

Modelling and Forecasting the Volatility of the Daily Returns of Nigerian Insurance Stocks

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Abstract

This paper examines the volatility of the daily returns of Nigerian insurance stocks. Using empirical analysis, the study shows that the Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) model is more suitable in modelling stock price returns as it outperforms the other models in model-estimation evaluation and out-of-sample volatility forecasting. Given the cardinal role of insurance in Nigeria's risk management system the present findings can be useful in understanding insurance industry's stock risk. The policy implications are also considered.

Keywords: Insurance Stocks Returns, Volatility modelling, GARCH, TARCH, EGARCH, Out-of Sample Forecasts

1. Introduction

Volatility modelling and forecasting have attracted much attention in recent years in emerging stock markets. For instance, many asset-pricing models used volatility estimates as a simple actuarial risk measure. In Nigeria volatility modelling and forecasting has not attracted the deserved attention possibly because the stock market is largely under-developed. This phenomenon is more pronounced in the insurance sector where many of the players appear to deliberately avoid listing on the stock exchange because no information would then need to be disclosed to their shareholders. However, changes are being observed as the last two decades have seen accelerated growth of insurance markets. Arena (2006) reports that "emerging markets have recently experienced significantly faster real growth of their insurance sectors than industrialized countries reflecting liberalization and financial integration, usually following the implementation of structural reforms".

Recapitalization of the insurance industry in Nigeria has no doubt recorded a huge volume of business, the sector was able to pull an aggregate gross premium income of N90 billion in 2006, over 18% more than 2005. Moreover, Nigerian investors' attitude and perception of insurance stocks are dramatically changing positively. In fact, discerning investors have since identified insurance stocks as a very important investment line since most of the insurance stocks are having impressive returns (Ibiwoye and Adeleke, 2008). Hence, there is currently a high level of investors' interest for insurance stocks in the market and subsequently a high level of volatility. Therefore, hedging against risk and for portfolio management, reliable risk volatility estimates and forecasts of these stocks are quite useful and need to be investigated. In Nigeria, volatility modelling and forecasting have not attracted much attention for the simple reason that the stock market is largely undeveloped. The few exceptions have been the study by Ologunde et al (2006) which fitted a regression model to the relationship between market capitalization and interest rate, Ibiwoye & Adeleke (2008) who analysed price movements in insurance stocks pre-and post- 2005 consolidation and that of Olowe (2009) on the impact of the 2005 re-capitalization of the insurance industry on the stock market. This paper fills the gap in the emerging economy literature by investigating the volatility of Nigerian insurance stocks returns using heteroskedastic conditional volatility models.

2. Literature Review

The pervasive daily return volatility in equity stock markets has attracted considerable attention in the literature in recent times (Galeotti and Schiantarelli, 1994; Mankiw et al 1991; Kumar and Makhija, 1986, Schwert, 1989; Eraker, 2004). Mathematical models are usually employed to predict the future behavior of stock prices because most transactions in stocks, whether to buy or sell, are activities that take place in the future (Chauvin, 2006). In the

past, much modelling attention had been focused on the predictable component of the stock return series. Later attention shifted to the error term whereby it is assumed that the latter is normally distributed.

Schwartz (1989) found that the amplitude of the fluctuations in aggregate stock volatility is difficult to explain using simple models of stock valuation and that there is a strong residual autocorrelation using least squares hence he applied ARMA (1, 3) model for the errors. Eraker (2004) developed an approach based on Markov Chain Monte Carlo (MCMC) simulation, which allows the investigation to estimate the posterior distributions of the parameters as well as the unobserved volatility and jump processes. Rydberg (2000) reviewed some models that have been used to describe the most important or stylized features of financial data. These include fact tools, asymmetry-symmetry, volatility clustering, aggregation Gaussianity, quasi-long-range dependence and seasonality. Rydberg (2000) classified the models into two broad categories: mathematical finance models and econometric models. Since the goal of the latter is usually forecasting it requires less rigorous probability theory than the previous and tends to focus more on the correlation structure of the data.

Models that assume normally distributed log returns like the Black & Scholes model had been extensively used in the mathematical finance literature but this assumption has been disputed (Rydberg, 2000). More recently, attention has shifted towards modelling financial-market asset returns by processes other than normal error distribution. It has been established that the variances of the error terms in ordinary least square (OLS) estimates are not equal, and are indeed larger for some points or ranges of data than for others (Engle, 2001). This incidence of heteroskedasticity in which the usual procedures for estimating standard errors and confidence intervals fall short are best addressed by ARCH/GARCH models (Engle, 2001). The ground breaking work of Engle (1982) introduced a means of capturing the property of time-varying volatility. Further research, however, has shown that in practical applications of the ARCH (q) model, large q's are usually required thereby necessitating the need for many parameters (Rydberg, 2000). To overcome this difficulty, Bollerslev (1986) and Taylor (1986) modified the basic ARCH model as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model.

