The Empirical Results

Data Collection

To examine the dependence structure and systematic risk between the prices of China oil futures and energy stocks, I employed daily data for China oil futures price and PetroChina Company Limited (PetroChina) stock price from March 26th ,2018 to March 23th, 2019. And all data employed in this paper are acquired from Wind. For modeling convenience, I use prices returns to stabilize the variability and make the data series stationary.

Results for Marginal Distribution Models

Figure 1 and 2 reveal dynamics for the price return of China oil Future and PetroChina, displaying the difference in price movements at different times: overall, China Oil Future shows greater volatility than PetroChina.

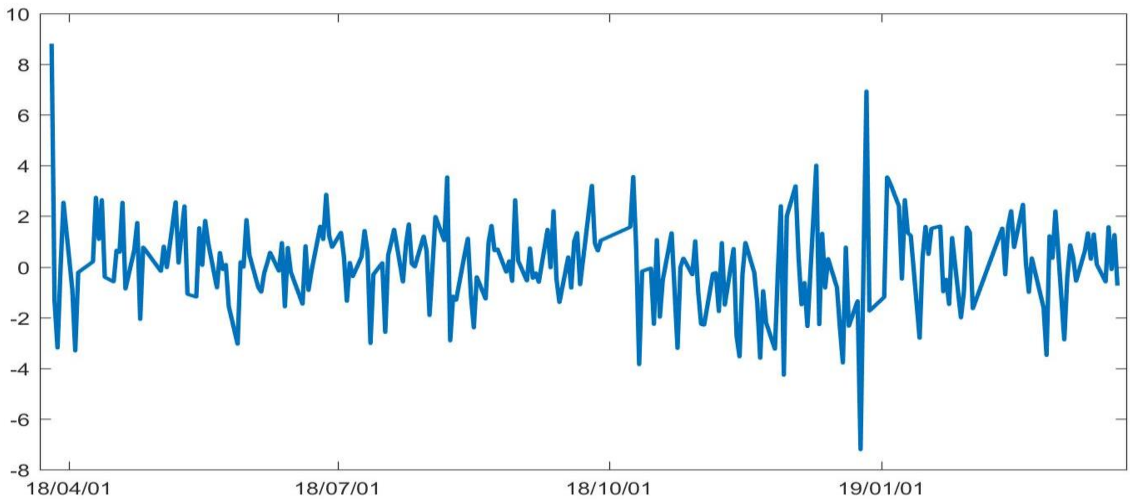

Figure 1 Price return dynamics for China oil future

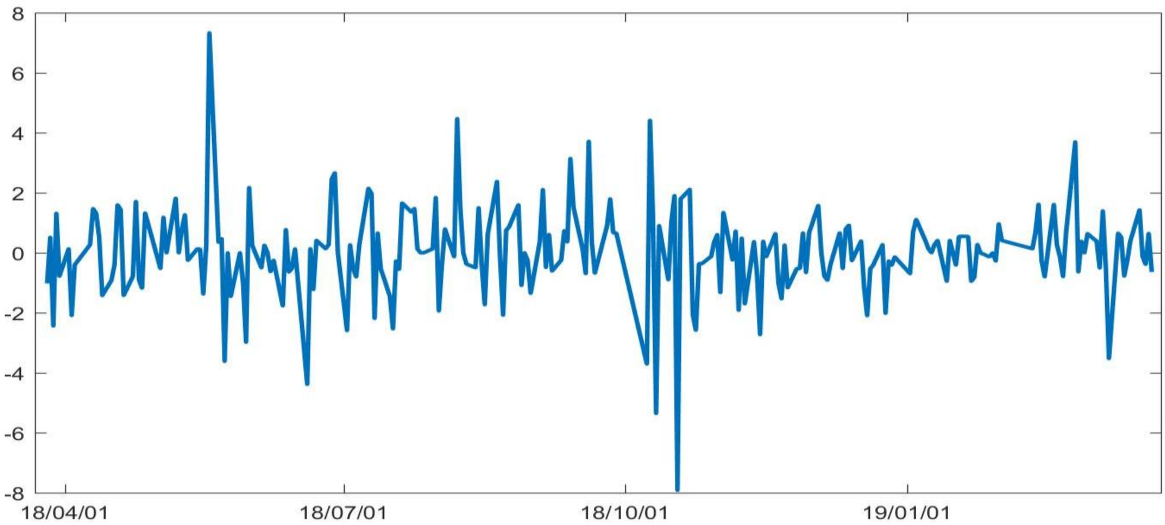

Figure 2 Price return dynamics for PetroChina

Table 4 shows descriptive statistics for price returns. Mean returns of all time series are close to zero and their corresponding standard deviations are bigger for China oil future price return. Skewness statistics was positive for China oil future and negative for PetroChina, indicating a larger possibility of great decline in this return. As for the kurtosis statistic, both returns exhibited positive values which are bigger than three, showing fat tails in the distribution, consistent with the result of Jarque-Bera test which gives strong rejection of the normality of this unconditional distribution. Besides, the performances of the Augmented Dickey and Fuller (1979) non stationarity tests verify that all price return series Ire stationary. Ljung-Box statistics and ARCH-LM statistics show that there is autocorrelation in the sequence of China's oil futures price returns, that is, there is residual variance. In contrast, the statistics of the two tests indicate that PetroChina's price-return series does not have serial correlation. In other words, the null hypothesis of variance-free variance should not be rejected.

Table 4 Descriptive statistic for price returns

	China oil future	PetroChina
Mean	0.081	0.016
Std.Dev.	1.799	1.499
Max	8.813	7.332
Min	-7.217	-7.921
Skewness	0.212	-0.287
Kurtosis	6.146	8.852
JB	101.613***	348.678***
Q(20)	21.314***	26.346
Q^2(20)	28.232***	18.648
ARCH-LM	47.455***	17.720
ADF	-15.634***	-16.626***

Note. The asterisks (∗∗∗) represent significance at the 1% level.

