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FINANCIAL ECONOMICS | RESEARCH ARTICLE

The impact of the Chinese cornstarch futures on spot market and corn futures market

Crentsil Kofi Agyekum^{1*}, Haifeng Huang¹ and Jianshu Chen¹

Abstract: This article investigates price transmission mechanism and volatility impact between Chinese cornstarch futures market and relevant markets through Johansen cointegration test, VEC model and GARCH model. The empirical results indicated that the Chinese cornstarch futures price could guide cornstarch spot price uni-directionally and there are long-term cointegration relationships between them. There is a co-integration and bi-directional lead relationship between cornstarch futures price and corn futures price. The launch of cornstarch futures market can slightly reduce volatility of domestic corn futures market. However, the launch of cornstarch futures market has no significant impact on the spot market.

Subjects: Social Sciences; Economics; Finance; Business, Management and Accounting

Keywords: cornstarch futures; spot price; price transmission; volatility

1. Introduction

In recent years, Chinese economy has come to a new period after 30 years' rapid development since the great reform and opening. In this period which is called "The New Normal", the adjustment of economy structure and the upgrade of industries are the most important. Therefore, a series of innovations are necessary.

Dalian Commodity Exchange (DCE) launched the RMB-denominated and physical delivery cornstarch futures on 19 December 2014, which made China the first country in the world to own cornstarch futures market. The official launch of cornstarch futures market is one of the important innovations that China need today. This event is a milestone in the history of Chinese commodity futures market and has great significance.

ABOUT THE AUTHOR

Crentsil Kofi Agyekum has published peer-reviewed articles on financial policies. He has one book published to his credit entitled "consumer perception quality on the sale of rice" and has also published in a lot of peer-reviewed journals on economics and management related issues. He is a PhD candidate in Beijing University of technology in the department of Economics and Management. He also serves as a business development and operation executive in one of the leading Information Technology Companies in China. He has been a research assistant since 2013 to 2017. This information in the current perspective article is important detail analysis for researchers and scholars who want to delve more into Agricultural products and future finances and marketability of corn and corn-starch.

PUBLIC INTEREST STATEMENT

The study focuses on the relationship between cornstarch futures price and corn futures price. The launch of cornstarch futures market can slightly reduce volatility of domestic corn futures market. However, the launch of cornstarch futures market has no significant impact on the spot market. This paper discusses in details cornstarch prices in future using some financial models. This study would be of interest to both academic and non-academician, and provides a base market study for marketers and investors who may need further knowledge on the subject.

Chinese cornstarch futures market is a new market and it's necessary to deepen research about this newborn market. This paper studies the impact of Chinese cornstarch futures market on domestic cornstarch spot market and domestic corn futures market. The two main research questions of this paper are: (1) the price transmission mechanism between cornstarch futures market and domestic cornstarch spot market, corn futures market. (2) The impact of the launch of cornstarch futures market on the volatility of domestic cornstarch spot market and corn futures market. According to the analysis above, the launch of Chinese cornstarch futures market benefits the domestic relevant market development overall. However, it has only limited effect. There are still a lot of areas that need to be refined and improved. Thus, this article proposes the following conclusions:

Firstly, to tighten controls of the speculative actions among Chinese cornstarch futures market is quite essential. The authorities are supposed to tighten controls of the speculative behaviors among Chinese cornstarch futures market including raising the threshold for the market access, increasing the transaction cost, and other methods to control the excessive speculative actions among the market.

Secondly, investors' education of risk consciousness should be enhanced. The authorities should reinforce the investors' education of risk consciousness as well as tighten controls of the market. Thus, investors would be aware of the risks of the speculative actions as to take the initiative away from risky speculative actions in both cornstarch futures market and spot market. This would avoid the risk at the source.

Thirdly, we should encourage the development of the hedge between future and spot market and adopt the market self-control mechanism to make the cornstarch futures market healthier.

2. Literature review

Price transmission is a common effect in the financial market. Price transmit describes the phenomenon that one market could influence another in one-way or two markets would influence each other. The precondition of price linkage is the financial liberalization, the inner motivation is information spillover effect and the immediate cause is the investor behavior. Yin (2006) proposes that the short-term causality of price return also reflect the price transmission.

This paper focuses on the agriculture spot and futures market. Thus, this paper refers to researches regarding different kinds of market price transmissions, especially the transmission mechanism of agricultural product markets. We sort the research findings home and abroad by time line.

Foreign scholars employ Granger causality test, co-integration test, VAR model, VEC model and GARCH model to study the transmission between prices, the leading and lag effect, and fluctuation over flow effect. Babula and Bessler (1990) use VAR model, impulse response function analysis and variance analysis to study the price transmission between corn and egg. They report that the price of corns pose great effects on the farm and retail eggs price, especially when the price of corns increase. Kawaller et al. (1987) demonstrates that there are long-term equilibriums between the prices of soybean future and soybean-related products future. Prices influence each other, and arbitrage exists. Yang and David (2004) use VECM model to study the stock index future.

They illustrate that the American and British markets are strong, German market has great effects on other European markets, and Japanese market is relatively independent.

Zhou and Buongiorno (2005) take VAR model, Granger causality test and impulse response and find that the rise of American forest products prices can lead to the increase of southern wood prices. Ben-Kaabia and Gil (2007) adopt TVECM model to study the price transmission of wholesale

and retail prices of lamb in Spain. They have two findings, in the long term, the two prices can affect each other, but in the short term, there is asymmetry between the two markets. They explain that this phenomenon is caused by demand-oriented mechanism.

Adeoye, Nguet, Badmus, and Amao (2011) use ADF use unit root test, VAR model and Granger causality test to study the price transmission of banana and plantain in the urban and rural areas in Nigeria. They report the co-integration of banana prices between the two areas, but there is no co-integration between two areas' plantain prices. There are two-direction transmissions of banana prices between two areas, but there are no significant relationships in plantain.

Esposti and Listorti (2013) take the weekly data of agricultural products of Italian and North American markets from 2006 to 2010 to study the transmission mechanism of products among different markets when there are price bubbles. They find that the first-order differences of agricultural products in the two markets and co-integration relationship between agricultural products from the two markets are stable.

Yan and Reed (2014) find that the price change of Chinese corn future can explain that of corn spot, but the price fluctuation of corn spot cannot explain corn future. They also report that the price of genetically modified soybean future can influence the genetically modified soybean spot price.

Lemma and Singh (2015) use Johansen test and VECM model and find that the producing price and retail price of milk in Ethiopia have strong co-integration relationship, and the retail price has one-way effect on the producing price.

Liu (2005) report that the future price is stronger than spot in the price transmission when she studied metal future, raw materials future, agricultural future, and their spots.

Chen and Cheng (2006) use VAR model, Johansen test, VEC model and variance differentiation to study the relationships among soybean price in DaLian Commodity Exchange and the soybean price in Chicago Commodity Exchange and Chinese soybean spot price. They reported the long-term equilibrium among the three and the mutual effects.

Gao and Liu (2007) take the OLS regression method, VAR model and VECM model to study the portfolio of stocks from CSI300 index, and empirically study and compare the hedge with different models.

Guo, Wang, Gao, and Wang (2010) employ the modified VAR model and co-integration test to study the interactive relationship between the same kinds of metal future listed in Shanghai and London future exchanges. They reported the long-term equilibrium, high correlation, and two-way transmission between the prices from two exchanges.

Zhang study the relationship between stock index future and spot after the Chinese stock index future is issued. They demonstrate the two can effectively influence each other. They also suggest that Chinese stock index future market needs further improvement to better guide the spot market.

Wen and Tian adopt VECM model to report the relationship among corn prices from different areas of China. They find the price in the selling area plays a leading role in the price transmission while the price of producing area follows, concluding that demand determines production in Chinese corn market.

Zhang, Asche, and Oglend (2014) find that Chinese egg future prices correspond to the egg spot prices in the long run. They also find that the effect of egg future on spot is larger than the effects of egg spot on future.

Xie, Chen, et al. study the relationship between international sugar future price and Chinese sugar future price with VAR model, and find the long-term co-integration between them. International sugar future price has one-way influence on Chinese sugar future price.

In a nutshell, foreign researches regarding price transmission mechanism are earlier and wider than domestic study. Many researchers find future price has one-way effects on spot price, while some others find there are bi-directional price guidance between futures and spot. And the related future products also have different influence on each other in the previous empirical research.

Price fluctuation is one of the basic characteristics of financial assets, reflecting risk. Bekaert and Harvey reported that the information transmission procedure includes mean spillover effect and volatility spillover effect. We collected the researches about market fluctuations especially that caused by future. At the same time, we collected papers studying the mutual effects between futures through arbitrage trading.

Powers (1970) study the effect of launching future market on spot market fluctuation. He finds that the future market will increase commodity information transmission speed, expand information transmission areas, and deepen the acceptance. So the launching of future market will increase the market efficiency, decrease blind trading, and mitigate the volatility of spot market.

Cox (1976) believe that future market can make spot market participants have a better understanding about the supply and demand, which will decrease the spot market fluctuation.

Brorsen (1991) reported that stock index future can decrease trading cost and add spot liquidity, making the short-term volatility of spot increase.

Baldauf and Santoni (1991) analyze the S&P 500 market with ARCH model, and find that there is no significant change of spot price fluctuation after introducing future trading.

Antoniou and Holmes (1995) divide the time into two periods according to the launching of FTSE 100, and report that as the coefficient of ARCH term increases and the coefficient of GARCH term decreases in the GARCH model variance equation, the information absorbing ability of FTSE 100 increases, and the stock spot market volatility increases.

