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Study of the Impact of Sino-US Trade Friction on Oil Prices

Ziping Wang

Beijing Internet Institute, Beijing, China

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***Abstract*— *Since 2017, Sino-US trade frictions have continued, while international crude oil prices have fluctuated sharply, and China's crude oil procurement is faced with greater risk of price fluctuations. This paper uses the EGARCH model to study the impact of Sino-US trade frictions on oil prices, and finds that intensified trade events significantly reduce oil price returns and increase the volatility of oil prices, but moderating trade events have no significant impact on oil prices. The impact of intensified trade events on oil prices has the feature of mean recovery. The yield of oil prices decreases most on the first day but recovers to the original level on the third day. Moreover, moderating trade events have no significant dynamic impact on oil prices. The research results of this paper show that there is a leverage effect on the impact of sino-US trade friction on oil prices, that is, negative news has a greater impact on the price than positive news. Further analysis shows that sino-US trade frictions affect oil prices mainly through the mechanism of market sentiment.*
***Keywords*— Sino-US trade friction；oil price；market sentiment；event study**

I. INTRODUCTION

In recent years, China's economic development has attracted worldwide attention, and China is playing an increasingly important role in the world economy, which poses a severe challenge to the developed countries in the world, including the United States. China and the United States have differences in economic systems, political systems and resource endowments, which eventually began with the "313 investigation" of the United States against China in 2017 and evolved into a "Sino-US trade war".

In the 18 months between July 2018 and May 2019, Donald Trump's administration-imposed tariffs on more than $360 billion of Chinese goods, with tariffs ranging from 10 percent to 25 percent. In response to U.S. tariffs, Beijing has imposed a new round of tit-for-tat tariffs ranging from 5 percent to 25 percent on $110 billion worth of American goods. Finally, after efforts, the two sides reached a "trade war" truce agreement at the end of 2010.

The United States is the world's largest producer of crude oil, while China is the largest importer of the commodity, which has an impact on oil prices during trade frictions between the two countries. In June and July 2019, benchmark Brent crude oil prices traded in a narrow range of $60-67. However, after the latest tariffs were announced, the benchmark price of West Texas Intermediate crude recorded its biggest one-day fall in four-and-a-half years on August 1, while Brent crude fell 7 per cent on the same day. China is already the world's largest crude oil importer, and the fluctuation of crude oil price poses a challenge to China's energy security. Studying the impact of Sino-US trade friction on oil price is helpful for China to prevent price risk and strengthen risk control in crude oil purchase.

In recent years, "Brexit", "Sino-US trade war" and other events have raised the uncertainty of economic policy to a historical level, which has aroused the attention of the academic community. Although many scholars have analyzed the impact of policy uncertainty on the economy, there is limited research on policy uncertainty and commodity prices. The index constructed by Baker et al. (2016) provides a measure of economic policy uncertainty, as international crude oil prices are closely related to the macro economy (Kilian, 2009; Kilian and Murphy, 2014), so some scholars use this index to study the relationship between economic policy uncertainty and international oil prices. Kang and Ratti (2013) analyzed the response of economic policy uncertainty in the United States to international crude oil supply, actual demand and speculative demand, and found that the increase of speculative demand for crude oil would lead to the increase of economic policy uncertainty in the United States, and the positive impact of actual demand for crude oil would reduce the economic policy uncertainty in the United States. But oil supply shocks have had no significant impact on US economic policy uncertainty. Kang et al. (2017a) studied the relationship between oil price, economic policy uncertainty and stock return of oil and gas companies, and concluded that demand-side oil price shock had a positive effect on stock return of oil and gas companies, while economic policy uncertainty reduced stock return. The historical variance decomposition shows that policy uncertainty amplifies the effect of oil price on stock returns of oil and gas companies.

