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An Empirical Analysis of the Correlation of Agricultural Sectors in the Chinese Stock Market Based on the DCC-GARCH Model

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Abstract

The paper selects the daily trading data of three stocks in the agricultural sector of the Chinese stock market from 1st September 2015 to 31st August 2021. It uses the DCC-GARCH model to study the correlation between these stocks to examine the volatility and conductivity of their risks. The results show that the correlation between the Shanghai Composite Index and stocks of agriculture of China exhibits time-varying characteristics and dynamic. The fluctuations in correlation are large. This study fills the blank of comparative study on risk volatility and correlation between different stocks in the same stock market by using DCC-GARCH model.

Keywords

DCC-GARCH Model, Chinese Stock Market, Stock Returns, Shanghai Composite Index, Agriculture

1. Introduction

The correlation between financial markets has always been a focus of intense attention and extensive research by scholars worldwide. Studying the correlation between different financial markets is conducive to grasping the law of changes in financial markets and can provide scientific decision-making basis for pricing financial products and hedging market risks. Most past studies focused on the correlation between different financial markets, such as oil futures and the spot market. For detail assessments based on DCC GARCH model can be found in the literatures [1] [2] [3] [4] [5].

Studying pairwise correlations between stocks in any financial market is of great significance for investors, policymakers, and financial analysts. The research on the correlation and volatility of stocks in the Chinese agricultural sector aims to achieve several objectives. Firstly, through the study, an investigation into the interdependence among different stocks within the Chinese agricultural sector is conducted, examining the correlation between individual stocks and major market indices. Secondly, the volatility of Chinese agricultural stocks is measured and analyzed. Factors causing volatility, such as market sentiment, economic indicators, and global commodity prices, are identified. Effective risk management strategies are then formulated based on the discovered correlations and volatility, providing insights for investors and policymakers to make informed decisions in the Chinese agricultural stock market. Lastly, an understanding is sought on how external factors like government policies, international trade, and climate change impact the correlation and volatility of stocks in the Chinese agricultural sector.

The significance of studying the correlation and volatility of stocks in the Chinese agricultural sector lies in several aspects. Firstly, by understanding the patterns of correlation and volatility in the Chinese agricultural industry, investors' decision-making abilities are enhanced, promoting the development of risk mitigation strategies and improving overall market stability. Secondly, valuable insights are provided for policymakers to design effective agricultural and economic policies, assisting in the establishment of regulatory frameworks that foster stability and growth in the agricultural stock market. Thirdly, it contributes to a better understanding of how the performance of the Chinese agricultural sector influences the global economy. The exploration of how the volatility of Chinese agricultural stocks affects international trade and the commodity market is discussed. Lastly, through a comprehensive analysis of the dynamics of correlation and volatility in the Chinese agricultural sector, this research makes a contribution to academic literature, laying the groundwork for future studies in the fields of finance, economics, and agriculture.

The Chinese stock market is one of the largest and most dynamic in the world. Understanding the pair-wise correlations between stocks in this market is vital for several reasons However, when it comes to the Chinese stock market, this analysis becomes even more crucial due to the unique characteristics and dynamics of this market. In this discussion, we will delve into the importance of studying pairwise correlations in the Chinese stock market, the rationale behind selecting specific stocks, the choice of a DCC-GARCH model, and the novelty and contributions of the research findings.

The rest of this paper is organized as follows. Section 2 focuses on the literature review. Section 3 describes the data and the DCC-GARCH model. Section 4 introduces the descriptive statistics of the stocks that are involved in the study, and discusses the empirical findings. Section 5 presents the discussions and conclusions by summarizing our primary findings and insights.

2. Literature Review

This section provides an overview of the past literature on the linkages between the DCC-GARCH model and financial markets.

Many recent studies on the stock markets are based on the DCC-GARCH model since this model has two advantages compared to the previous model. Firstly, the DCC model has obvious computational advantages and can estimate large correlation coefficient matrices. Secondly, the DCC model adopts a two-step estimation method, so that the parameters needed to be estimated in the correlation process can be easily estimated [6] [7] [8] [9].

Yang [10] examines the international stock market correlations between Japan and the Asian Four Tigers (Singapore, South Korea, Taiwan, and Hong Kong) using the DCC GARCH model. The results show that stock market correlations fluctuate widely over time, and volatilities appear contagious across markets. Besides, correlations rise during high market volatilities periods when risk diversification is needed most, which is bad news for international diversification. Savva [11] conducted an investigation into the transmission of prices and volatility spillovers between the US and European stock markets using bivariate combinations through DDC GARCH models. The model demonstrated its efficacy in capturing relationships for more than half of the bivariate combinations across markets. The results indicated volatility spillovers from the US to European markets and vice versa. Moreover, the correlation magnitude between markets was observed to be higher not only during adverse shocks in both markets but also when a combination of shocks with opposite signs occurred. In a separate study, Jones and Collins [12] analyzed the time-varying correlation between oil prices and stock prices, employing a multivariate DCC-GARCH model. Estimates revealed a shift in correlation since the financial crisis, transitioning from being close to zero or slightly negative in the past to a positive correlation. This positive correlation persisted through the first half of 2017.

