International Journal of Scientific Research in Mathematical and Statistical Sciences **Research Paper**
Volume-9, Issue-3, pp.43-60, June (2022) **E-ISSN:** 2348-4519

Application of GARCH Model for Accuracy Measures of Some Components of the Nigeria Economy

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Available online at: www.isroset.org

Received: 01/May/2022, Accepted: 05/Jun/2022, Online: 30/Jun/2022

***Abstract*—**The use of the GARCH model for accuracy measures of some components of the Nigerian economy was investigated in this study. Its goal was to create a GARCH model that could be used to forecast the Nigerian economy. The statistical database website of the Central Bank of Nigeria (CBN) was used to gather data for this study (www.cbn.gov.ng). Monthly capital formation, gross domestic product, labor force, savings accumulation, and capital market are among the variables from (2001-2021). The parameters that make up the GARCH model and the model selection criteria were obtained using the Gretl 19c and Minitab 16 programs (AIC, BIC, LHC, HQC, R^2, R^2-Adjusted, SSE and MSE). The GARCH model with the biggest effects on the Nigerian economy based on actual data is GARCH(1,1) from savings accumulations (SA), because all of its parameters are significant at 5% and 10%, and all of its model selection criteria are smaller and better than the other four GARCH models. This means that the impact of savings accumulations on the Nigerian economy is greater than the impact of other components. It was suggested that policymakers, investors, financial analysts, and economists investigate appropriate measures to improve saving accumulation stability because it has a greater impact on the Nigerian economy than other aspects considered in this study.

***Keywords*—** Accuracy Measures; Nigeria Economy; GARCH Model; Heteroscedasticity; Time Series Analysis

I. INTRODUCTION

In just was the last decade there has been several proposals about how precisely precisely to model heteroscedasticity. Among the most successful models are the car- regressive conditional heteroscedasticity(ARCH) family model established by]2] and the stochastic difference(SV) model pioneered by Taylor swift. Matching to [2], a fruitful movements model incorporates the stylized specifics inherent in stock return series such as volatility clustering, asymmetry, and autoregressive conditional heteroscadasticity(ARCH) effects. This can be one of the motives why we model variation for financial series data and foresee a large amount of movements. As a natural model collection requirement for volatility models, recreating out of sample forecasting potential has grown to be important.

A time series is something that is observed progressively across time. Only time series observed at regular periods of time will be considered in this study (i.e., monthly and yearly). Irregularly spaced time series are also possible, although they are outside the focus of this study. Time series data forecasting is going to predict that the sequence from observations will continue as time goes on.

The stock market has also recently become one of the most well-known investments due to its greater returns. Given that the exchange market has an effect on people's personal and professional life, as well as the economy of a nation, it has grown to be a significant component of the global economy. Because its prices reveal investors' assessments and expectations based on available evidence, Nigerian stock market forecasting is more well-known for its failures than for its achievements. For anybody looking to participate in the dynamic global economy, accuracy in forecasting stock market values or correctly detecting trends is essential. For a very long time, economists and financial experts have maintained that the best and most accurate method to show a commodity's actual scarcity is through its unrestricted market price or value. The performance of the Nigerian stock market (NSM) can be easily assessed using stock market indexes or returns. Stock market returns can be predicted using a range of financial and macroeconomic data, which has piqued the interest of equity investors. The use of a stock market index to measure a sector of the stock market has gotten a lot of press recently. The success of an investor's or fund manager's portfolio may be compared to a benchmark in large part thanks to the investing public [3].

Investors and financial managers use the stock market index as a tool to describe the market and contrast the return on various investments. A stock index is a statistic used to assess the value of a certain area of the stock market. A market index evaluates the performance of a collection of businesses deemed to be representative of a certain market sector in the Nigerian economy.

The Generalized Autoregressive Conditionally Heteroscedastic model, or GARCH model, was created in 1986 by doctoral candidate Tim Bollerslev. The goal of GARCH is to provide volatility metrics for heteoscedastic time series data, which are conceptually analogous to standard deviations in simpler models. The most fundamental GARCH model is the ARCH(1) model, and both models have many features in common. The more complex AR(p) models are known as ARCH(p) models. Finally, Generalized ARCH models describe conditional variances in a manner similar to how ARMA models handle conditional expectation.

Time series data can be analyzed using GARCH models in a variety of ways in the fields of finance and economics. When there are times of rapid change, they are especially useful (or volatility). For instance, they can precisely predict the volatility of financial assets like stocks, bonds, and market indices [4]. The usefulness of a GARCH model is not just limited to financial applications. A GARCH model was employed by [5] in their comparative study of various time series forecasting techniques to predict the number of patients in hospitals.

Simon Kuznets, an economist at the National Bureau of Economic Research, first suggested the concept of gross domestic product (GDP) in a report to the US Congress in response to the Great Depression in 1937. The most popular system of measurement at the time was GNP. After the Bretton Woods conference in 1944, GDP was widely adopted as the primary indicator of national economies, but oddly, the United States continued to use GNP as its official indicator of economic prosperity until 1991, when it switched to GDP.

But starting in the 1950s, a number of economists and decision-makers started to question GDP. Despite the fact that it ignores factors like health, happiness, (in)equity, and other aspects of public welfare, some people have noticed a tendency to embrace GDP as an absolute indicator of a country's failure or success. Or to put it another way, these opponents drew a line between social and economic progress.

One of the most popular metrics for evaluating a nation's economic health is its Gross Domestic Product (GDP). It can also be used to determine a person's standard of living in a specific economy. The market value of all officially acknowledged final goods and services produced within a nation during a given time period is what is known as the gross domestic product, on the other hand. In other words, the market value of each good or service is taken into account when calculating the gross domestic product rather than just adding up the quantities. Since it is used to assess whether a nation's economy is expanding more quickly or more slowly, the Gross Domestic Product (GDP) is essential to an economy. The size of various economies around the world is also compared using this method. Once more, the relative growth rates of nations around the world are compared using the Gross Domestic Product (GDP). For instance, the American Federal Reserve uses it as one of the indicators to decide whether the economy needs to be stimulated or controlled. The components of Gross Domestic Product determined by the expenditure method are consumption, investment, government spending, gross export, and gross import. GDP equals C + I + G + (X -M). Both the Income (or By Type) method and the Value Added (or Production) method can be used to determine the Gross Domestic Product. Both of the three methodologies only include "new" products (final goods and services) when calculating GDP in order to avoid double counting, which could result in the reporting of an incorrect GDP figure. There are two different types of GDP: real GDP and nominal GDP.

Real GDP is the estimated level of economic production of a nation less the impact of inflation, while nominal GDP is the estimate excluding price changes. The Nigerian economy will be examined using the gross domestic product and other financial indicators mentioned earlier in order to identify any obstacles to the country's economic development. The direction of currency misalignment alone determines whether a given exchange rate policy is successful or unsuccessful. While sustained exchange rate overvaluation causes efficiency losses, greater inflation, and poorer GDP growth, persistent exchange rate undervaluation has the opposite effect [6].

Without a doubt, because international trade and finance involve the exchanging of trading partners' currencies, exchange rate fluctuations can have both positive and negative effects on economic activities and the general public's standard of living in the short and long terms, depending on the prevailing economic conditions and preferences. As a result, the Central Bank prefers to occasionally implement a variety of policies to strengthen the domestic currency.

Nigeria, for example, has seen exchange rate fluctuations during the last decade. Nigeria's foreign exchange has been managed under direct control of exchange rate policy since its independence in 1960, until 1986, when the government changed its exchange rate policy from a fixed to a flexible one. Since then, market forces such as supply and demand have determined the exchange rate's value. First and second tiers of a dual exchange rate system (SFEM) were introduced in

1986, but it was renamed the Foreign Exchange Market in 1987. (FEM). During the 1994 reform, the exchange rate for the naira was once more set. In 1995, the Foreign Exchange Market was liberalized, and an Autonomous Foreign Exchange Market (AFEM) was created to give the monetary authority the ability to sell foreign currency to end-users through pre-selected authorized dealers at a rate set by the market. In 1999, the Interbank Foreign Exchange Market (IFEM) was created. In order to facilitate bidding between end users and authorized dealers, the retail Dutch Applied System was developed. Due to increased demand pressure in the foreign exchange market and the country's constant depletion of its external reverses, the Dutch Auction System (DAS) was reinstituted in 2002. The permissible margin for the wholesale DAS was established in 2006 [7]. The domestic economy experienced negative volatility in exchange rates against US Dollars shortly after the All Progressive Congress (APC) administration took office in 2015.

However, this is partly due to President Muhammadu Buhari's impression that Nigerians are systematically corrupt people, as he traveled to more than 8 countries in the first two years of his presidency, giving speeches that implied to the world community that Nigerians are consistently corrupt individuals. Due to the negative perception of the Nigerian economy, foreign investors withdrew a significant amount of money, which reduced the demand for and supply of foreign currency relative to the value of the Nigerian naira. It was challenging to attract enough foreign currencies to meet the rising demand for foreign currency, particularly US Dollars, because of the rising cost of doing business in Nigeria, Nigerians' preference for foreign goods over domestic goods, the drop in the price of oil internationally, and insecurity in the Niger Delta, which led to a significant reduction in crude oil output. The depreciation of the Nigerian naira and the increasing demand for US dollars, led in a dramatic collapse of the naira's value against the dollar, from N180 to almost N500 per dollar. These factors have caused immeasurable hardship for the Nigerian people, as the country's inflation rate has reached double digits, causing the Naira's purchasing power to plummet.

Since this paradigm's inception in the history of economic growth, there have been numerous works and studies on it; however, there doesn't seem to be any agreement in the study's conclusions. Human capital investment and economic growth have been found by some academics to be negatively correlated, while they have also been found to be positively correlated by others.

In any economy, capital formation is seen as a key determinant of economic development. It consists of both tangible and intangible products (plants, tools, and machines) (i.e., high standards of education, health, scientific, tradition and research). Domestic saving and investment determine the size of capital formation in any country. When savings are channeled as investments into productive activity, capital formation accelerates economic growth. In comparison to most of the world's established and fastest-growing economies, India's rate of capital production is low. Despite the fact that capital formation as a percentage of GDP appears to be declining, actual gross capital formation in industrialized and fast-growing nations is vastly larger than in developing economies such as India. The low rate of capital formation in India is due to persistent economic problems such as poverty, unemployment, and inflation; people's higher marginal propensity to consume; lack of financial inclusion; high liquidity preference among the people due to lower rates of interest on public savings deposits; and low per capita income. Increased capital accumulation can result in a permanent boost in growth rates, according to growth models proposed by [8]. The link between national capital formation and economic growth has been proven by a number of empirical studies. Numerous studies have come to the conclusion that capital accumulation and economic growth are causally related.