Pericli and Koutmos (1997) report that the S&P 500 future has no significant effect on spot market through EGARCH model.

Chang, Cheng, and Pinegar (1999) find that after the launching of NIXI future, the fluctuation of NIXI spot, but the volatility of stocks consisting non-NIXI which are listed in Osaka exchange don't change.

Liu (2005) study the co-integration and volatility relationship among hogs, corn and bean meal, and verify the arbitrage opportunity among these future products.

Kasman and Kasman (2008) analyze the effects of stock index future on stock market volatility in Turkey with EGARCH model, and find that the stock index future decreases the fluctuation of stock market volatility.

Singh and Tripathi (2014) use GARCH model to study the effect of foreign currency on exchange rate in Indian foreign currency market. They report that the sum of ARCH term and GARCH term decrease and the volatility of foreign currency decrease after launching foreign currency future.

Fong and Han (2015) adopt the GARCH model with dummy variable to study the impact of Hang Seng Index futures on the spot market volatility. They find that the launch of Hang Seng Index futures reduces the spot market volatility.

Zhang and Liu (2006) use two variables VEC-EGARCH model, co-integration and Granger causality test to study the relationship between the future price and spot price of aluminum and copper, respectively. They find there is long-term equilibrium between the future and spot.

Hua and Liu (2007) use the AR-EGARCH model to study the volatility spillover of soybean future home and abroad. They find there are close relationships between prices and between volatility, and the American future market has greater influence on Chinese future market.

Zhao studies the effect of Hong Kong HIS future on spot market. He finds the index future reduces the volatility of spot market, but very significantly.

Liu uses GARCH model and plugs in dummy variables to study how the index future affects Chinese stock spot market. He finds that the index future has no significant influence on CSI 300 index, but it has weak effect on Shanghai composite index and Shenzhen component index.

Gu and Lei summarizes the predecessors' researches and classifies the commodity arbitrages into two species, processing arbitrage and substitution arbitrage. What's more, they compare the effectiveness of different arbitrage methods.

Yan plugs in dummy variables into GARCH model, studies how the gold future influences the gold spot from the static perspective, and finds that the gold spot market becomes a little bit fluctuating after the gold future contract is launched.

In the nutshell, foreign researches about market volatility are wider and deeper than domestic researches although the latter have made obvious progress recently. Three different conclusions are drawn: (1)the launching of future market increases the volatility of spot market or other related markets; (2) the launching of future market reduces the volatility of spot market or other related markets; (3) the launching of future market poses no significant effect on the volatility of spot market or other related markets. Scholars haven't reached an accord on this issue. However, the classical theory corresponds to the second conclusion.

Cornstarch is the corn-processed product, which is separated from the germ, fiber, protein, and other byproducts by grinds and extraction. With the widespread use in different industries, cornstarch occupies an essential position in China's agricultural economy.

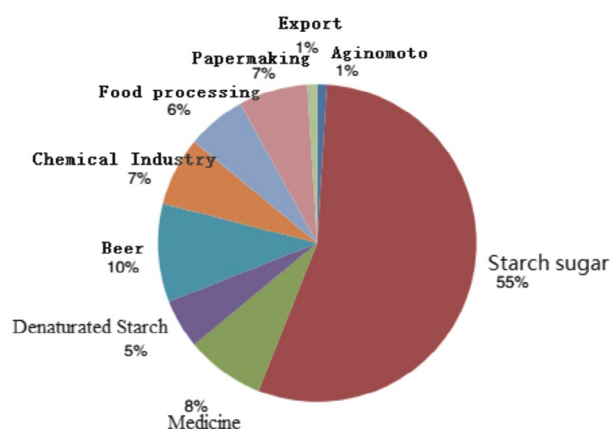
According to the statistics from China Starch Industry Association, Chinese starch production ranks second in the world. In 2013, the annual output of starch was about 25 million tons, which accounted for 36.3% of the world's total starch output. The cornstarch production in 2013 was about 23.5 million tons. It accounted for 94% of Chinese total starch production.

The past five decades have witnessed the tremendous development of Chinese cornstarch industry. It has undergone the three stages of development: slow development period, rapid growth period, and industry consolidation period. After the macro-control policies' implementation and the international financial crisis, China's cornstarch industry embarked on a healthy development. In 2013, China's cornstarch production reached its peak, up to 23.5 million tons. It increases its yield by 170% over the past decade with an average 10.4% compound annual growth rate.

Cornstarch has a wide field of downstream industries. The downstream demand mainly comes from the following seven industries: starch sugar, beer, pharmaceuticals, paper, chemicals, food

Figure 1. Domestic cornstarch downstream proportion.

Resource: China Starch Industry Association.



processing, and denatured starch. The starch sugar industry accounts for the largest amount with about 55% of the total consumption of cornstarch (Figure 1).

In recent years, China's starch market overall is at a net import state. Its import amount increases year by year while exports gradually reduce. And it is evident the net import amount increases year by year. The main reason is that foreign countries kept a low commercialization rate of cornstarch and tend to deeply process the cornstarch directly. However, China has a relatively higher commercialization rate. China has the largest cornstarch commodity production and trade amount around the world as to provide an ample supply to meet domestic market demand.

The prices of cornstarch have drastic fluctuations. According to the China Starch Industry Association, during January 2009 to June 2014, the national average prices of cornstarch fluctuated from 1606 to 3134 Yuan/Ton with the maximum volatility of 95%, which posed a great price fluctuation threat to the agriculture and other related entities. Under the circumstance of the price undulate of Chinese cornstarch market, the Dalian Commodity Exchange introduced cornstarch futures, which make China become the world's unique country with cornstarch futures.

The cornstarch future raises widespread concern around the society since it was introduced to the market. In order to have insight of the impact of Chinese cornstarch futures market resulted in the Chinese cornstarch spot market, it is necessary to understand the rules of Chinese cornstarch futures trading (see Table 1).

Table 1. Cornstarch futures contract specs

Product	Cornstarch
Contract unit	10 tons
Price quotation	RMB Yuan/ton
Minimum price fluctuation	1 Yuan/ton
Volatility limit	±4%
Contracts expire	Months of 1, 3, 5, 7, 9, 11
Trading time	9:00–11:30, 13:30–15:00 Beijing time
Last trading day	The tenth trading day of the contract month
Last delivery day	The third trading day after the last trading day
Minimum margin	8%
Delivery methods	Physical delivery
Code	CS
Exchange	Dalian commodity exchange

Resource: Dalian commodity exchange.

Table 2. The corn future trading rules in Dalian commodity exchange

Product	Cornstarch
Contract unit	10 tons
Price quotation	RMB Yuan/ton
Minimum price fluctuation	1 Yuan/ton
Volatility limit	±4%
Contracts expire	Months of 1, 3, 5, 7, 9, 11
Trading time	9:00–11:30, 13:30–15:00 Beijing time
Last trading day	The 10th trading day of the contract month
Last delivery day	The third trading day after the last trading day
Minimum margin	5%
Delivery methods	Physical delivery
Code	C
Exchange	Dalian commodity exchange
Product	Cornstarch
Contract unit	10 tons

Resource: Dalian commodity exchange.

According to Wind Database, the cornstarch trading volume in 2015 was 3.87 million while the open interest was 466 thousand. The average daily open interest in 2015 was 114.8 thousand. However, the daily average trading volume was 158.7 million, which was much more than the daily open interest amount. This implies that excessive speculation may occur in Chinese cornstarch futures market.

Dalian Commodity Exchange introduced the Chinese corn future in 22 September 2004. Corn future is a relatively mature agricultural future product and highly relevant to international corn futures. Until now, there is no empirical research to analyze what is the impact on corn future since the introduction of cornstarch futures. To gain an insight into the matter, we need to know about the rule of the Chinese Corn Future market (see Table 2).

According to Wind Database, the average daily trading volume of corn future in 2015 was 599 thousand while the daily average open interest was 222 thousand. Compared to cornstarch future market, corn future market is much more mature.

3. Empirical study

3.1. Research hypotheses

The preceding part briefly introduced the cornstarch spot & futures market and corn futures market, and summarized the conclusions of domestic and foreign research related to price transmission mechanism about commodity price. The classical theory implies that commodity futures price guides commodity spot price and the strongly correlated commodity futures prices could influence each other. In addition, Chinese cornstarch futures market is the unique cornstarch futures market in the world and there is no linkage mechanism with other foreign cornstarch futures market, thus there may exist speculative excess which could make the price of cornstarch futures is out of the influence of cornstarch spot market. According to that analysis above, this paper proposes the first two hypotheses:

Hypothesis 1: the Chinese cornstarch (CS) futures guide the domestic cornstarch (CS) spot market unidirectional.

Hypothesis 2: there are bi-directional relation and long-run equilibrium relationship between Chinese cornstarch (CS) futures and corn (C) futures.

There are three different viewpoints about the impact of the launch of one new future on the spot market volatility according to the preceding literature review: one conclusion believes the launch reduced the volatility; another conclusion believes the launch increased the volatility; the other conclusion believes the launch has no significant influence on the volatility. Scholars have not reached an agreement on this matter. However, the traditional theory believes the introduction of futures market can reduce the volatility of spot market. This research proposes the third hypothesis:

Hypothesis 3: The launch of Chinese CS futures market can reduce the volatility of domestic CS spot market.

