The Volatility Behavior and Dependence Structure of WTI Crude Oil Spot and Future Price

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ABSTRACT

This paper aims to investigate the volatility's dependence between WTI crude oil spot and future returns using the copula based AR-GJR-GARCH model. In empirical study, we apply the mode to fit the joint density function. Further to find the static and dynamic rank correlations. The data period contains Jan. 1, 2001 to Dec. 31, 2014. The results show that Clayton is the best model and rank correlation is high to 0.8 which implies that there is high dependence between oil spot and future return volatility. That will be helpful for risk management and investment decision.

Keywords: Crude Oil, Volatility, Dependence, Copula, AR-GJR-GARCH

1. INTRODUCTION

Oil and economic relations are closely linked and inseparable. In previous year, the crude oil price falls have been in the pipeline for a long time and they are set to continue. OPEC does not seem to be prepared to do anything and intends to debate whether to support a Brent Crude price of $90 at its next meeting in November 2014. The fact that this price level is not an urgent certainty for the club shows that it is unlikely to be defended. Meanwhile, the January 22, 2015 the European version of quantitative easing is another force pushing up the dollar index and indirectly affect the price of oil and other bulk materials denominated in dollars fell further. As describe above, we expect that the volatility will be more changeable in this year.

It is no doubt, prices tumbled prompted increased volatility. In United States, West Texas crude oil refining to benefit from good quality and easy to spot, and West Texas Intermediate crude oil futures of the most world-scale representation, and therefore have a key indicator of more significant.

There are dozen of previous researches concentrate on the investigation volatility behavior and dependence structure. Firstly, many empirical studies had examined the volatility time series by supposing that the DGP of volatility series is characterized by sudden changes in the volatility (Hamilton and Susmel, 1994; Gray, 1996; Klassen, 2002; Marcucci, 2005; Baillie and Morana, 2009). Secondly, a numbers of researches focus on the volatility forecasting and dependence of energy spot and futures. E.g. Wang (2011), Kang and Yoon (2013), Aloui et al. (2014), Charfeddine (2014), Mensi et al. (2014)
For this paper, the use of West Texas crude oil futures and spot trends to explore the relationship between volatility and dependence. The study investigates the relationship between WTI crude oil spot and futures. The period of time chosen is from Jan 1, 2001 to December 31, 2014. The structural transition is scheduled for Sep. 15, 2008 collapse of Lehman Brothers. The data is obtained from Taiwan Economic Journal data bank (TEJ).

In empirical study, we apply the copula based AR-GJR-GARCH model to investigate the correlation. Copula function was widely used in financial econometrics and risk management. These related studies like as Palaro and Hotta (2006) used conditional copula to estimate VaR. Junker et al. (2006) discussed the nonlinear term structure dependence and risk implication based on copula function. Hu (2006) proposed a mixed copula model that it can capture various patterns of dependence structures. Rodriguez (2007) modeled dependence with switching-parameter copulas to study financial contagion. Chiou and Tsay (2008) addressed a copula-based approach to option pricing and risk assessment. Hsu et al. (2008) proposed copula-based GARCH models for the estimation of the futures optimal hedge ratio. Manner et al. (2009) used copula models with time-varying dependence structure. Lai et al. (2009) exploited copula methodology, with two threshold GARCH models as marginals, to construct a bivariate copula-threshold-GARCH model. They found that the optimal dynamic hedge model for spot and futures market. Lee and Fang (2010) applied copula function in the pair event of operation risk based on Taiwan's commercial banks. Lee (2010) investigated the dynamic correlation between NASDAQ and Toronto Stock index through Copula-AR-GARCH Model. Wei et al. (2011) proposed a new hedging model combining the newly introduced multifractal volatility (MFV) model and the dynamic copula functions. They found that the multifractal analysis may offer a new way of quantitative hedging model design using financial futures.

Peng and Lee (2013) applied five static ARMAX-GJR-GARCH copula models and two time-varying dynamic copula models. The results show that the kendall tau is lower before the sub mortgage crisis. The contagion effect test exhibits the US sub mortgate crisis will affect Japan REITs. Chen et al. (2014) proposed a new approach based on copula multi fractal volatility method (MFV) to investigate the contagion effect between the U.S. and Chinese stock markets. The estimated static copula results for the entire period show that the SJC copula performs best.

