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Research on the Dynamic Volatility Relationship between Chinese and U.S. Stock Markets Based on the DCC-GARCH Model under the Background of the COVID-19 Pandemic

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Abstract

This study utilizes the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model to investigate the dynamic relationship between Chinese and U.S. stock markets amid the COVID-19 pandemic. Initially, a univariate GARCH model is developed to derive residual sequences, which are then used to estimate the DCC model parameters. The research reveals a significant rise in the interconnection between the Chinese and U.S. stock markets during the pandemic. The S&P 500 index displayed higher sensitivity and greater volatility in response to the pandemic, whereas the CSI 300 index showed superior resilience and stability. Analysis and model estimation suggest that the market's dependence on historical data has intensified and its sensitivity to recent shocks has heightened. Predictions from the model indicate increased market volatility during the pandemic. While the model is proficient in capturing market trends, there remains potential for enhancing the accuracy of specific volatility predictions. The study proposes recommendations for policymakers and investors, highlighting the importance of improved cooperation in international financial market regulation and investor education.

Keywords

DCC-GARCH Model, Stock Market Linkage, COVID-19, Market Volatility, Forecasting Analysis

1. Introduction

As China's economic strength grows and its stock market system improves, the interaction between the Chinese and U.S. stock markets has become increasingly close. Particularly since the outbreak of COVID-19, the linkage between the Chinese and U.S. stock markets has faced new challenges and changes, becoming a hot topic in academic research and practical operations. The pandemic has caused significant differences in economic structures and policy responses between the two countries, making the analysis of their stock market linkages more complex and challenging. This research aims to explore the linkage between the Chinese and U.S. stock markets during the pandemic, providing decision-making references for investors and policymakers.

This paper employs the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model to investigate the impact of COVID-19 on the linkage between the Chinese and U.S. stock markets. The performance of the Chinese and U.S. stock markets indicates the economic recovery in their respective countries. The study results reveal the commonalities and differences in stock market volatility during special periods, aiding investors in risk assessment and investment decision-making. Policymakers, by understanding the stock market linkage and the impact of the pandemic, can formulate more precise economic policies and intervention measures. This research enriches the theoretical study of stock market linkage and provides empirical support and policy recommendations for building a robust global financial system.

The risk spillover between financial markets in different countries has always attracted the attention of many scholars, especially since the outbreak of the COVID-19 pandemic. The DCC-GARCH model has been an important tool in this regard. Studies consistently show increased market integration and volatility spillovers during financial crises [1]-[3]. Emerging markets exhibit varying degrees of contagion from developed markets, influenced by the severity and origin of the crises [4] [5]. Intra-market sectoral analysis reveals asymmetrical volatility spillovers, with bad volatility shocks being more pronounced [6]. Relationships among different asset classes (e.g., fossil fuels, clean energy, cryptocurrencies) are dynamic and influenced by crises, presenting both challenges and opportunities for diversification [7] [8]. Smaller market cap portfolios are more adversely affected during crises, yet offer higher post-crisis returns, suggesting opportunities for targeted investment strategies [9]. Shariah-compliant markets show lower volatility and better diversification potential compared to conventional markets, particularly during crises [10]. COVID-19 news significantly impacts market volatility, with global news having a stronger effect on emerging markets [5]. State-mandated restrictions and local behaviors play crucial roles in shaping the epidemic's progression and its economic impact [11].

While many studies focus on short-term impacts, long-term analyses are relatively sparse. Extending the temporal scope to examine prolonged effects and recovery patterns would be valuable. Research often highlights the need for policy interventions but provides limited practical guidance. Future work could focus on translating findings into actionable policy recommendations for regulators and investors.

In this study, longer-term securities market data from China and the United States are used, with daily stock market return data of the S&P 500 Index (SPX) and the CSI 300 Index (CSI300) from before the epidemic (January 3, 2017 to December 31, 2019) and after the epidemic (January 2, 2020 to December 29, 2023) from China and the United States as the analysis objects. A more unified methodological framework can facilitate direct comparison and comprehensive results. Using the DCC-GARCH model for volatility analysis or using common indicators to measure spillover effects will provide clearer insights and more reliable conclusions. By addressing these issues and incorporating the suggested improvements, future research can provide more comprehensive and actionable insights into the impact of global crises such as COVID-19 on financial markets.

