KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY

Modelling Volatility and the Risk-return Relationship of Selected Equities on the Ghana Stock Exchange

By

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Declaration

I hereby declare that this submission is my own work towards the award of the M. Phil 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

This work is dedicated to my lovely wife Mrs. Anuwoje Ida L. Abonongo and my son Austin Abonongo.

Abstract

The volatility and the risk-return trade off of equities or stock markets play essential role in investment, decision making, financial stability among others. This study used secondary data of 35 equities from the Ghana Stock Exchange (GSE) and Annual Report Ghana databases comprising the daily closing prices from the period 02/01/2004 to 16/01/2015. Principal component analysis was used in selecting equities that characterized each sector.

The results revealed that, for the Finance sector, CAL, ETI and GCB were selected, the Distribution sector had PBC and TOTAL selected, the Food and Beverage sector had FML selected, the Information Communication Technology sector had CLYD selected, the Insurance sector had EGL selected, the Manufacturing and Mining sectors had PZC, UNIL and TLW, AGA selected respectively. The symmetry and asymmetry of the daily returns of the selected equities as well as the risk-return relationship was investigated using the univariate GARCH-M (1, 1), EGARCH-M (1, 1) and TGARCH-M (1, 1) models and the results indicated the existence of positive risk premium meaning investors were compensated for holding risky assets. The results also showed that, the asymmetry models gave a better fit than the symmetry model indicating the presence of leverage effect among the selected equities. TGARCH-M (1, 1) model with the student-t distribution was the appropriate model selected. It was revealed that, volatility was persistent (explosive process) in most of the selected equities with the three distributional assumptions. The persistence in volatility was extended in investigating the half-life measure of the selected equities. It was revealed that most of the equities had strong mean reversion and short half-life measure. The long-run trends in volatility was investigated by regressing the conditional variance against a time variable. The results showed that, most of the equities exhibited increasing volatility over the sample period.

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Contents

List of Tables

List of Figures

List of Acronyms

CAPM	Capital Asset Pricing Model
APT	Arbitrage Pricing Model
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GSE	Ghana Stock Exchange
PCA	Principal Component Analysis
GED	Generalized Error Distribution
ARMA	Autoregressive Moving Average
ARCH	Autoregressive Conditional Heteroskedasticity
JSE	Johannesburg Stock Exchange
ALSI	All Share Index
SA	South Africa
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
S and P	Standard and Poor
CNX	Consol Energy Inc.
TGARCH	Threshold Generalized Autoregressive Conditional Heteroskedasticity
PGARCH	Power Generalized Autoregressive Conditional Heteroskedasticity
MSE	Macedonian Stock Exchange
FINSAP	Financial Sector Adjustment Program
DSI	Databank Stock Index
GSE-CI	Ghana Stock Exchange Composite Index
GSE-FSI	Ghana Stock Exchange Financial Stock Index
VWAP	Volume Weighted Average Price
GARCH-M	Generalized Autoregressive Conditional Heteroskedasticity-in Mean
EGARCH-M	Exponential Generalized Autoregressive Conditional Heteroskedasticity in Mean
TGARCH-M	Threshold Generalized Autoregressive Conditional Heteroskedasticity-in Mean
GATS	GSE Automated Trading System
RW	Random Walk

ARCH-M	Autoregressive Conditional Heteroskedasticity-in Mean
ARIMA	Autoregressive Integrated-Moving Average
US	United States
GJR	Glosten-Jagannathan-Runkle
EWMA	Exponential Weighted Moving Average
GJR-GARCH	Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity
IBM	International Business Machines
NYSE	New York Stock Exchange
NARCH	Non-linear Autoregressive Conditional Heteroskedasticity
QTARCH	Qualitative Threshold Autoregressive Conditional Heteroskedasticity
CMA	Capital Market Authority
TASE	Tel Aviv Stock Exchange
CGARCH	Component Generalized Autoregressive Conditional Heteroskedasticity
KIBOR	Karachi Inter Bank Offering Rate
MIBOR	Mumbai Inter Bank Offering Rate
NSE	Nigeria Stock Exchange
ADF	Augmented Dickey Fuller
KPSS	Kwiatkowsky, Phillips, Schmidt and Shin
ACF	Autocorrelation Function
PACF	Partial Autocorrelation Function
DF	Dickey Fuller
AR	Autoregressive
PP	Phillips-Perron
B-G	Breusch-Godfrey
JB	Jarque-Bera
LM	Lagrange Multiplier
ARCH-LM	Autoregrssive Heteroskedasticity Lagrange Multiplier
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion

CV	Coefficient of Variation
LB	Ljung Box
D-W	Durbin-Watson

Chapter 1

Introduction

This chapter introduces the research on modelling volatility and the risk-return relationship of selected equities on the Ghana Stock Exchange (GSE). It entails the research background on volatility and risk-return, problem statement, general objective, specific objectives to aid in achieving the general objective, the methodology employed in analysing the data, the justification of the research and organization of the thesis.

1.1 Research Background

The stock market provides a framework within which capital formation takes place and where previously issued securities are traded among investors for productive investment. The Stock Exchange plays an integral role in the capital formation and wealth creation activities in any nation. Volatility can be defined as a statistical measure of the dispersion of returns for a given security and it can either be estimated using the standard deviation or variance of returns (Suliman and Winker, 2012). Also, volatility is an essential component in the area of risk management such as hedging, asset management, pricing and portfolio selection. From finance theories like Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Model (APT), the valuation of assets, or the expected returns, is related to their volatility or risk.

Volatility of stock market may hinder the smooth operation of the stock market which will eventually affect the economy because of its effect on consumer spending. Nevertheless, a drop in stock market weakens the confidence of the consumer hence decrease consumer spending.

Also stock market investors are apparently concern with the volatility of stock price since an increase in volatility could mean great gain and loss, thus leading to uncertainty. In volatile markets, it is difficult for companies to raise capital in the capital markets.

According to Brooks (2002), financial data exhibit some amount of important features such as volatility clustering or volatility pooling, leverage effects and so on.

However, the general consensus that causes volatility is the annual of current, unexpected information that affects anticipated stock returns (Engle and Ng, 1993). This implies that changes in market volatility would merely reflect changes in the local and international economic environment. Other causes of volatility are changes in trading volume, practices or patterns which are driven by modification in macroeconomic policies, shift in investors tolerance of risk and increase in uncertainty. Therefore, stock market volatility can help researchers to predict the path of an economy's growth.

The financial system is a significant segment of every economy. According to Amevor (2005), financial markets play a critical role in the proper functioning of capitalistic economies, because they serve as avenues for the release of funds from investors to borrowers. Also, Ross (2004) noted that, economic growth is extremely related to the level and performance of stock markets. Stock market volatility is paramount in the theory and practice of risk management, asset allocation and asset pricing. Hongu and Zhichao (2006), accented that volatility modelling in stock markets is important because it gives much insight into the data generating process of the returns series.

The study of risk and return is a basic idea in not only financial analysis, but in all facet of life. If one is deciding on how to maximize profit, it is essential that he/she takes into account the combined effect on expected return as well as on risk. Return shows the amount which an investor earned on an investment during a certain period. This includes the dividend payments, capital gains and interest; while risk characterises the uncertainty accompanying a particular task. Also in the field of finance, risk is seen as the chance that a certain investment may or may not deliver the actual or expected returns at a given time. Also theories like CAPM and APT says that, the potential return rises with an increase in risk. Diversification requires that, asset managers select assets that are negatively or lowly correlated. This selection of assets has no simple formula that can find the right asset allocation for an individual investor: such allocations are usually subject to the investor's unique characteristics pertaining to risk appetite, age and investment horizon

(Nutall et al., 2000). On account of this, it is imperative that the risk-return trade-off be accurately modelled in order to aid the investment decisions of investors and portfolio managers (Nutall et al., 2000).

Nevertheless, equities from developed markets has been extensively studied, little has however been done on equities from emerging markets like Ghana. This study therefore employs the univariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models to investigate the volatility and risk-return relationship of selected equities on the Ghana Stock Exchange (GSE). This is to ascertain the level of uncertain associated with the equities from each sector and also to determine the persistence in volatility among the equities and the risk-return dynamics of the equities among others.

1.2 Problem Statement

While volatility and risk-return relationship on stock markets (equities) in developed capital markets has been well studied, little attention has been paid towards an extensive study of the volatility and risk-return relationship of developing capital markets notably, Ghana stock market and for that matter equities on the market. Equities from developing stock markets have different characteristics as compared to equities from developed capital markets. Therefore, in line with developed markets studies, the main objective of this study is to model volatility and risk- return relationship of selected equities on the Ghana Stock Exchange.

1.3 General Objective of the Study

The main objective is to examine the volatility and the risk-return relationship of selected equities on the Ghana Stock Exchange.

1.3.1 Specific Objectives

i. To use the principal component analysis in selecting equities that characterize each sector.

ii. To investigate the symmetric and asymmetric in volatility of the daily returns of theselected equities.

iii. To determine the risk-return relationship of the selected equities and which among theGARCH family of models adequately captures the risk-return relationship of equity returns and under which error distributional assumption.

iv. To investigate the half-life and the persistence in volatility of the selected equities.

v. To determine the long term trend in volatility of the selected equities.

1.4 Methodology

For the empirical analysis, daily stock returns for the period January, 2004 to January, 2015 will be used. Several descriptive statistics which includes reporting on the mean, coefficient of variation, standard deviation, skewness, kurtosis and normality tests among others will be performed. This is to check the distributional properties of the returns before applying the formal econometric models. Before applying the various econometric tests, principal component analysis will be performed on all the sectors in selecting equities that characterize each sector.

In addressing the first sub-objective, Principal Component Analysis (PCA) will be used, the second and third sub-objectives will be addressed by using univariate GARCH family of models namely Generalized Autoregressive Conditional Heteroskedasticity-in Mean (GARCH-M), Exponential Generalized Autoregressive Conditional Heteroskedasticity-in Mean (EGARCH-M) and Threshold Generalized Autoregressive Conditional Heteroskedasticityin Mean (TGARCH-M) assuming three different distributions for the error term namely Student-t, Gaussian and the Generalized Error Distribution (GED). The risk-return parameter will be analysed to assess whether a relationship exist between risk and return.

The coefficients of the GARCH models will be used to investigate the half-life and the persistence of volatility in the selected equities which addressed the fourth sub-objective. The long term trend in volatility will be investigated using a simple regression which addresses the fifth sub objective

1.5 Justification

Much of the research on stock market volatility and risk-return relationship are centred on developed countries with very little on developing countries especially Ghana. Some of the research done in Ghana are much centred on the GSE All Share Index return which are mostly limited to Autoregressive Moving Average (ARMA) specifications which only captures the underlying structure of the GSE and failed to explain volatility and its stylised facts associated with the equities on the exchange (Frimpong and Oteng-Abayie, 2006). Others also used GARCH models to model and forecast volatility using the GSE All share index and to investigate calendar anomalies of the GSE. Therefore this study used univariate GARCH family of models which captures Autoregressive Conditional Heteroskedasticity (ARCH) effects in a series and persistence in volatility to model volatility and the risk-return relationship of selected equities on the GSE. Also the results of this study will offer insights into asset and risk management practices to aid in the evaluation of assets, the measurement of risk associated with each equity, the valuation of security and choice of investment. Investors on the GSE will be able to ascertain the nature of uncertainty associated with the equities and advice themselves accordingly. It will provide management of the GSE first-hand information on uncertainties associated with the equities as well as the sectors and so be able to regulate and monitor the activities on the exchange efficiently so as to attract more companies to list on the exchange and thereby improving economic development and growth of the GSE and Ghana as a whole.

1.6 Organization of the Thesis

This thesis is structured into five main chapters; chapter one gives the introduction and encompasses the research background, problem statement, summary of methodology, justification and objectives. Chapter two gives the review of literature. Chapter three gives detail outline of the methodology used. Chapter four encapsulates the analysis and discussion of results obtained whereas chapter five gives the conclusion and recommendations of the study.

Chapter 2

Literature Review

2.1 Overview

This chapter gives a review of the works of other researchers on the volatility and riskreturn relationship of equity returns. It provides review on volatility modelling techniques which forms the basis for this study. It encapsulates a review on univariate GARCH models which are paramount in this research. There is also a review on risk-return relationship pertaining to both developed and emerging stock markets. It also gives an in-depth view on volatility persistence and half-life measure.

2.2 Emerging Stock Markets

In modelling the volatility on the Johannesburg Stock Exchange (JSE) employing ARCHtype models, Mangani (2008) found that volatility was symmetric and was not a commonly priced factor. This result was obtained by considering two portfolios (with data from 1973 to 2002): the All Share Index (ALSI) and a portfolio with 42 stocks. The portfolio of 42 stocks was used because the ALSI is dominated by resource stocks and thus it was essential to have a portfolio that was not improperly influenced by the dynamics of the resource stocks. This result was echoed by Chinzara and Aziakpono (2009), who primarily studied the linkage between returns and volatility of the South Africa (SA) and the world major equity markets. Using a GARCH-M methodology to test the risk-premium hypothesis the authors, like Mangani (2008), found that volatility was not usually a priced factor and found that volatility is asymmetric, as opposed to symmetrical as found by (Mangani, 2008).

Harvey (1995) attributed high level volatility of returns to three factors: firstly, lack of diversification in the country index; secondly, high risk exposures to volatile economic factors; and thirdly, incomplete integration into world capital markets and differences in time in the risk exposures. Although there are few evidence to show that many emerging markets are becoming more incorporated into global capital markets overall, these markets however differ from developed stock markets in high liquidity risk. For these reasons, emerging markets have attracted much research in the modelling of time-varying nature of volatility as well as attempting to establish the risk-return relationship. Much of the literature that has been put forward to investigate this relationship has been conducted using the GARCH family of models.

Using GARCH-M model, Murinde and Poshakwale (2001) investigated stock market volatility in the East European emerging markets of Hungary and Poland. The study covered a period from 1994 to 1996 using daily data from the Bulgarian and Warsaw stock markets. A similar result was obtained by Yu and Hassan (2008) who used an extension to the GARCH model, the EGARCH model realized that, there was a positive and a significant relationship between risk and return in Bahrain, Oman and Saudi Arabia, while in Egypt, Jordan, Morocco and Turkey volatility was not priced. Using the same model, Karmakar (2007) found evidence in support of a negative risk-return relationship on the Indian stock market using the S and P CNX (Console Energy Inc.) Nifty for the period 1990 to 2004. Similarly, using the EGARCH-M model Saleem (2007) found that positive returns were matched with higher volatility on Pakistan's stock exchange (Karachi stock exchange).

Also, using the GARCH, EGARCH, TGARCH and PGARCH models, Kovacic (2008) found a weak relationship between risk and return in the Macedonian Stock Exchange (MSE). The study used the MBI-10 index, consisting of up to 10 shares listed on the official market of the MSE, covering a period from 2005 to 2007. Kovacic (2008) tested the result assuming three different distributions; the Gaussian, GED and Student-t and found that the TARCH model with a Student-t distribution was the best model to accurately model the data.

2.3 Ghana Stock Market

The Financial Sector Adjustment Program (FINSAP) which was launched in 1988 established the Ghana Stock Exchange in 1989. In November 1990, the exchange started operations with one Government bond and 12 listed companies with an increase in market capital from GHC 3 billion to GHC 4.3 billion between 1991 and 1992, the listed companies grew from 15 to 19 in 1995 and to 34 in June 2007 and 36 listed companies in 2015. The main indices from the time of operation to 2010 were the Databank Stock Index (DSI) and the GSE All Share Index. From 2011, the two main indices have been the Ghana Stock Exchange Compost Index (GSE-CI) and Ghana Stock Exchange Financial Stock Index (GSE-FSI). The GSE-CI consist of all the stocks except those listed on other stock exchange and the GSE-FSI consist of all the financial stocks on the exchange. The trading benchmark currently in use by the Ghana Stock Exchange is the Volume Weighted Average Price (VWAP). Its calculation commences when trading opens and ends when trading closes and represents the number of shares traded in a specific stock on a given day, divided by the total volume of shares traded in that stock on that day. It is also use to identify liquid and illiquid price points for a specific security over a very short time period and echoes price levels weighted by volume and can also be used to measure trading efficiency. Investors gets returns or profits from shares listed on the Ghana Stock Exchange basically in two forms. Firstly, capital gains, that is where the investors make profit by selling their shares. Secondly, dividend income may be earned, if the issuing company shares profit to shareholders. However, these two benefits are not assured if the firm does not perform well. The settlement of transactions on the exchange is perform using electronic web based application. The GSE uses an electronic trading system known as the GSE Automated Trading System (GATS) for transactions on the exchange. Settlement takes place three business days (T + 3) after the traded date. The System allows for mutual settlement of trade on T + 0 or T + 1 basis. The efficiency of capital markets is another issue of great importance. Financial literature mostly captures allocation, operational and informational efficiencies.

Frimpong and Oteng-Abayie (2006) suggested that, financial and investment decision making are usually based on the relationship between risk and return; the analysis of risk is hence an essential part of portfolio optimization, risk management and asset pricing. When the variances of the error terms of a data are not the same and the expectation of the error terms are not the same at some ranges of the data or some points it is said to suffer heteroskedasticity. In such a situation, the coefficients of the Ordinary Least Squares (OLS) regression models are still unbiased, but the warning lies in the fact that, the standard error and the confidence intervals are narrow. They modelled and forecasted volatility (conditional variance) on the Ghana Stock Exchange (GSE) using different types of GARCH models and a three days a week data from the GSE Databank Stock Index (DSI) over a period of 10 years and conclude that the symmetric GARCH(1,1) model gave a better fit compared to the other models (a basic random walk (RW), two asymmetric EGARCH(1,1), and TGARCH(1,1) models) under the assumption that the innovations follow a Gaussian distribution.

Alagidede and Panagiotidis (2006) investigated two prominent calendar anomalies of month of the year and day of the week effects on an emerging African market, the GSE which serves as an attempt of modelling seasonality and claims the GSE's three trading day per week (Mondays, Wednesdays, and Fridays) and the increased attention the exchange receives from both academics and practitioners is interesting. They adopted models from the non-linear GARCH family models in a rolling framework to examine the function of asymmetries using daily closing prices from 15/06/1994 to 28/04/2004. They attributed these anomalies to procedures in settlement, negative information releases among others. The January effect states that stock returns in January are higher than other months of the year and the day of the week effect holds that stock exhibit significantly lower returns over the period between Friday's close and Monday's close. They discovered and concluded an April effect rather than a January effect and claimed it's related to the submission of company reports in the late March which caused a build-up of momentum which translated into high positive April returns. Again, that TGARCH yields better results but fails to provide support for the existence of seasonality. This rather supports Efficient Market Hypothesis and the sceptics approach for the existence of seasonality.

2.4 Review of Risk-Return Relationship

A broad literature exists for developed stock markets when testing the basic hypothesis of the CAPM (Capital Asset Pricing Model) of Sharpe (1964) ,Lintner (1965), Mossin (1966) and Merton (1973) which hypothesises a positive risk-return relationship. In order to test this hypothesis the Autoregressive Conditional Heteroskedasticity- in Mean (ARCH-M) model developed by Engle et al. (1987) provides a natural tool for the estimation of this relationship. The current state of literature on the existence and nature of the relationship between risk and return is quite erroneous. Backus and Gregory (1993) noted that the relationship between risk and return may be increasing, decreasing, flat, or non-monotonic or increasing, as is the case in most of the ARCH-M literature.

French et al. (1987) used two methods to investigate risk-return relationship. Using daily returns, they first computed estimates of monthly volatility on a univariate Autoregressive Integrated-Moving Average (ARIMA) model. They also used daily returns from the Standard and Poor (S and P) composite portfolio to estimate ex ante measure of volatility using a GARCH-M model. The results from these two models showed evidence that the expected market risk premium, that is, the expected return on portfolio (stock) minus the Treasury bill yield was positively linked with the predictable volatility of stock returns. They also found that unexpected stock market returns were negatively related to the unexpected change in the volatility of stock returns.

Chou (1988) supported French et al. (1987) finding of a positive relation between the predictable components of stock returns and volatility in the United States. Chou (1988) used weekly data for the period July 1962 to December 1985 and used a GARCH-M specification. Using a monthly data set spanning from 1851 to 1989 for the United States (US), Glosten et al. (1993) used a modified GARCH-M model. This model was modified in three ways: firstly the model allowed for seasonal patterns in volatility ; secondly, the model allowed for asymmetries in the conditional variance equation; and lastly, the model allowed for nominal interest rates to predict volatility.

Lanne and Saikkonen (2004) used a modified GARCH-M model in order to cater for skewness and kurtosis. The study used monthly US stock returns for the period from 1946 to 2002. They motivated this modification by arguing that the modified model was capable of modelling moderate skewness and kurtosis typically encountered in financial return series. The results showed that there was a significantly positive relationship between risk and return. More extensions of the GARCH-M specifications have been used in literature to investigate the nature and existence of the time-varying risk premium. Also, Chan et al. (1992) used a bivariate GARCH-M model to test the International CAPM and found a statistically significant positive relationship between the expected returns and the covariance. They used the S and P 500 index to compute the covariance and the Nikei 225 index and Japan's Morgan Stanley index as a proxy to international excess returns. Bae (1995) used the bivariate GARCH-M model to test the Korean Composite Stock Price Index and the Morgan Stanley Capital International world index from 1980 to 1990. The results indicated a positive risk-return trade-off

Thomas and Wickens (1989) provided non-parametric estimates for the foreign exchange and equity risk premia for West Germany, Japan, the United Kingdom and United States for 1973 to 1988. The results indicated that, evidence in support of a positive risk-return relationship was lacking. In line with preceding authors, Pagan and Hong (1991) analysed US monthly stock volatility from 1834 to 1925 using a non-parametric model. The results indicated that the relationship between risk and return was negative. However, Harrison and Zhang (1999) found that the trade-off between risk and return was positive and significant at longer horizons.