Tsuji [13] conducted an in-depth examination of return transmission and volatility spillovers within the banking sector stocks in the United States and eight other countries. Employing the VAR-DCC-MEGARCH-M model, the study revealed a predominantly unidirectional transmission of stock returns from the US banking sector to all eight international banking sectors. Additionally, bidirectional volatility spillovers between the US and the international banking sector stocks were identified, with these spillovers being associated with the leverage effect. Similarly employing the VAR-DCC-MEGARCH-M model, Liu, Shehzad, Kocak and Zaman [14] investigated dynamic correlations and investments involving the S&P 500 and diverse commodities (gold, WTI crude oil, Brent oil, beverages, and wheat) both before and during the COVID-19 era. The results indicated that gold holds the potential to offer superior portfolio diversification benefits and mitigate downside risk, providing valuable insights for strategic decision-making by portfolio investors amid the COVID-19 outbreak. Further details and exploration of related research can be found in the following references [15]-[20].

However, there is a significant gap in the literature regarding the specific correlation and volatility of the Chinese agricultural sector. This study aims to fill this gap by conducting a detailed analysis of the interactions among various stocks within this industry, taking into consideration both internal and external influencing factors. This is particularly true for cases in China, of which, China's political system and economic characteristics are itself differs quite significantly from those of other countries. Thus, it would be more meaningful to study the dynamic correlations within the Chinese stock market in this work. This article will build an econometric model to study the dynamic correlation between different stocks in agricultural sector of the Chinese stock market and explore the time-varying characteristics of their dynamic correlation. This sector is deemed important for this study since because in the same financial market, other policy, environment, and other influencing factors are the same, so it is easier to obtain the relatively pure volatility influence between stocks, to further study the correlation between stocks. The findings of this research not only contribute to academic knowledge but also offer practical insights for investors, policymakers, and market participants involved in the Chinese agricultural stock market.

3. Data and DCC-GARCH Model

In this section we will introduce the data and model used in the study.

3.1. Data

There are currently three stock exchanges in the Chinese stock market: the Shanghai Stock Exchange, the Shenzhen Stock Exchange, and the Beijing Stock Ex-change. Since the Beijing Stock Exchange only opened for trading on November 15, 2021, and the amount of transaction data is not enough, so we research used transaction data from the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Since the agricultural sector is mainly affected by the environmental factors such as climate and less affected by the world financial market, we selected the agricultural sector for this research. China, being a significant global producer and consumer of food grains, has supported agriculture with policies, leading to increased grain production and comprehensive agricultural growth.

The choice of specific stocks for analysis depends on the market representation and the characteristics of the Chinese stock market. We selected three stocks (Bei-Da-Huang (BDH), Dun-Huang-Zhong-Ye (DHZY), Nong-Fa-Zhong-Ye (NFZY)) as the research objects in the agricultural section of the Shanghai Stock Exchange.

Bei-Da-Huang (BDH), stock code: 600598, is a major player in China's agricultural industry. It's one of the country's largest and most advanced publicly traded agricultural companies. They excel in commodity grain production, benefitting from abundant natural resources, robust infrastructure, modern machinery, agricultural technology, and efficient management.

Dun-Huang-Zhong-Ye (DHZY), stock code: 600354, is a prominent player in agricultural industrialization, with a significant annual capacity for various crop seeds. They rank among the top seed producers and sellers in the country, with a strong presence in hybrid corn and vegetable seeds. They also process a substantial amount of cotton. With multiple processing facilities, they have government-approved varieties in wheat, corn, rice, cotton, and vegetables.

Nong-Fa-Zhong-Ye (NFZY)), stock code: 600313, primarily focuses on agricultural crop seeds, custom farming, fertilizer trading, and pesticide production and sales. Their core business is producing and selling various crop seeds, including corn, rice, wheat, cotton, and more, through subsidiary companies. Corn, wheat, and rice seeds are their key products, playing a crucial role in ensuring national food security and agricultural industry safety.

And we selected the Shanghai composite index (SHC Index) as a representative of market fluctuations. The data range is from 1st Sep. 2015 to 31st Aug. 2021, using daily transaction data, a total of 1461 sets of observations. If the trading data of individual stocks is missing due to trading suspension and other reasons, the missing data will be corrected by the 10-day moving average method.

For the convenience of later analysis, we introduce the following variables and present them in **Table 1**.

3.2. DCC-GARCH Model

The current methods for estimating the dynamic correlation coefficient of financial assets mainly include: rolling historical correlation method, exponentially weighted moving averages (EMWA) method and multivariate GARCH (Multivariate GARCH-MGARCH) method. The main model used in the empirical analysis in this paper is the model proposed by Engle [21] can well describe the volatility of the securities market, an ARCH(q) model can be described as

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

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

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

Table 1. Variables and the labels.

