KWAME NKRUMAH UNIVERSITY OF SCIENCE AND

TECHNOLOGY, KUMASI

VOLATILITY ASSESSMENT AND VAR (P) MODEL FOR LISTED INSURANCE COMPANIES STOCK RETURNS, AN OVERVIEW OF GHANA STOCK EXCHANGE MARKET

By

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Declaration

I hereby declare that this submission is my own work towards the award of the MSc degree and that, to the best of my knowledge, it contains no material previously published by another person nor material which had been accepted for the award of any other degree of the university, except where due acknowledgement had been made in the text.

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Dedication

I dedicate this thesis to my parents Mr. and Mrs. Acheampong.

Abstract

The study investigated the presence of volatility in two insurance companies listed on the Ghana Stock Exchange as well as model the interdependencies between these two insurance companies. In checking the presence of volatility, several ARIMA (p,d,q) models were fitted separately to the log return series of the two companies and the best model selected using the AIC and BIC selection criterion. Using the selected ARIMA (p,d,q) models, the residuals of the model were obtained and presence of ARCH effects evaluated using the ARCH-LM test for each company. The ARCH-LM test revealed that there were no ARCH effects. The ARIMA (1,0,2) model was thus used in forecasting the returns of EGL whereas the ARIMA (1,0,1) model was used in forecasting returns of SIC. Finally, VAR (p) models were fitted to the combined series to check for interdependencies. Using the AIC and BIC, the VAR (7) model residuals were found to satisfy the null hypothesis of no serial correlation between the stocks, thus was selected as the best model. Investment with SIC and or EGL is strongly recommended since volatility is absent in their stock prices. The Ghana Stock Market is still developing, as a consequence management of these two listed companies is advised to put in place measures that will increase the frequency of trading these stocks.

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Throughout man's existence, he has been confronted with making choices. In business, in agriculture, in the industry, etc., we are presented with selecting an alternative possibility over the other. Usually, businesses, individuals companies and government agencies forecast increase in demand and need to raise additional capital to meet its needs. Some individuals and firms however, have incomes that are greater than On the other hand their current expenditure, thus, they have funds to invest. To a large extent, for an economy to be healthy, it depends on an efficient transfer of funds from people with surpluses to firms and those individuals who are in need of capital. Without such efficient transfer, capital economics simply would not function. People and organizations who wish to borrow money are brought together under the same umbrella with those who have surplus funds to invest in financial markets.

However, we live in a world of uncertainty, and the financial markets or security markets do have in inherit perils. Because an accurate measurement of forecast of expected future events is not easy asserting, because most activities has uncertain future or outcome we say such activities are risky. There is therefore risk in everything we do. Risk is a fact of life and for any investor risk must be considered in every financial decision making. When investors put up their money to buy shares of a company at the stock market, they expect to receive returns on their investment from future cash flows otherwise they would not invest. However, there is the potential variability in such future cash flows; there is the possibility that a new project we invest in may suffer delays and inflation.

There is also possibility that the sales of a company may decline relative to its past sales or the company may be bankruptcy and collapse. In such an uncertainty world, an accurate measurement of expected future cash flows is not easy for an investor to ascertain. Whatever, the risk inherent in a project affects the ability of a firm to repay the money investors put up and the returns the investors require.

1.1.1 Financial Market

Though there are several financial markets, the study is basically carried out in the primary and especially the secondary markets. A primary market is a market in which corporations raise new capital whereas secondary markets are markets in which existing and already outstanding securities are traded among or between investors (Brigham & Ehrhadardt, 2013). The stock market is most active and the most important secondary market.

1.1.2 The Stock Exchange

An organized market in which securities are traded is called a stock exchange. On this market, the individual can buy shares of companies and by so doing becomes a part owner or a shareholder of these companies. Individuals or companies can buy stocks and bond from other companies as well as government, becoming lenders or creditors of these companies or government. An individual or company who has ever lent money or bought shares through the stock exchange from a company can also resell to these securities through the stock exchange at any time.

1.1.3 The Stock

Stocks and bonds are long term securities that yield fixed interest issued by government and companies. A Share represents a part-ownership in a business entity. Shareholders are therefore, seen as owners of a company and are entitled to vote in in issues of the company. The higher the required rate of return the riskier the stock. If you invest in a stock instead of buying a bond, you will again expect to earn are turn on your money. A stocks return comes from dividends plus capital gains. The higher the probability of a firm failing to perform as expected, the higher the expected return must be, in order to induce an investor to invest in the stock.

Most firms may have a single type of common shares, in such a case, classified shares are used to meet the needs of the company. Classified shares are therefore used in order for the public to take a position in a conservatively financed growth company, without sacrificing income.

Since some companies are so small that their common shares are not actively traded, only a few people own their stocks or have shares in them. Their stocks are called closely held stocks. The companies and their stock are said to be unlisted. The stocks of larger companies however, are mostly owned by large number of investors, though majority of them are not active in management. Such companies are called publicly owned corporation and their stocks is called publicly held stock. Generally, large companies apply for listing and formal exchange and are said to be listed. Common shares represent an ownership interest in a corporation. To the typical investor, a stock is simply a piece of paper characterized by two features.

A stock gives its owner the right to dividends after the company has earnings. Out of these earnings, the dividends are paid. This happens only when management decides to pay dividends rather than holding and reinvesting all earnings. Though a bond contains a promise to pay interest, common shares provide no promise of interest payment (Raju *et al*, 2004). Once you own stocks, you may expect a dividend, but it does not necessarily mean the expectations will be met. Note, though, that a company will continue to pay interests on its bonds, even if the company does not make profit. Otherwise, the company will be declared bankrupt, and the bond holders may potentially take over the company.

Stocks could be sold at some future date, hope fully at a price greater than the purchasing price. If a share is sold at a price beyond its purchase price, the investor will receive a capital gain. Mostly, at the time people buy stocks/shares, they do expect to receive capital gains, otherwise, they would not purchase the shares. However, for a fact, one can end up with capital losses rather than capital gains.

1.1.4 The Internationalization of Stock Exchange

The globalization has come for needs of stock exchanges to integrate. In the US, the leading stock market is the New York Stock Exchange and the NASDAQ. In the United Kingdom, the London Stock Exchange is the most established stock market. The Ghana Stock Exchange is one of the emerging financial markets in Africa where there are established markets in South Africa and Nigeria. Whilst the European and the US stock markets have been in operation for most of Africa's 21 exchanges were opened with the hope of keeping domestic capital right at home (Charles & Todd, 1998).

The world's 16th largest stock market, the Johannesburg exchange has led to talks of Africa's exchanges getting closer and closer to forging close ties. The South African market is already in trading links with markets of Namibia, Zimbabwe, Zambia and Ghana. Many stock market watchers are already dreaming of a Pan-African Stock Market. For eight mainly Francophone West African countries, a joint bourse already exists. From the United Nations Development Programme, 2,200 African companies are listed on the continent's various exchanges. The international financial markets have experienced a lot of changes in the last two decades. Advances in technology along with the globalization of banking and commerce have led to deregulation, and this has increased competition throughout the world.

There is therefore a need to motive greater corporation among regulators at the international level. Factors that complicate such co-ordination include the differing structures between nations and security industries, the trends towards financial service conglomerates and the reluctance on the part of individual countries to hand over control of their various national monetary policies. Above all these, there is still the need to close the gaps in worldwide markets.

One of such important considerations when applying the market model is the measuring of the return series for both the stock and the market index. One has the choice to measure returns either discretely or continuously, however, consistency in the method used must be maintained between the asset returns and market index proxy. According to Bradfield (2003), it is a generally accepted idea, that returns are generated continuously through calendar time, but since trading occurs at discrete intervals, observers view returns as if they are generated at discrete intervals.

1.1.5 Length of the Estimation Period

The estimation period has always been greatly debated upon because different estimation periods give different values of beta. If beta is estimated based on several years of historical data it could be of little significance because the nature of the business including its risk undertaken by companies more probably than not may have changed significantly over a long period such as ten years (Bradfield, 2003). Bradfield claims that a five year estimation period is reasonable because research has shown that beta tends to be reasonably stable for five year periods.

Return on stock of a firm is crucial of area of investment management. The important aspect of it is returns on stock of a firm at the stock market. Return on stock is the most significance part of investment to investor. In theory, the objective of returns on investment is to maximize shareholders wealth.

A high return on stock means an appreciable return or an investment and on the other hand, a low return on stock means unappreciable return on stock at particular market. The situation describes above show how a market of particular type is volatile and that may affect or influence the return on a stock of a firm. In the past years, the return on a stock has become debatable in various stock market worldwide and various criticism have gone about the behavior of some stock at particular market. Due to this impasses some stock market have gone on numerous measures to check or control the volatility of the stock market as against its returns on particular market and Ghana is no exception (Burton, 2003).

In view of this, the study attempt to investigate the volatility of Ghana stock exchange using two listed companies.

1.2 Statement of the Problem

The recent economic trend of development in Ghana and as an emerging economy, a capital flight has a major role to play in execution of such developmental projects which needs high financial requirement of funds/capital to finance them which can be source it by both internal or external for such volume of capital flows into the economy.

