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International Oil Price Volatility Risk from the Perspective of Finance

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Nowadays, the international oil price remains high and has frequent volatility, the global oil supply and demand risk has turned into the volatility of financial risk. This study aims at uncovering the mystery behind the volatility of international oil price mechanism and finding a better way to calculate the value of Risk (VaR) of the volatility international oil price. This paper calculated VaR using traditional ARCH-class models and SWARCH model. Based on the results which is calculated by the two models, we found out that the SWARCH model is better on the prediction of international oil price volatility risk, which will have a very important reference meaning, for making the corresponding rules and regulations, and also, it is important for expanding the analysis of financial market.

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1. Introduction

Since the 21st Century, the price volatility of international crude oil has been abnormal; the supply and demand balance theory of classic economics cannot fully explain the profound reasons behind these abnormalities. What causes oil price to go up and down constantly and abruptly? How to calculate the value at Risk (VaR) of oil price? And which method is best used to determine the value at Risk (VaR) of oil price? Based on the above questions, this paper will focus on quantitative study of the degree of impact made by financial factors on the international oil price volatility, and accurately capture the inherent law and reason for the large oil price fluctuation. Different from previous papers, this paper introduces the SWARCH (Regime Swishing ARCH) model that has better performance to strengthen the financial factors and mutant state. The method has a more accurate effect on the measurement of value at Risk (VAR), and also, can detect the influence of invisible policies on oil price fluctuation. The theory depicts a phenomenal rise from one state to another in oil price profitability sequence and expands the breadth and depth of the oil price risk management theory. This work is organized as follows. Related literature will be reviewed in Section 2. Section 3 describes SWARCH methodology and model. Section 4 denotes empirical analysis of WTI crude oil futures prices. The main conclusions are summarized in Section 5.

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2. Literature Review

There are a lot of research literatures about the oil price fluctuation, most of them use the quantitative research methods, and these methods can be divided into two categories: statistical methods and complex computer simulation method. Many literatures have confirmed the financial attributes of oil. However, they do not consider the impact of financial factors, as exogenous variables of the fluctuation. After repeated trial, some financial factors, such as dollar index, are introduced into the model. Established ARMAX-ARCH model (X stand for financial factor) can truly reflect the influence of financial factors on the oil market. In addition to strengthening the volatility spillover effect of some financial factors on international oil price, the model can predict more accurately, the oil price from the financial angle.

For oil price volatility risk estimation, the existing research mainly uses the historical simulation method, GARCH model, extreme value theory and CAViaR method to estimate VaR, while the ARCH model is the most current computing method. Although, the ARCH model family has made some remarkable achievements in the estimation of volatility, the algorithm still has a flaw: it does not consider the financial time series, which occasionally and suddenly moves, and these discontinuous moves will be of immense benefit and will change the dynamic structure. So constant coefficients under ARCH model seems unconvinced at different periods. Therefore, Sun Yingpan (2013) used the Markoff switching model. This can perform the remarkable structural change described by a unified model. However, this model cannot accurately simulate the time series variable volatility changes like an ARCH model. Hamilton(2004) combines the first order Markoff process into the ARCH model(SWARCH model), which separates oil fluctuation into state persistence and ARCH persistence. When these two states are combined, we can better reflect the oil price changes. At present, it is difficult to find the application of this model. Su (2005) and Sun(2010) mainly apply it in the study of the stock market. Above all, this paper first applied the SWARCH model to oil price risk calculation. It explains the price fluctuations of crude oil with high persistence, which is actually "pseudo continuous". Because the variance structure makes a constant state of change, it has false "high memory" state. Namely high persistence of the data leading to volatility persistence is not the data itself, but the continuing state leads to long memory volatility.