Although international oil prices have fluctuated significantly during the Sino-US trade war, there has been no research and analysis of the impact of Sino-US trade friction on oil prices. The research of this paper has the following innovations: First, it analyzes the impact of Sino-US trade friction on international oil prices for the first time, providing new empirical evidence for oil price fluctuations when trade policy uncertainties are high; Second, the improved event analysis method is used to analyze the dynamic changes of oil prices when Sino-US trade disputes occur. Thirdly, through mechanism analysis, it is concluded that market sentiment is an important factor affecting oil price fluctuations, which supports Singleton's (2014) view that behavioral financial factors will affect international crude oil prices.

II. DATA

The most commonly used price indexes in the international crude oil market trading center are the North Sea BRENT crude oil price (BRENT) and the West Texas Light crude oil price (WTI), but Brent is gradually becoming the oil price index reflecting the fundamentals of the international crude oil market. Historically, BRENT and WTI crude oil prices have moved in much the same direction, but since 2010, WTI prices have increasingly reflected the fundamentals of the Americas rather than the global crude oil market due to the dramatic increase in crude production from the U.S. shale revolution. The weight of Brent in major commodity indices has been increased, while that of WTI has fallen. Therefore, in order to analyze the impact of Sino-US trade frictions on oil prices, this paper chooses the spot price of North Sea BRENT crude oil to represent oil prices, and the price adopts the form of logarithmic return.

The control variables used in this paper are the S&P 500 index, the US Federal funds rate and the open position of the crude oil futures market. The data comes from Thomas Reuters. Table 1 describes the statistical characteristics of the variables involved in this paper. During the sample period, oil prices rose as high as $86.07 / BBL and fell as low as $43.98 / BBL. The S&P 500 averages around 2,700 and the US federal funds rate is in the range of 0.56 to 2.45. Based on the Jarque-Bera test, the normal distribution hypothesis is rejected for all variables. In addition, all variables are stationary after log-difference transformation.

Table 1 Descriptive statistics of variables

	Oil Price	S&P 500	Fed Fund Rate	Open Interest
Mean	63.231	2703.749	1.655	2383614
Median	63.470	2724.440	1.680	2378104

Maximum	86.070	3240.020	2.450	2736659
Minimum	43.980	2257.830	0.560	2083255
Skewness	0.068	-0.055	-0.161	0.335
Kurtosis	-0.649	-0.776	-1.211	0.253
JB	13.819	19.260	48.854	15.757

The Sino-US trade friction events adopted in this paper are based on the data of the "Sino-US Trade Dispute Annals" of Pudaokou School of Finance of Tsinghua University. The Sino-US trade dispute events reported and commented on by the two most authoritative newspapers, the Wall Street Journal and the New York Times, are selected as the variables of Sino-US trade friction events in this paper. He and Fang (2019) only analyzed the impact of Sino-US trade disputes on China's financial market in the form of "0-1" dummy variables. This paper further divided Sino-US trade disputes into moderating and intensifying events, and analyzed the impact of Sino-US trade disputes on international oil prices in a more comprehensive way.

III. METHODOLOGY

3.1 EGARCH model

Since the change of oil price has the characteristic of fluctuation agglomeration after peak (Morana, 2001; Narayan and Narayan, 2007; Mohammadi and Su, 2010), and the existence of leverage effect makes the impact of positive and negative shocks on oil prices asymmetric (Loutia, 2016). EGARCH model is used in this paper to analyze the impact of Sino-US trade frictions on oil prices. Acute trade events represent negative trade friction events and are represented by BEARISH, which is BEARISH=1 when such events occur and 0 otherwise. Similarly, palliative trade events represent positive trade friction events, BULLISH with BULLISH=1 when such events occur and 0 otherwise. We add intensification and moderating trade event dummy variables to the oil price EGARCH model to analyze the impact of Sino-US trade frictions on oil price returns and fluctuations. The EGARCH model of basic trade friction events and oil prices is expressed as follows:

$$R_t = \mu + \sum_1^n R_{t-1} + \lambda BEARISH_t + \zeta BULLISH_t + \eta X_t + \epsilon_t \quad (1)$$

$$\epsilon_t \sim \text{iidN}(0, \sigma_t^2) \quad (2)$$

$$\ln\sigma_t^2 = \omega + \alpha \left[\frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right] + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \upsilon BEARISH_t + \varphi BULLISH_t + \tau X_t \quad (3)$$

