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Oil Price Shocks and Exchange Rates in Nigeria: A Forecasting Model

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ABSTRACT

Several empirical studies have revealed equivocal behavior in exchange rates as a result of unpredictable oil prices. This study forecasts the exchange rates of the Nigerian surrence, Naira using both dynamic and static forecasting procedures. The stationarity test which revealed that all variables are stationary at both level and first difference motivated the use of autorgressive distributed lag (ARDL) model to forecast exchange rates in this study. The ARDL reveals evidence of a short-run relationship between exchange rates and the explanatory variables that forecast exchange rates. The study compared the actual exchange rates with the forecasted exchange rates to form an analysis that measures the forecasting accuracy of the various models. The results show that all the estimates in the ARDL model behave well in forecasting exchange rates for Nigeria. Thus, the models performed well, and it is concluded that they are suitable to forecast exchange rates in the country. Findings from the study serve as a guide to policy makers. It could also assist policy makers to obtain early signals of future crises, hence, allowing them to make accurate exchange rates forecasts. As a result of globalization, the findings of this study are important to both importers and exporters since exchange rates instability has different effects on their decision making on matters relating to international transactions.

Keywords: Oil Price Shocks, ARDL, Exchange Rates, Theil's U, Forecasting

JEL Classification: E17, P28, Q35, L72.

INTRODUCTION

Literarature reveals that oil price shocks significantly impact the economy and that, variation in exchange rates is the medium through which such shocks transmit to other macroeconomic variables and influence output performance in Nigeria. Several empirical studies have revealed equivocal behavior in exchange rates as a result of unpredictable oil prices (see Babatunde, 2015) and unclearly documented exchange rates forecasts (Eslamloueyan and Kia, 2015). According to Ahmed (2017), exchange rates tend to be unstable, leading to economic uncertainty. While stabilizing the exchange rate is vital for sound economic performance, accurately estimating exchange rates is critical in the financial domain (Haskamp, 2017). As noted by Taylor and Allen (1992), it is not easy to consistently estimate exchange rates as various factors account for why exchange rates may deviate from their values. Therefore, the expectations of exchange rates forecasters could move in the opposite direction of the exchange rate's actual value (see Haskamp, 2017). In contrast, the forecaster's expectations could be correct, but unanticipated factors may abruptly cause the movement of exchange rates to vary. It is important to note that forecasters estimate the movement of currency in the future and that forecasting exchange rates allows economic agents to better anticipate future market conditions. Consequently, economic agents will be confronted with the risks of exchange rates. The serious consequences of these risks could be mitigated by reliable exchange rates forecasts. However, the best manner in which to achieve dependable exchange rates forecasts has remained a puzzle in the field of economics among other interrelated disciplines and professions. Taylor and Allen (1992) observe that the accuracy of exchange rates forecasts will determine the success or failure of individuals, firms, investors and government programs because the degree to which such forecasts vary from the actual price impacts on both financial success and the quality of policy decisions. Meese and Rogoff (1983) note that classical exchange rates models were not able to forecast better than a naive random walk. Cheung, Chinn and Fujii (2009) confirmed this finding for alternative models and a longer sample. Noting that an unexpected surge in oil prices resulting in sudden fluctuations in exchange rates might lead to imbalances in several essential macroeconomic variables such as the international account balance, therefore, exchange rates forecasting is necessary.

This study contributes to the literature in a number of ways. Firstly, it promotes understanding of the exchange rates dilemma by clarifying the roles that different variables play in the forecasting process. Secondly, it enhances understanding of the most suitable combination of evaluating techniques, such as mean absolute percentage error (MAPE), root mean square error (RMSE) and other fundamental macroeconomic variables to forecast exchange rates. Thirdly, the study considers Brent oil prices, which are the most traded among the AOECs (see Babatunde, 2015). Previous studies employed the United Arab Emirates price of oil (Dubai), the real US refiners' acquisition cost (RAC), the US West Texas Intermediate price of oil (WTI) and bonny light, among others (see Baumeister and Kilian, 2016; Wang, Zhu and Wu, 2017). Although factors like productivity differentials and interest rate differentials have been investigated (see Mark and Choi, 2001), the researcher is not aware of any study that has assessed the role of oil prices in predicting exchange rates over long horizons in Nigeria.. This study fills this gap by exploring the ability of oil prices to explain exchange rates behavior in a predictive regression framework. In this respect, it seeks to show that using information on the global oil price significantly improves the exchange rates of Africa's oil producing countries to the extent that they can aim to stabilize their currency (purchasing power).

There is a rich body of theoretical and empirical evidence on the connection between oil prices and exchange rates forecasts in oil-dominated economies around the world. However, appropriate research that offers effective policy guidelines is lacking (see Chen and Chen, 2007; Ferraro, Rogoff and Rossi, 2015; Habib and Kalamova, 2007). The fact that oil prices significantly account for movements in exchange rates does not preclude other macroeconomic fundamentals from forecasting exchange rates. Therefore, it is necessary to forecast exchange rates using existing methods, guided by appropriate theories[1]. This will serve as a guide and offer explanations on what accounts for exchange rates variation in Nigeria. This study seeks to ascertain whether information on exchange rates and their determinants improves exchange rates stabilization. It also analyzes various factors' ability to forecast exchange rates.

Following this introduction, the remainder of the study is structured as follows: section two reviews the literature. Section three presents the methodological framework employed. This includes the forecasting model which is presented in section four. Results and discussions of results were presented in section five and lastly, section six summarizes and concludes the study.

REVIEW OF LITERATURE

Theoretical Literature

Theoretically, exchange rate variations have a positive or negative effect on output growth. These can lead to expenditure switching between domestic and foreign goods both at home and among trading partners across international boundaries. Consequently, such variations can affect net exports, and firms' output and profitability, with the possibility of a second-round effect on firms' investment (Chit *et al.,* 2010). Duasa (2009) argues that exchange rates variations significantly affect fluctuations in exports and import prices. This concurs with Kandil and Mirzaie's (2005) who found that the impact of variations in exchange rates can determine economic performance either positively or negatively as some countries are susceptible to external shocks such as exchange rates. Such shocks could include an increase or a decrease, depending on whether exchange rates appreciate or depreciate, or whether or not this is anticipated. Thus, exchange rates depreciation may stimulate economic activities through the initial increase in the price of foreign goods, while appreciation decreases net exports through the initial decrease in the price of such goods.

[1] Exchange rates refer to the movement of the currency of one country against another country's currency (Mankiw, 1997). It could also be referred to as the price of a nation's currency in terms of another currency. The components of the exchange rate are divided into two parts - the domestic currency and a foreign currency, and these can be quoted either directly or indirectly. Exchange rates are officially quoted in values against the USD (Dooley *et al.,* 2004).

Several theories in the literature on exchange rates offer explanations on the circumstances surrounding variations in exchange rates across various economies. Theoretically, it is well established that an oil-exporting country might experience an appreciation in exchange rates when there is an increase in oil prices and a depreciation when oil prices decline (see Golub, 1983; Eslamloueyan and Kia, 2015). For instance, strong appreciation in the Nigerian Naira and Algerian Dinar in 1996/1997 and the subsequent depreciation of both currencies in 1998/1999 are generally attributed to the increase and decrease in oil prices during these periods (see OPEC, 2016). Similarly, depreciation in the currencies of these countries and other oil-exporting countries in 1986 is often explained with reference to low oil prices in 1985/1986 (see OPEC, 2016).

This study is based on the theoretical framework of exchange rates determination developed by Cashin, Sahay and Céspedes (2004), premised on De Gregorio and Wolf (1994). The framework emphasizes that an improvement in the terms of trade (the relative price of exports in terms of imports) produces appreciation of the domestic currency. According to this model, the economy comprises two different sectors: one produces an exportable good, and the other produces a non-traded good. In this context, a positive shock to the terms of trade leads to an increase in wages in the exporting sector and vice versa. Similar to the dynamics of the Balassa-Samuelson model of exchange rates, under the assumption of wage equalization across the two sectors, this translates to an increase in wages and prices in the non-traded goods sector and appreciation of the real exchange rate (see Habib and Kalamova, 2007; Canada *et al.,* 2016).

Empirical Literature Review

Since the early 1920s, various studies and econometric models have sought to produce efficient forecasts and estimation of the equilibrium of exchange rates (Van Thiel and Leeuw, 2002). However, exchange rates prediction remains one of the most challenging applications of modern time series forecasting as these rates are fundamentally noisy, non-stationary and deterministically chaotic (see Kim *et al.,* 2017; Chen and Rogoff, 2003; Frankel 1979). These features suggest that no perfect information is obtainable from the previous behavior of such markets to fully capture the dependency between future rates and those of the past. In such situations, it is widely assumed that historical data captures past behavior to some extent. As a result, historical data is a major player or input in the prediction process. Time series modeling is the conventional technique used to model exchange rates. However, these techniques have limitations as the exchange rate series are non-stationary and noisy (Chen and Rogoff, 2003).

Various empirical studies on exchange rate forecasts among individual and groups of oil-exporting nations have emphasized the importance of factors such as terms of trade or the Balassa-Samuelson "productivity hypothesis". In these studies, terms of trade are commonly approximated by real oil prices (see Baxter and Kourparitsas, 2000), while some studies have used labels like "Petrol-currency" or "oil currency" to describe the apparent significance of this factor in explaining real exchange rate movements. Nonetheless, empirical evidence has not been consistent (see Baxter and Kourparitsas, 2000; Korhonen and Juurikkala, 2007; Tiwari, Mutascu and Albulescu, 2013; Canada *et al.,* 2016).

While it is believed that variations in oil prices may trigger currency movements in some oil-exporting countries, there seems to be little evidence for the relationship in some of the biggest oil exporters in the world (see Rickne, 2009). Studies that document that oil prices play an important role in exchange rates determination include those of Korhonen and Juurikkala (2007), who focus on a group of nine OPEC countries (Venezuela, Saudi Arabia, Kuwait, Nigeria, Iran, Indonesia, Gabon, Ecuador, and Algeria) and Rickne (2009). These studies also examine the role played by institutions in oil prices and real exchange rate movements in oil-exporting countries.

From a country-specific perspective, Koranchelian (2005) document the key role played by the oil price as a trigger of real exchange rates movements in countries such as Venezuela. Other studies provide empirical evidence in favor of the Russian Ruble being an oil currency (see Oomes and Kalacheva, 2007; Spatafora and Stavrev, 2003). Contrary to these findings, Bjornland and Hungnes (2008) reported either numerically weak or statistically insignificant relationships between the Norwegian Krone and oil prices.

Empirical studies on the relationship between oil prices and exchange rates conducted in different countries using various estimating techniques have concluded that there is no certainty that oil prices affect the movement of the real exchange rate (see Bouoiyour and Selmi, 2015). Using a combination of nonlinear causality tests and wavelet analysis, Bouoiyour and Selmi (2015) reveal that the relationship between the USD and oil prices is very complex, and that it depends on the frequency range or time scale.