According to the literatures about the linkage between different commodity futures, there exist cointegration and arbitrage opportunity between strongly correlated futures. The arbitrage trade will decrease the volatility with each other. Based on that logic, this research proposes the fourth hypothesis:

Hypothesis 4: The launch of Chinese CS futures market can reduce the volatility of domestic C futures market.

Based on the hypothesis 3 and 4, we can know the impact of launch of cornstarch.

Futures on the relevant market volatility. If the hypothesis 3(or 4) is rejected, it implies the new futures have no significant impact on the relevant market volatility; if the hypothesis 3(or 4) is proved, to do further study on the volatility impact, we propose the hypothesis:

Hypothesis 5: There exists volatility spillover between cornstarch futures and relevant market. This hypothesis can be divided into two subclasses.

Hypothesis 5a: There exists volatility spillover between cornstarch futures and spot market.

Hypothesis 5b: There exists volatility spillover between cornstarch futures and corn futures market.

3.2. Data presentation

The data used in this article include the prices of Chinese cornstarch futures market and cornstarch spot market, the prices of domestic corn futures market, and the values of the dummy variable. The data of Chinese CS and C futures prices are from the closing prices of the January contracts, May contracts and September contracts, as the dominant contract of DCE was always from those three and changed by turn.

For the domestic CS spot market data, this article collects the daily average cornstarch prices of 20 main cities in China. The time period is from 4 January 2013 to 2 March 2016. The data are divided into two parts by the launch of Chinese CS futures market. There are 473 data from 4 January 2013 to 18 December 2014 and 291 data from 19 December 2014 to 2 March 2016. There are totally 764 spot prices.

For the CS futures market data, this article collects CS futures prices with two frequencies: (1) for the research on the impact of CS futures on the CS spot, this research collects the daily closing prices. This part collects 291 prices from 19 December 2014 to 2 March 2016. (2) For the research on the impact of CS futures on the C futures, to extend sample size enormously and make conclusions drawn more credible, this paper collects CS futures closing prices per Minute. This part collects 65,249 high frequency prices from 19 December 2014 to 2 March 2016.

For the domestic corn future market data, this article collects the corn futures dominant contract closing prices per minute. There are 53,906 from 2 January 2013 to 18 December 2014 and 65,249 data from 19 December 2014 to 2 March 2016. There are totally 119,155 spot prices.

This research introduces a dummy variable to study the launch of CS futures. Before the introduction of Chinese CS futures market, the values of the dummy variable are 0, while dummy variable changes to 1 after the introduction of CS futures market.

All the prices data used in the research are from WIND database and during the period from 19 December 2014 to 2 March 2016, the data that only could be found in one market are excluded.

The price quotation unit of CS futures market, domestic CS spot market, and domestic corn futures market are all yuan / ton. Hence, there is no need to modify the price quotation units to the same size.

For the convenience of research, the natural logarithm of all the prices is used. The prices in the following article refer to the logarithmic form prices. This article also gets the first-order difference of the price, which means the return of prices in practice. The abbreviations are in Table 3.

The descriptive statistics of data from 19 December 2014 to 2 March 2016 are in Appendix A (Table A2).

3.3. Methodology

3.3.1. VAR model

It's difficult to determine which variables are endogenous variables and which are exogenous if there is a correlation between some of them. To deal with this matter, Sims introduces vector auto-regression model (VAR), in which every endogenous variable is treated as the dependent variables and all other endogenous variables and lagged variables are independent variables. VAR model is mainly used to analyze the relationship between the different variables. Based on the VAR model, this article studies the transmission between CS futures and CS spot, C futures.

If a set of time series is stationary, it has constant mean and variance and the coefficient of auto-correlation is only influenced by the interval between the two terms. If the non-stationary time series are regressed, it will lead to spurious regression and the estimation results of the regression model will also lose meaningful interpretation. Stationarity test is used to identify whether a set of time series is stationary or not.

Table 3. Variables and symbols

Symbol	Variable
CS	Chinese cornstarch spot price
F	Chinese cornstarch futures price
F_m	Chinese cornstarch futures price per minute
C_m	Chinese corn futures price per minute
DCS	First-order difference of CS spot price
DF	First-order difference of CS futures price
DF_m	First-order difference of CS futures price per minute
DC_m	First-order difference of C futures price per minute
DUM	Dummy variable

Resource: WIND Database.

The common methods to test stationarity include DF test, ADF (Augmented Dickey-Fullerton) test, ERS-DGLS test, PP test, ERS Point-Optimal, and so on. The most commonly used method is ADF test. This article uses ADF test to test the stationarity of variables.

When the absolute value of ADF t-statistic is bigger than a certain critical value, it is proper to reject the null hypothesis that the set of time series has unit root and we can conclude that the set of time series is stationary.

The vector auto-regression model builds relationship between exogenous variables and the lag terms of exogenous variables. The VAR model has good flexibility that this kind of regression structure may not need too much theory support. Suppose the price of Chinese CS spot market (or Chinese corn futures market) is x_t , and the return of Chinese CS futures market is y_t , the VAR model used in this article is:

$$\Delta x_t = a_1 + \sum_{i=1}^k \alpha_{xi} \Delta x_{t-i} + \sum_{i=1}^k \beta_{xi} \Delta y_{t-i} + \varepsilon_{xt} \quad (1)$$

$$\Delta y_t = a_2 + \sum_{i=1}^k \alpha_{yi} \Delta x_{t-i} + \sum_{i=1}^k \beta_{yi} \Delta y_{t-i} + \varepsilon_{yt} \quad (2)$$

where Δx_t and Δy_t are the first-order difference of x_t and y_t , Δx_{t-i} and Δy_{t-i} are the i^{th} lag of Δx_t and Δy_t , a_1 and a_2 are intercept terms, ε_{xt} and ε_{yt} are white noise terms.

Stationarity test is used to make sure the set of time series is stationary so that the model result is meaningful. Box and Jenkins found that the economic and financial time series are often non-stationary. The non-stationary series may be converted to stationary series by differential, but the differential also lead to information lost in the process and model based on differential data does not have to explain meaning in economics.

Engle and Granger (1987) first put forward the concept of cointegration; they maintain that cointegration relationship is a long-term and stable relationship between economic variables. If two sets of time series are cointegrated, they share a long-term stable equilibrium. Under this circumstance, A VEC model may be used to avoid the improper.

There are two common ways to do cointegration test: E-G two step method and Johansen co-integration test method. This research uses Johansen co-integration test method to test co-integration relationship.

Co-integration maintains certain linear combinations of the explanatory variables that are stationary. To prevent the deviation from the long-term equilibrium, there exists error adjustment mechanism among any group of the co-integrated time series to adjust the deviation from the long-run equilibrium. The form of co-integration equation is as follows:

$$\Delta y_t = \alpha_0 + \alpha(y_{t-1} - k_0 - k_1 x_{t-1}) + \alpha_2 \Delta x_t + \mu_t \quad (3)$$

If the long-run equilibrium equation is $y^* = k_0 + k_1 x^*$, the error correction term is $(y_t - k_0 - k_1 x_t)$. The error correction term reflects the short-term deviations from y_t to x_t at time t . The adjustment factor α represents the adjusting speed for the deviation between y_{t-1} and $k_0 + k_1 x_t$. Both the long-run equilibrium relationship and short-term adjustment path are showed in the error correction model.

Generally speaking, the history cannot predict the futures. If the changes of variable x caused the change of variable y , then the changes in x should precede y changes. Granger Causality is proposed

on this basis. If the error value using x and y to predict y is less than the error value that is only using y , then x is the Granger cause of y .

The null hypothesis is x does not Granger cause y . Granger causality test may be conducted by constructing F -statistic.

$$F = \frac{(RSS_1 - RSS_2)/p}{RSS_2/(T - 2p - 1)} \sim F(p, T - 2p - 1) \quad (4)$$

where RSS_1 is the sum of the squares of residual errors before adding the lag terms of the second variable to the regression. RSS_2 is the sum of the squares of residual errors after adding the lag terms of the second variable to the regression. T is sample size, p is the number of the order of lag of the second variable.

If F -statistic is bigger than a certain critical value, it is proper to reject the null hypothesis that the second variable cannot Granger cause the first variable.

There are many lag terms in VAR model, analyzing the significance or the value of the coefficient of only one lag term cannot show a whole picture of VAR model

Impulse response analyzes how the change of the error term of one variable can affect another.

Impulse response function uses $\frac{\partial y_{i,t+s}}{\partial \varepsilon_{j,t}}$ to represent the change of $y_{i,t+s}$ at time $t + s$ when an error term $\varepsilon_{j,t}$ of $y_{j,t}$ has an impulse of one positive standard deviation at time t .

The error terms of one variable may have an influence on a certain variable. The influence may be represented by variance. The sum of all the variance is the whole influence on this certain variable. Variance decomposition method measures the influence of the error terms of one variable by dividing the variance of the error terms of one variable by the whole variance. Introducing the GARCH model the distributions of financial assets often exhibit “fat tail” feature, which means the yield reaches its peak around the mean, and appears thick tail in the vicinity of extreme value. Accepted explanation is that the volatility of financial assets is mainly from the information, which is not in the form of a smooth but of gathering. It is assumed that the information can be quickly digested. So piles of information cause market volatility and the market do not fluctuate in the absence of information. This results in a “fat tail” feature.

Volatility Clustering refers to fluctuations in the market often exhibit aggregation feature. That great fluctuation is followed by a large volatility, while after minor fluctuations the volatility does not change much. To deal with the volatility autocorrelation, Engle and Granger (1987) used ARCH model to simulate the volatility and developed other expand models.