Equation (1) is the mean oil price equation, indicating that oil price is a function of constant term μ, lag term of oil price yield, Sino-US trade friction events, some control variables. The mean value equation of equation (1) describes the change in the oil price yield. Equation (3) is the conditional heteroscedasticity equation, where ω is a constant; α is the ARCH term, which measures the impact of shock on conditional heteroscedasticity. β is the GARCH term, which measures the volatility concentration of the price. The higher the GARCH value, the longer the oil price volatility will last when the shock occurs. In addition, Sino-US trade frictions and some control variables also have an impact on the volatility of oil prices. γ measures the asymmetric effects of positive and negative shocks: when γ is negative, negative shocks have a greater impact on oil prices than positive shocks. When γ is positive, positive shocks have a greater impact on oil prices than negative shocks.

3.2 Event study

Event analysis is a widely used analysis method, which is often used in empirical financial literature to analyze the impact of important events on enterprises. Event analysis evaluates the impact of events such as mergers and acquisitions or financial announcements on corporate stock returns by measuring the abnormal returns of corporate stock around recurring related events.

In this paper, we take the Sino-US trade friction incident as the center and analyze the changes and significance of oil prices before and after the incident, so as to analyze the dynamic impact of trade friction events on oil prices. Based on the EGARCH model mentioned in the first part, trade friction events are included in the model. The EGARCH regression model of event analysis is as follows:

$$R_t = \mu + \sum_1^n R_{t-1} + \sum_{-m}^m \lambda_s BEARISH_s + \sum_{-m}^m \zeta_s BULLISH_s + \eta X_t + \epsilon_t \quad (4)$$

$$\epsilon_t \sim \text{iidN}(0, \sigma_t^2) \quad (5)$$

$$\ln\sigma_t^2 = \omega + \alpha\left[\frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right] + \beta\ln(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{-m}^{m}\lambda_s BEARISH_s + \sum_{-m}^{m}\zeta_s BULLISH_s + \tau X_t \quad (6)$$

Where R_t is the logarithmic yield of oil price. S measures the time interval of intensified and alleviated trade friction events, the unit of which is day, and the range of time interval is [-m,m], indicating that the window period for the occurrence of trade friction events ranges from m working days before the occurrence of trade friction events to m working days after the occurrence of trade friction events. $BEARISH_s$ and $BULLISH_s$ are active and moderating trade event dummy variables respectively: The intensified trade event dummy variable is formed by adding P dummy variables, where P is the number of the intensified trade event, that is, $BEARISH_s = \sum_{p=1}^{P} BEARISH_{ps}$, and $BEARISH_{ps}$ represents the dummy variable s trading days apart from the p intensified trade event. The mitigated trade event dummy variable is formed by adding Q dummy variables, where Q is the number of mitigated trade events, and $BULLISH_{qs}$ represents the bullish variable that is s trading days away from the q mitigated trade event. The details are as follows:

$$BEARISH_{ps} = \begin{cases} 1, t = t_{tf,p} + s \\ 0, Other \end{cases} \quad (7)$$

$$BULLISH_{qs} = \begin{cases} 1, t = t_{tf,q} + s \\ 0, Other \end{cases} \quad (8)$$