Jahan-Parvar and Mohammadi (2011) examine the relationship between real exchange rates and real oil prices in oil-exporting countries using a Bounds Testing Approach, to test the validity of the Dutch Disease hypothesis. The authors use the ARDL model and the results show a stable long-run relationship between real exchange rates and real oil prices in fourteen oil-exporting countries.

In practice, analysis of the factors influencing the exchange rate must consider their interdependence and the connection between them, which ultimately lead to currency appreciation or depreciation. Mariano *et al.* (2015) examine the factors affecting exchange rate changes in Pakistan from 1975 to 2000. The stationarity of the data is determined using the Augmented Dickey-Fuller (ADF) test and the ordinary least square (OLS) method is used to analyze the results. According to this study, the factors influencing exchange rates are exports, imports, economic growth, and inflation. The findings from the model reveal that 98.2 percent of changes in exchange rates are associated with these four factors. The findings further reveal that economic growth ranks second to significantly account for variations in exchange rates. Contrary to this claim, previous study like Twarowska and Kakol (2014) reveal that, as GDP increases, exchange rates depreciate. Studies produce similar results despite the fact that they use different methodologies. For instance, Goudarzi *et al.* (2012) use the evolution of the thirty-quarter rolling correlation coefficient between the cyclical components of real GDP and real effective exchange rates (REER), obtained by using HP-filtered series and their findings suggest that the real exchange rate depreciates when economic growth is strong.

Various empirical studies focus on exchange rates forecasts. The asset approach highlights the importance of asset prices in the exchange rate forecast. In this approach, the interest rates differential is identified as the main driving force behind exchange rate movement between countries. Therefore, the covered and uncovered interest parity conditions are used to forecast exchange rates. Another line of research uses the PPP hypothesis to study exchange rate dynamics. In these models, the relative price level mainly forecasts exchange rates movement. This strand of research can be linked to the money market to examine how money supply and demand can influence exchange rates through changing the interest rate, price levels, and expectations about future exchange rates variations. In brief, many monetary models of exchange rates forecasts are derived from the PPP hypothesis, interest parity condition, money demand, and money supply functions.

The existing literature on exchange rates forecasting ignores the fact that external factors such as foreign countries' debt and debt management (how governments finance their debt) as well as a crisis can affect the degree of competitiveness (exchange rate) of an oil-producing country. In addition, it is possible that a small deviation from a long-run equilibrium is ignored which could cause agents to react to a large deviation. This situation is also ignored in the existing literature. In addition to its focus, this study extends the literature by focusing on those factors that may forecast the exchange rates of oil-producing countries that rely heavily on revenue from exporting oil resources. More precisely, the study is narrowed down to consider those factors within the context of AOECs (Algeria, Egypt, Gabon, Libya, and Nigeria). Consequently, the model estimated is capable of investigating the effect of the factors that have been ignored in the literature on exchange rates forecasts for these countries.

Studies have found that, over the long run, besides money supply, domestic GDP and government expenditure, price level and interest rates also influence exchange rates.

METHODOLOGY

This study models exchange rates in Nigeria to understand exchange rate behavior to guide policy makers in their decision making. Dataset spanning 1980 to 2020 was considered. Data availability dictated the choice of both the starting and cut-off dates.

Following Kia (2013), this study employs the ARDL in the time series context. This is similar to, but deviates slightly from Eslamloueyan and Kia's (2015) study. Unlike Eslamloueyan and Kia's (2015) research that is based on panel investigation, this study focuses on the time series technique based on the belief that the factors that determine exchange rates may vary among the countries and over a given period of time (see Hueng, 1999). The choice of this technique is influenced by several reasons discussed below.

Model Specification

This study adopts the utility function of Kia (2013) and Eslamloueyan and Kia (2015) as presented in (1). This is also in line with Hueng (1999) and Goudarzi *et al.* (2012) who employ a model that assumes that the economy is a single consumer (representing many identical consumers), that labor is inelastic in supply, and that total output is exogenous. Note that none of the results will be affected if we relax these assumptions. The consumer is assumed to maximize the following utility function:

$$E\left\{\sum_{t=0}^{\infty} \propto^t U\left(\dot{C}_t, \dot{C}_t^*, \varpi_t, {}^{n_t}/_{k_t}, {}^{n_t^*}/_{k_t^*}\right)\right\} \quad (1)$$

$$\varpi = \omega/p \quad (1.2)$$

where: $\dot{C}_t$ and $\dot{C}_t^*$ respectively, represent single real domestic and foreign consumption goods; n_t and n_t^* respectively represent the holdings of domestic real $\left(n/p\right)$ and foreign real $\left(n^*/p^*\right)$ cash balances; E symbolizes the expectation operator, and the discount factor satisfies the $0 < \propto < 1$ condition; and ϖ represents real government expenditure on services and goods, and it is assumed to be a "good" in itself (see Eslamloueyan and Kia, 2015).

This study also follows Hueng (1999) and Kia (2013) in assuming that domestic and foreign goods are respectively purchased with domestic and foreign currencies. This suggests that the services of both domestic and foreign currencies can go into the utility function. Consequently, the study selects the units such that the services of domestic money and the services of foreign money are respectively equal to n and n^*. Then the risks inherent in holding n and n^* are respectively reflected by k_t and k_t^*. This implies that if the associated risks of holding n and n^*increase, the number of services that domestic currency and its counterpart, foreign currency could purchase will fall.

If we assume that the services of domestic money change for oil-exporting countries as the oil price changes, we specifically postulate that over the long run,

$$\log(k_t) = k_0 + k_1 \log(OP_t) \qquad (2)$$

Where:

k_0 and $k_1$are parameters, OP denotes oil price[2]. Ceteris paribus, it is expected that as the prices of oil rise, the associated risks of withholding the currency of an oil-exporting economy decline, suggesting that $k_1 < 0$. Inversely, the associated risks of withholding the currency of an oil-importing economy increase, implying that $k_1 > 0$. As the prices of oil rise, the demand for the money of net oil-exporting countries will simultaneously rise, resulting in appreciation in the value of their currency.

Following Kia (2013), this study assumes that (k^*) summarizes the risk associated with holding foreign currency (e.g., USD), given by:

$$\log(k_t^*) = k_0^* + k_1^* \xi gdp_t^* + k_2^* \zeta gdp_t^* \qquad (3)$$

Where, k_0^*, k_1^* and k_2^* are parameters. Variables ξgdp^* and ζgdp respectively, represent outstanding foreign debt per GDP and foreign-government financed debt per foreign GDP. A rise in foreign debt is assumed to be associated with future monetization of debt and a decline in the value of the foreign currency (i.e., a fall in demand for foreign currency), and thus, $k_1^* > 0$. Similarly, a rise in the amount of government debt held by foreign investors/governments may be considered a reason for future foreign currency devaluation, inferring that $k_2^* > 0$. It is necessary to note that the currency holders of net oil-importing nations consider that the deficit and/or outstanding debt of these countries increases the risk of holding the currency of these countries (see Eslamloueyan and Kia, 2015). Conversely, currency holders of net oil-exporting countries do not. The associated cause is that investors expect the various governments of net oil-exporting nations to finance their debt obligations and deficits solely through crude oil exports. Therefore, the change in the oil price is only relevant to the risk associated with the currency holding of these countries.

Thus (3) holds, subject to the short-run dynamics of the system. To be specific, it is assumed that the short-run dynamics of the risk variable associated with holding foreign currency $[\log(k)^*]$ include a set of interventional dummies that account for political changes, economic crisis, and policy regime changes that influence the value of money. According to Kia (2013), the utility function (U) is assumed to be rising in all its claims (except variables k and k*, which are declining), and is strictly concave and uninterruptedly differentiable. Accordingly, following Kia (2013) and Sidrauski (1967), demand for the services of money (both domestic and foreign), $\mathfrak{b}[= n]$ and $\mathfrak{b}^*[= n^*]$, will always be greater than zero ($\text{i.e} > 0$), if we assume that $\lim_{\mathfrak{b} \to 0} U_{\mathfrak{b}} \left(\dot{C}_t, \dot{C}_t^*, \varpi_t, {}^{n_t}/_{k_t}, {}^{n_t^*}/_{k_t^*} \right) = \infty$ and $\lim_{\mathfrak{b}^* \to 0} U_{\mathfrak{b}} \left(\dot{C}_t, \dot{C}_t^*, \varpi_t, {}^{n_t}/_{k_t}, {}^{n_t^*}/_{k_t^*} \right) = \infty$, for all $\dot{C}$ and $\dot{C}^*$, where, for instance,

$U_{\mathfrak{b}} = \partial U \left(\dot{C}_t, \dot{C}_t^*, \varpi_t, {}^{n_t}/_{k_t}, {}^{n_t^*}/_{k_t^*} \right) \partial \mathfrak{b}$. Similarly, let us assume that the USD denotes foreign currency. Therefore, given ϖ, the consumer maximizes equation 1, subject to the following budget constraint:

$$\phi_t + z_t + (1 + \Delta_t)^{-1} n_{t-1} + q_t (1 + \Delta_t^*)^{-1} n_{t-1}^* + (1 + \Delta_t)^{-1} (1 + \square_{t-1}) d_{t-1} + q_t (1 + \Delta_t^*)^{-1} (1 + \square_{t-1}^*) d_{t-1}^* = \dot{C}_t + q_t \dot{C}_t^* + n_t + q_t n_t^* + q_t d_t^* \qquad (4)$$

[2] Oil price is the price at which oil is sold on the international market and it is considered as exogenous.

where: ϕ denotes the real value of any lump-sum transfers/taxes received/paid by consumers; z_t represents the current real endowment (income) received by the individual; Δ denotes the price level proxied by the consumer price index; q denotes the real exchange rate[3]. n^*_{t-1} represents the foreign real money holdings at the beginning of the period; d_t is the one-period real domestically funded government debt, which pays □ rate of returns; and d^*_t symbolizes the real foreign-issued one-period bond, which pays a risk-free interest rate $□^*_t$. Assume further that d_t and d^*_t are the only two storable financial assets.

