The Effect of China-U.S. Trade Dispute and Tariffs on Soybean-Related Futures Markets

by

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An honors thesis submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Science

Business Honors Program

NYU Shanghai

May 2019

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Abstract

The 2018 trade dispute between China and the United States is one of the ongoing concerns in the world economy. During the dispute, the Chinese government has announced retaliatory tariffs targeting the U.S. agricultural products, including soybeans, in which China is one of the largest importers in the world.

In past studies, researchers have reported linkages between soybean-related futures markets in China and the United States. The main research question here is to test the linkage between these markets, in particular, to find out whether the linkage has diminished after the announcement of tariffs. Since the announcement of tariffs, China imports much fewer soybeans from the United States. This should potentially diminish the existing strong linkage between the two countries' soybean-related futures markets.

This thesis first uses statistical analysis to find out whether the market linkage among soybean-related futures markets has diminished. The model used is the log return (price) transmission model. Changes in significance and magnitude of cross-market coefficients in the model are used to identify the changes in the market linkage, by comparing the results before and after the announcement of tariffs. This thesis compares markets in China and the U.S., the log return (price) transmission model is adjusted to consider this fact. The results of statistical tests show the market linkage between two countries' soybean-related futures markets, have indeed declined. The results also show that the diminishing effect is more notable for soybean-related futures which depends more on imported soybeans.

This thesis also uses a machine learning approach to fit a return prediction model on Chinese Soybean Meal futures using the cross-market information. The results of the test indicate that when market linkage declines, the previous well-specified model will not perform accurately after the announcement of tariffs. This result implies the entities which use cross-market information to predict Soybean-related futures price need to adjust their model to account for the changes in these markets.

Acknowledgement

I would like to express my sincere thanks to Professor Menachem Brenner for his guidance of my thesis throughout the year, from the beginning of May 2018 to the end of Spring 2019 semester. Professor Brenner has given me valuable advice on choosing topics, collecting data, drafting hypotheses, performing tests, as well as many other fields regarding this research. During Summer 2018, Professor Brenner also helped me reaching out to researchers in the Volatility Institute at NYU Shanghai (VINS), who supported me in the preliminary research. In the meantime, I would also like to thank Dr. Xin Zhou, Mr. Jason Zhao, and Mr. Ruitao Wang from VINS for their help.

I would like to sincerely thank faculty advisers, Professor Marti G. Subrahmanyam, Professor Yiqing Lu, and Professor Shuang Zhang, of the Honors Program. They have coordinated the program and held individual appointments throughout the year in supporting the research.

Also, I would like to thank all professors who have attended the Honors Seminars to give their inspiring insights from different fields. I want to thank teaching associate Ms. Xinyi Yang for her supports of the seminars during the year.

Last but not least, I would like to thank my family and friends for their help, encouragements, and supports during my undergraduate studies.

I. Introduction

China and the United States are two major economic powers on the world stage nowadays, and trade has been an important topic related to the relationship of two countries ever since the People's Republic of China and the United States established formal diplomatic ties in 1979. Nevertheless, the trade relationship between China and the U.S. are not always smooth, for example, two countries were on the brink of a trade war in 1996 (Boxwell, 2018), but China and the U.S. reached an agreement before the tension escalated.

However, after 22 years, another trade dispute between China and the U.S. eventually leveled up to a trade war with far-reaching influence for both countries as well as the world. The current trade dispute, or trade war, between China and the U.S. was started in January 2018, when President Trump's administration imposed a tariff on solar panels (Eckhouse, 2018), of which China was one of the largest exporters. Even though global markets urged two countries to reach an agreement and cool down the hostility, tensions mounted while President Trump announced new tariffs on Chinese products (Diamond, 2018). As a response, the Chinese government announced retaliatory tariffs targeting various products imported from the U.S., including agricultural products like soybean (Meredith, 2018).

China is one of the most considerable importers of soybeans among the world; its imported volume of soybean reached 100 million tons in 2017-2018 (Thukral, 2018). However, since the trade dispute started in 2018, soybean has been the product that still bears the brunt of China's retaliatory tariffs. In the futures markets, certain soybean-related futures traded in China – for example, Soybean Meal futures – are one of the world's most actively traded commodity futures. Therefore, it is an important topic to further research the impact on Chinese soybean-related futures market under the current trade dispute.

Most soybean-related futures in China are traded in Dalian Commodity Exchange (DCE), which includes two soybean-related futures this thesis focuses on – the Soybean No.1 and Soybean Meal futures. Soybean No.1 futures in DCE are restricted to the soybeans that are not considered as Genetically Modified Organism (GMO), which are mainly designed for Chinese domestic soybeans, while most imported soybeans in China are GMO. However, due to the effect of the U.S. market as a global price settler of soybeans (B. J. Liu, Y. Wang, J. Wang, Wu, and Zhang, 2015), even though Soybean No.1 futures are designed for Non-Genetically Modified (Non-GM) soybeans, the futures' prices are still influenced by the prices of Soybean futures in the United States. Soybean Meal futures are also traded in DCE, in which soybean meals are the crushed products extracted from soybeans. In China, soybean meals could be crushed with imported or GM soybeans. This thesis also focuses on the soybean futures traded in the Chicago Board of Trade (CBOT) in the United States. Detailed information on three futures that will be investigated in this thesis is shown in Table 1.

	DCE Soybean No.1	DCE Soybean Meal	CBOT Soybean
Trading Exchange	Dalian Commodity Exchange, China	Dalian Commodity Exchange, China	Chicago Board of Trade, United States
Trading Hours	Monday – Friday, 9:00 – 11:30 a.m., 1:30 – 3:00 p.m., Beijing Time	Monday – Friday, 9:00 – 11:30 a.m., 1:30 – 3:00 p.m., Beijing Time	Sunday – Friday, 7:00 p.m. – 7:45 a.m. and Monday – Friday, 8:30 a.m. – 1:20 p.m. CT
Contract Months	Jan, Mar, May, Jul, Sep, Nov	Jan, Mar, May, Jul, Aug, Sep, Nov, Dec	Jan, Mar, May, Jul, Aug, Sep, Nov
Trading Unit	10 MT/Lot	10 MT/Lot	5,000 bushels (136 MT)
Last Trading Day	The 10th trading day of the contract month	The 10th trading day of the contract month	The business day prior to the 15th calendar day of the contract month
Last Delivery Day	The 3rd trading day after the last trading day	The 3rd trading day after the last trading day	The 2nd business day after the last trading day

Table 1: Information on Three Soybean-related Futures Contracts[1].

