

## COMPARING NET PROFIT FORECASTS OF INDIAN BANKS USING OLS AND GARCH 1,1 FRAMEWORK

ROHIT MALHOTRA & Dr. JIMMI KAPADIA  
Auro University  
Surat, India.

### ABSTRACT

In the present paper the Bi-variate Ordinary Least Square (OLS) and Generalized autoregressive conditional heteroskedasticity (GARCH 1, 1) model are applied to gather the fitted Net –Profit series of Two nationalized banks viz, State Bank of India SBI (being a leader) and ING Vysya bank (not a leader) in the Indian Banking sector. It is evident that OLS is non-parameterized method while QMLE or QML is a parameterized technique of coefficients estimation. The robustness must therefore need to see with respect to the data in consideration. The whole approach is to measure how both the models provide Earning forecasts and to analyze the behavior of regression coefficients. Also, the second objective could be to see how “Leader” bank earnings estimation process differs from the non-leader bank in the Indian banking setup. The results are clearly explaining differences in two banks in terms of their coefficient values, residual state and R-squared values.

KEYWORDS-, OLS, GARCH, Earning Forecasts

### INTRODUCTION

The present paper examine the role of OLS and GARCH 1,1 on actual financial data with mainly emphasizing on the residual analysis and regression parameters estimation.

(Chen, 2008) in the paper, the author used the GARCH 1,1 model on two different time period to study the impact of stock price prediction using interest rates and exchange rates as exogenous variables. The use of two regression models, 1<sup>st</sup> a regular regression and second with first difference and the results were compared.

(Hsing, 2013) under this paper, the author tried to use several fiscal and monetary policy variables to derive relationship with the stock price index, the author utilized GARCH volatility framework for this study.

(Badertscher, Christensen, Crawford, Easton, & Fairfield, 2010) in their paper the authors explained the use of disaggregating operating and financial items while presenting them in the formal financial statements, this is close to the consideration of FASB and IASB, 2008 proposal of converting all the accounting presentations in

operating and financial disaggregation's . Further the paper highlighted the importance of disaggregation of operating and financial along with the unusual or infrequent items both impacting the profitability forecasting.

(Watts, n.d.) in this interesting use of voluntary disclosure of quarterly balance sheet alongside quarterly income statement is emphasized. The hypothesized was that in the event of current earnings inaccuracy and uncertainty following future earnings, the balance sheet voluntary disclosures on high frequency improve shareholder expectations and thus reflect in the stock prices.

The paper is organized by first explaining the methodology, and later the outcome is disclosed in four parts, first part speaks of the R2 and Adjusted R2, second part talks on comparison of Regression coefficients, followed by Residual analysis and later the GARCH effects in form of persistence and decay factors in the data series.

#### EXPERIMENTAL SECTION:

In the present paper, a bi-variate model was utilized; the Quarterly income statement data from 2004-3<sup>rd</sup> quarter till 2014-3<sup>rd</sup> quarter was used.

The Net-profit (NP) was used as endogenous variable and Interest income (II) and Operating expense (OE) were used as two exogenous variables under this study

For a simple bi-variate OLS regression look like:

$$y_{NP_t} = \beta_1 + \beta_2 x_{II_t} + \beta_3 x_{OE_t} + u_t \quad \text{eq. 1}$$

$y_{NP_t}$  = Endogenous variable (Net profit)

$\beta_1$  = Const (drift)

$\beta_2 x_{II_t}$  = product of regression coefficient of Exogenous variable 1 (interest income)

$\beta_3 x_{OE_t}$  = product of regression coefficient of Exogenous variable 2 (operating expense)

$u_t$  = stochastic error term

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.

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

$\omega$  = long term weight

$\nu$  = long term volatility (191 months)

$\beta$  = it the parameter attached with the Lagged variance

$\alpha$  = it is the parameter attached with the lagged squared return

In terms of estimating the lagged parameters i.e.  $\omega$ ,  $\beta$  and  $\alpha$ , the use of Maximum Likelihood model (MLP) is used,

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

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

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

For MLP, the excel solver is utilized for calculation purposes.

Here, again a bi-variate GARCH model is utilized.

#### RESULT AND DICUSSION:

For, time-series estimation Gretl software was utilized, for OLS a HAC (Heteroskedacity and Autocorrelation corrected) measure was adopted. For, GARCH, QML (Quasi-Maximum Likelihood estimate) was utilized for estimation purposes.

TABLE 1: Comparing the R squared and Adjusted R squared of SBI and ING Vysya bank

OLS	R-squared	Adjusted-R squared
SBI	0.9548	0.9524
ING- Vysya	0.9436	0.9406

As can be witnessed above, the R-squared value of both the banks does not improve with higher order autoregressive function, reveals that first order auto regression stands better than higher order auto regression. But, SBI regression seems performed better compared to ING-Vysya.

