and Ethereum.

Katsiampa (2019), Katsiampa et al. (2019) and Beneki et al., 2019 used bivariate diagonal BEKK model to study the correlation between the dynamic volatility of Bitcoin and Ethereum, and found that Ethereum can be used as an effective hedging method (to decrease risk) for Bitcoin and configured it in optimal asset portfolio.

Among them, Bitcoin should have more weight than Ethereum. Nikolaos and Ioannis (2019) used the TVP-FAVAR model to explore the transmission mechanism of the currency in the digital money market, and concluded that the influence of the currency is large under the volatility of the market and the impact of ETH on the market fluctuation exceeds that of BTC. Scholars conducted a holistic study of most of the currency types in the digital money market. Stosic et al. (2018) used a random matrix model and a minimum spanning tree model to analyze the prices of several digital currencies, revealing the stable different community structures of cross-correlations of digital currencies.

3. MODEL

The linkage of the digital market means that the price change of a currency pair will affect the price fluctuation of other currency pairs, and the impact will be time lag (Jiang et al., 2023). Firstly, the indices of nine currencies are described and then the stationarity test is performed. The study of linkage relationship mainly selects GRANGER causality test (used to test the relationship between different currencies' mutual interpretation of price changes) and variance decomposition (used to measure the impact of one currency pair's price changes on other currencies' pairs).

3.1. VAR MODEL (VECTOR AUTO REGRESSION)

The VAR model is a combination of multiple autoregressive models (Davis et al., 2016).
Each endogenous variable in the system is used as a function of the lag value of all the endogenous variables in the system to construct the model. The structure of the model is mainly related to the number of variables N of the model and the maximum lag order k of the model (Masiak et al., 2020).

The autoregressive model of single variables is represented as follows:

$$Y_t = \mu + \pi_1 Y_{t-1} + \pi_2 Y_{t-1} + \ldots + \pi_k Y_{k-1} + u_t \qquad (1)$$

Among them, $E(u_t) = 0$, $E(u_t u_{t-1}) = 0$, $E(u_t u_t') = \Omega$ (Positive definite matrix of N*N)

The VAR model with the number of variables being N and the maximum lag ending at k is expressed as follows:

$$Y_t = \mu + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \ldots + \Pi_k Y_{t-k} + u_t \qquad (2)$$

Among them:

Y t = (Y 1,t ,Y 1,t-1 , Y 1,t-2 , Y 1,t-k)’ N*1 order column vector

μ = (μ1 , μ2, … , μN)’ N*1 order constant vector

$$\begin{bmatrix} \pi_{11.j} & \pi_{12.j} & \cdots & \pi_{1N.j} \\ \pi_{21.j} & \pi_{22.j} & \cdots & \pi_{2N.j} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{N1.j} & \pi_{N2.j} & \cdots & \pi_{NN.j} \end{bmatrix}, \quad j = 1,\ 2,\ ..k$$

Πj= Π1，Π2，…Πk N*N order parameter matrix

($U_{1,t}U_{2,t}$… $U_{n,t}$)’ N*1 order error vector

Before using the VAR model to analyze, we need to verify the stability of time series, that is, the unit root test, where all the eigenvalues of Formula (2) are within the unit circle.The observation of VAR model is performed using variance decomposition method.

3.2. GRANGER CAUSALITY TEST

The Granger causality test is widely used in the field of economics and finance. The principle of the test is to define causality as "the variance of the best least squares prediction which depends on all the information in some time points in the past"(Abhay, 1998). That is, if the value of X's lag term is added to the least squares estimation of Yt, the variance of Yt's prediction decreases, then it is assumed that X is the cause of Y. The original hypothesis of the test is that the lag term of the variable X does not affect the estimation of Yt, that is, the conditional distribution determined by the lag term of Yt and Xt is the same as the conditional distribution determined only by the lag term of Yt. The model is represented as follows:

$$y_t = \sum_{i=1}^{k} \alpha_i y_{t-i} + \sum_{i=1}^{k} \beta_i x_{t-i} + u_{1\ t} \qquad (3)$$

The original hypothesis that needs to be verified is:

$$H_0: \ \beta_1 = \beta_2 = \ldots = \beta_k = 0 \qquad (4)$$

If β1, β2, ... βk are not significant, then the above hypothesis cannot be rejected, that is, X is not the cause of Y. If any of the parameters β1, β2, ... βk is significant, the original hypothesis can be rejected and X is considered to be the cause of Y.