GARCH has since gained widespread acceptance in the literature and is often used for modelling stochastic risk volatility in financial time series. Floros (2007) used various GARCH models with bootstrapped out-of-sample period data to evaluate the performance of minimum capital risk requirement (MCRR) estimates. The models show that higher capital requirements are necessary for a short position, since a loss is then more likely.

David (1997) classified the models for describing the properties of stock market returns into two – the fast learning model and the slow learning model. Exploring the properties of exponential GARCH model for measuring the asymmetry between returns and volatility, David (1997) found that the fast learning model generates a negative relationship while the slow model generate returns that exhibit greater excess kurtosis. Other ARCH/GARCH based studies include Amin and Ng (1997); Baillie and DeGennaro (1990); Chahal and Wang (1998) and Chan et al (1991). Amin and Ng (1997) argue that implied volatility dominates the GARCH terms and therefore include an entire lag structure through GARCH persistence terms in their study.

However, as Rydberg (2000) had observed, neither the ARCH nor the GARCH models consider both asymmetry and leverage (the fact that volatility negatively correlated with changes in stock returns). Although GARCH (p, q) models give adequate fits for most equity-return dynamics, these models often fail to perform well in modelling the volatility of stock returns because GARCH models assume that there is a symmetric response between volatility and returns. GARCH models are thus unable to capture the "leverage effect" of stock returns. For equities, it is often observed that downward movements in the market are followed by higher volatilities than upward movements of the same magnitude. To account for this, Zakoian (1990) and Glostan, Jagannathan, and Runkle (1993) introduced the threshold GARCH (TGARCH) to take care of existing leverage effect. During the same period Nelson (1991) proposed the Exponential GARCH (EGARCH) models in order to model asymmetric variance effects.

3. Material and Methods

3.1 Data for the Study

The data for this study are from daily closing prices of insurance companies stocks traded on the floor of the Nigerian Stock Exchange (NSE). The time series data cover almost eight years starting from 15th of December 2000 to 9th of September 2008 and coincidentally the period corresponds to Nigeria's recent stable market economy and civil democratic governance. Although about twenty-six insurance companies are listed on the floor of NSE, some of them did not survive the consolidation exercise. We are considering only the data of nine major insurance companies which daily listed stock prices are available for the period considered in the study. We used the daily data from 15th of December 2000 to June 9th 2008 as training data set, and the data from 10 June 2008 to 9th September 2008 as evaluation test set or out-of-sample datasets (partial data sets excluding holidays). Details on

these companies can be found in Nigerian Insurance Digest (2007) and the data are available on <http://www.cascraft.com>.

3.2. Methods

3.2.1 Models Specification

Having observed P_t which is denoting the stock price at time t , let $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$ be the continuously compounded return series of interest. Usually, the return series is decomposed into two parts, the predictable and the unpredictable as:

$$r_t = E(r_t | \mathcal{I}_{t-1}) + \varepsilon_t \quad (1)$$

where $E(r_t | \mathcal{I}_{t-1})$ is the conditional mean of return at time t depending upon the information available at time $t-1$ and ε_t is the prediction error term. Unfortunately, the conditional mean does not have the ability to give useful predictions, hence, the recourse to methods (addressing the volatility of the error term) such as ARCH and stochastic volatility models in modern applied statistics and mathematical finance. Assuming the unpredictable component in (1) is an ARCH process, it can be written as

$$\varepsilon_t = z_t \sigma_t \quad (2)$$

where $z_t \stackrel{iid}{\sim} N(0, 1)$ and σ_t^2 is the conditional variance.

ARCH (p)

Since the seminal paper of Engle (1982) a rich literature has emerged for the modelling of heteroskedasticity in financial time series. Engle (1982) introduced the ARCH (p) model in which the conditional variance σ_t^2 is a linear function of lagged squared residuals ε_t

$$\sigma_t^2 = \alpha + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \varepsilon_{t-2}^2 + \dots + \beta_p \varepsilon_{t-p}^2, \quad (3)$$

Where, $\alpha > 0$ and $\beta_i \geq 0$ and $\varepsilon_t | \mathcal{I}_{t-1} \sim N(0, \sigma_t^2)$

and \mathcal{I}_t is the information set of all information up to time t . It is important to note that for ARCH models the unconditional distribution of ε_t is always leptokurtic. In applications of the ARCH (p) model, it often turned out that the required lag p was rather large. In order to achieve a more parsimonious parameterization, then, Bollerslev (1986) introduced the generalized ARCH (p, q) model (GARCH (p,q)).