[1] Source: "Contract Specification" pages from DCE (No.1 Soybean, n.d.; Soybean Meal, n.d.) and CBOT (Soybean Futures Contract Specs, n.d.) websites.

In the past studies, many researchers have discovered the existence of a market linkage between China and U.S. soybean-related futures markets. An example of the market linkage is the return of one market is influenced by the return information of another market certain time ago. However, the outbreak of trade dispute and the announcement of tariffs significantly reduced and interrupted the soybean trading between China and the United States, the trade restrictions on soybean product can probably have a negative impact on the existing linkage on soybean-related futures market between two countries. This thesis hypothesizes that after the trade dispute, and specifically, after China's announcement of retaliatory tariffs, the current market linkage of soybean-related futures market between China and the U.S. have been negatively affected and diminished. This effect will be tested by a log return (price) transmission model, which will be introduced in Section III. Besides the analysis on the statistical model, Section V of this thesis includes a case study on creating a prediction model using a machine learning algorithm. The analysis of the scenario will illustrate how the tariffs and diminishing in market linkage will impact the well-established return prediction models.

II. Literature Review

The market linkage is an important topic for this thesis as well as in the studies on the relationship between China and the U.S. markets. In the past studies, many researchers have focused on the market linkage between Chinese commodity futures markets and their foreign counterparts. In the research conducted by Fung, Leung, and Xu (2003), they use price transmission model and volatility spillover model to examine the information flows for copper, soybeans and wheat commodity futures traded in both Chinese and the U.S. markets. Their study demonstrates the U.S. market has a substantial impact on Chinese copper and soybean futures' price, but in the same time, no significant pricing interaction for wheat futures has been found.

Hua and Chen (2007) have studied such relation between China and the world's markets via various tests, include Johansen's cointegration test, error correction model, the Granger causality test, etc. Similar to Fung et al. (2003)'s findings, the testing results of the study of Hua and Chen (2007) also suggests that the prices of Chinese commodity futures are in cointegration with their world's counterpart, except for wheat futures, in which the Chinese government imposes restrictions on wheat price. Another research conducted by Q. Liu and An (2011) also concludes that overall the U.S. futures markets demonstrate information transmission on Chinese futures markets in the short run.

While most researchers have conducted research on testing multiple commodity futures, B. J. Liu et al. (2015) show the through time, the spillover effect of the U.S. market to Chinese DCE Soybean futures (Soybean No.1 futures) have decreased after the subprime mortgage crisis in the U.S. They also conclude that the pricing independency of DCE Soybean futures has increased.

Although many researchers have discovered and investigated in the market linkage of the soybean-related futures market between China and the United States, most of these studies are conducted before President Trump won the presidential election and at the time when the large-scale trade dispute between two countries had not started. Therefore, few of the past studies have mentioned the potential effect of the trade dispute and tariffs on the market linkage between the futures markets in two countries. Thus, it is meaningful to further examine the effect of trade dispute and tariffs. In addition, most research in the past focus only on Soybean No.1 futures traded in DCE, and few have conducted detailed studies on the linkage between Soybean Meal futures in DCE and Soybean futures in CBOT. However, the nature of soybean meal in China, which most of them are crushed from imported soybeans, indicates the DCE Soybean Meal futures probably also have excellent market linkage to the CBOT Soybean futures, and such linkage is potentially influenced by the trade tariffs imposed on imported soybeans.

III. Methodology and Data

1. Methodology

The statistical model used in this thesis is the log return (price) transmission model, which is similar to the price transmission model introduced in the study conducted by Fung et al. (2003). The model is described as equation (1) and equation (2) as shown below:

$$R_{DCE,t} = \beta_0 + \sum_{m=1}^{Dlag} \beta_{1,m} \cdot R_{DCE,t-m} + \sum_{n=1}^{Clag} \beta_{2,n} \cdot R_{CBOT,t-n} + \gamma \cdot HOL_t + \theta \cdot WKND_t + \epsilon_{DCE,t} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1)$$

$$R_{CBOT,t} = \beta_0 + \sum_{m=1}^{Clag} \beta_{1,m} \cdot R_{CBOT,t-m} + \sum_{n=1}^{Dlag} \beta_{2,n} \cdot R_{DCE,t-n+1} + \gamma \cdot HOL_t + \theta \cdot WKND_t + \epsilon_{CBOT,t} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (2)$$

R in the equation (1) and (2) is the log return of the futures on a specific day, in which the log return is calculated by:

$$R_{\mathrm{t}} = \ln\left(\frac{P_t}{P_{t-1}}\right) \ldots \ldots \ldots (3)$$

The P_t in equation (3) is the settlement price of a specific futures contract on day t, and $P_{t-1}$is the settlement price of that futures on the previous trading day.

In equation (1) and (2), β_0 is the constant term of the model. m (or n) in the β indicates the lag, i.e., the information on m (or n) trading days before; and $Dlag$ (or $Clag$) is the maximum number of lags used in the test for the futures from DCE (or CBOT). β_1 indicates the own market transmission, that is, to test whether the one futures' log return information on previous days is associated with its log return on day t. β_2 indicates the cross-market transmission, and it is used to test whether the log return information of the foreign market on previous trading days is associated with the target market. In equation (2), $R_{DCE,t-n+1}$ is used instead of $R_{DCE,t-n}$ because of the time zone difference between China and the United States. For the U.S. market, on day t (Central Time Zone), the previous trading day in China is day t (Beijing Time) instead of day t-1, therefore, "+1" is added in the lag after considering the time zone difference.