These tests use F statistics:

The above test uses the F statistic:

$$F = \frac{(SSE_r - SSE_u)/k}{SSE_u/(T - kN)} \qquad (5)$$

SSE_r is The sum of squared errors from the restricted model, SSE_u is the sum of squared errors from the unrestricted model, T is the sample capacity, k is the maximum number of hysteresis items, N is the number of variables, which is 2.
According to the description of Granger test by Zhao et al. (2008) and Abhay, 1998: Granger cause and effect is not the cause and effect in the normal sense. The reasons are as follows:

1) Exogenous variables affect the correctness of causality: Adding the lag term of the variable, X T makes the estimated square sum of the Y_t residual smaller than X_t and Y_t is not equivalent to the causal relationship between X_t and Y_t, especially when the Granger test can only be tested between two variables (Zhiyuan, 2017). For example, adding a new variable Z_t, Z_t is the reason of Y_t, Z_t is also the reason of X_t, but Z_t changes to X_t more quickly than Zt changes to Yt. At this time, in the Granger model which only considers X_t and Y_t. X_t is then likely to be verified as Y_t because X_t contains the influence of Z_t, but there is no causal relationship between the two. This problem is reflected in the following empirical analysis.

2) When one variable in the system is the expected result of another variable, and this variable artificially occurs before the other variable, Granger causality will produce the inverted result. In the "Inflation Expectation and Granger Causality Study", for example, a new year greeting card was sent in anticipation of a new year. The normal causality is, the arrival of the New Year has led to the sending of greeting cards, and the result of the Granger test is that greeting cards are the cause or reason of the New Year. However, this situation is not taken into account in the framework of the issues discussed in this paper.

4. EMPIRICAL ANALYSIS

4.1. DATA SOURCE

In this paper, the sample data of BITFINEX Exchange 24h trading volume of the top nine trading currency pairs include: BTCUSDT, ETHUSDT, EOSUSDT, LTCUSDT, XRPUSDT, NEOUSDT, ETCUSDT, ZECUSDT, IOTAUSDT.

Analyzing the price of the 9 pairs of currencies is taken as the research object, and the price of the closing unit is USDT. Tether USD uses a digital currency linked to the euro, traded on a blockchain of Bitcoin, to be issued at a rate of 1:1 equivalent to the dollar. Digital currency exchanges mostly use substitutes for the euro, a few directly use USD pairs. Pricing in BTCUSDT has been similar to BTCUSD for a long time, but short-term trends may diverge because of USDT's own volatility. The time period for intercepting data is from September 7, 2018 to January 30, 2020, totaling 510*9=4590. With the impact of the pandemic crisis, we didn't want to use the data after January 2020 to avoid any impact of this event during the analysis of our results. The data comes from the official API of the BITFINEX Exchange[6]. The data is crawled through with Python. The missing data is processed as the price at which the CLOSE price of the previous day is filled to the missing pointTaking into account the different magnitude and fluctuation amplitudes of different currencies, we take the LN value of the daily close data of the antenna and LN[Close(t)]- LN[Close(t-1)]] to solve the magnitude difference.

4.2. STATISTICAL DESCRIPTION

The statistical analysis of the logarithmic rate of return data of the pair is shown in Table 1：
From Table 1, it can be found that the digital money market yields are close to zero between July 2018 and January 2020. Among the nine pairs, except for EOS, the average value of XRP is greater than 0, and the logarithmic yield of XRP/USDT pairs is the highest. The market performance of XRP is closely related to the underlying information of XRP. Comparing the maximum and minimum values, it can be concluded that the XRP market performance is better, the extreme fluctuation of the XRP is also more obvious. The daily log yield can reach 63%, and the lowest can fall down to 37%. The BTC is relatively stable against other currencies in extreme markets, with daily logarithmic earnings up and down by about 20%.

According to the standard deviation of the logarithmic rate of Return of the pair, the two pairs of BTCUSDT and ETHUSDT, which account for a large share of the market value, fluctuate relatively little in the chosen time frame, which is only 0.047 and 0.058. The rest of the market value of the currency which is less volatile and is relatively strong. It is basically at about 0.078, far more than the standard deviation of BTCUSDT and ETHUSDT.

According to the Skewness statistics, the distribution of EOS, LTC, NEO, XRP has positive bias, XRP has a significant bias, the other five pairs have negative bias. The Kurtosis (peak) statistic shows that the yield of nine pairs is greater than the normal distribution peak (=3), indicating that the yield follows the "peak thick tail" distribution. The Jarque-Bera statistic indicates that the logarithmic rate of return of each currency pair is significantly different from the normal distribution at a significant level of 1%.

