Agricultural & Forestry Economics and Management (2023)
Clausius Scientific Press, Canada

DOI: 10.23977/agrfem.2023.060402
ISSN 2616-2202 Vol. 6 Num. 4

The Financialization of Agriculture Products in the Chinese Domestic Market: Time-varying Correlations between Chinese Agricultural Commodity and Financial Market Dynamics

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Keywords: Agricultural commodity, ARMA-DCC GARCH model, stock market

Abstract: The financialization of agriculture products is the result of a dramatic increase in commodity investing popularity over the last decade, which has resulted in an unprecedented infusion of institutional capital into commodity futures markets. This study analyses the dynamic relationship between financial markets and domestic agricultural commodity markets in China. The autoregressive moving-average dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (ARMA-DCC GARCH) model is used to identify whether the financialization of agriculture products exists in Chinese domestic markets (corn, soybean No. 1, soybean No. 2, soybean meal, and soybean oil) from 2006 to 2020. The results show that dynamic, long-term positive volatile time-varying relationships exist between markets over the last 14 years. The prices of soybean No. 1 and soybean oil appear to have been more affected by the contagion effect of the financial crisis of 2008 than the prices of soybean No. 2 and corn. These results show that the financialization of agriculture products exists in the Chinese domestic market.

1. Introduction

The tremendous rise in global demand for raw materials, represented by commodities, has raised concerns about commodity price volatility over recent decades. However, few studies have focused on the relationship between domestic financial and commodity markets in China. If the two markets have weak or negative correlations, the two asset classes are driven by separate factors and behave differently. If these correlations are strong, it could mean that China's economy affects demand for these commodities, investors or speculators view them as investment assets rather than consumer goods, international trade and financial integration, and government policies like subsidies or trade restrictions. Investors, politicians, and analysts must understand correlation drivers to make informed market decisions and forecasts. Basak and Pavlova (2016) [1] discovered that when financialization occurs, all commodity futures prices and volatilities rise. Additionally, cross-market relationships between commodity futures and equity-commodity correlations are significantly enhanced (Ordu et al. 2018) [2]. The transmission of financial shocks may significantly increase the volatility of commodity prices in times of financial turmoil. By examining the connection between the Chinese futures market and the international stock market, Su et al. (2022) [3] concluded that there is no agricultural financialization in the Chinese sugar market. They used monthly data covering the period from January 2006 to June 2019. Sun et al. (2019) [4] examine the interaction between money flows and interest rates, and metal prices (copper, metal aluminium, natural rubber, screw-thread steel, and nonferrous metals). Bohl et al. (2018) [5] analyse the relationship between speculative hedging ratios and return volatility in Chinese agricultural markets (soybeans, soybean meal, soybean oil, palm oil, corn, rapeseed oil, cotton, and sugar). They consider the performance of these financial markets, aside from the stock market, to be an important factor influencing the condition of the wider financial market.

The longest-running agricultural futures price records are at the Dalian Commodity Exchange. Soybean (No. 1 and No. 2), corn, soybean meal, and soybean oil have been actively traded on the Dalian Commodity Exchange platform since 2006. Therefore, these five agricultural products were chosen for this study to examine the markets' long-term status.

The financialization of agriculture products can be described as the influence of financial market participants' performance on the price of agricultural products. In this study, the existence of agricultural financialization is based on the extent to which there is a noticeable cross-market relationship between Chinese stocks and agricultural commodities, as well as the degree to which financial shocks during times of turbulence can significantly increase the volatility of agricultural commodity prices.

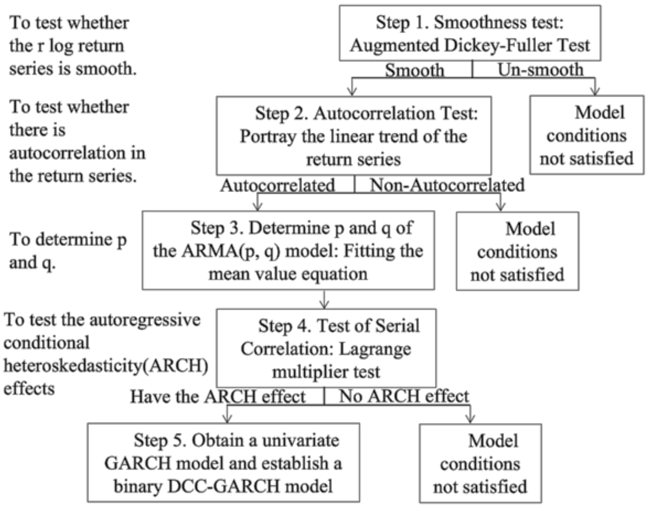
To further study the price situation in the Chinese agricultural market, this study focuses on China's domestic financial and agricultural commodity markets. The objective of this study is to identify the existence of the financialization of agriculture products in the Chinese domestic markets by using the autoregressive moving-average dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (ARMA-DCC GARCH) model.