HOL and $WKND$ in equation (1) and (2) are two dummy variables indicating whether the previous day of day t is a holiday day or weekend day, in which 1 means "yes" and 0 means "no." Therefore, γ and θ signal the potential holiday and weekend effect on the log return of a specific futures contract.

To test the market linkage between DCE Soybean-related futures and CBOT Soybean futures, the major coefficient researchers may be interested in is the cross-market transmission indicator, that is, the β_2 term in equation (1) and (2). If consider a one-day lag only, check whether the null hypothesis $H_0: \beta_{2,1} = 0$ is rejected in the statistical testing is needed. If the null hypothesis is rejected, it indicates the previous day's log return information from the cross-market is significantly associated with the log return information R_t on day t in the own market. Therefore, there exists a significant log return (price) transmission from the cross-market log return. Also, similar testing could be conducted with a lag larger than one day, which signals whether stronger market linkage between two markets exists.

The log return (price) transmission model as shown in equation (1) and (2) will be used in testing the market linkage between Chinese Soybean Meal futures and the U.S. Soybean futures, as well as the linkage between Chinese Soybean (Soybean No.1) futures and the U.S. Soybean futures. For each market pair, the market linkage or the log return transmission will be tested separately for the data before and after China's announcement of retaliatory tariffs on soybeans.

2. Data

Data used in this thesis are collected from the Wind terminal, which is a Bloomberg-like financial terminal in China that includes a large amount of Chinese financial data. Data for DCE Soybean Meal, DCE Soybean No.1, and CBOT Soybean have been collected; the specific time range used for tests in this thesis is from January 1, 2012, to December 14, 2018. For specific futures (DCE Soybean No.1, DCE Soybean Meal, and CBOT Soybean), daily data for each month's contract are collected. Attributes of the collected dataset include open, high, low, close, and settlement prices; as well as trading volume and open interest of specific contract. For specific futures, a continuous contract is created by splicing contracts which have the highest open interest (or the "leading" contract) for each day.

The day when the leading contract changes from one month to another month is called the "contract changing day." When calculating the log return data with equation (3), the contract changing days are omitted from the calculation. Because on the contract changing days, $R_{\mathrm{t}} = \ln\left(\frac{P_t}{P_{t-1}}\right)$ is comparing one contract with another (P_{t-1} is the settlement price for the last leading contract), which is meaningless and will create abnormal log returns on these days. Therefore, the contract changing days are omitted from the calculation. Figure 1 as shown below illustrates the procedure of creating continuous contract datasets, with the raw data gathered from the Wind terminal.

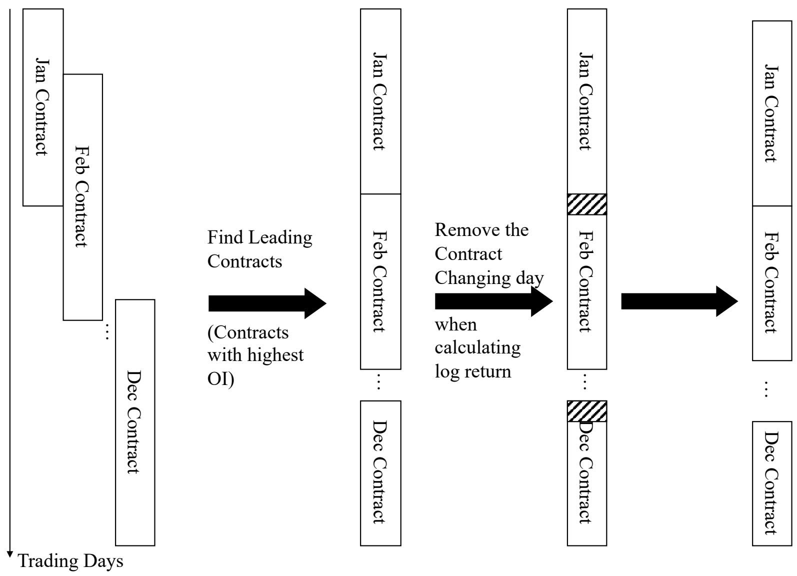

Figure 1: Procedure for creating continuous contracts

Also, additional information regarding the holidays and weekend days needs to be added to the dataset before calculating the log returns, in which the dummy variables will be used in equation (1) and (2). For each record in the datasets, if that day is a Monday, the "*WKND*" field will be written as 1, which indicates the previous day is a weekend day; otherwise, 0 is written.

If a piece of record has $WKND = 1$, then the previous trading day (or the previous record) should be 3 days ago. However, if the previous trading day of day t is more than 3 days ago, day t is considered as the day after "holiday," and record the corresponding "*HOL*" field as 1. Similarly, if a piece of record has $WKND = 0$, the previous trading day should be one day ago, if not, then write "*HOL*" as 1. The detailed procedure for determining the holiday variable please refer to Figure 2. When conducting the statistical tests, datasets from different markets will be joined on the trading dates, and needed attributes (i.e., log returns, holiday and weekend dummy variables, etc.) will be selected.

