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EXPLORING MACROECONOMIC DYNAMICS ON STOCK RETURNS IN AFRICAN COUNTRIES: GARCH-MIDAS AND REGULARIZATION REGRESSION APPROACH

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THIS THESIS IS SUBMITTED TO THE UNIVERSITY OF GHANA, LEGON IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF MASTER OF PHILOSOPHY IN ACTUARIAL SCIENCE DEGREE.

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DECLARATION

Candidate's Declaration

I hereby declare that, with the exception of references made to the work of others on the subject matter, this research is my own. I therefore state that this work has not been submitted to any academic setting or any other university for the award of another degree.

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Supervisors' Certification

We hereby certify that this thesis was prepared by the candidate and supervised in accordance with the rules and regulations guiding academic work at the University of Ghana.

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DEDICATION

I dedicate this research work to my beloved mother, Comfort Kpata, and my senior brothers, Rev. Emmanuel Kwasi Agbeli and Simon Kofi Agbeli.

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ABSTRACT

Measuring stock market volatility and its determinants is critical for stock market participants as volatility spillover effects alters corporate performance. This thesis adopted two different approaches where the analysis was distinctly implemented using GARCH-MIDAS and regularization regression methods. The classic GARCH as a benchmark and the univariate GARCH-MIDAS framework are the first two GARCH family models whose forecasting outcomes are examined in this thesis. The second analysis was a shrinkage approach that adopted two techniques: LASSO and ridge regularization approaches, which were used to determine the most influential regressors for stock index returns and volatility in the three markets. The outcome of GARCH-MIDAS analyses suggests that inflation, interest rate, currency exchange rate, and price of oil are significant determinants of the volatility of the Johannesburg Stock Market All Share Index. While for Nigeria the volatility reacts significantly to exchange rate and price of oil. Furthermore, Ghanaian equity volatility is significantly influenced by inflation, the exchange rate, the interest rate, and the price of oil, especially for the long-term volatility component. The significant shock of the oil price and exchange rate to volatility are present in all three markets using the GARCH-MIDAS framework. As an alternative, the machine learning algorithms selected the money supply, oil price, interest rate, and exchange rate as the most critical indicators for predicting South African stock returns. In the Nigeria scenario, the regularization algorithm produced conclusion where oil price and money supply were specified as the utmost relevant variables in predicting asset returns. Additionally, currency exchange rate, interest rate, and price of crude oil were the ultimate significant indicators that determined stock returns in Ghana.

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LIST OF ABBREVIATION

AIC .... Akaike Information Criteria

ARCH .... Autoregressive Conditional Heteroskedasticity

ARMA .... Autoregressive Moving Average

BIC .... Bayesian Information Criteria

BOG .... Bank of Ghana

CAPM .... Capital Asset Pricing Model

CPI .... Consumer Price Index

EXR .... Exchange Rate

GARCH .... General Autoregressive Conditional Heteroskedasticity

GM .... GARCH-MIDAS

GSE .... Ghana Stock Exchange

GSS .... Ghana Statistical Service

IFS .... International Finance Statistic

IN .... Inflation

IR .... Interest Rate

JSE .... Johannesburg Stock Exchange

LASSO .... Least Absolute Shrinkage and Selection Operator

LLF .... Log-likelihood Function

LM .... Langrage Multiplier

NSE .... Nigeria Stock Exchange

MIDAS .... Mixed Data Sampling

MS .... Money Supply

MSE .... Mean Square Error

SARB .... South Africa Reserve Bank

VR .... Variance Ratio

CHAPTER 1

INTRODUCTION

1.1 Background of the study

For deepening inclusive development that generates wealth and reduces poverty incidence in Africa, positive economic policy outcomes and stock market performance are crucial. Across the globe, the stock market is one of the most popular avenues for investing surplus funds and financing corporate growth. As a result, investor confidence and certainty are boosted when stock market volatility is estimated correctly.

Nevertheless, macro volatility is the primary concern for stock market participants, and it plays an important role in determining their risk-return assessment. Often, macroeconomic stability is cited as a factor that creates a favorable investment climate for rallying both domestic and foreign capital. In contrast, an unpredictable macroeconomic environment generates a source of shock to the economy's productive sectors and financial system as a result of information asymmetry. In Africa, financial crises and fluctuations in exchange rate and high inflation present volatility in value of products and services hence making investment in the equity market risky and less attractive. A stable macroeconomic environment is therefore necessary for the survival of the financial system and for the achievement of sustainable economic development.

According to the International Monetary Fund, the risks identified by investors in the financial market in developing countries includes macroeconomic volatility and markets' illiquidity, which are perceived to be higher in Sub-Saharan Africa (Yartey & Adjasi, 2007). In Africa, wide swings in macroeconomics variables and volatility in financial market have been recurrent, which makes forecasting more sophisticated and complex. Many policy interventions failed to create sustainable stable macroeconomic environment to build resilient economy. This is because low and predictable rate of macroeconomic variables are likely to improve stock market returns and liquidity which will reduce uncertainty and attract more investment that provides regular flow of capital to the business community.

Though using historical patterns of stock market data is the most popular method for forecasting stock returns, it has been discovered that other factors like macroeconomic and financial indicators also play an important role in predicting stock returns (Schwert,1989). These indicators have the potential to influence asset return patterns over time. The volatility of real and financial factors, such as fluctuations in exchange rates, oil prices, and credit crises have a significant influence on the equity investment. This necessitates the inclusion of these financial and economic conditions in forecasting and quantifying market risks as well as assessing volatility spillover effects.

Against this sobering backdrop, understanding the interrelationships and linkages between the economic fundamentals and equity market returns is vitally critical for practitioners, academics and policy makers. This suggest that volatility modeling and forecasting is imperative for achieving sound risk management, prudent assets allocation and pricing financial derivatives. Nonetheless, asset returns are determined by the listed companies' cash flow position. Hence, deceleration of economic conditions is deemed to negatively influence the risk level by eroding the cash flow of the companies triggered by rising crude prices, unfavorable financial conditions and soaring input costs. A slump in stock returns indicates greater investment risk, and volatility is likely to increase as macroeconomic activities worsen.

Over the earlier decades, the consequences of macroeconomic variables on the behavior of stock prices have been studied with a renewed sense of interest in developed and emerging market economies using various statistical models. Researchers are eager to explore whether the economic policies of the government have any effects on stock returns and volatility. For instance, Ashgarian et al. (2013); Comrade and Loch (2015); Adusei (2014); and Ali et al. (2020), linked stock market volatility to macroeconomic fundamentals. Many of these papers posit that fluctuations in macroeconomic fundamentals not only affect the real sector alone but also have an impact on financial markets such as stock and futures markets. Traditional models were used extensively in the available literature to establish the link between macroeconomic variables and stock returns in Africa include multiple linear regression, Granger causality test, cointegration, distributed lag, and VAR family models. However, Sub-Saharan Africa, as middle-income economies, have not witnessed much application of contemporary statistical methods such as novel GARCH-MIDAS and regularization regression models to assess the impact of economic variables such as exchange rate, interest rate, industrial production index, inflation and money supply etc. on equity market volatility. While, at the same time the performance of these tools has been corroborated in the literature in many emerging and developing economies.

In an attempt to advance volatility modeling, Engle (1982) pioneered and popularized the Autoregressive Conditional Heteroscedasticity (ARCH) model, and later, Bollerslev (1986) extended the ARCH model to the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. Both models challenge the assumptions of constant volatility and capture conditional variance, time-varying variance, mean reverting processes, and volatility clustering in high frequency financial time series data. In the ARCH model, the conditional variance depends only on the past lag square errors, while in the GARCH model it accommodates both the lagged of past square errors and the lagged term of past variance. Since variance is often used to measure volatility, an aspect that is fundamental to asset pricing theory. The two models have proved useful in modelling volatility involving high and uniform frequency data in empirical finance. However, data sampled at different frequencies continually poses a challenge to academics and practitioners studying relationships and dependency in financial and economic time series. This implies, dependent variable sampled at high-frequency cannot be modelled alongside with regressors sampled at low-frequency since most traditional time series regression models comprises of data sampled at the same frequency. As a result, modeling is often based on high-frequency data or low-frequency data single-handedly, while the combination of low and high-frequency variables has been underexplored. As part of an intervention to bridge this gap, Ghysels et al. (2006) introduced the Mixed Data Sampling (MIDAS) regression model, which allows incorporation of data from different frequencies into the same model. It combines and examines the relationship between the response variable and predictors sampled at different frequencies (i.e., the dependent variable is of high-frequency while the covariates are of low-frequency and vice versa). One positive contribution of MIDAS regression is to amend the problem associated with information loss that comes as a result of the transformation of variables sampled at high-frequency to low-frequency variables, as is the case with many classical regression models.

Engle and Rangel (2008) initially introduced the Spline-GARCH to allow high-frequency financial data to be linked with low-frequency macro data. The model is a multiplicative decomposition of slowly varying macro components and mean reverting unit GARCH, which makes it possible to estimate the effect of potential macroeconomic conditions on stock volatility. However, the Spline-GARCH could not impute directly the influence of macroeconomic variables on the determination of stock price volatility.

Engle et al. (2013) use MIDAS approach to develop the GARCH-MIDAS model that allows conditional variance to be segmented in to short-term (high-frequency) and long-term (low-frequency) component with the MIDAS polynomial filtering monthly, quarterly or semi-annual economic or financial factors. The approach permits daily stock returns as dependent variable to be linked to monthly or quarterly macroeconomics variables, in order to assess directly the role of macroeconomic fundamentals in explaining stock volatility. Under the GARCH-MIDAS scheme, the low-frequency variables are subjected to the MIDAS polynomial. It sought to explore whether information encompassed in short-run component can be used to predict the long-run component of the model. This approach to measure the contribution of macroeconomic series, can be regarded as regression involving filtering (Engle et. al, 2013). The GARCH-MIDAS approach gained prominence in modelling volatility because of its ability to improve prediction accuracy.

Furthermore, regularization methods such as LASSO (Tibshirani, 1996) and Ridge Regression (Hoerl & Kennard, 1970) have also been successfully applied in a variety of fields, including stock market outcome forecasting. These advanced regression models, known as Machine Learning Algorithms, have been introduced as an improved technique for developing robust predictive models for forecasting stock returns and providing an accurate view of market trends. This is because regularization can improve prediction. Choosing the relevant macroeconomic variables from a subset of variables is a critical step in developing models that improve prediction accuracy. This aids in the identification of the best fit covariates associated with asset returns. Since some macroeconomic variables may be highly correlated, shrinkage techniques reduce the impact or eliminate irrelevant macroeconomic variables as explanatory variables in the model for forecasting asset returns. The idea of regularization is to make the model less complex by increasing the model bias, which significantly reduces the variance. The appeal of the regularization technique is its ability to deal with the problem of multicollinearity and correlation among regressors, as it is the case of traditional regression models. In some conditions, over-fitting and under-fitting are common in multiple linear regression models, which often do not produce parsimonious models. In machine learning, regularization modifies the loss function by adding a shrinkage term. Although feature selection models have not been extensively used in finance, they have been implemented well in predicting market returns with many predictors.

1.2 Statement of the Problem

Many researchers, scholars, and practitioners agree that the financial market is the foundation of a sound financial system and an essential driver of economic growth in both advanced and developing economies. Since the inception of the Ghana stock exchange in 1990 as part of economic reforms, successive governments have implemented extensive restructuring to attract more participants and promote the progress of the capital market and its allied institutions in the country. These reforms included the establishment of regulatory and supervisory frameworks; the introduction of automated trading; market liberalization; and fair diversification of products and services.

Despite the fact that these interventions led to some improvement in the stock exchange, the performance of Ghanaian stocks has been dismal compared to their peers in other regions of the world. The total market capitalization witnessed a steep fall from GH¢57.1 billion in 2015 to GH¢56.8 billion in 2019 and equity trading has not seen significant improvement over the last ten years as trading volumes fell from about GH¢331 million in 2010 to about GH¢324 million in 2019. Capitalization of the stock market as a percentage of GDP has witnessed a sharp decline from about 31.7% in 2015 to about 16.3% in 2019, (Ghana Stock Exchange). Similarly, Nigeria has one of the largest economies in Sub-Saharan Africa, but capital market participation is low in comparison to the country's economy and population. In October 2018, the Nigeria All Share Index decreased from 32383 to 32763 points. Market capitalization dropped from 11.961 trillion Naira to 11.822 trillion in September the same year, (Nigeria Stock Exchange). These markets have been characterized by a low level of liquidity and capitalization, often centered on a few listed stocks. As the performance of businesses is linked to macroeconomic conditions, The situation is exacerbated by the perennially volatile macroeconomic environment in Sub-Saharan Africa. The highly volatile and unpredictable macroeconomic conditions have hampered the returns and growth of businesses.

However, there can be no doubt that the African economies have witnessed stability in macroeconomic conditions such as currency exchange rates, interest rates, inflation and attained significant economic advancement over the last two decades. On the other hand, macroeconomic and structural difficulties have always existed that make it impossible for the economy to remain stable for long periods of time. As a result of incessant poor fiscal management, the economy has fluctuated between short-term stability and long-term instability, causing large swings in macroeconomic variables in recent years. In addition, the high level of sovereign debt has aggravated the worsening macro conditions coupled with a surge in foreign currency-denominated debt has possible consequences for financial and macroeconomic stability. This is reflected in the volatility of prices, interest rate and foreign exchange rate as a consequence of high interest payment and amortization. There can be no certainty in forecasting macroeconomic outcomes or investment returns due to the unrelenting fall of the domestic currency in relation to key transaction currencies like the US dollar, the Euro, and the Pound Sterling. The deteriorating macro environment affects cost of doing business and prices of goods which may have negative impact on savings, household consumptions and viability of businesses in Sub-Saharan Africa.

As a result, capital flow to the stock markets is relatively low as returns are not often adequate to neutralize increasing systematic risk. However, whether these economic events influence the behavior of stock prices has been inconclusive in academic meetings and circles. Furthermore, Sub-Saharan Africa economies are still in development stage and have a growing working-age population, which has the potential to boost real economic activity and accelerate economic growth. However, the countries' unemployment rate is stubbornly high, and the majority of the populations are employed in the informal sector. The stock exchange, which is regarded as one means that can help in promoting industrial development, commerce, and the thriving fortunes of many businesses that will eventually lead to job creation. However, the three Stock Exchanges with exception of Johannesburg stock market have not fully deepened financial intermediation in order to drive more listing and equity investment from both domestic and international sources. Low private investment and the inability of the stock exchanges to provide capital to businesses, coupled with the unpredictable macroeconomic environment, have been major obstacles to promoting employment-intensive growth.

Based on methodological considerations, over the years, a multiplicity of research has been conducted in advanced and developing nations to understand the period-varying and conditional stock price volatility and their underlying causes using various statistical tools. Traditional techniques, such as VAR family type, and GARCH family type, were widely used to study the stylized behavior of stock returns (see, for instance, Sokpo et al., 2017; Ali et al., 2020; Nasir et al., 2021; Abbas et al., 2017). Though these models have been useful in finance and economics, they are bedeviled by data frequency incompatibility as a number of macro indicators are reported on a monthly, quarterly, and annual basis while stock prices are measured on a daily or hourly basis. To address the issue of frequency disparity, researchers often convert variables sampled at different (uneven) frequencies to uniform (match) frequencies by means of extrapolation or averaging and aggregating. Consequently, conversion of variables of diverse frequencies to avoid frequency mismatch would lead to loss of vital information in the data, which adversely affects forecast performance. Similarly, this phenomenon is usually accompanied by estimation bias. Additionally, these models are not able to segregate volatility into short- and long-run components and also fail to capture time-varying conditional variance. In this regard, many studies on volatility dynamics have been conducted using the novel GARCH-MIDAS because the component model allows for a concise representation of complex dependence. Furthermore, volatility component models have recently attracted considerable curiosity not only because of their potential to express complex dynamic data with a parsimonious model structure but also due to their ability to deal effectively with non-stationarity or structural breaks in equity price swings, (Wang & Ghysel, 2015).

In addition, this thesis also aims to pinpoint suitable macroeconomic factors for predicting variations in stock returns. Regressive modeling suffers from a number of statistical problems, including underfitting, overfitting, and multicollinearity, when too many variables, especially those that are closely related to one another, are used. These problems render predictions statistically insignificant. Overfitting is a problem that arises when a complex model fits the trained data extremely well but does not fit the test data as well, reducing the model's predictive power. When many macroeconomic variables are clearly highly correlated, this may lead to erroneous regression. The problem that normally arises in forecasting stock returns is how to discover the most predictive covariate or variable. It has been well documented that variable selection through the use of machine learning algorithms has impressive forecast performance compared to the 'classical' models (check, e.g., Chao et al., 2019; Zhang et al., 2019; Liang et al., 2022). Regularization regression techniques such as LASSO and Ridge have proven successful in many fields (like health and economics). However, these commonly used methods have not yet received much consideration in the existing literature on stock return forecasting using macroeconomic variables as predictors in the sampled countries.

1.3 Research Objectives

The aim of this thesis is to investigate and document appropriate macroeconomic variables that explain volatility in stock returns in three African countries (South Africa, Nigeria and Ghana).

1.3.1 Specific Objectives

The specific objectives are:

- Assess the relationship between inflation, money supply (M2), exchange rate, interest rate and oil price on stock returns in South Africa, Nigeria and Ghana using GARCH-MIDAS model.
- Examine the impact of these variables on the components volatility in South Africa, Nigeria and Ghana.
- To identify macroeconomic variable(s) that build the best fitting predicted model using LASSO and Ridge Regression.
- Examine the performance of competing GARCH and GARCH-MIDAS Models.

- Test the forecasting potential of the LASSO and Ridge Regression.

1.4 Research Questions

In pursuant to objectives stated above, this study strives to evaluate and scrutinize the following questions:

- Do macroeconomic factors affect stock market returns in Ghana, Nigeria and South Africa?
- Is there a short-run and long-run relationship between macroeconomic series and stock returns?
- Which macroeconomic variable(s) are important or produce the best fitted model?
- Which GARCH model makes better predictions?

1.5 Significance of the Study

A significance of a research identifies the relevance of the research findings to shaping local and regional policy debates as well as its contribution to existing literature on the subject matter of the study. Generally, government policies that promote macroeconomic stability can foster the evolution of the private sector and enhance its profitability. Thus, a stable macroeconomic environment would have a substantial impact on market returns and investment. To be precise, this research would provide insight on how the government should manipulate the macroeconomic environment, which may lead to better economic management practices that ensure stability and check volatility in the economy. In formulating and implementing policies that restore macroeconomic stability, the government has to take into consideration the effects of economic factors on capital market performance. Similarly, the government can help deepen activities on the stock market by ensuring prudent fiscal management policies to better serve the private sector.

Secondly, for investors in the stock market, it is appropriate for them to be abreast of the nature of the risk they face. The risks that daunt investors in private equity assets, such as unsystematic risks, liquidity of markets and macroeconomic instability, are pervasive in Sub-Saharan Africa. Concisely, the return on an investor's investment, investment risk, and the volatility or variability of that investment are important issues to investors. One of the consequences of macroeconomic volatility is that it creates uncertainty that limits the ability to generate optimum returns from investment in the equity market. This research would be of enormous benefit to the investor community in investment planning and asset allocation in order to achieve optimum returns. Similarly, the stock exchange provides an avenue for trading in equity and, as such, understanding the dynamic of macro volatility can help market participants (such as institutional investors, brokers) and analysts effectively manage their portfolio in order to maximize returns on their investments. Hence, asset return and asset price volatility are essential metrics.

From the academic perspective, as far as we are aware, this is the first instance at which GARCH-MIDAS and regularization regression models have been utilized to assess how the state of the macroeconomic environment affects stock returns in Ghana and Nigeria. As our study empirically investigates several macroeconomic variables that are likely to affect stock returns, it will add more in-depth knowledge to existing literature and will be a source of reference for the academic community. Moreover, studies conducted in more advanced economies revealed that these models performed better and had more predictive accuracy than the conventional volatility models (Asgharian, et.al 2013; Girardin & Joyeux, 2013).

1.6 Thesis Outline

This research is structured into five chapters. Chapter one provides an introduction, research objectives, and research questions. The second chapter provides a brief overview of the three stock exchanges (i.e. Ghana, Nigeria and South Africa), a theoretical perspective on macroeconomic variables and stock returns, and related literature. The third chapter presents the source of the data, variables description, diagnostic test, and methodology. Chapter four deliberates on the outcomes or findings derive from the research, and the final chapter offers the research summary, conclusion, and recommendation for policy decisions.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this part, the concept of macroeconomy and stock returns is provided. In the theoretical foundation section, a brief presentation of LASSO, Ridge regression, and asset pricing theory relevant to our research theme and objectives is presented. Also, this chapter further reviews empirical work in related literature on the subject matter, i.e., the relationship between macroeconomic fundamentals and market return in sub-Saharan Africa and across the world, for the purpose of forming the basis for comparison with the findings in this research.

2.2 An Overview of the Three Stock Exchanges

Ghana stock exchange

In July 1989, the Ghana Stock Exchange was established as a Private Limited Company. Company Status was granted in October 1990 in accordance with the Stock Exchange Act of 1971 (Act 384). The exchange commenced trading on November 12, 1990, preceding the inauguration of its council the same day. This was after a ten-member Committee was formed by the then government in February 1989 under the chairmanship of Dr. G.K Agama, then governor of the Bank of Ghana. The committee was tasked with consolidating all prior works relating to the Stock Exchange Project and develop mechanism for the actual establishment of the Exchange.

The establishment of the Ghana Stock Exchange was necessitated as part of the Economic and Structural Adjustment reform program spearheaded by the International Monetary Fund (IMF) and the World Bank. The strong economic recovery program and structural adjustment program implemented by Ghana in the 1980s paved the way for reactivating the stock exchange project.

A few years after its commencement, the GSE is structured as a public company limited by guarantee which implies it has no owners or shareholders, the statutory form of incorporation for non-profit organizations. The members of the GSE constitute the company. Depending on their role, memberships can either be classified as License Dealing Members or Associate Members. LDMs were those who were allowed to trade on the exchange. Associates were companies and individuals who have fulfilled the exchange's membership conditions and supported the exchange vision and mission but are not authorized to trade on the stock exchange. The exchange was premised on the two main objectives of facilitating the mobilization of long-term capital by corporate bodies/businesses and governments through the issuance of securities (shares, bonds) and providing a platform for the trading of issued securities.