2. Data and Methodology

Bollerslev (1986) [6] extended the ARCH model to a more general GARCH model. Engle's DCC-GARCH model explains the dynamic mechanisms connecting financial variables. The generated dynamic conditional coefficients can effectively reflect the consequences of modifications. By estimating time-varying conditional correlations, the DCC-GARCH model can evaluate market interdependence (Engle 2002) [7].

The ARMA-DCC GARCH model addresses correlation model limitations of fixed window sizes. It models time-varying volatility and correlation and adapts to market dynamics. It is commonly known that financial markets fluctuate between calm and upheaval. The ARMA-DCC GARCH model better captures these dynamics than other correlation models. Second, financial time series data are frequently non-stationary. Other correlation models may not correctly account for this, resulting in incorrect estimates. The GARCH model is better for financial data since it accounts for non-stationarity. Third, the Autoregressive moving-average (ARMA) aspect of the ARMA-DCC GARCH model allows autoregressive and moving average components, which can capture time series dependencies and patterns that other correlation models cannot (Tsay 2010) [8]. Fourth, ARMA-DCC GARCH models explicitly model time-varying conditional correlations using the DCC component. In financial analysis, understanding asset correlations with market conditions is crucial. Finally, ARMA-DCC GARCH models forecast volatility and correlations, essential for risk management and portfolio optimization. Different correlation models cannot anticipate such things.

To achieve the objective, our study employs the ARMA-DCC GARCH model, which reveals the dynamic volatility links between Chinese financial markets and each Chinese agricultural commodity sector. Rather than emphasizing the integration of markets together as in the copula model employed by Ouyang and Zhang (2020) [9], this model analyzes each model separately. To our knowledge, this study is the first to apply this method to analyze the financialization of agriculture products in China. Figure 1 describes the methodological steps.



Source: constructed by the author.

Figure 1: Modelling process of the ARMA-DCC GARCH

Table 1: List of variables

Variables	Explanation	Data source	Unit
Stock index price	SSE Composite Index (000001.SS) is a stock market index of all stocks (A and B shares) traded on the Shanghai Stock Exchange reflecting the volatility of China's financial markets. We use stock returns for the analysis in this study.	Yahoo Finance	Yuan (RMB)
Soybean No. 1 price	Soybean No. 1 price refers to soybean No.1 futures contract's price. The Soybean No. 1 futures contract, which uses the pure grain rate as the design technical standard, is applicable to edible beans while imported genetically modified soybeans cannot be used for delivery of the Soybean No. 1 contract.	Dalian Commodity Exchange	Yuan (RMB) per ton
Soybean No. 2 price	Soybean No. 2 price refers to soybean No.2 futures contract's price. The Soybean No. 2 futures contract is for genetically modified soybeans and uses a soybean index system for oil extraction based on international soybean quality standards, with oil content as the technical standard, focusing on oil extraction soybean standards. It covers imported soybeans and can directly meet the needs of oil crushing companies.	Dalian Commodity Exchange	Yuan (RMB) per ton
Corn price	Corn price refers to corn futures contract's price.	Dalian Commodity Exchange	Yuan (RMB) per ton
Soybean meal price	Soybean meal price refers to Soybean meal futures contract's price.	Dalian Commodity Exchange	Yuan (RMB) per ton
Soybean oil price	Soybean oil price refers to Soybean oil futures contract's price.	Dalian Commodity Exchange	Yuan (RMB) per ton

Source: collected by the author.
Notes: Yahoo Finance: *http://finance.yahoo.com*; Dalian Commodity Exchange: *http://www. dce. com.cn/*

We analyzed the relationship between agricultural commodity prices and Chinese stock market trends from January 2006 to December 2020. Commodity futures prices were chosen because the futures market has a large trading volume and is representative of trading prices in the Chinese commodity market. The Dalian Commodity Exchange (http://www.dce.com.cn/) was used to obtain futures prices for the five agricultural commodities traded on the China Agricultural Derivatives Exchange. The futures price time series for each commodity was calculated by averaging the weighted prices of all contracts with maturities of less than one year. Yahoo Finance (http://finance.yahoo.com) was used as the data source for the SSE Composite Index. Table 1 presents a list of variables. To minimize the impact of COVID-19, we decided not to include data covering 2021 to 2022.

