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Impact of US-China Trade War on the Volatility of China's Soybean Futures

—Based on GARCH Models

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***Abstract*—The US-China trade war has lasted for more than a year, while due to the hysteresis in macro data, the impact on the economies of the two countries, especially the passive part—China, has not fully manifested. This paper explores the impact of trade war on China's economy from the perspective of the soybean futures market which is sensitive to tariff changes. In the course of research, it is found that the yield series of futures contracts have obvious conditional heteroscedasticity. In order to further explore the symmetry of the yield of the futures market, the GARCH and EGARCH model are applied to model the data for a comparative analysis. Meanwhile, considering the characteristics of the leptokurtosis and fat-tail of the yield data, the T distribution and GED distribution are added to the model to compare the fitting effect of residuals with the traditional normal distribution. Among the 6 GARCH and EGARCH models based on different residual distributions, the AIC criterion is used to select the best fitting model. Then, a dummy variable is added to the variance equation of the selected model to estimate the impact of trade war on the volatilities of China's soybean futures market.**

***Keywords*—US-China trade war; Soybean futures; Market volatility; GARCH models**

I. INTRODUCTION

Since the beginning of 2018, the US-China trade friction has been upgraded step by step, which is now fermented into so-called "trade war". During this period, the two sides conducted rounds of sanctions and anti-sanctions on trade tariffs. Undoubtedly, this is a retrogressive measure in the process of trade liberalization and globalization. Although the negative impact of trade war has not been fully proved in the economic data disclosed by the two countries, as far as the trade aspect is concerned, damage is determinedly expected to see. The pessimism brought about by the trade war runs through China's stock market for the whole year of 2018, partially leading to the bear pattern. The commodity futures market in China has also been implicated, and the price trends fluctuate with the game between China and the US in many varieties of futures, especially those that have direct trade with the US, such as soybean, wheat, aluminum, crude oil and PTA [1].

As an important commodity imported from the US, soybean is one of the largest commodities in China-US trade, in terms of import volume and amount. In 2017, China imported more than 95 million tons of soybean overseas, 34% of which came from the US, and the transaction amount exceeded 10 billion US dollar.1 Moreover, China is the largest market country for US soybean, and China's soybean dependence on overseas is extremely high (the dependence on soybean imports in 2017 is as high as 86%) [2]. Under this premise, soybean-futures is a very representative variety to study the impact of US-China trade war on China's commodity futures market. From the analysis of the impact of soybean futures market, the consequences of US-China trade war can be observed in a certain perspective, and on this basis, some suggestions can be put forward to China to deal with the influence of trade wars.

II. MODELLING PRINCIPLE

(1)Due to the influence of many factors in the financial market, the fluctuations of return are often violent and complicated, thus, extreme data is prone to occur. This makes the financial time series frequently appear the phenomenon of "leptokurtosis and fat-tail". Furthermore, the residual term in the regression equation also likely to deviate from the normal distribution hypothesis required by the GARCH model. Therefore, in this study, when building the GARCH model, the residual distribution which is closer to the characteristics of the financial time series, such as: t distribution, GED (generalized error distribution) will be applied to fit the residual of the model.

(2)In reality, the time series on the financial market are most asymmetric in distribution, that is, the data are biased and usually tends to be negatively biased. Hence, when modelling the data, the application of asymmetric GARCH should be considered. In this study, the symmetric model, GARCH (1,1), and the asymmetric model, EGARCH (1,1), are established at the same time. On this basis, according to the different setting of residual distribution, a total of 6 models will be used for the comparative analysis, including GARCH-N (GARCH model based on normal residual distribution), GARCH-t (based on t residual distribution), GARCH-GED (based on GED residual distribution) and EGARCH-N, EGARCH-t, EGARCH-GED. Furthermore, the AIC criterion will be used to determine the optimal fit model: the model with the smallest AIC value is the best fit [3].

(3)In comparing the volatility changes before and after the US-China trade war, in order to segment data interval, a dummy variable D will be added to the variance equation of GARCH model. When the data belongs to the period before the trade war is taken, D equals to 0;[4] when the data belongs to the period

[1] Data from National Bureau of Statistics of China

after the trade war, D equals to 1. If the coefficient of D shown in the results is significant, then the trade war has an impact on market volatility. Besides, when the coefficient of the dummy variable D is positive, it indicates that the trade war increases the volatility of the market; when the coefficient of D is negative, it means that the trade war reduces the volatility of the market.