Building on the foundational concepts outlined in the introduction, the next section delves into the empirical methodology. This section will detail the methods and models employed to investigate the stock market linkages during the pandemic. With a clear understanding of the methodology in place, we now turn to the data and preliminary analysis in Section 3. This section provides the necessary context and justifications for the econometric models used in our empirical analysis. Having established the data foundation, Section 4 presents and interprets the results derived from the DCC-GARCH models. This analysis will shed light on the dynamic linkages and portfolio management implications during the pandemic. Finally, Section 5 synthesizes the findings from our analysis, offering concluding remarks. This section also discusses the policy implications of our findings, acknowledges the study's limitations, and suggests avenues for future research.

2. Methodology

This research utilizes time series analysis techniques, specifically the DCC-GARCH model and the cointegration tests, to examine whether a long-term stable proportional relationship exists between Chinese and U.S. stock market indices within the context of non-stationary data. The Johansen cointegration test is employed to assess the long-term equilibrium relationship between the CSI 300 Index and the SPX. Additionally, to capture and illustrate the dynamic correlation characteristics between these indices, the study applies the DCC-GARCH model to calculate the dynamic correlation coefficients. This approach effectively highlights the changes in linkage between the Chinese and U.S. stock markets across different periods, offering a fresh perspective and a detailed analysis of the interaction between the two major stock markets amid global economic fluctuations.

Current methods for estimating the dynamic correlation coefficient of financial assets primarily include the rolling historical correlation method, exponentially weighted moving averages (EWMA) method, and multivariate GARCH (MGARCH) method. The principal model utilized in this paper's empirical analysis is the one proposed by R.F. Engle [12]. This model adeptly describes the volatility of the securities market, with an ARCH (q) model [13] being described as follows:

$$x_t = f\left(t, x_{t-1}, x_{t-2}, \cdots\right) + \mu_t \tag{1}$$

$$\mu_t = \sqrt{h_t} e_t \tag{2}$$

$$h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \mu_{t-j}^2 \tag{3}$$

where Equation (1) is the mean equation, and x_t is a logarithmic returns series, x_{t-1}, x_{t-2} are the first-order and second-order lag variables of x_t, respectively, $f\left(t, x_{t-1}, x_{t-2}, \cdots\right)$ is the information set; μ_t is the residual series of the mean Equation (1), and $e_t \overset{iid}{\sim} N\left(0, \sigma^2\right)$; h_t is conditional variance and equation is called variance equation.

Bollerslev [14] enhanced the ARCH model by incorporating random disturbance terms into the variance equation, introducing the generalized autoregressive conditional heteroscedasticity (GARCH (p, q)) model, which can be formulated as:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{q} \alpha_j \mu_{t-j}^2 \tag{4}$$

Although the ARCH and GARCH models have been effective in modeling the volatility of individual assets, they fall short in describing the interdependencies among multiple assets. The ARCH model's requirement for numerous parameters to capture volatility patterns and the GARCH model's limitation to univariate time series, without addressing interdependencies between multiple series, highlight their lack of parsimony and comprehensiveness in modeling complex financial data. Consequently, the GARCH model evolved into the multivariate GARCH model to capture volatility and information spillover effects among different assets, yet it still could not fully account for the correlations and co-movements between assets. To address this limitation, Engle introduced the dynamic conditional correlation multivariate GARCH (DCC-GARCH) model, which better captures the time-varying correlations among assets [12].

The DCC-GARCH model assumes that the returns of k assets follow a mean of zero, with a covariance matrix following a conditional multivariate normal distribution:

$$r_t \mid F_{t-1} \sim N\left(0, H_t\right) \tag{5}$$

$$H_t \equiv D_t R_t D_t \tag{6}$$

Here, F_{t-1} is the information set of periods $t-1$, and $\boldsymbol{r}_t$ is a k dimensional vector of asset returns. The conditional covariance matrix $\boldsymbol{H}_t$ comprises the time-varying correlation matrix $\boldsymbol{R}_t$ and the time-varying standard deviation matrix $\boldsymbol{D}_t = diag\left\{\sqrt{h_{1,t}}, \sqrt{h_{2,t}}, \cdots, \sqrt{h_{k,t}}\right\}$, with $h_{i,t}$ is obtained from the univariate GARCH model:

$$h_{i,t} = \alpha_i + \sum_{p=1}^{p_i} \beta_{ip} h_{it-p} + \sum_{q=1}^{q_i} \alpha_{iq} \mu_{it-q}^2 \tag{7}$$

3. Data and Its Characteristics

With a solid grasp of the methodology, we now move on to Section 3, which explores the data and initial analysis. This section provides essential context and justifications for the econometric models used in our empirical study.