The enactment of a number of the regulatory framework and laws such as Securities Industry Law, 1993; Securities and Exchange Commission Regulations 2003 (L.I, 1728); Central Securities Depository Act, 2007 (Act 733); Securities Industry (Amendment) Act, 2000 (Act 590) and Ghana Stock Exchange rules have laid a solid legal framework that guides the effective operation of the stock market. The exchange currently operates three markets: the main market for regular trading of listed stocks; the Ghana Alternative Market, which focuses on small and medium-sized businesses with significant growth potential; and the Ghana Fixed Income Market, which provides liquidity for both government and corporate bonds.

In March 2022, it had a market capitalization and trading volume of GH¢64 trillion and GH¢214.97 million respectively, with a total of thirty-seven (37) listed companies ranging from different sectors such as manufacturing, mining, banking, agro-business, telecommunication, insurance, petroleum, and pharmaceuticals. A number of companies have listed since 2010, including Tullow Oil, Access Bank, and MTN, a telecommunications company based in Ghana. The Ghana Stock Exchange Composite Index (GSE-CI) is the main stock market index, which represents all equity trading on the exchange. This index tracks the performance of companies listed on the Ghana stock exchange, excluding those whose shares are traded on other markets. Additionally, there is a financial stocks index, which is comprised of listed stocks from the financial sector, including those from the banking and insurance sectors. This includes all ordinary shares of financial stocks listed on the GSE, except those listed on other markets. During the past ten years, the GSE-CI has experienced both highs and lows, posting a return of 79% in 2013 and a loss of 15.3% in 2016, (GSE market reports, 2022).

Nigerian Stock Market

The Nigerian Stock Exchange, now known as the Nigeria Exchange Group, was founded as the Lagos Stock Exchange on September 15, 1960. The stock exchange began official trading on 25 August 1961 with 19 securities listed. Trial operations began in June 1961, with trading taking place within the central bank building with market dealers John Holt, C.T. Bowring, and the Investment Company of Nigeria. After branches in some of the country's main commercial centers, the name became Nigerian Stock Exchange in December 1977. There were two trading floor branches opened in Kaduna and Port Harcourt in June and April 1978, respectively. A version of the All-Share Index was launched in 1984 by the exchange, which reached a peak of 1000 in 1992, eight years after it was launched.

A leading market in Africa in terms of market capitalization, turnover, and trading volumes, the Exchange is one of the most active markets in the continent. There are 168 companies listed on the exchange with a market capitalization of 36 billion. A global index ranking of equity markets ranked the Nigerian Equity Market 4th best performing as of June 2022. During the period of 30 June, 2022, the market capitalization was NGN 1.02 trillion. There was a 50% return on the market in January 2020. As measured by the All-Share Index, returns on equity in June 2021 were negative 5.87%, while NGN 1.02 trillion was recorded in market capitalization. The foreign component of equity investment revealed a downward trend. Foreign investments into equity were US$ 3.6 billion in 2017, US$ 2.4 billion in 2018, US$ 1.9 billion in 2019, US$ 0.8 billion in 2020, US$ 0.2 billion in 2021(National Bureau of statistic, CBN). The decline in foreign investor participation was attributed to high inflation, adverse exchange rate movements, and market instability (NSE, market highlight, 2022). Currently, there are 153 companies' constituent all share index component.

Johannesburg Stock Exchange

The JSE is the second oldest stock exchange and leading capital market in areas of trading volume and value in Africa. South Gold Rush in 1877 led to the establishment of this exchange. Regulation to formalize the operation of the financial market was passed in 1947.In the year 1963 the exchange joined the World Federation of Exchanges and introduce the Electronics trading platform in the early of 1990s. The DRDGOLD Limited was the largest company to have listed in 1895 and remained listed on the exchange to date. As a means of strengthening regulatory framework governing the operation of financial markets and institutions, new securities services Acts were enacted in 2004 in order to replace the Stock Exchange Control Act and the Financial Markets Control Act. Social responsibility indexes were introduced in 2004 to promote effective corporate governance. The goal is to assess companies' policies and reporting against triple bottom line benchmarks of social, economic, and environmental considerations. Moreover, 43 initial public offerings have been made since 2014 to raise capital amounting to US$59 billion, constituting 57% of IPOs and 34% of transactions in Africa. At the time of writing, there are 289 companies listed on JSE with a market capitalization of US$1123587. Nevertheless, in 2022, market capitalization falls to US$ 1046522.Overall market liquidity in the year 2021 and 2020 was 31.9% and 37.2%, respectively, (JSE Reports, 2022).

2.3 Theoretical Foundation

2.3.1 Capital Asset Pricing Model (CAPM)

Since the emergence of finance literature, one of the most important theories developed in the area of asset pricing is CAPM. It was first proposed by William Shape (1970) in his book Portfolio Theory and Capital Markets. This theory states risk and return on assets are linearly related, particularly stock returns. CAPM is a single factor model which deals with risks and returns. According to theory, asset returns are determined by the systematic risks of the market portfolio. The risk that upsets an asset return can be classified as systematic and unsystematic risk. Systematic risk is explained as economic wide risk, and all assets in an economy are exposed to this risk, which cannot be mitigated through diversification or holding a portfolio of different assets (the principle of not putting all your eggs in one basket). Unsystematic risks are an asset's particular risk and can be easily diversified through the holding of a portfolio of assets. The CAPM links the systematic risk of individual assets to the determination of their fair price and disregards the influence of asset specific risk on the valuation of assets. The Capital

Asset Pricing Model proposes that returns respond to market risks, which can be assessed based on the magnitude of the swings in return distribution. The linear relation between risk and return is known as Security Market Line, which compare the systematic risk of an asset with risk and returns of the market in order to determine a required return of the asset.

The equation of the Security Market line is defined as

$$R_l = R_f + \beta(R_m - R_f) \tag{2.1}$$

R_l the rate of return is, R_f represent the risk-free rate, R_m is average return on $(R_m - R_f)$ equity risk premium and β is the beta factor.

2.3.2 Arbitrage Pricing Theory

APT is a multifactor model originally proposed by Ross in 1976. The theory states that asset returns are driven by multiple factors. These factors could be financial and macroeconomic variables. Some of these factors are economic factors such as inflation, interest rates, unemployment, etc. and financial factors such as earnings, dividend yield, market liquidity, and market capitalization. The theory assumes linear relationships between an asset's expected return and macroeconomic variables that capture systematic risk. The APT is an extended model which posits expected returns to be influenced by many risk factors, including market-related and economic-wide factors.

$$r_i = E_i + \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \cdots + \beta_k X_{ik} + \varepsilon_i \tag{2.2}$$

r_i denote the return on asset i , E_i is given as expected return, β_0 represent risk free rate of return, β_i is the weights of factors influencing asset returns, X_{ik} is variables driving assets returns and ε_i represent unsystematic risk

2.3.3 Ridge Regression

Ridge Regression initially proposed by Hoerl and Kennard (1970) as Machine learning techniques for dealing with a model that suffers from multicollinearity in order to avoid over and under fitting. Its ultimate aim, is to obtain the regression model which leads to a lower Mean Square Error by introducing shrinkage penalty (L2 norm) to Ordinary Least Square estimator which substantially reduced model variance. Although it introduces some bias, it can significantly reduce variance, resulting in a lower mean-squared error. This can be achieved by imposing Lagrange multiplier to control the regularization function. Multicollinearity occurs in multiple regression when the variables are highly interrelated, resulting in predictions that are frequently inaccurate. In the literature, the ridge technique estimate has a higher prediction accuracy than the ordinary least square estimate, (Hoerl and Kennard, 1970). Despite the fact that ridge is not a variable selection technique, it does lessen the impact of less essential variables in the model by reducing their coefficient towards zero. The Ridge framework does not operate as variable selector since it does not reduce coefficient of regressors that contribute less to zero entirely.

2.3.4 Least Absolute Shrinkage Selection Operator

Tibshirani (1996) introduced LASSO Algorithm as a regression model that is used for variable selection and parameter estimating. The LASSO produces results involving only subset of explanation variables included in the regression equation. LASSO is an improved regression model in statistics. It is a type of regularization regression that performs both variable selection and regularization, minimizing the Residual Square of Error by shrinking the coefficient of unimportant regressors' to zero. It reduces model variance by imposing a penalty (L1 norm) on the size of the parameters to develop a robust predictive model. When there is a presence of correlation among explanatory variables, LASSO selects the most important variable from a larger set of variables and shrinks others to zero. This lowers the model variance of the estimated value and improves the prediction accuracy of the model. The technique has been effective in statistical modeling as it proves to produce a parsimonious model by completely eliminating trivial variables or regressors that contribute insignificantly in predicting the response variable from the model. Therefore, the L1 norm penalty constraint identifies variables that are most appropriate for prediction which often leads to a sparse form model and more interpretable. LASSO has good shrinkage and variable selection qualities due to the use of a tuning parameter that regulates the coefficient's level of Shrinkage. As the L1 norm penalty goes higher, the coefficients gradually drop towards zero. In LASSO regression, a zero turning parameter yields the same coefficient and outcome as Classical Least Squares regression.

2.3.5 MIDAS Regression

As far as linear and time series models are concerned, both explanatory variable and response variable must be sampled in a similar manner with the same frequency. In the world of finance and economics, however, data availability has always been a problem, especially when comparing data at par frequencies. This problem is addressed by Ghysel et al. (2004) with their proposed Mixed Data Sampled Regression Model, which involves variables on both sides of the equation to be sampled at different intervals. It is important to keep in mind that several macroeconomic variables have a frequency of monthly, quarterly or semi-annual in econometric time series models. There are several ways to handle the problem of frequency mismatches in the data, including interpolating and aggregating the data in order to address this problem, but this often results in the loss of valuable information regarding the dataset. In the MIDAS framework, high-frequency variables may be on the left-hand side, and low-frequency variables on the right-hand side of the regression equation. It captures the movement of a high-frequency variable in a very straightforward manner by prefiltering regressors of different frequencies with the aid of a polynomial weighting method. The order of the polynomial is taken to be finite. It is noted that, incorporating low-frequency variables directly into the model without aggregation or averaging is a way of addressing the varying interval between the explanatory and response variables and helps to provide better information in order to prevent information loss while reducing the number of parameters whose value is to be determined in the equation.

2.4 Empirical Review on GARCH-MIDAS Model

2.4.1 Literature in Sub-Saharan Africa

In a multi-country study by Akunga et al. (2022), to study how contagion affect stock markets of Sub-Saharan Africa. They employed crisis contingent methodology, which studied the effects of various events, and GARCH-MIDAS to explore the influence of regional macroeconomic indicators on volatility in sub-Saharan African stock markets. There are ten sub-Saharan African countries sampled in this study: Uganda Ghana, South Africa, Tanzania Kenya, Namibia, Cote d'lvoire, Nigeria, Zambia, and Botswana. The following events were investigated using crisis contingent methodology: the US stock market downturn in 2018, the 2016 Brexit vote in the United Kingdom, the 2015 Chinese stock market crash, the 2018 South African recession, the 2014 Nigerian stock market slump, and the 2015 Kenya foreign exchange market crisis. The macroeconomic variables used in their analysis were quarterly GDP growth and monthly inflation. Their findings revealed that using conditional correlation coefficient, there is no evidence of contagion in Sub-Saharan African stock markets during the 2018 US crisis, with the exception of Cote d'lvoire, but show evidence of contagion in South Africa, Kenya, and Zambia during the 2015 China crisis. Also, according to the results from the conditional correlation coefficient, only Nigeria demonstrated 2016 UK crisis contagion.; no evidence of contagion in Sub-Saharan African countries during the 2018 South African crisis with the exception of Ghana and Uganda; Only Ghana demonstrated a contagion of the 2014 Nigerian crisis.; no evidence of contagion in Sub-Saharan countries during the 2015 Kenya crisis with the exception of Nigeria and Uganda. The results of the GARCH-MIDAS framework showed monthly inflation and quarterly GDP are insignificant in explaining South African stock market volatility with the exception of Botswana GDP, which implies an increase in Botswana GDP growth rate led to high volatility in the South African stock market. Also, there is an insignificant relationship between regional monthly inflation and quarterly GDP and Nigerian stock market volatility, with the exception of Ghana. This indicates that an increase in the GDP growth rate in Ghana results in low volatility in the Nigerian stock market. Moreover, they also found that an increase in both Uganda's and Tanzania's inflation and GDP is associated with high volatility in the Kenyan stock market.

Abebe et al. (2020) conducted a study on macroeconomic variables and the volatility of selected commodities traded on the Ethiopia Commodity Exchange for the period November 4, 2009 to December 30, 2016. GARCH-MIDAS and the traditional GARCH model with exogenous variables like exchange rate, oil price, and inflation were used to assess the volatility of highly popular commodities like sesame and Jimma coffee price returns on the Commodity Exchange. The findings indicated that inflation and oil prices are the main influences on the volatility of both commodities on the Ethiopian Commodity Exchange. Moreover, the study employed the MSE, MAE, and DM tests to assess the forecasting performances of the GARCH and GARCH-MIDAS and concluded that the GARCH-MIDAS has good predicting performance than the GARCH model.

2.4.2 Literature in the world.

Asgharian et al. (2013) compared the forecasting ability of the GARCH-MIDAS model with the traditional GARCH model using US data from the period 1991 to 2008. They observed that GARCH-MIDAS model produced better forecasts than the traditional GARCH model. The inclusion of low-frequency (monthly) macroeconomic information enhanced the forecast capacity of the model, particularly for the long-term variance component. They used principal component analysis, which contains macroeconomic variables such as term spread, unemployment, and exchange rate, while they also included the level, volatility of the economic variable and realized volatility in the MIDAS equation. They separated the variables into three model specifications: the first includes only monthly realized volatility and no macroeconomic variables in the long-term component of the model; the second include both the level and variance of economic variables as well as realized volatility; and the third include both the variance and level of macroeconomic indicators in the model. Their result indicated that the model containing the realized volatility, level, and variance of macroeconomic variables has the lowest mean square error.

Girardin and Joyeux (2013) used the GARCH-MIDAS technique to model macro-fundamentals on stock market volatility in Chinese Stock Market A and B using data from 1994 to 2010. Based on their findings, it was determined that inflation is only an issue for the share market A, where domestic shares are listed, but foreign investors are not allowed to trade there. The paper estimates that an upsurge in inflation by 1% leads to a slight rise of 0.58% in the long-run volatility of share A and 0.0824% in B shares. Moreover, shares A are subject to significant credit volatility, but this has a very limited impact: a 1% increase in credit volatility increases volatility in long-term component of share A by only 0.07%, and share B volatility decreases by 0.382% when there is a 1% increase in credit. However, the B share market, which trades foreign shares, remains silent about inflation. Their research discovered that industrial output growth and inflation were responsible for China's stock market volatility.

Engle et al. (2013) used the same data as Schwert but extended it to later periods spanning from 1890 to 2004 for US stock market and macroeconomic variables. They established that industrial production growth and inflation result in between 10% and 35% of stock volatility. The study concluded that macroeconomic variables were important in both the short and long run.

Fang et al. (2020) studied how macroeconomic and financial variables predict long-term volatility of stock market using the S&P 500 index and six US financial variables namely, realized volatility, short-term reversal factor, default spread, implied volatility, equity market returns and term spread. They also included fourteen macroeconomic variables such as the housing starts, nominal corporate profits after tax, industrial production growth rate, unemployment rate, PPI, real GDP growth rate, the Chicago Fed national activity index, CPI, monetary base, the University of Michigan consumer sentiment index, real personal consumption and the new orders index of the Institute of Supply Management. Data from the first quarter of 1969 to the fourth quarter of 2018 were analyzed using GARCH-MIDAS and variable selection. Using an adaptive lasso penalty, they determined which variables have the greatest effect on long-term stock market volatility by maximizing the penalized log-likelihood. Three variables out of fourteen macroeconomic and six financial variables were found to have the greatest effect on long-term stock volatility, namely, realized volatility, default spread, and housing starts. In post estimation of these variables, housing starts are negatively affected while default spreads and realized volatility are positively affected. Additionally, the model with selected variables outperforms the GARCH-MIDAS model without variable selection in the out-of-sample forecast.

Xiaoling et al. (2021) conducted a study using sample data from 1 January 2002 to 31 October 2018 to examine the effects of Global Economic Policy Uncertainty on stock volatility for nine emerging economies including Turkey, Brazil, India, China, South Africa, Indonesia, Mexico, Russia, and South Korea. The monthly Global Economic Policy Uncertainty is regressed on daily stock observations for each country. A GARCH-MIDAS model was used in the analysis and fluctuation test to examine the model's time-varying forecast performance. In all countries examined, the study found that GEPU significantly influences stock market volatility.

Salisu and Swaray (2017) evaluate the relevant of macroeconomic variables, namely Industrial Production Index, Inflation and Realized volatility in predicting energy price return volatility. They adopted GARCH-MIDAS methodology to analyze US energy price data from the 1980 to 2017. The results showed that jet fuel, diesel, natural gas, propane, and crude oil volatility returns were well predicted by almost all the macroeconomic variables used, including output, realized volatility, headline and core inflation. Also, for sub-periods of the pre-Global Financial Crisis sample, all the variables emerge as potential predictors of diesel, gasoline, and propane return volatility, whereas headline and core inflation and realized volatility are predictors of natural gas and heating oil return volatility. They found that in the period after the Global Financial Crisis, output and realized volatility emerged as dependable explanatory variables of all seven energy markets.

Wang et al. (2020) extended the GARCH-MIDAS model to account for the asymmetry and extreme effects on the long and short-term volatility components. In their analysis, they used daily price data from the S&P 500 index from 1993 to 2016. The forecast was generated using fifteen extended GARCH-MIDAS models. They discovered significant evidence that bad news has a greater influence than good news, and negative and positive extreme shocks have significant and differential impacts on stock volatility. They also found that negative extreme shocks are more likely to affect stock volatility than positive extreme shocks, and that both the asymmetry effect and the extreme volatility effect can affect stock volatility in both the long and short term. Furthermore, they conducted MCS tests using five error function metrics to assess the model's prediction performance, and they discovered that models containing both the asymmetry and extreme volatility effects performed best out-of-sample, whereas the standard model performed worst, implying that a model comprising both the asymmetry and extreme volatility effects can forecast stock volatility.

In investigating the predictive link between macroeconomic series and financial vulnerability on the stock market volatility in India and China, Demirer et al. (2021) employed GARCH-MIDAS framework to examine data from January 2004 to May 2020 and January 2003 to May 2020 for

China and India, respectively. They developed three different models containing macroeconomic indicators (inflation, short-term interest rate and output growth) as well as various financial vulnerability indexes. A model containing only the macroeconomic variables without a financial vulnerability index was used as a benchmark. The result revealed evidence of the better predictive performance of the models containing financial vulnerability to domestic stock market volatility over models comprising macroeconomic variables in India and China.

Conrad and Kleen (2020) adopted the GARCH-MIDAS model to analyze the relationship between S&P 500 returns and US macroeconomic and financial variables, which include the Chicago Fed National Activity Index, housing starts, the National Financial Condition Index, and growth rates of industrial production. Their result disclosed that housing starts emerged as a good predictor for S&P 500 stock volatility.

Salisu and Ndako (2017) analyzed the return volatility of European share prices, including France, Austria, Finland, Germany, the Netherlands, UK, Turkey, and Spain, under different market conditions, namely, pre-Euro, euro regime/pre-Global Financial Crisis, and euro regime/Global Financial Crisis regime. They used high-frequency data for stock indices and low-frequency for the economic indicators (consumer price index and industrial production), including the realized volatility. They employed GARCH-MIDAS approach to analyze data from the period 1990-2017. They discovered realized volatility was a more consistent potential predictor of stock returns relative to other predictors. In euro/pre-Global Financial Crisis market conditions, where economic activity predicts stock returns for all countries considered, predictability of macroeconomic uncertainty for stock returns was obtained for five and four countries, respectively, in pre- and post-Global Financial Crisis market conditions. Furthermore, regardless of market condition, realized volatility and macroeconomic uncertainty provide more useful information in predicting return volatility of European equity markets than output, and the impact of output on return volatility tends to diminish during the post-Global Financial Crisis period.

Dimirer et al. (2021) explored systemic risk and financial turbulence to determine the volatility of the stock market, focusing on seven advanced and emerging economies, namely, Brazil, the United States, Germany, France, Hong Kong, the United Kingdom, and Japan. They modelled data spanning from October 28, 1996, to March 31, 2021, using the GARCH-MIDAS technique. They used principal component analysis, with model 1 containing only realized volatility used as a benchmark, model 2 made up of realized volatility and financial turbulence, model 3 containing a realized volatility and systemic indicator, and model 4 including systemic risk, realized volatility and financial turbulence They discovered that incorporating financial indicators outperformed the benchmark framework in out-of-sample predictive performance, with the financial turbulence indicator outperforming the systemic indicator. They also discovered that combining the financial indicators (i.e., financial turbulence and systemic risk) in the model significantly improved the predictive accuracy compared to the other methods that incorporated only one of the risk measures.

Conrad and Loch (2015) used the GARCH-MIDAS model for both one-sided and two-sided MIDAS filters to examine S&P 500 stock returns and US macroeconomic data from January 2nd, 1969, to December 30th, 2011.They employed various macroeconomic indicators, namely, the new orders index of the Institute for Supply Management, the unemployment rate, real GDP, industrial production, real personal consumption, housing starts, the Chicago Fed national activity index, nominal corporate profit after tax, and the University of Michigan consumer sentiment index. The study explained the lead-lag effect of macroeconomic variables as well as the contribution of present and future economic and financial expectations in determining variance. The final result of their analysis revealed that the term spread, the unemployment rate, corporate earnings and housing starts have superior forecasting ability for stock volatility among the variables used in the model.

Magrini and Donmez (2013) used GARCH-MIDAS framework to investigate the link between economic variables and agricultural products including corn, wheat, and soybeans collected from Chicago Board of Trade from January 1, 1986, to December 31, 2012. Their empirical findings indicate that macroeconomic circumstances influence agricultural commodity volatility.

Nieto et al. (2014) used a GARCH-MIDAS approach in the bond market to assess the influence of macroeconomic and financial indicators in predicting the volatility of corporate bond returns across six credit ratings from January 1997 to January 2012. The results demonstrate that out-of-sample and in-sample analyses indicated that incorporating low-frequency macroeconomics and financial factors increased the model's performance in forecasting bond return volatility better than the standard GARCH model.