III. Data Collection and Processing

March 22, 2018 (US EST) was universally acknowledged as the starting data of the US-China trade war, since on this day US President Donald Trump signed a memorandum at the White House, proclaiming that the value as high as 50 billion US dollars of import commodity from China will be imposed punitive tariffs. The Chinese government also issued corresponding counter-measure on the same day, which ended the usual trade friction between China and United States and escalated into a formal trade war. Therefore, this study uses March 22, 2018 as the boundary to distinguish between before and after the trade war. The raw collected are: the daily closing price of the main contract of soybean No.1 from January 2, 2003 to February 1, 2019; the daily closing price of the main contract of soybean No.2 from December 22, 2004 to February 1, 2019; the daily closing price of the main contract of soymeal from January 2, 2003 to February 1, 2019; the daily closing price of the main contract of soyoil from January 9, 2006 to February 1, 2019. All the transaction data is from the Dalian Commodity Exchange of China.

For the collected data, the following steps will be processed in order to build up the GARCH model.

(1)Convert the collected futures price sequence into a logarithmic yield series, following the formula:

$$\mathrm{R} = \ln(P_t/P_{t-1})$$

(2) Conduct the stationarity test to the yield series. Here the ADF test is applied. The results are as follows (Table 1):

TABLE I ADF TEST RESULTS

	t-Statistic	Prob.*
R_Soy I	-65.18829 ***	0.0001
R_Soy II	-31.96179 ***	0.0000
R_Soymeal	-65.77990 ***	0.0001
R_Soyoil	-57.18675 ***	0.0001

Note: '*'denotes significance at 10% level, '**'denotes significance at 5% level, '***'denotes significance at 1% level.

As we can see from the table above, the log yield series of all varieties were stable at a significant level of 1%, indicating that the properties derived from these sequences are statistically significant and it can be proceeded to the next step.

(3) Establishment of the mean equation

An ARMA mean equation should be built based on the stable yield sequence to isolate the linear characteristics which the data carries. Corregram of each yield series is first made, and the autocorrelation lag order of the series is roughly determined according to the Autocorrelation and Partial correlation graphs. The initially established mean equations using the Corregram are:

$$R\_SoyI_t = c_1 + \phi_1 R\_SoyI_{t-1} + \varepsilon_t + \varepsilon_{t-1}$$

$$R\_SoyII_t = c_2 + \phi_2 R\_SoyI_{t-1} + \varepsilon_t + \varepsilon_{t-1} + \varepsilon_{t-2}$$

$$R\_Soymeal_t = c_3 + \phi_3 R\_Soymeal_{t-1} + \varepsilon_t + \varepsilon_{t-1}$$

$$R\_Soyoil_t = c_4 + \phi_4 R\_Soyoil_{t-7} + \varepsilon_{t-7}$$

Further, to ensure the mean equations are reasonable and effective, the regression analysis is performed on them respectively. Table 2 shows that most of the established mean equations are significant at level 1%, thus valid.

TABLE II MEAN EQUATION REGRESSION RESULTS

	Coefficient	t-statistic	Prob.
R_SoyI_{t-1}	-0.746352	-5.543915 **	0.0000
$\varepsilon_{t-1}\_R\_SoyI_t$	0.717002	5.087004***	0.0000
R_SoyII_{t-1}	0.659953	3.281070***	0.0010
$\varepsilon_{t-1}\_R\_SoyII_t$	-1.026934	-5.017629***	0.0000
$\varepsilon_{t-2}\_R\_SoyII_t$	0.215193	2.471393**	0.0135
$R\_Soymeal_{t-1}$	-0.601881	-3.555517***	0.0004
$\varepsilon_{t-1}\_R\_Soymeal_t$	0.556063	3.160125***	0.0016
R_Soyoil_{t-7}	-0.720557	-4.975698***	0.0000
$\varepsilon_{t-7}\_R\_Soyoil_t$	0.747692	5.383945**	0.0000

Note: '*'denotes significance at 10% level, '**'denotes significance at 5% level, '***'denotes significance at 1% level.