With respect to constant volatility model, the performance of the ARCH model does not have a significant increase in the volatility forecasting. Diebold (1986), Lamoureux and Lastrapes (1990) pointed out that high persistence may be as a result of structural changes in the sample variance process. Hanilton and Susumel (1994) proposed a state transition ARCH model (SWARCH-Regime. swishing ARCH). From the angle of occasionality, and not from a continuous conversion model, many researchers conducted a study on economic and financial time series, which allows for nonlinear sequential variable, dynamic and sudden change. When considering stock in different growth state transformation, Ceccehetti, Lam and Mark (1990) pointed out that structural transformation mechanism can explain many characteristics of stock market returns, such as the peak thick tail and the mean recovery characteristics. Kim and Kon proposed that we need to consider the series structure change in the process of getting revenue, they confirmed the importance of structural transition and time-varying dependence on the stock return distribution. For Chinese scholars, Ke Ke and Zhang Shiying (2001), they put forward the analysis and diagnosis of the ARCH model. Using the SWARCH model, Zhan Yuanrui (2005) conducted an empirical analysis for China, in which the results indicated the need to improve the volatility measure. This paper aim to improve the SWARCH model volatility measure and also aim to improve the market risk measure of VaR.

3. The Methodology and Model

SWARCH mode take the Markov chain to the ARCH model, Markov chain has the characteristic of Markov which is a discrete process, while the current state will influence the future state, and the last state has nothing to do with the future state, these can be expressed as:

$$P_{ij} = P(s_t = j \mid s_{t-1} = i) = P(s_{t-1} = i, s_{t-2} = k, ..., y_{t-1}, y_{t-2}) \quad (1)$$

Suppose {l,…,K} is an integer, the range of i and j is from 1 ot K, St is a random state variable。Conversion from state i to state j state can be represented by P_{ij}, known as the transition probability, the state transition probability matrix is:

$$p = \begin{bmatrix} p_{11} & p_{11} & \cdots & p_{11} \\ p_{12} & p_{22} & \cdots & p_{k2} \\ \cdots & \cdots & \cdots & \cdots \\ p_{1k} & p_{2k} & \cdots & p_{kk} \end{bmatrix} \quad (2)$$

The total probability of state transition:

$$\sum_{j=1} p_{ij} = 1, 0 \le p_{ij} \le 1 (i = 1, 2, ..., k)$$

We can use the state vector auto regression method to represent Markov chain and to redefine the state, suppose:

$$u_t = \begin{cases} (1,0,0,...,0)^T, s_t = 1 \\ (0,1,0,...,0)^T, s_t = 2 \\ \cdots \\ (0,0,0,...,1)^T, s_t = K \end{cases} \quad (3)$$

u_t is a K×1 vector, which be changed along with the transfer of state.

Suppose s_t=i, and the j-th element of u_t+1 is a random variable. If P_{ij}=1 and others equal 0, the variable's expectation will be P_{ij}. When s_t=i , the expectation of u_{t+1} will be:

$$E(u_{t+1} \mid s_t = i) = (p_{i1}, p_{i2}, ..., p_{ik})^T$$

and :

$$E(u_{t+1} \mid u_t) = Pu_t$$

According to the definition of a Markov chain:

$$E(u_{t+1} \mid u_t, u_{t-1}, ...) = Pu_t$$

So the Markov chain can be expressed as:

$$u_{t+1} = Pu_t + \varepsilon_{t+1}$$

Where $\varepsilon_{t+1} = u_{t+1} - E(u_{t+1} | u_t, u_{t-1}, ...)$, and the average of ε_t will be 0

The first m forecast values of Markov chain will be:

$$E(u_{t+m} | u_t, u_{t-1}, ...) = P^m u_t$$

The financial time series is often dramatically interrupted by the significant changes of war, financial crisis and government policy, which made the traditional estimation is not always satisfactory. Financial trend can be best described by using the Markov chain.

For the process $\{Y_t\}$：

$$\begin{aligned} Y_t &= \tilde{Y}_t + \varepsilon_{s_t} \\ \tilde{Y}_t &= \beta_0 + \beta_1 \tilde{Y}_{t-1} + v_t \end{aligned} \tag{4}$$

$$\varepsilon_{s_t} = \begin{cases} \varepsilon_1, S_t = 1 \\ \varepsilon_2, S_t = 2, \\ \cdots \end{cases} \tag{5}$$

And ε_{s_t} is an ARCH(q) process：

$$\begin{aligned} \varepsilon_t \big| I_{t-1} &\sim N(0, \sigma_t^2) \\ \sigma_t^2 &= a_0 + a_1 \varepsilon_{t-1}^2 + \ldots + a_q \varepsilon_{t-q}^2 \end{aligned} \tag{6}$$

