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DEPARTMENT OF STATISTICS AND ACTUARIAL SCIENCE

MODELLING THE STOCK RETURNS OF GCB BANK LIMITED

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A Project work submitted to Kwame Nkrumah University of Science and Technology in Partial Fulfillment of the Requirements for the Bachelor of Science in Actuarial Science.

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Declaration

We, therefore, affirm that this paper is entirely our own original work and has not been submitted in whole or in part for another degree award in any other university. Due credit has also been given to previously published works and online publications through referencing.

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This thesis has been submitted and we as university supervisors affirm our approval of its submission.

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Dedication

We dedicate this project to the Almighty God, who has seen us through all of our challenges during this thesis period and has brought us this far. We also dedicate this effort to our families and friends, who have been there for us every step of the way with love and prayers. Finally, we dedicate this presentation to our supervisor, who stood by us through it all.

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List of Abbreviations

ATM	Automated Teller Machine
SME	Small and Medium Enterprise
GSE	Ghana Stock Exchange
BoG	Bank of Ghana
AR	Autoregressive
MA	Moving Average
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARCH	Autoregressive Conditional Heteroscedastic
GARCH	Generalized Autoregressive Conditional Heteroscedastic
GARCH-M	Generalized Autoregressive Conditional Heteroscedastic in Mean
IGARCH	Integrated Generalized Autoregressive Conditional Heteroscedastic
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedastic
TGARCH	Threshold Generalized Autoregressive Conditional Heteroscedastic
BIC	Bayesian Information Criterion
AIC	Akaike Information Criterion
GTB	Guarantee Trust Bank
UBA	United Bank of Africa
FBN	First Bank of Nigeria
STR	Smooth Transition Regression
OLS	Ordinary Least Square
TASI	Tadawul All Share Index
ADF	Augmented Dickey-Fuller
NSE	Nigerian Stock Exchange

MVA	Market Value Added
EVA	Economic Value Added
IDX	Indonesia Stock Exchange
BIST	Borsa Istanbul
WSJ	the Wall Street Journal
KPSS	Kwiatkowski Phillips Schmidt Shin
PP	Phillips Perron
SD	Standard Deviation
LRD	Long Range Dependence
ARFIMA	Autoregressive Integrated Moving Average
SGARCH	Stochastic Generalized Autoregressive Conditional Heteroscedastic
GJR GARCH	Glosten Jagannathan Runkle Generalized Autoregressive Conditional Heteroscedastic

Abstract

The study of the nature of stock returns and its modelling has been of great interest to many researchers in the field of Economics and Finance. Literatures of scholars published on this subject matter is intriguing and draws much attention. This research sought to study the nature of the stock returns of GCB Bank Limited and fit an appropriate model. The study examined the published stock prices of GCB Bank limited from January 4th 2012 to December 30th 2022. The study focused on the log returns of GCB Bank limited in the above stated time period. The log returns was examined for volatility and stationarity. The ARCH LM test indicated that volatility exists in the log returns of GCB Bank limited in this time period. Also stationarity was established for the log returns of GCB Bank limited with an Augmented Dickey-Fuller (ADF) test. The R Integrated Development Environment (R Studio) was used for the time series analysis on the log returns dataset. The general time series analysis steps of model identification, model fitting and model diagnostics was done using the latest version of R Studio as of the time this study was conducted. three competing models of different order was fitted for the returns and the appropriate model was selected via the Akaike Information Criterion (AIC). Among ARFIMA (1, 0, 1), ARFIMA (1, 0, 0) and ARFIMA (0, 0, 1), the appropriate model from the time series analysis is an ARFIMA (1, 0, 1) for the returns with the least AIC; -8.8681 and SGARCH (1, 1) for the conditional time varying variances. These were the suitable models and provides a good forecast for the GCB Bank Limited stock returns and volatility.

Chapter 1

INTRODUCTION

1.1 Background Of Study

Banks form an essential element and play a vital role in the functioning of the financial sector of every economy since a larger part of the financial sector is made up of banks. The study of volatility is important in risk management, the level of volatility in a financial market provides a measure of risk exposure to investors on their investments. According to Alexander (1999), as cited by Kolade (2013), most investors and financial analysts are concerned about the uncertainty of the returns on their investment assets, caused by the variability in speculative market prices (and market risk) and the instability of business performance. Stock returns can be defined as the profit that is gained or loss incurred from stock investment in a definite time period. Generally, it is known that future is uncertain hence predicting it is also a challenging task to perform. This uncertainty of the future applies to the financial markets as well. However, with data on the performance of the market in the past, one can forecast what is likely to happen in the near future with some level of confidence. Forecasting can be described as a tool for predicting what is likely to happen in the future by analyzing past observations and what is happening presently. Forecasting plays a vital role in areas such as finance, economics, business and industry, government, politics, medicine, among others. In recent years, with the rise of social media and other promising applications, stock market forecasting has attracted huge interest from people in general and business in particular.These advances in the financial sector are responsible for the growth and stability of the overall economy. In business domain, forecasting is considered as one of the difficult tasks owing to the various complexities of the market. However, it is important since it helps to plan for future by providing a solid idea about how to allocate resources and plan for foreseen costs in the forthcoming period of time. Investors always try to monitor the risks in real-time in order to achieve higher return on their investments. Forecasting helps in safeguarding the trade of securities among the buyers and the sellers as well as elimination of the risks involved, Mohammad et al (2019).

1.2 Overview of GCB Bank Limited

GCB Bank Limited is a financial institution based in Ghana. It was formerly known as Ghana Commercial Bank and was founded in 1953. GCB Bank is one of the largest banks in Ghana with over 180 branches across the country, serving both retail and corporate clients. The bank offers a range of financial products and services including personal and business banking, savings accounts, loans, credit cards, foreign exchange, treasury services, and project finance. The Bank's products are structured into five lines: Personal Banking, including savings and current accounts, such as Kudi Nkosuo account, Flexsave account, save and prosper account, overdrafts and loans, as well as ReadyCash automated teller machines (ATMs); Small and Medium Enterprises (SME), Corporate Services, Investment Services, such as call accounts, treasury bills and fixed deposit accounts, and Money Transfer, offering foreign banking and overseas inward money transfers. GCB Bank is listed on the Ghana Stock Exchange and is regulated by the Bank of Ghana (BoG), the country's central bank. The shares of stock of GCB Bank Ltd are listed on the Ghana Stock Exchange and are part of the exchange's GSE All-Share Index. The government of Ghana maintains 21.4% shareholding in the bank, while the remaining 78.6% is owned by institutional and private investors. GCB bank was listed on the Ghana Stock Exchange on May 17, 1996. Wikipedia (February 12, 2023).

1.3 Problem Statement

In investment and finance, there is a general notion that the higher the risk associated with an investment, the higher the returns. Investors are normally compensated for taking an extra risk by investing in such risky assets by the additional returns generated from such investments. In order to make meaningful investment decisions, it is necessary to forecast the returns associated with the risk component of such investments. Stock Market returns modeling and forecasting remains elusive and much sought after. The positive or negative change in the value of an asset or investment over time, Stock returns, has been of a great deal of interest in Financial Markets. Over the past two to three decades Financial Economists have done much in this area but this field is still worth exploring as the dynamics of the Stock Market keeps on changing and taking up a new adaptive nature. It is very evident in literature from the hundreds of articles and research papers from all parts of the world on the subject matter of stock returns predictability, that investors or stockholders in various firms are keen on the profitability of their investments in the face of changing market conditions. The average Ghanaian and foreign Stockholder in GCB Bank Limited has the same interest. The recent economic turmoil in the Ghanaian Stock Market has left investors in the Stock Market shaken and a research into this sector of the Ghanaian economy is worth taking up, not in the quest to leverage the devastating negative change in the value of assets or stocks, but to examine the financial data over the last years to guide investors. Hence the purpose of this study is to examine the Stock Market returns of GCB Bank Limited, model volatility if it exist and to fit a model to assist in the forecast of returns in the short run from past returns data. According to Hamadu (2010) as cited by Omari-Sasu et al (2015), volatility modeling and forecasting have attracted much attention in recent years in emerging stock markets. However, modeling volatility and forecasting has not attracted much attention in some West African countries like Nigeria for the simple reason that the stock market is largely under developed, Hamadu (2010). Ghana shares a similar condition. Modeling and forecasting volatility of a daily financial asset price return is an important and challenging financial problem that has received a lot of attention in recent days. The decision of the investors to sell, buy or hold depends directly on the volatility of securities prices that they expect to happen in the near future, since they build their predictions on the movements of the securities prices whether up or down, that is to protect themselves from the losses that they may meet, or to reduce it as much as possible, Krishna (2013).

1.4 Objectives of the study

This research study on the stock market returns of GCB Bank Limited has the following objectives;

i. To examine the Stock market returns of GCB bank.

ii. To model volatility of Stock returns with GARCH models.

iii. To formulate a model that can predict the Stock Market returns of GCB Bank.

To achieve these objectives, a time series analysis would be performed on the log returns series of GCB Bank Limited to fit an appropriate ARIMA Model for the returns and the GARCH Model for the volatility of the GCB Bank Limited dataset.

