Macroeconomics Uncertainty and Performance of GARCH Models in Forecasting Japan Stock Market Volatility

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Abstract

Since the introduction of ARCH/GARCH methods have been widely examined. However, the role played by macroeconomics environment in volatility forecasting has been ignored. This paper investigates the behavior of Japanese stock market volatility with respect to a few macroeconomic variables including gold price, crude oil price and currency exchange rates (Yen/US$). A comparison study has also been carried out on the performance of GARCH models and Ad Hoc methods. This empirical study employs the daily data over 12 years. The result reviews that macroeconomic variables used in this study have no impact on the volatility of Japanese stock markets and the simplest GARCH (1,1) model yields the best result. Further comparison on the best performing model suggest that GJRGARCH (1,1) model is superior to GARCH (1,1) model in one-step ahead forecast.

Keywords: Volatility forecasting; GARCH models; Exchange rates; Gold price; Oil price

1. Introduction

Establishment of the first Basel Accord in 1996 has shown the crucial central role of financial risk management. The 1997 ASIAN financial crisis, oil price shock since 2006 to 2007 and current subprime crisis triggered the needs for even more efficient risk management. A number of time series approaches have been developed thus far to forecast volatility of stock markets. However, the volatility forecasting research that account for the impact of macroeconomics variable is scarce. Fluctuation in exchange rate, oil price and gold price affected the economy movements over the world. ASIAN stock markets hit badly during 1997 due to financial collapse on Thai baht which caused the volatility spillover effect among ASIAN countries. The existence of relationship between stock prices and exchange rate has received considerable attention. At the same time, oil price fluctuations do affect the cost of production in major industries as well. This can be seen from world food price crisis in year 2007 and 2008 that caused by oil price spikes. Besides that, recent world economic recession associated with the depreciation of US Dollar encourage investors to reconstruct their investment portfolios by replacing part of their equity stocks with gold to hedge the downside risk. Such action definitely causes a high volatility in stock market.

Theoretically, stock price calculated by discounting expected future cash flows which are likely to be affected by macroeconomic movements. If a stock returns series have a factor structure, then that stock volatility will depend on the volatilities of those factors. But these links are found to be much weaker than it seems to be. Morelli (2002) reveals volatility in UK stock market cannot be explained by macroeconomics variables selected in the study. Schwert (1989, pg 1116) in fact conclude that volatility of stock market return can be explained by any shocks in macroeconomics volatility, although a weak relation has been revealed. Therefore, it is of our interest to find out the impact of macroeconomics on volatility forecast of Nikkei 225 Index. Macroeconomics variables that have been chosen for this study are gold price, crude oil price and currency exchange rates (Yen/US$). A comparison on best performing method also been carried out in our study.Historically, *ad hoc* methods which assume the homoscedastic volatility have been applied in volatility forecasting.

In fact, volatility clustering often shown in empirical findings and this has led to the development of Autoregressive Conditional Heteroscedasticity (ARCH) model (Engle, 1982). Later, this model has been extended to become GARCH model by Bollerslev (1986). Lately, observations show that positive and negative shocks of equal size have different impact on volatility. Both ARCH and GARCH models are linear models and unable to captured such asymmetry effect in return innovations. To address this non-linear problem, several non-linear GARCH models have been introduced and will be employed in our study as well. With the most popular non-linear GARCH models are GJRGARCH, EGARCH and PARCH. This paper is organized as follow. Section 2 reviews the literature regarding the relationship between macroeconomic variable and stock market volatility. Review of *Ad hoc* methods and GARCH models will also be discussed. In section 3, an empirical study on the effect of macroeconomics uncertainty on Nikkei 225 Index volatility and the parameter estimates of various models will be presented. Also, this section will discusses the evaluation criteria for both in-sample and out-sample performance. Section 4 presents the empirical result and conclusion become the last part of this study.

