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Modelling Abrupt Shift in Time Series Using Indicator Variable: Evidence of Nigerian Insurance Stock

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Abstract This study models abrupt shift in time series using indicator variable. Seven symmetric and five asymmetric models were considered by incorporating an indicator variable in the variance equation to monitor the changes of some selected Nigerian insurance stocks. The results showed that the daily returns were stationary but not normally distributed and eight out of ten stocks considered for the study showed evidence of ARCH effect. The performance of the different models was evaluated using the RMSE, MAE and MAPE. The model ARCH (1) proved to be the most suitable among the twelve competing volatility models considered. When the regime changes are incorporated into the model, it is found that the highly persistent volatility of the insurance stock return rate is reduced for most of the stocks.

Keywords Volatility, Heteroscedasticity, Root Mean Square Error, Indicator variable

1. Introduction

Dummy variables are variables that can take any values. They may be explanatory or outcome variables; however, the focus of this study is explanatory dummy variable construction and usage. Typically, dummy variables are used in the following applications: time series analysis with seasonality or regime switching; analysis of qualitative data, such as survey responses. Some scholars have argued based on statistical analysis of time series that certain phenomena do not correspond to regime shifts, [9]. Outliers, level shifts, and variance changes are common in applied time series analysis. However, their existence is often ignored and their impact is overlooked, for the lack of simple and useful methods to detect and handle those extraordinary events. The problem of detecting level shifts, and variance changes in a univariate time series is considered. Three different types of regime shift (smooth, abrupt and discontinuous) are identified on the basis of different patterns in the relationship between the responses. The smooth regime shifts is represented by a quasi-linear relationship between the response and control variables. The abrupt regime shift exhibits a nonlinear relationship between the response and control variables, and the discontinuous regime shift is characterized by the trajectory of the response variable differing when the forcing variable increases compared to when it decreases see [5].

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In order to apply the concept to a particular problem, one has to conceptually limit its range of dynamics by fixing analytical categories in time by considering the event and categorically applying it in achieving the significant of the study.

In this study we model the abrupt shift in a time series where the variable under study exhibits a nonlinear relationship between the response and control variables using some of the insurance company as a case study, that is, from stable and unstable economic. Therefore our indicator variable will take in the value of 0 for stable and 1 for unstable economy in order to study the abrupt shift in time series since we are considering a time series data to observe these nonlinear relationship in each of the stock with seven symmetric and five asymmetric models incorporating an indicator variable in the variance equation.

2. Literature Review

ARCH and GARCH models, which stand for autoregressive conditional heteroscedasticity and generalized autoregressive conditional heteroscedasticity, have become widespread tools for dealing with heteroscedastic time series. The goal of such models is to provide a volatility measure – like a standard deviation -- that can be used in financial decisions concerning risk analysis, portfolio selection and derivative pricing. Applications of the ARCH/GARCH approach are widespread in situations where volatility of returns is a central issue. Many banks and other financial institutions use the idea of “value at risk” as a way to measure the risks faced by their portfolios.

[7] first proposed the autoregressive conditional

heteroscedasticity (ARCH) model for modeling the changing variance of a time series; Engle used an ARCH model to study inflation in the United Kingdom. [3] showed that a GARCH model with a small number of terms may be more efficient than an ARCH model with many terms. Empirical studies in recent years have focused on volatility investigation on the pattern of financial assets such as ARCH effect, volatility clustering, and persistence and leverage effect. For example, [23], [18], [24], [21].

The use of dummy variables requires the imposition of additional constraints on the parameters of regression equations to obtain estimates for the model. Among the possible constraints the most useful are (a) to set the constant term of the equation to zero, or (b) to omit one of the dummy variables from the equation. In econometrics time series analysis, dummy variables may be used to indicate the occurrence of wars or major strikes. Dummy variables are used frequently in time series analysis with regime switching, seasonal analysis and qualitative data applications see [5]. Dummy variables are involved in studies for economic forecasting, bio-medical studies, credit scoring, response modelling, etc.

[2] used dummy variable to compare the year 2012 internally generated revenue (IGR) and wage bills of the six geopolitical zones in Nigeria by categorizing the geopolitical zones as dummy variables in a regression model to find out if the average internally generated revenue and wage bills of the geopolitical zone are statistically different from each other. From his analysis, he concluded that the northeast and northwest zones are statistically different. [19] used GARCH models with dummies to study the impact of U.S monetary policy on inflation. From the analysis, he concluded that the impact of U.S monetary policy on inflation is negative but not significant on the parameter of the dummy variable the parameter. Stock return volatility represents the variability of stock price changes during a period of time. This phenomenon has attracted growing attention of academia, policy makers and other players in this sector. This is because return is a major measure of risk associated with asset instead of price because if you want an investment that gives 10% of your return you invest on it than in price i.e. it is much better to deal with return than price. Also, high volatility in stocks, bonds and foreign exchange markets usually raise from important public policy issues about stability of financial market and impact of stock volatility on the economy cannot be sub estimated. [17] used volatility to model four Nigerian firms listed on the Nigerian Stock Exchange. [16] also conducted another study which focused on the impact of the 2005 recapitalization of the banking and insurance industry on the stock market. [6] carried out a research on modelling and forecasting daily returns of Nigerian insurance stock using [7] proposed model and [14] to estimate suitable models in, from the study the researcher concluded that the exponential generalized autoregressive conditional heteroscedastic (EGARCH) models is more suitable in modelling stock price returns as it outperforms the other models in goodness of fit and out-of-sample volatility forecasting.

3. Methodology

Data for this study were obtained from daily closing prices of insurance stocks traded on the floor of the Nigerian Stock Exchange (NSE) from 2nd January 2000 to 26th May, 2014. The ten insurance company used for this study are AIICO, GUINEAINS, GUINNESS, LASACO, LAWUNION, NEM, NIGERINS, PRESTIGE, UNIC AND WAPIC.

List of Tests and Models

Models specification

Let denote the returns by $$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{1}$$

where P_t and P_{t-1} are the present and previous closing prices and R_t been the continuously compounded return series because is simply the sum of continuously compounded one-period returns involved

Jarque-Bera Test for normality

Jarque-Bera is a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The statistic is computed using the expression:

$$JB = \frac{N-k}{6}\left[S^2 + \frac{(K-3)^2}{4}\right],$$

where S is the skewness, K is the kurtosis, and k represents the number of estimated coefficients

Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as a χ^2 with 2 degrees of freedom.

