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Predicting Stock Prices Returns Using Garch Model

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ABSTRACT
This study focus on forecasting properties of Linear GARCH model for daily closing stocks prices of Zenith bank Plc in Nigeria stocks Exchange. The Alaike and Bayesian Information Criteria (AIC $ BIC) techniques was used to obtain the order of the GARCH (p,q) that best fit the Zenith Bank Returned series . GARCH (1,2) was identified as the models. The results of statistical properties obtained supported the claim that the financial data are Leptokurtic. We therefore concluded that the Optimal values of p and q GARCH (p,q) model depends on location, the types of the data and model order selected techniques being used.

***KEYWORDS**: Linear GARCH, AIC, BIC, Leptokurtic.*

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I. INTRODUCTION

There has been considerable volatility (and uncertainty) in the past few years in mature and emerging financial markets worldwide. Most investors and financial analysts are concerned about the uncertainty of the returns on their investment assets, caused by the variability in speculative market prices (and market risk) and the instability of business performance (Alexander, 1999). Volatility has become a very important concept in different areas in financial theory and practice, such as risk management, portfolio selection, derivative pricing. In stock market, volatility is the key systematic risk faced by investors who hold a market portfolio (Schwert,1989) and investors want a premium for investing in these risky assets. The degree of stock market volatility can help forecasters predict the path of an economy's growth and the structure of volatility can imply that investors now need to hold more stocks in their portfolio to achieve diversification"(Krainer 2002). Non-linear GARCH models (see Hentschel, 1995, for a survey) extend the seminal contributions by Engle (1982) and Bollerslev (1986) to incorporate the asymmetric impacts of shocks or news of equal magnitude but opposite sign on the conditional variance of asset

It is well known that financial returns are often characterized by a number of typical 'stylized facts' such as volatility clustering, persistence and time variation of volatility. The generalized autoregressive conditional heteroskedasticity (GARCH) genre of volatility models is regarded as an appealing technique to cater to the aforesaid empirical phenomena. The existing literature has long been recognized that the distribution of returns can be skewed. For instance, for some stock market indices, returns are skewed toward the left, indicating that there are more negative than positive outlying observations. The intrinsically symmetric distribution, such as normal, student-t or generalized error distribution (GED) cannot cope with such skewness. Consequently, one can expect that forecasts and forecast error variances from a GARCH model may be biased for skewed financial time series.The focus of this work is on forecasting properties of Linear GARCH model for daily closing stocks prices of Zenith bank Plc in Nigeria stocks Exchange.

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II. METHODOLOGY

The data for this study are from daily closing prices of Zenith Bank Nigeria plc stocks traded on the floor of the Nigerian Stock Exchange (NSE). The time series data cover almost five years starting from 20th of April 2005 to 30th of December 2009 resulting in approximately 1,059 observations. The data are available on http://www.cascraft.com.

2.1.Autoregressive Conditional Heteroscadastic (ARCH) Model

The important property of ARCH models is their ability to capture the tendency for volatility clustering in financial data. In ARCH framework σ_t is the time-varying, positive and measurable function of the time t-1 information set. The ARCH(1) process is in the form:

$$\sigma_t^2 = a_0 + a_1 y_{t-1}^2$$

Where $$E(y_t|\Omega^{t-1}) = \sigma_t E(Z_t|\Omega^{t-1}) = \sigma_t E(Z_t) = 0$$
$$E(y_t^2|\Omega^{t-1}) = \sigma_t^2 E(Z_t^2|\Omega^{t-1}) = \sigma_t^2 E(Z_t^2) = \sigma_t^2$$

Ω^{t-1} is the information set which contains all the available information up to time t-1 . As σ_t^2 changes with y_{t-1}^2, y_t are conditional heteroscedastic.

The argument in Triantafallopoutus (2003)

$$y_t^2 = \sigma_t^2 + (y_t^2 - \sigma_t^2)$$

By using equation
$$X_t = \varepsilon_t - \Theta_1 \varepsilon_{t-1},$$

then its becomes

$$y_t^2 = a_0 + a_1 y_{t-1}^2 + y_t^2 - \sigma_t^2$$

$$y_t^2 = a_0 + a_1 y_{t-1}^2 + \sigma_t^2 (Z_t^2 - 1)$$
$$y_t^2 = a_0 + a_1 y_{t-1}^2 + v_t$$

Where $$v_t = \sigma_t^2 (Z_t^2 - 1)$$

The process y_t^2 follows a non-normal AR (1) model with the innovations $\sigma_t^2 (Z_t^2 - 1)$