This paper uses CARCH model to study the impact of launch of CS futures on the CS spot and C futures.

A set of stationary time series can be simulated using an AR model, an MA model or an ARMA model. These models can solve the problem of autocorrelation.

ARMA (p, q) model’s mathematical expression is:

$$y_t = \sum_{i=1}^p \alpha_i y_{t-i} + \varepsilon_t - \sum_{k=1}^q \beta_k \varepsilon_{t-k} \quad (5)$$

where α_i is the autoregressive coefficient. β_k is the moving average coefficient. ε_t is white noise term.

A set of financial time series usually has the characteristic of volatility clustering. That means the volatility of the time series is big in a continuous period, but the volatility is small in another continuous period. This phenomenon is called ARCH effect. In order to test whether ARCH effect exists or not, this article adopts ARCH-LM test. When the p -value of the test statistic is less than a certain critical value, it is proper to reject the null hypothesis that there is no ARCH effect and draw the conclusion that ARCH effect exists.

Bollerslev (1986) modified ARCH model and proposed GARCH model to better deal with the ARCH effect of a set of time series. This paper adopts GARCH(1,1) model to simulate time series.

$$y_t = x_t\gamma + \varepsilon_t \quad (6)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (7)$$

where y_t is exogenous variable and x_t is endogenous variable. ε_t is random error term. ε_{t-1}^2 is ARCH term and σ_{t-1}^2 is GARCH term. Equation (7) represents mean equation and Equation (8) represents variance equation. In this thesis, we introduce ARMA-GARCH model, so the mean equation will be replaced with an ARMA model.

To study the impact of the launch of cornstarch futures, this thesis regards the official launch of CS futures as a dummy variable. The dummy variable is adopted into the variance equation of the GARCH model and observes the significance level, the sign and the value of the coefficient to identify the impact on volatility. Hence, the variance equation is changed to:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \lambda DUM \quad (8)$$

When investigating the volatility relationship among different markets, the univariate GARCH model may neglect some necessary information, the multivariate GARCH model could solve this problem. In consideration of the research question and the model features, the BEKK-GARCH model is selected to study the volatility spillover effect among markets. The concept of volatility spillover effect is proposed by Ross, it describes the phenomenon that one market's fluctuation will cause the fluctuation change of other markets. The volatility represents asset risk in economy, so the volatility spillover implies the risk transmission.

BEKK representation of the multivariate GARCH model is formalized by Engle and Kroner. BEKK model can guarantee that the time varying covariance matrices are positive semi definite (PSD), and allows cross impacts between conditional variances and covariance of variables. This model is widely used in volatility spillover study.

The conditional variance equation of a bivariate GARCH-BEKK (1,1) model is given by:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B \quad (9)$$

$$H = \begin{pmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{pmatrix}; C = \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix}; A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}; B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$$

where H_t is the 2×2 conditional variance-covariance matrix of errors at time t ; C is defined as the parameter matrix which is restricted to be lower triangular; A is the matrix of ARCH parameters, captures own and cross-market ARCH effects; B is the matrix of GARCH parameters, captures own and cross-market GARCH effects.

The conditional variance equation can be further expanded by matrix multiplication:

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2h_{22,t-1} \quad (10)$$

$$h_{22,t} = c_{22}^2 + a_{12}^2 \varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2 \varepsilon_{2,t-1}^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + b_{22}^2 h_{22,t-1} \quad (11)$$

$$h_{12,t} = c_{11}c_{12} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + b_{11}b_{12}h_{11,t-1} + (b_{21}b_{12} + b_{11}b_{22})h_{12,t-1} + b_{21}b_{22}h_{22,t-1} \quad (12)$$

where $h_{11,t}$ the conditional variance of the first market is; $h_{22,t}$ is the conditional variances of the second market; $h_{12,t}$ is the conditional covariance; squared error terms represent former market shocks. Parameters a_{12}, a_{21} from matrix A represent error transmission between markets; parameters b_{12}, b_{21} from matrix B represent volatility transmission between markets. Error and volatility transmission are collectively known as volatility spillover. Therefore, for any two financial markets, if the impact from the other market is not significant, the current volatility of this market depends on its own ARCH and GARCH terms only.

To determine the direction of volatility spillover, we should further run Wald test on parameters of estimated conditional variance equation. Wald test is based on the maximum likelihood method. If there exist volatility spillover effects between these two markets, in the absence of constraints, the parameters estimated should follow the null hypothesis.

This paper adopts ADF test to test the stationarity of CS futures prices (F), CS spot prices (CS), first-order difference of CS futures prices (DF) and first order of CS spot prices (DCS). The tests for F and CS set test equation form with intercept term and trend term. The tests for DF and DCS set the test equation form without intercept term and trend term.

Table A5 shows that F and CS are nonstationary, while DF and DCS are stationary.

Since F and CS are integrated of order 1, there may be cointegration relationship between them. This thesis adopts Johansen co-integration test to identify the co-integration relationship between CS and F . Before the co-integration test, the lag order should be identified.

According to the lag order selection criteria, the optimal lag order should be 2 and order for co-integration should be 1.

The co-integration test shows that, the futures and the domestic spot are co-integrated at the 10% significant level in Trace critical value and 5% significant level in Max-Eigen critical value. Hence, there is co-integration between CS and F , which implies the long-term equilibrium between corn-starch futures and spot price. VEC model can be used for CS and F , and VAR model can be used for DCS and DF .

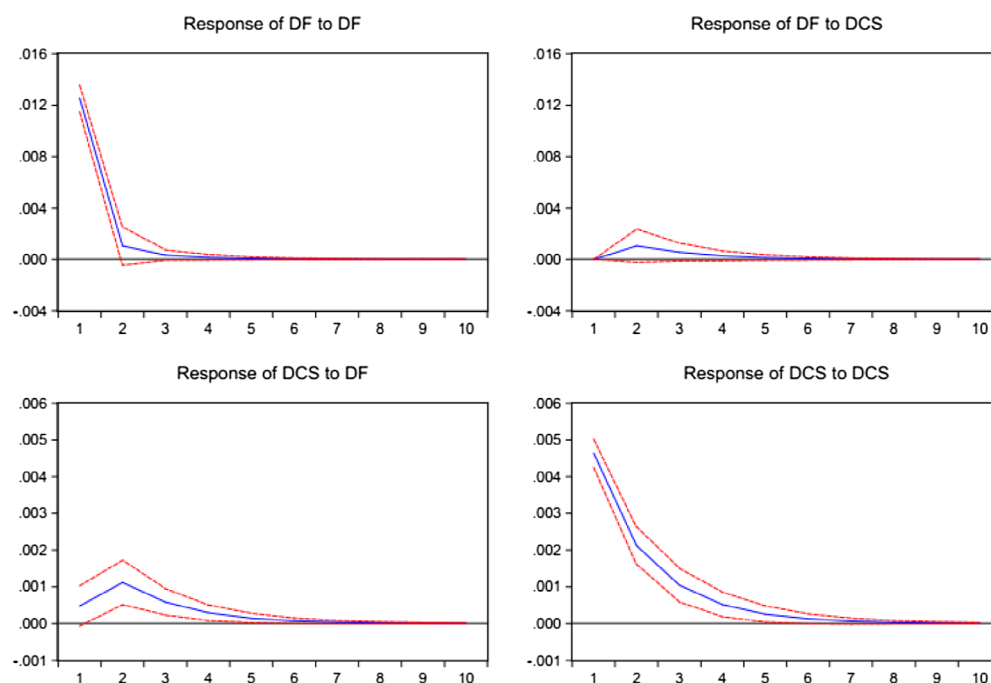
From the above analysis, the F are co-integrated with CS , so we can apply the vector error correction model for further analysis of the data.

The VECM showed that the DCS is significantly affected by the long-time correction term, first lag of DF & DCS . And the impact of the long-time correction term and first lag of DCS & DF on the DF is beyond the 10% confidence level.

In order to further study the price return transmission between CS and F , this article adopts Granger causality test for the price return DCS and DF .

The results show that it is not proper to reject the null hypothesis that DCS does not Granger cause DF , but it is proper to reject the null hypothesis that DF does not Granger cause DCS . The results confirms the conclusion that DF guide DCS unidirectional.

Figure 2. Impulse response of DCS & DF.



It could be found that the VEC model built above is stable. It is proper to adopt impulse response function method and variance decomposition method to further research. Impulse response function can show how variables react to the impulse of one positive standard deviation of the error term of a certain endogenous variable.

Figure 2 shows the reaction of DS and DF when their error terms have one standard deviation.

From Figure 2, it is easy to find that the response CS futures don't react at $t = 1$, while the response of the CS spot reaches positive peak at $t = 2$ then drops to 0.01% at $t = 6$. The response of DF to one standard deviation innovation in DF has dropped from 1.3% at $t = 1$ to 0.01% at $t = 4$ quickly. The response of DCS to one standard deviation innovation in DCS has dropped from 0.463% in the first period to 0.01% in the seventh period after which the response declines almost to 0.

Variance decomposition can measure the ratio of disturbance caused by the error term of the return of a market to the whole disturbance. Figure 3 shows the variance decomposition of DCS and DF.