Variable	Label	English Name
R_SH	returns of SHC Index	Shanghai Composite Index
R_1	returns of BDH	Bei-Da-Huang
R_2	returns of DHZY	Dun-Huang-Zhong-Ye
R_3	returns of NFZY	Nong-Fa-Zhong-Ye

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, $f(t, x_{t-1}, x_{t-2}, \cdots)$ is the information set; μ_t is the residual series of the mean Equation (1), and $e_t \overset{iid}{\sim} N(0, \sigma^2)$; h_t is conditional variance and equation is called variance equation.

Bollerslev [22] extended the ARCH model, introduced random interference terms into the variance equation, and proposed a generalized autoregressive conditional heteroscedasticity (GARCH (*p*, *q*)) model, which can be described as

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

The ARCH model and the GARCH model have been successfully used to characterize the volatility of a single asset, but they cannot characterize the correlation between multiple assets. Since then, the GARCH model has been expanded and developed into a multivariate GARCH model, which can characterize the volatility and information spillover effects of different assets, but it cannot characterize the correlation between assets and the coordinated movement of assets. Based on this, Engle [1] proposed a Dynamic Conditional Correlation GARCH (DCC GARCH) model, which can better capture the dynamic correlation between assets. The DCC-GARCH model is a sophisticated statistical tool commonly employed to study the time-varying correlation between financial time series data, particularly in the realm of stock returns. It integrates two components: the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model for modeling volatility and the DCC model for capturing dynamic correlations.

The DCC-GARCH model assumes that the rate of return r_t of *k* assets obeys a mean value of 0, and the covariance matrix H_t obeys conditional multivariate normal distribution:

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

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

where F_{t-1} is the information set of periods $t-1$, and r_t is a $k \times 1$ dimensional vector. H_t is the conditional covariance matrix, and R_t is the $k \times k$-dimensional time-varying correlation matrix. $D_t = diag\left\{\sqrt{h_{i,t}}\right\}$ is the time-varying standard deviation matrix, and $h_{i,t}$ is obtained from the univariate GARCH model

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

where $h_{i,t}$ is the conditional variance of the *i*-th series at time *t*, α_i is the constant term, α_{iq} and β_{ip} are parameters, and $\mu_{i,t-q}^2$ is the squared return of the *i*-th series at time $t-1$.

Engle, Focardi, and Fabozzi [23] proposed a two-stage method based on log-likelihood estimation to estimate the DCC-GARCH model.