(4) The autocorrelation test of the residuals of the mean equation

When the residual of the regression model exists autocorrelation, there are endogenous problem such as missing explanatory variables. Otherwise, the residual is a white noise sequence, and the endogeneity of the regression model is solved. Table 3 below shows the results of Breusch-Godfrey serial correlation LM test on the residual sequences. [5]The null hypothesis of the LM test is that: there is no autocorrelation of the sequence until the p-order lag. From the results, we can see no autocorrelation of the residuals of all the mean equations above, because the null hypothesis of the LM test cannot be rejected. Therefore, endogeneity problem does not exist in the mean equations.

TABLE III LM TEST RESULTS

	F-Statistic	Prob.*
ε_t_R_Soy I (lag include:2)	1.583190	0.2055
ε_t_R_Soy II (lag include:3)	1.076678	0.3577
ε_t_ R_Soymeal (lag include:2)	2.009943	0.1341
ε_t_ R_Soyoil (lag include:8)	0.875105	0.5367

Normality test of residual distribution

(5) In order to explore the distribution of the residuals of the mean equations established, it is necessary to perform a normality test. In the normal test of the data (due to the space limit, the empirical results are omitted here), the residuals of the all the mean equations do not conform to the normal distribution, exhibiting the characteristics of "leptokurtosis and fat-tails". This provides a basis for introducing the t-distribution and GED distribution of the residuals in the model to be built [6].

(6) ARCH effect test

The ARCH effect refers to the existence of conditional heteroscedasticity, which appears as a phenomenon of "fluctuating aggregation" on the graph of the yield series. If the residual of the mean equation has conditional heteroscedasticity, then the GARCH family model needs to be built to fit the data. The ARCH-LM test is used here as the conditional heteroscedasticity test, and the original hypothesis is that the sequence does not have an ARCH effect until the p-order lag. In Table 4, the original hypothesis is rejected at a significant level of 5% or higher, indicating that the residual of each mean equation has conditional heteroscedasticity, so the GARCH family models are appropriate for fitting the yields series.

TABLE IV ARCH-LM TEST RESULTS

	F-Statistic	Prob.*
$\varepsilon_{t\_}$ R_Soy I (lag include:2)	4.381961**	0.0126
$\varepsilon_{t\_}$ R_Soy II (lag include:3)	130.9202***	0.0000
$\varepsilon_{t\_}$ R_Soymeal (lag include:2)	40.14814***	0.0000
$\varepsilon_{t\_}$ R_Soyoil (lag include:8)	94.69599***	0.0000

Note: '*'denotes significance at 10% level, '**'denotes significance at 5% level, '***'denotes significance at 1% level.

IV. EMPIRICAL ANALYSIS

In this part, the key issues we need to address are: 1) For soybean futures contracts, is GARCH (1,1) model (representing symmetry model) or EGARCH (1,1) (representing asymmetric model) suitable for fitting the volatility? 2) Under the different residual distribution assumptions (Normal, t, GED), which one produces a better fitting result? 3) How does the volatility of soybean futures change before and after the US-China trade war?

A. Analysis of modelling results of GARCH family model

Based on the conclusions drawn in the precious section, GARCH (1,1) and EGARCH (1,1) are applied to determine the fitting effect of the symmetric model and the asymmetric model, and then select the optimal model. Meanwhile, for better fitting the distribution of the residual sequence, normal distribution, t-distribution and GED distribution are introduced to the model. Thus, each yield series will be calculated in 6 model: GARCH-N, GARCH-t, GARCH-GED, and EGARCH-N, EGARCH-t, EGARCH-GED. Among them, the general expressions of variance equation are:

GARCH(1,1):$\sigma^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

EGARCH(1,1):$\ln \sigma^2 = \alpha_0 + \theta \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_1 \ln \sigma_{t-1}^2$

