Study on Financial Market Risk Measurement Based on GJR-GARCH and FHS

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Abstract: In this paper, we establish GJR-GARCH models to extract the residuals of logarithmic returns of one kind of Chinese stock index--- Shanghai Composite Index and the series of independent and identically distribution standardized residuals is formed from the filtered model residuals and conditional volatilities from the return series with an GJR-GARCH model. The results show that from the contrast of actual value and lower limit of predicted VaR value, actual index value for 8 days breaks below the prediction lower limit. The fitting result of VaR method to the market risk of the Shanghai composite index is better than that of the Traditional Historical Simulation.

Keywords: VaR, FHS, GJR-GARCH Model, Financial Market Risk

1. Introduction

In this paper, we establish GJR-GARCH models to extract the residuals of logarithmic returns of Shanghai Composite Index. The estimation of residual-distribution is student-t distribution whose degrees of freedom is four. Independent and identically distributed random sequence is obtained after we got the marginal distribution of the residuals of index returns and standardized residuals. Secondly, Using the residual sequence of the FHS simulation(20000 times) to calculate the var value, in different confidence level. Lastly, Comparing the var floor with closing price whose sample interval is from 2003.1.4 to 2014.12.30.

Barone Adesi (1999)[1,13] proposed an improved historical simulation method based on FHS-GARCH model, to carry on the modelling of future assets and swap value distribution. Barone Adesi and Giannopoulos (2001)[2,9,12] studied the FHS method, the results show that it can make up for the deficiency of the traditional simulation method, and has carried on the comparative study with the traditional sampling method. Barone a Adesi et al (2002)[3,14,15] use FHS VaR calculated values for different combinations of assets, the results show that the method for the application of FHS risk management is more effective. Giannopoulos and Tunaru (2005)[4,10,11] study and proved FHS method is a method to calculate the expected short-loss (Expeeted short), And also got a statistical error formula for computing the model error. Pritsker (2006)[5-8]

from the perspective of theoretical and empirical study of three historical simulation VaR method: two traditional historical simulation method and the FHS method.FHS is considered to be a promising approach, but still needs further development.

There are 3 Level1titles in an article to make ideas clear:

(1) Obtaining independent and identically distributed random sequence.

(2) Calculating the var value through simulation.

(3) Comparing the var floor with closing price.

2. The Empirical Analysis

2.1. The Selection of Data and Its Characteristics

Selecting S.H.I (Shanghai composite index) as research object. Sample interval is from 2003.1.4 to 2014.12.30. The essential information is below.

Known from figuer 2, Distritution of daily logarithmic return of Shanghai composite index is fat-tail on both ends of gains and losses. And JB- statistic is significantly. So the results refuse the hypothesis of normal distribution.
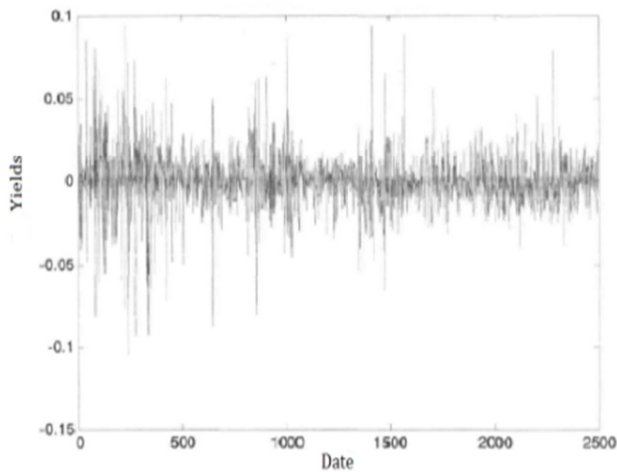
Figure 1. *Daily logarithmic return of Shanghai composite index.*

Table 1. *Statistical indicators of Shanghai composite index.*

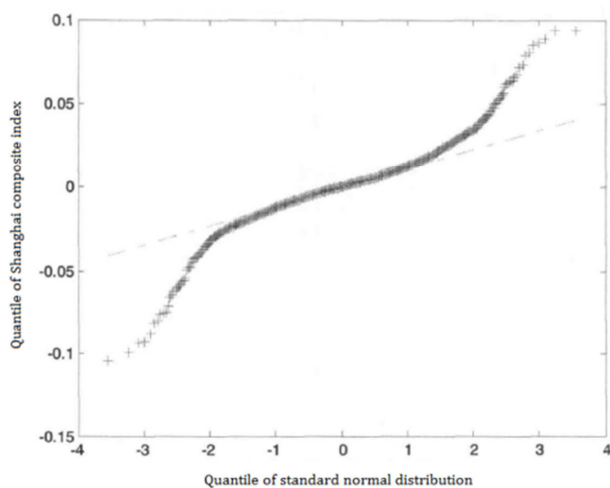| Name	Mean	STD
S.H.I	0.0003	0.0167
Slewness	Kurtosis	JB- statistic
-0.0701	9.2469	4052.248