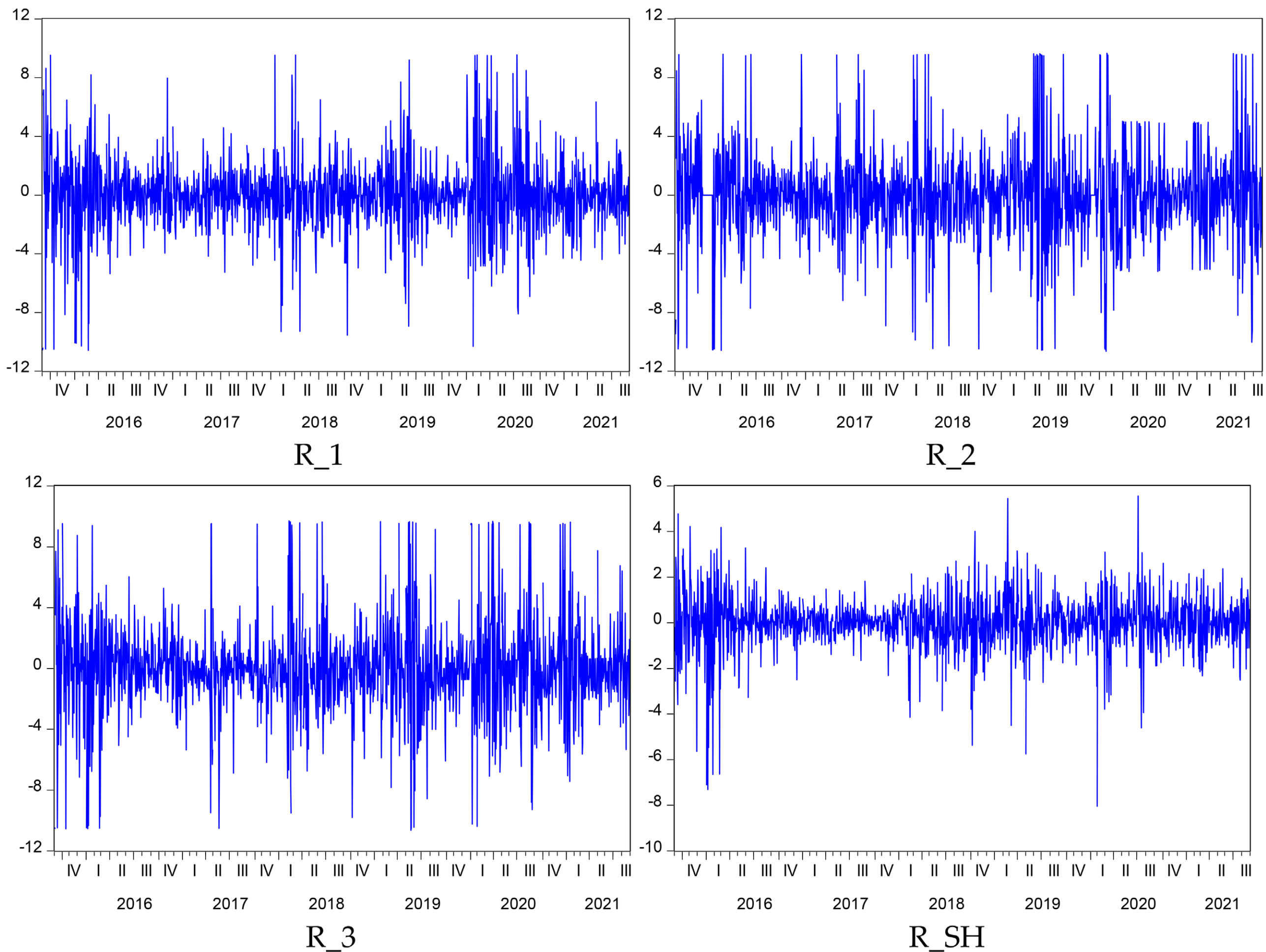
4. Results of Empirical Analysis

This paper used EViews 10.0 for data processing and analysis. In EViews 10.0, there are two add-ins which are DCCGARCH11 (Eren Ocakvaerdi, 2014) and DCC_RGARCH (Marcin Faldzinski, 2021) can be used to processing the DCC GARCH model. In this paper, we mainly used the DCC_RGARCH package to analyze the data.

4.1. Descriptive Statistics

The variables' descriptive statistics and timing diagrams are shown in Figure 1 and Table 2, and they show multiple abnormal peaks in the return sequence data of each stock and market index. And they also indicate that the volatility of the rate of return is sudden and significant. The series of the rate of return presents a notable feature of volatility clustering.

Table 2 obtains the following characteristics of the data. First, the Skewness and the Kurtosis show that the distribution of these four series is biased, thin



Note: Figure 1 shows the time series diagram of R_1 (BDH), R_2 (DHZY), R_3 (NFZY) and R_SH (SSEC Index) from 1st Sep. 2015 to 31st Aug. 2021.

Figure 1. Time series diagram of variables rate of return.

Table 2. Descriptive statistics of variables.

	R_1	R_2	R_3	R_SH
Mean	0.003484	−0.014249	−0.003031	0.006860
Maximum	9.536276	9.658977	9.696171	5.554206
Minimum	−10.57588	−10.64295	− 10.63575	−8.039173
Std. Dev.	2.518189	3.141480	3.092318	1.200679
Skewness	−0.069854	0.050789	0.182281	−0.927072
Kurtosis	6.506212	5.196194	5.470134	9.553869
Jarque-Bera	749.557***	294.245***	379.523***	2824.055***
Q (6)	17.013***	27.846***	3.3998	15.014**
F-statistic	26.413***	74.856***	72.856***	24.314***
$n \times R^2$	75.349***	195.042***	190.511***	69.646***
Observations	1461	1461	1461	1461

Note: Table 2 is based on EViews 10.0. *, **, ***Indicate that the null hypothesis is significantly rejected at the significance level of 10%, 5%, and 1%, respectively. F statistics and LM statistics ($n \times R^2$) are the results of the ARCH test.

peak and heavy tail.

The Jarque-Bera statistics and the corresponded p values suggesting that the log returns are not normal distribution. Secondly, Q (6) is the Ljung-Box statistics of the log returns series. In addition, Q (6) statistics show that at the 5% significance level, only the NFZY (R3) return series does not have autocorrelation, and the other stock returns have significant sequence correlation. Thirdly, the results of the ARCH test include F statistics and LM statistics ($n \times R^2$), and the ARCH statistics show that the four return rate series reject the null hypothesis at the 1% significance level, that is, there is a significant ARCH effect, which is completely consistent with the judgment obtained in **Figure 1**, the means and the standard deviations suggest that the market's volatility is smaller than the equities.

In practice, most time series will be affected by time, showing sequence instability [12] [24]. Granger and Newbold [25] found that if the economic time series is non-stationary, it may cause a false regression problem. Therefore, it is necessary to perform unit root test on the data before estimating the parameters. To ensure the accuracy of the inspection re-sults, two inspection methods are used here: ADF inspection and PP inspection. Among them, the number of lag periods is determined according to the Schwarz Criterion (SC), and the results are shown in **Table 3**. The unit root test results show that the ADF test statistic and the P-P test statistic of the sequence are far less than the critical value of 1%, indicating that the null hypothesis can be rejected at least at the 99% confidence level. The stock return series in each market has passed the unit root test, and the series is stationary. It is suitable for DCC-GARCH regression analysis and avoid false regression.

From the perspective of the correlation between stocks and indexes in Table 4, the correlation coefficients between Shanghai Composite Index (R_SH) and the three agricultural stocks are relatively small. Among them, the correlation coefficient between R_SH and BDH (R_1) is the largest, which is only 0.483906. The closest correlation among the three agricultural stocks is BDH (R_1) and NFZY (R_3), with a correlation coefficient of 0.638170.