1.5 Research Questions

The research questions are as follows;

i. Does volatility exist in the GCB Bank Limited Stock Market Returns data, thus is the Data Heteroskedastic?

ii. Can a Conditional Variance Equation (GARCH Model) be fitted, if Volatility exist?

1.6 Methodology

Several methods and techniques exist in literature for modeling the market stock returns of companies listed on the stock exchange, this study models the market stock returns of GCB Bank limited using Time Series Models. The Time Series Model used in this study is a GARCH Model. The choice of this Model was based on the time varying conditional variance of the GCB Bank time series dataset. The returns would be captured in the mean equation by a simple econometric ARIMA model and the time varying conditional variance would be modeled by conditional variance equation in a GARCH Model. To achieve all this, we would first convert the daily stock prices to weekly stock prices and find the log returns using Excel and then export to R Studio for a time series analysis. The GCB Bank Limited returns time series dataset would be put through the general steps of a time series analysis, and finally, a model would be developed as an abstract mathematical representation of the returns and volatility respectively.

1.7 Significance of the study

Investors have been trying to find a way to model stock market volatility and financial returns to find the right stocks and the right timing to trade. This research focus will be beneficial in these number of ways;

i. The study of risk and return would inform investors to know the profitability or performance of GCB Bank on the Ghana Stock Exchange.

ii. It would help the bank to restructure and make policies that will help reduce risk and increase returns.

iii. It will add up to existing literature on stock market volatility modelling and financial returns predictions.

iv. It would help investors to be guided on the right time to invest in GCB Bank stock.

1.8 Limitations of the Study

The limitation will be based on the methodology and assumptions that will be employed in the Research. Nevertheless, these are some limitations of the GARCH model; We assume that conditional volatility has only one regime over the entire period. Also, some disadvantage of GARCH processes in modelling financial returns is a symmetry of conditional variance of e_t^2 with respect to positive and negative values of e_{t-1}^2 , e_{t-2}^2, . . . In practice, one observes a leverage effect, i.e. asymmetric consequences of positive and negative innovations (the conditional variance tends to decrease if noise is positive implying bigger returns).

1.9 Organization of the study

This study is divided into five chapters. Chapter one talks about the introduction and gives a brief background of the study. It deals with the problem statement, overview of GCB Bank limited, objectives, methodology, research questions, scope and limitations, and basic assumptions. Chapter two deals with the general literature review of already existing research papers. Chapter three deals with the methodology of the work. Chapter four deals with data analysis and results, and chapter five presents conclusions and recommendations.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

Many researchers have conducted studies on modelling market stock returns of the various companies listed on the stock exchanges across the world. Different models and methods have been explored by these researchers. In this chapter, a literature review on the modeling of market stock returns is done. This chapter focuses on market stock returns, types of market stock returns, volatility, characteristics of volatility, and related studies on modeling stock returns.

2.2 Market Stock Returns

A stock, also known as equity or share, is a security that represents a fractional or part ownership in a company, which comes with the entitlement of dividends and voting rights. Stocks can be common (ordinary) shares or preferred Shares. A stock market, equity market, or share market is the aggregation of buyers and sellers of stocks (also called shares), which represent ownership claims on businesses; these may include securities listed on a public stock exchange, as well as stock that is only traded privately, such as shares of private companies which are sold to investors through equity crowdfunding platforms,Wikipedia (February 27, 2023). In the stock market, the investors invest their savings with the expectation of earning some income. This income may be termed as ”stock returns” which may be in the form of profits earned from trading of shares or the dividends received, Y V Reddy and Parab Narayan (2016). According to the editors of MoneySense on February 27, 2023, a stock market return is the positive or negative change in value of an investment or asset over time. A positive return means a profit has been made on the investment. A negative return means that there has been a loss on the investment. Total stock market returns include dividends and interest payments, as well as the price change in the stock. The change in stock price alone is referred to as a nominal return.

2.2.1 Types of Stock Returns

Prudent and rational investors in a firm on any scale or form expect returns or simply put profits on their investments or capital holding over the period of investing. These expected financial returns come in two major forms;

- **Capital Gains**

Capital gain results from the appreciation of the price of the stock from when it was acquired to the time a gain is being calculated. Capital gain refers to a positive difference between the selling price and the purchase price. capital gain means making money off an increase or decrease in the price of the share. Suppose you bought a company's stock at Ghc 18.50 then after a period its price increased to Ghc 25.60, then you get a return (profit) of Ghc 7.10.

- **Dividend**

Dividends are part of the profits that the company distributes to its shareholders. It can be cash, stock dividends, or a combination of the two. Dividends are a potential source of stock investment besides capital gain. The company may still pay dividends even though the stock has lost its value. These two main types of financial returns can be further categorized into One period simple or net returns, Multiple period simple or net returns, Continuously compounded returns (log returns), Portfolio returns, Dividend payments and Excess returns in Analysis of Financial Time Series Third Edition By Ruey S.Tsay (2010).

2.3 Volatility

In finance, volatility (usually denoted by σ) is the degree of variation of a trading price series over time, usually measured by the standard deviation of logarithmic return. Historic volatility measures a time series of past market prices. Implied volatility looks forward in time, being derived from the market price of a market-traded derivative (in particular, an option),Wikipedia (June 08, 2023). Volatility is a rate at which the price of a security increases or decreases for a given set of returns. It is measured by calculating the standard deviation of the annualized returns over a given period of time. It shows the range to which the price of a security may increase or decrease.

2.3.1 Characteristics of Volatility

Volatility is a financial measure of risk according to Analysis of Financial Time Series Third Edition by Ruey S.Tsay (2010) has the following characteristics;

- First, there exist volatility clusters (i.e., volatility may be high for certain time periods and low for other periods). There are periods when large changes (volatility) are followed by further large changes and periods when small changes are followed by further small changes. In this case the series are said to display time-varying volatility as well as "clustering" of changes.
- Volatility evolves over time in a continuous manner-that is, volatility jumps are rare.
- Volatility does not diverge to infinity-that is, volatility varies within some fixed range.
- Statistically speaking, this means that volatility is often stationary.
- Volatility seems to react differently to a big price increase or a big price drop, referred to as the leverage effect.
- These properties play an important role in the development of volatility models.

2.4 Related studies on Modelling Stock Returns and Volatility of stocks on the Stock Exchange

Many researchers used Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized ARCH models, ARIMA, sometimes regression models and other methodologies to analyze volatility and returns in their studies. Some of these articles captured in our study are summarized in the subsequent paragraphs of this chapter. Shittu et al (2009) in their paper examined the presence of volatility in the return on stock of the banking sector of the Nigerian stock market with the view to building models that provides the optimum forecast for future stocks using the ARCH and GARCH models. It seeks to measure the persistence of volatility of return on equity of some commercial banks on the Nigerian stock exchange using the BIC and AIC criteria to check model adequacy. The data used in the study are the weekly stock prices of some selected commercial banks in Nigeria from January, 2000 to December, 2007 inclusive. The Banks are Guarantee Trust bank Plc (GTB); Access Bank Plc. (ACCESS); United Bank for Africa (UBA); First Bank of Nigeria (FBN) and Union Bank Plc. (UNION). The data on the stock of five major banks in Nigeria show varying degree of persistence in volatility, the return on UBA stock appears to be non-stationary suggesting that First Bank shares may belong to the Integrated Generalized Autoregressive IGARCH (1,1) model. This study shows a general persistence in the volatility of the stock prices in the banking sector with a few exceptions that exhibit relative tranquility in their stock prices which could be attractive to investors. Lumengo Bonga-Bonga and Michael makahabule (2010) investigated the relationship between stock returns and macroeconomic variables, taking into account asymmetric adjustment behavior in the stock market. The study applies the Smooth Transition Regression (STR) model to account for the smooth asymmetric response of stock returns from economic variables. The results show that changes in dividend yields are an important factor in determining the asymmetric behavior of stock returns on the South African stock market. Furthermore, the forecast performance of the STR model is compared with Ordinary Least Square (OLS) and Random Walk models. The STR, as a nonlinear model, outperforms the OLS and Random Walk models in an out-of-sample forecast. The findings of the paper violate the weak and semi-strong form test of the efficient market hypothesis. Suliman Zakaria Suliman Abdalla (2012) modelled stock return volatility in the Saudi stock market by using daily closing prices on the general market index (Tadawul All Share Index; TASI) over the period of 1st January 2007 to 26th November 2011. The paper employed different univariate specifications of the generalized autoregressive conditional heteroscedastic (GARCH) model, including both symmetric and asymmetric models. An application of the GARCH (1,1) model provides strong evidence of the persistence of time varying volatility. By allowing the mean equation of the returns series to depend on a function of the conditional variance, the results provide evidence of the existence of a positive risk premium, which supports the positive correlation hypothesis between volatility and the expected stock returns. Furthermore, the asymmetric GARCH models show a significant evidence for asymmetry in stock returns, confirming the presence of leverage effect in the returns series. In 2013, another paper was published by Krishna Murari which tackled Volatility Modelling and Forecasting for Banking Sector Returns. In this paper, an attempt was made to model and forecast the short-term volatility of the Indian banking sector. A particular banking stock index (CNX Bank index) was used as time series. The observations were used in modeling the volatility of the banking stock returns using univariate Box-Jenkins (ARIMA model). ADF and unit root tests were performed to know the stationarity of the series. In this paper, volatility was defined as the measure of variability in the price of an asset. Volatility is associated with unpredictability and uncertainty about the price. It is the measure of how far the current price of an asset deviates from its average past prices. The greater the deviation, greater is the volatility, Krishna (2013). The daily stock prices were converted to daily returns and the logarithmic difference of prices of two successive periods were used in the calculation of the rate of return. Omari-Sasu et al (2015) examined and modeled stock market volatility of financial return series for three listed equities on the Ghana Stock Exchange