Figure 2. *Normal Q-Q Plot of daily logarithmic return of Shanghai composite index.*

2.2. The Establishment of the Model and the Analysis of the Results

Autocorrelogram and partial- autocorrelogram of the logarithmic return suggest that yield sequence presents a certain degree of serial correlation, Further, autocorrelogram of the square of the logarithmic return suggest that yield sequence square presents serial correlation significantly. (figure 3~5)
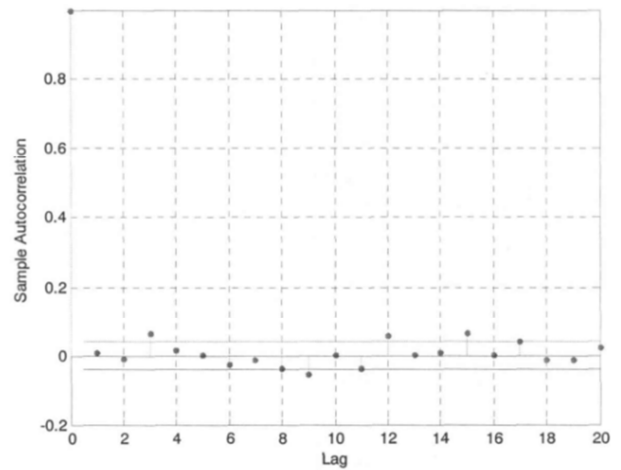

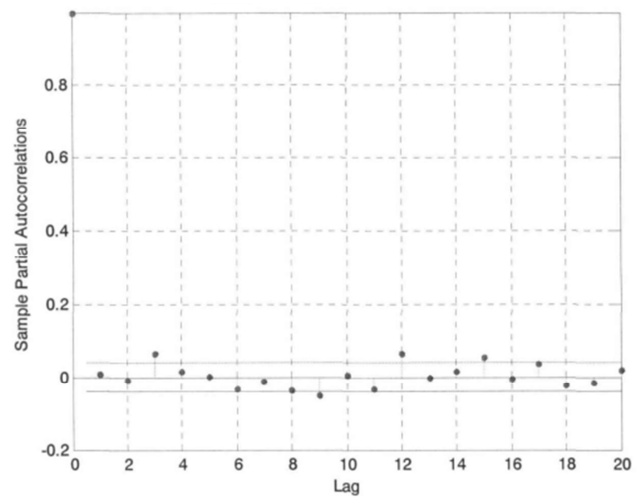*Figure 3*. *Autocorrelogram of logarithmic return of Shanghai composite index.*

Figure 4. *Partial Autocorrelogram of logarithmic return of Shanghai composite index.*
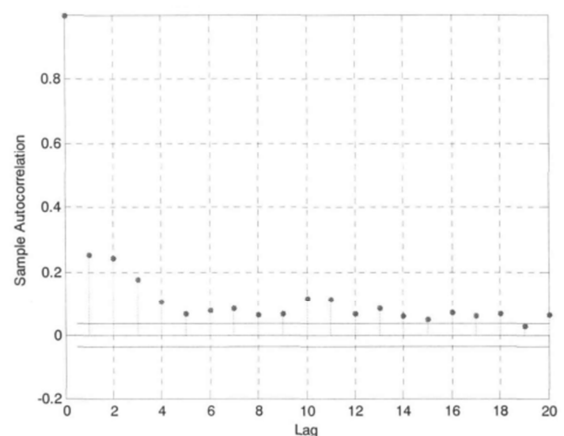

Figure 5. *Autocorrelogram of logarithmic return square of Shanghai composite index.*

The paper adopt Student-t distribution to estimate residuals instead of normal distribution. Next we estimate four ARMA-GJR-GARCH models. (table 2)