The flowchart of the method used in this study is shown in Figure 1. The data were selected from the daily closing price of each trading day, and the daily return was used as the object of study. Thus, the daily return series was obtained by first taking the logarithm of the daily closing price of the stock index and then differentiating it, that is,

$$r_{it} = lnp_{it} - lnp_{i,t-1} \tag{1}$$

Where t is the time, r_{it} is the daily return and p_{it} represents the daily closing price of asset i. i = 1 corresponds to stock index price, i = 2 corresponds to soybean No. 1 price, i = 3 corresponds to soybean No. 2 price, i = 4 corresponds to corn price, i = 5 corresponds to soybean meal price, i = 6 corresponds to soybean oil price.

This model assumes that there are k assets whose conditional returns obey a normal distribution with mean 0 and variance-covariance matrix $\boldsymbol{H}_t$, which can be expressed as:

$$\boldsymbol{r}_t|\Omega_{t-1} \sim N(0, \boldsymbol{H}_t) \tag{2}$$

$$\boldsymbol{H}_t \equiv \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t \tag{3}$$

Equation (2) represents the conditional distribution of asset returns, denoted as matrix $\boldsymbol{r}_t$, given the information set Ω_{t-1}. It follows a normal distribution with mean 0 and a conditional variance-covariance matrix denoted as $\boldsymbol{H}_t$. The information set Ω_{t-1}, denoted as the collection of past information generated by past events up to time t-1, represents all the available information and data up to the time period just before t.

In Equation (3), t is the time, $\boldsymbol{H}_t$ is defined as the product of three components: $\boldsymbol{D}_t$, $\boldsymbol{R}_t$ and $\boldsymbol{D}_t$. $\boldsymbol{D}_t$ is a diagonal matrix with time-varying elements, representing the conditional standard deviations obtained from univariate GARCH models. $\boldsymbol{D}_t$'s diagonal elements, indicate the conditional standard deviation of the i-th asset's returns. The conditional standard deviations are calculated separately for each asset using its own GARCH model, and these standard deviations are organized into a diagonal matrix $\boldsymbol{D}_t$.Specifically, $\boldsymbol{D}_t$ is calculated as $\boldsymbol{D}_t = diag(\sqrt{h_{it}})$, where h_{it} represents the conditional variances obtained from individual GARCH models for each asset in the portfolio. $\boldsymbol{R}_t$ is the dynamic conditional correlation coefficient matrix.

$$L = -\frac{1}{2}\sum_{t=1}^{T}[klog(2\pi) + log(|\boldsymbol{H}_t|) + r_t'\boldsymbol{H}_t^{-1}r_t]$$

$$= -\frac{1}{2}\sum_{t=1}^{T}[klog(2\pi) + log(|\boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t|) + r_t'\boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1}r_t]$$

$$= -\frac{1}{2}\sum_{t=1}^{T}[klog(2\pi) + log(|\boldsymbol{D}_t|) + log(|\boldsymbol{R}_t|) + \varepsilon_t'\boldsymbol{R}_t^{-1}\varepsilon_t] \tag{4}$$

The log-likelihood function (Equation 4) is used to estimate model parameters. It quantifies how well the model fits the observed data. In this equation, t is the time, ε_t represents the standardized residuals, assumed to follow a normal distribution with mean 0 and the dynamic conditional correlation coefficient matrix $\boldsymbol{R}_t$. The matrix $\boldsymbol{D}_t$ is derived from individual univariate GARCH models.

The univariate GARCH model is as follows.

