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Does US-China Trade War Cause Decoupling on Agricultural Trading?

Evidence from Spillovers in Soybean Meal Futures Markets

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Abstract

This thesis is designed to study the impacts of the US-China trade war on the agricultural trading between the two countries. Through the empirical research on the price and risk spillover effects, the evidence from the soybean meal futures markets are found out. To study the US- China futures price transmission, the VAR model and the cointegration method are applied to the datasets of futures price and the futures return. To study the volatility spillovers, the GARCH model is used to describe the volatility in each of the two markets, and a Diagonal-BEKK model is also applied to study the dynamic volatility correlation. From the empirical results, it is found that both the price and risk spillovers in the US-China soybean meal futures markets are weakened after the breaking out of the trade war. This indicates a decoupling of the US-China trade in the agriculture area.

Keyword: Trade war, soybean meal, price transmission, risk spillover

JEL: C58, C32, E44, F15, F51, G14, G15

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Contents

1. Introduction

In the modern history, the trade conflicts happen from time to time, which can cause huge impacts on countries from different aspects. The United States passed the Trade Act of 1974 in 1974. In this act, the No. 301 term allows the United States to impose extra tariff to their trade partners when determined to compete in a not improper way. In March 2018, President Trump announced a tariff to China, which signifies the opening of US-China trade war. As a return, China decides to cut the import of soybean from the United States in order to blow the ticket box of Trump.

A lot of people concern that the trade war may update to an overall decouple in terms of trade, technology, education and culture. This decouple may not only make the depressed global economy even worse but also create significant uncertainty. Since they offer standardized contract and convenient financing and have no need for physical delivery, the futures markets absorb new information and react quickly. The special features of futures market make it a perfect sample to study the impact of trade war on soybean meal trading.

The existing literature related to our topic mainly includes the studies on the US-China trade conflicts, the futures market and the spillover effects among different markets. Current studies tend to assess the reasons and impact of the trade war between the US and China. The methodologies, including the event analysis and computable general equilibrium (CGE) model, have been used to quantitatively identify the impacts of the trade war (Fang et al. 2019, Itakura 2019). Most studies on the impacts have focused on the financial risks on financial markets. For the studies on the spillovers of both price and volatility, the research methods range from the Vector Autoregressive Model (VAR), Vector Error Correction Model (VECM) to Generalized Autoregressive Conditional Heteroscedasticity

Model (GARCH) and various multivariate GARCH models. As most of them having focused on the stock, bond, foreign exchange and futures markets, these studies explore the spillover relationships among the regional markets and the global markets, as well as the spillovers among the developed markets and the developing markets (Eun and Shim 1989, Kasa 1992, etc.). Additionally, the price transmission process between the spot market and the futures market is a field of interest in early studies (Bigman 1983).

This thesis is designed to identify the impacts of the US-China trade war on the price and risk spillovers between the US-China soybean meal futures markets. To achieve that objective, we compare the spillovers before and after the breaking out of the trade war. The contribution to the literature would be: 1) provide insights on the substantial impact of trade war on the agricultural trading by means of the futures and expanding the research perspectives from stock market and a frequently researched area under the trade-war topic. 2) supplement the literature of spillovers among the futures markets through considering the stability of the spillovers after an external event shock from a dynamic perspective.

This thesis is structured in the following manner. In Section 2, we provide the background of soybean meal trade, including the production and usage, the big picture of international trade and the recent situation about soybean meal market in China and in US. In Section 3, we discuss some literature related to our topic in order to familiarize readers with the academic background. In Section 4, we build up empirical models, including VAR, cointegration, GARCH model and Diagonal-BEKK model in order to study the changes of price transmission and risk spillover effect. In Section 5, we summarize our conclusions and give out some suggestions for further studies.

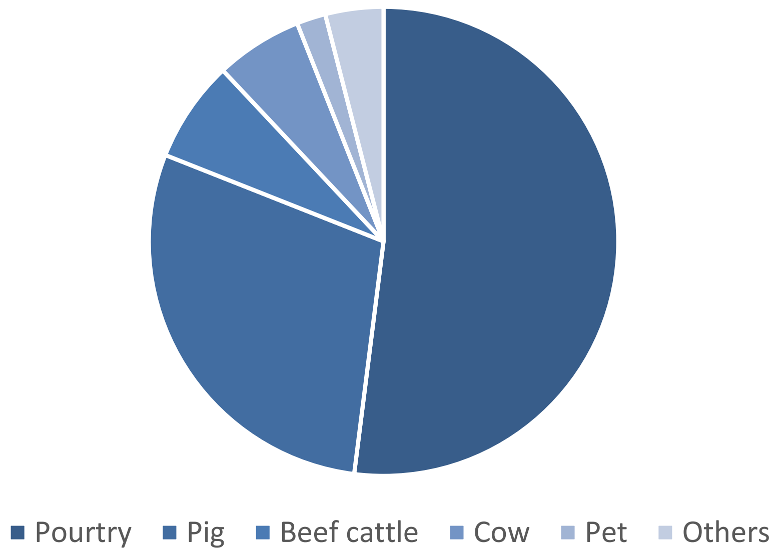
2. Background

2.1 The usage and production of soybean meal

Soybean meal is one of the most productive and widely used meal among 12 kinds of animal and plant oil and vegetable oil feed products, such as cotton seed meal, peanut meal and rapeseed meal.

As a high protein, soybean meal is mainly used in the livestock industry and feed processing industry, so as to produce the feed of livestock and poultry. Soybean meal is also used in the food processing, paper, coatings, pharmaceutical and other industries in order to produce pastry food, health food and cosmetics and antibiotic raw materials. In addition, about 85% of soybean meal is used to raise poultry and pigs. Since contains multiple amino acids, the soybean meal is a suitable source for the nutritional needs of poultry and pigs.

Figure 1: 2017 Soybean meal usage and proportion

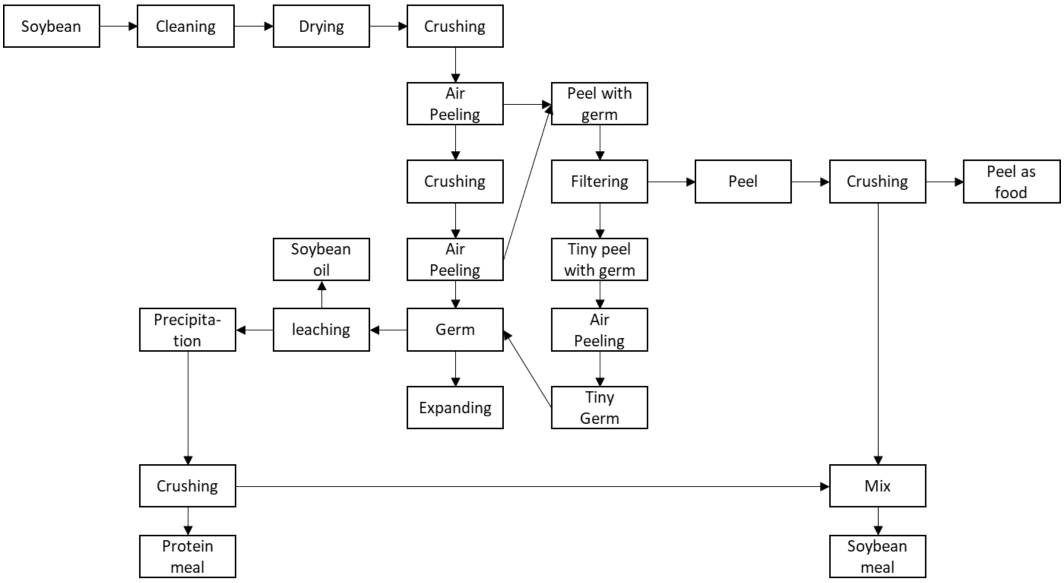


Source： China Feed Industry Association

Soybean meal is a by-product produced when crushing soybean to soybean oil. The basic process of producing soybean meal by dipping is as follows:

1. Oil plant buys soybeans
2. Remove impurities
3. Break (a soybean is about 6-8 pieces)
4. Warm and adjust the moisture content (destroy the original tissue, and easy to produce oil)
5. Press into pieces and continue to adjust the moisture content
6. Spray with solvent to quench soy oil
7. Dissolvent
8. Soybean meal produced

Figure 2: Soybean meal flowchart



Source： China Feed Industry Association

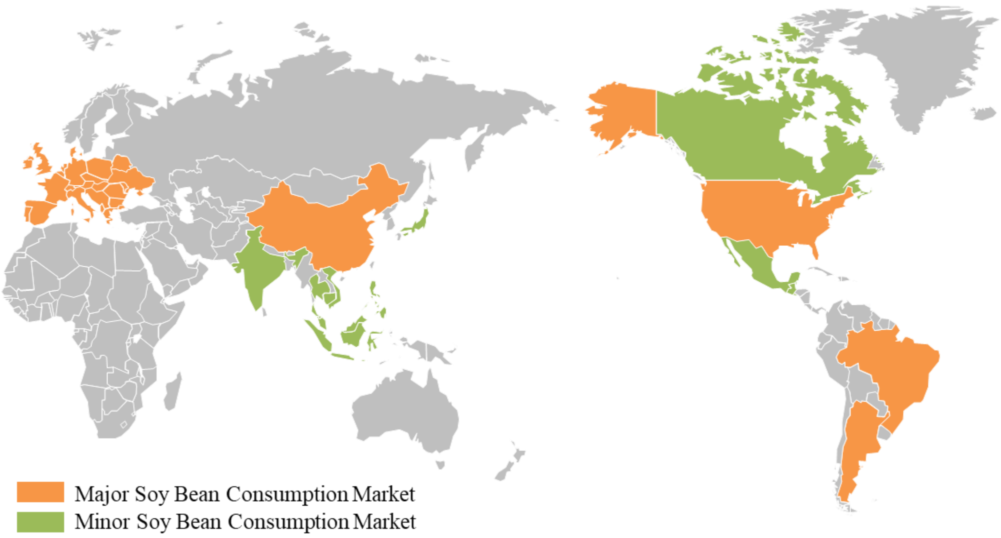
2.2 Global soybean and soybean meal business

The global soybean is mainly exported to China by the Americas. The United States, Brazil and Argentina are the world's three largest soybean producers, with the output of approximately 120 million tons, 113 million tons and 47 million tons in 2017/18, accounting for 82% of global production. China is the world's largest consumer of soybeans. In 2017, its consumption was 112 million tons, and its import volume was 95.54 million tons, accounting for about 65% of the total global trade.