3.3 Dynamic correlation

When oil prices are hit by an external shock, traders adjust their portfolios to avoid risk, which causes the price of the relevant market to move in tandem with the price of the crude oil market. For example, in times of trade war between China and the United States, trading in the crude oil market rises, and traders may shift funds to markets that can hold their value, such as gold. For cross-market linkage effect, this paper uses Engel (2002) dynamic correlation coefficient autoregressive conditional abnormal volatility (DCC GARCH) model to analyze. Assuming that$r_t$is n x 1 asset return vector and asset return is a first-order autoregressive process, then:

$$r_t = \mu + \alpha r_{t-1} + \varepsilon_t \quad (9)$$

$$\epsilon_t = H_t^{1/2} Z_t \quad (10)$$

Where H_t is the conditional covariance matrix of the asset return vector.The DCC GARCH model proposed by Engel (2002) is estimated by a two-step method. The first step is to calculate the parameters of the GARCH part of the model. The second step is to estimate the time-varying covariance volatility matrix, as follows:

$$H_t = D_t R_t D_t \quad (11)$$

Where H_t is the time-varying covariance volatility matrix, R_t is the conditional correlation matrix,$D_t$is the diagonal matrix obtained when calculating the standard deviation, $D_t = diag\left(h_{1,t}^{\frac{1}{2}}, \dots h_{n,t}^{\frac{1}{2}}\right)$, where h is a univariate GARCH model. Transform R_t as follows:

$$R_t = diag(q_{1,t}^{-\frac{1}{2}}, \dots q_{n,t}^{-\frac{1}{2}}) Q_t diag(q_{1,t}^{-\frac{1}{2}}, \dots q_{n,t}^{-\frac{1}{2}}) \quad (12)$$

Assuming h is of GARCH (1,1) form, then the time-varying covariance volatility matrix H_t is of the following form:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \quad (13)$$

In addition, Q_t is a symmetric positive definite matrix:

$$\boldsymbol{Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 z_{t-1} z_{t-1}' + \theta_2 Q_{t-1}} \quad (14)$$

$\boldsymbol{\bar{Q}}$ is an unconditional correlation matrix of normalized residuals with parameters θ_1 and θ_2 being non-negative. These parameters are related to the exponential smoothing process and are used to construct the dynamic correlation coefficients of the variables. The dynamic correlation coefficient is shown as follows:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{i,j,t}}} \quad (15)$$

IV. EMPIRICAL RESULTS

4.1 Basic result analysis

From the previous data analysis, we can see that the logarithmic yield form of oil prices, the S&P 500 index, the federal funds rate, and open positions are all stationary. Table 2 shows the estimated results under the baseline regression of the EGARCH model for the estimated period from January 1, 2017 to December 31, 2019. The first part of Table 2 describes the estimation results of the mean part, and the second part is the estimation results of the conditional heteroscedasticity part.

Table 2 Effects of Sino-US trade frictions on oil price returns and fluctuations

	Coefficient	Deviation	T statistic	P value
Mean				
Lag	-0.0423	0.0238	-1.7786	0.0753
BEARISH	-0.0066	0.0024	-2.7189	0.0066
BULLISH	0.0013	0.0007	1.7308	0.0835
S&P500	0.2603	0.0494	5.2679	0.0000
Fed fund rate	0.2218	0.0506	4.3838	0.0000
Open interest	0.0450	0.0014	31.4803	0.0000
Volatility				
Arch	-0.0549	0.0051	-10.6897	0.0000
Garch	0.9821	0.0057	171.8143	0.0000
Asymmetry	-0.0584	0.0022	-26.2436	0.0000
BEARISH	0.1112	0.0002	567.8626	0.0000
BULLISH	-0.3124	0.2113	-1.4789	0.1392
S&P500	-1.5994	0.2229	-7.1738	0.0000
Fed fund rate	-9.6220	0.0009	-10733.9267	0.0000
Open interest	-1.7269	0.0001	-20852.6679	0.0000