2.5 Volatility Modelling

Modelling the temporal behaviour of volatility on stock markets has been considered by various studies, most of it focuses on the estimation of the volatility of stock returns and the persistence of shocks to volatility (Choudhry, 1996). In 1982, Engle proposed a volatility process with time varying conditional variance; the Autoregressive Conditional Heteroscedasticity (ARCH) process. Notwithstanding, empirical evidence indicates that, high ARCH order has to be selected in order to capture the changing conditional variance. If the ARCH order is high then, many parameters have to be estimated and the estimations become more involving or complex. The Generalised ARCH (GARCH) model was proposed as a natural solution to the constraints with the high ARCH orders.

The analysis of stock market volatility has been the subject of vast theoretical and empirical inquiry. Many of the applications of volatility requires the forecast or estimation of parameters of volatility (Brooks, 2002). Various measures of risk are often considered when making investment decisions, and there are two commonly used measures of risk; Firstly, standard deviation measures the variability of returns above and below the mean return: this measure of risk is often used as a measure of volatility. Secondly, the Beta estimates the percentage of the movement in an investment that are due to movements in its benchmark index.

2.6 Review of Univariate GARCH Models

Volatility of stock prices is an crucial aspect in finance for numerous reasons. The literature on stock price volatility agrees on one key phenomenon. Thus, the evidence that there are several movements in stock prices. Again, the changing nature of stock prices is an accepted phenomenon and all players in stock markets have consensus about it. Nevertheless, the causes of the volatility of stock prices is a question that remains unanswered in the field of finance. This is because of the numerous number of complex variables. In essence, since late twentieth century and particularly after introducing ARCH model by

Engle (1982), as said by Bollerslev (1986) and Poon and Granger (2003), a lot of research that are much established in developed country and to some degree in developing countries has been undertaken by researchers in this area by applying different procedures.

Engle et al. (1987) presented the ARCH-M model as an extension of the ARCH model to permit for the conditional variance to be determined by the mean. Whereas in its general form, ARCH model shows the conditional variance as a linear function of the previous squared innovations, they also hypothesized that, the expected return on a portfolio is affected by the changing conditional variance. Also, they finalised that, risk premia are does not change with time; rather they change consistently with perceptions of the agent's towards risk.

Nelson (1991) extended the ARCH model in order to better account for the nature of volatilities in returns. The most essential effort was the proposing of the (Exponential Autoregressive Conditional Heteroskedasticity (EARCH)) to test the hypothesis that the variance of return was affected differently by positive and negative excess returns. The results showed that not only was the assertion true, but also that excess returns were related variance of the stock market negatively. Glosten et al. (1993) modified the primary restrictions of Generalized Autoregressive Conditional Heteroskedasticity- in Mean (GARCH-M) model based on the assertion that GARCH model impose a symmetric effect of volatility to negative and positive shocks, presented the Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity (GJRGARCH) and the Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) models. They emphasized that there is a positive and a significant relation between the conditional mean and conditional volatility of the excess return on stocks when the standard GARCH-M model was used to model the volatility of stock returns stochastically.

Engle and Ng (1993) investigated the effect of good and bad news on volatility and reported an asymmetry in stock market volatility towards good news as compared to bad news. Also, market volatility was perceived to be associated with the arrival of news. A drop in price was associated with bad news whereas an increase in price was said to be due to good news. They found that bad news created much volatility than good news of same magnitude. This asymmetric nature of market volatility is called the "leverage effect".

Christie (1982) and Nelson (1991) have showed evidence of asymmetric responses, indicating the leverage effect and differential financial risk relying on the direction of movements in price change. In responding to the weakness of symmetric assumption, Nelson (1991) introduced the exponential GARCH (EGARCH) models with a conditional variance formulation that adequately captured asymmetric response in the conditional variance. EGARCH models had been demonstrated to be superior compared to other competing asymmetric conditional variance in many studies (Alexander, 2009). Hojatallah and Ramanarayanan (2010) examined the volatility of Indian stock exchange and its stylized facts using ARCH models. Their results revealed that, GARCH (1, 1) model explains volatility of the Indian stock market and its stylized facts such as fat tails, mean reverting and volatility clustering.

Hansen and Lunde (2005), compared volatility models using daily exchange rate data and IBM (International Business Machines) Stock prices. Their results showed that, there was no winner among the models studied and that non of the models gave significantly better prediction than the GARCH (1, 1).

Neokosmidis (2009) asserted that financial data have some key features like leverage effects and volatility clustering which cannot be captured by models such as the ARMA model. He proposed the use of ARCH family of models to estimate financial time series. According to Giovanis (2008) the GARCH model was able to capture volatility clustering successfully making it an appropriate model for volatility forecasting. Bera and Higgins (1993), provided an informal details of some of the essential developments and their effect on applied work in the ARCH model since its origination by Engle in a seminar paper in 1982. They complement its usefulness in its ability to capture some stylised facts as well as its applicability to numerous and diverse areas such as in, asset pricing, interest rates, optimal dynamic hedging strategies, option pricing and risk modelling among others. They began with a short study on the rate of return on the U.S dollar/British pound exchange rate on weekly bases, changes in the three month growth rate and the Treasury bill rate of the New York Stock Exchange (NYSE) monthly composite index. The basic ARCH models were described. It began with the original ARCH model of Engle (1982) by explaining the ARCH process and describing and emphasizing its properties heuristically. Then the GARCH model of Bollerslev (1986) was then introduced before formally describing the unconditional moments of the properties of the ARCH process. They discussed extensions to the ARCH model such as the log ARCH model suggested by Geweke (1986), the nonlinear ARCH (NARCH) model proposed by Bera and Higgins (1993), the exponential GARCH (EGARCH) proposed by Nelson (1991) with a look at its properties, the threshold ARCH (TARCH) suggested by Glosten et al. (1991)) and Zakoian (1990), the qualitative TARCH (QTARCH) model proposed by Gourieroux and Manfort (1992) among several others.

Also from Engle and Patton (2001), predictability of volatility is a very vital financial aptitude and it is what is required in each of the following circumstances. The understanding of the future behaviour of a risk manager's portfolio was very essential to him as the future volatility of a life contract was to an option trader. They further discussed the stylised facts that a good volatility model must be able to capture and reflect. It included persistence, mean reversion, asymmetry as an impact of innovations, exogenous variables, and tail probabilities and forecast evaluation. They illustrate the above with daily closing price data on the Dow Jones Industrial index from 23 /08/1988 to 22/08/2000. Conditional volatility was found to be persistent and half-life of 73 days and the non-stationarity tests showed that its mean reverting. Again, it was realized that a negative lagged return innovation affected the conditional variance; four times as large as the innovation of a positive return.

The use of GARCH-type models on daily data from Egypt (Capital Market Authority (CMA) General index from 1997 to 2007 comprising 1987 daily observations) and Israel (TASE (Tel Aviv Stock Exchange)-100 index from 1997 to 2007 comprising 2063 daily observations) to model volatility and explain financial market risks illustrated strong evidence that, the simple GARCH model GARCH (p,q), threshold GARCH (TGARCH), power GARCH (PGARCH), exponential GARCH (EGARCH), component GARCH (CGARCH) and the asymmetric component GARCH (AGARCH) could characterise daily returns.

There was a conclusion to indicate that increased risk does not necessarily lead to a rise in the returns. The uncertainties in the prices in the Capital Market Authority (CMA) index of Egypt for the period under study makes it more volatile than the TASE-100 index of Israel.

Irfran et al. (2010) estimated the short term interest rates volatility with GARCH, EGARCH, TGARCH and PGARCH models using 1639 daily data observations from the Karachi Inter Bank Offering Rate (KIBOR) three month bid rates covering the period 2001 to 2008) and 2318 daily data observations Mumbai Inter Bank Offering Rate (MIBOR) three months bid rate covering the period 2001 to 2008) in Pakistan and India respectively with the aim to search out the best inter-bank offering rate. Holidays and weekends were exempted. A simple GARCH (1, 1) model was able to show the persistence in volatility for both returns, with KIBOR returns indicating high volatility shocks and non-stationarity in variance where as MIBOR returns indicated moderate presence of volatility shocks.

Emenike (2010) investigated the nature of volatility of stock return in the Nigerian Stock Exchange (NSE) using GARCH (1, 1) and the GJR-GARCH (1,1) models assuming the Generalized Error Distribution (GED). He sought to do this by examining the stock exchange returns for prove of leverage effects, fat-tails distribution and volatility clustering , because these provided important knowledge on how risky the assets market is. He discovered that there exists volatility clustering on the Nigeria Stock Exchange (NSE) and used GARCH (1,1) to model that. He captured the presence of leverage effects in the returns with the GJR- GARCH (1,1) model. The GED shape test also revealed a leptokurtic returns distribution. The entire results revealed that there was evidence of fat-tail distribution, leverage effects and volatility persistence on the NSE. He concluded volatility was persistent for the stocks in Nigeria and that the estimated GED revealed evidence of leptokurtosis in the returns.

2.7 Persistence in Volatility and Half-life

For stock markets, negative shocks increases volatility than positive shocks of the same magnitude. Persistence of volatility plays an essential role in forecasting of volatility and it has vast effect in portfolio management and risk management. Persistence in volatility indicates that shock(s) to volatility does not diminish immediately rather its effect stays for some time. Kang et al. (2009), Pindyck (2004), Serletis and Andreadis (2004) and

Tabak and Cajueiro (2007) examined persistence of volatility in oil returns . Pindyck (2004) estimated persistence of volatility in crude oil and natural gas using GARCH and 'half-life' measure of volatility and found the evidence of persistence in the volatility of natural gas and crude oil. Also, his measure of results indicated if there was a shock to natural gas prices or crude oil, it lasted up to 10 or 5 to weeks respectively.

Ahmed and Suliman (2011), estimated the daily returns of the Khartoum Stock Exchange using GARCH models. Their study showed that the process of the conditional variance was very persistent and concluded on the existence of risk premium for the KSE index returns. They also realised that, the model that provided the best fit was the asymmetric models which confirmed the existence of leverage effects. Salisu and Fasanya (2013) also estimated persistence of crude oil and found the existence of long memory.

More recently, Hasan et al. (2013) estimated and compared the persistence of volatility and asymmetry of natural gas and coal and crude oil. Their research revealed that, crude oil and natural gas return volatility endured shocks for comparatively higher periods whereas volatility in coal exhibited strong mean reversion.

2.8 Conclusion

This chapter gives insight on the various techniques employed by other researchers in modelling volatility and the risk-return relationship of equity returns. Among these methods reviewed, the GARCH family models with emphasis on GARCH-M models was employed in this study to model volatility and the risk-return relationship of selected equities on the Ghana Stock Exchange.

Chapter 3

Methodology

3.1 Overview

This chapter focuses on the various statistical techniques employed in analysing the data so as to achieve the objectives. It looks at the univariate Generalized Autoregressive Conditional Heteroskedasticity-in Mean (GARCH-M) family of models, volatility modelling techniques, persistence in volatility and half-life measure and diagnostic checking of the model estimated amongst others. The daily closing prices were converted into compound returns given by;

$$X_t = log\left(\frac{p_t}{p_{t-1}}\right) \tag{3.1}$$

where X_t is the continuous compound returns at time t, p_t is the current closing stock price index at time t and p_{t-1} is the previous closing stock price index.

3.2 Principal Component Analysis (PCA)

The principal component analysis (PCA) is more appropriate in estimating the covariance of a vector of time series. It is pertinent when one have obtained estimates on a number of observed variables and want to generate a fewer number of unreal variables which characterize much of the variance in the observed variables; a procedure for reducing variables. This study employed this method in selecting equities that characterized each sector. Given a n-dimensional variable $x = (x_1,...,x_n)^0$ with covariance matrix P_x is related with employing a few linear combinations of x_i to describe the P_x structure. If x is the daily lag returns of n stocks, then the Principal Component Analysis can be employed in studying the origin of variation of these n stocks returns. Applying covariance $_0$ matrix, if $w_i = (w_{i1},...,w_{in})$ where $i = 1,...,n$. Then

$$X_i = w_i^{'}x = \sum_{j=1}^{n} w_{ij}x_j \tag{3.2}$$

is a linear combination of the random vector x. If x comprises the returns of n stocks; X_i is the portfolio return that assigns weight w_{ij} to the j^{th} stock. By standardizing the vector w_i, we get $w_i'w_i = \sum_{j=1}^{n} w_{ij}^2 = 1$. From linear combination of random variables;

$$Var(X_i) = w_i' \sum_x w_i, \quad i = 1, ..., n \tag{3.3}$$

$$Cov(X_i, X_j) = w_i' \sum_x w_j, \; i,j = 1,...,n \tag{3.4}$$

PCA assists in determining linear combination w_i such that X_i and X_j are uncorrelated for $i \neq j$ and the variances of X_i are as large as possible.

More theoretically, the first principal component of x is the linear combinations w_i such that $X_1 = w_1'x$ that maximizes $Var(X_1)$ subject to the constraint that $w_1'w_1 = 1$. The second principal component of x is the linear combination $X_2 = w_2'x$ that maximizes $Var(X_2)$ subject to the constraints that $w_2'w_2 = 1$ and $Cov(X_1,X_2) = 0$. The i^{th} principal component of x is the linear combination $X_i = w_i'x$ that maximizes $Var(X_i)$ subject to the constraints that $w_i'w_i = 1$ and $Cov(X_i,X_j) = 0$. Since the covariance matrix Σ_x is non-negative definite, it has a spectral decomposition. If $(\lambda_1,e_1),...,(\lambda_k,e_k)$ are the eigenvalues and eigenvectors pairs of Σ_x, where $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_k \geq 0$. Then, the i^{th} principal component of x is given by;

$$X_i = e_i'x = \sum_{j=1}^{k} e_{ij}x_j, \qquad i = 1,...,k. \tag{3.5}$$

Also,

$$Var(X_i) = e_i' \sum_x e_i = \lambda_i, \quad i = 1, ..., k \tag{3.6}$$

$$Cov(X_i, X_j) = e_i' \sum_x e_j = 0, \quad i \neq j \tag{3.7}$$

Also,

$$\sum_{i=1}^{k} Var(x_i) = \sum_{i=1}^{k} \lambda_i = \sum_{i=1}^{k} Var(X_i) \quad (3.8)$$

$$\frac{Var(X_i)}{\sum_{i=1}^{k} Var(X_i)} = \frac{\lambda_i}{\lambda_1 + \ldots + \lambda_k} \quad (3.9)$$

Thus, the size of the total variance in x describe by the i^{th} principal component is simply the ratio between the i^{th} eigenvalue and the sum of all eigenvalues of P_x.

3.3 Stationarity/Unit Root Test

It is very paramount to establish the existence or non-existence of unit root in the time series under study so as to be able to ascertain the nature of the process that produces the time series. A variable exhibits covariance or weakly stationarity if the mean and autocovariance are finite and does not change with time (time invariant). That is, $E(X_t) = E(X_{t-1}) = \mu$ which is a constant and $Cov(X_t, X_{t-1}) = \gamma_l$.

For a covariance stationary series, the time series fluctuates around a constant long-run mean with finite variance which is time independent. This study employed three quantitative stationarity tests namely; the Augmented Dicker Fuller (ADF) test, the PhillipPerron unit root test and the Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) test in addition to the time series plots, Autocorrelation (ACF) and Partial Autocorrelation (PACF) graphical approaches.

3.4 Augmented Dickey-Fuller (ADF) Unit Root Test

This test is to determine whether the individual series studied have unit root or were covariance stationary. It was proposed by Dickey and Fuller (1979) as an upgraded form of the Dickey-Fuller (DF) test. It is based on the assumption that the series under study follows a random walk with model given by;

$$X_t = \Theta X_{t-1} + \varepsilon_t \quad (3.10)$$

The ADF test assumes the hypothesis:

H_o : $\Theta = 1$ (non-stationary) against H_1 : $\Theta < 1$ (covariance stationary) where Θ is the characteristics root of an AR polynomial and ε_t is an uncorrelated white noise series with constant variance and zero mean. When X_{t-1} is taken from both sides of Equation (3.10) we have

$$\Delta X_t = \varphi X_{t-1} + \varepsilon_t, \qquad t = (1,...,T) \tag{3.11}$$

where $\varphi = \Theta - 1$ and $\Delta X_t = X_t - X_{t-1}$. In determining the presence of unit roots from Equation (3.11), we test the hypothesis $H_o : \varphi = 0$ against $H_1 : \varphi \neq 0$.The series has a unit root and non-stationary if under $H_o : \varphi = 0$ and $\varphi = 1$. The rejection of H_o is based on the t-statistics critical values of the Dickey Fuller statistics. The ADF test includes the lags of the first difference series in the regression model to make ε_t a white noise series. The ADF test regression model then become;

$$\Delta X_t = \varphi X_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta X_{t-j} + \varepsilon_t, \qquad t = (1,...,T) \tag{3.12}$$

Equation (3.12) becomes;

$$\Delta X_t = \beta + \alpha t + \varphi X_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta X_{t-j} + \varepsilon_t, \qquad t = (1,...,T) \tag{3.13}$$

when the intercept and time trend $(\beta + \alpha t)$ are included.

where β is the intercept, α is the coefficient of the trend factor, $\sum_{j=1}^{p} \gamma_l \Delta X_{t-j}$ is the sum of the lagged values of the response variable ΔX_t and p is the order of the autoregressive process. There exist a unit root in the time series when φ of the ADF is zero and thus the series is not covariance stationary. The ADF test statistic is given by;

$$F_\tau = \frac{\hat{\phi}}{SE(\hat{\phi})} \tag{3.14}$$

where $\hat{\varphi}$ is the estimate of φ and $SE(\hat{\varphi})$ is the standard error of the least square estimate of $\hat{\varphi}$. The null hypothesis is rejected if the $p - value < \alpha$ significance level.

3.5 Kwiatkowsky-Phillips-Schmidt and Shin (KPSS) Test

This study also employed the KPSS test in testing the null hypothesis that the data generating process is stationary, $H_o : I(0)$ against the alternative that it is non-stationary, $H_1 : I(1)$. This test was developed by Kwiatkowsky et al. (1992). It assumes that there is no linear trend term and is given by;

$$Y_t = X_t + Z_t, \qquad Z_t I(0) \tag{3.15}$$

where X_t is a random walk, $X_t = X_{t-1} + v_t; vt \sim N(0, \sigma_v^2)$ and Z_t is a white noise series.
The previous pair of hypothesis is equivalent to;

$H_o : \sigma_{v2} = 0$ $H_1 :$

$\sigma_{v2} > 0$

If H_o is true, the model becomes $Y_t = constant + Z_t; Z_t I(0)$ hence Y_t is stationary. The test statistic is given by;

$$KPSS = \frac{1}{T^2} \sum_{t=1}^{T} \frac{s_t^2}{\hat{\sigma}_\infty^2} \tag{3.16}$$

where T is the number of observations, $\hat{\sigma}_\infty^2$ is an estimator of the long-run variance of the process Z_t.

$$S_t = \sum_{j=1}^{t} \hat{w}_j; \qquad \hat{w}_j = y_j - \bar{y} \tag{3.17}$$

!

$$\hat{\sigma}^2_\infty = \lim_{T\to\infty} T^{-1} var\left(\sum_{t=1}^{T} Z_t\right. \tag{3.18}$$

if S_t is integrated of order one and the denominator of the KPSS statistic is an estimator of its variance. Also, the term in the denominator ensures that the limiting distribution is devoid of unknown nuisance parameters. Nevertheless, the numerator increases without limit when it is integrated of order one. This causes the statistics to be large hence the null hypothesis is rejected for large KPSS values.

3.6 Phillips-Perron (PP)Unit Root Test

The Phillip-Perron test was employed to cater for the constraint of conditional heteroscedasticity and serial correlation in the residual error term of the ADF test. This test by Phillips (987a) corrects the original ADF unit root test to permit for a vast range of time series with heterogeneously and serially correlated residual errors. The PP semi-parametric test by Phillips and Perron (1988) is an extension of the Phillips (987a) approach and corrects for any serial correlation and heteroscedasticity in the error term, ε_t, non-parametrically. Therefore, by using Newey and West (1987) heteroscedasticity and autocorrelation consistent covariance matrix estimator, the test is regarded as a Dickey-Fuller test that have been made robust to serial correlation and conditional heteroscedasticity. The PP statistic test the hypothesis;

H_o : unit root against

H_1 : stationary about deterministic trend

Under the H_o of $p = 0$, the PP test Z_p and Z_τ statistics have the same asymptotic distributions as the ADF t-statistic and normalized bias statistics. One merit of the PP tests over the ADF tests is that the PP tests are robust to general forms of heteroscedasticity in the error term ε_t. Another advantage is that the user does not have to specify a lag length for the test regression.