We define $U_{\dot{C}} = \partial U\left(\dot{C}, \dot{C}^*_t, \varpi_t, {}^{n_t}\!/_{k_t}, {}^{n^*_t}\!/_{k^*_t}\right)\partial\dot{C}$; $U_{\dot{C}^*} = \partial U\left(\dot{C}_t, \dot{C}^*_t, \varpi_t, {}^{n_t}\!/_{k_t}, {}^{n^*_t}\!/_{k^*_t}\right)\partial\dot{C}^*$;

$U_n = \partial U\left(\dot{C}_t, \dot{C}^*_t, \varpi_t, {}^{n_t}\!/_{k_t}, {}^{n^*_t}\!/_{k^*_t}\right)\partial n$; $U_{n^*} = \partial U\left(\dot{C}_t, \dot{C}^*_t, \varpi_t, {}^{n_t}\!/_{k_t}, {}^{n^*_t}\!/_{k^*_t}\right)\partial n^*$ and $\lambda_t =$ marginal utility (MU) of wealth in period t. To derive the first-order conditions, we maximize the preferences with respect to $\dot{C}$, $\dot{C}^*$, n, n^*, d, and d^*, subject to the budget constraints (4) for the given output and fiscal variables.

$$U_{\dot{C}_t} = \lambda_t \tag{5}$$

$$U_{\dot{C}^*_t} = \lambda_t q_t \tag{6}$$

$$U_{n_t} + \lambda_t - \alpha\lambda^e_{t+1}\,(1 + \Delta^e_{t+1})^{-1} = 0 \tag{7}$$

$$U_{n^*_t} + \lambda_t q_t - \alpha\lambda^e_{t+1} q^e_{t+1}\,(1 + \Delta^{*e}_{t+1})^{-1} = 0 \tag{8}$$

$$\lambda_t - \alpha\lambda^e_{t+1}(1 + □_t)\,(1 + \Delta^e_{t+1})^{-1} = 0 \tag{9}$$

$$\lambda_t q_t - \alpha\lambda^e_{t+1} q^e_{t+1}(1 + □^*_t)\,(1 + \Delta^{*e}_{t+1})^{-1} = 0 \tag{10}$$

We derive equation (11) from (5) and (6)[4]. The equation shows that the marginal rate of substitution (MRS) between domestic and foreign goods equals their relative price.

$$\frac{U_{\dot{C}_t}}{U_{\dot{C}^*_t}} = \frac{1}{q_t} \tag{11}$$

However, equation 12 evolves by solving (6), (8) and (10):

$$U_{\dot{C}^*_t}\,(1 + □^*_t)^{-1} + U_{n^*_t} = U_{\dot{C}^*_t} \tag{12}$$

Building from these equations (i.e., (6), (8) and (10)) to derive (12), this suggests that the expected marginal advantage of adding to holdings at time t must be equal to the marginal utility from consuming foreign goods at time t. Note that the holding of foreign currency directly yields utility through its services$(U_{n^*_t})$. Consequently, from (6) and (10), we have $(-U_{\dot{C}^*_t}) = \alpha\lambda^e_{t+1}q^e_{t+1}(1 + □^*_t)\,(1 + \Delta^{*e}_{t+1})^{-1}$. This implies that the probable real foreign currency invested in foreign bonds has a forgone value of $U_{\dot{C}^*_t}$. Thus, the Total Marginal Benefit (TMB) of holding money at period t is $U_{\dot{C}^*_t} + U_{n^*_t}$.

Similar to (12), we derive (13) below by solving (6), (8) and (10):

$$U_{\dot{C}_t}\,(1 + □_t)^{-1} + U_{n_t} = U_{\dot{C}_t} \tag{13}$$

This equation (13) evolves with the implication that the expected marginal benefit from adding to domestic currency holdings at the time (t) must be equal to the marginal utility (MU) of consuming domestic goods at a time (t). Consequently, we assume that the utility has an immediate function to construct a parametric demand for real balances. Therefore, given that:

$$U(\dot{C}_t, \dot{C}^*_t, \varpi_t, n_t, k_t, n^*_t, k^*_t) = (1-\varphi)^{-1}\left(\dot{C}_t^{\varphi_1}\dot{C}_t^{*\varphi_2}\ \varpi_t^{\varphi_3}\right)^{1-\varphi} + v(1-r)^{-1}\left[\left({}^{n_t}\!/_{k_t}\right)^{r_1}\left({}^{n^*_t}\!/_{k^*_t}\right)^{r_2}\right]^{1-r} \tag{14}$$

Where $\varphi_1 > 0, \varphi_2 > 0, \varphi_3 > 0, \varphi > 0, r_1 > 0, r_2 > 0, r > 0$ and $v > 0$. They are all positive parameters. $0.5 < \varphi < 1$ and $0.5 < r < 1$. For the sake of convenience, these parameters are all assumed to be equal to one (1), since none of the following results is sensitive to the magnitude of $\varphi_1, \varphi_2, \varphi_3, r_1$ and r_2.[5] The utility function derived in equation (14) is similar to what Kia (2006) assumes. Nevertheless, the fact that there is also

[3] The real exchange rate is defined as $q_t = E_t\left(\frac{P^*_t}{p_t}\right)$ where: E_t represents the nominal market (nonofficial/black-market rate in some developing countries) exchange rate (domestic price of foreign currency); and P^*_t and P_t are the foreign and domestic price levels of foreign and domestic goods, respectively (see Kia, 2013).

[4] Note that, $y^e_{t-1} = E(y_{t+1}|I_t)$ is the conditional expectation of y_{t+1}, given current information I_t.

[5] However, if the assumption of inelastic supply of labor (income is exogenous) is relaxed, there would be a need to add an extra term: for instance, $-(1-\varphi_3)^{-1}(N_t)^{1-\varphi_3}$ (14). N denotes hours worked and $\varphi_3 \geq 0$, denotes Frisch labor elasticity of supply. In a situation like this, one can easily verify that none of our results will be different.

risk associated with holding foreign currency is ignored (see Kia, 2006). Using equations (11) and (14), we have equation (15) below:

$$\dot{C}_t^* = \left({}^{\varphi_2}/_{\varphi_1} \right) \dot{C}_t q_t^{-1}$$

Given that ${}^{\varphi_2}/_{\varphi_1} = 1$, we can express (15) as:

$\dot{C}_t^* = \dot{C}_t q_t^{-1}$, or linearize $\log\dot{C}_t^* = \log\dot{C}_t + \log(q_t^{-1})$

$$\log\dot{C}_t^* = \log\dot{C}_t + \log q_t^{-1} \qquad (15)$$

Following Kia (2006) and the assumption that $\varphi_1 = \varphi_2 = \varphi_3 = r_1 = r_2 = 1$, we solve (12), (14) and (15) to derive:

$$\left(\frac{ {}^{v}/_{k_t^*} \left({}^{n_t}/_{k_t} \right)^{r_1(1-r)} \left({}^{n_t^*}/_{k_t^*} \right)^{-r} }{ \left[\varphi_2 \dot{C}_t^{\varphi_1(1-\varphi)} \dot{C}_t^{*(\varphi_2-1)-\varphi_2\varphi} \varpi_t^{\varphi_3(1-\varphi)} \right] } \right) = \left({}^{\Box_t^*}/_{1-\Box_t^*} \right) \qquad (15.1)$$

Substituting (15) in (15.1) and solving for n_t^*,

$$n_t^* = k_t^{*\,{}^{(r-1)}/_{r}} \left({}^{\Box_t^*}/_{(1+\Box_t^*)} \right)^{(-1/r)} \left(\beta_t^{(1-2\varphi)} \omega_t^{(1-\varphi)} q_t^{\varphi} \right)^{(-1/r)} v^{(-1/r)} (k_t^{-1} n_t)^{(1-r/r)}, \text{ or}$$

$$\log(n_t^*) = {}^{(r-1)}/_{r} \log(k_t^*) - (r^{-1})\log\left({}^{\Box_t^*}/_{(1+\Box_t^*)} \right) - (r^{-1})(1-2\varphi)\log(\dot{C}_t) - (r^{-1})\varphi\log(q_t) - (r^{-1})(1-\varphi)\log(\varpi_t) + (r^{-1})\log(v) + (r^{-1}-1)\log(n_t) - (r^{-1}-1)\log(k_t) \qquad (16)$$

As noted in (16), $r < 1$. Therefore, a rise in the foreign risk leads to a reduction in demand for foreign currency while a rise in the domestic risk leads to a rise in demand for foreign currency. It should be noted that (16) is not a final equilibrium condition. With reference to our assumption of a utility function that is found in (14), a representative consumer must have both currencies in his/her satisfaction function (see Kia, 2006). The elimination of one will lead to the elimination of the other. For the sake of simplicity, we use (13), (14), (15), and (16), and assume that domestic real consumption$(\dot{C}_t)$ is some constant proportion $(\mho)$ of domestic real income z_t, where for simplicity's sake, we further assume that $\mho = 1$. We will then have:

$$\log((n_t) = n_0 + n_1 Int_t + n_2\log(z_t) + n_3\log(\varpi_t) + n_4\log(k_t) + n_5\log(q_t) + n_6\log(I_t) + n_7\log(k_t^*)^6 \qquad (17)$$

where; $I_t^* = \log\left[{}^{\Box_t^*}/_{(1+\Box_t^*)} \right]$; $I_t = \log\left[{}^{\Box_t}/_{(1+\Box_t)} \right]$, using $0.5 < \varphi < 0.5$ and $0.5 < r < 1$, we will have,

$$n_0 = -1\left({}^{1}/_{(1-2r)} \right)\log(v) > 0;\ n_1 = r(1-2r)^{-1} < 0;\ n_2 = (1-2r)^{-1}(1-2\varphi) > 0;\ n_3 = -(1-\varphi) < 0;\ n_4 = (1-2r)^{-1}(1-r) < 0;\ n_5 = -(1-2r)^{-1}(r-1)\varphi - r(1-r)] < 0;\ n_6 = -(r-1)(r-2r)^{-1} < 0 \text{ and } n_7 = (1-2r)^{-1}(1-r) < 0.$$

Consequently, it is important to understand that, as the risk associated with any of these currencies increases, demand for a bond, as well as goods and services, will rise. At the equilibrium, we will have $\log((n_t) = \log(n_t^s)$, where m^s denotes the supply of money. Substituting $\log(n^s)$ for $\log(n)$ in Equation (17) and Equations (2) and (3), for $\log(k)$ and $\log(k^*)$ in Equation (17), and solving for $\log(q_t)$ gives:

$$\log(q_t) = ȝ_0 + ȝ_1 lnms_t + ȝ_2 int_t + ȝ_3 lngdp_t + ȝ_4 lnop_t + ȝ_5 I_t + ȝ_6 dbtgdp_t + U_t \qquad (18)$$

where q is the exchange rates, ȝ represents the parameters of the forecasting model; lnms denotes log of money supply; int represents interest rates; lngdp denotes log of GDP; lnop is the log of the price of oil on the international market; I denotes inflation, and the *dbtgdp* is the percent of external debt to GDP.

