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Choosing A Suitable Garch Specification for Predicting The Crude Oil Future Return

Management

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ABSTRACT

The present paper predicts the crude oil return series data by using twenty different GARCH specifications of models. The validity of the models is examined by using four important forecasting error measures. From the findings, it is concluded that GARCH (3,3) model better suits for forecasting the crude oil return series. MSE is found to be better suitable model to estimate forecasting error for the estimated series

1. INTRODUCTION:

It is very important to predict various kinds of financial variables accurately in order to develop proper strategies and avoid the risk of potential large losses. The more efficiently the models estimated, the more accurate will be the decisions. In this context and more, the present work sets out to investigate the relative ability of various forecasting models ranging from GARCH families of models with twenty specifications in crude oil return series.

2. LITERATURE REVIEW:

The works of Mandelbort (1963) and Fema (1965) are the first few works that examined the statistical properties of stock returns. In the same stand, Akgiray's (1989) work proceeds further which not only investigates the statistical properties but also presents the evidence on the forecasting ability of ARCH and GARCH models vis-à-vis EWMA. Expanding further, Pagan and Schwert (1990) reported the GARCH and EGARCH models enhanced with terms suggested by non-parametric methods yields significant increase in explanatory power. Philip and Dick (1996) studied the performance of the GARCH models and two of its non-linear modifications to forecast weekly stock market volatility.

Some of the other works done by researchers such as Loudon et al. (2000), Yu (2002) and Balaban (2004) also examined the effectiveness of the forecasting models based on GARCH. Kumar (2006) in his paper evaluate the ability of ten different statistical and econometric volatility forecasting models in the context of Indian stock market and forex markets and concluded that GARCH (4,1) and EWMA methods lead to better volatility forecasts and GARCH (5,1) model best suite to forex market. Srivastava and Jain (2008) developed models to elucidate the volatility of BSE and NSE during April, 2000 to March, 2008 by using the ARCH, GARCH, EGARCH and TGARCH models. The findings suggest that both the stock market in India have the significant ARCH effect and it is appropriate to use GARCH models to estimate the process.

Singh and Kansal (2011) studies on the suitability of GARCH model by considering S&P CNX Nifty index by considering fourteen years. The findings suggest that stock market has significant ARCH effects and it is appropriate to use GARCH model to estimate the process. Sarangi and Dublish (2013) modeled eighteen various specifications of GARCH family of models and twenty various ANN models with four architectures are constructed to predict gold market return. ANN proved to be better than GARCH specifications. MSE is found to be best suitable for estimating forecasting errors for gold return series. From the above brief literature review, it emerges that there is no research yet done in this area by using crude oil return series data.

3. OBJECTIVES OF THE STUDY:

This study is based on following objectives:

i. Twelve different specifications of GARCH models, four models of both EGARCH and GJR-GARCH are formulated separately for crude oil return series.
ii. The forecasting performances of twenty specifications of GARCH family of models have been calculated.
iii. The quality of each model has been put in evidence by calculating four different error statistics across twenty models developed in this study to forecast daily volatility.

4. METHODOLOGY:

The return series consists of 1549 days closing values of crude oil data covering from 2nd January, 2009 to 18th February, 2014. For estimating the GARCH specifications, the rates of returns have been computed by taking a logarithmic difference of prices of two successive periods. Symbolically, it is:

$$y_t = \log \frac{P_{t+1}}{P_t} = \log P_{t+1} - \log P_t$$

where successive price observations made at time 't' and 't+1' as P_t and P_{t+1}, respectively and y_t is the return series.

Bollerslev (1986) proposed the famous GARCH (p,q) model as:

$$Var_{t-1}(y_t) = E_{t-1}(\varepsilon_t^2) = \sigma_t^2$$
$$where, \sigma_t^2 = k + \sum_{i=1}^{p} G_i \sigma_{t-i}^2 + \sum_{j=1}^{q} A_j \varepsilon_{t-j}^2$$

To the further extension to the GARCH model, Nelson (1991) proposed the Exponential Generalised Autoregressive Conditional Heteroscedasticity (EGARCH) model

$$r_t = \mu_t + \varepsilon_t$$
$$\ln(\sigma_t^2) = k + \sum_{i=1}^{p} G_i \sigma_{t-i}^2 + \sum_{l=1}^{o} \gamma_l \frac{\varepsilon_{t-l}}{\sigma_{t-l}} + \sum_{j=1}^{q} A_j \left(\left| \frac{\varepsilon_{t-q}}{\sigma_{t-q}} \right| - \sqrt{\frac{2}{\pi}} \right)$$