The stock market and other markets for trading different financial products are included in the capital market, which includes a wide range of marketable assets. However, trading equities publicly or privately is permitted on the stock market by both individuals and banking organizations [9]. On primary and secondary capital markets, financial assets like bonds, derivative contracts like options, different loans, commodity futures, and other debt instruments are traded [9]. The exchange trust fund (ETF), which was introduced in 2011, as well as government stocks and securities, debt instruments or bonds, shares, and other financial products can all be traded on Nigeria's capital market. The growth and activity of the capital market are governed and supervised by the Nigerian Stock Exchange. A stock exchange market is a framework that facilitates the trading of securities between buyers and sellers.

The process of accumulating additional capital stock is known as capital accumulation, and it is used in the productive process as a part of any society's economic development. The foundation of capital accumulation is savings, which takes place when a portion of current income is set aside and invested to increase future output and earnings. The degree to which savings can influence capital accumulation and growth depends on the economy's capacity to put savings to productive use. More savings result in more capital accumulation, which fuels economic growth. On a regular basis, numerous studies on the connection between capital accumulation and economic growth in developing countries are carried out (LDCs). The population of LDCs is thought to be incapable of high levels of individual savings due to factors such as low per capita income, indulgence in lavish and conspicuous consumption by the few who can afford to save, and so on. According to [10], it may seem that investing more of one's savings will lead to faster capital stock growth and

higher income growth, but it's important to remember that the connection between savings, capital accumulation, and growth is more complicated than it might first appear.

The emergence of central banking was prompted by economic problems like the Great Depression and the Great Inflation. The trajectory of nominal spending, inflation, and unemployment has not been maintained by monetary policy. People who are searching for employment but are unsuccessful in doing so do not contribute to the economy's production of goods and services. Concerns have been raised about the rate at which people are losing their jobs. Given that most people depend on income from their jobs to maintain their standard of living, losing a job may be the most traumatic financial event they ever experience.

Low savings have been proven to have a detrimental impact on capital accumulation, which is important in the development process. Like most developing economies, Nigeria, which has a population of over 140 million, is endowed with both natural and human resources. However, the economy faces numerous challenges. This is demonstrated by the fact that crude oil accounts for almost 90% of national income, yet the country is near to zero in terms of agricultural productivity, technical advancement, and industrialization. Saves and capital accumulation have had little synergy in Nigeria over the years, and neither savings nor investment have been encouraged. As a result, economic growth has stalled and economic activities have been overlooked. This study fills a gap by explicitly modeling the Nigerian economy's accuracy metrics using the GARCH model. It adds to our understanding of how to develop a viable time series model for forecasting the Nigerian economy and enhances the forecasting literature in Nigeria. It could also prompt more research into either sustaining or discrediting its forecast model. For every future investor, being able to accurately estimate stock market prices is critical. In order to fulfill the fundamental goals of stock market investors and operators, it is therefore necessary to forecast the stock exchange. This, nevertheless, compelled the need for this study to explore the Nigerian economy's measures in order to improve the Nigerian economy. The purpose of this study is to investigate how the GARCH model is used to measure some aspects of the Nigerian economy accurately. The purpose of the study is to:

i. To describe the series plot, yearly mean plot and monthly mean plot and obtain the stationarity of the series and determine the year with the highest Nigeria Economy rate.
ii. To calculate the parameters for the various GARCH models being researched.
iii. To obtain the estimated values for the model selection criteria (AIC, BIC, HQC, and LKH).
iv. To identify the suitable GARCH model to fit the model for Accuracy measures of Nigeria Economy (Capital Formation, Capital Market, real gross domestic product, Savings accumulation and Labour force).
v. Compare the analysis of these results objectives (iii) above.

Scope of the study

The project seeks to develop the most accurate model for forecasting the Nigerian economy by using GARCH models for accuracy measurements. It intends to employ the components of Capital Formation, Capital Market, Real Gross Domestic Product, Savings Accumulation, and Labor Force to calculate the monthly value of them all. It fills this gap by formally simulating Nigerian economic variables using several GARCH models. The Akaike (AIC), Bayalsian (BIC), and Schwarz (SIC) information criterion will be used to identify the model that fits the data the best. The research is limited to capital formation, capital markets, real gross domestic product, savings accumulation, and labor force data from 2001 to 2021, using GARCH time series models. The order of the *Generalized Autoregressive Conditionally Heteroscedastic* model required to effectively depict the time series model will be specified. The autocorrelation function (ACF) and partial autocorrelation function (PACF), two of the most fundamental time series forecasting components, will also be discussed.

II. RELATED WORK

In order to study the dynamics of oil prices (Brent and WTI crude oil markets) and their volatilities, Tatyana [11] linked four GARCH related models, namely GARCH (1,1), GJR-GARCH (1,1), EGARCH (1,1), and APARACH (1,1). (1,1). The study's conclusions showed that oil shocks have an enduring impact and have asymmetric effects on the studied markets' volatility.

In Nigeria, Ogolo and Nkpordee [12] investigated GARCH modeling of the covid-19 epidemic. Their research attempted to develop a Covid-19 Pandemic GARCH Model that could be used to compare the National Weekly Confirmed Cases (NWC) on Lagos and the Federal Capital Territory (Abuja). From March 16th, 2020 to May 9th, 2021, this study employed secondary statistical data retrieved from the National Center for Disease Control (NCDC) website on daily confirmed cases of covid-19 in Nigeria, which included daily and weekly reported and confirmed cases. The AIC, BIC, LHC, HQC, R^2, R^2-Adjusted, SSE, and MSE parameters of the GARCH model were obtained using the Gretl 18 and Minitab 17 programs. When the model selection criteria (AIB, BIC, HQC, and LKH) and parameter estimates (p-values) were compared between the two models, GARCH(0,1) of the FCT and GARCH(1,0) of Lagos, the outcome showed that GARCH (1,0) was better. The Lagos GARCH (1,0) was found to be the best model for describing the data in this

investigation. It was suggested that proper monitoring be implemented in Lagos state in order to prevent the virus's spread, as well as that policymakers implement a better health-care policy that is beneficial to all.

The GARCH model and its variants were used by Abduikareem and Abdulhakeem [13] to analyze oil price - macroeconomic volatility in Nigeria using daily, monthly, and quarterly data (GARCH-M, EGARCH, and TGARCH). The results show that the real gross domestic product, interest rate, exchange rate, and oil price are all highly volatile macroeconomic variables; the asymmetric models (TGARCH-M) also showed that the oil price is a significant contributor to economic volatility in Nigeria.

The exponential generalized Autoregressive conditional heteroskedasticity (EGARCH) model was also used by Narayem and Narayan [14] to explain the volatility of daily oil prices. The results also demonstrate that asymmetric impacts are present, ongoing, and permanent in the oil price series. Additionally, Olowe [15] used EGARCH (1,1) to examine the weekly volatility of the average spot price for oil across all countries between January 3, 1997, and March 6, 2009. The results show that there is significant volatility persistence, clustering, and asymmetries in the oil price return series.

The effect of oil price volatility on Nigerian investment decisions for marginal field development is examined by Olugbenga and Kehinde [16]. The study examined the relationship between oil price volatility and analyses of marginal field investment in Nigeria. An investment analysis was replaced with the crude oil production from a marginal field. From October 2015 to April 2016, the information was gathered on a monthly basis. The GARCH model, Johansen cointegration, and Granger causality tests were used to estimate the outcomes. But the findings showed a strong correlation between crude oil production and price volatility (P 0.05).

Using the Generalized Autoregressive Condition of Heteroscedasticity, Pokhariyal, Pundo, and Musyoke [17] examined the effect of real exchange rate volatility on Kenyan economic growth (GARCH). They used data from 1993 to 2009 to gauge volatility using the unconditional standard deviation of changes and to examine how real exchange rate volatility affected economic growth using Generalized Method Moments (GMM). The study found that the Real Exchange Rate (RER) was incredibly unstable over the course of the investigation. The RER in Kenya has a typical tendency to increase and fluctuate.

The effects of real effective exchange rate volatility on long-run economic development for a group of 82 established and emerging economies were examined by Holland, Vieira, Da, and Bottecchia [18] using a panel data set spanning 1970 to 2009. A more variable RER has a significant negative impact on economic growth, according to the results of the GMM panel growth models with a two-step system, and these findings hold true regardless of the model's various parameters..
Using monthly exchange rate return data for three currencies—the naira/US dollar returns from 1985:1 to 2011:7, the naira/British pound returns from 2004:1 to 2011:7, and the naira/euro returns from 2004:1 to 2011:7—Bala and Asemota [19] used GARCH models to investigate exchange rate volatility. In this work, estimates of different GARCH models with break in relation to US dollar rates and exogenously set break points were compared. The findings demonstrate that there is volatility in each of the three currencies, and the majority of asymmetric models—aside from those with a volatility break—reject the idea that there is a leverage effect. Autocorrelations of the squared residuals suggest that the three currencies show significant evidence of ARCH effects. Euro has a first-order autocorrelation of 0.937, which steadily decreases to 0.445 after 15 delays. These autocorrelations aren't very strong, and they're usually positive. The no ARCH hypothesis is disproved because the values are all zeros. Similar patterns could be seen in the returns on the US dollar and the British pound sterling. Additionally, the results of the estimation of the ARCH/GARCH mean and variance equations showed that all ARCH model coefficients for USD, BPS, and Euro returns are positive, including the model with volatility breaks, satisfying the necessary and sufficient conditions for ARCH family models.

The application of univariate symmetric and asymmetric GARCH models is also well-documented. Ahmad and Ping [20] used the standard GARCH, GARCH in mean, threshold GARCH, and exponential GARCH to simulate the volatility of Malaysian gold prices (EGARCH). The best-fitting model was chosen using the Akaike (AIC) and Schwarz (SIC) information criterion. The EGARCH model was found to be the most effective one. Additionally, the asymmetric GARCH models demonstrate that positive shocks increase volatility more than negative shocks do. To determine the most accurate model for the five Johannesburg Stock Exchange (JSE) indexes before, during, and after the GFC of 2008, the standard GARCH, GJR-GARCH, and EGARCH were all used in a similar analysis. Similar to Ahmad and Ping [19], the AIC and SIC were used to determine which GARCH model fit the data the best. The GJR-GARCH model was demonstrated to be the model that fits the JSE the best overall. The findings also hinted at the leverage effect, which happens when negative shocks cause more volatility than positive shocks. Asymmetric multivariate GARCH has been used extensively to represent conditional covariance and correlation among return series.