First of all, in the mean equation of EGARCH model, the impact of stock price (S&P 500 index) on oil price is positive and significant, with stock yield rising by 1 percentage point and oil yield rising by 0.26 percentage point. According to the "stability related theory" of stock market and macro economy, the fluctuation of macro economy is the basis of stock price changes, and the stock price reflects the macro economic situation. Fama (1990) and Schwert (1990) studied the changes of stock prices in the United States from 1953 to 1987, and the results showed that stock prices were closely related to macroeconomic conditions, and the results were significant in monthly, quarterly and annual cycles. Kilian (2019) uses the structural vector autoregressive model to study the effects of crude oil market supply, macroeconomic fluctuations and speculative demand on oil prices, and the results show that macroeconomic fluctuations are the most important factors affecting oil prices. Therefore, the overall price of the stock market reflects the macroeconomic situation, which will also affect the movement of oil prices. Kilian and Park (2007) also show that when unexpected economic expansion occurs, oil price changes are positively correlated with stock price changes. In terms of the volatility of oil prices, the change of the S&P 500 index is negatively correlated with the volatility of oil prices. According to the previous analysis, the stock market reflects the macroeconomic situation. If the stock market continues to decline, then the macro economy may turn into a recession. Nicholas (2014) pointed out that in a depression, the uncertainty in the economy would rise, so people would be more difficult to judge the future economic trend, and there would be greater differences in the future economic expectations. If reflected in the crude oil market, the divergence among crude oil traders has also increased, implying greater crude oil price volatility.

In the conditional heteroscedasticity, both the ARCH term and the GARCH term are highly significant. Moreover, the volatility cluster parameter ($\alpha+\beta$) is close to 1, indicating the volatility of oil prices has volatility cluster. In other words, when oil prices fluctuate due to external shocks to the oil market, the volatility of oil prices will take some time to gradually diminish. The ($\ln 0.5/\ln(\alpha+\beta)$) ratio can be used to calculate the half-life of oil price fluctuations in response to external shocks. According to this calculation, it takes about 9.1 days for oil price fluctuations to decrease by 50%. The leverage effect in the EGARCH model is also significant and negative. This means that under the same intensity conditions, negative shocks have a stronger impact on oil price fluctuations than positive shocks.

As for the impact of Sino-US trade frictions on oil prices, EGARCH model results show that the impact of intensified trade events on oil price returns is negative and significant. When an intensified trade friction event occurs, the oil price yield falls 0.7 percentage points, and the result is significant at the 1% level. Moreover, when an intensified trade event occurs, oil price volatility increases. Relatively speaking, the impact of palliative trade events on the oil price yield is positive and significant at the level of 10%, and when the palliative trade events appear, the oil price yield rises by 0.1 percentage points. In addition, easing trade events have reduced the volatility of oil prices.

4.2 The dynamic impact of Sino-US trade frictions

We use event analysis to study the dynamic impact of Sino-US trade frictions on oil prices. This method has been widely used in the field of financial research, but it is still rarely used in the study of oil prices. Event analysis studies the abnormal price fluctuations around a specific time. In this paper, it refers to the abnormal price fluctuations before and after the occurrence of trade friction events. The impact of the event may be reflected in the price immediately, or it may take time to be gradually reflected in the price. Since the international crude oil market is already a relatively mature market with high market liquidity, this paper chooses two days before and after the occurrence of trade friction events as the event analysis window. BEARISH(-1) and BEARISH(-2) represent the first day and the second day before the occurrence of an intensified trade friction event, and BEARISH(+1) and BEARISH(+2) represent the first day and the second day after the occurrence of an intensified trade friction event. BULLISH(-1) and BULLISH(-2) represent the first and second days before the event of palliative trade friction, while BULLISH(+1) and BULLISH(+2) represent the first and second days after the event of palliative trade friction.

