Volatility Spillovers of New Cryptocurrencies Over Traditional Cryptocurrencies in the NFT Market: A Case Study of Mana

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Abstract
This study uses the DCC-GARCH model to compare the correlation between two types of cryptocurrencies in two different fields. In the context of the popularity of NFTs and the metaverse, new cryptocurrencies based on the metaverse have been favored by investors. Through empirical analysis of mana cryptocurrencies in the NFT market, we find that the new cryptocurrencies in the NFT market have high volatility to Bitcoin, Ethereum, and traditional cryptocurrencies in the past year. Therefore, we conclude that new cryptocurrencies are more likely to be one of the factors for portfolio diversification.

Keywords: *NFT; cryptocurrency; DCC-GARCH model; Volatility Spillovers; Cryptofinance*

1. INTRODUCTION

Cryptocurrency is getting more and more attention as a brand new technology and investment product with incredible returns and risks. Also have the research of portfolio diversification, hedge and a safe haven in other financial assets, the stock market, etc. [1][3][5], research[1] has shown that although encryption monetary predictive power is completely different from stock, the tail dependence found two kinds of market volatility has a short-term impact, thus it is concluded that money can buy encryption to spread the risk of the stock market.

The correlation between cryptocurrencies and the stock market has also been observed through research[2] during periods of uncertainty. The study used quantile regression to estimate the bitcoin returns of the S&P index market during periods of a low, medium, and high uncertainty, Cryptocurrencies have shown a higher correlation with the stock market during periods of uncertainty (COVID-19). Research[7] suggests bitcoin is not a safe haven for securities. Some previous studies have pointed to Bitcoin as a hedge asset against the S&P 500 stock market[6].

Since the COVID-19 pandemic, METAVERSE and Non-fungible Token (NFT) concepts have come into focus. The concept of Metaverse is defined as the post-reality universe in the study[11]. Through the fusion of technologies, the virtual environment, digital objects, and human multi-sensory interaction can be realized. VR and AR are good examples. The study[12] points out that Non-Fungible Token (NFT) is an emerging technology prevailing in the Block-chain market.

Two interrelated new products come into the public's view, and many investors have predicted the market of NFT. Therefore, It is worth exploring the impact of new cryptocurrencies in NFT on the value of traditional cryptocurrencies (Bitcoin, Ethereum)We investigated the cryptocurrencies most represented in the NFT: Mana.

To study the influence of the NFT market on the traditional cryptocurrency stock market, we adopt[8] the Autoregressive conditional heteroskedasticity model (ARCH model).ARCH model is used to predict the variance of time series, which can measure the risk, so GARCH models are highly valued in the financial field. We adopt the [13]DCC-GARCH model, which is used to study the effect of risk transfer between different markets. By comparing the stock market fluctuations of traditional cryptocurrencies bitcoin and Ethereum with those of popular cryptocurrencies Mana in NFT, we illustrate the volatility and correlation between two different types of cryptocurrencies, analyze investors' preference for new

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cryptocurrencies in the NFT market, and study the volatility spillover effect between the two.

This method is The first is to establish a univariate ARMA-GARCH family model, select the most suitable model as the final univariate model, and then estimate the corresponding DCC-GARCH model. Finally, the risk overflow measurement and analysis are carried out through the DCC-GARCH model.

Through model analysis, some conclusions can be inferred: the overall risk spillover of the traditional cryptocurrency market to the Metaverse market is significantly lower than the risk spillover in the opposite direction, and both the conditional value at risk and the absolute risk spillover value are significantly smaller than the opposite direction. In addition, the data can show the degree of favor of investors in the meta-universe and NFT market. Finally, we can conclude whether there is bubble behavior in the popularity of the NFT market by comparing the data.

2. RELATED WORKS

At present, in times of high uncertainty, the correlation between stocks and cryptocurrencies is as long as the research direction is COVID-19[1][7]During periods of high uncertainty, the stock market's return in the previous week significantly affects bitcoin's return Comparing two different areas of cryptocurrencies also has significant implications.

