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Stock Return Modeling of Some Insurance Companies in Nigeria

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ABSTRACT

The stock price has become an economic entity of concern in recent times. Having an idea about the price is not sufficient for gaining full insight into the dynamics of the financial markets available for stocks. Hence, this study seeks to model the volatility of stock returns since it informs shareholders on how and when best to invest. The data for the study are extracts of daily trading series of stock prices from Fidelity National Financials (FNF) and Zenith Bank Insurance (ZENITHB) companies' database and span from 30th Sep. 2019 to 29th Oct. 2021. The methodology adopted for the study is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, a non-linear model for volatility modeling. The variants of the GARCH model explored are the standard GARCH, integrated GARCH, exponential GARCH, and the asymmetric power ARCH models with error conditioned to a normal distribution, student t, and generalized error distribution at identified first order as a result of Fat-tail properties underlying the series. Findings show that both stock returns exhibit the trait of stationarity in terms of the actual prices and are not normally distributed since the associated ARCH effects were found to be statistically significant. The 24 GARCH models estimated have the majority of their parameters (which include shock, persistence, shape, and asymmetric effects) being significant. Based on model evaluation using likelihood and other information criteria, student t error distribution outperformed other estimated models underlying FNF stock return while that of ZENITHB was discovered to be with generalized error distribution. The volatility forecast is estimated to have an increasing fashion for FNF and decline slowly in terms of ZENITHB. This shows that FNF stock return is more volatile.

Keywords: *volatility, returns, persistence, GARCH, asymmetric.*

INTRODUCTION

Volatility forecasting of stock return plays an important role in numerous financial applications in the financial markets. From the beginning of the 21st century, several researchers have analyzed how news and market sentiment influence the financial markets and their participants. The researchers arrived at different conclusions. For instance, Mitchell M. L. and Mulherin J. H. (1994) observed that the relation between news and market activity is not particularly strong and the patterns in news announcements do not explain the day-of-the-week seasonalities in market activity. In Engle R. F. and Ng V. K. (1993), the authors defined the news impact curve that measures how new information is incorporated into volatility estimates. Their results suggest that the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model, first proposed in Nelson B. D. (1991), can capture most of the asymmetry without the need of modeling news impact independently. However, they report evidence that the variability of conditional variance implied by the EGARCH model is too high. The early research on applying news analysis to financial markets focused on equities. Later, macroeconomic news and its impact on a fixed income have been studied extensively.

In the domain of fixed income, macro-economic announcements (news data) also influence asset prices. For example, Arshanapalli B. et al. (2006) investigated the effects of macroeconomic news on time-varying volatility as well as time-varying covariance for the US stock and bond markets; they found that stocks and bonds have higher volatility on the day of macroeconomic announcements. Tetlock P. C. (2010) measured public information using firms' stock returns on news days in the Dow Jones archive. He found four patterns in post-news returns and trading volume that are consistent with the asymmetric information model's predictions. Ho K. Y. et al. (2013) compared macroeconomic news sentiment with firm-specific news sentiment, they found that the latter accounts for a greater proportion of overall volatility persistence.

Crouhy M. and Rockinger M. (1997) confirmed that volatility raises more in response to bad news than to good news. Riordan et al. (2013) confirmed that negative news messages induce stronger market reactions than positive ones. Akanbi (2015) analyzed the Nigerian economy via its capital fight for both short and long runs and concluded that investment is one of the key factors affecting the country's capital flight. Thus, for stock returns investment, it is worthwhile to note that unexpected bad news about a particular portfolio tends to increase the volatility of the returns on other correlated portfolios, whereas unexpected good news about a particular portfolio has an opposite impact on the volatility of correlated portfolios.

Literature Review

Ugurlu E. et al (2014) models volatility stock markets returns for four European emerging countries and Turkey with the help of GARCH-types models. Findings show that GARCH, GJR-GARCH, and EGARCH effects are apparent for returns of PX and BUX, WIG, and XU whereas for SOFIX there is no significant GARCH effect. The authors suggest multivariate time series models using daily returns of international emerging markets for further study. Ladokhin S. (2009) modeled volatility in financial markets on real market data. The work was divided into two parts: estimation of conditional volatility and modeling of volatility skews. The first part deals with the determination of historical volatility models, the implied volatility, and autoregressive conditional heteroscedastic models accuracy while the second part examines the implied volatility skews and surfaces.

Some methods yield poor results (e.g., the heteroscedastic family of models), while the others provide improved results but are difficult to implement (e.g., model blending). The author found Exponentially Weighted Moving Average method is efficient and relatively easy to implement. The modeling of volatility can also be done through the use of exponentially moving average models. This method is an extension of the historical model which consists in allowing more recent observations to have more impact than older ones. Recent events are likely to affect Volatility and it is not accounted for in the simpler historical model. The volatility model also allows for a smoother transfer to shocks, in other words, a historical approach could lead to an artificial level of volatility that can lead to an erroneous market expectation (Hunter J. et al, 2014).

Mallikarjuna M. and Rao R. P. (2019) analyze daily stock market returns of selected indices from developed, emerging, and frontier markets for the period 2000 to 2018 using linear, nonlinear, artificial intelligence, frequency domain, and hybrid models to evaluate their predictive performances. In their results, there is no single model out of the five models that could be applied uniformly to all markets. However, traditional linear and nonlinear models outperformed artificial intelligence and frequency domain models in providing accurate forecasts. Jayasuriya S. (2002) studies the effect of stock market liberalization on stock returns volatility in Nigeria and fourteen other emerging market data, from December 1984 to March 2000 to estimate the symmetric GARCH model. The result indicates that positive (negative) changes in prices have been monitored by negative (positive) changes in volatility. The Nigeria portion of the result indicates that more business cycle behavior of stock return rather than volatility clustering.

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) techniques of stock return volatility for the daily S & P Global 1200 index from 1st September 2010 to 30th September 2020 was applied for the data analysis. The GARCH-M and TGARCH models results revealed that in the global stock market explosive volatility persistence and strong asymmetric news effect. The implication was that current volatility shocks influenced expected returns over a long period of volatility persistence. The asymmetric news effect showed that negative news (bad news) spurred stock returns volatility more than positive news (good news), especially in 2020 which was due to the COVID-19 crisis as shown by the plot of the conditional variance. The results were consistent with the empirical findings of several studies in emerging markets. Hence, the study concludes that the global stock market exhibited high volatility persistence and leverage effect during the sampled period (Onyele K. O. and Nwadike E. C., 2020).

