Improving Forecasts of Generalized Autoregressive Conditional Heteroskedasticity with Wavelet Transform

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Abstract: In the study, we discussed the generalized autoregressive conditional heteroskedasticity model and enhanced it with wavelet transform to evaluate the daily returns for 1/4/2002-30/12/2011 period in Brent oil market. We proposed discrete wavelet transform generalized autoregressive conditional heteroskedasticity model to increase the forecasting performance of the generalized autoregressive conditional heteroskedasticity model. Our new approach can overcome the defect of generalized autoregressive conditional heteroskedasticity family models which can’t describe the detail and partial features of times series and retain the advantages of them at the same time. Comparing with the generalized autoregressive conditional heteroskedasticity model, the new approach significantly improved forecast results and greatly reduces conditional variances.

Keywords: Brent oil, daily returns, DWT-GARCH, GARCH, volatility, wavelet transform

INTRODUCTION

The GARCH (abbr. Generalized Autoregressive Conditional Heteroskedasticity) family models found many important and significant characteristics of returns in financial assets. These characteristics could be stated as the following: heteroscedasticity and volatility clustering property (Engle, 1982; Bollerslev, 1986); asymmetric relation property (Nelson, 1991) and nonlinearity property (Higgens and Bera, 1992; Klaassen, 2002). Due to the advancement, GARCH family models have rapidly expanded. However, via literature review, we found that the GARCH family models could better simulate the nonlinear characteristics of time series, but it could not describe the detail and partial features of time series. Thus they lose a lot of information when modeling. In order to overcome this shortcoming of GARCH family models, we developed DWT-GARCH (abbr. Discrete Wavelet Transform GARCH) model by combining discrete wavelet transform with GARCH model to predict daily returns in Brent oil market.

Engle designed an ARCH (Abbr. Autoregressive Conditional Heteroscedasticity) model to estimate conditional variance of inflation sequence of the UK in 1982. The model assumed that the variance of random errors associated with the pre-random error and the model included the mean equation and the conditional variance equation. Via improving the ARCH model, there are a number of improved models, such as GARCH (Bollerslev, 1986), ARCH-in-mean (Engle et al., 1987), exponential GARCH (Nelson, 1991), nonlinear ARCH (Higgens and Bera, 1992), threshold ARCH (Glosten et al., 1993), dual-threshold GARCH (Yang and Chang, 2008). PARCH (Ding et al., 1993), long memory GARCH (Ding and Granger, 1996) and FIGARCH (abbr. fractional integrated GARCH) (Bailie et al., 1996). And vector GARCH are also developed.

In the applications, there are also lots of researches. Korkmaz et al. (2009) used FIGARCH model to test long-term memory of stock returns of Istanbul Stock Exchange. Their research shows that the market does not have weak validity. Liu and Bruce (2009) used the family of GARCH models, including ACGARCH model (abbr. asymmetric component GARCH), to forecast volatility of Hang Seng index. Their research shows that the family of GARCH models also shows “robustness” when using abnormal distribution data to do volatility forecast. Different news has different impact on markets. Impact of general news on markets is gentle, but some great news will cause sharp jump of prices. Das and Sundaram (1999) thought the models’ setting will have deviation if not consider characteristic of volatility jumping. Chan and Maheu (2002) developed GARCH model which can capture the jump intensity with time-varying. The model can well simulate the price jump. Time series often have characteristics of periodicity and seasonality. Kyrtou and Terraza (2003) proposed a GARCH model related to a seasonal variable, established a more general Seasonal Mackey-Glass-GARCH model (Kyrtou, 2005) and used this model to explain the long-term,
short-term memories and nonlinear structure of return series (Kyrtsou and Terraza, 2010). Racicot et al. (2008) used ultra high frequency GARCH model to predict data volatility of irregular time intervals. And they compared it with the forecast effect of realized volatility model (Bollerslev and Wright, 2001). The results show that forecast effect has not been improved. So they thought that combine artificial neural network with family of GARCH model or use spline function before modeling to carry on the pretreatment for the data may improve the forecast effect. Wang (2009) established a hybrid model which has used grey theory, non-linear neural network and Glosten-Jagannathan-Runkle GARCH and forecasted the stock index options returns in Taiwan Futures Exchange. Bildirici and Ersin (2009) combined artificial neural networks with GARCH family models to establish ANN-GARCH (abbr. artificial neural networks GARCH) models and separately use GARCH family models and ANN-GARCH models to study volatility characteristics of daily return rate in Istanbul Stock Exchange. Their results show that only partial models’ forecast accuracy of GARCH family model has been improved by network learning. Zhao et al. (2010) established Multiscale-IGARCH model by combining multi-scale analysis with IGARCH model and forecasted the China’s soya futures margin.