GARCH (p, q)

thus, the volatility model is now written as

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \dots + \beta_q \sigma_{t-q}^2 \quad (4)$$

where, $\alpha_i > 0$ and $\beta_j > 0$ for all i and j .

In general, the value of p in (4) will be much smaller than the value of p in equation (3).

Important limitations of ARCH and GARCH models are the non-negativity constraints of the α_i 's and β_j 's which ensure positive conditional variances. Moreover, GARCH models assume that the impact of news on the conditional volatility depends only on the magnitude, but not on the sign, of the innovation. As mentioned above, empirical studies have shown that changes in stock prices are negatively correlated with changes in volatility. To overcome this

TARCH (p, q) Model

The threshold GARCH, or TARCH (p, q), (Glosten et al. 1993,) is

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q (\alpha_i \varepsilon_{t-i}^2) + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^p (\beta_j \sigma_{t-j}^2) \quad (5)$$

where $d_t = 1$ if $\varepsilon_t < 0$, and $d_t = 0$ otherwise. In this, good news ($\varepsilon_t < 0$), and bad news ($\varepsilon_t > 0$), have differential effects on the conditional variance. In this work we consider popular TARCH (1, 1). In this case, good news has an impact of α and bad news has an impact of $\alpha + \gamma$.

EGARCH (p, q) Model

Similarly, to overcome the drawbacks, Nelson (1991) introduced the exponential GARCH. As:

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^q \left(\alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) \right) + \sum_{j=1}^p (\beta_j \ln(\sigma_{t-j}^2)), \quad (6)$$

The EGARCH (1, 1) used in the present study is the EViews specification given by:

$$\ln(\sigma_t^2) = \alpha_0 + \beta \ln(\sigma_{t-1}^2) + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

The fact that the EGARCH process is specified in terms of log of the conditional variance implies that σ_t^2 is always positive and, consequently, there are no restrictions on the sign of the model parameters. In fact, the leverage effect is exponential, rather than quadratic, and that the forecasts can be tested by the hypothesis $\gamma < 0$.

3.2.2 Model Selection Criteria

In a holistic, model comparison approach the underlying goal is to select the “best approximating model” from among competing models under consideration. Several model selection criteria have been proposed based on different considerations. The most prominently used method is the Akaike Information Criterion (AIC) (Akaike, 1978). The procedure selects the best model with the lowest AIC. Fundamentally, AIC involves the notion of cross-validation, but only on theoretical sense. Given AIC values of two or more models, the model satisfying minimum AIC is most representatives of the true model and, on this account, may be interpreted as the best approximating model among those being considered (Dayton, 2003).

Let y , k , n and LL be response variable, the number parameters, the number of observations and the maximised likelihood function respectively. The Bayesian Information Criterion is

$$AIC = 2K - 2 \ln(LL) = 2K + \ln\left(\frac{RSS}{n}\right) \quad (7)$$

where, $RSS = \sum_{i=1}^n \hat{\varepsilon}^2$ is the residual sum of squares.

The main reason for preferring the use of a model selection procedure such as AIC in comparison to traditional significance tests is the fact that, a single holistic decision can be made concerning the model that is best supported by the data in contrast to what is usually a series of possibly conflicting significance test. Moreover, models can be ranked from best to worst supported by the data at hand, thus, enlarging the possibilities of interpretation (for more insights see Dayton, 2003).

Since, AIC serves only the purpose of model comparison; we consider three diagnostic check methods based on Ljung-Box Q statistics for post-estimation evaluation analysis of the fitted models. There are the standardised residuals and squared residuals of the Autocorrelation (AC) and partial autocorrelation (PAC) functions, and the autoregressive conditional heteroscedastic ARCH-LM test

In addition, we employ two popular out-of sample model selection criteria to evaluate the predictive performance of the five competing models considered in the investigation. The criteria are namely the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). Thus, we have

$$RMSE = \sqrt{\frac{1}{m} \sum_{t=1}^m (\hat{y}_t - y_t)^2} \quad (8)$$

$$MAE = \frac{1}{m} \sum_{t=1}^m |y_t - \hat{y}_t| \quad (9)$$

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

The RMSE and the MAE can be jointly considered to diagnose the errors variation in a set of forecasts. The RMSE will always be larger or equal to the MAE; the greater difference between them, the greater the *variance* in the individual errors in the sample.

