International Journal of Science, Engineering & Environmental Technology (IJOSEET), 4(2): 10-17, 2019
ISSN 0794-9650

www.repcomseet.com

On Optimal Method of Forecasting Inflation Rates Data Using Parsimonious GARCH Models

[1]AKINTUNDE, M. O., [1]OLALUDE, G. A. AND [2]SANGODOYIN, D.K.
[1]Department of Statistics, Federal Polytechnic, Ede, Osun State Nigeria
[2]Department of Statistics, University Of Botswana, Gaborone

Abstract - This paper considers the optimum method of forecasting inflation rates data of United States of America (developed economy) and Federal Republic of Nigeria (developing economy) using derived models. The models used were GARCH, Bilinear-GARCH (BL-GARCH), STAR-GARCH (EAR-GARCH, ESTAR-GARCH and LSTAR-GARCH) and ST-GARCH (ET-GARCH, EST-GARCH and LST-GARCH). From the results obtained from the analysis using E-view software, it was discovered that the hybrid of Bilinear with GARCH (BL-GARCH) out performed Classical GARCH model. In the same way the hybrids of STAR-GARCH and ST- GARCH also out performed better classical GARCH model. However, LSTAR-GARCH from STAR-GARCH and LST-GARCH from ST-GARCH out-performed other models (EAR-GARCH, ESTAR-GARCH, ET- GARCH and EST-GARCH). Conclusively, in this study, the optimum forecast model was produced by LSTAR-GARCH (STAR-GARCH).

Keywords: GARCH, BL-GARCH, STAR-GARCH, ST-GARCH, optimum method, inflation rates

1. Introduction

The schools of thought differ on the meaning of inflation. However, the popular consensus among economists is that inflation is a measure of ceaseless rise in the prices of goods and services. It could also be seen as incessant soar in prices as measured by indicator such as the Consumer Price Index (CPI) or by the implicit price deflator for Gross National Product (GNP). The existence of inflation in an economy is best confirmed when currency loses purchasing power. Inflation rate forecasting or the concept of inflation rates volatility has been a focus of so many literatures of economic and financial time series, prominent among them is Berument and Sahin (2010) who disclosed that measure of inflation rates volatility and forecasting is far more important than its macro economist's implications.

Autoregressive Conditional Heteroscedasticity (ARCH) Model and her variants such as the such as Generalised ARCH (GARCH), Integrated GARCH and Exponential GARCH (EGARCH) models were evolved to model volatility fluctuation (non-constant) of such series. The ARCH model was initiated by Engle in (1982) this initiative of Engle was further extended by Bollerslev in (1986) to a more generalized one called GARCH. The GARCH are commonly used for the specification of the ARCH model. It exerts a kind of limitations on the parameters so as to assume positive variances. Nelson (1991) advanced an alternative to the GARCH model by remodelling or extending the GARCH model to a more advanced Exponential GARCH (EGARCH) model. Unlike the GARCH, the EGARCH does not impose any form of restrictions on the parameters in order to assume a positive variance. Ling & Li (1997) and Coshall, J.T. (2008) applied fractionally integrated moving Average (FIMA) models with conditional heteroscedasticity by combining hybrid of generalized autoregressive conditional heteroscedasticity (GARCH) and (ARIMA) models, their research confirmed that financial data set displayed conditional heteroscedasticity, consequent upon this, GARCH – type model are often used to model the in-built volatility in a series.

Autoregressive integrated moving average (ARIMA) was applied by Meyer et. Al. (1998) to forecast Irish inflation, their findings affirmed that ARIMA models are more potent relative to multivariate models. jean - Phillippe (2001) applied the popular Box and Jenkins (1976) method to model and forecast Finnish inflation and affirmed its reliability. Shittu, O. I., and Asemota. M. J. (2009) used the like of Box and Jenkins (1976) method to forecast short term inflation outburst in Croatia and concluded that this model performed excellently well. In so many other studies, researches in the area of forecasting, also applied the Box & Jenkins (1976) approach and concluded that the model perform better forecast wise and in relation to other well-known time series models.