Now, the Ghana stock exchange market is one of the important internal source for both companies or Government can raise amount capital require to finance their developments project, but the Ghana stock exchange market is considered to be an emerging market and however to raise huge capital funds from such market post a lot of treat to an investor due to damage or shock to investors as a result of variability in the market returns in Ghana stock exchange.

In theory, the objective of returns on investment is to maximize shareholders wealth. A high return on stock means an appreciable return or an investment and on the other hand, a low return on stock means unappreciable return on stock at particular market. The situation described above shows how a market of particular type is volatile and that may affect or influence the return on a stock of a firm. In the past years, the return on a stock has become debatable in various stock markets worldwide and various criticisms have gone on about the behaviour of some stock returns/prices at particular market.

Fundamental questions this thesis seeks to investigate are;

1. Volatility in the stock market.
2. Secondly, what accounts for the volatility and what conclusions can be drawn?

1.3 Objective of the Study

It is generally believed that over the year's risk factor effects has been a major issue between the investors and investing institutions/individual and the market stock return on asset.

The central focus of the study is;

1. To investigate the presence of volatility in the two companies.
2. To fit an appropriate ARIMA(p,d,q) model to the return series of the two companies, whether volatile or not.

3. To forecast returns of the two companies based on the selected model.

4. Modelling return series of the two companies using a VAR (p) model.

1.4 Justification/Significance of the Study

The study would aid us to estimate the expected future volatility rate of the two listed insurance companies thus State Insurance Company (SIC) and Enterprise Group Limited (EGL) at the Ghana Stock exchange index.

An essential part of estimating for market volatility among its stocks returns is creating provisions for market participants to know the market returns expected which is highly volatile and which of the two stocks institutional investors/Individuals should buy into in other to maximize the shareholder wealth of the capital market in Ghana.

The institutional investor/speculators can ensure financial security to those who meant the most corporate stakeholders who takes earns from the market.

This study seeks to provide fundamental model to forecast into the future market stock returns which may serve as predictive model to Ghana capital market. Stock prices change over time and one of the best tools to analyze this change is time series models.

1.5 Methodology

To achieve the proposed of objectives of this study various time series techniques will be used such as; Box-Jenkins model (ARIMA), ARCH/GARCH and a

VAR(p) model to investigate market volatility as well as interdependence between the two insurance companies. Data for the study was obtained from the Ghana Stock Exchange website (www.gse.com.gh). The R software is used for the analysis.

1.6 Limitation of the Study

The study is limited in terms of coverage nature of time size and data available to support fully comprehensive approach for model for the selected companies' stock return estimation.

1.7 Brief History of Ghana Stock Exchange

A stock exchange is regarded as an organized and regulated market where securities (shares, bonds, notes) are bought and sold at prices determined by the forces of demand and supply. A Stock exchange serves as a primary market where corporations and governments raise capital by channeling investors' savings into productive ventures. It is also seen as a secondary market where investors can sell their securities to other interested investors for cash. This in turn reduces volatility involved in investment returns and maintains liquidity in the system.

The Ghana Stock Exchange (GSE) is the main stock exchange of Ghana. It was incorporated in July 1989 with trading starting in 1990. Currently, there are 37 listed equities (from 35 companies and 2 corporate bonds). All types of securities can be listed on the GSE. The criteria for getting listed on the exchange include, capital adequacy, profitability, spread of shares, years of existence and management efficiency. The GSE's listings have been included in the All-Share index since its inception. The principal stock index of the GSE is the GSE Composite Index. This index is calculated from the values of each of the market's listings.

1.7.1 Brief History of Insurance Sector

Ghana's insurance industry is quite competitive with 43 companies competing for an insurance market with a total population of 25.4 million. Currently, 25 companies operate in the non-life insurance industry while 18 companies compete in the life insurance industry. However, top six companies in the non-life insurance and top four companies in the life assurance industry control over two-thirds of the respective markets. Ghana's insurance industry has low capital requirement compared to other African countries such as Nigeria and companies with 100% foreign ownership are allowed to operate in the domestic insurance sector. Driven by these easy entry norms, many international major companies with significant experience in insurance industry including Allianz and Prudential have entered into Ghana's insurance market. World Bank has also highlighted the concerns that there are far too many players in Ghana's insurance industry with most of the companies being under capitalised and operating at less than optimum level. In the non-life insurance industry, eight new players have entered the market between 2007 and 2012 and have gained a market share of 11.2%. This has reduced EGL's market share in non-life insurance industry from 11.6% to 8.7% during FY 2007–12 and has slipped to fourth position from being the second largest player earlier. On a comparative basis, the competitive intensity in nonlife insurance industry is significantly higher compared to life insurance industry.

1.8 Brief History Sic Insurance Company Limited

SIC Insurance Company Limited is one of the oldest non-life insurance companies in Ghana. It was established in the year 1955, when the Gold Coast Insurance Company was established. It was renamed Ghana Insurance Company in 1957 after Ghana attained independence. SIC is a leading provider of general or nonlife insurance products in Ghana. Business operations cover fire insurance, motor insurance, marine and aviation insurance, and accident insurance. SIC is also a provider of specialty insurance products such as hoteliers and leisure policy, a policy for the hospitality industry. The Company has consistently maintained steady market leadership. In 2006, SIC had approximately 40% of the insurance industry's total market share (www.sic-gh.com).

1.9 Brief History of Enterprise Group Limited

Enterprise Group Limited (EGL), a holding company with operations in Ghana's life and non-life insurance industry, with a SELL rating and P/B based target price of GHS 1.28 per share. EGL's revenue growth has been forecasted to slow down due to macro-economic headwinds and lower investment income compared to the previous year. In addition, the Ghanaian insurance industry has been found to be highly competitive with limited barriers to entry and price-based competition eroding operating margins. Enterprise Group was incorporated on 24th November 2008 and is the holding company of Enterprise Insurance, Enterprise Life, Enterprise Trustees (our pensions subsidiary) as well as Enterprise Properties (www.enterprisegroup.net.gh).

1.10 Organization of the study

The study made up five 5 main chapters. The current has provided general overview of the market volatility and its returns, Objectives of the study, Statement of the Problem and Significance of the study. The remainder of the study is organized as follows.

Chapter two presents the theoretical considerations and relevant prior work on market volatility and stock returns. It began with general introduction on the topic, and reviews of the historical background of market stock return and corporate stock return.

The chapter three drew it attention to the relevant statistical and actuarial models for the analysis of data and forecast into the future stock returns of the listed insurance companies. Chapter four critically examined and discussed the results of the empirical testing. The chapter provided a descriptive statistics of all variable and used in the study along with some models to make forecast into the future returns to the listed insurance company in Ghana.

Finally, chapter five provides a summary of the thesis and concluding remarks, including implications recommendations based on the outcome into the future.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The increased establishment and development of equity markets in developing economies since 1990 has been associated with the need to benefit from foreign portfolio investment. It is also to provide an attractive avenue for companies seeking to raise funds for much needed industrial and development projects. Issues of extreme illiquidity and high risk premiums, however, are cited as the major concerns of both potential investors and firms seeking to raise capital from cheaper sources and to diversify ownership through a domestic listing (Lesmond, 2005; Hearn *et al*., 2009)

Previous studies have shown that the absolute price change in the stock market has a positive correlation with the trading volume. Karpoff (1987) had a survey about the relationship between price changes and trading volume. In his study, both equity and futures market were examined by using different measurements of price changes and trading volume.

2.2 Concept of Volatility

Volatility can be described broadly as anything that is changeable or variable. Volatility can be defined as the changeableness of the variable under consideration; the more the variable fluctuates over a period of time, the more volatile the variable is said to be. The beta concept arises because all stocks tend to move to some degree with movements in the overall market.

However, the returns of some stocks move more aggressively than others when the market moves. It is thus important as academicians and investors to be able to measure the extent to which a stocks return moves relative to the overall market index. This is achieved by measuring a stocks beta coefficient. According to Brenner and Smith, an accurate estimation of beta is important for at least two reasons. Firstly, beta is important to understanding the risk return or risk - reward relationship in capital market theory. This theoretical relationship can be established by analyzing the expected return beta relationship as a reward risk equation (Bodie *et al*, 2008).

According to (Bodie *et al*, 2009), the beta of a security is the appropriate measure of its risk. This is because beta is proportional to the risk that a security contributes to an optimal risky portfolio. In the world of finance as in common reasoning, one would expect the reward or the risk premium on an individual asset to depend on the contribution of the individual asset to the overall risk of the portfolio. The required risk premium or expected return should be a function of its beta, since the beta of a stock measures its contribution to the variance of the market portfolio for any asset or security. Thus, the higher the beta value of a security, the higher the risk premium one should expect. Secondly, an accurate estimation of beta is important because it aids in making investment decisions (Alexander & Chervany, 1980).

Due to the fact that an understanding of a security's beta measures the effect of systematic risk on a particular security, beta is thus, an extremely useful tool for investors to understand how to create their own individual portfolios in accordance with their ability to take risk or in accordance to their risk profile. In addition, beta is important in investment decision process because it is very useful to a portfolio manager in assessing the downside risk of his portfolio during bear market (Ambachtsheer, 1974). Though beta estimates are widely used in estimating systematic risk, research revealed that one of its limitation as argued by critics is that, there is some level of confusion surrounding optimal estimation level interval. However Basel in his article, on the assessment of risk concludes that, a forecaster or analyst would be better off using a longer estimation interval such as yearly or monthly interval when calculating or estimating beta as it provides a more stable beta estimate.