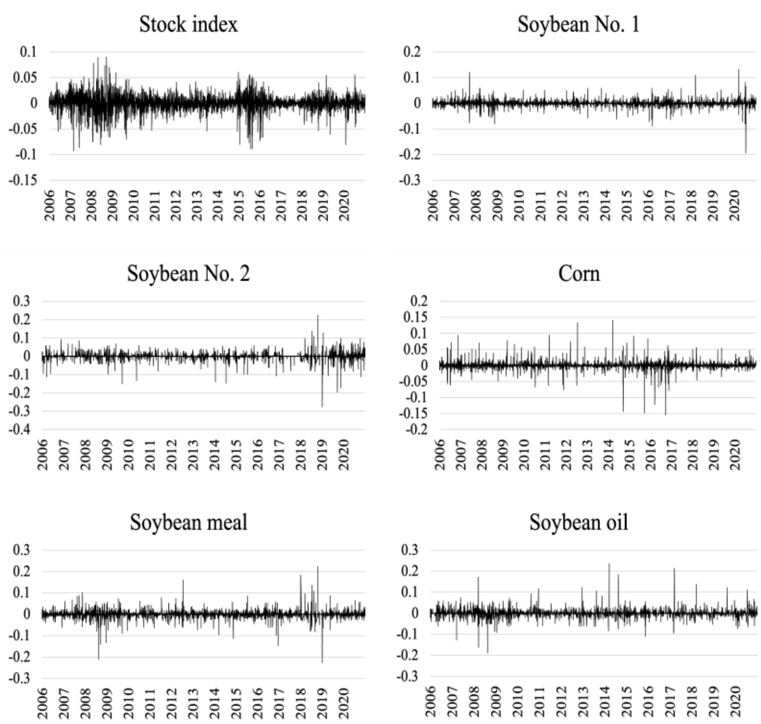
$$h_{it} = \omega_i + \sum_{p=1}^{p_i} \alpha_{ip}\varepsilon_{it-p}^2 + \sum_{q=1}^{q_i} \beta_{iq}h_{it-q} \tag{5}$$

Where t is the time, i=1,2,...,k; $\alpha_{ip}$and β_{iq} are the coefficients of the squared prior residuals and the coefficients of the prior conditional variance, respectively, and p and q are the lagged orders of the squared prior residuals and the prior conditional variance, respectively. Additionally, in this univariate GARCH model, h_{it} needs to satisfy the non-negative and smooth conditions, that is, $\alpha_{ip} \geq 0,\ \beta_{ip} \geq 0,\ \sum_{p=1}^{p_i} \alpha_{ip} + \sum_{q=1}^{q_i} \beta_{iq} < 1$.

The multivariate GARCH models encompass several parameters and formulations for the dynamic conditional correlation coefficients $\boldsymbol{R}_t$. To obtain a comprehensive understanding of the equations and their derivations, please refer to the work of Engle (2002) [7].

3. Results and Discussion

3.1 Descriptive Statistical Analysis



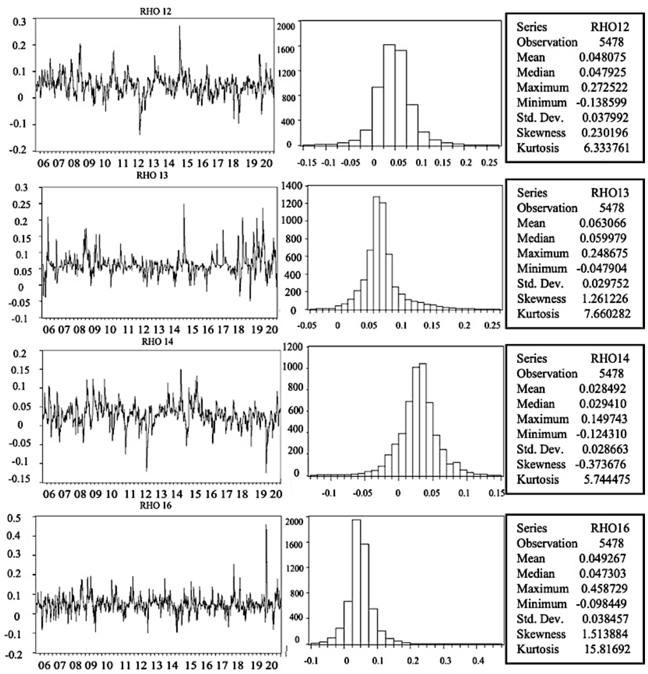
Source: calculated by the author.

Figure 2: Time series versus returns chart

The time series chart of returns (Figure 2) shows that the returns vary over time. Stock index returns are most volatile around the years 2008 and 2019; Soybean No. 1 returns are most volatile around 2008, 2018, and 2020; Soybean No. 2 returns are most volatile around 2018 and 2020; Corn returns are most volatile around 2016; Soybean meal returns are most volatile around 2008 and 2018; while Soybean oil returns are most volatile around 2008, 2014, and 2018. Volatility clustering reflects the convergence of price changes of financial assets in the market; that is, the degree of price volatility tends to be continuous over a certain period. High price volatility is often accompanied by large price fluctuations in the current time and similarly low volatility with smaller price fluctuations in the next. Because of this, fluctuations in stock index returns tend to have a degree of predictability and exhibit positive dynamic conditional correlations. For example, stock index returns are less volatile in the middle of Figure 3 and more volatile around 2008, 2016, and 2019. This figure shows the typical financial time series "volatility clustering phenomenon," which can be considered for GARCH modelling.