MODEL AND DATA

DWT-GARCH model: We recorded the daily returns as \( r_t \) (\( r_t = \ln(P_t) - \ln(P_{t-1}) \)) and chose GARCH models to predict \( r_t \). General GARCH models can only describe the overall volatility features of the series, but cannot describe partial volatility features of the series and multi-scale information. Ignoring partial volatility features and multi-scale information of the time series will affect the precision of the model. To take advantage of prices’ partial volatility features and multi-scale information of variables when forecasting, we established DWT-GARCH model by combining wavelet analysis theory with the GARCH. In accordance with the principle of DWT, we decompose \( r_t \) into different time scales, as model (1) shows:

\[
 r_t = r_{A_t,j} + \sum_{j=1}^{J} r_{D_t,j}
\]

where,
\( r_{A_t,j} \) = The approximate part of \( r_t \)
\( r_{D_t,j} \) = The detail part
\( J \) = The layers of decomposition

According to the principle of multi-scale analysis, series in each time scale after decomposing are orthogonal (\( \cdot \) denotes point multiplication between vectors), that is:

\[
 r_{A_t,j} \cdot r_{D_t,j} = 0, \quad r_{D_t,j} \cdot r_{D_t,j} = 0
\]

Discrete wavelet expression of model (1) is as follows:

\[
 r_t = \sum_{j=1}^{J} a_{j,k} \Phi_{j,k}(t) + \sum_{j=1}^{J} d_{j,k} \Psi_{j,k}(t) + \sum_{j=1}^{J} d_{j,k} \Psi_{1,j,k}(t)
\]

where,
\( J \leq \log N \)
\( k = N/2^j \)
\( N \) = The number of sample observations of \( r_t \)
\( \Phi(t) \) = Scaling function
\( \Psi(t) \) = Wavelet function

‘a’ = Scaling coefficients to capture trend of series \( r_t \), which can be obtained by the following formula:

\[
 a_{j,k} = \int \Phi_{j,k}(t) r_t dt
\]

‘d’ denotes wavelet coefficients, used to capture the partial features of series \( r_t \), which can be obtained by the following formula:

\[
 d_{j,k} = \int \Psi_{j,k}(t) r_t dt
\]

Here, \( r_{A_t,j} = \sum_{j}^{k} a_{j,k} \Phi_{j,k}(t) \) and 
\( \sum_{j}^{k} d_{j,k} \Psi_{j,k}(t) + \sum_{j}^{k} d_{j,k} \Psi_{1,j,k}(t) \).

Let \( r_{A_t,j} = \mu_{A_t,j} + e_{A_t,j}, \quad r_{D_t,j} = \mu_{D_t,j} + e_{D_t,j} \)

In model (6), suppose the residuals \( e_{A_t,j} \) and \( e_{D_t,j} \) are independent and:

\[
 e_{A_t,j} = e_{A_t,j} \sqrt{h_{A_t,j}}, \quad e_{D_t,j} = e_{D_t,j} \sqrt{h_{D_t,j}}
\]