The production of soybean meal is concentrated in 6 countries, including the United States, China, Argentina, Brazil, the European Union and India. Among them, Argentina is the world's largest exporter of soybean meal and soybean oil. In the recent years, the production of soybean meal is increasing with the increase of soybean.

In recent years, there is a rapid growth of consumption, especially in China. In addition, the European Union, the United States and Brazil soybean meal consumption is also in a stable growth stage. The consumption of the emerging market countries, such as Vietnam, Indonesia, Thailand, South Korea and other countries, is also growing rapidly.

Figure 3: Major soybean consumption markets



Source: China Feed Industry Association

2.3 Soybean meal business in China

2.3.1 Soybean meal production in China

In 2017, China imported a total of 95.54 million tons of soybeans, of which 32,857,700 tons came from the United States, accounting for 34.39% and ranking the second place. Brazil ranked first with 50.928 million tons, and the soybeans sold to China exceeded 50% of China's total imports. Before 2015, the United States was the largest importers of Chinese soybeans.

The world's major soybean meal production areas are the United States, Brazil, Argentina, China, India, the European Union and other countries. The U.S. has long accounted for more than 30% of the world's soybean meal. However, in recent years, China's soybean crushing industry has developed rapidly, and the growth rate of China's soybean meal industry has maintained a rate of more than 20% in each year.

In China, the annual output of soybean meal has exceeded 1500 tons for the first time in 2000. After 2001, the output of soybean meal has been growing rapidly. In 2004, the soybean meal production of China surpassed Brazil and Argentina for the first time, second only to the United States in the world.

2.3.2 Great changes from soybean meal net exporters to importer

Before 1996, the output of soybean meal in China was greater than its domestic consumption, making China one of the major exporters in international trade. With the improvement of people's living standards, the livestock industry has expanded significantly, and the demand for soybean meal in the domestic aquaculture industry has also risen sharply. Because of the higher prices of the domestic soybean meal production costs in China and the appealing prices of the international market soybean meal, more and more cheap soybean meal was imported into China. After 1996, China's role in soybean meal international trade transformed from a net exporter to a net importer.

In China's East China region, Shandong, Jiangsu and other provinces, the soybean processing capacity has been greatly improved since the middle of the 1990s, and thus these regions' soybean meal production is also increasing rapidly. These areas have becoming the main areas of soybean processing and soybean meal production. Among them, East China is one of the main soybean meal consumption areas in China.

There are 2 main factors that influence China soybean demand and price.

The first one is the scale cycle of domestic aquaculture production on soybean meal. The scale cycle majorly affects three segments, namely pig, poultry and aquatic products. The pig cycle will last 8 months in order to get a piglet ready for slaughter. When the number of piglets in inventory rises, the consumption of feed goes up and therefore the demand of soybean meal becomes strong.

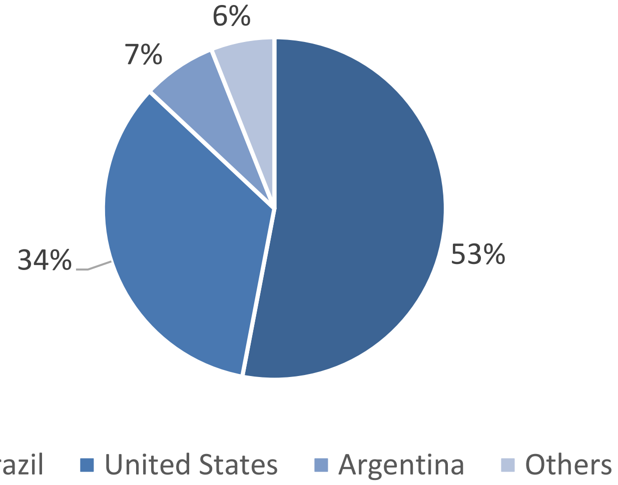
The second one is the consumption cycle of soybean meal. The peak of China's livestock consumption is majorly during the traditional festivals, namely the Spring Festival, the Later Festival and others. The catering industry is the main driver for the consumption. Due to the rapid economic growth, the meat demand is helpful to the soybean meal industry.

2.3.3 Recent situation of soybean meal in China

The outbreak of the US-China trade war has led to a change in the balance lasting for many years. The China's soybean imports supply chain entered into the stage of constant adjustment. Last year, 25% of China's tariff on U.S. soybean imports led to only 16.6 million tons of

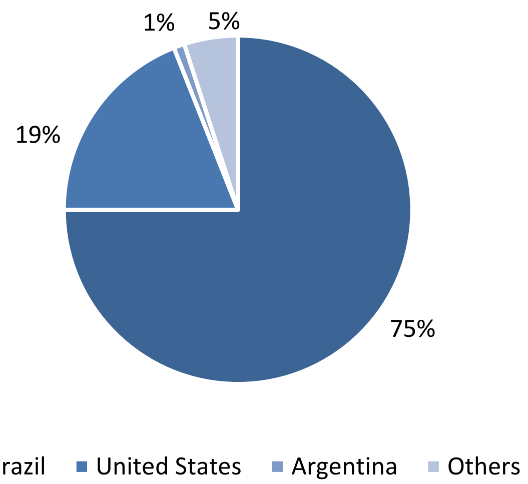
U.S. soybeans imported in 2018, which is about half the 32.9 million tons in 2017, a 10-year low. The imports of Brazilian soybeans surged 30% year-on-year to 66.1 million tons, accounting for 75.1% of China's total soybean imports. For the whole of 2018, China imported 88.031 million tons of soybeans, which is the first decline in total imports in seven years, a down of 7.9% year-on-year.

Figure 4: 2017 Source and proportion of soybean imports in China



Source： China Customs Database

Figure 5: 2018 Source and proportion of soybean imports in China

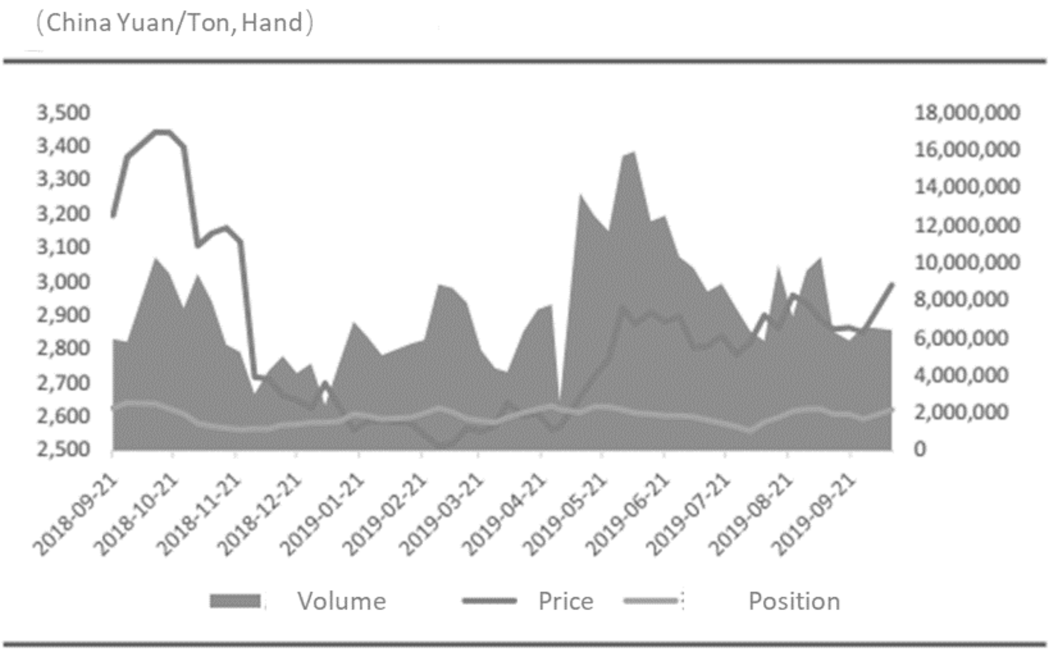


Source： China Customs Database

Since the African swine fever in August 2018 extended to the whole country, the affected area launched some emergency mechanisms. All dead pigs and culled pigs went for harmless treatment, resulting in the continuous declining of the pigs with ability of breeding. The year-on-year decline is more than 20%. According to the Ministry of Agriculture, pig stocks decreased by 4.2% month-on-month in May 2019 and by 22.9% compared to that of the last year. The number of sows decreased 4.1% month-on-month and 23.9% lower than that of the same period last year.

It is originally expected by the market that the epidemic will lead to a sharp decline in domestic pig feed demand, which seriously affected the demand for soybean meal. But unexpectedly, due to increased demand for poultry and aquatic product, the soybean meal demand didn’t drop significantly, and the trading volume even exceeded the last year. As a result, the inventories have fallen to a 3-year-low.