3.2 Smoothness Test

As time-series analysis is based on smoothness and the ARMA is modelled for a smooth time series of returns, the smoothness test of the time series is often tested by a unit root test. To test whether the return of stock markets ($\boldsymbol{r_1}$) of stock markets are smooth, we performed the augmented Dickey-Fuller (ADF) test. The ADF test assumes that the random perturbations in a time series are independent and identically distributed, which enables the use of statistical tests. The test is designed to determine whether a time series has a unit root or is non-stationary. Additionally, the analysis of log-return data may be conducted to further investigate the properties of the time series. A smoothness test was performed before modelling the time series to verify the model's validity. The examination revealed that the p-value corresponding to the test statistic value is less than 0.01 when the hypothesis of the existence of a unit root is rejected at the 1% significance level. This indicates that the index return series is smooth and no unit root exists.



Source: calculated by the author using an ARMA-DCC GARCH process.
Notes: ρ(RHO) (12), RHO (13), RHO (14), and RHO (16) are the dynamic conditional correlations between the financial market and the soybean No. 1, soybean No. 2, corn, and soybean oil markets, respectively.

Figure 3: Dynamic conditional correlations of soybean No. 1 and 2, corn, and soybean oil (2006-2020)

3.3 Autocorrelation Test of the Stock Market

There is autocorrelation in the return series of the stock market; therefore, an ARMA model is attempted to fit the mean equation of the series to portray the linear trend of the return series of the stock market.

3.4 Determine p and q of the ARMA(p, q) Model

The number of orders of p, q in the ARMA model is generally determined according to the autocorrelation and partial autocorrelation graph coefficients trailing truncation. The order in the ARMA(p, q) model can also be determined automatically according to the criterion that the smaller the AIC and BIC, the better the model.

According to our analysis, our model was chosen with a p-value of 2 and a q-value of 3, and the ARMA(2,3) model was used for subsequent calculations.

The fitted mean value equation is

$$r_t = 0.1327r_{t-1} + 0.4657r_{t-2} + \varepsilon_t + 0.1708\varepsilon_{t\text{-}1} + 0.4653\varepsilon_{t-2} - 0.0757\varepsilon_{t-3} \tag{6}$$

where t is the time.

The Q-test statistic of the residual series corresponds to a p-value greater than 0.05; therefore, the residual series of the model under testing is considered a white noise series. In other words, the ARMA(2,3) model established by the above steps can better extract data information and better fit the data change trend.

3.5 Test of Serial Correlation

The existence of ARCH effects is a prerequisite for using ARCH or GARCH models to characterize the time series of stock market returns. The residuals of the mean equation were tested for the ARCH effect. The p-value for each commodity is significantly less than 0.01, except for soybean meal. This rejects the original hypothesis that "the series does not have the ARCH effect," indicating that the model does, in fact, have an ARCH effect. Conditional heteroskedasticity exists, and the variance changes with time. This result reflects the risky nature of return changes, and there is no ARCH effect for soybean meal agricultural products.

3.6 Obtain a Univariate GARCH Model and Establish a Binary ARMA-DCC GARCH Model

A strong financialization of agriculture products can be considered to exist if financial market volatility can significantly increase the volatility of agricultural commodity prices. This is demonstrated by changes in the correlation coefficient matrix ($\boldsymbol{R}_t$) in the ARMA-DCC GARCH model, where increased volatility in financial markets can lead to larger changes in the conditional correlation at certain moments, ultimately resulting in higher volatility of agricultural commodity prices. Therefore, by analyzing the equation parameters of $\boldsymbol{R}_t$ in the ARMA-DCC GARCH model, we can determine the impact of financial market returns on agricultural commodity prices and the impact of increased financial market volatility on agricultural commodity price volatility. Additionally, we consider the relationship between the financial and agricultural commodity sectors on a sector-by-sector basis.

ρ(RHO) denotes the dynamic correlation coefficient in Figure 3. The results of the ARMA-DCC GARCH model indicate a relatively high degree of persistence of dynamic conditional correlations between the two markets (the stock market and soybean No. 1 agricultural product markets). The mean values of the dynamic conditional correlation coefficients differed significantly from 0. The positive and negative results were also consistent with our expectations. From the dynamic conditional correlation coefficients graph and the binary model, the results indicate that the dynamic conditional correlations between the stock and soybean No. 1 markets are relatively high, and the mean values of the dynamic conditional correlation coefficients are significantly different from 0. Moreover, the dynamic conditional correlations between the markets are more regular, staying in the range of 0 values.