(GSE). A historical data from 25th June 2007 to 31st October 2014 was considered for the analysis. The series for each of the three equities were tested for stationarity using the KPSS test. Series found to be non-stationary were transformed to be stationary. The study fitted a GARCH (p, q) model for volatility. GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and the GARCH (2, 2) models were fitted to residual series of some three equities. Results revealed the presence of volatilities in all three equities and also showed that volatility though present was not persistent in the three equities. For each of the companies under study, the GARCH (1, 1) model was found to outperform the other three models based on the comparison of the AIC for each model. The study recommended the use and comparison of other variants of the GARCH model in estimation of volatility. Kolade Sunday Adesina (2013) used symmetric and asymmetric GARCH models to estimate the stock return volatility and the persistence of shocks to volatility of the Nigerian Stock Exchange (NSE). There is substantial evidence for the GARCH modelling through Lagrange Multiplier Test, Correlogram and Ljung-Box Statistics before the estimation of the GARCH models. The study uses 324 monthly data from January 1985 to December 2011 of the NSE all share-index. The result reveals high persistent volatility for the NSE return series. . The GARCH (1, 1), GARCH-M (1, 1), EGARCH (1, 1), and TGARCH (1, 1) models were utilized to represent the volatility. The NSE return series showed strong sustained volatility as a result. In addition, there is no asymmetric shock phenomenon (leverage effect) for the return series. The objectives of the research by Willem et al (2014) was to analyse the effect of MVA and EVA on stock returns of banking industry at Indonesian Stock Exchange. The research method used is associative with multiple regression analysis. The populations used in the study are listed banking industry at Indonesia Stock Exchange (IDX) in 2009 to 2012 with 10 banks as the samples. Results and conclusions are the effect of MVA and EVA to Stock Return do not have significant effect simultaneously; partially, MVA have negative relationship and does not have significant effect on Stock Return, while EVA have positive relationship but does not have significant effect on Stock Return. These indicate that MVA and EVA concept is not appropriate to be used to predict stock returns on banking industry. This concept can be used in other industries to measure the company performance.

William Coffie (2015) did a study on Ghana and Nigeria stock market returns which focused on Modelling and Forecasting the Conditional Heteroscedasticity of Stock Returns Using Asymmetric Models. This paper examined and evaluated the performance of asymmetric first order generalized autoregressive conditional heteroscedasticity (GARCH (1,1)) model for Ghana and Nigeria stock market returns. They employed the Glosten Jagannathan Runkle (GJR) version of GARCH (GJR-GARCH) and Exponential GARCH (EGARCH) methodology to investigate the leverage effects of return volatility. The first (mean) and second (variance) moment equations were used to define the GARCH models. The return process was captured by the mean equation and the conditional variance was modelled using asymmetric GARCH (1,1) models of GJR and EGARCH. Oztekin et al. (2016) developed a generic methodology to predict daily stock price movements by deploying and integrating three data analytical prediction models: adaptive neurofuzzy inference systems, artificial neural networks, and support vector machines. The proposed approach is tested on the Borsa Istanbul BIST 100 Index over an 8 year period from 2007 to 2014, using accuracy, sensitivity, and specificity as metric to evaluate each model. This study demonstrates that the support vector machine outperforms the other models. For all three predictive models, accuracy in predicting down movements in the index outweighs accuracy in predicting the up movements. This efficient yet also effective data analytic approach can easily be applied to other emerging market stock return series.

Chapter 3

METHODOLOGY

3.1 Introduction

This is the third chapter per the organization of the project, we would tackle the various methods used in our modeling process, including data processing and analysis techniques. We would consider an in-depth explanation of all mathematical concepts and theorems used in this research work. This research work used time series analysis in its main methodology and this chapter details out, the concepts, assumptions, theorems and the various techniques used in time series analysis. The Chapter describes time series in general, steps in time series analysis, the concept of Stationarity, non-stationary time series models specifically the ARCH Model and its generalized form, the GARCH Model and the building of these Models. The chapter commences with data collection methods, data pre-processing and data analysis methods.

3.2 Data Collection

The GCB Bank stock data set was used in this study. This dataset was obtained from the website of WSJ Markets sourced from the Ghana Stock Exchange, which is open to the public. It comprises 2197 observations and 6 features: date, opening prices, closing prices, high, low, and volume. The GCB Bank stock dataset spans the past ten years' daily stock prices from 4th January 2012 to 30th December 2022.

Table 3.1: Data Description

Number	Features	Description	Value
1	Trade Date	The month, day, and year in which the security trade occurred.	Numeric
2	Open	The price at which the security first trades on a trading day	Numeric
3	High	The highest closing price	Numeric
4	Low	The lowest closing price	Numeric
5	Close	The last price at which the stock trades at the end of a trading day	Numeric
6	Volume	The number of shares traded in the day	Numeric

3.3 Data Pre-Processing

To enhance the quality of data worked on, the daily stock prices of GCB bank Limited obtained was transformed to weekly stock prices, this was to make the dataset periodic for time series analysis as stock markets are closed for the weekends. The weekly stock prices were then converted to returns (log returns) using excel, this conversion was done since direct statistical analysis of financial price is difficult, because consecutive prices are highly correlated and variances of prices often increase with time. In addition, the trading volume, high and low features of the dataset were removed since they are irrelevant for our analysis.

3.4 Log Returns

Log Returns is one of the three methods for calculating returns and it assumes returns are compounded continuously rather than across sub-periods. It is calculated by taking the Natural log of the ending value divided by the beginning value. The formula is given by;

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

$r_t = MarketReturns$

$p_t = ClosingPrice$

$p_{t-1} = OpeningPrice$

Natural log returns is preferred as it computes continuously compounded returns.

3.5 The Concepts of Time Series

Our daily lives are characterized by sequences of random events or outcomes that occur over specified periods of time, these random events or outcomes can me modelled mathematically by stochastic processes. Time series is an example of a stochastic process. It is a collection of observations or measurements sequentially occurring over regular intervals. Examples of time series data includes: annual interest rates, daily stock prices of an asset, weekly weather forecast, and so on. Time series seeks to understand the mechanism that gives rise to an observation, and based on that knowledge predict the future. The study of time series is very essential and worth its application in various sectors of the economy: health, education, agriculture, finance, insurance, and many others for the purpose of planning, forecasting, budgeting, and control.

3.6 Characteristics of Time Series

A time series possesses at least one of the following characteristics;

- Trend : One of the key features of time series is the trend, which means that the data show a general tendency to increase or decrease over time.
- Seasonality : This is when regular variations are observed in a time series data. It is a characteristic pattern that repeats itself over fixed time intervals. The period is usually under one year. It may be caused by natural and climatic factors or environmental factors. Their time intervals are therefore predictable.
- Cyclic : This refers to recurring patterns in a time series data that do not have

predictable time intervals. They are long-term, non-seasonal in nature and their periodicity is not known.

- Noise : This refers to the unpredictable component of the time series that is observed. The part that is left over when trend, seasonality, and cyclic components are removed.

3.7 Objectives of Time Series

A time series analysis on a data set is for at least one of the following reasons:

- Descriptive : The aim here is to be able to describe the various features and summary statistics of the data. Time series plots are used to identify trends, seasonality, noise, or cyclic component in the data.

- Modeling : This is where an appropriate statistical model is identified to describe the time dependency in the data. Depending on the characteristics of the data, various models are fitted and the most suitable is chosen to describe the data.

- Forecasting : Based on the model identified to describe the data, future values of the series are estimated. These predictions are based on the relationships identified in the historical data.

- Control: Knowing what is likely to happen in the future helps one take measures to mitigate its impact.

3.8 General Steps in Time Series Analysis

Time series analysis and its model building upon discovery has gone through stages of development with different models for both Stationary and non-stationary datasets. However, the general approach to model building and forecasting using time series remains the same, and these includes;

- Model Identification

  In this step, the suitable classes of time series models for the data are being identified. It involves visualizing the data through graphs and charts in order to appreciate the behavior of the data. Different statistics of the data are also computed here. ACF and PACF graphs helps to determine AR and MA lags. The time plot gives a fair idea of whether the data is stationary or not. Models identified here are subject to revision when further analysis are undertaken.