Put model (6) into model (1), we get the model (7) which is a mean equation of DWT-GARCH (p, q). Corresponding variance equations are showed in model (8) and model (9):

\[
 r_t = \mu_{A_t,j} + \sum_{i=1}^{p} \mu_{D_t,j} + \epsilon_{A_t,j} + \sum_{i=1}^{p} \epsilon_{D_t,j}
\]

\[
 h_{A_t,j} = \alpha_{A_t,j} + \sum_{i=1}^{q} \alpha_{A_t,j} \epsilon_{A_t,j}^2 + \beta_{A_t,j} h_{A_t,j-1}
\]

\[
 h_{D_t,j} = \alpha_{D_t,j} + \sum_{i=1}^{q} \alpha_{D_t,j} \epsilon_{D_t,j}^2 + \beta_{D_t,j} h_{D_t,j-1}
\]

DWT-GARCH can dig up self-correlation characteristics existing in multi-scale, thereby improve accuracy for forecasting. Record conditional variances

650
obtained via DWT-GARCH as $h_{DWT}$. DWT can enhances the prediction accuracy of GARCH models and makes predictive value of $r_t$ approach the actual value.

In order to compare prediction accuracy of DWT-GARCH with GARCH, these 2 kinds of models are used to conduct empirical research. When modeling with approximate series and detail series, we found that assumption of t distribution cannot pass the test in most cases. Therefore, we supposed the data follow the GED distribution. After model debugging, AR-GARCH (1, 1) can be written as follows:

The mean equation is as model (10):

$$r_t = \sum_{i=1}^{n} \theta_i A'R(i) + \varepsilon_t$$  \hspace{1cm} (10)

The conditional variance model is as model (11):

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$$  \hspace{1cm} (11)

Data: In dealing with high-frequency data, as density of singular point is very large and vanishing moments cannot be too high, therefore we chose db5 function to do wavelet decomposition. Via repeated test on high-frequency data about stock prices and returns, Ma et al. (2007) suggests the number of decomposition layer be no greater than 3 for they have many high-frequency components. We set the number of decomposition layer as 2. The 3 series obtained by decomposing were recorded as $a_2$, $d_2$ and $d_1$. Here, $a_2$ is the approximate series; $d_2$ and $d_1$ are detail series. Figure 1 showed the results of wavelet decomposition and daily returns for 1/4/2002-30/12/2011 period in Brent oil market. Multi-scale analysis excavates partial self-correlation feature of the series, but this feature cannot be directly observed from the original series. As mentioned, the original series is equal to the superposition of the 3 series obtained from wavelet lifting and there are no correlations between the 3 series. Because series after transform have significant self-correlation, we need to add AR item in the mean equation. Serial self-correlation is beneficial to improve forecast precision of time series.

RESULTS

Table 1 and 2 give the estimation results of AR-GARCH and AR-DWT-GARCH. In the process of AR-GARCH (1, 1) parameter estimation of original series, $R^2 = 0.0001$, Adj-$R^2 = 0.0001$, S.E. = 0.0233, SSR = 1.3527, Log likelihood = 6036, AIC = -4.8459 and SC = -4.8342 and HQC = -4.8416. In the process of AR-DWT-GARCH parameter estimation of $a_2$, $R^2 = 0.9509$, Adj-$R^2 = 0.9508$, S.E. = 0.0026, SSR = 0.0170, Log likelihood = 12056, AIC = -9.6819, SC = -9.6655 and HQC = -9.6759. In the process of AR-DWT-GARCH parameter estimation of $d_2$, $R^2 = 0.8292$, Adj-$R^2 = 0.8290$, S.E. = 0.0045, SSR = 0.0513, Log likelihood = 10335, AIC = -8.3018, SC = -8.2831 and HQC = -8.2951. In the process of AR-DWT-GARCH parameter estimation of $d_1$, $R^2 = 0.7641$, Adj-$R^2 = 0.7638$, S.E. = 0.0082, SSR = 0.16667.