In 2014, Sidorov S. et al. (2014) analyzed the impact of news intensity as extraneous sources of information on stock volatility. Their results showed that the GARCH (1, 1) model augmented with the news intensity performs better than the pure GARCH model. There is a strong, yet complex relationship between market sentiment and news. Traders and other market participants digest news rapidly and update their asset positions accordingly.

Dallah H. and Ade I. (2010) investigate the volatility of daily stock returns of Nigerian insurance stocks. Findings show that EGARCH is more suitable for modeling stock price returns. Ogum et al. (2005) apply the Nigeria and Kenya stock data on the EGARCH model to capture the emerging market volatility with evident volatility persistence in both markets' findings.

Yelamanchili (2020), uncovered stylized monthly stock market returns and identified an adequate GARCH model with appropriate distribution density that captures conditional variance in monthly stock market returns.

Data and Methods

Data for the Study

The data for the study are extracted from the databases of the two insurance companies FNF and ZENITHB of interest and span from (Sep. 30, 2019, to Oct. 29, 2021). It is a secondary source of data.

Methods

Exploratory Data Analysis

This entails the visualization of the dataset to ascertain the properties or attributes of the variables under study to apply the right statistical test in gaining full insight into achieving the target of the study. In this study, the variable, the stock price will be visualized by the use of the time plot since the dataset is time-series in nature.

The test of stationarity for this study is centered on the approach of augmented dickey fuller and Phillip Perrons tests. This investigates the null hypothesis of the presence of unit root based on the model with constant and trend expressed as

$$\Delta x_t = \mu + \beta t + \varepsilon_t \quad (1)$$

resulting to a test statistic defined as

$$t_{ADF} = \frac{\sum_{i=1}^{p} \hat{\phi}_i - 1}{s.e\left(\sum_{i=1}^{p} \hat{\phi}_i\right)} = \frac{\hat{\beta}}{s.e(\hat{\beta})} \quad (2)$$

The Phillip Perrons (PP) test is based on the model

$$\Delta x_t = (\rho - 1) y_{t-1} + \varepsilon_t \quad (3)$$

with the claim of unit root if $\rho = 1$.

In this study, the underlying test of normality on stock prices are the JarqueBera and the Shapiro Wilks testing procedure. The JarqueBera (JB) test is known be a fundamental testing procedure for normality since its hypothesis is centered on the skewness(Sk) and Kurtosis (Ku) parameters defined as

Null Hypothesis

$$H_0: Sk = 0 \;\&\; Ku = 3$$

Attributed to the properties of a normal distribution being mesokurtic and symmetric in nature. Skewness is a statistical measure asymmetric distribution of the data set while kurtosis is the numerical description of the peakedness of the data distribution. The Shapiro Wilks test is a standard formal test of normality in the presence of small and large sample sizes with hypothesis defined for null as

$$H_0: \textit{The distribution of stock prices is not differ from that of normal distribution}$$

Formal Statistical Technique Underlying the Study

The main or formal statistical technique for this study is termed the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model in the domain of volatility model. In the study, the return from stock price associated with the identified companies will be modeled on using the GARCH technique.

This technique is adopted to cater for the violations of normality and homoscedasticity associated with the series. It helps investigate the presence of Autoregressive Conditional Heteroscedasticity and correct it impact on the volatility.

The stock return could be computed as

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} \qquad (3.4)$$

wherer_t is the stock return, p_t is the current price of stock and p_{t-1} is the immediate past price of stock. This implies that by logarithmic transformation, the stock return becomes the difference of log return.

The Autoregressive Conditional Heteroscedasticity Test

This test is used to investigate the presence of ARCH effect whether the series is truly heteroscedastic in nature and it's attributed to the Lagrange multiplier techniques.

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

The GARCH model for volatility is made up of two different conditional equations: the mean and the variance with respect to diverse variants in relation to different error distributions. In this study, the variants of GARCH model used are standard GARCH, Integrated GARCH, exponential GARCH and the asymmetry power ARCH. This therefore establishes the fact that the variants of GARCH model are also subjected to the presence of asymmetry effect in the series.

Standard GARCH Model

The standard GARCH (sGARCH) model was proposed by Bollerslev (1986) and it is defined as

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 + u \qquad (3.5)$$

whereσ_t^2 is the conditional variance, ω is the intercept, and ε_t^2 is the residual from the mean filtration process. The GARCH order is defined as (p, q).

It is expedient to note that one of the importance of GARCH models is to capture volatility clustering the financial stock data and this can be quantified in terms of the persistence parameter $\hat{P}$. In respects of 'sGARCH' model we have

$$\hat{P} = \sum_{i=1}^{p} \alpha_i + \sum_{i=1}^{q} \beta_i \qquad (3.6)$$

Integrated GARCH Model

The simple IGARCH (1, 1) model with $\alpha + \beta = 1$ can be defined as

$$\sigma_t^2 = (1 - \beta_1 + \alpha_1) + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 \qquad (3.7)$$

It shows mean reversion, and is a constant for all time.

Asymmetric GARCH Models

The asymmetric effect is the basic manifestation of the market's reaction to shocks. It is also known as 'leverage effect', which is an important characteristic of many financial assets. In the capital market, market analysts often find that the stock price movement also possess traits asymmetric effect, which is the fact that when a stock suffers an impact of negative shocks, its volatility is much fiercer than that caused by positive shocks. Ap ARCH and EGARCH are the main two models describing such asymmetric shocks.

Exponential GARCH Model

Nelson D. B. (1991) proposed Exponential GARCH model, namely EGARCH model, on the basis of the GARCH model, he improved the model to:

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} - E\left[\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right] \right| + \sum_{j=1}^{q} \beta_j \log \sigma_{t-j}^2 + \sum_{g=1}^{u} \gamma_g \left[\frac{\varepsilon_{t-g}}{\sigma_{t-g}}\right] \qquad (3.8)$$

The left hand side of the equation is the logarithmic form of the conditional variance, which means the impact of leverage effect is not quadratic but exponential, so that the predicted value of the conditional variance must be nonnegative.

where the parameters $\omega > 0$, $\alpha_i \geq 0$ for $i = 1, \dots, p$, $\beta_j \geq 0$ for $j = 1, \dots, q$, $\beta(L) = \beta L = \sum_{j=1}^{q} \beta_j L^j$ is the polynomial of order q defined for the GARCH parameter, and $\gamma_g \neq 0$, which allows for the asymmetric effect. The component $E\left[\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right]$ in the model is given as $E\left[\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right] \approx \sqrt{\frac{2}{\pi}}$ under normally distributed innovations;

The component $E\left[\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right]$ in the model is given as $E\left[\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right] \approx \Gamma\left(\frac{v+1}{2}\right)^2$ under student t distributed innovations and the component $E\left[\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right]$ in the model is given as $E\left[\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right] \approx \lambda 2^{v-1} \frac{\Gamma(2v^{-1})}{\Gamma(v^{-1})}$ under generalized error distributed innovations.