Stationary Test (Augmented Dickey-Fuller test)

Stationarity of the return series is one of the major assumptions in financial time series modelling. This assumption can be checked using a unit root test. The **Augmented Dickey–Fuller test (ADF)** is a test for unit root in a time series.

Null hypothesis is $H_0 : \phi_1 = 1$

and alternative hypothesis is: $H_1 : \phi_1 < 1$

The Test Statistic (t-ratio): $$= \frac{\phi_1^n - 1}{std(\phi_1)} = \frac{\sum_{t=1}^{T} P_{t-1}e_t}{\sigma^2\sqrt{\sum_{t=1}^{T} P_{t-1}^2}} \tag{2}$$

The null hypothesis is rejected if the calculated value of t is greater than t critical value from nonstandard distributions table.

Test for ARCH effect (Test for heteroscedasticity)

One of the most important issue before consider Heteroskedastic models is examine the residuals for evidence of heteroscedasticity. To test for the presence of heteroscedasticity in residuals of Nigerian insurance stock return series, the Lagrange Multiplier (LM) test for ARCH effects proposed by Engle (1982) is applied. In summary, the test procedure is performed by first obtaining the residuals e_t from the ordinary least squares regression of the conditional mean equation which might be an autoregressive (AR) process, moving average (MA) process or a combination of AR and MA processes; (ARMA) process using EViews 7 statistical software. For example, in ARMA (1,1) process the conditional mean equation will be as:

$$r_t = \phi_1 r_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \quad (3)$$

After obtaining the residuals e_t, the next step is regress the squared residual on a constant and its q lags as in the following equation:

$$e_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \ldots + \alpha_q e_{t-q}^2 + v_t \quad (4)$$

The null hypothesis that there is no ARCH effect up to order q can be formulated as:

$$H_0 : \alpha_1 = \ldots = \alpha_q = 0 \quad (5)$$

against the alternative

$$H_a : \alpha_i \neq 0 \text{ for some i} \in \{1,..,m\} \quad (6)$$

The test statistic for the joint significance of the q-lagged squared residuals is the number of observations times the R-squared (TR^2) from the regression. TR^2 is tested against $\chi^2_{(q)}$ distribution. This is asymptotically locally most powerful test.

Volatility models

These models include the symmetric and asymmetric volatility models. The models are ARCH(1), ARCH(2), ARCH(3), GARCH(1, 1), GARCH(2, 1), GARCH(1, 2), GARCH(2, 2) E GARCH (1, 1), EGARCH (1, 2), EGARCH (2, 1), EGARCH (2, 2) and TARCH(1, 1). In each model we incorporated dummies variables.

ARCH Models (Autoregressive Conditional Heteroskedastic Model)

The ARCH(q) as proposed by Engle is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + r_t \quad (7)$$

where $\alpha_i > 0,$ for i=0, 1, 2… q are the parameters of the model.

ARCH model with dummy variable

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \delta_1 D_{Shift} + r_t \quad (8)$$

where $\delta_1 D_{Shift}$ is the dummy variable added to the conditional variance model.

GARCH Model (Generalize Autoregressive Conditional Heteroskedastic Model)

The GARCH(p,q) as proposed by Nelson is given by

$$\begin{aligned} \sigma_t^2 &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 \\ &+ \beta_1 \varepsilon_{t-1}^2 + \ldots + \beta_p \varepsilon_{t-p}^2 + r_t \end{aligned} \quad (9)$$

where $\alpha_i > 0$ and $\beta_i > 0$ for all i and j

GARCH model with dummy variable

$$\begin{aligned} \sigma_t^2 &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \varepsilon_{t-1}^2 \\ &+ \ldots + \beta_p \varepsilon_{t-p}^2 + \delta_1 D_{Shift} + r_t \end{aligned} \quad (10)$$

Where $\delta_1 D_{Shift}$ is the dummy variable added to the conditional variance model.

TARCH (p,q)

Threshold GARCH Model or TARCH (p,q), (Glosten et al.1993) is

$$\sigma_t^2 = \alpha_0 + \sum_{t=i}^{q} (\alpha_i \varepsilon_{t-i}^2) + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p} (\beta_j \sigma_{t-j}^2) \quad (11)$$

where $d_t = 1$ if $\varepsilon_t < 0$ and $d_t = 0$ otherwise. In this model, good news $(\varepsilon_t < 0)$ and bad news $(\varepsilon_t > 0)$, have different effects on the conditional variance.

TARCH (p, q) with dummy variable

$$\begin{aligned} \sigma_t^2 &= \alpha_0 + \sum_{t=i}^{q} (\alpha_i \varepsilon_{t-i}^2) + \gamma \varepsilon_{t-1}^2 d_{t-1} \\ &+ \sum_{j=1}^{p} (\beta_j \sigma_{t-j}^2) + \delta_1 D_{Shift} \end{aligned} \quad (12)$$

where $\delta_1 D_{Shift}$ is the dummy variable added to the conditional variance model.

The E-GARCH (p, q) is given by as proposed in Nelson (1991):

$$\begin{aligned} \ln(\sigma_t^2) &= \alpha_0 + \sum_{i=1}^{p} \alpha_i \left[\lambda \varepsilon_{t-i} + \gamma \left\{ \left| \varepsilon_{t-i} \right| - \sqrt{\frac{2}{\pi}} \right\} \right] \\ &+ \sum_{i}^{q} \beta_j \ln(\sigma_{t-j}^2) \end{aligned} \quad (13)$$

$\alpha_0, \alpha_i, \gamma, \beta_j$ are the parameters of the model.

If p =1 and q =1, the model above reduces to EGARCH (1, 1) given as

$$\varepsilon_t = z_t \sigma_t$$

$$\ln(\sigma_t^2) = \alpha_0 + \beta \ln \sigma_{t-1}^2 + \left[\alpha_1 \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \gamma \left(\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right) \right] \quad (14)$$

where $\alpha_0, \alpha_1, \gamma, \beta_1$ are the parameters of the model.