Table 1: Parametric estimation of the AR-GARCH

| Parameter | Coefficient | Z-value | Prob. |
|-----------|-------------|---------|-------|
| AR(3)     | 0.0339      | 1.7261  | 0.0843|
| $\omega$  | $7.29\times10^{-6}$ | 2.6523 | 0.0080 |
| $\alpha$  | 0.0424      | 5.2099  | 0.0000|
| $\beta$   | 0.9426      | 81.9112 | 0.0000|
| GED V     | 1.4681      | 25.6727 | 0.0000|

Table 2: Parametric estimation of the AR-DWT-GARCH

| Eqs. | Parameter | Coefficient | Z-value |
|------|-----------|-------------|---------|
| $a_2$ | a2_AR (1) | 2.4350      | 118.1642 |
| $a_2$ | a2_AR (2) | -2.1358     | -56.4578 |
| $a_2$ | a2_AR (3) | 0.6578      | 30.4777 |
| $a_2$ | $\omega$  | $2.99\times10^{-7}$ | 8.3272  |
| $a_2$ | $\alpha$  | 0.3761      | 14.0923 |
| $a_2$ | $\beta$   | 0.5992      | 30.3991 |
| $a_2$ | GED V     | 3.3520      | 19.1114 |
| $d_2$ | d2_AR (1) | 0.9091      | 81.8700 |
| $d_2$ | d2_AR (2) | -1.4265     | -106.9146|
| $d_2$ | d2_AR (3) | 0.7101      | 53.4988 |
| $d_2$ | d2_AR (4) | -0.5691     | -54.1029 |
| $d_2$ | $\omega$  | 7.86$\times10^{-7}$ | 3.5797  |
| $d_2$ | $\alpha$  | 0.1753      | 6.0050  |
| $d_2$ | $\beta$   | 0.8101      | 29.4602 |
| $d_2$ | GED V     | 1.4694      | 28.3377 |

Fig. 1: Wavelet decomposition and primary signal of daily returns of brent oil
Comparing various statistical values, we know, fitting precision of AR-DWT-GARCH model is higher than AR-GARCH and it uses more information in the time series.

Comparing $R^2$, Adj-$R^2$, Log likelihood, SE and SSR of AR-DWT-GARCH (1, 1) with those of AR-GARCH (1, 1), we found that fitting accuracy of AR-DWT-GARCH (1, 1) model is much better than AR-GARCH (1, 1) model. Values of AIC, SC and HQC showed that AR-DWT-GARCH (1, 1) model could excavate richer information from primary signal of daily returns than AR-GARCH (1, 1) model. Record $r_t$ obtains from the forecast which are based on DWT-GARCH and the GARCH as $r_{t1}$ and $r_{t2}$ respectively. Record conditional variances obtain from DWT-GARCH and GARCH as $h_{DWT}$ and $h$. Figure 2 showed the differences of original value $r_t$ and predictive value $r_{t1}$ and $r_{t2}$ respectively, which were recorded as $r_t - r_{t1}$ and $r_t - r_{t2}$. Prediction results in Fig. 2 showed that forecasting result of DWT-GARCH model was more precise. The smaller the conditional variance is, the better the forecast is. Figure 3 showed the values of conditional variance estimated by GARCH model and DWT-GARCH model. DWT-GARCH model had obvious advantages in forecasting the daily returns as shown.

CONCLUSION

In the study, we analyzed and combined GARCH with wavelet transform models. The main aim of the study is to augment the forecasting power of DWT-GARCH. Our results show that the GARCH family models combining with wavelet transform theory may be more powerful when forecasting the daily returns. It can not only describe the detail and partial features of volatility series, but also describe the heteroscedasticity, volatility clustering property, asymmetric relation property and nonlinearity property of volatility series. The DWT-GARCH model maintains approximate parts of the original series and captures the detail parts of volatility series at the same time. Via wavelet lifting, DWT-GARCH can dig up self-correlation characteristics existing in multi-scale, thereby improve forecast accuracy. These advantages make forecast accuracy of DWT-GARCH model higher than GARCH.