The dynamic conditional correlations between the stock and soybean No. 2 product markets have a relatively high degree of persistence. Moreover, the mean value of the dynamic conditional correlation coefficients is significantly different from 0. The dynamic conditional correlations between the markets are more regular, fluctuating within 0.05; in recent years, the linkage between the two markets has been in a slightly upward channel. However, the dynamic conditional correlations between the markets showed greater fluctuations, especially in 2018, and the dynamic conditional correlations between the two markets were more volatile, especially between 2018 and 2020.

The results show that the persistence of dynamic conditional correlations between the stock and corn product markets is relatively low, the mean value of the dynamic conditional correlation coefficients is 0.028492, and the dynamic conditional correlations are low. The dynamic conditional correlations between the two markets are comparatively more volatile and highly variable.

The persistence of dynamic conditional correlations between the stock market and soybean oil products is relatively high, the dynamic conditional correlation coefficients are interspersed with positive and negative dynamic conditional correlations, and the dynamic conditional correlations between the markets are more regular. As a result, the linkage between the two markets is relatively smooth.

The conditional correlations between these markets are dynamic (i.e., sometimes they rise sharply, and sometimes fall sharply). For example, the correlation between the agricultural commodity and stock markets shows strong volatility that increased considerably at the end of the financial crisis in 2008, reaching a peak in 2015 or 2019. In other words, there is a record of high volatility in the market at the same time. By fitting this model, it is possible to see how the conditional correlation between a pair of commodities evolves over time. This study also builds upon previous works demonstrating a similar co-movement between agricultural and stock market prices. Previous studies (Ouyang and Zhang 2020) [9] in this research area are consistent with the findings of this study. Each agricultural product market operates in a particular way and reacts differently to external financial shocks. Corn prices have the smallest standard deviation for their dynamic correlation coefficient. The relationship between the Chinese stock market and corn prices in China is, therefore, the steadiest. When we examine the 2008 financial crisis period, we observe that the dynamic correlation coefficient of soybean No. 1, soybean No. 2, corn, and soybean oil increased during the crisis period. The prices of soybean No. 1 and soybean oil appear to have been more affected by the contagion effect of the financial crisis than the prices of soybean No. 2 and corn.

4. Conclusion

We examined the time-varying correlations between the dynamics of domestic agricultural commodities and financial markets in China using the ARMA-DCC GARCH model. We conclude that there are dynamic, long-term positive volatile time-varying relationships between domestic agricultural commodity markets and the financial market over the last 14 years. This result indicates that the financialization of agriculture products exists in the Chinese domestic market.

We found that all dynamic correlation coefficients are highly volatile. The relationship between the Chinese stock and corn markets is the most stable among the four commodities studied. Four agricultural markets (soybean No. 1, soybean No. 2, corn, and soybean oil) are shown to be related to the financial market, and each reacts differently to the financial market. The prices of soybean No. 1 and soybean oil appear to be more affected by the contagion effect of the financial crisis than the prices of soybean No. 2 and corn.

Financial crises can trigger certain fluctuations that hinder the healthy development of agricultural markets. Therefore, the government could work to prevent financial crises and monitor price fluctuations in the stock market. Additionally, the government should attempt to keep the deficit and debt-burden ratios at safe levels at all times; keep commercial banks' non-performing loan balances and ratios down; improve the provision coverage and capital adequacy ratios; and strictly control speculative and investment demand.

The discussion of our research methodology and model selection is relevant to the overall goal of our study, which is to explore the short-term impact of financial markets on agricultural commodity prices. We acknowledge that studying core causal relationships is crucial. Still, we believe that analysing short-term effects is equally valuable and meaningful, particularly in complex markets such as the agricultural commodity market.

Our methodology involved a thorough analysis of the available data and literature, which led us to select the ARMA-DCC GARCH model as the most appropriate for our research purposes. This model has been widely used and validated in previous studies (Zinecker et al. 2016) [10], which gave us confidence in its ability to accurately capture the relationship between financialization and agricultural prices.

