

# The Linkage between Crude Oil and Stock market: Evidence from China and the United States

Shiyun Liu

School of Economics, Zhongnan University of Economics and Law, Wuhan, China

871520273@qq.com

**Abstract.** The global crude oil and stock markets have been extremely volatile in recent years, with prices fluctuating rapidly. We considered the linkages between the crude oil market and the stock market in China and the US, applying a time-varying t-Copula-GARCH model based on the Chinese INE crude oil futures price and the SSE, and American WTI crude oil futures price and the S&P 500. We found that there are positive correlations between crude oil and stock markets in both China and the United States. Although the linkages between the two markets are weaker in China than in the United States, the magnitude of the changes and the volatility are larger. In addition, the linkages between the two markets in China and the U.S. increase significantly under extreme risk events such as the COVID-19 pandemic. These findings enrich the research on the linkages between commodity and stock markets.

**Keywords:** Linkage, Crude Oil market, Stock market, Time-varying t-Copula-GARCH model.

## 1. Introduction

Crude oil is a commodity that can be price-volatile to a high degree (Regnier, 2007). Global stock and crude oil market prices have been violently fluctuating in recent years as a result of government policies, geopolitics, the economic situation, and the COVID-19. The outbreak of the COVID-19 in early 2020 leads to increased uncertainty in commodity and financial markets in countries hit by the virus (Mhalla and M., 2020; Zhang et al., 2020). Sharp reduction in output as a result of the epidemic, weakened economic situation, plummeting crude oil prices, depressed stock prices, and highly volatile oil and stock prices. For instance, like the "Crude Oil Treasure" incident in 2020, which even led to a negative oil price for the first time in history, it became a global sensation. Additionally, the oil and stock market prices of China and the U.S. suffered distinct changes driven by the festering trade war between China and the U.S. and the continuous control of crude oil supply by OPEC.

In this background, the volatility of stock market and oil market prices and the correlation between them are significant for exploring the hedging of systemic risks in financial markets and further regulating the new-born crude oil futures market in China. The term "linkage" was first proposed by Lucas in 1977 in his book "A Study of Economic Cycle Theory", which refers to the co-movement trend among macroeconomic variables under the business cycle. With the integration of international financial markets, the term "linkage" has been applied to the field of financial markets to describe the mutual influence relationship between financial markets, where different market prices interact to present linkage characteristics (Zeng et al., 2009).

Currently, there are quite a number of studies devoted to crude oil market and stock market correlation. Malik and Ewing (2009), Arouri et al. (2011) empirically identified a significant volatility spillover between the U.S. stock and oil markets. Tang et al. (2021) examined the impact of oil futures price fluctuations on U.S. stock market volatility, noting that petroleum price information is an important part of predicting American stock market volatility. Nguyen and Bhatti (2012) explored the relationship between China and international crude oil prices and found that the two markets do not display a tail-dependence. However, Zhao et al. (2021) discovered a mutual contagion between the Chinese stock and crude oil markets in 2008 and 2014, which may be attributed to China's unique energy structure, pricing mechanism, and speculative activities. Although there are quite a dozen studies that independently study the American or Chinese oil and stock markets, the literature that compares the two is relatively scarce. Jin Hongfei and Jin Eminent (2008) recognised that there is no yield spillover impact between the Chinese stock market and the worldwide crude oil market, while

America has a two-way volatility spillover. Broadstock and Filis (2014) concluded that China's stock market appears to be more resilient to shocks than the US. Lu Xunfa et al. (2021) found that the dynamic conditional correlations between the stock markets of China and the U.S. show a decreasing trend with crude oil futures prices after a breakpoint in returns, and that China suffers fewer crude oil price shocks relative to the U.S.

Therefore, we put forward two reasonable assumptions:

H1. Both the U.S. and Chinese equity markets and crude oil markets have relatively significant linkages.

H2. The linkage between crude oil and equity markets in China is weaker than in the U.S., but the variations are greater and more volatile.

In order to probe the crude oil market and stock market links and draw more effective conclusions in terms of model selection, scholars currently apply three main types of fairly mature methods. First, the VAR model or VEC model is applied to study (Huang et al., 1996; Papapetrou, 2001; Hammoudeh and Eleisa, 2004; Masih et al., 2011; Mensi et al., 2021). Second, GARCH family models are used to model price series (Qiang Ji and Ying Fan, 2010; Filis et al., 2011; Arouri et al., 2011; Lai et al., 2011; Liu et al., 2017). Third, a small number of scholars used the copula function to explore the correlation between markets (Zohrabyan, 2008; Nguyen and Bhatti, 2012; Kielmann et al., 2021). The time-varying Copula model proposed by Patton (2006) can avoid the static Copula model's shortcomings. Since the time-varying Copula model can not only well portray the nonlinear interdependence structure between markets, but also depict the dynamic change characteristics of the interdependence structure, it is widely used in the measurement of intermarket linkage.