Kwakye, J. K. (2004) studied the assessment between the conditional mean and variance of inflation data used in establishing the relationship in the series. His results affirmed Frimpong, J. M., & Oteng-Abayie, E. F. (2006) who's their study premised on testing for the rate of dependence and asymmetric in inflation uncertainty, they concluded that there was a strong relationship between inflation rate and inflation uncertainty. Alam, Z., & Rahman, A. (2012) evaluated the forecast performance of several time series models for forecasting cocoa bean prices at Bagan Datoh cocoa bean, four different types of univariate time series models vis-a vis the exponential smoothing, autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroscedasticity (GARCH) and the mixed ARIMA/ GARCH models were used. The study affirmed the superiority of GARCH models over others.

The inflation rate data used in this study were that of United States of America and Federal Republic of Nigeria. They were extracted from the Consumer Price Index (CPI-U) known as U.S inflation rate data.com and that of Nigeria was collected from Bureau of Statistics from 1996 to 2018 for both countries. The data covers period of 264 months. The choice of these two countries became imperative in order to confirm the reliability of the models used for both developed and developing economies.

2. General Representation

This study made use of final equations as derived by Akintunde et.al 2013 and Bollerslev 1986 for the estimation of models parameters (variances) of the four models vis-a vis GARCH, BL-GARCH, STAR-GARCH and ST-GARCH as shown below:

2.1 Generalized autoregressive model as derived is as follows:

$$Var\left(y_t\right) = \frac{\alpha_0}{1-\sum_{i=1}^{p}\left(\alpha_i+\beta_j\right)} \qquad 1$$

2.2 Bilinear-GARCH (BL-GARCH)

$$Var\left(y_t\right) = \frac{\alpha_0+\sum\alpha_i\sigma_{t-1}^2+\sum\beta_j\sigma_{t-1}^2}{1-\tau_i^2} - \sigma_\varepsilon^4\left(\sum\tau_i\right)^2 \qquad \forall \mathrm{i} \neq \mathrm{j} \qquad 2$$

2.3 STAR-GARCH models

$$Var\left\{y_{t(S-G)}\right\} = \frac{1}{1-\hat{\underline{\phi}}_t^2}\left[\underline{\lambda}_1^2 E\left(V_t^2\right) + \frac{\alpha_0}{1-\sum\left(\alpha_i+\beta_j\right)}\right] \qquad 3$$

$$\phi_2' - \phi_1' = \lambda_1 \text{ and } V_t = y_{t-j}G_t \;\forall\; j = 1,2,\ldots,p$$

2.4 ST-GARCH: The following models constituted ST-GARCH in this paper

(i) Exponential Transition-GARCH (ET-GARCH)

$$Var\left(G_{ET-GARCH}\right)=\gamma^2\left\{\frac{2\sigma^4}{n-1}\right\} \quad 4$$

(ii) Exponential Smooth Transition-GARCH (EST-GARCH)

$$Var\left\{G_{EST-GARCH}\right\}=2\gamma^2\sigma^2\left[\frac{\sigma^2+2c^2\sqrt{n-1}\sqrt{2}}{n-1}\right] \quad 5$$

(iii) Logistic Smooth Transition-GARCH (LST-GARCH)

$$Var\left\{G_{LST-GARCH}\right\}=2\gamma^2\sigma^2\sqrt{\frac{2}{n-1}} \quad 6$$

3. Empirical Illustration

For the analysis of data collected Econometric-view popularly called E-view, was used and the following results obtained for the models used.

3.1 GARCH MODEL

Based on Table1 below the estimated GARCH (1,1) model obtained for both U. S's and Nigeria's inflation rates are as follow:

$y_{U.S\ \text{inflation rate}}=\sigma_t\varepsilon_t$ where σ_t and ε_t are obtainable from the fitted model:

$y_{\ U.S\ \text{interest rate}}=0.9917y_{t-1}+\varepsilon_t$ and σ_t^2 = 0.4808+ 0.7598 ε_{t-1}^2 -0.2539$\left(\sigma_{t-1}^2\right)$

$y_{\text{Nigeria inflation rates}}=\sigma_t\varepsilon_t$ where σ_t and ε_t are obtainable from the fitted model:

$y_{\text{Nigeria inflation rates}}=1.0248y_{t-1}+\varepsilon_t$ and σ_t^2 = 2.0224 + 1.8368 ε_{t-1}^2 -0.9965$\left(\sigma_{t-1}^2\right)$

