CENTRAL BANK OF NIGERIA

Occasional Paper No. 77 FORECASTING REAL GDP GROWTH USING A DYNAMIC FACTOR AUGMENTED MIXED DATA SAMPLING (FAMIDAS) REGRESSION July 2023

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Research Department
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EXECUTIVE SUMMARY

The Gross Domestic product (GDP) forecasting requires several variables, given the important role it plays as one of the main indicators of the economic performance. In recent time, factor models have been used to estimate macroeconomic variables such as GDP, because of the huge data required. Factor models have proven particularly valuable for forecasting, given the wealth of information in the included models to and capacity to accommodate mixed-frequency data sampling (MIDAS). This has helped to circumvent unbalanced datasets, which result from publication lags and delays of both high and low-frequency indicators. Thus, in this study, we introduce a Factor (FA) MIDAS approach for nowcasting and forecasting low-frequency variables like gross domestic product (GDP) while taking advantage of the information in a large set of higher-frequency indicators.

This study utilised a factor augmented mixed data sampling (FAMIDAS) regression method to produce predictions for Nigeria's real GDP growth and its components (oil and non-oil GDP). To manage the size of the dimension of the explanatory variables, the study adopted the principal component (PC)

approach, which reduced the variables into two groups containing five monthly and quarterly PCs each. These groups were then integrated into the MIDAS regression framework to generate nowcasts and forecasts for real GDP growth, as well as oil and non-oil GDP. To achieve this, the autoregressive integrated moving average (ARIMA) technique was applied to each PC, generating out-of-sample forecasts for the endogenous variables and the time path of the PCs throughout the forecast horizon.

This was followed by a forecast accuracy assessment between the newly constructed FAMIDAS and the existing FAVAR model. The models' in- and out-of-sample forecast capacity were evaluated by comparing the forecast evaluation indicators from the FAMIDAS models with the forecast of the factor augmented vector autoregressive (FAVAR) model. The key finding is that the FAMIDAS outperformed the FAVAR model, as forecasts from the FAMIDAS exhibited similar trends and movements in their actual series, with very little deviations. The implication is that the FAMIDAS model has significant potential as a leading indicator for the growth of real GDP and its components in Nigeria.

1.0 INTRODUCTION

1.1 Background of the Study

The aim of this study is to determine the robustness of using mixed frequency data to forecast real GDP growth in Nigeria. Previous efforts, such as Adebiyi and Mordi (2012), was meant to provide the Monetary Policy Committee (MPC) with quality information. At the centre of the Bank's modelling strategy, is a continuous improvement of information credibility and integrity for policy analysis and decisions. In these efforts, the inclusion of datasets become limited for two fundamental reasons and can reduce the quality of forecasts that can be generated from a pool of datasets. The first is the dimensionality problem associated with having too many explanatory variables in a regression model, in the face of limited sample observations. The second is related to the differences in the frequency of variables. These problems become significant when attempting to explain the actual data-generating process (DGP) and undertaking forecasts of most time series. That way, forecast accuracy can be undermined due to larger forecast errors.

Cohen and Cohen (1975), Harris (1985) and Darlington (1990) suggest the need to always have large sample observations for every given number of variables. As a rule of thumb, Harris (1985) advocates that sample size *(r)* should exceed number of explanatory variables *(n)* by at least 50. Darlington (1990) has a more general rule of thumb for determining the most appropriate dimension for the matrix of explanatory variables. His rule is, "more is better." Though this suggestion is important, its practical implementation would be difficult under limited sample size and a large pool of important explanatory variables. Where the explanatory variables are reduced to improve the degrees of freedom, the estimated model tends to suffer from 'omitted variable bias'. As a solution, two approaches can be employed to reduce the dimensionality of the matrix of explanatory variables. These include the principal component analysis (PCA) and weighted-sum indices approaches.

The Principal Component approach enables the extraction of variances from the linear combination of several variables. These variances, called principal components (PCs), hold information that mimics the behaviour of the combination of these variables. The weighted-sum approach can convert several explanatory variables into a single variable in a regression model (Gonzales & Bautista, 2013; Osorio et al., 2011; Stock & Watson 1989, 1999; Gosselin & Tkacz, 2001). The weights assigned to each variable in the index are either calculated as their respective parameters from a regression of these explanatory variables, on the variable to be forecasted, or as the average of the impulse responses of the variable to be forecasted, from shocks to these explanatory variables, under a standard vector autoregressive (VAR) framework (Gosselin & Tkacz, 2001).

In terms of mixed frequency of variables in time series research, on one hand, higher frequency variables are converted into lower ones by taking the sum or average, depending on the variable type, of the observations, corresponding in time, to that of the lower frequency. This approach is, however, faulted because each observation, in this high-frequency variable enters into the newly-constructed low frequency, with equal weight. In this case, the information in their DGP is distorted, leading to biased predictions of their future path (Foroni & Marcellino, 2013).

On the other hand, all components of the high-frequency variable may be used as independent regressors. For example, to run a regression of inflation rate (INF), a monthly frequency data, on real gross domestic product (RGDP), a quarterly variable, INF would be divided into three variables. The first would contain observations for the first month of each quarter for INF, the second would be made of all observations in the second month of all the quarters, and the last would be a collection of all observations of the third month of every quarter. This approach is also not without fault. By adding more variables, the model becomes burdened with an excessive number of parameters, potentially leading to overfitting. This undermines the principle of parsimony in regression analysis, which seeks to include fewer variables with lower frequencies as regressors to maintain a simpler and more effective model. (Foroni & Marcellino, 2013).

Attempts to circumvent these problems (assigning equal weights to each observation and over-parameterisation of regression models) have led to the development of mixed data sampling (MIDAS) regression (Gyhsels et al., 2006; Ghysels et al., 2007; Andreou et al., 2010). MIDAS regression fits a parsimonious regression model of variables of different frequencies, without assigning equal weights to any set of observations in the series.

1.2 Statement of Research Problem

Economic indicators come in different frequencies. In Nigeria, for example, while GDP figures are released quarterly, inflation figures are released on a monthly basis by the National Bureau of Statistics (NBS). In addition, empirical evidence has revealed a large number of drivers of economic growth, over time, in Nigeria (Inim et al., 2020; Dahiru & Sulong, 2017; Bawa et al., 2016). However, there are limited samples for some of these variables, because the NBS did not initiate the collection of data for all these variables at the same time. Forecasting real GDP would, therefore, require time series models that adequately and jointly address the problems of dimensionality and mixed frequencies of economic indicators in Nigeria. Thus, this requires utilising a dynamic Factor Augmented Mixed Data Sampling (FAMIDAS) model. FAMIDAS reduces the dimensionality of the matrix of the explanatory variables into principal components (PCs) or indices of different frequencies and uses these PCs or indices in the framework of MIDAS regression.

1.3 Objective of the Study

This study seeks to enhance the quality of forecast of real GDP and its components (Oil and Non-oil GDP) in Nigeria under the prevailing conditions of limited sample and mixed frequencies using FAMIDAS.

Mixed-frequency factor models (FAMIDAS) incorporates both strands of mixed frequency sampling with the use of factor analysis tools, which have been proven to have better predictive power and produce more accurate results for short-term forecasting (Giannone et al., 2008; Barhoumi et al., 2010).

In order to check for robustness, the study would compare the forecast accuracy of the newly constructed FAMIDAS model with the existing FAVAR[1] model to determine if forecast performance improved after introducing the mixed data sampling.

In order to check for robustness, the study would compare the forecast accuracy of the newly constructed FAMIDAS

1 The FAVAR model is an operational forecasting model within the CBN Suite of macroeconometric models. The model uses PCs as explanatory variables within a VAR framework (See CBN, 2017)

model with the existing FAVAR[2] model to determine if forecast performance improved after introducing the mixed data sampling.

