Measuring Conditional Volatility using GARCH (2, 2) Model from Empirical Standpoint

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Abstract

The article covers the broader aspect of time-variant volatility function using GARCH (2, 2) vo-latility function. The postulate of conditional heteroskedasticity and autoregressive in relation to residual distribution is examined for four listed daily stock prices from Indian markets namely Infosys, TCS, HDFC and Tata Motors. The basic aim of the paper is to understand how the GARCH (2, 2) model perform as against the unconditional volatility and whether any volatility clusters appear in the price series. The overall idea of using a GARCH (2, 2) is to observe the lag orders for 2 days across conditional mean (first order) and conditional volatility (second order) autocorrelation effects across four prominent stocks. Also, to observe the static parameters and their role in defining the conditional elasticity of errors in the univariate setup. The results clearly highlighted that volatility clustering was observed at different time period defining the role of macroeconomic information and price adjustments with mean-reversion effects

Keywords : Mean-reversion, GARCH (2, 2), Heteroskedasticity, Conditional volatility

Introduction:

In Indian stock market context, the stock prices on high frequency usually possess a conditional volatility and it is observed that such conditional volatility and conditional mean values can have matrix properties i.e. they may have a temporal cross-correlations at higher lags. This phenomena can be well captured using GARCH (2, 2) model. However, in the current work the author started with GARCH (1, 1) and then introduced the GARCH (2, 2) setup.

Research Problem

The research problem is "**Conditional volatility for certain stocks might possess higher lagged cross-correlations even under high-frequency (daily) data series."**

Research Objectives:

- To ascertain the key descriptive outcomes to generalize the distribution pattern of stock price series
- To examine the strength of model using R-squared and other relevant model outcomes
- To use Hurst component to see whether the autocorrelation exists at various class-intervals
- Finally to examine (in whichever sample stocks possible) a comparison between the GARCH(1,1) and GARCH (2,2) outcomes

Literature Review:

Tsai and Chan (2008) clarified that for GARCH (p, q) model the non-negative of ARCH coeffi-cients must be applicable. This will indeed result in all conditional variances to be necessarily positive and by using GARCH p>= 2 and p< 2 process separately. It has been seen that the high-er order GARCH (p, q) fulfils stationary condition in comparison to lower order.

Aiube, Baidya, Blank, Mattos,Saboia and Siddiqui (2013) empirically examined how retail elec-tricity prices possess seasonality at various time-frequencies. The use of Seasonal Autoregressive Moving Average (SARMA), SARMA-GARCH and GARCH models were analyzed separately for Australian and Spanish markets. Due to highly seasonal pattern of hourly electricity prices. It was rather prepared to build 24 forecasting models for each hour of a day.

Suna and Zhou (2009) emphasized on downside risk associated with respect to the GARCH (1, 1) model innovations. A normal distributed GARCH-type innovation fail to capture large devia-tions. For this author used quasi maximum likelihood (QMLE) and General Pareto distribution (GPD).

Vošvrda and Žikeš (2004) utilized GARCH-t distribution since it is assumed that despite of MLE application, the error distribution may still remain non-normal. Instead of usual histogram a non-parametric kernel density estimator was used for this purpose.

Laplante, Desrochers and Préfontaine (2008) used covariance matrix approach by dividing the sample data into in-sample period (1988-1992) and (1992-1997) as out-of-sample data for testing purposes. For portfolio purposes, a hedging across international stock indices using short-selling or even CAPM like assumption of lending and borrowing at interest rates were also relaxed. The use of random walk, historical mean model (HMM), EWMA and GARCH (1, 1) model was used for ascertainment of conditional volatility. For model comparisons, Mean-error (ME), Mean Ab-solute Error (MAE), Root mean square error (RMSE) and Mean Absolute Percentage error (MAPE) were employed.

Huang (2011) demonstrated various implied volatility models including Random walk model, ARCH (q), GARCH (p, q), GJR (p, q) and EGARCH (pp.). The thesis work tried to fit the best model to predict the implied volatility.

Research Methodology

Mode of Data Collection-

For longitudinal data of four key equity prices (closing prices) from 3rd March 2017 till 29th September 2018 were taken cumulating to 453 observations. For out-of-sample forecasts, 107 observations were counted from 2nd May 2017 till 29th September 2018 respectively. For analy-sis EViews and Gretl were used.

GARCH model:

Malhotra (2014).Generalized Autoregressive Conditional Heteroskedacity model usually referred as GARCH depicts the ARCH type model with conditional volatility attached. ARCH allows only lagged parameter to work, while GARCH works with one additional conditional lagged parameter. That is why, in the present paper, the GARCH lagged optimization is also utilized.

$$\sigma^2{}_x n = \omega\nu + \beta\sigma_x{}^2{}_{(n-k)} + \alpha\mu^2{}_{(n-k)} \quad \textit{eq. 2}$$

ω = long term weight

ν =long term volatility (454 days)

β = it the parameter attached with the Lagged variance

α = it is the parameter attached with the lagged squared return

In terms of estimating the lagged parameters i.e. ω, β and α, the use of Maximum Likelihood model (MLP) is used,

$$MLF = -\log\sigma^2 - \frac{\mu^2}{\sigma}(where\,\omega, \alpha, \beta \geq 0, non-negative) \quad \text{Eq. 3}$$

- $\log\sigma^2$ = this is the log of variance

- $\frac{\mu^2}{\sigma}$ =This is also considered as Sharpe factor, since the return is divided by risk.