1) Soybean No.1 contract

TABLE V MODELLING RESULTS OF SOYBEAN NO.1 CONTRACT

GARCH(1,1)					
	α_0	α_1	β_1	AIC Value	
Normal Distribution	1.54E-06*** (0.0000)	0.029830*** (0.0000)	0.960676*** (0.0000)	-6.079495	
T Distribution	1.08E-06*** (0.0053)	0.061191*** (0.0000)	0.942355*** (0.0000)	-6.328268	
GED Distribution	1.46E-06*** (0.0000)	0.047163*** (0.0000)	0.942928*** (0.0000)	-6.309085	
EGARCH(1,1)					
	α_0	θ	α_1	β_1	AIC Value
Normal Distribution	-0.160974*** (0.0000)	0.004038 (0.2008)	0.077627*** (0.0000)	0.987977*** (0.0000)	-6.099091
T Distribution	-0.150371*** (0.0000)	0.016255*(0.0865)	0.130160*** (0.0000)	0.992891*** (0.0000)	-6.341285
GED Distribution	-0.181574*** (0.0000)	0.011679 (0.1745)	0.111483 (0.0000)	0.988612*** (0.0000)	-6.319661

Note: '*'denotes significance at 10% level, '**'denotes significance at 5% level, '***'denotes significance at 1% level.

In the results of the GARCH (1,1) model established for the soybean 1 contract yield series, the coefficient α_1 and β_1 are highly statistically significant under the 3 residual distributions, meaning that the fitting of GARCH (1,1) is basically effective. However, in the GARCH (1,1) –t model, the sum of the ARCH and GARCH coefficient, $\alpha_1 + \beta_1$, is larger than 1,[7] which disobeys the coefficient condition of the GARCH model, indicating that the GARCH model is inadaptable to the fit the yield series when the residual is subject to the t-distribution. The results of this situation should be excluded.

In addition, the sum of coefficient α_1 and β_1 of GARCH (1,1)-N and GARCH (1,1)-GED are smaller but pretty close to 1, which can reflect the aggregation and long-term effect of the fluctuation of the yield series to some extent. From the results of the EGARCH (1,1) model, the coefficient θ is basically not significant in every model, which shows that no leverage effect exist on the yield volatility of soybean No.1 (that is, the impact of bad news and good news cannot cancel each other out, or the impact of either party is no more intense than the other). The β_1 coefficient in the EGARCH model is very close to 1, confirming the existence of data fluctuation clustering. Considering the AIC values of the models (the smallest value represents the best fitting), it is appropriate to choose the EGARCH-t model.

2) Soybean No.2 contract

TABLE VI MODELLING RESULTS OF SOYBEAN NO.2 CONTRACT

GARCH(1,1)					
	α_0	α_1	β_1	AIC Value	
Normal Distribution	7.13E-06*** (0.0000)	0.200184*** (0.0000)	0.815530*** (0.0000)	-5.493683	
T Distribution	1.08E-05*** (0.0001)	0.456190*** (0.0000)	0.744102*** (0.0000)	-5.780261	
GED Distribution	6.32E-06*** (0.0000)	0.239077*** (0.0000)	0.788213*** (0.0000)	-5.791189	
EGARCH(1,1)					
	α_0	θ	α_1	β_1	AIC Value
Normal Distribution	-0.432271*** (0.0000)	0.068616*** (0.0000)	0.329105*** (0.0000)	0.974194*** (0.0000)	-5.504041
T Distribution	-0.652436*** (0.0000)	0.082207***(0.0000)	0.543332*** (0.0000)	0.955257*** (0.0000)	-5.790561
GED Distribution	-0.506773*** (0.0000)	0.067672*** (0.0009)	0.357522*** (0.0000)	0.96835***(0.0000)	-5.798035

From the results of the GARCH (1,1) model established for the soybean No.2 contract yield series, it can be known that although the coefficients of each model are highly statistically significant, the sums of ARCH coefficient and the GARCH coefficient in all the GARCH (1,1) models are all greater than 1, which is inconsistent with the coefficient constraint. Therefore, these models should be excluded. In the results of the EGARCH (1,1) model, all coefficients are highly statistically significant, indicating the fitting of the EGARCH model is valid. Further, we can find that both the coefficient θ and α_1 are significant, showing that the volatility of the soybean No.1 contract has a leverage effect. Moreover, since $\theta > 0$, and it makes $\theta + \alpha_1 > -\theta + \alpha_1$, meaning that the soybean No.2 contract actually has a positive leverage effect, namely, the impact of the good news on the volatility is greater than that caused by the bad news. Besides, the value of the coefficient β_1 is relatively big, which illustrates the fluctuation clustering of the yield series. Considering the AIC criterion, we can see that the AIC value of EGARCH-GED is -5.798035, which is the smallest of them. Hence, the model should be selected to fit the volatility of the soybean 2 yield series [8].