Table 1: Data Description

Sample:9/07/2018 1/30/2020									
	LN_BTC	LN_EOS	LN_ETC	LN_ETH	LN_LTC	LN_NEO	LN_ZEC	LN_XRP	LN_IOTA
Mean	-0,000403	0,002020	-0,002779	-0,002167	-0,001779	-0,002876	-0,003118	0,000715	-0,001743
Median	0,000536	-0,001101	-0,000831	-0,001963	-0,003783	-0,004770	-0,006244	-0,002218	-0,002867
Maximum	0,206589	0,355888	0,283121	0,207365	0,373660	0,338083	0,215794	0,631362	0,365627
Minimum	-0,206356	-0,327970	-0,365808	-0,225360	-0,314843	-0,295862	-0,306337	-0,375561	-0,338096
Std. Dev.	0,047686	0,084870	0,071047	0,058502	0,064432	0,000000	0,065969	0,078995	0,081949
Skewness	-0,142930	0,554602	-0,583198	-0,237691	0,675824	0,228558	0,001157	2,207426	0,383774
Kurtosis	5,368680	5,997538	6,951396	4,921408	8,663846	5,354811	4,486096	19,02585	5,751078
Jarque-Bera	120,9627	217,0808	360,6976	83,25320	720,5048	122,2744	46,93034	5871,7730	173,3482
Probability	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000
Sum	-0,205697	1,030002	-1,417272	-1,105339	-0,907187	-1,467000	-1,590036	0,364625	-0,888722
Sum Sq. Dev	1,157454	3,666322	2,569265	1,742027	2,113073	3,056762	2,215100	3,176244	3,418282

[6] The URL for obtaining the data is https://api.bitfinex.com/v2/candles/

Observations	510	510	510	510	510	510	510	510	510

4.3. STATIONARITY TEST

Before VAR test and GRANGER causality test for 9 time series, we need to ensure that all time series are stationary and avoid the problem of pseudo-regression.

The log yield of nine currency pairs is tested by Augmented Dickey-Fuller (shown in Table 2), which is used to determine whether the variance of the time series changes systematically. The test results are shown in Table 2. If the ADF statistics are all less than the critical value of -3.4456 at the significance level of 1%, it can be judged that the original hypothesis is rejected at the significance level of 1%.

According to Table 2, the ADF statistics of each currency pair are far less than the critical value, so the log yield sequence of each currency pair can be judged to be stationary at a significance level of 1%.

Table 2: ADF test results

ADF Test Statistics	
LN_BTC	-9.4715
LN_EOS	-10.1068
LN_ETC	-9.9505
LN_XRP	-9.0858
LN_LTC	-9.3647
LN_ZEC	-9.8473
LN_NEO	-9.6694
LN_ETH	-9.3007
LN_IOTA	-9.4411
1% critical value	-3.4456
2% critical value	-2.8676
3% critical value	-2.5700

4.4. STATIC CORRELATION COEFFICIENT

The formula for the Pearson correlation coefficient is as follows:

$$\rho = Cor(X,Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}}$$

The Pearson correlation coefficient is the most frequently used statistic for judging the correlation between two variables. According to the above formula, the correlation analysis of the nine currencies against the rate of return is shown in Table 3.

Table 3: Pearson correlation coefficient test (Correlation Matrix)

	LN_BTC	LN_EOS	LN_ETC	LN_ETH	LN_LTC	LN_NEO	LN_ZEC	LN_XRP	LN_IOTA
LN_ BTC	1,000000	0,604878	0,631022	-0,092724	-0,095048	-0,103611	-0,099404	-0,110799	-0,060559
LN_ EOS	0,604878	1,000000	0,618993	0,010174	0,032684	0,004080	0,015012	-0,030396	-0,036648
LN_ ETC	0,631022	0,618993	1,000000	-0,053548	-0,074217	-0,068365	-0,089501	-0,127575	-0,130239
LN_ ETH	-0,092724	0,010174	-0,053548	1,000000	0,816982	0,774315	0,781202	0,651142	0,683228
LN_ LTC	-0,095048	0,032684	-0,074217	0,816982	1,000000	0,656249	0,694587	0,593766	0,645910
LN_ NEO	-0,103611	0,004080	-0,068365	0,774315	0,656249	1,000000	0,705385	0,558745	0,618156
LN_ ZEC	-0,099404	0,015012	-0,089501	0,781202	0,694587	0,705385	1,000000	0,618442	0,652427
LN_ XRP	-0,110799	-0,030396	-0,127575	0,651142	0,593766	0,558745	0,618442	1,000000	0,511477