It estimates the model;

$$X_t = \beta + pX_{t-1} + \varepsilon_t \quad (3.19)$$

With time trend t and no constant β,

$$X_t = \alpha t + pX_{t-1} + \varepsilon_t \quad (3.20)$$

The PP test is categorized into two statistics known as Phillips Z_p and Z_τ tests given by;

$$Z_p = n(\hat{p}_n - 1) - \frac{1}{2}\frac{n^2\hat{\sigma}_2}{s_n^2}(\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}) \quad (3.21)$$

$$Z_\tau = \sqrt{\frac{\hat{\gamma}_{0,n}}{\hat{\lambda}_n^2}}.\frac{\hat{p}_n - 1}{\hat{\sigma}} - \frac{1}{2}(\hat{\lambda}_n^2 - \hat{\gamma}_{0,n})\frac{1}{\hat{\lambda}}.\frac{n\hat{\sigma}}{s_n} \quad (3.22)$$

$\hat{\gamma}_{j,n} = \frac{1}{n}\sum_{i=j+1}^{n}\hat{\varepsilon}_i.\hat{\varepsilon}_{i-j}$, for $j = 0$, then $\hat{\gamma}_{j,n}$ is a maximum likelihood estimate of the error terms whiles $\hat{\gamma}_{j,n}$ is the covariance between the error terms j-periods apart for $j > 0$.

$\hat{\lambda}_n^2 = \hat{\gamma}_{0,n} + 2\sum_{j=1}^{q}\left(1 - \frac{j}{q+1}\right)\hat{\gamma}_{j,n}$, when there exist no autocorrelation between the error terms, $\hat{\gamma}_{j,n} = 0$ for $j > 0$, then $\hat{\lambda}^2_n = \hat{\gamma}_{0,n}$. In this case, Z_τ reduces to $Z_\tau = \frac{\hat{p}_n - 1}{\hat{\sigma}}$ which is a t-statistic in the ADF test.

Also, the error terms have the constant variance property and $Z_p = n(\hat{p}_n - 1)$ if the covariance are equal.

$s_n^2 \frac{1}{n-k}\sum_{i=1}^{n}\hat{\varepsilon}_i^2$ is an ordinary least square estimator of the variance of the residual terms, where k is the number of covariate, $\hat{\sigma}$ is the OLS standard error of $\hat{p}$ and q is the number of Newey-West lags to be employed in computing $\hat{\lambda}_n^2$.

3.7 The Durbin-Watson Test

The Durbin and Watson (1950) was employed to determine whether the error term in the mean equation follows an AR (1) process. This test requires the error term ε_t to be distributed $N(0,\sigma^2)$ for the statistic to have an exact distribution.

The test statistic is given by;

$$d = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2} \quad (3.23)$$

where $e_i = y_i - \hat{y}_i$, y_i and $\hat{y}_i$ are the observed and predicted values of the response variable for individual i respectively. d becomes smaller as the serial correlations increases. The hypothesis is given by;

$H_o : \rho = 0$ $H_1 :$

$\rho > 0$

Values of d less than 2 suggest positive autocorrelation ($\rho > 0$), whereas values of d greater than 2 suggest negative autocorrelation ($\rho < 0$). When d is closer to 2, it suggest that there is no first order autocorrelation in the residuals.

3.8 The Breusch-Godfrey Test

It is also an LM test which is employed to test for higher-order serial correlation in the disturbance.

The test statistic is given by;

$$B - G = NR^2 \quad (3.24)$$

where N is the number of observations and R^2 forms the regression

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} + ... + \gamma_p \hat{u}_{t-p} + \beta_1 x_{1t} + ... + \beta_k x_{kt} + \varepsilon_t \quad (3.25)$$

The hypothesis is given by;

H_o : no autocorrelation

H_1 : autocorrelation

The test is asymptotically $\chi^2(p)$ distributed.

3.9 Jarque-Bera Test

This is a goodness-of-fit test which was employed to investigate whether the sample data was normally distributed. It test the null hypothesis that the sample data is normally distributed against the alternative that it is not normally distributed.

The test statistic is given by;

$$JB = T.\left(\frac{S^2}{6} + \frac{(K-3)^2}{24}\right) \tag{3.26}$$

where T is the total observations, S and K are the sample skewness and kurtosis respectively.

The Hypothesis is given by;

H_o : normality

H_1 : non-normality

The test is asymptotically $\chi^2(p)$ distributed.

3.10 Univariate Ljung-Box Test

The Ljung and Box (1978) was employed to test whether there exist autocorrelations γ_l in the returns series and the standardized residuals of the selected model or not. It is of the assumption that, the returns series and standardized residuals contain no serial correlation up to a given lag k.

The statistic is given by;

$$Q(K) = T(T+2)\sum_{i=1}^{k} \frac{\gamma_l^2}{T-l} \tag{3.27}$$

where γ_l is the residual sample autocorrelation at lag l, T is the size of the series, k is the number of time lags included in the test. $Q(K)$ has an approximately chi-square distribution with k degree of freedom.

3.11 Testing for ARCH Effects

In applying GARCH methodology, it is very essential to examine the residuals for evidence of ARCH effects. The fact that the magnitude of current residuals for any financial time series seems to be non-linearly linked to the magnitude of their past residual forms the reasoning for ARCH test. This study employed the ARCH-LM test since it is the most commonly used procedure to test for ARCH effects in empirical researches (Brooks and Ragunathan (2003); Chinzara and Aziakpono (2009); Magnus and Fosu (2006)). Also Lee and King (1993) as wrote that the Lagrange Multiplier (LM) test can be employed in testing for ARCH effect in a series.

By representing the i lag autocorrelation of the absolute and squared returns by $\hat{p}_i$, the Ljung-Box statistic is given by;

$$Q = T(T+2)\sum_{i=1}^{m}\frac{\hat{p}_i^2}{T-i} \sim \chi^2(m) \quad (3.28)$$

The LM hypothesis is given by;

$H_o : \alpha_1 = \alpha_2 = ... = \alpha_i = 0$ (no ARCH effect) against H_1 : Not

H_o (ARCH effect)

for at least $i = 1,2,...,q$

The LM test statistic is given by;

$$LM = T.R^2 \sim \chi^2(q) \quad (3.29)$$

where T is the total observations, R^2 forms the regression and q is the number of restrictions placed on the model,

3.12 The Mean Equation

In modelling volatility, it is very essential to specify an suitable mean equation. It can take the form of an autoregressive (AR) model or a standard structural model or both. The mean equation selected should be white noise series, that is it should have a finite mean and variance. Comparatively following Takaendesa et al. (2006) and Chinzara and Aziakpono (2009), this study employed the following mean equations:

$$X_t = \mu + \varepsilon_t \quad (3.30)$$

$$X_t = \mu + \lambda X_{t-1} + \varepsilon_t \quad (3.31)$$

where X_t is the returns for each equity in each sector, μ is a constant, λ is the coefficient of X_{t-1} and ε_t is the innovation. Employing the Breusch-Godfrey and the Durbin-Watson tests, the equations were tested for autocorrelation.

3.13 Univariate Generalized Autoregressive Conditional Heteroskedasticity-in Mean Models

Research has showed that, in stock markets risky assets attract greater returns compared with less risky assets (Brooks, 2002). Engle et al. (1987) proposed the application of the ARCH-M models which allows the conditional variance returns enters into the conditional mean equation, thus allowing the stock return to be partially ascertained by its risk. Most typical structural models are assumed to have a constant variance. However, if the variances of the errors are not constant, the deduction would be standard error estimates that are faulty. Also, it is not likely in the context of financial time series that the variance of the errors will always be constant, thus using non-linear models will prove to be prudent. Two classes of volatility models exist namely asymmetric and symmetric models. For the asymmetric models, the shocks of the same magnitude negative or positive have different effects on next level volatility whereas for the symmetric model, the conditional variance only relays on the magnitude and not the sign of the given asset. Again, the symmetric nature of volatility is captured by the GARCH-M and asymmetric nature captured by

EGARCH-M, TGARCH-M models in this case.

3.14 Symmetric GARCH Model-The GARCH-in Mean

(GARCH-M) Model

Mostly, security returns may rely on its risk or volatility. In other for a phenomenon like this be modelled, there is the need to consider the GARCH-M model of Engle et al. (1987).

This model is an upgraded form the basic GARCH model which permits the conditional mean of a series to rely on its conditional variance. Its general form is the GARCH (p,q) model given by;

$$\sigma_t^2 = \alpha_o + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (3.32)$$

where $\alpha_o > 0$ and $\alpha_i \geq 0, i = 1,...,p$ and $\beta_j \geq 0, j = 1,...,q$. σ_t^2 is the squared volatility, α_o, α_i is the coefficient ARCH component, ε_{t-i}^2 is the lagged squared residual and β_j is the coefficient of the GARCH component.

The simplest GARCH-M model is the GARCH-M (1, 1) given by;

Mean equation:

$$X_t = \mu + \lambda\sigma_t^2 + \varepsilon_t, \qquad \varepsilon_t \sim N(0,\sigma_t^2) \qquad (3.33)$$

Variance equation:

$$\sigma_t^2 = \alpha_o + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \qquad (3.34)$$

where μ and α_o are constants. X_t is the return on an equity, σ_t^2 is the squared volatility, λ is the coefficient of the standard deviation (risk premium parameter), The rest of the parameters are the same as defined earlier. To satisfy the stationary condition, $\alpha+\beta < 1$. When λ is positive or negative and significant statistically , then increased risk given by an increase in conditional variance, leads to a rise or fall in the return, that is λ can be said to be time-varying risk premium. A statistically positive relationship will indicate that investors are compensated for assuming greater risk. But a negative relationship will indicate that investors react to factor(s) other than the standard deviation of equities from their historical mean.

Engle et al. (1987) also assumed that risk premium is an increasing function of the conditional variance of ε_t in that the higher the conditional variance of the return, the higher the compensation needed to cause an investor to hold an asset for a long period (Enders, 2004). This model will be tested for ARCH effects and stationarity and if the ARCH LM test reveals evidence of ARCH effects and if most of the models are non-stationary, the EGARCH-M will be employed.

3.15 Asymmetric GARCH-M Models-The Exponential GARCH-M (EGARCH-M)

This model that ensures the variance is always positive and captures asymmetry responses of time-varying variance to shocks. It was introduced by Nelson (1991), the generalized form can be specified as EGARCH (p, q) given by;

$$\ln(\sigma_t^2) = \alpha_o + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left[\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}^2} \right| - \sqrt{\frac{2}{\pi}} \right] + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}^2} \tag{3.35}$$

where α_o is a constant, α and β are the same as in GARCH-M and γ is leverage parameter.

If $\varepsilon_{t-i} > 0$, the total effect of ε_{t-i} is $(1 + \gamma)|\varepsilon_{t-1}|$; if $\varepsilon_{t-i} < 0$, the total effect of ε_{t-i} is $(1 + \gamma)|\varepsilon_{t-1}|$. The model is stationary and has a finite kurtosis if $|\beta_j| < 1$. That is there is no restriction on the leverage effect.

Also if $\gamma < 0$ and significant statistically , then negative shocks means a higher next level conditional variance than positive shocks of the same magnitude.

Assuming the mean equation in Equation (3.31),the simplest form of EGARCH-M is the EGARCH-M (1, 1), the variance equation is given by;

$$\ln(\sigma_t^2) = \alpha_o + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left[\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \right| - \sqrt{\frac{2}{\pi}} \right] + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \tag{3.36}$$

$\alpha + \beta < 1$, $\gamma < 0$ if volatility is asymmetric.

In the original specification of the model, Nelson (1991) assumed GED (Generalized Error Distribution) for the errors. If the distributional assumption of the errors are altered from the original, the model specification will leave the estimates the same except for α_o. The TGARCH-M will also be explored if the EGARCH-M does not fully eliminate the ARCH effects and if most of the models are non-stationary.

3.15.1 The Threshold GARCH-M (TGARCH-M)

This model was proposed by Glosten et al. (1993) and Zakoian (1994). It is simply a respecification of the GARCH-M model with an additional term to account for asymmetry (leverage effect). In the general specification of this model, the TGARCH (p, q) model is given by;

$$\sigma_t^2 = \alpha_o + \sum_{i=1}^{p}(\alpha_i + \gamma_i d_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2 \tag{3.37}$$

where α_o is a constant, d is a dummy variable and γ is the asymmetric coefficient. α_i,γ_i and β_j are non-negative. Assuming the mean equation in Equation (3.31) the variance equation for TGARCH-M (1, 1) is given by;

$$\sigma_t^2 = \alpha_o + \alpha_1\varepsilon_{t-1}^2 + \gamma_1 d_{t-1}\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{3.38}$$

$$l_{t-1} = \begin{cases} 1 & \text{if } \varepsilon_{t-1} < 0, \quad \textit{bad news} \\ 0 & \text{if } \varepsilon_{t-1} \geq 0, \quad \textit{good news} \end{cases} \tag{3.39}$$

When $\gamma > 0$, there exist leverage effects on stock markets and if $\gamma \neq 0$ then the effect of news is asymmetric (Eview, 2007). Also when $\gamma = 0$, then the model reduces to the basic GARCH model. Nevertheless, when the shock is positive (good news), the volatility is α_1, whereas if the news is negative (bad news), the effect on volatility is $\alpha_1 + \gamma_1$. Similarly, if γ is positive and statistically significant then negative shocks will have a greater impact on σ_t^2 than positive shocks (Cater et al., 2007). Also, the constraints of the parameters are $\alpha_o > 0, \alpha_1 \geq 0, \beta_1 \geq 0$ and $\alpha_1 + \gamma_1 \geq 0$ for the conditional variance to be positive..

The model is stationary if $\gamma_1 < 2(1 - \alpha_1 - \beta_1)$.

3.16 Volatility Persistence

3.16.1 Mean Reversion

Mean reversion means that current information on volatility has no effect on the future forecast of volatility. Generally the GARCH coefficient(s) of a stationary GARCH model captures persistence dynamics in volatility. In stationary GARCH models, the volatility mean reverts to its long run level, at a rate given by the sum of ARCH and GARCH coefficients, which is usually close to one (1) for financial time series. The mean reverting formula for the general GARCH (1, 1) model is given by;

$$(\varepsilon_t^2 - \bar{\sigma}^2) = (\alpha_1 + \beta_1)(\varepsilon_{t-1}^2 - \bar{\sigma}^2) + X_t - \beta_1 X_{t-1} \quad (3.40)$$

where $\bar{\sigma}^2 = \frac{\alpha_o}{1-\alpha_1-\beta_1}$, the unconditional long run level of volatility and $X_t = (\varepsilon^2_t - \bar{\sigma}^2)$. The magnitude of $\alpha_1 + \beta_1$ controls the rate of the mean reversion.

3.16.2 Half-Life

The half-life τ is a measure of volatility persistence , Engle and Patton (2001) defined halflife as the time required for the volatility to move half way back towards its unconditional mean. If, τ is the least value of k such that

$$|\sigma_{t+k|t} - \bar{\sigma}^2| = \frac{1}{2}|\sigma_{t+1|t} - \bar{\sigma}^2| \quad (3.41)$$

where k is the number of days, $\sigma_{t+k|t}$ is the conditional expected value of volatility k days into the future and $\bar{\sigma}^2$ is the mean level to which the unconditional variance eventually reverts.

Also, the GARCH (1, 1) process is mean reverting if $(\alpha_1 + \beta_1) < 1$ since if this condition is satisfied, $\sigma_{t+k|t} \rightarrow \bar{\sigma}^2$ as $k \rightarrow \infty$. Thus, the forecast conditional variance reverts to the unconditional variance as the forecast horizon increases.

For $k \geq 2$ and a GARCH (1, 1) process, the value of $\sigma_{t+k|t}$ is given by;

$$\sigma_{t+k|t} = \bar{\sigma}^2 + (\alpha_1 + \beta_1)^{k-1}(\sigma_{t+1} - \bar{\sigma}^2), \qquad k \geq 2 \tag{3.42}$$

From Equation (3.41) and Equation (3.42), the number of days k for a GARCH (1, 1) process is given by;

$$|\bar{\sigma}^2 + (\alpha_1 + \beta_1)^{k-1}(\sigma_{t+1} - \bar{\sigma}^2) - \sigma^2| = \frac{1}{2}|\sigma_{t+1} - \bar{\sigma}^2| \tag{3.43}$$

This is the same as

$$(\alpha_1 + \beta_1)^k = \frac{1}{2}(\alpha_1 + \beta_1) \tag{3.44}$$

Taking logarithms of Equation (3.44) gives;

$$k = \frac{log\left[(\alpha_1 + \beta_1)/2\right]}{log(\alpha_1 + \beta_1)} \tag{3.45}$$

Therefore the half-life for a basic GARCH (1, 1) model is given by;

$$\tau = \frac{log\left[(\alpha_1 + \beta_1)/2\right]}{log(\alpha_1 + \beta_1)} \tag{3.46}$$

3.17 Distributional Assumptions of Error Term

In GARCH model specification, it is more appropriate to consider the choice on the distributional assumption of the error term. Following Kovacic (2008), this study assumed three distributional assumptions; Generalized Error Distribution (GED), Gaussian (Normal) distribution and Student-t distribution in order to cater for fat tails that are common in most financial data. The ARCH models are estimated using the maximum likelihood approach given a distributional assumption. The contribution to the likelihood for observation t for the Student-t distribution is given by;

$$l_t = -\frac{1}{2}log\left(\frac{\pi(v-2)\Gamma(\frac{1}{2})^2}{\Gamma(\frac{v+1}{2})^2}\right) - \frac{1}{2}log\sigma_t^2 - \frac{v+1}{2}log\left(1+\frac{(y_t - X_t'\theta)^2}{\sigma_t^2(v-2)}\right) \quad (3.47)$$

where Γ(.) is the gamma function and $v > 2$ is a shape parameter which controls the tail behaviour. When $v \to \infty$ the distribution converges to Gaussian distribution. Nelson (1991) proposed the use of the GED in order to account for fat-tails observed commonly in financial time series. It is given by;

$$l_t = -\frac{1}{2}log\left(\frac{\Gamma(\frac{1}{r})^3}{\Gamma(\frac{3}{r})(\frac{r}{2})^2}\right) - (-\frac{1}{2}log\sigma_t^2) - \left(\frac{\Gamma(\frac{3}{r})(y_t - X_t'\theta)^2}{\sigma_t^2\Gamma(\frac{1}{r})}\right)^{\frac{1}{2}} \quad (3.48)$$

where $r > 0$ is the tail parameter. The distribution has a fat tailed if $r < 2$ and becomes Gaussian distribution if $r = 2$

The contribution to the likelihood for observation t for the Gaussian distribution is given by;

$$l_t = -\frac{1}{2}log(2\pi) - \frac{1}{2}log\sigma_t^2 - \frac{(y_t - X_t'\theta)^2}{2\sigma_t^2} \quad (3.49)$$

3.18 Model Selection Criterion

This study employed two information criteria namely, Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) in selecting the best model. Their respective estimations are given by;

$$AIC = \ln(\hat{\sigma}^2) + \frac{2k}{T} \quad (3.50)$$

$$BIC = \ln(\hat{\sigma}^2) + \frac{k}{T}\ln T \quad (3.51)$$

where $\hat{\sigma}^2$ is residuals variance, T is the sample size, k is the total number parameters. For a GARCH (p, q) model, $k = p + q + 1$. The best model is the model that has least

AIC and BIC values.

3.19 Model Diagnostic

It is very essential to undertake a diagnostic checks on the model after determining the best model and its corresponding distribution for the error term so as to establish whether the model and distribution are correctly specified. This study employed the Ljung-Box test and Lagrange Multiplier (LM) test to test for the existence of autocorrelation and ARCH effects. The presence of autocorrelation and ARCH effects for both the raw series and the standardized residuals of the selected model were tested.

3.20 The long term trend in volatility

In examining the long term trend in volatility, the conditional variance was regress on a constant and a time variable to ascertain how volatility changes over time, thus from the works of (Frommel and Menkhoff (2003) and Chinzara and Aziakpono (2009)). It is of great importance to undertake this investigation since volatility on equity market thus affect financial stability. The model employed in this investigation is given by;

$$\sigma_t^2 = \alpha_1 + \alpha_2 T \tag{3.52}$$

where σ_t^2 is the conditional variance for each equity (sector), α_1 is a constant and T is the number of days or time. If α_2 is significant and positive, then volatility for that equity is increasing over time and volatility is decreasing over time when α_2 is negative and significant.

3.21 Cross Validation of GARCH-M (1,1) family of Models

The best model for further analysis was cross validated with an out-sample forecast from 5th January, 2015 to 16th January, 2015. The chi-square goodness of fit test was employed. This is a statistical test that examines the level to which a set of observed sample data deviates from the corresponding set of expected values of the sample. The test statistic is given by;

$$\chi^2 = \sum_{i=1}^{k} \frac{(o_i - e_i)^2}{e_i} \tag{3.53}$$

With $k-1$ degree of freedom, where o_i is the observed returns series and e_i is the expected returns series.

3.22 Conclusion

This chapter provides a detailed account of the statistical techniques employed in this study for analysing the data so as to achieve the set objectives. The ADF, PP and KPSS tests were employed in testing for stationarity. The Principal Component Analysis (PCA) was employed in selecting equities that characterize each sector. The ARCHLM test was employed in selecting equities from the PCA that exhibited ARCH effects. In choosing appropriate mean equation for the volatility modelling, the Durbin-Watson and Breusch-Godfrey tests were employed. The Jarque-Bera test was employed in testing for normality in the selected returns series. The univariate Ljung-Box was employed in testing for the presence of autocorrelation in the returns series and the standardized residuals of the selected model. The univariate GARCH-M family of models was employed in modelling the symmetry and asymmetry in volatility of the returns series. These models were extended in estimating the risk-return relationship. The persistent and half-life in volatility was determined from the ARCH and GARCH coefficients. The long run trends in volatility was investigated using a simple regression. The best model selected was cross validated using chi-square goodness of fit test.