[2] The FAVAR model is an operational forecasting model within the CBN Suite of macroeconometric models. The model uses PCs as explanatory variables within a VAR framework (See CBN, 2017)

2.0 LITERATURE REVIEW

The importance of effective monetary policy formulation and implementation necessitates the recognition of forecasts of key macroeconomic variables. Several methodologies exist to obtain a more accurate and reliable forecast for economic variables such as GDP and inflation[3].

Some of the most frequently used time series approaches include the ARIMA models based on Box and Jenkins (1976) for forecasting inflation (Meyler et al., 1998; Faisal, 2012; Olajide et al., 2012). This approach was extended in multivariate vector autoregression (VAR) models, following Sims (1980). Studies by Stock and Watson (2001) have shown that VAR models are powerful in forecasting various variables.

Furthermore, its extension, Bayesian VARs has also proven to be reliable (Koop, 2013; Louzis, 2016; Berg, 2016).

Dynamic factor models have gained significant popularity among practitioners and econometricians as an effective

[3] Time series models primarily rely on statistical techniques and historical data to make predictions, involving only a limited number of variables and minimal economic context. In contrast, structural models employ economic theory to define the connections between variables, achieved through estimation or calibration processes.

tool for short-term forecasting. Numerous studies have demonstrated their strong forecast performance, contributing to their widespread adoption in forecasting practices. These methods include mixed-frequency vector autoregression (MF-VAR), dynamic factor models (DFMs) and principal component regression models. These methodologies have been applied to forecasting GDP in various jurisdictions. See for instance, Giannone et al. (2008) and Stock and Watson (2002) for the United States; Angelini et al. (2011) and Rünstler et al. (2009) for the euro area; Schumacher and Breitung (2008) for Germany; Chernis and Sekkel (2017) for Canada; Luciani et al. (2018) for Indonesia; Modugno et al. (2016) for Turkey; Pliess and Poiana (2016) for Baltic States; Andersson and den Reijer (2015) for Sweden; and Mordi et al. (2015) for Nigeria.

The structural models have transited from the Cowles Commission models to the dynamic stochastic general equilibrium (DSGE) models. Various studies which have produced forecasts of macroeconomic variables include Del Nergo and Schorfheide (2013); Kolasa and Rubaszet (2015); Berg (2016); and Ca'Zorzi et al. (2017), to mention but a few.

Although these studies produce reasonably accurate results, they were also limited by the richness of the use of mixed frequency of variables, and dimensional constraints in the estimation process. As computational resources continue to improve and also, in a world of a data-rich environment when forecasting macroeconomic aggregates, the use of mixed frequency variables has become attractive. The extant literature has shown that a data-rich environment involves using both explanatory variables from various activity sectors regardless of their DGP, sampling frequency, and technical specifications. In estimating these models, data would be transformed to a common low frequency. Following Di Fonzo (1990), the four basic types of variables are averages of flows, averages of indices, beginning-of-period stocks or end-of-period stocks. Consequently, to attain a sample with the same frequency, be it quarterly or annually, it would be necessary to perform statistical methods of aggregation or averaging. This would lead to problems of 'loss of information' and distortion of the true DGP, which could produce inefficient results[4]. The MIDAS regression models provide a reliable framework that could circumvent this problem.

The literature on mixed frequency data regressions is still budding, starting with the seminal work of Ghysels et al. (2004), aimed at circumventing the limitations associated with pre-filtering procedure of aggregating high-frequency data or interpolating lower-frequency data to obtain a balanced dataset of the same frequency. This served as the turning point for the recent strand of literature referred to as mixed frequency or bridge models. This technique has become an important part of the modelling tools of central banks and other policy-making institutions for nowcasting GDP growth (Baffigi et al., 2004; Bencivelli et al., 2012). Since then, variants of the mixed-data sampling (MIDAS) and state-space mixed-frequency VAR (MF-VAR) approaches have been developed by extending the framework of Ghysels et al. (2004). In a survey of the methodological approaches for mixed frequency data, Foroni and Marcellino (2013), for instance, noted the extension of the root model to Factor-

[4] Wei (1978) proved that the loss of forecasting efficiency, due to aggregation is substantial. Furthermore, Lütkepohl (1987) discussed that there exists observable loss arising from aggregation that poses negative effects on forecast accuracy.

MIDAS by Marcellino and Schumacher (2010), which employs dynamic factors as explanatory variables to elicit information in large mixed-frequency datasets.

Armesto et al. (2010) used the exponential Almon polynomial MIDAS, along with simple time averaging and the step-weighting function approaches to forecast. The paper noted variances in the performances of the various techniques, indicating trade-offs between parsimony and flexibility for different datasets. While no discernable superiority was observed with some methods, such as the averaging of higher frequency data, the predictive ability of mixed data sampling was noted to be superior and beneficial for forecasting. Jiang et al. (2017) applied the mixed data sampling regression to forecast quarterly GDP growth for China using monthly and daily predictors and found the forecast accuracy for the mixed-frequency data outperforming the traditional linear regression forecasting methods. In the same vein, Foroni and Marcellino (2014) used mixed-data sampling (MIDAS) and mixed-frequency VAR (MF-VAR) approaches in forecasting the quarterly GDP growth rate and its components for the euro area. The study demonstrated the superiority of the MIDAS, with an AR component, to MF-VAR, while overall, bridge equations performance superseded others.

Schumacher (2016) undertook a comparative analysis between the MIDAS and bridge equations approaches in nowcasting the GDP growth rate for the euro area. The paper constructed and compared three variants or hybrids between the two approaches with different weights attached to the high-frequency predictor observations using a large set of business cycle indicators. For the euro area also, Kuzina et al. (2011) compared the performance of mixed-data sampling (MIDAS) with mixed-frequency VAR (MF-VAR) approaches in forecasting quarterly GDP growth on a monthly basis, using a set of 20 monthly indicators and their relevance in policy making. The results suggested that the two methods complemented, rather than substituted for, each other, especially as the MIDAS performance was more efficient in the short-term (four to five months horizon) than MF-VAR, which performs better at longer horizons of about nine months.

Testing for Granger causality in a mixed-frequency VAR that used a-two parameter reduction technique with the introduction of bootstrap versions that accounted for factor estimation uncertainty and corrects for large sample sized VARs, Gotz et al. (2016) estimated a Bayesian MF-VAR extension of mixed frequencies. The results were compared with outcomes from Ghysels et al. (2016a) max-test and Ghysels et al. (2016b) unrestricted VAR-based tests using Monte Carlo simulations. The findings showed different test results, indicating that the Granger non-causality testing behaviour, performs best, especially the causality from uncertainty in financial markets to business cycles fluctuations.

Duarte et al. (2017) constructed a MIDAS framework for nowcasting and forecasting quarterly private consumption for the Portuguese economy. To produce a reliable model for the tracking of private consumption, several of the MIDAS regression approaches in the literature were explored and compared, including different information sets: quarterly data for consumption and monthly and daily data for ATM and PoS. Evidence showed that ATM and PoS exhibited superior forecast performance over traditional macroeconomic indicators. This suggested the potential usefulness of ATM/PoS data and the significant role played by the ATM and the PoS technology in the Portuguese payments system for decision-making by policymakers and economic analysts, and practitioners.

For the US economy, Blasques et al. (2016) adopted the dynamic factor model, using the weighted likelihood-based estimation procedure to determine parameter estimates in a panel framework to improve the nowcasting and forecasting accuracy of key macroeconomic and financial variables. To achieve this, the authors split the likelihood function into two weighted parts: the part consisting of key macroeconomic and financial variables (observed quarterly) and the part associated with related variables to the forecasting of the key variables (observed monthly). The result showed that the estimators derived from the asymptotic properties outperformed the standard likelihood-based estimator. The authors noted significant improvements in the forecast, and in the forecast of GDP growth with the weighted likelihood-based estimation procedure.