The [2] shows that the predictive power of cryptocurrencies and the stock market is completely different, and the volatility of both markets has a short-term impact. With the tail dependence of bitcoin and the stock market during the COVID-19 pandemic, the same model can be used to compare the responsiveness of two different cryptocurrencies.

In article[3], the continuity of the stock market and investor sentiment is studied, and the volatility of bitcoin is judged by the GARCH model and STANDARD & POOR'S 500 indexes. It is found that bitcoin can serve as a safe haven during periods of high stock market volatility, and bitcoin is attractive to investors when the stock market is stable. In Russia, cryptocurrencies and the stock market may become even more closely linked.

At the same time, the GARCH model proposed in articles[8][9] to calculate the correlation between other markets and the stock market also provides a good model basis. We can use the same model to conduct data analysis on the volatility of two cryptocurrencies in different fields on the stock market.

The introduction of the concepts of Metaverse and NFT in two articles[11][12] helps us to better understand the new cryptocurrency market.

3. METHOD

3.1.Data selection

This paper adopts the one-year price data of ETH, BTC, and MANA in the website:http:coinmarketcap.com, among which BTC and ETH are traditional cryptocurrencies and MANA is a new cryptocurrency in the Metaverse. To maintain the consistency of data, we selected the data from March 17, 2019, to March 10, 2019, to calculate the risk spillover effect.

3.2.Univariate GARCH family modeling

3.2.1.Sequence ADF test

The premise of analyzing time series is to judge its stationarity. The main methods used are a graphical method, ADF test method, etc. This paper uses the ADF test method, namely unit root test method, null hypothesis: $\omega=0$, alternative hypothesis: $\omega<0$, when the t statistic is less than the critical value at a given significance level, it means that the null hypothesis is rejected, and the sequence does not have a unit root and is stationary, otherwise it is not stationary.

Most financial time series are non-stationary series, so firstly, the time series after taking the logarithm is automatically identified by the different order. The identification result shows that there is a first-order single integer, and then the ADF stationarity is performed on the differentially processed series. The results(Table 1) show that the series is stationary at the 99% significance level.

TABLE I. ADF STATIONARITY TEST 1

Augmented Dickey-Fuller Test
data: dbtc
Dickey-Fuller = -7.3741, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

TABLE II. ADF STATIONARITY TEST 2

Augmented Dickey-Fuller Test
data: deth
Dickey-Fuller = -6.618, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

TABLE III. ADF STATIONARITY TEST 3

Augmented Dickey-Fuller Test
data: dmana
Dickey-Fuller = -6.7603, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

3.2.2.LB Test

A conditional heteroskedasticity test, the so-called ARCH effect test, is performed. Two tests can be used for the ARCH effect test. The first test is to apply the commonly used Ljung-Box statistic Q(m) to the residuals of the mean equation. sequence, the null hypothesis of this test statistic is that the ACF values of the first m intervals of the residual sequence are all zero; the second is the Lagrange multiplier test.

This empirical test uses the Ljung-Box statistic Q(m) to test the conditional heteroskedasticity of the three series. The statistics corresponding to the square of the model residuals are 32.148, 79.291, and 20.535, and the corresponding p-values are 0.001313, 5.633e-12, and 0.05762, indicating that there is a strong ARCH effect.

3.2.3.The fitting results

Fit the selected model and summarize the parameters as follows. After screening the p-value, the fitting model for the logarithmic return series of BTC is selected: the innovation is a GED distribution with a degree of freedom of 1.199637 (generalized error distribution). for the EGARCH(1,1) model:

$$a_t = \sigma_t \varepsilon_t, \qquad \varepsilon_t \sim GED$$
$$\ln(\sigma_t^2) = -0.353076 - 0.076420(|\varepsilon_{t-1}| + 0.047389\varepsilon_{t-1}) + 0.9459200\ln(\sigma_{t-1}^2) \quad (1)$$