The settings are not easily calculated because each state has different parameter settings are not easy to be calculated, and the parameters are bloated, for ε_t, the model is as follows:

$$\varepsilon_t = \sqrt{g_{s_t}} \cdot \varepsilon_t \tag{7}$$

The value of g_{s_t} can also explain the impact on the fluctuation from the state of S_t. Assuming $g_1 = 1$, $g_j \geq 1 (j = 2,3)$:

$$\begin{aligned} \varepsilon_t &= \sigma_t e_t \\ \sigma_t^2 &= a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2 + \ldots + a_q \varepsilon_{t-q}^2 \\ \sigma_t^2(S_t, S_{t-1}) &= E[\varepsilon_t^2 \big| S_t, S_{t-1}; \varepsilon_{t-1}, \varepsilon_{t-2}, \cdots] = g_{s_t} \left\{ a_0 + (a_1 + a_2 + \ldots + a_q) \cdot (\varepsilon_{t-1}^2 / g_{s_{t-1}}) \right\} \end{aligned} \tag{8}$$

We will say that ε_t in (7) follows a K-state, qth-order Markov-switching ARCH process, the Integrated equation (4)-(8) is the SWARCH (K, q) model.

4. Empirical Analysis

In this paper, the WTI crude oil future prices, the dollar index and the standard Poor's 500 index (S&P) are used as the research object, we selected 3077 data from three market samples from January 4, 2000 to May 11, 2012:

(1) According to the WTI crude oil future market returns data, we established a series of ARMAX (6,6,2) -SWARCH-L (6,6,2) model, where (6,6,2) represents the equation which contains AR (6), MA (6) and 2 Exogenous financial factors (the US dollar index and S&P index). Suppose k represent the possible number of states, state variables that cannot be observed can be expressed as $g_i, i=1,2,\ldots,k$; q means a lag order of ARCH effect, its value equal 2, 3 respectively. Numbers to be selected, depends mainly on the degree of parameter estimation difficulty; L represents the leverage effect (Leverage Effect) of the ARMAX-SWARCH-L model

(2) Suppose Z_t of SWARCH-L model obey normal distribution and t distribution, then it can be recorded with $\text{SWARCH-L-}N(k,q)$ and $\text{SWARCH-L-}t(k,q)$ respectively.

(3) Comparing the $\text{SWARCH-}L(k,q)$ model with the traditional $GJR-GARCH(1,1)$ model, we can propose that Z_t obey t and GED distribution, which can be expressed by $GJR-GARCH-t(1,1)$ and $GJR-GARCH-GED(1,1)$.

4.1 Models Comparison

Comparing the results gotten by SWARCH-class model with the results gotten by GARCH-class model, we can deduce the following as shown in table 1.

Table 1: Comparison of traditional GARCH model and SWARCH model

Model	No. of param-eters	Log-likelihood	AIC	SC	Degrees of freedom	Persistence λ
GJR-GARCH-T(1,1)	9	7512.517	-4.89981	-4.87821	6.75	0.94372
GJR-GARCH-GED(1,1)	10	7535.419	-4.90873	-4.88712	6.72	0.96748
SWARCH-L-N(2,2)	11	7515.810	-4.89551	-4.87388	7.98	0.5645
SWARCH-L-t（2,2）	12	7526.953	-4.90277	-4.87853	8.25	0.6548
SWARCH-L-N（2,3）	12	7512.140	-4.89246	-4.85887	9.22	0.3652
SWARCH-L-t（2,3）	13	7538.699	-4.90913	-4.87357	9.18	0.2365
SWARCH-L-N（3,2）	15	7637.601	-4.97365	-4.93809	9.07	0.2657
SWARCH-L-t（3,2）	16	7695.401	-5.01070	-4.97317	8.63	0.2149

Note：1. All the models in the table is the leverage effect

2. Persistence λ represent sustainable levels of ARCH component model, and parameters in the conditional variance function are used to represent the sum of continuous parameters of the GARCH model, $\lambda = \sum_{i=1}^{q} a_i + \sum_{j=1}^{p} \theta_j$. Persistence of the SWARCH model is the characteristic maximum of matrix as follows:

$$\begin{pmatrix} a_1+\xi/2 & a_2 & \cdots & a_{q-1} & a_q \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & 1 & 0 \end{pmatrix}$$

3. In the progress of establishing the SWARCH model for the return data of WTI crude oil future market rate, most of people use the ARMAX (6,6,2) form is commonly used to express the mean equation, namely ARMAX (6,6,2)-SWARCH-L model. Because of the limited space, here we omitted the introduction here.