EGARCH (p, q) Model with dummy variable is given as

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{t=1}^{q} \left(\alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) \right) + \sum_{j=1}^{p} \left(\beta_j \ln\left(\sigma_{t-j}^2\right) \right) + \delta_1 D_{Shift} \quad (15)$$

where $\delta_1 D_{Shift}$ is the added dummy variable to the conditional variance model.

Goodness of fits certeria

Akaike Information Criteria (AIC) and Schwarz Criteria (SIC) are the most commonly used model selection criteria

$$\text{AIC} = 2K - 2\ln(LL) = 2K + \ln\left(\frac{RSS}{n}\right) \quad (16)$$

where $RSS = \sum e^2$ is the residual sum of squares.

Forecast error statistics

The forecast error statistics used in this study are the root mean square error (RMSE), mean absolute error (MAE) and the mean absolute percentage error (MAPE). These forecast error statistics are defined by:

$$RMSE = \sqrt{\frac{1}{m} \sum_{t=1}^{m} (\hat{y}_t - y)^2} \quad (17)$$

$$MAE = \frac{1}{m} \sum_{t=1}^{m} \left| y_t - \hat{y}_t \right| \quad (18)$$

$$MAPE = \frac{1}{m} \sum_{t=1}^{T} \left| \frac{\left(\hat{\sigma}_t^2 - \sigma_t^2\right)}{\sigma_t^2} \right| \times 100 \quad (19)$$

where, $t = 1,...,m$ with m, y_t, and $\hat{y}_t$ denoting the number of forecasts, volatility value and the forecast, respectively.

The RMSE and MAE depend on the scale of the dependent variable and the differences between volatility value and the forecasted values. The smaller the error statistic is, the better the forecasting ability of that model in consideration of that measure. The MAPE is scale invariant. The satisfactory forecasting model is expected to have MAPE close to 0% which indicate the best forecasting performance to the data.

4. Analysis Result

4.1. Preliminary Result

An initial descriptive statistics analysis of the ten Nigerian Insurance stocks were carried out and the result shown in Table 1. The obtained result as shown in Table 1, showed that the Mean return series for some of the insurance were negative indicating that these insurances incurred loss during the period under study. Despite this loss, two of the Insurances still reported positive return. Also, the result of Jarque-Bera statistic revealed that the return series for all the insurance were not normally distributed as the p-values were less than 1% and 5%.

Table 1. Descriptive Statistics of the return of Nigerian Insurance stocks

Insurance	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	P-Value
AIICO	-0.000409	0.587787	-0.70058	0.04386	-1.65049	66.62714	558324.2	0.00000
GUINEAINS	-0.000055	4.503507	-4.50351	0.112138	0.001071	1577.041	341000000	0.00000
GUINNESS	0.000550	2.437514	-2.36001	0.064577	1.251101	1158.406	184000000	0.00000
LASACO	-0.000188	0.169076	-0.74444	0.028115	-6.43315	161.7233	3487869	0.00000
LAWUNION	-0.000236	0.267204	-0.36101	0.026082	-0.75693	22.99468	55302.61	0.00000
NEM	0.000086	1.085189	-1.08519	0.039406	-0.01211	374.8869	19021994	0.00000
NIGERINS	-0.000782	2.107812	-2.10064	0.061868	-0.10295	813.5779	90369905	0.00000
PRESTIGE	-0.000517	1.499623	-1.49962	0.050971	-0.47472	468.2124	29767251	0.00000
UNIC	-0.000495	0.300105	-1.09861	0.037344	-7.60834	233.1766	7318982	0.00000
WAPIC	-0.000068	2.167385	-2.20303	0.065371	-0.72138	761.1758	79063428	0.00000

4.2. Analysis of the Main Result

In Table 2 below, the return series were all stationary. Hence, there is no unit root. Therefore, there is no need for differencing. In the Test for ARCH effect, the Lagrange Multiplier (LM) test proposed by Engle (1982) was applied. The F Statistic and the obtained p-values are summarized in Table 3. The results of F Statistic were significant at 1% for eight insurance stock returns while two of the insurance does not exhibit heteroscedasticity. Therefore we cannot run the heteroscedasticity model on them because they do not fulfill the condition of ARCH effect.

Table 2. Augmented Dickey-Fuller Test of stationarity test (ADF) of the return series of Nigerian Insurance stocks

Insurances	ADF Test Statistic	Comment
AIICO	-59.0846	Stationary at level without differencing
GUINEAINS	-21.7066	Stationary at level without differencing
GUINNESS	-33.5573	Stationary at level without differencing
LASACO	-26.3485	Stationary at level without differencing
LAWUNION	-28.5031	Stationary at level without differencing
NEM	-31.4748	Stationary at level without differencing
NIGERINS	-50.2719	Stationary at level without differencing
PRESTIGE	-48.5239	Stationary at level without differencing
UNIC	-33.2005	Stationary at level without differencing
WAPIC	-49.7348	Stationary at level without differencing

1% critical = -3.91

Table 3. Lagrange Multiplier test of the presence of ARCH effect

Insurance	F Statistic	P-values
AIICO	303.52	0.0000
GUINEAINS	0.0013	0.9710
GUINNESS	1087.58	0.0000
LASACO	0.1642	0.6853
LAWUNION	183.75	0.0000
NEM	1092.56	0.0000
NIGERINS	1092.76	0.0000
PRESTIGE	1079.61	0.0000
UNIC	10.79	0.0000
WAPIC	1091.77	0.0000

Twelve different heteroscedastic models were fitted by adding a dummy variable to the conditional variance model to test the significance of the hypothesis of the model on each of the model. For AIICO Insurance, all heteroscedastic models fitted had all their parameters significant ($p< 0.05$) except that some of the model in the abrupt shift showed a positive values with significant level of 0.01.

Moreover, NEM, PRESTIGE and UNIC the parameters estimated were significant except the leverage effect of the TARCH (1, 1) model ($p>0.05$). For PRESTIGE Insurance, the indicator variable is positive throughout the models indicating that the shift was positive. I.e. the global melt down did not affect it. Results are presented in Table 6 and Table 7 with others insurance stocks.