Asymmetric Power ARCH

Ding et al. (1993) introduced the Asymmetric power generalized autoregressive conditional Heteroscedasticity (APARCH (p, q)) model defined as;

$$\boldsymbol{\sigma_t^{\delta} = \omega + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^{\delta} + \sum_{j=1}^{q} \beta_j \log \sigma_{t-j}^{\delta}} \qquad \textbf{(3.9)}$$

where the asymmetric parameter $-1 < \gamma_i < 1 (i = 1, \dots, p)$, $\delta \in \mathbb{R}^+$ is the non-negative Box cox power transformation of the conditional standard deviation process and asymmetric absolute innovations. This power parameter is estimated along with other parameters in the model

Overview of Error Distribution

The error distributions underlying the variants of GARCH models in this study are the normal, student t and the generalized error distribution.

Normal Distribution

The normal distribution in nature is spherical and totally described in terms of the mean and variance. Conventionally, if the random variable y exists having mean μ and variance σ^2 which are both time varying, then

$$\boldsymbol{f(y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{1}{2\sigma^2}(y-\mu)^2\right]} \qquad \textbf{(3.10)}$$

Following the mean whitening process, the residuals ε being standardized by σ resulted to standard normal density expressed as

$$\boldsymbol{f\left(\frac{y-\mu}{\sigma}\right) = \frac{1}{\sigma} f(z) = \frac{1}{\sigma}\left(\frac{e^{0.5z^2}}{\sqrt{2\pi}}\right)} \qquad \textbf{(3.11)}$$

Generally, the normal distribution has zero skewness and zero excess kurtosis.

Student t Distribution

The Student t' GARCH model was first introduced in Bollerslev (1987) as a supplement for the normal distribution in modeling the standardized innovations. It is explained entirely in terms of the shape parameter, v but for standardization we have the 3 parameter representation as follows:

$$\boldsymbol{f(y) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\beta v \pi}\,\Gamma\left(\frac{v}{2}\right)}\left(1 + \frac{(1-\alpha)^2}{\beta v}\right)^{-\left(\frac{v+1}{2}\right)}} \qquad \textbf{(3.12)}$$

for α, β, and v are the location, scale and shape parameters respectively. $\Gamma$is the Gamma function. In relation to the GED distribution described as follows, the student t is a unimodal and symmetric distribution where the location parameter α is the mean (sometimes mode) of the distribution with the variance expressed as

$$\boldsymbol{var(y) = \frac{\beta v}{(v-2)}\ for\ v > 2} \qquad \textbf{(3.13)}$$

Based on standardization, the variance becomes

$$var(y) = \frac{\beta v}{v-2} = 1$$

Hence,

$$\beta = \frac{v-2}{v}$$

By substituting the last expression into the 3 parameter representation of the student t function we have:

$$f\left(\frac{y-\mu}{\sigma}\right) = \frac{1}{\sigma} f(z) = \frac{1}{\sigma} \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{(v-2)\pi}\backslash\Gamma\left(\frac{v}{2}\right)} \left(1 + \frac{z^2}{v-2}\right)^{-\left(\frac{k+1}{2}\right)} \quad (3.14)$$

On the general notes, the student t distribution has zero skewness and excess kurtosis equal to $\frac{6}{v-4}$for $v > 4$.

Generalized Error Distribution

In comparison with the aforementioned error distribution, the generalized error distribution GED also has a 3 parameter distribution belonging to the exponential family with conditional density expressed as

$$f(y) = \frac{ke^{-0.5\left|\frac{y-\alpha}{\beta}\right|}}{2^{1+k^{-1}}\beta\Gamma(k^{-1})} \quad (3.15)$$

whereα, β, and k denote the location, scale and shape parameters. The distribution is known to be symmetric and unimodal in nature with the location parameter having proxy as mode, median and mean of the distribution. Accounting for symmetry, the odd moments beyond the mean are zero. The variance and the kurtosis are expressed as

$$var(y) = \beta^2 2^{\frac{2}{k}} \frac{\Gamma(3k^{-1})}{\Gamma(k^{-1})}$$

$$Ku(y) = \frac{\Gamma(5k^{-1})\Gamma(k^{-1})}{\Gamma(3k^{-1})\Gamma(3k^{-1})}$$

The density is decreased by the value of k and the density tends to become flatter as k tends to infinity($k \to \infty$), the distribution therefore becomes more or less uniform. By standardization, we have that as $k = 1$, the density is rescaled to have a unit standard deviation with variance expressed as

$$var(y) = \beta^2 2^{\frac{2}{k}} \frac{\Gamma(3k^{-1})}{\Gamma(k^{-1})} = 1 \quad (3.15)$$

By change of variables,

$$\beta = \sqrt{2^{-\left(\frac{2}{k}\right)} \left(\frac{\Gamma(k^{-1})}{\Gamma(3k^{-1})}\right) 2^{1+k}\Gamma(k^{-1})} \quad (3.16)$$

By substitution, we have;

$$f\left(\frac{y-\mu}{\sigma}\right) = \frac{1}{\sigma} \frac{ke^{-0.5\left|\sqrt{2^{-\frac{2}{k}}\frac{\Gamma(k^{-1})}{\Gamma(3k^{-1})}}z\right|}}{\sqrt{2^{-\frac{2}{k}}\frac{\Gamma(k^{-1})}{\Gamma(3k^{-1})}}2^{1+k^{-1}}\Gamma(k^{-1})} \quad (3.17)$$

Result and Discussion

Exploratory Data Analysis

This entails the visualization of the data set for the study to gain lucid understanding of the nature of stock price attributed to the insurance companies.

