Volatility in Nigeria Financial markets the impact of Share index on Sustainable Economic Development in Nigeria. Hybrid Approach of GARCH-MIDAS, AND FIGARCH-MIDAS Regressions Models

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***Abstracts*: This Research considers the Comparison of forecasting performance between hybrid of GARCH-MIDAS and FIGARCH-MIDAS. The data employed for this study was secondary type in nature for all the variables and it is obtained from the publications of Central Bank of Nigerian bulletin, National Bureau of Statistics and World Bank Statistics Database dated, January ,2005 to Dec, 2019 for National Stock Exchange for all share index and seven macro-economic variables. Also, the result of ARCH-LM Test show that the presence of ARCH effects in the NSE series and Jarque- Bera Test indicated that the p-values for all variables are less than alpha level of significance (0.05). Hence, we would reject the null hypothesis that the data of all variables are normally distributed. Also, how we estimate the Fractional difference order, d, by Geweke and Porte-Hudak (GPH) method the results show that the value of d for the (NSE price) was found to be (0.043621) which falls within 0<d<0.5 indicating the presence of long-memory process of the data. The results show that based on the analysis of the table 6 above it is indicated that all variables have positive relationship with realized volatility except inflations rate that means increased in the variables can lead to attract more investor to invest in stock market with can be considered as a good proxy of the business cycle for the Economy development of Nigeria. Furthermore, based on the four models of the research we found that FIGARCH-MIDAS of forecast evaluations out-sample with shows that MSE (155.96) of RV+ PC have lest value than the remaining three models. Finally Based on the Table 38 we found that the models of RV+PC and PC are best models among the five models that's FIGARCH-MIDAS are perform better than GARCH-MIDAS. With indicated the accommodated long memory with volatility are perform better than the model without long memory.**

***Key work*: Volatility, FIGARCH, MIDAS, NATIONAL STOCK EXCHANGE and Hybrid.**

I. INTRODUCTION

Forecasting and modeling of Time Series data are not new terms to stakeholders, both in the economic and business fields respectively. Time Series data for financial market constantly display (volatility) variability and ambiguity in market fluctuations. Volatility when predicted in defines the measure of instabilities of currency. Volatility in exchange rate has elevated great anxiety to all economic and professional analysts as its after global trade macroeconomic variables (export and import) and the economic development of a nations. Volatility in Exchange rate result in international deal that may leads to the downtrends in international trade and economic safety (Wong and Lee, 2016). Thus, modeling and predicting of exchange rate show dynamic roles in a country's economy. Nigeria as a country is non left out in this exchange rate instability. as (exchange rate) is one of the momentous indicators that controls nation's economic development. To explain this fact, for instance; the increase or decrease of naira is of interest to financial experts, stockholders, policy makers academics, to mention but scarce; and smooth to the nations Hence, the scholar is interest in projected a competent modelling technique that will be appropriate in describing the volatility of time series data in a more lucid manner. The volatilities of daily futures returns are found to be well labelled by the FIGARCH model, with relatively alike estimates of the long memory constraint across commodities.

A right valuation of future volatility is vital for risk management and asset allocation. Limitless studies have observed the time-variation in volatility and the issues overdue, documented a clustering pattern and time variation. Different alternatives of the GARCH model have been followed in different directions to deal with these phenomena. Simultaneously, a huge literature has examined the relationships between volatility and financial variables. The main drive of presenting FIGARCH model was to develop a more flexible class of processes for the conditional variance, that are proficient of explaining and representative the observed temporal dependencies in financial market volatility. In particular, the FIGARCH model permits only a slow hyperbolic rate of decay for the lagged squared or absolute innovations in the conditional variance function. This model can lodge the time dependence of the variance and a leptokurtic unconditional distribution for the returns with a long memory behavior for the conditional variances.

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Engle et al. (2009) recommend the GARCH-MIDAS model inside the MIDAS context to evaluate market volatility of time-varying. inside this context, the conditional variance is divided into the short-term and long-term components. The low frequency variables disturb the conditional variance via the long- term component, this method combines the component model suggested by Engle and Lee (1999)1 with the MIDAS framework of Ghysels et al. (2006). The key advantage of the FIGARCH-MIDAS model is that it permits us to link the daily observations on stock returns with macroeconomic variables, sampled at lower frequencies, in order to examine directly the macroeconomic variables' influence on the stock volatility. In this research, we apply the recently proposed methodology, FIGARCH-MIDAS, to observe the effect of the macroeconomic variables on the stock market volatility for accommodated long memory behaviors. And also, investigate the ability of the FIGARCH-MIDAS models with Macroeconomic variables in stock volatilities. The presentations of these models are then related with the GARCH -MIDAS model as a yardstick. In order to capture the information contained in different economic variables and investigate their combined effect, we perform a principal component analysis. The benefit of this approach is to condense the number of parameters and rise the computational efficiency.

1.1.0 Nigerian Stock Exchange

1.1.1 Nigerian Stock Exchange

The Nigerian stock exchange the key participant in the capital market. It is a market place where individuals who request to sell shares or buy stocks, dand and government bonds, other approved securities can do so though only members of the stock exchange (Anyanwu, 1993). Thus, it is a market where small and large stockholders alike buy and sell through stock brokers. In this sense, the stock exchange offers the essential facilities for government and firms to raise money for development projects and business growth and complete stockholders who own shares in firms for ultimate economic reimbursements of all members of the society. The Beginning of Nigerian Stock Exchange dates before independence, the Nigerian government at various levels recognized the need for a stock exchange. According to Afolabi (1991), the need for establishment of a stock exchange in Nigeria ascended partly from the worsening government incomes fixed with the grief recurrent disbursement which leftward gap for capital budgeting, in such occurrence, budget shortage was expected if principal investments were to be increased. Purposes of the Nigerian Stock Exchange the Nigerian stock argument was set up to achieve a number of purposes. Again, these purposes have been recognized and stated by Anyanwu (1993) as follows:

(a) To encourage fitting machinery highest, enable further contributions of stock and shares to the general public,

(b) To endorse increasing input by the community in the sequestered division of the economy,

(c) To encourage the investments of savings as soon as it is clear that the stocks and shares are readily available,

(d) To afford a vital meeting place for followers to purchase and vend existing stocks and shares for conceding citations to new ones,

1.1.2 Markets of the Nigerian Stock Exchange

Mostly, nearby are two markets that are initiate in the stock exchange namely the primary market and the secondary market:

I. *Primary market:* This is the innovative issue market as it is concerned with issue and sale of new-fangled securities. In this market corporations and government (quoted companies) can issue new securities to raise money for advance, modernization. Or expansion
II. *The secondary market:* This is a market where already existing securities are exchanged. It is the mechanism for providing liquidity to investors in the stock exchange through the operations of brokers.