The paper is organized as follows. Section 2 presents a brief review of the literatures, section 3 introduce the research methodology. Section 4 contains data description and empirical results analysis followed by a few concluding remarks and ideas on future works.

2. LITERATURE REVIEW

Hamilton and Susmel (1994) are the first to employ the idea of combining the Markov switching model of Hamilton (1989) with the ARCH (q) process for modeling potential structural changes in the volatility. Baillie and Morana (2009) proposed an adaptative version of the FIGARCH model (A-FIGARCH) which allows for both long memory and structural change in a volatility process and which estimates endogenously the dates of breaks. Empirical results show that the A-FIGARCH model better describes this time series, in terms of in-sample and out-of-sample analyses, compared to the GARCH, Spline-GARCH, and Adaptative-GARCH, FIGARCH, and Spline-FIGARCH models. Wu(2012) have also investigated the presence of long range dependence in many price volatile energy futures contracts with different maturities. Their results exhibited strong evidence for long range dependence in the price volatility series of all energy futures contracts.

The volatility behavior between the spot and futures prices, mostly in practice, has had many studies done to explain this relationship using different techniques.

Jpsji (2012) used CARCH and TARCH model to investigate the volatility of Asia market under Financial Crisis. They found that the Asian stock markets has the persistence volatility and mean reverting. Gao and Liu (2014) Applied two-state regime switching model to discuss the volatility behavior and dependence of commodity futures and stocks. Empirical results show that commodity future is a good instrument for risk diversification. In addition, they also found that the lower correlation between future and stock. Diaz and Masa (2014) examined the dependence and asymmetric effect of the Largest Exchange Traded Note (ETNs) with ARFIMA and ARFIMA-FIGARCH models. The examined result exhibits the presence of volatility asymmetry in the AMJ ETN.

Liu et al. (2014) investigated the volatility and dependence of Chinese outside tourism demand for Singapore, Malaysia, and Thailand destinations via Vine copula-ARMA-GARCH model. They found that the time-varying vine copula model can fit the data well. Boonyanuphong and Sriboonchitta (2014) used GPD-Copula appropriated to explain the tail behaviors of financial data. The results found that the interdependence between the spot rubber price and the futures price of the AFET market is relatively low. Mensi et al. (2014) examined two global benchmark, namely WTI and Brent crude oil with ARMA-GARCH model. They found that OPEC's statement, especially the "“cut” and the “maintain" of the decision on both volatility of returns and significant impact on WTI Crude Oil market.

Aloui et al. (2014) used copula-GARCH approach to test the dependence behavior between the crude oil and natural gas markets. The study found that the oil and natural gas markets generally co-move closely together. Charfeddine (2014) used four types GARCH models to fit the volatility of energy futures markets. The results analyzed the NO.2 heating oil and propane futures series one month and three month period were characterized by only long memory behavior. They also found the FIGARCH (1, d,1) model was more appropriate to describe the evolution of these time series.

Fernanddes et al. (2014) investigated the characteristics of time series CBOE Market Volatility Index (VIX) in daily frequency. Evidence suggested that there be a negative correlation between the VIX Index and the S & P 500 index .They also found that the semiparametric HNHARX model performed as well as the linear HAR.

Prokopczuk and Simen (2014) described the importance of the volatility risk premium for volatility forecast. They used regression models and statistical loss functions. The results exhibited that the risk premium after adjusting the implied volatility significantly superior to other models. Glosnoy (2014) reported that the empirical similarity (ES) used for the purpose of daily volatility forecast. They also analyzed ES model and HAR component and found that the two models were better than the original HAR measured in various performance prediction sample. Volatility forecast supported during exercise and the subprime mortgage crisis, similar to the concept of sub-period empirical usefulness for describing complex dynamic volatility.

Chen et al.(2014) investigated the contagion effects between the US and Chinese markets with new method (MFV) multifractal fluctuations Method. The results showed that the time-varying t-copula can outperform the other models. The empirical found may help investors choose and international portfolio diversification, as well as the importance of risk management. Bentes (2014) applied long memory-FIGARCH model to check the return persistence of S & P, TSX 60, CAC 40, DAX 30, and MIB 30, the Nikkei 225 index, the FTSE 100 index and the S & P index. The results showed that all stock index returns had persistence. Smaller markets, such as the DAX 30, are less liquid and less efficient, and more likely to encounter related fluctuations, therefore, more susceptible to aggressive investors.