	-		-						
LN_IOTA	0,060559	-0,036648	0,130239	0,683228	0,645910	0,618156	0,652427	0,511477	1,000000

The correlation coefficient between the logarithmic returns of each currency pair in Table 3 shows that there is a significantly positive correlation between BTC, EOS, and ETC, and there is little or negative correlation with other currencies or correlations. There is a significantly positive correlation between ETH, LTC, NEO, ZEC, IOTA, and XRP. This contradicts BTC's common sense as Benchmark in the digital money market. Nikolaos and Ioannis (2019) explore the transmission mechanism of the digital money market through the TVP-FAVAR model and compared the influence of BTC and ETH on the market fluctuation. They concluded that, when the market volatility is large, the correlation between currencies is stronger than that of the stable market, and the influence of ETH on the market volatility exceeds that of BTC. Pearson correlation coefficient test results are consistent with the conclusion of this paper. Although the BTCUSDT accounts for a large share of all currency pairs in terms of volume and market value, it is relatively stable, in relation to ETHUSDT.

4.5. GRANGER TEST

After verifying that the log yields of nine pairs are all stationary series, this paper will carry out Granger test on the time series to analyze the linkage relationship of the digital money market. The test results are shown in Table 4.
Figure 1 shows the results from the Granger test that are compiled to show the causal relationship between the nine currencies and the changes that occurred.

The results of Granger causality test show that the BTCUSDT pair is the reason for the change in the rate of return of all the other currency pairs. But having no change in the rate of return of any currency pair, is the reason for the change in the BTC currency pairs under the condition of 1% significance. Except for BTC, there are three currency pairs: EOSUSDT, ETCUSDT and ETHUSDT, which have an effect on the rate of return change of all the remaining currency pairs. XRPUSDT and LTCUSDT are the reasons for the change in the price of some of the remaining currencies, but the results of Granger test are not as significant as those of BTCUSDT, ETCUSDT, ETHUSDT, EOSUSDT.

The above four currency pairs have low significane. It is likely that there is a logical loophole in the Granger causality test described in the model introduction. Through the Granger test, it cannot be denied that XRPUSDT and LTCUSDT have an impact on other currencies, because the change of BTCUSDT first affects these two currencies. Therefore, it is not included in the description of the conduction relationship in Figure 1.

Table 4: Granger causality test results

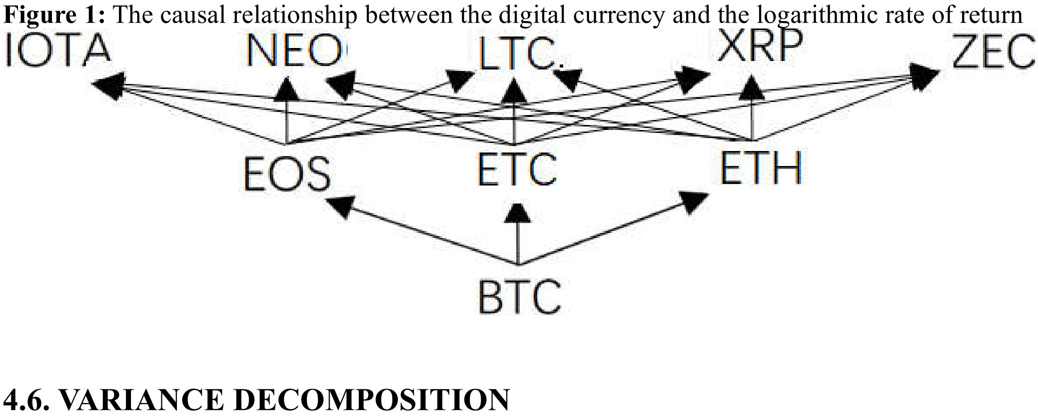
GRANGER CAUSALITY TESTS Y does not cause X									
X\Y	R_BTC	R_EOS	R_ETH	R_ETC	R_LTC	R_IOTA	R_NEO	R_XRP	R_ZEC
R_BTC		4.29394 0.0142	1.46138 0.2329	1.83967 0.1599	4.14822 0.0163	0.9911 0.3719	3.96479 0.0196	0.71357 0.4904	3.46303 0.0321
R_EOS	***143.344*** ***6E-50***		0.11113 0.8948	0.43501 0.6475	3.73711 0.0245	0.1942 0.8236	0.79834 0.4506	0.32861 0.7201	0.79633 0.4515
R_ETH	***269.336*** ***3E-80***	0.80488 0.4477		2.34865 0.0965	3.70826 0.0252	0.50823 0.6019	2.24484 0.107	1.53563 0.2163	1.37664 0.2534
R_ETC	***167.879*** ***1E-56***	3.74472 0.0243	2.25872 0.1055		***4.68695*** ***0.0096***	0.50618 0.6031	1.4102 0.2451	***4.90892*** ***0.0077***	4.43724 0.0123
R_LTC	***290.502*** ***2E-84***	***163.799*** ***2E-55***	***506.899*** ***3E-121***	***246.722*** ***2E-75***		4.21733 0.0153	4.25616 0.0147	3.19879 0.0416	2.97043 0.0522
R_IOTA	***144.668*** ***2E-50***	***141.412*** ***2E-49***	***238.519*** ***2E-73***	***208.142*** ***1E-66***	1.40709 0.2458		0.29767 7.44803	***5.0375*** ***0.0068***	2.66152 0.0708
R_NEO	***155.053*** ***4E-53***	***142.601*** ***9E-50***	***377.958*** ***7E-101***	***223.871*** ***3E-70***	***5.26253*** ***0.0055***	0.7427 0.0006		***4.81478*** ***0.0085***	3.08185 0.0467
R_XRP	***79.9905*** ***7E-31***	***103.956*** ***2E-38***	***181.064*** ***6E-60***	***121.422*** ***9E-44***	0.74644 0.4746	2.22123 0.1095	2.47189 0.0855		1.31699 0.2689
R_ZEC	***180.025*** ***1E-59***	***158.586*** ***4E-54***	***386.681*** ***2E-102***	***232.45*** ***3E-72***	***5.41291*** ***0.0047***	3.0454 0.0485	0.66399 0.5152	***6.81539*** ***0.0012***	