In terms of sample selection, most scholars have chosen international crude oil futures prices for empirical analysis in their studies on the linkages between the Chinese crude oil market and the stock market (Qian Chen and Xin Lv, 2015; Kielmann et al., 2021; Liu et al., 2020; Mensi et al., 2021), or by using crude oil spot price data, including Daqing and Shengli price data for empirical modelling (Zhao et al., 2021). Price discovery and price guidance functions are available in INE crude oil futures, allowing them to better reflect changes in subjects' needs and expectations, as well as shifts in market supply and demand. However, there is a scarcity of literature on market linkage studies using INE crude oil futures prices. Zhang Dayong and Ji Qiang (2018) first empirically analysed the dependency relationship between INE and SSE. Wang, et al. (2021) found a remarkable spillover effect between INE and WTI and Brent crude oil prices.

Furthermore, volatility spillovers between markets under extreme risk events tend to differ from the findings in smoother time periods. Academics have found that stock and oil markets are significantly correlated during financial crises (e.g., Souek and Todorova, 2013; Awartani and Maghyreh, 2013; Filis et al., 2011), and that in post-crisis periods, fuel prices generate a strikingly negative impact on stock returns, while a lagged rise produces a positive impact (Liu et al., 2020), and that the COVID-19 exacerbates crude oil market and stock market correlations in the US and China (e.g., Mensi et al., 2021; Kielmann et al., 2021).

Given this, one alternative hypothesis is reasonably proposed.

H3. The linkages between both the American and Chinese equity and crude oil markets strengthen under extreme risk events.

In summary, although numerous studies have been conducted on the relationship between crude oil and the stock market, the vast majority of existing research has considered the relationship between the two markets in China and the U.S. separately, while those differences between China and the U.S. are still lacking. Meanwhile, international crude oil prices are commonly used to evaluate the association between the Chinese stock and oil market without selecting the Chinese crude oil futures price, which may have poor sample representativeness. Therefore, we made a targeted innovation with the following three main contributions:

First, in terms of research perspective, we studied the linkages between crude oil and the stock markets in China and America, where we innovatively compared the similarities and differences in linkages between the two markets in China and America.

Second, for sample selection, we picked INE crude oil futures to reflect the price volatility of the Chinese crude oil market, making it more representative. In addition, the sample interval covers the period before, during, and after the epidemic, and the dynamic conditional correlations of the two markets were contrasted within the sample interval between the normal period and the episodes of extreme risk events, rendering the data more up-to-date and complete.

Third, from the perspective of the research model, the time-varying t-Copula-GARCH was applied to obtain the dynamic conditional correlation coefficients between the oil market and the stock market. In comparison with the traditional linear model, this model can better portray the nonlinear dynamic correlation between markets.

## 2. Method

### 2.1 Copula function

Copula function can be used to describe the correlation between diverse variables, and is frequently used to calculate the correlation of return series. Copula function, also called link function, can connect the marginal distribution of each random variable to form a multivariate joint distribution, which was first proposed by Sklar's theorem in 1959.

Based on Copula theory, for each p-dimensional distribution F, there is a Copula function C,

$$F(x_1, x_1, \dots, x_n) = C(F_1(x_1), \dots, F_p(x_p)) \quad (1)$$

And all the marginal distributions of random variables are continuous functions, then the function C is the only copula function.

Let  $y_i = F_i(x_i)$ , if F is p-order differentiable, then the copula density function is

$$c(y_1, \dots, y_n) = \frac{f(F_1^{-1}(y_1), \dots, F_p^{-1}(y_p))}{\prod_{i=1}^p f_i(F_i^{-1}(y_i))} \quad (2)$$

The log-likelihood function is

$$L((\lambda, \theta), x) = \sum_{j=1}^T \left( \sum_{i=1}^p \log(f_i(x_{i,t}; \lambda)) + \log(c(y_1, \dots, y_p); \theta) \right) \quad (3)$$

The above equation contains the parameters  $\lambda$ ,  $\theta$  of the marginal distribution and the copula function, which can be decomposed into the log-likelihood function of the marginal distribution and the copula likelihood function, and then the estimation of the parameters is completed by the independent two-step method.