3. RESEARCH METHODOLOGY

The AR-GJR-GARCH (1, 1) model assume two return series $r_{spot,t}$, $r_{future,t}$ following the Gaussian residuals.[1]

$$r_{spot,t} = \mu_{spot} + \varepsilon_{spot,t}, \tag{1a}$$

$$\varepsilon_{spot,t} = \sqrt{h}_{spot,t} z_{spot,t}, \quad z_{spot,t} \sim N(0,1) \tag{1b}$$

$$h_{spot,t} = \sigma^2_{spot,t} = \omega + \alpha\varepsilon^2_{spot,t-1} + \beta h_{spot,t-1} + \gamma\varepsilon^2_{spot,t-1} d_{spot,t-1} \tag{1c}$$

where

$$d_{spot,t} = \begin{cases} 1, if & \varepsilon_{spot,t} < 0 \\ 0, if & \varepsilon_{spot,t} \geq 0 \end{cases} \tag{1d}$$

$$r_{future,t} = \mu_{future} + \varepsilon_{spot,t}, \tag{1e}$$

$$\varepsilon_{future,t} = \sqrt{h}_{future,t} z_{future,t}, \quad z_{future,t} \sim N(0,1) \tag{1f}$$

$$h_{future,t} = \sigma^2_{future,t} = \omega + \alpha\varepsilon^2_{future,t-1} + \beta h_{future,t-1} + \gamma\varepsilon^2_{future,t-1} d_{future,t-1} \tag{1g}$$

where

$$d_{future,t} = \begin{cases} 1, if & \varepsilon_{future,t} < 0 \\ 0, if & \varepsilon_{future,t} \geq 0 \end{cases} \tag{1h}$$

Then ,we set the joint distribution of $z_t = (z_{spot,t}, z_{future,t})$ as (1e)

$$(z_{spot,t}, z_{future,t}) \sim C_t(F(z_{spot,t}), F(z_{future,t})) \tag{1e}$$

Where, $z_{i,t} = \varepsilon_{i,t} / \sqrt{h_{i,t}}$ is the conditional distribution of standardized innovations. In this study, we set i=spot, future. The distribution of the innovation vector $z_t = (z_{spot,t}, z_{future,t})$ is modeled by copula. C_t (……,.). Here, C was modeled by Normal, student-t, Clayton-Copula, Gumbel Copula and Frank Copula function and time varying copula, namely time varying normal copula[2]

Normal copula is the copula of multivariate normal distribution. It is defined as follows: Assuming $X = (X_1, X_2, ..., X_n)$ is multivariate normal, if and only if (a) its margins $F_1, ..., F_n$ are normally distribution, and (b) a unique copula function[3] exists, such that

$$C_R^N(u_1, ..., u_n) = \Phi_R(\phi^{-1}(u_1), ..., \phi^{-1}(u_n)) \tag{2}$$

where Φ_R denotes the standard multivariate normal distribution with correlation matrix R and ϕ^{-1} is the inverse function of standard univariate normal distribution. When n=2, we can obtain the copula function as follows:

$$C_R^N(u,v) = \int_{-\infty}^{\phi^{-1}(u)} \int_{-\infty}^{\phi^{-1}(v)} \frac{1}{2\pi(1-R_{12}^2)^{1/2}} \exp\{-\frac{s^2 - 2R_{12}st + t^2}{2(1-R_{12}^2)}\} dsdt \tag{3}$$

By the same concept, t-copula is the copula function of multivariate Student's t distribution. Assuming $X = (X_1, X_2, ..., X_n)$ observes standard multivariate normal distribution with correlation matrix R, Y is the random variable of χ^2 distribution with v degree of freedom, then t-copula function is:

$$C_{v,R}^t(u_1, ..., u_n) = t_{v,R}(t_v^{-1}(u_1), ..., t_v^{-1}(u_n)) \tag{4}$$

where $u_i = \frac{\sqrt{v}}{\sqrt{Y}} X_i, \quad i = 1, ..., n$

When n=2, we can obtain the t-copula as follows:

$$C_{v,R}^t(u,v) = \int_{-\infty}^{t_v^{-1}(u)} \int_{-\infty}^{t_v^{-1}(v)} \frac{1}{2\pi(1-R_{12}^2)^{1/2}} \{1 + \frac{s^2 - 2R_{12}st + t^2}{v(1-R_{12}^2)}\}^{-(v+2)/2} dsdt \tag{5}$$

[1] Based on the min: AIC (Akaike(1974) information criterion), we set optimal order of AR-GJR-GARCH (1,1).This specification is able to solve both the autocorrelation and heteroscedasticity and asymmetric problems.