4.2 SWARCH-L-t(3,2) Parameter Estimation

Based on the above description, SWARCH-L-t(3,2) model is the best and we can get the estimated value of every parameter, and the final model estimation result as follows:

$$r_t = 0.001109\text{-}1.77678X_1 + 0.05627X_2 + 0.75687\text{AR(6)-}0.91257\text{MA(6)+}u_t \quad (8)$$

（0.000315*） （0.102942*） （0.008915*） （0.139238*） （0.134160*）

$$u_t = \sqrt{g_{st}}\tilde{u}_t \quad \tilde{u}_t = h_t v_t \ ,$$

v_t □ $i.i.d.$ Student t with unit variance $h_t^2 = 0.00032{+}0.00534\tilde{u}_{t-1}^2{+}0.07041\tilde{u}_{t-2}^2 + 0.05090 d_{t-1}\tilde{u}_{t-1}^2$ (9)

（0.000374*） （0.008033*） （0.068908*） （0.000482*）

$$\begin{cases} d_{t-1} = 1, & 当 \mu_{t-1} \le 0 \\ d_{t-1} = 0, & 当 \mu_{t-1} > 0 \end{cases}$$

$$g_1 = 1, \qquad \hat{g}_2 = 2.196, \qquad \hat{g}_3 = 10.692$$

（0.196179*） （0.015672*）

The freedom of t distribution is 8.63, The log likelihood value is 7695.401, AIC=-5.01070, SC=-4.97317, Transition probability matrix：

$$p = \begin{pmatrix} 0.98932 & 0 & 0.00505 \\ (0.0000^*) & & (0.0157) \\ 0.01067 & 0.99746 & 0.00031 \\ (0.0022) & (0.0000^*) & (0.0006) \\ 0 & 0.00257 & 0.89905 \\ & (0.0069) & (0.0018^*) \end{pmatrix}$$

Where r_t 、 X_1 and X_2 represent WTI crude oil futures market, the dollar and the S&P index return series respectively. The value in the parentheses means the standard deviation of coefficient estimates, * shows that it is significant at the 99% level of confidence * $g_i, i = 1,2,3$ means i-th state and d express leverage effect parameters

Above all:

(1) The variance in the medium-volatility state (s_t = 2) is two times greater than those in the low-volatility state, while the variance in the high-volatility state (s_t = 3) is 10.6 times greater than those in the low-volatility state, which has a greater impact on volatility and yields a strong fluctuation on return data.

(2) The estimated transition probabilities describes each state as highly persistent. State 1 would be expected to last on average for $(1\text{-}P_{11})^{-1}$ = 94 trading days, while states 2 and 3 typically last for 391 trading days and 10 trading days respectively. The market was quiet in state 1 for only a single episode in the sample, which episode was preceded by state 3 and followed by state 2. Hence the maximum likelihood estimate is that state 1 is

never preceded by state 2 (P_{21}, = 0) and state 1 is never followed by state 3 (P_{13} = 0). The frequencies of the three states are: 19%, 80% and 1%. If considering 250 trading days each year, oil price returns will have 47 days of the year in state1,200 days in state 2 and 3 days in state 3 .

(3) If satisfying the condition $P_{22}>P_{11}>P_{33}$, the stability's sorting order is just according to the value of size. From a comparison between the three states, we discovered that state 3 has the characteristic of a big variance, short duration, bad stability and it is prone to change.

(4) Parameters d_{t-1} is significant at 1%, it indicates the existence of leverage effect, when $\varepsilon_{t-1}<0$, $d_{t-1}=1$. impact factor from ε_{t-1}^2 to h_t is 0.0509; when $\varepsilon_{t-1}>0$, $d_{t-1}=0$, impact factor from ε_{t-1}^2 to h_t is 0.0053; When absolute value is the same, the impact of negative volatility on the next phase of fluctuation is more severe than the forward volatility.

4.3 Analysis of Fluctuation Smoothing Probability

The top panel of Fig. 2 plots the WTI oil price return series, while the other three panels plot the smoothed probabilities Problem. The low-volatility state describes the quiet period. Most of the other observations comes from the medium-volatility state. State 3 appeared at a time when returns have high-volatility episodes, like the outbreak of the American financial crisis in 2008. In state 3, the variance structure suddenly moved, which shows that state 3 is in continuous high probability.