Out of the twelve competing models, the selection of the model that could give best prediction was carried out using the Log likelihood (LL), Akaike Info Criteria (AIC) and Schwartz Information Criterion (SIC). Schwartz Information has been considered to be the best of these criteria to as SIC give the heaviest penalties for loss of degrees of freedom (Afees and Ismail, 2012). Hence, it was EGARCH (2, 2) for AIICO, NEM, WAPIC and EGARCH (2, 1) for GUINNESS, LAWUNION, UNIC and TARCH (1, 1) for NIGERINS and PRESTIGE. Results are presented in Table 6 and Table 7.

Forecasting performance of these estimated models were investigated using our sample data and statistics like Root Mean Square Error, Mean Absolute Error as well as the Mean Absolute Percentage error were computed. Model with the smallest Mean Square Error was considered to the most suitable for forecasting. Hence, from the results obtained showed that some insurance stocks are having model than one model suitable. Therefore we are going to adopt the Principle of Parsimony – "that the best model is the simplest model that can captures the important features of the data". Hence EGARCH (1, 1) proved to most suitable for AIICO and NEM, LAWUNION is EGARCH (2, 1), GUINNESS is GARCH (1, 2) while ARCH (1) for NIGERINS, UNIC and WAPIC while ARCH (2) suitable for PRESTIGE. The results are shown in Table 5 and 6.

5. Conclusions

This study had examined the daily return volatility of Nigerian Insurance sector stocks. The best model was computed using the AIC and SIC, the bolded models are considered the best fits model to be used in each of the stocks. The forecasting performance of several variants of conditional heteroscedasticity volatility models were evaluated using model evaluation performance measures like the Root Mean Square Error. The post estimation evaluation carried out revealed various conditional heteroscedasticity models to be most suitable for modelling the return pattern of the each insurance. The EGARCH (1, 1) was suitable for AIICO and NEM, LAWUNION is EGARCH (2, 1), GUINNESS is GARCH (1, 2) while ARCH (1) for NIGERINS, UNIC and WAPIC while ARCH (2) suitable for PRESTIGE. But looking at the insurance and by evaluation one can say ARCH (1) was most suitable followed by EARCH (1, 1). This finding is very crucial and informative to investors and intending investors who might want to invest in insurance stocks

Table 4. Parameter Estimates of the heteroscedastic models of AIICO, GUINNESS, LAWUNION and NEM

		Parameters Estimates							
Insurances	Model	α_0	α_1	α_2	α_3	β_1	β_2	γ	$\delta_1 D_{Shift}$
AIICO	ARCH(1)	0.000861**	0.72940**						0.000147**
	ARCH(2)	0.000700**	0.412316**						-2.32 x 10^{-5}*
	ARCH(3)	0.000702**	0.412557**	0.516570**					-2.36 x 10^{-5}**
	GARCH(1, 1)	4.81 x 10^{-5}**	0.528641**	0.516548**		-0.320052**			-4.60 x 10^{-5}**
	GARCH(1, 2)	0.001843*	0.310132**			0.440429**	-0.110176**		-9.25 x 10^{-5}
	GARCH(2, 1)	0.000703**	0.412493**			-0.002242			-2.35 x 10^{-5}*
	GARCH(2, 2)	0.000704**	0.412044**	0.517515**	-0.001167	-0.003354	0.00629		-2.29 x10^{-5}
	E-GARCH (1, 1)	-0.214902**	0.065416**	0.518978**		0.016909**		0.972833**	-0.007654**
	E-GARCH (1, 2)	-0.213505**	0.071962**			0.031670**	1.016937**	-0.042939	0.003011**
	E-GARCH (2, 1)	-1.035493**	0.405694**	-0.002804		0.128492**		0.876267**	-0.037338**
	E-GARCH (2, 2)	-0.448589**	0.232128**	0.048482**		0.069805**	0.235766**	0.719694**	-0.026649**
	TARCH(1, 1)	0.000868**	1.015785**			-0.641668**		-0.320052**	0.000172**
GUINNESS	ARCH(1)	0.004142**	0.176437**						-0.003991**
	ARCH(2)	0.000308**	3.203975**	0.028851**					-7.91 x 10^{-5}**
	ARCH(3)	0.004133**	0.142449**	6.57 x 10^{-5}					-0.003628**
	GARCH(1, 1)	0.000363**	5.678915**			-5.110868**			-0.000112**
	GARCH(1, 2)	0.003409**	2.854225**			-0.002376	0.001797		-0.003215**
	GARCH(2, 1)	0.004080	0.138673**	-0.073473		0.522728			-0.003965
	GARCH(2, 2)	0.004142	0.196576**	-0.093979	-0.000746**	0.477563	-0.004714		-0.004077
	E-GARCH (1, 1)	-5.549953**	1.365304**			0.594444**		0.343897**	-0.030317*
	E-GARCH (1, 2)	-4.110825**	0.159584**			-0.052359**	1.387252**	-0.981015**	-0.267766**
	E-GARCH (2, 1)	-6.947548**	1.311339**	0.294884**		0.523658**		0.172873**	-0.098547**
	E-GARCH (2, 2)	-6.927521**	1.302047**	0.303727**		0.520277**	0.167164**	0.008454	-0.100983**
	TARCH(1, 1)	0.000363**	5.684310**			0.005136		-5.116270**	-0.000112**
LAWUNION	ARCH(1)	0.000453**	0.532188**						-0.000209**
	ARCH(2)	0.000372**	0.455261**	0.255742**					-0.000211**
	ARCH(3)	0.000302**	0.407693**	0.190474**					-0.000194**
	GARCH(1, 1)	1.13 x 10^{-5}**	0.168003**			0.051593**			-9.87 x 10^{-6}**
	GARCH(1, 2)	1.49 x 10^{-5}**	0.276092**			0.267966**	0.493133**		-1.29 x 10^{-5}**
	GARCH(2, 1)	8.98 x 10^{-6}**	0.285134**	-0.118785**		0.855631**			-7.78 x 10^{-6}**
	GARCH(2, 2)	1.70 x 10^{-5}**	0.228645**	0.098761**	0.258386**	-0.017382	0.734773**		-1.48 x 10^{-5}**
	E-GARCH (1, 1)	-0.451078**	0.268525**			-0.018169**		0.956946**	-0.047876**
	E-GARCH (1, 2)	-0.980625**	0.121379**			0.022217**	0.451623**	0.427186**	-0.067313**
	E-GARCH (2, 1)	0.339725**	0.440794**	-0.23657**		-0.021795**		0.967728**	-0.035861**
	E-GARCH (2, 2)	-0.466532**	0.420677**	-0.147345**		-0.024897**	0.738705**	0.216679**	-0.047921**
	TARCH (1, 1)	1.2 x 10^{-5}**	0.166717**			0.831598**		0.055682**	-9.83 x 10^{-6}**
NEM	ARCH(1)	0.001190**	0.349210**						-0.000680**
	ARCH(2)	0.001211**	0.281492**	0.221150**					-0.000847**
	ARCH(3)	0.001190**	0.265545**	0.182405**					-0.000945**
	GARCH(1, 1)	0.000412**	0.292840**			0.653475**			-0.000381**
	GARCH(1, 2)	0.000490**	0.297220**			0.897124**	-0.232626**		-0.000458**
	GARCH(2, 1)	0.000455**	0.261149**	0.049446		0.630360**			-0.000421**
	GARCH(2, 2)	0.002033**	0.218706**	0.079893	0.181524**	0.418112**	-0.085309**		-0.001772**
	E-GARCH(1, 1)	-2.761874**	0.348923**			0.594471**		0.035363	-0.474964**
	E-GARCH(1, 2)	-2.636114**	0.338985**			0.035320	0.719009**	-0.103746	-0.441557**
	E-GARCH(2, 1)	-2.850477**	0.346879**	0.012137		0.035046		0.580553**	-0.495016**
	E-GARCH(2, 2)	-0.317840**	0.526263**	-0.493989**		0.028090**	1.985812**	-1.027633**	0.001204
	TARCH(1, 1)	0.000437**	0.254763**			0.661106**		0.059178	-0.000407**