3.1. Data Selection and Collection

3.1.1. Data Selection

In this subsection, we concentrate on the connection between the Chinese and U.S. stock markets, using the SPX and CSI300 as representative indices. These indices are widely recognized as benchmarks of their respective national capital markets. The daily return data for these indices were obtained from the Choice Financial Terminal, ensuring their official status and accuracy. This selection method effectively captures the macroeconomic performance of the two major stock markets and their interaction within the global economy.

3.1.2. Data Collection

To examine whether the linkage between the Chinese and U.S. stock markets has changed before and after the COVID-19 outbreak, this study employs a time-segmented approach for data analysis. To comprehensively assess the pandemic's impact on the stock markets, we selected data from three years before and after the pandemic, dividing it into specific time periods. The two primary periods, Sample A and Sample B, cover the following timeframes: January 3, 2017, to December 31, 2019 (pre-pandemic), and January 2, 2020, to December 29, 2023 (post-pandemic). This division allows for a deeper understanding of how the pandemic has influenced stock market behavior.

During these periods, we collected daily return data for the CSI 300 and SPX indices, capturing market reactions before and after the pandemic. Specifically, the pre-pandemic CSI300 data includes 731 observations, and the post-pandemic data includes 971 observations, while the SPX data includes 755 pre-pandemic and 1008 post-pandemic observations. This detailed data collection approach aids in accurately assessing and comparing changes in the volatility and correlation of the Chinese and U.S. stock markets.

3.2. Data Preprocessing

To ensure the accuracy of this study, we conducted extensive preprocessing on the daily return data of the CSI300 and the SPX, covering two critical periods: January 3, 2017, to December 31, 2019, and January 2, 2020, to December 29, 2023.

1) Data Cleaning. Initially, the collected data were thoroughly cleaned by removing incomplete or incorrectly formatted records. This process included checking for missing values and outliers to ensure data completeness and consistency.

2) Synchronization of Trading Days. Since the trading days of the CSI300 and SPX do not completely align, we used Excel tools to exclude dates when either market was closed, ensuring consistency and comparability. After filtering, the

pre-pandemic and post-pandemic periods had 701 and 932 matching data points, respectively, providing a continuous and equivalent time series foundation for further analysis.

3) Daily Return Calculation. Daily returns were calculated using the formula:

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{8}$$

where P_t and P_{t-1} represent the closing prices on consecutive trading days. This formula captures the fine dynamics of daily market movements, providing fundamental data for analyzing stock market responses.

4) Data Segmentation. Considering the impact of the COVID-19 pandemic, the time series data were segmented into pre-pandemic and post-pandemic phases for independent analysis. This phased approach allows for a more accurate assessment of the pandemic's impact on the volatility and linkage of the Chinese and U.S. stock markets.

5) Selection of Empirical Analysis Tools. All data processing and preliminary analysis were completed in Excel, with further statistical tests and model estimations conducted using Eviews13 software. This combination of tools ensures efficient data processing and scientific validity of the analysis results.

These steps ensure the accuracy of the analysis data and the rigor of the empirical research. This approach not only aids in understanding changes in the linkage between the Chinese and U.S. stock markets but also provides reliable data support for studying the impact of the pandemic on global financial markets.

3.3. Descriptive Statistics

In this subsection, we will study the descriptive statistics of the daily returns of the CSI300 and the SPX to compare their performances before and after the COVID-19 pandemic. Table 1 presents key statistics for pre-pandemic periods (January 3, 2017, to December 31, 2019) and post-pandemic (January 2, 2020, to December 29, 2023). we observe significant differences in the performance of the two markets before and after the pandemic. Although both markets exhibit similarities in their data distribution characteristics, distinct economic performances are evident.

Table 1. Descriptive statistics of daily returns of the SPX and the CSI 300.

Statistic	Pre-pandemic		Post-pandemic	
	CSI300	SPX	CSI300	SPX
Observations	700	700	931	931
Mean	0.000364	0.000542	−0.000108	0.000503
Median	0.000487	0.001003	−0.000639	0.001057
Maximum	0.046992	0.035118	0.061310	0.106381
Minimum	−0.043479	−0.051342	−0.110768	−0.064876

Continued

Std. Dev.	0.011617	0.008141	0.012941	0.012336
Skewness	0.039290	−0.898035	−0.544716	0.225911
Kurtosis	4.897721	9.618580	10.06498	11.14005
Jarque-Bera Statistic (p-value)	105.2193 (0.00000)	1371.751 (0.00000)	1982.286 (0.00000)	2578.273 (0.00000)

Mean Returns. Pre-pandemic, both indices had positive mean returns, indicating an upward trend. However, while SPX maintained a positive mean, albeit lower post-pandemic, CSI300's mean turned negative, reflecting greater adjustment and downward pressure.

