ISSN 2616-7433 Vol. 6, Issue 9: 15-20, DOI: 10.25236/FSST.2024.060903

Study on the Relationship between Chinese and American Soybean Futures Prices Based on GARCH and DCC-GARCH Models

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Abstract: *This paper aims to conduct an in-depth study of the relationship between Chinese and American soybean futures prices using GARCH and DCC-GARCH models. The data are sourced from the Dalian Commodity Exchange (DCE) and the Chicago Board of Trade (CBOT), covering the period from January 4, 1999, to September 14, 2023. Through model analysis, we find that the volatility of soybean futures prices in China and the USA is persistent and exhibits strong dynamic correlation, which varies over time. These findings are significant for understanding the dynamics and risks of the global soybean market.*

Keywords: *Futures Prices, Dynamic Correlation, GARCH Model*

1. Introduction

In recent years, with the acceleration of global economic integration, the volatility of the soybean market has increased significantly. This not only poses substantial risks to related businesses and investors but also presents severe challenges to global food security. Thus, research on the relationship between Chinese and American soybean futures prices not only helps in understanding the operational patterns of the global soybean market but also aids in formulating more scientific and reasonable agricultural policies to ensure global food security.

Accordingly, this study conducts an in-depth analysis of the relationship between Chinese and American soybean futures prices using the GARCH and DCC-GARCH models. The research finds that the volatility and dynamic correlation of soybean futures prices between China and the USA have distinct characteristics. These findings not only help us better understand the operational patterns of the global soybean market but also assist in formulating more scientific and reasonable agricultural policies to ensure global food security.

2. Literature Review

2.1. Soybean Futures Price Research

Zhao Xia and Yuan Jiewei (2020)[1] employed econometric models such as the Copula-DCC-GARCH to analyze the effects of trade frictions on the volatility spillover characteristics, volatility structure changes, and transmission directions of the soybean futures market. Shang Haiyan and Li Shunan (2021) [2]established VAR and GARCH models to comparatively study the spillover effects of the Chinese and American soybean futures markets in terms of mean spillover and volatility spillover, as well as the interconnectivity changes in soybean futures returns at different stages. Ye Wuyi, Li Ailin, and Jiao Shoukun (2023)[3] used Dynamic Model Averaging and Local Quantile Conditional Value at Risk methods to study the risk spillover effects of U.S. policies and economic environment changes on China's soybean futures market and analyzed the impact of exogenous variables such as the spot market, downstream soy products, macroeconomic variables, and international market transactions on risk spillover.

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2.2. Application of the DCC-GARCH Model

Zhong Linzhou, Tan Mei, Zhao Jiangqi, and Shen Min (2022)[4] applied the DCC-GARCH model to perform multivariate analysis on the daily closing prices of three typical service industries: education, hotels and catering, and tourism. Yu Ke, Zi Jie, and Xue Qiuxia (2023)[5] used the DCC-GARCH model to analyze the dynamic relationship between the international crude oil futures market and China's new energy stock index market. Guo Sen, Zhang Kaiwen, and Qi Ze (2023)[6] utilized the DCC-GARCH model to study the nonlinear correlation between carbon market and coal market returns.

2.3. Factors Influencing Soybean Prices

Gu Cong and Dong Mei (2021)[7] combined the Autoregressive Integrated Moving Average (ARIMA) with the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (ARIMA-GARCH) to introduce and forecast research on soybean spot prices. Yang Yingce, Guo Junjie, and Deng Mujun (2023)[8] used data on monthly international crude oil prices and Chinese agricultural product prices from January 2000 to March 2021, along with a new method of oil price decomposition to break down international crude oil price shocks into supply shocks, demand shocks, and risk shocks, then applied a Multiple Threshold Nonlinear Autoregressive Distributed Lag model to examine the asymmetric effects of these structural shocks on Chinese agricultural product prices. Yin Lan (2023)[9] researched the factors significantly affecting soybean futures trading prices through descriptive statistics, correlation, multicollinearity, regression analysis, and other methods

