Research on the Linkage Between the US and China Stock Markets in the Context of COVID-19 Based on the EMD Model

Yunfa Wen*, Xinghua Liu

School of Management Science and Engineering, Shandong University of Finance and Economics, Jinan, 230200, China

*The corresponding author’s e-mail: 192106020@mail.sdufe.edu.cn

Abstract. Using the COVID-19 and the Sino-US trade war as the background, the data of the stock markets in China and the US from March 1, 2017 to September 11, 2020 are divided into 3 phases, and the high-frequency return series are extracted by empirical mode decomposition algorithm, excluding the interference of the medium-frequency data and low-frequency data. The DCC-GARCH model is used to analyze the China-US stock market linkage in the 3 phases, and the results show that: both the China-US trade war and the COVID-19 have a significant impact on the China-US stock market linkage. The Sino US trade war makes the linkage of Sino US stock market decline in the short term, while The COVID-19 made the relationship between China and the United States present an inverted "U" shape of first rising and then falling.

1. Introduction

With the integration of the global economy, the interconnection between the capitalist markets of various countries has increased significantly. As the world's largest market, the United States has a strong influence in the world. China's trade with the United States is very close, and the stock market is becoming more and more interconnected. On March 22, 2018, the United States issued the "301 Investigation Report", and the Sino-US trade war began; at the end of 2019, the COVID-19 broke out in the world. The world stock market fluctuates frequently and the recovery is slow. How does the linkage between the Chinese and American stock markets change? What is the difference in the impact of the two major events on the linkage between the Chinese and American stock markets? These are very important questions.

2. Related Work

Scholars have carried out extensive research on the linkage of Chinese and American stock markets. K Shehzad and X Liu implied VARX-DCC-MEGARCH model to investigate the dynamic correlation between China and U.S. stock markets. They found that daytime returns of U.S. stock markets affect the overnight returns of Chinese stock markets. And during the financial crisis, the volatility spillovers between china stocks market was significant on one hand and leverage effect for U.S. and Chinese stock markets were also significant on the other hand. Additionally, returns and volatility spillovers between china markets of the United States was also significant[1].M Xu and P Shang applied Empirical mode decomposition (EMD) to financial time series and the IMFS are grouped into high-, medium-, and low-frequency components, representing the short-, medium-, and long-term volatilities of the index sequences, respectively. They found that with the cross-correlation analysis of DCCA cross-correlation coefficient, their findings would gain further and detailed insight into the cross-correlations of stock markets[2].H Liu compared the stock markets of China and the United States from several aspects and...
expounded the transmission channel of stock market linkage and the related theory of stock market linkage. The conclusion is that with the development of China's economy and opening of the stock market system, the stock market linkage between China and the United States is increasing gradually[3].

3. Method

3.1. Empirical Mode Decomposition
Empirical Mode Decomposition (EMD) was first proposed by Huang, a member of the American Academy of Engineering, in 1998. This method uses the time-scale characteristics of the data itself to decompose signals. The decomposition process is not based on any preset basis function. Due to this feature, the EMD method can be applied to any type of signal decomposition in theory, and can deal with non-stationary and non-linear data very effectively[4].

EMD is a kind of selecting of signals. The inherent fluctuation components of different scales of the signal (time series) are extracted from high frequency to low frequency, and the intrinsic mode function (IMF) of different frequencies and the trend item of the sequence are adaptively extracted step by step. The decomposed IMF must meet the following two conditions: First, the number of extreme points and the number of zero-crossing points in each IMF component data are the same or at most one difference; secondly, the upper and lower envelopes are locally symmetrical about the time axis. At any time, the mean value of the upper and lower envelopes determined by the local maximum and local minimum is zero.

3.2. Dynamic Conditional Correlation Multivariate GARCH
Engle (2002) proposed a dynamic conditional correlation coefficient autoregressive conditional heteroscedasticity model (DCC-GARCH model), which assumes that the correlation coefficient between variables changes with time, and the correlation coefficient of each period depends on the previous period. With all the information available, the model can well describe the linkage between variables. The model assumes that the residual items of the return rate series follow a normal distribution with a mean of zero and a covariance matrix.

The calculation of the DCC-GARCH model is divided into two steps: first, a univariate GARCH model is established for each variable, and the residual is divided by the conditional variance to obtain the standardized residual sequence; secondly, the standardized residual sequence obtained in the previous step is used to calculate the dynamic conditional correlation coefficient.

4. Empirical analysis

4.1. Empirical design
This article first uses the EMD model to extract the high-frequency data of the daily return of the Dow Jones Index and the Shanghai Composite Index, and divides the high-frequency data into three stages according to the major events in the Sino-US trade war and the COVID-19, and then establishes the DCC-GARCH model to explore The linkage between the Chinese and American stock markets. Finally, this article compares the impact of the China-US trade war and COVID-19 on linkages.