Volatility. Pre-pandemic, CSI300 exhibited higher volatility (standard deviation) than SPX. Post-pandemic, both indices saw increased volatility, with SPX experiencing a more significant rise.

Median Returns. Furthermore, SPX's median returns remained relatively stable, while CSI300's median dropped significantly, indicating greater downward pressure.

Extreme Values. Additionally, post-pandemic, SPX had higher maximum returns, suggesting higher positive volatility, whereas CSI300's maximum returns were lower.

On the other hand, CSI300 had more severe minimum returns, indicating higher negative volatility.

Skewness and Kurtosis. Moreover, both indices were negatively skewed, indicating a higher likelihood of extreme negative values.

Both indices exhibited leptokurtosis, with sharper peaks and thicker tails, indicating a higher probability of extreme values compared to a normal distribution.

Jarque-Bera Statistic. Importantly, both indices significantly deviated from the normal distribution, indicating that traditional financial models based on normal distribution may not capture actual market dynamics accurately.

In conclusion, the analysis reveals significant differences in the performance and volatility of SPX and CSI300 before and after the COVID-19 pandemic. SPX showed greater resilience and stability, while CSI300 exhibited higher volatility and sensitivity to the pandemic. These findings highlight the need for adjusted financial models to better assess and manage risks under extreme market conditions.

3.4. Time Series Figures and Stationarity Test

In this subsection, the time series figure and stationarity test of the data will be presented. Before conducting data analysis, it is essential to ensure the stationarity of the data. Descriptive statistics of the daily returns for the CSI300 and the SPX were performed to compare the performance of the two markets before (January 3, 2017, to December 31, 2019) and after (January 2, 2020, to December 30, 2023) the COVID-19 pandemic. Figures 1(a)-(d) show that the daily returns series are stationary, thus logarithmic transformation of the returns is not required.