- Model Fitting

  Estimating the model's parameters, which were identified in step one, is the focus of this stage. To estimate these parameters, one can use maximum likelihood or least squares approaches.

- Model Evaluation and Selection

  Model evaluation and selection deals with assessing the competing fitted models of different orders and selecting the best suitable model via the analysis of the information criteria of the fitted models or its ACF and PACF plots. The Information Criteria estimates the amount of information lost by the models and the lesser the value the better. The ACF and PACF plots also helps select the best suitable model by looking at the lags for the order of the model, a model with fewer parameters are deem good thus upholding the principle of parsimony.

- Model Diagnostics

  Model diagnostics entail reviewing and assessing the fitted model to ascertain its appropriateness and quality. This requires examining the model's residuals to determine whether they satisfy particular requirements and display desired characteristics. Model diagnostics are used to evaluate the applicability and dependability of the selected model. The model can be utilized for predicting if it is considered suitable and conforms to the required assumptions. However, if problems are found during the diagnostic procedure, we return to the first few steps and make the necessary corrections.

3.9 The Concepts of Stationarity

A time series is said to be stationary if its statistical properties (mean, variance and autocorrelation) are constant over time, thus does not depend on time and the value of the covariance between the two time periods depends only on the distance or gap between the two time periods and not the actual time at which the covariance is computed. Why are stationary time series so important? For a non-stationary series, we can only study its behavior for the time period under consideration. This makes it difficult to generalize other time periods. A non-stationary time series has its statistical properties changing over time; hence it is difficult to model and predict future data points with certainty. Therefore, data is desired to be stationary to make prediction or forecasting of future data points easier and reliable. To make a non-stationary time series stationary, it is often necessary to take the difference of consecutive observations. This can help remove trends and patterns in the data. However, for large datasets such as economic and financial data with time varying variance, it is difficult to difference in order to achieve stationarity. To address this shortfall, the ARCH Model and its generalized form, the GARCH Model are utilized.

3.9.1 Stationary Models

Time series Models exist for data sets that are stationary. These Stationary models range from simple AR models, MA models and their combination ARMA models which require differencing to make them stationary. An ARMA model being differenced results in an ARIMA model which is stationary. An ARMA model can be differenced once or more than once if the need be. The order of differencing is indicated by the d in ARIMA (p, d, q) models. The p indicates the order of the AR present and the q, order of the MA. The differencing order required to acheive stationarity is not limited to non-negative integers but can be extended to non integers. Models that allow non-integer values of the differencing parameter, d, in the ARIMA models are referred to as ARFIMA Models.

3.9.2 Autoregressive Fractionally Integrated Moving Average, ARFIMA(p, d, q)

ARFIMA(p, d, q) processes are widely used in modeling long Range Dependence(LRD) or long Memory time series, especially for the high frequency trading data, network traffic and hydrology dataset, etc. In practice, several time series exhibit LRD in their observations, leading to the development of a number of estimation and prediction methodologies to account for the slowly decaying autocorrelations. The ARFIMA process is one of the best-known classes of long-memory models. LRD indicates that the decay of the autocorrelation function (ACF) is algebraic and slower than exponential decay so that the area under the function's curve is infinite, Kai Liu et al (2017). The general form of ARIMA$(p.d.q)$ process;

$$(1 - \sum_{i=1}^{p} \phi_i B^i)(1 - B)^d (X_t - \mu) = (1 - \sum_{i=1}^{q} \theta_i B^i) e_t \tag{3.2}$$

$$= \phi(B)(1 - B)^d Y_t = \theta(B) e_t. \tag{3.3}$$

The ARFIMA(p, d, q) Model is also generalised as

$$\phi(B)(1 - B)^d Y_t = \theta(B) e_t \tag{3.4}$$

where d $\in (-0.5, 0.5)$ *and* (1-B)^d is defined as the fractional difference operator.Thus the order of differencing is allowed to take a fractional value between - 0.5 and 0.5. The larger the value of d, the more closely it approximates to a simple integrated series, and it may approximate a general integrated series better than a mixed fractional difference and ARMA model. Fractional differencing and the ARFIMA model were introduced in the early 1980s by Clive Granger,Roselyne Joyeux, and Jonathan Hosking.

3.9.3 Test of Stationarity

Scholars over the years have developed tools to test for the stationarity of a time series data set. These tools are called the unit root test. These are statistical hypothesis test of stationarity that are designed for determining whether differencing is required. The unit root tests include; Augmented Dickey-Fuller (ADF) test, Elliott-Rothenberg-Stock Test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test, Phillips-Perron (PP) Test and Zivot-Andrews test. In this study we will restrict ourselves to only the Augmented Dickey-Fuller (ADF) test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test, and the Phillips-Perron (PP) Test. We would also consider the graphical methods of ACF and PACF, which is done by looking at the ACF and PACF plots. ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) are not used for testing stationarity directly, but they can be used to help identify the order of a time series model, such as an ARIMA model, which can help in testing for stationarity. The ACF measures the correlation between a time series and its lags, while the PACF measures the correlation between a time series and its lags after removing the effects of any intermediate lags. If the ACF and PACF plots show that the autocorrelations decay quickly to zero, this suggests that the time series is stationary. However, if the autocorrelations decay slowly or not at all, this suggests that the time series is non-stationary. Therefore, while ACF and PACF are not used directly for testing stationarity, they can be helpful in identifying the order of a time series model, which in turn can be used to test for stationarity.

3.9.4 Augmented Dickey-Fuller (ADF) Test

Augmented Dickey Fuller (ADF) Test is a common statistical test used to test whether a given Time series is stationary or not. This deals with a statistical hypothesis; a null hypothesis(H_0) and alternative hypothesis(H_1). The hypotheses include;

H_0: The time series is not stationary

$H1$: The time series is Stationary

If the null hypothesis is rejected, it indicates that the time series is Stationary and needs no differencing to achieve stationarity. The decision to fail to reject the null hypothesis base on the p-value imply the time series is not stationary and requires difference.

The rejection rule states;

Reject H_0 if p-Value is less than α, the level of significance. This study uses α value of 0.05, thus 5% level of significance.

3.9.5 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is a statistical test used to assess the stationarity of a time series data set. It is often used in econometrics and time series analysis to determine whether a time series is stationary around a deterministic trend or whether it has a unit root, indicating non-stationarity.

The KPSS test examines the null hypothesis (H_0) and an alternative hypothesis (H_1):

H_0: The time series is stationary

H_1: The time series is non-stationary.

If the null hypothesis is rejected, it indicates that the time series is not stationary and needs differencing to achieve stationarity. If we fail to reject the null hypothesis, it imply the time series is stationary.

The rejection rule states;

Reject H_0 if p-Value is less than α, the level of significance. This study uses α value of 0.05, thus 5% level of significance.

3.9.6 Phillips-Perron (PP) Test

The Phillips-Perron test is a statistical test used for unit root testing in time series data. The null hypothesis for the Phillips-Perron test is that the time series data has a unit root, which means that it is non-stationary. Thus, the null hypothesis assumes that the data follows a stochastic process with a unit root, indicating that it has a trend component that prevents it from being stationary and the alternative hypothesis (Ha) would be that the time series does not have a unit root, implying that it is stationary.

Mathematically, the null hypothesis (H_0) and the alternate hypothesis (H_1) for the Phillips-Perron test can be expressed as:

H_0: The time series is non-stationary.

H_1: The time series is stationary

The Phillips-Perron test is used to assess whether there is enough evidence to reject the null hypothesis in favor of the alternative hypothesis, which would suggest that the data is stationary.

The rejection rule states;

Reject H_0 if p-Value is less than α, the level of significance. This study uses α value of 0.05, thus 5% level of significance.

3.10 Model Selection via Information Criteria

Usually time series analysis done on data set require that a set competing models of different orders are fitted to the data set and the best suitable model is selected. This section of the chapter talks about the model selection via information criteria which this study made use of. The results of the computation of the information criteria estimates the amount of information lost in the model fitting process, therefore in model selection, models with the least value for the information Criteria is desired. The conventional information criteria used in time series analysis includes; the Akaike Information Criterion (AIC), Akaike (1974), the Bayesian Information Criterion (BIC) or Schwarz Criterion (also SBC, SBIC), Schwarz (1978), the Shibata Information Criterion, Shibata(2002) and the Hanna-Quinn Information Criterion (HQIC), Quinn (1979). This study used the Akaike Information Criterion (AIC) in its model selection.

3.10.1 The Akaike Information Criterion (AIC)

The Akaike information criterion (AIC) is an estimator of prediction error and thereby relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Statistical models used to represent data sets, never exactly represent the data set some information are lost by using the model to represent the data set. AIC estimates the relative amount of information lost by a given model: the less information a model loses, the higher the quality of that model. AIC is computed via the formula below;

AIC = -2($log-likelihood$) $+2k$, where k is the number of parameters in the fitted model.

3.11 Non-Stationary Models

The concepts of time series analysis are not limited to stationary dataset alone, but can be extended to datasets that are not stationary, typical examples of such dataset is stock prices, economic and financial data. Non stationary time series models are used to model such datasets. The main type of non-stationary model this study captures is the ARCH Model and its generalized form, the GARCH Model.