The beta coefficient of the market model has gained wide acceptance as a relevant measure of risk in portfolio. Securities analysis as such is used to measure the risk profile of companies over different markets. As an index, the beta value of systematic risk, measures the sensitivity of stock returns to changes in returns on market portfolio (Klemkosky & Martin, 1975). The beta value of a portfolio is a weighted average of the individual stock beta values in the portfolio.

2.3 The Market Index

According to (Bradfield, 1993), market capitalization weighted indices, in theory, are preferred to equally weighted indices since they are superior proxies to the true market portfolio. In Ghana for example, it would be preferred that the GSE All Share Index be used as the market index. Some critics have argued that market must be segmented and the market index taken from the segmented market (Bradfield, 1993). Whichever index one decides to use, the received and accepted theory is that the index used must be comprehensive as possible in representing the entire market.

2.4 The Returns Measures

One of such important considerations when applying the market model is measuring of the returns series for the stock and the market index. One has a choice to measure returns either discretely or continuously, however, consistency in the method used must be maintained between the asset returns and market index proxy. The estimation period has always been greatly debated upon because different estimation periods give different values of beta. If beta is estimated based on several years of historical data it could be of little significance because the nature of the business including its risk undertaken by companies more probably than not may have changed significantly over a long period such as ten years (Bradfield, 2003). Bradfield claims that a five year estimation period is reasonable because research has shown that beta tends to be reasonably stable of five yearly periods. He reasoned that, selecting a five-year period represents a satisfactory trade-off between a large enough sample size in order to enable reasonably efficient estimation and a short enough period over which the underlying beta could be assumed to be stable.

Theodossiou et al provides evidence that volatility in Japan and the UK stock markets were the same during both the pre and post October 1987 crash while US volatility was higher prior to the October 1987 crash period.

Analysis of the stock market for the evaluation of risk has assumed greater significance since usefulness of efficient stock market in mobilizing resources is well known. Volatility in the price of stocks can arise because of several reasons and it adversely affects individual earnings and health of the economy.

The growing role of the financial sector in efficiently allocating resources at appropriate prices could significantly improve the efficiency of an economy. If financial markets work well, they will direct resources to their most productive uses whereas risk will be accurately priced and borne by those who are not risk averse.

A volatility model should be able to forecast volatility. Financial uses of volatility include forecasting aspects of future returns. The study of financial assets volatility is important to academics, policy makers and financial market participants for reasons which includes serving as a measure of risk in investments. A volatile market is also a concern for policy makers since instability of the stock market creates uncertainty which no investor likes. This adversely affects growth prospects. There was evidence that when markets were perceived to be of high volatility, it may act as a potential barrier to investing (Raju, M. T., Ghosh and Anirban 2004).

Hien (2008) examined stock return volatility in Vietnam stock market. In his work, he used variants of the GARCH models (both symmetric and asymmetric) with a data set of VN-index over six years. His studies revealed the inappropriateness of asymmetric GARCH in modeling the Vietnam stock return volatility. The results also showed that the GARCH (1,1) and GARCH (2,1) were better than the other GARCH models used in the work. The study however showed that the excess kurtosis and skewness in residual series of the Vietnam stock return were profound.

Bhardwaj *et. al*, (2014), in a study of time series with models which were non-structural-mechanical in nature used the Box-Jenkins autoregressive integrated moving average (ARIMA) and the Generalized Autoregressive Conditional Heteroscedastic (GARCH) models. The models were used for the modeling and forecasting of spot prices of Gram in the Delhi market. The Augmented Dickey Fuller (ADF) test was used to assess stationarity of the series and the ARCH LM test used to check for the volatility. They found out that the ARIMA model could not capture the volatility present in the data set whereas the GARCH model successfully captured the volatility. The GARCH (1,1) model was found to be a better model for estimating daily price of Gram than the ARIMA model.

Bhushan *et. al*, (2012), discussed the techniques of modeling of analytics for forecasting. They investigated the application of ARMA and GARCH models to fit historical data and estimate the coefficients for the prediction of a day-ahead electricity demand.

Pesaran & Timmermann (2004), present analytical results that quantify the effects of structural breaks on the correlation between forecast, realization and ability to forecast the sign or direction of time series subject to breaks. Their results suggested that it could be very costly to forego breaks. They concluded that forecasting approaches conditioned on the most recent breaks were more likely to perform better than unconditional approaches that used expanding or rolling estimation windows.

Joshi (2010), investigated the stock market volatility in the India and China stock markets using their closing prices. The results revealed the presence of non-linearity using BDSL. The ARCH-LM test also revealed conditional heteroscedasticity. The findings revealed that the GARCH (1,1) model successfully captured non-linearity and clustering of volatility. The analysis showed that volatility was more persistent in the Chinese market more than in the Indian market.

Ederington & Guan (2004), compare existing volatility models in using the following attributes; the relative weighting of recent versus older observations, the estimation criterion, the trade-off in terms of out-of-sample forecasting error between simple and complex model, the emphasis placed on large shocks. Their study found out that financial markets have longer memories than what is depicted in the GARCH (1,1) model estimates. Though it had little impact on an out-of-sample ability to forecast. The study revealed that, more complex models that allow for a more flexible weighting pattern than the exponential model, forecast better on an in-sample basis. Since there is the additional estimation error introduced by an additional parameter. Their study again showed that, with the exception of GARCH models, those based on absolute return deviations generally, forecasted volatility much better than those based on squared return deviations. The GARCH (1,1) was found to generally produce better forecasts when compared with the historical standard deviation and exponentially weighted moving average models.

Aguilar (1999) investigated the information content and predictive power of implied volatility from currency options traded on the OTC-market. His study evaluated implied volatility against other forecasts based on option prices and against volatility forecast models that were strictly historical by nature. He found that, implied volatility had predictive power in forecasting future volatility for shorter forecast horizons. Although in most cases the forecasts were biased. He found also that, for some currencies, the GARCH volatility forecasts outperformed implied volatility forecasts.

Antonakakis & Darby (2012) identified the best models for forecasting volatility of daily exchange returns of some developing countries. Emerging consensus on countries noted the superior performance of the FIGARCH model and this was affirmed in their study. They however show that when dealing with developing countries' data, the IGARCH model results performed best.

Ahmed & Shabri (2013) apply GARCH model in modeling time series of crude oil. This was done to illustrate the advantages of these non-linear models. They fit three GARCH models; the GARCH-N, the GARCH-t and the GARCH-G to forecast crude oil spot prices. The study used two crude oil prices from West Texas intermediate and Brent to evaluate the performance of the models developed. Their results revealed that whereas the GARCH-N model was best for forecasting for Brent, the GARCH-G model was best for forecasting for WTI crude oil spot prices. This was done by checking their Mean Square Error (MSE) and Mean Absolute Error (MAE).

Aziz & Uddin (2014) studied the volatility of the Dhaka Stock Exchange (DSE). Their study used GARCH models to estimate the presence of volatility in the DSE. Though volatility was a common phenomenon in their capital market, their study recommended a careful monitoring of volatility. They also recommended that the activities of corporate insiders should be properly checked and that information should be made available to all of the interested investors.

Kamel *et.al* (2014) measured the contagion phenomenon between foreign exchange markets during Subprime crisis and Eurozone crisis. The data used was daily data from 03/01/2005 to 02/01/2014 for fourteen selected countries. The GARCH (1,1), the GJR-GARCH (1,1), the EGARCH (1,1) and the
APARCH (1,1) models were employed. In the study, they discriminated between independent floaters and managed floaters exchange rate as well as separated the period estimates in two period's crises. They concluded that all the exchange rates return series influenced by the contagion effects came from the USA and the Euro area over 2007-2012 periods. Volatility was found to be high in the countries that adopted independent floating exchange rates compared with countries that supported managed floaters.

Hansen & Lund (2001) used intra-day estimated measures of volatility in their study, to compare volatility models. They evaluated whether the evolution of volatility models had led to better forecasts of volatility when compared to the first "species" of volatility models. They used an out-of-sample comparison of 330 different volatility models using daily exchange rate data and IBM stock prices. Their study found that the best models did not provide significantly better forecasts than the GARCH (1,1) model.

Ahmed & Suliman (2011) used GARCH models to estimate volatility using the daily returns of the Khartoum Stock Exchange (KSE). The models included both symmetric and asymmetric models that captured the common stylized facts about index returns such as volatility clustering and leverage effect. Their results revealed that the volatility process is highly persistent and also explained that high volatility of index return series, over the sample period, is present in the Sudanese stock market.

Kumar (2006) evaluated the ability of ten different statistical and econometric volatility forecasting models using the Indian Stock market. This was based on out-of sample forecasts and the use of several evaluation measures. The study concluded that GARCH (4,1) model and EWMA methods led to a better forecast of volatility whereas the GARCH (5,1) model was best suited to the forex market.

Mahajan & Singh (2012) examined the impact of futures trading on contemporaneous and inter-temporal relationship between return, volume and volatility in the Indian Stock market using daily closing prices. The results of ARMA (3,2), GARCH (1,1), EGARCH (1,1) as well as the Granger causality test revealed that, information asymmetry, inefficiency and leverage effect were present.