III. METHODOLOGY

The GARCH model was utilized for accuracy measurements of some components of the Nigerian economy in this study, which used a cross-sectional research approach. The time series analysis model (GARCH) methodology was used in this investigation. The statistical database website of the Central Bank of Nigeria (CBN) was used to gather data for this study (www.cbn.gov.ng). Among the variables for the time period from January 2001 to December 2021 are monthly capital formation, gross domestic product, labor force, savings accumulation, and capital market. The Gretl statistical program was used to analyze the GARCH model's input parameters. It was also utilized to calculate the AIC, BIC, LHC, HQC, R^2, R^2-Adjusted, SSE, and MSE values, as well as the models' AIC, BIC, LHC, HQC, R^2, R^2-Adjusted, SSE, and MSE. The parameters were obtained using the Minitab 16 application.that constitute the descriptive statistics.

Heteroscedasticity with Generalized Autoregressive Condition (GARCH Model)

Bollerslev is credited with creating the GARCH model [21]. The representation of GARCH (1, 1) is

$R_1 = \boldsymbol{\mu} + \sum_1$ (1)

where $\sum_1 \sim (0, \sigma_i^2)$

$\sigma_i^2 = \beta_o + \beta_1 \sum_{i-1}^2 + \beta_2 \sigma_{i-1}^2$ (2)

where,

$\boldsymbol{\mu}$ is the mean

σ_i^2 is that variance of the error at time t

$\sum_{i-1}^2$ is the squared error at time t-1

$\frac{\omega}{(1-\beta_1-\alpha_1)}$ is the unconditional variance

α_1 is the first (lag 1) ARCH Parameter

β_1 is the (lag 1) GAECH parameter

Estimation of GARCH model:

Following is a definition of the well-known GARCH (1,1) model:

$\sigma_i^2 = \bar{\omega} + \alpha_i \varepsilon_{i-1}^2 + \beta_1 \sigma_{i-1}^2$ (3)

For α_i^2 to be non-negative, we require the coefficients to be non-negative.

Using the definition $\sigma_i^2 = \varepsilon_i^2 + v_i$, we have,

$\sigma_i^2 = \bar{\omega} + \alpha_i \varepsilon_{i-1}^2 + \beta_1 \sigma_{i-1}^2$

$\varepsilon_i^2 - v_i = \bar{\omega} + \alpha_i \varepsilon_{i-1}^2 + \beta_1 (\varepsilon_{i-1}^2 - v_{i-1})$

$\varepsilon_i^2 - v_i = \bar{\omega} + (\alpha_i + \beta_1) + \varepsilon_{i-1}^2 + v_i - \beta_1 v_{i-1}$

Which is an ARIMA (1,1) model for the squared innovation.

Stationarity requires that $\alpha_i + \beta_i < 1$ generalizes to a GARCH (p, q) model:

$\sigma_i^2 = \bar{\omega} + \sum_{i=1}^q \alpha_i \varepsilon_{i-1}^2 + \sum_{j=1}^p \beta_j \sigma_{i-1}^2$ (4)

The GARCH model is equivalent to an infinite ARCH model.

The GARCH model built in the research are GARCH models with independent variable (The state weekly confirmed cases). That is

GARCH (1, 1) model: $\sigma_i^2 = \bar{\omega} + \alpha_i \varepsilon_{i-1}^2 + \beta_1 \sigma_{i-1}^2 + \lambda_1 X_i^2$ (5)

GARCH (1, 0) model: $\sigma_i^2 = \bar{\omega}_i + \beta_1 \sigma_{i-1}^2 + \lambda_1 X_i^2$ (6)

GARCH (0, 1) model: $\sigma_i^2 = \bar{\omega} + \alpha_i \varepsilon_{i-1}^2 + \lambda_1 X_i^2$ (7)

where λ_1 is coefficient of independent variable, X_i^2 is theindependent variable and $\bar{\omega}$ is the constant coefficient.

The regression equation may be an autoregressive (AR) process, a moving average (MA), or a combination of AR and MA process, depending on the validity of the researcher's model (ARMA). This is how an AR(1) regression equation might look if we have the return series variable y_t:

$y_t = \beta_0 + \beta_1 y_{t-1} + e_t$ (8)

3.2 Tests for Heteroskedasticity

The Langrange Multiplier (LM) test will be used to check for heteroskedasticity. As a result, testing for heteroskedasticity merely entails testing for the ARCH –effect. A null hypothesis of no ARCH effect must be provided, and if the test is significant, we will proceed to estimation using GARCH models. The Langrange Multiplier test use OLS to find the most acceptable regression equation. The purpose of the linear regression model is to find the residuals.

3.3 Estimation: Error Distributions

To demonstrate that modeling the return series with a Gaussian process is wasteful for high frequency financial time series, Equations 1, 2, 5, 6, 7, and 8 are estimated using a normal distribution by maximizing the likelihood function

$$L(\theta_t) = -1/2 \sum_{t-1}^{T} (ln2\pi + ln\sigma_t^2 + \frac{\varepsilon_t^2}{\sigma_t^2}) \quad (9)$$

σ_t^2 is described in every GARCH model.

The normalcy assumption does not adequately account for the kurtosis in returns, and the assumption that GARCH models follow GED tends to do so. By maximizing the likelihood function below, as in (9) above, the volatility models are estimated using GED:

$$L(\theta_t) = -\frac{1}{2}\log\left(\frac{\Gamma\left(\frac{1}{v^3}\right)}{\Gamma\left(\frac{3}{v}\right)\left(\frac{v}{2}\right)^2}\right) - \frac{1}{2} log\sigma_t^2 - \left(\frac{\Gamma\left(\frac{3}{v}\right)(y_t - x_t'\theta)^2}{\sigma_t^2\Gamma\left(\frac{1}{v}\right)}\right)^{\frac{v}{2}} \quad (10)$$

v explains the skewness of the returns which is the shape parameter, and $\boldsymbol{v > 0}$. The weight of the tail increases with the value of v. If the GED returns to the normal distribution, $v = 0$

The volatility models under consideration in the case of the t distribution are estimated to maximize the likelihood function of a Student's t distribution:

$$L(\theta)_t = -\frac{1}{2} log\left(\frac{\pi(r)\Gamma r/2^2}{\Gamma((r+1)/2)^2}\right) - \frac{1}{2} log\sigma_t^2 - \frac{(r+1)}{2} log\left(1 + \frac{(y_t - X_t'\theta)^2}{\sigma_t^2(r-2)}\right) \quad (11)$$

The tail behavior is controlled by r the degree of freedom. All estimations made in this study are implemented in the econometric software, and $r > 2$ equations 9, 10, and 11 are as specified in the Minitab 16 manual.

Models Selection Criteria

The most popular information criteria for selection models are the Akaike Information Criteria (AIC), Schwarz-Bayesian Information Criteria (BIC), Likelihood Criteria (LHC), and Hannan-Quinn Information Criteria (HQC).

Akaike Information Criteria

The AIC evaluates a statistical model's relative goodness of fit. The AIC value is given by

$$AIC = \mathrm{T}\ln\left[RSS/\mathrm{T}\right] + 2p \quad (12)$$

$where$ T is the quantity of observations (data points); ln is the natural logarithm; an unbiased estimator of the true variance is called RSS, which stands for residual sum of squares ((σ^2). p stands for the model's parameter count.

Schwartz-Bayesian Information Criteria (SBC or BIC)

The SBC or "BIC" is a model selection criterion that involves selections among a finite set of models. The BIC is given by

$$BIC = \mathrm{T}\ln\left[RSS/\mathrm{T}\right] + p\ln(\mathrm{T}) \quad (13)$$

Hannan-Quinn Criteria (HQC)

The HQC is a model selection criterion that involves selections among a finite set of models. The HQC is given by

$$HQC = \mathrm{T}\ln\left[RSS/\mathrm{T}\right] + p\ln\left(\ln(\mathrm{T})\right) \quad (14)$$

IV. RESULTS AND DISCUSSION

Data set for this study is the monthly capital formation, gross domestic product; labour force, savings accumulation, and capital market for the period January 2001 to December 2021 as shown in Appendix I to IV at the end of this work.

Monthly Plot, Yearly Plot and Series plot of the Data Sets

The monthly mean, yearly mean, and series plots of (Capital Formation, Capital Market, real gross domestic product, Savings accumulation, and Labor Force) were used in this section to evaluate the relationships, trend component, and seasonality effect, if they were present in the data sets.

Monthly Plot, Yearly Plot and Series plot of Real Gross Domestic Product

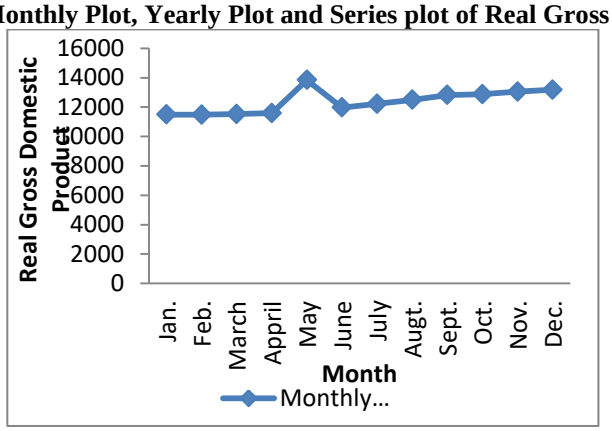

Figure 1: Monthly Means Plot of Real Gross Domestic Product

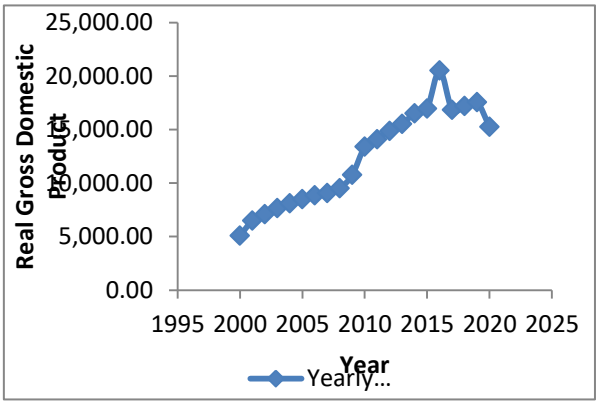

Figure 2: Yearly Means Plot of Real Gross Domestic Product

The monthly mean behavior of real gross domestic product is shown in Figure 1, with the peak in May and the lowest in February. The monthly mean series, on the other hand, shows a rise from January to May (or a swing higher). Then, in June, display a random downward movement, followed by an upward movement from July through December. Figure 2 depicts a random ascending trend followed by downward fluctuations. There appears to be a peak in 2016 and depressions practically all the way through the early periods.