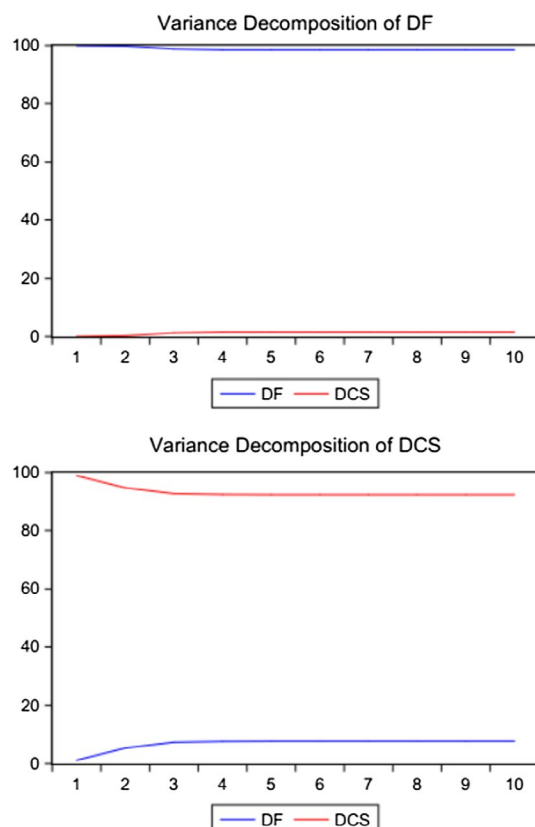
From Figure 3, it is obvious to find that in DF variance decomposition process, the variance contributed by DCS is less than 0.1%. In the DCS variance decomposition process, the variance contributed by DF is 8.35%.

The data used in this part are the return on Chinese CS spot market from 4 January 2013 to 2 March 2016. At first, the DCS time series needs to do stationarity test and statistical analysis.

The return distribution figure showing a fat tail characteristic and the characteristic can be further verified in the statistics. The J-B statistic is 12,703.8, so we reject the hypothesis that the return are normal distributed at 1% significance level.

In order to avoid spurious regression, it is necessary to do stationarity test. The ADF test is adopted without intercept term or trend term.

Figure 3. Variance decomposition.



The result shows that the DCS time series is stationary, thus the time series model could be built.

After confirming the DCS series are stationary, it is possible to build ARMA model to simulate the DCS series. Through the figure of autocorrelation and partial autocorrelation of the series of DCS, it is easy to identify the existence of autocorrelation and which model should be adopted. Secondly, proper lag order should be chosen to build appropriate model.

The result shows that DCS has autocorrelation, the figure of autocorrelation has short tail and the figure of partial autocorrelation also has short tail. To make sure the optimal value of p and q in $AR(p)$ $MA(q)$ model, this article compares the three criteria value in different ARMA model with distinctive p & q . From Table A13, $AR(1)$ $MA(2)$ has the smallest values of the three criteria, so $AR(1)$ $MA(2)$ is the proper model to simulate the series of DCS.

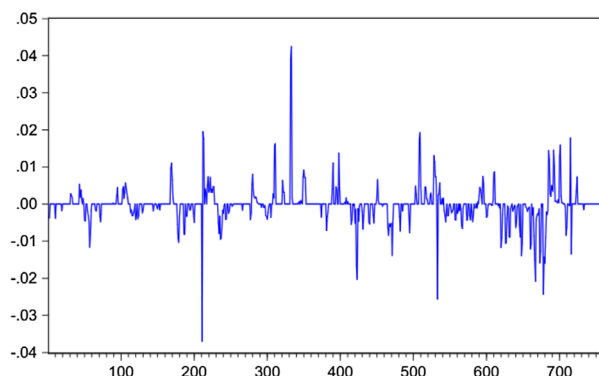
The results of $AR(1)$ $MA(2)$ model are clear that the coefficients are quiet significant in 1% level.

GARCH model can be adopted to simulate the series after confirming the existence of ARCH effect. This paper adopts ARCH-LM test to test the existence of ARCH effect.

Firstly, a diagram of the series of DCS is shown in Figure 4 directly identify the existence of ARCH effect.

It can be seen from the figure that the yield changes slowly and fluctuates around the vicinity of zero value and the yield has the cluster effect. That is ARCH effect. Next, this paper adopt ARCH-LM test to identify the ARCH effect and the lag order is 10.

Figure 4. The daily return of cornstarch.



The GARCH term in GARCH model can replace high rank ARCH terms in a sense, so the p -value in GARCH(p, q) model is usually small. The values of AIC, SC and HQC are shown in Table 4 when p equals to 1 or 2 and q equals to 1 or 2.

Table 4 shows that GARCH(1,1) model has the smallest values of AIC, SC and HQC, and further check shows that except GARCH(1,1) model, the coefficients of GARCH terms or ARCH terms are not significant or even the model is not stable. GARCH(1,1) model is the most proper model to simulate the series of DCS. The model above assumes that the residuals follow normal distribution, which does not match the results of J-B test above. We try to estimate the variance equation based on student's t -distribution. Based on maximum likelihood value, AR(1) MA(2)-GARCH(1,1) model based on t -distribution was built.

(1) More all significant, the sum of the coefficients of ARCH and GARCH is $0.87 < 1$, implying that AR(1)MA(2)-GARCH(1,1) model is stable.

In order to test the disappearance of ARCH effect, ARCH-LM test is adopted again MA(2)-GARCH(1,1) model simulate the series of DS quite well.

The Dummy variable DUM represents the introduction of Chinese egg futures market. By putting DUM into the variance equation of AR(1)MA(2)-GARCH(1,1) model, AR(1)MA(2)-GARCH(1,1)-DUM based on t -distribution is built to test the impact of the introduction of Chinese cornstarch futures market of the volatility of Chinese cornstarch spot market (Tables 5 and 6).

The results in Table 6 show that AR(1) MA(2)-GARCH(1,1)-DUM model eliminates ARCH effect.

After adding DUM, the coefficients in the mean equation and the variance equation are also significant. The sum of the coefficient of the ARCH term and the coefficient of the GARCH term is 0.86 which is less than 1, implying that AR(1) MA(2)-GARCH(1,1)-DUM model is stable.

Overall, AR(1)MA(2)-GARCH(1,1)-DUM model is valid and is proper to test the impact of the introduction of Chinese CS futures market on the volatility of the return on Chinese CS spot market.

From the statistics of DUM, it is not difficult to find the following results:

Table 4. Selection of GARCH(p, q)

	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)
AIC	-9.4620	-9.2538	-9.1966	-9.3405
SC	-9.4316	-9.2174	-9.1602	-9.2980
HQC	-9.4503	-9.2398	-9.1826	-9.3241

Table 5. AR(1)MA(2)-GARCH(1,1)-DUM model

Variable	Coefficient	Std. Error	z-Statistics	Prob.
Mean equation				
AR(1)	0.4330***	0.0310	13.9581	0.0000
MA(2)	-0.0740***	0.0237	-3.1161	0.0018
Variance equation				
C	4.01E-07***	2.83E-08	14.1911	0.0000
ARCH(-1)	0.7933***	0.1047	7.5745	0.0000
GARCH(-1)	0.0743***	0.0204	3.6366	0.0003
DUM	-9.84E-05	0.0001	-0.9842	0.3250

***Significance at 1%.

Table 6. AR(1)MA(2)-GARCH(1,1)-DUM ARCH-LM test

F-Statistics	0.092085	Prob. F(1,760)	0.7616
Obs R^2 statistics	0.092316	Prob. $\chi^2(1)$	0.7613

Firstly, the corresponding p -value of DUM is 0.889300 which is very big, implying that the impact of the introduction of Chinese CS futures market on the volatility of the return on Chinese CS spot market insignificant.

Secondly, the sign of the coefficient of DUM is negative, implying that even if the introduction of Chinese CS futures market on volatility of Chinese CS spot market is significant, the introduction may decrease the volatility

Thirdly, the absolute value of the coefficient of DUM is quite small, implying that even if the impact of the introduction of Chinese CS futures market is significant, it is too small to attract any attention.

Same as the above part, this paper applies ADF test to identify the stationarity of cornstarch futures price F_m , domestic corn futures C_m , the first-order difference of F_m and C_m which are the return of cornstarch futures and corn futures.

The result shows that F_m , C_m are nonstationary, while DF_m and DC_m are stationary. VAR model can be adopted for DF_m and DC_m .

As F_m , C_m are both integrated of order 1, they may have co-integration relationship.

The result shows that, the DC_m and DF_m are co-integrated at the 10% significant level in Trace critical value and 5% significant level in Max-Eigen critical value.

From the above analysis, the F_m are co-integrated with C_m , so we can use the vector error correction model for further analysis of the data.

Both DF_m and DC_m are significantly affected by DF_m (-1) and DC_m (-1). The long-term correction also leads DF_m while the effect on DC_m is not significant in 10% level.

To further study, this paper adopts Granger causality test for the DF_m and DC_m . The results are shown in Table 7.

Table 7. Granger Causality test

Null hypothesis	F-Statistics	Prob.
DC_m does not Granger cause DF_m	9.8677***	0
DF_m does not Granger cause DC_m	56.1551***	0

***Significance at 1%.

Table 7 shows the two null hypotheses are both proper to be rejected, which further confirms bi-directional lead relations.

Same as confirming that VAR model is stable, this paper adopts impulse response function method and variance decomposition method.

Figure 5 shows that, the DF_m and DC_m, both have small shock on each other.

Figure 6 shows the variance decomposition of DC_m and DF_m.

It is obvious to find that in DC_m variance decomposition process, the variance contributed by DF_m is less than 0.1%. In the DF_m variance decomposition process, the variance contributed by DC_m is about 2%. That further confirms that the impact on each other of DF_m and DC_m is small. Moreover, the impact of corn futures on cornstarch futures is relatively bigger.