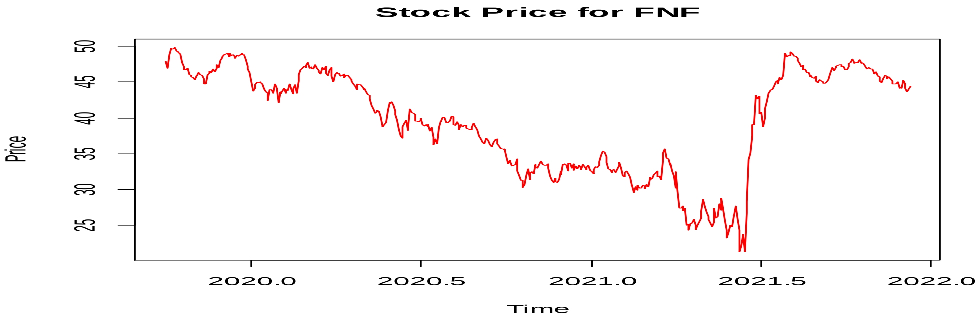

Figure1a. *Stock price time plot for FNF*

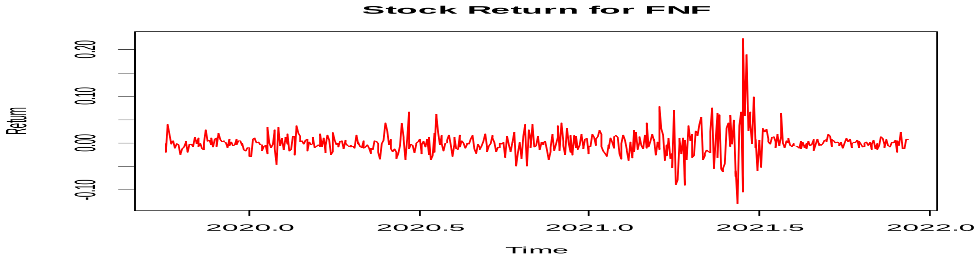

Figure1b. *Stock return time plot for FNF*

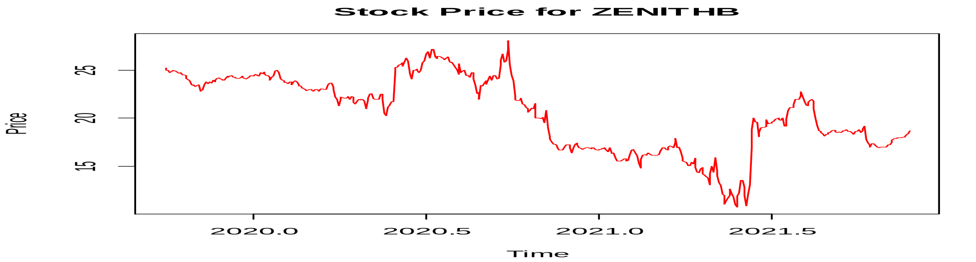

Figure2a. *Stock price time plot for ZENITHB*

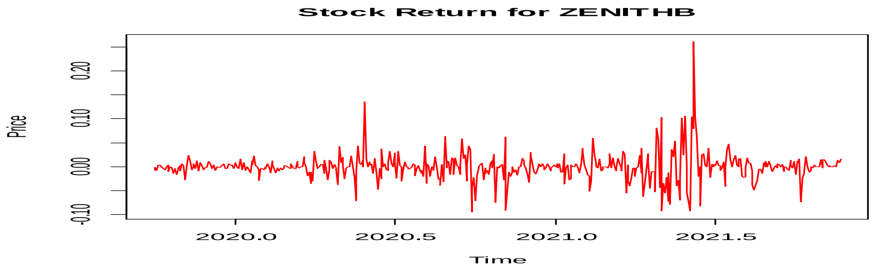

Figure2b. *Stock return for ZENITHB*

Figures 1 and 2 show that stock price is a non-stationary series since it has no constant mean and variance. Stock returns are plagued with clustering suggesting the evidence of Heteroscedasticity for both insurance companies.

Test of Normality

Hypothesis:

H_0:Stock price is normally distributed

H_1: Stock price is not normally distributed.

Table1. *Test of normality for stock price*

Company	JarqueBera Test		Shapiro-Wilk Test	
	Statistic	**P-Value**	**Statistics**	**P-Value**
FNF	6329.8	2.2×10^{-16}	0.83004	2.2×10^{-16}
ZENITHB	26.836	1.4×10^{6}	0.7927	2.2×10^{-16}

Table 1 suggests that on the basis of the JarqueBera and Shapiro Wilk tests of normality, Stock price is non-normally distributed. This does not contradict findings from related literatures.

Test of Stationarity

Hypothesis:

H_0:Stock price is not stationary versus H_1: Stock price is stationary

Table2. *Test for stationarity for stock price and return.*

Company	Item	Augmented Dickey Fuller			Phillips-Perron		
		Statistic	Lag Order	P-Value	Statistic	TLP	P-Value
FNF	Price	-5.2352	8	0.3522	-1.2362	6	0.4771
	Return	-7.8469	8	0.01	-575.75	6	0.01
ZENITHB	Price	-2.2439		0.4751	-9.3864	6	0.5861
	Return	-6.643	8	0.01	-363.89	6	0.01

Table 2 shows that stock price is non-stationary in nature as a result of the estimated P-values which are greater than 0.05 level of significance for both series. The Stock return is found to be stationary based on the estimated P-values which are less than the level of significance.

ARCH Test

Hypothesis

H_0: No ARCH effect

H_1: There is ARCH effect.

Table3. *ARCH Test*

Test Statistic	Degree of freedom	P-Value
χ^2 = 601.43	12	< 2.2e-16
χ^2= 69.05	12	4.82e-10

Table 3 shows the ARCH test the selected stock returns. Result from the table based on the χ^2 test values corresponding to P-values less than 0.05 for both series shows that there is presence of autoregressive conditional heteroscedastic effect. Thus GARCH model could be constructed for parameter estimation and forecast.

GARCH Model Parameters' Estimation for FNF Stock Return

Table4. *Standard GARCH Model [$sGARCH$ (1, 1)]*

Model Parameter	Error Distribution	Equation	Parameters	Estimate	Std. Error	t value	Pr(>|t|)
$\boldsymbol{sGARCH}$ $(\mathbf{1},\mathbf{1})$	Normal	Mean	μ	-0.000877	0.000604	-1.4527	0.14630
		Variance	ω	0.000009	0.000006	1.5727	0.11579
			$ARCH$	0.222128	0.042981	5.1681	0.00000
			$GARCH$	0.776872	0.037472	20.7323	0.00000
	Student t	Mean	μ	-0.001356	0.000590	-2.2966	0.021644
		Variance	ω	0.000017	0.000006	2.5989	0.009353
			$ARCH$	0.287939	0.069766	1272	0.000037
			$GARCH$	0.706099	0.059835	11.8008	0.000000
			$Shape$	6.864232	1.932330	3.5523	0.000382
	Generalized Error Distribution	Mean	μ	-0.001274	0.000595	-2.1401	0.032348
		Variance	ω	0.000013	0.000007	1.9072	0.056499
			$ARCH$	0.260190	0.064354	4.0431	0.000053
			$GARCH$	0.735976	0.056434	13.0414	0.000000
			Shape	1.431488	0.122377	11.6973	0.000000

Table 4 gives the estimate of the $sGARCH(1,1)$ model based on different error innovations. Considering the mean equations, that which is attributed to normal distribution is insignificant on the basis of estimated P-value (0.14630) < 0.05 as compared to those of student t and generalized error distribution. All parameters associated with student t error innovation for variance are found to be significant: an indication that $sGARCH$ (1,1) having student t error distribution could be best for the standard GARCH modelling of stock price for FNF insurance company.