4. Analysis of Results

4.1 Preliminary Results

Table 4.1 shows the preliminary analysis statistics of various insurance stocks returns. The mean return and standard deviation are reported, as well as the highest and lowest returns observe for each stock. The standard deviation of stock returns is the measure of dispersion of returns around the average return over the period of study.

This is not always the best indicator of risk variability. Clearly, the return series displayed in Figure 4.1 has too many extremes values to be generated by a normal curve. Sample departures from the normal distribution are summarized by the coefficients of skewness and Kurtosis. The excess kurtosis coefficients are very large and statistically significant for all the stocks. All the stocks are negatively skewed. GARCH models allow the volatility, or conditional heteroskedascity, to vary over time; therefore it can easily take care of the fourth moment or kurtosis to the data. Nerveless, clustering conditional volatility has a limited effect on the very high skewness.

4.2 Analysis of Main Results

The main empirical results are summarized in the following Tables 4.2, 4.3, and 4.4 respectively. Table 4.2 gives the statistics of model variance parameters estimates and Aikake performance evaluation criterion under various fitting techniques. The results indicate with a good level of confidence the suitability of various fitting methods. In fact, the ARCH coefficient(s) of the estimated models are significant except in the cases of the second order of ARCH (2) results of UNIC and WAPIC insurance stocks price returns. Similarly, the beta coefficients of all the stocks are also significant at 99% confidence level, which indeed shows the presence of time-clustering volatility of insurance stocks in Nigerian market. On the other hand, the asymmetry gamma coefficients of the EGARCH are significant in for all the nine companies whereas the TGARCH are significant in six out of the nine stocks. But even in the case of the latter three companies, the non linear asymmetric TGARCH model is very competitive as expected based on the kurtosis and skewness coefficients results given in Table 4.1. Moreover, the EGARCH (1, 1) is in general the preferred model for these stocks using the AIC model selection criterion results as shown in Table 4.2.

The post-estimation evaluation using the Lung-Jung and Box-Pierce statistics are quite informative in assessing the diagnostic checks of various simulated models. Table 4.3 results show that, the Autocorrelation (AC) and Partial Autocorrelation (PAC) Q(16) statistics are significant for all the fitted models in case Crusader, Guinea and UNIC insurance stocks whereas only ARCH(1) is significant for Cornerstone and Prestige Insurance companies stocks. Similarly, in the case of Niger Insurance only ARCH (1) and EGARCH (1, 1) are not significant. On the other hand, the Q(16) statistics for the standardized squared residuals are significant for all the simulated models only in the case of UNIC Insurance. In fact, the situation remains persistent even when we tried higher level Lags. This can be seen also easily from the ARCH-LM test Q statistics results. In fact, the ARCH test is only significant in the case of UNIC with even higher order ARCH, GARCH, TGARCH and EGARCH. This corroborates Chahal and Wang (1998) findings that time-varying conditional volatility has a limited effect on the third moments or skewness.

Table 4.4 results show the RMSE and MAE out-of sample forecasts comparison. The results suggest that, the non-linear methods perform better than other competing methods. In fact, the Exponential GARCH (1, 1) model proves to be very competitive as it performs better than other competing methods using the RMSE and MAE model forecast evaluation criteria. This is closely follows by the TGARCH (1, 1) and as distant third the GARCH (1, 1) model. However, it is important to note the closeness amongst the magnitudes of all the methods in both (RMSE and MAE) model performance statistics measures, which on a nutshell confirmed the adequacy of these conditional volatility models in modelling Nigerian insurance stock prices returns.

5. Conclusion

We have examined the volatility behaviour of the Nigerian insurance stocks price. Several variants of heteroskedastic conditional volatility models were evaluated using model evaluation performance metrics. The post estimation evaluation revealed that most of the models studied were competitive. However, the results show that the EGARCH is a more preferred modelling framework for evaluating risk volatility of Nigerian insurance stocks. These findings are substantiated by using AIC, RMSE, and MAE evaluation information measures. The present findings are relevant to the investing community as a whole who invest their hard-earned money on corporate insurance business expecting reasonable returns. Keeping in mind that insurance stock returns are exponentially volatile, and particularly because the Nigerian financial system is currently undergoing reforms, investors are better informed on insurance stocks in their portfolio profile.