The correlation coefficient obtained in Table 4 does not consider that the correlation changes dynamically with time, and is a static correlation coefficient. Therefore, it is not appropriate to determine the correlation between the Chinese stock market and the inter national stock market based on the static correlation coefficient alone. In this paper, we employ Engle's multivariate dynamic conditional correlation model, known as the DCC-GARCH model [1]. Our aim is to analyze the connection between the Chinese stock market and international stock markets. This approach allows for a more precise capture of the dynamic correlation between these stock markets.

4.2. Estimation Results of Univariate GARCH Model

The parameter estimation process for the DCC-GARCH model involves two sequential steps [26] [27]. Firstly, the univariate GARCH model is estimated for each market rate of return. Secondly, the obtained conditional variance is utilized to eliminate the residuals, resulting in the standardized residual sequence. The standardized residuals obtained in the first step are then used to estimate the

Table 3. Results of ADF test and PP test of stationarity.

	R_1	R_2	R_3	R_SH
ADF	−40.76321	−34.76644	−39.73579	−39.75036
Test critical values: 1% level	−2.566547	−2.566547	−3.434621	−2.566547
PP	−41.13480	−34.62386	−36.42566	−39.73579
Test critical values: 1% level	−3.434621	−3.434621	−3.434621	−3.434621

Table 4. Unconditional correlation coefficients among stocks.

Correlation Probability	R_1	R_2	R_3	R_SH
R_1	1.000000			

R_2	0.524212	1.000000		
	0.0000	-----		
R_3	0.638170	0.571065	1.000000	
	0.0000	0.0000	-----	
R_SH	0.483906	0.343359	0.350729	1.000000
	0.0000	0.0000	0.0000	-----

difference sequence, yielding the correlation coefficient of the model's dynamic condition.

According to the previous correlation test of the four return rate series (see Table 2 for the results), all series have significant serial correlation phenomena. Therefore, when establishing the mean equation of the univariate GARCH model, the equation structure of the ARMA model is adopted. After multiple estimates and comparisons using EViews, according to the Schwarz Criterion (SC) statistics, the optimal mean equations obtained are in the form of

$$\begin{gathered} \mathrm{R\_1} = 0.0110 - 0.059 \times \mathrm{R\_1}(-1) \\ (0.8669)^{*} \quad (0.0233)^{*} \end{gathered} \tag{8}$$

$$\begin{gathered} \mathrm{R\_2} = -0.0065 + 0.0968 \times \mathrm{R\_2}(-1) \\ (0.9362) \quad (0.0002) \end{gathered} \tag{9}$$

$$\begin{gathered} \mathrm{R\_3} = 0.0043 + 0.0517 \times \mathrm{R\_3}(-1) \\ (0.9578) \quad (0.047) \end{gathered} \tag{10}$$

$$\begin{gathered} \mathrm{R\_SH} = 0.0068 + 0.3225 \times \mathrm{R\_SH}(-1) - 0.5481 \times \mathrm{R\_SH}(-2) - 0.3650\mu_t + 0.6140\mu_{t-1} \\ (0.8433) \quad (0.0905) \qquad\qquad (0.0001) \qquad\qquad (0.0422) \quad (0.0000) \end{gathered} \tag{11}$$

Note: *The values in parentheses for equations (8 - 11) represent the p-values of the T-test.

It can be seen from the above results (Equations (8)-(11)) that, except for the Equation (11) which is in the form of ARMA (2, 2), the rest of the equations are in the form of AR (1). At the 10% significance level, all parameters are significant except for the constant term. At the 5% significance level, all except the constant term and the coefficient of R_SH (−1) are significant. The Ljung-Box Q statistic test is performed on the residual sequence of the above four equations (Equations (8)-(11)), and the corresponding p-values are all larger. Accepting the null hypothesis indicates that the equation no longer has autocorrelation. ARCH test is performed on the residual series, and the results show that there is a significant ARCH effect in the residual series, and the GARCH model can be further established for the analysis.

The study of Bollerslev, Chou, and Kroner [28] showed that GARCH (1, 1) can fit the volatility of stock market returns well, while considering the simplicity of the model. Therefore, this article directly selects the GARCH (1, 1) model to analyze the volatility of the rate of return. According to the mean value equation in the autoregressive form determined above (Equations (8)-(11)), the GARCH (1, 1) model is used to refit the return volatility. The maximum likelihood estimation results of the parameters are shown in Table 5. From the estimated results of the parameters in Table 5, the estimated values of each parameter are significantly non-zero. Among them, the value of $\alpha + \beta$ is close to 1, indicating that the fluctuations in each market have significant continuity.

Ljung-Box Q statistic test and ARCH test were performed on the residual series of each univariate GARCH (1, 1) model. The results are shown in Table 6.

Table 5. Parameters estimation of the univariate GARCH model.

	ω	α	β	$\alpha+\beta$
R_1	0.13043***	0.08719***	0.89007***	0.97727
R_2	0.74471***	0.18191***	0.74342***	0.92533
R_3	0.55203***	0.14103***	0.79754***	0.93857
R_SH	0.01318***	0.08769***	0.90862***	0.99630

Note: ***Indicate that the null hypothesis is significantly rejected at the significance 1%.