Belcaid and Ghini (2021) used the GARCH-MIDAS to ascertain the micro-finance effects of development of stock market in Morocco from January 1998 to December 2018 using daily stock index data obtained from the Casablanca Stock Exchange. They used macroeconomic and financial variables such as money market rates as a substitute for interest rate and quarterly deposit, trade openness, the rate of inflation, industrial production, Moroccan GDP growth rate, the European Union GDP growth, and the monthly exchange rate. According to the results, long-term components such as rate of inflation, European GDP, and the currency exchange rate contribute to large volatility of more than 4.20 percent, while interest rates (money market and deposit rates) account for roughly 2.5 percent of the fluctuation. Other components calculated are 0.967 percent and 1.243 percent, respectively, based on the currency rate and industrial production. The findings also show that realized volatility plays a larger role in predicting future long-term volatility.

2.5 Empirical Review Based on Shrinkage Methodology

2.5.1 Literature in the world

Chao et al. (2019) researched the predictability of oil price volatility using economic uncertainty indices for the US. Geopolitical risk index, a US economic policy uncertainty index, a US equity market volatility index a monetary policy uncertainty index, and global economic policy uncertainty indices were used as predictors for oil price volatility for the period January 1997 to July 2017. They used the autoregressive model and shrinkage approach (LASSO and Elastic net) in their study. The economic uncertainty indices were split into five individual autoregressive forecasting models and a shrinkage model containing all five economic uncertainty indices. In addition to autoregressive principal component analysis containing all five economic uncertainty indices They discovered that shrinkage models outperformed all competitive models, including five individual ones.

Zhang et al. (2019) reported that LASSO and elastic net models produced substantially better predictive values than the competing models such as DMA, ridge, combination approaches, PLS, PC, and DMS for predicting oil price with fourteen economic variables and eighteen (18) technical variables. They used crude oil price data obtained from the US Energy Information Administration, spanning the period from February 1986 to December 2016. They are findings revealed that elastic nets and LASSO selected five explanatory variables or predictors. They point out that elastic net and LASSO models have a larger R^2 and success ratio than the contending methods.

Dai et al. (2021) employed the Autoregressive model as a benchmark and the shrinkage techniques—the elastic net, LASSO, Ridge regression, and adaptive LASSO to predict volatility in stock returns. The GARCH model was used as another benchmark. The US S&P 500 index was used in their analysis for the period January 1995 to December 2018. They considered a large number of variables, including oil price volatility, economic indicators, investor sentiment indexes, and technical indicators, and. They found the shrinkage method outperformed all the competing univariate regression models, with elastic net having better prediction accuracy. They conclude that out-of-sample tests showed that shrinkage methods performed well in a data-rich environment.

Liang et al. (2022) investigated forecasting performance of shrinkage methods, namely: adaptive lasso, classical lasso, and five combination methods using fifteen predictors, which include growth rate of industrial value added, producer price index, exchange rate, and the consumer price index, among others, for China's stock market using the SSEC index for the period March 1, 2011, to September 30, 2019. They examine the out-sample prediction superiority for realized volatility of lasso model, the Alasso model, and other combinations by applying the loss metrics of HMAE and HMSE. According to the study, adaptive lasso selected the most powerful predictors and had more accurate forecasting performance than the classic Lasso model and other combinations models.

Huag and Gao (2021) explored predictors for Bitcoin returns using the Least Absolute and Shrinkage operators for predictor selection and regularization. Using intraday high-frequency data sourced from the Bitstamp exchange, covering the period from January 1, 2012, to August 12, 2019, using thirty predictors as explanatory variables. The study's findings established that

LASSO selected the eight most powerful factors from thirty candidate variables. The chosen predictors were used to forecast Bitcoin returns for the testing period, which lasted from May 18th to August 12th, 2019. Another vital conclusion of the paper was that the out-of-sample RMSE for LASSO, neural networks, and ordinary least squares posit that LASSO has the lowest value among the competing models.

2.6 Empirical review based on other statistical Models

2.6.1 Literature in Sub-Saharan Africa

Quadir (2012) used Autoregressive Integrated Moving Average (ARIMA) model to analyze the effects of Treasury bill interest rates and industrial production on stock returns on the Dhaka Stock Exchange. He used time series data collected monthly from 01/ 2000 to 02/2007.The study showed that even though a positive association exists between macroeconomic variables (industrial production and treasury bill rate) and market returns, it is statistically insignificant.
Adusei (2014) investigated the link between stock returns and inflation in Ghana. The statistical analyses were performed using the ARDL approach to co-integration, Granger Causality in Error Correction techniques, and Unit Root Tests from January 1992 to December 2010. The study discovered a statistically significant negative relationship between inflation and stock returns in the short run and a statistically significant positive relationship in the long run. The findings suggested that inflation is a significant driver of stock returns in Ghana.
Kwofie and Ansah (2018) evaluated the impact of exchange rates and inflation on Ghanaian stock market returns using monthly data from January 2000 to December 2013.The study adopted the ARDL bounds testing approach to establish the short and long-run relationship between the GES market returns, inflation, and exchange rate. The study found a significant positive long-run link between GSE market returns and inflation, but not a statistically significant short-run relation. They also documented that there is a significant short and long-run link between exchange rate and the GSE market returns, and concluded that the exchange rate and inflation are important macroeconomic indicators as they exhibit long-term relationships, that provides useful information for market participants on the stock exchange. Sokpo et al. (2017) employed

GARCH and E-GARCH techniques to model inflation and stock market return volatility. They used data from the consumer price index and the All-Share Index of the Nigerian Stock Exchange Market from January 1995 to December 2016. The study discovered no statistically significant connection between stock market returns and inflation. The paper concluded that stock returns on the Nigerian stock exchange are not explained by inflation.

Nkoro and Uko (2013) examined the impact of macroeconomic variables on Nigerian stock returns. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH-M) model was explored to analyze data over the period 1985–2007. They found the inflation rate, interest rate, index of manufacturing output, and government expenditure to have a stronger effect on stock market mean returns, whereas the broad money supply and foreign exchange rate have no influence. They also observed volatility clustering in the Nigerian stock market and discovered that returns were influenced more by previous volatility than by previous economic news.

Ibrahim and Musah (2014) researched the role of economic fundamentals on market returns in Ghana. They assessed data from September 2000 to September 2010 using the Johansen multivariate cointegration approach and the vector error correction model. Economic indicators such as the broad money supply (M2), interest rate, exchange rate, and inflation, were modeled on market returns proxied by market index. They found that the Johansen Multivariate Cointegration Test result revealed that in the long run, a 1% rise in exchange rate decreases market returns by 3%, a 1% growth in interest rate decreases market performance by 0.6%, following a 1% increase in the money supply, market returns rise by 2.5%, a 1% rise in inflation raises market returns by 0.35%, and a 1% rise in the industrial production index reduces market returns by 12%. implying that all the macroeconomic variables were significant in explaining stock returns with the exception of the interest rate. They discovered, on the other hand, that money supply inflation and the index of industrial production have insubstantial short-run effects, whereas the exchange rate has a negative but significant influence on stock returns and the interest rate has a substantial and positive effect on market returns.

Ali et al. (2020) applied GARCH-X (1, 1) to assess the effects of macroeconomic indicators on stock return volatility in South Africa, Ghana, and Nigeria using data spanning from the period January 2000 to December 2017. The inflation rate, interest rate, and All-Share Index price are the variables used in the study. According to their findings, interest rates and inflation rates do not have any significant effect on market returns in South Africa, Ghana, and Nigeria. The study concludes that the chosen economic indicators should not be taken into account when predicting stock returns. They advocated for additional research that considers macroeconomic variables other than interest rates and inflation.

2.6.2 Literature in the world

Sirucek (2012) examine macroeconomic variables, namely: unemployment, inflation, money supply, industrial production index, oil price, interest rate, and producer price index, and their impact on the Dow Jones Industrial Average (DJIA) and US S&P 500 between 1999 and 2019. The study employed standard regressive multi-dimensional model and other coherent mathematic-statistic methods. He observed that unemployment and interest rates were the most crucial predictor of the S&P 500 index, whereas unemployment and industrial manufacturing, followed by changes in interest rates and oil prices, had the greatest effect on the Dow Jones Industrial Average (DJIA). This confirmed his preposition about a deeper relationship between "industrial" factors and the Dow Jones index.

Bhuiyan and Chowdhury (2019) adopted cointegration analysis to determine the link between various sector indices and long-term interest rates, money supply, and industrial production. They used monthly data covering the period 2000 to 2018. They investigated how these macroeconomic variables affect different industries of the stock market in the United States and Canada, such as consumer staples, financial, real estate, consumer discretionary, industrial, healthcare, and energy. Their findings revealed a long-term stable relationship between macroeconomic variables used in the study and various sector indices for the United States but not for Canada. whereas the Canadian stock market can be explained by the US money supply and interest rate. The Canadian analysis also revealed that long-term interest rate, money supply, and industrial production the had no cointegration relationships with the Canadian benchmark S&T or any of the sector indices.

Abbas et al. (2017) analyzed the link between stock market volatility and macroeconomic fundamentals such as broad money supply (M2), industrial production, the consumer price index, the Treasury bill rate, the crude oil price, and the exchange rate for the G-7 countries, namely the United Kingdom, the United States, Germany, Italy, Japan, France, and Canada, was examined. They adopted the GARCH and VAR methodologies to analyze the monthly data from July 1985 to June 2015. Their findings show that money supply and the volatility of industrial production growth have a significant effect on US stock market volatility, and only the CPI has a significant impact on UK stock market volatility, whereas the money supply and the consumer price index have an influence on stock market volatility in Canada, Japan, Germany, France, and Italy. They also discovered that the volatility of industrial production growth is a significant macroeconomic factor influencing stock market volatility in France and Italy, while oil price volatility is a significant determinant of stock market volatility in Canada and Japan. Kalam (2020) examined the effects of macroeconomic variables on Malaysian stock market returns using secondary data from 2000 to 2019. Multiple linear regression and ARDL were used to examine long and short run effects of macroeconomic variables such as foreign direct investment, exchange rate, inflation, and interest rate on stock returns. The study discovered that GDP, FDI, and the exchange rate have a long-run effect and a positive impact on Malaysian stock returns, whereas inflation and interest rates have a significant negative impact in the short run.

In a study by Nasir et al. (2021), they employed time-varying structural vector autoregression to examine the impact of the national macroeconomic environment and regional stock markets on the dynamics of the Vietnam stock exchange market. GDP, inflation, the interest rate, and the real exchange rate, were analyzed on the market returns for the period June 2005 to September 2016. Moreover, they considered volatility transmission from other regional stock markets to the stock market of Vietnam. The markets considered in their analysis are Japan, Hong Kong, Thailand, and China. They reported a positive significant effect on interest rates, exchange rates, and economic growth on market returns in Vietnam, while the rate of inflation did not contribute positively to stock market returns. They also revealed that regional markets are greatly influenced the Vietnamese stock market.

Shahzad et al. (2020) looked into macroeconomic variables and US stock prices for the period spanning 1985 to 2015. They used at three economic indicators including the 10-year Treasury bond yield in the United States, the West Texas Intermediate oil price, and the US industrial production index. They adopted the Quantile Autoregressive Distributed Lag model in their analysis. The study's findings revealed that, regardless of time period or stock market status, the industrial production index has a long-run influence on the US stock market. Furthermore, regardless of the stock market environment, the US 10-year Treasury bond yield did not appear to be a significant predictor of the long-run performance of the US stock market during the sample period. Furthermore, 10-year Treasury yields have negative quantile parameters, which suggests that falling long-term bond interest rates are beneficial for US stocks in the long run. The WTI crude oil price is also the macroeconomic component that has the least long-term impact on US share prices. This means that the US stock market as a whole is rather resistant to rising oil prices. In a multi-country analysis of five BRICS countries, namely South Africa, Russia, Brazil, China, and India, Sousa et al. (2016) examined the role of macroeconomic, macro-financial, and global predictors in predicting stock returns over the period 1995Q1-2013Q2.Using a predictive regression approach, they found that output is the most significant factor influencing stock returns for Brazil, Russia, and China; inflation, interest rates, the monetary aggregate growth rate, and macro-finance are less predictive of BRICS stock returns.

A regression framework involving a predictive model was used by Gupta and Modise (2013) to assess the impact of twelve broad categories of macroeconomic information, including the Treasury bill rate, broad money supply growth rate, real effective exchange rate, narrow money supply growth rate, inflation rate, and crude oil price in South Africa, spanning from January 1990 to June 2010. They found that at shorter time horizons, interest rate variables offer both in-sample and out-of-sample predictive capabilities. Further, a narrowly defined money supply and oil production provide good forecast for South African stock market returns, while Inflation, on the other hand, is a good predictor over the long and medium term.

2.7 Summary of Literature Review

The review of existing literature on the subject matter affirmed the link between macroeconomic conditions and stock market returns and volatility across the world. However, the evidence of the sensitivity of macroeconomic data on stock market performance is stronger and more robust in developed economies than in developing countries. The degree of the findings varies depending on the methodology, period, and economy of the study. While Some researchers found strong evidence of improving out-sample predictions of stock returns by including macroeconomic series. In contrast, others reported disappointing results, suggesting that the literature on stock returns and macroeconomic indicators are mixed and inconsistent. An empirical application of GARCH-MIDAS approach by Asgharian et al.,2013; Engle et al.,2013; Giradin & Joyex, 2013; Fang et al., 2020; Xaoling et al.,2021; Salisu and Swaray,2017; Wang et al.,2020; Demirer et al.,2021; Conrad and Kleen, 2020; Salisu and Ndako, 2017; Conrad and Loch, 2015 validate the effects of macroeconomic series and other indices on equity market returns in both emerging and developed markets. On the other hand, the only literature, as far as we are aware, on the application of GARCH-MIDAS in Africa was conducted by Akunga et al. 2022, which used limited macroeconomic data (inflation and GDP) and found a weak association between these variables and market returns. In addition, there is limited literature on the application of a variable selection algorithm for market returns in Africa. Thus, this research was necessary to fill this gap by providing further empirical evidence of macroeconomics and equity market returns in Africa.

CHAPTER 3

DATA AND METHODOLOGY

3.1 Introduction

In this part, an extensive outline of how the study was conducted has been provided. The chapter provides details on the source and characteristics of the data, defines the key variables of interest that meet the research objectives and provide answers to the research questions, and also gives a detailed description of the statistical techniques adopted to analyse the data.

3.2 Data, Source, and Study Period

The study considered macroeconomic indicators as predictor variables, and there are five macroeconomic variables employed in the analysis. A secondary data set of the daily stock price of the stock market Indexes are gathered from three African stock exchanges (South Africa, Nigeria, Ghana). Data on macroeconomic variables, comprising the exchange rate per US dollar the money supply (M2), the consumer price index, interest rates, and oil prices which the reseacher loosely considered to be one of the macroeconomic variables, are based on information from the central banks of the respective countries, the statistical service, and the International Finance Statistics database. The international crude oil price is included in the study because the level of the oil price has a significant impact on all sectors of the economy. Although the price of oil can have much influence on the consumer index, it cannot be regarded as the sole contributory factor to rising inflation. With regard to South Africa, FTSE/JSE all share index, which is a component of about 90% of companies listed on Johannesburg Exchange, was used. NGX All Share Index represents weighted performance of Nigerian companies listed on NGX, and GSE All Share Index represents companies listed on GSE.

Preliminary test is conducted to remove outliers. Outliers are observations that differ significantly from the rest of the sample in size or magnitude. To check that the results were consistent, the researcher utilised the R statistical software to exclude outliers. Utilising the R package's subset function, the analysis is done to determine the lower and upper limits of outliers that can be eliminated. Regression analysis can be substantially altered by incorporating or including such observations, especially when the sample size is small. This step is necessary to prevent spurious regression which may lead to bad forecasting.

Table 3.1: Summary of variables and their sources

Country	Variables	No of obs	Source of Data
South Africa	Stock returns	3077	JSE
	CPI	144	IFS database
	EXR	144	IFS database
	IR	144	SARB
	OP	144	"
	MS	144	"
Nigeria	Stock returns	3078	NSE
	CPI	144	CBN
	EXR	144	"
	IR	144	"
	OP	144	"
	MS	144	"
Ghana	Stock returns	2948	GSE
	CPI	144	GSS
	EXR	144	IFS database
	IR	144	BOG
	OP	144	"
	MS	144	"

Source: Author's construct

Choosing these markets is based on their significance to the growth of the Sub-Saharan African region. A model and second largest economy in Africa is South Africa. It has one of the most developed stock market in the region due to its deepening. Several businesses listed on the country's stock exchange are operating in other African countries. Therefore, its economy prospects have a direct bearing on the sub-region. Likewise, Africa largest economy is Nigeria and its status economically is vastly relevant to the development of the entire region. Also, Ghana is a middle-income economy and one of the most rapidly growing economies in Africa. These countries were also chosen because of market deregulation and the development of an efficient capital market where data and other information are readily accessible. The sample period runs from January 2009 to December 2021. In-sample periods range from January 2010 to 2019 while hold-out periods run from January 2020 to December 2021. The rationale for choosing that time frame depends on the availability of credible data for all selected countries in order to avoid gaps and disparities in the analysis and to ensure that the results represent the contemporary patterns in the markets.

3.3 Description of Variables and Data Characteristics

3.3.1 Stock Returns

In these three countries, the Composite Index serves as a proxy for Stock Prices, which is an indicator of performance for all ordinary stocks on the stock exchange, based on volume-weighted average closing prices across all stocks. The index consists of all ordinary shares listed on the Ghana, Nigeria and Johannesburg stock exchanges, with exclusion of those listed companies which have their shares listed on another stock exchanges. The Index is weighted based on the market capitalization of the companies listed on the exchange. It is available on a daily and monthly basis and reflects the overall stock price of companies. The stock return is considered in this study as the response variable. The All-Share Index which accounts for about Eighty percent of equity listed in the three countries in terms of market capitalization is considered as a substitute for aggregate performance of the equity market. The index reveals or benchmark inclusively the happening in the three Sub-Saharan Africa stock markets and serve as an important reference yardstick for players to understand the development within the market. The stock returns are obtained from the all-share index of the countries selected for the study by taking the log first deference for the daily closing prices of the index. $R_{it} = (\ln(P_t - P_{t-1})) * 100$ where R_{it} stands for daily return, P_t denotes stock price on a particular day and P_{t-1} represents stock price for the previous day or past period.

3.3.2 Exchange Rate

The currency exchange rate measures the value at which the local currency of all the countries is exchanged for the US dollar. It is the mechanism of demand and supply that determines the exchange rate movement. The choice of Ghana Cedis, South Africa Rand and Nigeria Naira to US dollar are made because of the larger trading volumes in the US dollar than in other currencies. Globally, the exchange rate market is the largest and most liquid asset. The higher price implies the depreciation of the local currency, and the lower price indicates an appreciation of the local currency. Most Sub-Saharan countries economy is highly import-dependent. As a result, the depreciation of currency in these countries affects all sectors of their economies. Both depreciation and appreciation of the local currency may have positive and negative impacts on stock performance depending on the circumstances. The foreign exchange rate affects imports, exports, and prices in the country. It is observed that exchange rates fluctuate over the years with periods of stability alternating with periods of variation, which are caused by the strength of foreign currencies, the level of commodities price, and investment inflows.

3.3.3 Consumer Price Index

The consumer price index is used as inflation proxy. Basically, it measures the country's overall price level. The Statistical Service announces an index of prices of goods each month. A country's inflation rate is measured by its percentage change in consumer prices. The high level of inflation increases the cost of financing the production of goods and services. The acceleration of inflation may be a result of the high expansionary fiscal and monetary policies pursued by the government A high level of inflation erodes the purchasing power and disposable income of consumers, which stagnates the growth of the economy. The consumer price index determines the level of inflation, which specifies the average price of goods consumed by households in the country. Between 2009 and 2011, the region average inflation rate remained well below 20%. However, inflation has fluctuated over a single digit in recent years until the COVID 19 pandemic leading to high pressure due supply chain destruction cause by looked down in advanced countries due high infection rate.

3.3.4 Money Supply

In an economy, the supply of money is the total amount of currency in circulation in the economy at a given point. The three countries supply of money is controlled and manipulated by their respective central banks. Foreign money, demand deposits, other checkable deposits, and travelers' checks are all included. In this study, broad money (M2) is employed as a proxy for money supply and represents the countries' whole money stock. This is one of the central banks' monetary policy tools for controlling the economy. An expansionary monetary policy expands the money supply, increasing the amount of money in circulation for investment and consumption. M2, a measure of all cash and near-cash in the economy such as savings deposits and others, will be used to monitor the money supply.

3.3.5 Oil Price

The price of crude oil is a primary factor contributing to every aspect of any economy and constitutes the mainstay of an industrial economy. This is due to the fact that it is the most widely used energy source in the world. Africa is heavily dependent on non-renewable energy source, hence volatility in oil price largely impacts all sectors of Africa economies. Oil price determines the cost of doing business in Africa countries since it is the main source of input to many businesses in the economy. Also, large volatility in oil price affects the real economy and general price level which often account for a phenomenon of volatility transmission to the financial market. As a result, central banks and governments regard crude prices as an important element in gauging macro volatility and forecasting macroeconomic projections. Similarly, investors and portfolio managers frequently take into consideration the oil price estimate when allocating assets. Volatility in oil price affects stock performance as they may be disruption of expected cash flow and claim to outsiders. The oil price is regarded as one of the most swings economic indices as a result of high dependence on oil consumption and importation around the world.

3.3.6 Interest Rate

The 91-day treasury bill rate is a short-term instrument and serve as an indicator for interest rate. Investment in the short-term government bill is the alternative cost of investing in venture capital funds and shares traded on the stock exchange market. The interest rate on short-term treasury bills is an important benchmark of return on investment in general in Sub-Saharan. It serves as a yardstick of measuring investment performance of the economy and determinant of the cost of borrowing. High borrowing costs erode the profit of many businesses as it the claim on the assets of the business before distribution of profit to equity holders. If the treasury bill rate is high investors will prefer to invest in short-term government securities rather than investing in stocks. Interest is seen as a return from the borrower to the creditor for deferring consumption for the lender utilizing the cash for a period of time. Interest rate however, determine the level of capital and social investment as moderate interest rate spur more investment in capital expenditure of corporate bodies hence expansion of business activities.