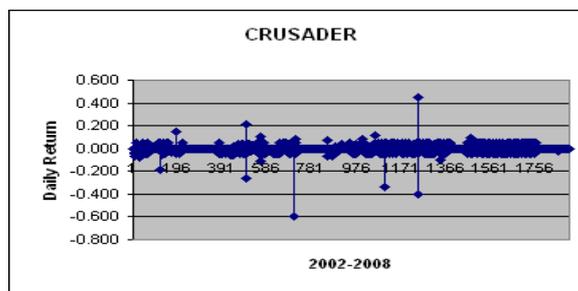
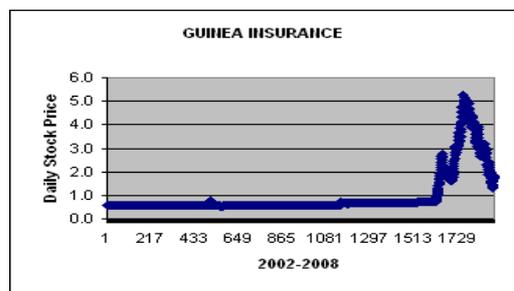
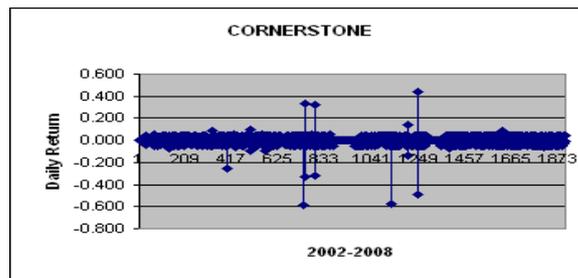
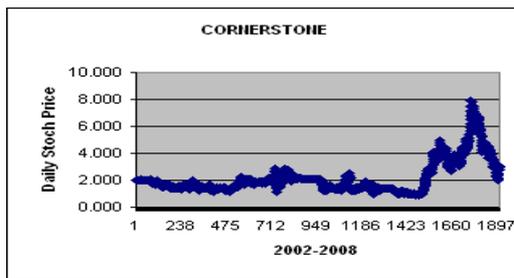
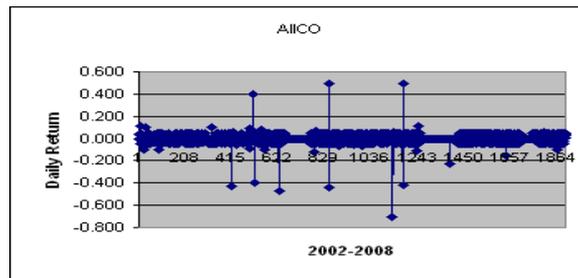
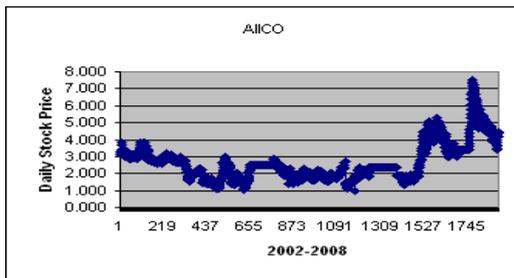
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Table 4.1. Summary of Descriptive Statistics of Stocks Returns

	N	Minimum	Maximum	Mean	Std. Deviation	Higher Moments	
	Statistic	Statistic	Statistic	Statistic	Statistic	Skewness	Kurtosis
AIICO	1902	-.701	.499	.00019	.045752	-2.508	65.311
Cornerstone	1902	-.589	.435	.00022	.042087	-3.131	60.339
Crusader	1902	-.599	.451	.00068	.033880	-3.235	85.909
GUINEA	1902	-.288	.288	.00058	.018662	-.001	62.017
Law Union	1902	-.361	.267	.00073	.028789	-.967	23.139
NIGER	1902	-.458	.153	-.00007	.037106	-1.955	20.297
Prestige	1902	-.440	.307	.00053	.032567	-2.362	35.255
UNIC	1902	-1.099	.300	-.00005	.045919	-7.124	174.714
WAPIC	1902	-.517	.454	.00100	.038572	-1.428	51.581