3.12 Basic Assumptions

A dataset that exhibits properties of market trends and fluctuations, extreme values that deviate from the general pattern of the data, seasonal patterns and as well having observations at one time point that are correlated with the observations at another time point is deemed to be non-stationary and as a result some assumptions are made. The assumptions are;

- Heteroscedascity: The variance of data set is assumed not to be constant over time. Its heteroscedastic property can lead to biased standard errors and incorrect statistical inference.

- Independence: We assume that the dataset is independent and identically distributed (iid) which means that each data point is not influenced by a previous data point and that each data point has the same distribution as others.

- Serially correlated error terms: We assume that the dataset has serially correlated error terms. Thus, the errors associated with a given time period carry over into future time periods.

- Non-Stationary: We assume that the dataset is not stationary, which means their statistical properties such as mean and variance do change over time. Non-stationary data can lead to spurious result.

3.13 ARCH (q) Models

Autoregressive Conditional Heteroscedasticity (ARCH) model is a statistical model for time series data that describes the variance of the current error term or the difference between the observed value of a variable at time t and the optimal forecast of that value based on information available prior to time t. as a function of the actual sizes of the previous time periods' error terms; often the variance is related to the squares of the previous difference between the observed value of a variable at time t and the optimal forecast of that value based on information available prior to time t. The ARCH model is appropriate when the error variance in a time series follows an autoregressive (AR) model; if an autoregressive moving average (ARMA) model is assumed for the error variance, the model is a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. ARCH models are commonly employed in modeling financial time series that exhibit time-varying volatility and volatility clustering, i.e., periods of swings interspersed with periods of relative calm. ARCH-type models are sometimes considered to be in the family of stochastic volatility models, although this is strictly incorrect since at time t the volatility is completely pre-determined (deterministic) given previous values. ARCH Model has parameter q, indicating the number of lagged errors regressed. It is often written as ARCH (q).

3.13.1 Structure of the ARCH (q) Model

Let y_t be the log return of an asset at time index t. The basic idea behind volatility study is that the series y_t is either serially uncorrelated or with minor lower order serial correlations, but it is a dependent series. To put the volatility models in proper perspective, it is informative to consider the conditional mean and variance of y_t given I_{t-1} ; that is

$$y_t = \phi + e_t \tag{3.5}$$

$$e_t | I_{t-1}(0, h_t) \tag{3.6}$$

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2, \alpha_0 > 0, 0 \leq \alpha_1 < 1 \tag{3.7}$$

Equations 3.2 and 3.3 describe the autoregressive conditional heteroskedastic (ARCH) class of models. The second equation says that the error term is conditionally normal e_t—I_{t-1} (0, h_t) where I_{t-1} represents the information available at time t_1 with mean 0 and time-varying variance, denoted as h_{t-1}, following popular terminology. The third equation models h_t as a function of a constant term and the lagged error squared, e_{t-1}^2 .

3.13.2 Test for ARCH Effect

Before we can model volatility, we need to test for its presence in the return's series. A Lagrange multiplier (LM) test is often used to test for the presence of ARCH effects. To perform this test, first estimate the mean equation, which can be a regression of the variable on a constant or may include other variables. Then save the estimated residuals $\hat{e}_t$ and obtain their squares $\hat{e}_t^2$. To test for first-order ARCH, regress $\hat{e}_t^2$ on the squared residuals lagged $\hat{e}_t$;

$$e_t^2 = \gamma_0 + \gamma_1 e_{t-1}^2 + v_t \tag{3.8}$$

where v_t is a random term. The null and alternative hypotheses are

Null Hypothesis, H_0 : There is no ARCH effect

Alternative Hypothesis, H_1 : There is ARCH effect

If the null hypothesis is rejected, it indicates that there is ARCH effect and an ARCH Model can be fitted to the data set. The rejection rule states; Reject H_0 if p-Value is less than α, the level of significance. This study uses α value of 0.05, thus 5% level of significance. The LM test statistic is $(T-q)^2$ where T is the sample size, is the number of e_{t-1}^2 terms on the right-hand side of the equation, and R^2 is the coefficient of determination. If the null hypothesis is true, then the test statistic $(T-q)^2$ is distributed (in large samples) as $\chi^2(q)$, where q is the order of lag, and $T-q$ is the number of complete observations. If $(T-q)^2 \geq \chi^2\ (1-\alpha, q)$.

3.13.3 Developing the ARCH (q) Model

Building a volatility model for an asset return series consists of four steps:

1. Specify a mean equation by testing for serial dependence in the data and, if necessary, building an econometric model (e.g., an ARIMA model) for the return series to remove any linear dependence

2. Use the residuals of the mean equation to test for ARCH effects.

3. Specify a volatility model if ARCH effects are statistically significant and perform a joint estimation of the mean and volatility equations.

4. Check the fitted model carefully and refine it if necessary.

For most asset return series, the serial correlations are weak, if any. Thus, building a mean equation amounts to removing the sample mean from the data if the sample mean is significantly different from zero. For some asset return series, a simple AR model might be needed.

3.14 GARCH (p, q) Models

Although the ARCH model is simple, it often requires many parameters to adequately describe the volatility process of an asset return. The ARCH Model like other models has pitfalls, one of the shortcomings of an ARCH (q) model is that there are $q+1$ parameters to estimate. If q is a large number, we may lose accuracy in the estimation. The generalized ARCH model, or GARCH, is an alternative way to capture long lagged effects with fewer parameters. It is a special generalization of the ARCH model, GARCH (p, q).

3.14.1 Model Structure and Specifications

The GARCH (p, q) model (where p is the order of the GARCH terms σ^2 and q is the order of the ARCH terms ϵ^2), the notations of the parameters of the GARCH model are given below;

$$y_t = \phi + e_t, e_t|I_{t-1}(0, h_t) \tag{3.9}$$

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2 + ... + \alpha_q e_{t-q}^2 + \beta_1 h_{t-1} + ... + \beta_p h_{t-p} = \alpha_0 + \sum_{i=1}^{q} \alpha_i e_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{3.10}$$

The GARCH (1,1) model;

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 h_{t-1} \tag{3.11}$$

is a very popular specification because it fits many data series well. It tells us that the volatility changes with lagged shocks e_{t-1}^2 , but there is also momentum in the system working via h_{t-1}, One reason why this model is so popular is that it can capture long lags in the shocks with only a few parameters. For the GARCH (1, 1), We need $\alpha_1 + \beta_1 < 1$ for stationarity; if $\alpha_1 + \beta_1 > 1$, we difference to obtain integrated GARCH process, or IGARCH. A GARCH (1,1) model with three parameters $(\alpha_0, \alpha_1, \beta_1)$ can capture similar effects to an ARCH (q) model requiring the estimation of $(q + 1)$ parameters, where (q) is large.

3.15 The ARCH (q) and GARCH (p, q) Models

In this section of the chapter the steps of fitting an ARCH (q) or GARCH (p, q) model to a data set in R is listed as used in this study. The steps listed follow in the required order after loading the necessary R packages, importing the data set into R and converting to a time series data.

1. Plot the data set to get a graphical view of the dataset.
2. Check for Stationarity
3. Check for the Presence of Volatility
4. Test for ARCH effect.
5. Identify the suitable order of the ARCH or GARCH model.
6. Fit competing models of different order.
7. Evaluate and Select the best suitable model (this study used the Akaike Information criterion (AIC)).

Chapter 4

RESULTS AND DISCUSSION

4.1 Introduction

In this chapter, the results of this study and a discussion pertaining to its objectives is presented. The chapter presents tables, plots and console outputs per the methodology used in this project work. The time series analysis done on the GCB Bank limited transformed data set is presented in details. The outputs, plots, and tables presented here are obtained from console of the latest version of R studio as of the time of the research. The codes used are displayed in the appendix of the study. The time series model, GARCH Model, used in modelling the GCB Bank Limited stock returns per the statistical properties of the data set and its specific type is presented in this chapter. The chapter details, the model building, diagnostics and evaluation.

4.2 Data Description and Summary

We explore the few statistics of the various features of the GCB Bank limited dataset.

Table 4.1: Summary Statistics of the features of the GCB Bank Limited dataset

	Open	Close	Low	High	Returns
Minimum	1.840	1.840	1.838	1.840	-0.053
1st Quartile	3.805	3.811	3.800	3.821	0.000
Median	4.708	4.679	4.594	4.756	0.000
Mean	4.386	4.387	4.354	4.411	0.0004
3rd Quartile	5.156	5.160	5.117	5.184	0.0007
Maximum	7.450	7.480	7.434	7.500	0.075
SD	1.085	1.084	1.074	1.098	0.008

4.3 Model Building

The tseries, forecast, rugarch, FinTs, and e1071 packages were used in this section of the study. This packages of the R studio were fundamental in our time series analysis, model identification, model fitting, model evaluation and model diagnostics. The tseries package facilitated the time series analysis and computational finance, the rugarch package provides a flexible and rich univariate GARCH modelling and testing environment, FinTs is a companion to Tsay (2005) Analysis of Financial Time Series, e1071 provides functions for statistic and probabilistic algorithms and the forecast package for displaying and analyzing univariate time series forecasts.