Corhay & Rad (1994) checked whether autoregressive conditional heteroscadastic models could adequately describe stock price behaviour in European capital markets. Their study was to assess whether the models were suitable in markets which were smaller than those in American. They looked at the France, Germany, Italy, the Netherlands and the UK markets. Estimating ARCH and GARCH models of various orders revealed that the GARCH (1,1) model generally outperformed other ARCH/GARCH models in all the markets with the exception of Italy.

Kang, Cho & Yoon (2009) in their work observed that controlling sudden changes effectively did reduce the long memory property in the Korean market and Japanese stock market using a fractionally integrated GARCH (FIGARCH) model. Their study identified that sudden change is generally associated with several major economic and political events. The study suggested that adding information regarding sudden changes in variances improved the accuracy of estimating volatility.

Marzo & Zagalia (2007) study the properties of forecasting of linear GARCH models for closing-day futures prices of crude oil that is sold on the NYMEX. Their study compared volatility models based on the normal innovations, the Student's t innovations and the Generalized Exponential Distribution (GED). The main aim of the study was to check an out-of-sample predictability. Based on the test for predictive ability, the results revealed that the GARCH-GED performed far better one to three days ahead.

Mohan, G. *et.al* (2002), studied the change in volatility in the Indian stock market due to the introduction of futures trading. The study used daily closing prices of Nifty and weekly closing prices of Satyam Computers Ltd. The stocks were found to be slightly volatile and their volatility had become less dependent on past volatility but more dependent upon news in the current period. The studied revealed that the average long-term volatility had decreased at an index level.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The methodology of this study deployed for the performance of the required analysis to address the stated objectives depends on daily stock returns data recorded on two insurances companies listed in GSE market.

3.2 Source Of Data

The study would focus on the application of specifically secondary data.
The secondary data consist of daily market stock returns. Currently, there are thirty-six (36) listed commercial entity in GSE market and out of this number only two (2) insurance companies are directly listed entity in the market namely States Insurance Company and Enterprises Group Limited. A daily market stock return and the firms stock returns data were sample from range of 2008-2014, obtained from Ghana stock exchange market would be analyzed to investigate the market's volatility as against stock returns of the listed companies. Descriptive statistics would be used to present graphs and tables for returns the stock returns of the companies.

3.3 Review of the ARIMA Model

An autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. ARIMA models are fitted to time series data in order to better understand the data or in order to forecast.

They are applied in various cases where the data showed evidence of nonstationarity. In a case where an initial differencing step can be applied to remove the non-stationarity. The general form of the ARIMA (p,d,q) model is given as:

$$\phi(B)(1-B)^d(y_t-\mu)=\theta_q(B)\varepsilon_t \quad (3.1)$$

Where, $\varphi(B)=1-\sum_{i=1}^{p}\varphi_i B^i$ and $\theta_q(B)=1-\sum_{j=1}^{q}\theta_j B^j$ are polynomials in terms of B of degree p and q and B is the backward shift operator. $\phi_1,\phi_2,\ldots,\phi_p$ are the autoregressive parameters with order p $\theta_1,\theta_2,\ldots,\theta_q$ are the moving average parameters with order q

3.4 General Patterns of Time Series Analysis

Time Series patterns can be described in terms of four basic components, the trend, cyclical, irregular and the seasonality. The trend represents a general systematic linear or non-linear components that change with time and do not repeat within the time range captured by the data. The seasonality may have a similar nature, however, it repeats itself in systematic intervals over time. These general classes of Time Series components may both appear in a data.

3.5 Trend Analysis

The trend of a Time Series, such as registration of members of vehicles can be approximated by a straight line or a non-linear curve. A linear trend equation is used to represent a Time Series data that can be increasing or decreasing by equal amount from one period to another. The linear trend equation can be fitted to a Time Series using the least square method of fitting a straight line. However, if the there is a large number of time periods, say 12 years and the magnitude of time figures is large, then it is computationally easier to fit the least squares line by using what is called the coded method. For example, given $Y = a+bx$ as the least square line equation, the estimate of 'a' and 'b' in the least square line can be computed and therefore, the forecasting for Y can be estimated.If the Time Series data tend to approximate a straight line trend, the equation develop by the least squares method can be used to predict (or forecast) figures for some future periods. This is done first by coding the year value for which a prediction is to be made. Then, by substituting the coded value to the least square equation, the predicted value can be computed.

3.6 Seasonality Analysis

The analysis of a seasonal variation over a period of time can also be useful in evaluating current figures. There are several ways of analyzing a time series in order to isolate the seasonal variation. The most popular one is the method of moving average. The moving average method is used in measuring the seasonal fluctuation of a time series. It can also be used to smooth out fluctuations by moving the mean values through the data

3.7 Cyclical Analysis

This type of component is very common with data on business and economic activities. It consists of a period of Prosperity followed by periods of recession, depression and recovery in that order. An important example of cyclical variation is what is called business cycles. In business and economic activities, if variations recur after yearly intervals, then they are considered cyclical.

3.8 Irregular Analysis

Irregular component or variation in Time Series refers to the odd movements of a time series, which are due to chance. Events that may lead to such odd movements include industrial actions, earthquakes, floods, outbreak of epidemics and many more. Irregular variation is a combination of episodic and residual (chance) variations. Episodic variation, though unpredictable, can be identified. For example, the effect of an earthquake on a national economy could easily be brought to bear, but earthquake itself could not have been predicted. Residual variation, on the other hand, is unpredictable and cannot be identified.

3.9 White Noise Processes

A white noise process is a serially uncorrelated, zero- mean, constant and finite variance. That is, a time series y_t is a white noise process if;

$$E(y_t) = 0, \forall t$$

$$var(y_t) = \sigma^2, \ \ \forall t, \ \ \sigma^2 < \infty$$

$Cov(y_t, y_s) = 0$ if $t = s$.
In this case we often write,

$$Y_t \text{WN}(0,\sigma^2) \text{ if } Y_t \text{WN}(0,\sigma^2) \text{ then } \gamma(\tau) = \sigma^2, \tau = 0, \text{ if } \tau = 0$$

$$P(\tau), p(\tau) = 1, \text{ if } \tau = 0$$

3.10 Continuously Compounded Return (Log Return)

The continuously compounded return or log return is the natural logarithm of the simple gross return of an asset.

$$r_t = \text{In}(1 + R_t) = \text{In}\frac{P_t}{P_{t-1}} \tag{3.2}$$

Continuously compounded returns r_t have some advantages over the simple net returns R_t. Considering multi-period returns;

$$r_t = \ln(1 + R_t[k]) = \ln[(1 + R_t)(1 + R_{t-1})\ldots(1 + R_{t-k+1})$$

$$= \ln(1 + R_t) + \ln(1 + R_{t-1}) + \ldots + \ln(1 + R_{t-k+1})$$

$$= r_t + r_{t-1} + \ldots + r_{t-k+1} \tag{3.3}$$

Therefore, the continuously compounded multi-period return can be seen as the continuously compounded one period returns involved. Also, the statistical properties of the log return are more easily managed.

3.11 Method of Estimation for GARCH(p,q) model parameters

Maximum likelihood estimation is commonly used in estimating GARCH models. The log-likelihood function of GARCH (p,q) is:

$$l(\theta|\omega_1,\ldots,\omega_T) = \log[f(\omega_T|F_{T-1})f(\omega_{T-1}|F_{T-2})\ldots f(\omega_{p+1}|F_p)f(\omega_1,\ldots,\omega_p;\theta)]$$

$$= \log f(\varepsilon_1,\ldots,\varepsilon_p;\theta)\log\left[\prod_{t=p+1}^{T}\frac{1}{\sqrt{2\pi\sigma_t^2}}\exp\left(-\frac{\varepsilon_t^2}{2\sigma_t^2}\right)\right]$$

$$= \log f(\varepsilon_1,\ldots,\varepsilon_p;\theta)\left[-\frac{1}{2}\sum_{t=p+1}^{T}\left(\log(2\pi)+\log(\sigma_t^2)+\frac{\varepsilon_t^2}{\sigma_t^2}\right)\right]$$

Where θ is the set of all parameters to be estimated, $f(\varepsilon_s|F_{s-1})$ is the density of ε_t thus the error term conditional on the information contained in (ε_t) up to time $s - 1$ and $f(\varepsilon_1,\ldots,\varepsilon_p;\theta)$ is the joint distribution of $\varepsilon_1,\ldots,\varepsilon_p$.

Due to the complicated nature of $f(\varepsilon_1,\ldots,\varepsilon_p;\theta)$, the usual practice is to discard that term and use the log-likelihood, that is:

$$l(\theta|\varepsilon_1,\ldots,\varepsilon_T) = -\frac{1}{2}\sum_{t=p+1}^{T}\left(\log(2\pi)+\log(\sigma_t^2)+\frac{\varepsilon_t^2}{\sigma_t^2}\right) \tag{3.4}$$

The σ_t^2 in the log-likelihood function is not observable and has to be estimated recursively

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \varepsilon_{t-1}^2 + \ldots + \beta_p \varepsilon_{t-p}^2$$

The initial values of σ_t^2 are usually assigned to be the unconditional variance of ε_t, which is given by:

$$\frac{\omega}{\left(1 - \sum_i \alpha_i + \sum_i \beta_i\right)}$$

Maximizing the log-likelihood yields what is called the quasi-likelihood estimation.