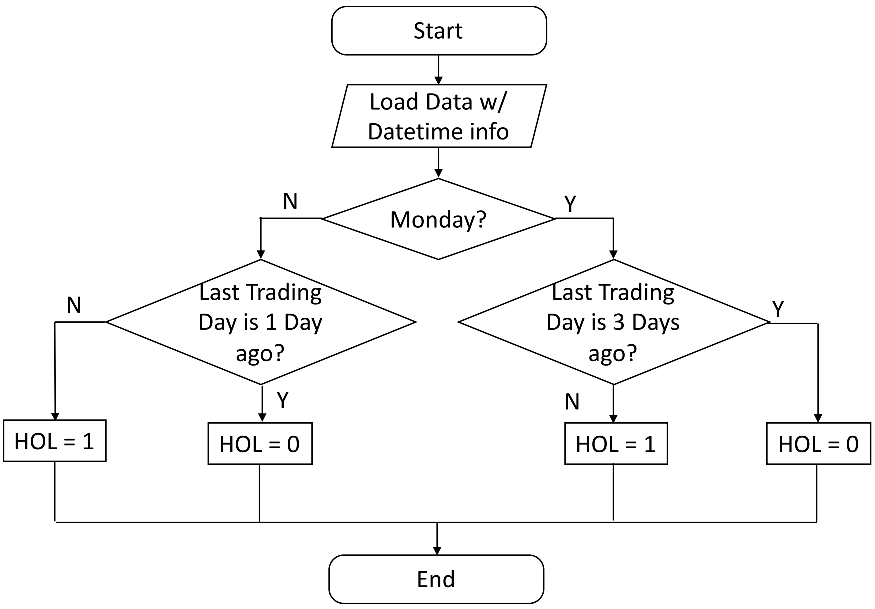

Figure 2: Procedure for determining dummy variable *HOL*

3. Summary Statistics

Table 2 and Table 3 show the descriptive statistics for DCE Soybean No.1, DCE Soybean Meal, and CBOT Soybean futures from Jan 1, 2012, to Dec 14, 2018. Since the contract changing days are omitted from the datasets, even if futures are traded in one commodity exchange, the number of records could be different.

	DCE Soybean No.1	DCE Soybean Meal	CBOT Soybean
count	1605	1592	1634
mean	4159.646	3043.434	1121.171
std	425.5759	383.1399	226.0569
skew	-0.0225	0.55194	0.7699
kurt	-1.2616	0.26034	-0.6186
min	3139	2296	814
25%	3776	2775	954.8125
50%	4216	2973	1025
75%	4513	3283	1316.438
max	5035	4346	1768.2

Table 2: Descriptive statistics on settlement price

	DCE Soybean No.1	DCE Soybean Meal	CBOT Soybean
count	1605	1592	1634
mean	-0.00027	0.000478	-0.000052
std	0.007732	0.009975	0.012682
skew	0.23449	0.33123	-0.111438
kurt	3.182	2.07893	2.130688
min	-0.0348	-0.03727	-0.065397
25%	-0.00433	-0.00522	-0.007221
50%	0	0.000132	0
75%	0.0036	0.006014	0.007222
max	0.037643	0.056768	0.056776

Table 3: Descriptive statistics on log return

		DCE Soybean No.1	DCE Soybean Meal	CBOT Soybean
		t		
t	DCE Soybean No.1	1	0.59258	--
	DCE Soybean Meal	0.59258	1	--
	CBOT Soybean	0.19346	0.24103	1
		t-1		
t	DCE Soybean No.1	0.16703	0.01276	0.37716
	DCE Soybean Meal	0.11211	0.16667	0.6386
	CBOT Soybean	-0.0439	-0.0225	-0.0233
		t-2		
t	DCE Soybean No.1	-0.0485	-0.0199	-0.0297
	DCE Soybean Meal	-0.0148	0.00432	0.05561
	CBOT Soybean	-0.0016	-0.015	-0.0267

Table 4: Correlation between different soybean-related contracts before Apr 4, 2018

		DCE Soybean No.1	DCE Soybean Meal	CBOT Soybean
		t		
t	DCE Soybean No.1	1	0.76959	--
	DCE Soybean Meal	0.76959	1	--
	CBOT Soybean	-0.1728	-0.1211	1
		t-1		
t	DCE Soybean No.1	0.21992	0.14434	0.1941
	DCE Soybean Meal	0.23195	0.23175	0.179
	CBOT Soybean	0.01153	-0.0237	-0.0802
		t-2		
t	DCE Soybean No.1	-0.12	-0.1441	-0.0424
	DCE Soybean Meal	-0.0906	-0.1154	-0.0728
	CBOT Soybean	-0.0807	0.0556	0.06359

Table 5: Correlation between different soybean-related contracts after Apr 4, 2018

Table 4 and Table 5 show the cross-market correlation on the log return before and after China's announcement of tariffs on soybeans (before and after Apr 4, 2018). The correlations are conducted between day t to day t, day t-1, and day t-2.

Overall, the cross-market correlation coefficients declined after the announcement of tariffs. For example, the log-return correlation between DCE Soybean Meal's Day t with CBOT Soybean's Day t-1 declined from 0.64 to 0.18; and such correlation between DCE Soybean No.1's day t with CBOT Soybean's Day t-1 declined from 0.38 to 0.19. The decline in correlations shows a potential impact on the market linkage after the announcement of tariffs, which will be further tested in the following sections.

IV. Tests Using Return Transmission and Results

Based on the model as shown in equation (1) and (2), the log return transmission before and after the announcement of tariffs are tested separately. The result for log return transmission from CBOT Soybean (CBOT) to DCE Soybean Meal (DCE_M) is shown in Table 6[2].

DCE Soybean Meal <- CBOT Soybean				
Dep. Variable: DCE_M(t)				
	Before the Announcement		After the Announcement	
const	0.0003	(0.000)	-0.0009	(0.001)
DCE_M(t-1)	-0.0588	(0.029)	**0.3191****	(0.071)
DCE_M(t-2)	-0.0139	(0.022)	**-0.1681***	(0.067)
CBOT(t-1)	**0.5180****	(0.018)	**0.1534****	(0.056)
CBOT(t-2)	**0.0870****	(0.022)	-0.0669	(0.057)
HOL	**0.0039****	(0.001)	**0.0264****	(0.004)
WKND	-0.0001	(0.001)	-0.0011	(0.002)
	R-squared: 0.419		R-squared: 0.335	
	Adj. R-squared: 0.416		Adj. R-squared: 0.307	
** p<0.01	* p<0.05			

Table 6: Transmission from CBOT Soybean to DCE Soybean Meal

[2] For Table 6-9, standard error is shown in parentheses, rounded to 3 decimal places.