In their study, Chen and Tsay (2011) utilised a generalised autoregressive distributed lag (GADL) model to conduct regression estimations, incorporating mixed-frequency data.

They employed a Vandermonde matrix to parameterise the weighting functions for the higher-frequency observations. The research findings indicated that by incorporating daily asset market information, currency, and equity market movements, they were able to produce forecasts of quarterly commodity price changes that outperformed previous literature's forecasting methods.

Barsoum and Stankiewicz (2015) introduced the Markov-switching MIDAS model with unrestricted lag polynomial (MS-U-MIDAS) as a method to forecast US GDP growth. Asimakopoulos et al (2013) utilised quarterly fiscal data to predict a disaggregated set of annual fiscal series and found that the MIDAS model offered the most effective approach for analyzing mixed-frequency data. Subsequent research on mixed frequency modeling includes the works of He and Lin (2018), Andreou et al., (2013), Pan et al. (2018), Xu et al. (2018), and Jiang et al. (2017). These studies contribute to the advancement of forecasting techniques for mixed-frequency data, providing valuable insights into their applicability and performance in various economic contexts.

In a previous study conducted by Marcellino and Schumacher (2010), they combined factor models with the MIDAS approach to generate nowcasts and forecasts for quarterly GDP in Germany. By incorporating a wide range of timely monthly economic indicators, they discovered that Factor-MIDAS nowcasts outperformed standard factor model quarterly forecasts that were based on time-aggregated data. This approach demonstrated enhanced accuracy and effectiveness in predicting quarterly GDP by utilising more up-to-date and relevant information from the monthly indicators.

Though, Cann (2016) had used regression models with an autoregressive component and five additional high frequency independent variables to forecast Yen and US dollar spot exchange rates. Results showed that such an exercise might be favourable to better track the underlying DGP, and may not necessarily improve the forecast performance.

However, for Nigeria, the literature in mixed data sampling and most of all factor augmented mixed data sampling remains scanty. Some of these are Uwatt et al. (2018) and Mordi et al. (2015). Uwatt et al. (2018), employed factor analysis to forecast GDP and its components. The model incorporated a vast amount of data while circumventing the curse of dimensionality. The model also considered the role of economic structure in policy formulation by forecasting the oil and non-oil components of GDP. An earlier study by the CBN, Mordi et al. (2015), employed a dynamic factor model (DFM) in a state space framework. The study was able to extract underlining factors, which generated more robust forecasts for GDP.

Other studies which have attempted to forecast Nigeria's GDP, through time series modeling, include Fatoki et al. (2010) and Uwimana et al. (2018), and Okereke and Bernard (2014). However, as shown by Cann (2016), these model types are unable to improve forecast performance.

Thus, this presents a gap and motivation for the study, to employ a factor-augmented mixed data sampling (FAMIDAS) methodology to forecast GDP in Nigeria. Mixed data modeling is an econometric novelty to be adopted, with growing literature, using MIDAS models and its extensions to accommodate mixed frequency with a large set of timely higher frequency data. In this regard, the following chapter addresses different issues related to the use of mixed frequency data due to the weighting technique to adopt and also outlines the Factor Augmented MIDAS model.

3.0 METHODOLOGY

3.1 Data and Sources of Data

Against the backdrop of improving forecast capabilities of key macroeconomic variables in Nigeria, monthly and quarterly data covering the periods 2000M1 to 2018M8 and 2006Q1 to 2018Q2, respectively, were utilised for the analysis within the framework of a Factor-Augmented Mixed Data Sampling (FAMIDAS). The rationale is to utilise the high-frequency (monthly) series to generate out-of-sample forecasts of low-frequency series such as GDP. This is against the backdrop that most critical data in this study, such as GDP and external balances, are reported quarterly and with lags in Nigeria. The data for the study were obtained from the statistical databases of both the CBN and the National Bureau of Statistics (NBS). Hence, in this study, we considered high-frequency (monthly) and low (quarterly) frequency variables. Thus, we grouped the variables accordingly and obtained a group of 35 quarterly and 42 monthly variables. We generated five (5) principal components each from the quarterly and monthly series.

The data covers real, fiscal, monetary, and external variables. Specifically, the quarterly data include the gross domestic product, unemployment, industrial/ manufacturing capacity utilization, government expenditure, government revenue, and fiscal balance. Others include agricultural GDP, industrial and manufacturing GDP, services, trade and construction and communication, and debt stock. However, the high-frequency data collected monthly are oil prices, consumer price index, broad money supply, credit to the private sector, current account balances, exchange rate, exports, imports and remittances. The series were log-transformed to keep them in the same magnitude and produce better fits.

3.2 Trimming the Dimensionality of Matrix of Explanatory Variables

The dimensionality of a model is the order of the matrix of explanatory variables. For example, where the sample size and number of explanatory variables of a model are r and n, respectively, dimensionality of the model is an r x n ordered matrix. In regression analysis, the degree of freedom (DF) of a model, which is estimated as difference between the sample size and the number of estimated parameters, is directly related to the dimension of the model. In this connection, the DF reduces with increases in the number of explanatory variables. It can take the value of zero or even negative. The implication is that the usual tests statistics - R-square and adjusted R-square; the standard errors and, by implication, the t-statistics and F-statistics - cannot be estimated. For this reason, when estimating a regression model, there is invariably a need to have a sufficient number of observations for all explanatory variables, such that r is sufficiently greater than n.

To reduce the dimension of the matrix of explanatory variables, this study would apply the principal components approach. The variables were categorised into two sets, the quarterly and the monthly without the variable to be forecasted prior to extraction (i.e. GDP and its components).

3.2.1 Principal Component Analysis

Principal components analysis is a statistical technique for expressing and classifying data set based of underlining patterns that reveal both differences and similarities in the data. This technique is also a tool for reducing the dimension of large data set in such as way as to retain the information content of each of the variables in set. This involves the compression of the data into smaller dimensions, called principal components. These Principal Components (PCs) can, therefore, be used to replace the explanatory variables in a regression model. The top PCs, accounting for most of the cumulative proportion of total variances (at least 50.0 per cent cumulative proportion of total variances), are selected. This study adopts the methodology for principal component analysis outlined by Smith (2002).

Assuming an *n x m* matrix of explanatory variables, which have all been predetermined to drivers of real GDP, for example, according to Smith, the process of constructing PCs from the set of variables begins with the construction of a covariance matric of the mean deviation of each of the variables in the set of data. Thereafter, the column vectors of the resulting squared matrix of covariances are rearranged in a descending order other respective and renamed Feature vectors. The matrix of PCs can be gotten by simply multiplying matrix of explanatory variables by the transpose of the feature vector.

The matrix of principal components (PCs) is organised with the most important PCs listed in descending order of their corresponding eigenvalues. The initial set of PCs, representing at least 50.0 per cent of the total eigenvalues, can be regarded as the new explanatory variables for real GDP. Despite losing some information from the entire set of explanatory variables by selecting only a subset of PCs, the chosen ones typically encompass enough information about the larger variable set. This approach facilitates the retention of crucial information about the explanatory variables while reducing the dimensionality of the variable matrix.

3.3 MIDAS Weighting Techniques

Conventional methods for time series estimation and forecasting typically assume that both the predictors and the target variable have the same frequency. Nevertheless, many macroeconomic and financial indicators are reported or updated at different frequencies. This necessitates the transformation of higher-frequency variables to align with the lower-frequency ones in order to deal with the mixed-frequency data effectively.