(Note: The first row of the table represents Y, the first column of the table represents X, and the null hypothesis detected in the table is why Y is not X. The first line of each cell in the table indicates F in the formula (5),

$$F = \frac{(SSE_r - SSE_u)/k}{SSE_u/(T-kN)}$$

, is the value of the F statistic, in the empirical analysis, T=508, k=2, N=2, the P value of the second behavior F statistic. The F statistics and their P values at a significance the level of 1%, are expressed in italics).

Figure 1: The causal relationship between the digital currency and the logarithmic rate of return



4.6. VARIANCE DECOMPOSITION

In order to further verify the degree of mutual influence between currency pairs, this paper divides the currency pairs into six groups based on the results of Granger's test, and performs the method of variance decomposition on the four groups of currency pairs respectively. The Granger test results show that BTCUSDT is the reason for the changes in the rate of return of all remaining currency pairs. The three currency pairs EOSUST, ETCUSDT, and ETHUSDT do not constitute a causal relationship with each other but are the reason for the changes in the remaining five currency pairs. Therefore, first verify the degree of mutual influence between the four main currency pairs, and then put one of the five affected currency pairs and the four main currency pairs into a group to perform variance decomposition so as to avoid the influence of other currency pairs.

Table 5: Grouping of variance decomposition

GROUP 1	BTCUSDT	EOSUSDT	ETHUSDT	ETCUSDT	
GROUP 2	BTCUSDT	EOSUSDT	ETHUSDT	ETCUSDT	IOTAUSDT
GROUP 3	BTCUSDT	EOSUSDT	ETHUSDT	ETCUSDT	NEOUSDT
GROUP 4	BTCUSDT	EOSUSDT	ETHUSDT	ETCUSDT	LTCUSDT
GROUP 5	BTCUSDT	EOSUSDT	ETHUSDT	ETCUSDT	XRPUSDT
GROUP 6	BTCUSDT	EOSUSDT	ETHUSDT	ETCUSDT	ZECUSDT

The variance decomposition results of GROUP1 are shown in Table 6. It shows that the volatility of BTCUSDT's return is largely not affected by other currencies. In the fluctuation of the return rate of EOSUSDT, without considering the contribution rate of EOSUSDT, the contribution rate of BTCUSDT to EOSUSDT is the largest, reaching above 36%, followed by ETHUSDT, where the contribution rate is more than 13%. However, the contribution rate of ETCUSDT is negligible. In the ETHUSDT's rate of return fluctuation, its contribution rate is less than 50%. The remaining fluctuation is mainly explained by the BTCUSDT fluctuation. The explanatory power is more than 51%, while EOSUSDT and ETCUSDT have no effect on its fluctuation. In the ETCUSDT rate of return fluctuation, the ETCUSDT fluctuation is only a small part due to its own influence, the proportion is only 38%, most of it comes from the fluctuation of BTCUSDT and ETHUSDT, and their contribution rates are 40% and 20% respectively, that is, the impact of EOSUSDT is insignificant.