4.3.1 Empirical Model Building

In this section, a model is fitted for the GCB Bank Limited returns time series dataset using this time series analysis and model building procedures below:

4.3.2 Plots of Opening and Closing Stock prices

The first step of data visualization involved creating time plots of the weekly opening and closing stock prices of GCB Bank Limited from 2012 to 2022. The resulting plots are presented below:

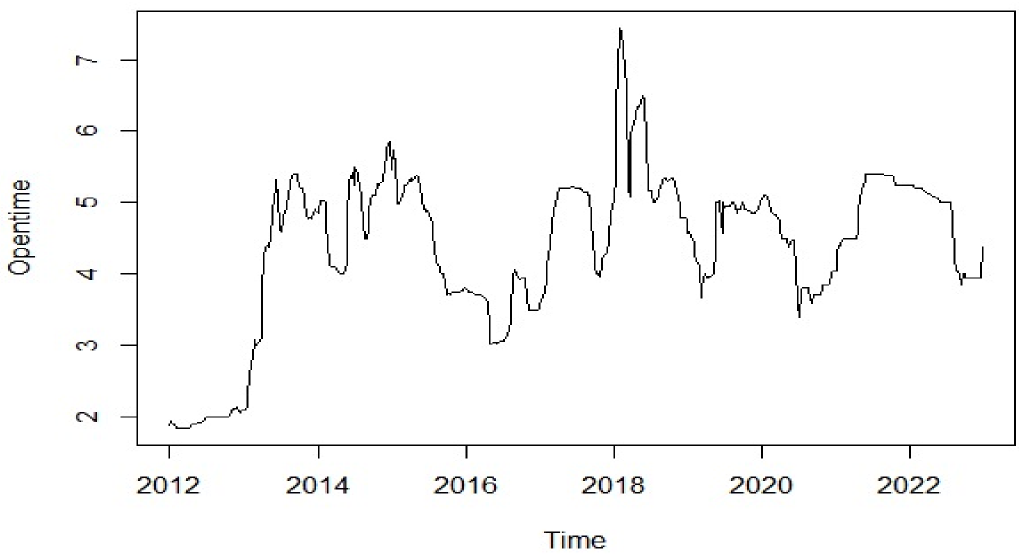

Figure 4.1: Time plot of the opening stock prices of the GCB Bank limited from 2012 to 2022.

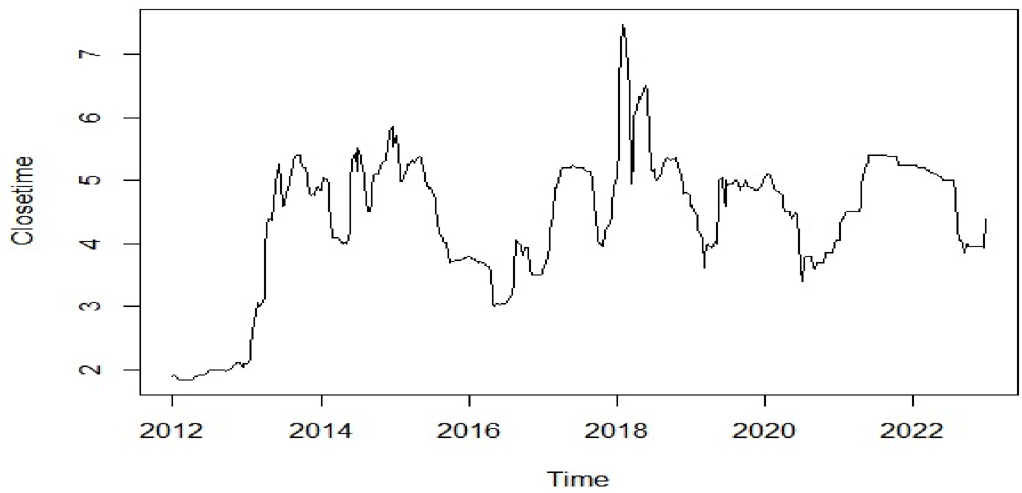

Figure 4.2: Time plot of the closing stock prices of the GCB Bank limited from 2012 to 2022.

4.3.3 Test for Stationarity

This sections presents the results of the test of stationarity done on the GCB Bank Limited returns time series dataset. The unit root tests presented here are the Augmented Dickey-Fuller (ADF) Test,Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test, and the Phillips-Perron (PP) Test . ACF and PACF indirect graphical method were also used and results presented accordingly;

4.3.4 Output of the Tests of Stationarity

The table below displays the p-values of the tests of stationarity.

Table 4.2: The p-values of the Tests of Stationarity

	ADF	KPSS	PP
p-value	0.01	0.1	0.01

Interpretation:From the output above, the p-value of 0.01 for the ADF and PP tests are less than our α value of 0.05, hence we reject the null hypothesis(the time series is non stationary) and conclude that the GCB Bank limited time series dataset is stationary.

Also the p-value for the KPSS test: 0.1, is greater than 0.05 hence we fail to reject the null hypothesis(the time series is stationary) and conclude that the GCB Bank limited time series dataset is stationary.

We can infer from the three unit root tests that the GCB Bank limited time series dataset is stationary.

4.3.5 ACF and PACF Plots

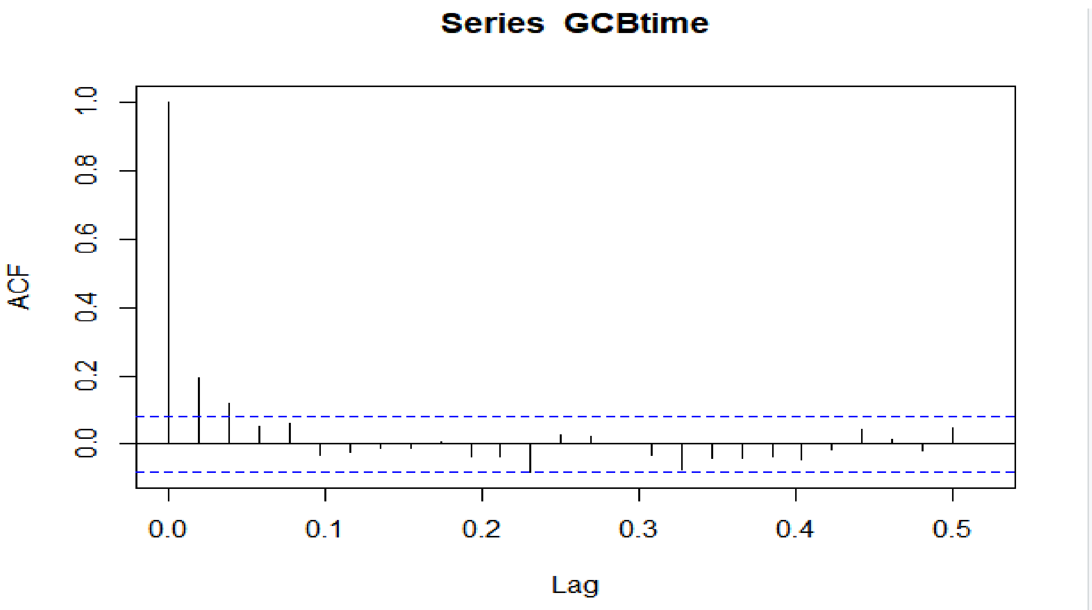

Figure 4.3: The ACF plot of the GCB Bank Limited returns time series dataset

Interpretation: The ACF plot above displays an exponential decay, therefore we can conclude that the GCB Bank Returns series is stationary.

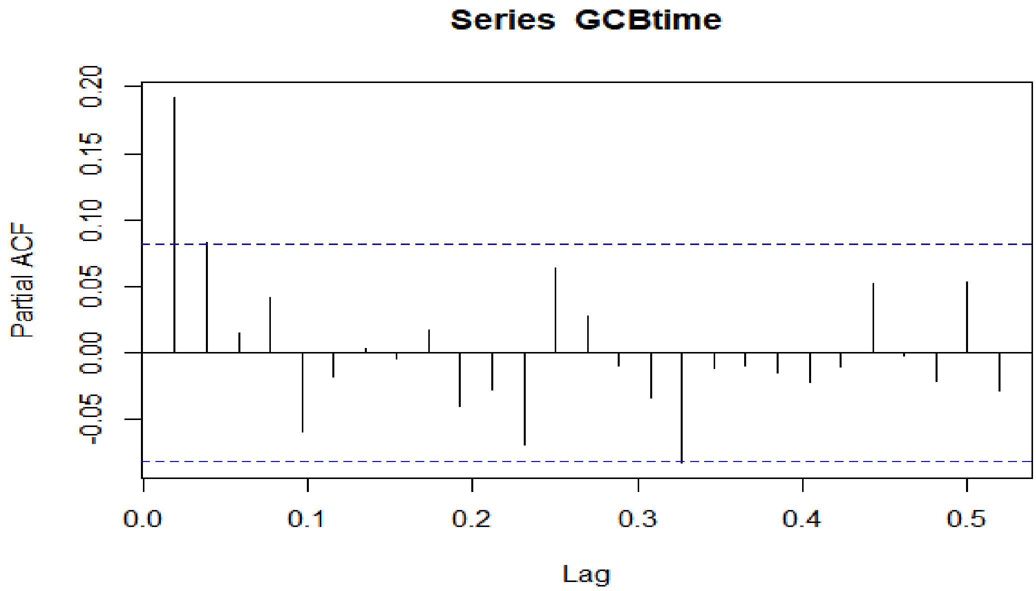

Figure 4.4: The PACF plot of the GCB Bank Limited returns time series dataset

Interpretation: The PACF plot above displays an exponential decay, therefore we can conclude that the GCB Bank Returns series is stationary.