3.12 Vector Auto Regression (VAR) Model

The vector autoregression (VAR) is a model used to capture the linear interdependencies among multiple time series. The VAR models are a generalization of the univariate autoregressive (AR). The VAR model does this by allowing for more than one evolving variable. A VAR model is used to describe the evolution of a set of n variables over the same sample period (t = 1,...,T) as a linear function of only their past values. The variables are collected in a $k \times 1$ vector y_t, which has as the i th element, $y_{i,t}$, the observation at time "t" of the i th variable. A p-th order VAR, denoted VAR (p), is

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + e_t \qquad (3.5)$$

where the l-periods back observation y_{t-1} is called the l-th lag of y, c is a $k \times 1$ vector of constants (intercepts), A_i is a time-invariant $k \times k$ matrix and e_t is a $k \times 1$ vector of error terms satisfying.

3.13 Applied Tests

3.13.1 KPSS Test for stationarity

The KPSS test provides a test for the null hypothesis of trend stationarity against the alternative of a unit root.

$$Y_t = \beta t + (r_t + \alpha) + e_t \tag{3.6}$$

Where; $r_t = r_{t-1} + \mu_t$ is a random walk, the initial value $r_0 = \alpha$ serves as an intercept t is the time index.

μ_t are independent and identically distributed $(0,\sigma_\mu{}^2)$

The null and alternative hypotheses are;

H_0 : Y_t is trend (level) stationary

H_0 : Y_t is a unit root process

3.13.2 ARCH LM Test

The ARCH LM test is equivalent to the usual F-statistic for testing $\alpha_i = 0$, $i = 1,\ldots,m$ in the linear regression

$$\alpha_t^2 = \alpha_0 + \alpha_1\alpha_{t-1} + \ldots + \alpha_m\alpha_{t-m}^2 + e_t, \quad t = m+1, \ldots, T \tag{3.7}$$

Where, e_t denotes the error term m is a prespecified positive integer T is the sample size

The null and alternative hypotheses are;

$H_0 : \alpha_1 = \ldots = \alpha_m = 0$

$H_1 : \alpha_1 = \ldots = \alpha_m \neq 0$

Let $SSR_0 = \sum_{t=m+1}^{T} (\alpha_t^2 - \bar{\omega})$, where $\bar{\omega} = \frac{1}{T}\sum_{t=1}^{T} \alpha_t^2$ is the sample mean of α_t^2 and $SSR_1 = \sum_{t=m+1}^{T} \hat{e}_t^2$, where $\hat{e}_t^2$ is the least squares residual of the prior linear regression. This gives; $F = \frac{(SSR_0 - SSR_1)/m}{SSR_1/(T-2m-1)}$ which is asymptotically distributed as a chi-squared distribution with m degrees of freedom under the null hypothesis. The decision rule is to reject the null hypothesis if $F > \chi^2_m(\alpha)$, where $\chi^2_m(\alpha)$ is the upper $100(1-\alpha)$th percentile of χ^2_m or if the p-value of F is less than α.

CHAPTER 4

DATA ANALYSIS AND RESULTS

4.1 Introduction

The study uses the daily log returns (continuously compounded returns) of two (2) listed companies, which is Enterprise Group Limited (EGL) and State Insurance Company (SIC) from the year 2008 to 2014. The daily return series for each of the companies was obtained and transformed accordingly (log transformation).

	LOG RETURNS	
SUMMARY MEASURES	EGL	SIC
MEAN	0.1457394	0.2794709
VARIANCE	0.01706041	0.03335803
SKEWNESS	4.833418	6.08801
KURTOSIS	54.14957	112.48

Table 4.1: Descriptive Statistics of Daily Log Returns of EGL And SIC

Table 4.1 above gives some descriptive statistics of the log return series of both EGL and SIC. SIC is seen to have the highest log return (0.2794709) with that of EGL being 0.1457394.

4.2 Analysis Of EGL Series

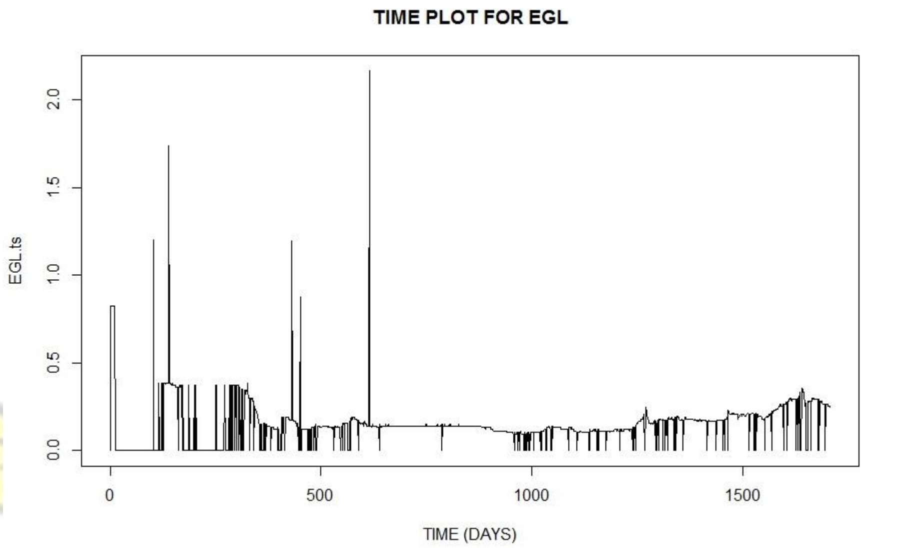

Figure 4.1: Time plot for log return series of EGL.

The highest spike corresponds to a log return of 2.1656 which occurred on 9/7/2010 with actual return of 7.72 cedis.

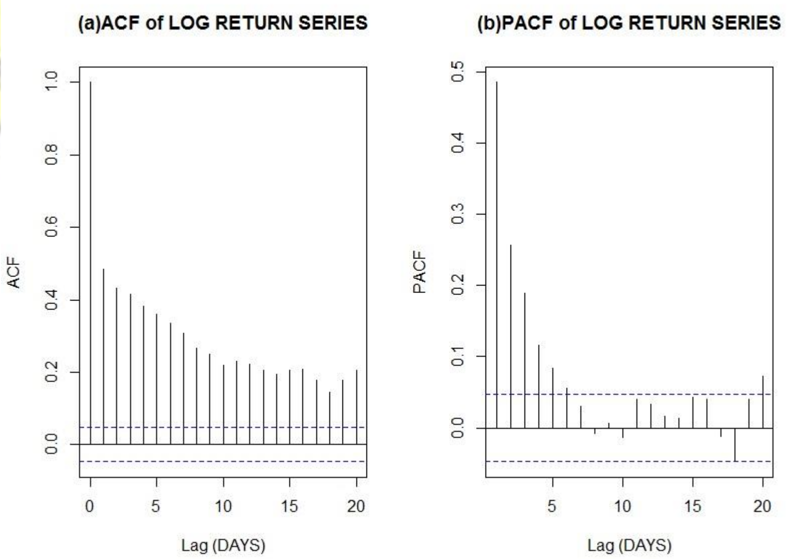

Figure 4.2: (a) ACF of log return series of EGL (b) PACF of log returns series of EGL

4.2.1 Test for Stationarity EGL

KPSS Test for Level Stationarity

H_0: level stationary

H_1: not stationary

KPSS Level = 1.0044, Truncation lag parameter = 9, p-value = 0.01

Augmented Dickey-Fuller Test

Dickey-Fuller = -8.5495, Lag order = 11, p-value = 0.10

H_1: stationary

With a p-value of 0.01, the null hypothesis for the KPSS test is rejected. This implies that the series is not stationary. The ADF test with a p-value of 0.10 fails to reject that the null hypothesis of non-stationarity in the EGL log return series.

4.2.2 First Difference of Log Return Series of EGL

The log return series of EGL were differenced the first time and the KPSS test and ADF test applied again in order to achieve stationarity.

KPSS Test for Level Stationarity

KPSS Level = 0.0042, Truncation lag parameter = 9, p-value = 0.1

Augmented Dickey-Fuller Test

Dickey-Fuller = -17.1777, Lag order = 11, p-value = 0.01

H_1: stationary

From the above, both the KPSS test and ADF test confirmed that the first differenced series was stationary.

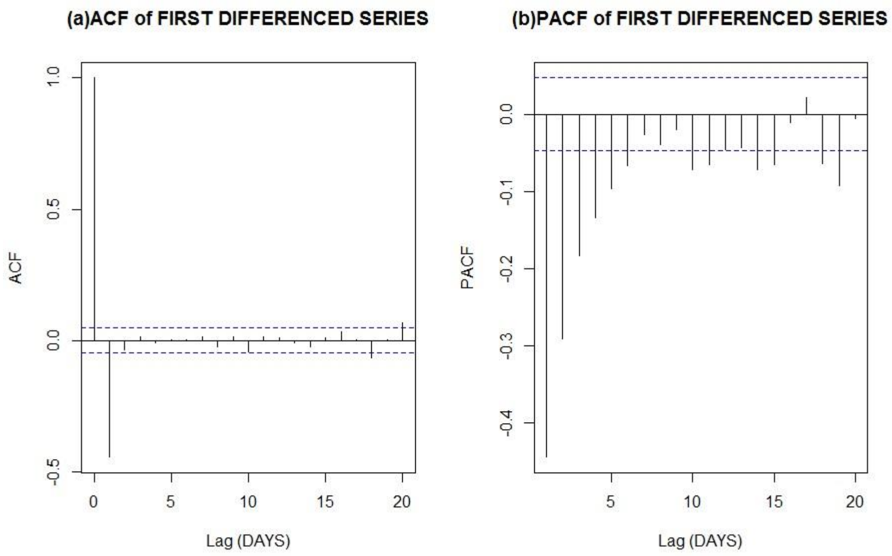

Figure 4.3: (a) ACF of first differenced series (b) PACF of first differenced series

4.2.3 ARIMA Model Evaluation For Log Return Series Of EGL

Based on the ACF and PACF plots of the first differenced series, several ARIMA (p,d,q) models were fitted to the log return series of EGL.