Monthly Plot, Yearly Plot and Series plot of Capital Market

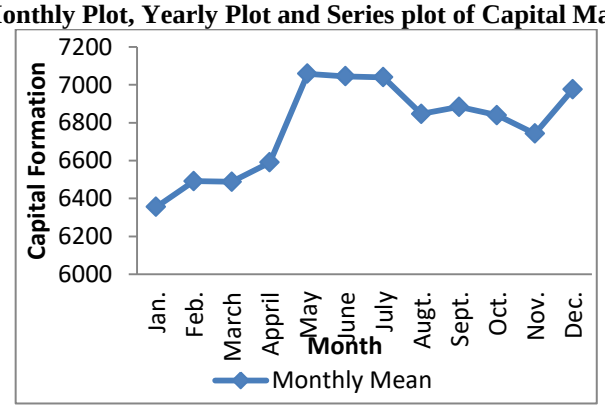

Figure 3: Monthly Means Plot of Capital Market

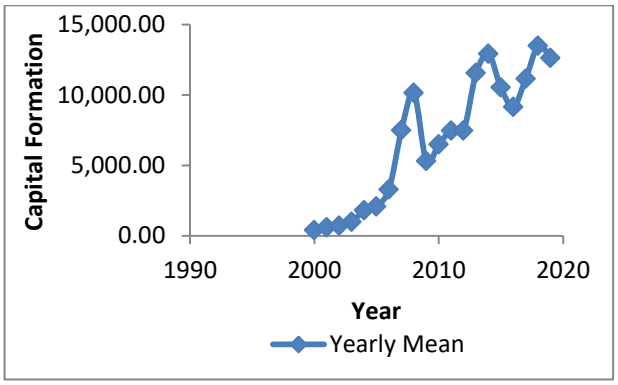

Figure 4: Yearly Means Plot of Capital Market

Figure 3 depicts the capital Market's monthly mean behavior, with the peak in May and the lowest CM values in January. The monthly mean series, on the other hand, shows a rise from January to May (or a swing higher). Then, from June to December, show a downward and fluctuating movement in a random manner. Figure 4 depicts a random ascending trend followed by downward fluctuations. There appears to be a high in 2018 and swings practically all the way through the early months.

Monthly Plot, Yearly Plot and Series plot of Savings Accumulation

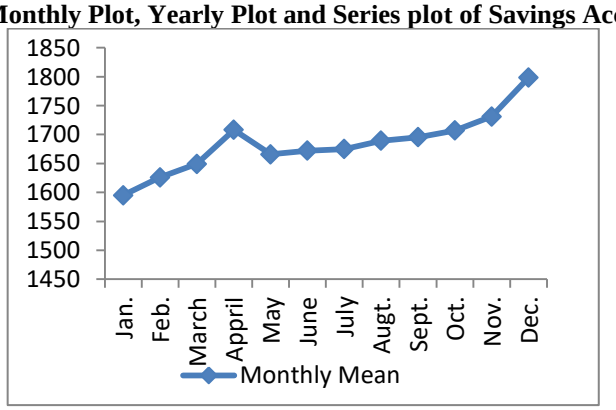

Figure 5: Monthly Means Plot of Savings Accln.

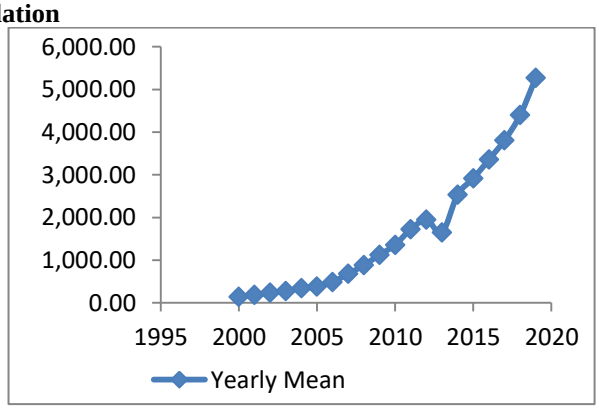

Figure 6: Yearly Means Plot of Savings Accumulation

Figure 5 depicts the monthly mean behavior of savings accumulation, with the highest SA values in December and the lowest in January. The monthly mean series on the other hand shows an increase in the series from the start (or swing upward) of January to December. Figure 6 depicts a random ascending trend followed by downward fluctuations. There appears to be a peak in 2019 and variations practically all the way through the early months.

Monthly Plot, Yearly Plot and Series plot of Capital Formation

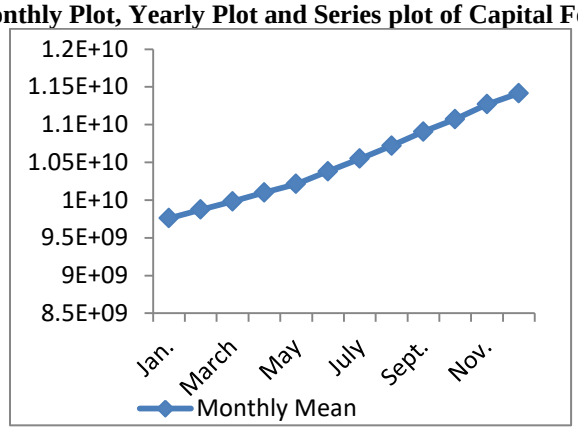

Figure 7: Monthly Means Plot of Capital Formation

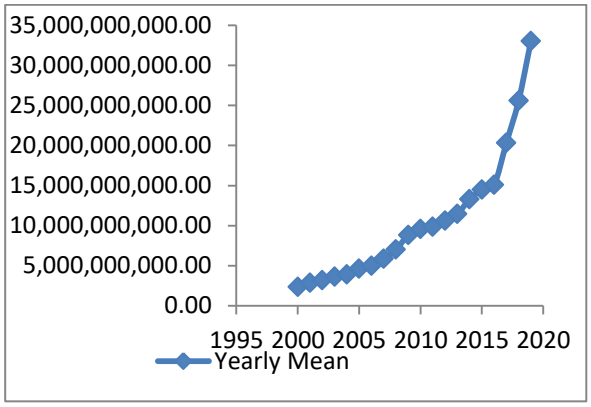

Figure 8: Yearly Means Plot of Capital Formation

Figure 7 depicts the monthly mean capital formation behavior, with the peak in December and the lowest CF values in January. The monthly mean series, on the other hand, shows a rise from the start (or swing upward) of January through December. Figure 8 depicts an ascending trend and random upward movements throughout the data set's eras. There appears to be a peak in the year 2019 and practically steady increase throughout the early and later decades.

Monthly Plot, Yearly Plot and Series plot of Labour Force

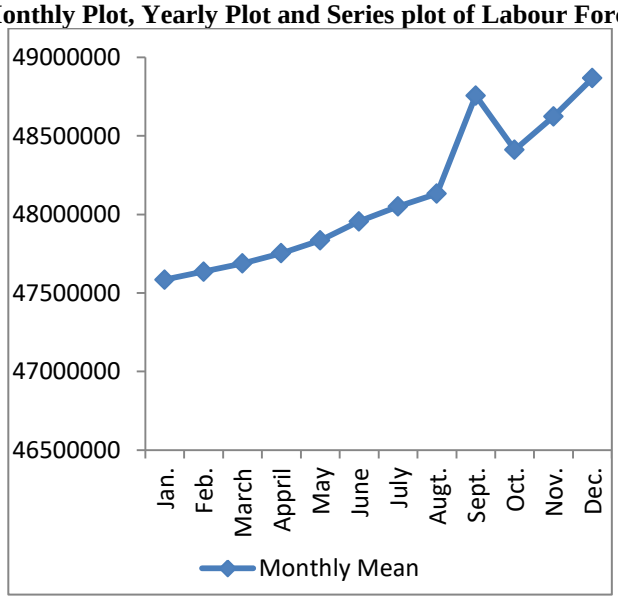

Figure 9: Monthly Means Plot of Labour Force

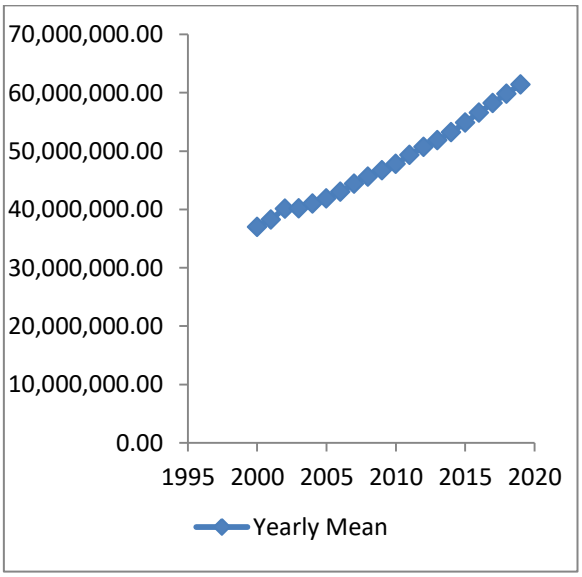

Figure 10 Yearly Means Plot of Labour

Figure 9 depicts the labor force's monthly average behavior, with the peak in December and the lowest CF values in January. The monthly mean series, on the other hand, show an increase from January's beginning (or swing upward) to September, followed by a fluctuating movement from September to December. Figure 10 depicts an ascending trend and random upward movements throughout the data set's eras. There appears to be a peak in the year 2019 and practically steady increase throughout the early and later decades.
Then, as illustrated in Figure 11, we use Time Series Plot to compare all of the plots;