### 2.2 Time-varying t-Copula-GARCH-skew-t model

Based on historical information, the time-varying Copula-GARCH model is able to capture the nonlinear dynamic dependence between the two markets and provides a better fit to the actual data than traditional linear models.

Define  $R_{stock,t}$  (stock=S&P 500, SSE) to be the return of S&P 500,  $R_{oil\ prices,t}$  (oil prices=WTI, INE) to be the return of WTI and INE crude oil at time t. Let  $\mu_1 = F_{stock}(R_{stock,t}|\psi_{t-1})$  and  $\mu_2 = F_{oil\ prices}(R_{oil\ prices,t}|\psi_{t-1})$  be the conditional accumulation distribution functions of stocks and crude oil, respectively, where  $\psi_{t-1}$  denotes all of the relevant returns for both stocks and both crude oils in the sample interval past information,  $\mu_1, \mu_2$  obey uniform distribution on the (0, 1) interval and are continuous. The conditional Copula density function is

$$c_t(\mu_{1,t}, \mu_{1,t}|\psi_{t-1}) = \frac{\delta^2 C_t(\mu_{1,t}, \mu_{1,t}|\psi_{t-1})}{\delta \mu_{1,t} \delta \mu_{2,t}} \quad (4)$$

In the independent two-step process, the two marginal distributions are first estimated separately with Maximum likelihood estimation (MLE), and then the joint distribution of the conditional copula functions is estimated with MLE.

### 2.2.1 Marginal distribution

Financial time-series data tend to be characterized by spikes, thick tails and skewness, while asymmetric data do not conform to the assumption of normal distribution. The skew-t distribution is considered and a GARCH-skew-t model is developed to fit the return data. To eliminate the autocorrelation and heteroskedasticity problems of the original return series, the ARMA (p, q) method will be introduced to deal with these issues. Therefore, for better fitting effect, the marginal distributions of  $R_{stock,t}$  (stock=S&P 500, SSEC) and  $R_{oil\ prices,t}$  (oil prices=WTI, INE) are specified as GRACH (1, 1)-skew-t models. The specific process can be expressed as

$$R_{i,t} = \mu_{i,j} + \sum_{j=1}^p \varphi_{i,j} R_{i,t-j} + a_{i,j} - \sum_{j=1}^q \eta_{i,j} a_{i,t-j} \tag{5}$$

$$a_{i,t} = \sigma_{i,t} \varepsilon_{i,t}, \varepsilon_{i,t} \sim i. i. d. skst(v, \xi) \tag{6}$$

$$\sigma_{i,t}^2 = \alpha_{i,0} + \alpha_i a_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \tag{7}$$

$$t = 1, 2, 3, \dots, T$$

Where  $R_{i,t}$  denotes the actual return at moment t,  $\mu_{i,j}$  represents the expected return at moment t,  $\varphi_{i,j}$  and  $\eta_{i,j}$  indicate the parameters to be sought in the model, p is the order of the autoregressive model AR(p), and q is the order of the moving average model MA(p), and  $\alpha_{i,0} > 0, a_{i,t} \geq 0, \beta_i \geq 0$ .  $\varepsilon_{i,t}$  is independent and identically distributed random variables, denotes the residual term of the asset return with the mean removed and autocorrelation eliminated and obeying the skew-t distribution.  $v$  and  $\xi$  are the degrees of freedom and asymmetric parameters of the skew-t distribution, correspondingly.  $\alpha_i + \beta_i < 1$  is a sufficient necessary condition for GARCH (1, 1) to be smooth.

### 2.2.2 Time-varying t-Copula function

The estimated parameters  $\mu_1$  and  $\mu_2$  are obtained above and made equal to  $u_1$  and  $u_2$ , respectively, for the second step of parameter estimation of the dependency relationship.