Further defining the parameters, they are expressed below:

$$ȝ_0 = -\left({}^{n_0}/_{n_5} \right) - \left({}^{n_4}/_{n_5 k_0} \right) - \left({}^{n_7}/_{n_5 k_0^*} \right) > 0;\ ȝ_1 = \left({}^{1}/_{n_5} \right) < 0;\ ȝ_2 = -\left({}^{n_1}/_{n_5} \right) < 0;$$
$$ȝ_3 = -\left({}^{n_2}/_{n_5} \right) > 0;\ ȝ_4 = -\left({}^{n_4}/_{n_5 k_1} \right) > 0;\ ȝ_5 = -\left({}^{n_6}/_{n_5} \right) > 0;\ ȝ_6 = -\left({}^{n_7}/_{n_5 k_1^*} \right) < 0$$

[6] The coefficients of both k_t and k_t^* are negative. This implies that both the domestic and foreign risks associated with holding domestic and foreign currencies reduce demand for domestic currency. This is because, as indicated in (16), demand for domestic currency (n) has a positive relationship with demand for foreign currency(n^*). Therefore, as (k^*) goes up, (n^*) will fall, which results in a fall of (n).

Equation (18) expresses a long-run real exchange rates relationship. The error term U is added and assumed to be white noise or random walk in the model. Following Eslamloueyan and Kia (2015) and Kia (2006), this equation assumes that an increase in the interest rate and money supply may lead to lower exchange rates over the long-run period. This is associated with the fact that a rise in the interest rate or money supply could cause a rise in prices over the long run, which eventually results in lower real exchange rates.

The ARDL estimating technique is employed to forecast the exchange rates, and it is expressed as:

$$\Delta q_t = \varphi_0 + \varphi_1 \Delta\vartheta_{t-1} + \varphi_2 \Delta\vartheta_{t-2} + \cdots + \varphi_p \Delta\vartheta_{t-p} + \Pi_1 \Delta q_{t-1} + \Pi_2 \Delta q_{t-2} + \ldots \Pi_q \Delta q_{t-q} + v_t \quad (19)$$

Where q_t is a (k x 1) vector of endogenous variables capturing the exchange rates; φ_0 is a vector of intercept/drift components of the constant term; Δ represents the first difference operator; ϑ_{t-q} and q_{t-q} are lagged explanatory variables in the long and short run and in the long run, respectively; $\varphi_1 - \varphi_p$ represent the short-run dynamics of the model; $\Pi_1 - \Pi_p$ represent the long-run relationships; and v_1 is a vector of disturbance terms/random walk.

As earlier expressed, recall that,

$$ꞡ_0 > 0;\ ꞡ_1 < 0;\ ꞡ_2 < 0;\ ꞡ_3 > 0;\ ꞡ_4 > 0;\ ꞡ_5 < 0;\ ꞡ_6 < 0.$$

To examine the factors forecasting exchange rates in Nigeria, this study analyzes the short-run relationships between exchange rates and the forecasting factors to determine whether the effect of these factors may foster output growth.

For suitable modeling to establish the connections between exchange rates and the selected macroeconomic variables, this study considers the existence of unit roots and cointegration of data to determine the proper methodology. To achieve these preliminary tests, the study follows Giles (2013) who enumerates four circumstances that usually confront data and afterwards determines the choice of technique. Firstly, the Ordinary Least Squares (OLS) estimating technique is suitable for analysis when all data series are I(0) and thus stationary. Secondly, when data are not cointegrated, but series are proven integrated of the same order (e.g., I(1)), the appropriate estimating technique is an estimation in first differences comprising no long-run elements. Thirdly, when all data series are found to be integrated of the same order as well as cointegrated, the two types of regression estimating models suggested are: (a) a Vector Error Correction Model (VECM) or Error Correction Model (ECM), estimated by the OLS technique (see Gujarati, 2004) which represents the short-run dynamics of the connection between the selected variables; and (b) an OLS regression approach, using the levels of the data. This approach is advantageous because it is believed to provide a long-run equilibrium relationship between the examined variables. Finally, the fourth situation differs from the other three scenarios and is seen to be more complex. In this situation, some of the variables examined are stationary in levels (that is, I(0)) while some are stationary at first differences (i.e., I(1)) or even proportionally integrated, resulting in no definite integration order as in the other scenarios above. Giles (2013) and Pesaran, Shin and Smith (2001) suggest a more advanced estimating technique that is suitable to handle fractional integration order referred to as the ARDL model. This study falls into that category, necessitating the choice of the ARDL model introduced in Pesaran *et al.* (2001). Various studies have applied this estimating approach and found it suitable for capturing series with varied integration order. For, Mercan, Gocer, Bulut and Dam (2013) use the ARDL model to examine the effect of openness on economic growth in the BRICS-T (Brazil, Russia, India, China and South Africa - Turkey) countries. Al Mamun *et al.* (2013) employ the ARDL dynamic analysis technique to identify the financial determinants of corporate social responsibility (CSR) in Bangladesh's banking industry. instance Bakar, Abdullah and Abdullah (2013) employ the ARDL model to examine the determinants of fertility in Malaysia, while Dritsakis (2011) employs it to estimate demand for money in Hungary and recently, Shin, Yu, and Greenwood-Nimmo (2014) model asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework.

Data, Data Sources and Measurement of Data

The study uses quarterly time series data obtained from the World Development Indicators (WDI). The data spans1980Q1 to 2020Q4. The starting date is chosen to capture a period of major oil price shocks that caused an imbalance in the world economy and the exchange rates of oil-exporting countries. The cut off period coincides with the period when the latest data of interest was available. The choice of the variables employed in this study is informed by theory and previous studies (see Yin, Peng and Tang, 2018; Eslamloueyan and Kia, 2015; Lee and Huh, 2017). The variables include Exchange Rates (EXR), Money Supply (MS), Interest Rate (INT), Gross Domestic Product (GDP), Oil Price (OP), Inflation (INF), Debt to GDP. They are modeled in the ARDL forecasting framework. The exchange rate is the dependent variable and the independent variables are money supply, interest rates, GDP, dbtgdp and inflation rates. Apart from interest and inflation rates, the other variables are expressed in their natural logarithms. Due to the requirements for using the ARDL model, the variables are subjected to a test for stationarity which reveals that the variables are a mixture of I(0) and I(1) but not I(2) variables (see Tables 1a-1c). Consequently, the study proceeds with an estimation of the ARDL forecasting technique in equation 21.

Estimation Technique

The study adopts Pesaran *et al.*'s (2001) ARDL estimating technique. In addition to the forecasting, the model examines whether short-run and long-run relationships exist between exchange rates and the identified forecasting variables of exchange rates. The choice of this technique is premised on Al Mamun *et al.* (2013), and Eslamloueyan and Kia (2015). The reasons presented in these studies for preferring an ARDL to other conventional short-run and long-run techniques are as follows: (a) the ARDL is suitable for combining the I(0) and I(1) series, implying that variables integrated of order zero and one can be estimated in one regression. The variables can be mutually cointegrated, disregarding their integration order but not I(2) (see Katircioglu, 2009; Sari *et al.,* 2008). This renders the ARDL model a more advantageous estimating technique over other approaches to estimate short-run and long-run relationships; (b) the ARDL has the capacity to concurrently estimate the long-run and short-run parameters of a model (Dritsakis, 2011; Shin *et al.,* 2014); (c) the ARDL model is suitable for both large and small sample sizes (Narayan and Gupta, 2015; Rafindadi and Yosuf, 2013); (d) according to Giles (2013), the ARDL model is a contemporary method to examine short-run and long-run dynamics; (e) variables used in a ARDL estimating technique can be assigned different lags (see Giles, 2013); (f) an ARDL involves a single-equation set-up, making it easy to implement and interpret (Giles, 2013); and (g) the ARDL model can accept more than two lags and up to seven variables (see Giles, 2013).

Unit Root Tests

Following Bornhorst and Baum (2006) and Moon *et al.* (2007), this study considers unit root test to estimate the properties of the variables before conducting an ARDL analysis to avoid incorrect specification of a model and spurious results (see Hamid and Shabri, 2017). The Dickey Fuller (DF), Augmented Dickey Fuller (ADF) and Philip-Perron (PP) unit root tests are used. Testing whether a series, say π_t, is integrated or equivalent to testing for significance of α_2 i.e. $H_0: \alpha_2 = 0$, in the regression below where, η is a linear trend.

$$\Delta\pi_t = \alpha_0 + \alpha_1\eta + \alpha_2\pi_{t-1} + \sum_{i=1}^{k}(\zeta\pi_{t-1} + \pi_t) \quad (20)$$

Lag Length

To select an appropriate optimal lag length, the study is guided by established criteria in the literature that the lag with the lowest criterion be considered (see Lutkepohl, 2006). Therefore, the study tests for various order lag selection criteria to allow for adjustments in the model using the robust criteria comprising SIC, FPE, HQIC and AIC (Raza, Shahbaz and Nguyen, 2015).

Diagnostic Tests

To examine the reliability of ARDL model. This study conducts various diagnostic tests consisting of serial correlation, heteroscedasticity, normality and stability tests to demonstrate the suitability, robustness, and reliability of the model.

FORECASTING: AN OVERVIEW

Heizer and Render (2004) refer to forecasting as the science and art of predicting a future event. "It is the estimating of a future outcome of a random process". The data forecasting procedure is well discussed in the literature. The main assumption guiding data forecasting is that the outcome obtained from a random process provides accurate and dependable evidence of the future. Therefore, there is a limitation to the outcome of a forecast. Forecasting may offer much insight, but it is hardly ever flawless (Mendenhall, Reinmuth and Beaver, 1993). Various unpredictable situations could affect the actual result. Nonetheless, the economy and businesses cannot afford to eliminate forecasting as effective policymaking and planning in both the short and long run rely significantly on forecasts (see Heizer and Render, 2004; Mendenhall *et al.,* 1993).

ARDL Forecasting of Variables

Using the ARDL model, this study forecasts the AOECs' exchange rates and also examines the accuracy and predictive power of the model. This approach follows the graphical technique of Haskamp (2017). The study employs the out-of-sample forecasting procedure to illustrate the different trend types that comprise irregular components, seasonal components, and trend components. Using an ex-post forecasting (all sata are known), it follows Diebold and Li (2006) to estimate a regression model using data for the period 1980 to 2015 to estimate the ARDL model and forecasting data for the period 2016 to 2020 for the out of sample (the forecast is beyond the ARDL regression model). The results are presented in static and dynamic forecasting. Following Crepso Cuaresma and Breitenfellner (2008) and MacDonald and Taylor (1994) in determining the benchmark for the forecasting, the model is computed and compared based on several evaluations of forecast statistics comprising the mean absolute error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Theil Inequality Coefficient (TIE). These statistics were derived for a forecast horizon of twelve periods, for the three-year out-of-sample space.