3.4 Diagnostic Test

3.4.1 Stationarity Test

This section describes the preliminary analysis needed to unravel the time-series features of all variables used in the model. To avoid spurious regression, a diagnostic test is very important in building robust financial and econometric models. The stationary of series is one of the fundamental assumptions in time series. It serves as a pre-condition for developing a robust and reliable model in time series literature. However, many financial and economic time series at their levels demonstrate non-stationary in the mean implying the series follows stochastic behavior. In a situation where financial series data is not stationary, the model parameters may not be appropriately estimated, resulting in erroneous models. The most widely used technique to ascertain the incidence of unit root in the series is the Augmented Dickey-Fuller Test. The ADF test is conducted at the level and by differencing to determine the existence of unit root in the variables. The unit root is carried out with both intercept and trend. The unit root is performed on the response variable (stock returns) and explanatory variable variables: inflation, currency exchange rate, interest rate, money supply (M2), and crude price. The test's null hypothesis is that the series has a unit root, indicating that it is non-stationary.

$$\Delta X_t = U + \alpha_t + \sum_{j=1}^{p} \delta \Delta y_{t-j} + U_t + \phi y_{t-1}, \qquad U_t \sim IID(0, \sigma^2) \tag{3.1}$$

ΔX_t denote the difference between the variable and its own lag

U represent constant trend

α_t denote the parameter of time trend

δ is the unit root

Null Hypothesis $H_0 : \rho \geq 1$

Alternative Hypothesis $H_0 : \rho < 1$

3.4.2 Heteroscedasticity Test

Heteroscedasticity occurs when the assumption that disturbances should have constant variance is violated. This problem occurs when the variance of distribution changes over each observation of the explanatory variables. A homoscedasticity test is important to make sure that the regression can predict the dependent variable consistently across all independent variables. The current error term should be independent of the previous period lag shocks. Considering that the variance of errors remains constant, it is assumed that this assumption holds. In statistics, this assumption is called homoscedasticity. White noises whose variances are not constant are heteroscedastic

3.4.3 Normality Test

This study employed linear and non-linear analysis. To produce effective results. It is assumed that the data used in the model follows a normal distribution. Changing the data into its logarithmic equivalent ensures that the distribution of the data is normal. The data, however, were tested individually to determine whether they followed a normal distribution. The Jarque-Bera test is a commonly used measure of normality. Based on the property of normal distribution, the first two moments of a distribution, its mean and variance, define the entire distribution. In statistical distributions, it is standard to measure the third and fourth moments by skewness and kurtosis. The kurtosis determines how fat the tails of the distribution are, while skewness measures how symmetric distribution is about its average value. JB test is defined as

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right) \tag{3.2}$$

$$S = \frac{\hat{\mu}_3}{\hat{\sigma}^3} = \frac{\frac{1}{n}\sum_{i=1}^{n}(\chi_i - \bar{\chi})^3}{\left(\frac{1}{n}\sum_{i=0}^{n}(\chi_i - \bar{\chi})^2\right)^{\frac{3}{2}}} \tag{3.3}$$

$$K = \frac{\hat{\mu}_4}{\hat{\sigma}^4} = \frac{\frac{1}{n}\sum_{i=1}^{n}(\chi_i - \bar{\chi})^4}{\left(\frac{1}{n}\sum_{i=0}^{n}(\chi_i - \bar{\chi})^2\right)^{2}} \tag{3.4}$$

Where n stands for the number of observations, S denotes the skewness sample, $\bar{\chi}$ is the sample mean, $\hat{\sigma}$ is the variance, K represents the kurtosis sample, $\hat{\mu}_3$ and $\hat{\mu}_4$ are the third and fourth central moment estimates, respectively.

3.4.4 Lagrange Multiplier Test for ARCH Disturbances

The GARCH family of models must contain Arch effect in the series, which is a basic requirement. ARCH-LM test is employed in this study to test the existence of Arch effect in ARMA residuals (mean equation). Depending on the difference between the real and expected values, also known as residuals of the mean equation, the square residuals are used to determine conditional heteroskedacity. Engle (1982) proposed LM test, which comprises regressing the square residuals of the first lag of past values as

$$\hat{\varepsilon}^2_{i,t} = X_0 + X_1\hat{\varepsilon}^2_{t-1,t} + X_2\hat{\varepsilon}^2_{t-2,t} + X_3\hat{\varepsilon}^2_{t-3,t} + \cdots + X_q\hat{\varepsilon}^2_{t-q,t} + \omega_{i,t} \tag{3.5}$$

Where $\hat{\varepsilon}^2_{i,t}$=square errors from the mean equation,

$\omega_{i,t}$= denote the white noise

The null and alternative Hypotheses are stated as:

$$H_0 : X_i = 0, \quad i = 1, 2, 3, \dots, q \quad \text{(No ARCH effects)}$$

$$H_0 : X_i \neq 0, \quad i = 1, 2, 3, \dots, q \quad \text{(ARCH effects)}$$

Rejecting the null hypothesis means there is the existence of ARCH effects. The t statistic stated as $LM = obs * R^2$ follows distribution of chi-square with q degrees of freedom, obs is abbreviation for number of observations and R^2 is the coefficient of determination calculated based on Equation (3.5).

3.4.5 Ljung-Box Test

Serial correlation is synonymous with Autocorrelation and is a time series phenomenon in which white noise from distinct time periods is correlated. This test is used to ensure that previous error terms are not connected to the current error term. A fundamental assumption of the time series model is that white noise over time has zero covariance. If this assumption is satisfied, it would appear that they are serially correlated. Detecting this can be accomplished with the Ljung-Box test. This test only evaluates square residuals based on their immediately preceding values. In order to interpret the test statistic, it would help to think about t error in relation to its prior time t value. It follows that if the null hypothesis were rejected, the residuals at times $t-1$ and t are separate from one another, and this would mean that there is some connection among previous residuals.

The test statistic is given:

$$\mathbb{Q}(h) = S \sum_{i=1}^{h} \hat{\rho}_i^2 \sim X^2(h) \tag{3.6}$$

Where $\hat{\rho}_i^2$ is the estimator of the autocorrelation function and S is the sample size. The parameter $\mathbb{Q}$ is distributed as chi-square with h degrees of freedom. For finite samples, the $\mathbb{Q}(h$ is altered to increase the potency of the test and is stated as:

$$\mathbb{Q}^* = S(S+2)\sum_{i=1}^{h}\frac{\hat{\rho}_i^2}{S-i} \sim X^2(h) \tag{3.7}$$

$\mathbb{Q}^*$ = is distributed as chi-square with h degrees of freedom under the null hypothesis. The null hypothesis is rejected of no autocorrelation of residuals if the calculated value of the test is greater than the critical value of the distribution with h degrees of freedom

3.5 Model Selection Criteria

Identifying the order or lag length of the model is an essential step before estimating the model. Accordingly, the information criteria are designed to provide information concerning the order of the model, in order to strike a balance between the measure of goodness of fit and the sparse specification of the model. To select the most suitable model, a number of criteria have been proposed. The information criteria employed in this study include the AIC developed by Akaike (1974), the BIC proposed by Schwartz (1978)

Akaike Information Criteria

Akaike Information Criterion was introduced by Hirotogu Akaike in 1973. Model selection criteria of this type were the first to be widely accepted. By extending the maximum principle to the AIC, once the structure of the model is understood, its parameters can be estimated using the maximum likelihood principle.

$$AIC = -2\ln(loglikelihood) + 2K \tag{3.8}$$

Bayesian information Criteria

The BIC is a criterion developed under the Bayesian statistic context for selecting among a set of finite models. It selects the best model from a candidate model space for more inferences. The likelihood function is used to determine whether a model is good. It evaluates various models with varying asymptotic features.

$$BIC = -2\ln(loglikelihood) + K\ln(T) \tag{3.9}$$

Where T denote the number of observations and K represent the figure of parameters to be estimated. The ideal lags for GARCH-MIDAS and GARCH model is arrived at using AIC and BIC information criteria.

3.6 GARCH Type Models

In this investigation, two competing models—ARMA-GARCH and GARCH-MIDAS—were used. The condition mean in traditional GARCH models is calculated using the ARMA (p, q) process, and the conditional variance is calculated using the GARCH (p, q) process after the residuals. Based on minimal BIC and AIC model selection criteria that assess the goodness of fit, the best ARMA-GARCH is fitted. Likewise, the GARCH-MIDAS is fitted taking into consideration the best models' information criteria, and the lags were chosen based on the shape of the beta polynomial scheme.

3.6.1 GARCH model

Engle developed the Autoregressive Conditional Heteroscedasticity model in 1982 to model financial time series that do not satisfy the homoscedasticity assumption. There was recognition of the approach due to its potential application to stock markets and its use for modelling volatility of returns where there is volatility clustering in the data. Under this framework the conditional variance depends on past square errors and previous period variance. Using the ARMA-GARCH model the mean equation is a linear ARMA (p, q) model that is univariate and comprises an autoregressive and moving average component. The model was first introduced by Box-Jenkins, where the current period value depends on the previous period value and past period error terms. The combination of ARMA and GARCH model has been widely used to model both fluctuating stationery and non-stationery in financial and economic time series.
Thus, the general ARMA (p, q) is defined as:

$$Y_t = \varphi_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \gamma_1 \xi_{t-1} + \gamma_2 \xi_{t-2} + \cdots + \gamma_q \xi_{t-q} + \xi_t \qquad (3.10)$$

Where φ_0 is intercept, ξ_t is the white noise, $(\varphi_1, \varphi_2, \cdots, \varphi_p)$ and $(\gamma_1, \gamma_2, \cdots, \gamma_q)$ represent AR and MA components respectively

Then, the GARCH (p, q) is written as:

$$\sigma^2_{t/t-1} = \phi + \sum_{i=1}^{p} \alpha_i \xi^2_{t-1} + \sum_{j=1}^{q} \beta_l \sigma^2_{t-1} \qquad (3.11)$$

Where ϕ is the intercept, $\alpha_1, \alpha_2, \alpha_3, \cdots, \alpha_p$ are the weights of past lagged square error term, and $\beta_1, \beta_2, \beta_3, \cdots, \beta_q$ represent the weights of past lagged volatility terms or the parameters to be estimated of the GARCH process. To ensure non-negativity and to get the value of conditional variance to be always non-negative the following conditions have to be met: $\phi > 0, \alpha_i \geq 0$ and $\beta_l \geq 0$

3.6.2 GARCH-MIDAS

In this thesis we employed a multiplicative two class volatility component GARCH-MIDAS model introduced by Engle et al. (2013). The GARCH-MIDAS technique models return as the product of a unit variance GARCH model, which denotes volatility swings in a short-term perspective, and an explanatory variable based on components, which illustrates macroeconomic changes over time. The model combines short-run GARCH (1, 1) high frequency volatility with low-frequency macroeconomic variable taken care by the MIDAS regression introduced by Gysels et al. (2006). The daily Stock return is calculated as $r_{it} = \ln P_t - \ln P_{t-1}$

The daily return is assumed to follow the following processes:

$$r_{it} = u + \sqrt{\tau_t g_{it} \varepsilon_{it}} \quad \forall_{i=1} \ldots\ldots N_t \qquad (3.12)$$

$$\varepsilon_{it}/\phi_{i-1,t} \sim N(0, 1)$$

r_{it} denote daily return in day i in month t, u is the unconditional expectation, $\sigma^2_t = g_{it}\tau_t$ is the multiplicative total condition variance segregated into short and long-run components where τ_t is the low frequency (long-term) component which explains sources of stock returns volatility and g_{it} is the high frequency segment which accounts for daily returns volatility $\phi_{i-1,t}$ Is the information set available up to $(i-1)$ i.e., the previous period. N_t is the number of returns in month t. ε_{it} indicate stochastic process condition on previous information set available at time $t-1$ and it follows normal distribution.

$$(r_{it} - u) = \sqrt{\tau_t g_{it} \varepsilon_{it}} \tag{3.13}$$

$$\frac{(r_{it} - u)^2}{\tau_t} = g_{it}\varepsilon_{it} \tag{3.14}$$

Where the volatility component g_{it} act in accordance to a GARCH (1, 1) process

$$g_t = \alpha_0 + \sum_{t=1}^{q} \alpha_1 \varepsilon_{t-1} + \sum_{j=1}^{p} \beta_j h_{t-j} = \alpha_0 + \beta(L) g_t + \alpha(L)\varepsilon_t^2 \tag{3.15}$$

$$g_t = \alpha_0 + \alpha(L)\frac{(r_{it} - u)^2}{\tau_t} + \beta(L) g_t \tag{3.16}$$

Where $\alpha_0 = \alpha + \beta \leq 1 = (1 - \beta - \alpha)$

$$g_t = (1 - \beta - \alpha) + \alpha_{i-t}\frac{(r_{it} - u)^2}{\tau_t} + \beta_{j-t} g_{t-j} \tag{3.17}$$

Where β and α are GARCH and ARCH parameters respectively, such that $\alpha > 0, \beta \geq 0$ β indicate the level of volatility clustering

$$\tau_t = m + \beta_1 \beta(L\overset{1}{\overline{m}}; \theta) X_t^m + \varepsilon_t \tag{3.18}$$

τ_t is follows the concept of MIDAS regression and defined as the long-term volatility component.

$$\log \tau_t = m_l + \theta_l \sum_{k_i=1}^{k_l} \varphi_k(\omega_{1l}, \omega_{2l}) X_{l,t-k} \tag{3.19}$$

τ_t represent the long-term component which accommodate the low-frequency variables such as macroeconomic variables or financial variables and realized volatility through MIDAS filtering. m_l is the constant term and θ_l quantifies the effect of the low-frequency factors on volatility long term. Where $X_{l,t-k}$ is the level of macroeconomic variables which is denoted by taking the log difference of the variables. To ensure non-negativity of τ_t logarithm term can be taken of long term volatility to ensure positive value.

We adopted beta polynomial weighing scheme to filter macroeconomic variables in the MIDAS equation

$$\varepsilon_\kappa(\omega_1, \omega_2) = \frac{\kappa}{K}^{\omega1-1}(1 - \frac{\kappa}{K})^{\omega1-1}\sum_{j=1}^{\kappa_\nu}\frac{j}{K}^{\omega-1}(1 - \frac{j}{K})^{w2-1} \tag{3.20}$$

A flexible or unrestricted beta smoothing scheme can be used to estimate ω_1, ω_2 in Equation 3.19. These are weighting to be computed in the beta polynomial function as a weighted factor of low frequency economic series. κ denotes the number of lag periods. In these situations, K represents the maximum lag order of the series under consideration. MIDAS regressions and their input variables are independently smoothed by beta polynomial smoothing. $\varphi_\kappa(\omega_1, \omega_2)$are beta polynomial function which is the weight corresponding to macroeconomic variables which is contained in the lag period of κ. The weighting scheme directly consider macroeconomic series into the long-run components as a weighted average of lagged values of monthly macroeconomic indicators. However, the study employed a restricted version of beta polynomial scheme by fixing ω_1 to 1 and ω_2 is estimated to determine the decaying pattern. A high value of ω_2 indicates rapid decay, whereas a low value indicates slow decay Therefore the two two-parameter polynomials now become single parameter beta polynomial and define as:

$$\varphi_\kappa(\omega_2) = \frac{(1 - \frac{\kappa}{K})^{\omega-1}}{\sum_{i=1}^{n}(1 - \frac{j}{K})^{\omega-1}} \tag{3.21}$$

Based on a variance ratio analysis, it can be determined what influence each macroeconomic variable has on total conditional volatility (Engle et al, 2013). Macroeconomic variables with a high variance ratio contribute more to the conditional variance of returns. A decrease in variance ratio for a macroeconomic variable represents less or insignificant contribution to the conditional variance of returns. To determine whether large or small swings in the stock market are driven by macroeconomic variance, it is important to assess the importance of the variance ratio of each of the exogeneous variables. As a result, equation (3.22) is used to calculate the ratio.

$$VR(X) = \frac{Var(\log(\tau_t^x))}{Var(\log(\tau_t^x * g_{i,t}^x)} \tag{3.22}$$

3.6.3 GARCH-MIDAS Model Estimation Process

Non-linear volatility models are mainly estimated using maximum likelihood estimation. In the GARCH-MIDAS Model, the parameters are estimated using the Maximum Likelihood Method. An estimation of log-likelihood seeks to determine the parameter value that is most similar to the value predicted by actual data. The log-likelihood function is then estimated by estimating the parameters that maximize it.

Given $r_{it} = u + \sqrt{\tau_t g_{it} \varepsilon_{it}}$ which specified the approach, the parameters involve in the GARCH-MIDAS equation to be estimated are represented by $LLF = (u, \alpha, \beta, \theta, \omega_2)$ for restricted version with the log-likelihood function for the estimation is given by:

$$LLF = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\left(\log(2\pi) + \log(g_t\tau_t) + \frac{(r_{it}-u)^2}{g_t\tau_t}\right) \tag{3.23}$$

The log-likelihood function can follow either the Gaussian distribution or Student-t distribution

The log-likelihood function for the Gaussian distribution:

$$\ln(\phi) = \sum_{t=1}^{T}\sum_{i=1}^{N_t}\left\{\log\left(\frac{\nu}{\lambda}\right) - \frac{1}{2}\left|\frac{r_{i,t}-\mu}{\sqrt{\tau_t g_{i,t}\lambda}}\right|^{\nu} - (1+\nu^{-1})\log(2) - \log\left[\Gamma\left(\frac{1}{\nu}\right)\right] - \frac{1}{2}\log(\tau_t g_{i,t})\right\} \tag{3.24}$$

Student-t distribution log-likelihood function:

$$\ln(\phi) = \sum_{t=1}^{T}\sum_{i=1}^{N_t}\left\{\log\Gamma\left(\frac{\nu+1}{2}\right) - \log\Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2}\log(\pi(\nu-2)) - \frac{1}{2}\log\tau_t g_{i,t} - \frac{(\nu+1)}{2}\log\left(1+\frac{(r_{i,t}-\mu)^2}{\tau_t g_{i,t}(\nu-2)}\right)\right\} \tag{3.25}$$

3.7 Regularization Regression

3.7.1 Ridge Regression

Ridge regression limit the impact of less important economic indicators in the model. This is done by introducing penalty on regression coefficient in order to minimize residual sum of square. It follows that as the tuning parameter increases the bias rises and as the tuning parameter becomes larger the variance reduces. LASSO does not perform variable selection but minimizes the impact of irrelevant predictors in the model shrinking the estimated coefficient near zero but not completely zero.

Linearly, I consider the general model a

$$Y_l = \sum_{l=1}^{p}\beta_{lj}X_l + \varepsilon, \qquad l = 1, \cdots, N \tag{3.26}$$

Can be illustrated in matrix Notation as

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_3 \end{pmatrix} = \begin{pmatrix} 1 & X_{1,1} & \cdots X_{1,p} \\ 1 & X_{2,1} & \cdots X_{2,p} \\ \vdots & \vdots & \cdots \vdots \\ 1 & X_{N,1} & \cdots X_{N,p} \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_2 \end{pmatrix} \tag{3.27}$$

$$RSS = \sum_{l=1}^{n}\left\{Y_l - \beta_0\left(\sum_{l=1}^{p}\beta_{lj}X_l\right)\right\}^2 \tag{3.28}$$

The maximization problem is subject to constraint by imposing Ridge penalty

$$\hat{\beta}^{ridge} = argmin \sum_{l=1}^{n} \left\{ Y_l - \beta_0 \left(\sum_{l=1}^{p} \beta_{lj} X_l \right) \right\}^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{3.29}$$

$$argmin \sum_{l=1}^{n} (Y_l - X_l^T \beta)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{3.30}$$

$$argmin \, \|Y - X\beta\|_2^2 + \lambda \, \|\beta\|_2^2 \tag{3.31}$$

Y_l denote the ith observation of response variable (stock returns), β_0 is a constant term X_l represent the ith observation of the jth explanatory variables (macroeconomic and financial variables), β_{lj} is the associated coefficient. $\lambda \geq 0$ is the regularization parameter and as λ increases the coefficient shrinkage towards zero. Whenever $\lambda = 0$ it produces the result of normal Ordinary Least Square regression and $\sum_{j=1}^{p} \beta_j^2$ Ridge penalty or regularization function

3.7.2 LASSO Regression

LASSO implements variable selection to pick the best predictors. This method allows for simultaneous estimation and selection of variables. By using turning parameter to control shrinkage power, LASSO picks explanatory factors by shrinking less useful coefficients and constraining them to nil. In line with OLS estimates of beta coefficient of predictors to Minimizes Residual Sum of Square (RSS) can be written as

$$RSS = \sum_{l=1}^{n} \left\{ Y_l - \beta_0 \left(\sum_{l=1}^{p} \beta_{lk} X_l \right) \right\}^2 \tag{3.32}$$

Given a vector of returns $y \in \mathbb{R}^n$ and macroeconomic variable matrix $X \in \mathbb{R}^{n*p}$ LASSO shrinks some of the coefficients $\beta_1, \cdots, \beta_k$ of the less important variables to zero.

$$\hat{\beta}^{lasso} = argmin \sum_{l=1}^{n} \left\{ Y_l - \beta_0 \left(\sum_{k=1}^{p} \beta_{lk} X_l \right) \right\}^2 + \lambda \sum_{j=1}^{p} |\beta_k| \tag{3.33}$$

$$argmin \sum_{l=1}^{n}(Y_l - X_{[l]}^T\beta)^2 + \lambda\sum_{k=1}^{p}|\beta_h| \tag{3.34}$$

$$argmin \left\|Y - X\beta\right\|_2^2 + \lambda\left\|\beta\right\|_1 \tag{3.35}$$

X_l in equation 3.32 is the vector of macroeconomic variables, λ represents the regularization parameter which determines the strength of the penalty, as λ goes higher, the absolute value amount of estimated coefficient shrink towards zero. $\left\|Y - X\beta\right\|_2^2$ Stands for loss function, $\left\|\beta\right\|_1$ denotes the regularization function. Under LASSO the coefficient of unimportant variables is reduced completely to zero.