Two primary methods have been utilised for estimating mixed frequency datasets: the time averaging and individual coefficient approaches. The time averaging approach incorporates sums and averages of higher frequency data into lower frequency regressions, considering whether the variable represents a stock or flow variable. However, a flaw in this method is that each observation from the high-frequency variable is given equal weight in the newly constructed low-frequency data, which distorts the information from its data generating process (DGP) and results in biased predictions of its future trajectory.

The second method, known as the individual coefficients approach, employs all components of the high-frequency variable as separate regressors. However, this approach has a drawback in that it increases the number of variables and results in an over-parameterised model. This goes against the principle of simplicity in regression analysis, where the goal is to include fewer variables of lower frequencies as regressors. Therefore, in dealing with these challenges, we begin with a general specification of the Mixed Data Sampling (MIDAS) model.

A time series model involving data of different frequencies is usually of the form:

$$y_t = X_t^{'}\beta + f\left(\left\{X_{t/S}^{H}\right\}, \theta, \lambda\right) + \varepsilon_t \qquad (1)$$

where:

- y_t is any low-frequency any regress and, at date t;
- X_t is a vector of regressors with the same frequency as y_t;
- $\left\{X_{t/S}^{H}\right\}$ is a vector of high-frequency regressors, with S values for each low frequency value;
- f denotes the function that describes how the higher frequency data influences the lower frequency values.
- $\beta, \lambda, and \theta$ capture the vectors of parameters to be estimated.

Given the difficulties posed by mixed frequency regression, recent studies have introduced various techniques to address these issues. One such approach is proposed by Ghysels et al. (2006), which involves regressions that can handle variables sampled at different frequencies without relying on equal weights. The MIDAS model offers a straightforward, concise, and adaptable set of time series models that enable the incorporation of dependent and independent variables sampled at different frequencies. To identify the best algorithm, several weighting options are applied, as outlined below.

3.3.1 Step Weighting MIDAS

The Step weighting approach of MIDAS regression is of the form:

$$y_t = X_t^{'}\beta + \sum_{\tau=0}^{k-1} X^H_{(t-\tau)/S^{'}\varphi_\tau + \varepsilon_t} \tag{2}$$

where:

- K is the preselected lagged frequency periods, which may be either greater than or less than *S;*
- η is a step length; and
- $\varphi_m = \theta_i$ for $k = \text{int}(m/\eta)$

This weighting utilises a step function to constrain the coefficients on the high-frequency data, with high-frequency lags within a stipulated step, having values φ **.** For example, assume η=3, the first three lagged higher frequency lags

$X^{H}_{(t-\tau)/S}$, $\tau = 0,1,2$, make use of the same coefficient θ_0, and the following three lags employ θ_1, up until the maximum lag of k.

With the augmentation of high-frequency lags, the step-weighting model sees a rise in the number of high-frequency coefficients. Nonetheless, when contrasted with the individual coefficient approach, the step-weighting model reduces the number of coefficients by approximately $1/\eta$ times.

3.3.2 Almon (PDL) Weighting MIDAS

The Almon weighting technique, also called the polynomial distributed lag, is imposes restrictions on lag coefficients within the framework of an autoregressive model and utilised as one of the mixed frequency weighting techniques.

The technique models coefficients of standard regression models as a p dimensional lag polynomial, using the MIDAS parameters θ, for every high-frequency lag up to k. The restricted regression model is specified as follows:

$$y_t = X_t^{'}\beta + \sum_{\tau=0}^{k-1} X^{H}_{(t-\tau)/S^{'}} \left(\sum_{j=0}^{p} \tau^{j} \theta_j \right) + \varepsilon_t \qquad (3)$$

where, p is the almon polynomial order, and the chosen number of lags k may be less than or greater than S.

It is worth emphasising that the number of coefficients to be estimated is determined by the polynomial order and not the number of high-frequency lags. This becomes evident when rearranging the terms and expressing the model in terms of a constructed variable.

$$y_t = X_t^{'}\beta + \sum_{i=0}^{p} Z_{i,t}{}^{'}\theta_i + \varepsilon_t \tag{4}$$

$$Z_{i.t} = \sum_{\tau=0}^{k-1} \tau^i X^H_{(t-\tau)/S} \tag{5}$$

Here, Θ_i, is the distinct coefficient associated with each of the p sets of constructed variables $Z_{i.t}$.

3.3.3 Exponential Almon Weighting MIDAS

The exponential Almon weighting technique employs exponential weights and a second-degree lag polynomial, which can be expressed as:

$$y_t = X_t^{'} + \sum_{\tau=0}^{k-1} X^H_{(t-\tau)/S^{'}} \left(\frac{\exp\left(\tau\theta_1 + \tau^2\theta_2\right)}{\sum_{j=0}^{k} \exp\left(j\theta_1 + j^2\theta_2\right)} \right) \lambda + \varepsilon_t \tag{6}$$

In this context, the variable k represents the selected number of lags, while the coefficient is constant across these lags. The distinctive response is introduced through both the exponential weighting function and the lag polynomial, which, in turn, depends on the two MIDAS coefficients $\theta_1 and \theta_2$

This technique can be written as:

$$y_t = X_t^{'}\beta + \sum_{i=0}^{k} Z_{i.t}{}^{'}\lambda + \varepsilon_t \tag{7}$$

$$Z_{i,t} = \left(\frac{\exp\left(i\theta_1 + i^2\theta_2\right)}{\sum_{j=0}^{k} \exp\left(j\theta_1 + j^2\theta_2\right)} \right) X_{(t-i)/S}^{H} \tag{8}$$

However, it is essential to acknowledge that this regression model is strongly nonlinear in its parameters.

3.3.4 Beta Weighting MIDAS

The Beta weighting technique of MIDAS regression, proposed by Ghysels et al. (2006), utilises the normalised beta weighting function in estimating the impact of higher-frequency regressors on a low-frequency dependent variable. It is generic form; the model is specified as follows:

$$y_t = X_t^{'}\beta + \sum_{\tau=0}^{k-1} X_{t-\tau}^{H} \left(\frac{\omega_\tau^{\theta_1 - 1}(1-\omega_\tau)^{\theta_2 - 1}}{\sum_{j=0}^{k} \omega_j^{\theta_1 - 1}(1-\omega_j)^{\theta_2 - 1}} + \theta_3 \right)^{'} \lambda + \varepsilon_t \tag{9}$$

Where is λ a lag-invariant slope coefficient, and k is the number of lags.

$$\omega_i = \begin{cases} \delta & \mathrm{i} = 0 \\ i/(k-1) & \mathrm{i} = 1,\ldots,\mathrm{k} - 2 \\ 1-\delta & \mathrm{i} = \mathrm{k} \end{cases} \tag{10}$$

From equation 10, δ is a constant, which is fixed at approximately $2.22e^{-16}$.

The constructed variable form is written as:

$$y_t = X_t^{'}\beta + \sum_{i=0}^{k} Z_{i,t}^{'}\lambda + \varepsilon_t$$

$$Z_{i,t} = \left(\frac{\omega_i^{\theta_1 - 1}(1-\omega_i)^{\theta_2 - 1}}{\sum_{j=0}^{k} \omega_j^{\theta_1 - 1}(1-\omega_j)^{\theta_2 - 1}} + \theta_3 \right) X_{(t-i)/S}^{H} \tag{11}$$

The beta function offers great flexibility and can be transformed into various forms, including flat, U-shaped, humped, gradually increasing, or decreasing, depending on the specific values assigned to the three MIDAS parameters,

(Θ_1, Θ_2, Θ_3). In addition, the restriction $\Theta_1 = 1$, $\Theta_3 = 0$, or $\Theta_1 = 1$ and $\Theta_3 = 0$ are further imposed on the parameters of the beta function.