Figure 6: DCE soybean meal market performance

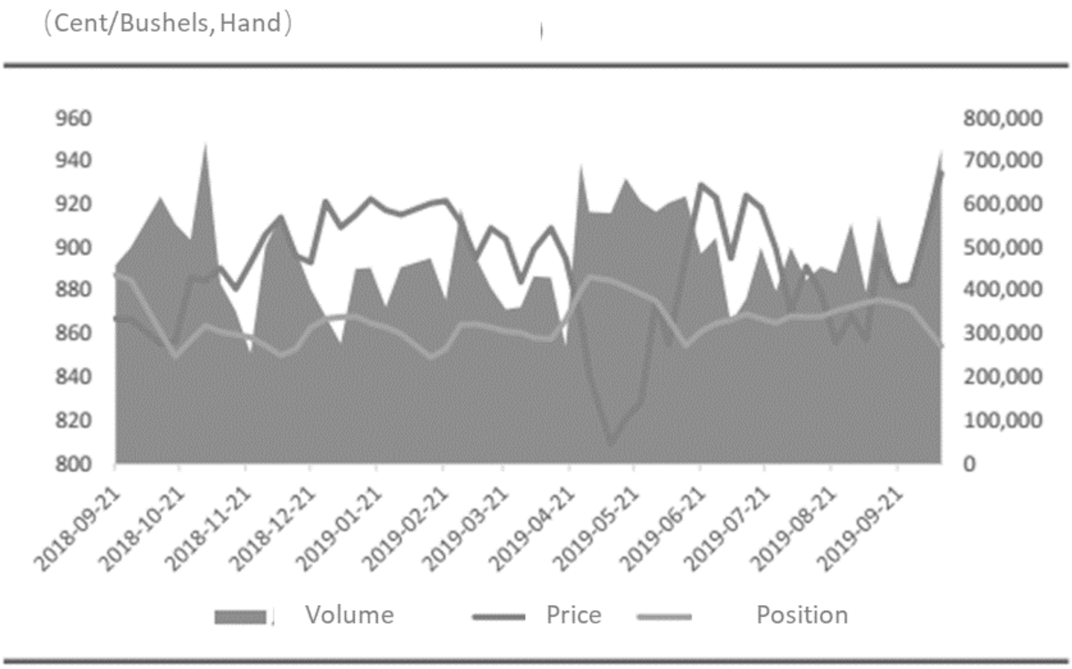


Source：Qianzhan Database

2.4 Soybean meal in the United States

The U.S. Department of Agriculture (USDA) continued to cut its end-of-year U.S. soybean inventory for 2019/20 in its October WASDE report, as it cut US soybean production for the month by 19/20 and until the current year. This report has a lot of impacts on the market. The report exceeded expectations by 19/20 to 46.9 bushels per acre, and the planting area remained unchangeable, resulting in an annual output reduction of 2.25 million tons to 96.62 million tons.

Figure 7: CBOT soybean meal market performance



Source: Qianzhan Database

In the fall, wet weather in the Midwest is not conducive to soybean maturation, thus leading to slow crop drying, frosty weather in the northern Great Plains, or damage to immature crops. According to USDA data, the soybean deciduous rate was 72% as of October 6th, up from 90% a year earlier and 87% over five years. Soybean harvesting was 14%, 31% year-on-year and 24% over five years. Soybean growth is 53%, with the market average estimated at 55% and compared with 55% the week before. This is compared with 68% in the same period last year.

After the breaking of the US-China trade war, the soybean industry of the United State received a heavy blow for China’s boycott. In an article published on its official website on June 15, the American Soybean Association (ASA) said that “the American Soybean Association is disappointed with the government’s decision on behalf of all US soybean growers, all of which will soon be affected by retaliatory tariffs.” It is reported that the ASA has twice asked for a meeting with President Trump, so as to discuss how to reduce the US trade deficit by increasing the export of Chinese soybeans without resorting to “destructive tariffs”.

Former Oregon Senator Larry George said that Sino-US relations are important to both countries and their people, so "the current escalation of trade conflicts is very painful." In 2017, the Oregon House of Representatives and the Senate passed a joint resolution on strengthening economic and trade relations with China, becoming the first state in the United States to support the economic and trade cooperation with China in the form of a legislative resolution. The resolution states that China is Oregon's largest trading partner. In 2016, Oregon's exports to China reached US$5.8 billion, and there were over 20,000 jobs in Oregon gain benefits from the state's trade with China. In addition, China is the largest source of international tourists in Oregon, with more than 60,000 Chinese visitors to Oregon each year.

3. Literature review

3.1. US-China trade conflicts

There are majorly qualitative and quantitative studies of US-China trade conflicts in terms of the cause and impact of the trade war. Generally speaking, the reasons of the trade conflicts come from multiple factors including the economics and politics. Xie (2006) argues that the economic reasons mainly lead to the anti-dumping to China by the United States. The frequency of anti-dumping investigation to China is significantly increased by the huge trade deficit with China and the deterioration of the US's industry. He argues that political factors are also one of the causes of the US-China trade conflict. Ren (2017) suggests that the economic cause of the US's "301" investigation to China includes the intention to restrict China's industrial upgrading and narrow the US trade deficit with China. She also thinks that the political factors include the mid-term elections in the US in 2018, and the active upgrading the industrial structure and expanding imports from the United States can better deal with trade conflicts. Miao (2009) proposes that the cause of the US-China trade friction contains the unbalanced economic development, industry structure superposition, China's concentrated export market, and the U.S. strategic limitation of China's development and so on. Feinberg and Hirsch (1989), Krupp (1994) studies the driving factors of anti-dumping from the perspective of micro industries. It is found by all these studies that more frequent anti-dumping can be caused by the overall industry outlook, the volatility of the employment market and the market demand. Anti-dumping has become the effective tools for the protection of some certain industries in the US. From another perspective, Feinberg and Reynolds (2006), Knetter and Prusa (2003) studies the impact of macroeconomic factors on the US's anti-dumping. With the anti-dumping data from 1981 to 1995 for 15 sample countries, these studies found that the macroeconomic situation is an important influencing factor of America's anti-dumping. During the recession, the foreign products are more vulnerable to the anti-dumping litigation by the US's manufacturers. Through the negative binomial regression model, Shen(2007) analyzes the macro factors of the US's anti-dumping to China. He finds the anti-dumping is more often associated with the lower industrial production growth rate and higher unemployment rate. For the US, there is less anti-dumping to China if the proportion of export increases.

For the impact of US-China trade conflicts, the studies have tried to quantitatively identify the effects by means of various models. Fang et al. (2019) used the event method to quantify the impact of the trade war on China's bond market, stock market, and foreign exchange market, and the risk spillover effect between markets. It is indicated by the empirical results that the trade friction in the short term will cause the rise of risks in all the financial markets of China. There is both significant and lasting cross-market risk spillover effect of trade friction. With the data of Shanghai stock market index and the Dow Jones index, Li (2019) conducted research on China and US's stock market before and after the US-China trade war. Through the risk comparison based on IGARCH model and VaR, he also concluded that the trade war increased the absolute financial risks in China and the United States, and China is also facing the greater financial risk than the United States from the point of overall risk mean size. Itakura (2019) evaluated the impact of the US-China trade conflict with a dynamic computable general equilibrium (CGE) model. Due to the acceleration of the trade conflict, the gross domestic product (GDP) of China and the US has been negatively influenced by -1.41% and -1.35% respectively.

3.2. Studies on futures market

There are many studies on the price and volatility relationships among different futures markets, of which it is common to see the price guide mechanism between a local market and an international market. In these studies, there is a broad use of the Granger causality test, VECM models, multivariate GARCH models and so on.

Goodwin (2000) found that the Canada wheat futures market is significantly influenced by the US market, while the Canada wheat futures market does not show the impact of the US market. Through studying the relationship between the oil futures at New York mercantile exchange (NYMEX) and the London international petroleum exchange (LIPE), Lin and Tamvakis (2001) showed that the risk spillovers are between the two futures markets. With the VAR models, Booth and Ciner (1997) studied the relationship and volatility correlation between the corn futures price at the Tokyo Grain Exchange (TGE) and the corn futures price at the Chicago Board of Trade (CBOT). The results show that the CBOT futures price determines the price transmission process. Likewise, with the VECM models, Tse and Booth (1997) studied the price guide mechanism between the New York oil futures market and the London oil futures market. Hernandez (2012) also studied the co-movement and the volatility effect among the global agricultural futures markets by means of the MGARCH models.

3.3. Studies on the spillover effect among markets

There are many studies on the spillover effect among different markets. From the perspective of the researching methodology, there is a wide application of the first order moment models and second order moment models. The first order moment models mainly include linear model, cointegration model, Vector Autoregressive Model (VAR) and Vector Error Correction Model (VECM). Besides, the second order moment models mainly include volatility variance model and autoregressive conditional heteroscedasticity model.

In the early stage, the linear models are the scholars' major research methods on the spillover relationship between or among markets. Garbade and Silber (1983) reveal the impacts of futures price and spot price on the process of price discovery and the guide law of futures on the spot market prices. Through the linear regression analysis on the futures price and the spot price of corn, soybean meal and wheat contracts traded at the Chicago Board of Trade (CBOT), Bigman (1983) verified the futures market’s price discovery function.

When studying the nonstationary sequences, Engel and Granger (1987) proposed the cointegration test, a new way, to study the equilibrium relationship between the nonstationary variables. The cointegration model has become a classical theoretical method and has been widely recognized in the research on the dynamic relationship between futures markets. Brenner and Kroner (1995), Kavussanos and Nomikos (1999) verified the effectiveness of the discovery function of futures price and found the existence of the cointegration relationships between the spot price and futures price for a lot of futures varieties. With the co-integration model, and the statistical inference of tools based on the maximum likelihood estimation method—Johansen rule, Johansen (1988), Johansen and Juselius (1990) tested the price discovery function of the futures markets.

Engle and Granger (1987) put forward the vector autoregressive model (VAR) and the error correction model (ECM), which have been used to fit the dynamic relationship among the different markets. By means of the vector autoregressive models (VAR), Kasa (1992) gained insight into the dependencies between global stock markets. He concluded that there is a consistent trend among the stock markets of the Britain, Germany, Japan, Canada and the United States. Based on the VAR, Eun and Shim (1989) also verified the strong impact of the US's stock market on the global stock market.