Table 6: variance decomposition of GROUP1

Variance Decomposition of R_BTC:

Period	S,E	R_BTC	R_ETH	R_EOS	R_ETC
1	0,047615	100	0	0	0
2	0,047978	98,51938	0,089054	1,376094	0,015473
3	0,048139	98,17999	0,305746	1,395296	0,118972
4	0,048197	98,17114	0,306954	1,393992	0,127909
5	0,048198	98,16477	0,310668	1,39442	0,130138
6	0,048199	98,16274	0,311797	1,394839	0,130623
7	0,048199	98,16269	0,311841	1,394838	0,130635
8	0,048199	98,16265	0,31186	1,394837	0,130649
9	0,048199	98,16265	0,311864	1,394839	0,130649
10	0,048199	98,16265	0,311865	1,394839	0,130649

Variance Decomposition of R_EOS:

Period	S,E	R_BTC	R_ETH	R_EOS	R_ETC
1	0,067675	0,035608	20,64815	79,31625	0
2	0,085269	36,41084	13,42876	50,09823	0,062174
3	0,085531	36,02057	13,46835	50,08657	0,239364
4	0,085633	36,19562	13,5607	49,98669	0,256986
5	0,085671	36,24533	13,55386	49,94401	0,256805
6	0,085672	36,24435	13,55509	49,94249	0,258067
7	0,085672	36,2444	13,55544	49,94207	0,258085
8	0,085673	36,24449	13,55545	49,94198	0,258085
9	0,085673	36,24448	13,55545	49,94197	0,258088
10	0,085673	36,24448	13,55545	49,94197	0,258088

Variance Decomposition of R_ETH:					
Period	S,E	R_BTC	R_ETH	R_EOS	R_ETC
1	0,040377	1,232957	98,76704	0	0
2	0,05854	51,98398	47,56089	0,428167	0,026966
3	0,058837	51,68964	47,42557	0,525106	0,359681
4	0,058966	51,60237	47,40103	0,600272	0,396327
5	0,058994	51,64093	47,36068	0,601324	0,397061
6	0,058995	51,63886	47,36095	0,601299	0,39889
7	0,058996	51,63868	47,36079	0,601575	0,398851
8	0,058996	51,63873	47,36073	0,601589	0,398851
9	0,058996	51,63872	47,36073	0,60159	0,398856
10	0,058996	51,63872	47,36073	0,60159	0,398856

Variance Decomposition of R_ETC:					
Period	S,E	R_BTC	R_ETH	R_EOS	R_ETC
1	0,054796	1,277096	34,38312	1,562244	62,77753
2	0,070966	40,80911	20,55218	1,040018	37,5987
3	0,071611	40,18343	20,22035	1,532342	38,06388
4	0,071707	40,07841	20,30268	1,569072	38,04984
5	0,071747	40,13566	20,2828	1,57107	38,01047
6	0,071749	40,13566	20,28226	1,571362	38,01277
7	0,071749	40,13341	20,28256	1,571446	38,01258
8	0,071749	40,13349	20,28254	1,571468	38,0125
9	0,071749	40,13348	20,28254	1,571468	38,0125
10	0,071749	40,13348	20,28254	1,571468	38,0125

From Table 7, you can see the results of variance decomposition from GROUP2 to GROUP6. The results show that only 44% of the IOTAUSDT fluctuation can be explained by its own fluctuation. BTCUSDT's interpretation ability is 35%, followed by EOSUSDT and ETHUSDT accounting for 9% and 7% of the interpretation ability. With regard to NEOUSDT, the contribution rate of its own fluctuation is 38%, BTCUSDT's fluctuation is approximately the same as its contribution rate, ETHUSDT's contribution is about 15%, and the contribution of EOSUSDT is about 8%. Only less than 2% can be explained by ETCUSDT. With LTCUSDT fluctuations, 52% can be explained by BTCUSDT, 30% can be self-explained, 12% by ETHUSDT, EOSUSDT. ETCUSDT interpretation capabilities are very small, only 5.3% and 0.8%. Compared with the other currency pairs whose interpretation ability of their own fluctuation is less than 50% (except BTCUSDT), the fluctuation of XRPUSDT is about 55% as explained by its own fluctuation. This result shows that XRPUSDT is relatively independent of all the remaining currency pairs except for BTCUSDT, which is less than 24% being affected by the fluctuation of BTCUSDT, followed by ETHUSDT and EOSUSDT, accounting for about 10%. However, ETCUSDT's interpretation ability is only about 1%. The variance decomposition results of ZECUSDT are in agreement with the results of NEOUSDT. The contribution rate of its own fluctuation is 36%, the interpretation ability of BTCUSDT fluctuation is 41%, the contribution of ETHUSDT is about 13%, the contribution of EOSUSDT is about 8%, and the contribution which is less than 2% can be explained by ETCUSDT.