Table5. *Integrated GARCH Model [iGARCH (1,1)]*

Model Parameter	Error Distribution	Equation	Parameters	Estimate	Std. Error	t value	Pr(>|t|)
***iGARCH* (1,1)**	Normal	Mean	μ	-0.000877	0.000603	-1.4530	0.146213
		Variance	ω	0.000009	0.000003	2.6468	0.008125
			$ARCH$	0.223138	0.035855	6.2234	0.000000
			$GARCH$	0.776862	NA	NA	NA
	Student t	Mean	μ	-0.001358	0.000590	-2.3027	0.021295
		Variance	ω	0.000016	0.000005	3.0282	0.002460
			$ARCH$	0.294186	0.059766	4.9223	0.000001
			$GARCH$	0.705814	NA	NA	NA
			$Shape$	6.768956	1.795974	3.7690	0.000164
	Generalized Error Distribution	Mean	μ	-0.001272	0.000588	-2.1622	0.030600
		Variance	ω	0.000013	0.000004	3.3127	0.000924
			$ARCH$	0.264602	0.053689	4.9284	0.000001
			$GARCH$	0.735398	NA	NA	NA
			Shape	1.430652	0.118007	12.1234	0.000000

Table 5 highlights the estimates of the parameters of the $iGARCH$ (1,1) model in terms of their error distribution, standard errors, t-value and the P-values. Findings shows that the significance of the GARCH effect is not estimable since the standard errors are not definite. The ARCH effect are all found to be significant. Also the asymmetric effect captured in stock return attributed to student t and generalized error distributions are highly significant at 0.05.

Table6. *Exponential GARCH Model [eGARCH (1,1)]*

Model Parameter	Error Distribution	Equation	Parameters	Estimate	Std. Error	t value	Pr(>|t|)
***eGARCH* (1,1)**	Normal	Mean	μ	-0.001788	0.000584	-3.0623	0.002197
		Variance	ω	-0.086278	0.048660	-1.7731	0.076212
			$ARCH$	-0.179026	0.028667	-6.2449	0.000000
			$GARCH$	0.988097	0.006282	157.300	0.000000
			γ	0.255425	0.047403	5.3884	0.000000
	Student t	Mean	μ	-0.001851	0.000550	-3.3670	0.000760
		Variance	ω	-0.134765	0.060128	-2.2413	0.025007
			$ARCH$	-0.182219	0.034754	-5.2430	0.000000
			$GARCH$	0.982654	0.007548	130.184	0.000000
			γ	0.285127	0.060085	4.7454	0.000002
			$Shape$	10.357016	4.259232	2.4317	0.015030
	Generalized Error Distribution	Mean	μ	-0.001824	0.000565	-3.2301	0.001238
		Variance	ω	-0.114723	0.072111	-1.5909	0.111627
			$ARCH$	-0.178884	0.033119	-5.4013	0.000000
			$GARCH$	0.985235	0.009127	107.948	0.000000
			γ	0.269621	0.061045	4.4168	0.000010
			Shape	1.595367	0.140589	11.3477	0.000000

Table 6 presents the parameter estimates for the exponential GARCH model with respect to the different error innovations. On this basis, findings show that the mean equation, the ARCH effect, the GARCH effect, and the shock are significant for all models while the asymmetric effect is more significant in case of the generalized error distribution as compared to the student t. for FNF stock return.

Table7. *Asymmetric Power ARCH Model [apARCH (1,1)]*

Model Parameter	Error Distribution	Equation	Parameters	Estimate	Std. Error	t value	Pr(>|t|)
***apARCH* (1,1)**	Normal	Mean	μ	-0.001868	0.000351	-5.3184	0.000000
		Variance	ω	0.000259	0.000283	0.91641	0.359451
			$ARCH$	0.119220	0.021874	5.45025	0.000000
			$GARCH$	0.907971	0.022709	39.9821	0.000000
			γ	0.845797	0.171380	4.93522	0.000001
			δ	0.898652	0.312811	2.87283	0.004068
	Student t	Mean	μ	-0.001989	0.002745	-0.7248	0.468578

		Variance	ω	0.000456	0.000909	0.50108	0.616318
			$ARCH$	0.130951	0.028618	4.57579	0.000005
			$GARCH$	0.897304	0.018544	48.3880	0.000000
			γ	0.802346	0.063453	12.6447	0.000000
			δ	0.839116	0.303360	2.76608	0.005674
			$Shape$	10.999272	4.733409	2.32375	0.020139
	Generalized Error Distribution	Mean	μ	-0.001926	0.005016	-0.3840	0.701002
		Variance	ω	0.000365	0.001289	0.28303	0.777155
			$ARCH$	0.123477	0.027466	4.49568	0.000007
			$GARCH$	0.904971	0.036802	24.5903	0.000000
			γ	0.825679	0.317188	2.60312	0.009238
			δ	0.843557	0.556687	1.51531	0.129693
			Shape	1.610246	0.143473	11.2233	0.000000

Table 7 gives the parameter estimates of the asymmetric Power ARCH model attributed to different error innovations. In this regard, the mean equation is only significant for normal distribution. Shocks, asymmetric effect and persistence are all found to be significant except persistence of the generalized error distribution. Student t has the highest tendency of modelling volatility in comparison to other error innovation for the $apARCH$.