The ARMA-DCC GARCH model exhibits certain limitations, including its inability to forecast long-term trends or meta-events, infer causality, and effectively capture high volatility swings in financial markets. If future studies require the consideration of additional relationships and causal relationships, other models, such as the BEKK-GARCH model, may be used for further analysis. We hope to contribute to the ongoing discussion surrounding the appropriate methods for analysing the short-term impact of financial markets on agricultural commodity prices.

This study covers several research topics that can be further explored in future research. First, the behaviour of Chinese financial market participants, such as the impact of financial derivatives trading on agricultural markets, could be further documented and assessed. Second, some researchers could explore how COVID-19 has affected the Chinese agricultural market through financial markets. Third, correlations' volatility causes, Economic indicators, policy changes, seasonal factors, and external shocks may impact these associations, therefore this may require further investigation. Forth, further research could consider incorporating time-varying expected returns into the modelling framework. This would involve extending the model to allow for a non-zero mean in the distribution of asset returns.

Acknowledgements

This study was supported by Japan Society for the Promotion of Science (JSPS) KAKENHI program (Grant number JP19H00960).

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Appendix

Appendix 1: Descriptive statistic results table of the original data

	Stock index	Soybean No. 1 price	Soybean No. 2 price	Corn price	Soybean meal price	Soybean oil price
Count	5479	5479	5479	5479	5479	5479
Mean	2846.979	3948.976	3808.964	1922.430	3075.032	7055.015
Median	2868.800	3900.000	3765.000	1852.000	3041.000	6638.000
Mode	1258.046	4000.000	3200.000	2363.000	3557.000	5095.000
Standard Deviation	762.329	688.488	749.133	352.201	513.790	1704.624
Sample Variance	581145.085	474015.291	561200.641	124045.269	263980.218	2905741.300
Kurtosis	2.279	-0.050	-0.692	-1.098	0.223	0.926
Skewness	0.984	0.009	0.177	0.113	0.394	1.124
Range	4911.094	3752.000	3703.000	1530.000	3036.000	10658.000
Minimum	1180.963	2370.000	2100.000	1210.000	2050.000	4560.000
Maximum	6092.057	6122.000	5803.000	2740.000	5086.000	15218.000
Sum	15598599.500	21636440.000	20869316.000	10532994.000	16848100.000	38654425.000

Source: calculated by the author.

Appendix 2: Table of correlation coefficient between original data

	Stock index price	Soybean No. 1 price	Soybean No. 2 price	Corn price	Soybean meal price	Soybean oil price
Stock index price	1					
Soybean No. 1 price	0.142	1				
Soybean No. 2 price	0.060	0.670	1			
Corn price	-0.093	0.640	0.386	1		
Soybean meal price	-0.063	0.689	0.739	0.437	1	
Soybean oil price	0.200	0.507	0.837	0.193	0.509	1

Source: calculated by the author.

Appendix 3: Descriptive statistic results table of returns

	Stock index return	Soybean No. 1 price return	Soybean No. 2 price return	Corn price return	Soybean meal price return	Soybean oil price return
Number of observations	5478	5478	5478	5478	5478	5478
Minimum	-0.092561	-0.193475	-0.276036	-0.154702	-0.227228	-0.188174
Maximum	0.090345	0.131569	0.223349	0.141027	0.223349	0.235602
1. Quartile	-0.002111	-0.000778	0.000000	-0.000602	0.000000	0.000000
3. Quartile	0.003671	0.001056	0.000000	0.000634	0.000617	0.000000
Mean	0.000197	0.000141	0.000085	0.000138	0.000061	0.000098
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1.078708	0.770532	0.464439	0.756618	0.331421	0.538567
SE Mean	0.000179	0.000136	0.000203	0.000134	0.000193	0.000195
LCL Mean	-0.000153	-0.000126	-0.000314	-0.000124	-0.000317	-0.000285
UCL Mean	0.000547	0.000407	0.000483	0.000400	0.000438	0.000482
Variance	0.000175	0.000101	0.000227	0.000098	0.000203	0.000209
Std. Dev.	0.013213	0.010053	0.015052	0.009894	0.014259	0.014468
Skewness	-0.751300	-0.799839	-1.912460	-0.429261	-0.472595	1.464390
Kurtosis	8.492556	48.823417	55.642160	62.441286	53.453170	49.347748

Source: calculated by the author.

Appendix 4: Table of determine p and q of stock return

	AIC	AICc	BIC
ARMA(2,3)	-31875.01	-31874.99	-31835.36
ARMA(0,0)	-34848.45	-34848.45	-34841.84
ARMA(0,1)	-35043.95	-35043.95	-35030.74

Source: calculated by the author.