Root Mean Square Error (RMSE)

The "root mean squared error" is a benchmark to evaluate an estimated regression model and ascertain the variance between the forecasted and the actual values (see Clarida *et al.,* 2003). According to Hassani *et al.* (2010) and Pradhan and Kumar (2010), the RMSE is a common technique to estimate forecasting accuracy and is frequently cited in forecasting literature. The approach suggests that the lower the RMSE (value) or the smaller the error margin (i.e., the gap between the forecasted value and the actual value), the more satisfactory the predictive power of the model. The forecasting procedure presents a line graph obtained using scientific software, e-views, to verify the true correlation and movement path between the forecasted and actual values to substantiate and validate the forecasting strength of the model. However, given that $P_i^f(n)$ is the ith prediction of a given model for oil price for $n-$ steps into the future, and $P_i^{\propto}$ is the actual output realized in the future, then the RMSE and Theil U[7] statistics can be expressed as.

$$\mathrm{RMSE}(n) = \sqrt{\frac{1}{T}\sum_i^T (P_i^{\propto} - P_i^f(n))^2} \quad (21)$$

Theil's U Inequality Test (TUIT)

This test suggests that if the RMSE of the unrestricted ARDL model ($RMSE_{UR}$) is less than the RMSE of the restricted model ($RMSF_R$), that is ($RMSE_{UR} < RMSE_R$), then the model has a "better" forecasting ability with a low forecasting error. Consequently, if $U(n)$ in equation (22) below holds, such that $U(n) < 1$, it shows that the unrestricted ARDL model forecast is good and reliable. The Theil's U coefficient is expressed as follows:

$$U(n) = \sqrt{\frac{1}{T}\sum_i^T (P_i^{\propto} - P_i^f(n))^2} \Big/ \sqrt{\frac{1}{T}\sum_i^T (P_i^{\propto} - P_i^*(n))^2} \quad (22)$$

Where T is the forecast computed and $P_i^*(n)$ is the forecasted value based on the "naive forecast" $n-$ steps into the future, using the data ranging up to $i-T$. T is the number of out-of-sample forecasts that is carried out. Root Mean Squared Errors (RMSE) are computed for forecasting horizons (n), spanning from one quarter ahead to quarter twelve ahead. It is apparent that a Theil U statistic greater than 1 $(U > 1)$ suggests that the model used for the forecast is worse in terms of quality of forecasting than a "naive forecast"[8]. However, a Theil U statistic less than one $(U < 1)$ suggests that the model used for the forecast is appropriate and reliable in terms of predictability or the quality of forecasting (see Gupta and Sichei, 2006).

Mean Absolute Percentage Error (MAPE)

The MAPE overcomes one shortcoming of using the Mean Absolute Deviation (MAD) and Mean Square Error (MSE) in estimating forecasting accuracy (see Heizer and Render, 2004). This shortcoming occurs because the values of the two are dependent on the magnitude of the items that are forecasted. The values of MSE and MAD have a tendency to be very large when the forecasted item is measured in real terms. Using the MAPE eliminates this shortcoming. However, the MAPE may not be effective when a forecasted item is measured in very insignificant terms. Following Mendenhall *et al.* (1993) and Heizer and Render (2004), the MAPE is estimated using the formula:

$$\mathrm{MAPE} = \frac{100*(\sum_{i=1}^{n}\frac{|ð_i - g_i|}{ð_i})}{n} \quad (24)$$

Where the MAPE=> the mean absolute error; $\sum_{i=1}^{n} =>$ the summation of the nth period; $ð_i$ is the actual value in the nth period; g_i is the forecasted value in the nth period; and $|ð_i - g_i|$ is the absolute value of the difference in absolute and actual values. Given that the MAPE is estimated as a percentage, it is easy to interpret its outcome. According to Heizer and Render (2004), application of the MAPE method is mainly useful to compare the performance of a model for a variety of series.

[7] The Theil's U inequality coefficient employs a random walk model procedure as a benchmark. However, this study follows Rapach and Weber (2004) in the applications of the Theil's U coefficient, using the Autoregressive (AR) model as a benchmark. Nonetheless, the study refers to the ratio of the RMSE from the restricted and unrestricted models as the Theil's U coefficient.

[8] Naive Forecast: an estimating method in which the actual values of the previous period are used as the present period's forecast, without having to adjust them or attempting to establish causal factors. It is usually only used for comparison with forecasts generated by the better (sophisticated) methods.

Forecasting Variables: Static and Dynamic Models

This study forecasts Nigeria's exchange rates. As noted in the previous chapter, oil prices significantly determine exchange rates movement in the AOECs. This section performs a forecasting analysis to show the influence of oil prices and other factors in forecasting exchange rates. In view of this, exchange rates and other variables are forecasted within the ARDL framework, using the RMSE evaluation technique. Following Eslamloueyan and Kia (2015) and Kia (2013), the specification may be interpreted as a monetary model of exchange rates determination augmented by oil prices (see Crepso Cuaresma and Breitenfellner, 2008; MacDonald and Taylor, 1994). Exchange rates behavior is assumed to be influenced by changes in the relative money supply, and variations in the interest rate, inflation rate, debt, output and oil price. In achieving this, two major approaches that are widely discussed in the literature on forecasting are employed. They are the Dynamic Forecasting Model (DFM) and the Static Forecasting Model (SFM) (see Wang *et al.*, 2015). Accordingly, the DFM and SFM are superior and suitable for forecasting economic variables. Kose and Baimaganbetov (2015) argue that the superiority of these techniques not only captures the time-varying property of the variables, but could also automatically select the optimum model. Baumeister and Kilian (2016) propose these techniques with inverse recursive mean-squared prediction error (MSPE). Similarly, Manescu and Van Robays (2016) utilize this method to predict real Brent oil prices.

This study carries out combined forecasting, differentiating between the dynamic and static methods using the RMSE, Theil coefficient, and MAE as a benchmark. Engle and Granger (1987) introduced the combined forecasting technique and since then, it has been widely applied in the literature (see Haskamp, 2017; Yin *et al.,* 2018). In addition, this procedure adheres to strict scientific means of achieving empirical outcomes which is usually done using a robust Popperian methodological approach(es) as a way of proving its scientific existence (see Heizer and Render, 2004). Generally, the static forecasting (simulation modeling) technique is based on existing exposures and therefore, assumes a constant balance with no new growth. The procedure uses actual rather than forecasted values (this is only possible when actual data or series are available). On the other hand, dynamic forecasting depends on detailed assumptions concerning distinctions (rises or falls) in the economy. It relies on a formerly forecasted outcome of a lagged variable. According to De Menezes *et al.* (2000), a review of the two techniques leads to different preferences. Hibon and Evgeniou (2005) are of the view that it is not that the combined forecast is more beneficial than possible individual forecasts, but that it could be less risky in practice because it combines more forecast methods than is possible when forecasting methods are individually selected. Therefore, they posit that using both static and dynamic forecasting in a study offers researchers the chance to make a better choice than alternative forecasting techniques. It also helps to choose the outcome with the highest level of forecasting accuracy.

RESULTS AND DISCUSSIONS OF RESULTS

Unit Root Results

Tables 1 present the results of the DF, ADF and PP tests for unit roots at individual intercept, and trend and individual intercept for various variables employed in this study. Oil prices are stationary in level (i.e., I(0)). Inflation rate and DBT/GDP are stationary at level. Interest rate is stationary at first difference. No variable is stationary at the second difference (i.e., I(2)). The stationarity results reveal a combination of I(0) and I(1) making ARDL model appropriate (see Peseran *et al.,* 2001; Dritsakis, 2011; Shin, Yu, and Greenwood-Nimmo, 2014 and Bakar *et al.*, 2013).

Table 1a. The Dickey Fuller (DF) Unit Root Test.

Variable	DF (Individual intercept)			DF (individual intercept and trend)		
	Order of integration	t* Statistics	P-Value	Order of integration	t* Statistics	P-Value
LNEXR	I(1)	-2.7715	0.0000	I(1)	-3.9843	0.0001
LNMS	I(1)	-2.9495	0.0211	I(1)	-4.2479	0.0000
INT	I(1)	-2.6193	0.0002	I(1)	-3.6392	0.0005
LNGDP	I(1)	-3.4412	0.0000	I(1)	-3.6518	0.0000
LNOP	I(0)	-3.0352	0.0000	I(0)	-4.3932	0.0002
INF	I(0)	-2.5095	0.0040	I(0)	-3.5833	0.0014
LNDBT	I(1)	-2.6332	0.0022	I(1)	-3.8904	0.0011

Note: "***", "**" and "*" respectively represent statistical sign at 1 percent, 5 percent and 10 percent.

Table 1b. The Augmented Dickey Fuller (ADF) Unit Root Test.

Variable	ADF (Individual intercept)			ADF (individual intercept and trend)		
	Order of integration	t* Statistics	P-Value	Order of integration	t* Statistics	P-Value

LNEXR	I(1)	-3.7932	0.0017	I(1)	-3.4960	0.0435
LNMS	I(1)	-3.5751	0.0015	I(1)	-4.6671	0.0251
INT	I(1)	-3.5383	0.0086	I(1)	-4.6537	0.0275
LNGDP	I(1)	-3.8181	0.0052	I(1)	-4.1091	0.0133
LNOP	I(0)	-3.2346	0.0200	I(0)	-4.3666	0.0460
INF	I(0)	-3.8655	0.0029	I(0)	-3.8417	0.0170
LNDBT	I(1)	-6.5039	0.0000	I(1)	-6.5031	0.0000

Note: "***", "**" and "*" respectively represent statistical sign at 1 percent, 5 percent and 10 percent.

Table 1c. The Philip-Perron (PP) Unit Root Test.

Variable	Philip-Perron (individual intercept)			Philip-Perron (individual intercept and trend)		
	Order of integration	t* Statistics	P-Value	Order of integration	t* Statistics	P-Value
LNEXR	I(1)	-4.0153	0.0017	I(1)	-4.0453	0.0092
LNMS	I(1)	-2.9351	0.0437	I(1)	-4.9616	0.0146
INT	I(1)	-4.3878	0.0005	I(1)	-4.3313	0.0037
LNGDP	I(1)	-3.9030	0.0026	I(1)	-4.0684	0.0086
LNOP	I(0)	-4.1550	0.0011	I(0)	-4.0550	0.0089
INF	I(0)	-4.7889	0.0001	I(0)	-4.7727	0.0008
LNDBT	I(1)	-4.05270	0.0015	I(1)	-4.0292	0.0097

Note: "***", "**" and "*" respectively represent statistical sign at 1 percent, 5 percent and 10 percent.

Lag Length

The optimal lag length selection order for this study is presented in Table 2. The various criteria suggest lag 2 to be the most appropriate for this study.

Table 2. Optimal Lag Length Selection Criteria for Nigeria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1211.370	NA	0.561965	16.45094	16.57245	16.50031
1	1205.579	4605.267	5.98e-15	-15.72404	-14.87348	-15.37846
2	1599.547	156.2873*	3.25e-17*	-21.00250*	-14.58675	-19.91965*
3	1608.218	18.28584	4.62e-17	-20.69017	-18.98184*	-19.25413
4	1626.027	33.36220	5.65e-17	-20.54067	-17.88347	-18.71209
5	1671.994	718.7258	4.75e-17	-20.56145	-15.46530	-18.55057
6	1776.185	15.11565	6.91e-17	-20.19214	-16.90859	-19.17586
7	1789.072	29.60114	8.94e-17	-19.94631	-16.31423	-18.56731
8	1814.010	72.67721	7.95e-17	-20.08100	-16.50668	-18.12161

Table 3. ARDL Dynamic Regression Estimates.