3) Soymeal contract

TABLE VII MODELLING RESULTS OF SOYMEAL CONTRACT

GARCH(1,1)					
	α_0	α_1	β_1	AIC Value	
Normal Distribution	9.67E-06*** (0.0000)	0.086367*** (0.0000)	0.872542*** (0.0000)	-5.693998	
T Distribution	6.60E-06*** (0.0001)	0.089292*** (0.0000)	0.891389*** (0.0000)	-5.839203	
GED Distribution	6.83E-06*** (0.0000)	0.080137*** (0.0000)	0.889793*** (0.0000)	-5.839110	
EGARCH(1,1)					
	α_0	θ	α_1	β_1	AIC Value
Normal Distribution	-0.525953*** (0.0000)	0.015761*** (0.0158)	0.199825*** (0.0000)	0.955035*** (0.0000)	-5.702525
T Distribution	-0.198163*** (0.0000)	0.040913***(0.0000)	0.128463*** (0.0000)	0.987084*** (0.0000)	-5.853725
GED Distribution	-0.285635*** (0.0000)	0.032198*** (0.0023)	0.146446*** (0.0000)	0.978939***(0.0000)	-5.848770

From the results of the GARCH (1,1) model established for the soymeal contract yield series, we can see that the sum of the ARCH and GARCH coefficient is consistent with the coefficient constraint of the GARCH model. Moreover, all coefficients are highly statistically significant, so the GARCH (1,1) models based on the 3 residual distributions are valid. Looking at the results of EGARCH (1,1), all the coefficients ate significant, also meaning the effectiveness of EGARCH (1,1). Where, the coefficient θ and α_1 are both significant, and $\theta > 0$, $\theta + \alpha_1 > -\theta + \alpha_1$, indicating that there is a positive leverage in the market volatility of the soymeal contract. The coefficient β_1 has a large value, which corresponds to the aggregation of volatility. In this case, both the GARCH and EGARCH models are valid, we can select the optimal fitting model by comparing the AIC values. Clearly, in the soymeal contract market, the optimal model is EGARCH-t.

4) Soyoil contract

TABLE VIII MODELLING RESULTS OF SOYOIL CONTRACT

GARCH(1,1)					
	α_0	α_1	β_1	AIC Value	
Normal Distribution	1.72E-06*** (0.0000)	0.041389*** (0.0000)	0.945873*** (0.0000)	-6.140812	
T Distribution	6.34E-07*** (0.0586)	0.045402*** (0.0000)	0.952829*** (0.0000)	-6.195102	
GED Distribution	1.02E-06*** (0.0096)	0.041798*** (0.0000)	0.951417*** (0.0000)	-6.194896	
EGARCH(1,1)					
	α_0	θ	α_1	β_1	AIC Value
Normal Distribution	-0.166868*** (0.0000)	0.009171* (0.0546)	0.088319*** (0.0000)	0.988734*** (0.0000)	-6.136173
T Distribution	-0.128742*** (0.0000)	0.014921*(0.0756)	0.109164*** (0.0000)	0.994603*** (0.0000)	-6.194393
GED Distribution	-0.143200*** (0.0000)	0.011692 (0.1411)	0.097738*** (0.0000)	0.992174***(0.0000)	-6.193143

From the results of the modelling, the GARCH and EGARCH models are basically effective. However, the coefficient θ in the EGARCH results are all poorly significant, which indicates that the leverage effect of fluctuation in the soyoil contract market does not exist. According to the comparison of AIC values, the GARCH-t model has the smallest figure, and is very close to that of GARCH-GED. While the effective degree of these 2 models are quite different, which is specifically reflected in the fact that the significance of the constant term in GARCH-GED is higher than that of the GARCH-t. Therefore, under a comprehensive consideration, the GARCH-GED model should be chosen to fit the yield volatility of the soyoil contract.