Table 7: variance decomposition results of GROUP2-GROUP6

Variance Decomposition of R_IOTA:

Period	S,E	R_IOTA	R_BTC	R_EOS	R_ETH	R_ETC
1	0,054101	100,000000	0,000000	0,000000	0,000000	0,000000
2	0,065317	69,15099	0,638866	14,140160	11,28040	4,789584
3	0,081866	44,66312	35,74234	9,092369	7,240765	3,261406
4	0,082234	44,27061	35,43589	9,779345	7,176136	3,338021
5	0,082465	44,04029	35,62670	9,738880	7,237624	3,356502
6	0,082519	43,98261	35,70755	9,726154	7,228571	3,355116
7	0,082526	43,97649	35,71125	9,725928	7,230472	3,355858
8	0,082528	43,97449	35,71298	9,725983	7,230780	3,355763
9	0,082528	43,97440	35,71298	9,725979	7,230763	3,355878
10	0,082528	43,97433	35,71304	9,725963	7,230800	3,355872

Variance Decomposition of R_NEO:

Period	S,E	R_NEO	R_BTC	R_EOS	R_ETH	R_ETC
1	0,047412	100,000000	0,000000	0,000000	0,000000	0,000000
2	0,060807	60,80948	1,185997	12,742880	23,36007	1,901576
3	0,077255	37,93840	37,62905	8,033523	15,08986	1,309156
4	0,077530	37,69344	37,45805	8,241764	14,98718	1,619575
5	0,077686	37,70717	37,32071	8,210050	15,09790	1,664176
6	0,077778	37,61870	37,39654	8,229442	15,08948	1,665843
7	0,077839	37,55989	37,48941	8,220941	15,06581	1,663955
8	0,077842	37,55820	37,48963	8,221574	15,06496	1,665632
9	0,077843	37,55799	37,48881	8,221515	15,06574	1,665934
10	0,077844	37,55708	37,48995	8,221541	15,06551	1,665918

Variance Decomposition of R_LTC:

Period	S,E	R_LTC	R_BTC	R_EOS	R_ETH	R_ETC
1	0,034146	100,0000	0,000000	0,000000	0,000000	0,000000
2	0,044003	62,33712	1,301337	9,648727	25,46528	1,247535
3	0,064502	29,17183	52,84358	5,096550	12,18233	0,705706
4	0,064813	29,30256	52,41839	5,361507	12,06785	0,849693
5	0,064920	29,24513	52,38493	5,345641	12,14533	0,878966
6	0,065046	29,13216	52,50703	5,355733	12,12946	0,875617
7	0,065109	29,07593	52,58778	5,354363	12,10617	0,875751
8	0,065114	29,07404	52,58895	5,355755	12,10443	0,876831
9	0,065115	29,07371	52,58815	5,355665	12,10546	0,877022
10	0,065116	29,07260	52,58964	5,355656	12,10511	0,876988

Variance Decomposition of R_XRP:						
Period	S,E	R_XRP	R_BTC	R_EOS	R_ETH	R_ETC
1	0,058420	100,0000	0,000000	0,000000	0,000000	0,000000
2	0,068763	72,20011	1,600985	12,629110	12,74744	0,822357
3	0,079155	55,68566	23,59581	9,567612	10,06324	1,23173
4	0,079495	55,22665	23,41616	9,938980	10,18648	1,23173
5	0,079730	55,90169	23,60726	9,882498	10,36301	1,245539
6	0,079779	54,83752	23,68577	9,870882	10,35849	1,247337
7	0,079781	54,83437	23,68441	9,871095	10,36226	1,24754
8	0,079783	54,83233	23,68580	9,870728	10,36328	1,247866
9	0,079783	54,83210	23,68602	9,870686	10,36330	1,247883
10	0,079783	54,83208	23,68601	9,870684	10,36333	1,247883