The binary t-Copula distribution function is

$$C(u_1, u_2, \rho, v) = \int_{-\infty}^{T_v^{-1}(u_1)} \int_{-\infty}^{T_v^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \left[ 1 + \frac{x^2 + y^2 - 2\rho xy}{v(1-\rho^2)} \right]^{-\frac{(v+2)}{2}} dx dy \tag{8}$$

$$\text{Let } \phi_i = t_v^{-1}(u_i), \phi_t = (t_v^{-1}(u_{1,t}), t_v^{-1}(u_{2,t})),$$

The log-likelihood function constructed for the log returns of crude oil prices and stock indices is

$$LL(\rho, v, u_t) = -T \log \frac{\Gamma(\frac{v+2}{2})}{\Gamma(\frac{v}{2})} - 2T \log \frac{\Gamma(\frac{v+1}{2})}{\Gamma(\frac{v}{2})} - \frac{v+2}{2} \sum_{t=1}^T \left( 1 + \frac{\phi_t' \rho^{-1} \phi_t}{v} \right) - \sum_{t=1}^T \log |\rho| + \frac{v+1}{2} \sum_{t=1}^T \sum_{i=1}^2 \log \left( 1 + \frac{\phi_{it}^2}{v} \right) \tag{9}$$

Consider the time-varying dynamic process as follows.

$$Q_t = (1 - \alpha - \beta) \cdot \bar{Q} + \alpha \phi_{t-1}' \phi_{t-1} + \beta Q_{t-1} \tag{10}$$

$$\rho_t = \bar{Q}_t^{-1} Q_t \bar{Q}_t^{-1} \tag{11}$$

Where the model is stable provided  $\alpha + \beta < 1, \alpha, \beta \in (0, 1)$ , and  $\alpha, \beta$  are parameters.  $\bar{Q}$  is the sample variance of  $\phi_t$ ,  $\bar{Q}_t$  is a 2x2-dimensional diagonal matrix whose diagonal elements have values of the square root of the diagonal elements of  $Q_t$ . In this time-varying t-Copula model, the parameters of the copula function are the two-return series tail correlation coefficients.

### 3. Empirical analysis

#### 3.1 Data and processing

##### 3.1.1 Data

We use the Shanghai Composite Index and the INE crude oil futures price as price volatility indicators for the Chinese stock market and the crude oil market separately. Meanwhile, the U.S. West Texas light crude oil futures price (WTI) and the S&P 500 index have been chosen as the price fluctuation indicators for the American stock market and the crude oil market. The data period is set from March 27, 2018 to August 30, 2021, and the data is daily frequency from the Wind database.

##### 3.1.2 Variable processing

Considering the smoothness of the data, the series of WTI crude oil futures prices, American S&P 500 Index, China Shanghai Composite Index and INE crude oil futures prices are logarithmicized. The expression is as follows:

$$R_t = \ln P_t - \ln P_{t-1} \quad (12)$$

In which,  $R_t$  denotes the daily price yield at time  $t$ ,  $P_t$  is the daily closing price at moment  $t$ , and  $P_{t-1}$  represents the daily closing price at moment  $t-1$

After the logarithmic processing, the data series have small values, which are not conducive to model building and analysis of the results. Accordingly, referring to the data processing method of Huiming Zhu et al. (2015), all the data were subjected to an expanded numerical treatment of multiplying by 100, a processing that does not affect the data nature and data structure.

On this basis, three more steps were carried out successively: first, the inconsistent data were eliminated in consideration of the inconsistent sample size of the data series caused by holiday closures and data omissions; second, the data range was limited to the -10 to 10 interval to ensure the stability of the data; third, the mean value was used to fill in and replace the missing data and outlier data.

#### 3.2 Basic data characteristics

**Table 1.** Results of descriptive statistical analysis of log returns

	WTI	S&P 500	INE	SSEC
Mean	0.0432	0.0765	-0.0201	0.0414
Median	0.0253	0.0702	0.0227	0.0000
Maximum	9.8721	8.9683	9.7319	9.8365
Minimum	-9.8652	-9.9945	-9.7063	-9.6796
Std.Dev	2.2317	1.2731	2.3022	1.4926
Skewness	-0.4871	-0.2577	-0.1921	0.8201
Kurtosis	3.0008	14.1704	3.0616	14.0005
Unit root test	0.00***	0.00***	0.00***	0.00***
Normality test	0.00***	0.00***	0.00***	0.00***
Autocorrelation test	0.00***	0.00***	0.00***	0.00***
Heteroscedasticity test	0.00***	0.00***	0.00***	0.00***

Notes: (1) Data for all three tests in the table are p-probability values; (2) \*\*\* indicates rejection of the original hypothesis at a significance level of 1%; (3) The kurtosis data are the excess kurtosis after deducting the value 3; (4) We used the ADF function for the unit root test, with the original hypothesis that there is a unit root in the series. (5) We used the normaltest function for the normality test to calculate the JB statistic and p-value, with the original hypothesis that the series obeys a normal distribution. (6) We tested for autocorrelation using the function Box.test for the Ljung-Box test to

obtain the Q statistic, with the original hypothesis that the serial autocorrelation coefficient is equal to zero for lags of at most 6 orders. (7) We tested for heteroskedasticity using the Archtest function of the FinTS package, with the original hypothesis that there is no ARCH effect. (8) The above calculations were done using Rstudio software.