The constraint $\Theta_1 = 1$ means that the weight function's shape is determined by a single parameter, resulting in a slow decay when $\Theta_1 > 1$ and a slow increase when $\Theta_2 < 1$.

Furthermore, while the restriction $\Theta_3 = 0$ means that zero weights are applied at the endpoints of the high-frequency lag (when $\tau = 0$ and $\tau = k - 1$), $\Theta_1 = 1$ and $\Theta_3 = 0$ implies that that both the shape and the zero endpoint weight restrictions are imposed.

It is important to highlight that in cases where the number of MIDAS lags is limited, the zero endpoint restrictions can be excessively restrictive and may lead to considerable bias. On the other hand, the beta weighting model has a maximum of 3 parameters, which remains constant regardless of the number of lags. However, estimating this model involves optimising a highly nonlinear objective.

3.4 FAMIDAS Framework

The proposed FAMIDAS framework incorporates PCs of different frequencies as an autoregressive distributed lag, with the regressors, which in this case are PCs measured ate differenct frequencies. It is denoted as:

$$ry_t = a_0 + a_1 ry_{t-1} + \sum_{i=1}^{p=5} a_2 qPC_t^i + \sum_{i=1}^{p=5} a_3 mPC_t^i + \varepsilon_t \qquad (12)$$

where, ry_t is RGDP growth at period t, ry_{t-1} represents the lag of RGDP growth, qPC_t^i is the quarterly PC at period t for PC1 to PC5, mPC_t^i is the monthly PC at period t for PC1 to PC5, and ε_t the error term.

Similarly, the equations for oil and non-oil GDP growth are as follows:

$$cgry_t = a_0 + a_1 cgry_{t-1} + \sum_{i=1}^{p=5} a_2 qPC_t^i + \sum_{i=1}^{p=5} a_3 mPC_t^i + \varepsilon_t \qquad (13)$$

$$nory_t = a_0 + a_1 nory_{t-1} + \sum_{i=1}^{p=5} a_2 qPC_t^i + \sum_{i=1}^{p=5} a_3 mPC_t^i + \varepsilon_t \qquad (14)$$

where, $cgry$ and $nory$ represent oil and non-oil GDP growth, respectively.

4.0 ANALYSIS OF RESULTS

4.1 Results of Estimation using FAMIDAS

The obtained results from the principal components analysis revealed that the proportion of variation explained by the first five (5) quarterly principal components is 59.7 per cent, which accounted for more than half of the overall variability in the dataset by Bernanke et al. (2005). Also, from the monthly data group, the cumulative proportion of the first five principal components accounted for 64.1 per cent of the variability in the dataset (Tables 1 and 2).

Table 1: Principal Component Analysis - Eigenvalues for First 10 Components (Quarterly)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	7.6372	2.8680	0.2182	7.6372	0.2182
2	4.7691	0.8733	0.1363	12.4063	0.3545
3	3.8958	1.3848	0.1113	16.3021	0.4658
4	2.5110	0.4222	0.0717	18.8132	0.5375
5	2.0888	0.2340	0.0597	20.9020	0.5972
6	1.8548	0.0892	0.0530	22.7568	0.6502
7	1.7656	0.3483	0.0504	24.5224	0.7006
8	1.4173	0.2180	0.0405	25.9398	0.7411
9	1.1993	0.0531	0.0343	27.1391	0.7754
10	1.1462	0.0982	0.0327	28.2853	0.8082

Source: Authors' estimation.

Table 2: Principal Component Analysis - Eigenvalues for First 10 Components (Monthly)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	8.0853	1.8254	0.1925	8.0853	0.1925
2	6.2599	0.9778	0.1490	14.3451	0.3416
3	5.2821	0.6301	0.1258	19.6272	0.4673
4	4.6520	2.0191	0.1108	24.2792	0.5781
5	2.6329	0.7439	0.0627	26.9121	0.6408
6	1.8890	0.1526	0.0450	28.8011	0.6857
7	1.7364	0.4231	0.0413	30.5375	0.7271
8	1.3134	0.0791	0.0313	31.8509	0.7584
9	1.2343	0.1611	0.0294	33.0852	0.7877
10	1.0732	0.0833	0.0256	34.1583	0.8133

Source: Authors' estimation.

To ensure the stability of the models and avoid spurious results (Gujarati, 2005), augmented Dickey-Fuller (ADF) tests were conducted, and the findings revealed that three (3), out of the five (5) selected PCs, were non-stationary for both the monthly and quarterly variable groups. Consequently, all the non-stationary series were differenced accordingly.

Thereafter, the ARMA processes of each PC were identified using the Box-Jenkins (1976) methodology, to estimate and forecast the time path of the PCs across the forecast horizon, spanning 2018Q3 to 2019Q2. The AR processes for the quarterly PCs were identified as ARMA(1,1), while for the monthly PCs, PC1 and PC4 were AR(1) processes, PC2 and PC5 followed an ARMA(1,1) process and PC3 was an ARMA (2,2) process.

After determining the time path of the principal components (PCs), a MIDAS regression with the PDL/Almon weighting technique was utilised, using the monthly and quarterly PCs as predictors to forecast GDP growth.

The MIDAS regression model was applied to produce both in-sample and out-of-sample forecasts of Nigeria's GDP growth. In conducting in-sample forecasts, three (3) sub-samples were used to estimate and forecast oil, non-oil and total real GDP growth rates. The sub-samples are: pre-global financial crisis (GFC), spanning 2004Q1 – 2008Q3; post-GFC, which covers the period 2008Q4 – 2018Q2; and the total sample covering 2004Q1 - 2018Q2. The sub-samples were employed to estimate both the MIDAS and Factor-Augmented Vector Autoregressive (FAVAR)[5] models, assessing their performance and comparing the forecast accuracy of the mixed-

[5] The FAVAR model is an operational forecasting model within the CBN which uses PCs as explanatory variables within a VAR framework (See CBN, 2017).

frequency model with the FAVAR model. The evaluation was based on metrics such as the root mean squared forecast error (RMSE) and mean absolute percentage error (MAPE) presented in Table 4. Finally, an out-of-sample forecast was generated from 2018Q3 to 2019Q4.

4.2 The Relationship between Principal Components and the Growth of Real GDP

Following the construction of the PCs, we estimated the correlation between each of the PCs and real GDP growth. This was, however, computed for only the quarterly PCs because of the inherent complexities in measuring the correlation between real GDP, which is in quarterly frequency, and the monthly PCs.

Table 3 presents the correlation coefficients between growth of oil GDP (DLCGRY), non-oil GDP (DLNORY), total GDP (DLRY) and the selected principal components (PC1 to PC5). There is a weak and negative relationship (-0.02) between oil GDP growth and PC1, while a strong and positive correlation (0.51) exists between oil GDP growth and PC2. Moreover, a strong but negative correlation exists between PC3 and oil GDP growth (-0.56). The correlation coefficients of PC4 and PC5 in relation to the oil GDP growth are positive and relatively low at 0.28 and 0.03, respectively.

The correlation coefficient between non-oil GDP growth and PC1 was high and positive (0.80), which implies a strong co-movement of PC1 and non-oil GDP growth. The correlation coefficients between non-oil GDP and PC3, PC4 and PC5, were, -0.07, -0.28 and -0.25, respectively, are low and negative, while PC2 and non-oil GDP growth have a low positive relationship (0.07). The correlation coefficients between total GDP growth and PC1 and PC2 were 0.77 and 0.31, respectively, indicating a moderate to strong positive association. However, PC3, PC4, and PC5 exhibited low and negative correlation coefficients with total GDP growth, suggesting a weak and negative relationship with the overall GDP growth.