The results in Table 3 show that, within the event analysis window, the impact of intensified trade friction events on the benefit of oil prices is significant. On the day of the intensified trade friction event, the oil price fell the most, the oil price yield fell by 0.7%, but the decline narrowed to 0.1% on the second day, and resumed the decline on the third day, with a significant mean recovery feature. As Delong et al. (1990) pointed out, because there are many noise traders in the market, they will buy financial assets when the price rises and sell financial assets when the price falls, which makes the price of financial assets reflect the mean-recovery feature. For example, when good news is released in the market, rational speculators expect prices to rise and buy financial assets, but at the same time they expect noisy traders in the market to blindly chase up the price, so rational speculators will buy more financial assets, pushing the price of financial assets to a higher level. Noise traders then see the price rise and enter the market to trade, keeping the price above the fundamentals, at which point some rational speculators begin to sell for profit. While the price rise is partly rational, it is partly due to rational anticipation trading by speculators and the positive feedback effect of traders on such trades. In the long run, financial asset prices converge towards fundamentals and are expected to fully revert to the mean.

Table 3 Dynamic impact of Sino-US trade frictions on oil prices

	Coefficient	**Deviation**	**T statistic**	**P value**
LAG	-0.049	0.028	-1.714	0.086
S&P500	0.629	0.070	8.950	0.000
Fed fund rate	0.014	0.006	2.250	0.024
Open interest	0.232	0.042	5.565	0.000
BEARISH	-0.007	0.000	-14.967	0.000
BULLISH	0.006	0.004	1.427	0.154
BEARISH(-1)	-0.004	0.001	-6.114	0.000
BEARISH(-2)	0.005	0.001	7.027	0.000
BEARISH(+1)	-0.001	0.001	-2.117	0.034
BEARISH(+2)	0.000	0.004	0.020	0.984
BULLISH(-1)	0.003	0.004	0.745	0.456
BULLISH(-2)	-0.001	0.005	-0.227	0.820

BULLISH(+1)	-0.006	0.007	-0.771	0.441
BULLISH(+2)	0.004	0.004	1.055	0.291
Arch	-0.076	0.023	-3.281	0.001
Garch	0.979	0.002	600.125	0.000
Asymmetry	0.104	0.035	2.957	0.003
S&P500	-10.301	2.654	-3.881	0.000
Fed fund rate	-1.504	0.727	-2.068	0.039
Open interest	-4.292	3.059	-1.403	0.161
BEARISH	0.223	0.460	0.484	0.629
BULLISH	0.683	0.730	0.936	0.349
BEARISH(-1)	0.667	0.342	1.950	0.051
BEARISH(-2)	-0.699	0.273	-2.560	0.010
BEARISH(+1)	-0.308	0.587	-0.524	0.600
BEARISH(+2)	0.198	0.360	0.552	0.581
BULLISH(-1)	-0.133	0.620	-0.214	0.831
BULLISH(-2)	-1.159	0.284	-4.078	0.000
BULLISH(+1)	-0.029	1.131	-0.026	0.979
BULLISH(+2)	0.388	0.608	0.638	0.523

In the EGARCH model of event analysis, the impact of mitigated trade frictions on oil prices is not significant. Because people are generally more sensitive to negative news, negative news has a greater impact on market sentiment, and market prices reflect negative news more obviously.

In addition, this paper finds that market traders have expectations for the occurrence of trade friction events. In the case of intensified trade frictions, the oil price yield declined gradually from 0.5% to -0.4% two days before the trade frictions occurred. Although the effect of the mitigated trade friction event was not significant, the oil price yield rose from -0.1% to 0.3% in the two days before the mitigated trade friction event. As Demirer and Kutan (2010) pointed out, information leakage is a common phenomenon in the information age, and some transactions may obtain inside information in advance.

4.3 Mechanism analysis

4.3.1 Risk premium mechanism

In the previous analysis, we have shown that Sino-US trade frictions have an impact on oil prices. Among them, intensified trade friction events make the return on oil prices decline, and moderated trade friction events make the return on oil prices rise. Intensified trade friction events have a greater and significant impact on oil prices than moderated trade friction events. In this part, we study whether Sino-US trade frictions have an impact on oil prices through the risk premium channel.