ARIMA (p,d,q)	AIC	BIC
ARIMA (1,1,1)	-2769.04	-2752.72
ARIMA (1,1,2)	-2786.42	-2764.66
ARIMA (1,1,3)	-2764.98	-2737.77
ARIMA (1,1,4)	-2768.75	-2736.1
ARIMA (1,1,5)	-2766.79	-2728.7
ARIMA (1,1,6)	-2765.59	-2722.05
ARIMA (1,1,10)	-2760.46	-2695.16
ARIMA (1,1,11)	-2760.12	-2689.38

Table 4.2: ARIMA (p,d,q) with AIC and BIC

From table 4.2 above, the model with smallest AIC and BIC was the ARIMA (1,1,2) model, thus it is the selected model.

4.2.4 Residuals Of The ARIMA (p,d,q) Model

The residuals of the selected ARIMA (p,d,q) model as shown in fig 4.4 indicate that the model is adequate.

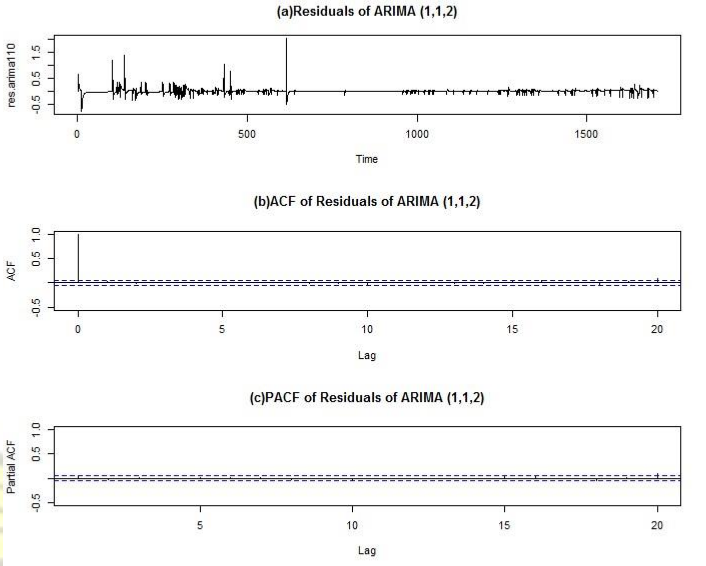

Figure 4.4: (a) plot of residuals of ARIMA (1,1,2) (b) ACF of residuals of ARIMA (1,1,2) (c) PACF of residuals of ARIMA (1,1,2)

4.3 ARCH LM Test For Heteroscedasticity of EGL Series

In order to apply an ARCH/GARCH model or any of its variants to a series, the residuals of that series need to be tested for conditional heteroscedasticity. The ARCH Lagrange Multiplier (ARCH LM) test is employed for this process.

Degrees of Freedom	P-value
5	0.06973
12	0.5715
18	0.9802
20	0.9827

Table 4.3: ARCH Test With Degrees Of Freedom and P-Values

Table 4.3 above shows that the residual series of EGL exhibited no ARCH effects, implying that the series are homoscedastic. Thus, the ARIMA (1,1,2) is adequate enough to represent the log return series of EGL. The ARCH/GARCH models are therefore not required for this series.

4.4 ARIMA (1,1,2) Model

Coefficients:

	ar1	ma1	ma2
	0.9492	-1.7050	0.7052
s.e.	0.0121	0.0263	0.0260

sigma^2 estimated as 0.01136: log likelihood=1397.21

AIC=-2786.42 AICc=-2786.4 BIC=-2764.66

Thus, the full ARIMA (1,1,2) is given as;

$$Y_t - Y_{t-1} = 0.9492(Y_{t-1} - Y_{t-2}) - 1.7050\varepsilon_{t-1} + 0.7052\varepsilon_{t-2}$$

4.5 Forecast of EGL Series

Point	Forecast	Lo 95	Hi 95
1708	0.2356304	0.026757308	0.4445036
1709	0.2316121	0.016592498	0.4466318
1710	0.2277978	0.007374037	0.4482216
1711	0.2241772	-0.001016710	0.4493710
1712	0.2207403	-0.008677648	0.4501582
1713	0.2174779	-0.015690824	0.4506467
1714	0.2143812	-0.022125874	0.4508882
1715	0.2114416	-0.028042526	0.4509258
1716	0.2086513	-0.033492467	0.4507951
1717	0.2060027	-0.038520765	0.4505261

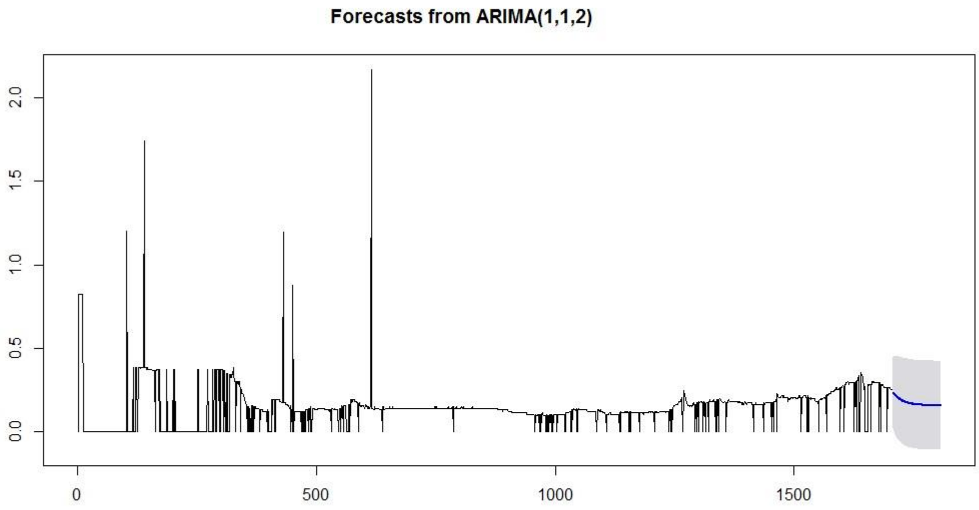

Figure 4.5: Plot of forecast for 100 days ahead for the EGL series

4.5.1 Forecast Performance of ARIMA (1,1,2) for EGL

POINT (DAY)	FORECAST (LOG RETURN)	FORECAST (RETURN)	ACTUAL RETURN	ERROR
1708	0.2356304	0.2657064	0.0000000	-0.2657064
1709	0.2316121	0.2606306	0.0000000	-0.2606306
1710	0.2277978	0.2558313	-0.010000	-0.2658313
1711	0.2241772	0.2512927	-0.010000	-0.2612927
1712	0.2207403	0.2469995	0.0000000	-0.2469995

The table above indicates the performance of the ARIMA (1,1,2) model with respect to the log return series of EGL. Since the log return was used, the forecast as a normal return instead of the log return is given following the procedure below; $r_t = \ln(1 + R_t)$ where r_t is the log return and R_t is the normal return.

To obtain the return (normal),

$$R_t = e^{r_t} - 1$$

Example: To obtain the forecast return for point (day) 1708 with log return of 0.2356304

$$R_t = e^{0.2356304} - 1 = 0.2657064$$

4.6 Analysis of Log Return Series for SIC

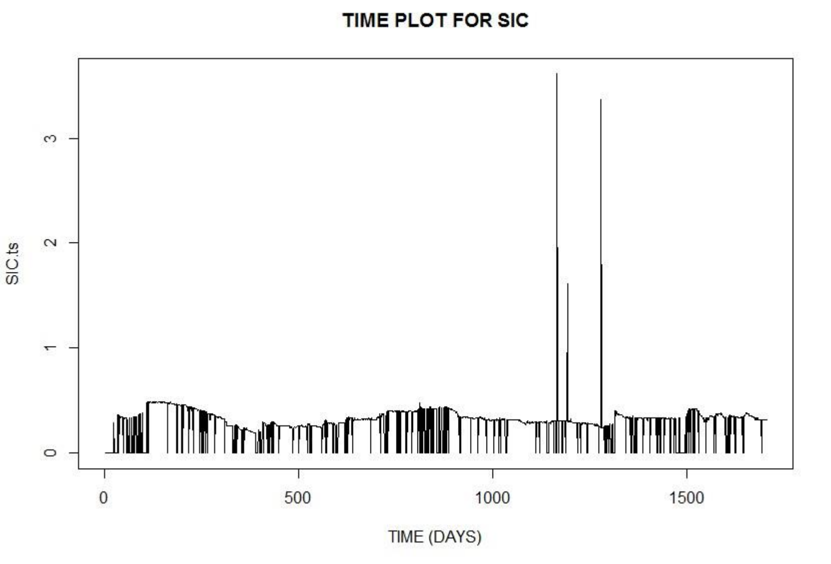

Figure 4.6: Time plot for log return series of SIC.