[2] To save space, copula functions will not be shown here. The books of Joe (1997) and Nelsen (2006) presented a good introduction to the copula theory.

[3] i.e. the normal copula.

Another important class of copulas is known as Archimedean copulas. These copulas find a wide range of applications. A n-dimension copula function,

$$C\left(x_1,\cdots x_n\right)=\Psi^{-1}\left(\sum_{i=1}^{n}\Psi\left(F_i\left(x_i\right)\right)\right) \tag{6}$$

where Ψ : generator function and satisfies $\Psi(1)=0$;

$\lim_{x\to 0}\Psi(x)=\infty$; $\Psi'(x)<0$; $\Psi''(x)>0$

then there are three types of Archimedean copulas functions, namely Clayton-n-Copula, Gumbel-n-Copula and Frank-n-Copula function, respectively.

Clayton-n-Copula function: when $\alpha>0$,

$$C\left(u_1,\ldots,u_n\right)=\left[\sum_{i=1}^{n}u_i^{-\alpha}-n+1\right]^{-1/\alpha} \tag{7}$$

We further use the Kendall tau (τ) coefficient to calculate the rank correlation coefficient of operation events-pair. It is a non-parametric statistic used to measure the association or statistical dependence between two measured quantities. For a pair (X, Y), we can construct a two-dimension copula C and obtain the Kendall tau as equation (8),

$$\tau=4\iint C(u,v)\,dC(u,v)-1 \tag{8}$$

The time-varying normal copula tau function is given:

$$\rho_{1,2,t}=\widetilde{L}[\omega_\rho+\beta_\rho\rho_{1,2,t-1}+\alpha_\rho\frac{1}{10}\sum_{j=1}^{10}\Phi^{-1}(u_{t-j})\Phi^{-1}(v_{t-j})] \tag{9}$$

Where ρ is normal kendall'tau, $\widetilde{L}(x)=\dfrac{1-e^{-x}}{1+e^{-x}}$, the modified logistic function ; Φ^{-1} is the inverse of the standard normal CDF.

4 Empirical Results and Analysis

4.1 Data description and Descriptive Statistics

The study investigate the volatility behavior and dependence structure of WTI Crude Oil Spot and Future Price. The period of time chosen is from Jan. 1, 2001 to December 31, 2014. The data is obtained from Taiwan Economic Journal databank (TEJ). Table-1 reports the summary statistics of WTI crude oil spot and future price and return series. It shows a high correlation 0.9998 and 0.8588 between the price and return series of WTI Crude oil spot and futures, respectively. The mean values are ranging between 67.8358 and 67.8634 for the WTI Crude oil spot and WTI Crude oil futures. Standard deviations are equal to 28.564 and 28.56; relatively high volatility exhibited all price series.

Both of the prices are low kurtosis, left skewness. However, the return of spot and future are high kurtosis. In addition, all of the Jarque-Bera (J-B) statistics reject the null hypotheses of normality distribution. (also see the Figure 1 to 4).The Ljung and Box statistics provides the test of the presence of autocorrelation for return series. All the series exist the autocorrelation. What is more, the square of Ljung and Box statistics provides the test of the presence of ARCH effect for return series. The results show that all the series have ARCH effect. This is why we consider the GJR-GARCH model in the paper.

The Figure 5 and Figure 6 exhibits the time series of WTI Crude Oil Spot and Future Price and return. The two series are almost the same trend. So, the scatter plot of Figure 7 also indicates a high correlation.

Table 1 Summary statistics of WTI Crude oil (Full sample)

variable	SPOT	FUTURE	RET_SOPT	RET_FUTURE
correlation	**0.9998**		**0.8588**	
Mean	67.8358	67.8634	0.0002	0.0002
Std	28.5640	28.5600	0.0245	0.0233
Max	145.3100	145.2900	0.2095	0.1641
min	17.4700	17.4500	-0.1870	-0.1654
Kurtotsis	1.9531	1.9569	11.1466	8.1181
Skewness	-0.0276	-0.0303	0.0378	-0.1027
JB stat	161.7970***	160.7047***	9767.8626***	3861.1810***
LQ(6)	20990.7366***	20992.7222***	28.1277***	14.6423***
LQ(6)^2	20894.0241***	20887.7898***	1645.8808***	764.0644***

Note:

1.Std means the standard deviation, J-B stat is obtained from Jarque -Bera normality test.