Table1: GARCH model fitted for the series

SERIES	COEFFICIENT (S.E) α_0	α_1	β_1	MODEL VARIANCE
U.S INFLATION	$\underset{(0.0137)}{0.4808}$ $\underset{(0.0854)}{-0.2539}$		$\underset{(0.2300)}{0.7598}$	1.3214
NIG INFLATION	$\underset{(0.0526)}{2.0224}$ $\underset{(0.0040)}{-0.9965}$		$\underset{(0.0483)}{1.8368}$	407.1799

3.2. Bilinear-GARCH Models

Parameters' estimation was carried out in two stages as the variances computed for classical GARCH model were used to obtain the estimate of parameters of hybrid of Bilinear-GARCH models. The choice of BL-GARCH (1.1) becomes inevitable as few parameters make the models to be parsimonious. From where sets of data were obtained and OLS applied. The following results were obtained for the series (U.S and Nigeria inflation rates), using the values so generated in table (2) the AGM fitted is

$y_{tU.S\text{ inflation rate}} = \sigma_t\varepsilon_t + \underset{(0.0063)}{0.0032}\, y_{t-1}\varepsilon_{t-1}$ with variance of 1.2562 and $y_{tNig\text{ inflation rates}} = \sigma_t\varepsilon_t + \underset{(0.0016)}{0.6602}\, y_{t-1}\varepsilon_{t-1}$ with variance of 57.7326.

Table 2: Bilinear-GARCH model fitted

SERIES	COEFFICIENT (S.E)	MODEL VARIANCE
U.S INFLATION	$\underset{(0.0063)}{0.0032}$	1.2562
NIG INFLATION	$\underset{(0.0016)}{0.0660}$	57.7326

3.3 Smooth Transition Autoregressive GARCH Models

Two-dimensional grid searches were used to obtain the initial values of γ and c .The smallest estimated values for the residual variance were selected. The two-dimensional grid searches gave the following tabulated values as contains in the tables (3) and (4). The asterisk values were selected because they gave minimum values.

Table 3: Values of grid of c

SERIES	I	II	III
U.S INFLATION RATES	0.35•	155.76	30
NIGERIA INFLATION RATES	0.48•	2.42	30

Table 1: Values of grid of γ

SERIES	I	II	III
U.S INFLATION RATES	0.50•	10.00	30
NIGERIA INFLATION RATES	0.50•	10.00	30

(i) EAR-GARCH

$$y_{t(S-G)} = \sigma_t\varepsilon_t + \underline{\phi}_1' y_{t-1}\left(-\exp-\left(\gamma\left(y_{t-1}^2\right)\right)\right) + \underline{\phi}_2' y_{t-1}\left(1-\exp-\left(\gamma\left(y_{t-1}^2\right)\right)\right)$$

(i) $y_{U.S\text{ inflation rate }(S-G)} = \sigma_t\varepsilon_t + -\underset{(0.1111)}{2.3441}{*}\, y_{t-1}\left(1-G_t\right)_t + \underset{(0.0083)}{0.1075}{*}\, y_{t-1}\left(G_t\right)$ and var. 1.1113

(ii) $y_{Nigeria\text{ inflation rates}(S-G)} = \sigma_t\varepsilon_t - \underset{0.9612}{14.1042}{*}\, y_{t-1}\left(1-G_t\right) + \underset{(0.011)}{0.5030}{*}\, y_{t-1}\left(G_t\right)$ and var. 95.3103

Table 5: Fitted model for EAR-GARCH series

SERIES	COEFFICIENT (SE) C(1)	C(2)	Variance
U.S INFLATION	$\underset{(0.1111)}{-2.3441}$	$\underset{(0.0083)}{0.1075}$	1.1113
NIG INFLATION	$\underset{(0.96121)}{-14.1042}$	$\underset{(0.01113)}{0.50296}$	95.3103

(ii) ESTAR-GARCH

$$y_{t(S-G)} = \sigma_t \varepsilon_t + \underline{\phi}_1' y_{t-1}\left(-\exp-\left(\gamma\left(y_{t-1}-c\right)^2\right) + \underline{\phi}_2' y_{t-1}\left(1-\exp-\left(\gamma\left(y_{t-1}-c\right)^2\right)\right.\right.$$