Table 4 Analysis of risk premium effect of Sino-US trade frictions

	Coefficient	Deviation	T statistic	P value
LAG	-0.020	0.0365	-0.546	0.5852
BEARISH	-0.005	0.0053	-0.980	0.3271
BULLISH	0.0030	0.0045	0.6646	0.5063
S&P500	0.3099	0.0585	5.2939	0.0000
Fed fund rate	0.3493	0.0956	3.6523	0.0003
Open inetrest	0.0325	0.0192	1.6977	0.0896
Conditional heteroscedasticity	0.0103	0.1994	0.0514	0.9590

ARCH	-0.051	0.0288	-1.764	0.0777
GARCH	0.915	0.0000	1283000.000	0.0000
gamma1	-0.080	0.0636	-1.264	0.2061
BEARISH	0.143	0.0926	1.545	0.1223
BULLISH	-0.125	0.2217	-0.562	0.5743
S&P500	-5.496	2.4626	-2.232	0.0256
Fed fund rate	-1.226	3.7425	-0.327	0.7433
Open interest	-0.515	1.2281	-0.420	0.6748

Risk premium refers to the expected return on financial assets exceeding the risk-free return on investment. The risk premium of financial assets is a form of compensation to investors, which represents the reward paid to investors for taking more risk in a given investment than in a risk-free asset. The size of the risk premium depends on the level of risk of a particular investment and also changes over time with fluctuations in market risk. In general, high-risk investments can command a higher premium. Most economists agree that the concept of an equity risk premium, in which the market pays investors more in the long run for taking on more risk, is correct. Hamilton and Wu (2009) established a risk premium model for crude oil market, indicating that with more and more financial institutions participating in crude oil futures trading, the risk premium mechanism of crude oil market has changed. In this paper, in the crude oil market, Sino-US trade frictions will increase the risk of crude oil price fluctuations. If the risk premium mechanism exists, the fluctuations of oil prices will have an impact on the return rate of oil prices.

In order to test whether trade friction events affect oil price returns through risk premium channels, we construct an EGARCH-M model using conditional heteroscedasticity as an independent variable for analysis. As described by Hudson et al. (2020) and Jiang (2019), if we control the conditional variance in the model and assume that the coefficient of the conditional variance term is significant, while the Sino-US trade friction event coefficient becomes insignificant or significantly smaller, then the risk premium is the reason why Sino-US trade friction events affect the oil price yield.

Table 4 reports the estimated results of the EGARCH-M model that includes trade friction events. We can see that the impact of S&P 500 index, federal funds rate and open interest on oil prices is still significant, but the impact of oil price fluctuations on yields is not significant, which cannot support the conclusion that there is an intermediary effect of risk premium.

4.3.2 Market sentiment mechanism

Qadan and Nama (2018) point out that as more financial institutions participate in crude oil futures trading, market sentiment has become increasingly important in determining oil prices. First, crude oil prices have been significantly more volatile since the new millennium, which is difficult to explain by fundamental factors. Second, the participants in the oil market trading have undergone profound changes, and the financialization of crude oil is increasing. More scholars have also realized the importance of behavioral finance factors in the analysis of oil prices, and the "animal spirits" of traders will have an impact on oil prices, and even cause large changes in oil prices. Singleton(2014) points out that the results of traditional SVAR analysis can be misleading due to the lack of representation of market participants' emotions. Because there is information friction in the market, market participants will have different opinions, which will cause oil prices to drift. Xiong and Yan(2009) demonstrated. A large number of financial institutions began trading in the crude oil market, which was an important reason for the sharp rise in crude oil prices from 2002 to 2008, and trader sentiment has an impact on oil prices. Banerjee(2009) believes that the phenomenon of price drift may be caused by fluctuations in market sentiment.