Dependent Variable: LNEXR				
Method: ARDL				
Sample (adjusted): 1980Q3 2020Q4				
Included observations: 154 after adjustments				
Maximum dependent lags: 2 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (2 lags, automatic): INF INT LNDBT LNGDP LNMS LNOP				
Selected Model: ARDL(2, 2, 2, 0, 2, 0, 0)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.***
LNEXR(-1)	1.646047	0.060810	27.06889	0.0000
LNEXR(-2)	-0.685843	0.062078	-11.04810	0.0000
INF	0.001114	0.000636	1.752773	0.0019
INF(-1)	-0.002080	0.001156	-1.799740	0.0741
INF(-2)	0.001364	0.000635	2.147145	0.0335
INT	-0.010863	0.002919	-3.721539	0.0003
INT(-1)	0.016942	0.005165	3.280500	0.0013
INT(-2)	-0.007361	0.002942	-2.501786	0.0135

LNDBT	0.012365	0.015222	0.812303	0.4180
LNGDP	-1.530751	0.372797	-4.106126	0.0001
LNGDP(-1)	3.010639	0.679766	4.428932	0.0000
LNGDP(-2)	-1.475198	0.370187	-3.985003	0.0001
LNMS	0.033843	0.015157	2.232792	0.0272
LNOP	0.022397	0.057468	0.389734	0.0073
LNOP(-1)	-0.081042	0.058649	-1.381808	0.1693
C	-0.197638	0.431696	-0.457818	0.6478

Interpretation of the ARDL Regression Model

Table 3 presents the ARDL estimates for the short-run relationship between exchange rates and the series that forecast it in Nigeria. A total of six independent variables, namely, inflation rates, interest rates, debts, GDP, money supply and oil prices are regressed against exchange rates adding up to seven variables. The findings show that debts are not sufficiently statistically significant to impact exchange rates in the short run. The implication is that debts in Nigeria do not influence exchange rates in the short run. However, its coefficient suggests that a fall in debts will lead to currency appreciation (an increase in the value of the Naira). The Nigeria currency, Naira will appreciate by 1.2 percent. A region that is significantly indebted is expected to suffer exchange rates depreciation. Therefore, this study supports Eslamloueyan and Kia's (2015) finding that increases in debts may impede exchange rates appreciation. Interest rates show a negative relationship with exchange rates at 5 percent significance level. This implies that an increase in interest rates will cause a 1 percent appreciation in exchange rates. That is, higher interest rates in Nigeria tend to attract foreign investment, which is likely to increase demand for Naira. This finding is in line with Olomola (2011) who argues that higher interest rates will offer lenders in an economy higher returns relative to other countries. Consequently, a higher interest rate attracts foreign capital and causes the exchange rate to rise. The opposite relationship occurs when interest rates decrease; that is, lower interest rates tend to reduce exchange rates.

Money supply shows a positive relationship with exchange rates at 5 percent level of significance. This implies that an increase in money supply will lead to 3.3 percent depreciation in exchange rates. In other words, higher money supply in Nigeria tends to reduce interest rates, which may lead to a fall in demand for Naira. In addition, an increase in money supply can cause depreciation in exchange rates because there will be decreased demand for the currency and its value will tend to decrease in exchange rate markets. This finding validates earlier studies (see Olomola, 2011) which argue that higher money supply accounts for lower interest rates and consequently currency depreciation. The opposite relationship occurs when the money supply decreases. Inflation rates are sufficiently statistically significant to influence exchange rates in the short run. The findings show that inflation rates negatively impact exchange rates. This suggests that an increase in inflation rates leads to a 0.1 percent depreciation in Nigerian Naira. This study supports Iwayemi and Fowowe (2011) who contend that a very low rate of inflation does not guarantee favorable exchange rates for a country, but that an extremely high inflation rate is very likely to negatively impact the country's exchange rates with other nations.

Oil prices show a positive relationship with exchange rates at 5 percent level of significance. The implication is that rises in oil prices lead to 8.1 percent appreciation in exchange rates. That is, higher oil prices account for appreciation of the Nigerian Naira. This finding validates earlier studies that assert that an increase in oil prices Granger causes the currency of oil-exporting countries (Iwayemi and Fowowe, 2011; Ahmed, 2017).

Measuring the Strength of the Model Selection Criteria

This section employs the criteria graph technique (see Figure 1) to establish the strength of the AIC model selection summary over other models such as the HQIC and the Schwarz criterion. The criteria graph is also engaged in the ARDL regression model to ascertain the short-run relationships in the ARDL model. Consequently, the criteria graph presented in figure 4.39 determines the top twenty ARDL models. The figure shows that the ARDL criteria graph having (2, 2, 2, 0, 2, 0, 1) and -5.205 AIC value is the most preferred because it has the lowest AIC value, followed by ARDL (2, 2, 2, 0, 2, 0, 0) with -5.204 AIC value. The ARDL (2, 1, 2, 0, 2, 0, 1) has the highest AIC value, -5.185 and is the least preferred.

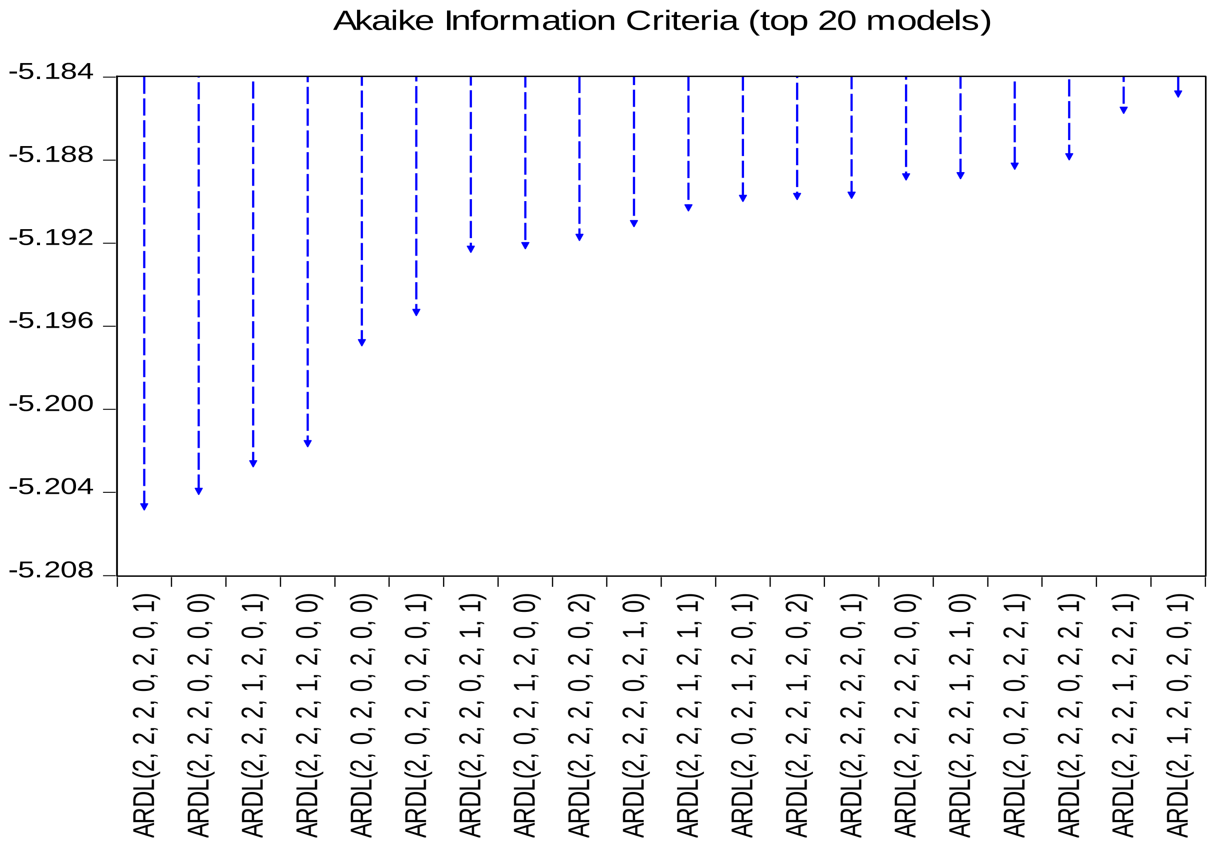

Figure 1. Strength of the ARDL Model Selection.

Serial Correlation Results

Table 4 presents the results of serial correlation. There is no evidence of serial correlation because the probability of the F-statistics is 45 percent which is greater than 5 percent. This suggests that the null hypothesis cannot be rejected. As a result, the study suggests that the model is free from serial correlation. The results also support that the parameter estimates of the model do not suffer from the autocorrelation problem.

Table 4. Breusch-Godfrey Serial Correlation LM Test.

F-statistic	1.155132	Prob. F(2,136)	0.3181
Obs*R-squared	2.572337	Prob. Chi-Square(2)	0.2763

Heteroskedasticity Result

Table 4.7 presents the results for the heteroskedasticity test. The heteroskedasticity test demonstrates the robustness and suitability of the model. The benchmark null hypotheses that are tested for the heteroskedasticity tests are:

$$H_0\text{: there is no heteroskedasticity}$$
$$H_1\text{: there is heteroskedasticity}$$

Both the chi square and F-statistics are insignificant at 5 percent, implying that the null hypothesis of no heteroskedasticity cannot be rejected. Therefore, it is concluded that the estimated model is reliable and there is no problem of heteroskedasticity.

Normality Test

Figure 2 shows the normality test result. The test is conducted based on the three common tests in the literature, the skewness, Jarque-Bera and kurtosis tests. Ninety-eight percent of the variables in the model passed the normality test, both individually and jointly. This implies that the residuals of the model are normally distributed, and the data sets are appropriately modelled. In addition, the null hypothesis of "no normality of the residuals" cannot be rejected. Therefore, the result validates the model as consistent and favorable in forecasting exchange rates in Nigeria.