2. Prior Research

2.1. Relation between Macroeconomics Variables and Stock Market Volatility

Abundant of empirical works have been carried out on forecast the volatility of stock market returns, very little work has been done on the impact of macroeconomics uncertainty on stock market volatility. Currency exchange rate risk affects the firm's value as the firm's future cash flow alters according to the fluctuation in foreign exchange rates. Solnik (1987) finds a negative relationship between domestic stock returns and real exchange rate movements. Stock price of an export-dominant economy is found to be negative related to exchange rate but exchange rate movement does have positive effects on stock price of an import-dominant economy (Ma and Kao, 1990). As shown in Luehrman (1991), depreciation of a currency of a country increase the competitiveness of the firms engaged in international business by leading an increase in the demand for its export goods. Adler and Dumas (1984) report that fluctuations in foreign exchange rates do affect domestically operate firms as their input and output prices are subject to change by currency movements. All this changes are possibly affect stock prices. However, Tabak (2006) analyze the dynamic relation between stock prices and exchange rate in Brazilian economy and showed that there is no long-term relationship between these variables.Expected earning tend to decline when oil price increase; and bring to immediate decrease in stock prices across different industries. Jones and Kaul (1996) show that Canadian and US stock prices completely react to oil price shocks; but this result is not strongly showed in Japan and UK. At the same time, Huang et al. (1996) state that oil future returns do not have much impact on S&P 500 Index. On the other hand, there is study indicates that the forecast error variance after year 1986 largely explained by oil price movement than do interest rate (Sadorsky, 1999). Driesprong, Jacobsen and Maat (2004) in fact, reveal that investors in stock markets under react to oil price changes in the short run. Recent work done by Charles (2009), found that higher volatility in both gold price and oil price reduces volatility of stock price.

2.2. Volatility Forecasting Methods

2.2.1. Linear GARCH Models

One of the most well-known statistical modelling approaches in volatility forecasting is known as Autoregressive Conditional Heteroskedasticity (ARCH), introduced by Engle (1982). ARCH model express the conditional variance of log return as a linear function of past disturbance. It is mathematically show as follow:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{1}$$

This model was then modified by Bollerslev (1986) to become Generalized Autoregressive Conditional Heteroscedasticity (GARCH). GARCH model reduced a more complicated dynamic structure for time-varying, conditional, higher order moments of ARCH model by just add in an additional lagged conditional variance term. It can be expressed as:

$$\phi_s(B) r_t = \mu + \varepsilon_t, \qquad with\ \phi_s(B) = 1 - \phi_1 B - \dots - \phi_s B^s$$

$$\varepsilon_t = \sqrt{h_t} e_t$$

$e_t \sim N(0,1)$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (2)$$

where $p \geq 0$, q>0, w>0, $\alpha_i \geq 0$ and $\beta_j \geq 0$ for non-negative GARCH process to be defined. The parameters of GARCH model are estimated using maximum likelihood function. The simple GARCH (1, 1) model is given as follow:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad (3)$$

In Martens (2001), GARCH (1,1) model was used to forecast daily exchange rate using intraday returns. The GARCH model was applied in the area of risk management as well to allow a better financial decision making as in Brooks and Persand (2003). Other than that, GARCH model was extended in the usage of volatility forecasting in the futures market. The wide usage of GARCH model in studies has prompted many researchers to improve and extend the model. Integrated GARCH (IGARCH) proposed in Engle and Bollerslev (1986) constraint $\alpha_i + \beta_i = 1$. This indicates an infinite persistency of current shocks on future variance. Degree of persistency is greater when sum of α_i and β_i approaches unity. Interestingly, IGARCH model can be strongly stationary although it is not weakly stationary (Nelson, 1990). It is formulated as follow:

$$\sigma_t^2 = \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (4)$$

IGARCH model had been largely employed by researchers in examine the persistency of volatility. Choudhry (1995) find that current shocks persistent in future volatility in five European markets. Akgiray (1989), Dimson and Marsh (1990), Franses and Dijk (1996), Brooks (1998), and Choo et al. (1999) employ various GARCH models to forecast stock market volatility and compare their forecast performance. Most of them yielded inconsistent result. Although linear GARCH model takes into account of excess kurtosis, but it still encountered some problem in dealing with a highly irregular condition of stock market such as unstable market fluctuations. Unable to cope with the skewness of the distribution returns in most stock market indices will lead the forecast error to be biased. With this implication, there are few modifications to the GARCH models emerged for further research on this issue. EGARCH was the first asymmetric GARCH model and followed by GJRGARCH model.