Table 5 represents parameter estimations of the marginal distribution models. According to the AIC values, ARMA(3,2)-GARCH(1,1) model with skewed Student-t distribution is the best model for China oil future price return. As for the PetroChina stock, the ARMA(0,3)- GARCH(1,1) model with skewed Student-t innovation is the adequate model since there is no autocorrelations. It is shown by the significance GARCH component(β) that the volatility is quite persistent for all series. The estimated values corresponding to the degrees of freedom and skewness of the skewed Student-t distribution imply that residuals of the regression follow a symmetrical distribution.

Table 5 shows the results for the test of the goodness-of-fit of my marginal models. can see from the Ljung-Box and ARCH statistics that there doesn’t present serial correlation in the residuals anymore. At 1% significance level, the reported p-values prove that the correct specification of all marginal functions should not be rejected. Therefore, the results of our goodness-of-fit test demonstrates that these are not incorrect specified marginal distribution models, which means that the Copula model used in this paper can rightly outline the relationship between the prices of China oil future and energy stocks.

Table 5 Parameter estimations for marginal models

	China Oil future	PetroChina
Mean		
Φ_0	0.132	0.018
	(0.130)	(0.090)
AR(1)	0.594***	N
	(0.140)	N
AR(2)	-0.747***	N
	(0.060)	N
AR(3)	0.123*	N
	(0.070)	N
MA(1)	-0.512***	-0.040
	(0.120)	(0.090)
MA(2)	0.672***	-0.147*
	(0.080)	(0.080)
MA(3)	N	0.056
	N	(0.070)
Variance		
ω	0.123	0.134
	(0.120)	(0.100)
α	0.887***	0.894***
	-0.080	(0.060)
β	0.067	0.045**
	(0.050)	(0.020)
Deg. of freedom	10.536	3.367***
	(6.670)	(0.500)
λ	-0.107	-0.033
	(0.070)	(0.050)
Log-Likelihood	460.626	433.667
Q(10)	0.483	0.301
Q^2(10)	0.389	0.255
ARCH	0.440	0.337
KS	0.990	0.871

Note. The asterisks (∗∗∗), (∗∗) and (∗) represent significance at the 1%, 5% and 10% levels, respectively.

Results for Copulas

Table 6 and Table 7 report parameter estimates for the six different kinds of Copulas. The estimated parameters of Gaussian and Student-t Copulas are positive, indicating the presence of optimistic and symmetrical dependence between those two price series. As for constant asymmetric Copulas, except for the Clayton and Rotated Clayton, I find significant statistics values for the Gumbel Copula and Rotated Gumbel Copula, which indicates positive and asymmetric tail dependence between oil future price and energy stocks price. I use the best AIC value to select the best Copula models and according to the empirical result, static Student-t Copula is our best model, indicating there is symmetrical tail dependence between the two marginal distributions. Finally, the estimated AIC parameters for the time-varying parameter (TVP) Copulas suggest that the TVP-Symmetrical Joe Clayton is the best fitted model among all the non-static Copulas, but no better than the static Student-t Copula.