By the law of iterated expectation,

$$E = E\left(E(y_t|\Omega^{t-1})\right) = 0$$
$$V(y_t) = E(y_t^2) = E\left(E(y_t|\Omega^{t-1})\right) = E(Z_t^2)E(\sigma_t^2) = a_0 + a_1 V(y_{t-1}^2)$$

But unconditional variance of y_t is identical to y_{t-1} . If $a_1 < 1$, the process is stationary and

$$\text{Var } (y_t) = \frac{a_0}{1-a_1} \quad \text{(unconditional)}$$

Assuming that y_t are conditional normal distribution,

$$E(y_t^2 \,|\, \Omega^{t-1}) = 3\sigma_t^4$$

So that,

$$E(y_t^4) E[E(y_t^4 \,|\, \Omega^{t-1})] = 3E(a_0^2 + 2a_0 a_1 y_{t-1}^2 + a_t^2 y_{t-1}^4)$$
$$= 3(a_0^2 + 2a_0 a_1 Var(y_{t-1}^2) + E(y_{t-1}^4)$$

When E (y_t^4) is constant, then

$$m_4 = \frac{(3a_0^2(1+a_1))}{(1-a_1)(1-3a_1^2))}$$

This implies that $0 \le a_1^2 \le \frac{1}{3}$. The kurtosis coefficient of y_t is then

$$K = \frac{E(y_t^4)}{(E(y_t)} = \frac{m_4}{(Var(y_t))} > 3$$

According to this result, it can be deduced that the unconditional distribution of y_t is leptokurtosis. This means that even if y_t are conditionally normal distributed, the resulting ARCH(1) processes cannot be normal (kuan,2003).

An ARCH(1) process is easily generated to an ARCH(p) process such that,

$$y_t = \sigma_1 Z_t$$

Then

$$a_t^2 = a_0 + \sum_{i=1}^{p} a_i y_{t-i}^2$$

Where $a_0 > 0$, $a_1 \ge 0$ (i=1,2,..p). For stability of the processes, $a_1 + a_2 + \cdots + a_p < 1$ (Li et al 2002)

2.3Generalized Autoregressive Conditional Heteroscadastic (GARCH) Model

The process $\{\{X_t\}\}$ is a Generalized Autoregressive Conditional Heteroscedastic model of orders p and q, GARCH (p; q) (Bollerslev, 1986) if:

$$(X_t|F_{t-1}) \sim N(0, h_t), \text{ with}$$

$$h_t = \alpha_0 + \alpha_1 X_{t-1}^2 + \ldots + \alpha_q X_{t-q}^2 + \beta_1 h_{t-1}^2 + \ldots + \beta_p h_{t-p}^2$$

$$= \alpha_0 + \sum_i^p \alpha_i X_{t-i}^2 + \sum_i^p \beta_j h_{t-j}^2$$

Where q > 0, p ≥ 0, α_0>0 and α_i≥ 0 for i= 1,…,q, β_j≥ 0 for j= 1,…,p. Again, the conditions α_0>0, α_i≥ 0 and β_j≥ 0 are needed to guarantee that the
Conditional variance ht > 0..

2.4.The ARCH(q) and the GARCH(1; 1) Models

The simplest and often most useful GARCH process is the GARCH (1; 1) process given by:

$(X_t|F_{t-1}) \sim N(0, h_t)$, with

$$h_t = \alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 h_{t-1}^2$$

Where α_0>0 and α_i≥ 0 and β_j≥ 0

It is often found that when fitting ARCH models to financial data a high order is required to get a satisfactory fit (Bollerslev, 1986). We can see that this is expected for data which is really from a GARCH (1; 1) process by substituting h_t > 1 into the
formula (31) recursively. This gives

$$\begin{aligned} h_t &= \alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1(\alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 h_{t-2}) \\ &= \alpha_0(1+\beta_1) + \alpha_1 X_{t-1}^2 + \alpha_1\beta_1 X_{t-1}^2 + \beta_1^2 h_{t-2} \\ &= \alpha_0(1+\beta_1) + \alpha_1 X_{t-1}^2 + \alpha_1\beta_1 X_{t-1}^2 + \beta_1^2(\\ &\alpha_0 + \alpha_1 X_{t-3}^2 + \beta_1 h_{t-3}) \\ &= \alpha_0\left(1+\beta_1+\beta_1^2\right) + \alpha_1 X_{t-1}^2 + \alpha_1\beta_1 X_{t-1}^2 + \alpha_2\beta_1^2 h_{t-2} + \\ &\alpha_1\beta_1^2 X_{t-3}^2 \beta_1^3 h_{t-3} \\ &= \alpha_0 \sum_i^k \beta_1^{j-1} + \alpha_1 \sum_i^k \beta_1^{j-1} X_{t-j}^2 + \beta_1^k h_{t-k} \end{aligned}$$