***Table 2.** Parameters estimation&Significant level& Evaluation index of the models.*

Parameters		The models of Shanghai composite index			
		Model 1	Model 2	Model 3	Model 4
θ_1				-0.7788(0.0000)	0.1526(0.0000)
θ_2					0.8161(0.0000)
θ_3		0.07776(0.0000)	0.07766(0.0000)		
θ_4		-0.04721(0.0012)	-0.04852(0.0085)		
η_1				0.80000(0.0000)	-0.11141(0.0000)
η_2					-0.85214(0.0000)
α_1		0.08947(0.0056)	0.08421(0.0001)	0.00112(0.0000)	0.07254(0.00004)
α_2		0.02141(0.0005)	-0.05482(0.0002)		0.05412(0.0001)
λ_1		0.05412(0.0120)	0.19584(0.0000)	0.07514(0.0144)	0.12405(0.0018)
λ_2			-0.19852(0.0007)		-0.14521(0.2541)
β_1		0.85412(0.0000)	1.52412(0.0000)	0.85412(0.0000)	0.74125(0.0000)
β_2			-0.52369(0.000)		
SSR		0.75412	0.76521	0.77120	0.77475
AIC		-5.32145	-5.69264	-5.68125	-5.21455
SBC		-5.23412	-5.67415	-5.6666	-5.66542
residual	Q(4)	6.52412(0.0374)	8.45215(0.0145)	11.06452(0.0040)	6.00007
	Q(8)	8.82415(0.1847)	10.65475(0.1082)	15.49995(0.0145)	11.70004(0.0145)
	Q(12)	15.42253(0.1174)	16.65415(0.0852)	24.25411(0.0006)	21.1750(0.0025)
Residual square	Q(4)	1.96524(0.3777)	0.98524(0.6325)	1.36520(0.5236)	0.96541
	Q(8)	5.20122(0.5241)	2.32145(0.8852)	4.75821(0.5821)	5.21425(0.2541)
	Q(12)	6.21425(0.7514)	4.12585(0.9899)	6.00000(0.8521)	6.21452(0.6321)

According to SSR, Parameters significantly 、AIC and SBC determine the final model .The SSR of model 1 is the smallest; but Q-statistic of model 3 and model 4 both significant suggest that there are still some residual serial correlation. while Q-statistic of model 1 and model 2 are no significant, suggesting that the mean model and variance model are both great. And according to the principle of AIC and SBC, we chose the model whose AIC and SBC are minimum, that is model 1. Establishing model:

$$r(t) = \theta_3 r(t-3) + \theta_6 r(t-6) + \varepsilon(t) \qquad (1)$$

Model 1's Asymmetric GARCH model is GJR-GARCH (1,2):

$$h(t) = k + \alpha_1 \varepsilon(t-1)^2 + \beta_1 h(t-1) + \lambda_1 S_{t-1}^- \varepsilon(t-1)^2 + \lambda_2 S_{t-2}^- \varepsilon(t-2)^2 \qquad (2)$$
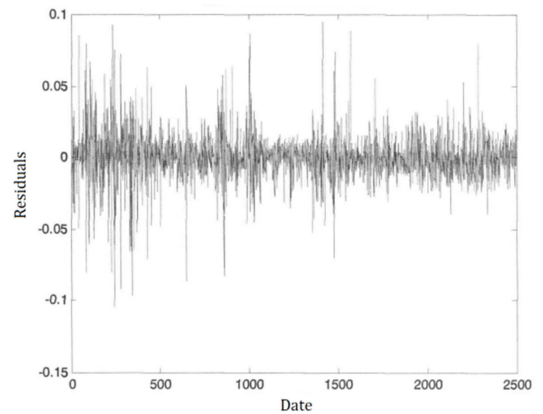
Where

$$\begin{cases} k, \alpha_1, \alpha_2, \beta_1 > 0, \\ \alpha_i + \lambda_i > 0, i = 1, 2 \\ S_{t-1}^- = \begin{cases} 1, \varepsilon(t-1) < 0 \\ 0, \varepsilon(t-1) \geq 0 \end{cases} \\ \beta_1 + \sum_{j=1}^{2} \alpha_j + \frac{1}{2} \sum_{j=1}^{2} \lambda_j < 1 \end{cases} \qquad (3)$$

The Seasonal ARMA model is adopted in the paper to get residual series of S.H.I; and conditional standard deviation filtering of Shanghai composite index is obtained with GJR-GARCH. (figure 6 and figure 7)

We standardize filtered residual with (3) in order to applying FHS. (z(t) is the filtered standard residual at time t ;e(t) is the filtered residual at t ; Conditional standard deviation of filtered residual at t). Go a step further, we analysis residual filtering of Shanghai composite index and conditional standard deviation filtering of Shanghai composite index. (figure 8 and figure 9)