1.1.3 Nigeria Stocks Exchange as A Tool for Sustainable Economic Development

The Nigerian stock exchange has meanwhile its outline sustained to serve as an authentic tool for advance of the country's economy. In circumstance, Nigeria's contemporary economic growth is greatly smoothed by the creation of the Nigerian stock exchange which plays its role as an assessor of cheap and steady sources of long-term funds for desired economic growth. The outcome of the Nigerian stock exchange as an economic growth tool is consequently real and considerable can be observed from diverse perspectives:

(1) Platform for Implementation of Economic Reforms:

The Nigerians stock exchange has ended it likely to implement the privatization programme which is intended to encourage a market-based economy that will hasten growth and development of the economy. It should be recalled that in indigenization programmed of 1972, government intervened to acquire and control on behalf of the citizens of the greater proportion of the capital assets of the country. However, government could not efficiently and effectively manage those productive assets or many reasons including the failure to put the right people in the right managerial positions.

(2) Attract direct foreign investment:

The Nigerian stock exchange has attracted foreign participation in investment in the country through its internationalization by the federal government. It should be recalled that following the regulation of the capital market in 1993, the federal government in 1955 internationalized the Nigerian stock exchange with abrogation of laws that constrained foreign participation. Consequent upon the abrogation of the exchange Act of 1962 and Nigerian enterprises promotion decree of 1989, foreign investors have been participating in the Nigerian capital market both as investors and operators.

(3) Employment generation:

The influence of Nigerian stock exchange can also be observed in the area of employment generation for Nigerians. Not only has the stock exchange promoted employment by encouraging expansion of businesses, it has also led to the direct employment of many people in the country through establishment of branch offices and subsidiaries in the major industrial cities of the country

(4) Increased market capitalization:

The growth in the number of securities listed on the Nigerian stock exchange since its introduction has left credence to the effect of Nigerian stock exchange as tool for increased market capitalization.

1.1.4 Problems Affecting Nigerian Stock Exchange

The effect of the Nigerian stock exchange as economic development tool could have been more tremendous if the exchange were not impeded by certain problems. These problems, according to Okaro (2002) are as follows:

(a) Poor partnership spirit of Nigerians that has inhibited the development of public limited liability companies.

(b) Persuasive poverty that has impacted adversely on the saving culture of Nigerians.

(c) An underdeveloped savings/investment system

(d) Hostile and inconsistent macro-economic policy and regulatory environments and lack of transparency in economic management

(e) Inadequate market infrastructural facilities

1.2 Statement Of The Problem

In recent times, stake holders, policy makers, financial economist, academic researchers to mention but few – have picked interest in movement, and fluctuations in financial Time Series. In an attempt to bring the situation under control, several types of case studies, and approaches have been applied to the data in order to handle some characteristics that exist in the series. However, same as the main weakness of the original GARCH model, it assumes that the conditional volatility has only one regime over the entire period. Unfortunately, it is not always true. To overcome this drawback, many studies have suggested that structural breaks should be combined into the hybrid models to properly fit financial return volatility (Baillie and Morana, 2009; Belkhouja and Boutahary, 2011). The primary purpose of introducing FIGARCH model was to develop a more flexible class of processes for the conditional variance, that are capable of explaining and representing the observed temporal dependencies in financial market volatility. This model can accommodate the time dependence of the variance and a leptokurtic unconditional distribution for the returns with a long memory behavior for the conditional variances. Though most of the models are strictly limited to imputing data at the same frequency. In 2004 Ghysels *et al* (2004) present a mixed model data sampling (MIDAS) regressions model which successfully address the data frequency problem. To investigate the ability of the FIGARCH-MIDAS model with economic variables to predict both short-term and long-term volatilities. The performances of these models are then compared with the GARCH-MIDAS model as a benchmark as a benchmark

1.3 Aim and Objectives:

The main aim to examine the role of macroeconomic variables in forecasting the return volatility of the National Stock Exchange for substantiable Economic development of Nigeria. will achieved through the following objectives

I. To develop a hybrid of FIGARCH-MIDAS model
II. To estimate the parameters of the proposed hybrid models.
III. To select the best candidate of FIGARCH-MIDAS and GARCH-MIDAS according to Forecasting evaluations Criteria.
IV. To assess the role of macroeconomic variables in economic development and to ascertain the success achieved through a viable working model for the Nigerian economy.

1.4 Definitions of the Terms

- **National Stock Exchange** is a premier market place for companies preparing to list on a major exchange. The sheer volume of trading activity and application of automated systems promotes greater transparency in trade matching and the settlement process.
- **Inflation rate** is the percentage increase or decrease in prices during a specified period, usually a month or a year. The percentage tells you how quickly prices rose during period
- **Currency Circulations** is currency that is physically used to conduct transactions between consumers and business rather than stored in a bank that's financial institution or central bank.
- **Fixed assets** are long -term assets that a company has purchased and is using for the production of its goods and service**.**

- **Bank reserves are** the cash minimum that financial institutions must have on hand in order to meet central bank requirements. This is real paper money that must be kept by the bank in a vault on -sit.
- **Exchange rate** is the value of a nation's currency in terms of currency of another nation or economic zone.
- **Money supply** is the supply as comprising narrow and broad money.
- **USD-** is the Nigeria naira is made up of 100 kobo's AS of December 2020, 1 U.S. dollar is equal to around 380 NGN**.**
- Data cover the period from January 2005 to December 2019.