The data in Table 1 show that the log returns for WTI, INE, SSE, and S&P 500 are all spiky, thick-tailed, and skewed. The data rejects the original hypothesis under unit root, normality, heteroskedasticity, and autocorrelation tests. Therefore, all the above data series do not obey the standard normal distribution and have no unit root, autocorrelation, or heteroskedasticity.

### 3.3 Empirical results

#### 3.3.1 GARCH model

Table 2 shows that the sum of  $\alpha$  and  $\beta$  of the S&P 500, WTI, SSEC and INE are smaller than 1, and the values of  $\alpha$  and  $\beta$  coefficients are significant, indicating that the model is stable and the index volatility is more persistent. Considering three criteria of AIC, BIC, and LL as well as the significance of coefficients for model selection, we chose the GARCH-Skew-t model with the best fit

**Table 2.** Results of the GARCH-Skew-t model

	S&P 500 index		WTI		SSEC		INE	
	parameter	t-status	parameter	t-status	parameter	t-status	parameter	t-status
$\mu_i$	0.1017 (0.024)	4.2158	0.0390 (0.068)	0.5746	0.0039 (0.041)	0.096	0.0444 (0.068)	0.6506
$\varphi_i$	0.0319 (0.011)	2.8284	0.2135 (0.112)	1.9125	0.0842 (0.053)	1.5951	0.2943 (0.198)	1.4831
$\alpha_i$	0.1938 (0.044)	4.3634	0.0816 (0.028)	2.9509	0.0611 (0.036)	1.6989	0.1313 (0.055)	2.3872
$\beta_i$	0.7893 (0.040)	19.896	0.8877 (0.039)	22.5632	0.9345 (0.023)	39.8267	0.8406 (0.070)	12.0237
$\nu_i$	5.1534 (0.929)	5.5478	4.0757 (0.613)	6.6438	2.4148 (0.196)	12.3431	3.4779 (0.442)	7.8716
$\xi_i$	-0.1753 (0.047)	-3.7626	-0.1429 (0.039)	-3.6783	0.0409 (0.031)	1.3040	-0.0478 (0.036)	-1.3460
AIC	2244.6551		3867.9398		2742.4479		3834.3474	
BIC	2278.2329		3901.5175		2776.0257		3867.9251	
LL	-1115.328		-1926.97		-1364.224		-1910.174	

**Table 3.** Residual test results

Inspection type	S&P500	WTI	SSEC	INE
Residual autocorrelation test	0.968	0.995	0.997	0.968
Residual variance	0.6578	0.1518	0.3522	0.4889
Residual square autocorrelation test	0.24	0.323	0.167	0.218
Residual square heteroscedasticity test	0.2412	0.3237	0.1676	0.2192

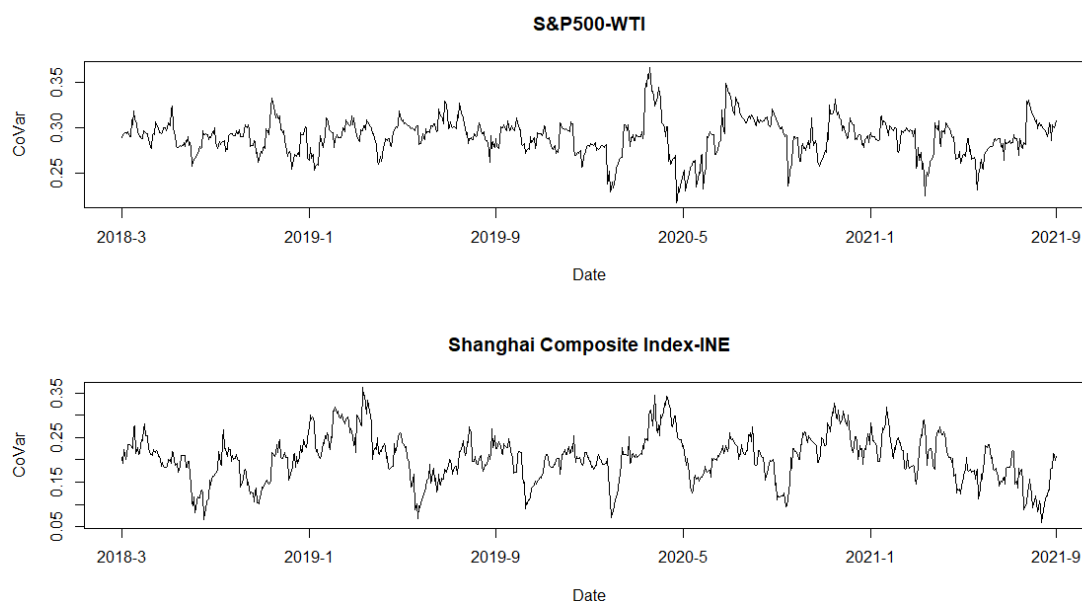
Furthermore, we performed autocorrelation and heteroskedasticity tests on the residuals of the four sets of return series after the model is fitted. The original hypothesis of both tests is that there is no autocorrelation, namely, there is no heteroskedasticity effect. The p-value of the test results is large, and the original hypothesis cannot be rejected at the significance level of 0.1. Therefore, it can be concluded that the data series fitted by the GARCH model is a series without autocorrelation and heteroskedasticity, and the Copula model can be further established.