Table 6. Residual diagnostic ARCH_LM test.

	Q (6)	Prob.	ARCH (6)			
			F-statistic	Prob.	Obs * R2	Prob.
R_1	8.5946	0.198	0.7633	0.5988	4.5875	0.5977
R_2	3.5990	0.731	1.6363	0.1334	9.7985	0.1334
R_3	4.1820	0.652	0.8499	0.5314	5.1060	0.5303
R_SH	9.2476	0.150	1.3566	0.2289	8.1332	0.2285

Note: ***Indicate that the null hypothesis is significantly rejected at the significance 1%.

We found that both Q (6) statistics and ARCH (6) statistics reject the null hypothesis at the 1% significance level, indicating that the model's mean equation and variance equation are reasonable.

It can be clearly seen from Figure 2 that the variance changes with time, which verifies the hypothesis about the time-varying nature of stock market volatility. It can also be seen from the figure that due to the impact of the COVID19 pandemic, both the market index and individual stocks have relatively large fluctuations since 2020, and the general trend is downward.

4.3. Estimation Results of DCC GARCH Model

Below we use the DCC-GARCH model to examine the correlation between the Shanghai Composite Index (R_SH) and the three stocks (R_1, R_2, R_3). Here, the conditional variances are set to GARCH (1, 1) form, and the order of the DCC model is also set to 1. The estimated results of each parameter of the model are shown in Table 7. From the DCC model parameter estimation results obtained in Table 7, α and β are significantly different from zero, indicating the influence of the standardized residual product of the lagging period on the dynamic correlation coefficient, and β is not only significant but also very close to 1, reflecting correlation has a very strong persistent characteristic.

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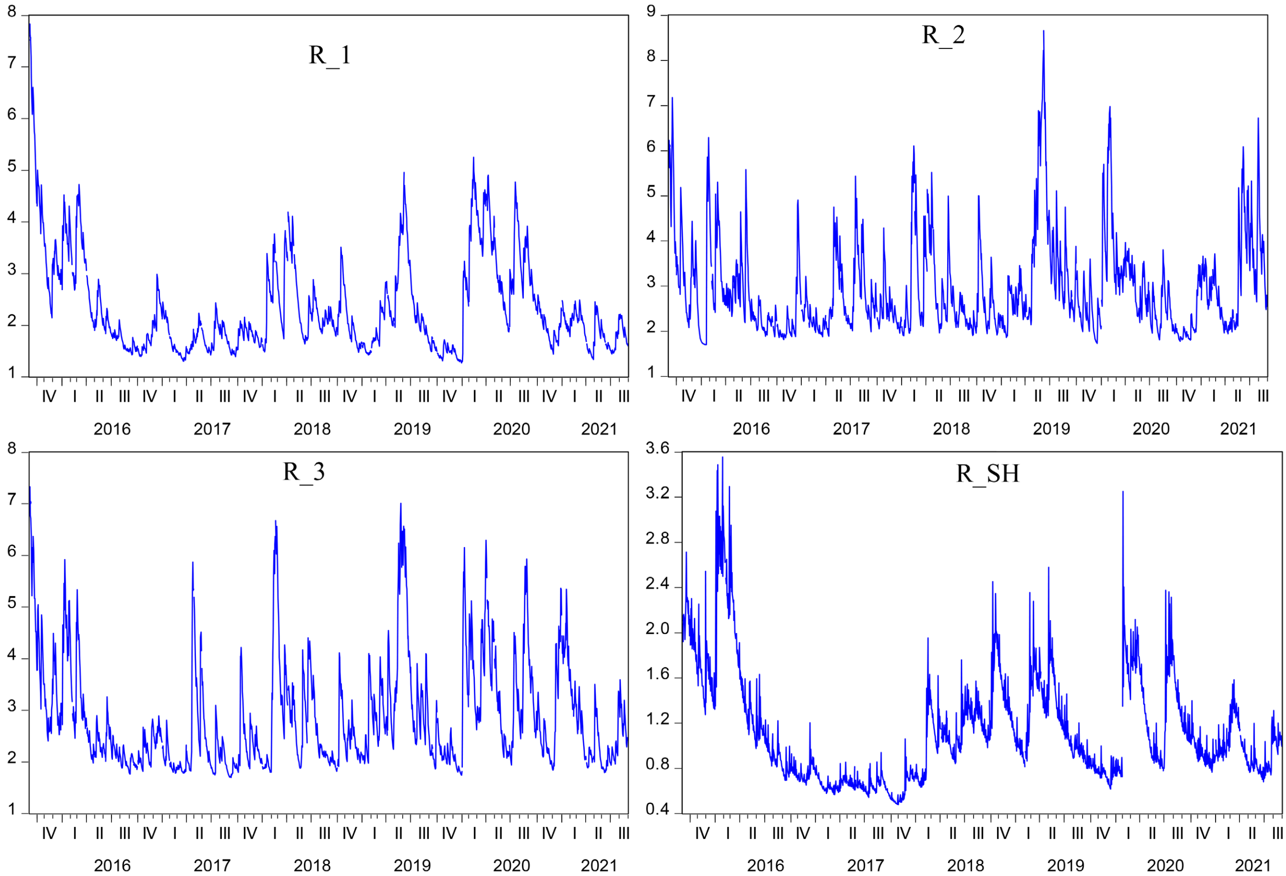

Figure 2. Conditional standard deviation of return series.