On the impact of the lunch of CS futures on C market volatility.

The data used in this part are the return on Chinese corn futures market from 2 January 2013 to 2 March 2016. From the statistical test result, the J-B statistics is very big and reject the hypothesis that the return are normal distributed at 1% significance level. The ADF test is adopted without intercept term or trend term.

Figure 5. Impulse response.

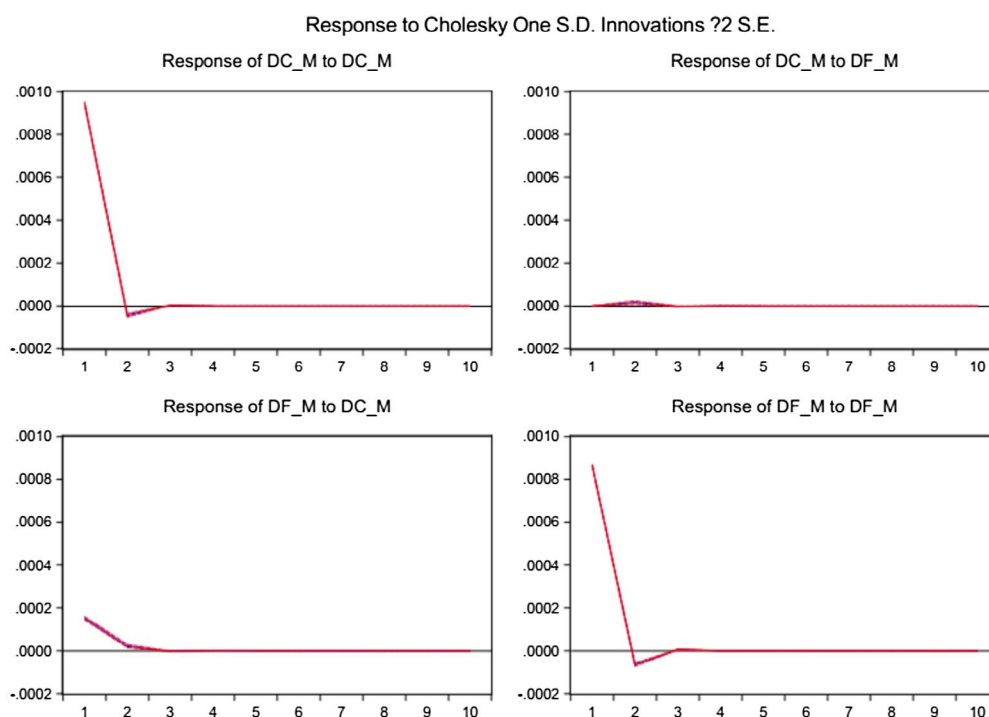
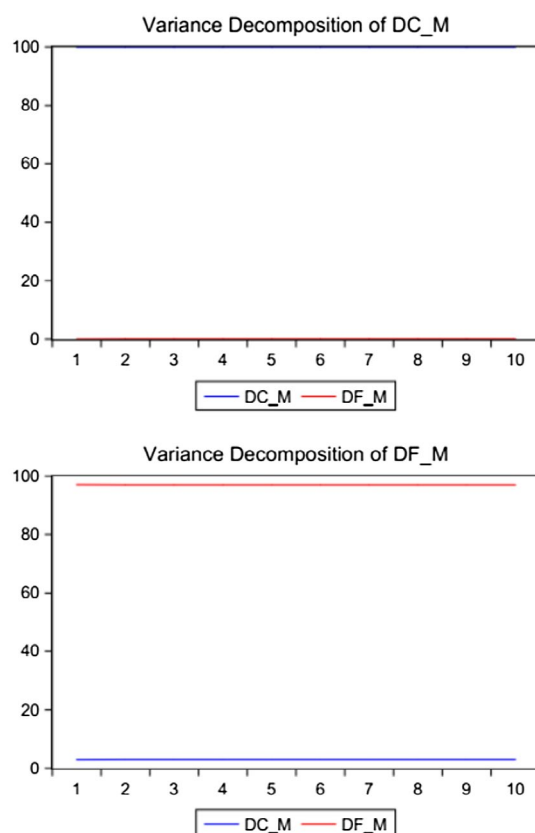


Figure 6. Variance decomposition.



After confirming the DC_m series are stationary, this article builds ARMA model to simulate the DC_m series. From the above study, it is easy to find that autocorrelation exists. Both the figure of autocorrelation and the figure of partial correlation have short tail (see Figure 7).

Next, the AR(1) MA(1) model is chosen according to the values of AIC, SC, and HQC criteria (see Table 8).

The results of AR(1) MA(1) model are shown in Table 9 and it is clear that the coefficients are quiet significant.

In order to further study the characteristics of the series of DC_m, the ARCH effect is tested.

At the same time, ARCH-LM is used to test the ARCH effect (see Table 10).

The results imply the existence of ARCH effect.

According to the value of AIC, SC and HQC, the GARCH(1,1) model is chosen. The initial model above assumes that the residuals follow normal distribution, which does not match the results of J-B tests above. Hence, this article estimate the variance equation based on student's t-distribution and AR(1) MA(1)-GARCH(1,1) model is built (see Table 11).

The results in Table 11 show that the coefficients are significant. The sum of the coefficient of the ARCH term and the coefficient of the GARCH term is 0.93 which is less than 1, implying that AR(1) MA(1)-GARCH(1,1) model is stable.

Figure 7. Autocorrelation function and partial correlation function of DC_m.

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.187	-0.187	4171.3	0.000
		2 -0.012	-0.048	4187.6	0.000
		3 -0.002	-0.014	4188.3	0.000
		4 -0.003	-0.007	4189.8	0.000
		5 0.001	-0.002	4189.8	0.000
		6 -0.006	-0.007	4194.3	0.000
		7 -0.001	-0.003	4194.3	0.000
		8 -0.008	-0.009	4201.8	0.000
		9 -0.000	-0.004	4201.8	0.000
		10 -0.007	-0.008	4207.3	0.000
		11 -0.001	-0.005	4207.5	0.000
		12 -0.001	-0.002	4207.5	0.000
		13 0.002	0.001	4208.1	0.000
		14 0.006	0.007	4212.2	0.000
		15 -0.000	0.002	4212.2	0.000
		16 -0.004	-0.004	4214.2	0.000
		17 -0.004	-0.006	4216.0	0.000
		18 0.001	-0.001	4216.1	0.000
		19 -0.004	-0.004	4218.0	0.000
		20 0.006	0.005	4223.0	0.000
		21 -0.004	-0.002	4224.7	0.000
		22 0.001	0.000	4224.8	0.000
		23 -0.006	-0.006	4228.5	0.000
		24 0.005	0.003	4231.3	0.000
		25 0.011	0.013	4247.0	0.000
		26 -0.003	0.002	4247.8	0.000
		27 0.002	0.003	4248.5	0.000
		28 0.002	0.003	4248.9	0.000
		29 0.004	0.006	4251.2	0.000
		30 -0.002	0.000	4251.7	0.000

Table 8. Lag order of ARMA model

	AR(1)	AR(1)MA(1)	MA(1)
AIC	-12.3553	-12.3578	-12.3577
SC	-12.3551	-12.3576	-12.3575
HQC	-12.3552	-12.3578	-12.3576

Table 9. AR(1) MA(1) model

Variable	Coefficient	Std. Error	t-Statistics	Prob.
AR(1)	0.0715***	0.0049	14.4096	0.0000
MA(1)	-0.2684***	0.0049	-54.7768	0.0000

***Significance at 1%.

Table 10. ARCH-LM test

F-Statistics	2619.062***	Prob. F(1,119152)	0
Obs*R ² statistics	2562.774***	Prob. $\chi^2(10)$	0

*Significance at 10%.

***Significance at 1%.

Table 11. AR(1) MA(1)-GARCH(1,1) on student's t-distribution

Variable	Coefficient	Std. Error	z-Statistics	Prob.
Mean equation				
AR(1)	0.118410***	0.008272	14.31486	0.0000
MA(1)	-0.44946***	0.007415	-60.6161	0.0000
Variance equation				
C	5.61E-09***	1.77E-10	31.71217	0.0000
ARCH(-1)	0.102839***	0.002181	47.15545	0.0000
GARCH(-1)	0.828877***	0.002347	370.1426	0.0000

***Significance at 1%.

The ARCH-LM analysis shows that AR(1) MA(1)-GARCH(1,1) model simulates the series of DC_m quite well (see Table 12).

The Dummy variable DUM represents the introduction of Chinese CS futures market. By putting DUM into the variance equation, the AR(1) MA(1)-GARCH(1,1)-DUM model on *t*-distribution is built (see Table 13).

The results in Table 14 show that AR(1) MA(1)-GARCH(1,1)-DUM model eliminates ARCH effect.

After adding DUM, the coefficients in the mean equation and the variance equation are also significant. The sum of the coefficient of the ARCH term and the coefficient of the GARCH term is 0.92 which is less than 1, imply that AR(1) MA(1)-GARCH(1,1)-DUM model is stable.

From the statistics of DUM, it is not difficult to find the following results:

Firstly, the corresponding *p*-value of DUM is 0.06 in 10% significant level, which implies that the impact of the introduction of Chinese CS futures market on the volatility of the return on Chinese corn futures market significant (see Figure 8).