**significance at 1%, * significance at 5%

Table 5. Parameter Estimates of the heteroscedastic models of NIGERINS, PRESTIGE, UNIC and WAPIC

		Parameters Estimates							
Insurances	Model	α_0	α_1	α_2	α_3	β_1	β_2	γ	$\delta_1 D_{Shift}$
NIGERINS	ARCH(1)	0.000569**	2.411643**						0-000197**
	ARCH(2)	0.000396**	0.457784**	1.797308**					-0.000122**
	ARCH(3)	0.000281**	0.400595**	1.913240**	0.170278**				-4.03×10^{-5}**
	GARCH(1, 1)	2.55×10^{-5}**	1.107434**			-0.713453**			-2.18×10^{-5}**
	GARCH(1, 2)	0.000774**	0.911256**			0.395912**	0.192960**		-0.000766**
	GARCH(2, 1)	3.07×10^{-5}**	0.369194**	0.480764**		0.691948**			-2.59×10^{-5}**
	GARCH(2, 2)	6.07×10^{-5}**	0.246357**	1.216567**		0.021147**	0.429776**		-5.13×10^{-5}**
	E-GARCH(1, 1)	-1.201204**	1.091828**			0.555485**		0.863769**	-0.269194**
	E-GARCH(1, 2)	-0.299011**	0.137050**			0.103992**	0.044508**	0.921806**	-0.007308**
	E-GARCH(2, 1)	-1.695976**	0.132956**	0.617107**		0.099629**		0.736092**	-0.162614**
	E-GARCH(2, 2)	-6.22795**	0.485505**	0.564740**		0.409586**	0.072541**	0.147713**	-0.352482**
	TARCH(1, 1)	2.5×10^{-5}**	1.106952**			0.740445**		-0.713044**	-2.16×10^{-5}**
PRESTIGE	ARCH(1)	0.001622**	0.381281**						0.002212**
	ARCH(2)	0.000399**	0.300501**	0.444226**					0.002536**
	ARCH(3)	0.000776*	0.255295**	0.244930**	-0.001434**				0.001895**
	GARCH(1, 1)	0.000124**	0.343015**			0.584547**			0.001086**
	GARCH(1, 2)	0.000189**	0.306789**			0.700160**	-0.165881**		0.002139**
	GARCH(2, 1)	0.002403**	0.080574**	-0.042101**		0.502210**			0.000257**
	GARCH(2, 2)	0.002469	0.077297**	-0.037866		0.456860	0.017086		0.000273
	E-GARCH(1, 1)	-0.284985**	0.042581**			-0.017395**		0.961111**	0.053088**
	E-GARCH(1, 2)	-0.680407**	0.183025**			-0.012592**	0.472859**	0.444352**	0.168226**
	E-GARCH(2, 1)	-1.481429**	0.225856**	0.010699		0.003500		0.807790**	0.386868**
	E-GARCH(2, 2)	-1.043110**	0.257289**	-0.040400		-0.006191	0.681939	0.188253	0.260315**
	TARCH(1, 1)	0.000127**	0.377383**			0.586002**		-0.082956	0.001158**
UNIC	ARCH(1)	0.000892**	0.922466**						-0.000792**
	ARCH(2)	0.000737**	0.674998**	0.409029**					-0.000702**
	ARCH(3)	0.000659**	0.585304**	0.240969**	0.285278**				-0.000650**
	GARCH(1, 1)	0.001268**	0.333989**			0.525055**			-0.001266**
	GARCH(1, 2)	0.001275**	0.219732**			0.512936**	0.026444		-0.001274**
	GARCH(2, 1)	0.001277**	0.165640**	0.078663**		0.514105**			-0.001276**
	GARCH(2, 2)	0.001286**	0.160815**	0.083924*		0.462501**	0.024886		-0.001284**
	E-GARCH(1, 1)	-0.389482**	0.192889**			-0.052131**			-0.038210**
	E-GARCH(1, 2)	-0.240392**	0.128505**			-0.028767**	0.532535*	0.965301**	0.007753**
	E-GARCH(2, 1)	-0.176364**	0.269192**	-0.158864*		-0.024051**		0.450057**	0.011481**
	E-GARCH(2, 2)	-0.376363**	0.171840**	0.028003**		-0.077531**	0.438586**	0.986282**	-0.055469**
	TARCH(1, 1)	0.001287**	0.262833**			0.545749**		0.0003555	-0.001286**
WAPIC	ARCH(1)	0.000725**	1.788643**						-0.000155**
	ARCH(2)	0.000662**	1.790699**	0.156249**					-0.000292**
	ARCH(3)	0.003750**	0.334744**	0.161726**	-0.000872**				-0.000325**
	GARCH(1, 1)	0.001792**	0.474146**			0.050508**			-0.001618**
	GARCH(1, 2)	0.000595**	1.925519**			0.081577**	-0.002749		-0.000272**
	GARCH(2, 1)	0.000799**	2.828744**	0.141375**		-0.001782**			-0.000488**
	GARCH(2, 2)	2.70×10^{-5}**	1.168353**	-0.943461**		0.858555**	-0.027777**		-2.41×10^{-5}**
	E-GARCH(1, 1)	-5.040781**	1.255809**			0.596857**		0.361576**	-0.046490
	E-GARCH(1, 2)	-5.273761**	1.266183**			0.595229*	0.388317**	-0.061643*	-0.041490
	E-GARCH(2, 1)	-7.857651**	1.116577**	0.625484**		0.613013**		-0.030337	-0.153876**
	E-GARCH(2, 2)	-7.430896**	1.103515**	0.705319**		0.597730**	-0.073731	0.113779**	-0.201297**
	TARCH(1, 1)	0.000651**	3.228761**			0.051865**		-2.801941**	-0.000141**