Figure 1: Return Series

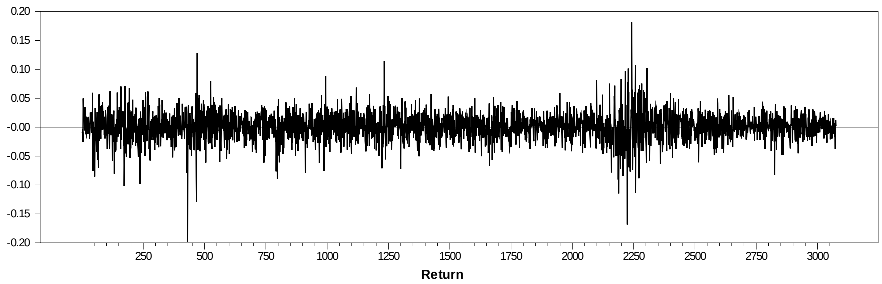


Figure 2: State 1 Smooth Probability

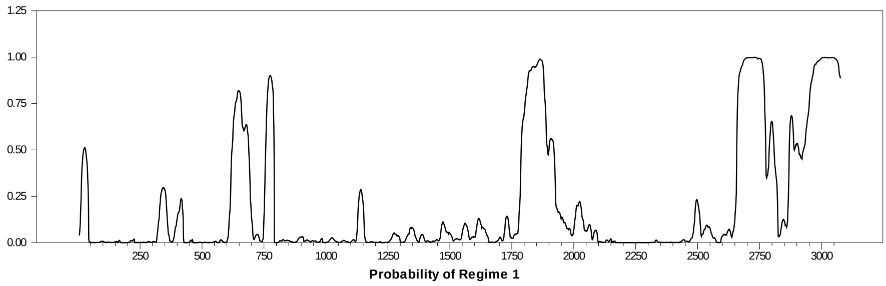


Figure 3: State 2 Smoothing Probability Graph

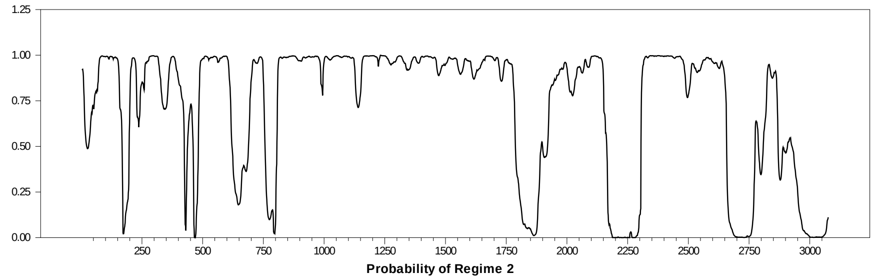
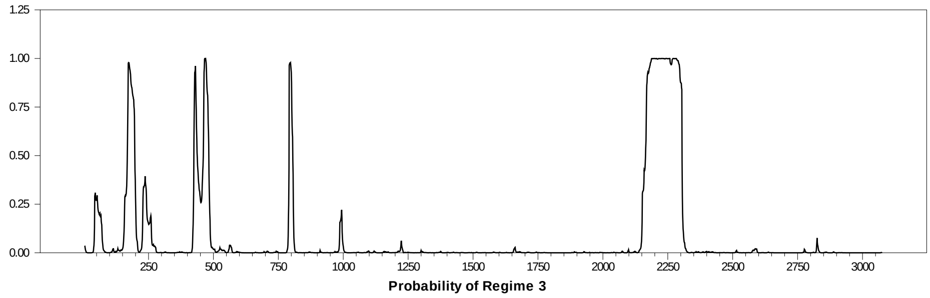


Figure 4: State 3 Smooth Probability Graph



4.4 Estimation of VaR Under SWARCH Model

We can evaluate the parameter we want according to the above SWARCH model, thereafter, we can obtain VAR in state transition under the ARCH model, the VaR is the estimated value of the day when confidence level equal 1, the expression is as follows:

$$\alpha = \sum_{j=1}^{k} P(s_{t+1} = j \mid I_t;\theta) \times \int_{-\infty}^{-VaR_{t+1}(c)} f(x \mid s_{t+1} = j, I_{t+1} = j, I_t;\theta)dx \tag{10}$$