3.8 Model Evaluation

In order to assess the predictive power of the different models, the data is separated into two samples, In-sample (training set) and hold-out sample indicating the proportion which was used for train and test data. An in-sample data set is used to estimate parameter estimates for the models, and a hold-over data set is used to evaluate the models. As this research focuses more on the model's predictive capability than its performance on training sets, it is more pertinent to consider its hold-over performance in hold-over samples than its training set performance. Concisely, model evaluation shows how actual and forecast values differ. As a method of evaluating the model's forecasting accuracy, we used the following loss function

Mean Square Error

In this statistical loss function, large deviations between predictions and actual values are given more weight. Outliers can adversely affect the MSE estimate, so if the prediction is substantially different from the observed value, the MSE will be high.

$$MSE = N^{-1} \sum_{t=1}^{N} (\sigma_{t+1}^2 - \hat{\sigma}_{t+1}^2)^2 \tag{3.36}$$

Where N stands for the number of observations in the out-of-sample data, σ_{t+1}^2 is realized variance the proxy for actual volatility and $\hat{\sigma}_{t+1}^2$ is the forecast from the model.

Mean Absolute Error

The MAE is a measure of the average magnitude of the difference between the actual loss and the forecast loss. In order to calculate the error, the average of the absolute variation between the actual value and the forecast value is taken. The robustness of this measure comes from the fact that it is not heavily influenced by outliers.

$$MAE = N^{-1} \sum_{t=1}^{N} |\sigma_{t+1}^2 - \hat{\sigma}_{t+1}^2| \tag{3.37}$$

Where σ_{t+1} represent actual value and $\hat{\sigma}_{t+1}$ represent the forecast from the model

Root Mean Square Error

The RMSE is the mean square error's square root. It represents the square root of the deviation of the predicted value from the observed value. The RMSE, which is the square root of the average of squared residuals, assesses the prediction's accuracy by comparing it with the estimator's residuals. Since errors are squared before averaging. RMSE is always non-negative, gives a quite high weight to large residuals and a lower RMSE is better than higher RMSE. A major advantage of this loss function is that it handles large residuals, especially undesirable residuals. Essentially, it represents the standard deviation of the residuals after the model is fitted.

$$RMSE = \sqrt{N^{-1}\sum_{t=1}^{N}(\sigma_{t+1}^2 - \hat{\sigma}_{t+1}^2)^2} \tag{3.38}$$

$$RMAE = \sqrt{N^{-1}\sum_{t=1}^{N}|\sigma_{t+1}^2 - \hat{\sigma}_{t+1}^2|} \tag{3.39}$$

Where σ_{t+1} represent actual value and $\hat{\sigma}_{t+1}$ represent the forecast from the model

HMSE

The HMSE is the non-linear statistical loss function. It serves as heteroscedasticity-adjusted version of Mean Square Error, (Wang et al.2020).

$$HMSE = N^{-1}\sum_{t=1}^{N}(1 - \frac{\sigma_{t+1}^2}{\hat{\sigma}_{t+1}^2})^2 \tag{3.40}$$

HMAE

Are non-linear loss measures used, and is the MAE heteroskedacity adjusted.

$$HMSE = N^{-1}\sum_{t=1}^{N}|1 - \frac{\sigma_{t+1}^2}{\hat{\sigma}_{t+1}^2}| \tag{3.41}$$

CHAPTER 4

DATA ANALYSIS AND DISCUSSION OF RESULTS

4.1 Introduction

Here, the chapter presents the outcome of the analysis of the data for the variables employed in the study. It produced an overview of descriptive statistics, a graphical presentation of the variables, stationary test results, diagnostic tests for model fittings, the estimated results of various models adopted in this study, and a model performance evaluation. The graphs, diagrams, and parameter estimates were obtained using the R statistical package version 4.2.1.

4.2 Graphical Presentation of the Variables

The graph depicts the behavior of macroeconomic variables at their respective levels for each country. The line graphs present the patterns and trends of all variables. The graph of the dependent variable for each country exhibits the trend of downward and upward movement, a well-known characteristic of stock market price behavior (Figure 4.1, 4.2 and 4.3). For South Africa, the treasury bill rate, which serves as a substitute for interest rates, displayed downward movement between 2011 and 2014. In Nigeria, the interest rate has displayed an irregular pattern, which is the same as the case with Ghana's interest rate. Money supply shows an upward trend for all the countries, indicating an increase in money supply for the period. The exchange rate for South Africa and Ghana demonstrates an upward trend, indicating that their currencies are depreciating against the US dollar. On the other hand, the Nigerian naira appears to be stable between 2017 to 2019. Consumer price index, which is used as approximation for inflation, shows an upward and downward pattern for all countries.

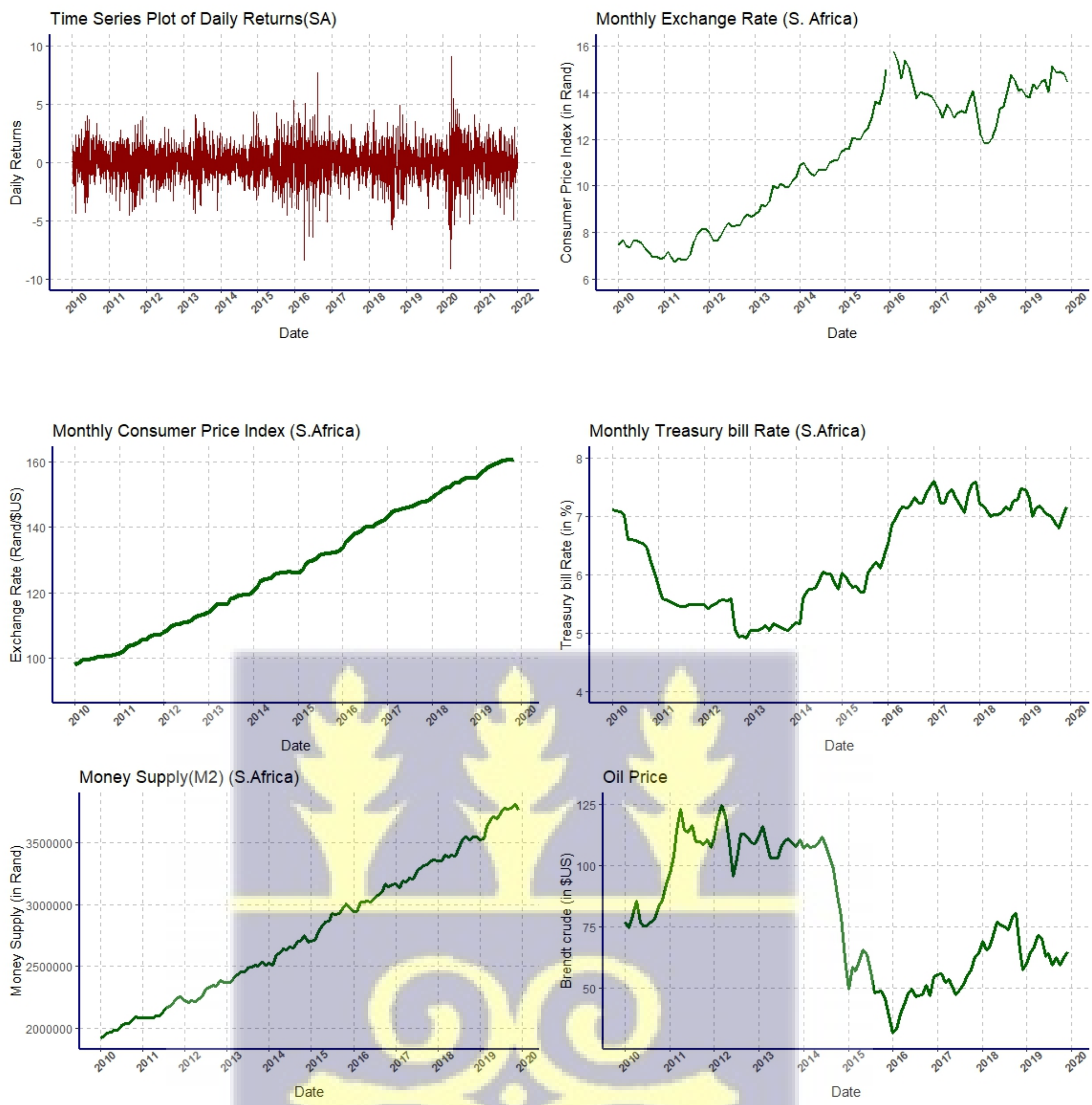

Figure 4.1: Daily plot of stock returns and monthly economic variables for SA

Source: Author's construct based on data obtained from IFS/SARB

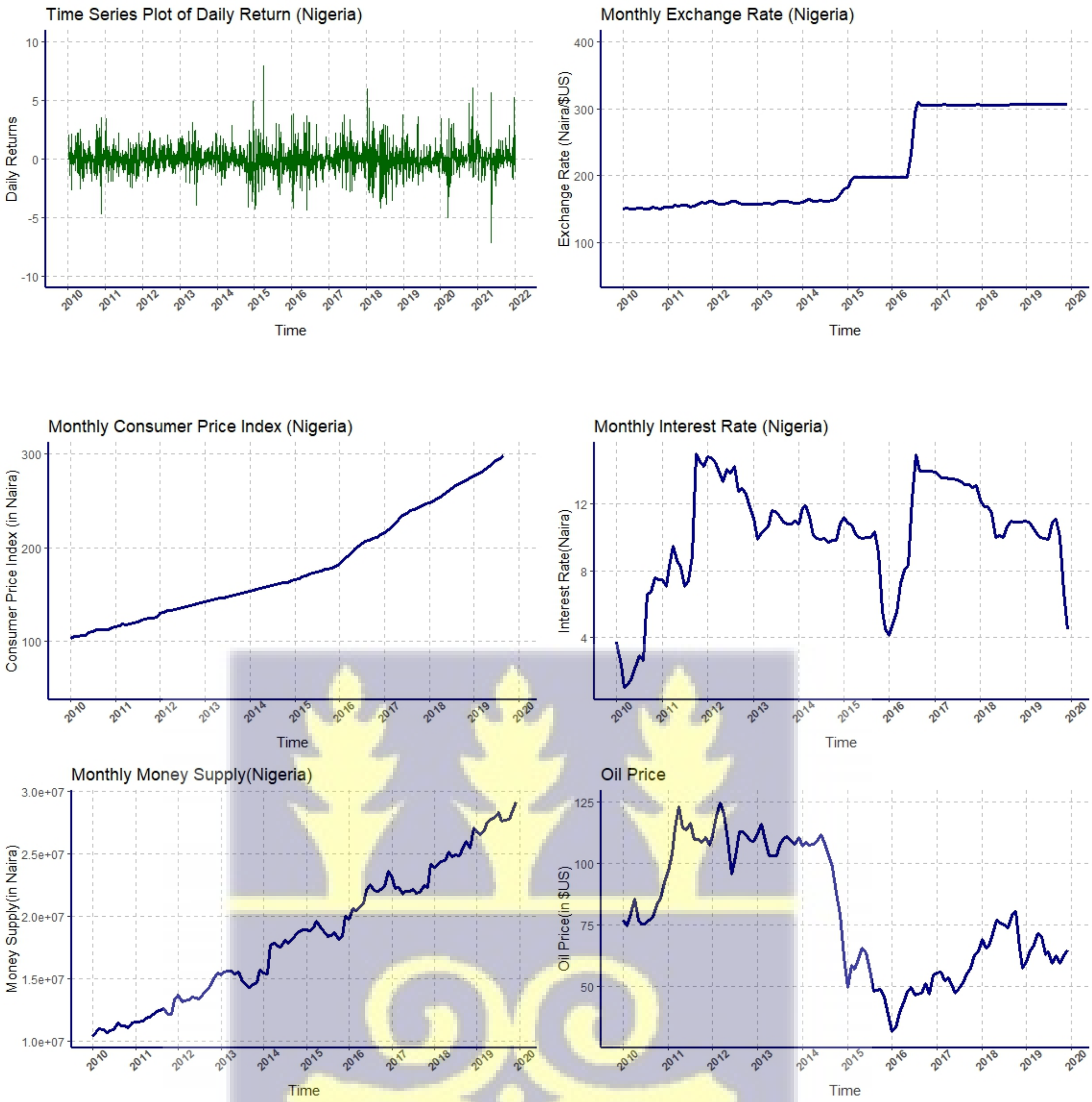

Figure 4.2: Daily plot of stock returns and monthly macroeconomic variables for Nigeria

Source: Author's construct based on data obtained from Nigeria Central Bank

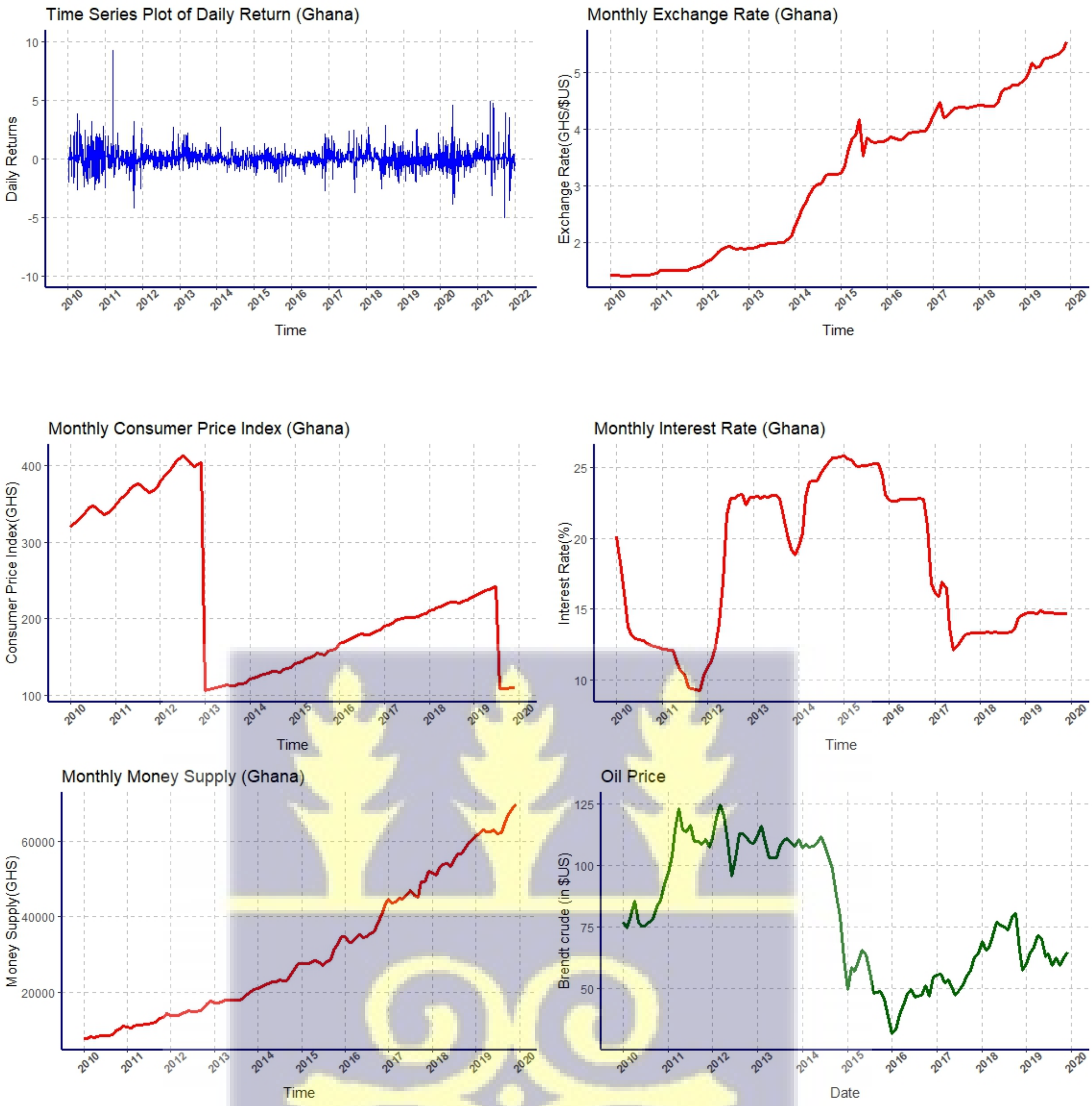

Figure 4.3: Daily plot of stock returns and monthly economic variables for Ghana

Source: Author's construct based on data obtained from IFS/BOG

4.3 Descriptive Statistics

Table 4.1 offers summary statistics of in-sample raw data for macroeconomic indicators and the natural log for stock returns for the period spanning from 1/1/2010 to 12/31/2019. From the Table 4.1, it can be observed that the South African stock index has been more volatile (with a standard deviation of 1.42) compared to the Nigerian stock index, which recorded a standard deviation of 1.01. This indicates that the Nigerian equity market is more stable than the South African stock market. This is because the latter has a standard deviation value above the SA returns. When compared to counterpart markets, the standard deviation for the GSE-All Share Index is high, indicating that the Ghanaian stock market experienced greater volatility, and the average return is negative and insignificant. This is not surprising since the mean of log returns is always close to zero. The South Africa and Nigeria exchange index returns have positive and insignificant mean values. The average monthly inflation for Nigeria is 183.07 and for South Africa is 11.8. The inflation cannot be compared between the two countries because the study used the consumer price index as a equivalent for inflation, which is computed in their respective local currencies. The expected monthly exchange rate for Nigerian Naira per US dollar is N215.78 and the average exchange rate for the South African Rand against the US dollar is R128.48. Furthermore, South Africa's interest rate is low (6.3%), compared to a higher average of 10.21% in Nigeria and 17% in Ghana. For South Africa and Ghana, there is a negative skewness of returns.

The Nigeria and Ghana stock returns have kurtosis that has a value larger than three, which is indicative that the data is distributed normally, and is consistent with features that appear in financial and economic series data. South Africa, however, have kurtosis value less than three. When a fat-tailed distribution is present, it indicates an increased possibility of experiencing higher variation from the mean compared to when a normal distribution is present. This demonstrates a greater possibility of fluctuating from the mean. In simple terms, in Nigeria and Ghana the distribution of returns is essentially leptokurtic. Moreover, the daily stock returns are negatively skewed for South Africa and Ghana and positively skewed for Nigeria.

Table 4.1: Summary Statistics for Stock Return economic variables

variables	obs	sd	median	min	Max	skew	kurtosis
South Africa							
Returns	2574	1.42	0.03	-8.37	7.73	-0.22	1.64
INF	120	2.84	11.52	6.74	16.37	-0.13	-1.43
EXR	120	19.50	126.32	98.17	161.15	0.09	-1.31
IR	120	0.86	6.21	4.92	7.61	-0.08	-1.54
OP	120	25.73	75.80	31.93	124.62	0.09	-1.44
MS(M2)	120	551837	2708945	1924798	3806876	0.18	-1.22
Nigeria	obs	sd	median	min	Max	skew	kurtosis
Returns	2581	1.01	0	-4.66	7.98	0.28	4.88
INF	120	59.25	165.09	103.13	307.47	0.54	-0.99
EXR	120	68.05	181.06	150.08	309.73	0.5	-1.64
IR	120	3.25	10.79	1.04	15	-0.94	0.52
OP	120	25.73	75.8	31.93	124.62	0.09	-1.44
MS(M2)	120	5375874	18458138	10446374	29137800	0.2	-1.17
Ghana	obs	sd	median	min	Max	skew	kurtosis
Returns	2461	3.90	0.005	-30.5	21.49	-46.20	61.75
INF	120	99.16	179.35	106.5	412.4	0.80	-0.82
EXR	120	1.55	3.84	1.42	5.95	-0.05	-1.44
IR	120	5.10	14.70	9.25	25.83	0.41	-1.41
OP	120	25.95	71.67	26.63	124.62	0.21	-1.2
MS	120	27410.45	33204.02	7753.02	105997.55	0.72	-0.59

Note: The return is the Natural Log of first difference of daily stock index and monthly economic variables for the three Africa countries from January, 2010 to December, 2019.

4.4 Pairwise Correlation

Table 4.2 showed the relationship between the macroeconomic indicators used in the analysis. The currency exchange rate is highly correlated with inflation (0.934) in Nigeria. The situation is similar in South Africa, where the exchange rate is greatly correlated with inflation. High levels of importation of foreign goods might have explained the correlation between the currency exchange rate and inflation. The high cost of imports might have been passed on to consumers in many emerging and developing markets. This infers that if the Nigerian Naira depreciates against the US dollar, inflation tends to be higher. The money supply is positively and highly correlated (0.979) with inflation in Nigeria. This is expected because increases in the quantity of money in circulation normally bring about high inflationary pressures where a large volume of money chases fewer goods in the economy. In South Africa, MS is moderately correlated with inflation at about 0.649. The interest rate in Nigeria is positively correlated (0.263) with inflation and 0.33 with the exchange rate. In South Africa, the interest rate is extremely correlated (0.913) with inflation. This is envisaged as a high cost of borrowing associated with high inflation. The oil price is negatively correlated (-0.788) with inflation in SA, which indicates a weak association. This is unexpected and surprising because an increase in oil price often result in high inflation. The situation is the same in Nigeria, where the oil price is negatively correlated with inflation. In Ghana, there is a negative relationship between the exchange rate and inflation. They move in the opposite direction, thus. Money supply and inflation have a positive connection, which shows that they are directly related to one another. This implies that as the money supply grows, inflation increase as well. Exchange and inflation both move in the same direction, so inflation rises when the value of the cedi declines. Money supply and exchange rate have a strong and positive relationship in Ghana.

Table 4.2: Correlation Between the Macroeconomic Variables

South Africa	INF	EXR	IR	MS	OP
INF	1				
EXR	0.916	1			
IR	0.913	0.997	1		
MS	0.649	0.682	0.679	1	
OP	-0.788	-0.647	-0.653	-0.781	1
Nigeria	INF	EXR	IR	MS	OP
INF	1				
EXR	0.934	1			
IR	0.263	0.33	1		
MS	0.979	0.908	0.267	1	
OP	-0.591	-0.655	0.119	-0.638	1
Ghana	INF	EXR	IR	MS	OP
INF	1				
EXR	-0.62	1			
IR	-0.34	-0.18	1		
MS	0.54	0.95	-0.35	1	
OP	0.46	0.72	-0.01	-0.57	1

Source: Author's construct of correlation matrix from data sets using R statistical Package

4.5 Test for Normality

The research employed the Jacque-Bera Test to check whether the data sets were normally distributed. It should be noted that the Jacque-Bera test is performed with the null hypothesis that the data is normally distributed and the alternative hypothesis that the data is not normally distributed. All the series reject the Jarque-Bera test for normality because they show features of non-normality.