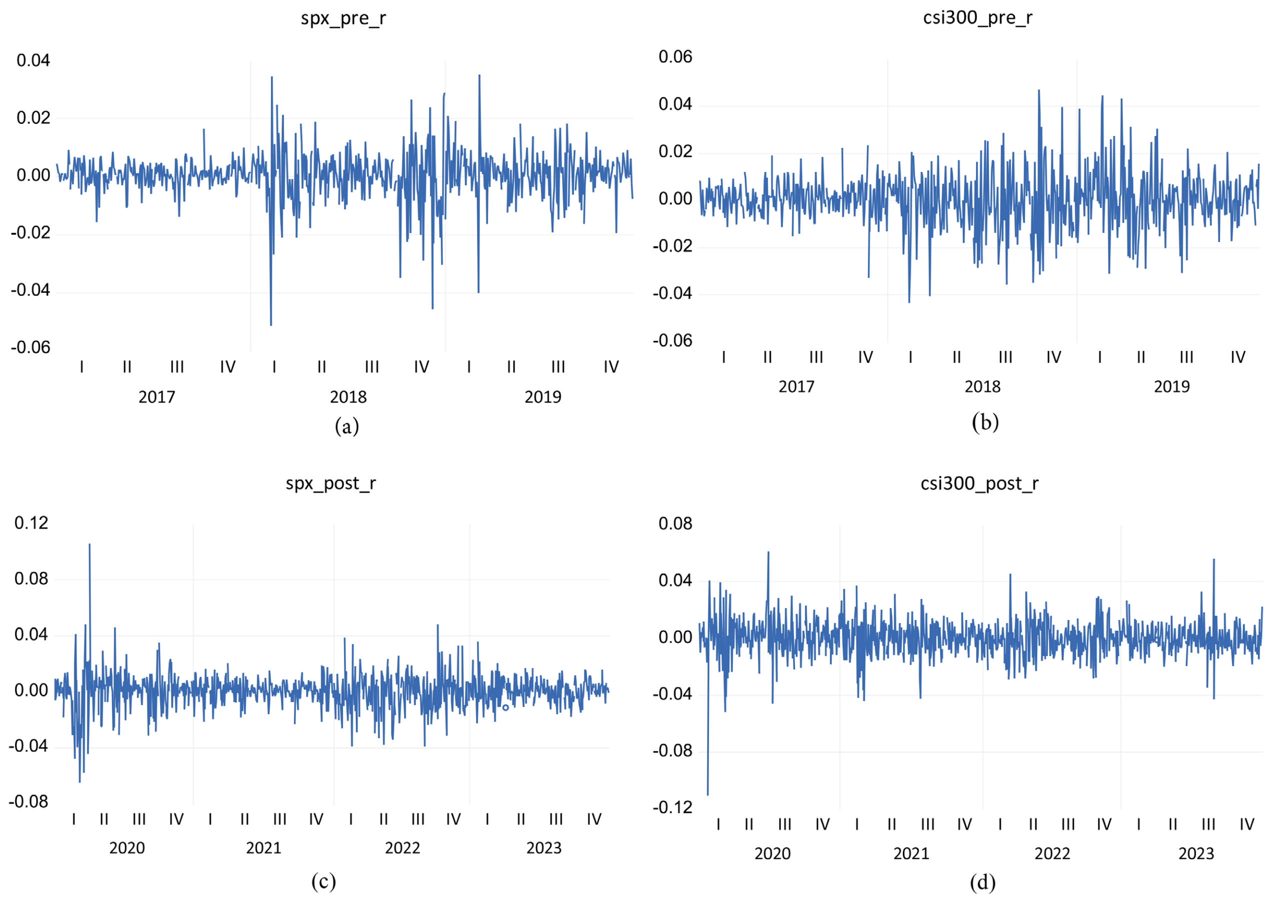


Figure 1. Time series figures of the daily returns. (a) Pre-pandemic SPX Daily Returns; (b) Pre-pandemic CSI300 Daily Returns; (c) Post-pandemic SPX Daily Returns; (d) Post-pandemic CSI300 Daily Returns.

Figure 1(a) shows the daily returns of the SPX Index from 2017 to 2019. The data fluctuates around zero with occasional spikes, indicating relatively stable volatility with some extreme events. Figure 1(b) shows the daily returns of the CSI 300 Index from 2017 to 2019. The data fluctuates around zero with notable spikes, particularly in 2018, indicating more significant volatility. Figure 1(c) illustrates the daily returns of the SPX from 2020 to 2023, marked with red arrows indicating three significant events in March 2020, May 2020, and December 2021. These events caused noticeable increases in market volatility, highlighting the market's sensitivity to major occurrences. Figure 1(d) shows the daily returns of the CSI300 from 2020 to 2023. Similar to the SPX, the volatility increased, especially with negative spikes. The same three significant events marked in red arrows indicate increased market volatility.

To further confirm stationarity and check for unit roots, an Augmented Dickey-Fuller (ADF) test was conducted. The results indicated p-values of 0.0000 for both periods and indices, confirming that the daily returns are stationary and free of unit roots. Subsequently, autocorrelation tests were performed. This involved establishing the mean equation and identifying its optimal order, followed by constructing the mean equation using the least squares method and conducting autoregressive tests.

The autoregressive tests revealed that the optimal order for pre-pandemic SPX data is 4, while for CSI300 it is also 4; post-pandemic, the optimal order for SPX data is 1, and for CSI300 it is 1. For example, the pre-pandemic autocorrelation test for SPX with an order of 4 showed a p-value of 0.0442, confirming it as the optimal order.

4. Results of Empirical Analysis

In this chapter, we employ the DCC-GARCH model to study the dynamic correlation between the stock markets of China and the United States. The DCC-GARCH model refers to a two-step process that first models the volatility of each individual stock market using GARCH and then captures the changing correlations between these markets over time using the DCC framework. This approach allows us to observe how the relationship between the Chinese and U.S. stock markets evolves, highlighting periods of stronger or weaker connections. The DCC-GARCH model estimates dynamic conditional correlation coefficients using the standardized residuals from a GARCH (1, 1) model, effectively capturing the dynamic interdependence between the stock markets. Before implementing the GARCH model, we conducted a unit root test (ADF test) on the daily return series of the CSI300 and the SPX to determine the stationarity of the data. The results indicated that the return series of both indices do not have unit roots, confirming their stationarity. This provides a reliable foundation for the subsequent estimation of the GARCH model.

4.1. ARCH Test

To derive the ARCH test results for SPX and CSI300, an ARCH effect test was conducted. The results showed significant ARCH effects with p-values of 0.0011, necessitating the construction of a GARCH model. The final GARCH model effectively eliminated the ARCH effects, enabling the construction of a DCC-GARCH model to analyze dynamic conditional correlations. These steps provide a robust foundation for analyzing the behavior of the U.S. and Chinese stock markets during the pandemic.