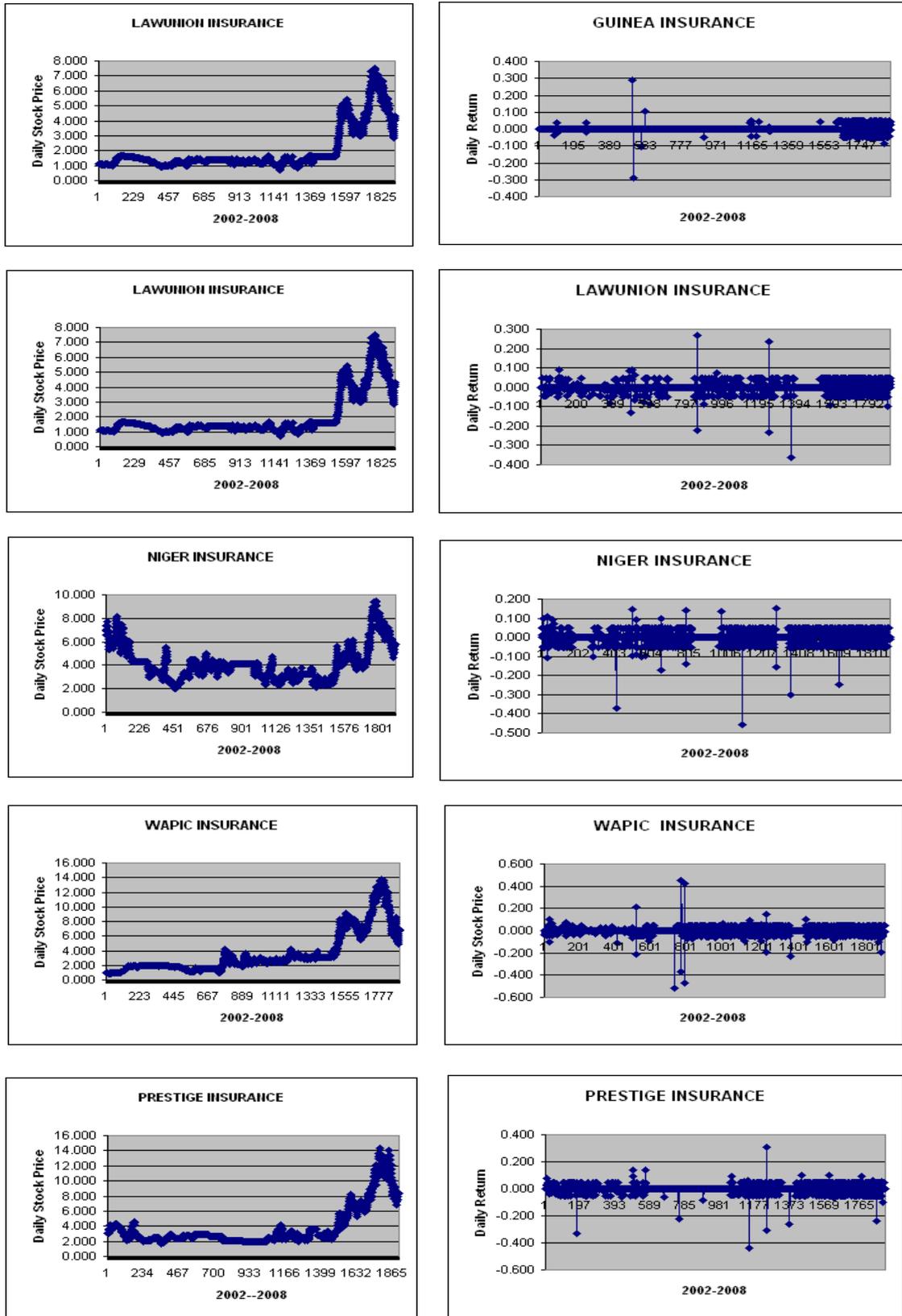


Figure 4.1. Stocks Prices and their Rates of Return Plots

Table 4.2. Summary of Model Parameters Estimation Statistics and Goodness of Fit

Insurance Stocks Return	Coefficients					Model Fit
	Model	α_1	α_2	β	γ	AIC
AIICO	ARCH(1)	0.5993*				-3.5070
Cornerstone	ARCH(2)	0.2830*	1.1449*			-3.6823
Crusader	GARCH (1,1)	0.6735*		0.6043*		-3.6390
Guinea	TARCH(1,1)	0.8370*		0.6637*	-0.6202*	-3.6802
LawUnion	EGARCH(1,1)	0.5805*		0.8002*	0.2542*	-3.7451
Niger	ARCH(1)	0.6875*				-3.6151
Prestige	ARCH(2)	0.3405	0.8349*			-3.7813
Unic	GARCH (1,1)	0.2856*		0.8128*		-3.9609
Wapic	TARCH(1,1)	0.2942*		0.8224*	-0.0514*	-3.9601
	EGARCH(1,1)	0.4516*		0.6558*	-0.2131*	-4.0170
	ARCH(1)	1.0829*				-4.3249
	ARCH(2)	0.9798**	0.4796*			-4.4873
	GARCH (1,1)	0.3487*		0.7747*		-4.7079
	TARCH(1,1)	0.4257*		0.7784*	-0.1732*	-4.7208
	EGARCH(1,1)	0.8225*		0.4005*	0.2010*	-4.7511
	ARCH(1)	1.0821*				-5.6918
	ARCH(2)	0.6135*	0.2904*			-5.7227
	GARCH (1,1)	0.2870*		0.6624*		-6.1059
	TARCH(1,1)	0.2774*		0.6760*	-0.0274	-6.1109
	EGARCH(1,1)	0.5935*		0.5965*	0.0776**	-6.1121