Chapter 4

Analysis and Results

4.1 Introduction

This chapter gives the analysis, interpretations and discussion of results of the study. It comprises the source of data, preliminary analysis, further analysis, discussion of results and conclusion.

4.2 Source of Data

This study used secondary data of 35 equities and a later reduction to 8 equities (CAL, PBC, FML, CLYD, EGL, UNIL, TLW and BOPP) from the Ghana Stock Exchange (GSE) and Annual Report Ghana databases comprising the daily closing prices from the period 02/01/2004 to 16/01/2015, totalling 7616 observations. The statistical packages employed for analysing the data were Gretle, STATA and R.

4.3 Preliminary Analysis

This section presents and explains the descriptive statistics of 35 equities from 8 sectors on the Ghana Stock Exchange (GSE). Thus, giving the general overview of the equities on the exchange. From Table 5.1 in Appendix A, it is evident that, the Finance sector had seven of the mean returns found to be positive, ranging from 0.0006 to 0.0022 and two of the mean returns was found to be negative (-0.0006 to -0.0003). Volatility (standard deviation) in was high in ETI (0.0646) with the least found in HCF (0.0124). The highest and least mean returns were found in ETI and TBL respectively. The variability between risk and returns as a measure of coefficient of variation (CV %) ranges from -7144.1700 (SOGEGH) to 7749.5900 (ETI). Also five mean returns were positively skewed (4.6600 to 28.3400) and the rest four negatively skewed (-20.8100 to -0.1700) and the kurtosis was high ranging 108.5460 to 850.2200. The Distribution sector had three of its mean returns been positive (0.0001 to 0.0017) with the exception of PBC (-0.0019). MLC and PBC had the highest and least mean returns respectively. The sector had volatility been high in MLC (0.0582) with the least found in GOIL (0.0210). Also the sector exhibited variability ranging 230.6400 (PBC) to 16906.9400 (GOIL). Two mean returns were positively skewed (1.9100 to 9.4500) and the other two negatively skewed (-13.9600 to -1.0800). The kurtosis was high ranging 132.8100 to 363.0600. The Food and Beverage sector had two positive mean returns, ranging from 0.0008 to 0.0012 with the exception of CPC (-0.0005). FML and CPC had the highest and least mean returns respectively. The sector exhibited high volatility in CPC (0.0458) whereas GGBL (0.0155) exhibited low volatility. The CV% ranged from -14476.9400 (CPC) to 1953.0700 (GGBL). Also two out of the three mean returns were negatively skewed (-3.5600 to -0.0300) and the kurtosis was high ranging 11.0700 to 71.0900. The Information Communication Technology sector have the two mean returns negative, ranging from -0.0002 to -0.0001. The sector recorded a higher volatility in TRANSOL (0.0352) and low volatility in CLYD (0.0260). The sector had CV% ranging from -95087.0400 (TRANSOL) to -24856.2300 (CLYD). Also this sector had all the two mean returns positively skewed. The kurtosis ranged from 32.8200 to 79.8900. Also, the Insurance sector also have its two mean returns positive (0.0002 to 0.0010). Volatility was high in EGL (0.0380) than SIC (0.0304). The sector had CV% ranging 3159.3300 (SIC) to 16299.1900 (EGL). The sector exhibited negative skewness in EGL (-16.8800) and positive skewness in SIC (24.3700). Also the sector had kurtosis ranging 347.1800 to 692.5800. The ten equities in the Manufacturing sector had five positive mean returns, ranging from 0.0001 to 0.0009 and five negative mean returns, ranging from -0.0014 to -0.0001 with the highest mean returns found in UNIL and least mean returns found in ALW. Volatility was high in ALW (0.0445) compared to PKL (0.0038).

The sector was found to have CV% ranging from -51723.4200 (SPL) to 65846.8300 (PZC). Out of the ten equities, six were positively skewed ranging 0.2800 to 6.9500 whereas the other four were negatively skewed ranging -15.2300 to -0.5800. The kurtosis was ranging from 35.9900 to 390.0100. The Mining sector had all the equities recording positive mean returns, ranging 0.0011 to 0.0018. Volatility was high in GRS (0.0609) and low in ADDs (0.0263). The sector had coefficient of variation (CV) ranging from 2441.7100 (AADs) to 3341.0500 (GSR). The skewness was all positive ranging 28.7400 to 29.800. This sector had kurtosis ranging from 866.000 to 909.04000. Lastly, the Agriculture sector had mean returns been positive. The volatility was at 0.0420 and also CV% was 2154.5100 (BOPP). The returns was positively skewed (14.5100). The kurtosis was also positive and greater than three.

Furthermore, the highest mean returns for the period under study was found in EBG (0.0022) and the least mean returns found in PBC (-0.0019). Also 24 of the equities exhibited positive mean returns whereas 11 exhibited negative mean returns over the sample period. It is also evident that, over the sample period, volatility was high in ETI (0.0646) from the Finance sector and lower in PKL (0.0038) from the Manufacturing sector. The coefficient of variation for the entire sample period was high in PZC (65846.8300) and low TRANSOL (-95087.0400) i.e. from the Manufacturing sector and Information Communication Technology sector respectively. The Manufacturing sector have six of the mean returns positively skewed (0.2800 to 6.9500) and four negatively skewed (-15.2300 to 0.5800). Out of the 35 equities, 22 had their mean returns positively skewed as against 13 equities having their mean returns negatively skewed. The excess kurtosis for all the sectors and equities for that matter were all positive indicating that all the mean returns were more peaked. Also the excess kurtosis for the entire sample period had the mean returns of GSR (909.0400) in the Mining sector more peaked than CPC (11.0700) in Food and Beverage sector.

Figure (4.1), (4.2), (4.3), (4.4), (4.5), (4.6), (4.7) and (4.8) which shows the time series plots of CAL, PBC, FML, CLYD, EGL, UNIL, TLW and BOPP respectively, it is evident that the selected returns series (CAL, PBC, FML, CLYD, EGL, UNIL, TLW and BOPP) did not clearly indicate any trend but there is evidence of volatility clustering an indication that high values of volatility tends to be followed by high values whereas low values of volatility tends to be followed by low values.

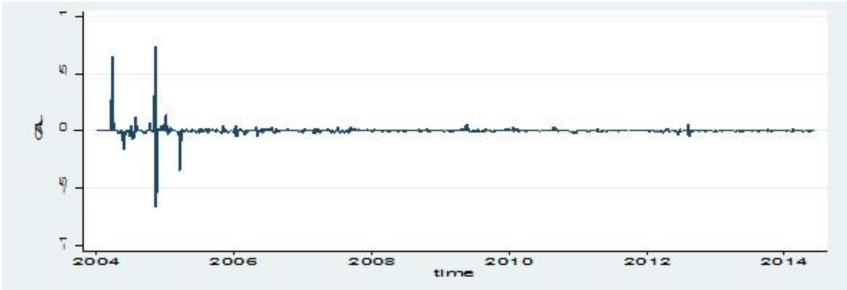

Figure 4.1: Time Series plot of CAL Returns Series

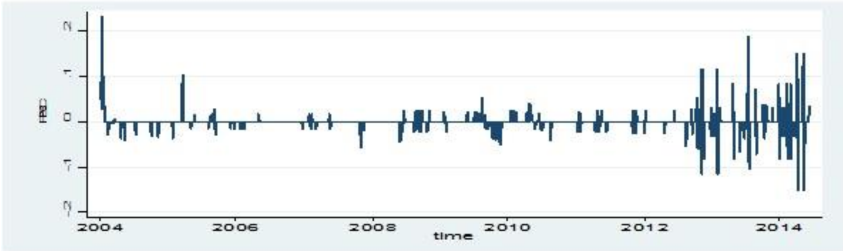

Figure 4.2: Time Series plot of PBC Returns Series

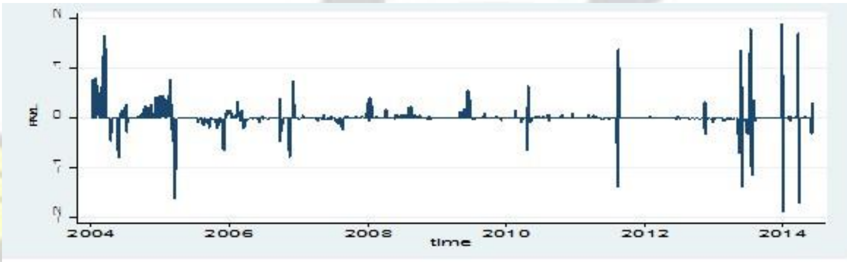

Figure 4.3: Time Series plot of FML Returns Series

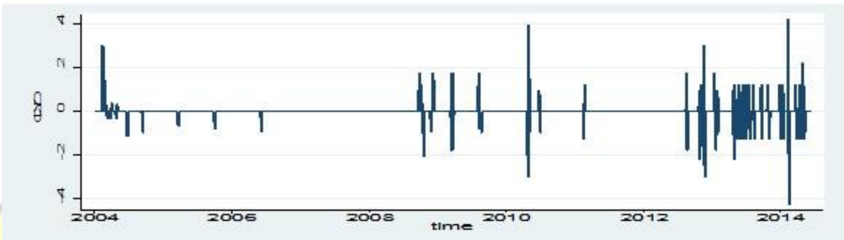

Figure 4.4: Time Series Plot of CLYD Returns Series

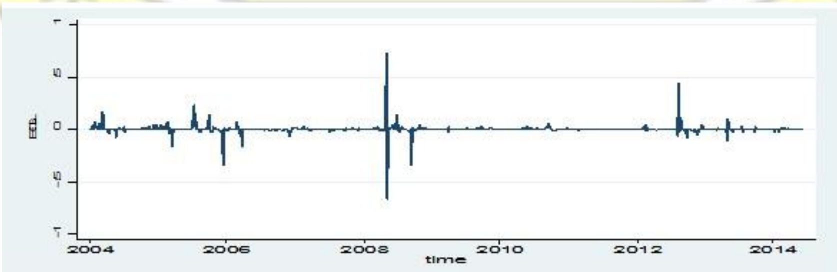

Figure 4.5: Time Series Plot of EGL Returns Series

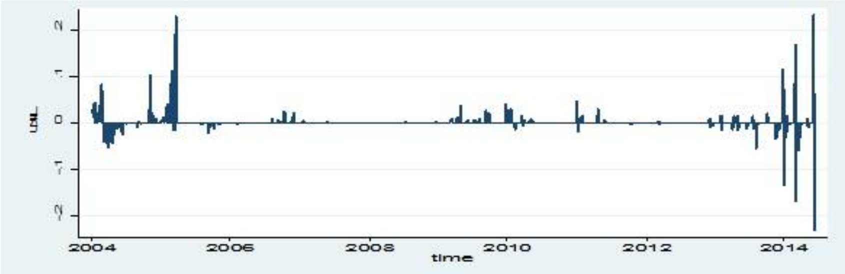

Figure 4.6: Time Series plot of UNIL Returns Series

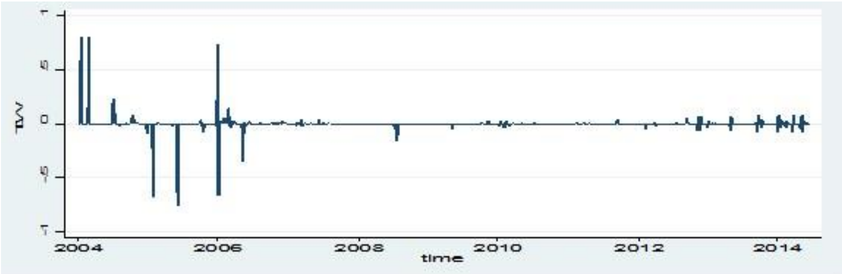

Figure 4.7: Time Series plot of TLW Returns Series

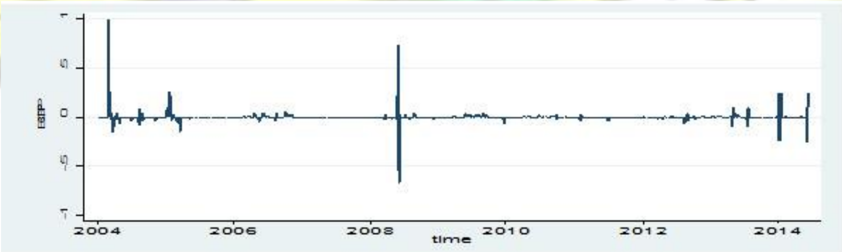

Figure 4.8: Time Series plot of BOPP Returns Series

4.4 Further Analysis

The further analysis comprises investigating all the 35 equities returns series for stationarity and ARCH effects among others. The Principal Component Analysis (PCA) was employed in selecting equities that characterized each sector. The family of univariate GARCH models; GARCH-M, EGARCH-M and TGARCH-M were employed in investigating the volatility and the risk-return relationship of the selected equities. The data consisted of 7616 observations for fitting the models and the rest of the 10 observations for cross validation of the selected model fitted.

4.4.1 Stationarity Test of the Returns Series

The returns series were tested for stationarity or unit root to ascertain whether the levels of the series change over time or not. From the time series plot in Figure (4.1), (4.2), (4.3), (4.4), (4.5), (4.6), (4.7) and (4.8) it is evident that, the returns series of CAL, PBC, FML, CLYD, EGL, UNIL, TLW and BOPP respectively had no trends but rather fluctuates over time giving a strong indication of stationarity in the levels of the series. From Figure (4.9), (4.10), (4.11), (4.12), (4.13), (4.14), (4.15), (4.16) and (4.17), (4.18), (4.19), (4.20), (4.21), (4.22), (4.23), (4.24), it is also evident that the ACF and PACF plots of the returns series and squared returns series of CAL, PBC, FML, CLYD, EGL, UNIL, TLW and BOPP respectively did not clearly showed stationarity. Also the ACF and PACF plots of CAL, PBC, FML, CLYD, EGL, UNIL, TLW and BOPP did not vividly indicate whether the returns series were serially correlated except at lag (1) and the ACF plots does not decay slowly, an indication of long memory behaviour.