The highest spike has a log return of 3.6109 and occurred on 28/11/2012 with an actual return of 4 cedis.

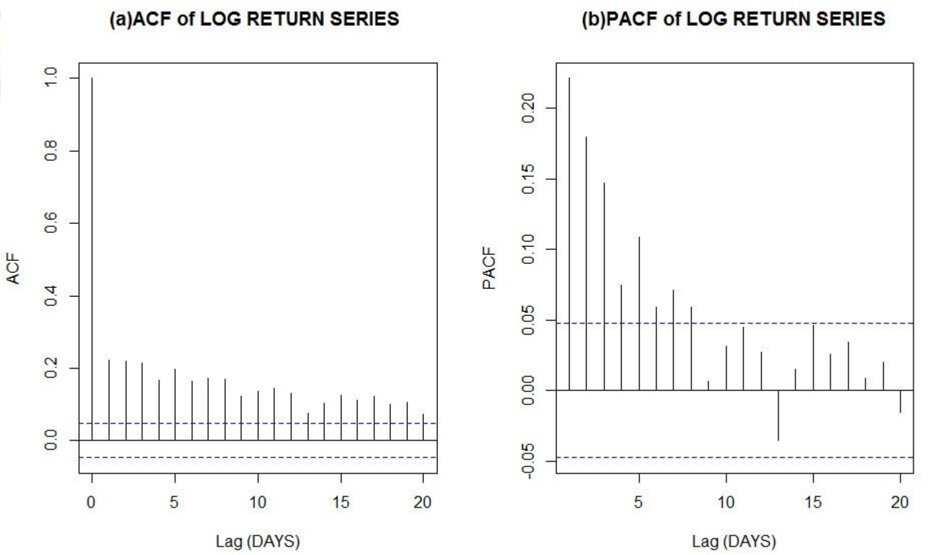

Figure 4.7: (a) ACF of log return series of SIC (b) PACF of log returns series of SIC

4.7 Test for Stationarity EGL

KPSS Test for Level Stationarity

KPSS Level = 0.2688, Truncation lag parameter = 9, p-value = 0.1

Augmented Dickey-Fuller Test

Dickey-Fuller = -7.6363, Lag order = 11, p-value = 0.01

H_1: stationary

4.7.1 ARIMA Model Evaluation for Log Return Series for SIC

Based on the ACF and PACF plots of the log return series of SIC, several ARIMA (p,d,q) models are fitted to the series and the on with the smallest AIC and BIC selected.

ARIMA (p,d,q)	AIC	BIC
ARIMA (1,0,1)	-1187.28	-1165.51
ARIMA (1,0,2)	-1185.33	-1158.11
ARIMA (1,0,3)	-1183.46	-1150.8
ARIMA (1,0,4)	-1182.33	-1144.23
ARIMA (1,0,5)	-1181.71	-1138.17
ARIMA (2,0,1)	-1185.33	-1158.12
ARIMA (2,0,2)	-1183.63	-1150.97
ARIMA (2,0,3)	-1182.1	-1144
ARIMA (2,0,4)	-1181.92	-1138.38
ARIMA (2,0,5)	-1180.36	-1131.37

ARIMA (3,0,1)	-1183.44	-1150.79
ARIMA (3,0,2)	-1182.17	-1144.08
ARIMA (3,0,3)	-1186.78	-1143.24
ARIMA (3,0,4)	-1181.15	-1132.16
ARIMA (3,0,5)	-1179.09	-1124.66

Table 4.4: ARIMA (p,d,q) with AIC and BIC

4.7.2 Residuals of the Selected ARIMA (p,d,q) Model

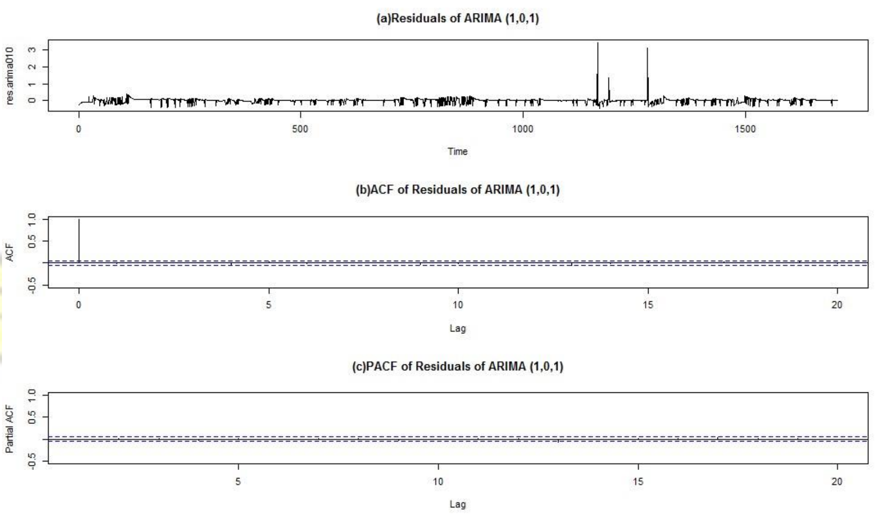

Figure 4.8: (a) plot of residuals of ARIMA (1,0,1) (b) ACF of residuals of ARIMA (1,0,1) (c) PACF of residuals of ARIMA (1,0,1)

4.8 ARCH LM Test for Heteroscedasticity of SIC Series

In order to apply an ARCH/GARCH model or any of its variants to a series, the residuals of that series need to be tested for conditional heteroscedasticity. The ARCH Lagrange Multiplier (ARCH LM) test is employed for this process.

Degrees of Freedom	P-value
5	0.9867
12	1
18	1
20	1

Table 4.5: ARCH Test With Degrees Of Freedom and P-Values

Table 4.5 above shows that the residual series of SIC exhibited no ARCH effects, implying that the series are homoscedastic. Thus, the ARIMA (1,0,1) model is adequate enough to represent the log return series of SIC. The ARCH/GARCH models are therefore not required for this series.

4.9 ARIMA (1,0,1) Model

Coefficients:

	ar1	ma1	intercept
	0.9543	-0.8368	0.2778
s.e.	0.0134	0.0243	0.0146

sigma^2 estimated as 0.02906: log likelihood=597.64

AIC=-1187.28 AICc=-1187.26 BIC=-1165.51

Thus, the full ARIMA (1,0,1) is given as;

$$Y_t - Y_{t-1} = 0.2778 + 0.9543(Y_{t-1} - Y_{t-2}) - 0.8638\varepsilon_{t-1}$$

4.10 Forecast of SIC Series

Point	Forecast	Lo 95	Hi 95
1708	0.3017376	-0.03238573	0.6358609
1709	0.3006456	-0.03577478	0.6370660
1710	0.2996035	-0.03889515	0.6381022
1711	0.2986091	-0.04177119	0.6389893
1712	0.2976601	-0.04442468	0.6397448
1713	0.2967545	-0.04687516	0.6403841
1714	0.2958903	-0.04914022	0.6409207
1715	0.2950656	-0.05123570	0.6413668
1716	0.2942785	-0.05317592	0.6417330
1717	0.2935275	-0.05497382	0.6420288

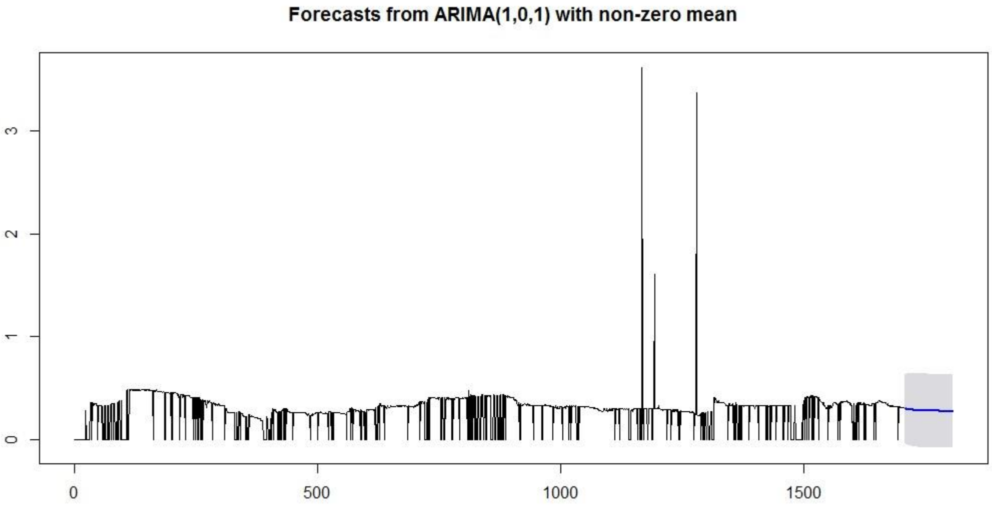

Figure 4.9: Plot of forecast for 100 days ahead for the SIC series

4.10.1 Forecast Performance of ARIMA (1,0,1) for SIC

POINT (DAY)	FORECAST (LOG RETURN)	FORECAST (RETURN)	ACTUAL RETURN	ERROR
1708	0.3017376	0.3522063	0.0000000	-0.3522063
1709	0.3006456	0.3507305	0.0000000	-0.3507305
1710	0.2996035	0.3493236	0.0000000	-0.3493236
1711	0.2986091	0.3479825	-0.010000	-0.3579825
1712	0.2976601	0.3467039	0.0000000	-0.3467039

The table above indicates the performance of the ARIMA (1,0,1) model with respect to the log return series of SIC. Since the log return was used, the forecast as a normal return instead of the log return is given following the procedure below; $r_t = \ln(1 + R_t)$ where r_t is the log return and R_t is the normal return.