2.2.2. Non-linear GARCH Models

Nelson (1991) developed the first non-linear GARCH model, which is EGARCH model. EGARCH no longer modelled the conditional variance as a linear function of lagged squared error and lagged variance. It has lagged residuals that accounted for the asymmetry effect; in which greater volatility period tend to follow after negative return as compared to positive return with equal size. It is functioned as:

$$\ln \sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{j=1}^{p} \beta_j \ln \sigma_{t-j}^2 \qquad (5)$$

Where $g(z_t) = \theta_1 z_t + \theta_2 \left[|z_t| - E|z_t| \right]$

with $z_t = \varepsilon_t / \sigma_t$ is the normalized residual series. The function of z_t represents both the magnitude ($\theta_2 \left[|z_t| - E|z_t| \right]$) and sign ($\theta_1 z_t$) of z_t. Choo et al. (1999) investigate the best volatility forecasting model applied in Malaysia stock market and conclude that EGARCH model outperform other models. In another study, Gokchan (2000) show that GARCH model performed better than EGARCH model although having skewed return distribution. However, there is an exaggerate impact for large shocks due to log formulation in EGARCH. Hence, a simpler model to accommodate the asymmetry effect is GJRGARCH.

GJRGARCH was introduced by Glosten, Jagannathan, and Runkle (1993) and it is written as:

$$\sigma_t^2 = \omega + \left[1 - I(\varepsilon_{t-i} > 0)\right] \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \left[I(\varepsilon_{t-i} > 0) \right] \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (6)$$

where $I[\varepsilon_{t-1} > 0]$ is the indicator function, taking a value of 0 if $\varepsilon_{t-1} < 0$ and 1 otherwise. Presence of leverage effect in return innovation can be determined by comparing the value of □$_i$and □$_i$.

There is an leverage effect if $\square_i > \square_i$. Study done by Frances and Van Dijk (1996) showed that QGARCH outperform standard GARCH and GJRGARCH models with estimation samples do not contain extreme observations. Asymmetry Power ARCH is a special case in ARCH class family. The models discussed above along with five other models were then generalized by Ding et al. (1993) to have a Power ARCH specification. Box-Cox power transformation enable one to estimate the optimal power term of standard deviation rather than imposed. PARCH model make the nonlinear models to be linearized and is defined as:

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{q} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^{\delta} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^{\delta} \tag{7}$$

where $\omega > 0, \delta \geq 0, \alpha_i \geq 0, \beta_j \geq 0, -1 < \gamma_i < 1$. γ_i is the leverage parameter and δ is the power term. Ding et al. (1993) and Hentschel (1995) find that PARCH provides a good-fit of data to US market and is useful in modeling leverage effects, long memory and nonlinear conditional error distribution that characterize the data. Again, this evidence has been proved in Brooks et al. (2000) which applied on 10 stock markets plus a world index.

2.2.3. Ad Hoc Methods

2.2.3.1. Random Walk (RW)

This forecasting model says the best forecast for today volatility is yesterday volatility, in which squared residual is used as proxy for yesterday variance . It is stated as follow:

$$\sigma_t^2 = \varepsilon_{t-1}^2 \tag{8}$$

2.2.3.2. Naïve Var Forecast

According to this method, variance forecast is simply based on the simple average of past squared residuals. Due to the simplicity nature of the naive forecasting method, it can only be used to forecast up to one period in the future. It is not at all useful as a medium-long range forecasting tool. The formula is:

$$\sigma_t^2 = \frac{1}{t-1}\left(\sum_{j=1}^{t-1} \varepsilon_j^2\right) \tag{9}$$

2.2.3.3. 30 days Moving Average (MA 30)