2.* indicates the statistical significance and the rejection of null hypothesis at 1% significance level.

3.The Ling and Box statistics provides the test of the presence of autocorrelation for return series.

4.The square of Ljung and Box statistics provides the test of the presence of ARCH effect for return series.

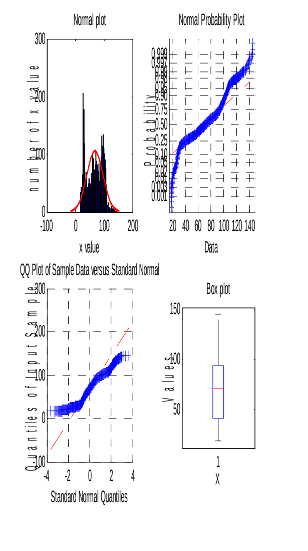

Figure 1 Statistics Descriptive of WTI crude oil spot price

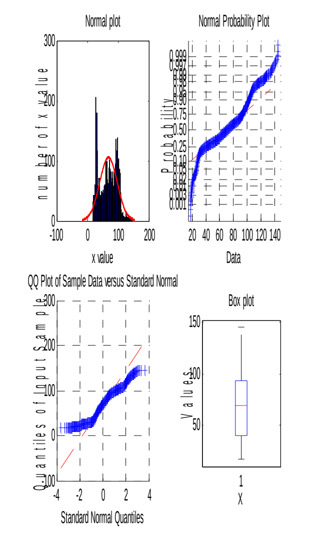

Figure 2 Statistics Descriptive of WTI crude oil future price

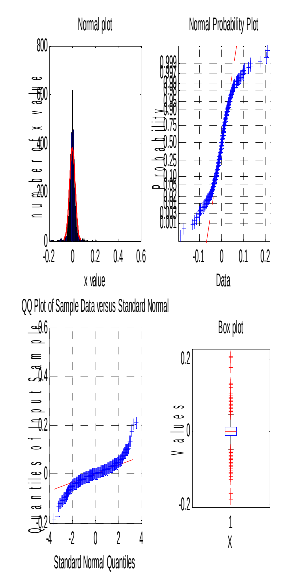

Figure 3 Statistics Descriptive of return of WTI crude oil spot

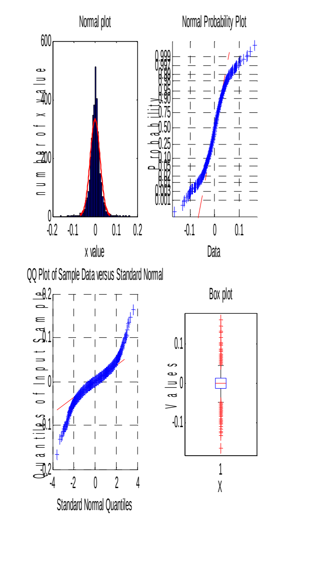

Figure 4 Statistics Descriptive of return of WTI crude oil future

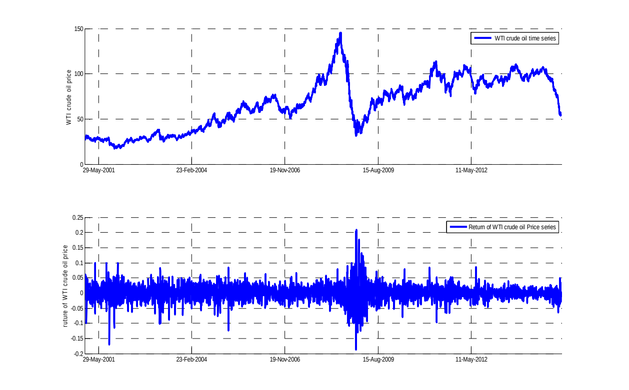

Figure 5 Time series of WTI crude oil spot price and return

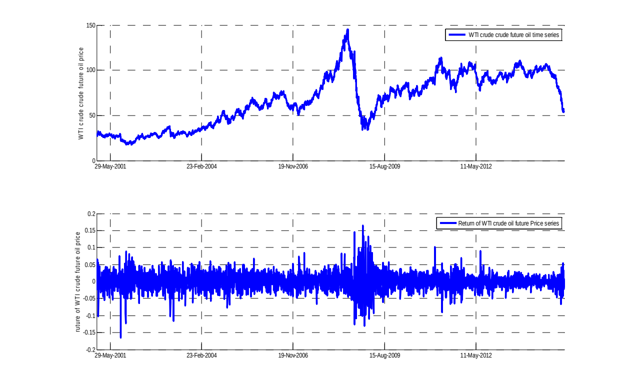

Figure 6 Time series of WTI crude oil future price and return

We used a Chow test (1960) to verify this hypothesis and the results show structural breaks indeed exist. Therefore, we divided the sample period into two subsets (pre- and post- July 14, 2008) to examine if volatility behavior exhibits different characteristics during the point. where an uptrend in sport and future price began. The period before the date is labeled as "before the uptrend." The data period includes Jan. 1, 2001 to July 14, 2008. On the other hand, after the date is described as "during the uptrend." In the data period containing July 15, 2008 to Dec. 31 2014.

4.2 Empirical Results Analysis

Table 2 presents the AR-GJR-GARCH (1, 1) result of full sample. The parameters in the conditional mean equation are significant. In addition to, the parameters of conditional variance equation are also significant. Especially, the leverage effect is also significant which represents the volatility asymmetric effect among full sample. Table 3 represents the three static copula results including their AIC, BIC and kendall's tau. The best model is Clayton copula via the minimum AIC criteria. The kendall's tau is 0.7103 which implies the crude oil return of spot and future has a higher positive relationship during the period. It is also shows in the scatter plot of Figure 7.