	ARCH(1)	0.3952*				-4.4568
	ARCH(2)	0.3194*	0.2041*			-4.4813
	GARCH (1,1)	0.1116*		0.9155*		-4.6944
	TARCH(1,1)	0.1180**		0.9168*	-0.0197	-4.6626
	EGARCH(1,1)	0.3549*		0.6853*	0.0569**	-4.6504
	ARCH(1)	0.7097*				-3.8990
	ARCH(2)	0.4751*	0.5148*			-3.9928
	GARCH (1,1)	0.2375*		0.8152*		-4.1665
	TARCH(1,1)	0.2320*		0.8149*	0.0116	-4.1655
	EGARCH(1,1)	0.2938*		0.8699*	0.0650**	-4.1747
	ARCH(1)	0.6546*				-4.2656
	ARCH(2)	0.6457*	0.3578*			-4.2999
	GARCH (1,1)	0.3897*		0.6120*		-4.3854
	TARCH(1,1)	0.4222*		0.6176*	-0.0774*	-4.3852
	EGARCH(1,1)	0.5302*		0.5115*	-0.0767*	-4.3849
	ARCH(1)	0.4861*				-3.7806
	ARCH(2)	0.4854*	4.49E-05			-3.7795
	GARCH (1,1)	0.4816*		0.1729*		-3.7793
	TARCH(1,1)	0.4373*		0.1463*	0.0864*	-3.7789
	EGARCH(1,1)	0.5611*		0.8177*	-0.0709*	-3.8360
	ARCH(1)	0.3545*				-3.9061
	ARCH(2)	0.3498*	0.0041			-3.9052
	GARCH (1,1)	0.3495*		0.1280*		-3.9052
	TARCH(1,1)	0.4155*		0.0990*	-0.1240*	-3.9052
	EGARCH(1,1)	0.4654*		0.6391*	0.0382*	-3.9075

* Significant at 1%; ** is significance at 5%; AIC is the Aikake Information Criterion