### 3.3.2 Time-varying t-Copula model

The model fitting results are shown in Table 4. The sum of  $\alpha$  and  $\beta$  coefficients of the two sets of t-Copula model fits is less than 1, which satisfies the condition of model stability. The model fit results of INE and SSEC show that the  $\alpha$  coefficient is significant at the level of 0.05 and the  $\beta$  coefficient is significant at the level of 0.01. The model fitting results for the S&P 500 and WTI indicate that the coefficient is insignificant, but it can be significant at the 0.01 level.

**Table 4.** Fitting results of Copula-t model

	S&P500 Index-WTI		INE-SSEC	
	parameter	t-status	parameter	t-status
$\omega^L$	9.5862 (3.736)	2.5660	23.0158 (20.337)	1.1317
$\alpha^L$	0.0093 (0.014)	0.6670	0.0204 (0.015)	1.3837
$\beta^L$	0.8757 (0.066)	13.2989	0.9071 (0.048)	19.0519
AIC	-73.9196		-36.3896	
BIC	-59.5291		-21.9991	
LL	39.9600		21.1950	



**Fig. 1** Plot of dynamic conditional correlation coefficient

Based on Fig. 1, we analyzed the following.

First, there are positive correlations between the crude oil and stock markets in both China and the United States. China's economy has been maintaining a high growth rate and the good economic development has driven the prices of both markets up (Broadstock and Filis, 2014). Besides, China, as an emerging economy with the world's top-ranked manufacturing industry and the world's largest oil importer, has a large market demand for crude oil. Therefore, the Chinese stock market is sensitive to movements in crude oil prices. Although the rise in oil prices increases the cost of production for firms, this negative effect is mitigated to a large extent by China's unique oil price pricing mechanism, and the Chinese stock market and oil market still manage to maintain a positive linkage.

The United States is a representative of developed economies and the good economic situation makes the interaction between crude oil price returns and stock market price returns strong. Also, the United States is a major crude oil importer and the largest oil producer. It is reasonable that the importance of crude oil to the U.S. creates a robust linkage between the American oil market and the

stock market. Despite the rise in crude oil prices, the import of crude oil will cost more to some extent. However, as the global demand for oil grows, the U.S. earns more profits as a net oil exporter by increasing sales, so it can have a positive impact on the stock market, showing a positive linkage between the two markets.

Second, the linkage between the U.S. crude oil market and the stock market is stronger than that of China. There may be several reasons: In terms of government policies, the Chinese government limits stock market price fluctuations to 10% a day and sets "floor" and "ceiling" prices to control oil prices, thus limiting sharp fluctuations in stock prices and refined oil prices. Furthermore, the Chinese government's multi-faceted market regulation makes the Chinese market more resilient to shocks and creates a more stable market environment, which can help to prevent risk transfer between markets to some extent. In terms of market nature, the Chinese stock market often deviates from the efficient market, while the market in general is always efficient in the United States (Hou, 2018), and the volatility of crude oil prices will be more reflected in the U.S. stock market. There is a lot of speculative trading activity in the Chinese stock market, and volatile oil prices make it difficult to fully reflect changes in economic fundamentals (Jin, Hongfei, and Jin, 2008). In terms of the energy structure, crude oil accounts for the largest share of energy consumption in the U.S., while China is still dominated by coal. Coal accounts for about 57.64% of energy consumption in China in 2019, and oil accounts for about 19.69%, while the share of oil in the U.S. reaches 36.66% and coal's market share falls to 11.31%.