In all, our empirical analysis of the relationship between the price returns of China oil future and PetroChina stock implicates that oil future and energy stocks returns reveal symmetric tail dependence. Therefore, considering information exchange between them, these two return series will move upward or downward together.

Table 6 Parameter estimates for constant Copulas

	Oil future-PetroChina
Gaussian	
ρ	0.422
	(0.047)
AIC	-45.297
Clayton's	
α	0.564
	(0.106)
AIC	-38.567
Rotated Clayton	
α	0.537
	(0.106)

AIC	-33.045
Gumbel	
δ	1.354
	(0.069)
AIC	-44.371
Rotated Gumbel	
δ	1.363
	(0.069)
AIC	-46.329
Student's t	
ρ	0.429
	(0.052)
υ	0.162
	(0.088)
AIC	**-49.096**
Symmetrical Joe Clayton	
λ_U	0.205
	(0.098)
λ_L	0.264
	(0.079)
AIC	-46.916

Table. 7. Parameter estimates for time-varing Copulas

	Oil future-PetroChina
TVP-Gaussian	
Ψ_0	0.001
	(0.009)
Ψ_1	0.070
	(0.050)
Ψ_2	2.064
	(0.038)
AIC	-43.051
TVP-Clayton's	
ω	1.073
	(0.121)
α	0.082
	(0.123)

β	-1.565
	(0.503)
AIC	-37.162
TVP-Rotated Clayton	
ω_U	1.300
	(0.842)
α_U	-0.153
	(0.465)
β_U	-2.034
	(2.659)
AIC	-31.418
TVP-Gumbel	
ω	1.106
	(0.157)
α	-0.100
	(0.114)
β	-1.578
	(0.785)
AIC	-43.119
TVP-Rotated Gumbel	
ω_L	0.934
	(0.114)
α_L	0.001
	(0.075)
β_L	-1.422
	(0.590)
AIC	-45.072
TVP-Student-t	
Ψ_0	1.917
	(0.306)
Ψ_1	-0.143
	(0.253)
Ψ_2	-2.257
	(0.433)
υ	5.971
	(3.642)
AIC	-47.577
TVP-Symmetrical Joe Clayton	
ω_U	1.322
	(1.888)

α_U	-9.993 (7.656)
β_U	-1.845 (0.874)
ω_L	0.046 (0.859)
α_L	-5.404 (2.885)
β_L	0.668 (1.061)
AIC	**-48.231**

1.4 Results for VaR and CoVaR

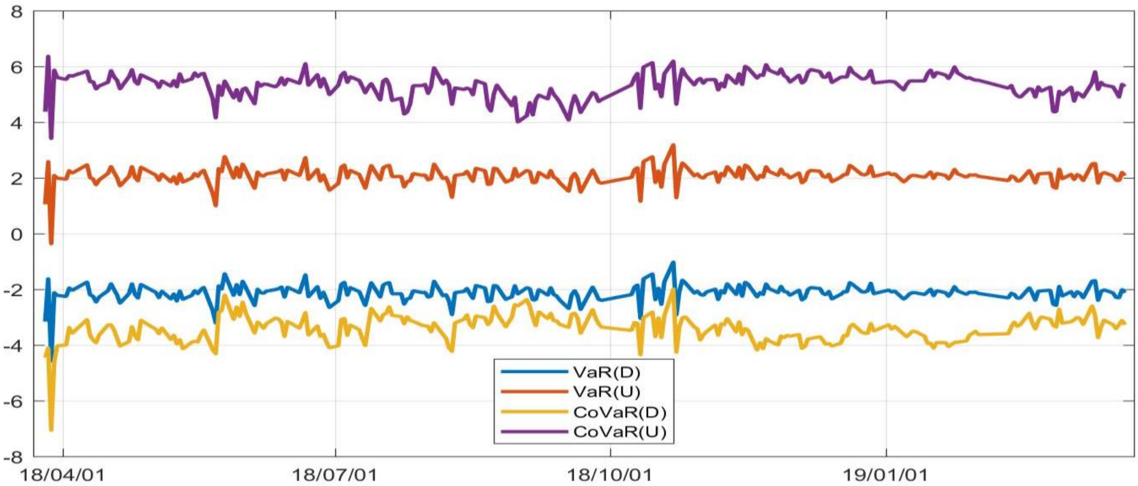

Figure 3 VaR of stock markets and CoVaR from oil future to energy stocks

Adopting the best Copula model, I calculat CoVaR and ΔCoVaR at the 95% confidence level (α=0.05) both on lower side and upper side between those two series.