The GJR-GARCH model was introduced by a group of authors Glosten, Jagannathan, and Runkle (1993) and was named with the first letter of each author. It extends the standard GARCH (p,q) model to include asymmetric terms.

$$r_t = \mu_t + \varepsilon_t$$
$$\sigma_t^2 = k + \sum_{i=1}^{p} G_i \sigma_{t-i}^2 + \sum_{l=1}^{o} \gamma_l \varepsilon_{t-l}^2 I_{[\varepsilon_{t-l}<0]} + \sum_{j=1}^{q} A_j \varepsilon_{t-j}^2$$

The symbols have their usual meaning.

5. EMPERICAL ESTIMATIONS:

Table-1 presents the results of the error statistics. In this table all the twenty models are presented along with the four forecasting error measures. From the results presented in the table, following observations are highlighted.

Firstly, among the four error statistics, MSE measures the errors in a quite significant manner. Among the twenty specifications estimated in this study GARCH (3,3) proved to be the best model for the estimated crude oil return series. In other words, the predictive power of GARCH (3,3) specification is the best among the rest nineteen specifications, as error statistics is minimum in comparison to other models. Both in MAE and ME the forecasting error is found to be very nominal for GARCH (3,3) model.

It can also be seen that for GARCH (0,1), GARCH (0,2) and GARCH (0,3) the forecasting error value of ME and MSE are negative. This indicates that these three models under perform the forecasting value. The error calculated for other models by the four error measures are estimated to be higher than then GARCH (3,3) model. Thus it can be concluded that, the GARCH (3,3) models performs clearly ahead of EGARCH and GJR-GARCH models for the estimated series. Secondly, among the formulated GARCH family of models, GJR model's performance is better than EGARCH specification next to GARCH models. All the four measures reject EGARCH specifications of models as a good performing model. Within the GJR specifications, GJR (2,2) is found to be the best model as the forecasting error is minimum in this model between the four specifications.

6. CONCLUSION:

While forecasting efficiency of twenty GARCH models examined in this study, GARCH specifications have shown their superiority over EGARCH and GJR specifications with minimum error value for crude oil return series. GARCH (3, 3) followed by GJR (2, 2) proved to be the best forecasting models specifically. Again, MSE proved to be the best measure in estimating the forecasting errors for the estimated return series. EGARCH specifications of models disappointed more while forecasting the estimated return series.

Table 1: Forecasting errors for Crude Oil return

Models & Measures	ME	MAE	RMSE	MSE
GARCH(1,1)	0.0107	0.0107	0.1032	2.2E-06
GARCH(0,1)	-0.006	0.006	NA	-2.8E-07
GARCH(0,2)	-0.005	0.005	NA	-2.8E-07
GARCH(0,3)	-0.005	0.005	NA	-2.9E-07
GARCH(1,2)	0.0079	0.0075	0.0891	1.4E-06
GARCH(1,3)	0.0081	0.0083	0.0899	1.5E-06
GARCH(2,1)	0.0052	0.0053	0.0726	8.2E-07
GARCH(2,2)	0.0046	0.0047	0.0681	6.9E-07
GARCH(2,3)	0.0047	0.0048	0.0686	7.07E-07
GARCH(3,2)	0.0046	0.0047	0.0675	6.7E-07
GARCH (3,1)	0.0046	0.0047	0.0675	6.7E-07
GARCH(3,3)	0.0023	0.0028	0.0475	2.6E-08
EGARCH(1,1)	0.0768	0.0775	0.2771	7.3E-05
EGARCH(1,2)	0.0622	0.0623	0.2494	4.8E-05
EGARCH(2,2)	0.0573	0.0575	0.2394	4.2E-05
EGARCH(2,1)	0.0719	0.0721	0.2681	6.5E-05
GJR (1,1)	0.0084	0.0079	0.0919	1.6E-06
GJR(1,2)	0.0004	0.0013	0.0799	-6.8E-08
GJR (2,2)	0.0041	0.0042	0.0641	5.8E-07
GJR (2,1)	0.0053	0.0054	0.0734	8.4e-07

Note: Calculated value. Bold values are minimum values.

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