B. Analysis of volatility impact

In order to study the impact of the event - "after the outbreak of the trade war" on the volatility of the soybean futures market, the data is divided into 2 sections: before and after the trade, with the boundary data on March 22, 2018. Moreover, since there are some major events in the history that have significant impact on the market, which can affect the volatility, to eliminate the influence of historical factors on market volatility, I will exclude some historical data in this study, and two segments were divided in the remaining data to do a control study.

A segment of data represents nearly one year before the outbreak of the trade war, and the other segment represents the period of nearly one year after the outbreak of the trade war. And then we can compare the volatility changes between the two intervals to determine the impact of the trade war. [9]

The specific data division is set as: the data of official outbreak of the trade war (March 22, 2018) as the boundary, the data from March 1, 2017 to March 22, 2018 will be set as the control group, data from March 23, 2018 to February 1, 2019 were set as research group. To do this, it is necessary to add a dummy variable to the model, that is, adding variable D_i to the variance equation of GARCH and EGARCH. When the data belongs to the control group, $D_i = 0$; when the data belongs to the research group, D_i=1. The equations can be expressed as follows:

GARCH(1,1):$\sigma^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \phi D_i$,

EGARCH(1,1): $\ln\sigma^2 = \alpha_0 + \theta\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha_1\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_1\ln\sigma_{t-1}^2 + \phi D_i$

1) Soybean No.1 contract

Based on the analysis in part 4, the optimal fitting model of soybean No.1 contract is GARCH-GED model, therefore this model is still used to analyze the fluctuations of the control group and research group. The results are shown in Table 9. According to the results, the coefficient ϕ of the dummy variable is positive and highly significant. Therefore, we can to a certain extend to draw that the US-China trade war has a positive impact on the market yield volatility of the soybean No.1 contract. In other words, the US-China trade war has increased the market volatility of soybean No.1 contract.

TABLE IX VARIANCE EQUATION REGRESSION RESULTS FOR SOYBEAN NO.1 CONTRACT

$EGARCH - t$				
α_0	θ	α_1	β_1	ϕ
-16.06399*** (0.0000)	-0.145123 (0.2014)	0.268884*** (0.0000)	-0.686452*** (0.0000)	0.990001*** (0.0000)

2) Soybean No.2 contract

Similarly, the coefficient ϕ of the dummy variable is positive, and a significance test is passed at a level of 5%, indicating that the US-China trade war has increased the market volatility of the soybean No.2 contract.

TABLE X VARIANCE EQUATION REGRESSION RESULTS FOR SOYBEAN NO.2 CONTRACT

$EGARCH - GED$				
α_0	θ	α_1	β_1	ϕ
-3.030309*** (0.0079)	0.425606 (0.0000)	0.276063*** (0.0077)	0.711186*** (0.0000)	0.310538** (0.0116)

3) Soymeal contract

TABLE XI VARIANCE EQUATION REGRESSION RESULTS FOR SOYMEAL CONTRACT

$EGARCH-t$				
α_0	θ	α_1	β_1	ϕ
-8.493044 ***(0.0000)	0.374848 ***(0.0001)	-0.674614 *** (0.0000)	-0.004868 *** (0.9816)	0.421963*** * (0.0047)

It can be observed that in Table 11, except for the coefficient of $\ln\sigma_{t-1}^2$, the other coefficients are highly significant. This does not affect us to draw conclusions, because using the short-term data often does not observe significant volatility aggregation effect, that is, the conditional heteroscedasticity is not significant. Because in fact, the EGARCH model has actually been transformed into a special ARCH model, but the conclusions of the volatility changes derived from it are still desirable. Therefore, we can still use the positive (and significant) coefficient ϕ to conclude that the US-China trade war has increased the market volatility of soybean No.2 contract.

4) Soyoil contract

TABLE XII VARIANCE EQUATION REGRESSION RESULTS FOR SOYMEAL CONTRACT

$GARCH-GED$			
α_0	α_1	β_1	ϕ
6.17E-06 (0.1060)	-0.028226 ** (0.0238)	0.946667 *** (0.0000)	-1.29E-06*** (0.2429)

In Table 12, the coefficient α_1 of the ARCH item has a p value of 0.0238, though the value is not ideal, it can still pass the significance test of 5% level. Together with the result of the GARCH item coefficient (significant), it can be seen that the fitting result of GARCH-GED is basically effective. However, unlike the previous contracts, the coefficient ϕ of the dummy variable here is negative, and fails to pass the significance test, meaning that the US-China trade war has not had a significant impact on the market fluctuation of the soyoil contract.