From Table 8, the summarized descriptive statistics of CoVaR and ΔCoVaR are shown respectively. Figure 3 shows the dynamics of the values of CoVaR and abrupt changes can be seen right after the time when the China oil future just came out. This peculiar result might be explained by the news' unexpected shock in the market and high price uncertainties at the beginning time. Furthermore, according to the characteristics of Student-t Copulas, the upside and downside CoVaR measurements of these two marginal distributions should be symmetrical. Their average values are very close, as shown in Table 8.

The influence of extreme oil future price dynamics on Energy stocks, measured by ΔCoVaR, is also symmetric, both on the upper and lower tails. This contribution is around 90%, indicating an unexpected China oil future price motion will increase the risk intensity of the PetroChina energy stocks by 90% when the values of oil future price are close to median. This contribution is extremely large and strongly confirms that the oil future price uncertainties do have systemic risk impacts on PetroChina stock return.

Table 9 shows that the p-values for the KS statistic reported are close to zero, which means it can significantly reject the null hypothesis and prove the existence of symmetric risk spillovers in this time horizon.

Table 8 Descriptive statistics for VaR and CoVaR

Down（5%）			Up（95%）		
VaR	CoVaR	ΔCoVaR	VaR	CoVaR	ΔCoVaR
2.1383	4.9993	0.9159	2.0701	4.7090	0.9729
(0.3121)	(0.3388)	(0.1016)	(0.3121)	(0.3176)	(1.5100)

Table 9 Tests of equalities of VaR and CoVaR

Tests	Values
H_0: CoVaR(D)=VaR(D)	0.9959
H_1: CoVaR(D)<VaR(D)	(0.0000)
H_0: CoVaR(U)=VaR(U)	0.9959
H_1: CoVaR(U)>VaR(U)	(0.0000)

H_0:CoVaR/VaR(D)=CoVaR/VaR(U)	0.2727
H_1: CoVaR/VaR(D)>CoVaR/VaR(U)	(0.0000)
H_0: ΔCoVaR(D)= ΔCoVaR(U)	0.2851
H_1: ΔCoVaR(D)> ΔCoVaR(U)	(0.0000)

Conclusion and Policy Implications

Since the emergence of oil futures in 1978, its function of discovering prices, avoiding risks, and regulating speculation has received wide recognition. Therefore, all countries in the world have actively participated in oil futures trading to achieve the goal of maintaining stable economic and social development. The oil futures price is also considerably affecting the development of the energy industry. Therefore, determining how changes in oil futures prices influence energy companies has significant implications. Energy stockholders have to analyze the dependence and systematic risk between the prices of crude oil and energy stocks. Policymakers should learn about the quantified risk spillover intensity to provide the necessary policy to support energy companies which are under the influence of extreme oil price changes.

In our study, in order to capture tail dependence, I analyze the relationship between oil futures prices and PetroChina energy stocks prices. Besides, I test and quantify the systematic impact of extreme oil future price changes on energy stocks prices by calculating the CoVaR values based on copula models using the data from this one year horizon since the public listing of China oil future.

First, our evidence indicates that oil futures and PetroChina stock price returns are moving together on average and at the tails. Therefore, during this period, changes in oil futures prices can have a significant impact on investors' decision on whether to invest in energy stocks. In other words, the rise or fall in China's crude oil futures prices has a direct impact on energy stocks investments, which can further help the government to develop appropriate policies to stimulate the energy stocks market. But this incentive policy should not be symmetrical. Government works should implement policies in time when crude oil futures prices appear extremely low values in order to continue to support energy companies' profitability. For example, the government can determine the oil future price risk (systemic risk) of subsidies and quantify the compensation for the risks caused by (extreme) oil future price changes.

Second, this analysis has certain implications for investors in decision-making and risk management practices, especially for institutional and individual investors who own energy stocks. Because fluctuations in energy stocks prices directly affect the profitability of the portfolio, this effect is particularly important when crude oil future prices show great uncertainties. Furthermore, our results show that large oil future price changes on average raises the risk intensity of energy stocks by about 90%, so energy investors should consider this fact to prevent losses from their hedges in crude oil future. And it also shows that their tail dependence is symmetrical.