For studies based on the second order moment models, it is concluded by French and Roll (1986) that the volatility variance could be used as the main source of information in order to study the dynamic spillover effect. T Ito and WL Lin (1994) identified the two-way volatility spillovers between the US's and Japan's stock markets by means of the volatility variance models. Engle proposed the autoregressive conditional heteroscedasticity (ARCH) models in 1982. Bollerslev (1986) further improved the ARCH models into generalized autoregressive conditional heteroscedasticity (GARCH) models, which could be used to fit the dynamic financial data series. When studying the volatility relationships among different markets, the multivariate GARCH models have been widely applied. With a Diagonal-BEKK model, P Katsiampa (2019) studied the dynamic volatility relationships of Bitcoin and Ether. Through the BEKK-MVGARCH models, Li and Giles (2014) discussed the volatility spillover effect of stock return among Japan, the US and six Asian emerging market and found that there is a significant two-way spillover between the US and the other six emerging economies.

4. Empirical research

4.1. Data

We select the price of soybean meal futures of Chicago Mercantile Exchange (CBOT) and the price of soybean meal futures of Dalian Commodity Exchange (DCE) as the research index of soybean meal futures prices in the United States and China. The time span for the sample is from January 2, 2013 to October 21, 2019. To identify the impact of the US-China trade war on the spillover effect between the two markets, the data are divided into two stages through taking the August 18, 2017 as a beginning of the trade war, at which time the Office of the United States Trade Representative officially launched the 301 investigation into China. Therefore, the data from January 2, 2013 to August 17, 2017 is the first-stage sample, accordingly before the trade war, and the data from August 18, 2017 to October 21, 2019 is the second-stage sample, accordingly after the trade war. Bloomberg provides the data for both the two futures market. In the following parts of this paper, we mainly use the econometrical software Stata to do the data processing and modeling.

4.1.1. Data preprocessing

Before using the data in the empirical analysis, the data preprocessing needs to be carried out. Because the statutory holidays in China and the United States are not the same, sometimes normally with one market trading and the other closed, we choose to weed out non-resulting data and retain the common data at the same point. For the sample with the large time span, as in our paper, this method can stabilize the error in the controllable range to a large extent. Finally, we have 1588 observations in total after weeding out 178 observations from 1766 observations in the raw data. For the first stage, we have 1079 observations for CBOT and DCE soybean meal futures prices respectively from January 4, 2013 to August 17, 2017. In addition, for the second stage, we have 509 observations for CBOT and DCE soybean meal futures prices respectively from August 18, 2017 to October 21, 2019.

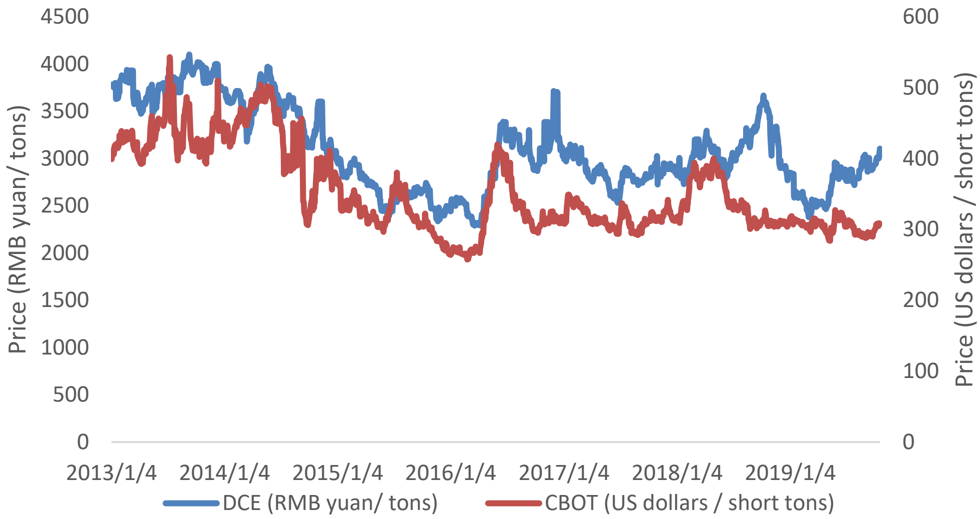
Table 1: Main indicators

Indicators	Meaning
cbot	the price of soybean meal futures of CBOT
dce	the price of soybean meal futures of DCE
dlcbot	the logarithmic rate of return: take the value after logarithmic difference for cbot
dldce	the logarithmic rate of return: take the value after logarithmic difference for dce
Lp.dlcbot	P order lag value of dlcbot (p = 1,2,3,…)
Lq.dldce	Q order lag value of dldce (q = 1,2,3,…)

4.1.3. Data description

In Figure 8, it is able to see the price evolution of soybean meal futures of CBOT and DCE from 2013 to 2019, respectively. There seem to be equal price trends. From 2014 to 2016, both the soybean meal prices of CBOT and DCE show a continuous downward trend. Starting from the beginning of 2016, the futures prices in both markets rebounded slightly and continuously until the mid-and late July 2016, after which began to fluctuate up and down.

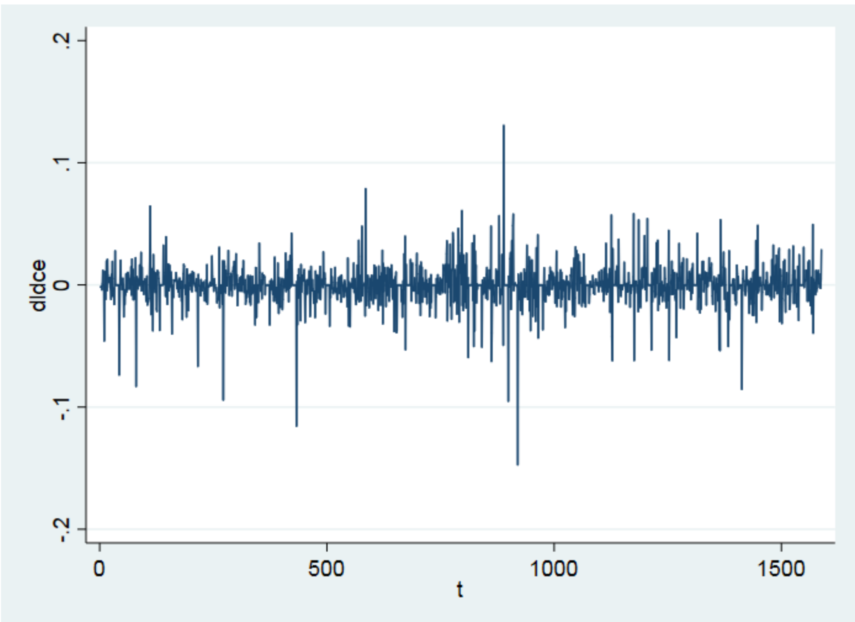
Figure 8: 2013-2019 Soybean meal futures prices of CBOT and DCE



Source: Bloomberg

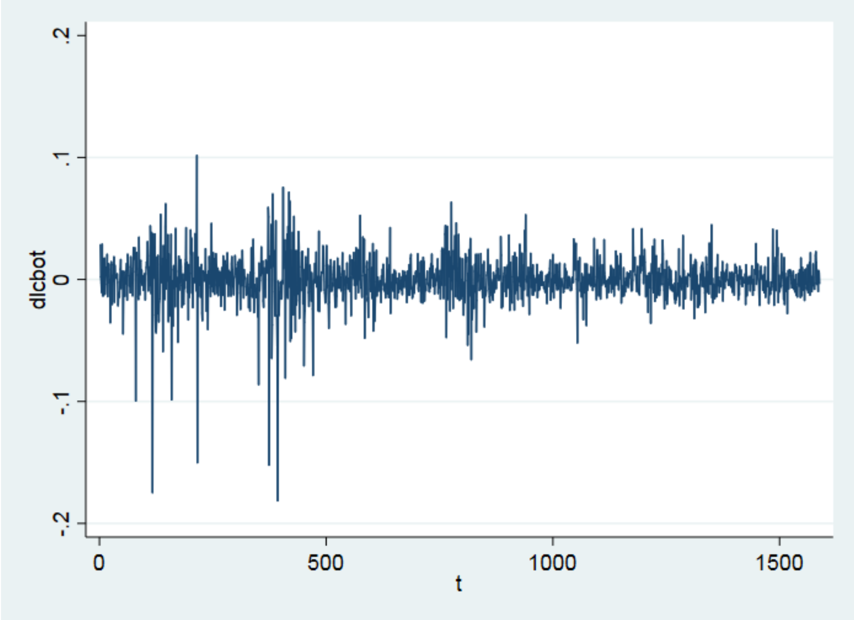
In figure 9 and 10, it is able to see the volatility clustering effect in both markets. Compared with the CBOT market, the volatility in DCE market is relatively more stable over the years. Besides, the CBOT market shows higher volatility level during the first two years.

Figure 9: 2013-2019 Soybean meal futures return of DCE



Source: Bloomberg

Figure 10: 2013-2019 Soybean meal futures return of CBOT



Source: Bloomberg

Table 2 indicates the summary statistics of the identified variables. There are 1588 observations for the price variables and 1587 observations for the return rate variables. For the soybean meal futures on the CBOT market, the average price is 352 RMB yuan per tons, and the min and max prices are 258 and 543 RMB yuan per tons. The skewness is about 0.8 as the distribution shows a slight right deviation. The kurtosis is 2.6, which is close to the kurtosis of normal distribution at 3. For the soybean meal futures on the DCE market, the average price is 3085 USD dollars per tons, and the min and max prices are 2290 and 4100 USD dollars per tons. The skewness is about 0.4, basically consistent with the normal distribution. The kurtosis is lower than 3, showing a slightly low peak distribution compared with the normal distribution. Generally speaking, the price distributions for both the two markets are relatively concentrated, which suggests a slightly similar pattern with the normal distribution, although the dispersion degree of data is higher for the DCE market than the CBOT market according to the variances comparison. For the return rate in the two markets, both of them propose the distribution patterns with the spike thick tail. The DCE market has a slightly higher average rate of return but a slightly lower variance than the CBOT market.