3. Data Processing and Statistical Analysis

3.1. Data Processing

This paper selects the daily closing prices of No. 1 Yellow Soybean futures from the Dalian Commodity Exchange (DCE) and the daily closing prices of soybean futures from the Chicago Board of Trade (CBOT) between January 4, 1999, and September 14, 2023. To facilitate the research, all non-matching trading days were removed to align the trading dates of the two markets. After filtering, a total of 5785 data sets were obtained. Converting units into RMB per ton using the conversion of 1 cent per bushel = 0.36744 USD/ton, and the daily USD to RMB exchange rate issued by the State Administration of Foreign Exchange, was performed. To prevent the phenomenon of heteroscedasticity in the futures price return series from being non-stationary, the soybean futures price indices were first log-transformed, and then the return series of the two futures markets were obtained using the first difference method, thus avoiding the possibility of spurious regression in the parameter results. The data were processed as follows

$$r_t = lnP_t - lnP_{t-1} \tag{1}$$

Where r_t represents the log returns of the index, and P_t refers to the daily closing price of the futures

3.2. Statistical Analysis

Table 1: Descriptive Statistics

	dce	cbot
Mean	0.000154	0.000133
Standard Deviation	0.012206	0.016726
Kurtosis	11.985499	23.410176
Skewness	-0.434027	-1.845980
Minimum	-0.150645	-0.245373
Maximum	0.107152	0.126297
Jarque-Bera Test (P-value)	34735.88 (0.0000)	135120.1 (0.0000)

In this paper, 'dce' denotes the logarithmic returns of Soybean No. 1 futures prices at the Dalian Commodity Exchange, while 'cbot' refers to the logarithmic returns of soybean futures prices at the Chicago Board of Trade. As shown in Table 1, the average returns of soybean futures in both markets are positive. Comparing the standard deviations of the return series from the two futures prices, the volatility of dce is lower than that of cbot, indicating that the returns of Soybean No. 1 futures at the Dalian

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Commodity Exchange are relatively more stable. Both dce and cbot have skewness less than zero, presenting an asymmetric left-skewed distribution, and both have kurtosis greater than 3 with a p-value of 0 for the J-B statistic, suggesting that dce and cbot exhibit leptokurtic and heavy-tailed characteristics and do not conform to a normal distribution.

4. Empirical Analysis

4.1. Stationarity Test and ARCH Effect Test

This paper employs the ADF (Augmented Dickey-Fuller) test method to conduct stationarity tests on the logarithmic returns series of soybean futures prices in the two futures markets. The results of the tests are shown in Table 2.

Table 2: Results of Stationarity Tests

	1%	5%	10%	t-statistic	P value
dce	-2.5654	-1.9409	-1.6167	-77.3891	0.0001
cbot	-2.5654	-1.9409	-1.6167	-79.5467	0.0001

The t-statistic values for the soybean futures price return series in both markets are significantly lower than their corresponding critical values at the 1%, 5%, and 10% significance levels, indicating that there are no unit roots in the futures return series of the soybean markets in both China and the United States. This means that the return series of soybean futures prices in both markets are stationary and possess good statistical properties. On this basis, it is necessary to establish a mean-variance for the two series and conduct a conditional heteroscedasticity test, namely constructing an ARMA model to test for ARCH effects. The expression for the mean equation is as follows:

$$y_t = c + \sum \emptyset_p y_{t-p} + \varepsilon_t + \sum \theta_q \varepsilon_{t-q} \tag{2}$$

According to the criteria of minimizing AIC and SC, the mean equation for the cbot series is determined to be AR(1), and for the dce series, it is AR(2). The parameter estimation results are shown in Table 3

Table 3: Parameter Estimation Results for Mean Equation

		Estimate	Standard Error	t-statistic	P value
cbot	C	0.00013	0.00021	0.62717	0.5306
	AR(1)	-0.04504	0.00964	-4.67276	0.0000
dce	C	0.00016	0.00016	0.97127	0.3315
	AR(1)	-0.01703	0.01315	-1.30842	0.1908
	AR(2)	0.02384	0.01082	2.20337	0.0276

Therefore, the mean equation for the logarithmic returns of soybean futures at the Chicago Board of Trade (CBOT) is as follows:

$$cbot_t = 0.00013 - 0.04504 cbot_{t-1} + \varepsilon_t \tag{3}$$

The mean equation for the logarithmic returns of Soybean No. 1 futures at the Dalian Commodity Exchange (DCE) is as follows:

$$dce_t = 0.00016 - 0.01703 dce_{t-1} + 0.02384 dce_{t-2} + \varepsilon_t \tag{4}$$