Table 3: Correlation Matrix of Quarterly PCs and GDP

	DLCGRY	DLNORY	DLRY	PC1	PC2	PC3	PC4	PC5
DLCGRY	1.00	-0.14	0.32	-0.02	0.51	-0.56	0.28	0.03
DLNORY	-0.14	1.00	0.87	0.80	0.07	-0.07	-0.28	-0.25
DLRY	0.32	0.87	1.00	0.77	0.31	-0.27	-0.17	-0.23
PC1A	-0.02	0.80	0.77	1.00	0.00	0.00	0.00	0.00
PC2A	0.51	0.07	0.31	0.00	1.00	0.00	0.00	0.00
PC3A	-0.56	-0.07	-0.27	0.00	0.00	1.00	0.00	0.00
PC4A	0.28	-0.28	-0.17	0.00	0.00	0.00	1.00	0.00
PC5A	0.03	-0.25	-0.23	0.00	0.00	0.00	0.00	1.00

Source: Authors' estimation.

4.3 Forecast Evaluation

This section evaluates the performance of the FAMIDAS to ascertain the predictive power of the models in tracking the trajectory of real GDP growth and its components. This was done by comparing its forecast evaluation statistics with the FAVAR model[6]. For this purpose, the sample data were split into two parts; the pre-and the post-global economic and financial crisis of 2007-09. The in-sample forecast evaluation

6 For a comprehensive discussion on the FAVAR methodology, see Adebiyi & Mordi (2012).

was conducted for oil, non-oil and total real GDP growth rates.

4.3.1 In-sample Forecast Evaluation

This section analyses the performance of FAMIDAS and FAVAR models' in-sample forecasts of total GDP, oil GDP and non-oil GDP during the 2004Q1-2018Q2 period. The forecasting period is categorised into two distinct phases: pre-global financial crisis (PRE-GFC) and post-global financial crisis (POST-GFC). Additionally, we assess the forecast's precision by employing the root mean square error (RMSE) and mean absolute percentage error (MAPE) as evaluation criteria. The RMSE measures the quality of point forecasts by showing how close the observed data points are to the predicted values, while MAPE measures the size of the percentage error.

Analysis of the total GDP forecast in Table 4 indicates that FAMIDAS model captures the trajectory better than FAVAR model during pre-GFC. The RMSE of 0.003 and MAPE of 3.3 per cent show that FAMIDAS model forecasts have smaller forecast errors than the forecast of FAVAR in the pre-GFC period. However, during post-GFC, the performance of the forecasts is mixed, FAMIDAS RMSE of 0.01 is lower than 0.03 of FAVAR. This suggests that FAMIDAS model has better forecasting power, but comparing MAPEs for the two models, 48.9 per cents of FAMIDAS is higher than 42.0 per cent of FAVAR, suggests that FAVAR model is preferred or has better performance.

For the oil GDP forecast, using both RMSE and MAPE criteria, FAMIDAS model provides more stable and accurate forecasts than FAVAR model in the pre-GFC and post-GFC periods. The overall RMSE (0.06) and MAPE (190.0 per cent) of FAMIDAS model are the lowest compared with the FAVAR model of 0.09 and 340.5 per cent, respectively. Similarly, both RMSE and MAPE suggest that FAMIDAS has better forecasting power than FAVAR model for the non-oil GDP forecast during the pre-GFC period. The pre-GFC period RMSE (0.001) and MAPE (0.8 per cent) of FAMIDAS compare with RMSE (0.011) and MAPE (9.5 per cent) of FAVAR. However, the post-GFC non-oil forecast analysis using MAPE indicates that the FAVAR model is preferable.

Table 4: The In-sample Forecast Evaluation of the FAMIDAS

		FAMIDAS			FAVAR		
		PRE-GFC	POST-GFC	TOTAL	PRE-GFC	POST-GFC	TOTAL
TOTAL GDP	RMSE	0.0028	0.0129	0.0152	0.0077	0.0274	0.0232
	MAPE	3.31	48.94	39.69	8.10	42.00	37.72
OIL GDP	RMSE	0.0039	0.0583	0.0629	0.0342	0.1132	0.0959
	MAPE	25.84	133.77	190.55	171.92	716.73	340.47
NON-OIL GDP	RMSE	0.0010	0.0147	0.0206	0.0109	0.0255	0.0354
	MAPE	0.84	219.69	246.02	9.46	59.04	50.45

Source: Authors' estimation.

In addition, a cursory view of charts of the in-sample forecasts and their respective actual data (panels A, B, and C) shows that, generally, the FAMIDAS model performed better in terms of tracking and reflecting the turning points, especially during the banking sector consolidation exercise of 2005 and the global financial crises of 2007, compared with the FAVAR model for oil, non-oil and total GDP.

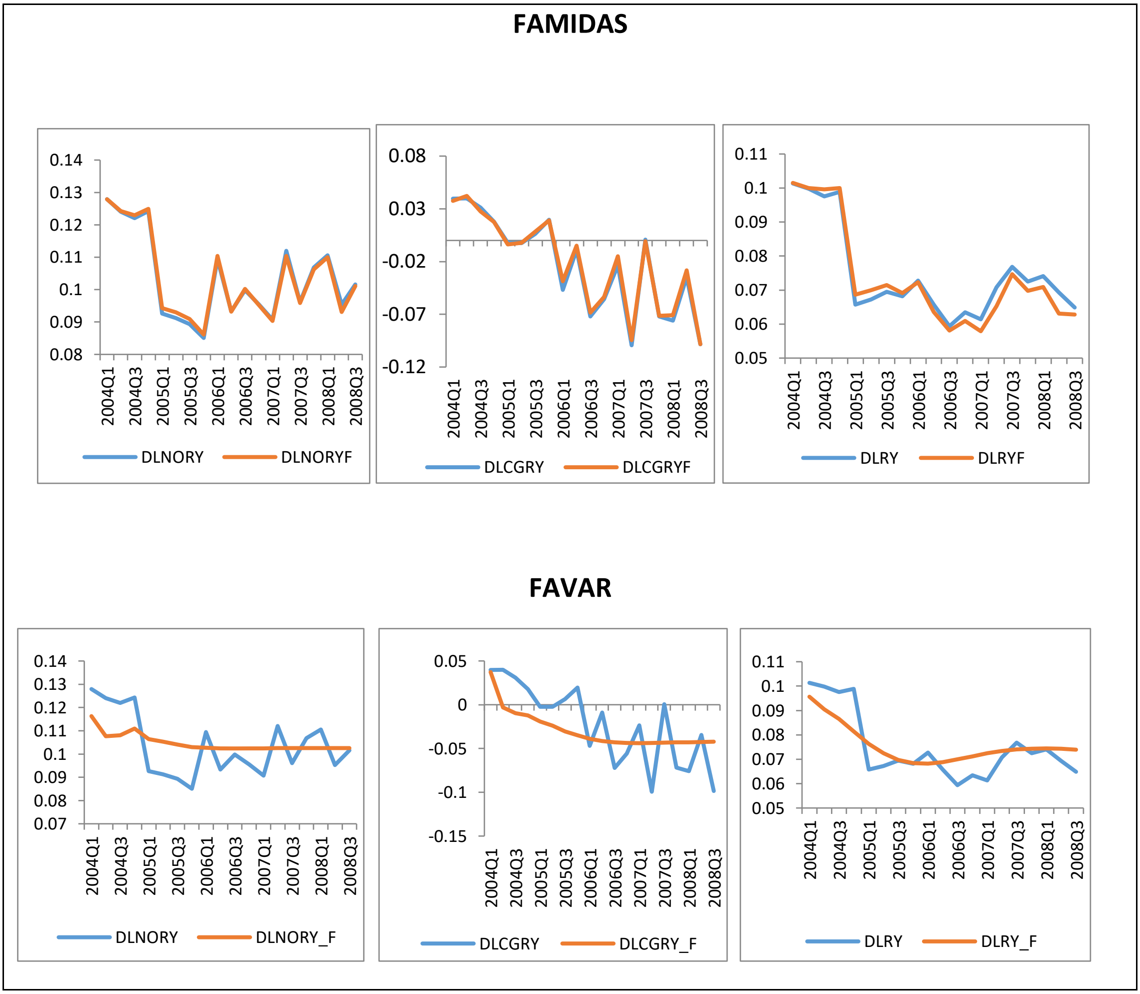
In the panel "b" of the second sub-sample, the forecast mimics the actual for the oil, non-oil and total GDP for the FAMIDAS model, indicating the predictive robustness of the model if used for forecasting output in the economy. As in panel "a", FAVAR model performed weakly as the in-sample forecast diverged significantly away from the actual. Moreover, while the oil and total GDP forecast mimic the actual, the non-oil forecast remained non-responsive and unchanged for most of the period, except in the early years.