**significance at 1%, * significance at 5%

Table 6. Model Selection criteria (Goodness of fit criteria and diagnostic checking) of AIICO GUINNESS, LAWUNION and NEM

		Model selection Criteria			Diagnostic check for ARCH Effect	
Insurances	Model	Log-Likelihood	AIC	SIC	F statistic	P value
AIICO	ARCH(1)	6045.050	-3.660133	-3.662739	0.023563	0.8658
	ARCH(2)	6101.796	-3.693903	-3.684666	0.007724	0.9300
	ARCH(3)	6101.875	-3.693350	-3.682259	0.007712	0.9300
	GARCH(1, 1)	6219.597	-3.765281	-3.756039	0.002649	0.9590
	GARCH(1, 2)	5591.796	-3.384305	-3.373214	0.731843	0.3923
	GARCH(2, 1)	6101.874	-3.693350	-3.682259	0.007732	0.9299
	GARCH(2, 2)	6101.874	-3.692744	-3.679805	0.007865	0.9293
	E-GARCH(1, 1)	6091.083	-3.686812	-3.675721	94.92425	0.0000
	E-GARCH(1, 2)	6128.344	-3.708782	-3.695842	57.23603	0.0000
	E-GARCH(2, 1)	6258.722	-3.787755	-3.774832	0.017820	0.8938
	E-GARCH(2, 2)	6319.827	**-3.824191**	**-3.809403**	0.326808	0.5676
	TARCH(1, 1)	6246.355	-3.780888	-3.769797	1.03×10^{-8}	0.9992
GUINNESS	ARCH(1)	5982.689	-3.622350	-3.614950	0.047890	0.8268
	ARCH(2)	7112.285	-4.306140	-4.296898	0.004435	0.9469
	ARCH(3)	6051.456	-3.662803	-3.651712	0.076088	0.7827
	GARCH(1, 1)	5881.237	-3.560277	-3.551034	0.001440	0.9697
	GARCH(1, 2)	6318.345	-3.824505	-3.813414	0.006886	0.9339
	GARCH(2, 1)	5826.806	-3.526692	-3.515601	0.443412	0.5055
	GARCH(2, 2)	5886.497	-3.563464	-3.550524	0.173199	0.6773
	E-GARCH(1, 1)	7424.154	-4.494489	-4.483398	0.031588	0.8589
	E-GARCH(1, 2)	6637.697	-4.017387	-4.004447	75.19469	0.0000
	E-GARCH(2, 1)	7427.089	**-4.495661**	**-4.482721**	0.023469	0.8783
	E-GARCH(2, 2)	7427.085	-4.495053	-4.80265	0.018841	0.8908
	TARCH(1, 1)	7300.223	-4.419402	-4.408311	0.008973	0.9245
LAWUNION	ARCH(1)	7766.867	-4.703343	-4.695949	0.057020	0.8113
	ARCH(2)	7875.705	-4.768679	-4.759436	0.016039	0.8993
	ARCH(3)	7991.378	-4.838157	-4.827066	0.092906	0.7605
	GARCH(1, 1)	8731.146	-5.286971	-5.277729	3.313763	0.0688
	GARCH(1, 2)	8742.428	-5.293201	-5.282110	1.095194	0.2954
	GARCH(2, 1)	8741.210	-5.292463	-5.281370	0.953929	0.3288
	GARCH(2, 2)	8743.204	-5.293065	-5.280125	2.252450	0.1335
	E-GARCH(1, 1)	8962.703	-5.426660	-5.415569	12.21933	0.0000
	E-GARCH(1, 2)	8080.650	-4.891689	-4.878699	46.53113	0.0000
	E-GARCH(2, 1)	9043.422	**-5.474960**	**-5.462021**	0.367288	0.5445
	E-GARCH(2, 2)	8997.851	-5.446744	-5.431956	0.735968	0.3910
	TARCH(1, 1)	8735.242	-5.28847	-5.277756	2.797523	0.0945
NEM	ARCH(1)	6654.086	-4.029134	-4.021740	0.015385	0.9013
	ARCH(2)	6675.085	-4.041251	-4.032008	0.033424	0.8549
	ARCH(3)	6699.606	-4.055502	-4.044411	0.039862	0.8418
	GARCH(1, 1)	6713.959	-4.064804	-4.055562	0.032062	0.8579
	GARCH(1, 2)	6697.307	-4.054109	-4.043018	0.059223	0.8077
	GARCH(2, 1)	6713.118	-4.063688	-4.052597	0.050222	0.8227
	GARCH(2, 2)	6378.151	-3.860134	-3.847194	0.812828	0.3674
	E-GARCH(1, 1)	6671.191	-4.038286	-4.027195	0.000815	0.9772
	E-GARCH(1, 2)	6671.451	-4.037837	-4.024898	0.000732	0.9784
	E-GARCH(2, 1)	6670.871	-4.037486	-4.024547	0.000680	0.9792
	E-GARCH(2, 2)	7022.910	**-4.250173**	**-4.235385**	0.120800	0.7282
	TARCH(1, 1)	6710.006	-4.061803	-4.050712	0.034329	0.8530