Variance Decomposition of R_ZEC:						
Period	S,E	R_ZEC	R_BTC	R_EOS	R_ETH	R_ETC
1	0,039708	100,0000	0,000000	0,000000	0,000000	0,000000
2	0,050656	61,44828	1,206365	13,841250	21,55576	1,948348
3	0,066098	36,18394	41,54443	8,148057	12,97437	1,149200
4	0,066329	35,95820	41,33347	8,403578	12,89255	1,412202
5	0,066481	35,95368	41,21230	8,373308	13,02290	1,437814
6	0,066571	35,85869	41,30767	8,384401	13,01021	1,439037
7	0,066629	35,79687	41,40482	8,372392	12,98761	1,438314
8	0,066632	35,79485	41,40553	8,373121	12,98685	1,439645
9	0,066632	35,79470	41,40455	8,373145	12,98772	1,439884
10	0,066633	35,79368	41,40592	8,373065	12,98748	1,439855

The above results can show that the influence of BTCUSDT and ETHUSDT are the most important factors with the overall market volatility. In order to compare the degree of influence of the two currencies, excluding the market value, the results of the variance decomposition are averaged. Following are the results: BTCUSDT's volatility accounted for 46.36% of the overall movements in digital currencies, but ETHUSDT's explanatory power was only 15.46%. Compared with the two, the fluctuation influence of BTCUSDT is about three times that of ETHUSDT. This result is different from the conclusion drawn by Nikolaos and Ioannis (2019). Most market fluctuations are explained by BTCUSDT without taking into account, the market value. Its explanatory ability far exceeds the interpretation ability of ETHUSDT.

5. CONCLUSION

Results from the analysis of the main currency-to-price fluctuation in digital money market, using the Granger causality test, Pearson correlation coefficient and variance decomposition show: 1) The price change of BTCUSDT is the reason behind all other currency price change, but the fluctuation change of BTCUSDT can be explained by its own fluctuation. The fluctuation of other currency makes little contribution to the fluctuation of BTCUSDT. 2) In terms of the contribution made to the overall market volatility, the impact of BTC on the market volatility is greater than the impact of ETH on the market volatility. 3) XRP volatility can be explained by its own volatility, and the currency's trend is quite different from other currencies.

The change in BTC price causes change in other currency prices. However, other currencies have little effect on the fluctuation of BTC, which is consistent with the situation of most investors in the digital money market. Bitcoin is the "big-cap index" of the digital money market, accounting for 50% of the market capitalization. The interaction of other currencies has little effect on the change of Bitcoin price. Part of the reason for the fluctuation of Bitcoin price comes from investors' overall expectations of the digital money market and partly comes from the market's expectations of the trend of Bitcoin's individual currency. However, there is great uncertainty as to whether bitcoin's dominance will continue. CoinMarketcap's market capitalization announcement showed that bitcoin, which accounted for 70% of the digital money market before 2017, had an absolute dominant role, according to CoinMarketcap's market value announcement. But by early 2017, its dominance had gradually declined, falling below 40% in late 2017 and returning to 50% in 2019. The emergence of many currencies in the digital money market and the rapid expansion of XRP have led to a gradual dispersion

of market share and a decline in the dominance of Bitcoin.
BTC and ETH, as the two main currencies used to hedge overall digital money market risks, have long been debated by investors as to which has better hedging effect. Based on Pearson correlation coefficient, ETH has been found to have better hedging effect on the overall market in the period from September 2018 to January 2020. However, the variance decomposition results show that BTC contributes more to the overall market than ETH. How to have a better hedge against the market risk requires the use of DCC or BEKK model to estimate the dynamic correlation between them. But according to the test results of this paper, it can be preliminarily concluded that the dominant volatility of the digital money market is still due to the price fluctuation of BTC.

The relative independence of XRP (Ripple) correlated stronger with its underlying information. Unlike Bitcoin, which has the concept of value storage, the concept of XRP comes from Ripple system (Rock, 2018)—an open payment network, which serves as a credit intermediary for currency circulation and automatically provides the search function of the optimal payment path. The main function of XRP is to pay the transaction cost in the Ripple system. Unlike Bitcoin's energy-intensive mining, XRP is initially limited to issuing 100 bn dollars. After each payment is completed, the XRP that is used for payment is destroyed and Ripple's development company OpenCoin will make a profit by issuing and selling new XRP. XRP's characteristics as a source of value for the Ripple system are very different from that of other digital currencies. This leads to the volatility of XRP which is only partly dependent on the expectation of the overall digital currency. This is mostly due to investors' expectation of the sophistication of the Ripple system and the function of replacing the traditional bank currency in the future.

DISCLOSURE OF POTENTIAL CONFLICTS OF INTEREST

No potential conflict of interest was reported by the author(s).

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