Total output for the oil, non-oil and total output for the entire sub-sample adequately captured the banking sector consolidation exercise, the global financial crisis and the period of recession experienced in 2016Q2. Expectedly, the tracking and turning points for the FAMIDAS outperformed the FAVAR in-sample, as the forecast from the FAVAR deviated largely from the actual in most periods.

It could be inferred from the analysis that predictions generated from the FAMIDAS model outperformed the FAVAR model regarding oil, non-oil and total GDP components, demonstrating the high information content of the FAMIDAS model.

Figure 1: In-sample forecast and actual values of GDP growth rate and its components

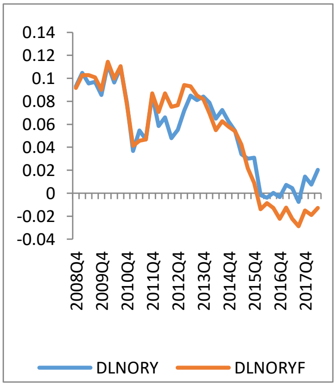
Panel A: In-sample forecast, 2004Q1 – 2008Q3



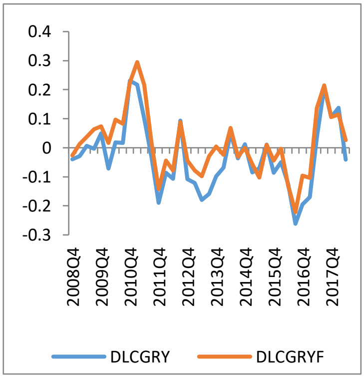
Source: Authors' estimation.

Panel B: In-sample forecast, 2008Q4 – 2017Q3

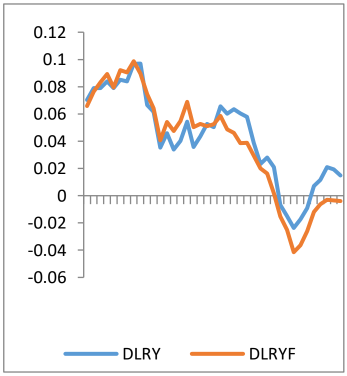
FAMIDAS



Post-non-oil

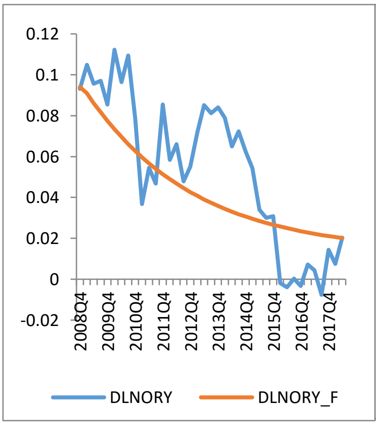


Post-oil

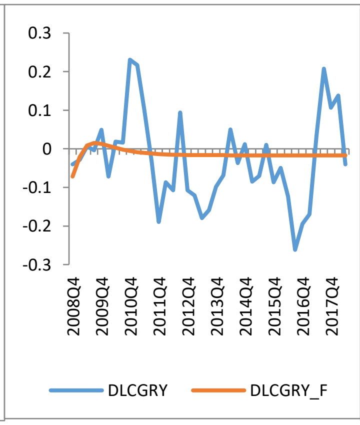


Post-total

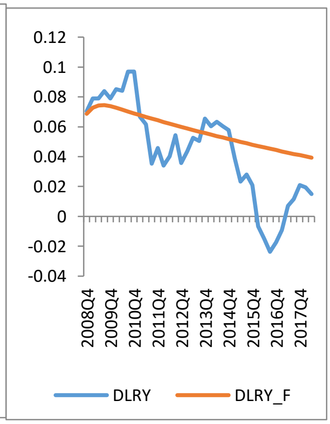
FAVAR



Post-non-oil



Post-oil

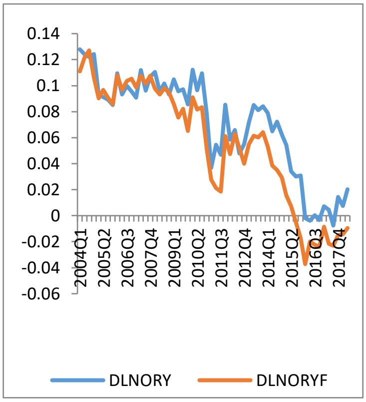


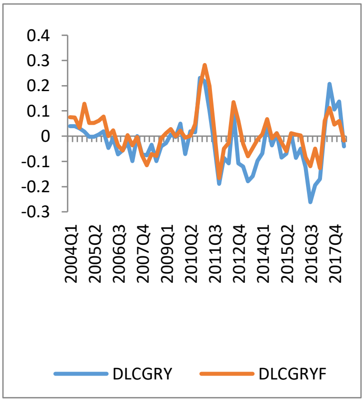
Post-total

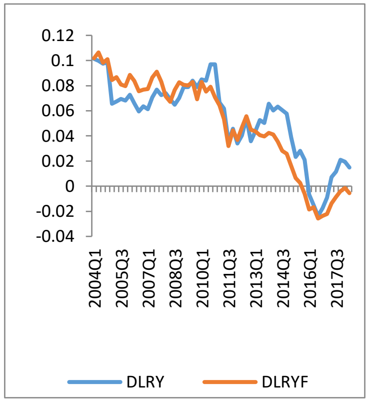
Source: Authors' estimation.

Panel C: In-sample forecast, 2004Q1- 2018Q1

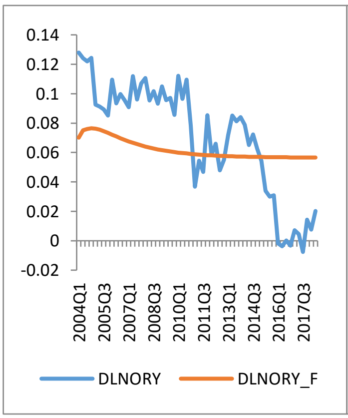
FAMIDAS

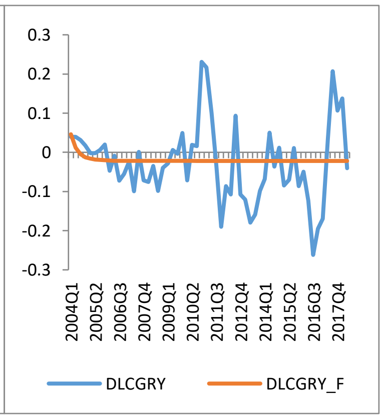


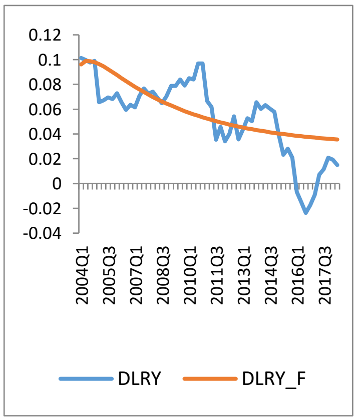




Total-nonoil Total-total FAVAR Total-Oil







Total-nonoil Total-total Total-Oil

Source: Authors' estimation.