Secondly, the sign of the coefficient of DUM is negative, implying that the introduction may decrease the volatility.

The above discussion shows that the launch of cornstarch futures has significant impact on the corn futures market volatility. To do further study on the volatility transmission between the two markets, the multivariate GARCH model is adopted to investigate the volatility spillover.

Table 12. AR(1) MA(1)-GARCH(1,1) ARCH-LM test

<i>F</i> -statistic	0.0060	Prob. <i>F</i> (1,119152)	0.9380
Obs <i>R</i> ² statistics	0.0060	Prob. χ^2 (1)	0.9380

Table 13. AR(1) MA(1)-GARCH(1,1)-DUM on *t*-distribution

Variable	Coefficient	Std. Error	z-Statistics	Prob.
Mean equation				
AR(1)	0.1406***	0.0081	17.2131	0.0000
MA(1)	-0.4558***	0.0073	-61.6261	0.0000
Variance equation				
C	8.29E-09***	2.98E-10	27.8336	0.0000
ARCH(-1)	0.1001***	0.0042	42.4525	0.0000
GARCH(-1)	0.8223***	0.0028	295.5263	0.0000
DUM	-1.49E-06*	8.13E-07	-1.8320	0.0669

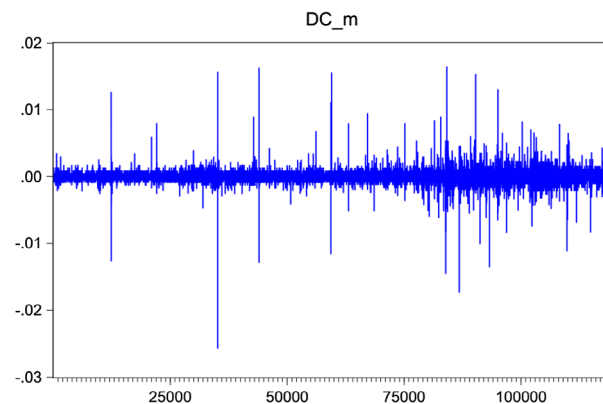
*Significance at 10%.

***Significance at 1%.

Table 14. AR(1)MA(1)-GARCH(1,1)-DUM ARCH-LM test

<i>F</i> -Statistics	1.90E-05	Prob. <i>F</i> (1,119152)	0.9965
Obs <i>R</i> ² statistics	1.90E-05	Prob. χ^2 (1)	0.9965

Figure 8. Return of corn futures.



The same methods are used to study the cornstarch futures price return from 19 December 2014 to 2 March 2016. According to the tests and AIC, BIC criterion, the AR(1) MA(1)-GARCH(1,1) is selected to fit the volatility of DF_m (see Table 15).

As the DC_m and DF_m series both can be matched by GARCH(1,1), we can adopt GARCH(1,1)-BEKK to study the volatility spillover.

The VAR model is adopted for the mean equation and the variance equation is GARCH(1,1)-BEKK. The model is based on student's *t*-distribution. The variance equation results are as follows (see Table 16)

The table 16 shows that, a_{12} and a_{21} are significant, indicating that past shocks in the two markets can affect each other. In matrix B, off diagonal elements b_{12} and b_{21} are significant, indicating that the two markets have significant responses to previous volatility.

In the other market $|a_{12}| > |a_{21}|$ indicates that the new information has larger influence on the DC_m. Since error and volatility transmission are collectively known as volatility spillover, to determine the significance and direction of volatility spillover effect, we should run Wald test on estimated parameters of BEKK models.

The Wald test results are reported in Table 17.

The result implies significant two-way volatility spillovers between the cornstarch futures market and corn futures market.

Table 15. AR(1) MA(1)-GARCH(1,1) of DF_m

Variable	Coefficient	Std. Error	z-Statistics	Prob.
Mean equation				
AR(1)	0.3717	0.0201	18.412	0.0000
MA(1)	-0.5220	0.0184	-28.3240	0.0000
Variance equation				
C	1.13E-08	4.15E-10	27.18911	0.0000
ARCH(-1)	0.1279	0.002839	45.05607	0.0000
GARCH(-1)	0.8394	0.002924	287.0462	0.0000

Table 16. GARCH(1,1)-BEKK results

Coefficient	Estimate value	t-Statistics	Prob.
a_{11}	0.3132	65.679	0
a_{12}	0.0857	14.5854	0
a_{21}	0.0189	6.0634	0
a_{22}	0.3281	69.0466	0
b_{11}	0.9437	524.1222	0
b_{12}	-5.69E-03	-2.5412	0.011
b_{21}	-7.22E-03	-5.746	0
b_{22}	0.9208	442.8232	0
<i>Standardized residual test</i>			
	DC_m	DF_m	
Q(12)	16.8775	15.2627	
Q ² (12)	3.5050	6.79608	

Table 17. Wald test for volatility spillover effects

Null hypothesis	H0	F-Statistics	Results
No volatility spillover effects in any direction	$a_{21} = a_{12} = b_{12} = b_{21} = 0$	176.72 (0.0000)	Reject
No volatility spillover effect from C to CS	$a_{12} = b_{12} = 0$	310.2651 (0.0000)	Reject
No volatility spillover effect from CS to C	$a_{21} = b_{21} = 0$	136.2887 (0.0000)	Reject

4. Conclusion

Based on the result above, there is a long-term co-integration relationship between CS futures and C futures. Besides, C future and CS futures Two-way guide each other and their return are Granger causes each other.

The further research by impulse response analysis and variance decomposition show that the impact of CS futures and C futures on each other is very small, and the impact of corn futures is relatively bigger. From the prior analysis, it can be drawn that the new CS future markets exist over speculation which could undermine the information effectiveness. As a result, the volatility transmission between CS futures and C futures is no efficient enough; the impact on each other is small.

In the study the impact of launch of CS future on the domestic Corn future market volatility via ARMA-GARCH-DUM model. The result shows that the launch of CS futures has impact on the corn futures market in 10% significant level, but the coefficient of dummy variable is negative and has very small absolute value. That is, although the launch of CS futures market has impact on the C futures market volatility, the impact is small and will decrease the corn futures market volatility.

When there exist extraordinary volatility difference between CS and Corn futures, a part of investors will do arbitrage trade to correct the volatility, thus the CS future market will shock the C futures market. As the over speculation in the CS future market, the proportion of rational investors to do the inter-market arbitrage will be few, thus the impact of CS futures on the corn futures market is little. In addition, the domestic CS futures market is influenced by international corn futures market which also weakens the impact of CS futures market.

The study confirms the two-way volatility spillover between corn futures and cornstarch futures. When a sharp fluctuation appears in the corn futures market, it will cause the volatility expectation of investors in cornstarch futures market. In the same way, the volatility in the cornstarch futures market will also be transmitted to the corn futures market and change the investors' expectation.

That implies the cornstarch futures have influenced the corn industrial chain. That result also reflects the good effect of new cornstarch innovation to a certain degree. What's the long-term impact of CS futures market on the CS spot market and domestic corn futures market? Will the CS futures market and CS spot market become two-way guidance? Will the impact of CS futures on the spot market and corn futures market become more significant? These questions need the further studies in the future.

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Authors' contributions

Crentsil Kofi Agyekum conceptualized the study with Jianshu Chen and performed the data analysis. Professor Huang designed, coordinated, and supervised the study. All authors were also responsible for the interpretation of the model results and write up of the manuscript. Both authors read and approved the final manuscript.

Availability of data and materials

The data that support the findings of this study can be obtained from the author based on request.

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Appendix A

Table A1. Stationarity test of DCS

Time series	Criterion	Lags	t-Statistics	Critical value			Result
				1%	5%	10%	
DCS	AIC	2	−11.9234	−2.56801	−1.9412	−1.61642	Stationary

Tables A1 shows that the DCS time series is stationary, thus the time series model could be built.

After confirming the DCS series are stationary, it is possible to build ARMA model to simulate the DCS series. Through the figure of autocorrelation and partial autocorrelation of the descriptive statistics of data during 19 December 2014 to 2 March 2016 are in Table A2.

Table A2. Descriptive statistics of data from 19 December 2014 to 2 March 2016

Variable	N	Mean	Max	Min	SD	Skewness	Kurtosis	Jarque-Bera test	p-value
DCS	763	−0.0003	0	0.0425	−0.0370	0.0050	0.7566	22.9325	12,703.8200
CS	764	8.0395	8.0504	8.1951	7.7626	0.0902	−0.9556	3.6896	131.3941
DC_m	119,155	−3.20E-06	0	0.0164	−0.1540	0.0008	−95.6427	17,448.8600	1.51E + 12
C_m	119,155	7.7135	7.7681	7.8524	7.3304	0.1139	−0.9921	2.7175	19,944.1600

Resource: WIND Database.

The descriptive statistics of dummy variable are in Table A3.

Table A3. Values of dummy

Variable	2 January 2014 to 18 December 2014	19 December 2014 to 2 March 2016
DUM	0	1

Table A4. Wald test for a Bivariate GARCH-BEKK model

Null hypothesis	H ₀
No volatility spillover between these two markets	$a_{21} = a_{12} = b_{12} = b_{21} = 0$
No volatility spillover from market one to market two	$a_{12} = b_{12} = 0$
No volatility spillover from market two to market one	$a_{21} = b_{21} = 0$

Table A5. Stationarity test results

Time series	Criterion	Lags	t-Statistics	Critical value			Result
				1%	5%	10%	
F	AIC	0	-1.5516	-3.990	-3.4254	-3.1358	Nonstationary
CS	AIC	6	-2.1660	-3.990	-3.4257	-3.1360	Nonstationary
DF	AIC	0	-15.5734***	-2.5730	-1.9419	-1.6160	Stationary
DCS	AIC	5	-4.2872***	-2.5731	-1.9420	-1.6160	Stationary

***Significance at 1%.

Table A5 shows that *F* and *CS* are nonstationary, while *DF* and *DCS* are stationary.