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REFERENCES

Bailie, R.T., T. Bollerslev and H. Mikkelsen, 1996. Fractional integrated generalized autoregressive conditional heteroskedasticity. J. Econom., 74(1): 3-30.

Bildirici, M. and O.O. Ersin, 2009. Improving forecasts of GARCH family models with the artificial neural networks: An application to the daily returns in Istanbul stock exchange. Exp. Syst. Appl., 36(4): 7355-7362.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. J. Econom., 31(3): 307-327.

Bollerslev, T. and J.H. Wright, 2001. High-frequency data, frequency domain inference and volatility forecasting. Rev. Econ. Statist., 83(4): 596-602.

Chan, W.H. and J.M. Maheu, 2002. Conditional jump dynamics in stock market return. J. Bus. Econ. Statist., 20(3): 377-389.

Das, S.R. and R.K. Sundaram, 1999. Of smiles and smirks: A term structure perspective. J. Financ. Quantit. Anal., 34(2): 211-240.

Ding, Z., C.W.J. Granger and R.F. Engle, 1993. A long memory property of stock market return and a new model. J. Empir. Financ., 1(1): 83-106.

Ding, Z. and C.W.J. Granger, 1996. Modeling volatility persistence of speculative returns: A new approach. J. Econom., 73: 185-215.

Engle, R.F., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4): 987-1007.
Engle, R.F., D.M. Lilien and R.P. Robins, 1987. Estimating time varying risk premia in the term structure: The ARCH-M model. Econometrica, 55(2): 391-406.
Glösten, L., R. Jagannathan and D. Runkle, 1993. On the relation between expected return on stocks. J. Financ., 48(5): 1779-1801.
Higgins, M.L. and A.K. Bera, 1992. A class of nonlinear ARCH models. Int. Econ. Rev., 33: 137-158.
Klaassen, F., 2002. Improving GARCH volatility forecasts with regime-switching GARCH. Empir. Econ., 27: 363-394.
Korkmaz, T., E.I. Cevik and N. Oztac, 2009. Testing for long memory in ISE using ARFIMA-FIGARCH model and structural break test. Int. Res. J. Financ. Econ., 26: 186-191.
Kyrtsou, C. and M. Terraza, 2003. Is it possible to study chaotic and ARCH behavior jointly? Application of a noisy Mackey-Glass equation with heteroskedastic errors to the Paris stock exchange returns series. Computat. Econ., 21(3): 257-276.
Kyrtsou, C., 2005. Evidence for neglected linearity in noisy chaotic models. Int. J. Bifurcat. Chaos, 15(10): 3391-3394.
Kyrtsou, C. and M. Terraza, 2010. Seasonal Mackey-Glass-GARCH process and short-term dynamics. Empir. Econ., 38(2): 325-345.
Liu, W. and B. Morley, 2009. Volatility forecasting in the Hang Seng index using the GARCH approach. Asia-Pacific Financ. Market., 16(1): 51-63.
Ma, C.Q., Q.J. Lan and W.M. Chen, 2007. Data Mining in Finance. Science Press, Beijing.
Nelson, D.B., 1991. Conditional heteroscedasticity in asset returns: A new approach. Econometrica, 59(2): 349-370.
Racicot, F.E., R. Théoret and A. Coën, 2008. Forecasting irregularly spaced UHF financial data: Realized volatility vs. UHF-GARCH models. Int. Adv. Econ. Res., 14(1): 112-124.
Wang, Y.H., 2009. Nonlinear neural network forecasting model for stock index option price: Hybrid GJR-GARCH approach. Exp. Syst. Appl., 36(1): 564-570.
Yang, Y.L. and C.L. Chang, 2008. A double-threshold GARCH model of stock market and currency shocks on stock returns. Math. Comput. Simulat., 79(3): 458-474.
Zhao, Y., Y. Zhang and C.J. Qi, 2010. Futures margin forecasting and simulating based on multiscale-IGARCH model. J. Computat. Inform. Syst., 6(6): 1843-1853.