Moving Average method is in class of “naive” method as well. It takes the average of 30 daily squared residual; the result is a dampened or smoothed data set. Moving average routinely designed to remove the seasonal and random noise variation in a time series. What is left over in the original series is a successor series retaining some combination of trend and cyclical behavior.The smoothing effect of the moving average method delivers a “cleaner” data set, which may or may not help in estimating the future level of a variable. The formula is shown as below:

$$\sigma_t^2 = \frac{1}{30}\left(\sum_{j=t-30}^{t-1} \varepsilon_j^2\right) \tag{10}$$

2.2.3.4. Exponentially Weighted Moving Average (EWMA)

EWMA is a simple and well-known volatility forecasting method. The EWMA allows the latest observations to have a stronger impact on the volatility forecast. The equation for the EWMA is shown and written as exponential smoothing in recursive form. α is the smoothing parameter. The equation:

$$\sigma_t^2 = \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} (1-\alpha_j) \sigma_{t-j}^2 \tag{11}$$

Generally, literature suggested the use of minimization in the sum of in-sample one-step-ahead estimation of errors (Taylor, 2004 cited from Gardner, 1985) to arrive at an optimized smoothing parameter as stated as follow:

$$\min \sum_i (\varepsilon_t^2 - \hat{\sigma}_t^2)^2 \tag{12}$$

where ε_t^2 is the in-sample squared error which acted as the proxy for actual variance.

3. Empirical Study

3.1. Description of the Study

The data sets used in this study are daily closing prices of Nikkei 225, gold, crude oil, and exchange rate (yen/1USD). These series are obtained from *Yahoo Finance* (http://finance.yahoo.com) and crosschecked with the data downloaded from *Bloomberg* Terminal and DATASTREAM. The data was collected from May 1997 to July 2009. The sample period spanned approximately 12 years and delivers 3000 daily log return. We focus solely on one-step ahead forecast for the simplicity of the study. We used the first 2000 log returns to estimate the parameters of various forecasting methods and the rest 1000 observations are reserved for the post-sample forecast evaluation.

3.2. Forecasting Methods & Parameters Description

In this study, daily closing prices are considered as the daily observations and natural log return is computed, in which $\ln(r_t) = \ln(r_t / r_{t-1})$. Some characteristics of log return are shown in Table 1. The variance is relatively small and all series in this study has excess kurtosis. Hence, this indicates a necessity of fat-tailed distribution.

Insert Table (1) about here

To investigate the possible macroeconomics variables to describe the behavior of Japan stock market, gold price, oil price and exchange rate will include in GARCH (1,1) parameter estimation process as a regressor. We opted for order (1,1) in all GARCH models as it is proved to be sufficient to model the changing variance over long sample periods by Frances and Dijk (1996). Choo et al. (1999) and Taylor (2004) also apply the same in their study.Ten forecasting methods used for comparison include *Ad Hoc* methods and GARCH models as discussed in section 2. Parameters of GARCH models estimated using maximum likelihood based on a *t*-distribution to capture the highs kurtosis. The log-likelihood function of *t*-distribution can be written as:

$$L_V(\theta | r_t) = T \ln\left\{\Gamma \frac{[(\nu+1)/2]}{\pi^{1/2}\Gamma(\nu/2)}(\nu-2)^{-1/2}\right\} - \frac{1}{2}\sum_{t=1}^{T} \ln h_t^2 - \frac{\nu+1}{2}\sum_{t=1}^{T} \ln\left[1 + \frac{\varepsilon_t^2}{h_t(\nu-2)}\right] \quad (13)$$

We then produce daily variance forecast from these three models using the formulae as stated in previous section. The diagnostic of the estimate models is compared using various goodness-of-fit statistics. This includes the log likelihood (Log L), Schwarz's Bayesian Information criterion (SBC) and also the Akaike's Information Criterion (AIC), and Root Mean Squared Error (RMSE).