GARCH Model Parameters' Estimation for ZENITHB Stock Return

Table8. *Standard GARCH Model [sGARCH* $(1,1)$*]*

Model Parameter	Error Distribution	Equation	Parameters	Estimate	Std. Error	t value	Pr(>|t|)
$sGARCH$ $(1,1)$	Normal	Mean	μ	-0.000585	0.000587	-0.9962	0.319165
		Variance	ω	0.000026	0.000009	2.87326	0.004063
			$ARCH$	0.353351	0.049494	7.13924	0.000000
			$GARCH$	0.645649	0.043516	14.83693	0.000000
	Student t	Mean	μ	-0.001356	0.000590	-2.2966	0.021644
		Variance	ω	0.000017	0.000006	2.5989	0.009353
			$ARCH$	0.287939	0.069766	1272	0.000037
			$GARCH$	0.706099	0.059835	11.8008	0.000000
			$Shape$	6.864232	1.932330	3.5523	0.000382
	Generalized Error Distribution	Mean	μ	-0.001274	0.000595	-2.1401	0.032348
		Variance	ω	0.000013	0.000007	1.9072	0.056499
			$ARCH$	0.260190	0.064354	4.0431	0.000053
			$GARCH$	0.735976	0.056434	13.0414	0.000000
			Shape	1.431488	0.122377	11.6973	0.000000

Table 8 shows the estimates of the standard GARCH model for ZENITHB insurance company. Findings show that the normal distribution is not capable of capturing the asymmetric effect in the stock return. The ARCH and GARCH effects are found to statistically significant while the asymmetric effect captured by the student t and generalized error distribution are found to be significant. Student t distribution has all parameters to be more significant than the other error innovations

Table9. *Integrated GARCH Model [iGARCH* $(1,1)$*]*

Model Parameter	Error Distribution	Equation	Parameters	Estimate	Std. Error	t value	Pr(>|t|)
$iGARCH$ $(1,1)$	Normal	Mean	μ	-0.000584	0.000586	-0.9972	0.318693
		Variance	ω	0.000025	0.000007	3.70169	0.000214
			$ARCH$	0.354031	0.041883	8.45279	0.000000
			$GARCH$	0.645969	NA	NA	NA
	Student t	Mean	μ	-0.000272	0.000474	-0.5722	0.567174
		Variance	ω	0.000042	0.000015	2.80699	0.005001
			$ARCH$	0.489241	0.070957	6.89486	0.000000
			$GARCH$	0.510759	NA	NA	NA
			$Shape$	3.275157	0.335514	9.76162	0.000000
	Generalized Error Distribution	Mean	μ	0.000000	0.000003	-0.0003	0.99978
		Variance	ω	0.000001	0.000004	0.22366	0.82302
			$ARCH$	0.092128	0.060280	1.52833	0.12643
			$GARCH$	0.907872	NA	NA	NA
			Shape	0.520396	0.118023	4.40929	0.00001

Table 9 gives the estimates of the integrated GARCH model for ZENITHB based on different error distributions under study. Results show that the GARCH effect parameters could not be ascertained for statistical significance since its standard errors are not estimable. Looking at the student t and generalized error distribution, we found that the asymmetric effect is significant and more pronounced for student t. the ARCH effect associated with GED was discovered to be insignificant.

Table10. *Exponential GARCH Model [eGARCH $(1,1)$]*

Model Parameter	Error Distribution	Equation	Parameters	Estimate	Std. Error	t value	Pr(>|t|)
***eGARCH* (1, 1)**	Normal	Mean	μ	-0.000773	0.000609	-1.2707	0.203827
		Variance	ω	-0.460774	0.134552	-3.4245	0.000616
			ARCH	0.026945	0.046099	0.5845	0.558884
			GARCH	0.932699	0.017293	53.9358	0.000000
			γ	0.575199	0.062450	9.2106	0.000000
	Student t	Mean	μ	-0.000498	0.000433	-1.1524	0.249168
		Variance	ω	-0.552929	0.208574	-2.6510	0.008026
			ARCH	-0.012289	0.174981	-0.0702	0.944010
			GARCH	0.900332	0.034607	26.0159	0.000000
			γ	1.694472	0.460831	3.67700	0.000236
			Shape	2.101112	0.049938	42.0744	0.000000
	Generalized Error Distribution	Mean	μ	0.000000	0.000000	-6.0e-06	0.999995
		Variance	ω	-0.052544	0.044890	-1.1705	0.241794
			ARCH	-0.431127	0.728601	-5.9e-01	0.554039
			GARCH	0.968933	0.000029	3.4e+04	0.000000
			γ	-0.659037	0.222008	-2.9685	0.002992
			Shape	0.123471	0.002747	4.5e+01	0.000000

The estimates of the exponential GARCH model were presented in table 10 with results showing that the ARCH effects underlying all error distributions are insignificant. The GARCH effects were all found to be statistically significant. The persistence and asymmetric parameters were statistically significant based on student t and generalized error distributions.

Table11. *Asymmetric Power ARCH Model [apARCH $(1,1)$]*

Model Parameter	Error Distribution	Equation	Parameters	Estimate	Std. Error	t value	Pr(>|t|)
***apARCH* (1, 1)**	Normal	Mean	μ	-0.001514	0.000585	-2.5897	0.009605
		Variance	ω	0.006512	0.009402	0.69266	0.488523
			ARCH	0.278720	0.061950	4.49912	0.000007
			GARCH	0.743485	0.038578	19.2723	0.000000
			γ	-0.144427	0.115755	-1.2477	0.212140
			δ	0.578149	0.338038	1.71031	0.087209
	Student t	Mean	μ	-0.000358	0.000450	-0.7952	0.426492
		Variance	ω	0.001070	0.001729	0.61879	0.536055
			ARCH	0.880743	0.533943	1.64951	0.099043
			GARCH	0.563885	0.084192	6.69765	0.000000
			γ	0.035671	0.106276	0.33564	0.737140
			δ	1.293656	0.411691	3.14229	0.001676
			Shape	2.365437	0.334766	7.06593	0.000000
	Generalized Error Distribution	Mean	μ	0.000000	0.000001	-0.0000	0.999972
		Variance	ω	0.000019	0.000005	3.96142	0.000075
			ARCH	0.000045	0.000378	0.11840	0.905753
			GARCH	0.989164	0.003416	289.556	0.000000
			γ	-0.770414	0.243178	-3.1681	0.001534
			δ	2.770502	0.213830	12.9566	0.000000
			Shape	0.167270	0.017147	9.75476	0.000000

Findings from table 11 shows that the asymmetric effects except that of normal distribution are statistically significant including the GARCH effects, the power parameter was found to be significant for student t and generalized error distributions.