Table 4.3: Normality Test

South Africa	χ^2	P-value	Nigeria	χ^2	P-value	Ghana	χ^2	P-value
R	3287	0.000	R	513819	0.000	R	84978	0.000
IN	10.148	0.006	IN	11	0.005	IN	13	0.002
EXR	8.3474	0.015	EXR	18	0.000	EXR	11	0.004
IR	11.545	0.003	IR	20	0.000	IR	12	0.002
OP	10.084	0.006	OP	10	0.006	OP	10	0.006
MS(M2)	7.7509	0.021	MS(M2)	7	0.030	MS(M2)	11	0.006

4.6 Test for stationarity

To avoid spurious regression, the stationarity of the series is examined using the Augmented Dicked-Fuller (ADF) to test the unit root of the series. The data is examined to determine the stationarity of the response and explanatory variables. The outcome of the test is provided in Table 4.4 for Nigeria, South Africa and Ghana, respectively, with test statistics and p-values at level and first difference. The null hypothesis is stated as the series has a unit root and is conducted with only the intercept or with both the trend and the intercept. To determine stationarity at level and first difference, the test is run on daily stock returns and all five macroeconomic series used in the study. The outcome shows that, with the exclusion of money supply at first difference, the data reject the null hypothesis of stock returns and macroeconomic indicators at first difference, indicating that most of the variables have no unit root or are non-stationary at first difference. To deal with extreme values, the money supply is transformed at the log of the first difference, implying that the money supply rejects the null hypothesis at the log of the difference for all countries.

Table 4.4: Stationarity Test

South Africa	**Intercept**	**Intercept & Constant**
CPI	-0.938 (0.775)	-2.13 (0.528)
EXR	-0.108 (0.949)	-2.282 (0.444)
IR	-1.100 (0.716)	-2.94 (0.575)
OP	-1.272 (0.642)	-2.39 (0.387)
MS	-1.51 (0.617)	-2.39 (0.395)
Nigeria		
CPI	1.047 (0.995)	-1.399 (0.861)
EXR	-0.452 (0.901)	-2.231 (0.472)
IR	-2.943 (0.04)	-2.502 (0.327)
OP	-1.272 (0.642)	-2.39 (0.387)
MS	0.973 (0.994)	-3.423 (0.048)
Ghana		
CPI	-1.766 (0.397)	-2.134 (0.527)
EXR	0.037 (0.961)	-2.295 (0.436)
IR	-1.575 (0.496)	-1.735 (0.735)
OP	-1.554 (0.507)	-2.050 (0.574)
MS	-1.951 (0.999)	-1.322 (0.619)

Source: Author's Construct

Note: The reported values are the result of the ADF test conducted on the series at their level. The values in the bracket are the P-value of the test statistics. The p-values revealed that all the variables are non-stationary at their level. After conducting differencing and logarithm transformation. Most of the series achieved stationarity at their first difference and some also achieved stationarity at the log of first difference.

4.7 ARCH-LM Test

A test is conducted on the selected model to determine whether ARCH effects exist. By using the ARCH-LM test, the heteroscedasticity test is conducted on 12 lags of residuals of the chosen ARMA and GARCH models for all countries. The observe p-values of the model indicate that it is the most appropriate fit because the residuals of the fitted models show ARCH effects. For all market indices, the ARCH-LM test rejects the null hypothesis of no ARCH effects, indicating that there are no serial correlations. Based on the results, the series exhibits volatility clustering, therefore it is suitable for implementation using GARCH family models. Moreover, In order to assess the possibility of serial correlation in the residuals of appropriate ARMA (p, q) and GARCH (p, q) models, the Box-Ljung test was performed. According to the null hypothesis, there is no serial correlation in the residuals, while the alternative hypothesis implies that there is a serial correlation.Therefore the results of the test on ARMA (p, q) and GARCH(p, q) rejected the null hypothesis of no ARCH effects for all countries.

Table 4.5: Lagrange-Multiplier Test and Box-Ljung Test

ARCH-LM			Box-Ljung Test	
Series	T-statistic	P-value	Q	P-value
South Africa				
ARMA (1,0)	150	0.0000	0.0145	0.904
GARCH (1,2)	239.77	2.2E-16	2.6322	0.1054
Nigeria				
ARMA (1,0)	148	0.0000	0.0145	0.9093
GARCH (1,2)	239.9	2.2E-16	2.2899	0.1308
Ghana				
ARMA (2,2)	507	0.0000	0.05266	0.8185
GARCH (1,3)	613.66	2.2E-16	18.362	1.83E-05

Source: author's construct of LM-test using R programing

4.8 ARMA-GARCH Model fitting Results

Here, the main objective is to identify a suitable ARMA model that will fit and in turn be able to estimate the mean equation as well as forecast accurately the future volatility of returns for each country under study. In order to accomplish this, we perform a wide range of ARMA (p, q) specifications on the dataset for each country. Based on BIC, AIC, and Log-likelihood values, possible orders of p and q are compared. In the table below, the best ARMA (p, q) model is determined by its minimum AIC and BIC. In order to compute the best model fit for ARMA (p, q)-GARCH (p, q), the chosen ARMA (p, q) model is combined with various GARCH (p, q) models according to the best model information criteria for the respective countries (Table 4.6). The results indicate that ARMA (1,0), ARMA (1,0) and ARMA (2,2) models are best suited for South Africa, Nigeria and Ghana, respectively. For each country, this is determined by ARMAs (p, q) fitted to returns depending on a minimum AIC and BIC. According to this, the lag return of one period affects volatility on the South African and Nigerian stock markets when using the ARMA model. Whereas there are consequences of a lag return of two periods for the volatility of the Ghanaian stock exchange. Hence, Ghana's stock exchange has a longer memory than those in South Africa and Nigeria

Table 4.6: Results of Fitting Appropriate ARMA model

SA			Nigeria			Ghana		
ARMA (p,q)	AIC	BIC	ARMA (p,q)	AIC	BIC	ARMA (p,q)	AIC	BIC
(0,1)	9108.36	9125.92	(1,0)*	7222.58	7240.15	(2,2)*	5166.11	5200.95
(1,0)*	9108.36	9125.92	(2,0)	7224.28	7247.7	(2,1)	5168.82	5197.85
(2,0)	9110.36	9133.77	(1,1)	7224.28	7247.7	(3,1)	5168.87	5203.71
(0,2)	9110.36	9133.77	(0,2)	7224.86	7248.28	(3,3)	5168.94	5215.39
(1,1)	9110.36	9133.77	(2,1)	7226.28	7255.56	(3,0)	5242.98	5272.01
(1,2)	9112.33	9141.6	(1,2)	7226.28	7255.56	(0,3)	5249.79	5278.82
(2,1)	9112.35	9141.62	(2,2)	7228.2	7263.34	(2,0)	5258.60	5281.83
(0, 4)	9113.74	9148.86	(0,1)	7231.66	7249.22	(0,2)	5261.22	5284.45
(4,0)	9113.84	9148.96	(2,3)	7228.36	7269.35	(1,0)	5275.37	5292.78
(3,1)	9113.86	9148.98	(3,1)	7228.15	7263.29	(0,1)	5275.37	5292.79

*Indicates the best fitted ARMA (p, q) model based on minimum AIC and BIC model selection criteria.

The study experimented with every potential pairing of the ARMA and GARCH approach in order to find the best suitable one. Based on the results of fitting ARMA (p, q) - GARCH (p, q), the best fitted models for each country were determined to be the ARMA (1,0) - GARCH (1,1), ARMA (1,0) - GARCH (1,2), and ARMA (2,2) - GARCH (1,3) models for South Africa, Nigeria, and Ghana, respectively, taking into consideration the goodness of fit test. The GARCH model for Ghana with higher-order terms indicates that the Ghanaian stock exchange has higher memory, and it is necessary to include more lags to explain how past information influences current market behavior. As shown in Table 4.7, these models displayed the least information criteria among all the fitted models.

Table 4.7: Result of Fitting Appropriate ARMA-GARCH Model

South Africa			Nigeria			Ghana		
GARCH (P Q)	AIC	BIC	GARCH (P,Q)	AIC	BIC	GARCH (P,Q)	AIC	BIC
(1,1)*	2.4713	2.499	(1,1)	2.6094	2.6207	(1,1)	1.8164	1.8424
(1,2)	2.6022	2.6294	(1,2)*	2.6028	2.616	(1,2)	1.8162	1.8446
(1,3)	2.6009	2.6304	(1,3)	2.6029	2.6187	(1,3)*	1.8082	1.8390
(2,1)	2.6068	2.634	(2,1)	2.6101	2.6238	(2,1)	1.8109	1.8392
(3,1)	2.6076	2.6371	(3,1)	2.6109	2.6267	(3,1)	1.8117	1.8424
(2,2)	2.6030	2.6325	(2,2)	2.6036	2.6195	(2,2)	1.8176	1.8412

Note: *is the appropriate fitted ARMA (p, q)-GARCH (p, q) model based on minimum AIC and BIC model criteria.

4.9 ARMA-GARCH Parameter Estimate Results

In this section, we present the volatility of Nigeria Stock Market, Johannesburg and Ghanaian Stock Market for the in-sample period. The fitted GARCH (p, q) parameters are estimated for each country. As the competing models, GARCH coefficients are estimated without the inclusion of exogenous variables. Table 4.8 contain the estimate of conditional variance and mean equation.

It has been shown that almost all parameters calculated using the best fitting ARMA-GARCH models are significant for all countries at the 1% levels with the exception of the mean which statistical insignificant. The intercept from the variance equation is significant at the 1% level. There is statistical significance at the 1% level for the mean equation terms AR(1), AR(2), MA(1) and MA(2) in all three markets. Additionally, statistical significance is observed for the coefficients β_1 that assess volatility persistence. Combining ARCH and GARCH results in a sum roughly equal to one and close to unity for all three countries. This implies that volatility clustering is common across all the stock exchanges studied and expected to be triggered by past conditional variance for South Africa since the ARCH coefficient is smaller than the GARCH coefficient (0.1539 < 0.7791). On the contrary the ARCH parameter estimate is greater than the GARCH (1) parameter estimates for Nigeria and Ghana. This shows the weight of the past period shocks is associated with the variance of the current period residual.

Table 4.8: Parameter Estimates for GARCH Model

South Africa				
Coefficients	Estimates	Std Error	T value	P-value
μ	-0.0129	0.0199	-0.64814	0.5169
ϕ_1	0.1939	0.0227	8.5471	0.0000
Φ	0.0685	0.0144	4.7533	0.0000
α	0.1539	0.0214	7.1834	0.0000
β	0.7791	0.0315	24.7595	0.0000
Nigeria				
Coefficients	Estimates	Std Error	T value	P-value
μ	-0.00879	0.0199	-0.4412	0.6591
$\phi 1$	0.1961	0.0228	8.589	0.0000
Φ	0.0883	0.0166	5.323	0.0000
α	0.2055	0.0242	8.4771	0.0000
β_1	0.1774	0.0772	2.2964	0.0217
β_2	0.5285	0.0766	6.9009	0.0000
Ghana				
Coefficients	Estimates	Std Error	T value	P-value
μ	-0.00599	0.0242	-0.2477	0.8043
ϕ_1	1.6145	0.0144	112.253	0.0000
ϕ_2	-0.6387	0.0143	-44.712	0.0000
γ_1	-1.5676	0.000033	-47606.98	0.0000
γ_2	0.6215	0.000126	4933.13	0.0000
Φ	0.0274	0.0059	4.648	0.0000
α	0.2465	0.0312	7.913	0.0000
β_1	0.1854	0.0811	2.286	0.0223
β_2	0.1723	0.0516	3.337	0.0008
β_3	0.3668	0.0551	6.657	0.0000

Source: author's construct

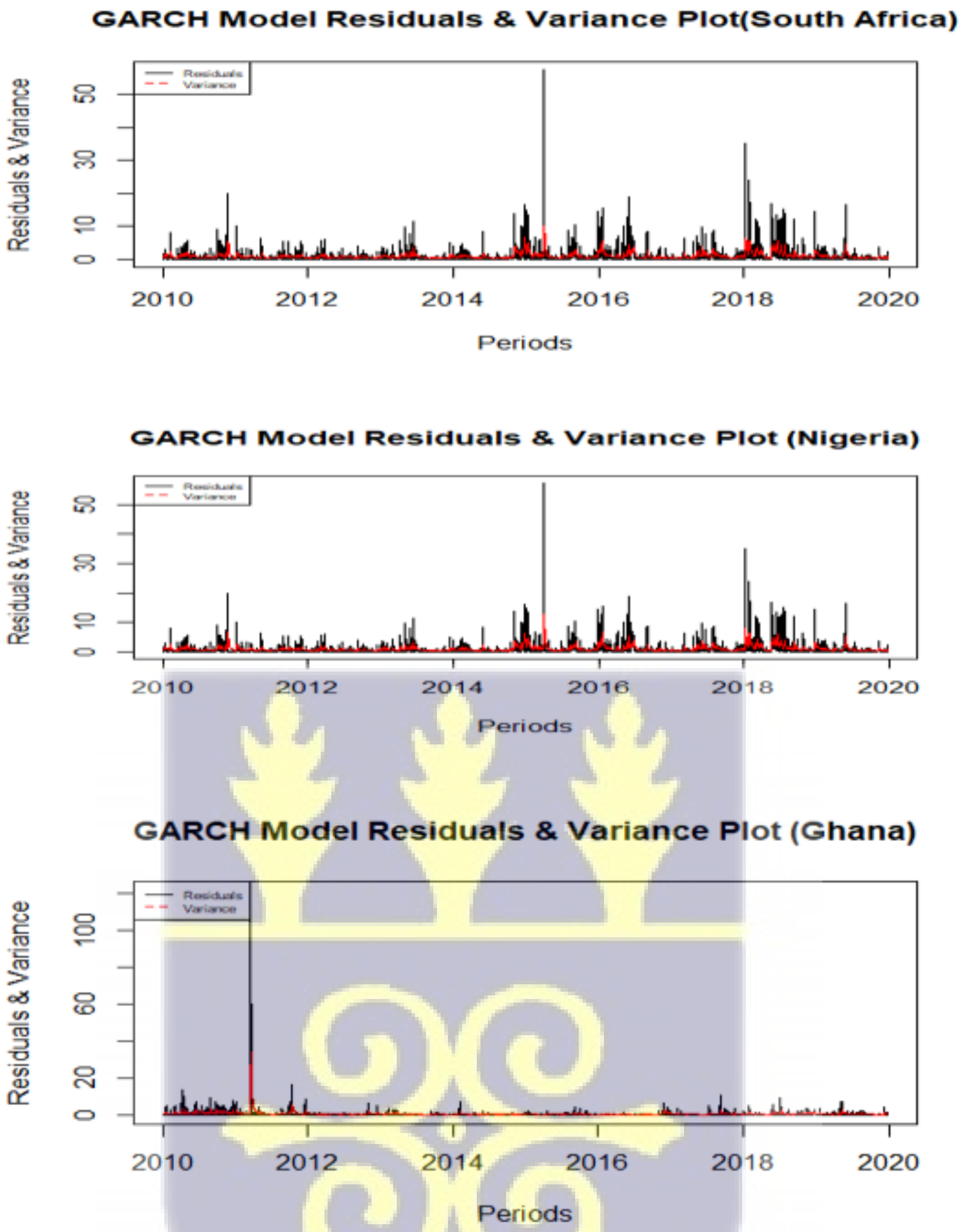

Figure 4.4: Plot of Variance and Residual of GARCH Estimation

4.10 GARCH-MIDAS Results

This section presents and discusses the estimated coefficients of the GARCH-MIDAS volatility models for the in-sample period 2010-2019. This study is designed to examine whether sample macroeconomic indicators affect volatility of stock markets in the selected Sub-Saharan African nations (Ghana, Nigeria, and South Africa). An estimated coefficient of the model is presented in the Table 4.9. Additionally, it includes the model information criterion, log likelihood value, and variance ratio of each regressor. The result was classified for each country and how each macroeconomic variables affect volatility in each country. The lags periods included in each model based on the fast-decaying pattern of pictorial or visual presentation of various Beta polynomial scheme. Based on the probabilistic analysis for all possible choice, 36 months lag periods of K are included in the MIDAS filter for all macroeconomic variables for South Africa. In Nigeria 36 months lag periods of K was included in the MIDAS filter with exception of inflation which achieves 24 months of K in the MIDAS weighting scheme. Ghana's data exhibit slight deviation from her peers, as 48 months lag periods of K fit inflation, 24 months lag period of K for interest rate and 36 months lag periods of K fit exchange rate, oil price and money supply (see Figure 5.1, 5.2 & 5.3). These results were arrived at taking in to consideration minimum Bayesian Information Criteria and maximum log-likelihood values (Table 4.9). The magnitude impact of various macroeconomic variables is measure as a percentage change effect of these variables on the volatility using $e^{\theta \frac{\varphi(\omega)}{k}} - 1$ (Engel et al., 2013). Where θ represents the directional effect of macroeconomic series, $\varphi(\omega)$ denotes the weight assigned to the lags and k signifies the number of lags used for the parameter estimation.

4.10.1 GARCH-MIDAS Inflation Discussion

The short run parameters in the model sum to 1 and are statistically significant at 5%, indicating that short-run term components are highly volatile when inflation is included in the estimation of GM parameters for South Africa. This shows a pattern of volatility clustering, where periods with high volatility extend into subsequent periods and also low volatility extend to the following periods. There is a positive unconditional mean for South Africa, and significant at 5%. The coefficient Theta(θ) is positive and significant for South Africa, showing a direct relationship which means that swelling inflation is associated with greater stock volatility. This reveal inflation affects or explains variation in the Johannesburg stock exchange. Additionally, inflation contributes 49.46 of total conditional variance, as computed by variance ratio. Based on the weighted coefficient of W2 at 10% significant level, the first observation of inflation has a lag of 0.0341. Usually, the smaller the weight, the slower the wind-off pattern, while the higher the weight show, the faster the wind-off pattern. Thus, a growth in inflation of 1% for the previous period would increase volatility by 26.59% for the next period. ($e^{0.0341*6.9} - 1$).This result corresponds with the result of similar work of Engle et al. (2013) that inflation is positively related with the long-term component of the market return.

In the Nigerian case, inflation account 1.34% to conditional volatility. The average market returns are lower than expected, indicating that there have been more negative returns. At 1% significant level, the short-term component coefficient is less than 1 (i.e. 0.946) when added together. The MIDAS slope parameter (θ) is positive but not significant. As a result, inflation and stock market volatility are directly related. An insignificant slope parameter (θ) implies that inflation has insignificant effect on the long-term volatility of the Nigeria equity market. This outcome is congruent with that obtained in 2017 by Sokpo et al.,(2017) who similarly discovered that there was no substantial relationship between inflation and Nigerian stock return.

For Ghana, the average return is positive (0.004513) but insignificant. There is a 67.68% contribution to volatility from inflation. It is anticipated that inflation will contribute a significant amount to total volatility. This is attributed to the fact that the country experienced high inflation from 2012 to 2017. Also, the weight coefficient is significant at the 1% confidence level. The slope coefficient, which is the most important coefficient produced positive value and achieved 10% significant level.Thus, when MIDAS slope parameter has a positive value, then the frequency of market volatility increases with increasing inflation. Therefore, the allocated weight for the first lags is 0.02083 hence 1% increase in inflation in time t-1 leads to 0.481% rise in volatility at time t+1 ($e^{0.02083*0.2304} - 1$). This low magnitude effect of inflation to volatility of long-term component is insignificant can be explained from the point of view that the country witness low inflation prior to the COVID 19 pandemic.

4.10.2 GARCH-MIDAS Exchange Rate Discussion

The lags are selected based on Bayesian Information Criteria and maximum log-likelihood. A three year MIDAS lag for exchange rate is the best fit for all countries using the model. The short-term parameter α and β add up to 1 and is statistically significant at 1% level for all countries. In South Africa, the unconditional mean is 0.0103, and it is significant at the 5% level. The weighting parameter w_1 is 1.00 which shows quick decaying weighting pattern of exchange rate. Conditional volatility in South Africa is 50.65% explained by the exchange rate. Compared to other countries, Johannesburg stock Exchange is highly impacted by volatility of the exchange rate. The coefficient θ is positive and significant at 10% level which suggest the depreciation of south African Rand against the US dollar accelerate the volatility of stock market. Thus, the incremental effect of exchange rate on the long-term component of GM model shows that 1% depreciation of South rand against the US dollar in past period result in 16.61% surge in the long-term volatility component of Johannesburg stock returns ($e^{0.0278*5.5269} - 1$). This is obtained by assigning weight of 0.0278 on the initial lags of the observation taking into consideration the estimated value of w_2. In addition, a deteriorating local currency would negatively affect the cash flow of importers and simultaneously reduce their buying power, which could explain the increasing volatility of stock market. Furthermore, investors may have changed their expectations regarding the market's return. Consequently, the market may become extremely volatile.

The situation is a bit different in Nigeria. The unconditional mean is -0.0395 at the 10% significant level. The weighting parameter is 253.56 and significant at 1%, and the alpha ($\alpha = 0.1562$) and beta ($\beta = 0.8017$) are significant at 1% and sum up to 0.9579, suggesting a sign of leverage effect. Moreover, the exchange rate contributes to 10.74% of total conditional volatility. The slope(θ) is negative and significant at 10% level. This revealed that exchange rate can reduce volatility, implying depreciation of Nigerian Naira against the US dollar result in deceleration of long-term component volatility hence 1% depreciation of Naira against the US dollar leads reduce volatility of long-term component by 19.05% ($e^{0.0278*5.5269} - 1$). By indicating a negative slope coefficient, the depreciating Nigerian Naira is causing stocks to be less attractive to investors, therefore decelerating volatility. Currency depreciation could be caused by high import patronage, as is common in Sub-Saharan Africa countries. When the exchange rate is low, exports may increase, which may speed up economic activity.