II. LITERATURE REVIEW

Financial Time Series show certain features which are referred to as 'stylized facts. The term stylized facts were introduced in the work of Kaldor (1961) on economic development theory. (Sewell, 2011), defined stylized facts as a term in economics used to refer to the empirical results that are highly steady across market and recognized as truth. In financial time series, there are two existing stylized structures which are leverage effect, and volatility clustering. Stylized fact attributed asymmetry to that volatility is higher after negative shocks occurred. This characteristic is referred as leverage effect, (Black, 1976). He recognized that volatility tends to increase in response to bad news and decrease in response to good news as stock returns are negatively correlated to variations in returns volatility clustering has been shown to be existing in a wide variety of financial assets comprising, exchange rates and market indices securities, interest rate (Bollerslev, 1986). As stated by (Mandelbrot, 1963), volatility clustering's can be defined as large variations that tend to be monitored by" large fluctuations, of either sign, or small variations that tend to be followed by small fluctuations. In other word, when volatility is high, it will possibly be remaining for certain periods of time, and it may be short for other times. In financial market, fluctuations of shock stock exchange return either positive or negative would determine volatility

2.1.0 Review of Literature on Arima Model of the National Stock Exchange

Uzuke et.al (2016**)** study was aimed at analyzing the Nigerian Stock Exchange All Share Index. The data was extracted from the Central Bank of Nigeria's Statistical Bulletin from January 1985 to September 2014. The Box and Jenkins approach of model identification, parameter estimation and diagnostic checking was adopted in the analysis with the aid of S-plus Package. From the analysis, the result revealed that Autoregressive model of order two AR (2) after differencing once gives Akaike Information Criteria (AIC) optimal order for Nigeria Stock Exchange All Share Index. Therefore, the model generated shows that ARIMA (2, 1, 0) is adequate to define the optimal order of Nigerian Stock Exchange All Share index. The All-Share Index of the Nigerian Stock Exchange is non-random. The investigations show that the series is void of seasonal component. The forecast for All Share Index of the Nigerian Stock Exchange for October 2014, November 2014, December 2014 and January 2015 are 40460, 40220, 39630, and 39230, respectively thus, the All-Share Index will decrease in the next four months. Based on this paper there's many limitations on the forecast all share index forecast will be decrease in short period of time there's need to measured volatility clustered of the data and also long-run component of the forecast**.**

Godknows, (2014) studied Prediction Nigerian Stock Market Returns using ARIMA and Artificial Neural Network Models and eported experimental sign that artificial neural network-based models are appropriate to predicting of stock market returns. The Nigerian stock market logarithmic returns time series was tested for the presence of memory using the Hurst coefficient before the models were proficient. The test showed that the logarithmic returns process is not a random walk and that the Nigerian stock market is not efficient. The results obtained in the study showed that artificial neural network-based models are capable of mimicking closely the log-returns as compared to the based model. The out-of-sample evaluations of the trained models were based on the and the directional change metric respectively. Based on these metrics, it was found that the artificial neural network-based models outperformed the based model in forecasting future developments of the returns process. Another result of the study shows that instead of using extensive market data, simple technical indicators can be used as predictors for forecasting future values of the stock market returns given that the returns have memory of its past.

Similarly, from the ARIMA scheme's perspective of forecasting the Nigerian stock market returns, Ojo and Olatayo (2009) studied the estimation and performance of subset autoregressive integrated moving average (ARIMA) models. They estimated parameters for ARIMA and subset ARIMA processes using numerical iterative schemes of Newton-Raphson and the Marquardt Levenberg algorithms. The performance of the models and their residual variance were examined using AIC and BIC. The result of their study showed that the SARIMA model outperformed the ARIMA model with smaller residual variance. On the other hand, Emenike (2010) studied the NSE market returns series using monthly data of the All-Share-Index for the period January 1985 through December 2008. In his study, an ARIMA (1,1,1) model was selected as a tentative model for predicting index points and growth rates. The results revealed that the global meltdown destroyed the correlation structure existing between the NSE All-Share-Index and its past values. But it has limitations of not non-random walk and also not accommodated volatility clustering.

W.B Arowolo, (2013) This study focuses on predicting properties of Linear GARCH model for daily closing stocks prices of Zenith bank Plc in Nigeria stocks Exchange. The

Alaike and Bayesian Information Criteria (AIC $ BIC) techniques was used to obtain the order of the GARCH (p, q) that best fit the Zenith Bank Returned series. GARCH (1,2) was identified as the models. The results of statistical properties obtained supported the claim that the financial data are Leptokurtic. We therefore concluded that the Optimal values of p and q GARCH (p, q) model depends on location, the types of the data and model order selected techniques being used.

2.2.0 Review of Literature on FiGARCH Model

Davidson (2004) required certain some intuition on the memory possessions of the FIGARCH. According to Davidson (2004), the degree of persistence of the FIGARCH model operates in the opposite direction as that of ARFIMA, as the d parameter gets closer to zero, the memory of the process increases. This is due to the inverse relationship between the integration coefficient and the conditional variance. The memory parameter acts directly on the squared errors, not on the t, this particular behavior may also influence the stationarity properties of the process (Davidson, 2004). These observations are strictly related to the impulse response analysis on the effects of a shock on a system driven by a FIGARCH process. In such a system, a shock v_t at time t, should be interpreted as the difference between the squared mean-residuals ε_t^2 at time t and the one-step-ahead forecast to the variance h_t, made at time t−1. This shock is exactly the innovation in the ARMA representation of the FIGARCH process and also it shows had shown that a FIGARCH model possesses more memory than a GARCH or IGARCH model. Review of Some Applications There is a large collection of research papers where FIGARCH models are found to be performing better than many of the other conditional Heteroscedastic models.

Jin and Frechette (2004) estimate FIGARCH volatility models for 14 agricultural futures series and find that FIGARCH fits the data significantly better than a traditional GARCH volatility model. While these studies have provided valuable information on the long memory properties of commodity futures price volatilities, much more work remains to be done. while Jin and Frechette (2004) argue in favor of the FIGARCH model over the GARCH model for commodity futures volatilities, they did not undertake a formal statistical test comparing the two models. Here we undertake a robust Wald test, which formally compares the fit of the GARCH and FIGARCH models. Second, in addition to the standard quasi-maximum likelihood estimator (QMLE), we also apply the semi parametric Local Whittle estimator of the long memory parameter. This provides additional information on the robustness of long-memory inferences concerning daily commodity price volatilities. Third, in addition to daily returns we study high frequency returns on futures contracts using intraday tick data. This study is the first to systematically examine volatility using high frequency commodity futures data. We find that estimated models at different sampling frequencies are consistent with the theory that commodity futures returns are "self-similar" processes, and hence have long memory parameters that are invariant to the sampling frequency; see Beran (1994). The "self-similarity" of the estimates of the long memory volatility parameter across relatively short spans of high frequency data strongly suggests that the long memory property is an intrinsic feature of the system rather than being due to exogenous shocks or regime shifts.