Third, the correlation between crude oil and equity markets in China is more volatile and variable than in the US. In detail, starting in March 2018, the dynamic conditional correlation between the two markets in China has been falling until 2019, when it shows a clear upward trend. After November 2020, the two-market correlation again shows a volatile downward trend. In contrast, the dynamic conditional correlation between the two markets in the U.S. fluctuates more moderately, with fluctuations largely ranging from 0.25 to 0.35. It fluctuates slightly around the value of 0.3, up and down, in the interval from March 2018 to November 2019, and increases in volatility from January 2020.

Fourth, the linkages between the two markets in China and the U.S. increase significantly under extreme risk events. In detail, the dynamic conditional correlation coefficient for China increases distinctly from 2018 to 2019 during the escalation of the trade war between the U.S. and China, and from 2020 during the period of the COVID-19, suggesting that there is indeed a stronger positive linkage between the two markets in China. Under COVID-19 in 2020, the two markets also present a stronger positive linkage in the U.S. On the one hand, extreme risk events can influence market linkages by affecting investor sentiment. When oil prices fall rapidly, an important indicator of economic expansion, they may signal economic weakness to investors, creating negative sentiment and reducing confidence in the market. The herding effect can further amplify such emotions, thereby enlarging the impact of oil price volatility and sending stock market prices downward. As the Chinese economy was severely hit by COVID-19 in 2020, investors' confidence in stocks was tremendously reduced and they sold off stocks. Both the oil and stock markets were very depressed at this time, and China showed a stronger linkage between the two markets. On the other hand, the market itself during a crisis is in a more unstable state and is more vulnerable to price shocks from other markets, which in turn exhibit a stronger linkage.

#### 4. Conclusion

We investigated and analyzed the correlation between crude oil and the stock markets in China and the United States by developing a time-varying t-Copula-GARCH model using Chinese INE crude oil futures and the Shanghai Stock Exchange Index, and US WTI crude oil futures and the S&P 500 Index, respectively, from March 28, 2018 to August 30, 2021. The following are the major conclusions:

First, there is a significant dynamic conditional dependence between the crude oil and stock markets in China and the US, which always remains positive. China's good economic situation, stock market's higher sensitivity to oil price shocks, and special oil pricing mechanism can explain the positive correlation to some extent. The US is not only the most developed economy, but also reaps huge profits from the huge amount of net oil exports, making it reasonable for its oil and stock markets to have a positive dependency.

Second, the average value of the dynamic conditional correlation coefficients for the U.S. is larger than that of China, which indicates that the positive dependence between the two markets in the U.S. is stronger than that of China. It can be explained by three aspects: government policies, market nature, and the energy structure. More stringent market regulations, more frequent market interventions, and a more stable market environment in China allow for a certain degree of effectiveness in blocking risk contagion between the crude oil market and the stock market.

Third, inter-market linkages in China are more variable and volatile than in the US. China is still a non-effective market, while the US is a semi-effective market; the US has the largest share of crude oil in energy, while China is still dominated by coal.

Fourth, the dependence between the equity and crude oil markets of both countries can increase rapidly during periods of extreme risk events. Extreme risk events can affect market linkages by influencing investor sentiment, and herding effects can magnify such emotions and thus strengthen such effects.

## References

- [1] David C. Broadstock, George Filis. Oil price shocks and stock market returns: New evidence from the United States and China[J]. *Journal of International Financial Markets, Institutions & Money*, 2014, 33.
- [2] Cuong C. Nguyen, M. Ishaq Bhatti. Copula model dependency between oil prices and stock markets: Evidence from China and Vietnam[J]. *Journal of International Financial Markets, Institutions & Money*, 2012, 22(4).
- [3] Michael Souček, Neda Todorova. Realized volatility transmission between crude oil and equity futures markets: A multivariate HAR approach[J]. *Energy Economics*, 2013, 40.
- [4] Farooq Malik, Bradley T. Ewing. Volatility transmission between oil prices and equity sector returns[J]. *International Review of Financial Analysis*, 2009, 18(3).
- [5] George Filis, Stavros Degiannakis, Christos Floros. Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries[J]. *International Review of Financial Analysis*, 2011, 20(3).
- [6] Mohamed El Hedi Arouri, Jamel Jouini, Duc Khuong Nguyen. Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management[J]. *Journal of International Money and Finance*, 2011, 30(7).
- [7] Basel Awartani, Aktham Issa Maghyreh. Dynamic spillovers between oil and stock markets in the Gulf Cooperation Council Countries[J]. *Energy Economics*, 2013, 36.
- [8] Mensi Walid, Reboredo Juan C., Ugolini Andrea. Price-switching spillovers between gold, oil, and stock markets: Evidence from the USA and China during the COVID-19 pandemic[J]. *Resources Policy*, 2021, 73.
- [9] Zhao Zhao, Huwei Wen, Ke Li. Identifying bubbles and the contagion effect between oil and stock markets: New evidence from China[J]. *Economic Modelling*, 2021, 94.
- [10] Liu X., An H., Huang S. The evolution of spillover effects between oil and stock markets across multi-scales using a wavelet-based GARCH-BEKK model[J]. *Physica A Statistical Mechanics & Its Applications*, 2017, 465:374-383.
- [11] Zeng Zhijian, Xu Di and Xie Chi. A Study on the Interaction Effect between Securities Markets under the Influence of Financial Crisis [J]. *Management Review*, 2009, 21(02):33-39+91.
- [12] Liu Feng, Shao Shuai, Zhang Chuanguo. How do China's petrochemical markets react to oil price jumps? A comparative analysis of stocks and commodities[J]. *Energy Economics*, 2020, 92.