4.3.6 Volatility Clustering

The volatility present in the GCB Bank Limited log returns tends to cluster,periods of high volatility are followed by more periods of high volatility, and periods of low volatility are followed by more periods of low volatility. There are few very high spikes in volatility influenced by news events and economic data releases. The Volatility beginning somewhere in 2020 to 2022 seem to be in a stable period which can be attributed to restoration of somewhat investors confidence in the economy after the seemly recovery of the economy. Volatility here displays a bit of seasonality which is not really clear. A graphical representation of the volatility clustering present in the GCB Bank Limited returns time series dataset is shown below.

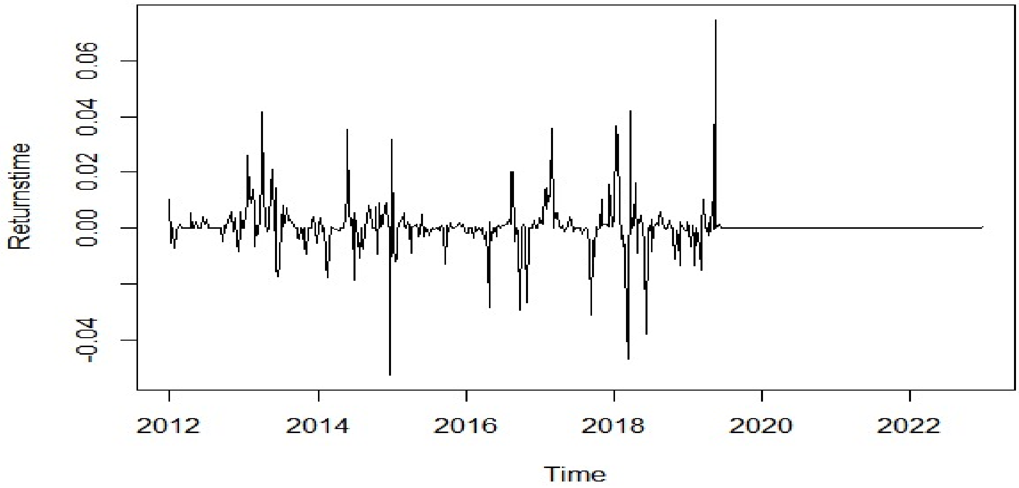

Figure 4.5: volatility clustering in the GCB Bank Limited returns time series dataset

4.3.7 Test for ARCH Effect

In this section, a test for the presence of ARCH effect was performed, the tool used in the test for the ARCH effect is the ARCH LM Test (Lagrange Multiplier Test). The output of the test is displayed below;

Table 4.3: Output of the ARCH LM-test

Chi-squared	df	p-value
22.193	12	0.03542

Interpretation: Since the p-value of 0.03542 is less than our α value of 0.05 we reject the null Hypothesis and conclude that there is an ARCH effect in the GCB Bank limited time series data set.

4.3.8 Model Identification

The suitable class of time series model for the GCB Bank limited returns time series dataset is being identified in this section. The model identified here is subject to revision with further analysis for a specified suitable model. The output for identification is presented below;

Table 4.4: Output of GARCH order identification

	α_0	α_1	β_1
Coefficient(s)	4.963e-05	5.000e-02	5.000e-02

Interpretation: The output above indicates that, the suitable model for the GCB Bank limited returns time series dataset is a GARCH (1,1) model. The GARCH (1,1) model identified with estimated parameters is:

$$h_t = 0.000049663 + 0.05\alpha_1 + 0.05\beta_1 \tag{4.1}$$

However, this identified model is subject to change upon further analysis and a final suitable Model would be presented in the later section of this study.

4.4 Model Evaluation, Selection and Diagnostics

The rugarch package providing a flexible and rich univariate GARCH modeling and testing Environment was employed in the model fitting, evaluation, selection and diagnostics step to find the final suitable model for the GCB Bank limited returns time series dataset. Upon the use of rugarch package, the most appropriate GARCH Model for the conditional time varying variances of the GCB Bank returns series is the sGARCH (1,1). Three competing Returns models of different order was fitted with the output of their Parameter Estimates and Standard Errors(shown in bracket) presented in the table below;

Table 4.5: Parameter Estimates and Robust Standard Errors

Parameter	ARFIMA(1,0,1)	ARFIMA(1,0,0)	ARFIMA(0,0,1)
mu	-0.000001(0.079632)*	0.000001(0.096273)*	0.000004(0.001521)*
ar1	0.721449(214.443017)*	0.606217(31.700787)*	
ma1	-0.024362(203.703070)*		0.525572(305.180025)*
omega	0.000000(0.000354)	0.00000(0.000925)	0.00000(0.018411)
alpha1	0.163915(6.380071)*	0.1219279(8.975878)*	0.136367(91.842672)*
beta1	0.828723(3.526842)*	0.869027(6.403486)*	0.847630(69.257663)*

* 5% level of significance

4.4.1 Information Criterion

In this section,the Information Criterion of the fitted Returns Model are presented . The Akiake Information Criterion was considered in the Model Selection.

Table 4.6: Information Criterion of Fitted Models

	ARFIMA(1,0,1)	ARFIMA(1,0,0)	ARFIMA(0,0,1)
Akaike	-8.8681	-8.7067	-8.6981
Bayes	-8.8225	-8.6687	-8.6601
Shibata	-8.8683	-8.7069	-8.6983
Hannan-Quinn	-8.8503	-8.6919	-8.6833

Comparing the AIC for the three models fitted above indicates that the specified suitable models fit for the GCB Bank Limited time series dataset are; ARFIMA (1, 0, 1) for the Mean equation (Returns Equation) and, SGARCH (1, 1) for the Conditional Variance Equation. This Model has an AIC of -8.8681 which is the least among the AICs; -8.7067 for ARFIMA (1, 0, 0) and -8.6981 for ARFIMA (0, 0, 1).

4.5 Fitted Model

On the back of the Model diagnostics, evaluation and selection done in the just preceding Section (Section 4.6), we obtained estimates for the various parameters of the ARFIMA (1, 0, 1) and SGARCH (1, 1).

4.5.1 The Mean(Returns) Equation

The mean (Returns) equation, ARFIMA(1,0,1), with estimated parameters is:

$$r_t = -0.000001 + 0.0721449y_{t-1} - 0.024362e_{t-1} \tag{4.2}$$

4.5.2 The Conditional Variance Equation

The conditional variance equation, SGARCH(1,1), with estimated parameters is:

$$h_t = 0.163915e_{t-1}^2 + 0.828723h_{t-1} \tag{4.3}$$

4.6 Forecast of Returns and Volatility

With the Model, we can obtain a forecast for the GCB Bank Limited weekly stock returns and volatility for any defined time period. In this section a forecast for the returns and volatility for the next 30 weeks is presented using suitable fitted model. The figures below displays the returns and volatility forecast respectively.