In order to analyze the mediating effect of market sentiment on the impact of trade friction events on oil price returns, we refer to Zhou (2018) and use the Williams market technical indicators to measure market sentiment. Incorporating market sentiment into the EGARCH model, Table 5 shows that market sentiment has a significant impact on oil prices. During the Sino-US trade war period from 2017 to the end of 2019, market sentiment has a negative impact on oil price returns. But at the same time, we can see that the coefficients of both intensified and mitigated trade friction events become insignificant, indicating that when trade friction events occur, market sentiment will change and then affect the oil price yield.

Table 5 Analysis of market sentiment effect of Sino-US trade frictions

	Coefficient	Deviation	T statistic	P value
Lag	-0.1750	0.0413	-4.2351	0.0000
BEARISH	-0.0046	0.0053	-0.8625	0.3884
BULLISH	0.0015	0.0054	0.2701	0.7871
S&P500	0.3184	0.1002	3.1760	0.0015
Fed fund rate	0.0363	0.0196	1.8543	0.0637
Open interest	0.2170	0.0587	3.6960	0.0002
Sentiment	-0.0003	0.0000	-12.7507	0.0000
ARCH	-0.0035	0.0266	-0.1308	0.8959
GARCH	0.9351	0.0058	161.4094	0.0000
Asymmetry	0.0963	0.0202	4.7662	0.0000
BEARISH	0.2862	0.1252	2.2848	0.0223
BULLISH	0.1163	0.3358	0.3462	0.7292
S&P500	-4.0828	4.2386	-0.9633	0.3354
Fed fund rate	-0.5427	1.2986	-0.4179	0.6760
Open interest	-0.5112	3.0822	-0.1659	0.8683
Sentiment	0.0024	0.0009	2.6053	0.0092

4.3.3 Asset portfolio adjustment mechanism

When the market suffers from external shocks, market risks rise, and investors may adjust their asset portfolios and invest more funds in safe assets (Goyenko and Ukhov, 2009; Fang Yi et al., 2019). For many years, gold has been a generally accepted medium of exchange due to the effectiveness of gold trading and the value of gold. Today, many investors choose to invest in gold rather than other assets because it holds its value over the long term. Even in times of political turmoil, inflation, and financial crisis, gold is not a credit risk. Moreover, it is the world's only common currency. Simply put, gold acts as a safe-haven asset to protect your savings in the event of turbulence.

In order to test whether the occurrence of Sino-US trade frictions causes traders to adjust asset portfolios and transfer funds from the crude oil market to the gold market, we first adopted the DCC-GARCH model to obtain the dynamic correlation coefficient between crude oil and gold during the Sino-US trade war, and then referred to Fang Yi et al. (2019) and used the following formula:

$$DCC_t = BEARISH_t + BULLISH_t + \varepsilon_t \quad (17)$$

$$DCC_t = DCC_{t-1} + BEARISH_t + BULLISH_t + \varepsilon_t \quad (18)$$

If the occurrence of trade friction events affects the dynamic relationship of the price of gold, then the coefficient of intensified trade friction events or mitigated trade friction events should be significant. However, according to the results of formula regression, the event coefficient of trade friction is not significant, which cannot support the conclusion that investors' risk-averse adjustment of asset portfolio leads to the change of oil price yield.

V. CONCLUDING REMARKS

Since 2017, Sino-US trade frictions have been continuous, during which the international crude oil prices have also fluctuated greatly. This paper divides Sino-US trade frictions into intensified and moderated trade events, and uses the EGARCH model to analyze their impact on oil prices. The regression results show that the intensive-type trade events significantly reduce oil price returns and increase oil price volatility, but the moderate-type trade events have no significant impact on oil prices. The impact of intensified trade events on oil prices has the feature of mean recovery. The oil price yield decreases the most on the first day but recovers to the original level on the third day, and the dynamic impact of moderated trade events on oil prices is not significant. The results of this paper show that Sino-US trade friction has a leverage effect on oil prices, that is, negative news has a greater impact on prices than positive news. Further analysis shows that Sino-US trade frictions mainly affect oil prices through the market sentiment mechanism.

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