For Ghana, the unconditional mean is 0.0348 and achieve 10% significant level. The sum of α and β is 0.9773, which is close to 1, indicating well-known volatility clustering in the short-term. A significant decaying pattern is indicated by the weighting parameter being bigger than one. The long-run component's intercept has a negative value (m = -0.0102). Approximately 3.5% of conditional volatility is caused by the exchange rate. It is disappointing, however, that the exchange rate contributes so little to Ghana's stock market volatility since the nation has experienced instability of its local currency over the years. It has contributed to high uncertainty and higher prices, but it can also be said that the local currency had enjoyed relative stability in period 2010 and 2011. This may have account for the exchange rate's insignificant contribution to market volatility. The coefficient θ is positive for the exchange rate, significant at 10%, and indicative of a direct forecasting association with the Ghana cedi per dollar currency exchange rate and the returns, which means depreciation of the Ghana cedi in relation to the US dollar results in high volatility. Therefore, a 1% depreciation of Ghanaian cedis last month against the US dollar generates a 4.64% increase in volatility of stock market next month ($e^{0.03175*1.4278} - 1$).

4.10.3 GARCH-MIDAS Interest Rate Discussion

For South Africa, the parameter estimated for the short-term volatility component alpha and beta are 0.0377 and 0.9531, respectively, and both estimates are significant at the 1% level of confidence. The GARCH (1,1) process's alpha and beta values add up to 0.9908, which is proof that the process is mean-reverting. Returns are insignificant, with a mean of 0.00858. It has been determined that interest rates contribute 39.50% of volatility of stock market in South Africa. The coefficient θ indicating the directional effect of a variable in the model on the volatility of the long-run component is positive and significant at 10%. This suggests that interest rate increases can trigger high volatility of the long-run component. In specifications of magnitude of directional effect, a 1% rise in interest rate in the previous month would cause 28.34% acceleration in volatility on the Johannesburg stock exchange in the following month ($e^{0.03002*8.30780} - 1$).

As with Nigeria, the unconditional mean is negative and significant at 10%. In the short-term volatility component, which is denoted by ARCH and GARCH terms, 0.1661 and 0.7790 show significant results with a 1% confidence level. In contrast with the South Africa case, the interest rate accounts for a little over 2.94% of swings in the stock market in Nigeria. It was unexpected that interest rate, one of the factors influencing business expansion costs, contributed less to variation in market returns. In estimating the direction of interest rates relative to long-term components, the slope parameter is positive but insignificant, which indicates a direct linkage with interest rates and long-term volatility. Accordingly, the Nigerian stock exchange shows an insufficient relationship with interest rates. The computed value for marginal effect has validate the insignificant value of the θ hence a 1% movement in interest (T-bill rate) at time t-1 results in 1.78 increase in stock market volatility at time t+1 ($e^{0.040025*0.4406} - 1$). In light of the fact that Treasury bills are the opportunity cost of an investment in stocks and venture capital funds, so this is expected to be the case.

For Ghana, the mean return (0.02969) is significant at 10%. The combined value of ARCH and GARCH terms is closer to one and achieves significance at 1% level, demonstrating volatility clustering, a well-known characteristic of high frequency series. According to the observation, interest drove conditional volatility by 31.8%. This is expected due to high interest rates witness in the country over the years which makes the cost of running a business high. Whereas the weight parameter (w_2) is one and at 1% significant level. Interestingly, the most relevant parameter θ is negative and significant at 10%. In this case, the slope value being negative, mean the high interest rate (T-bill rate) leads to low volatility. Considering the magnitude of direction, the Treasury bill rate shows negative, revealing a 1% increment in the T-bill rate in the preceding period brings about a 4.65% deceleration in stock market volatility in the subsequent period ($e^{1.71406*0.4406} - 1$). Stock market volatility is insignificantly affected by interest rates stems from the fact that high interest rates on government bonds discourage investment in capital assets. This is Because investors may choose assets with low risks to channel their surplus funds. Higher T-bill rate does limit investment in stocks hence the activities in exchange rate deteriorate.

4.10.4 GARCH-MIDAS Oil Price Discussion

According to the empirical results for South Africa, the estimated coefficient for mean returns is 0.00752, although empirically insignificant. The weighting parameter is 1.5 and at 10% significant level. Observations on the proportion of contribution of oil price to conditional volatility have shown that oil prices account for 36.89% of variation on Johannesburg Stock Exchange. The estimated parameter θ that describes how oil price influences the MIDAS component of South African stock returns is negative and significant at 10%, signifying an inverse relationship between oil price and stock volatility. For marginal effects expressed in percentage terms, if oil price rises by 1% at time t-1, stock market will decrease by 1.011% at time t+1 due to the increase in oil ($e^{0.24032*0.0423} - 1$). Nevertheless, price of oil plays a large part in determining overall volatility of equity returns, accounting for 36.89% of total volatility.

In Nigeria, the oil price drives inflation by 20% as calculated by the variance ratio. This is anticipated because the oil price dictates the pace of economic activities in the country. The coefficient w_2 is high and significant at 1% level thus implying fast decaying pattern of weighting scheme. The oil price estimated parameter for θ produced a 1% significant level with negative value. It seems that high oil prices tend to curtail volatility in the market, especially when it comes to the long-term volatility component. The outcome is surprising since a 1% increase in price of oil during the past period resulted in a 0.453% downward movement in long-term component volatility in the following period ($e^{0.0641*0.07051} - 1$). On the other hand, the computation of variance ratio shows that oil price is responsible for 20% of total conditional volatility in the Nigerian stock exchange.

In the case of Ghana, the ARCH and GARCH terms for the short-term element are significant at 1%. The weight coefficient w_2 is 1.77 and at a 1% significant level. The long-term constant term is negative but significant at 1% level. Moreover, the oil price has positive and 5% significant outcome for MIDAS slope coefficient θ. The marginal effect of positive coefficient reported a 1% hike in oil price at t-1 would raise long-term component volatility by 40% in time t+1 ($e^{0.3633*0.0492} - 1$). Consequently, the variance ratio reported that oil price accounts for 24.78% to total conditional volatility in the market. Long term volatility is positively affected by the oil price since it is the main series that determines the price of goods and services. Furthermore, the country relied heavily on non-renewable and non-diversify energy sources.

4.10.5 GARCH-MIDAS Money Supply(M2) Discussion

In estimating the GARCH-MIDAS coefficient for South Africa, it was observed that the unconditional mean was insignificant. The short-term coefficients (ARCH and GARCH terms) α and β sum up to 0.9922 and are significant at 1%, demonstrating evidence of high volatility in the short-term component of FTSE/ALL index stock returns. As shown in Table 4.9, the weighting parameter w_2 is greater than one at 1% significance level, suggesting immediate observations are more significant. It is interesting to note that the money supply makes an insignificant contribution of 0.22% to the total conditional volatility. The slope θ of the long-term component is positive but not significant.

It is imperative to note that the Nigerian instance presents a negative value that is insignificant. For both the ARCH term and the GARCH term, there are no significant parameters. The intercept of the long-run component is 0.8639 but are insignificant. However, money supply account for 7.02% to total conditional volatility. The MIDAS slope coefficient θ is negative but insignificant. All the estimated parameters show money supply do not have significant impact of both short-run and long-run component volatility of stock market.

For Ghana, the unconditional mean is positive and significant at 10% level. The short-term parameters α and β are significant at 10% and 1% level respectively. The weight is 1.05 and significant at 1% level showing it considered the most recent observations in the estimation. It also revealed that quantity of money in circulation contribute 42.8% to total conditional variance in the stock market. The Money supply estimate for theta is negative and insignificant. In addition to stimulating economic growth, a negative theta is expected to lead to a deceleration in volatility, and thereby a decrease in risk.

Table 4.9: Parameter Estimate for GARCH-MIDAS Model for the Three Countries

SA	μ	α	β	M	θ	W2	VR	LLF	BIC
EXR	0.00859	0.03585***	0.9574***	0.10676	5.52692*	1.00*	50.647	-3115.8	6283.593
	(0.03147)	(0.00857)	(0.01108)	(0.33803)	(3.02656)	(0.5752)			
IN	0.0103**	0.0354**	0.958**	-3.2854	6.9165	1.2267*	49.46	-3119.3	6276.62
	(0.0307)	(0.0074)	(0.0091)	(1.3518)	(2.4774)	(0.1633)			
IR	0.0086	0.0378***	0.9531***	0.4928**	8.3078**	1.0808***	39.5	-3119.4	6283.69
	(0.0309)	(0.009)	(0.0117)	(0.1743)	(4.1317)	(0.2768)			
OP	0.0075	0.0402***	0.9497***	0.4748***	-0.2403*	1.5181***	36.89	-3120.5	6285.93
	(0.0312)	(0.0101)	(0.0134)	(0.1748)	(0.1669)	(0.3306)			
MS	0.0084	0.0369***	0.9554***	0.3513	61.044	2.4503***	0.22	-3122.1	6289.16
	(0.0316)	(0.0094)	(0.0137)	(0.5906)	(0.8811)	(0.3378)			

NIG	μ	α	β	M	θ	W2	VR	LLF	BIC
IN	-0.033*	0.166**	0.78***	0.06	0.102	1.014	1.34	-2445	4935.04
	(0.217)	(0.0582)	(0.0836)	(0.4369)	(0.0034)	(1.7474)			
EXR	-0.0395*	0.1562***	0.8017***	0.3148	-0.0300*	253.56***	10.75	-2438.8	4922.54
	(0.0234)	(0.044)	(0.0573)	(0.3103)	(0.0174)	(36.23)			
IR	-0.0354*	0.1661***	0.779***	0.2349	0.4406	1.4409***	2.94	-2444.5	4933.94
	(0.0219)	(0.0582)	(0.0837)	(0.2562)	(0.5059)	(0.3367)			
OP	-0.0418**	0.1741***	0.7626***	0.1419	0.0641**	253.86***	20.77	-2428.8	4902.61
	(0.0212)	(0.0549)	(0.0833)	(0.2305)	(0.0221)	(74.4028)			
MS	-0.00334	0.1832	0.7519	0.8639	-152.12	1.00	7.03	-2442	4928.87
	(0.0742)	(0.3336)	(0.7908)	(1.1453)	(452.23)	(9.7467)			

GH	μ	α	β	M	θ	W2	VR	LLF	BIC
IN	0.004513	0.1539*	0.8306***	0.4390	0.2304*	1.00	67.68	-1339	2722
	(0.0334)	(0.0903)	(0.1004)	(0.786)	(0.8116)	(6.0352)			
EXR	0.0348*	0.1591***	0.8281***	-0.0102	1.4278*	114.32	3.59	-1529	3102
	(0.023)	(0.0514)	(0.0629)	(0.7744)	(1.045)	(255.8)			
IR	0.02969*	0.1968*	0.7805***	0.00728*	-1.7141*	1.0001***	31.8	-1527	3099
	(0.0207)	(0.1088)	(0.1292)	(0.8215)	(1.0594)	(0.3236)			
OP	0.0155***	0.5159**	0.7485**	-1.0298	36.33**	1.7717	24.78	-1313	2672
	(0.0124)	(0.0392)	(0.0704)	(0.1526)	(15.678)	(0.3758)			
MS	0.0315*	0.1396*	0.8455***	5.711	-71.59	1.0574***	42.8	-1519	3082
	(0.0203)	(0.104)	(0.1224)	(5.079)	(57.29)	(0.2614)			

Note: the asterisks represent significance level of ***1%, **5% and *10% level. Values in the bracket represent Bollerslev-Wooldridge standard errors. Where the value with the asterisks is the estimated coefficient of short-run and long-run components of GARCH-MIDAS model.

4.11 LASSO Results Discussion

A ten-fold Cross-validation procedure is conducted to come up with the optimum lambda. In the initial stage of parameter estimation, the lambda with the least forecast error is chosen by Cross-validation. According to the Table 4.12, LASSO estimates the coefficient of the most relevant exogenous variables included in the regression and runs the coefficient of insignificant macroeconomic factors to zero.

Specifically for South Africa, currency exchange rate, interest rate, oil price and supply of money are the utmost important indicators that explained stock returns, whereas inflation does not have a significant impact. Therefore, the LASSO algorithm shrinks these insignificant parameters to Zero based on the optimal lambda of 0.174, which produces the lowest RMSE. As the exchange rate coefficient is negative (-1.450), a depreciation of the South Rand in relation the US dollar does not result in a favourable stock return on the Johannesburg Stock Exchange. It might be that, depreciation of local currency is associated with higher input costs, which can adversely affect forecasting stock market returns. According to lasso algorithm, one of the variables influencing equity returns is money supply, which has a negative coefficient, which means that expansionary monetary policy erodes equity returns. Additionally, the estimated coefficient between oil price and stock return stands at 0.558, indicating that stock returns directly respond to oil price increases. LASSO algorithm produces a coefficient of money supply of -0.429, which explains the inverse relationship between money supply and stock returns, meaning expansionary monetary policy reduces.

For Nigeria, the LASSO selected oil price and supply of money as the substantial relevant factors in determining stock returns. while inflation, currency exchange rate, and interest rate are considered less important in predicting stock returns and are therefore excluded from the results by the algorithm. These variables are therefore excluded by turning their coefficients to zero in the LASSO model. A shrinkage parameter (lambda) of 0.644 is chosen after cross validation to determine the one with the lowest RMSE. Meanwhile, the Nigerian stock market reacts positively and strongly to the oil price (Table 4.10) as a result of the LASSO algorithm producing a high and positive coefficient for oil price (1.031). This posits that rising oil prices boost the acceleration of stock returns. Fig. 4.5 exhibits the macroeconomic variables that have higher performance among the candidate macroeconomic variables employed in the study.

As a result of cross validation, the LASSO algorithm selects 0.4 as the optimum lambda for Ghana. Among the variables explaining stock returns were exchange rate (Ghana cedis per US dollar), interest rate, and oil price, whereas inflation and money supply had less influence. This result can be explained by the low inflation experienced in the country during the sample period, which may have contributed to the insignificant or nil contribution of inflation to stock returns. Figure 4.4 shows the hierarchical importance of variables on stock returns. The outcome suggests a depreciation of Ghanaian cedis against the US dollar will increase stock returns. In contrast, the coefficient of interest rate is negative, indicating that the rising level of interest rate (Treasury bill) leads to a reduction in market returns because an increasing rate of interest makes the stock less attractive to investors.

Table 4.12: Results of LASSO Estimates

South Africa		Nigeria		Ghana	
Indicators	Coefficients	Indicators	Coefficients	Indicators	coefficients
Intercept	0.061	Intercept	0.214	Intercept	0.904
INF	——	INF	——-	INF	——
EXR	-1.450	EXR	——-	EXR	0.142
IR	0.198	IR	——-	IR	-0.095
OP	0.558	OP	1.031	OP	0.375
MS	-0.429	MS	0.045	MS	——-
Lambda	0.174	Lambda	0.644	Lambda	0.4

Source: Author's construct

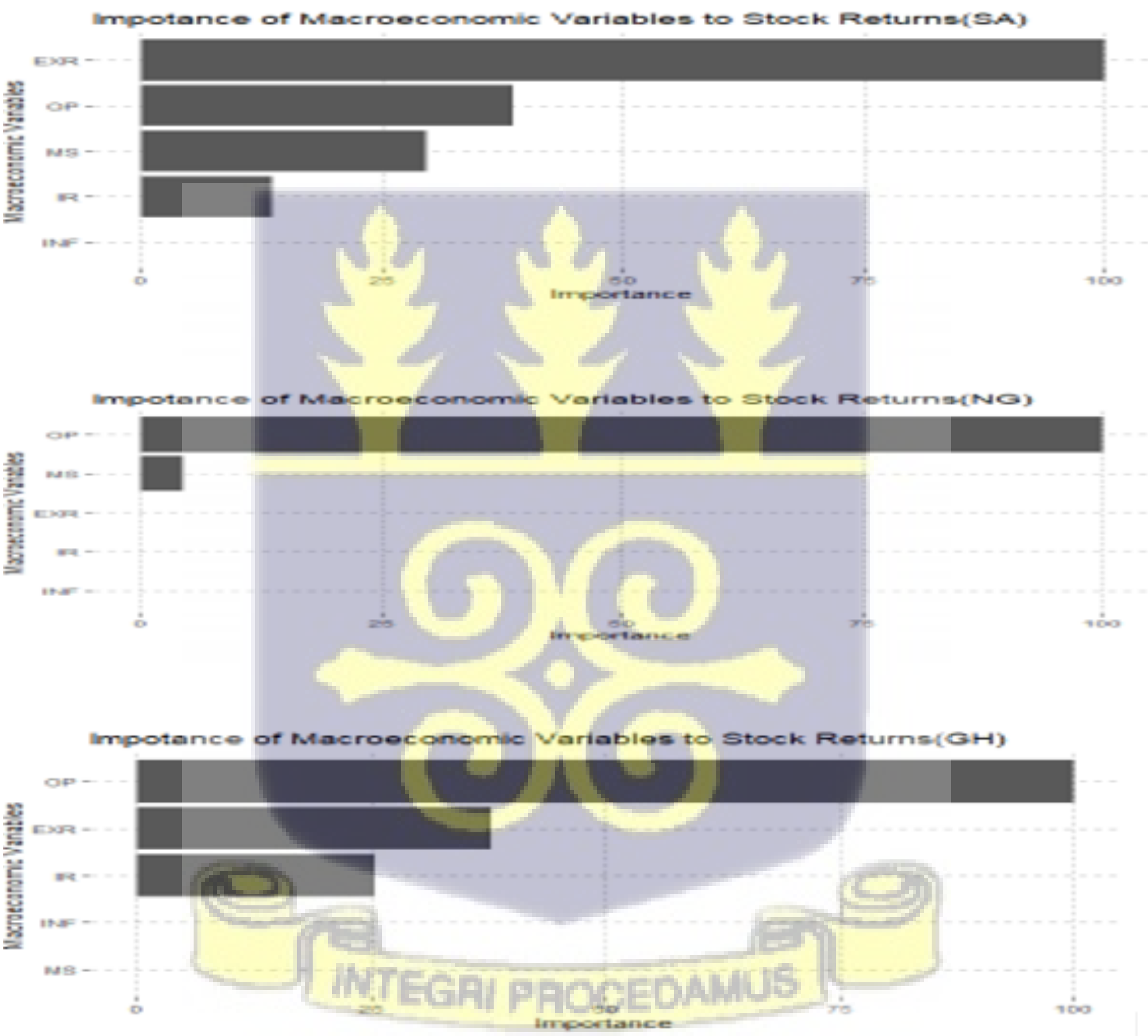

Figure 4.5: Result of Relevant Macroeconomic Variables for LASSO

Source: Author's construct from the LASSO results

4.12 Ridge Regression Results Discussion

From the parameter estimate, it can be observed that the ridge regression estimates the regression coefficients of all indicators included in the model. The ridge estimate does not reduce any of the coefficients to zero, but it does reduce the impact of an unimportant macroeconomic variable in the model. For South Africa, the optimal lambda for the ridge algorithm is 1.417, and among the candidate variables, the coefficient of inflation is the least and most insignificant (Table 4.11).

Table 4.13: Results for Ridge Regression

South Africa		Nigeria		Ghana	
Indicators	Coefficients	Indicators	Coefficients	Indicators	coefficients
Intercept	0.061	Intercept	0.214	Intercept	0.904
INF	0.045	INF	0.149	INF	-0.097
EXR	-1.279	EXR	-0.149	EXR	0.209
IR	0.299	IR	-0.254	IR	-.0.199
OP	0.623	OP	0.962	OP	0.277
MS	-0.487	MS	0.370	MS	-0.117
Lambda	1.417	Lambda	4.100	Lambda	7.94

Source: Author's construct

4.13 Out-of-sample Evaluation Result (GARCH Type)

The out-of-sample assessment of a model is one of the important areas in predictive modelling since the users are concerned about the ability of the model to accurately forecast future market volatility. This section explores the evaluation of the univariate GARCH as the benchmark and the bivariate GARCH-MIDAS model. It presupposes that incorporating macroeconomic conditions will have any significant impact on the model's performance. Table 4.12, reports the comparative performance of six different statistical loss functions. The assessment measures the extent of variation between forecasted and actual volatility (proxied as realized variance). Since volatility is hard to observe in empirical setting, we used realised volatility as a substitute for observed volatility. The lower value indicates a lower variation between the actual value and forecasted volatility. Thus, the model that produced the lower statistical loss function has better predictive performance. The result of the evaluation shows the model of GARCH-MIDAS produces improve predictive performance compared to the GARCH model. Models with exogenous variables result in lower loss functions than the benchmark GARCH model. All the loss functions used provide a smaller minimum error for GARCH-MIDAS than the GARCH. The GARCH-MIDAS better predicts the realized volatility for all variables than the traditional GARCH framework. However, the results of this study are in agreement with those obtained by Conrad and Loch (2015) and Engle et al. (2013).

Table 4.14: Results of Out-of-sample Forecast Loss Function for GARCH Type Models

LOSS FUNCTIONS	GARCH	GM-INF	GM-EXR	GM-IR	GM-MS	GM-OP
South Africa						
MSE	174.96	170.16	169.97	168.87	168.85	168.85
MAE	4.32	3.94	3.96	3.98	3.99	3.98
RMSE	13.22	13.04	13.03	12.95	12.99	12.99
RMAE	2.07	1.98	1.98	1.98	1.99	1.99
HMSE	168.33	146.86	144.34	104.5	105.5	104.37
HMAE	3.9	3.54	3.44	2.97	2.95	2.96
Nigeria						
MSE	632.02	629.35	630.2	629.35	629.18	630.09
MAE	3.56	3.26	3.05	2.88	3.3	3.07
RMSE	25.64	25.09	25.1	25.12	25.08	25.1
RMAE	1.89	1.81	1.74	1.7	1.82	1.75
HMSE	635.18	314.55	519.38	932.9	287.67	490.01
HMAE	3.03	2.24	2.77	2.71	2.31	3.5
Ghana						
MSE	19.57	9.13	9.14	9.15	9.13	9.45
MAE	3.95	1.32	1.41	1.44	1.35	0.97
RMSE	4.42	3.02	3.02	3.02	3.02	3.07
RMAE	1.20	1.45	1.19	1.20	1.16	0.99
HMSE	85.17	11.05	8.47	7.82	1.13	9.99
HMAE	2.92	1.47	1.37	1.35	0.97	1.42

Source: Author's construct

4.14 Out-sample Evaluation of Shrinkage Algorithm

This section evaluates the out-of-sample forecasting measurement of LASSO and ridge regression for the three countries. In the estimation of the model coefficients, the period 2010-2019 is used as the in-sample period. A forecast of the stock return for the testing period 2020-2021 is then made using the estimated coefficients, and forecast performance assessment of the model was determined by calculating the MSE, RMSE, MAE and RMAE.