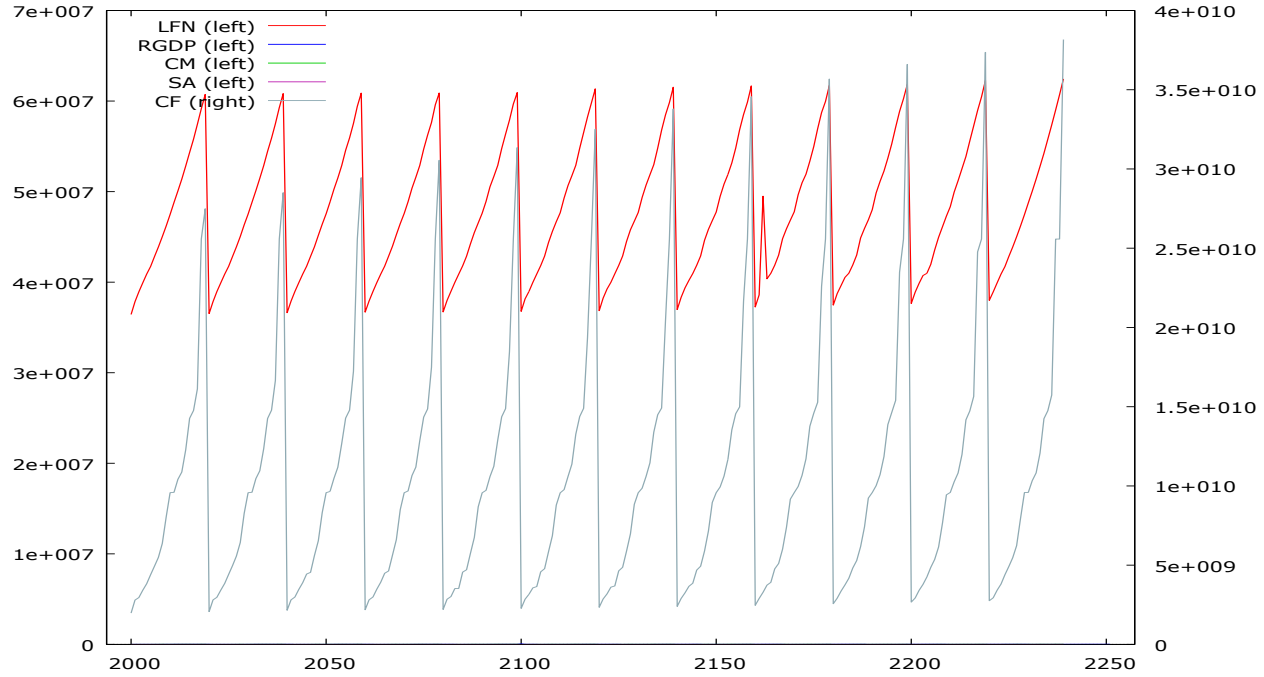

Figure 11: The RGDP, CM, SA, CF and LFN Time Series Comparison

In Figure 11, comparing all the series, it is noticed that there is a similar behaviour between the five series which show an upward trend component. It also indicated that the five series are not stationary.

The variables' descriptive statistics

Here are estimated descriptive statistics for the Nigerian economy's capital formation, capital market, real gross domestic product, savings accumulation, and labor force services.

Table 1: Descriptive Statistics of Nigeria Economy

Variable	Mean	SE Mean	StD.	Minim	Maximum	Skewness	Kurtosis
RGDPC(x_1)	12380	331	5253	4204	61688	3.22	29.31
CM (x_2)	6780	296	4589	321	15896	0.00	-1.35
SA (x_3)	1682.4	98.0	1518.6	111.3	5605.9	0.91	-0.27
CF (x_4)	1052019641	515637812	7988226636	1976543289	38166990521	1.43	1.72
LF (x_5)	48107971	475046	7359374	36435546	62447230	0.24	-1.12

Sources: Author's Computation (2022)

The estimated value of 12380 billion for real gross domestic product (RGDP), 6780 billion for capital market (CM), 1682.4 billion for savings accumulation (SA), 1052019641 billion for capital formation (CF), and 48107971 billion for labor force is shown in Table 1.

Unit Root Test

Table 2: Unit Root Test for the Components of the Nigeria Economy

Variable	Critical Values		Selection Criteria		ADF-test Parameters Estimate				
	Percentage	Values			Variable	Coefficient	Std. Error	t-ratio	p-value
RGDP	1%	-3.48	AIC	4595.62	Const	22261.3	2755.94	8.078	0.0000***
	2.5%	-3.15	BIC	4658.05	**RGDP_1**	**−1.98502**	**0.233439**	**−8.503**	**0.0000 *****
	5%	-2.89	HQC	4620.78	d_RGDP_1	1.19568	0.208335	5.739	0.0000***
	10%	-2.57			d_RGDP_2	1.23162	0.190039	6.481	0.0000***
CM	1%	-3.48	AIC	4160.04	Const	19034.2	1720.56	11.06	0.0000***
	2.5%	-3.15	BIC	4221.53	**CM_1**	**−3.11548**	**0.264881**	**−11.76**	**0.0000*****
	5%	-2.89	HQC	4184.86	d_CM_1	2.32144	0.223926	10.37	0.0000***
	10%	-2.57			d_CM_2	2.04693	0.203652	10.05	0.0000***
SA	1%	-3.48	AIC	3716.01	Const	4523.03	441.528	10.24	0.0000***
	2.5%	-3.15	BIC	3777.5	**SA_1**	**−2.79272**	**0.238948**	**−11.69**	**0.0000 *****
	5%	-2.89	HQC	3740.83	d_SA_1	2.10412	0.202358	10.40	0.0000 ***
	10%	-2.57			d_SA_2	2.00988	0.194551	10.33	0.0000 ***
	1%	-3.48	AIC	10765	Const	2.75102e+010	2.92721e+09	9.398	0.0000***

	2.5%	-3.15	BIC	10826.5	**CF_1**	**−2.81444**	**0.267577**	**−10.52**	**0.0000 *** **
CF	5%	-2.89	HQC	10789.9	d_CF_1	2.12630	0.235247	9.039	0.0000 ***
	10%	-2.57			d_CF_2	1.99744	0.221325	9.025	0.0000 ***
	1%	-3.48	AIC	7523.34	Const	1.31066e+08	1.11220e+07	11.78	0.0000***
	2.5%	-3.15	BIC	7584.83	**RGDP_1**	**−2.75465**	**0.233631**	**−11.79**	**0.0000*** **
LFN	5%	-2.89	HQC	7548.16	d_RGDP_1	2.10362	0.200717	10.48	0.0000***
	10%	-2.57			d_RGDP_2	1.94031	0.188746	10.28	0.0000***

Footnote: *-Sig. at 1%; **-Sig. at 5%; *-Sig. at 10%**
Sources: Author's Computation (2022)

The RGDP, CM, SA, CF, and LFN were logged and transformed into continuously compounded monthly data in order to lower variance. The results in Table 2 demonstrate that the series is stationary at all levels for the RGDP, CM, SA, CF, and LFN series in (15) after the order of integration was determined using the ADF. Since the probability of 0.0000 is less than 0.05, the unit root null hypothesis is rejected. Since all of the data (RGDP, CM, SA, CF, and LFN) became stationary at the beginning and after differencing, the Augmented Dickey-Fuller-test (p=0.0000) confirms this.

Parameter Estimates and GARCH Model Identification

Table 3: GARCH (p,q) Models Parameter estimate and Selection Criteria values for RGDP

Variable	Model	Parameter Estimate (p-values)	Selection Criteria	Remark Suitable Model
	GARCH(2,1) With constant	$\hat{\mu}$ = 12609.0(0.0000**) ϖ = 1.70949e-06(1.0000) α_1 = -0.0246385(0.5784) β_1 = 1.09634(0.5213) β_2 = -0.0755911(0.9655)	AIC=5002.2854 HQC=5009.3863 LKH=-2496.1427 BIC=5019.9326	
RGDP(σ_t^2)	**GARCH(0,1) With constant**	**$\hat{\mu}$ = 8579.88(0.0000**) ϖ = 97569.4(0.0136**) α_1 = 1.53915(0.0000**)**	**AIC=4822.3883 HQC=4826.6488 LKH=-2408.1942 BIC=4832.9766**	**GARCH(0,1)**
	GARCH(4,1) With constant	$\hat{\mu}$ = 12641.1(0.0000**) ϖ = 7.27897e-07(1.0000) α_1 = -0.0369729(0.1561) β_1 = 0.689770(0.3781) β_2 = 0.294129(0.8140) β_3 = 0.474213(0.5042) β_4 = -0.428852(0.5596)	AIC=5004.2994 HQC=5014.2406 LKH=-2495.1497 BIC=5029.0054	
	GARCH(4,2) With constant	$\hat{\mu}$ = 12682.5(0.0000**) ϖ = 1.51490e-06(1.0000) α_1 = -0.0290936(0.6227) α_2 = -0.0426195(0.2775) β_1 = 0.255196(0.5735) β_2 = 0.811813(0.3738) β_3 = 0.316833(0.6923) β_4 = -0.328516(0.6557)	AIC=5003.4869 HQC=5014.8482 LKH=-2493.7434 BIC=5031.7223	

Footnote: **-Sig. at 5%; *-Sig. at 10%.

The identified GARCH model is GARCH (0,1), because all of its parameters are significant at 5% and all of its model selection criteria (AIC=4822.3883, HQC=4826.6488, LKH=-2408.1942, and BIC=4832.9766) are better than the other three GARCH models (AIC=4822.3883, HQC=4826.6488, LKH=-2408.1942, and BIC=4832.

Table 4: GARCH (p,q) Models Parameter estimate and Selection Criteria values for CM

Variable	Model	Parameter Estimate (p-values)	Selection Criteria	Remark Suitable Model
	GARCH(1,1) With constant	$\hat{\mu}$ = 7682.11(0.0000**) ϖ = 9.10460e+06(0.0000**) α_1 =0.594537(0.0000**) β_1 = -0.021646(0. 8782)	AIC= 4708.3649 HQC= 4713.9747 LKH=-2350.18247 BIC= 4722.2875	
CM(σ_t^2)	GARCH(0,1) With constant	$\hat{\mu}$ = 7688.96(0.0000**) ϖ = 8.86687e+06(0.0000**) α_1 = 0.582390(0.0000**)	AIC= 4706.3872 HQC= 4710.5945 LKH=-2350.1936 BIC= 4716.8291	
	GARCH(2,1) With constant	$\hat{\mu}$ = 7786.64(0.0000**) ϖ = 1.06974e+07(0.0000**) α_1 =0.634883(0.0000**) β_1 =-0.0396172(0.7708) β_2 =-0.0940845(0.5442)	AIC= 4709.9855 HQC= 4716.9977 LKH=-2349.9928 BIC= 4727.3887	
	GARCH(3,1) With constant	$\hat{\mu}$ = 7284.56(0.0000**) ϖ = 5.06379e+06(0.0000**) α_1 =0.230153(0.0000**) β_1 = 0.810622(0.0000**) β_2 = 0.315188(0.3147) β_3 = -0.598035(0.0005**)	AIC= 4676.9045 HQC= 4685.3192 LKH=-2332.4523 BIC= 4697.7884	
	GARCH(2,2) With constant	$\hat{\mu}$ = **7471.11(0.0000**)** ϖ = **2.14648e+06(0.0000**)** α_1 =**0.0687073(0.0000**)** α_2 = **-0.0881488(0.0000**)** β_1 =**1.82865(0.0.0000**)** β_2 =**-0.908457(0.0.0000**)**	**AIC=4660.7266 HQC=4669.1412 LKH=-2324.3633 BIC=4681.6104**	**GARCH(2,2)**

Footnote: **-Sig. at 5%; *-Sig. at 10%.