Fit the selected model and summarize the parameters as follows. After screening the p-value, the fitting model of the logarithmic return series ETH is selected: the innovation is a GED distribution with a degree of freedom of 1.119098 (generalized error distribution). for the ARMA(5,5)-GARCH(1,1) model:

$$\begin{aligned} r_t = 0.002388 + a_t - 2.813126r_{t-1} - 3.862388r_{t-2} \\ - 3.699524r_{t-3} - 2.336678r_{t-4} \\ - 0.643243r_{t-5} - 2.804753a_{t-1} \\ - 3.876088a_{t-2} - 3.783924a_{t-3} \\ - 2.442052a_{t-4} - 0.677763a_{t-5}, \end{aligned}$$
$$a_t = \sigma_t \varepsilon_t, \qquad \varepsilon_t \sim GED$$
$$\sigma_t^2 = 0.000136 + 0.050773a_{t-1}^2 + 0.894805\sigma_{t-1}^2 \quad (2)$$

Fit the selected model and summarize the parameters as follows. After screening the p value, the fitting model of the logarithmic return series MANA is selected: the innovation is a SNORM distribution with a skewness of 1.024078 (skewed normal distribution) of the ARMA(5,5)-TGARCH(1,1) model:

$$\begin{aligned} r_t = 0.002107 + a_t - 0.455116r_{t-1} + 0.322024r_{t-2} \\ + 0.570679r_{t-3} + 0.591861r_{t-4} \\ - 0.053573r_{t-5} - 0.440228a_{t-1} \\ + 0.434652a_{t-2} + 0.6173164a_{t-3} \\ + 0.552264a_{t-4} - 0.048222a_{t-5}, \end{aligned}$$
$$a_t = \sigma_t \varepsilon_t, \qquad \varepsilon_t \sim N^*$$
$$\sigma_t^2 = 0.034195 + (0.359678 - 0.246546N_{t-1})a_{t-1}^2 + 0.291636\sigma_{t-1}^2 \quad (3)$$

3.3.DCC-GARCH family model construction

3.3.1.Dynamic Correlation Analysis

The parameters of the DCC-GARCH model are obtained by a two-step method. First, a univariate ARMA-GARCH family model is established, and the most suitable model is selected as the final univariate model, and then the corresponding DCC-GARCH model is carried out. Model estimates. The three indicators have been modeled separately before, so the R software is used to estimate the parameters of the model.

First, the model based on the BTC and MANA logarithmic return series is investigated. The estimation results show that the parameters are significantly significant. Among them, are the parameters of the DCC model, these two parameters are non-negative scalar parameters, and the two are added together. Less than one, it meets the constraints of the model. Among them, it can be seen from the definition formula of the dynamic correlation coefficient that it is too small, indicating that the product of the standardized residuals of one lag period has little influence on it, and the value is too large, indicating that it is more affected by the previous period.

Secondly, the model based on the ETH and MANA logarithmic rate of return series is investigated. The estimation results show that the parameters are significantly significant. The parameters of the DCC model, as can be seen from the dynamic correlation coefficient definition formula, are relatively small, indicating a lag of one period. The product of the standardized residuals has little effect on it, and the value is too large, indicating that it is greatly affected by the previous period. Compared with ETH and BTC, the parameters of the DCC model constructed by MANA are smaller, but larger, indicating that the feedback of the latter's dynamic correlation coefficient on the previous impact and the impact of the product of the standardized residuals of one lag period is made. The feedback is stronger than that.

3.3.2.Calculation of Risk Spillover Effects

According to the DCC-GARCH model constructed in the previous chapter, the risk spillover effects between BTC, ETH and MANA are calculated respectively. CoVaR measures the risk loss faced by another market when the maximum possible risk loss occurs in one market, not only The risk loss of a single market is considered and the risk spillover information of another market is also included, while ΔCoVaR deducts the unconditional risk loss faced by the market. In order to reflect the degree of risk spillover of the two markets to each other under different market conditions, especially under extremely severe market risks, the q values are selected as 0.05 and 0.01. The smaller the q value, the worse the market conditions are. The size of the risk spillover effect, the empirical results are shown below, and the descriptive statistics of CoVaR and ΔCoVaR are given respectively. Taking bm_0.05 as an example, the meaning of this indicator in the following two tables is at the significance level of 0.05. The result of the conditional value-at-risk and absolute risk-overflow value of BTC to MANA. ΔCoVaR reflects the absolute magnitude of risk spillovers, while %ΔCoVaR, which is different from this, eliminates the dimensional impact, reflects the relative magnitude of risk spillovers, and can more accurately reflect when one market is in an extreme situation, the other A market risk spillover effect.