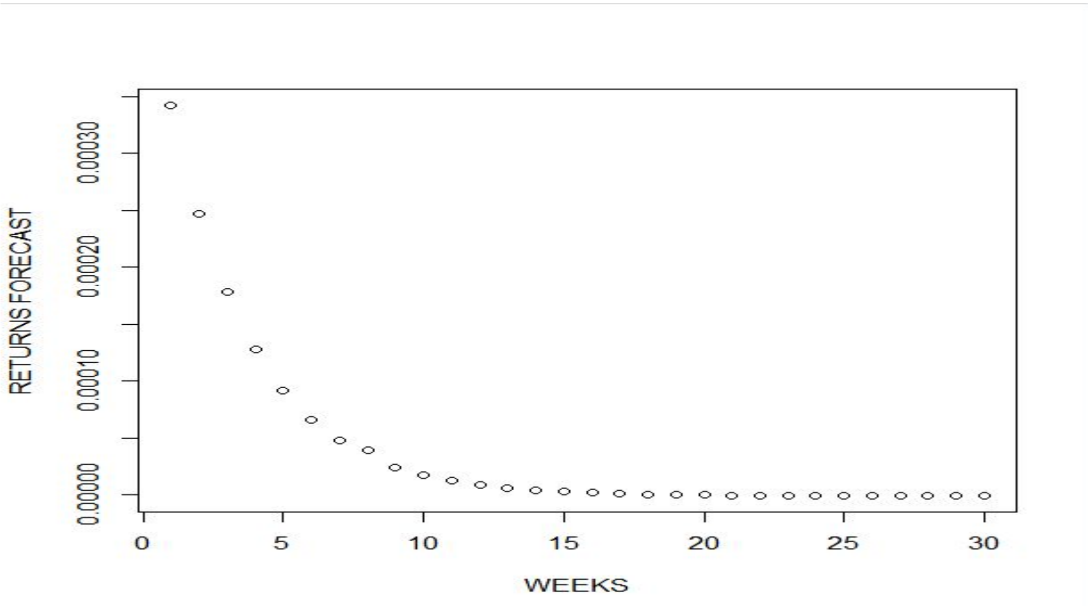

Figure 4.6: Returns forecast for the next 30 weeks

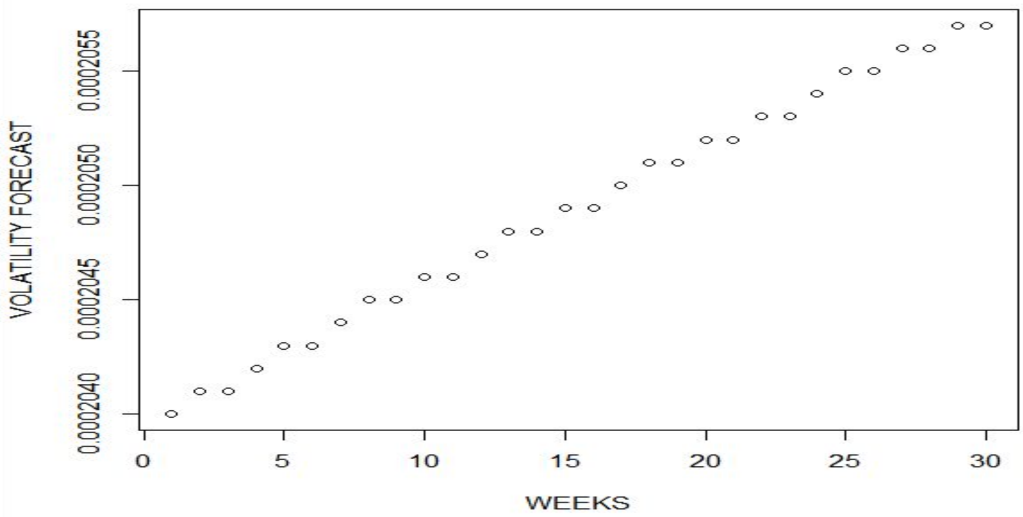

Figure 4.7: Volatility forecast for the next 30 weeks

4.7 Chapter Summary

Findings of this study are presented in this chapter, the results of the practical implementation of the general time series analysis steps are displayed accordingly and in depth interpretations given where needed. Final suitable model for the GCB Bank Limited returns dataset is:

$$r_t = -0.000001 + 0.0721449y_{t-1} - 0.024362e_{t-1} \tag{4.4}$$

$$h_t = 0.163915e_{t-1}^2 + 0.828723h_{t-1} \tag{4.5}$$

Chapter 5

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATION

5.1 Introduction

This is the last chapter of the study, it contains a summary of the study and conclusions per the objectives of the study. Analysis of the GCB Bank Limited stock price dataset from 2012 to 2022, modelling of its volatility and returns are the objectives of the research per the chapter one of this study, and a summary and conclusion of findings are presented in this chapter. The summary and conclusion presented gives a practical and mathematical understanding of the nature of the GCB Bank stock returns from 2012 to 2022 and how the future returns look like.

5.2 Summary of Findings

The focal interest of this study was the returns of GCB Bank Limited, log returns were obtained from the stock prices dataset from 2012 to 2022 so we could proceed with the analysis. The GCB Bank Limited log returns dataset was converted to a time series dataset in R Studio to facilitate a time series analysis of the dataset. The log returns dataset was plotted to get a graphical perspective. Stationarity test performed was essential because the log returns dataset possessing this feature makes forecast easy and reliable. To be able to capture the time varying variance of the log returns dataset if present, an ARCH effect test was performed. The test confirmed the presence of ARCH effect which informed the fitting of a GARCH Model. The results of the time series analysis done in R, is an ARFIMA (1, 0, 1) econometric model for the returns and SGARCH (1, 1) model for the time varying conditional variances. These models were the most suitable models after Model diagnostics and evaluation and provides a very good forecast for GCB Bank Limited.

5.3 Conclusions

Driven by the objectives of this research, this section presents the conclusions on findings. The conclusions are as follows;

1. The analysis on the GCB Bank Limited log returns obtained from stock prices from 2012 to 2022 concludes that volatility clustering exists in the dataset.

2. The study concluded that the suitable Model for the volatility of GCB Bank Limited log returns dataset is SGARCH (1, 1).

3. The suitable model for the returns of GCB Bank Limited is ARFIMA (1, 0, 1).

4. In the short term, the returns of GCB Bank Limited stocks would decline as volatility is increasing.

5.4 Recommendation

This section presents recommendations based on the study's findings. From the forecast of the stock returns and volatility of GCB Bank Limited for the next 30 weeks, recommendations to the investors and management of GCB Bank Limited are as follows:

- In view of the decline in stock returns affected by high volatility, existing investors should hold their stocks in GCB Bank Limited and potential investors should not buy GCB Bank Limited stocks in the short term. However in the long term with improved policies and good economic conditions the selling and buying of GCB Bank Limited stocks can be considered.

- The management of GCB Bank Limited should put measures in place to resolve the decline in the stock returns and increasing volatility.

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APPENDIX

R Codes

$> class(WRDGCB)$

$> GCBtime = ts(WRDGCB$'Weekly Returns' ,start = c(2012,01),frequency = 52)

$> plot(GCBtime)$

$> CheckforStationarity$

$> acf(GCBtime)$

$> pacf(GCBtime)$

$> adf.test(GCBtime)$

$> CheckforVolatilityClustering$

$> plot.ts(GCBtime)$

$> CheckforARCHEffect$

$> ArchTest(GCBtime)$

$> SuitableModel$

$> garch(GCBtime, grad =' numerical', trace = FALSE)$

$> GCBtime\_spec = ugarchspec(variance.model = list(garchOrder = c(1,1)), mean.model = list(armaOrder = c(1,1)))$

$> GCBtime\_spec.fit = ugarchfit(GCBtime\_spec, data = GCB\_time)$

$> GCBtime\_spec.fit$

$> GCBtime\_spec = ugarchspec(variance.model = list(garchOrder = c(1, 1)), mean.model = list(armaOrder = c(0, 0)))$

$> GCBtime\_spec.fit = ugarchfit(GCBtime\_spec, data = GCB\_time)$

$> GCBtime\_spec.fit$

$> GCBtime\_spec = ugarchspec(variance.model = list(garchOrder = c(1, 1)), mean.model = list(armaOrder = c(1, 0)))$

$> GCBtime\_spec.fit = ugarchfit(GCBtime\_spec, data = GCB\_time)$

$> GCBtime\_spec.fit$

$> GCBtime\_spec = ugarchspec(variance.model = list(garchOrder = c(1, 1)), mean.model = list(armaOrder = c(0, 1)))$

$> GCBtime\_spec.fit = ugarchfit(GCBtime\_spec, data = GCB\_time)$

$> GCBtime\_spec.fit$

$> GCBtimeospec.fit\_forecast = ugarchforecast(GCBtimeospec.fit, level = c(95), n.ahead = 30)$

$> GCBtimeospec.fit\_forecast$

Table 5.1: Returns forecast for the next 30 weeks

Weeks	Returns Forecast
1	0.0003424
2	0.0002468
3	0.0001778
4	0.0001280
5	0.00009203
6	0.00006611
7	0.00004742
8	0.00003933
9	0.00002419
10	0.00001717
11	0.00001211
12	0.000008452
13	0.000005815
14	0.000003913
15	0.000002541
16	0.000001551
17	0.0000008364
18	0.00000003211
19	-0.000000005070
20	-0.00000003189
21	-0.00000005124
22	-0.00000006520
23	-0.00000007527
24	-0.00000008254
25	-0.00000008778
26	-0.00000009156
27	-0.00000009429
28	-0.00000009626
29	-0.0000009768
30	-0.0000009871

Table 5.2: Volatility forecast for the next 30 weeks

Weeks	Volatility Forecast
1	0.0002040
2	0.0002041
3	0.0002041
4	0.0002042
5	0.0002043
6	0.0002043
7	0.0002044
8	0.0002045
9	0.0002045
10	0.0002046
11	0.0002046
12	0.0002047
13	0.0002048
14	0.0002048
15	0.0002049
16	0.0002049
17	0.0002050
18	0.0002051
19	0.0002051
20	0.0002052
21	0.0002052
22	0.0002053
23	0.0002053
24	0.0002054
25	0.0002055
26	0.0002055
27	0.0002056
28	0.0002056
29	0.0002057
30	0.0002057