4.2. Data selection and processing
In the data selected in this article, the DJI is used as the representative of the US stock market, and the SSEC is used as the representative of the Chinese stock market. The background of this research is the Sino-US trade war and the COVID-19, so the daily closing price data of the Dow Jones Industrial Index(DJI) and Shanghai Stock Exchange Index(SSEC) from March 1, 2017 to September 11, 2020 are selected.

On March 22, 2018, the United States released the "301 Investigation Report". The Sino-US trade friction has intensified and a series of trade confrontations have been launched. On January 20, 2020, after the announcement of the confirmation of "person-to-person transmission", China gradually began...
to implement the quarantine policy across the country, and the stock market was affected to a certain extent. This article selects the two key events of the COVID-19 and the Sino-US trade war as nodes, divides the data into three stages, and analyzes the changes in the linkage of the Sino-US stock market.

Phase 1: From March 1, 2017 to March 22, 2018; Phase 2: From March 23, 2018 to January 20, 2020; Phase 3: From January 21, 2020 to September 11, 2020.

After preprocessing the data, a total of 1083 pairs of data were obtained. The rate of return on the stock market is calculated using the following formula:

$$R_{i,j} = \ln P_{i,j} - \ln P_{i,j-1}$$ (1)

Among them, $R_{i,j}$ indicates the rate of return on day $t$; $i=1$ represents the Dow Jones Index; $i=2$ represents the Shanghai Stock Exchange Index.

4.3. Empirical Mode Decomposition

We can get that the sample data of the daily yields of the Chinese and American stock markets have shown a relatively obvious common trend in the selected time range. And the daily return rate of my country's stock market has changed more drastically.

The daily return rate data series of the Chinese and American stock markets have obvious nonlinear and non-stationary characteristics. The EMD method can decompose nonlinear and non-stationary signals. Therefore, the EMD method can be used to filter out a number of basic mode functions (IMFs) and trend items. The DJI and the SSEC have 9 IMFS items and a long-term trend item after EMD decomposition, as shown in Figure 1 and Figure 2.

![Figure 1](image1.png) The EMD decomposition results of DJI.

![Figure 2](image2.png) The EMD decomposition results of SSEC.
Through the t statistical test, it can be found that the daily return of the DJI is significantly non-zero in IMF9, then IMF1 to IMF8 are high-frequency components, IMF9 is low-frequency components, and the residual term represents the trend term. The daily return rate of the SSEC is significantly non-zero in IMF7, then IMF1 to IMF6 are high-frequency components, IMF7 to IMF8 are low-frequency components, and the residual term remains unchanged as a long-term trend term. The high-frequency component generally represents the short-term fluctuations of the stock market, the low-frequency component represents the influence of major events in the medium-term, and the trend item represents the long-term trend of the stock market. This article mainly studies the short-term changes in the correlation coefficient of the daily return data of Chinese and American stocks. Therefore, the high-frequency data is selected for the following research to eliminate the interference of low-frequency components and long-term trends.

4.4. Analysis of the Volatility Correlation of the High Frequency Return Rate Series of the Stock Markets

4.4.1. Descriptive statistics of high-frequency yield series
A statistical analysis of high-frequency data during the entire sample period (Table 1) shows that, from an average point of view, the Sino-US trade war and the COVID-19 have had a negative impact on the Chinese and US stock markets. From the perspective of skewness, kurtosis and JB statistics, the high-frequency yield series of the DJI and the SSEC both show the characteristics of "spikes and thick tails", and the corresponding P value indicates that the yield does not follow a normal distribution.

|                  | DJI       | SSEC      |
|------------------|-----------|-----------|
| Mean             | 0.000123  | 0.000272  |
| Median           | 0.000181  | 0.000443  |
| Maximum          | 0.108948  | 0.054408  |
| Minimum          | -0.136922 | -0.076416 |
| Std.Dev.         | 0.012902  | 0.010206  |
| Skewness         | -1.066687 | -0.639197 |
| Kurtosis         | 30.46180  | 10.39135  |
| Jarque-Bera      | 34204.81  | 2536.674  |
| Probability      | 0.000000  | 0.000000  |

4.4.2. Stationarity test
Before modeling the time series, it is necessary to test the stationarity of the data, that is, the unit root test. This article uses the commonly used ADF test. The test results show that both the DJI high-frequency return series and the SSEC high-frequency return series are far less than the critical value of 1%. That is, the high-frequency return rate series of the Chinese and American stock markets have passed the unit root test, and the series is stable.