Figure 2 shows the dynamic correlation coefficient between the volatilities of SPX and CSI300 before and after the pandemic. **Figure 2(a)** displays correlations from 2017 to 2019, while **Figure 2(b)** shows correlations from 2020 to 2023. The pandemic significantly impacted the correlation, which decreased in the later period, indicating changes in the intermarket linkage.

Before the pandemic, the dynamic correlation coefficient mainly ranged between 0.1 and 0.2, showing a positive correlation with strong time-varying characteristics. Post-pandemic, the coefficient initially spiked to 0.5 but later stabilized around 0.1, with occasional negative correlations, indicating a weakened intermarket relationship. This analysis clearly demonstrates the impact of COVID-19 on the volatility and behavior of the U.S. and Chinese stock markets, providing valuable insights for future economic decision-making and risk management.

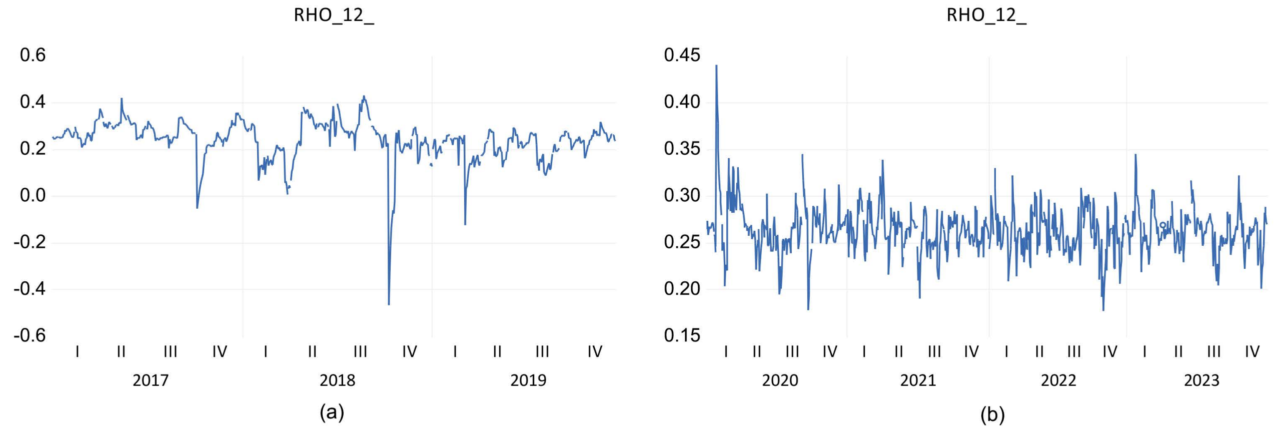


Figure 2. Dynamic correlation coefficient of SPX and CSI300 volatility. (a) Pre-pandemic; (b) Post-pandemic.

4.2. Parameters of the DCC-GARCH Model

The model establishment is conducted in two steps. The first step involves constructing univariate GARCH models: a separate GARCH model is built for each market index to obtain the residual series. The second step entails standardizing the residuals and estimating the parameters: the residuals are divided by their standard deviations to obtain standardized residual series, which are then used to estimate the parameters of the DCC model.

Initially, we construct univariate GARCH models for the stock indices of both China and the United States to obtain their respective residual series. Each GARCH model comprises two main equations: the mean equation and the variance equation. After obtaining the residual series, we proceed by dividing these residuals by their standard deviations to derive the standardized residual series. This step is crucial for estimating the parameters of the DCC model. The DCC model assumes that the returns of financial assets follow a multivariate normal distribution with a mean of zero and a dynamic covariance matrix.

During the parameter estimation of the GARCH (1, 1) model, the response speed parameter (α) for the SPX is relatively high, indicating a quicker reaction to new information. Conversely, the decay speed parameter (β) for the CSI 300 is higher, demonstrating stronger volatility persistence. **Table 2** presents the parameter estimation results for both indices before and after the pandemic, revealing the changes in parameters across different stages.

Table 2. Parameter estimation results for CSI 300 and SPX.