(i) $y_{U.S\ \text{inflation rates}\ (S-G)} = \sigma_t \varepsilon_t + \underset{(0.0081)}{0.0988} * P_t + \underset{(0.0441)}{0.8726} * Q_t$ and var. 0.5735

(ii) $y_{Nigeria\ \text{inflation rates}\ (S-G)} = \sigma_t \varepsilon_t + \underset{(0.00698)}{0.41596} * P_t + \underset{(0.35966)}{10.35029} * Q_t$ and var. 64.2819

Table 6: Fitted model for ESTAR-GARCH series

SERIES	COEFFICIENT (SE) C(1)	C(2)	VARIANCE
U.S INFLATION	$\underset{(0.0081)}{0.0988}$	$\underset{(0.0441)}{0.8726}$	0.5735
NIG INFLATION	$\underset{(0.00698)}{0.41596}$	$\underset{(0.35966)}{10.35029}$	64.2819

(iii) LSTAR-GARCH

$$y_{t(S-G)} = \sigma_t \varepsilon_t + \underline{\phi}_1' y_{t-1}\left(1-\left(1+\exp-\left(\gamma\left(y_{t-1}-c\right)\right)^{-1}\right) + \underline{\phi}_2' y_{t-1}\left(1+\exp-\left(\gamma\left(y_{t-1}-c\right)\right)^{-1}\right.\right.$$

(i) $y_{U.S\ \text{Inflation rates}(S-G)} = \sigma_t \varepsilon_t + \underset{(0.0984)}{0.0803} * P_t + \underset{(0.0183)}{0.0240} * Q_t$ with var. 0.5047

(ii) $y_{Nigeria\ \text{inflation rates}\ (S-G)} = \sigma_t \varepsilon_t - \underset{(0.39845)}{18.91187} * P_t + \underset{(0.00584)}{0.42033} * Q_t$ with var.57.9593

Table 7: Fitted model for LSTAR-GARCH series

SERIES	COEFFICIENT (SE) C(1)	C(2)	VARIANCE
U.S INFLATION	$\underset{(0.0984)}{0.0803}$	$\underset{(0.0183)}{0.0240}$	0.5047
NIG INFLATION	$\underset{(0.39845)}{-18.9119}$	$\underset{(0.00584)}{0.42033}$	57.9593

3.4 Smooth transition GARCH model (ST- GARCH)

By making use of equations (4), (5) and (6), the variances of all the series for Smooth Transition GARCH models (ET-GARCH, EST-GARCH and LST-GARCH) were obtained and LST-GARCH was adjudged as having the minimum variance, closely followed by EST- GARCH and ET-GARCH in that order as shown in the table 8 below. The importance of this results is that LST-GARCH produced the best model.

Table 8: Computed Variances of ST-GARCH

SERIES	ET-GARCH	EST-GARCH	LST-GARCH
US INFLATION RATES	0.0333	0.0132	0.0057
NIGERIA INFLATION RATES	244.2500	235.0794	15.3319

4. Empirical Comparison of Models

4.1. Variances of GARCH and Bilinear- GARCH Models

Table 9. Summarized the results obtained for the variances of both classical GARCH models (GM) and Bilinear-GARCH models (AGM). The superiority of Bilinear-GARCH model was asserted on GARCH model as the variance of the GARCH model is greater than that of Bilinear-GARCH models. For instance, the variances of classical GARCH models for U.S's and Nigeria's inflation rates are 1.3214 and 407.1799 while Bilinear-GARCH models produces 1.2562 and 57.7326 respectively.

4.2. Variances of BL-GARCH and GARCH Models

Table 9: Variances of GARCH And Bilinear- GARCH Models

SERIES	G.M	Bilinear-GARCH
U.S INFLATION RATE	1.3214	1.2562
NIG. INFLATION RATE	407.1799	57.7326

4.3. Variances Of Star- GARCH and GARCH Models

Table 10 below shows the variances of all STAR-GARCH models with GARCH. It is clear from this table that the STAR-GARCH models out-performed the classical GARCH model. This is because the variances of all STAR-GARCH are less compared to classical GARCH model. However, LSTAR-GARCH appeared to be the best, followed by ESTAR-GARCH and EAR-GARCH in that order.