Table 7. Estimated results of DCC model coefficients.

	α (Prob.)	β (Prob.)
R_SH & R_1	0.0311 (0.0003)	0.9579 (0.0000)
R_SH & R_2	0.0393 (0.0000)	0.9448 (0.0000)
R_SH & R_3	0.0451 (0.0000)	0.9388 (0.0000)
R_1 & R_2	0.0423 (0.0130)*	0.8622 (0.0000)
R_1 & R_3	0.0440 (0.0000)	0.9260 (0.0000)
R_2 & R_3	0.0552 (0.0000)	0.9162 (0.0000)

Note: The value in brackets is the corresponding adjoint probability. The correlation coefficients are all significant at a significance level of 1% except the α of R_1 and R_2 which is marked *.

To observe the changes more intuitively in the dynamic conditional correlation coefficients between the market index (R_SH) and individual stocks (R_1, R _2, R _3), Figure 3 shows the dynamic correlation coefficient time series diagrams of the pairwise combinations of these 4 variables.

As shown in Figure 3, the following four characteristics can be seen intuitively: First, in the entire sample period, the dynamic conditional correlation coefficient

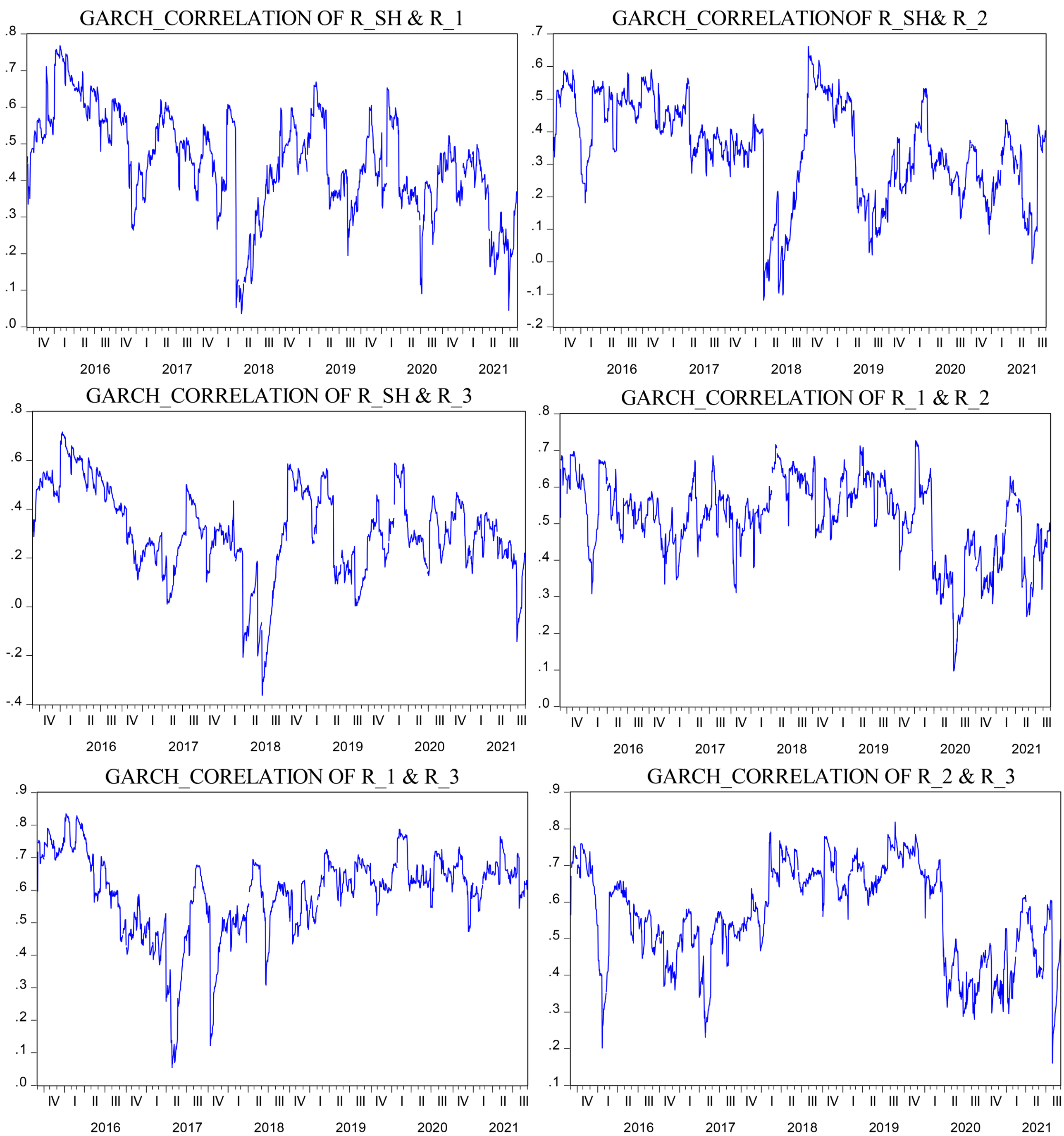

Figure 3. Dynamic correlation coefficient graph.