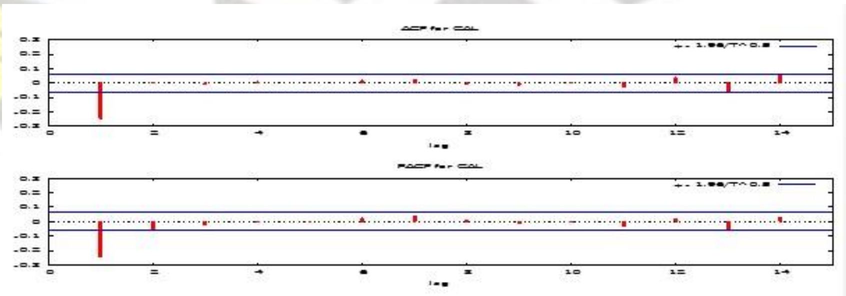

Figure 4.9: ACF and PACF plot of CAL Returns Series

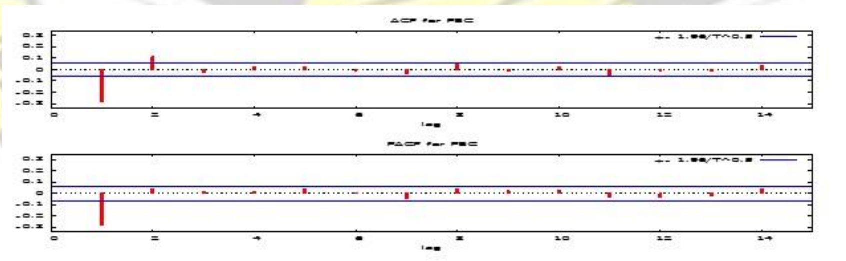

Figure 4.10: ACF and PACF plot of PBC Returns Series

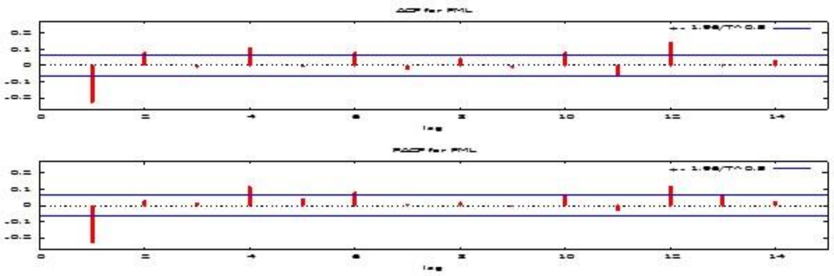

Figure 4.11: ACF and PACF plot of FML Returns Series

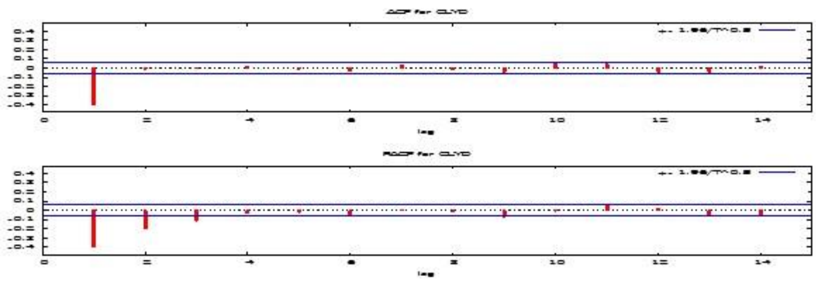

Figure 4.12: ACF and PACF plot of CLYD Returns Series

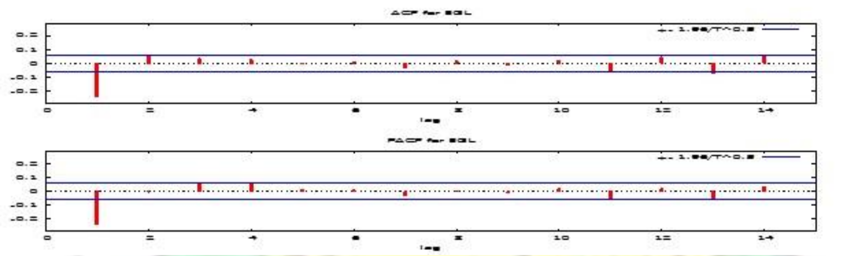

Figure 4.13: ACF and PACF plot of EGL Returns Series

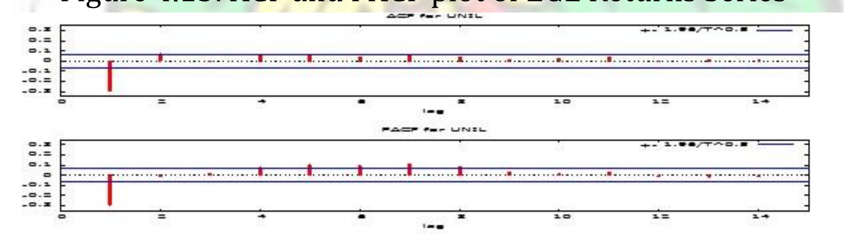

Figure 4.14: ACF and PACF plot of UNIL Returns Series

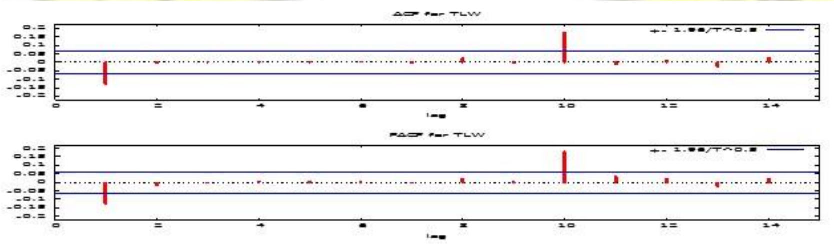

Figure 4.15: ACF and PACF plot of TLW Returns Series

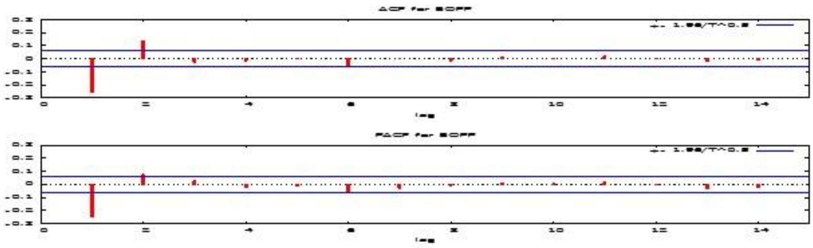

Figure 4.16: ACF and PACF plot of BOPP Returns Series

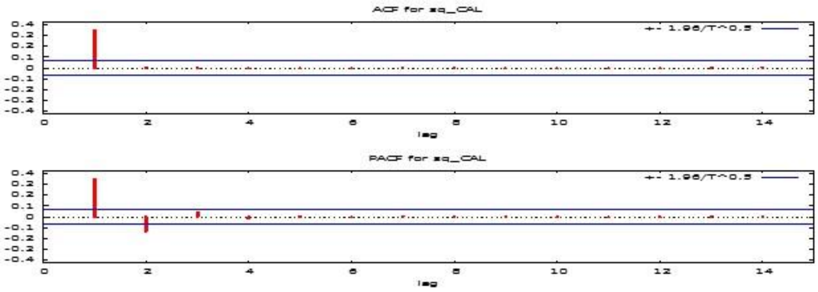

Figure 4.17: ACF and PACF plot of the squared Returns Series of CAL

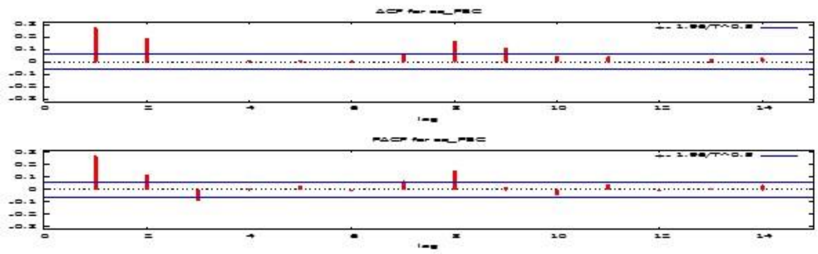

Figure 4.18: ACF and PACF plot of the squared Returns Series of PBC

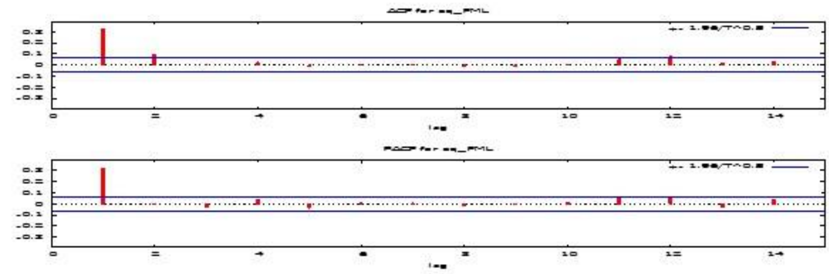

Figure 4.19: ACF and PACF plot of the squared Returns Series of FML

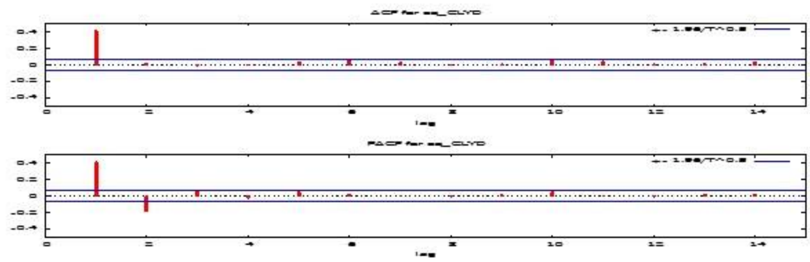

Figure 4.20: ACF and PACF plot of the squared Returns Series of CLYD

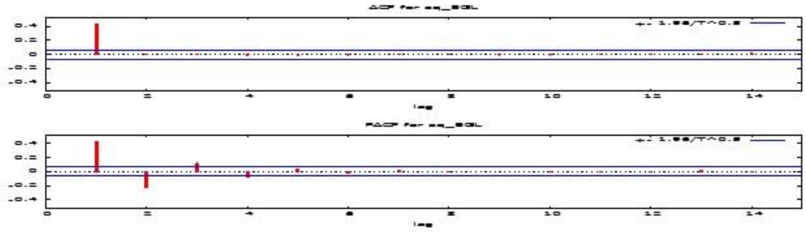

Figure 4.21: ACF and PACF plot of the squared Returns Series of EGL

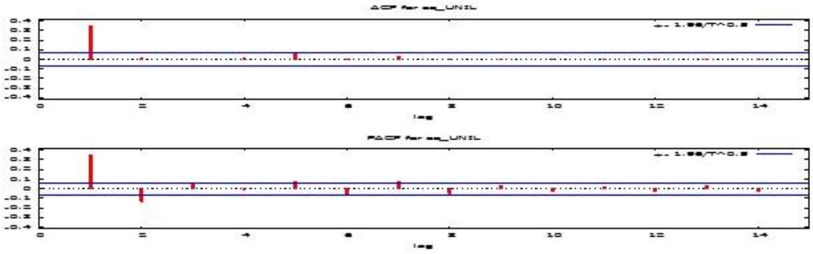

Figure 4.22: ACF and PACF plot of the squared Returns Series of UNIL

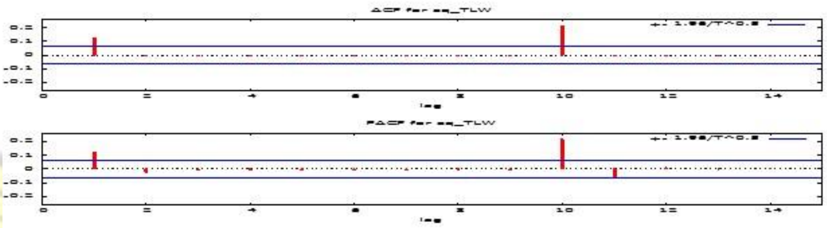

Figure 4.23: ACF and PACF plot of the squared Returns Series of TLW

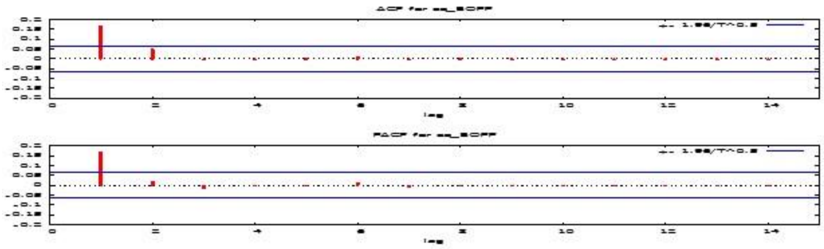

Figure 4.24: ACF and PACF plot of the squared Returns Series of BOPP

In confirming stationarity of the return series, three stationarity tests were conducted namely the ADF, PP and KPSS tests. All these tests as shown in Table 4.1 and 4.2 revealed that, for the ADF and PP tests, p-values were very significant at the 5% significance level and therefore the null hypothesis of non-stationary or unit root was rejected. In the case of the KPSS test, I failed to reject the null hypothesis of stationary since the test was significant at the 5% significance level. Therefore, the returns series were all stationary at the 5% level of significance for all the three tests.

Table 4.1: ADF Test of the Return Series

	Constant only		Constant and Trend	
Sector	Test Statistic	P-value	Test Statistic	P-value
Finance				
CAL	-25.8229	0.0000**	-25.8425	0.0000**
EBG	-31.0061	0.0000**	-31.0944	0.0000**
ETI	-31.0959	0.0000**	-31.0827	0.0000**
GCB	-13.4455	0.0000**	-13.4383	0.0000**
HFC	-15.7011	0.0000**	-15.7756	0.0000**
SCB	-30.0684	0.0000**	-30.0948	0.0000**
SOGEGH	-17.9228	0.0000**	-17.9879	0.0000**
TBL	-20.5866	0.0000**	-20.5769	0.0000**
UTB	-31.4249	0.0000**	-31.4935	0.0000**
Distribution				
GOIL	-37.2757	0.0000**	-37.2856	0.0000**
MLC	-42.8146	0.0000**	-42.8636	0.0000**
PBC	-41.5265	0.0000**	-41.5408	0.0000**
TOTAL	-31.1439	0.0000**	-31.2334	0.0000**
Food and Beverage				
CPC	-16.0858	0.0000**	-16.1131	0.0000**
FML	-10.7141	0.0000**	-10.8630	0.0000**
GGBL	-11.2390	0.0000**	-11.2837	0.0000**
Info. Technology				
CLYD	-24.5964	0.0000**	-24.5907	0.0000**
TRANSOL	-19.8505	0.0000**	-19.8533	0.0000**
Insurance				
EGL	-16.8608	0.0000**	-16.8858	0.0000**
SIC	-19.5736	0.0000**	-19.6251	0.0000**
Manufacturing				
ALW	-13.8718	0.0000**	-13.9067	0.0000**
AYRTN	-16.6947	0.0000**	-16.7928	0.0000**
CMLT	-11.1780	0.0000**	-11.2341	0.0000**
PZC	-35.6791	0.0000**	-35.6780	0.0000**
SPL	-13.6934	0.0000**	-10.1852	0.0000**
UNIL	-10.0682	0.0000**	-10.1852	0.0000**
PKL	-30.8112	0.0000**	-30.7985	0.0000**
GWEB	-18.9782	0.0000**	-18.9687	0.0000**

SWL	-15.0403	0.0000**	-15.1535	0.0000**
ACI	-28.0411	0.0000**	-28.2016	0.0000**
Mining				
TLW	-31.4693	0.0000**	-31.5073	0.0000**
AGA	-31.1581	0.0000**	-31.2464	0.0000**
GSR	-31.03093	0.0000**	-31.0797	0.0000**
AADs	-30.8726	0.0000**	-30.9989	0.0000**
Agriculture				
BOPP	-13.3981	0.0000**	-13.5204	0.0000**

** Significant at 5% significance level Table 4.2: PP Test and KPSS Test of the Return Series

	PP Test		KPSS Test	
Sector	Test Statistic	P-value	Test Statistic	Critical value (5%)
Finance				
CAL	-40.2780	0.0000**	0.0423	0.1480
EBG	-31.0930	0.0000**	0.1170	0.1480
ETI	-31.0870	0.0000**	0.0268	0.1480
GCB	-31.3140	0.0000**	0.0404	0.1480
HFC	-32.9370	0.0000**	0.0504	0.1480
SCB	-30.1270	0.0000**	0.0243	0.1480
SOGEGH	-28.2020	0.0000**	0.0370	0.1480
TBL	-32.4470	0.0000**	0.0542	0.1480
UTB	-31.5000	0.0000**	0.0370	0.1480
Distribution				
GOIL	-37.3130	0.0000**	0.1119	0.1480
MLC	-51.0150	0.0000**	0.0973	0.1480
PBC	-41.6420	0.0000**	0.0615	0.1480
TOTAL	-31.2340	0.0000**	0.1007	0.1480
Food and Beverage				
CPC	-48.2120	0.0000**	0.0103	0.1480
FML	-38.4000	0.0000**	0.0167	0.1480
GGBL	-31.4690	0.0000**	0.0517	0.1480
Info. Technology				
CLYD	-54.0670	0.0000**	0.0230	0.1480
TRANSOL	-52.9740	0.0000**	0.0175	0.1480
Insurance				
EGL	-30.3310	0.0000**	0.0497	0.1480

SIC	-31.2470	0.0000**	0.0695	0.1480
Manufacturing				
ALW	-14.9730	0.0000**	0.0510	0.1480
AYRTN	-35.1650	0.0000**	0.0603	0.1480
CMLT	-46.2060	0.0000**	0.1335	0.1480
PZC	-35.6130	0.0000**	0.1436	0.1480
SPL	-35.3890	0.0000**	0.0220	0.1480
UNIL	-39.8050	0.0000**	0.0734	0.1480
PKL	-30.7990	0.0000**	0.4480	0.1480
GWEB	-56.0410	0.0000**	0.0390	0.1480
SWL	-51.4340	0.0000**	0.0208	0.1480
ACI	-46.4080	0.0000**	0.0270	0.1480
Mining				
TLW	-31.5120	0.0000**	0.0511	0.1480
AGA	-31.2520	0.0000**	0.1278	0.1480
GSR	-31.0840	0.0000**	0.0563	0.1480
AADs	-30.0030	0.0000**	0.1477	0.1480
Agriculture				
BOPP	-35.0780	0.0000**	0.0678	0.1480

** Significant at 5% significance level

4.4.2 Principal Component Analysis (PCA) of the Returns Series

The principal component analysis was employed to reduce the number of variables (equities) in each sector i.e. selecting variables that characterize each sector. For each sector, the PCA was employed in selecting the components that explains much of the variance in that sector. Using the Eigen-value-one criterion, component(s) with eigenvalue greater than one (1) were retained. It is therefore evident from Table 4.3 that, component 1 and 2 were retained by most of the sectors. The component loadings was set at 0.5 and that variable(s) with loadings greater than 0.5 was/were selected. The Finance sector had ETI, GCB and CAL selected with loadings 0.670, 0.7576 and -0.6696 respectively. The Distribution sector had PBC and TOTAL selected with loadings 0.7391 and 0.6022 respectively. The Food and Beverage sector had FML selected from comp1 with loadings 0.8835. The information communication technology sector had CLYD

selected in comp1 with loadings -0.7071. The insurance sector had EGL selected with loadings 0.7071. The manufacturing sector had PZC and UNIL selected in comp1 and comp2 with loadings
0.5932 and 0.6121 respectively. Also, the mining sector had TLW and AGA with loadings -0.7076 and 0.7071 selected respectively. The Agriculture sector was not considered for this analysis since already there was only one equity (BOPP).

Table 4.3: Principal Component Analysis of the Returns Series

Eigenanalysis		Eigenvectors		
Component	Eigenvalue	Variable	Comp1	Comp2
Finance				
Comp1	1.9427	**CAL**	0.3410	-0.6696*
Comp2	1.1120	EBG	0.1203	0.0989
Comp3	1.0284	**ETI**	0.6760*	0.0672
Comp4	0.9948	**GCB**	-0.4761	0.7576*
Comp5	0.9527	HFC	0.4084	0.4604
Comp6	0.9085	SCB	-0.2928	0.2650
Comp7	0.8445	SOGEGH	0.3021	0.1046
Comp8	0.6696	TBL	-0.0010	0.2696
Comp9	0.5388	UTB	0.0252	-0.1060
Distribution				
Comp1	1.1419	GOIL	0.5069	-0.4923
Comp2	1.0699	MLC	-0.4223	0.3927
Comp3	0.9704	**PBC**	0.7391*	-0.0617
Comp4	0.8178	**TOTAL**	0.5291	-0.6022*
Food and Beverage				
Comp1	1.3153	CPC	0.4404	-0.4270
Comp2	0.92970	**FML**	0.8835*	0.6168
Comp3	0.7551	GGBL	-0.1927	0.6524*
Info. Technology				
Comp1	1.2246	**CLYD**	-0.7071	0.7071*
Comp2	0.7754	TRANSOL	0.7071	0.7071
Insurance				
Comp1	1.0249	**EGL**	0.7071	0.7071*

Comp2	0.9752	SIC	0.7071	-0.7071
Manufacturing				
Comp1	1.7249	ALW	0.1948	0.3752
Comp2	1.3642	AYRTN	0.0382	0.0736
Comp3	1.1156	CMLT	0.4806	0.2934
Comp4	1.0187	**PZC**	0.5932*	0.1777
Comp5	1.0114	SPL	0.3371	0.2577
Comp6	0.9610	**UNIL**	-0.4500	0.6121*
Comp7	0.8175	PKL	0.0276	-0.0162
Comp8	0.7604	GWEB	0.1550	0.5424
Comp9	0.6501	SWL	0.4932	-0.2705
Comp10	0.5761	ACI	-0.2103	0.2690
Mining				
Comp1	1.9774	**TLW**	-0.7076*	0.0007
Comp2	1.0019	**AGA**	0.0020	0.7071*
Comp3	0.9981	GSR	-0.0023	0.7066
Comp4	0.0226	AADs	0.7071	0.0010

* Selected equity under each component.

4.4.3 Test for ARCH Effects of the Returns Series

In fitting ARCH/GARCH model, it is very important to examine the residuals for evidence of ARCH effects. This is to check for the existence or non-existence of conditional Heteroskedasticity in the residuals of the individual equations fitted. The selected equities from the principal component analysis were considered for the ARCH-LM test. The ARCH-LM test was conducted at lags 1, 7 and 14. It is therefore evidence from Table 4.4 that, the Finance sector had CAL exhibiting the presence of ARCH effects at the 5% significance level. The distribution sector had PBC exhibiting ARCH effects at the 5% significance level. The Food and Beverage sector had FML exhibiting ARCH effects. Also, the rest of the sectors i.e. information communication technology, insurance, manufacturing, mining and Agricultural had CLYD, EGL, PZC, TLW and BOPP exhibiting ARCH effects at the 5% significance level. Therefore CAL, PBC, FML, CLYD, EGL, PZC, TLW and BOPP from the Finance, Distribution, Food and Beverage, Information Communication Technology, Insurance, Manufacturing, Mining and Agricultural sectors respectively were considered for fitting the GARCH models since they exhibited ARCH effects.

Table 4.4: ARCH-LM Test of the Selected Returns Series from the PCA

Sector	Lag	Test Statistic	P-value
Finance			
	1	0.0012	0.9722
ETI	7	0.0086	1.0000
	14	0.0158	1.0000
	1	0.0011	0.9738
GCB	7	0.0080	1.0000
	14	0.0168	1.0000
	1	125.1810	0.0000**
CAL	7	148.5370	0.0000**
	14	186.9760	0.0000**
Distribution			
	1	0.0045	0.9722
TOTAL	7	0.0318	1.0000
	14	0.0650	1.0000
	1	6.8591	0.0088**
PBC	7	21.8946	0.0026**
	14	40.7375	0.0002**
Food and Beverage			
	1	73.3761	0.0000**
FML	7	77.4349	0.0000**
	14	80.9421	0.0000**
Info. Technology			
	1	130.3180	0.0000**
CLYD	7	133.4630	0.0000**
	14	138.8120	0.0000**
Insurance			
	1	26.6978	0.0000**
EGL	7	36.6906	0.0000**
	14	36.4258	0.0000**
Manufacturing			
	1	0.0052	0.9941
PZC	7	0.0077	1.0000

	14	0.0169	1.0000
UNIL	1	59.7481	0.0000**
	7	61.2771	0.0000**
	14	60.9034	0.0000**
Mining			
TLW	1	15.1319	0.0000**
	7	24.9135	0.0008**
	14	40.8408	0.0002**
AGA	1	0.0011	0.9741
	7	231.2610	0.0000**
	14	395.0200	0.0000**
Agriculture			
BOPP	1	23.8970	0.0003**
	7	56.0000	0.0001**
	14	163.8830	0.0000**

** Significant at 5% significance level[54]

4.4.4 Normality, Autocorrelation and Heteroscedascitity Test of the Returns Series

The Jarque-Bera and Ljung- Box (LB) tests were employed to test for normality and autocorrelation respectively. The lag length selection for the ADF test was determined by BIC. It is evident from Table 4.5 that, the Jarque-Bera test for normality was significant at the 5% significance level for all the returns series, I therefore rejected the null hypothesis of normality and concluded that the returns series were not normally distributed. The Ljung-Box statistic $LB(14)$ and $LB^2(14)$ of the returns series and squared returns series were all statistically significant at the 5% level of significance. I therefore rejected the null hypothesis of no autocorrelation in the levels of the returns series and squared returns series.

Table 4.5: Test for Normality, Autocorrelation and Heteroscedascitity of Return Series

Sector	Jarque-Bera	$LB(14)$	$LB^2(14)$
Finance			
CAL	1.9098*	30.5740*	52.7909*

Distribution			
PBC	42803.6000*	22.3281*	32.7670*
Food and Beverage			
FML	66302.5000*	51.9865*	38.6640*
Info. Technology			
CLYD	42308.9000*	68.4155*	42.4638*
Insurance			
EGL	987916.0000*	33.8373*	56.0461*
Manufacturing			
UNIL	337264.0000*	58.9513*	46.8042*
Mining			
TLW	634210.0000*	34.5074*	49.7469*
Agriculture			
BOPP	1.5759*	38.7833*	32.8956*

* Significant at 5% significance level.

4.4.5 Volatility Analysis of the Returns Series

In fitting volatility models, it is more appropriate to specify a suitable mean equation. The Mean Equation 3.30 in chapter 3 was estimated and tested for serial correlation using the Breush-Godfrey LM test and for autocorrelation using the Durbin-Watson (DW) tests. As the results of the mean equation in Table 4.6 depicted, there was evident of autocorrelation for this specification of the Mean Equation 3.30. Since most of the d statistic for the DW test were greater than 2, the null hypothesis of no first order autocorrelation was rejected. In the same vein, the Breush-Godfrey (B-G) for the same Mean Equation 3.30 was significant at the 5% level of significance , hence the null hypothesis of no autocorrelation was rejected. Therefore, a single lagged value of the exogenous variable was added to the right hand side of Equation 3.30 giving rise to Equation 3.31 in chapter

3. This new mean equation was then tested for autocorrelation. As it is evident from Table 4.6 that, the DW-AR(1) had indications of autocorrelation but the B-G AR(1) showed no evidence of autocorrelation since it was not significant at the 5% significance level across the entire returns series and therefore I failed to reject the null hypothesis of no autocorrelation. The use of this specification of the Mean Equation 3.31 with an AR (1) component eliminated autocorrelation hence making it more appropriate for all the

GARCH estimations (GARCH-M, EGARCH-M and TGARCH-M) even though the ARCHLM test for both equations were significant at the 5% significance level for all the returns series.

Table 4.6: Mean Equation Results for the Returns Series

Sector	DW	B-G	ARCHLM	DW-AR(1)	B-G(1)	ARCHLM AR(1)
Finance						
CAL	2.4939	0.0000*	0.0000*	2.0300	0.0609	0.0000*
Distribution						
PBC	2.3440	0.0000*	0.0000*	1.9930	0.9129	0.0000*
Food and Beverage						
FML	2.4528	0.0000*	0.0000*	1.9856	0.3787	0.0000*
Info. Technology						
CLYD	2.1951	0.0000*	0.0000*	2.1602	0.5620	0.0000*
Insurance						
EGL	2.4808	0.0000*	0.0000*	2.0019	0.9014	0.0000*
Manufacturing						
UNIL	2.4236	0.0000*	0.0000*	1.9043	0.3965	0.0000*
Mining						
TLW	2.2514	0.0000*	0.0000*	2.0043	0.5908	0.0000*
Agriculture						
BOPP	2.2582	0.0000*	0.0000*	2.9043	0.2899	0.0000*

* Significant at 5% significance level.