Table 10: Variances of STAR-GARCH with GARCH model

SERIES	GARCH MODEL	EAR MODEL	ESTAR MODEL	LSTAR MODEL
U.S INFLATION RATES	1.3214	1.1113	0.5735	0.5047
NIGERIA INFLATION RATES	407.1799	95.3103	64.2819	57.9593

4.4 Variances of GARCH model and all Smooth Transition -GARCH Models (ST- GARCH)

Table (11) gives a clearer picture of the variances of classical GARCH model with ST-GARCH. It is evident that all ST-GARCH out-performed GARCH model. However, within this group, LST-GARCH had the least variance, followed by EST-GARCH and ET-GARCH in that order. If a researcher is considering forecasting with ST-GARCH, it is advisable to use LST-GARCH as it performed better than others.

Table 11: The Variances of ST-GARCH Models with Classical GARCH Model

SERIES	G.M	ET-GARCH	EST-GARCH	LST-GARCH
US INFLATION RATES	1.3214	0.0333	0.0132	0.0057
NIGERIA INFLATION RATES	407.1799	244.250	235.0794	15.3319

5. Conclusion

The variances of Bilinear-GARCH STAR-GARCH and ST-GARCH models are measure of improvement over GARCH model. However, LSTAR-GACH model produced the best resultl in this study and for the series used. This is closely followed by LST-GARCH and Bilinear-GARCH models in that order. The policy statement here is that for would be policy formulator/ analyst the use of LSTARGARCH is recommended. However, policy makers, investors can make use of LST-GARCH as well.

References

Akintunde M.O., D.K. Shangodoyin and P.M. Kgosi. (2013): "Measuring the forecast performance of GARCH and BL-linear-GARCH models in time series data", Vol.1 No.1.PP (17-23). American journal of Applied Mathematics.

Alam, Z., & Rahman, A. (2012). Modelling Volatility of the BDT/USD exchange rate with GARCH Model. *International Journal of Economics and Finance*, *4* (11), 193-204.

Andersen, T.G., and T. Bollerslev (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. International Economic Review 39(4), 885-905.

Berument, M.H., & Sahin, A. (2010). Seasonality in inflation volatility: Evidence from Turkey. *Journal of Applied Economics*, 13(1), 39-65.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity.Journal of Econometrics 31, 307-327.

Box, G.E.P. Jenkins, G.M., (1976). Time Series Analysis: Forecasting and Control, Holdan-Day, San Francisco.

Coshall, J.T. (2008). Combining volatility and smoothing forecasts of UK demand for international tourism. *Tourism Management*, Vol. 30, No.4, pp.495-511.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflations. Econometrical 50, 987-1007.

Frimpong, J. M., & Oteng-Abayie, E. F. (2006). Modelling and Forecasting Volatility of Returns on the Ghana Stock Exchange using GARCH Models. *Munich Personel RePE Archive MPRA* No 593.

Jean - Philippe, P. (2001). *Estimating and Forecasting Volatility of Stock indices using Asymmetric GARCH models and (Skewed) Student-t densities.*

Kwakye, J. K. (2004). *Assessment of Inflation Trends, Management and Macroeconomic Effects in Ghana.* The Institute of Economic Affairs Monograph, No. 28.

Ling, S., & Li, W.K. (1997). On fractionally integrated autoregressive moving averages time series models with conditional heteroscedasticity. *Journal of American Statistical Association*, 92, 1184-1194.

Meyler, Aidan, Kenny Geoff, and Terry Quinn. 1998. "Forecasting Irish inflation using ARIMA models." *Central Bank and Financial Services Authority of Ireland Technical Paper Series* 3/RT/98: 1–48.

Nelson, Daniel B., (2007), "Conditional Heteroskedasticity in Asset Returns: A new Approach", Econometrica, Vol. 59, pp. 347-70.

Shittu, O. I., & Asemota. M. J. (2009). Comparison of Criteria for Estimating the Order of Autoregressive Process: A Monte Carlo Approach. *European Journal of Scientific Research, 30* (3), 409 - 416.