Table 2: Basic statistics for variables

Variable	cbot	dce	dlcbot	dldce
Obs	1,588	1,588	1,587	1,587
Mean	351.9372	3085.224	-0.00016	-0.00012
Std.	59.62073	449.3523	0.01875	0.016113
Min	257.5	2290	-0.18134	-0.14714
Max	543	4100	0.101664	0.130497
Variance	3554.631	201917.5	0.000352	0.00026
Skewness	0.829	0.407	-1.749	-0.766
Kurtosis	2.620	2.099	20.604	15.973

4.2. Stationarity test

Before establishing the time series models, it is necessary to test the stationarity of the data in order to avoid spurious regression. ADF test proposed by Said and Dickey in 1984 is used, which is one of the common methods to test the stationarity of the series. There are three types of model specifications for ADF test:

i) Mean-zero data: under the null hypothesis is a random walk without drift.

$$\Delta y_t = \gamma y_{t-1} + \sum_{t=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t$$

ii) Mean non-zero data: under the null hypothesis is a random walk with nonzero drift.

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{t=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t$$

iii) Linear trend: under the null hypothesis is a random walk, perhaps with drift.

$$\Delta y_t = a_0 + a_2 t + \gamma y_{t-1} + \sum_{t=1}^{k} \beta_i \, \Delta y_{t-i} + \varepsilon_t$$

Criterion rules:

$$H_0: \gamma \ = 0$$

$$H_1: \gamma \ \in (-2, 0)$$

$$t = \frac{\hat{\gamma} - 0}{se(\hat{\gamma})}$$

From the visual inspection of the variables in the data description section, we apply model ii) and model iii) for the variables of prices, and apply model i) for the variables of returns. The test is carried out for the series divided into two stages.

Table 3: Unit root test

Stages	**Variables**	**Model**	**lag**	**T statistics**	**1% Critical value**	**5% Critical value**	**10% Critical value**	**Stationary**
Stage 1	cbot	ii	7	-1.879	-3.43	-2.86	-2.57	N
		iii	7	-3.088	-3.96	-3.41	-3.12	N
	dce	ii	6	-1.878	-3.43	-2.86	-2.57	N
		iii	6	-2.4	-3.96	-3.41	-3.12	N
	dlcbot	i	5	-13.927	-2.58	-1.95	-1.62	Y
	dldce	i	10	-11.007	-2.58	-1.95	-1.62	Y
Stage 2	cbot	ii	8	-1.766	-3.44	-2.87	-2.57	N
		iii	8	-2.531	-3.98	-3.42	-3.13	N
	dce	ii	1	-1.831	-3.43	-2.86	-2.57	N
		iii	1	-1.852	-3.96	-3.41	-3.12	N
	dlcbot	i	7	-8.719	-2.58	-1.95	-1.62	Y
	dldce	i	0	-25.458	-2.58	-1.95	-1.62	Y

From the test results, we could see the T statistics are all greater than the 5% critical values in terms of the price variables. Besides, we fail to reject the null hypothesis, and conclude that both the price variables contain the unit root before and after the trade war. For the return variables, the T statistics are all less than the 5% critical values, and thus we should reject the null hypothesis and conclude that both the price variables contain the unit root during both stages.

4.3. Vector Auto Regression models

Basically, the price of the soybean meal futures is determined by the supply and demand of the soybean meal in China's and the US's soybean meal market respectively. Due to the factors like global trading, it is able to propose that there is an equilibrium relationship between the price of soybean meal futures in different markets. From Figure 9, we could see that there is a roughly the same price evolution of soybean meal futures in the two markets. For example, the investors in DCE market could turn to buy the futures in the CBOT market if the price of soybean meals futures in DCE market rises. Besides, China imposes a 25% tariff on US soybeans during the trade war, which not only has impact on the demand and supply of the commodity, but also may have changed the equilibrium relationship between the two markets. Therefore, to verify the mean value spillover effect between the markets and to identify whether there is any change of the spillover effect before and after the US-China trade war, we set up the Vector Auto Regression (VAR) models for the two stages respectively as the following. To avoid spurious regression, the stationary variables of return, dlcbot and dldce are also used in the VAR models.

4.3.1. Model specification

Under the circumstance where the exogeneity of a variable is not certain, VAR models treat each variable symmetrically. Therefore, a VAR is in a sense a systems regression model with more than one dependent variable. The simplest case is a bivariate VAR as follows:

$$y_{1,t} = \beta_{10} + \beta_{11}y_{1,t-1} + \cdots + \beta_{1k}y_{1,t-k} + \alpha_{11}y_{2,t-1} + \cdots + \alpha_{1k}y_{2,t-k} + \mu_{1,t}$$
$$y_{2,t} = \beta_{20} + \beta_{21}y_{2,t-1} + \cdots + \beta_{2k}y_{2,t-k} + \alpha_{21}y_{1,t-1} + \cdots + \alpha_{2k}y_{1,t-k} + \mu_{2,t}$$

Where $u_{i,t}$is an i.i.d. disturbance term with $E[u_{i,t}] = 0, i = 1,2$ and $E[u_{1,t}u_{2,t}] = 0$

The model could be extended to the case of g variables with k lags. Write the VAR(k) model with g variables in the compact form:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} \dots + \beta_k y_{t-k} + \mu_t$$

Where, $$y_t = \begin{bmatrix} y_{1,t} \\ \vdots \\ y_{g,t} \end{bmatrix},\ \beta_0 = \begin{bmatrix} \beta_{1,0} \\ \vdots \\ \beta_{g,0} \end{bmatrix},\ \beta_k = \begin{bmatrix} \beta_{1,k} \\ \vdots \\ \beta_{g,0} \end{bmatrix},\ \mu_t = \begin{bmatrix} \mu_{1,t} \\ \vdots \\ \mu_{g,t} \end{bmatrix}$$

4.3.2. Empirical specification

To set up a VAR model, the optimal lags should be determined, usually based on the indicators, such as LR, AIC, SC, HQIC and FPE. According to the selection-order criteria, the indicators, including FPE, AIC, HQIC and SBIC, select the one-lag model for the first stage. The indicators, including LR, FPE, AIC and HQIC, select the one-lag model for the second stage.

Hence, the VAR (1) model is set up for both stages, considering the selected optimal lag.

$$X_t = \mathrm{C} + A_1 X_{t-1} + e_t$$

Where:

$$X_t = \begin{pmatrix} dlcbot_t \\ dldce_t \end{pmatrix} \ \mathrm{C} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} \ A_1 = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \ e_t = \begin{pmatrix} e_{1,t} \\ e_{2,t} \end{pmatrix}$$

$dlcbot_t$ and $dldce_t$ are the logarithmic rate of the return of soybean meal futures on the CBOT market and DCE market, respectively. $A_1$is the coefficient matrix of the impact of return rate in the lag period on the return rate of the current period. C represents a constant term, and e_t is a vector write noise process.

4.3.3. Estimation results

The following are the estimation results for the two stages:

Table 4: VAR (1) Estimation Results for Stage One

Variables	**dlcbot**	**dldce**
L.dlcbot	-0.0573	0.105***
	(-1.87)	(4.50)
L.dldce	0.0092	-0.126***
	(0.23)	(-4.16)
Constant	-0.0003	-0.0003
	(-0.49)	(-0.60)
Observations	1077	1077

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

For stage one, the return rate of soybean meal futures on CBOT market in the lag period has a positive impact on the return rate of soybean meal futures on DCE market in the current period. The coefficient is 0.105, which is significant at 0.1% significance level, indicating that one additional percent of increase in the price of soybean meal futures on CBOT market in the one lag period will lead to 10.5% of increase in the price of soybean meal futures on DCE market in the current period. In addition, the return rate on DCE market in the one lag period itself has a significant impact (at 0.1% significance level) on the return rate on DCE market in the current period. From the Table, one additional percent of increase in the price of soybean meal futures on DCE market in the one lag period will lead to a 12.6% of decrease in the price of soybean meal futures on DCE market in the current period.

Table 5: VAR (1) Estimation Results for Stage Two

c	**dlcbot**	**dldce**
L.dlcbot	0.0100	0.213***
	(0.23)	(3.66)
L.dldce	0.0165	-0.130**
	(0.50)	(-2.98)
Constant	0.0001	0.0002
	(0.14)	-0.35
Observations	507	507

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Equally, for stage two, the impact of return rate in CBOT market and DCE market in one lag period on the return rate in DCE market in the current period is significant at 0.1% and 1% significance levels, respectively. With one additional percent of increase in the price of soybean meal futures on CBOT market in the one lag period, the price on DCE market in the current period will increase by 10.8% higher compared with the stage 1. The impact of the return rate in DCE market in the one lag period itself on the return rate on DCE market in the current period does not change much after the trade war (stage two).

4.3.4. Tests for the models

We test the residual normality with the Jarque-Bera Test for the two stages respectively, as the follows. From Table 6, it is able to conclude that all of the statistics are significant, and we reject the hypothesis that the residuals do not follow the normal distribution. Thus, the residuals from the regressions for both stages are normally distributed.

Table 6: Jarque-Bera Test

Equation	**Stage**	**Chi2**	**Prob >chi2**
dlcbot	Stage one	1.0e+04	0.00000
	Stage two	84.139	0.00000
dldce	Stage one	1.2e+04	0.00000
	Stage two	659.506	0.00000
All	Stage one	2.3e+04	0.00000
	Stage two	743.645	0.00000

Next, we check the eigenvalue stability condition to verify the stability of the models. The results show that all the eigenvalues lie in the unit circle, and thus the VAR models can satisfy the stability condition.

4.3.5. Granger Causality Test

To identify the spillover effect between the variables, the Granger Causality Test are carried out for the two stages. From Table 7 and Table 8, we could conclude that, for bot stages, the return rate of soybean meal futures on CBOT market Granger Cause the return rate of soybean meal futures on DCE market, but not vice versa.