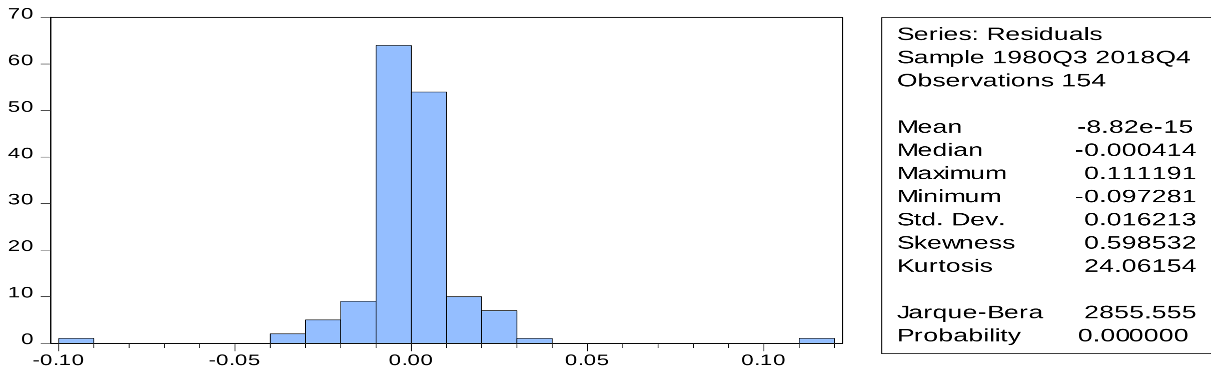

Figure 2. Normality Test Results.

CUSUM Stability Test

The CUSUM test result is presented in Figure 3, showing that the model is stable over time and could forecast exchange rates in Nigeria.

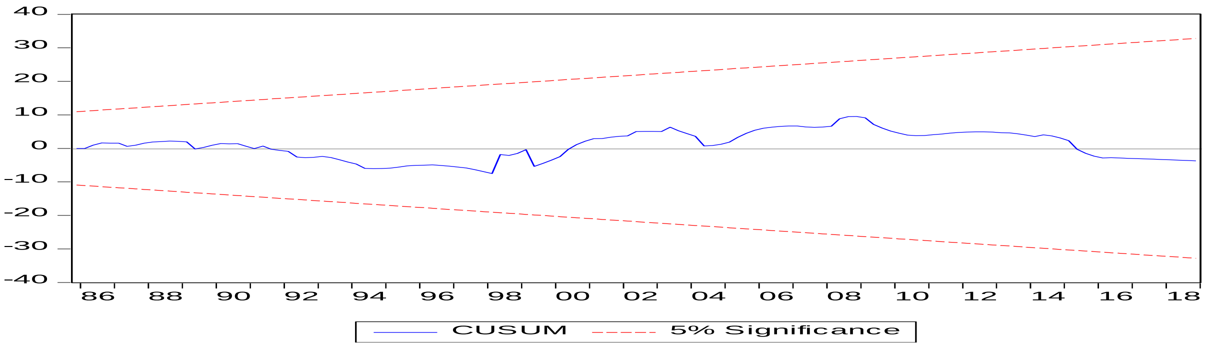

Figure 3. CUSUM Test Result.

Forecasting Exchange Rates: Static and Dynamic Results

Having established that the estimated model is free from statistical errors and it is suitable to forecast exchange rates, the study forecasts exchange rates in this section. The estimated data for exchange rates ranges from 1980Q1 to 2020Q4. 1980Q1 to 2015Q4 is the period for the sample regression model for both the dynamic and static forecasts respectively, presented in figures 4.4 and 4.5. As revealed in the figures, the sample regressions are both significant at 95 percent confidence interval. This validates their robustness and appropriateness to make dynamic and static forecasts of exchange rates in Nigeria.

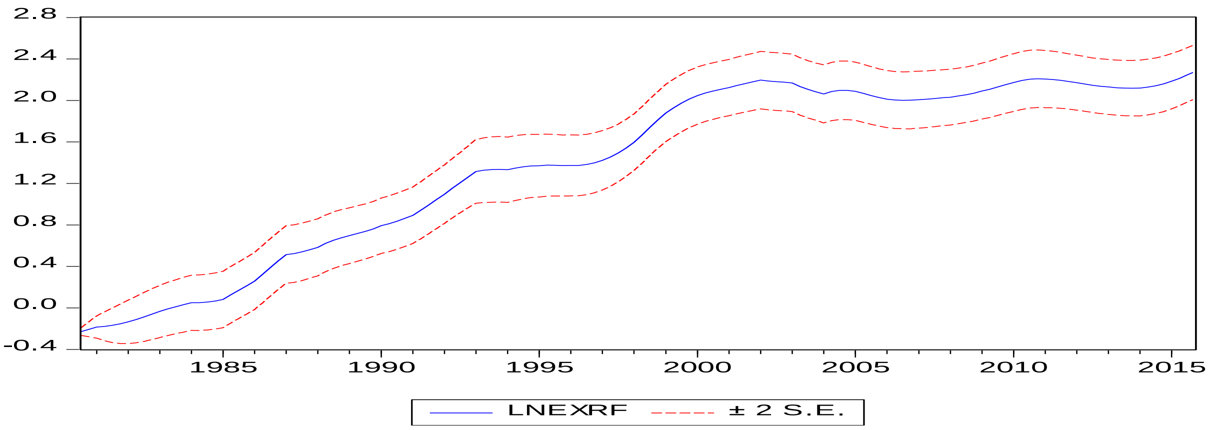

Figure 4. Exchange Rates In-Sample Forecasting Equation: *Dynamic.*

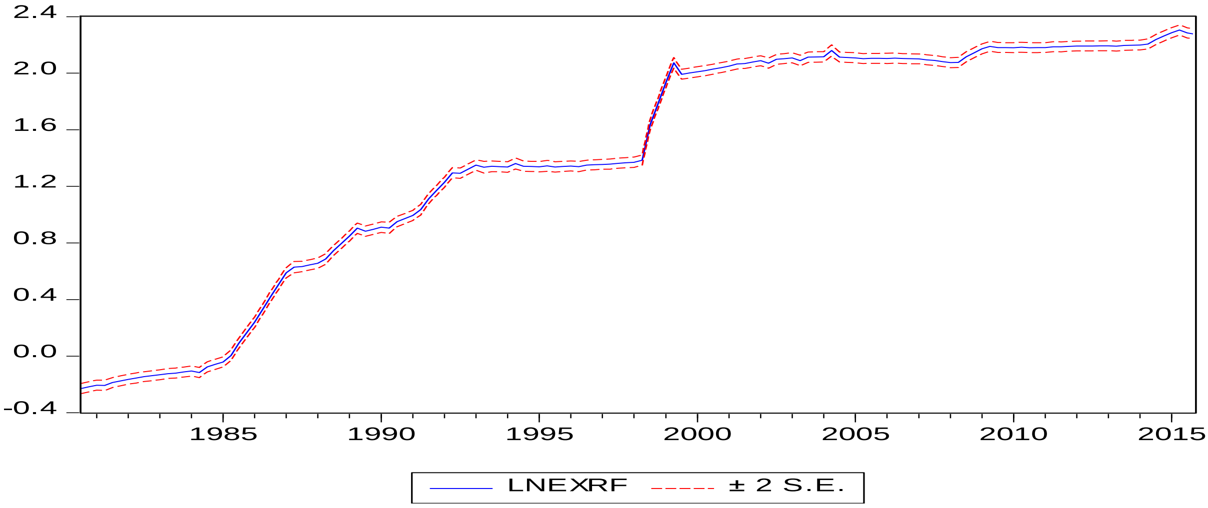

Figure 5. Exchange Rates In-Sample Forecasting Equation: *Static.*

The study employs the forecasting evaluation criteria utilized in the literature to determine the robustness and suitability of both the dynamic and static forecasts models (see Table 5). The evaluating coefficients for the dynamic forecast are 0.085197, 0.070959, 0.018975 and 0.026225 for the RMSE, MAE, MAPE and Theil coefficients, respectively. Likewise, the evaluating coefficients for the static forecast are 0.016812, 0.009637, 0.021657 and 0.005149 for the RMSE, MAE, MAPE and Theil coefficients, respectively. The outcomes of these coefficients are close to zero, satisfying the analysis benchmark for forecasting. These results support the reliability of the model to forecast exchange rates.

Table 5. Exchange Rates In-Sample Forecast Equation 1980Q1-2015Q4.

	Evaluation Coefficients			
	RMSE	**MAE**	**MAPE**	**THEIL**
Dynamic	0.085197	0.070959	0.018975	0.026225
Static	0.016812	0.009637	0.021657	0.005149

The out-of-sample forecasting horizon runs from 2016Q1 to 2020Q4 (see Figures 6 and 7). The results reveal that the forecasts are statistically significant at 95 percent confidence interval within the two (± 2) standard deviation error lines. These results support the suitability of the sample regression models to forecast exchange rates.

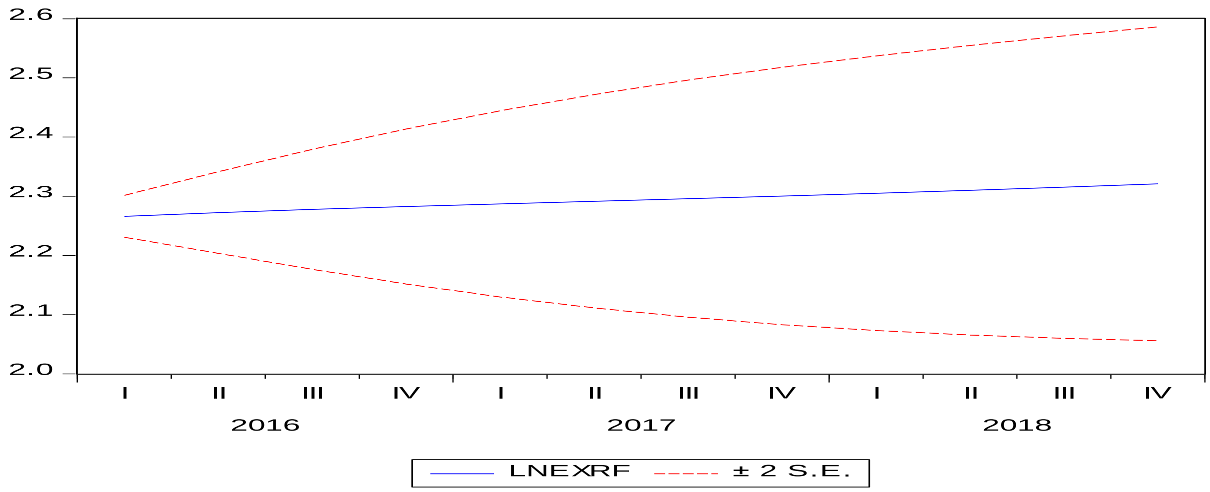

Figure 6. Exchange Rates Out-of-Sample Forecast: *Dynamic.*

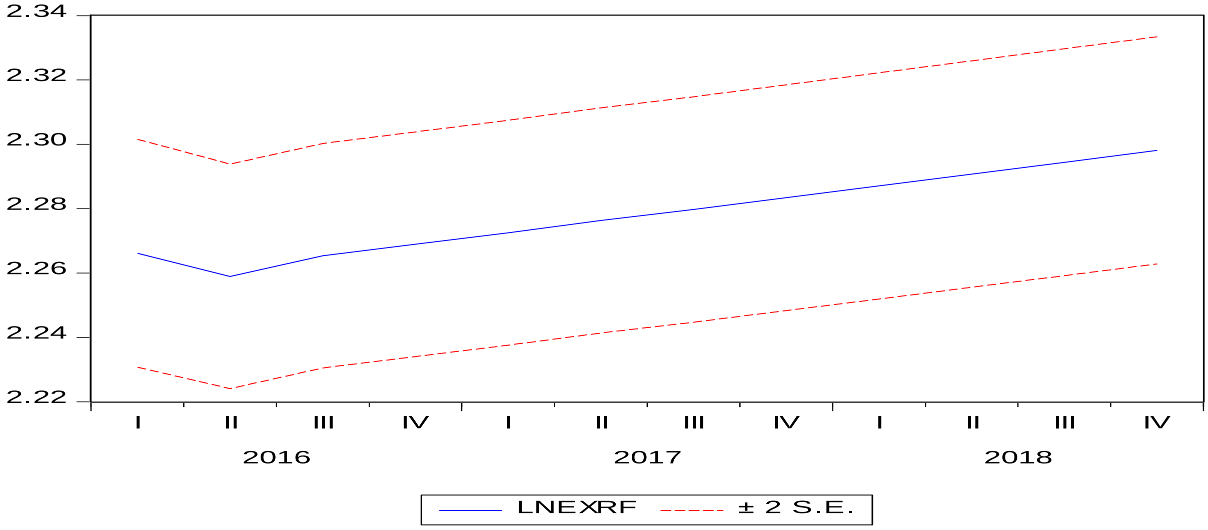

Figure 7. Exchange Rates Out-of-Sample Forecast: Static.