It is important to note that in order to have a finite variance of Xt, the condition $\alpha_1 + \beta_1 < 1$ is needed. This means β_1 is strictly less than one Thus, if k →ф

$$h_t = \frac{\alpha_0}{1-\beta_1} + \alpha_1 \sum_i^{\Phi} \beta_1^{j-1} X_{t-j}^2$$

which corresponds to an ARCH(Φ) model $h_t = \alpha_0^* + \alpha_1 \sum_i^{\Phi} \alpha_j^* X_{t-j}^2$ with $\alpha_0^* = \frac{\alpha_0}{1-\beta_1}$ and $\alpha_j^* = \alpha_1 \beta_1^{j-1}$ for j = 1,…, Φ

This result suggests that a GARCH(1; 1) model might replace a high order ARCH(q), giving a more parsimonious model.

Results

III. MODEL SPECIFICATION

To Estimate the procedure for the Zenith Bank model, the p and q for the standard GARCH model were chosen, the Parameters for the chosen model were presented and the error terms of the identified model were checked using Alaike and Bayesian Information Criteria (AIC and BIC respectively), the optimum order of the system, up to lag 30, is given below.

BIC has better properties and its is preferred to AIC in comparison (Enders, 2005). If the various BIC values are compared, it could be seen that the GARCH (1,2) is the one with the minimum BIC value which is also the one with AIC value (Table 1) . Also, the likelihood value in Table 1 suggested that the identified model is GARCH (1,2) model

3.1.Model Parameter Estimation

It was observed from Table 2 that the results of the four selected distribution namely: Normal distribution, Student- t distribution, Generalized error distribution (GED) and Double exponential distribution for the estimation of the Parameters of the chosen model. Using AIC, BIC and the Likelihood value, the best distribution was GED because it has smallest AIC and BIC with the highest likelihood rule.

Table 3 shows the value of the parameters for the identified model, consequently, the following GARCH (1,2) process fitted to the data in order to model the volatility

σ_{τ}^{2}= 0.0002314+0.7091y_{t-1}^{2}+0.1091σ_{t-1}^{2}+0.1461σ_{t-2}^{2}

When we check for the persistency satisfied by the chosen model, we have that the

0.7091+0.1461=0.8552<1

This shows that the parameter satisfy the second order stationary conditions with high degree of persistence in the conditional variance.

3.2.Model Diagnostics Checking

The GARCH (1,2) was identified as the model of interest , We proceed with the diagnostic checking to assess the goodness-fit of the selected model . Various test statistics carried out to assess the performance of the GARCH (1,2) model as shown in Table 4and 5. In table 6, all the parameters including the constant value are significantly different from zero at 5 rcent of significant also, the test for serial correlation stricture (Table 5) shows that no autocorrelation was left in the standardized residuals and the squared standardized residuals since we fail to reject the null hypothesis in the Ljung-Box test. The Jarque- Bera test for normality was rejected as shown in table 5 which considering non-normality assumption to be more appropriate. Table 6 shows the estimate Coefficient for the leverage effect denoted by LEV(1) is Zero. This implies that the impact is symmetry, that is, negative and positive shocks have the same effects on the volatility of Zenith Bank

3.3.Forecasting Results Using Selected GARCH Model

The selected model σ_{τ}^{2}= 0.0002314+0.7091y_{t-1}^{2}+0.1091σ_{t-1}^{2}+0.1461σ_{t-2}^{2} has been tested for diagnostic checking and there is no doubt of its accuracy for forecasting based on previous tests. We can use our model to predict the future volatility value. Table 7 shows the forecast value for k$\leq$ 20. It is seen that the forecasts of the conditional variance indicates a gradual increase in the volatility of the stock returns.

The Alaike and Bayesian Information Criteria (AIC $ BIC) technique was used to obtain the optimum order of the GARCH (p,q) model that best fits the First Bank return series. The technique showed that the optimum order of the model is p=1 , q=2.Four different conditional distributions were used for the estimation of the parameters of the identified model and the distribution that caters for the excess kurtosis was selected using AIC and BIC as well as their likelihood values. The results indicated GED to be the best conditional distribution that would reduced the kurtosis displayed by the residuals of GARCH (1,2). Hence, using the identified distribution, the model

σ_{τ}^{2}= 0.0002314+0.7091y_{t-1}^{2}+0.1091σ_{t-1}^{2}+0.1461σ_{t-2}^{2} was fitted to the data.