The ARCH and GARCH coefficients which measures the persistence in volatility for a given model was investigated by summing them. As it is reported in Table 4.7, the GARCH model have most of the summations been less than one (1) with the exception of CAL (Gaussian), PBC (GED), CLYD (GED) and EGL (Gaussian and student-t). The EGGARCH model as reported in Table 4.8, shows evident of most of the summations been greater than one (1) with the exception of CAL (Gaussian), PBC (Gaussian and GED), FML (GED), CLYD (Gaussian and student-t), EGL (Gaussian), UNIL (studentt), TLW (Gaussian and GED) and BOPP (Gaussian). Also as is evident from Table 4.9, the TGARCH have most of the summations been less than one (1) with the exception of PBC (GED), FML (GED), EGL (GED) and BOPP (GED). The models with the summation of α and β greater than one (1) indicates that the model is non-stationary with the given distribution. Since most of the models for GARCH-M (1,1) was non-stationary, the EGARCH (1,1) and TGARCH (1,1) were employed.

The two asymmetry models (EGARCH and TGARCH) were investigated further for leverage effects by reporting on the leverage effect coefficient γ. As it is reported from Table 4.8, the leverage effects coefficient for the EGARCH model were mostly negative and significant at the 5% significance level indicating the presence of leverage effect with the exception of CAL (Gaussian) and UNIL (Gaussian) which were positive and significant and CLYD (GED), EGL (GED) and BOPP (GED) were negative and not significant. Also, the coefficient of asymmetry of the EGARCH-M (1, 1) model with the student-t distribution was high in CAL (-0.0151) and least in UNIL (-0.6075) from the Finance and Manufacturing sectors respectively. The TGARCH-M (1, 1) model as reported in Table 4.9, showed that most of the leverage effects coefficient were positive and significant at the 5% significance level indicating the existence of leverage effect with the exception of PBC (Gaussian), CLYD (Gaussian), UNIL (GED), and BOPP (Gaussian) showing a insignificantly negative asymmetry coefficient. The asymmetric coefficient of TGARCH-M (1, 1) model with the student-t distribution was high in UNIL (0.4105) and low in CLYD (0.0063) from the Manufacturing and Information Communication Technology sectors respectively.

4.4.6 Analysis of the Risk-Return Relationship of the Returns Series

In establishing the risk-return trade-off for the three models, λ was employed as the coefficient in estimating this relationship. As it is reported in Table 4.7, 4.8 and 4.9 of the GARCH-M (1, 1), EGARCH-M (1, 1) and the TGARCH-M (1, 1) models respectively. The risk-return coefficient of the GARCH-M (1, 1) model showed a positive and a significant relationship (positive risk premium) with the exception of CAL (Gaussian) and TLW (GED) negative but not significant, FML (GED), TLW (Gaussian) and BOPP (Gaussian) positive and not significant. The EGARCH-M (1, 1) model also had most of the coefficients positive and significant like that of the GARCH-M (1, 1) model with the exception PBC (student-t and GED), EGL (GED), TLW (GED) and BOPP (Gaussian) negative and not significant, UNIL (student-t) negative and significant and CLYD (Gaussian) positive not significant. Also, the TGARCH-M (1, 1) model had the risk-return coefficients mostly significant and positive with the exception of CAL (Gaussian), PBC (Gaussian), UNIL (GED), TLW (student-t) showing negative risk premium, CAL (GED), CLYD (GED), TLW (GED) positive and not significant. Again, the risk-return coefficient for the GARCH-M (1, 1) model showed that 17 out of the 24 models were positive and significant (positive risk premium). For the EGARCH-M (1, 1) , 18 out of the 24 models estimated were positive and significant whereas 17 out of the 24 models of the TGARCHM (1, 1) were positive and significant. In essence, 52 out of the 72 models estimated showed evident of positive risk premium under the various distribution assumptions with the exception of a few.

4.4.7 ARCHLM Test of the GARCH-M, EGARCH-M and TGARCH-M Models

The ARCHLM test which shows whether a model fully captured ARCH effects was reported in Table 4.7, 4.8 and 4.9 for the GARCH-M (1, 1), EGARCH-M (1, 1) and the TGARCH-M (1, 1) models respectively. The GARCH-M (1, 1) model was able to capture some of the ARCH effects at the 5% significance level with the exception of CAL (Gaussian), PBC (GED), FML (Gaussian), CLYD (Gaussian), EGL (GED), CLYD (Gaussian), UNIL (student-t) and BOPP (Gaussian). Therefore the null hypothesis of no ARCH effects was rejected. The EGARCH-M (1, 1) also captured some of the ARCH effects at the
5% significance level with the exception of CAL (GED), PBC (Gaussian and GED), FML (GED), CLYD (Gaussian), EGL (student-t), UNIL (GED) and BOPP (Gaussian). Hence, the null hypothesis of no ARCH effects was also rejected. Nevertheless, the TGARCHM (1, 1) model eliminated most of the ARCH effects with the exception of CAL (GED), PBC (Gaussian), CLYD (GED), TLW (Gaussian) and BOPP (Gaussian). Therefore, I failed to reject the null hypothesis of no ARCH effects. Among the three models, the
TGARCH-M (1, 1) was able to eliminate much of the ARCH effects and most of the

ARCH and GARCH summations were less than indicating stationarity.

4.4.8 Model Selection

The suitable model and the distribution under which it performs best was selected by taking into account the summation of α and β to be less than one (1) for the stationarity of the model, capturing asymmetry in the returns series and been able to eliminate much of the ARCH effects in the returns series. When the above criterion are met, the information criteria (BIC and AIC) are employed in selecting the appropriate distribution assumption. Since BIC places a much stiffer penalty term compared to AIC (Brooks, 2002, 257), it was the information criterion that was employed even though the AIC as reported in Table 4.7, 4.8 and 4.9 does not contradict the BIC. As is reported of the three models in Table 4.7, 4.8 and 4.9 of the GARCH-M (1, 1), EGARCH-M (1, 1) and TGARCH-M (1, 1) respectively, the TGARCH-M (1, 1) met the model selection criteria compared to the other two models. The BIC selected the student-t distribution assumption for the TGARCH-M (1, 1) since 5 out of the 8 returns series selected the student-t distribution.

Table 4.7: Estimated GARCH-M (1,1) Model

Sector	λ	$\alpha + \beta$	ARCHLM	BIC	AIC
Finance					
CAL					
Gaussian Distribution	-0.0743	1.1880	0.0652	-3966.1520	-3990.4450
Student-t Distribution	0.2046*	0.8221	0.0000*	-6252.4630	6276.7560
GED	0.0070*	0.6979	0.0308*	-6365.8690	-6390.1620
Distribution					
PBC					
Gaussian Distribution	0.0240*	0.9944	0.0080*	5330.3940	-5349.8290
Student-t Distribution	0.0013*	0.6807	0.0010*	-3540.2450	-3825.1450
GED	0.0001*	1.0807	0.1400	-4592.1960	-4611.6310
Food and Beverage					
FML					
Gaussian Distribution	0.0340*	0.9964	0.0730	-5135.8460	-5155.2800
Student-t Distribution	0.3102*	0.8183	0.0000*	-7350.1910	-7369.6260
GED	0.0004	0.9026	0.0206*	-7244.4100	-7263.8440
Info. Technology					
CLYD					
Gaussian Distribution	-0.0722*	0.9848	0.0582	-3773.1100	-3767.4030
Student-t Distribution	0.3050*	0.6752	0.0000*	-3284.1671	-3520.8141
GED	0.0970*	1.0780	0.0000*	-2767.8720	-2792.1640
Insurance					
EGL					
Gaussian Distribution	0.0067*	1.0601	0.0000*	-4810.7930	-4835.0860
Student-t Distribution	0.0475*	1.1032	0.0640	-6127.2900	-6151.5830
GED	0.0075*	0.8420	0.1805	-3986.8510	-4011.1440
Manufacturing					

UNIL					
Gaussian Distribution	0.5958*	0.9470	0.0000*	-6487.0910	-6511.3840
Student-t Distribution	0.0002*	0.9354	0.0940	-8848.4440	-8872.7370
GED	0.0072*	0.6281	0.0000*	-6183.8450	-6201.3520
Mining					
TLW					
Gaussian Distribution	0.0043	0.8736	0.0173*	-6379.0014	-6438.3106
Student-t Distribution	0.0309*	0.7082	0.0000*	-7300.0170	-7324.3090
GED	-0.0285	0.8503	0.0000*	-5241.2710	-5328.7240
Agriculture					
BOPP					
Gaussian Distribution	0.0561	0.9021	0.1364	-3341.4040	-3365.6970
Student-t Distribution	0.2134*	0.6513	0.0348*	-6814.1500	-6838.4430
GED	0.0008*	0.7360	0.0013*	-6430.9500	-6723.2436

* Significant at 5% significance level

Table 4.8: Estimated EGARCH-M (1,1) Model

Sector	λ	$\alpha + \beta$	γ	ARCHLM	BIC	AIC
Finance						
CAL						
Gaussian Dist.	-0.0314*	0.8128	0.0712*	0.0000*	-4071.0230	-4095.3160
Student-t Dist.	0.7149*	1.0610	-0.0151*	0.0000*	-6184.5320	-6213.6830
GED	0.0532*	0.6979	-0.5879*	0.0840	-2533.7700	-2558.0620
Distribution						
PBC						
Gaussian Dist.	0.0214*	0.7243	-0.1800*	0.2160	-3452.8700	-3830.2102
Student-t Dist.	-0.0813	1.2908	-0.1301*	0.0030*	-6445.2830	-6469.5760
GED	-0.3418*	0.7634	-0.0401*	0.0574	-4375.6010	-4736.6720
Food and Beverage						

FML						
Gaussian Dist.	0.0901*	1.2673	-0.2450*	0.0000*	-5099.3920	-5123.6850
Student-t Dist.	0.0045*	1.0173	-0.0810*	0.0000*	-7131.7480	-7156.0401
GED	0.0310*	0.9977	-0.3171*	0.1040	-4187.5670	-4211.8600
Info. Technology						
CLYD						
Gaussian Dist.	0.0184	0.9938	-0.2796*	0.1502	-3769.1350	-3793.4280
Student-t Dist.	0.5914*	0.7750	-0.0658*	0.0201*	-3257.1230	-3406.3086
GED	0.8301*	1.0660	-0.1773	0.0000*	-2516.9550	-2641.2480
Insurance						
EGL						
Gaussian Dist.	0.6104*	0.9864	-0.2949*	0.0000*	-3589.1590	-3613.4510
Student-t Dist.	0.0850*	1.1341	-0.0515*	0.2600	-6868.6860	-6892.9790
GED	-0.0432	1.3927	-1.4550	0.0000*	-3922.5290	-3946.8210
Manufacturing						
UNIL						
Gaussian Dist.	0.8013*	1.5590	0.2480*	0.0000*	-4780.1680	-4903.8000
Student-t Dist.	-0.0018*	0.9680	-0.6075*	0.0000*	-3010.7100	-3208.1802
GED	0.5096*	1.0860	-1.0222*	0.0735	-5321.4101	-5452.7120
Mining						
TLW						
Gaussian Dist.	0.4728*	0.7928	-0.0214*	0.0000*	-7345.8120	-7532.2100
Student-t Dist.	0.0842*	1.0435	-0.1630*	0.0000*	-5492.1210	-5664.4200
GED	-0.0083	0.0846	-0.0294*	0.0000*	-4612.7130	-4930.0901
Agriculture						
BOPP						
Gaussian Dist.	-0.4120	0.8903	-1.2232*	0.1350	-1786.4730	-1810.7660
Student-t Dist.	-0.0702*	1.0823	-0.0912*	0.0017*	-6627.9850	-6652.2780

GED	0.5016*	1.4267	-0.7390	0.0082*	-3334.3690	-3358.6610

* Significant at 5% significance level

Table 4.9: Estimated TGARCH-M (1,1) Model

Sector	λ	$\alpha + \beta$	γ	ARCHLM	BIC	AIC
Finance						
CAL						
Gaussian Dist.	-0.0082*	0.9507	0.0650*	0.0000*	-5488.1230	-5512.4160
Student-t Dist.	0.0729*	0.8712	0.0816*	0.6183	**-6092.7070****	-6117.0000
GED	0.2856	0.9780	0.1212*	0.5052	-4970.8690	-4995.1610
Distribution						
PBC						
Gaussian Dist.	-0.9000*	0.5926	-0.5941*	0.0000*	-4946.9410	-4976.0920
Student-t Dist.	1.0824*	0.7580	0.0974*	0.6103	-3201.8921	-3481.5401
GED	0.9516*	1.1017	0.0464*	0.0558	-4592.6530	4621.8040
Food and Beverage						
FML						
Gaussian Dist.	0.0431*	0.6346	0.0085	0.0896	-5129.2620	-5153.5550
Student-t Dist.	0.2580*	0.9622	0.2940*	0.0925	-4354.25900	-4378.5510
GED	-0.0017	1.0406	0.0293*	0.0264*	-4179.1490	-4203.4420
Info. Technology						
CLYD						
Gaussian Dist.	-0.0373	0.9520	-0.0705*	0.7105	-3742.5000	-3771.6510
Student-t Dist.	0.5081*	0.8275	0.0063*	0.8461	**-4258.3920****	-4529.1124
GED	0.4230	0.9737	0.2552*	0.0020*	-2773.5910	-2797.8840
Insurance						
EGL						
Gaussian Dist.	0.0506*	0.6680	0.0319*	0.0003*	-5601.8400	-5828.3200
Student-t Dist.	0.0239*	0.8927	0.1546*	0.0572	**-6121.6860****	-6150.8380

GED	-0.6342	1.0235	0.0845*	0.0626	-4273.4501	-4602.6210
Manufacturing						
UNIL						
Gaussian Dist.	0.1435*	0.5970	0.0814*	0.0604	-6502.1120	-6531.2630
Student-t Dist.	0.6107*	0.8149	0.4105*	0.5812	-4860.3210	-4884.0680
GED	-0.3840*	0.6466	-0.2063*	0.2075	-5544.0270	-5568.3190
Mining						
TLW						
Gaussian Dist.	0.2813*	0.6938	1.4145*	0.0402*	-3879.0100	-3893.8000
Student-t Dist.	-0.3024*	0.8301	0.3827*	0.3086	**-5480.1720****	-5802.3210
GED	0.0832	0.6810	0.4210*	0.0104*	-4325.8307	-4538.7512
Agriculture						
BOPP						
Gaussian Dist.	-0.0872	0.5138	-0.4382*	0.0063*	-3360.4710	-3384.7640
Student-t Dist.	0.1820*	0.7789	0.3030*	0.7154	**-4829.9430****	-4857.0940
GED	0.3058*	1.0250	1.8793*	0.1520	-1804.2300	-1828.5200

* Significant at 5% significance level. ** Selected error distribution.

Thus, the fitted TGARCH-M (1,1) with student-t distributional assumption models of the returns series becomes:

$$CAL; \quad \sigma_t^2 = 0.0002 + 0.2508\varepsilon_{t-1}^2 + 0.6204\sigma_{t-1}^2 + 0.6183d_{t-1}\varepsilon_{t-1}^2 \qquad (4.1)$$

$$PBC; \quad \sigma_t^2 = 0.0017 + 0.2527\varepsilon_{t-1}^2 + 0.5053\sigma_{t-1}^2 + 0.0974d_{t-1}\varepsilon_{t-1}^2 \qquad (4.2)$$

$$FML; \quad \sigma_t^2 = 0.0001 + 0.4562\varepsilon_{t-1}^2 + 0.5060\sigma_{t-1}^2 + 0.2940d_{t-1}\varepsilon_{t-1}^2 \qquad (4.3)$$

$$CLYD; \quad \sigma_t^2 = 0.0064 + 0.3592\varepsilon_{t-1}^2 + 0.4683\sigma_{t-1}^2 + 0.0063d_{t-1}\varepsilon_{t-1}^2 \qquad (4.4)$$

$$EGL; \quad \sigma_t^2 = 0.0001 + 0.2841\varepsilon_{t-1}^2 + 0.6086\sigma_{t-1}^2 + 0.1546d_{t-1}\varepsilon_{t-1}^2 \qquad (4.5)$$

$$UNIL; \quad \sigma_t^2 = 0.0024 + 0.2417\varepsilon_{t-1}^2 + 0.4732\sigma_{t-1}^2 + 0.4105 d_{t-1}\varepsilon_{t-1}^2 \quad (4.6)$$

$$TLW; \quad \sigma_t^2 = 0.0002 + 0.2842\varepsilon_{t-1}^2 + 0.5459\sigma_{t-1}^2 + 0.3827 d_{t-1}\varepsilon_{t-1}^2 \quad (4.7)$$

$$BOPP; \quad \sigma_t^2 = 0.0001 + 0.1022\varepsilon_{t-1}^2 + 0.6767\sigma_{t-1}^2 + 0.3030 d_{t-1}\varepsilon_{t-1}^2 \quad (4.8)$$

4.4.9 Model Diagnostic Checks

A diagnostic checks was performed on the selected model (TGARCH-M (1, 1)) to ascertain whether it was well specified. Table 4.10 reveals the descriptive statistics of the returns series and the standardized residuals of the TGARCH-M (1, 1) model with the student-t distributional assumption. The standard deviation was lower for the selected model with the exception of FML, CLYD, TLW and BOPP. Also, the Jarque-Bera test for normality was significant at the 5% significance level for both the returns series and the standardized residuals of the TGARCH-M (1, 1). Therefore, the null hypothesis of normality was rejected for the returns series and the standardized residuals and that both were not normally distributed. The selected model had most of the skewness been lower than that of the returns series with the exception of FML, CLYD and EGL. Also, the kurtosis for the selected model were lower with the exception of PBC. Moreover, the $LB(14)$ statistic which test for the absence of autocorrelation in the return series was statistically significant at all levels of the returns series indicating the presence of ARCH effects whereas the same statistic for the standardized residuals of the selected model were mostly insignificant at the 5% significance level with the exception of FML and UNIL indicating that most of the returns series have no further ARCH effects. Also, the $LB^2(14)$ statistic which test for the absence of heteroscedacitity in the returns series and the standardized residuals, revealed that, for the returns series, there was evident of heteroscedacitity since the test was statistically significant at the 5% significance level. In the case of the standardized residuals, it was revealed that the test was insignificant with the exception of PBC and CLYD indicating the absence of heteroscedacitity. The above details indicates that the selected model was well specified for most of the estimated returns series.

Table 4.10: Diagnostic Checks of the TGARCH-M (1,1) (student-t distribution)

Sector	Mean	St. Dev.	Jarque-Bera	Skewness	Kurtosis	$LB(14)$	$LB^2(14)$
Finance							
CAL							
Raw returns	0.0013	0.0425	1.9098*	4.6600	220.3900	30.5740*	52.7909*
TGARCH-M	0.0006	0.0247	1.8609*	4.3509	212.2387	18.8130	19.1500
Distribution							
PBC							
Raw returns	-0.0019	0.0223	42803.6000*	132.8100	1.9100	22.3281*	32.7670*
TGARCH-M	-0.0026	0.0218	50460.9000*	34.9070	3.6615	14.0286	56.0643*
Food and Beverage							
FML							
Raw returns	0.0012	0.0216	66302.5000*	0.7200	41.0800	51.9865*	38.6640*
TGARCH-M	0.0215	0.0375	50460.5000*	0.7381	40.8590	51.9865*	11.0000
Info. Technology							
CLYD							
Raw returns	-0.0002	0.0460	42308.9000*	0.5900	32.8200	68.4155*	42.4638*
TGARCH-M	-0.0007	0.8275	42249.4000*	0.5975	32.6140	22.3249	41.9848*
Insurance							
EGL							
Raw returns	0.0002	0.0380	987916.0000*	-16.8800	347.1800	33.8373*	56.0461*
TGARCH-M	0.0321	0.0438	945696.0000*	1.5114	157.7900	10.4620	17.0643
Manufacturing							
UNIL							
Raw returns	0.0009	0.0187	337264.0000*	2.2300	92.5900	58.9513*	46.8042*
TGARCH-M	0.0004	0.0148	336613.0000*	0.0412	92.0180	58.1395*	16.8994
Mining							
TLW							
Raw returns	0.0017	0.0527	634210.0000*	28.7400	866.0000	34.5074*	49.7469*
TGARCH-M	0.0119	0.0653	5237.8400*	24.7321	506.2420	11.0150	13.0965
Agriculture							
BOPP							
Raw returns	0.0020	0.0420	1.5759*	14.5100	346.4800	38.7833*	32.8956*
TGARCH-M	0.1820	0.7789	1.5367*	7.8850	198.7000	16.0830	0.8940

* Significant at 5% significance level.