The result suggests that there is no serial correlation within them; they are independent identically distributed random variables

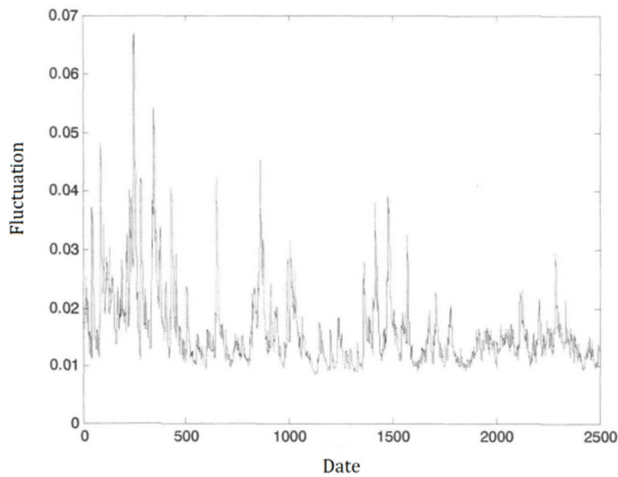
Figure 6. Residual filtering of Shanghai composite index.

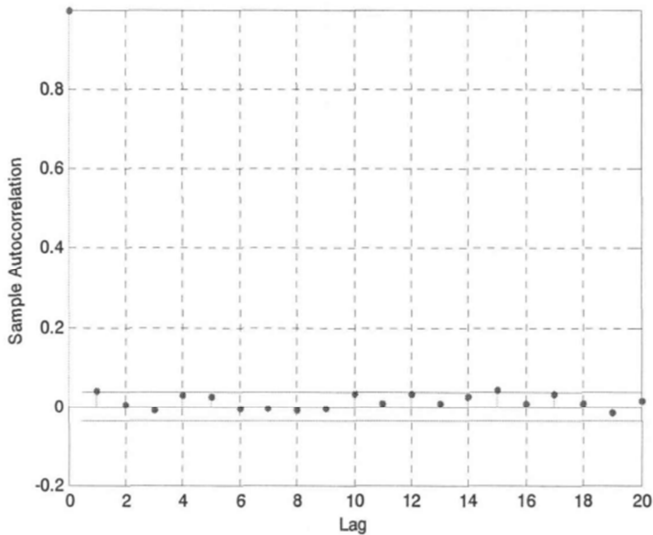*Figure 7. Conditional standard deviation filtering of Shanghai composite index.*

Figure 8. Autocorrelogram of standard error of Shanghai composite index.
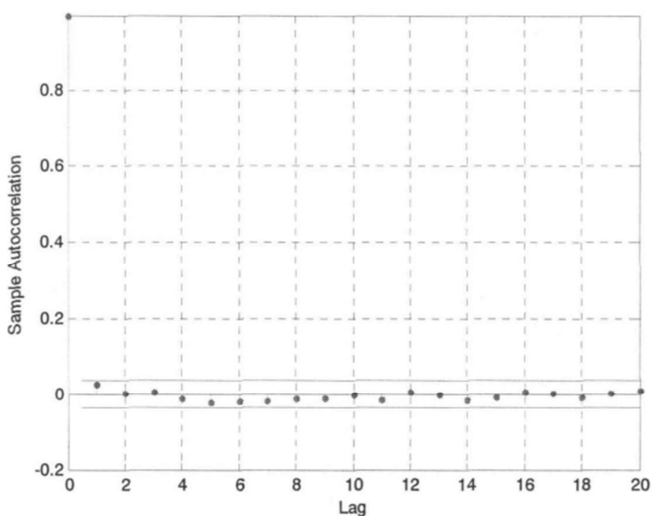

Figure 9. Autocorrelogram of standard error square of Shanghai composite index.

We sampling for 20000 times on the filtered standard

residual with bootstrapping. And regard it as the input of independent identically distributed noise process of the holding period for a day of earnings forecast model.