AIC is the Akaike Info Criteria, SIC is the Schwartz info criterion, Log is the log likelihood
Bolded AIC and SIC are the best model selection (Goodness of fits)

Table 7. Model Selection criteria (Goodness of fit criteria and diagnostic checking) of NIGERINS, PRESTIGE, UNIC and WAPIC

		Model selection Criteria				
Insurances	Model	Log-Likelihood	AIC	SIC	F statistic	P value
NIGERINS	ARCH(1)	6041.817	-3.658174	-3.650780	0.013995	0.9058
	ARCH(2)	6338.803	-3.837505	-3.828263	0.011229	0.9156
	ARCH(3)	6378.672	-3.861055	-3.849964	0.023157	0.8791
	GARCH(1, 1)	6865.353	-4.156530	-4.147287	7.66×10^{-6}	0.9978
	GARCH(1, 2)	6443.547	-3.900362	-3.889271	1.89×10^{-11}	1.0000
	GARCH(2, 1)	6874.028	-4.161180	-4.150089	0.018535	0.8917
	GARCH(2, 2)	6964.494	**-4.215386**	**-4.202446**	0.092115	0.7615
	E-GARCH(1, 1)	6918.048	-4.187351	-4.176760	0.012121	0.9123
	E-GARCH(1, 2)	6128.450	-3.708846	-3.695906	851.8590	0.0000
	E-GARCH(2, 1)	6230.074	-3.770418	-3.757478	177.7913	0.0000
	E-GARCH(2, 2)	6347.140	-3.840739	-3.825951	659.1661	0.0000
	TARCH(1, 1)	6880.248	-4.164949	-4.153858	0.011420	0.9149
PRESTIGE	ARCH(1)	6071.889	-3.696394	-3.669000	0.006891	0.9338
	ARCH(2)	6163.899	-3.731535	-3.722293	0.017037	0.8962
	ARCH(3)	6085.502	-3.683430	-3.672339	0.042095	0.8375
	GARCH(1, 1)	6176.482	**-3.739159**	**-3.729916**	0.005523	0.9408
	GARCH(1, 2)	6104.832	-3.695142	-3.684051	0.052522	0.8187
	GARCH(2, 1)	5102.288	-3.087724	-3.076632	3.079360	0.0794
	GARCH(2, 2)	5128.262	-3.102855	-3.089915	3.188343	0.0743
	E-GARCH(1, 1)	5887.479	-3.563453	-3.552362	560.7922	0.0000
	E-GARCH(1, 2)	6161.531	-3.728889	-3.715949	0.411519	0.5212
	E-GARCH(2, 1)	6128.065	-3.708612	-3.695673	0.106498	0.7442
	E-GARCH(2, 2)	6166,719	-3.731426	-3.716638	0.003799	0.9509
	TARCH(1, 1)	6177.254	-3.727930	-3.727930	0.005359	0.9414
UNIC	ARCH(1)	7286.944	-4.412568	-4.405174	0.095173	0.7577
	ARCH(2)	7688.622	-4.655330	-4.646087	0.021590	0.8832
	ARCH(3)	8252.387	-4.996297	-4.985205	0.002862	0.9573
	GARCH(1, 1)	8697.586	-5.266638	-5.257395	0.000376	0.9845
	GARCH(1, 2)	8649.952	-5.237172	-5.226080	0.006041	0.9380
	GARCH(2, 1)	8616.648	-5.216994	-5.205902	0.048111	0.8264
	GARCH(2, 2)	8641.043	-5.231168	-5.218228	0.053066	0.8178
	E-GARCH(1, 1)	8988.611	-5.442358	-5.431266	0.102757	0.7486
	E-GARCH(1, 2)	9187.473	-5.562237	-5.549298	0.046806	0.8287
	E-GARCH(2, 1)	9258.969	**-5.605556**	**-5.592616**	0.033931	0.8539
	E-GARCH(2, 2)	9137.266	-5.531212	-5.516424	0.004915	0.9441
	TARCH(1, 1)	8669.908	-5.249263	-5.238171	0.002572	0.9596
WAPIC	ARCH(1)	5848.465	-3.541027	-3.533633	0.000183	0.9892
	ARCH(2)	5876.886	-3.557641	-3.548398	0.000333	0.9854
	ARCH(3)	5442.712	-3.293979	-3.282887	0.021170	0.8843
	GARCH(1, 1)	5875.411	-3.556747	-3.547505	0.000194	0.9889
	GARCH(1, 2)	5874.766	-3.555751	-3.544659	0.000194	0.9896
	GARCH(2, 1)	5789.903	-3.504334	-3.493243	0.000169	0.9964
	GARCH(2, 2)	5982.443	-3.620383	-3.607444	2.07×10^{-5}	0.9829
	E-GARCH(1, 1)	6197.620	-3.751360	-3.740269	0.000462	0.8961
	E-GARCH(1, 2)	6200.209	-3.752323	-3.739383	0.017069	0.8892
	E-GARCH(2, 1)	6246.834	-3.780572	-3.767632	0.019415	0.9531
	E-GARCH(2, 2)	6253.674	**-3.784111**	**-3.769322**	0.003459	0.9582
	TARCH(1, 1)	6029.095	-3.649255	-3.638163	0.014998	0.9025

AIC is the Akaike Info Criteria, SIC is the Schwartz info criterion, Log is the log likelihood
Bolded AIC and SIC are the best model selection (Goodness of fits)

Table 8. Forecast Performance of estimated model of AIICO, GUINNESS, LAWUNION and NEM