Antonakak (2007) investigated the forecasting performance of daily exchange rate volatility in industrialized and developing countries. His study indicated that among all heteroscedastic models, FIGARCH fitted the data better. Also, the performance of FIGARCH model in out-of-sample forecasting was superior.

2.3.0 Review of Hybridize of MIDAS-ADL and GARCH-MIDAS models

Ghysels and Sohn (2013) to forecast the return volatility of energy prices. Other variants of the Midas regressions are the Midas-Adl (Midas Autoregressive Distributed Lag) regression, Midas Quantile regression, and DCC-Midas (the multivariate extension to the GARCH-MIDAS model with dynamic conditional correlations (DCC)). However, we favour the GARCH-MIDAS over other univariate variants of the MIDAS regressions as the former accounts for conditional heteroscedasticity which is a prominent feature of most energy prices (see Narayan and Liu, 2015). Information about the volatility of energy prices is crucial for the valuation of cost of production. In other words, as long as energy continues to serve as input to production, producers of goods and services and by implication, final consumers will be constantly exposed to risk as changes in the volatility of energy prices persist. Also, there is a strong positive link between energy prices and inflation; higher energy prices drive a higher rate of inflation (see Salisu et al, 2017). Most of these studies however focus on oil price volatilities in isolation of other prominent energy prices. Nonetheless, they differ in terms of methodological approaches adopted. While Degiannakis and Filis, (2017) employ the heterogeneous autoregressive (HAR) model, others adopt multivariate GARCH models such as Artificial Neural Network (ANN)-GARCH model (see Kristjanpoller and Minutolo, 2016) and a regime switching GARCH-MIDAS model (see Pan et al., 2017).

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III. METHODOLOGY

This chapter discusses the techniques that will be employed by the researcher when conducting the study on modelling and predicting financial Time Series data. The hybridization between Fractionally Integrated Generalized Autoregressive Conditional Heteroscedastic (FIGARCH) process. with MIDAS Regressions will be used to develop the most appropriate model for forecasting financial Time Series data**.**

Proposed Modifications Hybrid Model of FIGARCH-MIDAS

In this research, we use a new class of component FIGARCH model based on the MIDAS (Mixed Data Sampling) regression. MIDAS regression models are introduced by Ghysels et al. (2006). MIDAS offers a framework to incorporate macroeconomic variables sampled at different frequency along with the financial series. This new component FIGARCH model is referred as FIGARCH-MIDAS, where macroeconomic variables enter directly into the specification of the long- term component. The FIGARCH-MIDAS model can formally be described as below. Assume the return on day i in month t follows the following process:

$$r_{i,t} = \mu + (\tau_i h_t \varepsilon_{it})^{\frac{1}{2}} \forall_i = 1 \dots N_t \quad (1)$$

$$\frac{\varepsilon_{i,t}}{\varphi_{i-1,t}} \sim \text{N}(0,1)$$

Now i is the short scale (for example, $\varepsilon_{i,t}$ is a daily return), and t is the long or aggregated scale (the unit is one month or one quarter). The short-run component h_t is measured in days, whereas the long-run τ_i

is available on a monthly or may be a quarterly basis. Where $\varphi_{i-1,t}$ is the information set up to $(i-1)^{th}$ day of period t. Equation (20) expresses the variance into a short-term component defined by h_t and a long-term component defined by τ_i

The conditional variance dynamics of the component h_t is a (daily) FIGARCH process is given by $(1-\beta(L))h_t = \alpha_0 + (1-\beta(L)-\varphi(L)(1-L)^d \varepsilon_t^2$ (2)

$$h_t = \frac{\alpha_0}{(1-\beta(L))} + \frac{(1-\beta(L)-\varphi(L)(1-L)^d)}{(1-\beta(L))} \varepsilon_{t,i}^2 \quad (3)$$

If $\beta(L) = \beta(1)$ at lag, where L=1 then

$$h_t = \frac{\alpha_0(1-\beta(L))}{(1-\beta(L))} - \frac{\varphi(L)(1-L)^d}{(1-\beta(L))} \varepsilon_{t,i}^2 \quad (4)$$

$$h_t = \alpha_0(1-\beta(1))^{-1} + (1-(1-\beta(L))^{-1}\varphi(L)(1-L)^d \varepsilon_{t,i}^2 \quad (5)$$

$$h_t = \alpha_0(1-\beta(1))^{-1} + \delta(L)\varepsilon_{t,i}^2 \quad (6)$$

Where $\delta(L) = (1-(1-\beta(L))^{-1}\phi(L)(1-L)^d$ (7)

From eqn (20) the returns of the stock can be derived as follow to find the value of $\varepsilon_{i,t}^2$ $r_{it} = \mu + \sqrt{h_t}\tau_i \varepsilon_{t,i}^2$

$$r_{it} - \mu = (h_t \tau_i \varepsilon_{t,i}^2)$$

Square both side of the equations

$$(r_{it} - \mu)^2 = (h_t \tau_i \varepsilon_{t,i}^2) \quad (8)$$

Divided both side by τ_i

$$\frac{(r_{it}-\mu)^2}{\tau_i} = (h_t \varepsilon_{t,i}^2) \quad (9).$$

The proposed FIGARCH-MIDAS model

$$h_t = \alpha_0(1-\beta(1))^{-1} + \delta(L)\frac{(r_{it}-\mu)}{\tau_i} \quad (10)$$

$$h_t = \alpha_0(1-\beta(1))^{-1} + \delta(L)\frac{(r_{it}-\mu)}{m+\theta\sum_{k=1}^{K}(\omega_1,\omega_2)Rv_{i-k}} \quad (11)$$

and τ_i is defined as smoothed realized volatility in the spirit of MIDAS regression, and definitions of the long-term volatility component $\tau_i = m + \theta\sum_{k=1}^{K}\phi_k(\omega_1,\omega_2)Rv_{i-k}$

where

$$Rv_t = \sum_{i=1}^{m_i}\varepsilon_t^2 \quad (12)$$

where h_t is the conditional variance of ε_t, $0 < d < 1$, and Φ (L) ≡ [1 − α (L) − β (L)]. In particular, zt is an identically and independently distributed (iid) innovation sequence following a known distribution with zero mean and unit variance

Data

We use the Stock market returns in Nigeria are considered monthly realized volatility, daily realized variance of a close price in Nigeria to calculate stock returns. In our conditional variance model, we use a number of macroeconomic Variables considered are observed at a monthly which have been found by previous studies to be important for return variance.