shows a strong time-varying characteristic, the time-variation is significant. Second, the trend of the time series chart of the dynamic correlation coefficient between the Shanghai Composite Index (R_SH) and individual stocks is very similar. For example, R_SH and R_1 had the smallest correlation coefficient on April 18, 2018, while R_SH and R_2, R_SH and R_3 was on June 20, 2018. Date and June 21, 2018 achieved the minimum value. Except for individual periods, most of the time there is a positive correlation between the Shanghai Composite

Index (R_SH) and individual stocks. Third, in the sample interval, the fluctuation interval of the dynamic correlation coefficient is very large. But the average value of the dynamic correlation coefficient is between 0.3 and 0.6, which is not high. Whether it is between the market index and individual stocks, or between individual stocks and individual stocks, their relationship is not particularly strong.

Finally, starting from 2020, the dynamic correlation coefficient between the Shanghai Composite Index (R_SH) and individual stocks is declining, indicating that the trend of agricultural stocks and the Shanghai Composite Index (R_SH) under the influence of the COVID 19 pandemic has become complicated. And the agriculture stocks are less affected by the COVID 19 pandemic. These results are different with the findings by Jones and Collins [12], who found that the correlation of financial assets has changed and continued to be positive since the financial crisis. We believe that there are several main reasons. First, agriculture is a basic industry and will be relatively less affected by the pandemic. Second, the production cycle of agriculture is long, and the impact of the pandemic will lag.

5. Discussions and Conclusions

To enhance the robustness and comprehensiveness of our research findings, we can strengthen our analysis by combining the time-varying BEKK-GARCH and DCC-GARCH models. This extended approach allows for a more thorough exploration of the dynamic changes in pairwise correlations within the Chinese stock market. By comparing the results generated by both models, our aim is to provide a more reliable and precise analysis.

In addition to presenting results, our study can further delve into detailed explanations and interpretations of significant discoveries. These discussions will encompass an exploration of the factors influencing correlations between specific pairs of stocks, the impact of regulatory changes and economic events on these correlations, and the practical applications of these findings for investors and policymakers.

Our analysis can expand its scope beyond correlation measurements to include the estimation of optimal portfolio weights, hedge ratios, hedging effectiveness, and Sharpe ratios for pairs of agriculture stocks. These practical metrics are of paramount importance for investors seeking to optimize their investment portfolios and manage risk judiciously. By utilizing variances and covariances derived from the DCC-GARCH model, our research will offer valuable insights into portfolio construction.

This paper uses the DCC GARCH model to estimate the correlation between Chinese Shanghai Composite Index and the returns of three Chinese agricultural stocks. The results show that the correlation between the Shanghai Composite Index and China's agricultural stocks exhibits dynamic and time-varying characteristics. The fluctuations in correlation are large. This means that for investors who want to judge the trend of individual stocks by observing the market index, they must pay enough attention to the correlation between the market index and the price fluctuation of individual stocks. The upward increase of the market index does not mean that the stock price of individual stocks also increases.

At the same time, the average value of the dynamic correlation coefficient is between 0.3 and 0.6, indicating that the correlation between the market index and individual stocks is not very strong, and their mutual influence is not large. The market index reflects the trading activity and atmosphere of the entire securities exchange market. The performance of individual stocks may be completely different from the market. Therefore, we must conduct serious and in-depth research on a stock before investing it. We can further try to use the evolution model of DCC GARCH to study the correlation between stocks and stocks to provide better guidance for investment.

The research findings on the correlation and volatility of Chinese agricultural stocks have far-reaching implications for stakeholders such as investors, policymakers, and other market participants. Investors can optimize portfolio allocation by understanding time-varying correlations, considering alternative strategies during periods of high correlation, such as industry rotation or dynamic asset allocation. Insight into volatility facilitates the implementation of more effective risk management strategies, such as adjusting position sizes or employing hedging techniques during periods of heightened volatility. The results also provide investors with a basis for identifying market timing opportunities, anticipating changes in market sentiment, or significant market events.

Policymakers can leverage these insights to implement targeted regulatory measures to stabilize the market, mitigate external impacts on Chinese agriculture, and guide adaptive economic policies. The research results contribute to risk assessment for financial stability, aiding policymakers in identifying potential systemic risks in the trends of agricultural stocks. Other stakeholders, including agricultural companies, financial analysts, and the academic community, can benefit from the study by enhancing decision-making wisdom and promoting further research. In summary, these research findings empower stakeholders in the Chinese agricultural sector to navigate evolving market conditions and enhance overall market resilience.

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Conflicts of Interest

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

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