As shown in Table 6, before the announcement of tariffs, the coefficients for CBOT(t-1) and CBOT(t-2) terms are significant under a significance level of 1%, which indicates DCE Soybean Meal futures market received log return transmission from CBOT Soybean futures market for both one-day and two-day lags. After the announcement of tariffs, DCE_M(t-1) and DCE_M(t-2) become significant, this indicates that after the announcement of tariffs, DCE Soybean Meal futures market receives more log return information from its own market. The coefficient for CBOT(t-1) term declines from 0.52 to 0.15, and CBOT(t-2) becomes no longer significant, which indicates the cross-market transmission from the CBOT Soybean futures has been diminished. This result is in accord with the hypothesis.

Another set of tests is conducted for the log return transmission on the other way around, that is, the transmission from DCE Soybean Meal futures to CBOT Soybean futures.

CBOT Soybean <- DCE Soybean Meal				
Dep. Variable: CBOT(t)				
	Before the Announcement		After the Announcement	
const	-0.00001875	(0.000)	-0.0004	(0.001)
CBOT(t-1)	**-0.3139****	(0.036)	-0.0365	(0.086)
CBOT(t-2)	-0.0433	(0.035)	0.0846	(0.085)
DCE_M(t)	**0.5606****	(0.044)	-0.1293	(0.108)
DCE_M(t-1)	0.010	(0.045)	-0.0309	(0.109)
HOL	0.00004	(0.002)	-0.0031	(0.009)
WKND	0.00001	(0.001)	-0.0032	(0.003)
	R-squared: 0.116		R-squared: 0.033	
	Adj. R-squared: 0.111		Adj. R-squared: -0.008	
** p<0.01	* p<0.05			

Table 7: Transmission from DCE Soybean Meal to CBOT Soybean

Similarly, the log return transmission from DCE Soybean Meal futures to CBOT Soybean futures also diminished after the announcement of tariffs, which is no longer significant after the announcement. This shows the diminishing effect of cross-market transmission is bilateral.

Corresponding tests on the log return transmission between DCE Soybean No.1 (DCE_A) futures and CBOT soybean futures have also been conducted, and results are displayed in Table 8 and Table 9.

DCE Soybean No.1 <- CBOT Soybean				
Dep. Variable: DCE_A(t)				
	Before the Announcement		After the Announcement	
const	-0.0002	(0.000)	**-0.0017***	(0.001)
DCE_A(t-1)	**0.1121****	(0.028)	**0.3313****	(0.074)
DCE_A(t-2)	-0.0502	(0.026)	**-0.1801***	(0.070)
CBOT(t-1)	**0.2134****	(0.016)	**0.1485****	(0.047)
CBOT(t-2)	-0.0328	(0.017)	-0.0474	(0.048)
HOL	0.0009	(0.001)	**0.0116****	(0.004)
WKND	0.0004	(0.001)	0.0018	(0.001)
	R-squared: 0.156		R-squared: 0.233	
	Adj. R-squared: 0.152		Adj. R-squared: 0.202	
** p<0.01	* p<0.05			

Table 8: Transmission from CBOT Soybean to DCE Soybean No.1

As shown in Table 8, after the announcement of tariffs, DCE_A(t-2) becomes significant and the coefficient of DCE_A(t-1) increases, which indicates DCE Soybean No.1 futures receive more information from its own market, similar to the effect demonstrated in DCE Soybean Meal futures in the previous paragraphs. Also, the effect of cross-market transmission declines after the announcement, from 0.21 to 0.15.

CBOT Soybean <- DCE Soybean No.1				
Dep. Variable: CBOT(t)				
	Before the Announcement		After the Announcement	
const	-0.00002	(0.000)	-0.0006	(0.001)
CBOT(t-1)	**-0.0966****	(0.030)	-0.0075	(0.085)
CBOT(t-2)	0.0243	(0.029)	0.0593	(0.083)
DCE_A(t)	**0.4000****	(0.049)	-0.2639	(0.136)
DCE_A(t-1)	**-0.1158***	(0.049)	0.0574	(0.135)
HOL	0.0017	(0.002)	-0.0037	(0.009)
WKND	-0.0002	(0.001)	-0.0035	(0.003)
	R-squared: 0.052		R-squared: 0.048	
	Adj. R-squared: 0.048		Adj. R-squared: 0.010	
** p<0.01	* p<0.05			

Table 9: Transmission from DCE Soybean No.1 to CBOT Soybean

As shown in Table 9, the cross-market transmission from DCE Soybean No.1 futures to CBOT Soybean futures become no longer significant after the announcement of tariffs, for both one-day and two-day lags, under the significance level of 0.05. This result is similar to the result in the changes of log return transmission from DCE Soybean Meal futures to CBOT soybean futures.

All in all, the cross-market linkage between DCE and CBOT soybean-related futures diminished after China's announcement on retaliatory tariffs targeting the U.S. products, which is in accord with the hypothesis in Section I. Also, through the results, a difference has been discovered in market linkage diminishing between DCE Soybean Meal from CBOT and DCE Soybean No.1 from CBOT. For DCE Soybean Meal futures, the two-day lag transmission from CBOT is not significant after the announcement, and the one-day lag transmission decreases from 0.52 to 0.15; for DCE Soybean No.1 futures, the one-day lag transmission from CBOT decreases from 0.21 to 0.15. Comparing the magnitude, the decline in Soybean Meal is more notable than Soybean No.1. This could probably because DCE

Soybean No.1 futures are restricted for Non-GM soybeans, which are mostly domestic soybeans in China; but on the other hand, Soybean Meals in China are mainly extracted from the GM Soybeans, which are mostly imported soybeans. Therefore, DCE's Soybean Meal futures are more exposed to the effect of tariffs on soybean compare to DCE Soybean No.1 futures.