4.3.2 Out-of-Sample Forecast Evaluation

To evaluate the out-of-sample forecasting performance of the FAMIDAS model, one-step ahead forecasts were computed for both models during the period from 2016Q1 to 2018Q2. The period h=1 corresponds to the one-step ahead forecast for 2016Q1, with 10 periods corresponding to the period 2016Q1- 2018Q2. We measured the forecast errors using the RMSE, across the forecast horizon. This process was also applied to the FAVAR model. The objective was to compare the out-of-sample forecasting capability of the FAMIDAS model to that of the FAVAR model. This comparison aimed to assess which model performed better in predicting future data beyond the estimation period. From Table 5, it can be seen that the FAMIDAS models outperformed the FAVAR models in this regard by having lower RMSE of the forecasts of real GDP growth and the growth of non-oil GDP. However, the FAVAR exhibits better forecast capacity than FAMIDAS model in predicting the future path of the growth of oil GDP. This may be due to its ability to incorporate and utilise drivers of oil GDP in their original frequencies.

Table 5: RMSE Out-of-sample Forecast Evaluation

	Total		Oil		Non-oil	
Period	FAMIDAS	FAVAR	FAMIDAS	FAVAR	FAMIDAS	FAVAR
H=1	0.0224	0.0254	0.1549	0.0021	0.0192	0.0385
H=2	0.0299	0.0302	0.1317	0.0645	0.0378	0.0455
H=3	0.0301	0.0357	0.2278	0.1457	0.0390	0.0498
H=4	0.0285	0.0372	0.2890	0.1526	0.4140	0.0552
H=5	0.0261	0.0370	0.2641	0.1516	0.0447	0.0572
H=6	0.0239	0.0351	0.2477	0.1402	0.0433	0.0600
H=7	0.0223	0.0335	0.2335	0.1559	0.0436	0.0647
H=8	0.0216	0.0318	0.2214	0.1526	0.0419	0.0651
H=9	0.0216	0.0308	0.2116	0.1533	0.0405	0.0665
H=10	0.0207	0.0305	0.2008	0.1456	0.0389	0.0663

Source: Authors' estimation.

4.4 Result of the Nowcasts and Forecasts from the FAMIDAS and FAVAR Models

The total real GDP growth forecasts for the 2018Q3 – 2019Q2 period suggest that the FAVAR model produced more conservative forecasts, while the FAMIDAS model produced higher forecasts of total real GDP growth. The results were similar for the oil real GDP growth forecasts, with the FAMIDAS model producing higher estimates across the forecast horizon, except for 2018Q3. However, for the non-oil real GDP growth forecasts, the FAVAR model produced higher forecasts for the 2018Q4 – 2019Q2 period, while the FAMIDAS model only produced a higher forecast for the 2018Q3 period.

Table 6: Out-of-sample Forecast from the FAMIDAS and FAVAR Models

	FAMIDAS			FAVAR		
	DLRYF	DLNORYF	DLCGRYF	DLRY_F	DLNORY_F	DLCGRY_F
2018Q3	1.30	1.82	-2.93	1.10	1.73	-2.03
2018Q4	1.40	1.89	-1.39	1.09	2.08	-1.83
2019Q1	1.36	1.92	-0.94	1.07	2.31	-1.77
2019Q2	1.33	1.94	-0.61	1.05	2.52	-1.85

Source: Authors' estimation.

5.0 SUMMARY, CONCLUSION, LIMITATIONS AND RECOMMENDATIONS

5.1 Summary and Conclusion

In this study, the factor augmented mixed data sampling (FAMIDAS) regression framework was employed to forecast real GDP growth and its components (oil and non-oil GDP) for Nigeria. The use of FAMIDAS was necessary due to the extensive range of leading indicators of real GDP growth, even though they had mixed-ordered frequencies. To manage the complexity of these indicators, the principal component (PC) approach was applied to reduce their dimensionality. Subsequently, the leading indicators were grouped into five monthly and five quarterly PCs each. These groups were integrated into the MIDAS regression framework to generate nowcasts and forecasts for real GDP growth, as well as oil and non-oil GDP. To achieve this, the autoregressive integrated moving average (ARIMA) technique was used on each of the PCs to generate out-of-sample forecasts for the endogenous variables and the time path of the PCs throughout the forecast horizon.

Furthermore, the study evaluated both the in-sample and out-of-sample forecast performance of the models by comparing the forecast evaluation indicators of the FAMIDAS models with those of the factor augmented vector autoregressive (FAVAR) model. The key finding was that the FAMIDAS model exhibited superior performance in tracking the time path of real GDP growth and its components compared to the FAVAR model. The forecasts generated by the FAMIDAS model closely followed the actual series, showing minimal deviations. On the other hand, the forecasts from the FAVAR model exhibited substantial deviations from the actual values throughout the forecast period. This suggests that the FAMIDAS model has strong potential as a leading indicator for predicting the growth of real GDP and its components in Nigeria.

In the Central Bank of Nigeria, this is the first attempt to develop FAMIDAS model that incorporates variables of mixed frequencies in its estimation to forecast GDP growth rate and its components. Its good performance, compared with the FAVAR model, is a pointer to its potential ability to become a key model for generating near-term forecasts of economic indicators, which would be a useful framework for monetary policy decisions at the MPC meetings. Its uniqueness is further complemented by its ability to perform scenario-based forecasts.

Although the model has demonstrated immense capacity in forecasting Nigeria's GDP growth and its components, there remains room for improvement. The model is flexible and can be adapted to incorporate necessary adjustments, to improve its forecasting prowess.

5.2 Policy Implications and Options

The forecast reveals an expectation of a rise in aggregate GDP from 1.3 per cent in the third quarter of 2018 to 1.3 per cent by 2019Q4. Positive growth rates are also projected for the non-oil GDP over the forecast horizon, although the offsetting the effect of the accelerating growth rate of the non-oil sector and the negative growth rate of the oil sector is observed in aggregate GDP growth over the forecast horizon. This may be explained by their sectoral contribution observed over time.

In light of the findings, this study recommends that:

i. The monetary authority should maintain an accommodative monetary policy stance given that the economy is still in its recovery stage to rein in inflation and stem capital reversal, which could trigger another recession;

ii. The government should intensify and incentivise investments and commitments in critical non-oil activity sub-sectors, especially in the agriculture and manufacturing sectors, given the contribution of these sectors to total output and because the non-oil output is expected to increase significantly over the forecast horizon; and

iii. Furthermore, the government should judiciously utilise oil proceeds given the declining future growth path of the oil sector, by channeling these proceeds to bridging infrastructural gaps and promoting growth-inducing sectors such as the services sector.

5.3 Limitations of the Study

i. Due to data limitations, variables, such as market instruments, were not employed in their true DGPs, as the data available does not cover the entire scope of the study.

5.4 Areas for Further Study

In the course of the study, the following areas were identified:

i. There is a need to validate the forecasts' response to the weighting technique of FAMIDAS. To this end, estimating the FAMIDAS equation with alternate weighting techniques is important; and

ii. The mixed frequency modeling technique was applied using a dynamic factor framework, going forward, several approaches could be employed. These include regime-changing FAMIDAS; DSGE FAMIDAS; Reverse FAMIDAS, among others.

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