4.4.10 Volatility Persistence and Half-life Measure of the Returns Series

The selected model was used in investigating the persistence and half-life measure of volatility of the returns series. The summation of α and β of the TGARCH-M (1,1) with the student-t distributional assumption was used. As it is evident from Table 4.11, all the 8 returns series (CAL, PBC, FML, CLYD, EGL, UNIL, TLW and BOPP) were persistent exhibiting long-memory since their summation of α and β were closer to one (1). Also, in terms of mean reversion, almost all the returns series have strong mean reversion with the exception of FML. FML exhibited the highest persistence level. The half-life measure of volatility also revealed the same trend. The half-life of most of returns series were short (CAL (6 days), PBC (4 days), CLYD (5 days), EGL (7 days), UNIL (4 days), TLW (5 days) and BOPP (4 days)) with the exception of FML (19 days). It was also clear that, once the returns series were highly persistent, their half-life measure of volatility tends to be high.

Table 4.11: Persistence and Half-life Volatility measure of the Returns Series

Sector	$\alpha + \beta$	Half-life volatility measure (days)
Finance		
CAL	0.8712	6
Distribution		
PBC	0.7580	4
Food and Beverage		
FML	0.9622	19
Info. Technology		
CLYD	0.8275	5
Insurance		
EGL	0.8927	7
Manufacturing		
UNIL	0.8149	4
Mining		
TLW	0.8301	5
Agriculture		
BOPP	0.7789	4

4.4.11 Analysis of the Trends in Volatility of the Returns Series

The trends in volatility over the sample period of the returns series was investigated by regressing the conditional volatility series with a time variable. The sign of α_2 was used in identifying whether the volatility was increasing or decreasing over time and the p-value for the significance checks. As it is reported from Table 4.12, PBC, FML and CLYD had their conditional volatility significantly increasing over time whereas CAL, TLW and BOPP had their conditional volatility significantly decreasing over time. Also, the conditional volatility of EGL and UNIL though were decreasing but not significant over time.

It is also evident that, PBC exhibited the highest conditional volatility trends followed by FML and CLYD whereas the least conditional volatility trends was exhibited by BOPP and followed by CAL and TLW.

Table 4.12: Trends in Volatility of the Returns Series

Sector	α_1	P-value	α_2	P-value
Finance				
CAL	0.0083	0.0000*	-0.0001	0.0010*
Distribution				
PBC	0.0000	0.0300*	0.0009	0.0000*
Food and Beverage				
FML	0.0003	0.0000*	0.0005	0.0000*
Info. Technology				
CLYD	-0.0003	0.0260*	0.0003	0.0000*
Insurance				
EGL	0.0124	0.0190*	-0.0008	0.4030
Manufacturing				
UNIL	0.0006	0.0000*	-0.0002	0.0810
Mining				
TLW	0.0000	0.0000*	-0.0001	0.0000*
Agriculture				
BOPP	0.0077	0.0040*	-0.0006	0.0160*

* Significant at 5% significance level

Moreover, the plots of the trends in volatility as reported in Figure 4.25, 4.26, 4.27, 4.28, 4.29, 4.30, 4.31 and 4.32 revealed that most of the returns series exhibited trends in them. From Figure 4.25, it could be seen that CAL had an increasing trend from the year 2004 till late 2004 when the trend decreased significantly all the way to 2014. From Figure 4.26, the volatility trend of PBC was also increasing significantly in the year 2004 but decreased drastically from 2005 to 2012. From the year 2013 to 2014, the volatility trend increased. It is also evident from Figure 4.27 that, the volatility trend in FML was increasing in the year 2004 but decreased from 2005 to latter 2011. The trend increased significantly in 2012 and decreased thereafter till latter 2013. From 2014, FML exhibited significant increase in volatility. From Figure 4.28 the trend in volatility for CLYD was not increasing significantly from 2004 to 2008. But in 2009 there was some increase which became significant in 2010 and 2014. Also it is evident from Figure 4.29, EGL indicated decreasing volatility in 2004, 2006, 2009 and 2014. But in 2005 and 2008 showed significant increase. Form Figure 4.30 it is evident that, the volatility for UNIL was increasing from 2004 to 2006 and decreased from latter 2006 to 2013. The year 2014 showed very significant increase. Lastly from Figure 4.31, the volatility trend for TLW was decreasing from 2004 to 2014. The same trend was reported of BOPP as is reported in Figure 4.32.

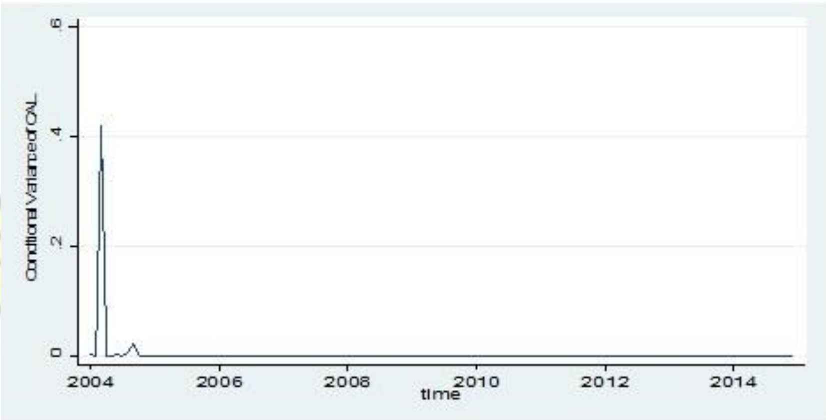

Figure 4.25: Plot of the Conditional Variance of the CAL Returns over time

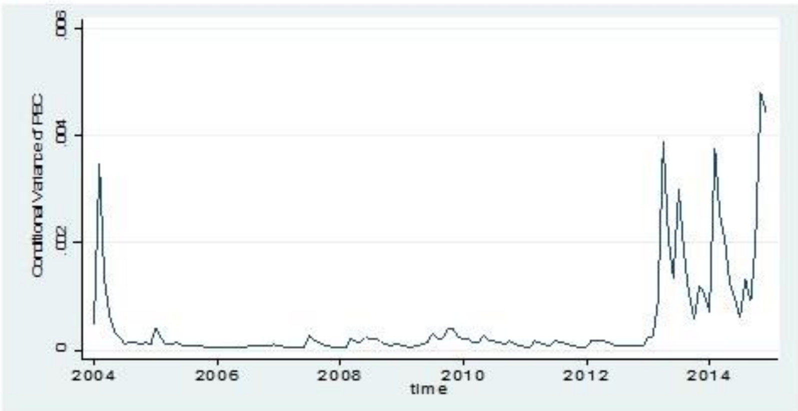

Figure 4.26: Plot of the Conditional Variance of the PBC Returns over time

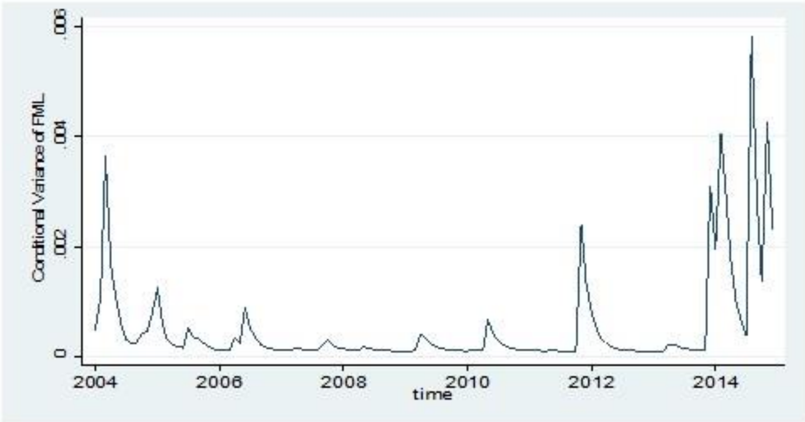

Figure 4.27: Plot of the Conditional Variance of the FML Returns over time

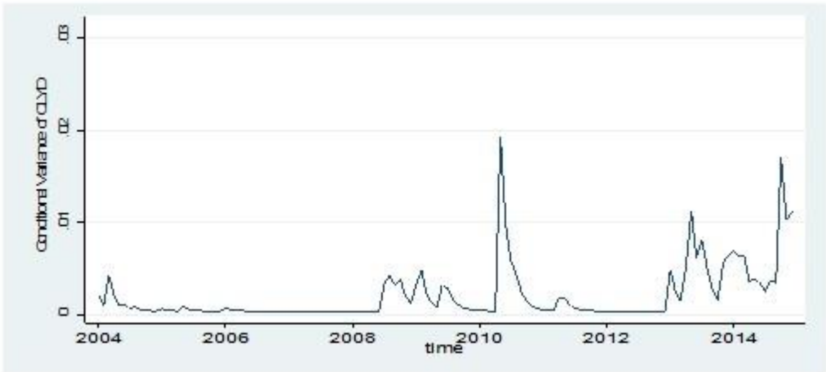

Figure 4.28: Plot of the Conditional Variance of the CLYD Returns over time

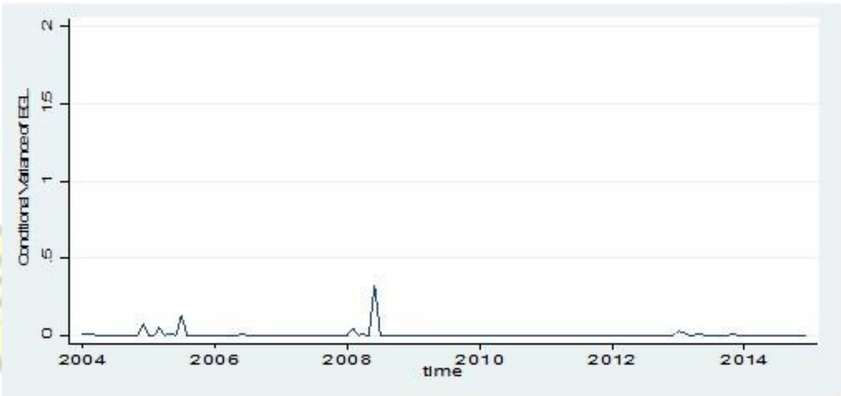

Figure 4.29: Plot of the Conditional Variance of the EGL Returns over time

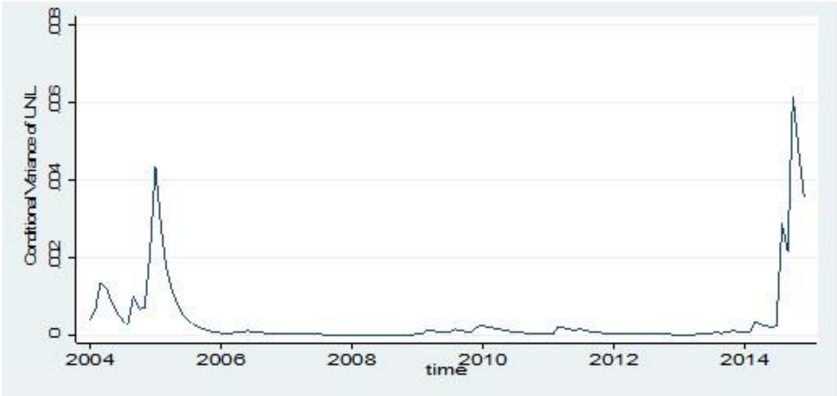

Figure 4.30: Plot of the Conditional Variance of the UNIL Returns over time

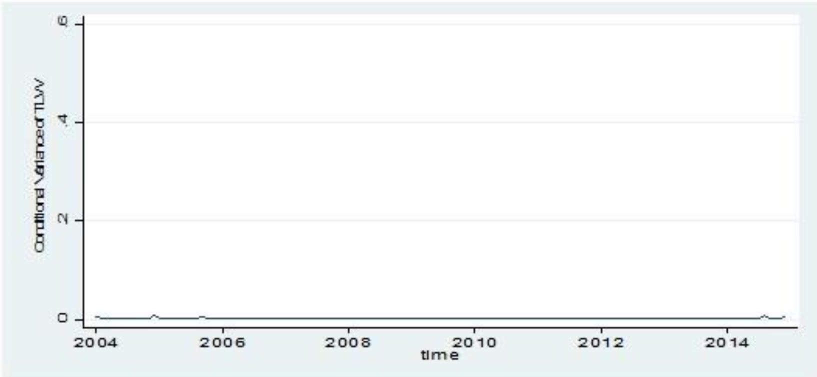

Figure 4.31: Plot of the Conditional Variance of the TLW Returns over time

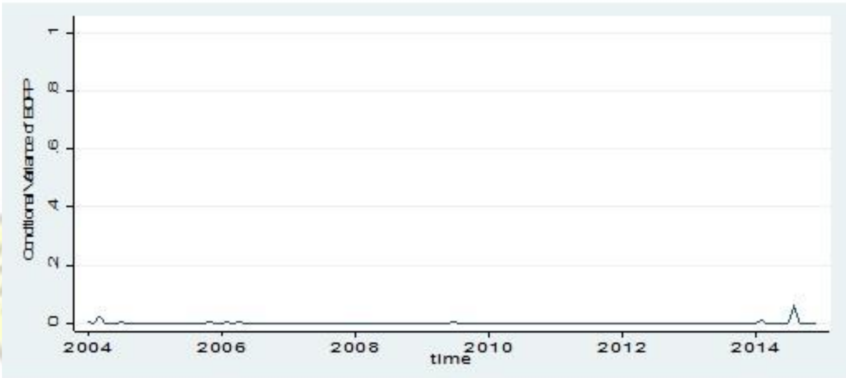

Figure 4.32: Plot of the Conditional Variance of the BOPP Returns over time

4.4.12 Goodness of Fit Test of the TGARCH-M (1, 1) Model

The TGARCH-M (1, 1) model fitted was cross validated by employing the chi-square goodness of fit statistic with an out-of-sample forecast from 5th January 2015 to 16th

January, 2015. As it is reported in Table 4.13 of the chi-square test, the results reveals that there is no significant difference between the observed returns series and the predicted (forecasted) returns series for all the variables. This is supported by an insignificant chisquare obtained for all the models. It is also evident that, the fitted model produce returns that are similar to the nature of the returns series even though the returns series of the observed and expected may differ.

Table 4.13: Chi-square Goodness of Test for the TGARCH-M (1,1) Model

Model	Chi-square χ^2 Statistic	Critical value
Finance		
CAL	12.3727	16.9200
Distribution		
PBC	-14.1981	16.9200
Food and Beverage		
FML	0.0579	16.9200
Info. Technology		
CLYD	-11.8958	16.9200
Insurance		
EGL	-0.8820	16.9200
Manufacturing		
UNIL	5.51776	16.9200
Mining		
TLW	0.0236	16.9200
Agriculture		
BOPP	1.7710	16.9200

Reject if χ^2 Statistic > critical value

4.5 Discussion of Results

The results revealed that, investors in the Finance sector saw gains in CAL, EBG, ETI, GCB, HFC, SCB and UTB since their mean returns were positive whereas investors of SOGEGH and TBL recorded losses (negative mean returns). Volatility (standard deviation) was high in ETI, CAL and EBG as indication of their risk levels. There was high probability of gains for investors of CAL, EBG, ETI, GCB and UTB whereas there was high probability of loss for investors of HCF, SCB, SOGEGH and TBL because the two groups recorded positive and negative skewness respectively. The sector was seen to be volatile since all the excess kurtosis were greater than three. The Distribution sector recorded much gains than losses that is, the mean returns of GOIL, MLC and TOTAL were positive whereas that of PBC was negative, an indication of loss for investors. The mean returns of MLC was commensurated with risk taken by investors since it recorded the highest mean returns and standard deviation in the distribution sector. The skewness of GOIL and TOTAL was negative posing investors of these two equities to high probability of loss whereas investors of MLC and PBC had high chances of gains (positive skewness). There existed high volatility trends in these equities. Also, the Food and Beverage sector saw investors of FML and GGBL making gains compared to CPC investors who experienced losses during the same period. Investors of CPC were not compensated for assuming risk since they made losses but recorded the highest volatility (standard deviation) in the sector. It was also clear that investors of CPC had high chances of making losses. Investors GGBL also had high chances of making losses than gains. Investors of FML had high chances of gains than losses since it recorded a positive skewness. Investing in this sector was also volatile. Investors in the Information Communication Technology sector saw the two equities (EGL and SIC) making losses even though the two had high chances of making gains than losses once the skewness were all positive and that investors were compensated for the risk they assumed. The sector was also seen to be volatile. Again, investors in the Insurance sector saw gains but there was high probability for investors of EGL making losses compared with investors of SIC who had high chances of making gains. This sector was also seen to be volatile since all the excess kurtosis was greater than three. The Manufacturing sector had investors of AYRTN, CLMT, PZC, UNIL and SWL making gains as compared to investors of ALW, SPL, PKL, GWEB and ACI who recorded losses in the same period. It is also evident that investors who made losses in this sector were not compensated as their mean returns recorded high standard deviations. Also, there was high probability of gains for investors of AYRTN, CMLT, SPL, UNIL, SWL and ACI even though investors of SPL and ACI recorded losses. The sector even though recorded same losses as gains but there was high chances of making gains than losses as it is evident of the skewness signs. Lastly, the Mining and

Agricultural sectors saw investors making gains and that the two sectors also saw investors having high chances of gains. The two sectors were all volatile.

Moreover, from the above details, it was clear that most of the sectors and equities for that matter recorded much gains than losses for investors since most of them recorded positive of their mean returns. Most of the volatility (standard deviation) of the equities was in line with the returns made and therefore investors on the GSE were mostly compensated for the risk they assumed. For the entire sample period, most of the equities had their skewness positive or asymmetric in nature indicating that the upper tail of the distribution of the returns were ticker than the lower tail and that there were more chance of gains than losses. There was also an indication of non-symmetry in the returns. Therefore, there was much probability of gains than losses for investors on the exchange. The excess kurtosis for all the equities were greater than three (3) meaning the underlying distribution of the returns were leptokurtic in nature and heavy tailed and that there was more frequently extremely large deviations from the mean returns than a Gaussian distribution. This confirms that investors have been experiencing high levels of volatility on the GSE. Notwithstanding the volatile nature of the market, the sample period was good (bullish) for investors on the exchange since there was a lot of gains for most of the equities. Also there was evident of a positive relationship between risk and return for the sample period.

For modelling purposes, the returns series were subjected to stationarity tests. Three unit-root or stationarity tests (ADF, PP and KPSS) were employed. The results showed that, the three tests were all significant at the 5% significance level indicating that the returns series were stationary.

All the returns series with the exception of BOPP returns series were subjected to principal component analysis so as to select the equity or equities that best describe each sector. It was used as a data reduction procedure. The test was performed for each sector; selecting the component(s) that best explains much of the variance and the equity that had much of the loadings in the components. It was revealed that, for the Finance sector, ETI, GCB and CAL were selected since they had high components loadings. The

Distribution sector had PBC and TOTAL selected. Also, the Food and Beverage sector had FML selected. The Information Communication Technology and insurance sectors had CLYD and EGL selected respectively. More also, the Manufacturing sector had PZC and UNIL selected whiles the Mining sector had TLW and AGA selected. These selected equities from the PCA along side BOPP from the Agricultural sector were then used for further analysis.

The selected equities from each sector was/were subjected to ARCHLM test since it forms the basis for volatility modelling. The test was performed at lags (1 7 14) across all the sectors. The LM test showed that, CAL, PBC, FML, CLYD, EGL, UNIL, TLW and BOPP exhibited the presence of ARCH effects in the Finance, Distribution, Food and Beverage, Information communication technology, Insurance, Manufacturing, Mining and Agricultural sectors respectively. The LM test confirms that these series were having ARCH effects and therefore were considered for volatility modelling. The presence of ARCH effect indicates volatility clustering.

The equities that exhibited ARCH effects had normality, autocorrelation and heteroscedascitity checks performed on them. The results showed that, the Jarque-Bera test for normality was significant for all the returns series indicating that the returns series were not normally distributed. Also, the Ljung-Box statistic $LB(14)$ for the returns series was significant for all the series indicating that there was no clear probability of investors earning above average gains for the mere fact of using historical data from the stock exchange. The significance of $LB^2(14)$ statistic as it was evident from results suggests the presence of ARCH effects and hence making an AR (1) conditional mean model more appropriate for GARCH specifications. It also indicates the presence of volatility clustering in the distribution of the returns (Kovacic (2008)).

Moreover, in deciding on a good mean equation for fitting the GARCH models, the Durbin-Watson and the Breush-Godfrey tests for serial correlation were employed. The results showed that for Mean Equation 3.30, the two tests rejected the null hypothesis indicating that, the Mean Equation 3.30 exhibited autocorrelation. In order to eliminate this effect, Mean Equation 3.30 was transformed to Mean Equation 3.31 and the results showed that the effect of autocorrelation was removed since the B-G tests was not significant at all levels of the returns series. Thus, making this specification of the mean equation more suitable for the three volatility models. It was also evident that, ARCH effect was present in both specification of the mean equation an indication of volatility clustering which is attributed to the autocorrelation in the absolute and squared returns from the estimated conditional mean equation (Zivot, 2008).

The stationarity of the three models was examined and the results showed that, for the GARCH-M (1,1) model, most of the ARCH and GARCH summations were greater than one (1) indicating the non-stationarity of the model with the distribution assumption.

This led to the use to of the EGARCH-M model and it was realized that the EGARCHM (1, 1) model also had most of the ARCH and GARCH summation to be greater than one (1) making most of the models non-stationary, hence the TGARCH- M (1, 1) models was employed, it was realized that most of the ARCH and GARCH summation were closer to one (1) making most of the models stationary. All the three models were able to exhibit some level of persistence in volatility. The implications of these are that, for the models with ARCH and GARCH summations greater than one (1), a shock to volatility do not die quickly i.e. a shock will mean that the effect on the returns will continue to grow infinitely into the future and models with their summation closer to one (1) means that the returns generating process is described by a high degree of persistence or long memory in the volatility. Therefore, a shock at any time will persist for many future periods as the value becomes closer to one (1) (Magnus and Fosu, 2006). Also the size of the ARCH and GARCH coefficients measures how persistent a model is and for that matter, it was realized that all the three models exhibited high level of volatility persistence since most of the ARCH and GARCH summations were greater than one (1) or closer to one (1).