Table 4: Results of ARCH Effect Test

	ARCH-statistic	P-value
dce	48.3338	0.0000
cbot	6.5079	0.0108

The residuals of the mean equations are tested for ARCH (1) effects. In Table 4, the null hypothesis of the ARCH effect test posits that there is no ARCH effect in the residual series. It is observed that the P-values for the residual tests of the mean equations for both U.S. soybean futures and Chinese soybean futures are less than 0.05. At a 5% significance level, the null hypothesis is rejected, indicating that there is a significant ARCH effect in the residuals of both mean equations. This satisfies the prerequisite conditions for proceeding with GARCH modeling.

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4.2. GARCH Model Construction

Based on the analysis above, the logarithmic return series of the two futures prices are stable and exhibit ARCH effects, therefore allowing for the construction of a GARCH model. As low-order GARCH models are generally sufficient to capture the volatility characteristics of financial data in most applications, a GARCH (1,1) model is used to achieve good results. The GARCH model consists of two parts: the mean equation and the variance equation.

$$y_t = c + \sum \emptyset_p y_{t-p} + \varepsilon_t + \sum \theta_q \varepsilon_{t-q} \tag{5}$$

$$\sigma_t^2 = \alpha_0 + \sum \alpha_i \varepsilon_{t-i}^2 + \sum \beta_j \sigma_{t-j}^2 \tag{6}$$

From Tables 5 and 6, it is evident that for both U.S. soybean futures and Chinese soybean futures, the coefficients of the GARCH (1,1) model are significantly non-zero, and the coefficients of both the ARCH and GARCH terms are greater than zero, satisfying the parameter constraints.

Table 5: GARCH Model Parameter Estimation Results for DCE Soybeans

Variable	Parameter Value	Standard Error	t-statistic	P-value
C	8.15E-07	2.95E-07	2.76426	0.0057
ARCH	0.04502	0.00602	7.47827	0.0000
GARCH	0.95842	0.00468	204.73250	0.0000

Table 6: GARCH Model Parameter Estimation Results for CBOT Soybeans

Variable	Parameter Value	Standard Error	t-statistic	P-value
C	5.53E-06	9.81E-07	5.6354	0.0000
ARCH	0.0494	0.0060	8.2674	0.0000
GARCH	0.9276	0.0080	115.7700	0.0000

Therefore, the GARCH (1,1) model for the logarithmic returns of Soybean No. 1 futures at the Dalian Commodity Exchange (DCE) is as follows:

$$dce_t = 0.00016 - 0.01703 dce_{t-1} + 0.02384 dce_{t-2} + \varepsilon_t \tag{7}$$

$$\sigma_t^2 = 8.15\mathrm{E} - 07 + 0.04502 \varepsilon_{t-1}^2 + 0.95842 \sigma_{t-1}^2 \tag{8}$$

The GARCH (1,1) model for the logarithmic returns of soybean futures at the Chicago Board of Trade (CBOT) is as follows:

$$cbot_t = 0.00013 - 0.04504 cbot_{t-1} + \varepsilon_t \tag{9}$$

$$\sigma_t^2 = 5.53\mathrm{E} - 06 + 0.0494 \varepsilon_{t-1}^2 + 0.9276 \sigma_{t-1}^2 \tag{10}$$

4.3. DCC-GARCH Model Construction

Table 7: DCC-GARCH Model Parameter Estimation Results

	Estimate	Standard Error	t-statistic	P-value
a	0.00294	0.00093	3.16141	0.00157
b	0.99685	0.00122	815.96625	0.00000

To further study the interconnection effects between the two markets, this paper constructs a DCC-GARCH model using R language. From the parameter estimation results shown in the Table 7, it is known that both a and b are greater than 0 and a+b<1, satisfying the model specifications. According to the results, 'a' represents the impact of the lagged standardized residuals on the correlation coefficient, and in this model, this estimation result is relatively small. 'b' is 0.99685, close to 1, indicating that most of the current period's dynamic heteroscedasticity in both markets stems from the volatility of the previous period, with a minor influence from the squared residuals of the previous period. It is also evident that the dynamic correlation between the soybean futures markets of China and the United States has strong persistence.