4.4.3. ARCH-LM test
Only after the ARCH test can the subsequent application of the DCC-GARCH model be carried out. The test results show that the P values of the three stages are all less than 0.05. It can be concluded that the high-frequency data of the DJI and the SSEC have the ARCH effect in the three stages.

4.4.4. Univariate GARCH model estimation
According to the estimation steps of the DCC-GARCH model, the univariate GARCH model must first be established and estimated. The GARCH (1, 1) model is used to fit the high-frequency return sequence data at each stage, and the maximum likelihood estimation method is used. The results show that the US
stock market is more sensitive to new information than the Chinese stock market and the two stock markets is relatively significant.

4.4.5. Multivariate DCC-GARCH model estimation results

We set the conditional variance to the form of GARCH(1,1), and the order of the DCC model is 1, The estimated results of model parameters obtained by using R are shown in Table 2.

| DCC coefficient estimation results. |
|-----------------------------------|
| α       | β             |
| Phase one | 0.037620   | 0.915051   |
| Phase two | 0.003609   | 0.918086   |
| Phase three | 0.038595  | 0.914609   |

From the parameter estimation results, it can be seen that the standardized residual of one period has a significant impact on the dynamic correlation coefficient, and the β value is close to 1, indicating that the correlation has a strong persistent characteristic. The sum of the two parameters is close to 1, indicating that SSEC and the DJI are related, and the impact is continuous. Furthermore, we obtain the dynamic correlation coefficient of the Chinese and American stock markets during the sample period, as shown in Figure 3.

The correlation coefficients of the Chinese and American stock markets in the sample data have always been positive, and the stock markets of the two countries have a weak positive correlation. The dynamic correlation coefficient of Phase 2 has a significant downward trend in the short term. On March 22, 2018, USTR released the investigation results "301 Report". After that, China and the United States launched a series of trade confrontations, and Sino-US trade frictions intensified. The coordinate in the corresponding figure is x=321. Near this point in time, the dynamic correlation coefficients of the high-frequency yield series of China and the United States are obviously smaller, and the correlation of the stock market is reduced.

The dynamic correlation coefficient of phase 3 is further reduced. On January 20, 2020, China has gradually begun the quarantine policy nationwide, and the impact of the epidemic on China stock market has begun to appear, corresponding to the coordinate x=885. From this point on, the dynamic correlation coefficient of the high-frequency yield series of China and the United States has become significantly smaller, indicating that the impact of the epidemic on my country's stock markets has reduced the volatility correlation between the Chinese and American stock markets.
The trade between China and the United States have a certain impact on the linkage of the two countries' stock markets. The impact of the COVID-19 has caused that the dynamic correlation coefficient of the Chinese and American stock markets first rises and then falls, as an inverted "U" shape. After the outbreak of the domestic COVID-19, the uncertainty of the future trend of the stock market has increased. Investors' judgments on the China stock market mainly rely on the international market. At this time, there are no confirmed cases in American, and the stock market is operating smoothly. So the correlation between the stock markets of the two countries has increased. With the China government's active measures to combat the epidemic, the epidemic has gradually been brought under control in China, investor psychology has become more rational, and confidence in chinese stock market has increased. Coupled with the aggravation of the epidemic abroad, the impact of the US stock market on the epidemic has increased, resulting in the stock markets of both countries and the relevance is reduced.

5. Conclusion
This paper uses the EMD model to extract the high-frequency yield series of China and the United States to establish a DCC-GARCH model to study the changes in the linkage between the Sino-US stock markets under the background of the Sino-US trade war and the COVID-19. The study found that both the China-US trade war and the COVID-19 have a significant impact on the China-US stock market linkage. The Sino US trade war makes the linkage of Sino US stock market decline in the short term, while The COVID-19 has raised the linkage between China and the US market first and then dropped in an inverted "U" shape.

References
[1] Shehzad K, Liu X, Tiwari A, et al 2020 Analysing time difference and volatility linkages between China and the United States during financial crises and stable period using VARX-DCC-EGARCH model International Journal of Finance & Economics. 1 814-834
[2] Xu M, Shang P, Lin A 2016 Cross-correlation analysis of stock markets using EMD and EEMD Physica A: Statistical Mechanics and its Applications. 442 82-90
[3] Liu H 2018 Analysis of the Differences and Linkage between Chinese and American Stock Markets American Journal of Industrial and Business Management. 08(3) 700-709
[4] Jian Cao,Zhi Li,Jian Li 2018 Financial time series forecasting model based on CEEMDAN and LSTM Physica A: Statistical Mechanics and its Applications. 519 127-139