Variable	Pre-pandemic		Post-pandemic	
	SPX	CSI300	SPX	CSI300
Constant term	3.9 E−06	1.57E−06	3.64E−06	2.4Ee−05
ARCH (α)	0.254310	0.082758	0.136067	0.131113
GARCH (β)	0.711084	0.908727	0.843724	0.730214
$\alpha+\beta$	0.965394	0.991485	0.979791	0.861327

Upon examining the correlation between Chinese and U.S. stock market returns using the DCC-GARCH model, we find that $\alpha + \beta$ is significant at the 99% confidence level and approaches 1, indicating strong persistence in correlation. This suggests a robust dynamic linkage between the two markets during the pandemic. The correlation analysis reveals significant changes in the correlation during the initial COVID-19 outbreak, as shown in Figure 1(c) and Figure 1(d), highlighting the impact of major events on market interdependence.

This study demonstrates the statistical diagnostics and parameter estimation of the model, uncovering the dynamic correlation between the two stock markets during the pandemic and providing valuable insights for market behavior analysis and policy formulation.

In Table 3 DCC-GARCH Model Parameter Estimates for SPX and CSI300, we present the DCC (1, 1) model parameter estimates for the SPX and the CSI300 before and after the COVID-19 pandemic. The parameters include sensitivity to current shocks (Θ_1) and the degree of memory of historical correlation (Θ_2).

Table 3. DCC-GARCH Model Parameter Estimates for SPX and CSI300.

Variable		Pre-pandemic	Post-pandemic
DCC	Θ_1	−0.025365	0.020971
	Θ_2	0.933010	0.686876
	$\Theta_1 + \Theta_2$	0.907645	0.707847

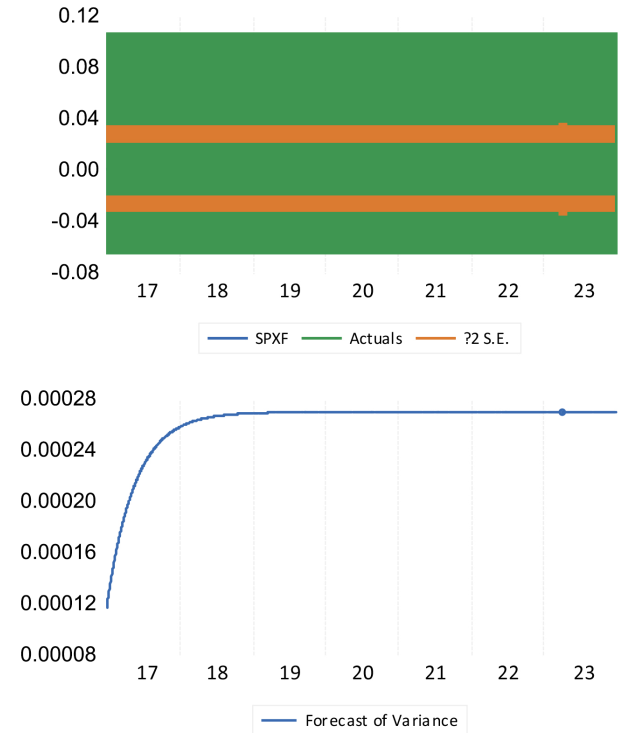
The Θ_1 value indicates market sensitivity to current shocks, with higher values post-pandemic for both SPX and CSI300, suggesting increased responsiveness to new information. The Θ_2 value reflects reliance on historical data, with higher post-pandemic values indicating stronger market memory. The sum of Θ_1 and Θ_2 approaching 1 shows persistent dynamic correlation. Despite slight differences post-pandemic, both markets exhibit persistent correlation.

Table 3 illustrates the pandemic's significant impact on the dynamic correlation between Chinese and U.S. stock markets. Both SPX and CSI300 show increased sensitivity to new information and stronger reliance on historical data during the pandemic, indicating heightened market volatility and uncertainty.