Table 2 Results from the AR–GJR-GARCH (1, 1) model

	Full sample	
	Ret_spot	**Ret_future**
	Panel A: Conditional mean equation	
μ	0.0001*	0.0002*
	(1.9720)	(1.9308)
	Panel B: Conditional variance equation	
ω	2.1863e-006***	2.5439e-006***
	(3.5312)	(4.0598)
α	0.9501***	0.9469***
	(269.3350)	(229.5766)
β	0.0261***	0.0288***

	(5.0150)	(6.0745)
γ	0.0415 ***	0.0407 ***
	(6.1905)	(5.1763)
LL	8.6691e+003	8.7167e+003

Note: 1. The estimated parameters correspond to equations (1a) to (1g). LL corresponds to the log - likelihood function value.
2. The t values are in the parenthesis.
3. The * **, ** stand for 10%, 5%, 1%, respectively.

Table 3 The Kendall's tau of copula functions (Full sample)

	AIC	BIC	Kendall tau
Normal Copula	6312.2	6312.2	0.7362
Student T Copula	8277.8	8277.8	0.7028
Clayton Copula	6192.4	6192.4	0.7103

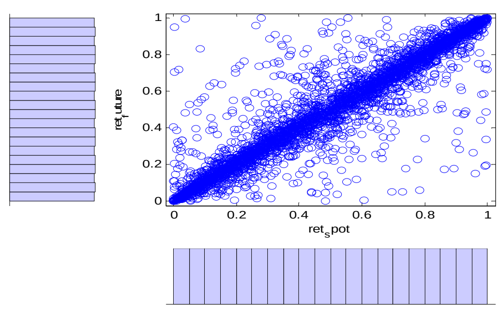

Figure 7 Scatter plot of return of WTI crude oil spot and future price(full sample)

Table 4 presents the AR-GJR-GARCH (1, 1) result of before the submortgage. The parameters in the conditional mean equation are significant. In addition to, the parameters of conditional variance equation are also significant. Especially, the leverage effect is also significant which represents the volatility asymmetric effect among the period. Table 5 represents the three static copula results including their AIC, BIC and kendall tau. According to the minimum AIC criteria, The best model is still the Clayton copula which kendall's tau is 0.7025, lower than the full sample period. This implies the crude oil return of spot and future has a higher positive relationship during the period. It is also shows in the scatter plot of Figure-8.