Table 7: Granger Causality Test for stage one

Null hypothesis	F statistics	P value	Conclusion
dlcbot does not Granger Cause dldce	20.22	0.0000	Reject
dldce does not Granger Cause dlcbot	0.05	0.8170	Accept

Table 8: Granger Causality Test for stage two

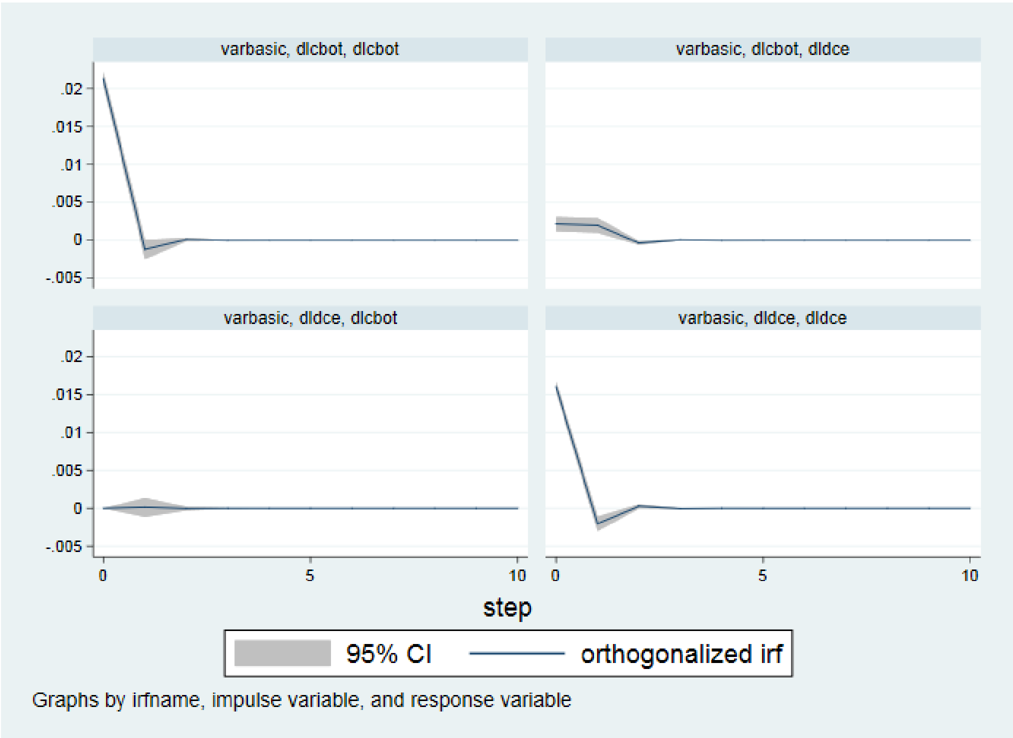
Null hypothesis	F statistics	P value	Conclusion
dlcbot does not Granger Cause dldce	13.41	0.0003	Reject
dldce does not Granger Cause dlcbot	0.25	0.6188	Accept

4.3.6. Impulse Response Analysis

To study the marginal effects of the parameters in the coefficient matrix A_1 in the VAR models, the impulse response analysis is carried out to identify the impact on the objective functions when a unit external shock occurs to the error terms. In order to conduct a pure analysis even when $\mathrm{corr}(e_{1t}, e_{1t}) \neq 0$, where we cannot keep e_{1t} unchanged and study the effect of e_{1t}, the orthogonalized impulse response functions (OIRF) are carried out.

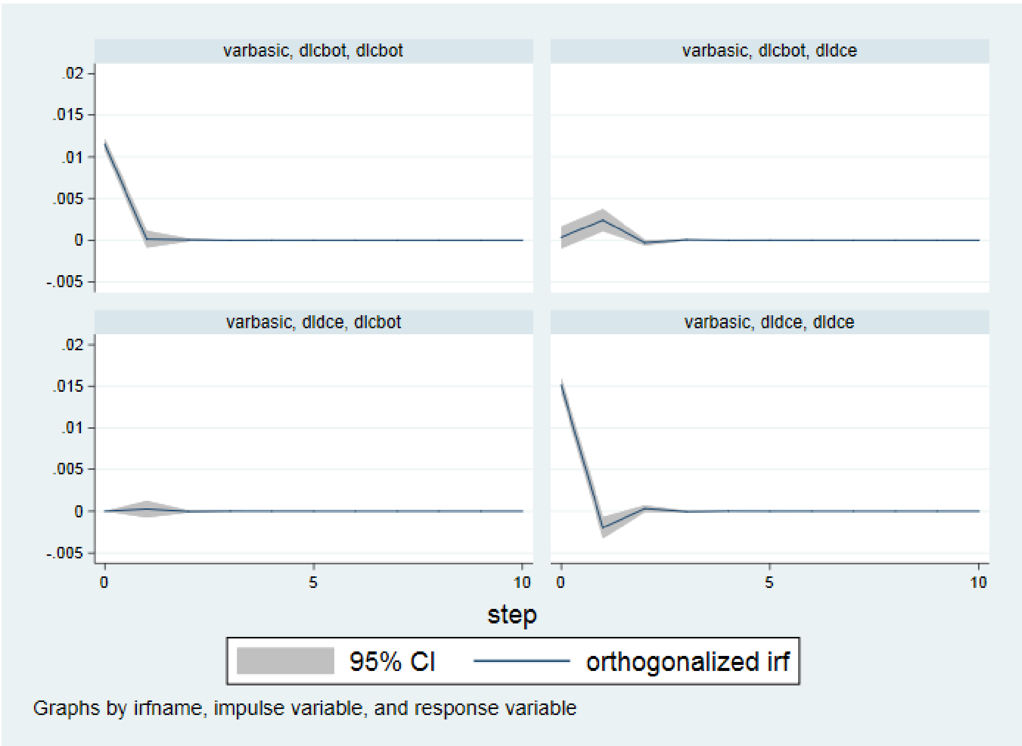
From Figure 11, it is able to see the impulse response graph for the stage one (before the trade war). The sending of the unit shock to the return rate of soybean meal futures on a market would lead to the obvious response by the return rate of soybean meal futures on the same market in the phase zero. In the first phase, the returns on both markets show an adverse response, which can be understood as a callback to the overreaction. In the second phase, the impulse is gradually digested by the market. No response occurs starting from the third phase. For the impulse response between the two different markets, the CBOT market shows spillover effect on the DCE market, while the DCE market barely has impact on the CBOT market, conforming to the findings from our Granger Causality Tests. When the return rate of soybean meal futures on the CBOT market acts as the impulse variable, the DCE soybean meal futures return shows a moderate response in the phase zero immediately and maintained the response to the first phase. The impulse is gradually digested by the market in the second phase and disappears from then on.

Figure 11: OIRF for stage one



Comparatively, Figure 12 shows the impulse response graph for the stage two (after the trade war). Likewise, the sending of the unit shock to the return rate of soybean meal futures on a market would lead to the obvious response by the return rate of the soybean meal futures on the same market in the phase zero. But, only the returns on DCE market show an adverse response in the first phase. For the impulse response between the two different markets, the spillover effect of CBOT market on the DCE market in stage two are likely to be weakened compared with the stage one. When sending a unit shock to the return rate of soybean meal futures on the CBOT market, there is barely an immediate response of DCE soybean meal futures return, as in the first stage. In the first phase, we did not observe obvious changes to the impact of CBOT impulse on the DCE response. In addition, similar to the first stage, the impulse is gradually digested by the market in the second phase and then disappears, as shown in the figure 12. Equally, the DCE market barely indicates the impact on the CBOT market.

Figure 12: OIRF for stage two



4.4. Cointegration testing

From the previous unit root testing, we have concluded that the return variables are stationary while the price variables are not. To find whither there is a long-run equilibrium relationship between the price variables containing a unit root, and to identify the impact of trade war on the cointegration relationship if any, we now conduct the cointegration tests with the Johansen methodology for both the stages.

Johansen methodology is based on the Vector Error-correction Model (VECM). To conduct the Johansen test, we should select an appropriate lag length for the underlying VAR model of the VECM form. We use Stata to calculate various information criteria with up to six lags. According to the selection-order criteria, the indicators, including FPE, AIC and HQIC, select the lag length 2 for the first stage. The indicators, including LR, FPE, AIC and HQIC, select the lag length 2 for the second stage. Therefore, the VECM model has the form as VECM (1) for both stages.

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \mu_t$$

$$where, \quad y_t = \begin{pmatrix} cbot_t \\ dce_t \end{pmatrix}, \; u_t = \begin{pmatrix} u_{1,t} \\ u_{2,t} \end{pmatrix} \sim \text{VWN}$$

The test for the cointegration between the variables is calculated by observing the rank r of the $\prod$ matrix via its eigenvalues λ. The rank of a matrix is equal to the number of its characteristic roots (eigenvalues) which are different from zero. A cointegration system of n variables has the maximum value of its ranks at n-1. The number of the cointegration relationships equals to the value of rank r. When the rank of a system that consists of the unit root series is zero, it is indicated that the system is not a cointegrated one.

The trace test statistics for cointegration are formulated as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} \ln(1 - \hat{\lambda}_i)$$

where λ_i is the estimated value for the ith ordered eigenvalue from the $\prod$ matrix. The testing sequence under the null is r = 0, 1, … …, g-1, and thus the hypotheses for $\lambda_{trace}(r)$ are:

$$H_0: r = 0 \quad vs \quad H_1: 0 < r \leq g$$

$$H_0: r = 1 \quad vs \quad H_1: 1 < r \leq g$$

$$H_0: r = 2 \quad vs \quad H_1: 2 < r \leq g$$

$$\dots \dots$$

$$H_0: r = g - 1 \quad vs \quad H_1: r = g$$

Where g is the maximum value of the possible ranks.