Table 5: GARCH (p,q) Models Parameter Estimate and Selection Criteria values for SA

Variable	Model	Parameter Estimate (p-values)	Selection Criteria	Remark Suitable Model
	GARCH(1,1) With constant	$\hat{\mu}$ = **275.445(0.0000**)** ϖ = **2762.97(0.0065**)** α_1 = **1.68127(0.0000**)** β_1 = **-0.0004931 (0. 0000**)**	**AIC= 3880.01439 HQC= 3885.62416 LKH=-1936.00719 BIC= 3893.93694**	**GARCH(1,1)**
SA(σ_t^2)	GARCH(0,1) With constant	$\hat{\mu}$ = 1624.58(0.0470**) ϖ = 91476.8(0.0000**) α_1 = 1.06057(0.0000**)	AIC= 4057.07451 HQC= 4061.28184 LKH=-2025.53726 BIC= 4067.51643	
	GARCH(1,2) With constant	$\hat{\mu}$ = 1622.82(0.0000**) ϖ = 131905(0.0000**) α_1 =1.25415(0.0000**) α_2 = -1.17011(0.0000**) β_1 =0.877084(0.0.0000**)	AIC=4030.59373 HQC=4037.60595 LKH=-2010.29687 BIC=4047.99693	

Footnote: **-Sig. at 5%; *-Sig. at 10%.

The identified GARCH model is GARCH (2, 2), because all of its parameters are significant at 5% and all of its model selection criteria (AIC=4660.7266, HQC=4669.1412, LKH=-2324.3633 and BIC=4681.6104) are better than the other four GARCH models (AIC=4660.7266, HQC=4669.1412, LKH=-2324.3633 and BIC=4681.6104) as shown in Table 4 above.

The identified GARCH model is GARCH (1,1), because all of its parameters are significant at 5%, and all of its model selection criteria (AIC=3880.01439, HQC=3885.62416, LKH=-1936.00719, and BIC=3893.93694) are better than the other two GARCH models (AIC=3880.01439, HQC=3885.62416, LKH=-1936.00719, and BIC as shown in Table 5 above.

Table 6: GARCH (p,q) Models Parameter Estimate and Selection Criteria values for CF

Variable	Model	Parameter Estimate (p-values)	Selection Criteria	Remark Suitable Model
	GARCH(1,1) With constant	$\hat{\mu} =$ **4.03673e+09(0.0000**)** $\varpi =$ **2.29926e+017(0.0106**)** $\alpha_1 =$ **1.44449(0.0000**)** $\beta_1 =$**-0.00118267(0. 0000**)**	**AIC= 11337.11287 HQC= 3885.62416 LKH=-5664.55644 BIC= 11342.72264**	**GARCH(1,1)**
CF(σ_t^2)	GARCH(0,1) With constant	$\hat{\mu} =$ 9.58261e+09(0.0000**) $\varpi =$ 3.88492e+017(0.0030**) $\alpha_1 =$ 1.40124(0.0000**)	AIC= 11363.81824 HQC= 4061.28184 LKH=-5678.90912 BIC= 11368.02558	

Footnote: **-Sig. at 5%; *-Sig. at 10%.

Table 7: GARCH (p,q) Models Parameter Estimate and Selection Criteria values for LFN

Variable	Model	Parameter Estimate (p-values)	Selection Criteria	Remark Suitable Model
	GARCH(1,1) With constant	$\hat{\mu} =$ 4.57148e+07(0.0000**) $\varpi =$ 1.02750e+012(0.0113**) $\alpha_1 =$1.36463(0.0000**) $\beta_1 =$-0.208096(0.0000**)	AIC= 8113.46894 HQC= 8119.07871 LKH=-4052.73447 BIC= 8127.39149	
LFN(σ_t^2)	GARCH(0,1) With constant	$\hat{\mu} =$ 4.60727e+07(0.0000**) $\varpi =$ 1.38424e+012(0.0043**) $\alpha_1 =$1.04347(0.0000**)	AIC= 8122.63264 HQC= 8126.83997 LKH=-4058.31632 BIC= 8133.07455	
	GARCH(1,2) With constant	$\hat{\mu} =$ **4.58222e+07(0.0000**)** $\varpi =$ **1.11211e+012(0.0000**)** $\alpha_1 =$**1.40305(0.0000**)** $\alpha_2 =$ **-0.439616 (0.0163**)** $\beta_1 =$**0.146568(0.4922)**	**AIC= 8106.47812 HQC= 8113.49033 LKH=-4048.23906 BIC= 8123.88131**	**GARCH(1,2)**

Footnote: **-Sig. at 5%; *-Sig. at 10%.

Because all of its parameters are significant at 5% and all of its model selection criteria (AIC=11337.11287, HQC=3885.62416, LKH=-5664.55644, and BIC=11342.72264) are better than the other GARCH models, the identified GARCH model is GARCH (1,1) as shown in Table 6 above. The identified GARCH model is GARCH (1,2), because all of its parameters are significant at 5% and all of its model selection criteria (AIC=8106.47812, HQC=8113.49033, LKH=-4048.23906 and BIC=8123.88131) are better than the other two GARCH models (AIC=8106.47812, HQC=8113.49033, LKH=-4048.23906 and BIC=8123 as shown in Table 7 above.

Comparison of the Identified GARCH Model

We compared the five identified GARCH models in the five economic sectors to determine the model that has more effect on the Nigeria economy in Table 8.

Table 8: GARCH (p,q) Models Parameter estimate and Selection Criteria values

Variable	Model	Parameter Estimate (p-values)	Selection Criteria	Remark
RGDP(σ_t^2)	GARCH(0,1) With constant	$\hat{\mu} =$ 8579.88(0.0000**) $\varpi =$ 97569.4(0.0136**) $\alpha_1 =$1.53915(0.0000**)	AIC=4822.3883 HQC=4826.6488 LKH=-2408.1942 BIC=4832.9766	
CM(σ_t^2)	GARCH(2,2) With constant	$\hat{\mu} =$ 7471.11(0.0000**) $\varpi =$ 2.14648e+06(0.0000**) $\alpha_1 =$0.0687073(0.0000**) $\alpha_2 =$ -0.0881488(0.0000**) $\beta_1 =$1.82865(0.0.0000**)	AIC=4660.7266 HQC=4669.1412 LKH=-2324.3633 BIC=4681.6104	

		β_2 =-0.908457(0.0.0000**)		
SA(σ_t^2)	**GARCH(1,1) With constant**	$\hat{\mu}$ = **275.445(0.0000**)** ϖ = **2762.97(0.0065**)** α_1 = **1.68127(0.0000**)** β_1 = **-0.0004931 (0. 0000**)**	**AIC= 3880.01439 HQC= 3885.62416 LKH=-1936.00719 BIC= 3893.93694**	**GARCH(1,1)**
CF(σ_t^2)	GARCH(1,1) With constant	$\hat{\mu}$ = 4.03673e+09(0.0000**) ϖ = 2.29926e+017(0.0106**) α_1 = 1.44449(0.0000**) β_1 =-0.00118267(0. 0000**)	AIC= 11337.11287 HQC= 3885.62416 LKH=-5664.55644 BIC= 11342.72264	
LFN(σ_t^2)	GARCH(1,2) With constant	$\hat{\mu}$ = 4.58222e+07(0.0000**) ϖ = 1.11211e+012(0.0000**) α_1 =1.40305(0.0000**) α_2 = -0.439616 (0.0163**) β_1 =0.146568(0.4922)	AIC= 8106.47812 HQC= 8113.49033 LKH=-4048.23906 BIC= 8123.88131	

Footnote: **-Sig. at 5%; *-Sig. at 10%;

Table 8 reveals that the GARCH model for savings accumulations (SA) has the most impact on the Nigerian economy, since all of its parameters are significant at 5% and 10%, and all of its model selection criteria are smaller and better than the other four GARCH models.

V. CONCLUSION AND FUTURE SCOPE

Because all of its parameters are significant at 5% and 10%, and all of its model selection criteria are smaller and better than those of the other four GARCH models, GARCH(1,1) from savings accumulations (SA) has the biggest effects on the Nigerian economy based on the actual data. Between the five categories of data (Capital Formation, Capital Market, Real Gross Domestic Product, Savings Accumulation, and Labour Force), the GARCH model with the biggest influence on the Nigerian economy was GARCH(1,1), the data set for savings accumulations (SA). Because all of its parameters are significant at 5% and 10%, and all of its model selection criteria (AIC, BIC, HQC, and LKH) and parameter estimates (p-values) are smaller and better than those of the other GARCH models based on various data on the Nigerian economy's other components, We found that GARCH (1,1) of the data set for savings accumulations (SA) was the best GARCH model among all fitted GARCH models in this study. This suggests that relative to other aspects of the Nigerian economy, the impact of savings accumulations is greater. This study has given several key pointers on how to accurately model the Nigerian economy. The researcher suggests that based on the findings and contributions of this study;

1. To improve the quality of life for citizens, policymakers should take the necessary steps to strengthen the governance and economic stability of Nigeria. This will make it possible to evaluate the country's financial strength more precisely, among other things.
2. Given the degree of risk associated with obtaining facilities in deposit money banks and investing in stocks, as well as the price of an asset with its corresponding return in interest rate, financial trade analysts, investors, companies, and the government are advised to exercise caution when trading or doing business involving interest rates. The Nigerian economy is significantly impacted by this.
3. Policymakers, investors, financial analysts, and economists should examine appropriate measures to improve saving accumulation stability because it has a greater impact on the Nigerian economy than other aspects considered in this study.