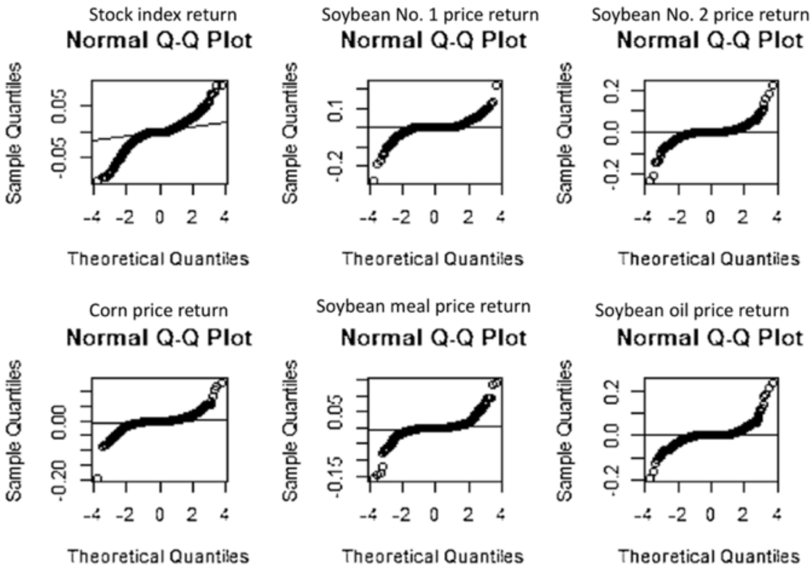
Appendix 5: Summary table of results for each market

Commodities	Stock return	Soybean No. 1 price	Soybean No. 2 price	Corn price	Soybean meal price	Soybean oil price
Step 1. Smoothness test:Augmented Dickey-Fuller Test	smooth					
Step 2. Autocorrelation test: Portray the linear trend of the return series	auto correlated					
Step 3. Determine p and q of the ARMA(p, q) model: Fitting the mean value equation	p=2, q=3					
Step 4. Test of Serial Correlation:Lagrange multiplier test		Have ARCH effects	Have ARCH effects	Have ARCH effects	No ARCH effects	Have ARCH effects
Step 5. Obtain a univariate GARCH model and establish a binary DCC-GARCH model		$\bar{\rho} = 0.048075$	$\bar{\rho} = 0.063066$	$\bar{\rho} = 0.028492$	NA	$\bar{\rho} = 0.049267$

Source: calculated by the author.

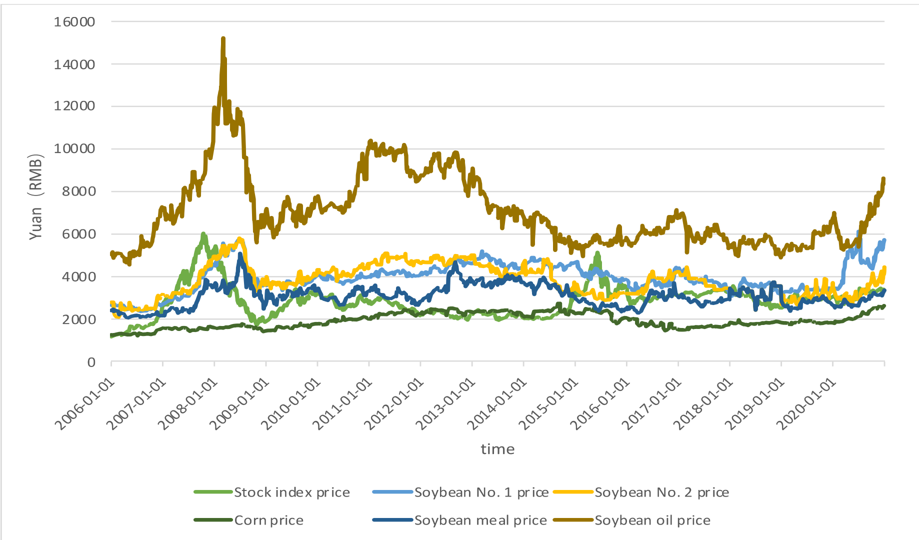
Note: (1) NA stands for no answer because the previous test showed no ARCH effect; therefore, there is no model to show.

(2) Blank parts of the table indicate that there is no data to display for the model results.



Note: Units of agricultural products are calculated in yuan per ton
Source: calculated by the author.

Appendix 6: Figure of relative performance of all markets



Source: calculated by the author.

Appendix 7: Figure of normal distribution of returns