The forecasting evaluation criteria for the out-of-sample dynamic forecast are respectively revealed as 0.017183, 0.016570, 0.072664 and 0.003759 for the RMSE, MAE, MAPE and Theil coefficients (see Table 6). Likewise, the forecasting evaluation criteria for the out-of-sample static forecast are respectively estimated as 0.002676, 0.001762, 0.077586 and 0.000587 for the RMSE, MAE, MAPE and Theil coefficients. The goodness of these criteria offers support for the appropriateness of the forecasting models for both the dynamic and static out-of-sample forecasts models.

Table 6. Exchange Rates Out-of-Sample Forecast lines: 1980Q1-2015Q4.

	Evaluation Coefficients			
	RMSE	**MAE**	**MAPE**	**THEIL**
Dynamic	0.017183	0.016570	0.072664	0.003759
Static	0.002676	0.001762	0.077586	0.000587

The actual and forecasted exchange rates are presented in figures 8 and 9, respectively. The findings reveal co-movement in the actual and forecasted models. This displays a strong co-movement in the actual and forecasted exchange rates, implying that the model is appropriate. The closeness in the actual and forecasted exchange rates in the dynamic and static forecasts reflects the Theil coefficient nearing zero. The actual and forecasted exchange rates show a co-movement with negligible variance. This could serve as a guide to policymakers when making decisions on how to stabilize exchange rates in Nigeria.

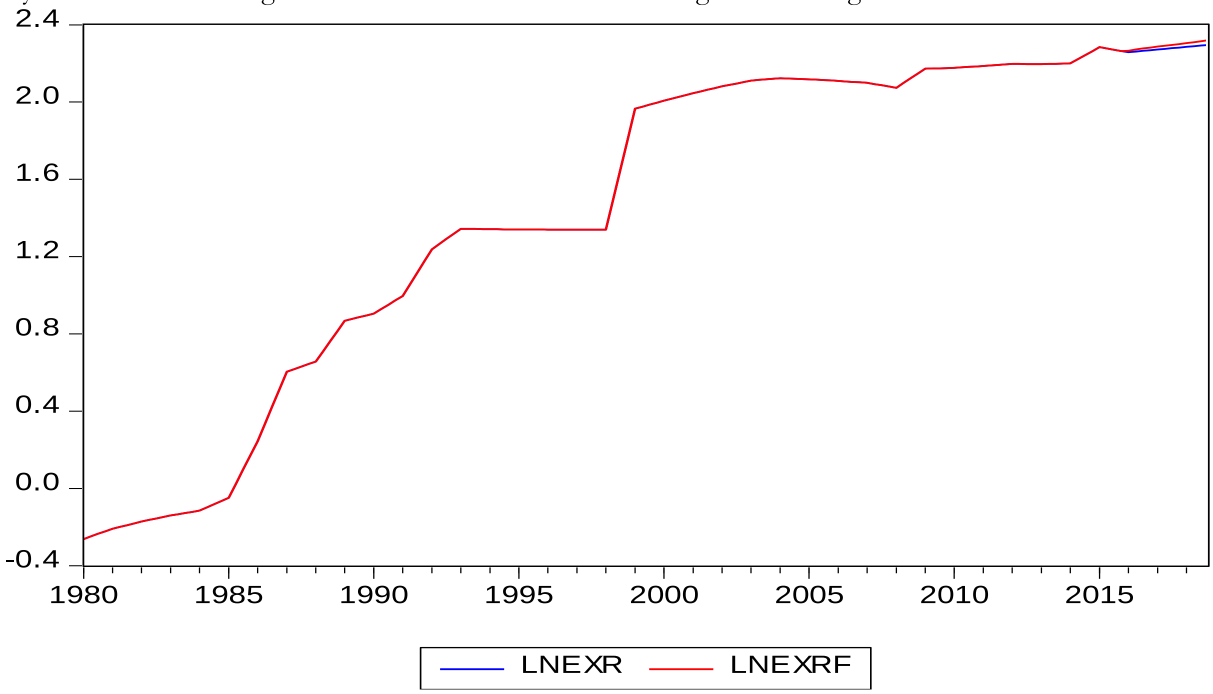

Figure 8. Dynamic forecast.

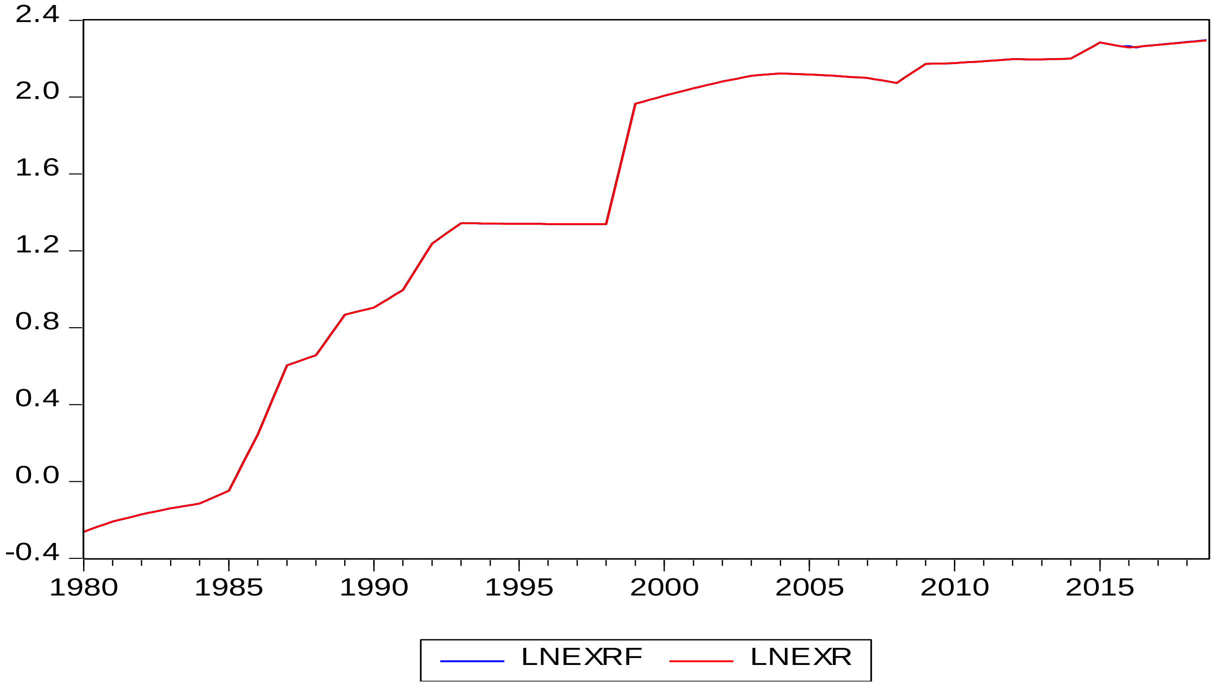

Figure 9. Static forecast.

Discussions and Inferences

This study forecasts an exchange rates model for Nigeria as a guide to exchange rates determination to aid decision making. Sample variables covering 1980Q1-2015Q4 are employed and out-of-sample variables cover 2016Q1-2020Q4. The model is found appropriate to forecast exchange rates following the various evaluation coefficients estimated to complement the statistical significance of our various tests of significance for the regressions and forecasting lines for both the dynamic and static forecasts. The various evaluation coefficients comprising the RMSE, MAE, MAPE and the Theil coefficients are nearing zero. This validates the appropriateness of the model. It is in line with the stretch of the benchmark for the suitability of a forecasting model. By implication, the satisfactory outcomes of the sample model and the significant results obtained in both the dynamic and static forecasts strongly support the claim that the selected explanatory variables are suitable to forecast the exchange rates of the Naira[9]. This finding aligns with Eslamloueyan and Kia (2015), Kao (1999) and Kia (2015). The study concludes that future exchange rates can be forecasted with INF, INT, LNDBT, LNGDP, and LNMS in addition to LNOP. This finding contributes to knowledge that exchange rates forecasting in Nigeria strongly depends on these factors. Therefore, to overcome the possibility of an exchange rates surge arising from oil price shocks causing economic imbalances as noted in Gali and Monacelli (2005) and emphasized in Hameed *et al.* (2012), which Etuk *et al.* (2016) conclude is a major issue in the global economy, this study provides information to international economic agents who are continuously seeking guidelines to address uncertainties and unforeseen fluctuations.

SUMMARY AND CONCLUSIONS

The study forecasts the exchange rates of the Nigerian Naira using both dynamic and static forecasting procedures. The ARDL model used to forecast exchange rates is motivated by the stationarity test which reveals that all variables are stationary at both level and first difference. The ARDL reveals evidence of a short-run relationship between exchange rates and the explanatory variables that forecast exchange rates. The actual exchange rates are compared with the forecasted exchange rates to form an analysis that measures the forecasting accuracy of the various models. The results show that all the estimates in the ARDL model behave well in forecasting exchange rates for Nigeria. Thus, the models perform well, and it can be concluded that they are suitable to forecast exchange rates in the country.

Findings from the study serve as guide to policy makers. It will allow policy makers to obtain early signals of future crises, hence, allowing them to make accurate exchange rates forecasts. As a result of globalization, the findings of this study are important to both importers and exporters since exchange rates instability has different effects on their decision making on matters relating to international transactions.

[9] Naira is the term used to express the Nigeria's currency.

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