V. CONCLUSIONS FROM EMPIRICAL ANALYSIS

A. About leverage

From the modelling results, it is known that there is no significant leverage effect on the volatility of soybean No.1 contract and soyoil contract, while the volatility of soybean No.2 contract and soymeal contract has a positive leverage effect. This is obviously different from the volatility of the stock market. A large number of documents show that the volatility of the stock market generally has significant leverage effect, and is usually negative leverage, this is to say, the volatility shock brought by bad news is stronger than the bullish factor.

The reason for this difference may relate to the fact that the futures market can conduct two-way trading (ie, can open a long position or a short position freely), In China's stock market, the short-selling mechanism is quite limited, investors can only do the "securities lending business" with the securities companies to short the stock, and the business has a large capital threshold. Small and medium investors, accounting for the vast majority of investors in China's stock market will be less involved in that business. Hence, China's stock market is basically in the stage of unilateral investment, which basically only allows investors to open a long position in stock. Whereas, the futures market has a two-way transaction in the trading mechanism, which can do both long and short in every contract. Investors can invest in both the bullish news and the bearish news.[10] There will not appear such situation that a majority of investors buy in collectively according to some bullish factors, but sell out collectively based on negative factors. The bear market concept is not suitable in the futures market, and the market panic is also less common. The psychology of pubic panic is one of the main reasons for the negative leverage effect of the stock market.

In view of the particularity of the volatility of the futures market in terms of leverage, the choice of GARCH family model for volatility fitting depends on the validity of the model and other criteria (such as the AIC guidelines used in this study). Different treatments for different situations, no absolutization is suggested.

B. About residual distribution

According to the normality test of the soybean futures yield series, the data of the 4 varieties all reject the original hypothesis of the normal distribution, but showing obvious features of leptokurtosis and fat-tail. This conclusion is consistent with the study of futures data in a large number of literature. Furthermore, the residuals derived from the ARMA equation equations established for the soybean futures yield series also disobey normal distribution. On the assumption of residual distribution, on the basis of the results of part 5, the residuals of soybean No.1 contract and soymeal contract are t distributed. And the residuals of soybean No.2 contract and soyoil contract is more suitable for GED distribution. Hence, the assumption of non-normal distribution is more appropriate for residuals of soybean futures data.

C. About the impact of US-China trade war

From the empirical results in part 5, we can learn that the market volatility of soybean No.1, No.2 and soymeal futures contracts are significantly affected by the US-China trade war. Specifically, the volatilities of the 3 markets increase after the occurrence of the trade war. While, the volatility of soyoil futures contract shows no significant trade war effect.

As we all know, soybean No.1 and No.2 contracts trade China-made soybeans, which are mainly used for food production. The quality indicators of No.1 contract are based on grain component and is oriented to foodstuff. Differently, the quality indicators of No.2 contract are based on oil output rate and is positioned at the oil press. However, China's domestic soybean supply is quite limited, which is unable to meet the domestic consumer demand for soy products. Most of the soybean raw materials still heavily rely on a large amount of soybean imported from overseas. Almost 98% soymeal used in the production of fodder (for feeding poultry, pigs, etc.) comes from the crushing of overseas soybeans; besides, more than 90% of the soyoil production comes from overseas soybeans.

Due to the escalation of the trade war between China and the USA, China has also imposed a 25% tariff on US soybean products as a counter-measure in response to a series of tariff escalation action by the US. This has made China's soybean spot supply tight furtherly, and futures prices have skyrocketed.

Meanwhile, during the course of trade war, there were many bullish or bearish news keep coming up the market, such as: high-level confrontation between the two sides, the formation of bilateral talks, the increase in soybean supply from south America, the protests of US soybean farmers, etc., all making the uncertainty of the soybean futures market increase. This may be the reason for the increased volatility of the soybean futures market.

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