The set of information at time T can be expressed by It and the estimation of parameter vector is shown by θ, $f(x \mid s_{t+1} = j, I_{t+1} = j, I_t;\theta)$ which is the probability density function of return rate, which is calculated by variable s_{t+1} and it information is set under the condition j. Suppose the parameters in the equation ZT obeys normal distribution, the probability density function can be expressed as follows:

$$f(x \mid s_{t+1} = j \mid I_t;\theta) = \frac{1}{\sqrt{2\pi \cdot g_j \tilde{h}_{t+1|t}}} \exp(-\frac{(x-u)^2}{2g_j \tilde{h}_{t+1|t}}) \tag{11}$$

When variable ZT at the degree of freedom is in the t distribution of v, the conditional density function expression is as follows:

$$f(x \mid s_{t+1} = j \mid I_t;\theta) = \frac{\Gamma(\frac{v+1}{2})}{\Gamma(\frac{v}{2})\sqrt{\pi(v-2)g_j \tilde{h}_{t+1|t}}} \times (1 + \frac{(x-\mu)^2}{(v-2)g_j \tilde{h}_{t+1|t}})^{\frac{v+1}{2}} \tag{12}$$

Where

$$\tilde{h}_{t+1|t} = E(\tilde{h}_{t+1|t} \mid I_t;\theta) = \sum_{s_t=1}^{k} \cdots \sum_{s_{t-q+1}=1}^{k} \tilde{h}_{t+1}(s_t, \cdots s_{t-q+1} \mid I_t;\theta) \cdot \Pr(s_t, \cdots s_{t-q+1} \mid I_t;\theta)$$

$$\tilde{h}_{t+1}(s_t, \cdots s_{t-q+1} \mid I_t;\theta) = \alpha_0 + \alpha_1 \frac{(r_t - \mu)^2}{g(s_t)} \cdots + \alpha_q \frac{(r_{t-q+1} - \mu)^2}{g(s_{t-q+1})} \quad (13)$$

Above all, SWARCH-L-t (3,2) model has the best fitting on fluctuation. So we use this model to estimate VaR, and put the SWARCH-L model parameters gotten from formula 3 and 4 into 5 and 6. Then the estimation confidence levels that equal 95% and 99% is the next day's VaR values. Finally, we can return to test the validity of the model.

The estimation results are shown in Table 2 which includes: VaR maximum in different confidence levels, VaR mean, standard deviation, VaR number of failures, the failure rate, the Likelihood Ratio (LR value) and the relative error of failure time estimation, estimation results are in the table 2.

Table 2: SWARCH-L-t (3,2) VaR measurement results of each ARMAX-GARCH group model

Model	GJR-GARCH-GED(1,1)		SWARCH-L-t(3,2)	
Confidence level (a)	0.95	0.99	0.95	0.99
VaR Maximum	-0.02073	-0.03177	-0.02446	-0.03480
VaR Mean	-0.03631	-0.05546	-0.03771	-0.05354
VaR Standard deviation	0.01136	0.01727	0.01049	0.01484
Number of failures	168	33	157	30
Failure rate	0.05462	0.01073	0.05109	0.00976
LR value	1.34158** [9.2]	0.16095** [7.3]	0.07636** [2.2]	0.01765** [-2.4]

Note：[ ] is relative error of actual failure rate to a (=100*(Actual number of failures- expectation)/expectation)

From table 2, we can obtain the following results

(1) Putting GJR-GARCH-GED (1,1) model and SWARCH-L-t (3,2) model at the same confidence level, the calculated differences of VaR value is not very obvious. VaR mean, maximum value and standard deviation obtained from the SWARCH-L-t (3,2) model were slightly less than the one obtained from GJR-GARCH-GED (1,1) under the two confidence levels.

(2) From the number of failures and failure rates, calculation results gotten from SWARCH-L-t(3,2) model are slightly less than the one obtained from GJR-GARCH-GED(1,1) model. For example, at a confidence level of 95%, the theoretical failure expectation value should be the sample number multiplied by 5%, that is 3076*5%=154. Estimation value of GJR-GARCH-GED (1,1) model failed for 168 times, and SWARCH-L-t (3,2) model failed 157 times, the failure rate was 5.1% which is less than GJR-GARCH-GED (1,1) model at the failure rate of 5.5%.