To obtain the return (normal),

$$R_t = e^{r_t} - 1$$

Example: To obtain the forecast return for point (day) 1708 with log return of 0.3017376

$$R_t = e^{0.3017376} - 1 = 0.3522063$$

4.11 VAR (P) Model for EGL and SIC

AIC(n)	HQ(n)	SC(n)	FPE(n)
7	6	5	7

The R output above shows the lag length selected by each of the information criteria. A VAR (7) selected by the AIC and a VAR (5) selected by the BIC. This is not unusual. As a result we first fit a VAR (5), selected by the BIC. In similar fashion to the univariate ARIMA methodology we test that the residuals are uncorrelated using a Portmanteau test.

4.11.1 Portmanteau Test (asymptotic) for VAR (5)

data: Residuals of VAR object var

Chi-squared = 35.1763, df = 20, p-value = 0.01919

The null hypothesis of no serial correlation is rejected in the case of VAR (5) based on a p-value of 0.01919.

4.11.2 Portmanteau Test (asymptotic) for VAR (7)

Chi-squared = 12.6276, df = 12, p-value = 0.3967

The null hypothesis of no serial correlation is not rejected in the case of VAR (7) based on a p-value of 0.3967. Thus a VAR (7) is selected as best fitted model.

4.11.3 Estimation results for equation EGL:

EGL = EGL.l1 + SIC.l1 + EGL.l2 + SIC.l2 + EGL.l3 + SIC.l3 + EGL.l4 +

SIC.l4 + EGL.l5 + SIC.l5 + EGL.l6 + SIC.l6 + EGL.l7 + SIC.l7 + const

	Estimate	Std. Error	t value	Pr(>|t|)
EGL.l1	0.2284163	0.0242979	9.401	< 2e-16 ***
SIC.l1	0.0092941	0.0147314	0.631	0.52819
EGL.l2	0.1241323	0.0248444	4.996	6.45e-07 ***
SIC.l2	-0.0016772	0.0148158	-0.113	0.90988
EGL.l3	0.1194678	0.0249382	4.791	1.81e-06 ***
SIC.l3	0.0116345	0.0148349	0.784	0.43299
EGL.l4	0.0813414	0.0249910	3.255	0.00116 **
SIC.l4	0.0126098	0.0149014	0.846	0.39755
EGL.l5	0.0744121	0.0248515	2.994	0.00279 **
SIC.l5	0.0054933	0.0148280	0.370	0.71108
EGL.l6	0.0636374	0.0246412	2.583	0.00989 **
SIC.l6	0.0208084	0.0147888	1.407	0.15960
EGL.l7	0.0449670	0.0236423	1.902	0.05735 .
SIC.l7	-0.0005229	0.0146986	-0.036	0.97162
const	0.0209518	0.0081514	2.570	0.01024 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.104 on 1685 degrees of freedom

Multiple R-Squared: 0.3077, Adjusted R-squared: 0.3019

F-statistic: 53.49 on 14 and 1685 DF, p-value: < 2.2e-16

Var (7) Model For EGL

$$Y_t = 0.02095 + 0.2284163E_{t-1} + 0.0092941S_{t-1} + 0.1241323E_{t-2} - 0.0016772S_{t-2}$$

$$+0.1194678E_{t-3}+0.0116345S_{t-3}+0.0813414E_{t-4}+0.0126098S_{t-4}+0.0744121E_{t-5}$$

$$+0.0054933S_{t-5}+0.0636374E_{t-6}+0.0208084S_{t-6}+0.0449670E_{t-7}-0.0005229S_{t-7}$$

4.11.4 Estimation results for equation SIC:

SIC = EGL.l1 + SIC.l1 + EGL.l2 + SIC.l2 + EGL.l3 + SIC.l3 + EGL.l4 + SIC.l4 + EGL.l5 + SIC.l5 + EGL.l6 + SIC.l6 + EGL.l7 + SIC.l7 + const

	Estimate	Std. Error	t value	Pr(>|t|)
EGL.l1	0.005083	0.040073	0.127	0.89907
SIC.l1	0.121941	0.024296	5.019	5.74e-07 ***
EGL.l3	0.016493	0.041129	0.401	0.68846
SIC.l3	0.107315	0.024466	4.386	1.22e-05 ***
EGL.l4	-0.034910	0.041216	-0.847	0.39712
SIC.l4	0.042814	0.024576	1.742	0.08168 .
EGL.l5	0.059033	0.040986	1.440	0.14997
SIC.l5	0.091479	0.024455	3.741	0.00019 ***
EGL.l6	-0.050975	0.040640	-1.254	0.20990
SIC.l6	0.050630	0.024390	2.076	0.03806 *
EGL.l7	0.006756	0.038992	0.173	0.86247
SIC.l7	0.072901	0.024242	3.007	0.00268 **
const	0.111973	0.013444	8.329	< 2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Var (7) Model For SIC

$$Y_t = 0.111973 + 0.005083E_{t-1} + 0.121941S_{t-1} + 0.005781E_{t-2} + 0.111641S_{t-2}$$

$$+0.016493E_{t-3} + 0.107315S_{t-3} - 0.034910E_{t-4} + 0.042814S_{t-4} + 0.059033E_{t-5}$$

$$+0.091479S_{t-5} - 0.050975E_{t-6} + 0.050630S_{t-6} + 0.006756E_{t-7} + 0.072901S_{t-7}$$

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The study investigated the presence of volatility in two insurance companies and attempted to fit a VAR (p) model to the series of the two companies. The process of modelling volatility involves fitting an ARIMA (p,d,q) model, obtaining the residuals of the said model and testing for ARCH effects on the residuals. If the residual series exhibit ARCH effects, then ARCH/GARCH models can be considered.

The returns series of these two companies were obtained and each of them was tested for stationarity using both the KPSS test and ADF test. The series for EGL were found to be non-stationary, thus, a first difference was applied to the series and stationarity was achieved. Based on the ACF and PACF plots of the differenced EGL series, several ARIMA (p,d,q) models were fitted to the series. The model that performed best was found to be ARIMA (1,1,2). The residuals of the ARIMA (1,1,2) model were obtained and subjected to the ARCH-LM test for conditional heteroscedasticity. Using lags 5, 12, 18 and 20, the series were found to have constant variance (thus, heteroscedasticity not present). Since there were no ARCH effects, there was no need to fit an ARCH/GARCH model or any of its variants. The ARIMA (1,1,2) was thus adequately sufficient for prediction.

Analysing the SIC log return series, it was found to be stationary by the KPSS and ADF tests. An assessment of the ACF and PACF plots led to fitting several ARIMA (p,d,q) models. Among those models, the ARIMA (1,0,1) model was found to have the least AIC as well as BIC. Residuals of the model were obtained and tested for conditional heteroscedasticity. Once again, the residual series were found to have no ARCH effects. Thus, an ARCH/GARCH or any of its variants were not needed.

In fitting the VAR (p) model, several selection criteria were considered. These included the AIC, SC (BIC), HQ and FPE. The focus though was on the AIC and BIC. The AIC selected a lag of 7 whereas the SC (BIC) selected a lag of 5. A portmanteau test was applied the VAR (5) selected by the SC (BIC) and the null hypothesis of no serial correlation was rejected. The test however for the selection by the AIC did not reject the null hypothesis of serial correlation. Thus, the VAR (7) model was fitted to the log return series of the two companies in order to capture the linear interdependencies among the companies.

Finally, in relation to the study objectives:

- The two companies were not found to have ARCH effects, therefore, it would not be prudent to fit either ARCH/GARCH or any of its variants.
- The model for the companies were all ARIMA (p,d,q) models, thus ARIMA(1,1,2) for EGL and ARIMA(1,0,1) for SIC; and they were adequate for forecasting according to the study.
- The ARIMA (p,d,q) models were used for forecasting log return series and returns of the two companies specifically ARIMA(1,1,2) for EGL and ARIMA(1,0,1) for SIC.
- The VAR (p), that is VAR (7) model was fitted to the series.

5.2 Recommendations

Based on the analysis and findings of the study, the following recommendations are made;

- Investment with SIC and or EGL is strongly recommended since volatility is absent thus they exhibit stability.
- Since the Ghana Stock Market is still developing, management is advised to put in place measures that will increase the frequency/rate of trading.
- A careful look at the inter relation between the two companies could boost investor confidence in those companies.
- Different companies on the Ghana Stock Market can be used in future research and a comparison drawn.

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