According to the results of this study, in relations of macroeconomic variables and stock returns for South Africa, the LASSO prediction produces the least MSE, RMSE, MAE, and RMAE than the ridge regression. According to this analysis, the loss function produced by LASSO algorithm has the least value. One impressive finding is that LASSO consistently produces the lowest loss function. Furthermore, the ridge is the one that delivers the highest value of the loss function. Thus, LASSO achieves a higher predictive power than ridge regression (Table 4.13). This further proof, demonstrates how effective LASSO is at predicting stock returns.

The empirical result in Nigeria is not different. LASSO is the appropriate forecasting tool for stock returns. The LASSO model has the lowest MSE, RMSE, MAE, and RMAE values, indicating that the LASSO results based on the loss functions used have better predictive performance than the Ridge regression model. An intriguing phenomenon has been observed for Ghana data, where both LASSO and ridge produce results for the loss function that are practically identical. The finding is that the out-of-sample loss for mean square error is 32.52 and 33 for LASSO and Ridge regression, respectively. This means that virtually the same MSE results were obtained for the two techniques.

Table 4.15: Loss Functions for LASSO and Ridge Regression

LOSS FUNCTIONS		MSE	RMSE	MAE	RMAE
South Africa					
	LASSO	61.26	7.82	3.72	1.93
	RIDGE	64	8.00	3.88	1.96
Nigeria					
	LASSO	58.25	7.63	4.99	2.23
	RIDGE	131.62	11.47	3.54	1.88
Ghana					
	LASSO	32.52	5.7	2.78	1.67
	RIDGE	33	5.74	2.82	1.68

Source: Author's construct

CHAPTER 5

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter provide an abridge version of the research, conclusion and recommendations based on the outcome of findings in this research.

5.2 Summary

In this thesis, GARCH-MIDAS regression, LASSO, and Ridge machine learning algorithms were used to examine how macroeconomic variables affect stock market performance. Three Sub-Saharan African countries were chosen based on data accessibility and the level of capital market development. A model based on five macroeconomic indicators, including oil price, exchange rate, interest rate, inflation, and money supply, as predictor variables and stock index returns as response variable. The Univariate GARCH-MIDAS combines high-frequency stock index returns with low-frequency macroeconomic series, while LASSO performs variable selection and ridge regression shrinks a less important variable's coefficient towards zero.

The outcomes of the GARCH-MIDAS model reveal the following: Inflation, exchange rate, interest rate, and money supply have a direct impact on stock return volatility, meaning a surge in these variables is accompanied by increased volatility on the Johannesburg stock exchange in the long-run component. While the price of oil has a negative effect on volatility. In terms of contribution to total volatility computed via the variance ratio, inflation, exchange rate, interest rate, and supply of money provide contributions of 49.46%, 50.64%, and 39.50%, respectively, to total volatility in South Africa.

In Nigeria, inflation and interest rates are positive but statistically insignificant effect on stock return volatility, while money supply and oil price have a negative effect on equity market volatility. This implies that increases in these variables lead to a deceleration in stock return volatility. At the same time, inflation and interest rates contribute a little bit of 1.3% and 2.94%, respectively to total volatility. However, oil prices account for 20.77% of total volatility, exchange rates account for 10.75%, and money supply accounts for 7.03%.

In Ghana, inflation, the currency exchange rate, and the oil price have a direct relationship with volatility of the stock market. On the other hand, interest rates and money supply reveal opposite relationships. Turning to the variance of respective variables, inflation contributes 67.68% to total volatility, exchange rate influences volatility by 3.59%, oil price drives volatility by 24.78%, interest rate contributes 31.8%, and money supply accounts for 42.8% of total conditional volatility.

Moreover, the findings from the machine learning algorithm are summarized as follows: Firstly, the most suitable fit lambda was chosen based on ten-fold cross validation for the LASSO and Ridge algorithms for all three markets sampled for the study. Five macroeconomic series were regressed on stock market returns for each market. The LASSO found the exchange rate, interest rate, price of crude oil, and supply of money to be statistically significant in explaining the returns of South African stock market. In contrast, interest contributes less to market returns.

In the case of Nigeria, two variables, price of crude oil and money supply, were chosen as the best predictor variables because they were the most effective and statistically significant for determining stock among the candidate variables. Meanwhile, the inflation, exchange rate, and interest rate have insignificant contributions to stock return, hence their coefficients have run to zero.

In Ghana, the LASSO picks currency exchange rate, interest rate, and supply of money as the best regressors among the five macroeconomic variables employed. However, inflation and the money supply had an insignificant contribution to returns.

The out-of-sample analysis that is performed on the hold-out sample shows GARCH-MIDAS has better predictive performance than the GARCH model. By incorporating macroeconomic variables into the model, it yields better results. Second, when comparing the results of the two competing machine learning models, the LASSO algorithm outperforms the Ridge algorithm.

5.3 Conclusion

There is some evidence that the macroeconomic environment has some impact on business performance in Sub-Saharan Africa (Ghana, Nigeria, and South Africa). The object of this thesis is to diagnose the influence of macroeconomic conditions on stock market volatility in the three markets in Africa. To meet these objectives, the research carried out an in-depth analysis of five economic variables, including inflation, currency exchange rate, interest rate, oil price, and money supply. Two GARCH models and regularization regression were used to perform the analysis, with varying results due to the models' varying behavior patterns. According to the results, the GARCH-MIDAS models tend to outperform the simple GARCH model. The crude oil price is found to have a significant impact on stock returns in all three countries, and its impact is stronger than that of other macroeconomic variables. The plausible reason would be the high dependence of African countries on crude oil importation, despite the fact that most of these countries are oil producing economies. The outcome of the research provides some insightful perspective on the extent to which macroeconomic policies exert favorable or adverse impacts on activity in the equity market.

The thesis also explored machine learning algorithms such as LASSO and ridge regression to select the best economic factors as predictors of stock returns and perform forecasting performance tests using MSE, RMSE, MAE, and RMAE loss functions. This study concludes that the most important predictors of South African equity returns are the oil price, exchange rate, interest rate, and money supply. Similarly, foreign exchange rate, oil price and interest rate are identified as the utmost useful explanatory variables for stock return on the Ghanaian stock exchange for the sampled period. Therefore, it provides valuable insight for market participants to hedge against the risks of their investments.

The current turbulent economic environment emanating from COVID 19 pandemic and instability around the world has necessitated the relevant of a better comprehension of the relationship between macroeconomic factors and stock market volatility. A clear understanding of how volatility in the stock market reacts to dynamic conditions in the macroeconomic environment is an ingrained prerequisite for policy formulation.

5.4 Recommendations

Sub-Saharan Africa policy makers need to focus on the real sectors of the economy in order to regain macroeconomic stability, as oil price, especially international price of crude oil, and foreign exchange rate are the main factors destabilizing these economies that have a source of shocks to the business environment. To serve their economies from destabilizing shocks emanating from surging crude oil price, they should also invest in cheaper and alternative energy sources or improve their ability to refine their own crude. Stabilizing their currencies requires economic and structural reforms as well as reducing reliance on foreign goods. A vigorous policy of controlling the surging demand for foreign products should be pursued across the region. Moreover, deteriorating macroeconomic conditions are unlikely to inspire investment. To attract more investment into their stock exchange, national policy makers should put in place measures to manage macroeconomic variables that adversely affect the volatility of the capital market. As a prerequisite for actualizing economic evolution in Africa, the stock exchange's activity is essential.

5.5 Suggestions for Further Research

In terms of methodology, the research utilized GARCH-MIDAS, LASSO, and Ridge regression models. In the Univariate GARCH-MIDAS, one variable can be considered at a time. In order to provide a comprehensive explanation, all explanatory variables must be considered at once with the slope coefficient of each candidate variable estimated in the model. Also, A study of the DCC-MIDAS could provide an insight into the dynamic correlation between macroeconomic variables and asset returns. Furthermore, researchers could also consider applying logistic LASSO algorithm as another machine learning framework to estimate the relationship between macroeconomic factors and equity returns.

Secondly, in this era of data abundance environments, it would be appropriate to assess the predictive ability of technical indicators (market capitalization, trading volume, dividends pay-out ratio and number of foreign listings etc.) by combining them with macroeconomic variables. The incorporation of these variables could provide further information for forecasting stock returns. Despite the fact data availability is a major issue in Africa, but it is imperative that further research explores the influence of other macroeconomic variables such as industrial production indexes, unemployment rates, producer price indexes, and exports on stock returns and volatility.

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APPENDIX

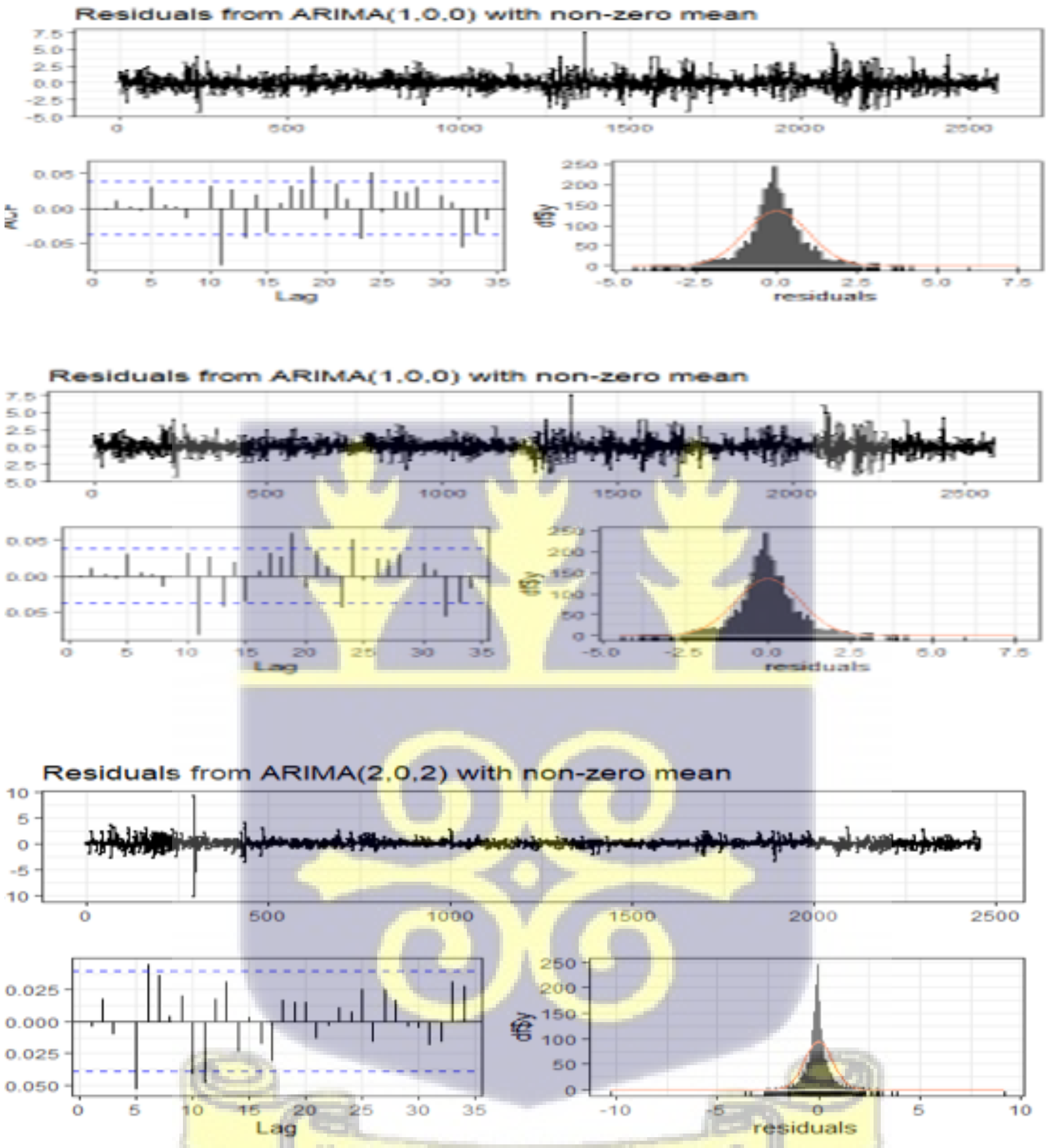

Figure 5.1: Diagram of Best fitted ARMA model for each country

Source: Author's Construct using R

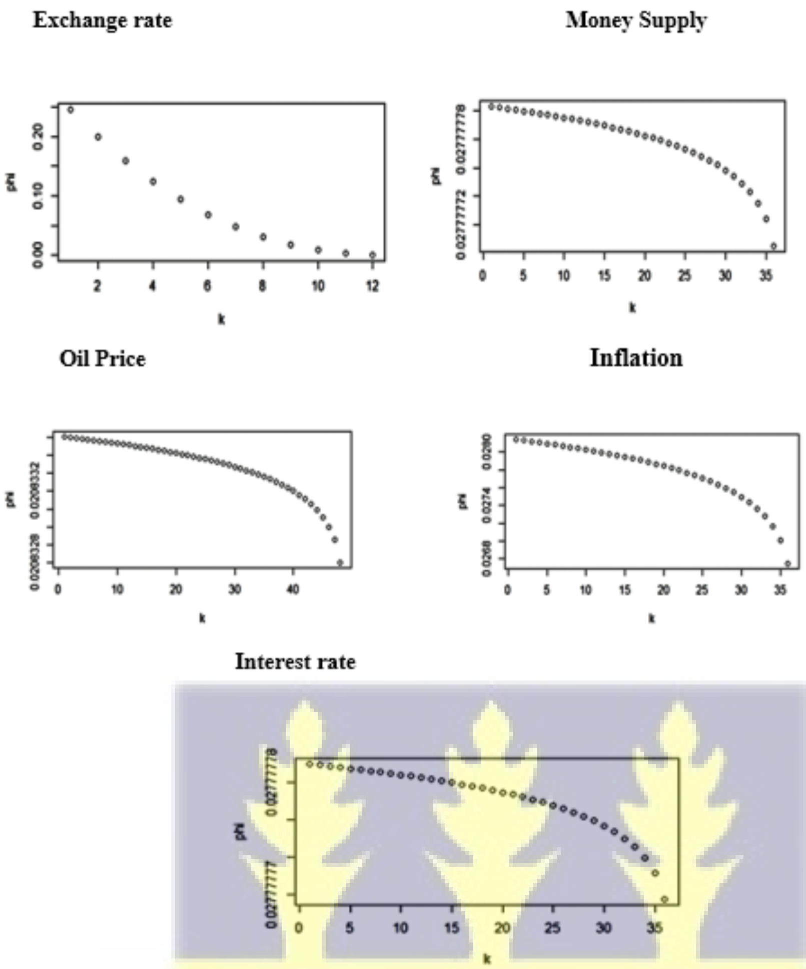

Figure 5.2: Visualization of weighting scheme for Appropriate lags length Ghana

Source: Author's Construct using R

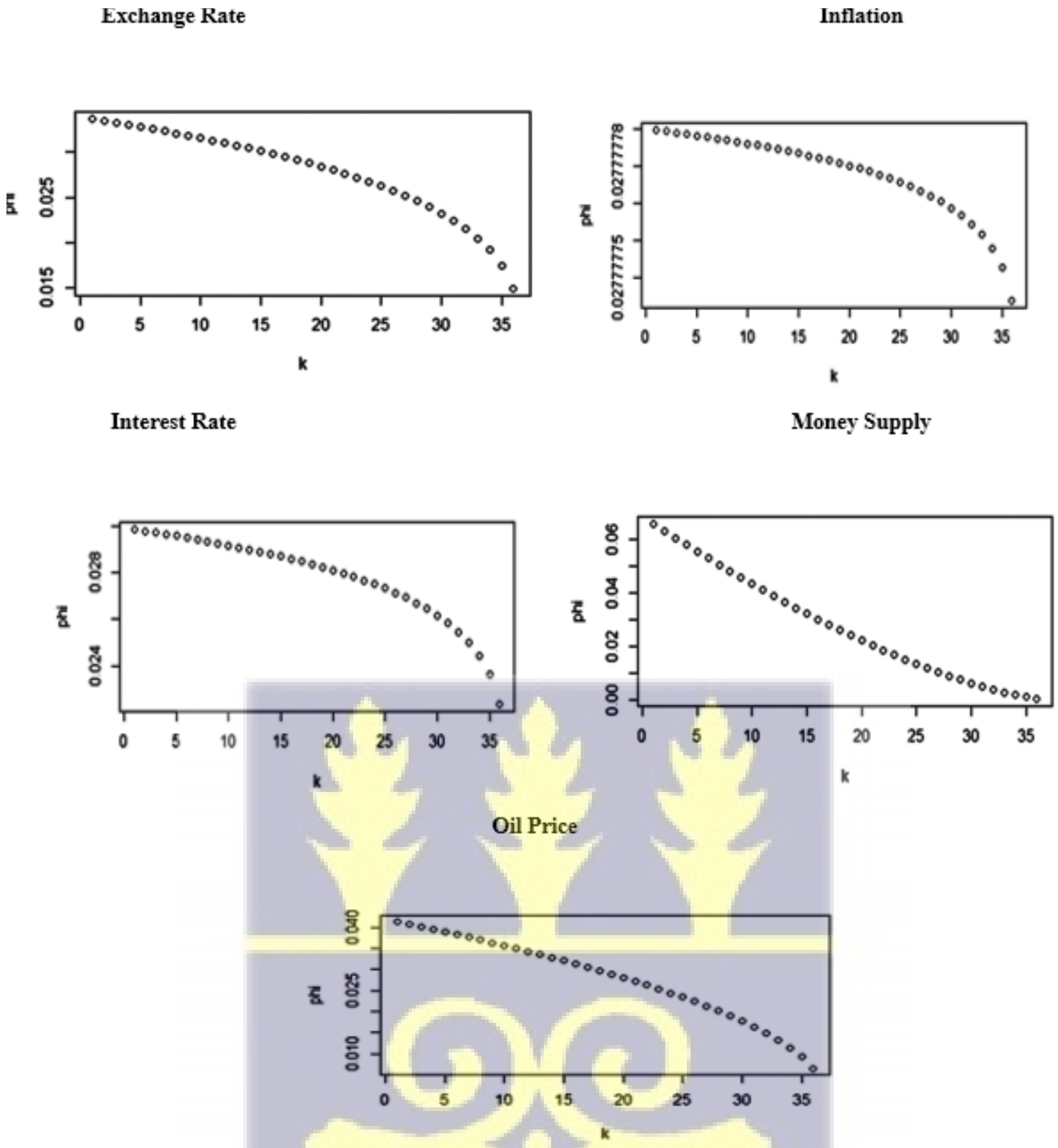

Figure 5.3: Visualization of weighting scheme for Appropriate lags length South Africa

Source: Author's Construct using R

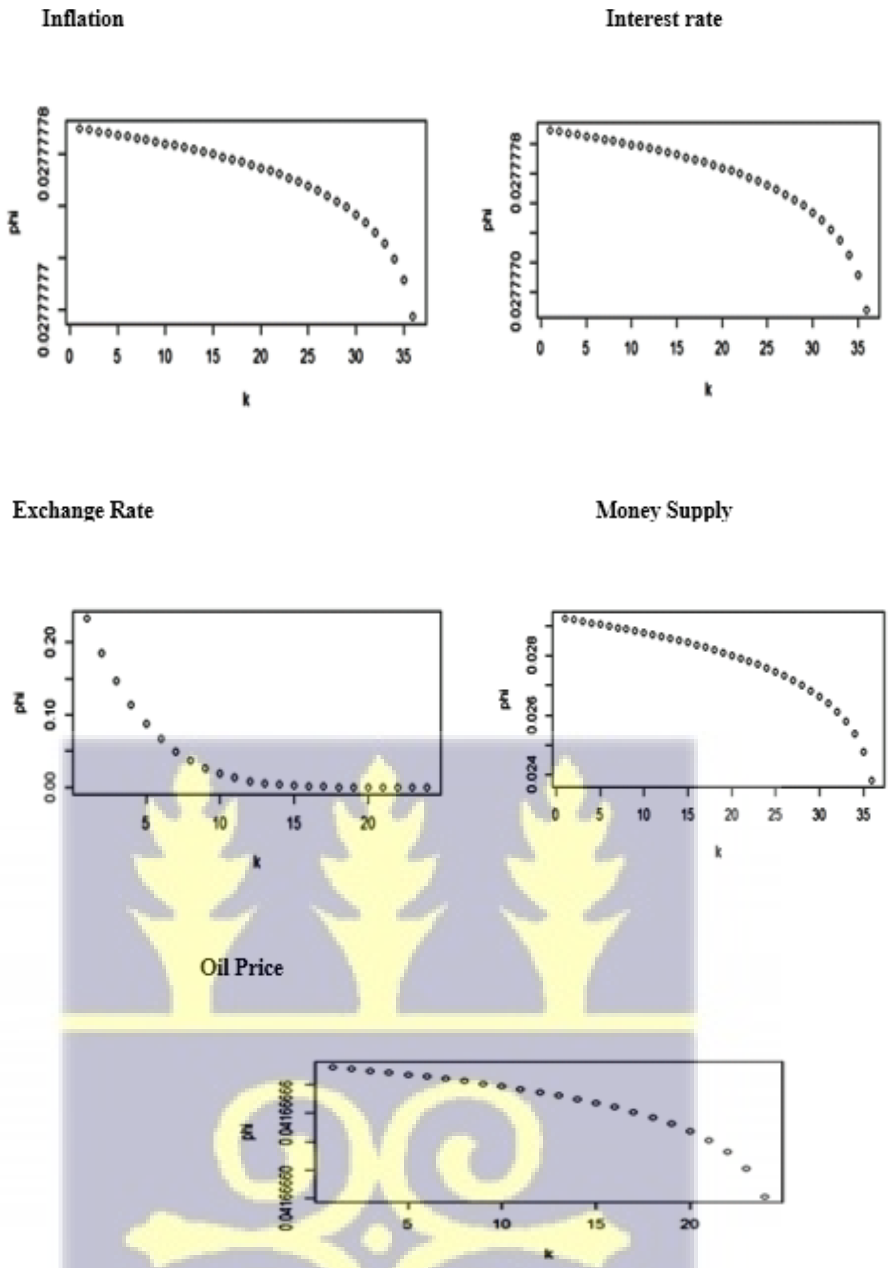

Figure 5.4: Visualization of weighting scheme for Appropriate lags length Nigeria

Source: Author's Construct using R