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APPENDIX I

			REAL GROSS DOMESTIC PRODUCT AT CONSTANT FACTOR COST 2000-2019									
Year	**January**	**February**	**March**	**April**	**May**	**June**	**July**	**August**	**September**	**October**	**November**	**December**
2000	4,204.34	4,361.74	4,635.11	4,735.44	4,854.90	5,109.56	5,209.54	5,331.21	5,479.10	5,521.44	5,765.89	5,893.55
2001	5,921.23	5,987.99	6,146.20	6,211.65	6,267.35	6,489.70	6,655.68	6,754.32	6,799.05	6,856.76	6,877.14	6,893.73
2002	6,898.22	6,932.42	6,956.86	6,978.76	6,985.73	6,994.08	7,007.67	7,165.59	7,201.58	7,287.68	7,300.21	7,365.11
2003	7,299.74	7,432.04	7,498.15	7,588.34	7,622.08	7,679.05	7,711.76	7,769.17	7,789.56	7,803.51	7,843.21	7,879.31
2004	7,905.42	7,922.10	7,943.33	7,956.51	7,975.39	7,987.47	8,113.98	8,241.76	8,267.17	8,278.60	8,284.12	8,323.57
2005	8,312.10	8,333.87	8,376.41	8,434.24	8,478.20	8,506.64	8,532.82	8,547.11	8,587.66	8,622.16	8,652.73	8,689.48
2006	8,700.4	8,711.81	8,743.3	8,777.5	8,785.4	8,854.5	8,887.7	8,921.5	8,933.21	8,957.6	8,966.88	8,975.32

	5		7	2	3	0	2	5		6		
2007	8,981.23	8,993.41	9,006.82	9,010.78	9,032.93	9,076.09	9,089.42	9,099.47	9,123.40	9,167.54	9,187.21	9,193.74
2008	9,231.31	9,267.56	9,345.75	9,398.86	9,427.22	9,477.54	9,489.98	9,533.71	9,644.03	9,743.31	9,827.57	9,955.92
2009	10,176.21	10,246.84	10,355.12	10,428.02	10,520.16	10,678.08	10,789.56	10,879.60	10,923.11	11,234.75	11,432.83	11,578.07
2010	11,798.80	11,909.88	12,583.48	12,643.83	12,822.38	12,934.53	13,765.68	13,897.46	14,304.44	14,544.72	14,688.59	14,789.82
2011	13,359.56	13,402.77	13,450.72	13,525.89	13,600.95	13,757.73	13,795.90	13,766.67	14,819.62	14,935.31	15,289.47	15,482.97
2012	14,456.84	14,211.31	13,915.51	14,176.78	14,267.40	14,323.05	14,677.61	15,278.35	15,645.43	15,745.28	15,876.72	16,045.90
2013	14,287.98	14,388.25	14,535.42	14,786.13	14,874.33	15,096.76	15,432.19	15,934.93	16,454.37	16,699.09	16,855.34	17,132.16
2014	15,189.88	15,321.38	15,438.68	15,677.10	15,878.32	16,084.62	16,444.75	16,856.58	17,479.13	17,644.45	17,987.34	18,150.36
2015	15,399.67	15,769.14	16,050.60	16,178.57	16,387.57	16,463.34	16,789.24	17,543.68	17,976.23	18,155.48	18,387.61	18,533.75
2016	15,342.86	15,754.89	15,943.71	16,098.29	61,688.22	16,218.54	16,756.90	17,298.58	17,555.44	17,743.67	17,833.65	18,213.54
2017	15,357.89	15,523.75	15,797.97	16,187.77	16,279.32	16,334.72	16,834.48	17,441.10	17,760.23	17,833.29	18,333.34	18,563.50
2018	15,699.07	15,855.41	16,096.65	16,278.54	16,421.37	16,580.51	17,276.55	17,799.36	18,081.34	18,354.88	18,800.94	19,041.44
2019	16,187.99	16,297.09	16,434.55	16,677.53	16,821.57	16,931.43	17,453.12	17,854.69	18,494.11	18,755.42	19,276.10	19,527.72
2020	16,682.61	14,583.09	12,881.06	11,631.73	11,754.88	15,854.76	15,987.33	16,453.23	17,885.16	16,409.85	16,641.52	16,500.68
M/Mean	11,494.92	11,486.04	11,530.26	11,589.63	13,845.03	11,972.99	12,223.90	12,493.72	12,819.21	12,871.18	13,052.78	13,177.60

APPENDIX II

			MARKET CAPITALIZATION 2000-2020									
Year	**January**	**February**	**March**	**April**	**May**	**June**	**July**	**August**	**September**	**October**	**November**	**December**
2000	321.3	332.6	333.2	329.1	340.4	361.1	394.9	423.1	417.6	425.8	411.4	466.06
2001	506.1	542.8	541.5	567.1	600.3	646.6	625.3	610.7	607.4	655.7	660.7	648.45
2002	629.9	625.9	663.3	680.9	679.4	742	751.9	754.8	723.2	706.4	716.9	748.7
2003	841.2	864.6	846.9	840.1	877.3	896.9	859.7	949.9	1,028.50	1,168.30	1,250.30	1,324.90
2004	1,534.86	1,740.20	1,635.00	1,833.00	1,977.40	2,066.00	1,919.30	1,686.10	1,688.00	1,824.00	1,872.00	1,925.94
2005	1,863.69	1,783.16	1,680.00	1,798.74	1,844.59	1,886.20	1,951.27	2,076.64	2,362.85	2,578.53	2,452.40	2,523.49
2006	2,566.40	2,574.10	2,510.80	2,611.40	2,803.60	2,958.62	3,170.70	3,829.20	4,083.70	4,027.00	3,937.84	4,227.13
2007	4,976.30	5,510.15	6,150.05	6,745.54	7,383.06	7,817.85	8,262.78	7,819.72	8,020.59	8,047.41	8,990.81	10,180.29
2008	10,692.74	12,503.20	12,125.90	11,491.25	11,614.46	10,920.32	10,640.65	9,744.46	9,836.91	7,969.05	7,305.86	6,957.45
2009	4,879.10	5,231.90	4,483.50	4,883.30	6,759.64	5,986.30	5,796.50	5,274.42	5,130.25	5,144.00	4,998.12	4,989.39
2010	5,441.59	5,535.75	6,280.60	6,398.38	6,368.78	6,174.42	6,320.56	5,946.77	5,648.28	7,982.47	7,908.30	7,913.75
2011	8,744.17	8,315.59	7,866.57	8,000.91	8,270.50	7,987.08	7,621.66	6,876.55	6,496.74	6,626.81	6,294.93	6,532.58
2012	6,579.11	6,342.01	6,549.84	7,030.62	7,042.75	6,895.29	7,340.06	7,560.06	8,282.28	8,422.74	8,465.60	8,974.45
2013	10,191.32	10,583.81	10,733.29	10,691.69	12,075.23	11,426.25	12,007.17	11,496.61	11,652.87	12,020.86	12,448.88	13,226.00
2014	13,005.47	12,706.76	12,445.69	12,671.64	13,694.73	14,027.71	13,900.46	13,713.86	13,607.40	12,436.97	11,404.30	11,477.66
2015	9,846.63	10,044.55	10,717.53	11,786.95	11,658.81	11,421.02	10,344.42	10,336.86	10,728.90	10,027.78	9,495.50	9,850.61
2016	8,225.21	8,452.46	8,704.87	8,621.01	9,500.90	10,165.34	9,619.99	9,478.87	9,733.37	9,349.56	8,720.80	9,246.92
2017	8,972.99	8,765.92	8,828.96	8,912.90	10,197.73	11,452.12	12,705.45	12,237.48	12,216.93	12,694.94	13,214.58	13,609.47
2018	15,895.	15,549.	14,992.	14,948.	13,802.	13,866.	13,409.	12,722.	11,962.2	11,852.	11,271.4	11,720.7

	88	79	96	51	61	42	71	38	6	70	8	2
2019	11,394.93	11,829.53	11,672.10	10,958.72	13,684.62	13,205.54	13,154.61	13,391.01	13,450.44	12,829.67	13,032.66	12,968.59
M/Mean	**6,355.44**	**6,491.74**	**6,488.13**	**6,590.09**	**7,058.84**	**7,045.15**	**7,039.85**	**6,846.47**	**6,883.92**	**6,839.53**	**6,742.67**	**6,975.63**
			SAVINGS ACCUMULATION 2000-2019									
Year	**January**	**February**	**March**	**April**	**May**	**June**	**July**	**August**	**September**	**October**	**November**	**December**
2000	111.27	123.32	126.61	135.35	139.09	143.37	147.93	149.52	153.43	157.11	161.78	164.62
2001	165.45	166.87	169.33	173.09	176.45	185.32	189.9	192.21	195.58	199.39	208.55	216.51
2002	218.44	221.78	226.88	228.03	231.5	234.22	236.67	238.65	239.11	240.61	242.71	244.06
2003	245.42	247.04	249.58	254.02	259.36	265.38	272.29	278.15	288.25	294.94	307.19	312.37
2004	315.63	321.66	326.79	329.11	343.21	348.65	350.17	350.92	351.03	354.98	356.87	359.31
2005	361.56	364.11	367.09	373.56	377.97	380.22	382.75	386.61	390.25	393.22	397.41	401.99
2006	403.84	416.66	438.21	448.56	455.03	462.61	489.01	512.9	523.08	547.23	573.27	592.51
2007	597.8	621.73	638.72	658.12	669.43	678.99	687.45	693.31	704.84	718.06	726.57	735.87
2008	756.85	784.95	799.08	820.38	845.54	866.27	873.43	893.22	930.88	955.52	977.06	1,091.81
2009	1,095.49	1,098.45	1,099.41	1,100.48	1,105.56	1,107.98	1,109.65	1,125.34	1,136.76	1,151.06	1,164.41	1,171.92
2010	1,183.32	1,195.75	1,199.35	1,256.40	1,276.11	1,348.76	1,382.90	1,395.66	1,411.73	1,478.16	1,557.88	1,589.18
2011	1,601.61	1,609.56	1,617.78	1,645.56	1,692.69	1,726.79	1,733.30	1,769.93	1,778.44	1,794.37	1,846.26	1,861.41
2012	1,898.10	1,899.24	1,905.21	1,917.51	1,926.28	1,938.73	1,944.39	1,959.47	1,966.08	1,987.63	1,986.31	2,017.85
2013	2,023.68	2,139.09	2,178.57	2,193.44	1,233.38	1,241.09	1,249.54	1,256.13	1,269.08	1,285.34	1,338.91	2,365.03
2014	2,405.40	2,438.11	2,459.74	2,477.68	2,485.66	2,493.28	2,521.84	2,556.83	2,572.94	2,626.74	2,668.34	2,698.31
2015	2,792.45	2,844.89	2,853.22	2,865.89	2,877.24	2,915.51	2,932.29	2,943.05	2,956.39	2,967.79	2,981.11	3,048.88
2016	3,057.25	3,087.45	3,177.20	3,236.30	3,254.32	3,322.53	3,362.39	3,476.18	3,479.31	3,511.65	3,648.42	3,674.54
2017	3,683.67	3,729.40	3,734.54	3,756.65	3,774.28	3,795.13	3,811.39	3,836.47	3,844.31	3,869.51	3,920.38	3,945.35
2018	4,086.43	4,220.68	4,347.12	4,696.26	4,587.90	4,502.65	4,447.33	4,441.23	4,440.64	4,339.73	4,338.20	4,337.62
2019	4,893.73	4,987.35	5,070.78	5,597.97	5,605.87	5,488.67	5,376.43	5,330.77	5,278.50	5,265.47	5,221.09	5,137.46
M/Mean	**1,594.87**	**1,625.90**	**1,649.26**	**1,708.22**	**1,665.84**	**1,672.31**	**1,675.05**	**1,689.33**	**1,695.53**	**1,706.93**	**1,731.14**	**1,798.33**