Model Performance Measures

Table12. *Model Performance for FNF Company*

Model	Error Distribution	Likelihood	AIC	BIC	SIC	HQIC
$sGARCH(1,1)$	Normal	1361.623	-5.1719	-5.1394	-5.1720	-5.1592
	Student t	1371.078	-5.2041	-5.1635	-5.2043	-5.1882
	Generalized Error Distribution	1369.574	-5.1984	-5.1578	-5.1986	-5.1825
$iGARCH(1,1)$	Normal	1361.631	-5.1757	-5.1514	-5.1758	-5.1662
	Student t	1371.065	-5.2079	-5.1754	-5.2080	-5.1951
	Generalized Error Distribution	1369.567	-5.2022	-5.1697	-5.2023	-5.1894
$eGARCH(1,1)$	Normal	1379.365	-5.2357	-5.1951	-5.2359	-5.2198
	Student t	1383.479	-5.2475	-5.1988	-5.2478	-5.2285
	Generalized Error Distribution	1382.684	-5.2445	-5.1958	-5.2448	-5.2254
$apARCH(1,1)$	Normal	1381.368	-5.2395	-5.1908	-5.2398	-5.2204
	Student t	1385.083	-5.2498	-5.1930	-5.2502	-5.2276
	Generalized Error Distribution	1384.435	-5.2474	-5.1905	-5.2477	-5.2251

The model performance measure for the study are likelihood, AIC, BIC, SIC and the HQIC on the basis of bets model having the highest value of likelihood corresponding to the minimum value of at least two information criterion inclusively AIC.

Regarding the stock returns' models generated for FNF insurance company we discovered that $apARCH$ (1,1) with student t error distribution outperformed all other 11 models estimated. This therefore gives room for the forecast of volatility to be guaranteed on the basis of the best model (See table 11).

Table13. *Model Performance for ZENITHB Company*

Model	Error Distribution	Likelihood	AIC	BIC	SIC	HQIC
$sGARCH(1,1)$	Normal	1302.519	-5.0253	-4.9759	-5.0255	-5.0059
	Student t	1364.766	-5.2665	-5.2172	-5.2668	-5.2472
	Generalized Error Distribution	1413.654	-5.4599	-5.4188	-5.4601	-5.4438
$iGARCH(1,1)$	Normal	1302.289	-5.0360	-5.0113	-5.0361	-5.0263
	Student t	1363.09	-5.2678	-5.2349	-5.2679	-5.2549
	Generalized Error Distribution	1372.844	-5.3056	-5.2727	-5.3057	-5.2927
$eGARCH(1,1)$	Normal	1308.859	-5.0537	-5.0126	-5.0539	-5.0376
	Student t	1364.766	-5.2665	-5.2172	-5.2668	-5.2472
	Generalized Error Distribution	1555.807	-6.0070	-5.9576	-6.0073	-5.9877
$apARCH(1,1)$	Normal	1312.338	-5.0633	-5.0140	-5.0636	-5.0440
	Student t	1369.058	-5.2793	-5.2217	-5.2797	-5.2567
	Generalized Error Distribution	1482.318	-5.7183	-5.6607	-5.7186	- 5.6957

Regarding the stock returns' models generated for ZENITHB insurance company we discovered that $eGARCH$ (1,1) with generalized error distribution outperformed all other 11 models estimated. This therefore gives room for the forecast of volatility to be guaranteed on the basis of the best model (See table 13).

Model Diagnostic Plots for FNF Best Estimated Model

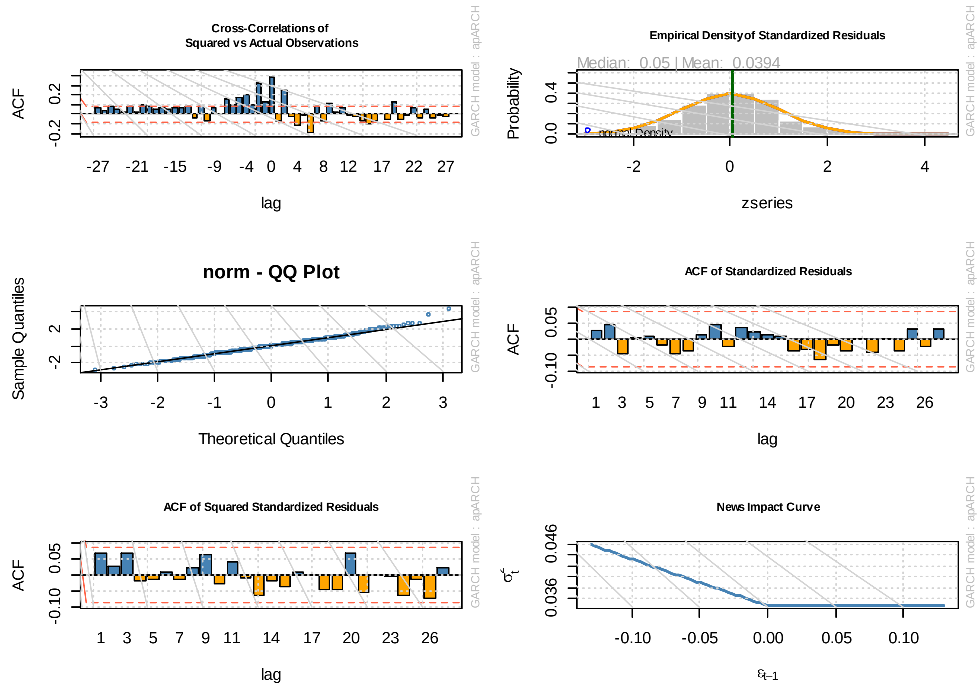

Figure3. *Diagnostic plot for ap ARCH (1, 1) with student t innovation*

Figure 3 shows the diagnostic plot for $apARCH(1,1)$ with respect to student t innovation. The plot presents the autocorrelation function plot for the cross-conditional versus actual observation with more significant lags observed in the negative direction. The empirical density of standardized residuals shows that the distribution is positively skewed with median values greater than the mean value. Considering the Norm-QQ plot we observed that there is a fashion of normality associated with the series. The news impact curve shows that positive news and negative news are not equally likely.