- [13] Zohrabyan T. Essays on time series and causality analysis in financial markets[M].Dissertations& Theses-Gradworks,2008.
- [14] Tang Yusui,Xiao Xiao,Wahab M.I.M.,Ma Feng. The role of oil futures intraday information on predicting US stock market volatility[J]. Journal of Management Science and Engineering,2021,6.
- [15] Julia Kielmann,Hans Manner,Aleksey Min. Stock market returns and oil price shocks: A CoVaR analysis based on dynamic vine copula models[J]. Empirical Economics,2021.
- [16] Lu Xunfa,Liu Kai,Lai Kin Keung,Cui Hairong. The Relationship between Crude Oil Futures Market and Chinese/US Stock Index Futures Market Based on Breakpoint Test[J]. Entropy,2021,23(9).
- [17] Patton A J. Modeling Asymmetric Exchange Rate Dependence [J].In-ternational Economic Review, 2006,47(2).
- [18] Qian Chen,Xin Lv. The extreme-value dependence between the crude oil price and Chinese stock markets[J]. International Review of Economics and Finance,2015,39.
- [19] Hongfei Jin,Eminent Jin. Spillover Effects of Oil Prices and Stock Markets - A Comparative Analysis Based on Chinese and U.S. Data [J]. Journal of Financial Research,2008(02):83-97.
- [20] WANG Liang,LI Bi-xiao,MA Xu-tao,ZHENG Wei.The Price Volatility Effect and Its Sustainability between Chinese Crude Oil Future and International Crude Oil Futures[J]. Systems Engineering,2021,39(03):102-120.
- [21] ZHANG Da-yong,JI Qiang. Studies on the Dynamic Risk Spillovers for China's Crude Oil Futures[J]. Chinese Journal of Management Science,2018,26(11):42-49.DOI:10.16381/j.cnki.issn1003-207x.2018.11.005.
- [22] Li Su-fang, ZHU Hui-ming, LI Rong. The Asymmetric Relationship of Oil-stock Markets Based on Bayesian Regime Switching Cointegration Model[J].Chinese Journal of Management Science,2015,23(09):46-54.DOI:10.16381/j.cnki.issn1003-207x.2015.09.006.
- [23] Wang Hu,Li Shouwei. Asymmetric volatility spillovers between crude oil and China's financial markets[J]. Energy,2021,233.
- [24] Huang R. D., Masulis R. W., Stoll H. R. Energy Shocks and Financial Markets[J].Journal of Futures Markets, 1996, 16:1-27.
- [25] Hammoudeh S., Aleisa E. Dynamic Relationships among GCC Stock Markets and NYMEX Oil Futures[J]. Contemporary Economic Policy, 2004, 22:250-269.
- [26] Masih R., Peters S., Mello L. D. Oil price volatility and stock price fluctuations in an emerging market: Evidence from South Korea[J]. Energy Economics, 2011,33:975-986.
- [27] JI Qiang, FAN Ying. Analysis of the Comovement Between International Crude Oil Market and China and U. S. Stock Market Before and After the U. S. Sub- prime Crisis [J]. Chinese Journal of Management Science,2010(6):42-50.
- [28] Hou Yunfei. A Research on the Difference of stock market Efficiency and its Mechanism between China and the US——based on Permutation entropy and Hurst parameter [D]. Guangxi University, 2018.