APPENDIX III

			GROSS FIXED CAPITAL FORMATION 2000-2020									
YEARS	**January**	**February**	**March**	**April**	**May**	**June**	**July**	**August**	**September**	**October**	**November**	**December**
2000	1,976,543,289	2,065,785,321	2,156,432,897	2,187,564,809	2,209,472,306	2,276,903,468	2,344,908,675	2,399,760,543	2,465,489,744	2,565,611,897	2,669,511,260	2,753,932,734
2001	2,798,056,432	2,809,471,390	2,810,566,931	2,812,888,567	2,848,709,341	2,851,105,378	2,863,399,056	2,895,552,320	2,898,442,786	2,914,597,863	2,925,906,367	2,939,661,845
2002	2,957,821,597	2,969,007,342	2,987,546,704	2,991,234,566	3,018,786,490	3,165,568,921	3,187,324,786	3,253,498,745	3,288,876,452	3,365,564,387	3,408,276,365	3,416,206,501
2003	3,419,564,749	3,425,490,865	3,469,593,275	3,485,008,543	3,521,895,634	3,567,773,219	3,612,786,404	3,666,904,321	3,738,953,561	3,756,444,908	3,785,254,849	3,807,456,829
2004	3,826,745,906	3,851,118,904	3,894,576,893	3,925,258,909	3,532,112,378	3,649,086,321	3,688,764,534	3,859,084,327	3,915,131,808	4,170,895,421	4,256,876,041	4,397,464,081
2005	4,398,098,564	4,417,856,901	4,438,534,897	4,487,118,006	4,559,034,712	4,575,489,760	4,638,063,757	4,688,406,129	4,765,908,632	4,822,119,076	4,859,952,713	4,911,068,443
2006	4,939,658,742	4,974,532,900	4,545,548,978	4,634,554,386	4,711,348,760	4,779,085,321	4,865,349,870	4,932,165,487	5,106,538,649	5,289,985,036	5,360,235,178	5,469,361,363
2007	5,487,509,341	5,567,212,157	5,598,006,453	5,628,754,769	5,754,906,523	5,843,218,965	5,887,095,634	5,893,331,278	6,007,453,897	6,167,908,543	6,145,875,698	6,230,072,940
2008	6,367,908,734	6,432,190,876	6,534,986,731	6,611,140,986	6,750,906,743	6,855,595,321	6,976,908,754	7,156,498,764	7,389,756,430	7,416,189,379	7,659,086,426	7,949,687,979
2009	8,043,876,083	8,266,996,633	8,315,167,098	8,506,931,869	8,690,053,217	8,790,674,312	8,845,328,705	8,959,031,686	9,165,895,432	9,231,675,987	9,437,690,537	9,583,049,888

2010	9,573,963,279	9,571,907,643	9,570,453,798	9,568,342,765	9,564,879,065	9,561,870,945	9,569,453,785	9,573,781,276	9,578,444,986	9,580,666,341	9,587,548,703	9,591,062,087
2011	9,596,430,895	9,598,765,980	9,650,516,497	9,684,275,601	9,723,786,590	9,766,742,318	9,854,679,841	9,934,587,085	9,965,983,331	10,016,759,504	10,259,686,734	10,329,197,507
2012	10,412,786,054	10,458,906,543	10,479,962,310	10,653,287,098	10,585,743,895	10,593,600,511	10,597,006,453	10,621,843,278	10,669,609,342	10,715,654,908	10,816,754,398	10,822,927,783
2013	10,876,453,851	10,956,431,287	11,176,432,780	11,189,065,342	11,237,908,453	11,376,549,812	11,455,322,877	11,683,407,963	11,711,489,065	11,854,769,858	11,987,456,847	12,073,648,919
2014	12,278,656,580	12,345,349,876	12,678,904,376	12,854,809,632	12,900,675,435	13,259,854,290	13,387,945,318	13,534,769,874	13,763,460,538	13,867,934,617	14,167,459,856	14,244,079,774
2015	14,265,897,054	14,258,342,167	14,279,564,987	14,343,786,098	14,361,178,453	14,378,590,521	14,489,405,623	14,555,443,899	14,587,548,041	14,633,879,450	14,726,776,984	14,743,130,327
2016	14,757,321,453	14,778,543,213	14,779,453,786	14,854,890,431	14,876,098,453	14,897,004,231	14,912,345,670	14,987,654,321	15,278,954,326	15,399,786,453	15,643,698,737	15,735,104,737
2017	16,123,456,789	16,654,321,786	17,234,567,890	17,487,609,834	18,476,590,873	19,354,867,786	20,432,167,895	21,657,382,910	22,598,564,231	23,488,743,659	24,765,345,908	25,576,989,132
2018	25,576,989,132	25,576,989,132	25,576,989,132	25,576,989,132	25,576,989,132	25,576,989,132	25,576,989,132	25,576,989,132	25,576,989,132	25,576,989,132	25,576,989,132	25,576,989,132
2019	27,487,954,218	28,502,011,689	29,444,786,421	30,548,967,512	31,349,876,549	32,509,896,542	33,789,054,328	34,555,123,098	35,675,489,231	36,599,844,231	37,360,738,528	38,166,990,521

APPENDIX IV

			LABOUR FORCE IN NIGERIA FROM 2000-2019									
Year	**January**	**February**	**March**	**April**	**May**	**June**	**July**	**August**	**September**	**October**	**November**	**December**
2000	36,435,546	36,533,897	36,623,908	36,689,765	36,711,270	36,778,675	36,850,732	36,964,923	37,255,762	37,465,908	37,648,123	37,993,680
2001	37,848,056	37,852,398	37,895,476	37,912,764	37,976,908	38,156,894	38,233,762	38,322,745	38,600,645	38,733,856	38,888,453	38,927,760
2002	38,934,987	38,952,118	38,967,758	38,972,675	38,985,657	38,979,006	39,244,897	39,367,590	49,499,675	39,634,675	39,866,438	39,914,970
2003	39,926,798	39,934,812	39,941,233	39,956,801	39,968,562	39,977,505	39,986,211	40,199,034	40,367,511	40,532,856	40,734,321	40,890,770
2004	40,891,344	40,891,378	40,891,500	40,892,444	40,892,599	40,903,467	40,923,953	40,956,275	40,976,416	40,985,300	40,979,569	41,723,320
2005	41,733,847	41,745,654	41,758,623	41,763,908	41,793,721	41,821,653	41,844,777	41,865,895	41,875,232	41,900,111	41,965,490	42,828,200
2006	42,830,675	42,838,005	42,841,323	42,856,765	42,867,485	42,879,526	42,885,333	42,894,832	42,992,069	42,995,897	43,549,756	43,882,210
2007	43,884,231	43,886,908	43,889,564	43,965,780	44,237,869	44,376,592	44,498,063	44,622,786	44,799,431	44,878,527	44,956,498	45,010,410
2008	45,021,675	45,045,812	45,165,932	45,237,609	45,476,934	45,600,321	45,786,340	45,833,212	45,901,638	45,934,769	46,123,786	46,203,880
2009	46,204,684	46,328,760	46,400,897	46,467,311	46,547,908	46,675,555	46,732,347	46,798,403	46,844,565	46,875,490	47,297,527	47,453,580
2010	47,478,654	47,511,786	47,544,321	47,579,564	47,611,890	47,658,363	47,694,851	47,743,847	47,775,908	47,995,438	48,333,785	48,753,690
2011	48,805,676	48,823,753	48,867,004	48,880,453	48,921,769	49,289,073	49,355,611	49,465,895	49,654,897	49,855,893	49,947,659	50,041,200
2012	50,067,453	50,102,673	50,265,908	50,376,341	50,532,786	50,666,984	50,711,795	50,834,900	50,976,453	51,132,854	51,206,589	51,387,350
2013	51,378,694	51,466,980	51,499,056	51,589,765	51,673,541	51,755,808	51,866,535	51,897,654	51,922,675	52,267,098	52,543,623	52,794,890
2014	52,823,786	52,865,963	52,879,564	52,886,503	52,894,511	52,904,672	52,976,545	53,167,578	53,367,543	53,689,705	53,876,564	54,234,990
2015	54,321,675	54,456,897	54,566,845	54,689,076	54,745,890	54,789,612	54,795,462	54,812,696	54,976,833	55,266,787	55,587,321	55,790,870
2016	55,789,432	55,897,345	55,925,786	56,234,432	56,345,654	56,521,453	56,785,631	56,833,678	56,944,123	57,111,675	57,265,896	57,369,990
2017	57,432,786	57,488,767	57,532,897	57,634,387	57,897,453	58,238,760	58,478,532	58,511,897	58,734,289	58,855,432	58,956,496	59,012,450
2018	59,154,876	59,278,608	59,421,865	59,588,675	59,678,904	59,789,765	59,832,456	59,879,657	59,954,777	60,256,897	60,456,845	60,698,490
2019	60,732,564	60,822,743	60,879,920	60,887,654	60,934,786	61,347,963	61,533,879	61,677,555	61,723,786	61,855,634	62,278,095	62,447,230

