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

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

Abstract - This paper evaluates the optimum method of forecasting inflation rates data of United States of America and Federal Republic of Nigeria 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 analysis, it was discovered that Bilinear-GARCH performed better than Classical GARCH model. Similarly, STAR- GARCH and ST- GARCH performed better than GARCH. However, LSTAR-GARCH and LST-GARCH out-performed other models (EAR-GARCH, ESTAR-GARCH, ET- GARCH and EST-GARCH). In conclusion 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 vary on the meaning and concept of inflation. However, the general consensus among economists is that inflation is a continuous rise in the prices of goods and services. It could also be defined as a continuous rise in prices as measured by indices such as the Consumer Price Index (CPI) or by the implicit price deflator for Gross National Product (GNP). When there is inflation, the currency loses purchasing power. Inflation rate forecasting or the concept of inflation rates volatility has been discussed severally in the literature. Prominent among them are Berument and Sahin (2010) pointed out that inflation level in an economy may not be what matter to macroeconomists, but its volatility and forecasting is important.

Several models such as the Autoregressive Conditional Heteroscedasticity (ARCH) model and its variants like the Generalised ARCH (GARCH) and Exponential GARCH (EGARCH) models have therefore been developed to model the non-constant volatility of such series. The ARCH model was introduced by Engle (1982) and later it was modified by Bollerslev (1986) to a more generalized form known as the GARCH. The GARCH model has been used most widely for the specification of the ARCH. It imposes restrictions on the parameters to assure positive variances. Nelson (1991) therefore presented an alternative to the GARCH model by modifying the GARCH to Exponential GARCH (EGARCH) model. Unlike the GARCH, the EGARCH does not need the inequality restrictions on the parameters to assume a positive variance.

Ling and Li (1997); Drost and Klaassen (1997) used fractionally integrated moving Average (FIMA) models with conditional heteroscedasticity, which combined with popular generalized autoregressive conditional heteroscedasticity (GARCH) and (ARIMA) models, their studies show that financial data set exhibit conditional heteroscedasticity as a result GARCH – type model are often used to model this volatility. Meyer et al; (1998) used autoregressive integrated moving average (ARIMA) for forecasting Irish inflation and concluded that ARIMA models are robust relative to alternative (multivariate) model.

Jean - Phillippe (2001) applied the Box and Jenkins (1976) approach to model and forecast Finnish inflation. Also, Shittu and Asemota (2009) applied the similar approach to forecast short term inflation in Croatia. In many researches in the area of forecasting, the Box and Jenkins (1976) models tends to perform better in terms of forecasting compared to other well-known time series models. Kwakye (2004) analyzed the relationship between inflation and inflation uncertainty in the United Kingdom from 1973 to 2003 with monthly and quarterly data. Different types of GARCH Mean (M)-Level (L) models that allow for simultaneous feedback between the conditional mean and variance of inflation was used to test the relationship. He concluded that there was a positive relationship between past inflation and uncertainty about future inflation, in line with Frimpong and Oteng-Abayie (2006) to which in their study of testing for rate of dependence and asymmetric in inflation uncertainty they concluded that there was a link between inflation rate and inflation uncertainty. Alam and Rahman (2012) examined the forecasting performance of different time series methods for forecasting cocoa bean prices at Bagan Datoh cocoa bean. Four different types of univariate time series models were used namely the exponential smoothing, autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroscedasticity (GARCH) and the mixed ARIMA/ GARCH models.

The inflation rate data used in this study were that of United States of America and Federal Republic of Nigeria. They were obtained from the Consumer Price Index (CPI-U) known as U.S inflation rate data.com and that of Nigeria from Bureau of Statistics from 1995 to 2017 for both countries. These data covered 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

The final results of derivations for the variances of the models used for the computations in this paper were as derived by Akintunde et.al 2013, Engle 1982 and Bollerslev 1986, are as shown below. The variance of GARCH model as an existing model was derived by Bollerslev as:

(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) Bilinear-GARCH (BL-GARCH)

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

(3) STAR-GARCH models

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

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

(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

The software used for the empirical illustration is Econometric-view software popularly called E-view. And the following results were obtained for all the models used in the study.

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:

$y_{U.S\text{ interest rate}} = 0.9917 y_{t-1} + \varepsilon_t$ 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:

$y_{\text{Nigeria inflation rates}} = 1.0248 y_{t-1} + \varepsilon_t$ 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)			MODEL VARIANCE
	α_0	α_1	β_1	
U.S INFLATION	0.4808 (0.0137)		0.7598 (0.2300)	1.3214

	$\underset{(0.0854)}{-0.2539}$	
NIG INFLATION	$\underset{(0.0526)}{2.0224}$ $\underset{(0.0483)}{1.8368}$ $\underset{(0.0040)}{-0.9965}$	407.1799

3.2 Bilinear-Garch Models

Estimation of parameters here was done in two stages, as the variances obtained from classical GARCH were used to obtain the parameters of Bilinear-GARCH models. The reason for the choice of bilinear (1.1) was due to the fact that few parameters make the models to be parsimonious; from where sets of data were generated and OLS applied and the following results were obtained for the series (U.S and Nigeria inflation rates). By using the values 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

The initial values of γ and C were obtained using two dimensional grid searches. The smallest estimated values for the residual variance were selected. The two dimensional grid gave three possible values as tabulated in the tables (3) and (4). All the asterisk values were selected because they have 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	$0.50^{\bullet}$	10.00	30
NIGERIA INFLATION RATES	$0.50^{\bullet}$	10.00	30

(i) EAR-GARCH

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

(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

(iii) 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

(iv) 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

Table 8: Summary of all the variances computed for ST-GARCH

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

3.4 Smooth Transition Garch Model (St- Garch)

Using 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 show that LST-GARCH has the minimum variance, followed by EST- GARCH and ET-GARCH in that order as shown in the table below. The implication of this is that LST-GARCH has the least variances and, as such, 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). From this table, 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.

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

4.2**.**Variances Of Star-Garch With Garch Model

The table 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 minimal 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

4.3.Variances Of Gm And All Smooth Transition Garch Model (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 has the variances, 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 out-performed 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 appeared to have produced the best model 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 LSTAR-GARCH is recommended. However, policy makers, investors can make use of other hybrids.

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