The dynamic correlation chart between the two soybean futures markets is as follows Figure 1, showing that the dynamic conditional correlation coefficients between the Chinese and American soybean futures markets change over time.

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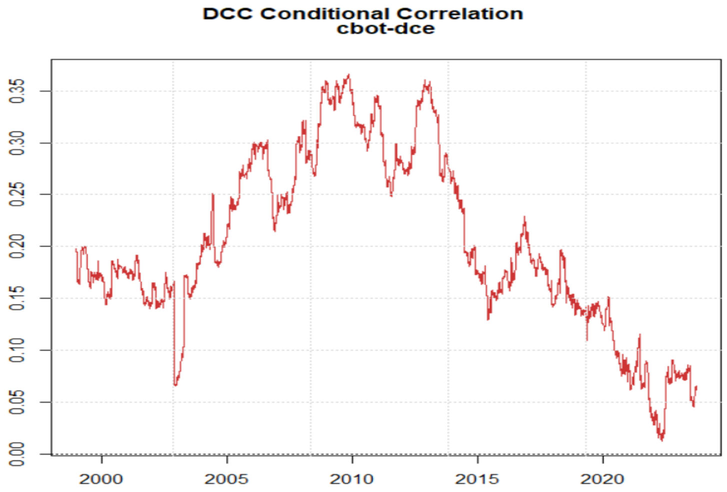

Figure 1: Dynamic Correlation Chart

4.4. Conclusion

This paper constructs a DCC-GARCH model to study the interconnection effects between the Chinese and U.S. soybean futures markets using daily closing prices of Soybean No. 1 futures from the Dalian Commodity Exchange (DCE) and soybean futures from the Chicago Board of Trade (CBOT) from January 4, 1999, to September 14, 2023. The empirical conclusions are as follows:

Firstly, the ADF test reveals that the logarithmic returns of soybean futures prices in both markets are stationary. By constructing an AR model, it is found that the residuals exhibit ARCH effects, meeting the prerequisites for GARCH modeling.

Secondly, the parameters of the DCC-GARCH model are estimated using a two-step method. In the first step, univariate GARCH models are estimated to obtain the residual series, which, after processing, serve as input variables for the second step. In the second step, the dynamic correlation equation is estimated, yielding parameters a and b, with $a+b<1$, indicating that the dynamic correlation between the Chinese and U.S. soybean futures markets has strong persistence.

Finally, the dynamic correlation chart between the Chinese and U.S. soybean futures markets shows that the dynamic conditional correlation coefficients between these markets change over time and fluctuate significantly.

5. Recommendations

Based on the research results above, the following suggestions are offered:

Firstly, for investors, understanding the interconnection effects between the Chinese and U.S. soybean futures markets is crucial. In the investment decision-making process, it is important to fully consider the dynamic correlation between the two markets, as well as the volatility of the correlation coefficients. In addition, investors should also delve into the fundamentals of the market, including supply and demand relationships, planting areas, and climate change. These fundamental factors significantly impact soybean futures prices, and a deeper understanding of these factors can help investors make more accurate predictions and judgments. By integrating market fundamentals with price dynamics, investors can develop more effective investment strategies and improve the accuracy of investment decisions.

Secondly, for policymakers, a deep understanding of the interconnection effects between the Chinese and U.S. soybean futures markets can provide an important basis for formulating relevant policies. When dynamic correlations between the two markets exhibit abnormal fluctuations, policymakers need to adjust policies in a timely manner according to the actual situation to ensure the stable operation of the markets.

Thirdly, for futures exchanges, enhancing communication and cooperation with international futures markets and improving market transparency and the quality of information disclosure can help reduce market interconnection effects, decrease market volatility, and thus attract more investors to participate

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in trading.

In summary, the interconnection effects between the Chinese and U.S. soybean futures markets are a complex and interesting issue worthy of further in-depth study. By continuously deepening our understanding of this issue, we can better respond to market changes, enhance the scientific and accuracy of investment decisions, and also contribute to the healthy development of China's futures market, enhancing China's discourse power and influence in the international commodity markets

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