Analysis:

Unit-root tests

See Table 1, 4, 7 and 10 for ADF tests. It can be easily observed that in all the four companies the stock prices growth rates experienced no unit roots i.e. null was rejected. Hence the relative first differences of prices exhibited some stationary. For Infosys, R square of ADF test was 45%, for HDFC it was at 49.28%, for Tata Motors it was at 42.43% and TCS it ends with 48.25%. Hence, under the univariate settings Squared on lower side depicts some weak stationary.

Observing GARCH (1, 1) with GARCH (2, 2) results

After applying Garch (1, 1) and Garch (2, 2) one observation worth differentiating the two mod-els were the number of iterations for convergence purposes. Except for Infosys (refer Tables 2, 3,5,6,8,9,11 and 12) rest of three companies Garch (2, 2) took significantly more number of ite-rations for convergence purposes.

The most important analysis is the role of covariates, particularly surround by conditional volatil-ity and is common among the two models i.e. Garch (-1) covariate. For Infosys, we can observe that it moved from 0.037 to 0.3831 while Garch (2, 2) it was -0.063 and was insignificant.

Observing Residual analysis (Refer Figures 3, 6, 9 and 12), there were identical patterns on time series.

For forecasting purposes out of total 453 observations, only 107 observations were used which started from 2nd May 2018. And almost in all the four companies the common observation (see Figures 1,2,4,5,7,8,10 and 11) there was more steepness in the forecasting variance while moving from Garch (1,1) to Garch (2,2) model respectively.

Now, unlike Infosys for HDFC it took 304 iteration and 19 iterations in comparison to Garch (2, 2). Observing the covariates associated with Garch (-1). In particular, Garch (1, 1) showed 0.8051 while for Garch (2, 2) it was 0.6119. However, both covariates were significant as per p-values. Garch (-2) was insignificant.

For forecasting purpose the results were almost identical however the steepness was usually re-mained higher in Garch (2, 2) due to second-order and higher number of covariate interventions. But this also increase the level of steepness in Garch (2, 2) model from 0.0036 from 0.0034 in Garch (1, 1) case.

In terms of third stock, i.e. Tata Motors we can also see that covariate from Garch (1, 1) to Garch (2, 2) improved significantly from 0.266 to 1.026. However it took more number of iterations from 22 in Garch (1, 1) to 48 in the latter case. In terms of forecasting there are similar characte-ristics, a faster steepness was observed at the Garch (2, 2) model. However, the position of out-lier variance was somewhat different in compared to other stocks. Residual movement was found identical in both the models.

Finally for TCS, just like last 2 stocks, it was 328 iterations for Garch (1, 1) but moved to 500 iterations for Garch (2, 2) to reach to convergence. The covariates values were almost identical. The conditional mean covariate was insignificant and weak. Similarly, Garch (-2) was also in-significant. The forecast variance as usual was moving from 0.003 to as high as 0.012, contrary to this for Garch (2,2) it started at 0.004 and settled much higher at 0.020 respectively.

Analysis of Conditional variance graphs

For conditional variance as far as Infosys stock goes (as observed in Figures 13 and 14) Garch (2, 2) volatility was little suppressed in comparison to Garch (1, 1) values. Most of the spikes were upward in nature. This was an observation for rest of the two stocks viz. HDFC and Tata Motors (see figures 15 to 18), while for TCS a sudden downside risk is clearly observable (refer figures 19 and 20)

Conclusion

After closely monitoring the process of Garch (1, 1) to Garch (2, 2) it can be witnessed that due to possibility of major spikes (very large and sudden change in values) the Garch (2, 2) even with more information structure (better covariate strength) failed to capture the "true" forecasts. The out of sample observations were found little smoother for Garch (2, 2), however in all the four sampled stocks the results of both the models were identical.

Empirical Scope

The field of conditional volatility through use of autoregressive procedures somehow emanates from the broader realm of asset pricing under incomplete markets. Autoregressive nature of resi-duals explain a hidden information which the model is not able to capture resulting into informa-tion arbitrage. Hence, more advance models using frequency domains can be utilized for the same purpose.

References

Suna, P., & Zhou, C. (2009). How to apply GARCH model in risk management? *Tang, Dragon, and Hong Yan, (2007), Liquidity and credit default swap spreads, Working Paper.*

Vošvrda, M., &Žikeš, F. (2004). An application of the GARCH-t model on Central European stock returns. *Prague Economic Papers, 1*, 26-39.

Laplante, J., Desrochers, J., &Préfontaine, J. (2008). The GARCH (1, 1) model as a risk predictor for international portfolios. International Business & Economics Research Journal, 7(11), 23-34.

Huang, K. (2011). Modeling volatility of S&P 500 index daily returns: a comparison between models based forecasts and implied volatility. *Finance and Statistics, Hanken School of Econom-ics.*

Aiube, F. L., Baidya, T. K., Blank, F. F., Mattos, A. B., Saboia, W., & Siddiqui, A. S. (2013). Modeling Hourly European Electricity Spot Prices via a SARMA-GARCH Approach. (Http: //www. enrima-project. eu/sites/default/files/paper_apr.

Tsai, H., & Chan, K. S. (2008). A note on inequality constraints in the GARCH model. Econo-metric Theory, 24(3), 823-828.