Various model specifications

We use three different model specifications. The models differ with respect to the definition of the long-term variance component, τ_t, while the equation for the short-term variance, h_t remains the same in all the three cases. The three specifications are:

I. The RV model: In this specification, we solely use the monthly realized volatility (RV) in $\tau_i = m + \theta\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)RV_{i-k}$ (13)

2. The RV + PC model: Here, we augment the model by adding both the level and the variance of an economic variable to the MIDAS equation, τ_t. This modification is supposed to capture the information explained by both the macroeconomic factor and the monthly RV. we can write Mathematically as:

$$\tau_i = m + \theta_1\sum_{k=1}^{K}\varphi_k((\omega_1,\omega_2)RV_{t-k} + PC \quad (14)$$

$$where\ PC\ is\ the\ macro\ economics\ variables\ are\ defined\ below$$

$$PC_{i-k} = \theta_1\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)INF_{i-k} + \theta_2\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)EXR_{i-k} + \theta_3\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)CC_{i-k} + \theta_4\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)FA_{i-k} + \theta_5\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)BR_{i-k} + \theta_6\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)MS_{i-k} + \theta_7\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2) \quad (15)$$

3. The PC model: In this specification, we only study the effect of macroeconomic variables, both level and variance, on the long-term variance component

By analyzing these three alternatives, we can investigate to what extent the long-term memory variance can be explained by the past realized return volatility and the macroeconomic variables.

Estimations Procedure of the Hybrid Model of FIGARCH-MIDAS Model

The estimations of the FIGARCH-MIDAS Model follow the following steps:

I. Conduct some Statistical tests like ARCH-LM Test, and Jarque- Bera Test. For ours to investigated adequacy of the model, presence of the autocorrelations in the residuals of the fitted model and normality of the time series model residuals
II. Estimate the Fractional difference order, d, by either Local Whittle Estimator (LWE) or Geweke and Porte-Hudak (GPH) method.
III. Carry out the Comparative Test for three Regression models on macro-economic variables to know with one is best for regressions model which are ARDL, MLR and MIDAS regression model on data to select best candidate.
IV. Carry out the principal component with Realized volatility test of Regression with Newey-West Standard Errors
V. Consider the Anderson etal (2007) approach to identify the parameters of the FIGARCH (p, d, q)-MIDAS (r, u) model.
VI. Select the best candidates of FIGARCH-MIDAS and GARCH-MIDAS according to the Mean Absolute Error (MSE) values.

IV. RESULT DISCUSSIONS OF THE ANALYSIS

Table 1: ARCH- LM Test of the National Stock Exchange for all share index

	Statistics	Prob. Distributions	P-value
F-statistic	5.786775	Prob. F (4,5468)	0.0001
Obs*R-squared	23.07060	Prob. Chi-Square (4)	0.0001

Alternative hypothesis: ARCH effects of order are present

Both the F-statistics and R-square are very significant, suggesting the presence of ARCH effects in the NSE series. Thus, it is necessary to proceed with the estimation of the GARCH process.

Table 2: Jargue Bera Test of Normality for Both variables:

Variables	Degreen of freedom	Statistics	P-value
NSE price	2	82.696	<2.26e-16
CC	2	9.9552	0.006891
INF	2	356.66	<2.24e-16
MS	2	7.5393	0.02306
FA	2	40.824	1.365e-09

BR	2	30084	2.25e-16
EXR	2	24.485	4.821e-06
DAS	2	9.7206	0.007748

This indicated that the p-values for all variables are less than alpha level of significance (0.05). Hence, we would reject the null hypothesis that the data of all variables are normally distributed.

Table3: Test the Present of Long-memory of the National Stock Exchange for all share index

Difference	value
FdGPH (NSE price)	0.043621

The value of d for the (NSE price) was found to be (0.043621) which falls within $0<d<0.5$ indicating the presence of long-memory process of the data.

Table 4: Forecast evaluations of out- sample of MIDAS, MLR and ARDL models for macroeconomics variables:

Models	MSE	**MAPE**	**RMSE**	MAE
MLR	295.23	178.34	239.46	
MIDAS	195.23	**128.34**	**139.46**	
ARDL		156.19	631.49	492.8421

Based on the result of table 4: it shows **MAPE and RMSE of Midas** have the least value (128.34 and 139.46) than MLR and ARDL Models.

Based on the results of table 3: on Test of present of long memory and forecast evaluations of out sample of table 4. It shows that the NSE price data have the present of long-memory and MIDAS Regressions model are the best model among the three-regression models with has least value of forecast evaluations. Finally in this research we are adopt **FIGARCH and MIDAS regressions model** for forecasting volatility of National Stock Exchange for all share index.

Table 5: Descriptive Statistics of macroeconomics variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Currency Circulation	181	1.266e+09	4.919e+08	4.949e+08	2.330e+09
Exchange Rate	181	198.748	272.642	0.497	423.435
Inflation	181	11.919	17.175	-0.4	41.2
MS	181	27505885	6197843.1	16260346	42961403
FA	181	3.854e+08	1.004e+08	1.145e+08	6.881e+08
BR	181	9597634	99330759	132780.86	3.226e+08
DAS(USD)	181	141.962	13.871	110.818	169.68
Realized Volatility	181	271.58	21.022	248.151	300.248

The estimated results of the above table describe that, the measure of central tendency as well as a measure of dispersion. The reported statistics vary among the variables. The reported series are indicated that not bell-shaped due to high volatility exist in macro variables. The most of series is right-skewed with high volatility. All appropriate indicators are a high deviation from their mean value. There is no missing observation has been observed in the data and the results are described in the above table.