To conduct the Johansen test, an appropriate lag length should be selected for the underlying VAR model of the VECM form. Stata is used to calculate various information criteria up to six lags. According to the selection-order criteria, the indicators, including FPE, AIC and HQIC, can select the lag length 2 for the first stage. The indicators, including LR, FPE, AIC and HQIC, can select the lag length 2 for the second stage. Therefore, The VECM model has the form as VECM (1) for both stages.

Then, we calculate the eigenvalues/characteristic roots of the matrix in a VECM (1), and conduct the trace tests in Stata. From the results, $\lambda_{trace}(0)$ is 22.60 for the first stage, which is greater than 19.96, the 5% critical value. Thus, it is able to reject the null of $r = 0$, and accept the alternative hypothesis of $0 < r \leq 1$. In addition, $\lambda_{trace}(1)$ is 2.68, which is less than 9.42, the 5% critical value. Accordingly, we fail to reject the null of $r = 1$. Besides, there is also one cointegration relationship for the price of soybean meal futures on the two markets before the trade war.

For the second stage, $\lambda_{trace}(0)$ is 6.54, which is less than 19.96, the 5% critical value.Thus, we fail to reject the null of $r = 0$. Besides, there is no cointegration relationship for the price of soybean meal futures on the two markets after the trade war.

4.5. Modeling volatility

After analyzing the mean spillover effect between the DCE and CBOT soybean meal futures markets and the change of the relationships before and after the trade war, the spillover effect and the impact of the trade war are analysed from the perspective of volatility.

4.5.1. GARCH Models

Before analyzing the volatility correlation between the two markets for both the stages, we firstly model the volatility characteristics of the return series of the soybean meal futures at DCE and CBOT markets during the two stages, respectively.

In the conventional econometric models, it is assumed that the variance of the disturbance term is constant, which is referred as the homoskedasticity assumption. However, many economic time series show the volatility clustering, in which case it is inappropriate to assume the variance is constant. Therefore, it is necessary to model the volatility, which is measured by the standard deviation or variance of returns. The basic idea behind volatility study lies in that the studied series is either serially uncorrelated or with minor lower order serial correlations, but a dependent series. To put the volatility models in a proper perspective, it is informative to not only consider the conditional variance of the series but also reveal the variance evolution. Therefore, the modeling of the conditional heteroscedasticity amounts to augmenting a dynamic equation, which can govern the time evolution of the conditional variance.

To model the series volatility, we use the univariate Generalized Autoregressive Conditional Heteroskedasticity Model (GARCH model). GARCH model, which is proposed by Bollerslev (1986), is the generalized form of the Autoregressive Conditional Heteroskedasticity Model (ARCH model). Both ARCH and GARCH models are classified to be a type of the conditional heteroscedastic models, which govern the evolution of the variance with an exact function. The ARCH model takes available information as a condition and uses an autoregressive form to characterize variance variation. For a time series, there are different corresponding conditional variances due to the different available information at various times. The ARCH model can be used to characterize conditional variance evolution over time. Compared with ARCH, the generalized form allows us to capture the persistence of conditional volatility parsimoniously. Here, the GARCH model is used to continue with the empirical research in this paper.

Taking into account the trade-off between the introduction of parameters and the estimation accuracy, the GARCH (1,1) model is selected for the empirical specification. In fact, the GARCH (1, 1) models the volatility greatly for most practical purposes.

For GARCH (1, 1):

$$\sigma_t^2 = w + \alpha\mu_{t-1}^2 + \beta\sigma_{t-1}^2$$

We estimate the univariable GARCH models for soybean meal futures return in DCE and CBOT within the two stages. We use Function AUTO.ARIMA in the RUGARCH package in R program in order to identify the most suitable mean model for the four groups of data with AICs. After that, the ARCH effect is examined with the model residuals. From Table 9, it is able to reject the null of no ARCH effect.

Table 9: Best models by AICs

Data	**model**	**P value of ARCH effect**
dldce in stage 1	ARMA (0,1)	0.000000
dlcbot in stage 1	ARMA (2,2)	0.000000
dldce in stage 2	ARMA (0,1)	0.000000
dlcbot in stage 2	ARMA (0,0)	0.000000

The results of the GARCH estimations are as follows:

Table 10: Estimation for GARCH (1,1) model of DCE in stage 1

Parameters	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
μ	- 0.000774	0.000416	-1.8594	0.062974
α_1	0.027243	0.002408	11.3149	0.00000
β_1	0.943979	0.004544	207.7240	0.00000

According to Table 10, the variance model of DCE soybean meal futures return can be described as

$$\sigma_t^2 = -0.000774 + 0.027243\mu_{t-1}^2 + 0.943979\sigma_{t-1}^2$$

P values of alpha1 and beta1 are smaller than 0.05, which means both the ARCH effect and the GARCH effect are significant. The ARCH effect of the equation is 0. 027243 and the GARCH effect is 0. 943979. This means the volatility of DCE soybean meal futures return is affected by both exogenous shock and previous volatility. Besides, the effect of previous volatility is the main source of volatility. The sum of alpha and beta is 0. 971222, which is smaller than 1, indicating that the equation satisfies the stationarity requirements.

Table 11: Estimation for GARCH (1,1) model of DCE in stage 2

Parameter	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
μ	0.000172	0.000584	-0.66269	0.768238
α_1	0.000154	0.000641	4.84012	0.810001
β_1	0.996346	0.000232	4286.71346	0.000000

According to table 11, the variance model of DCE soybean meal futures return can be described as

$$\sigma_t^2 = -0.000172 + 0.000154\mu_{t-1}^2 + 0.996346\sigma_{t-1}^2$$

P value of alpha1 become higher than 0.1 in stage2, which means the effect of exogenous shock becomes not so significant after the breaking out of the US-China trade war. The P value of beta1 is still smaller than 0.05, indicating that the GARCH effect is significant. The sum of alpha and beta is less than 1, which suggests that the equation satisfies the stationarity requirements.

Table 12: Estimation for GARCH (1,1) model of CBOT in stage1

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
μ	-0.001022	0.000404	-2.5289	0.011441
α_1	0.156905	0.024637	6.3686	0.000000
β_1	0.842095	0.031654	26.6029	0.000000

According to Table 12, the variance model of CBOT soybean meal futures return can be described as

$$\sigma_t^2 = -0.001022 + 0.156905\mu_{t-1}^2 + 0.842095\sigma_{t-1}^2$$

P values of other parameters are much smaller than 0.05, which means that all of them are significant. The ARCH effect of the equation is 0. 156905 and the GARCH effect is 0. 842095. This means the volatility of DCE soybean meal futures return is affected by both exogenous shock and previous volatility. In addition, the effect of previous volatility is the main source of volatility. The sum of alpha and beta is 0.999000, which is smaller than 1, indicating that the equation satisfies the stationarity requirements.

Table 13: Estimation for GARCH (1,1) model of CBOT in stage2

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
μ	0.000109	0.000498	0.2183	0.8272
α_1	0.027081	0.003376	8.0221	0.000000
β_1	0.933870	0.007881	118.4908	0.000000

According to Table 13, the variance model of CBOT soybean meal futures return can be described as

$$\sigma_t^2 = -0.000109 + 0.027081\mu_{t-1}^2 + 0.933870\sigma_{t-1}^2$$

P values of alpha1 and beta1 are smaller than 0.05, which means both the ARCH effect and the GARCH effect are significant. The ARCH effect equals to 0. 027081 and the GARCH effect is 0.933870. This means that the effect of previous volatility is still the main source of volatility and has been playing a bigger role since the breaking of the trade war. The sum of alpha and beta is 0. 960951, smaller than 1, indicating that the equation satisfies the stationarity requirements.

Table 14: ARCH LM Test result

Model	Lag	Statistic	P-Value
DCE stage 1	ARCH Lag [3]	0.7081	0.4001
	ARCH Lag [5]	2.5676	0.3589
	ARCH Lag [7]	3.4696	0.4295
CBOT stage 1	ARCH Lag [3]	2.770	0.09604
	ARCH Lag [5]	3.202	0.26175
	ARCH Lag [7]	4.670	0.26009
DCE stage 2	ARCH Lag [3]	0.0079	0.9288
	ARCH Lag [5]	2.2639	0.4158
	ARCH Lag [7]	3.5211	0.4209
CBOT stage 1	ARCH Lag [3]	0.2364	0.6268
	ARCH Lag [5]	0.3941	0.9143
	ARCH Lag [7]	0.6129	0.9671

Table 14 is the result of the ARCH LM method, which examines the ARCH effect of the residual of GARCH model. According to Table 14, all the corresponding P values are much higher than 0.05. This means the hypothesis that “the residuals of the GARCH models have no ARCH effect” can be accepted.

4.5.2. Diagonal-BEKK model

Next, we apply the multivariate GARCH model to capture the relationships, so as to understand the correlation of volatility between the different markets. We also use the Diagonal-BEKK model to conduct the empirical analysis. The Diagonal-BEKK model sets the parameter matrix to be diagonal, which has an advantage of simplifying the estimation. To find out the changes of the volatility correlation between the CBOT and DCE markets, the Diagonal-BEKK models are established for the two stages respectively. The mean equations are the same as those identified in the univariable GARCH models. When the lag order in the multivariate GARCH models is 1, the model could show better fitting effects. Therefore, the Diagonal-BEKK (1,1) models is estimated with the following variance and covariance equation, obtaining the estimation results by EViews.

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon_{t-1}{}'A + B'H_{t-1}B$$

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix}, C = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}, A = \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix}, B = \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}$$

Where $h_{11,t}$ represents the variance of the CBOT return rate of the soybean meal futures at time t, and $h_{22,t}$ represents the variance of the DCE return rate of the soybean meal futures at time t, and $h_{12,t}$ (or $h_{21,t}$) represents the covariance of the return series on the two markets at time t.

The following are the estimation results of the two stages.