(3) Under the 95% significance level, the LR statistic value of SWARCH-L-t (3,2) model is 0.076, which is less than the critical value of 3.841 and also less than 1.34 gotten by the GJR-GARCH-GED (1,1) model. It means SWARCH-L-t(3,2) model is better than the traditional GARCH model at estimating the VAR value under 95% level of significance.

Under 99% level of significance, LR statistic of SWARCH-L-t (3,2) model is 0.81, which is less than the critical value of 6.635 and 95% confidence level, but more than the LR value of 0.16 under GJR-GARCH-GED (1,1) model. All of these show that the SWARCH-L-t(3,2) model is not optimal for calculating VAR value under 99%.

(4) The negative number in brackets indicates underestimation of risk, while the positive number suggests overestimation of risk. However, the two models have shown little difference in calculating the deviation of risk assessment. Among them, risk degree of SWARCH-L-t (3,2) model is not high. When the confidence level equals 99%, failure probability is not more than expected, and underestimation error is only at 2.4%. Overestimated risk phenomenon occurs at the 95% confidence level, and overestimate error value is only at 2.2%. Therefore, all the parameters of SWARCH-L-t (3,2) model are better than the GJR-GARCH-GED (1,1) model.

Return rate curve and VaR curve based on the SWARCH-L-t (3,2) under 95% confidence level and the confidence level of 99% is shown in Fig. 6. To see the graph more clearly, take the last 200 prediction results from July 20, 2011 to May 11, 2013.

Figure 5: SWARCH-L-t (3,2) -VaR trend at confidence level of 95%

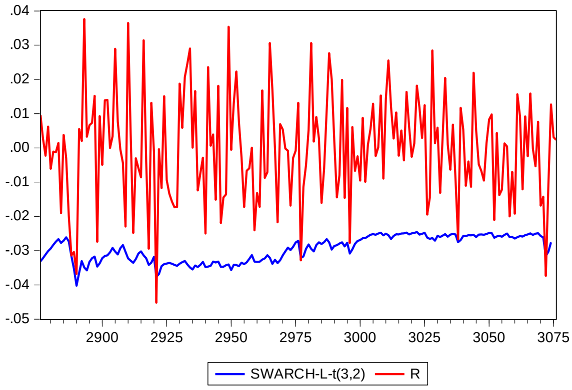
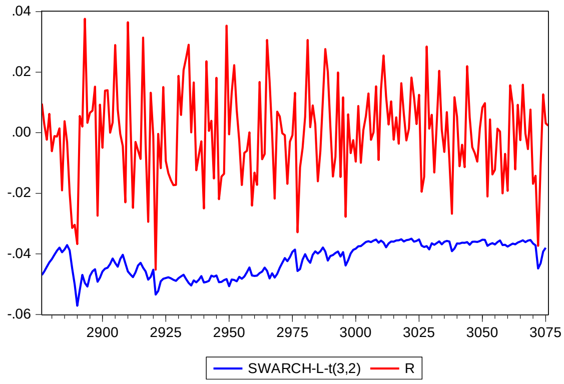


Figure 6: SWARCH-L-t (3,2)-VaR trend at confidence level of 99%



5. Summary and Conclusions

Although, remarkable achievements have been recorded by the traditional model in estimating volatility, it still ignores a fact that both macroeconomic variables and financial time series can move from one state to another. Especially under an increasing opening in the financial markets, financial factors have great influence on the market. It seems unconvincing to use the constant coefficient ARCH model in different period. So this paper studies volatility model with volatility jumping. Empirical display of SWARCH model with Markov transfer is better than traditional ARCH in describing fluctuation and VAR. Also, the reason for continuous fluctuation is not in the data, but in the state of continuity.

However, there are still some points to be expanded. This paper mainly focuses on the financial factors affecting the international oil price fluctuations, such as: oil dollars, exchange rate, derivatives of oil speculation and economics. So, it is slightly insufficient to analyze the inherent mechanism of the effect of financial factors in the analysis of oil price fluctuation, while the VaR accuracy for SWARCH model still needs to be further improved.

Endnotes

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