To assess the goodness-of-fit of the selected model, various tests on the estimated parameters and standardized residuals were used to assess the performance of the GARCH (1,2) model. However, an important task of modelling conditional volatility is to generate accurate forecasts for future value of financial time series as well as its conditional volatility .The chosen model was used to forecast volatility for 20 steps ahead.

3.4.Discussion and Conclusion

This work studies the forecasting properties of linear GARCH model for daily closing stock prices of the Zenith Bank Plc trade in the Nigeria Stock Exchange from April, 2005 to December, 2009. The results of statistical properties obtained supported the claim that the financial data are leptokurtic. Several orders of GARCH model were compared and among the orders and in contrast to Jafari et al (2008), the GARCH model was identified to be the most appropriate for the time-varying volatility of the data. In order to account for the fat tails, the chosen model was compared based on the Normal, Student-t, Generalized Error and Double Exponential distribution and the parameter of GARCH (1,2) model using GED.

In contrast to the asymmetric shocks to volatility discussed in Engle and Ng (1993), Zakonian (1994) and Nelson (1991) among others in the sense that the negative shocks (bad news) has a greater impact on the conditional volatility than the positive shocks (good news), the conditional volatility of the Zenith bank daily stock returns has no asymmetric effects since the leverage effect is zero.Therefore, we can conclude that the optimal values of p and q GARCH (p,q) model depend on the location, the types of the data set and the model order selected techniques being used.

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Table 1 GARCH (p,q) model for various order

Order	AIC	BIC	Likelihood
0,1	-716.163	-701.153	400.6
0,2	-521.8	-558.7	336.7
1,0	-1719.51	-1702.78	867.1
1,1	-2179.81	-2189.7	1700
1,2	-2416.163	-2388.48	1113
2,0	8971	84000	4034
2,1	-1021	-1176.1	1106
2,2	-2101.56	-2118.44	1049

Table 2 GARCH (1,2) model with conditional Distribution.

Distribution	AIC	BIC	Likelihood
Normal	-2106	-2188	1114
Student-t	-9141	-9101	4629
Generalized Error	-9210	-9112	4712
Double Exponential	-7650	-7601	3830

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Table 3. Estimation of GARCH (1,2) with conditional GED with Estimated Parameter, V=0.74341, and Standard Error=0.00613118

Parameter	Value
Constant	2.314e4
ARCH(1)	0.7091
GARCH(1)	0.1091
GARCH(2)	0.1461

Table 4 Results for the parameters of the chosen model.

Parameter	Value	Std Error	t-value	Null Hypothesis	P-value
Constant	2.314e4	0.0000174	14.64	Zero	0.00000
ARCH(1)	0.7091	0.0825021	8.9217	Zero	0.00000
GARCH(1)	0.1091	0.018317	5.50018	Zero	1.2e-8
GARCH(2)	0.1461	0.021892	7.0001	Zero	1.598e-12
X					

Table 5 Test Results for Testing Hypothesis for the chosen Model

Test	Test Statistics	Null Hypothesis	P-value
Jarque-Bera	1398400117	Normal Distribution	0.0000
Ljung-Box	0.6112	No Autocorrelation	1.0000
Ljung-Box(std	0.0312	No Autocorrelation	1.0000
error)	0.001	No ARCH	0.9713
LM(Lag1)	0.0021	No ARCH	0.9999
LM(Lag2)	0.0002	No ARCH	1.0000
LM(Lag3)	0.03168	No ARCH	1.0000
LM(Lag30)			

Table 6 The Fitted Model for EGARCH (1,2)

Coefficient	Value
a_0	-0.1479928
ARCH(1)	0.10000
GARCH(1)	0.9800
GARCH(2)	0.01000
LEV(1)	0.00000

Table 10 Forecasting Results Using Selected GARCH Model

K	σ_{T+K}
1	0.02269820
2	0.02789971
3	0.03090137
4	0.03402238
5	0.03682254
6	0.03931760
7	0.04171760
8	0.04369170
9	0.04734120
10	0.04962140
11	0.04967116
12	0.05132170
13	0.05291709
14	0.05316210
15	0.05521920
16	0.05714200
17	0.05861940
18	0.05992860
19	0.06115211
20	0.06237209