Descriptive statistics for the results of the CoVaR value calculation:

TABLE IV. CALCULATION RESULT TABLE OF CoVaR VALUE

	Min.	1stQu.	Median	Mean	3rdQu.	Max.
bm0.05	*-2.154e-03*	*-1.313e-03*	*-9.386e-04*	*-9.883e-04*	*-6.823e-04*	*-3.796e-05*
bm0.01	*-3.478e-03*	*-2.083e-03*	*-1.475e-03*	*-1.560e-03*	*-1.066e-03*	*-5.992e-05*
mb0.05	*-0.389712*	*-0.018592*	*-0.007101*	*-0.009400*	*0.001380*	*0.081652*
mb0.01	*-0.647200*	*-0.026264*	*-0.013164*	*-0.017965*	*-0.003814*	*0.059091*
em0.05	*-0.0377788*	*-0.0033337*	*-0.0003544*	*-0.0005919*	*0.0023313*	*0.0368862*

Descriptive statistics for the results of the ΔCoVaR value calculation:

TABLE V. CALCULATION RESULT TABLE OF ΔCoVaR VALUE

	Min.	1stQu.	Median	Mean	3rdQu.	Max.
bm0.05	*-1.786e-03*	*-1.038e-03*	*-7.236e-04*	*-7.715e-04*	*-5.153e-04*	*-2.962e-05*
bm0.01	*-3.110e-03*	*-1.808e-03*	*-1.260e-03*	*-1.343e-03*	*-8.971e-04*	*-5.157e-05*
mb0.05	*-0.3194524*	*-0.0109295*	*-0.0076449*	*-0.0106262*	*-0.0054818*	*-0.0008439*
mb0.01	*-0.576941*	*-0.019739*	*-0.013807*	*-0.019191*	*-0.009900*	*-0.001524*
em0.05	*-0.0063895*	*-0.0019819*	*-0.0014407*	*-0.0016031*	*-0.0009900*	*-0.0001002*
em0.01	*-0.0114434*	*-0.0035495*	*-0.0025803*	*-0.0028710*	*-0.0017730*	*-0.0001795*
me0.05	*-0.209147*	*-0.008735*	*-0.006035*	*-0.008200*	*-0.004594*	*-0.001457*
me0.01	*-0.377725*	*-0.015776*	*-0.010899*	*-0.014810*	*-0.008297*	*-0.002631*
bm0.05	*-1.786e-03*	*-1.038e-03*	*-7.236e-04*	*-7.715e-04*	*-5.153e-04*	*-2.962e-05*

Descriptive statistics for the calculation of the %ΔCoVaR value:

TABLE VI. CALCULATION RESULT TABLE OF %ΔCoVaR VALUE

	Min.	1stQu.	Median	Mean	3rdQu.	Max.
bm0.05	*0.009065*	*0.173549*	*0.227402*	*0.235084*	*0.309589*	*0.462743*
bm0.01	*0.01578*	*0.30215*	*0.39591*	*0.40929*	*0.53900*	*0.80565*
mb0.05	*-58.0842*	*-0.2485*	*0.4664*	*-0.1380*	*0.9528*	*66.1529*
mb0.01	*-104.9019*	*-0.4488*	*0.8423*	*-0.2492*	*1.7208*	*119.4741*
em0.05	*-16.05380*	*-0.14497*	*0.04209*	*-0.12316*	*0.17026*	*4.46429*
em0.01	*-28.75164*	*-0.25964*	*0.07538*	*-0.22057*	*0.30493*	*7.99534*
me0.05	*-49.2784*	*-0.2470*	*0.3523*	*-0.1747*	*0.7465*	*51.7132*
me0.01	*-88.9982*	*-0.4461*	*0.6362*	*-0.3155*	*1.3481*	*93.3957*
bm0.05	*0.009065*	*0.173549*	*0.227402*	*0.235084*	*0.309589*	*0.462743*

4. DISCUSSION

Since the concept of Metaverse was put forward and NFT has been active in the public's field of vision in the past year, many investors have a very positive attitude towards NFT, so the research on NFT is indispensable. Based on the DCC-GARCH model, it is applied to two different cryptocurrencies to study their volatility, which is very helpful for the connection between cryptocurrencies.