3.3. Post-sample Forecast Evaluation Criteria

The best performing method within sample period may not yield the same result in post-sample period. The squared residual, ε_t is used as proxy to actual volatility. Squared residual is measured as $\varepsilon_t^2 = (r_t - \bar{r})^2$. RMSE and MAE are used to evaluate the forecast performance of various models. Both formulae are expressed as follow:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=0}^{N}(v_t - \hat{v}_t)^2} \quad (14)$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|v_t - \hat{v}_t| \quad (15)$$

where v_t is 'actual volatility' and N denotes the post-sample observations.

4. Empirical Results

4.1. Goodness-of-fit Statistics

Table 2a summarized the goodness-of-fit statistics of GARCH models and GARCH model with gold, crude oil and exchange rate as regresses for Nikkei 225 Index. Their ranking based goodness-of-fit test is summarized under Table 2b. Based on the ranking, RMSE, Log L, SBC, and AIC suggest that the EGARCH (1, 1) is the best model following by GJRGARCH (1, 1) for the Nikkei 225 Index. We further look into the impact of macroeconomics uncertainty on volatility forecasting for Nikkei 225 Index, in which GARCH models with gold, crude oil price and exchange rate as regresses.

Referring to Table 2a and 2b, GARCH (1,1) with gold as regressor is presented in second part of the table, crude oil as regressor result in third part of the table and lastly is the GARCH (1,1) with exchange rate (Yen/USD) as regressor. Based on ranking show in Table 2b, RMSE, Log L, SBC and AIC give a consistent result, in which GARCH (1,1) is the best model for Nikkei 225 in-sample period. This shows that inclusion of macroeconomics variables in GARCH does not improve the estimation result.

Insert Table 2(a) and 2(b) about here

4.2. Post-Sample Forecasting Result

In any case, the good performance in goodness-of-fit statistics does not guarantee good performance in forecasting. The effect of macroeconomics variables on volatility forecasting of Nikkei 225 Index for post sample period is summarized in Table 3. Both MAE and RMSE yield the same results. The results clearly show that there is no any benefit of considering the changes of exchange rate, gold and oil price on volatility forecast. GARCH (1,1) model outperformed all GARCH models that include macroeconomics variables as regresses. This result is consistent with within-sample results. Hence, macroeconomics variables neither explain the volatility of Japan stock market nor help in forecasting volatility of Japan stock market.

Insert Table (3) about here

A post-sample evaluation based only on RMSE is conducted to confirm the result obtained from goodness-of-fit test. Table 4 summarized the post sample accuracy of various forecasting methods employed in this study. Theil-U measure has been employed to summarize the relative performances of the forecasting models. It is calculated as ratio of RMSE for particular method to the RMSE for the GJRGARCH model. The lower the value of Theil-U, the better the model it is. GJRGARCH model dominated the other forecasting methods in terms of Theil-U ranking in post-sample period. It is immediately followed by EGARCH and GARCH models. The result indicate that asymmetry effect is important in forecasting volatility of Nikkei 225 and must be taken into consideration by financial analyst when they deal with Japan stock market. The RW method and PARCH model are the least performing methods.

Insert Table (4) about here

5. Conclusion

We have investigated the macroeconomics determinants that affect the volatility of Nikkei 225 Index by considering three macroeconomics as regressors in the GARCH (1,1) model. Thereafter, the best performing model in previous analysis is then compared to various forecasting models on Japan stock market. Ten different forecasting models are being employed in our empirical study. Our empirical evidences suggest that none of the macroeconomics variables i.e., exchange rate, gold and oil price do improve the forecast accuracy of GARCH (1,1). Within-sample result also reach at same finding. It indicates that uncertainty in these macroeconomics variables does not explain the volatility of Nikkei 225 Index. Albeit, this is not unexpected result due to other macroeconomics fundamentals such as inflation rate, Gross Domestic Products, interest rate and so on possibly have more impact on Nikkei 225 Index volatility. Comparison between GARCH (1,1) and various forecasting methods was then computed to find out the forecasting method that deliver the least forecast error. In-sample results conclude that EGARCH model is the best estimation model. Whereas, GJRGARCH model outperformed all other forecasting methods in one-step ahead forecast result and followed by EGARCH. These findings are important to investors, speculators and financial analysts when Japan stock market become one of their investment destinations. They should pay more concern on the negative news or shocks that might affect the stability of Japan stock market.