Insurance	Heteroscedastic models	Statistic		
		RMSE	MAE	MAPE
AIICO	ARCH(1)	0.043916	0.026295	66.24321
	ARCH(2)	0.043969	0.026578	66.32234
	ARCH(3)	0.043969	0.026576	66.32053
	GARCH(1, 1)	0.043855	0.025684	66.49007
	GARCH(1, 2)	0.044286	0.027610	67.56222
	GARCH(2, 1)	0.043969	0.026576	66.32090
	GARCH(2, 2)	0.043969	0.026576	66.32070
	E-GARCH(1, 1)	**0.043855**	0.025399	66.67920
	E-GARCH(1, 2)	**0.043855**	0.025401	66.68043
	E-GARCH(2, 1)	**0.043855**	0.025395	66.67687
	E-GARCH(2, 2)	**0.043855**	0.025396	66.67734
	TARCH(1, 1)	**0.043855**	0.025684	66.49007
GUINNESS	ARCH(1)	0.039412	0.016955	43.56628
	ARCH(2)	0.039411	0.016939	43.57113
	ARCH(3)	0.039410	0.016921	43.57648
	GARCH(1, 1)	0.039406	0.016807	43.61010
	GARCH(1, 2)	**0.039403**	0.016715	43.63736
	GARCH(2, 1)	0.039406	0.016802	43.61165
	GARCH(2, 2)	0.039414	0.016996	43.55442
	E-GARCH(1, 1)	0.039405	0.016779	43.61840
	E-GARCH(1, 2)	**0.039403**	0.016715	43.63736
	E-GARCH(2, 1)	0.039405	0.016758	43.62453
	E-GARCH(2, 2)	0.039406	0.016725	43.61436
	TARCH(1, 1)	0.039411	0.016949	43.56814
LAWUNION	ARCH(1)	0.026086	0.014222	35.00189
	ARCH(2)	0.026085	0.014204	35.00426
	ARCH(3)	0.026079	0.013969	35.03598
	GARCH(1, 1)	0.026078	0.013797	35.05909
	GARCH(1, 2)	0.026078	0.013786	35.06050
	GARCH(2, 1)	0.026078	0.013787	35.06034
	GARCH(2, 2)	0.026078	0.013787	35.06043
	E-GARCH(1, 1)	0.026079	0.013639	35.08029
	E-GARCH(1, 2)	0.026079	0.013639	35.08028
	E-GARCH(2, 1)	**0.026076**	0.013521	35.06023
	E-GARCH(2, 2)	0.026079	0.013639	35.08025
	TARCH(1, 1)	0.026078	0.013812	35.05708
NEM	ARCH(1)	0.039412	0.016954	43.56684
	ARCH(2)	0.039411	0.016938	43.57145
	ARCH(3)	0.039411	0.016930	43.57370
	GARCH(1, 1)	0.039406	0.016800	43.61229
	GARCH(1, 2)	0.039406	0.016800	43.61233
	GARCH(2, 1)	0.039406	0.016802	43.61157
	GARCH(2, 2)	0.039414	0.016996	43.55443
	E-GARCH(1, 1)	**0.039405**	0.016776	43.61930
	E-GARCH(1, 2)	**0.039405**	0.016766	43.62253
	E-GARCH(2, 1)	0.039414	0.017002	43.55257
	E-GARCH(2, 2)	0.039416	0.017042	43.54060
	TARCH(1, 1)	0.039426	0.017209	43.49129

Bolded values are the least values of RMSE. RMSE is the Root Mean Square Error.

Table 9. Forecast Performance of estimated model of NIGERINS, PRESTIGE, UNIC and WAPIC

Insurance	Heteroscedastic models	Statistic		
		RMSE	MAE	MAPE
NIGERINS	ARCH(1)	**0.060377**	0.020892	57.20856
	ARCH(2)	0.060378	0.020952	58.07010
	ARCH(3)	0.061892	0.023027	51.17111
	GARCH(1, 1)	0.060416	0.023198	51.60603
	GARCH(1, 2)	0.060442	0.023157	52.91916
	GARCH(2, 1)	0.061552	0.023471	52.02622
	GARCH(2, 2)	0.061406	0.023289	51.89754
	E-GARCH(1, 1)	0.061864	0.021661	50.92395
	E-GARCH(1, 2)	0.061864	0.021662	50.92393
	E-GARCH(2, 1)	0.061864	0.021661	50.92396
	E-GARCH(2, 2)	0.061864	0.021661	50.92396
	TARCH(1, 1)	0.061587	0.023605	51.43241
PRESTIGE	ARCH(1)	0.050967	0.018683	39.31535
	ARCH(2)	**0.050963**	0.018352	39.21700
	ARCH(3)	**0.050963**	0.018234	39.19354
	GARCH(1, 1)	**0.050963**	0.018387	39.22383
	GARCH(1, 2)	0.050966	0.018256	39.19802
	GARCH(2, 1)	0.050972	0.017997	39.13251
	GARCH(2, 2)	0.050965	0.018231	39.08664
	E-GARCH(1, 1)	0.050965	0.017978	39.14307
	E-GARCH(1, 2)	0.050974	0.017965	39.14045
	E-GARCH(2, 1)	0.050974	0.018935	39.45446
	E-GARCH(2, 2)	0.050965	0.017974	39.14225
	TARCH(1, 1)	0.050963	0.018387	39.22383
UNIC	ARCH(1)	**0.037339**	0.021143	52.39968
	ARCH(2)	**0.037339**	0.020926	52.45966
	ARCH(3)	0.037340	0.020841	52.48334
	GARCH(1, 1)	0.037340	0.020856	52.47930
	GARCH(1, 2)	**0.037339**	0.020896	52.46822
	GARCH(2, 1)	0.037346	0.020909	52.53300
	GARCH(2, 2)	0.037340	0.020828	52.48704
	E-GARCH(1, 1)	0.037342	0.020784	52.49921
	E-GARCH(1, 2)	0.037342	0.020784	52.49928
	E-GARCH(2, 1)	0.037342	0.020784	52.49921
	E-GARCH(2, 2)	0.037342	0.020784	52.49920
	TARCH(1, 1)	**0.037339**	0.020788	52.47030
WAPIC	ARCH(1)	**0.017852**	0.012190	30.46455
	ARCH(2)	0.017853	0.012136	30.53715
	ARCH(3)	0.017400	0.015122	39.42793
	GARCH(1, 1)	0.018179	0.010530	32.69196
	GARCH(1, 2)	0.018098	0.010750	34.38379
	GARCH(2, 1)	0.018568	0.016399	33.65042
	GARCH(2, 2)	0.018148	0.018665	37.38135
	E-GARCH(1, 1)	0.018507	0.016031	38.92679
	E-GARCH(1, 2)	0.018498	0.015976	38.82007
	E-GARCH(2, 1)	0.018410	0.015242	39.59612
	E-GARCH(2, 2)	0.018427	0.015414	39.84669
	TARCH(1, 1)	0.018095	0.015074	38.56607

Bolded values are the least values of RMSE. RMSE is the Root Mean Square Error.

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