In this paper, two DCC-GARCH models are established based on the BTC and MANA logarithmic yield sequence, and the ETH and MANA logarithmic yield sequence. Various CoVaR values were used to measure the risk spillover effect. At a higher or lower level of significance, that is, under the condition of different degrees of market risk, (1) the risk spillover effect between the two markets is asymmetric. It can be clearly seen from various descriptive statistical indicators that traditional The overall risk spillover of the cryptocurrency market to the Metaverse market is significantly lower than the risk spillover in the opposite direction, and both the conditional value at risk and the absolute risk spillover value are significantly smaller than the opposite direction; (2) From a horizontal perspective, the risk spillover of BTC to MANA Slightly lower than ETH; MANA's risk spillover to BTC is generally higher than to ETH.

Taking the mean as the observation indicator, (1) overall, the risk spillover effect of BTC on MANA is stronger, and the risk spillover direction of the two is opposite; (2) the risk spillover effect of the Metaverse market on BTC is significantly smaller than that of ETH, and the risk The overflow direction is the same. In addition to the positive relative risk spillover from ETC to MANA, the mean values of CoVaR, ΔCoVaR and %ΔCoVaR are all negative, indicating that there are basically mutual, significant and negative risks between these two markets Spillover Effect. (3) At a smaller significance level, the risk spillover effect is more obvious, indicating that under different market risk conditions, there are significant differences in the degree of risk spillover between markets. The worse the market risk condition, the more obvious the risk spillover effect.

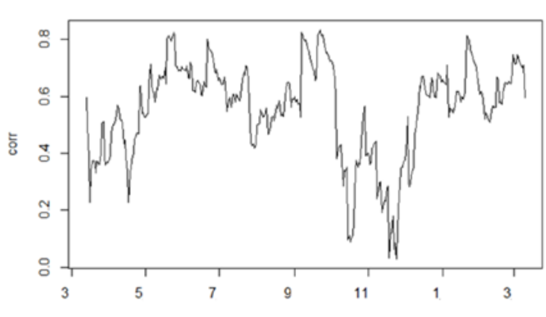

Figure 1. BTC-MANA market dynamic correlation coefficient trend chart

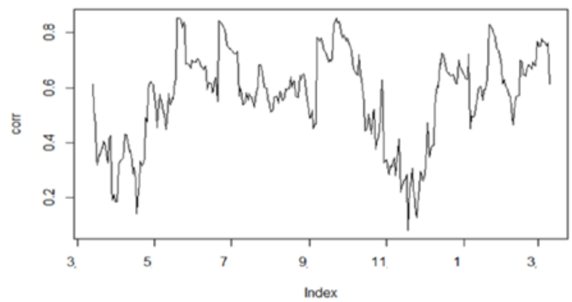

Figure 2. ETH-MANA market dynamic correlation coefficient trend chart

This data only includes the one-year closing price of a cryptocurrency in the Metaverse. It does not form a general overview of the overall NFT market, and the NFT market may have a different impact on the stock market. In the future, it may be possible to analyze the bubbles in the NFT market from multiple angles, which will have a deeper meaning for investors.

5. CONCLUSION

We study the volatility spillover effect of new cryptocurrencies on traditional cryptocurrencies in the context of the Metaverse and NFT in recent years.

Through the DCC-GARCH model, we established the relationship between the two types of cryptocurrencies and found a strong correlation between the two cryptocurrencies. It can be inferred that under the background of NFT, the new cryptocurrency will have an impact on the traditional cryptocurrency.

This research is conducive to the study of bubbles in the NFT market and the emotional behavior of investors, to speculate that the NFT market has an impact on the traditional cryptocurrency market, and the volatility of the NFT market on the stock market is also worthy of our research and exploration.

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