4.3. Forecasting

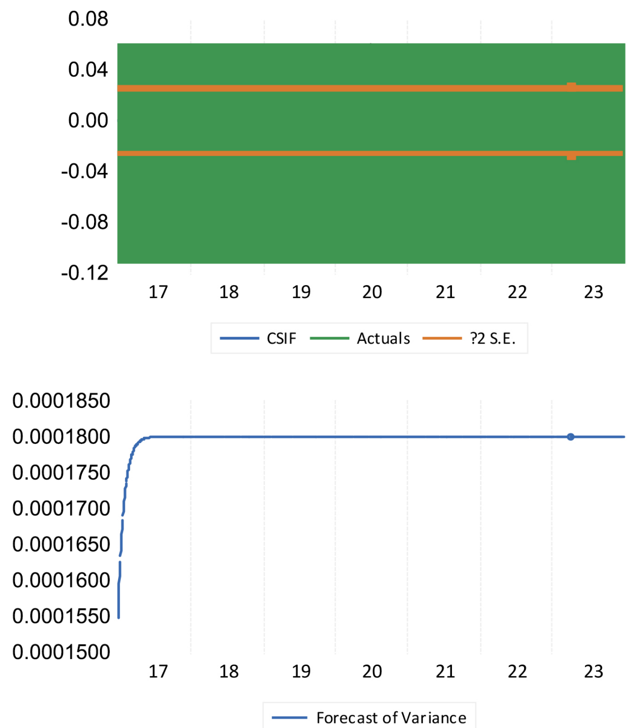
This subsection employs the DCC-GARCH model to analyze the daily return data of the CSI 300 Index and the S&P 500 Index from January 3, 2017, to December 29, 2023. The aim is to investigate the interconnectedness of the Chinese and U.S. stock markets in the context of the COVID-19 pandemic.

Figure 3 comprises two parts (a) and (b). In (a) and (b), the upper part shows a comparison between the predicted and actual daily return trends during the forecast period, with alternating red and blue lines indicating general directional alignment but differences in volatility magnitude. The lower part displays the predicted variance, revealing expected changes in market volatility during the forecast period, with notable increases in certain months.



Forecast: SPXF	
Actual: SPX	
Forecast sample: 1/03/2017 12/29/2023	
Adjusted sample: 1/04/2017 12/29/2023	
Included observations: 1631	
Root Mean Squared Error	0.010741
Mean Absolute Error	0.007152
Mean Abs. Percent Error	NA
Theil Inequality Coef.	0.918440
Bias Proportion	0.001604
Variance Proportion	NA
Covariance Proportion	NA
Theil U2 Coefficient	NA
Symmetric MAPE	156.3927

(a)



Forecast: CSIF	
Actual: CSI	
Forecast sample: 1/03/2017 12/29/2023	
Adjusted sample: 1/04/2017 12/29/2023	
Included observations: 1631	
Root Mean Squared Error	0.012389
Mean Absolute Error	0.008984
Mean Abs. Percent Error	112.0362
Theil Inequality Coef.	0.968233
Bias Proportion	0.000648
Variance Proportion	NA
Covariance Proportion	NA
Theil U2 Coefficient	0.973177
Symmetric MAPE	181.2229

(b)

Figure 3. Details of return forecast and variance. (a) Forecas of SPX; (b) Forecas of CSI300.

The model's predictions demonstrate a certain level of effectiveness, particularly in tracking market trends. However, there is room for improvement in forecasting the specific magnitude of market volatility. The large predicted variance indicates considerable market uncertainty, which investors should consider when developing investment strategies. Additionally, the covariance results suggest low correlation between the predicted and actual data in certain periods, possibly due to the model's inability to fully capture all critical market-influencing factors.

5. Conclusions

This study uses the DCC-GARCH model to analyze the linkage between Chinese and U.S. stock markets during the COVID-19 pandemic, focusing on the daily returns of the CSI300 and SPX indices from 2017 to 2023. Key findings include: 1) COVID-19 significantly increased the linkage between the Chinese and U.S. stock markets, especially during global downturns, demonstrating the cross-border impact of global health crises on financial volatility; 2) The SPX showed greater sensitivity and volatility to COVID-19 compared to the CSI300, likely due to the U.S. market's structure and central role in the global financial system; 3) The CSI300 displayed stronger recovery capabilities and stability, reflecting effective crisis management and economic adjustments in China.

These insights are crucial for understanding global pandemic impacts on financial markets and guiding investors and policymakers in managing economic uncertainties. The findings emphasize the importance of understanding cross-border market linkages for effective financial and economic policy formulation during global crises.

Policymakers should enhance economic cooperation, strengthen financial regulatory communication, and develop emergency plans for financial crises. This includes establishing transparent regulatory frameworks and effective market monitoring systems to stabilize investor confidence during volatility. Investors should improve their market analysis skills and make rational decisions to avoid unnecessary losses. Regulatory bodies should enhance public education on investment strategies and risk management. Given the increasing interconnectivity, global investors should adjust portfolios to predict market trends and achieve risk diversification.

Future research should explore broader influencing factors, apply advanced econometric models, and expand empirical data to improve prediction accuracy and robustness. These measures will better capture global financial market dynamics, aiding decision-making for market participants and policymakers.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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