Table 6: Correlations Analysis of the Macroeconomic Variables

Variables	Realized Volatility	Currency Circulation	Exchange Rate	Inflation	MS	FA	BR	DAS (USD)
Realized Volatility	1.000							
Currency Circulation	0.562	1.000						
Exchange Rate	0.009	0.071	1.000					
Inflation	-0.124	-0.297	-0.007	1.000				
MS	0.014	0.261	-0.120	-0.319	1.000			
FA	0.112	0.586	-0.041	-0.445	0.344	1.000		
BR	0.155	-0.137	0.083	-0.007	-0.048	-0.194	1.000	
DAS(USD)	0.417	0.606	0.055	-0.181	-0.013	0.592	-0.186	1.000

The table depicts the relationship between monthly macroeconomic variable observations and observed monthly volatility of the National stock exchange return. Currency circulation, exchange rate, MS, FA, and BR are all macroeconomic factors to consider. Changes in the consumer price index, the exchange rate, and the gap between DAS every month (USD). From January 2005 through December 2019, data is available. The results are confirmed that all variables are positively associated with RV expect inflation. This result indicated that the six variables have related to change in volatility of national stock exchange the increase in the **currency circulation** can lead increase in exchange rate, money supply, fixed assets and USD but also, have negative correlations with inflations rate and bank reserved the more currency circulations increased it also affect inflations and Bank reserved of the country. That is the currency circulations increased our investor can increase because money supply, fixed assets and USD also increased

Exchange rate has positive correlations of Bank reserved, USD that is the increase in exchange rate can lead to increased Bank reserved and USD while have Negative correlations with inflations, money supply and fixed assets that means increased in exchange rate can have positive impact to National stock Exchange because bank reserved can increase with USD for international business.

Inflation rate has negative correlations with Money supply, fixed assets, Bank reserved and USD.That is the more country have high inflations rate can affect money supply, fixed assets, Bank reserved and also USD it has effect on investor because people cannot invest due to uncertainty because high inflation can lead to recessions

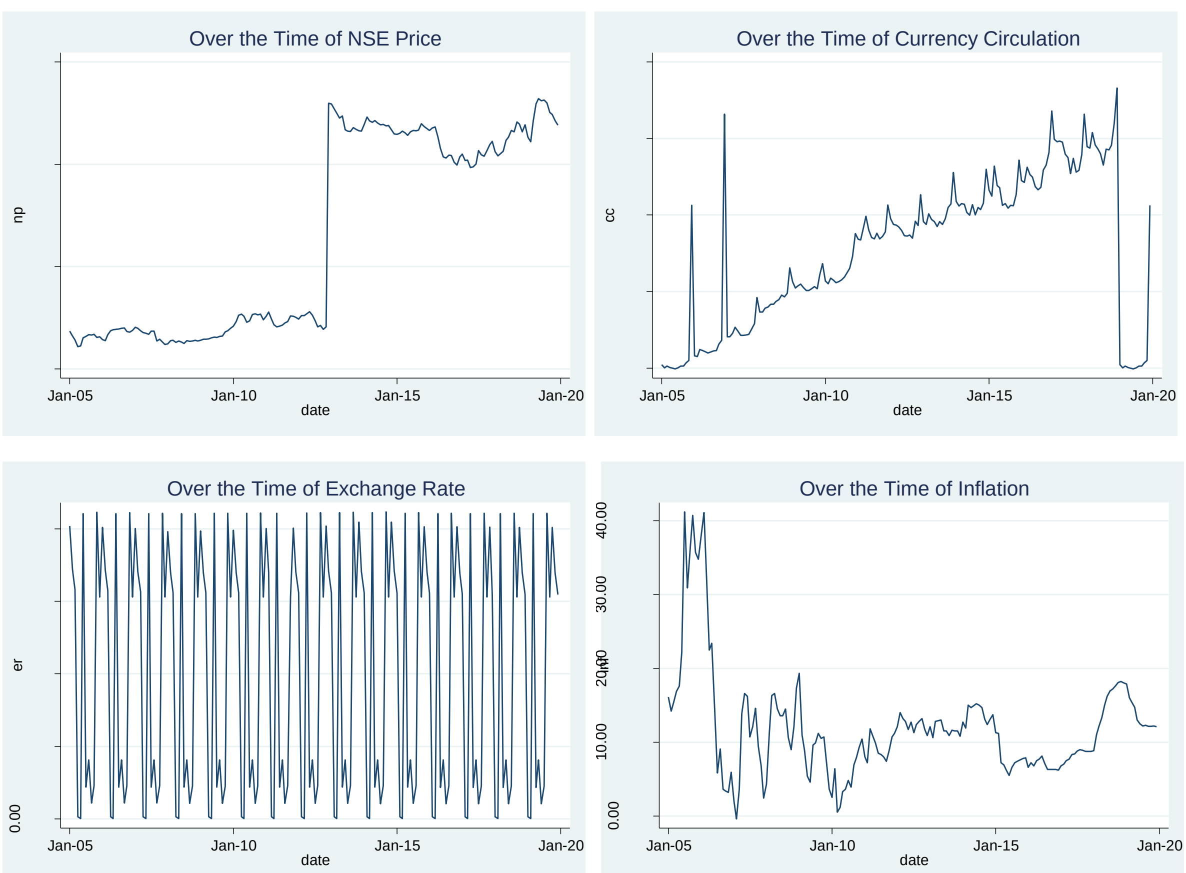
Money supply has positive correlations with fixed assets and also negative correlation with Bank reserved and USD. The increased money supply can lead to more fixed asset in a country while decreased in bank reserved and USD.