Therefore, the degree of persistence is crucial in establishing the relationship between risk and return since only persistent volatility justifies changes in the risk premium (Devaney, 2001). This results supports three volatility stylized facts, that volatility exhibits mean reverting ,persistence and innovations have an asymmetry effect on volatility (Engle and Patton, 2001). Investors on the exchange may look out for equities that have their persistence in volatility been much lesser than one so that if there is any shock in volatility it does not take much time to revert.

Furthermore, the EGARCH-M (1, 1) and TGARCH-M (1, 1) models were used in investigating the asymmetry in volatility of the returns series. The asymmetry coefficients for the EGARCH-M (1, 1) model was mostly negative and significant, suggesting the presence of leverage effect which indicates that negative shock imply a higher period volatility than positive shocks of the same magnitude. Also, most of the asymmetry coefficient for the TGARCH-M (1, 1) model were positive and significant, indicating that negative shocks (bad news) have higher effect on next level volatility of the returns series than positive shock (good news) of the same magnitude. This findings is supported by the results of Engle and Ng (1993) who found that bad news increases volatility than good news of same importance and Emenike (2010) who captured leverage effects on the NSE using TGARCH (1,1); evidence of volatility persistence and leverage effects. For equities that had the expected sign under a given distribution, the asymmetry effect takes place when an unexpected decline in price (bad news) tends to increase volatility more than an unexpected increase in price (good news) of the same magnitude. On the other hand, if negative shock increase volatility than positive shock of the same magnitude, from leverage effects hypothesis postulated by Black (1976) and Christie (1982) ; if the price of a share drops (negative returns), financial leverage increases leading to an increase in the equity return volatility. Also, in an event of an anticipated increase in volatility, expected returns tends to decrease, leading to a decline in the share price. Thus, a situation where there exist a negative relationship between risk and return, an anticipated increase in volatility tends to cause a decline in returns, thus decreasing the share price. Also in a market where risk is priced, an anticipated increase in volatility on the market will mean that risk lovers will buy more shares in anticipation that at the end of the day it will commensurate with their returns. Nevertheless, an anticipated increase in risk for a market that exhibits a negative relationship between risk and return, investors sell off their shares since an increase in risk does not raise the required returns on the asset hence causing a decline in share price often known as volatility feedback effect (Karmakar, 2007). This decline in share price tends to increase leverage ratio which may lead to further decline in share price according to the leverage effect hypothesis (Karmakar, 2007).

Also, news of increasing volatility tends to reduce the demand for an equity because of risk aversion. If the asymmetry coefficient of an equity is higher it indicates that, when the returns increases, the equity return volatility is affected much higher than the rest of the equities. The magnitude of asymmetry coefficient for the EGARCH- M (1, 1) model showed that, an increase in the returns of CAL will increase its volatility more than the other equities whereas for the TGARCH- M (1, 1) model, an increase in the returns of UNIL will increase its volatility more than the rest of the equities. The implication of asymmetry is that it affects the pricing of a security and portfolio selection since investors may not be sure of the time of arrival of good or bad news on the market so as to inform their investments choices.

The relationship between risk and return was investigated by the three models. All the three models showed a positive relationship between risk and return. This results is in line with the findings of Murinde and Poshakwale (2001), Saleem (2007), Chou (1988), French et al. (1987), Baillie and DeGennaro (1990) and Suliman and Winker (2012) who also found a positive relationship between risk and returns on other markets. The results also supports the usual view in financial market that high risk suggests higher returns. The presence of a positive relationship between risk and return means that, investors had the required returns for holding risky assets. This is also in conformity with the predictions of many asset pricing models like the APT and CAPM. In the event of risk neutral investors on the market, they will decide to invest in equities that have a risk-return coefficient which are closer to one (1) since they have a linear risk-return relationship and would not therefore like to take a lot of risk. Therefore, for a positive risk-return relationship, if an investor is a risk lover, an increase in risk will lead to an increase in the demand for that equity leading to an increase in share price but for a negative relationship between risk and return, risk averse investors will sell off their shares in anticipation of volatility leading to a decline in share price. Therefore, for the

GARCH- M (1, 1) model, they will prefer to invest in UNIL, for the EGARCH- M (1, 1) model they would like to invest in either CAL, CLYD, EGL or BOPP. The same investors would prefer investing in PBC, CLYD and UNIL for the TGARCH- M (1, 1) model.

The best model that describes the returns series estimated was selected. It was clear from the results that, the TGARCH-M (1, 1) was the appropriate model since it was able to meet the model selection criterion of having the ARCH and GARCH summations mostly less than one i.e. ensuring stationairty of the model, been able to capture leverage effect and its ability in eliminate ARCH effects. It was then subjected to BIC in selecting the distributional assumption. The student-t distributional assumption was selected by the BIC. The model was then diagnosed to ascertain whether it was well specified for the returns series estimated. It was realized that, the skewness and kurtosis for the model was low for most of the returns series. Also the $LB^2(14)$ statistic was able to eliminate any further ARCH effect in the returns series. This makes the TGARCH-M (1, 1) well specified for most of the estimated returns series in this study.

The persistence and half-life in volatility showed that all the eight returns series exhibited some level of volatility persistence. This degree of persistence was extended in measuring the half-life in volatility. Equities that exhibited high degree of persistence means their volatility will not move quickly to their long-run volatility levels whereas those with less degree of persistence will have their volatility moving very quickly to their long-run volatility levels. That is, there is the expectation that equities with high degree of persistence will have high half-life and weak mean reversion whereas those with least persistence will have low half-life and strong mean reversion. The implication of weak and strong mean reversion is that, for equities with strong mean reversion means that, the returns of those equities approaches their average volatility very quickly whereas for equities with weak mean reversion, their returns takes a long period to return towards their average volatility. Therefore, the results showed that, PBC, UNIL and BOPP had strong mean reversion since they all had their half-life measure been four (4 days). This means that, any shock to any of these equities takes 4 days to return half-way back without any further volatility (i.e. a shock takes 4 days to return half-way back to its volatility). Also, CAL, CLYD, EGL and TLW have strong mean reversion since the half-life measure were 6 days, 5 days, 7 days and 5 days respectively. This implies that a shock to CAL will take 6 days to return half-way back to its volatility, a shock to CLYD will take 5 days to revert, any shock to EGL and TLW will take 7 days and 5 days respectively to return half-way back without any further volatility. The half-life measure of FML was 19 days indicating that any shock to FML will take 19 days to mean revert. This implies that, investors will prefer equities that have strong mean reversion since their volatility does not stay for a long time. But in the situation where positive shocks increases volatility, investors will prefer to invest in equities that have high persistence measure of volatility and weak mean reversion. Also in a market where risk is priced, investors will prefer investing in equities with high half-life measure since at the end of the day their returns will match the risk taken.

The trends in volatility for the sampled period showed that most of the equities exhibited trends in them. This will build uncertainty in an economy leading to capital flight. Also, a rise in volatility on the exchange is an evidence of an increase in the risk levels of equities and this can lead to the movement of investment funds towards assets that are less risky. Thus, increasing the cost of funds for new companies as investors desire to invest in well-known companies. Hence, the flow of funds from the market could make it tough for new and well-known companies to prepare accurately and budget for future projects as the available investment funds from the stock market remains indeterminate. This developments could impact negatively on the performance of the equities, the stock exchange and economy at large. Also, investors will be concerned with the trends of volatility over time on the stock market as this would inform their investment decisions such as portfolio selection and diversification. Policy makers also need knowledge on volatility trends to enable them create the desirable environment for investing so as to also get more companies list on the exchange.

4.6 Conclusion

This chapter presented the source of data, analysis and discussion of the results obtained. The preliminary analysis gave the general nature of the returns series. The principal component analysis was used in selecting equities that characterized each sector. The ARCHLM test was then employed to test the selected equities for ARCH effects and that those that exhibited ARCH effects were considered for the volatility analysis. The symmetry and asymmetry of the daily returns of the selected equities as well as the risk-return relationship was investigated using the GARCH-M (1, 1), EGARCH-M (1, 1) and TGARCH-M (1, 1). There exist a positive relationship between risk and return and TGARCH-M (1,1) with the student-t distribution was the most appropriate model.

Volatility was persistent and half-life measure was short indicating strong mean reversion among the equities. The trend in volatility was increasing over time.

Chapter 5

Conclusion and Recommendations

5.1 Introduction

This chapter gives the conclusion and recommendations of the study.

5.2 Conclusion

This research examined the volatility and the risk-return relationship of selected equities on the Ghana Stock Exchange using data from the Ghana Stock Exchange and Annual Report Ghana databases from 02/01/2004 to 16/01/2015 comprising 35 equities and a later reduction to 8 equities. Before selecting the equities that characterized each sector, several preliminary analysis were performed on all the equities on the exchange. The descriptive statistics revealed that, the data exhibited non-normality, excess kurtosis, skewness and excess volatility which are common with financial data. Most of the equities made gains than losses.

The three stationarity tests employed revealed that, the returns series for all the equities were stationary. In selecting the equities that characterized each sector, the principal component analysis was employed and the results revealed that, for the Finance sector CAL, ETI and GCB were selected, the Distribution sector had PBC and TOTAL selected, the Food and Beverage sector had FML selected, the Information Communication Technology sector had CLYD selected, the Insurance sector had EGL selected, the Manufacturing and Mining sector had PZC, UNIL and TLW, AGA selected respectively. The selected equities from the principal component analysis were tested for the existence of ARCH effect since this forms the basis for volatility modelling. The results revealed that, the Finance sector had CAL exhibiting ARCH effect, the Distribution sector had PBC exhibiting ARCH effect, FML from the Food and Beverage sector exhibited ARCH effect, CLYD from the Information Communication Technology sector exhibited ARCH effect, the

Manufacturing, Mining and Agriculture sectors had UNIL, TLW and BOPP exhibiting ARCH effect respectively. These equities (returns series) were then tested for normality, autocorrelation and heteroscedascitity. The results revealed that, the returns series were not normally distributed and there exist autocorrelation in the returns series and the squared returns series.

In analysing the volatility in the returns series, the appropriate mean equation was selected. The GARCH-M family of models were employed (GARCH-M (1, 1), EGARCH-M (1, 1) and TGARCH-M (1, 1)) with three distributional assumptions (Gaussian, Studentt and GED). The GARCH-M (1, 1) was used in investigating the symmetry in volatility and since most of the models were not stationary, the EGARCH-M (1,1) was employed. The EGARCH-M (1, 1) and the TGARCH-M (1, 1) were used in investigating the asymmetry in volatility. The TGARCH-M (1, 1) was employed in the event the EGARCH-M does not eliminate ARCH effects and had most of the models been non-stationary. All the three models were used in examining the volatility and the risk return relationship of the selected equities. The results from the three models indicated a positive relationship between risk and return (positive risk premium). That is, investors were compensated for assuming risk. The persistence measure of volatility across the three models revealed that volatility was persistent in most of the equities since the summation of the ARCH and GARCH coefficients were greater than or closer to one. The leverage effect parameter was also investigated using the EGARCH-M (1, 1) and TGARCH-M (1, 1) models and the results revealed that, leverage effect exist on the exchange with reference to the selected equities. Thus, there was also the possibility of bad news increasing volatility more than good news of the same magnitude since volatility was asymmetric. The three models were tested for the presence of ARCH effects. The results revealed that, the GARCH-M (1, 1) model exhibited the presence of ARCH effects compared to the EGARCH-M (1, 1) and TGARCH-M (1, 1) models. The TGARCH was able to eliminate much of the ARCH effects. The best model was selected using the BIC in selecting the error distributional assumption. The results indicated that, the TGARCH-M (1, 1) model with the student-t distributional assumption was the most appropriate model. In all, 72 models were estimated. The diagnostic checks revealed that, the TGARCH-M (1, 1) model was well specified for most of the returns series estimated.

The persistence and half-life measure in volatility revealed that most of the equities had persistent volatility and strong mean reversion. FML was highly persistent with a weak mean reversion and half-life of 19 days as compared to CAL, PBC, CLYD, EGL, UNIL, TLW and BOPP which had strong mean reversion and half-life of 6 days, 4 days, 5 days, 7 days, 4 days, 5 days and 4 days respectively. The long-run trends in volatility was investigated by regressing the conditional variance against a time variable. The results showed that, most of the equities exhibited increasing volatility over the sample period.

5.3 Recommendations

From the findings of this research it is recommended that;

i. Investors need to consider other factors that influences equity returns like skewnessand market capitalization other than the standard deviation even though there exist a positive relationship between risk and return and it does not mean that investors will always make gains for investing in a particular equity or sector.

ii. Since investors are interested in less volatile and more stable equities, policy makersare to ensure that volatility is priced on the exchange in other to boost investors' confidence for holding risky assets and as such urge more companies to list on the exchange and increase the number of investors on the exchange. This will lead to more capital inflow to the exchange causing financial stability and macroeconomic stability since its going to control consumer spending.

iii. Policy makers must be cautious of the arrival of news on the exchange since bad newscould also increase volatility and in the event that volatility is not priced, investors will sell off their shares in anticipating of increase in volatility leading to capital flight which may increase consumer spending and as such cause financial instability.

iv. Investors must be aware of the volatility persistence and half-life measure of equities soas to make inform decision when investing. This is because, highly persistent equities exhibits weak mean reversion and long half-life measure and as such investing in those equities takes a longer time to revert half way back to it volatility, so in the event that risk is not priced, investing in such equities will not be favourable. Also equities that are persistent but have shorter half-life measure have strong mean reversion, meaning volatility will revert faster in the event risk is not priced. But in event where risk is priced, investors are to stay with equities that are highly persistent and with weak mean reversion.

v. Investors and policy makers must be aware of the long run trends in volatility of theequities in other to make informed decisions. Since investors may tend to invest only in equities that exhibit increasing volatility in other to make gains neglecting equities that does not exhibit much volatility when risk is priced neglecting the other equities with decreasing trends in volatility to perform badly which may make the blue chip companies or equities with much market capitalization favourable to invest which may drive new companies from listing on the exchange.

5.4 Further Research

While this research tackled the volatility and the risk-return relationship of selected equities on the Ghana Stock Exchange, further research should consider all the equities on the Ghana Stock Exchange.

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Appendix A

Below is the list of equities considered in this study and the sectoral distribution of trade of equities on the Ghana Stock Exchange.

Table 5.1: Descriptive Statistics of the Returns Series

Sector	Mean	St. Dev	CV	Min	Max	Skewness	Kurtosis
Finance							
CAL	0.0013	0.0425	338.3000	-0.6652	0.7360	4.6600	220.3900
EBG	0.0022	0.0436	1951.6000	-0.1280	1.3075	28.3400	850.2200
ETI	0.0008	0.0646	7749.5900	-0.6934	1.7029	17.3300	542.7100
GCB	0.0009	0.0193	2258.1400	-0.1214	0.4202	11.4400	246.0000
HFC	0.0006	0.0124	2052.6200	-0.1903	0.1597	-0.1700	108.5400
SCB	0.0006	0.0287	5221.8800	-0.7851	0.2331	-20.8100	597.2100
SOGEGH	-0.0003	0.0209	-7144.1700	-0.4314	0.0926	-12.7100	238.7600
TBL	-0.0006	0.0235	-3682.0600	-0.5218	0.1675	-13.0600	288.6200
UTB	0.0011	0.0388	3587.1800	-0.1139	1.1493	27.3600	811.8400
Distribution							
GOIL	0.0001	0.0210	16906.9400	-0.5039	0.1871	-13.9600	363.0600
MLC	0.0017	0.0582	3458.9500	-0.7640	1.0512	9.4500	246.4900
PBC	-0.0019	0.0223	2309.6400	-0.1513	0.2319	1.9100	132.8100
TOTAL	0.0009	0.0433	4638.8700	-0.9029	0.8354	-1.0800	353.8000
Food and Beverage							
CPC	-0.0005	0.0758	-14476.9400	-0.3010	0.3010	-0.0300	11.0700
FML	0.0012	0.0216	1800.6600	-0.1878	0.1886	0.7200	41.0800
GGBL	0.0008	0.0155	1953.0700	-0.2218	0.1160	-3.5600	71.0900
Info. Technology							
CLYD	-0.0002	0.0460	-24856.2300	-0.4260	0.4260	0.5900	32.8200
TRANSOL	-0.0001	0.0352	-95087.0400	-0.4771	0.7782	2.4900	79.8900
Insurance							
EGL	0.0002	0.0380	16299.1900	-0.8248	0.1552	-16.8800	347.1800
SIC	0.0010	0.0304	3159.3300	-0.1139	0.8653	24.3700	692.5800
Manufacturing							
ALW	-0.0014	0.0445	-3255.4600	-0.5136	0.4467	-0.5800	347.1800
AYRTN	0.0005	0.0146	3233.0300	-0.1681	0.2865	6.9500	186.5500
CMLT	0.0003	0.0185	3796.4500	-0.1249	0.1249	0.3900	35.9900
PZC	0.0001	0.0317	65846.8300	-0.7721	0.2956	-15.2300	390.0100
SPL	-0.0001	0.0330	65846.8300	-0.2219	0.5133	3.4900	72.2200
UNIL	0.0009	0.0187	2031.5300	-0.2333	0.2333	2.2300	92.5900
PKL	-0.0001	0.0038	-7560.0700	-0.0670	0.0770	-0.6900	332.8000
GWEB	-0.0003	0.0187	-6560.9500	-0.2218	0.1249	-1.7300	56.0600

SLW	0.0002	0.0192	12812.0800	-0.1761	0.1761	0.2800	45.6600
ACI	-0.0002	0.0261	- 12157.5100	-0.3010	0.3980	4.1600	121.3700
Mining							
TLW	0.0017	0.0527	3058.0600	-0.0792	1.5883	28.7400	866.0000
AGA	0.0012	0.0335	2867.3500	-0.0911	1.0200	29.7400	906.2200
GSR	0.0018	0.0609	3341.0500	-0.0748	1.8579	29.8000	909.0400
AADs	0.0011	0.0263	2441.5100	-0.0258	0.7959	29.1690	873.0800
Agriculture							
BOPP	0.0020	0.0420	2154.5100	-0.2511	1.0000	14.5100	346.4800

Table 5.2: List of Equities on the Ghana Stock Exchange

Equity	ISIN	Share Code
African Champion Ltd	GH0000000193	ACI
AngloGold Ashanti Ltd.	GH0000000607	AGA
Aluworks Limited	GH0000000037	ALW
Ayrton Drug Manufacturing Ltd.	GH0000000672	AYRTN
Benso Oil Palm Plantation	GH0000000581	BOPP
Cal Bank Ltd	GH0000000649	CAL
Clydestone (Ghana) Ltd.	GH0000000573	CLYD
Camelot Ghana Ltd.	GH0000000227	CMLT
Cocoa Processing Co. Ltd.	GH0000000540	CPC
Ecobank Ghana Ltd.	GH0000000680	EBG
Enterprise Group Ltd.	GH0000001001	EGL
Ecobank Transnational Inc.	TG0000000132	ETI
Fan Milk Ltd.	GH0000000078	FML
GCB Bank Ltd.	GH0000000094	GCB
Guinness Ghana Breweries Ltd.	GH0000000102	GGBL
Ghana Oil Company Limited	GH0000000722	GOIL
Golden Star Resources Ltd.	GH0000000748	GSR
Golden Web Ltd	GH0000000631	GWEB
HFC Bank (Ghana) Ltd.	GH0000000110	HFC
AngloGold Ashanti Depository Shares	GH0000000615	AADS
Mechanical Lloyd Co. Ltd.	GH0000000136	MLC
Pioneer Kitchenware Ltd.	GH0000000151	PKL
Produce Buying Company Ltd.	GH0000000169	PBC
PZ Cussons Ghana Ltd.	GH0000000177	PZC
Standard Chartered Bank Gh. Ltd.	GH0000000185	SCB
SIC Insurance Company Ltd.	GH0000000730	SIC
Starwin Products Ltd.	GH0000000623	SPL
Societe Generale Ghana Limited	GH0000000201	SOGEGH
Sam Woode Ltd.	GH0000000516	SWL

Trust Bank Gambia Ltd	GH0000000532	TBL
Total Petroleum Ghana Ltd.	GH0000000144	TOTAL
Transaction Solutions (Ghana) Ltd.	GH0000000706	TRANSOL
Tullow Oil Plc	GH0000001050	TLW
Unilever Ghana Ltd.	GH0000000219	UNIL
UT BankLtd	GH0000000755	UTB

Source: GSE website (2013).

Table 5.3: Sectorial Distribution of Trade

Finance
CAL
EBG
ETI
GCB
HFC
SCB
SOGEGH
TBL
UTB
Distribution
GOIL
MLC
PBC
TOTAL
Food and Beverage
CPC
FML
GGBL
Info. Technology
CLYD
TRANSOL
Insurance
EGL
SIC
Manufacturing
ACI
ALW
AYRTN
CMLT
PZC
SPL
UNIL
PKL
GWEB
SWL

Mining
TLW AGA GSR AADs
Agriculture
BOPP

Source: GSE Market Report 2013

Appendix B