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Table 1: Summary statistics of data on rate of returns from year 1997 to 2009

Series	n	Mean	Variance	Skewness	Kurtosis
Nikkei 225	3000	-0.051	0.000997	0.008	3.34
Exchange rate	3000	-0.0083	0.000989	0.38	4.7
Gold price	3000	0.0626	0.000985	0.31	3.97
Oil price	3000	0.051	0.00115	-3.02	22.88

Table 2a: Goodness-of Fit statistics on rate of return for Nikkei 225 Index

	Goodness-of-Fit Statistics			
Model	RMSE	Log L	SBC	AIC
GJRGARCH	2322	5711.398	-5.6924	-5.7064
GARCH	2320	5695.332	-5.68013	-5.69133
PARCH	2551	5696.575	-5.67757	-5.69158
IGARCH	2337	5685.689	-5.67809	-5.68369
EGARCH	2318	5711.613	-5.69261	-5.70661
GARCH	338.76	6180.11	-6.1649	-6.1761
GARCH-G	428282	5686.04	-5.6622	-5.6903
G-GARCH	338.88	5686.71	-5.6629	-5.6909
G-GARCH-G	617855	5630.78	-5.584	-5.6289
GARCH	4	11709.4	-11.694	-11.705
GARCH -Oil	77361	5686.47	-5.6626	-5.6907
Oil-GARCH	23	5687.38	-5.6636	-5.6916
Oil-GARCH -Oil	378103	5691.7	-5.645	-5.6899
GARCH	178.77	7313	-7.2978	-7.309
GARCH -EXR	723709	5689.86	-5.666	-5.6941
EXR-GARCH	179.2	5689.27	-5.6655	-5.6935
EXR-GARCH-EXR	502345	5698.52	-5.6519	-5.6968

Table 2b: Rankings of the models averaged of Japan market index based on the performance of various goodness-of-fit statistics

	Goodness-of-Fit Statistics (Ranking)			
Model	RMSE	Log L	SBC	AIC
GJRGARCH	3	2	2	2
GARCH	2	4	3	4
PARCH	4	3	5	3
IGARCH	5	5	4	5
EGARCH	1	1	1	1
GARCH	1	1	1	1
GARCH-G	3	3	3	3
G-GARCH	2	2	2	2
G-GARCH-G	4	4	4	4
GARCH	1	1	1	1
GARCH -Oil	3	4	3	4
Oil-GARCH	2	3	2	2
Oil- GARCH -Oil	4	2	4	3
GARCH	1	1	1	1
GARCH -EXR	3	3	2	3
EXR-GARCH	2	4	3	4
EXR-GARCH-EXR	4	2	4	2

Table 3: Variables in out-of-sample forecasting performance and rankings of GARCH models for Nikkei 225 Index

	MAE	Ranking	RMSE	Ranking
Gold				
GARCH	112	1	339	1
GARCH-G	427830	3	428282	3
G-GARCH	117	2	339	2
G-GARCH-G	617072	4	617855	4
Crude Oil				
GARCH	1	1	4	1
Oil-GARCH	75178	3	77361	3
GARCH-Oil	23	2	23	2
Oil-GARCH-Oil	367137	4	378103	4
Exchange Rate				
GARCH	74	1	179	1
GARCH-EXR	720921	4	723709	4
EXR-GARCH	88	2	179	2
EXR-GARCH-EXR	500419	3	502345	3

Table 4: Rankings of the methods based on Root Mean Square Error (RMSE)

RMSE	Nikkei 225	Theil-U Ranking
Random Walk	407.61	9
Naïve var forecast	347.85	8
MA 30	344.37	7
GJRGARCH	337.46	1
RiskMetrics RMSE	339.37	5
Optimized RMSE	339.41	6
GARCH	338.76	3
IGARCH	339.33	4
EGARCH	337.99	2
PARCH	2013.19	10