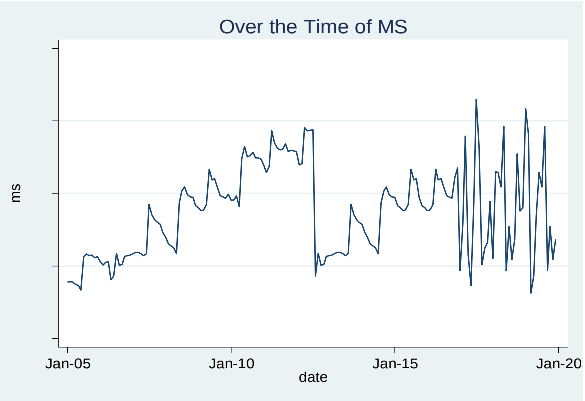
Fixed assets have positive correlations with USD while have negative correlations with Bank reserved.

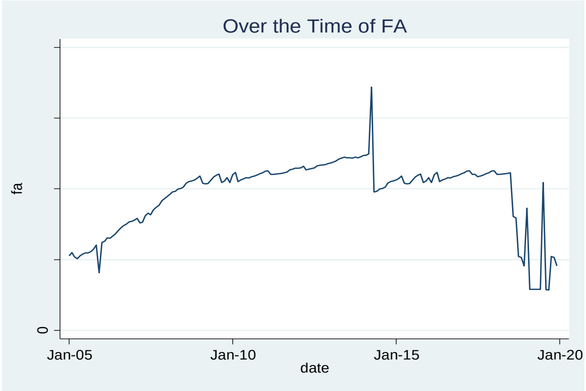
Bank reserved has negative correlations with USD.

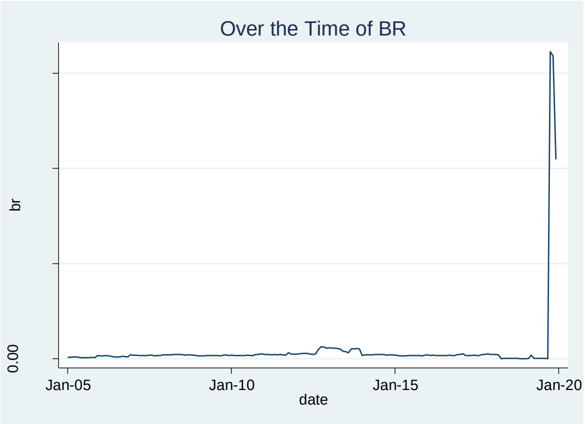
Based on the analysis of the table above it is indicated that all variables have positive relationship with realized volatility except inflations rate that means increased in the variables can lead to attract more investor to invest in stock market with can be considered as a good proxy of the business cycle for the Economy development of Nigeria.

Over the time Realized Volatility and Economic Variables Graph









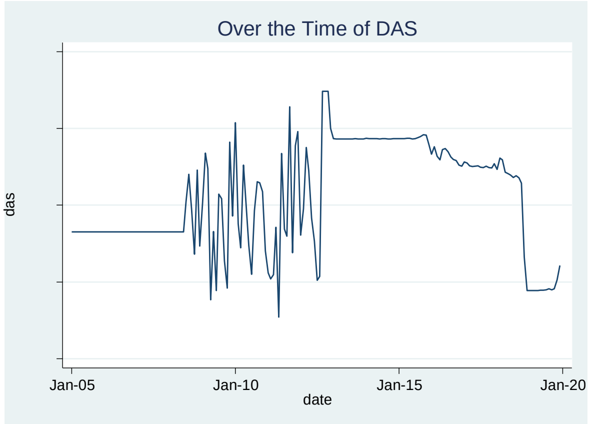


Table 7: Regression with Newey-West Standard Errors

Realized Volatility	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Currency Circulation	0.275	0.026	13.75	0.000	1.7108	3.7908	**
Exchange Rate	-0.011	0.005	-2.24	0.034	-0.022	-0.001	**
Inflation	-0.232	0.095	-2.44	0.054	-0.841	0.378	
MS	0.812	0.285	2.84	0.076	0.459	0.985	
FA	0.927	0.425	2.18	0.036	0.698	1.698	**
BR	0.114	0.032	3.56	0.001	0.025	0.875	**
DAS(USD)	0.485	0.149	3.22	0.002	0.186	0.775	**
Constant	210.5	33.496	6.29	0.000	144.4	276.6	**

Mean dependent var	271.580	SD dependent var	21.022
Number of obs	180.000	F-test	28.886

*** *p*<.01, ** *p*<.05, * *p*<.1

The above table describes sensitivity estimation before the empirical estimation of FIGARCH-MIDAS. The approximated model seems to be good and the expected sign of the estimated coefficient as per prior literature. All variables in the estimation are significant at various levels of the confidence interval. Based on the table about we found that all the variables are statistically significant at 5% level of significant except inflations and money supply that's means there's positive relationships between National Stock Exchange and macro-Economic variables in Nigeria Since currency circulations , exchange rate , fixed assets , Bank reserved and USD are statistically significant at 5% level of significant ,that is increase in currency circulation , fixed assets can motivated investor to invest in capital market with can increase our economy while have negative relationships with money supply and inflations rate that's aren't significant at 5% level of significant with show the economy are good in a nations the inflations rate are minima cannot affect the capital market .

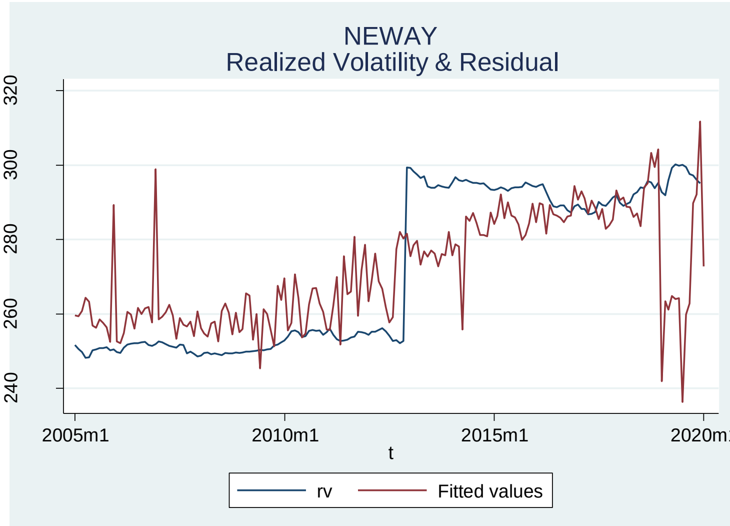


Table 8: Estimated Parameters of the GARCH-MIDAS model

	mu	alpha	beta	m	RV	level	var	w_2
GARCH	0.191	0.048**	0.725**	0.675**		0.329**	0.778**	6.789
RV	0.053**	0.064**	0.436**	-0.998**	0.056**			
RV+PC	0.067**	0.056**	0.659**	0.646**	0.083**	-0.198**	-2.789**	
PC	0.055**	0.068**	0.478**	0.484**		-0.359**	-3.579**	