In addition, unlike many other financial derivative markets which the U.S. markets show dominant power over the Chinese markets. For soybean-related futures in the previous tests, in terms of return transmissions, there is no notable dominant market before the announcement of tariffs. This probably because before the announcement of tariffs, China was one of the largest buyers of the U.S. soybeans, which led to price transmissions from China to the United States. However, after the announcement of tariffs, the log return (price) transmission from China to the U.S. market becomes no longer significant under significance level of 5%, such transmission from the U.S. to China has diminished but still exists. This probably because the U.S. is still a global price settler in soybean products. Even if China imports much fewer soybeans from the U.S., the soybean-related futures markets in China are still affected by the U.S. market, although with less significant effects.

V. Case Study: Effect of Tariffs on Soybean Meal Futures Return Prediction Model

Ever since data science has become a popular discipline, many financial service or technology companies, as well as data analysts, have implemented machine learning models to make a more accurate prediction on the return of specific financial derivatives. Section IV of this thesis indicates that China's Soybean Meal futures have demonstrated an excellent linkage to CBOT Soybean futures historically. In this section, a well-specified model is proposed based on historical data before the current China – U.S. trade dispute, the method used is "Ridge Regression" (Hoerl and Kennard, 1970).

$$\underset{\boldsymbol{w}}{\operatorname{argmin}} \sum_{i=1}^{N} (y - \boldsymbol{w}^{\boldsymbol{T}} \boldsymbol{X})^2 + \alpha \|\boldsymbol{w}\|_2^2 \dots \dots \dots \dots \dots (4)$$

Function (4) shows the purpose of the model is to find a set of parameters $\boldsymbol{w}$ that minimizes the objective function of the Ridge Regression, and to make an optimal prediction based on the given data. In this case study, y is the log return of DCE Soybean Meal futures. $\boldsymbol{X}$'s non-constant variables include log returns of DCE Soybean Meal futures on day t-1, day t-2, log returns of CBOT Soybean futures on day t-1, day t-2, and dummy variables HOL, $WKND$. All of these variables are described in equation (1) from Section III. $\alpha\|\boldsymbol{w}\|_2^2$ is the regularization term in the Ridge Regression, which is used to prevent overfitting on the given dataset.

The dataset used in this section is the same dataset used to perform the test in Table 6. To evaluate the performance of the prediction model, the original dataset is separated into the training set (data used for fitting the model), and testing sets (data used for evaluating the model performance). The training set contains data from Jan 1, 2012, to Apr 3, 2017. There are two testing set, in which testing set 1 contains data from Apr 4, 2017, to Apr 3, 2018, before the announcement of tariffs on the U.S. soybeans. And testing set 2 contains data from Apr 4, 2018, to Dec 14, 2018. The training set data contain 74.34% of all data, the testing set 1 contains 15.09%, and the testing set 2 contains 10.57%.

The result of the prediction model is evaluated by the Mean Square Error (MSE) or Root Mean Square Error (RMSE) between the predicted values and actual values, with data from the testing sets. To examine whether the prediction model has demonstrated predictive power, a baseline prediction model is also included to make comparisons.

$$\hat{y} = \mu \dots \dots \dots (5)$$

As shown in equation (5), μ is the mean of DCE Soybean Meal futures' log returns in the training set, and $\hat{y}$ is the predicted log return for the baseline model. A smaller prediction model RMSE compares to baseline RMSE indicates the proposed prediction model has more predictive power compares to the baseline. On the other hand, if the prediction model RMSE is similar or larger than the baseline RMSE, the model has no notable predictive power on the testing dataset.

The results from statistical tests in Section IV show the diminishing in the market linkage between China and the U.S. after the announcement of tariffs. Therefore, a well-specified model which yields a low RMSE on the testing set 1 probably result in a high RMSE for testing set 2.

After tuning hyperparameters (α in function (4) and the degree of the polynomial) through the cross-validation process, a model is fitted to predict the log return of DCE Soybean Meal futures based on the data in the training set.

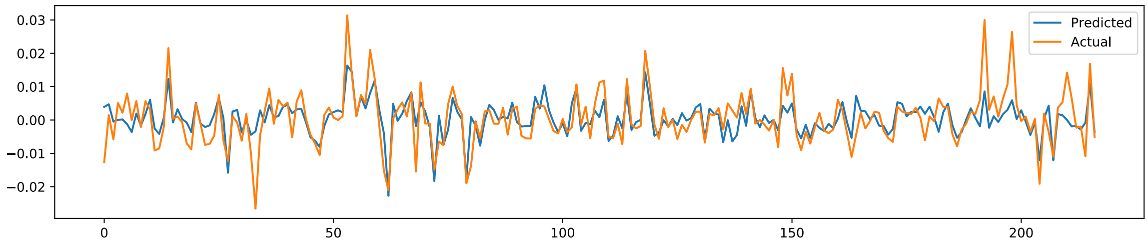

Figure 3: Predicted vs. actual log return for the testing set 1 (Testing set's data are from Apr 4, 2017, to Apr 3, 2018, before the announcement of tariffs)

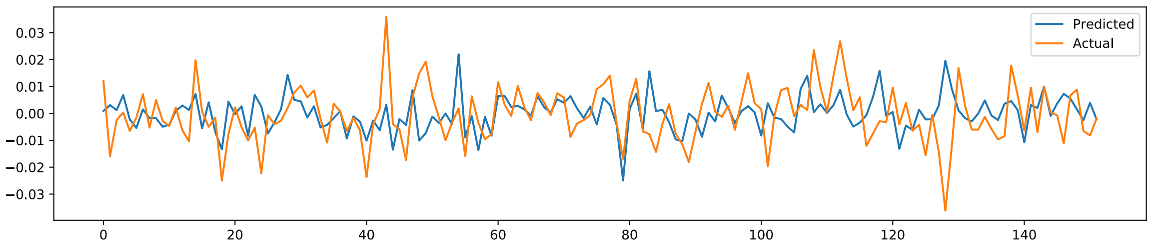

Figure 4: Predicted vs. actual log return for the testing set 2 (Testing set's data are from Apr 4, 2018, to Dec 14, 2018, after the announcement of tariffs)

	Testing Set 1	Testing Set 2
Model RMSE	0.005366	0.010904
Baseline RMSE	0.007813	0.010118
Decrease in %	31.32	-7.77

Table 10: Comparison between the testing sets results

The results are shown in Figure 3, Figure 4, and Table 10. Based on the historical data, a prediction model, which includes the information of cross-market (CBOT Soybean) log return, would yield a good predicting result for the testing data before the announcement of tariffs (Testing Set 1), which is 31.32% decrease in RMSE compared to the baseline model. However, the same model would lose predictive power for the data after the announcement of tariffs (Testing Set 2), in which the model RMSE is even worse than the baseline RMSE, showing no notable predictive power.