Since *F* and *CS* are integrated of order 1, there may be co-integration relationship between them. This thesis adopts Johansen co-integration test to identify the co-integration relationship between *CS* and *F*. Before the co-integration test, the lag order should be identified.

Table A6. VAR Optimal lag order choice

Lag order	Statistics					
	LogL	LR	FPE	AIC	SC	HQ
0	706.0508	NA	0.0000	-4.9756	-4.9499	-4.9653
1	1934.3910	2430.6380	0.0000	-13.6282	-13.5509	-13.5972
2	1964.7250	59.5959*	3.43e-09*	-13.8143*	-13.6855*	-13.7626*
3	1966.9700	4.3786	0.0000	-13.8019	-13.6216	-13.7296
4	1967.7500	1.5108	0.0000	-13.7792	-13.5473	-13.6862

*Represents the optimal lag order chosen by the criteria.

According to the lag order selection criteria, the optimal lag order should be 2 and order for co-integration should be 1. The co-integration test result is showed in Table A7.

Table A7. Co-integration test between *CS* and *F*

	Statistics		5% Critical value	
	Trace	Max-Eigen	Trace	Max-Eigen
$r = 0$	15.3623*	14.8951**	15.4947	14.2646
$r = 1$	0.4672	0.4671	3.8415	3.8415

*Significance at 10%. **Significance at 5%.

The co-integration test shows that, the futures and the domestic spot are co-integrated at the 10% significant level in Trace critical value and 5% significant level in Max-Eigen critical value. Hence, there is co-integration between *CS* and *F*, which implies the long term equilibrium between cornstarch futures and spot price. VEC model can be used for *CS* and *F*, and VAR model can be used for *DCS* and *DF*.

From the above analysis, the *F* are co-integrated with *CS*, so we can apply the vector error correction model for further analysis of the data.

Table A8. Result of VECM between CS and F

Cointegrating Eq:	CointEq1	
F(-1)	1	
CS(-1)	-1.3809***	
Error correction:	DF	DCS
CointEq1	0.0026	0.0292***
DF(-1)	0.0688	0.0409*
DCS(-1)	0.2067	0.3989***
C	-0.0007	-0.0004

*Significance at 10%. ***Significance at 1%.

The VECM showed that the DCS is significantly affected by the long-time correction term, first lag of DF & DCS. And the impact of the long-time correction term and first lag of DCS & DF on the DF is beyond the 10% confidence level.

In order to further study the price return transmission between CS and F, this article adopts Granger causality test for the price return DCS and DF. The results are shown in Table A8.

Table A9. Granger causality test

Null hypothesis	F-statistic	p-value
DCS does not Granger cause DF	2.2998	0.1294
DF does not Granger cause DCS	10.1783	0.0014***

***Significance at 1%.

The results in Table A9 shows that it is not proper to reject the null hypothesis that DCS does not Granger cause DF, but it is proper to reject the null hypothesis that DF does not Granger cause DCS. The results confirms the conclusion that DF guide DCS unidirectionally.

It could be found that the VEC model built above is stable. It is proper to adopt impulse response function method and variance decomposition method to further research. Impulse response function can show how variables react to the impulse of one positive standard deviation of the error term of a certain endogenous variable.

Table A10. ARMA lag order comparison

	AR(1)MA(1)	AR(1)MA(2)	AR(2)MA(1)	AR(2)MA(2)
AIC	-8.001943	-8.007435	-8.004419	-7.803266
SC	-7.989775	-7.995267	-7.992239	-7.791086
HQC	-7.997258	-8.00275	-7.999729	-7.798576

The results of AR(1)MA(2) model are shown in Table and it is clear that the coefficients are quiet significant in 1% level.

Table A11. AR(1)MA(2) model

Variable	Coefficient	Std. Error	t-Statistics	p-value
AR(1)	0.505571	0.031288	16.15871	0
MA(2)	-0.125062	0.001075	-116.3501	0

GARCH model can be adopted to simulate the series after confirming the existence of ARCH effect. This paper adopts ARCH-LM test to test the existence of ARCH effect.

Table A12. ARCH-LM test

F-Statistics	14.68548***	Prob. F(10,741)	0
Obs*R ²	124.3839***	Prob. $\chi^2(10)$	0

*Significance at 10%. ***Significance at 1%.

Table A12 shows the result of ARCH-LM test which implies the existence of ARCH effect. The lag order adopted in the test is 10, so it is proper to adopt GARCH model to simulate the series of DS because GARCH model is proper to deal with high order ARCH effect.

Table A13. AR(1)MA(2)-GARCH(1,2) Based on student's t-distribution

Variable	Coefficient	Std. Error	z-Statistics	Prob.
Mean equation				
AR(1)	0.4350***	0.0301	14.4101	0.0000
MA(2)	-0.0737***	0.0235	-3.1278	0.0018
Variance equation				
C	3.90E-07***	2.73E-08	14.2966	0.0000
ARCH(-1)	0.8033***	0.1050	7.6507	0.0000
GARCH(-1)	0.0737***	0.0200	3.6794	0.0002

***Significance at 1%.

Table A13 shows that the coefficients of AR(1),MA(2),ARCH(-1) and GARCH(-1) are all significant, the sum of the coefficients of ARCH and GARCH is $0.87 < 1$, implying that AR(1)MA(2)-GARCH(1,1) model is stable.

In order to test the disappearance of ARCH effect, ARCH-LM test is adopted again. The results are shown in Table A14.

Table A14. AR(1)MA(2)-GARCH(1,1) ARCH-LM test

F-Statistics	0.0903	Prob. F(1,760)	0.7638
Obs R ² statistics	0.0905	Prob. $\chi^2(1)$	0.7635

It is easy to find that ARCH effect no longer exists. And the analysis shows that AR(1)MA(2)-GARCH(1,1) model simulate the series of DS quite well.

The test results are shown in Table A15.

Table A15. Stationarity test on F_m, C_m, DF_m and DC_m

Time Series	Criterion	Lags	t-Statistics	Critical value			Results
				1%	5%	10%	
F_m	AIC	5	-1.6126	-3.9581	-3.4098	-3.1266	Nonstationary
C_m	AIC	1	-1.9599	-3.9581	-3.4098	-3.1266	Nonstationary
DF_m	AIC	4	-113.7956***	-2.5649	-1.9408	-1.6166	Stationary
DC_m	AIC	0	267.7857***	-2.5649	-1.9408	-1.6166	Stationary

***Significance at 1%.

Table shows that F_m , C_m are nonstationary, while DF_m and DC_m are stationary. VAR model can be adopted for DF_m and DC_m .

As F_m , C_m are both integrated of order 1, they may have cointegration relationship. According to the lag order selection criteria and statistics in table, the lag order should be 6.

Table A16. VAR model lags

Lags	Statistics					
	LogL	LR	FPE	AIC	SC	HQ
0	125,839.3	NA	7.24e-05	-3.8576	-3.8573	-3.8575
1	728,999.2	1,206,264.	6.75e-13	-22.3480	-22.3472	-22.3477
2	729,317.4	636.3862	6.69e-13	-22.3576	-22.3562*	-22.3572
3	729,333.4	31.95533	6.68e-13	-22.3580	-22.3561	-22.3574*
4	729,340.3	13.8314	6.68e-13	-22.3581	-22.3556	-22.3573
5	729,351.3	21.98325	6.68e-13	-22.3583	-22.3552	-22.3574
6	729,355.3	8.005845	6.68e-13*	-22.3583*	-22.35473	-22.3572

*mean the optimal choice.

This paper chooses 5 order lag to do Johansen co-integration test on F_m and C_m . The results are shown in table.

Table A17. Co-integration test of F_m and C_m

	Statistics		5% Critical value	
	Trace	Max-Eigen	Trace	Max-Eigen
$r = 0$	14.3916*	14.3909**	15.4947	14.2646
$r = 1$	0.0011	0.0011	3.8415	3.8415

*Significance at 10%. **Significance at 5%.

The table shows that, the DC_m and DF_m are co-integrated at the 10% significant level in Trace critical value and 5% significant level in Max-Eigen critical value.

From the above analysis, the F_m are co-integrated with C_m , so we can use the vector error correction model for further analysis of the data.

Table A18. VECM results

Cointegrating Eq:	CointEq1	
$F_m(-1)$	1	
$C_m(-1)$	-1.1925***	
Error correction:	DF_m	DC_m
CointEq1	-0.0002***	-5.00E-05
$DF_m(-1)$	-0.0757***	0.0176***
$DC_m(-1)$	0.0335***	-0.0501***
C	-4.74E-06	-6.40E-06*

*Significance at 10%. ***Significance at 1%.

The results show that both DF_m and DC_m are significantly affected by $DF_m(-1)$ and $DC_m(-1)$. The long-term correction also leads DF_m while the effect on DC_m is not significant in 10% level.

Table A19. Stationarity test of DC_m

Time series	Criterion	Lags	t-Statistics	Critical value			Results
				1%	5%	10%	
DC_m	AIC	0	-220.1856	-2.56801	-1.9412	-1.6164	Stationary



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