Table 4 Results from the AR–GJR-GARCH (1, 1) model

	Subsample-1(before)	
	Ret_spot	**Ret_future**
	Panel A: Conditional mean equation	
μ	0.0010**	0.0009*
	(2.0059)	(1.9618)
	Panel B: Conditional variance equation	
ω	0.0001***	2.5135e-005***
	(5.7183)	(5.2150)
α	0.6596***	0.9019***
	(12.7247)	(73.0542
β	0.0406***	0.0190***
	(2.9400)	(2.4002)
γ	0.1681***	0.0563 ***
	(6.0341)	(4.2495)
LL	4.4356e+003	4.4765e+003

Note: 1. The estimated parameters correspond to equations (1a) and (1g). LL corresponds to the log - likelihood function value.
2. The t values are in the parenthesis.
3. The * **, ** stand for 10%, 5%, 1%, respectively.

Table 5 The Kendall's tau of copula functions (Subsample-1)

	AIC	BIC	Kendall tau
Normal Copula	3029.6	3029.5	0.7162
Student T Copula	4023.4	4023.3	0.7012
Clayton Copula	2836.0	2836.1	0.7025

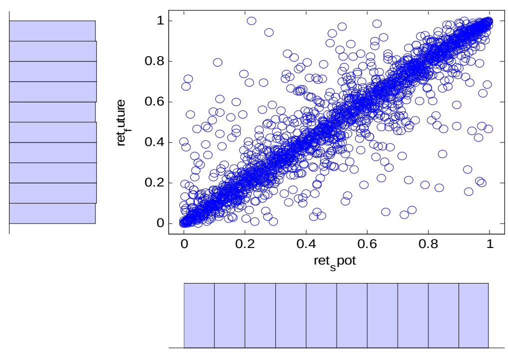

Figure 8 Scatter plot of return of WTI crude oil spot and future price(subsample-1)

Table 6 presents the AR-GJR-GARCH (1, 1) result of after the submortgage. The parameters in the conditional mean equation are also significant. In addition to, the parameters of conditional variance equation are significant. Especially, the leverage effect is also significant which represents the volatility asymmetric effect among the period. Table 7 represents the three static copula results including their AIC, BIC and kendall's tau. The best model is Normal copula via the minimum AIC criteria. The kendall's tau is 0.7385, higher than the full sample and before the sub mortgage crisis period, which still implies the sub mortgage crisis raised the correlation between crude oil return of spot and future. The scatter plot of Figure-9 exhibits the high correlation.

Table 6 Results from the AR–GJR-GARCH (1, 1) model

	Subsample-2(after)	
	Ret_spot	**Ret_future**
Panel A: Conditional mean equation		
μ	-0.0003* (-1.8900)	-0.0003* (1.9138)
Panel B: Conditional variance equation		
ω	2.4613e-006*** (3.0137)	2.3164e-006*** (3.2181)
α	0.9401*** (115.9671)	0.9413 *** (115.9671)
β	0.0101 *** (1.3804)	0.0193*** (2.9765)
γ	0.0889*** (6.8160)	0.0699*** (5.6770)
LL	4.2639e+003	4.2579e+003

Note: 1. The estimated parameters correspond to equations (1a) and (1g). LL corresponds to the log - likelihood function value.
2. The t values are in the parenthesis.
3. The * **, ** stand for 10%, 5%, 1%, respectively.

Table 7 The Kendall's tau of copula functions (Subsample-2)

	AIC	BIC	Kendall tau
Normal Copula	3123.6	3123.5	0.7385
Student T Copula	4076.3	4075.7	0.7136
Clayton Copula	3249.6	3249.8	0.7295

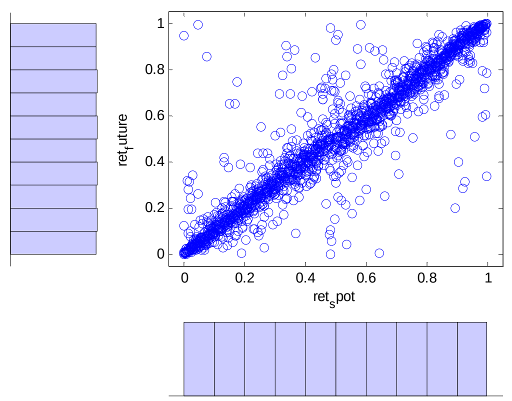

Figure 9 Scatter plot of return of WTI crude oil spot and future price(subsample-2)

In order the investigate the dynamic correlation during the full sample, before and after the sub mortgage crisis each day, we further to conduct the time-varying normal copula. Form figure 10, the average rank correlation is 0.9126, standard deviation is 0.0056, max value is 0.9375, minimum value is 0.8976, and the skewness and kurtosis tend to positive and high.