The prediction model is based on the cross-market information, and it works well for predicting log returns before the announcement. This implies a strong market linkage between China and the U.S. soybean-related futures. However, because of the diminishing of market linkage after the announcement of tariffs, a well-specified model would not make an accurate prediction anymore. This also shows that if any financial service or technology companies, or analysts, have specified a similar model based on cross-market information, they should actively change the original model. Otherwise, a previous well-specified model would not perform accurate prediction result after the announcement of tariffs.

VI. Conclusion and Discussion

This thesis studies the effect of China-United States trade dispute and tariffs on soybean-related futures markets in these two countries. Specifically, DCE Soybean No.1, DCE Soybean Meal, and CBOT Soybean futures are examined. The main hypothesis is that tariffs and the interruption of the soybean trades have negatively affected and decreased the linkage between soybean-related futures markets in the two countries.

The market linkages are tested using a log return (price) transmission model. The results indicate that the transmission effect cross-market has substantially diminished after China's announcement of retaliatory tariffs. Also, the return transmission decreases both from China to the U.S. and the U.S. to China. Furthermore, a difference in diminishing is discovered for DCE Soybean Meal futures and DCE Soybean No.1 futures. The decline in the return transmission for DCE Soybean Meal futures from CBOT Soybean is larger than the decline for DCE Soybean No.1 futures. This difference in the magnitude is probably due to the essential difference between two futures. DCE Soybean No.1 futures are designed for Non-GM soybeans, which are mainly domestic produced soybeans in China, potentially affected less by the tariffs targeting the imported soybeans. However, the soybean meals in China are mainly extracted from GM soybeans – which are mostly imported soybeans; therefore, the DCE Soybean Meal futures would potentially suffer more from the trade dispute between China and the United States. Also, before the announcement of tariffs, China was one of the largest buyers of the U.S. soybeans, and in terms of return transmissions, there was no notable dominant market in the soybean-related futures among two countries. But after the announcement of tariffs, the U.S. soybean futures shows dominate effect on the Chinese soybean-related futures in the return transmission, even though the market linkage weakened.

Besides the statistical/econometric model used in testing the log return (price) transmission, this thesis also shows that the decline in market linkage would make a well-specified model provide less accurate conditional predictions after China's announcement of tariffs. This actually has broader implications. For example, financial service or technology companies need to change their return prediction model if their model is based on cross-market information.

The U.S. agricultural products are the focus of Chinese retaliatory actions, however, many other products from both countries are also affected by the trade dispute. Many pieces of research have investigated trade wars and their impact, which have focused mainly on macro-economic effects. This thesis shows that there are also potentials to examine how the trade war will affect specific products or financial derivatives. Even though many market participants are expecting China and the U.S. to reach an agreement and to end the current trade dispute in the near future; for the next following years, there could still be small disputes between the two countries. Therefore, the effect of the trade dispute on specific products or financial derivatives is also an appealing and necessary field to keep tracking for future studies.

Appendix

Appendix I. Packages used in the research

In this research, most data processing and testing programs are conducted in `Python`. Packages used in data processing are `Pandas` (Python data analysis library, n.d.) and `NumPy` (Numpy, n.d.). The package used for statistical test is `statsmodels` (StatsModels: Statistics in Python, n.d.). The package used in the machine learning approach is `scikit-learn` (Pedregosa et al., 2011).

Appendix II. Results of the statistical tests

1. Transmission from CBOT Soybean to DCE Soybean Meal, before the announcement.

```
==============================================================================
Dep. Variable:               DCE_M(t)   R-squared:                       0.419
No. Observations:                1286   Adj. R-squared:                  0.416
Df Residuals:                    1279   F-statistic:                     153.8
Df Model:                           6   Prob (F-statistic):          5.18e-147
Log-Likelihood:                4452.7
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0003      0.000      1.104      0.270      -0.000       0.001
DCE_M(t-1)    -0.0588      0.029     -2.034      0.042      -0.115      -0.002
DCE_M(t-2)    -0.0139      0.022     -0.636      0.525      -0.057       0.029
CBOT(t-1)      0.5180      0.018     28.898      0.000       0.483       0.553
CBOT(t-2)      0.0870      0.022      3.891      0.000       0.043       0.131
HOL            0.0039      0.001      3.067      0.002       0.001       0.006
WKND        -5.53e-05      0.001     -0.101      0.920      -0.001       0.001
==============================================================================
```

2. Transmission from CBOT Soybean to DCE Soybean Meal, after the announcement.

```
==============================================================================
Dep. Variable:               DCE_M(t)   R-squared:                       0.335
No. Observations:                 151   Adj. R-squared:                  0.307
Df Residuals:                     144   F-statistic:                     12.08
Df Model:                           6   Prob (F-statistic):           5.73e-11
Log-Likelihood:                511.15
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0009      0.001     -1.234      0.219      -0.002       0.001
DCE_M(t-1)     0.3191      0.071      4.476      0.000       0.178       0.460
DCE_M(t-2)    -0.1681      0.067     -2.502      0.013      -0.301      -0.035
CBOT(t-1)      0.1534      0.056      2.735      0.007       0.043       0.264
CBOT(t-2)     -0.0669      0.057     -1.166      0.245      -0.180       0.046
HOL            0.0264      0.004      6.158      0.000       0.018       0.035
WKND          -0.0011      0.002     -0.583      0.561      -0.005       0.003
==============================================================================
```