TABLE 2: Regression Coefficient analysis:

OLS	II-Coefficient ( $\beta_2$ )	OE-Coefficient ( $\beta_3$ )	GARCH 1,1	II-Coefficient ( $\beta_2$ )	OE-Coefficient ( $\beta_3$ )
SBI	0.2757	-0.1410	SBI	0.3284	-0.2032
ING- Vysya	-0.0141	0.1462	ING-V	-0.019	0.1395

Now, to compare the parameters estimated through OLS and GARCH 1, 1, it is again important to witness that in SBI the parameter attached to interest income is more informative in GARCH 1, 1 compared to OLS. This is also true for Operating expenses too. While, for ING Vysya, although, the sensitivity of Interest income as information factor was slightly better in GARCH 1, 1 it does not hold true for operating expenses. The regression parameters closely reveal that how GARCH 1, 1 improve the results and also that SBI clearly perform better in providing regression estimates.

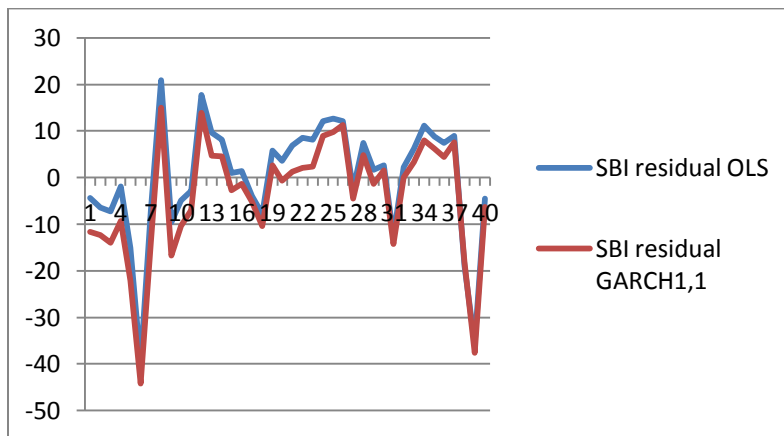


FIGURE 1: SBI-Residual Analysis (40 quarters)

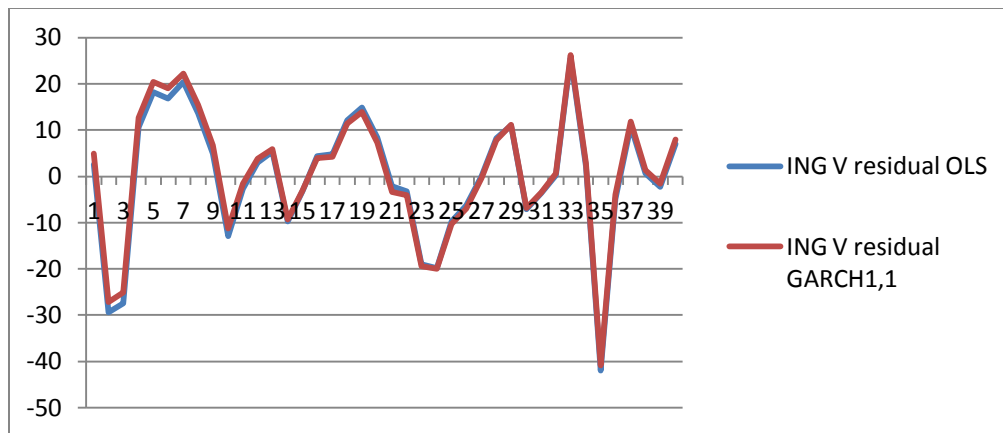


FIGURE 2: ING Vysya Residual analysis (40 quarters)

Seeing the graphics, it is immediately conceived that for SBI the GARCH1, 1 was the clear winner in terms of NP fitted estimates, in ING Vysya, GARCH 1, 1 and OLS stood almost same in the residual component. Although, these residual are not standardized, if we use the standardized residuals the results will not differ since the “scale or unit” is the same for both the companies in consideration, further performing Normality test on Residual closely reveal that SBI residuals are normally distributed in case of GARCH, but ING Vysya does not. (p value exceeds 0.05). For OLS, the results are consistent, i.e. the residuals were having normality in case of SBI data, but for ING Vysya, the residuals were non-normal in appearance.

With regard to “persistence of mean” and “decay of volatility” parameters:

While in SBI, for GARCH 1, 1 the persistence of mean is very high as alpha is at 0.896 while beta was at 1e-012 showing a very long memory. This is however, not true for ING Vysya, since Alpha was 0.1548 but beta was 0.4276 which makes two banks very different two studies. Usually, high decay means faster “mean reverting” nature of data.

## CONCLUSION

The paper clearly distinguishes the benefit of GARCH 1, 1 model over OLS. One pertinent reason is the assumption of normal distribution under GARCH 1, 1. Also, it is worth to mention that within more consistent financial results definitely yield better regression results as it can be witnessed in case of two sample banks for this case study. More robust study of residual series can explain more distinct pattern of the financial time series modeling. This study definitely provide some unique contribution to the ever increasing field of earning forecasts and will help the researchers in this direction to make some empirical gain from it. Non-normal error term show a reason to control and study the higher moments and therefore demand robust regression estimation.

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