Model Diagnostic for ZENITHB Best Estimated Model

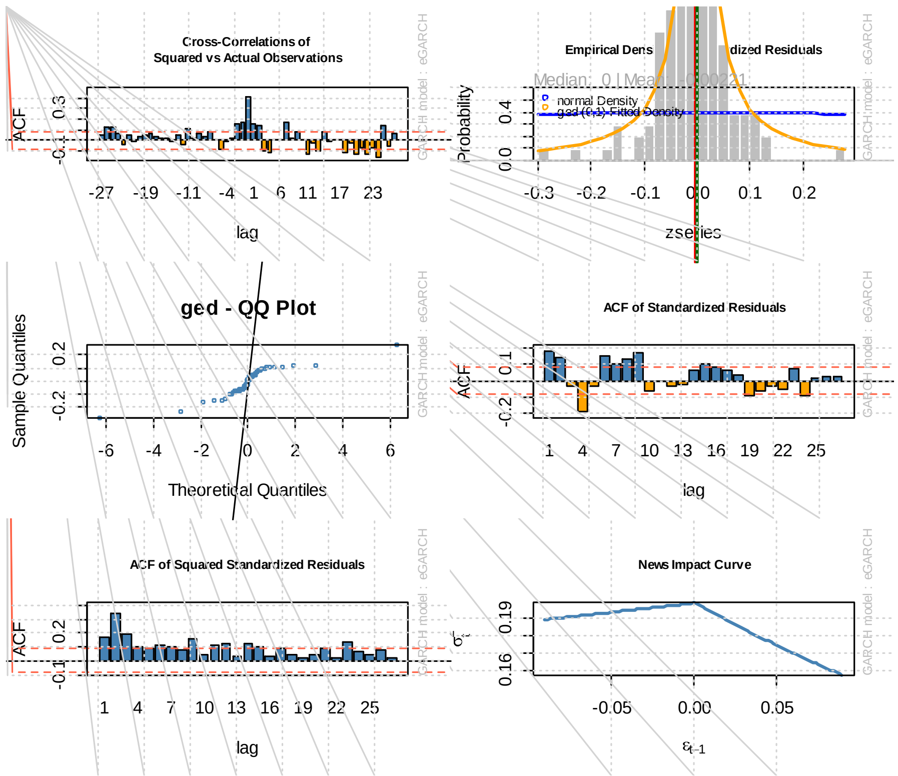

Figure4. *Diagnostic plot for eGARCH (1, 1) with generalized error distribution*

Figure 4 presents the $eGARCH$ model with generalized error distribution. The model is suggested to not being able to capture the dynamics of stock return in relation to ZENITHB insurance company since all point tail off the straight line of the ged-QQ plot. The news impact curve generated suggests unequal reaction to shocks

Forecast's Estimation

Table14. *Volatility forecast*

Time	Sigma(FNF Volatility)	Sigma (ZENITHB Volatility)
T+1	0.01297040	1.2727
T+2	0.01313961	1.2304
T+3	0.01330806	1.1908
T+4	0.01347573	1.1537
T+5	0.01364264	1.1188
T+6	0.01380877	1.0860
T+7	0.01397412	1.0551
T+8	0.01413871	1.0260
T+9	0.01430251	0.9986
T+10	0.01446554	0.9728
T+11	0.01462778	0.9484
T+12	0.01478925	0.9253
T+13	0.01494994	0.9035
T+14	0.01510985	0.8828
T+15	0.01526899	0.8633
T+16	0.01542734	0.8447
T+17	0.01558491	0.8272
T+18	0.01574170	0.8105
T+19	0.01589771	0.7946
T+20	0.01605294	0.7796

Table 14 gives the volatility forecast of 20 working days ahead. The volatility for FNF insurance company decreases over time at a very slow rate while that of FNF increase over time at a higher rate as compared to that of ZENITHB. This shows that stock returns for FNF could be easily predicted as compared to ZENITHB and worthwhile min nature.

Forecast Plot with Estimated Persistence

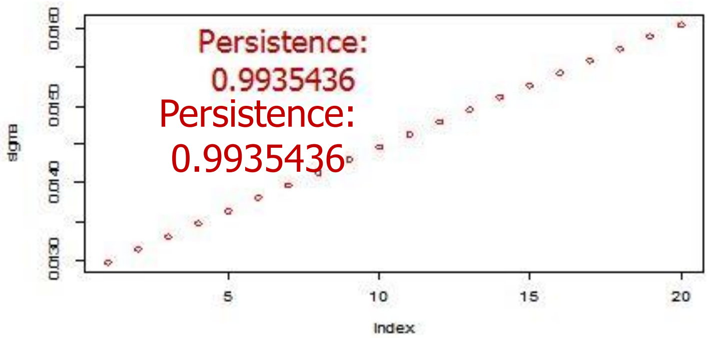

Figure5. *FNF forecast plot with estimated persistence [apARCH (1, 1)] with student t error distribution.*

Figure 5 presents the forecast volatility alongside with its persistence for FNF.

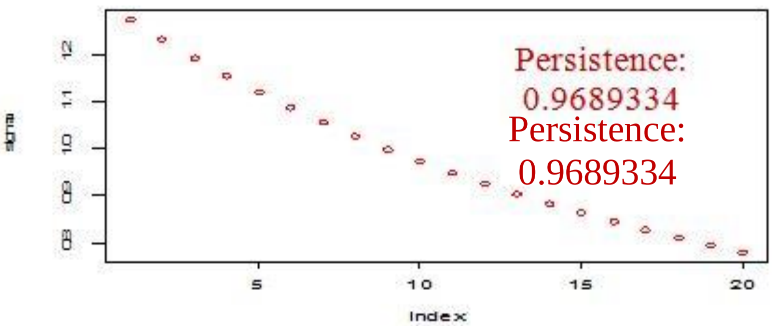

Figure6. *ZENITHB forecast plot with estimated persistence [eGARCH (1, 1)] with generalized error distribution.*

Figure 6 presents the forecast volatility alongside with its persistence for ZENITHB in no contrast to the findings from volatility forecast presented in table 14.

Discussion

This revealed that Stock prices for both FNF and ZENITHB insurance companies were non-stationary and non-normally distributed and the stock return series possess clustering and shock from the exploratory data analysis carried out.

The test of stationarity based on the augmented dickey fuller and Phillip Perrons procedure shows that stock returns accounted for by the selected insurance companies are statistically significant.

ARCH effect tests for both series resulted to presence of significant shock attributed to volatility clustering and the results on parameters estimation show that all most all model parameters (including shocks, asymmetric effects, power, and persistence) were statistically significant for both insurance companies

Normal error innovation estimated GARCH models were found to be not worthwhile in the modelling of stock return since majority of series tail off from a straight line on the norm-QQ plot.

However, Student t and generalized error innovations were more suitable in modelling stock returns in relations to the selected insurance companies.

Based on the model performance for best model identification, we discovered that the best model for FNF is $apARCH(1,1)$ with generalized error innovation while that of ZENITHB is $eGARCH(1,1)$ model with student error innovation since they both have the highest likelihood corresponding to lowest AIC and at least 1 other information criteria.

A 20-day volatility forecast was carried out for both series and findings show that, FNF volatility would increase in due time with a higher persistency while ZENITHB volatility declines in due time with a lower persistency.

Conclusion

Stock returns are known to be volatile in nature. Findings from this study have shown that the most suitable volatility model for evaluating stock returns in ZENITHB is eGARCH (1, 1) with generalized error innovation and FNF is apARCH (1, 1) with student t error distribution since they have the highest likelihood corresponding to the smallest AIC, SIC and HQIC value. Hence, first-Order models are most adequate in evaluating stock return volatility.

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