Table 15: Diagonal-BEKK (1,1) Estimation Results for Stage One

Parameters	Coefficient	Std. Error	z-Statistic	Prob.
C (1,1)	1.00E-05	3.95E-06	2.533505	0.0113
C (1,2)	3.38E-05	1.32E-05	2.561058	0.0104
C (2,2)	0.000187	2.96E-05	6.33081	0.0000
A (1,1)	0.252574	0.037378	6.757292	0.0000
A (2,2)	0.668133	0.083477	8.003841	0.0000
B (1,1)	0.968798	0.007496	129.2462	0.0000
B (2,2)	0.120836	0.107764	1.1213	0.2622

Table 16: Diagonal-BEKK (1,1) Estimation Results for Stage Two

Parameters	Coefficient	Std. Error	z-Statistic	Prob.
C (1,1)	2.48E-05	2.23E-05	1.115534	0.2646
C (1,2)	1.19E-05	1.26E-05	0.944298	0.3450
C (2,2)	0.000158	2.93E-05	5.380100	0.0000
A (1,1)	0.238175	0.094563	2.518679	0.0118
A (2,2)	0.645839	0.102651	6.291597	0.0000
B (1,1)	0.909853	0.071457	12.732860	0.0000
B (2,2)	0.069880	0.395979	0.176473	0.8599

For stage one, the table 15 shows that all the parameters are significant at 5% significance level, only except the parameter b_{22} in the B matrix as defined. For stage two, the table 16 shows that b_{11}, c_{22} and the two parameters in matrix A are all significant at 5% significance level.

Next, it is able to derive the dynamic correlation coefficients by the variance and covariance equations, and the equation is as below:

$$Corr(1,2)_t = h_{12,t} / \left(\sqrt{h_{11,t}}\sqrt{h_{22,t}}\right)$$

Figure 13: Conditional correlation in stage one

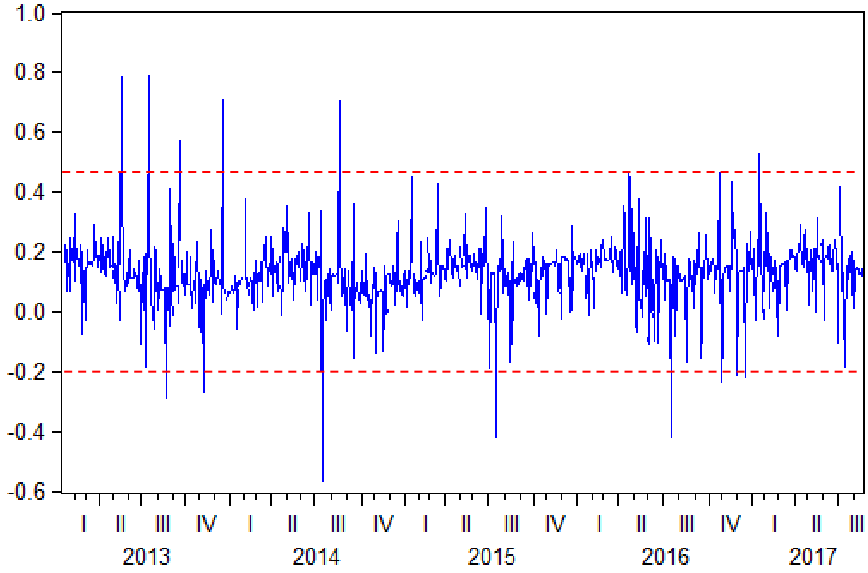


Figure 14: Conditional correlation in stage two

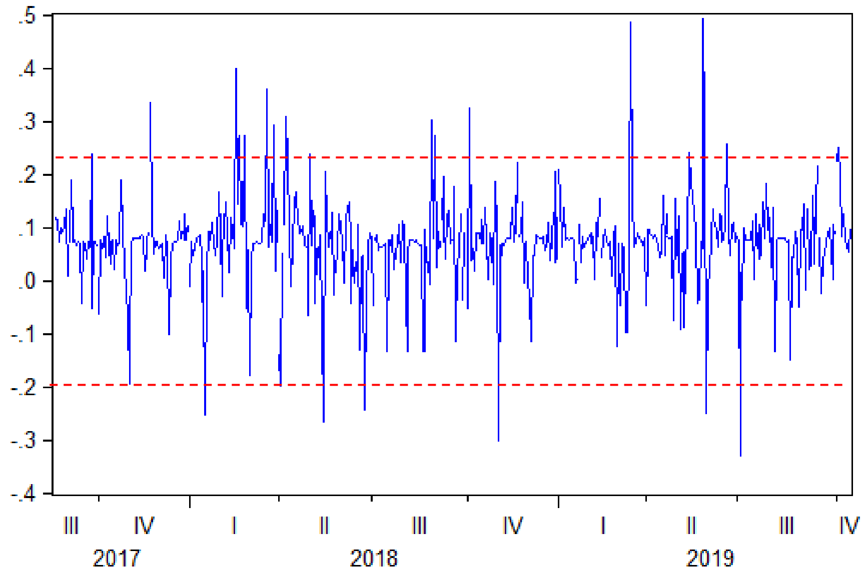
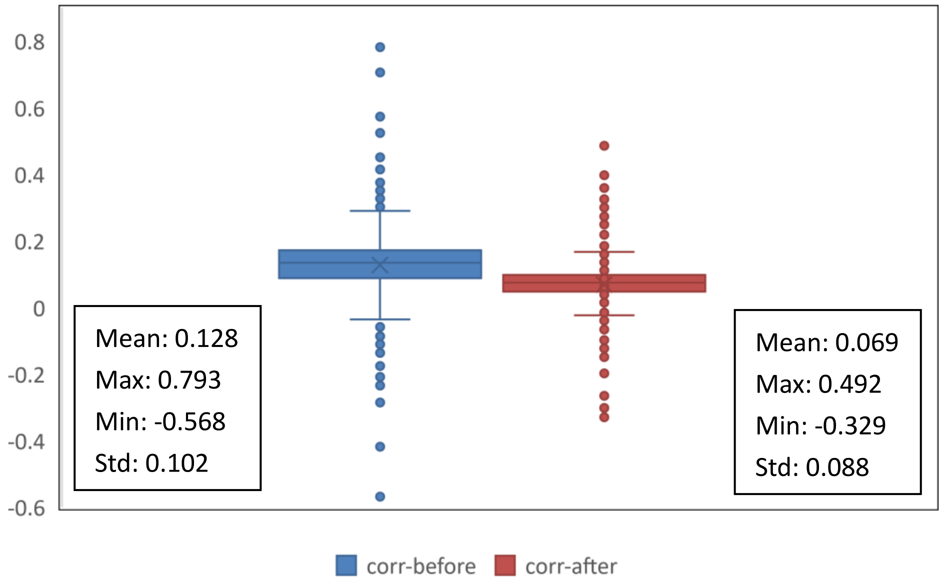


Figure 13 and figure 14 show the evolution of conditional correlation over time between the return rate of soybean meal futures on the CBOT market and on the DCE market in stage one and stage two, respectively. From the figures, we could see that the values of dynamic correlation in stage one fluctuates around 0.2, while the values of dynamic correlation in stage two fluctuate around 0.1. After the trade war, the fluctuation interval is narrowed. To further illustrate the impact of the trade war, we look at the summary statistics and the boxplot in figure 15. It indicates that the mean value of the correlation decreases from 0.128 to 0.069 after the trade war, and the standard deviation declines from 0.102 to 0.088. Generally speaking, the volatility correlation is weakened after the trade war.

Figure 15: Basic statistics for conditional correlation in both stages



5. Conclusions

In this thesis, three empirical models are built up, including VAR, cointegration and Diagonal-BEKK, to identify the impact of US-China trade war on the soybean meal trade. Based on those results, we believe the soybean meal trade between the US and China starts to uncouple after the breaking of the trade war, both in the mean level and in the volatility level.

Firstly, in terms of the mean of soybean meal futures return in CBOT and DCE, we find that the CBOT return has a direct impact on DCE return while the DCE return is not affecting the CBOT return. This makes sense because the CBOT soybean meal futures is basically the center of global trading and DCE is only the center of a local market. It is shown by the result of impulse responds that the CBOT impact decreased after the trade war.

Also, we find that there was a cointegration between the return of CBOT and DCE soybean meal futures before the trade war, which disappears after the breaking of the trade war. It is indicated that the equilibrium relationship of the soybean meal futures return in these two markets also breaks down because of the trade war.

Lastly, we find that the correlation between two volatilities is weakened after the trade war after building up the models for the conditional heteroskedasticity. We interpret that to the change of risk transmission mechanism because of the trade war.

Under the background of US-China conflict, some people predict that the trade war would upgrade from tariff punishment to economic decouple. From our research, it can be clearly seen that the soybean meal is decoupling in terms of the spillover effects. Since soybean is the most important component in and takes one-fourth of the US-China agriculture product trading, it is thought that our findings will be an alarming signal for the decoupling of US-China trade on agriculture. In addition, the decoupling will be a big challenge for not only the US and China government but also the globalization process.

6. Suggestions for future research

The US-China trade conflict has great influences on every aspect of US-China trade, and the influence itself is also a brand-new area to study. Among those influences, the price transmission and risk spillover effect are only a small part. Besides, further researches could be conducted in this area.

In the data aspect, data from the beginning of 2012 to the end of October 2019 is selected. Since the trade conflict is still in the process, we suggest researchers to include data after October 2019 in order to comprehensively evaluate the influence of the event. Also, the futures return of soybean meal is also traced with the daily data. If possible, further researcher could use minute-level price to better describe the volatility and risk of soybean meal return.

In the model aspect, Diagonal-BEKK model is used to describe the conditional heteroskedasticity. In further study, researchers can try other models like DCC-GARCH, so as to identify that whether different models tell a same story or not.

Also, soybean is only one part of the agriculture trading. Thus, the researchers can also conduct studies on other important agriculture products in order to reveal the full picture of US-China agriculture trading.

Finally, it will be an interesting topic to study on what kind of impact this decoupling will make to the global economy and what can we do to prevent the damage caused by the anti-globalization course.

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