Figure 11 exhibits the before sub mortgage crisis dynamic rank correlation. The average rank correlation is 0.8938, lower the full sample, standard deviation is 0.0281, maximum value is 0.9605, minimum value is 0.6816, and the skewness and kurtosis tend to negative and extreme high.

Figure 12 presents the dynamic rank correlation after the sub mortgage crisis. Similar to the static copula results, the average rank correlation is 0.9211, higher than the full sample, standard deviation is 0.0073, maximum value is 0.9541, minimum value is 0.8994, and the skewness and kurtosis tend to positive and normal distribution.

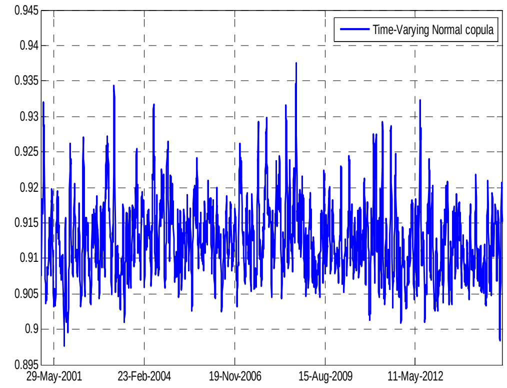

Figure 10 Time varying Normal (full sample)
Note: Mean= 0.9126;Std= 0.0056;Max= 0.9375;Min= 0.8976;skewness= 0.6586 Kurtosis= 3.8550

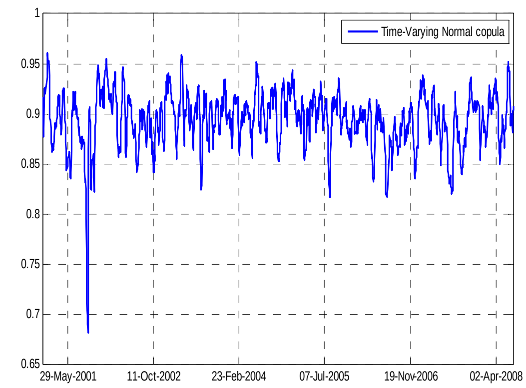

Figure 11 Time varying Normal (subsample-1)
Mean=0.8938 ; Std= 0.0281; Max= 0.9605; Min= 0.6816; Skewness= 1.3285; Kurtosis= 9.3221

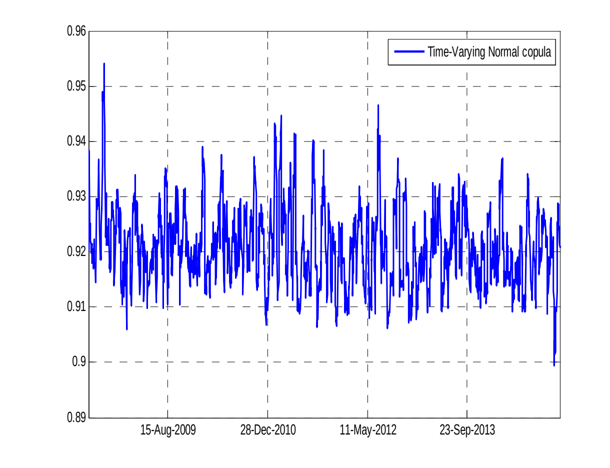

Figure 12 Time varying Normal (subsample-2)
Note: Mean= 0.9211; Std =0.0073; Max=0.9541; Min=0.8994; Skewness=0.6117; Kurtosis=3.7775

4. CONCLUSION

In this article, we have used AR-GJR-GARCH-Copula model to examine the volatility behavior and dependence structure of WTI crude oil spot and future Price. We find strong evidence of rank correlation. Our empirical results show that the best model is Clayton copula in full sample and before the sub mortgage crisis. the kendall tau implies the crude oil return of spot and future has a higher positive relationship during the period. The best model is Normal copula after the sub mortgage crisis and the kendall tau is higher than the full sample and before the sub mortgage crisis period, which still implies the sub mortgage crisis raised the correlation between crude oil return of spot and future.

In addition, the dynamic normal copula model also finds the same results as static copula models. By comparison, the average rank correlation is higher than full sample and before the sub mortgage crisis on after the crisis. Which implies that raised the hedge demand after sub mortgage crisis.

Further research may apply different econometric models, for example the copula based markov-switching GARCH model or long-memory GARCH model.

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