The GARCH (1,1) model's estimation results show that in the case of observed NSE-Price returns, the sum of the estimates is very close to one for all the periods examined, indicating that the volatility process is highly persistent, implying that current information is relevant in forecasting the future for the short and medium term. When the total of alpha + beta is less than one, the variance process is said to be reverting. Furthermore, the GARCH (1,1) model is valid for all periods in the case of adjusted NSE-Price returns. The total of coefficients is less than one, indicating that a mean reverting variance process is present. In call estimate regression model as well as significant at 95 % confidence interval.

Table 9: Estimated Parameters of the FIGRACH-MIDAS model

	mu	alpha	beta	m	δ	RV	level	var	w_2
FIGARCH	0.098**	0.068**	0.915**	0.875**	0.0231**		0.459**	0.578**	4.789
RV	0.063**	0.054**	0.536**	-0.798**	0.0426**	0.026**			
RV+PC	0.057**	0.036**	0.459**	0.546**	0.0318**	0.083**	-0.198**	-2.789**	
PC	0.045**	0.068**	0.378**	0.484**	0.0827**		-0.259**	-3.679**	

The estimated parameters of the FIGARCH-MIDAS model with various MIDAS equation settings can be seen in the table. The first row of the table shows the model's conclusions when just the realization volatility (RV) of returns is included in the MIDAS equation, while the remaining rows show the estimated parameters when the level and variance of the economic variables. The results above indicate that the estimated parameters of μ are significant at a 95 percent confidence interval that mean the mean equations and (alpha and beta) in the equation for the conditional variance are significant. Furthermore, the sum of the alpha and beta parameters is close to unity ($\alpha + \beta = 0.983$), indicating that the persistence of the NSE return is high. Although the returns volatility appears to have what seems to be long memory, it is still mean reverting: the sum of α and β is significantly less than one, implying that although it takes some time, the volatility process does return to its mean. Furthermore, the results indicate that the coefficient gamma is significant, at

5% level of significant implying that the sign of the innovation has significant influence on the volatility of returns. The results for the first and second main components, which were formed using seven macroeconomic variables, are presented. The information pertains to the first estimate period, which began in January 2005 and ended in December 2019. The reported results showed all models are significant at a 95 percent confidence interval. Only the findings for PC of the parameters in the equations for returns and the short-term variance component (g) are significant at the 5% level, showing a clustering pattern in the short-term return variance. When we look at the long-term component, we can see that the RV in all three models is substantial at 5%. When we augment the model with macroeconomic variables, we need to maintain the same degree of smoothness for all variables estimated from the model with the only RV. The findings reveal that the amount of PC, along with RV, is significant, but not its variance. When RV is removed from the long-term component equation, both the levels and variation of PC are reduced. The vast majority of them are vital. When PC is used as a macroeconomic variable, RV quantifies the influence of PC's variation, and RV is still significant at the 5% level. The parameter for PC variance is similarly significant, but only at a 5% level. When RV is removed from the equation, only the level of PC is determined to be important. We may extrapolate that the aggregate impact of the economic variables recorded by PC provides a little insight into the driving force behind stock market return variation. We analyze the FIGARCH-MIDAS model's estimated short-term, long-term, and total variance, using just relevant to the phenomenon in the MIDAS equation (RV model). Despite several high peaks in the short-term variance (perhaps owing to Asian crises), the long-term variance is quite modest in the early half of the estimate window. We see a significant increase in the long-term variance component after 2015, whereas the short-term component is almost always lower than the long-term component. We compare the RV model's findings to two alternative specifications: the RV model with a macroeconomic variable added on top of it and a model with only the macroeconomic variable. The macroeconomic variables are represented in the first graph by PC, while the estimated variances are shown in the second graph by PC. It can be seen that the RV+PC model's predicted variance closely resembles that of the RV model, but the PC model goes in the opposite direction. When all three models are compared, it appears that the RV+PC model combines the two others, with RV determining the variations and PC affecting the predicted variance level. When we employ the PC variable as the macroeconomic indicator, all three models provide a very similar pattern.

Table 10: Comparisons of the out of sample prediction error

	Long Term Variance			**Total Variance**		
	MSE	**FIGARCH**	**RV Model**	**MSE**	**FIGARCH**	**RV Model**
GARCH	241.89		-	15.95		+
RV	316.65	+	-	16.36	-	-
RV+PC	155.96	+	+	19.78	-	-
PC	278.96	-	+	13.35	-	-

For the out-of-sample performance of the different models in forecasting daily and monthly variances, the table provides the results of the estimated mean square error (MSE) and DM-test. In the MIDAS equation, we use three different models: one that only considers realized stock return volatility (RV model), one that considers realized return volatility as well as the level and variance of economic variables, and finally one that only considers the level and variance of economic variables. The findings for the long-term variance component are shown on the left panel, while the conditional daily total variance is shown on the right panel. The FIGARCH-MIDA S findings are compared to equivalent FIGARCH estimations. In the MIDAS equation, we employ the two initial principal components, PC and PC, as macro variables. We employ a ten-year estimate window and maintain the parameters year after year.

Based on the four models of the research we found that FIGARCH-MIDAS of forecast evaluations out- sample with shows that **MSE (155.96) of RV+ PC** have lest value than the remaining three models. Finally Based on the Table 38 we found that the models of RV+PC and PC are best models among the five models that's **FIGARCH-MIDAS** are perform better than GARCH-MIDAS. With indicated the accommodated long memory with volatility are perform better than the model without long memory that is GARCH-MIDAS (2019) Volatility forecasting using multiplicative component GARCH-MIDAS models.

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