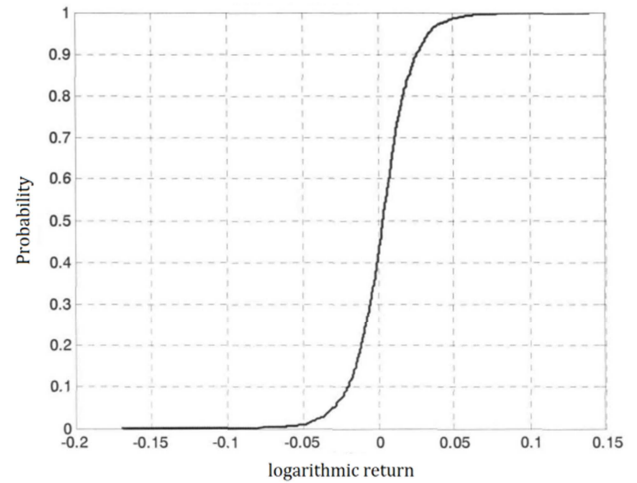Figure 10 is cumulative function of simulation of one day return;

Figure 10. Cumulative function of simulation of one day return.

Figure 11 is probability density function of simulation of one day return.
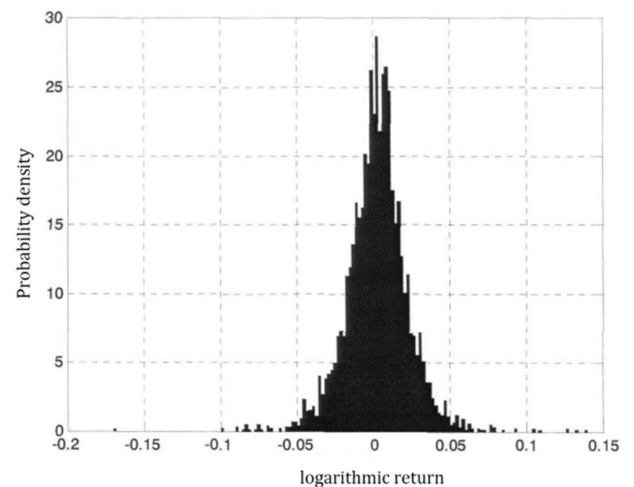

Figure 11. Probability density function of simulation of one day return.

Further, the earnings forecast is converted to the form of the closing price.

The paper chose three different confidence levels: 1%, 5% and 10%, and calculate the VAR value in the corresponding confidence level.

In 5% confidence level, we compare the lower limit of the predicted VAR with actual day's closing price. The results suggest that there are eight days of the actual value is less than the lower limit of the predicted VAR. Due to the confidence level that we choose is 95, The number of days that is to say, the actual value is lower than the predicted value is not more than 240*5%=12 days (240 is the number of forecast sample), while actually only 8 days. The fitting effect of VAR for this phase of the market risk is very good. Through the observation

of historical data, when the market is relatively stable, the prediction effect of VAR is better. When the high volatility in the market, the VAR will underestimate the market risk. Therefore, in order to avoid losses of small probability event, we can consider together with the stress testing method to calculate. Obtaining a more comprehensive financial market risk assessment.
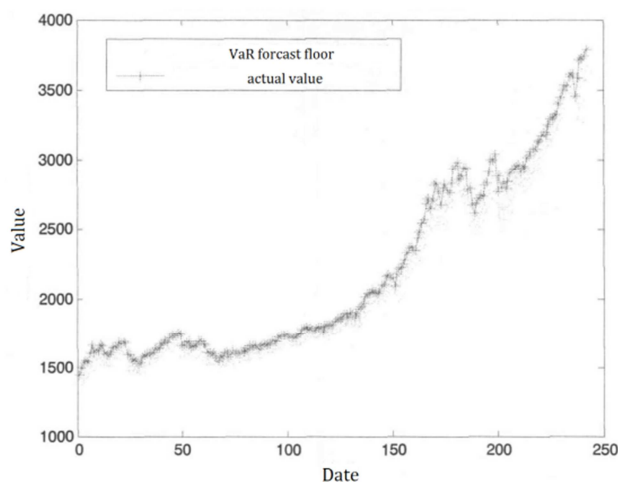

Figure 12. Trend of actual value and VaR forcast floor of S.H.I.

3. Summary

The fitting effect of the VAR model based on GJR of market risk is great.The results suggest that there are eight days of the actual value is less than the lower limit of the predicted VAR.Due to the confidence level that we choose is 95, The number of days that is to say, the actual value is lower than the predicted value is not more than 240*5%=12 days (240 is the number of forecast sample),while actually only 8 days.The fitting effect of VAR for this phase of the market risk is very good . Through the observation of historical data, when the market is relatively stable, the prediction effect of VAR is better. When the high volatility in the market, the VAR will underestimate the market risk. Therefore, in order to avoid losses of small probability event, we can consider together with the stress testing method to calculate. Obtaining a more comprehensive financial market risk assessment.

4. Acknowledgements

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