3. Transmission from DCE Soybean Meal to CBOT Soybean, before the announcement.

Dep. Variable:	CBOT(t)	R-squared:	0.116
No. Observations:	1286	Adj. R-squared:	0.111
Df Residuals:	1279	F-statistic:	27.87
Df Model:	6	Prob (F-statistic):	2.10e-31
Log-Likelihood:	3877.9		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.875e-05	0.000	-0.050	0.960	-0.001	0.001
CBOT(t-1)	-0.3139	0.036	-8.715	0.000	-0.385	-0.243
CBOT(t-2)	-0.0433	0.035	-1.252	0.211	-0.111	0.025
DCE_M(t)	0.5606	0.044	12.871	0.000	0.475	0.646
DCE_M(t-1)	0.0100	0.045	0.220	0.826	-0.079	0.099
HOL	3.682e-05	0.002	0.018	0.986	-0.004	0.004
WKND	1.407e-05	0.001	0.016	0.987	-0.002	0.002

4. Transmission from DCE Soybean Meal to CBOT Soybean, after the announcement.

Dep. Variable:	CBOT(t)	R-squared:	0.033
No. Observations:	151	Adj. R-squared:	-0.008
Df Residuals:	144	F-statistic:	0.8069
Df Model:	6	Prob (F-statistic):	0.566
Log-Likelihood:	451.35		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0004	0.001	-0.368	0.714	-0.003	0.002
CBOT(t-1)	-0.0365	0.086	-0.426	0.671	-0.206	0.133
CBOT(t-2)	0.0846	0.085	0.999	0.319	-0.083	0.252
DCE_M(t)	-0.1293	0.108	-1.193	0.235	-0.343	0.085
DCE_M(t-1)	-0.0309	0.109	-0.283	0.777	-0.246	0.185
HOL	-0.0031	0.009	-0.348	0.728	-0.021	0.015
WKND	-0.0032	0.003	-1.159	0.248	-0.009	0.002

5. Transmission from CBOT Soybean to DCE Soybean No.1, before the announcement.

Dep. Variable:	DCE_A(t)	R-squared:	0.156
No. Observations:	1297	Adj. R-squared:	0.152
Df Residuals:	1290	F-statistic:	39.67
Df Model:	6	Prob (F-statistic):	1.90e-44
Log-Likelihood:	4585.4		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0002	0.000	-1.101	0.271	-0.001	0.000
DCE_A(t-1)	0.1121	0.028	4.005	0.000	0.057	0.167
DCE_A(t-2)	-0.0502	0.026	-1.945	0.052	-0.101	0.000
CBOT(t-1)	0.2134	0.016	13.286	0.000	0.182	0.245
CBOT(t-2)	-0.0328	0.017	-1.947	0.052	-0.066	0.000
HOL	0.0009	0.001	0.775	0.439	-0.001	0.003
WKND	0.0004	0.001	0.709	0.479	-0.001	0.001

6. Transmission from CBOT Soybean to DCE Soybean No.1, after the announcement.

```
==============================================================================
Dep. Variable:                 DCE_A(t)   R-squared:                       0.233
No. Observations:                   157   Adj. R-squared:                  0.202
Df Residuals:                       150   F-statistic:                     7.601
Df Model:                             6   Prob (F-statistic):           3.91e-07
Log-Likelihood:                  558.55
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0017      0.001     -2.591      0.011      -0.003      -0.000
DCE_A(t-1)     0.3313      0.074      4.450      0.000       0.184       0.478
DCE_A(t-2)    -0.1801      0.070     -2.574      0.011      -0.318      -0.042
CBOT(t-1)      0.1485      0.047      3.177      0.002       0.056       0.241
CBOT(t-2)     -0.0474      0.048     -0.991      0.323      -0.142       0.047
HOL            0.0116      0.004      3.218      0.002       0.004       0.019
WKND           0.0018      0.001      1.225      0.222      -0.001       0.005
==============================================================================
```

7. Transmission from DCE Soybean No.1 to CBOT Soybean, before the announcement.

```
==============================================================================
Dep. Variable:                  CBOT(t)   R-squared:                       0.052
No. Observations:                  1297   Adj. R-squared:                  0.048
Df Residuals:                      1290   F-statistic:                     11.84
Df Model:                             6   Prob (F-statistic):           5.85e-13
Log-Likelihood:                  3862.8
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       1.643e-05      0.000      0.043      0.966      -0.001       0.001
CBOT(t-1)     -0.0966      0.030     -3.237      0.001      -0.155      -0.038
CBOT(t-2)      0.0243      0.029      0.834      0.404      -0.033       0.082
DCE_A(t)       0.4000      0.049      8.239      0.000       0.305       0.495
DCE_A(t-1)    -0.1158      0.049     -2.373      0.018      -0.212      -0.020
HOL            0.0017      0.002      0.769      0.442      -0.003       0.006
WKND          -0.0002      0.001     -0.254      0.800      -0.002       0.002
==============================================================================
```

8. Transmission from DCE Soybean No.1 to CBOT Soybean, after the announcement.

```
==============================================================================
Dep. Variable:                  CBOT(t)   R-squared:                       0.048
No. Observations:                   157   Adj. R-squared:                  0.010
Df Residuals:                       150   F-statistic:                     1.259
Df Model:                             6   Prob (F-statistic):              0.280
Log-Likelihood:                  469.75
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0006      0.001     -0.490      0.625      -0.003       0.002
CBOT(t-1)     -0.0075      0.085     -0.088      0.930      -0.176       0.161
CBOT(t-2)      0.0593      0.083      0.715      0.476      -0.105       0.223
DCE_A(t)      -0.2639      0.136     -1.945      0.054      -0.532       0.004
DCE_A(t-1)     0.0574      0.135      0.425      0.671      -0.209       0.324
HOL           -0.0037      0.009     -0.417      0.678      -0.021       0.014
WKND          -0.0035      0.003     -1.316      0.190      -0.009       0.002
==============================================================================
```

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