Table 4.3. Post Estimation Model Evaluation of Various Fitting Methods

Insurance Stocks Return	Lung-Jung-Box Statistics			ARCH-LM Test	
	Model	Residuals Q(16)	Standardized Squared Residuals Q(16)	L-Jung Q	P-value
AIICO	ARCH(1)	19.757	0.1232	0.010688	0.917660
Cornerstone	ARCH(2)	19.757	0.1232	0.161795	0.687509
Crusader	GARCH (1,1)	13.863	1.1424	0.041407	0.838755
Guinea	TARCH(1,1)	13.627	1.3104	0.100305	0.751465
Law Union	EGARCH(1,1)	18.381	0.9271	0.058057	0.809593
Niger	ARCH(1)	26.885**	19.925	0.003300	0.954200
Prestige	ARCH(2)	17.362	9.4460	0.012200	0.912000
Unic	GARCH (1,1)	21.076	1.7556	0.040550	0.840409
Wapic	TARCH(1,1)	20.426	1.6544	0.022327	0.881220
	EGARCH(1,1)	19.684	5.2043	0.074763	0.784524
	ARCH(1)	61.852*	11.331	0.079619	0.777814
	ARCH(2)	42.491*	10.166	0.474655	0.490854
	GARCH(1,1)	38.375*	9.9142	0.001800	0.966156
	TARCH(1,1)	50.028*	13.712	0.037943	0.845557
	EGARCH(1,1)	68.713*	5.5487	0.222644	0.637032
	ARCH(1)	163.93*	443.59*	0.009700	0.921542
	ARCH(2)	192.69*	444.82*	0.007498	0.930998
	GARCH(1,1)	41.135*	3.4633	0.002899	0.957060
	TARCH(1,1)	38.956*	2.7416	0.002840	0.957497
	EGARCH(1,1)	39.92*	2.9118	0.003848	0.950539
	ARCH(1)	21.416	4.9148	0.006354	0.936467
	ARCH(2)	17.564	1.7476	0.000537	0.981507
	GARCH (1,1)	8.5880	7.8475	1.122434	0.289395
	TARCH(1,1)	7.9477	8.0402	1.268512	0.260046
	EGARCH(1,1)	17.0780	1.1301	0.009131	0.923871
	ARCH(1)	21.8410	6.5390	0.767083	0.381121
	ARCH(2)	25.103**	2.7032	0.161860	0.687450
	GARCH (1,1)	33.754*	5.5467	0.011698	0.913870
	TARCH(1,1)	33.657*	5.5275	0.015006	0.902503
	EGARCH(1,1)	23.103	1.0384	0.164605	0.684952
				0.175493	0.675276
	ARCH(1)	30.300**	0.7677	0.138989	0.709289
	ARCH(2)	23.643	0.6835	0.065338	0.798249
	GARCH (1,1)	20.533	0.8526	0.062927	0.801927
	TARCH(1,1)	20.682	0.8697	0.031917	0.858209
	EGARCH(1,1)	20.799	0.3953	27.87219	0.000000
	ARCH(1)	149.43*	34.083*	27.99006	0.000000
	ARCH(2)	149.52*	34.196*	30.27402	0.000000
	GARCH (1,1)	142.23*	37.434*	30.12383	0.000000
	TARCH(1,1)	148.57*	37.769*	16.33927	0.000053
	EGARCH(1,1)	142.18*	35.066*	0.011449	0.914789
	ARCH(1)	17.839	0.2004	0.012948	0.909406
	ARCH(2)	17.519	0.1947	0.013028	0.909126
	GARCH (1,1)	17.503	0.1943	0.026365	0.871012
	TARCH(1,1)	17.448	0.2079	0.000258	0.987193
	EGARCH(1,1)	18.021	0.1931		

* Significant at 1%

** significance at 5%

Table 4.4. Out-of Sample Forecast Performance of Fitted Volatility Models

Insurance Return	Stocks	Model	RMSE	MAE
AIICO		ARCH(1)	0.045946	0.026017
		ARCH(2)	0.045942	0.025999
Cornerstone		GARCH (1,1)	0.045890	0.025735
		TARCH(1,1)	0.045788	0.025049
Crusader		EGARCH(1,1)	0.045741	0.024257
		ARCH(1)	0.042076	0.023657
Guinea		ARCH(2)	0.042103	0.024229
		GARCH (1,1)	0.042081	0.023784
Law-Union		TARCH(1,1)	0.042081	0.023781
		EGARCH(1,1)	0.042076	0.023615
Niger		ARCH(1)	0.033918	0.015998
		ARCH(2)	0.033911	0.015914
Prestige		GARCH (1,1)	0.033895	0.015666
		TARCH(1,1)	0.033886	0.015477
Unic		EGARCH(1,1)	0.033878	0.015283
		ARCH(1)	0.018666	0.006173
Wapic		ARCH(2)	0.018664	0.006210
		GARCH (1,1)	0.018660	0.006337
		TARCH(1,1)	0.018658	0.006439
		EGARCH(1,1)	0.018660	0.006161
		ARCH(1)	0.028822	0.015122
		ARCH(2)	0.028827	0.015187
		GARCH (1,1)	0.028827	0.015187
		TARCH(1,1)	0.028825	0.015160
		EGARCH(1,1)	0.028819	0.015074
		ARCH(1)	0.037125	0.024738
		ARCH(2)	0.037100	0.024316
		GARCH (1,1)	0.037100	0.024336
		TARCH(1,1)	0.037101	0.024341
		EGARCH(1,1)	0.037097	0.024131
		ARCH(1)	0.032594	0.017305
		ARCH(2)	0.032617	0.017609
		GARCH (1,1)	0.032602	0.016867
		TARCH(1,1)	0.032598	0.016802
		EGARCH(1,1)	0.032580	0.016377
		ARCH(1)	0.045908	0.028630
		ARCH(2)	0.045908	0.028630
		GARCH (1,1)	0.045910	0.028703
		TARCH(1,1)	0.045912	0.028735
		EGARCH(1,1)	0.045907	0.028516
		ARCH(1)	0.038597	0.020857
		ARCH(2)	0.038597	0.020852
		GARCH (1,1)	0.038597	0.020852
		TARCH(1,1)	0.038589	0.020726
		EGARCH(1,1)	0.038582	0.020711

RMSE = Root Mean Square Error, MAE = Mean Absolute Error