TIME SERIES FORECAST MODELS FOR FOREIGN EXCHANGE MARKET IN A DEVELOPING ECONOMY

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Abstract: *Technicalities in foreign exchange forecasting have been of interest to investors and academia, particularly in a developing economy. Data of foreign exchange are time series in nature and several techniques have been developed to modeling and forecasting foreign exchange rate. In this study, Nigeria foreign exchange rate against three world leading currencies (US Dollars, Euro and Pounds Sterling) are modeled with ARIMA, Auto.arima ,Box-Cox, random walk forecast, and Exponential Smoothing and subjected to comparative tests using Diebold-Mariano criteria with a modern model time series model. The empirical analysis shows that that the modern model outperforms some of the other techniques in forecasting Nigeria exchange rates against world leading currencies particularly when the forecast horizon is low.*

Key words*: Foreign Exchange, Diebold-Mariano, Forecasting, Time series, TBATS*

1. INTRODUCTION

Modeling future financial state of a nation and organizations, for the purpose of planning and policy making is crucial to any economy. Diverse techniques have been developed and concerted efforts should be made to employ an efficient technique to model a given set of data. Adeleke et al (2015) modeled daily exchange rate with extreme value theory, modeling the tail area of the distribution and the model is found to be effective in predicting daily exchange rate. Forecasting a time series data, particularly foreign exchange is observed to tasking because it is noisy, non-stationary and deterministically chaotic (Box et al 1994).

De Livera, Hyndman and Snyder (2010) identified that complex seasonal patterns are found in many time series data, and most current time series models are considered to estimate simple seasonal patterns with a small integer-valued period. Hamadu and Adeleke (2009) compared Multilayer Perception Back Propagation Neural Network (MLPBPNN) model with several models, including ARIMA generated by Expert Modeler System (EMS) to model foreign exchange in a developing economy, the empirical study shows that (MLPBPNN) outperforms other techniques. In the class of ARIMA models, the auto.arima proposed by Hyndman & Khandankar (2008) is found to be more accurate than ARIMA, which is determined with criteria such as AIC, AIC_c or BIC. Nevaz (2008) in his study to investigate the performance of time series models in forecasting foreign exchange, ARIMA models were found to be preferred to exponential smoothing. Meese and Rogoff (1983) compared a number of time series models on the basis of out of sample forecasting accuracy and discovered that in short horizon, random walk outperforms a range of fundamental based models of exchange rate determination. The same authors found out that beyond a year, random walk forecast does not meet the minimum forecast errors.

Clement (2014) identifies that macroeconomics forecast gives is satisfactory at horizons of a year or more, but overestimate the uncertainty of their predictions at short horizons. Manzan (2015) considers accuracy relative to stochastic volatilty model (AR-SV) as a benchmark to evaluate performance of different models, also carried out quantile auotoregressive (QAR) model selected by LASSO, the results shows that the multivariate model outperforms the time series forecast, specifically at long horizons and in tails of distribution. On Exponential smoothing; the Holt-Winters (HW) exponential smoothing is adopted when a dataset exhibits both trend and seasonality and two main HW models are Additive model for time series which exhibits additive seasonality and Multiplicative model for time series Kalekar (2004). Akram et al (2009) observed that the non-linear forms of the state space models supporting exponential smoothing commonly used suffers some important weaknesses in that, most non-linear seasonal version can be unsteady. The model used for smoothing assumes that the prediction error is serially uncorrelated, and introduction of Box-Cox transformation is aimed to avoid problem of non-linear models (Box & Cox 1964).

The aim of this study is first, to carry out a Diebold-Mariano (DM) test to examine forecast effectiveness of the models at different horizon, second is to carry out a comparative test among models using the DM test, also use traditional approach.

The remaining part of this paper is sectionalized as follows: in section (2), time series model is discussed, in section (3), the Diebold-Mariano test is discussed, and Section (4) is the empirical application is considered to draw comparison between the models, while section (5) is discussion and conclusion.

2. TIME SERIES MODEL

In this section, we discuss briefly time series models, which serve as foundation for the models being used in this study. Holt-Winters' additive and multiplicative methods which are the most frequently used seasonal models in the innovations state space context is given below:

$$y_t = \iota_{t-1} + \phi_{t-1} + c_t + d_t \qquad (1)$$

Taylor (2003) further introduced a second seasonal component to the linear version of the Holt-Winters as follows:

$$y_t = \iota_{t-1} + \theta_{t-1} + c_t^{(1)} + c_t^{(2)} + d_t \qquad (2)$$

$$\iota_t = \iota_{t-1} + \theta_{t-1} + \alpha d_t \qquad (3)$$

$$\theta_t = \theta_{t-1} + \beta dt \qquad (4)$$

$$c_t^{(1)} = c_{t-p_1} + \gamma_1 d_t \qquad (5)$$

$$c_t^{(2)} = c^{(2)}{}_{t-p_2} + \gamma_2 d_t \qquad (6)$$

Where p_1 and p_2 are periods of the seasonal cycles and d_t is the white noise random variable indicating the prediction error. Modifying the above model using Box-Cox transformation allows some non-linearity and the methodology is limited to only positive time series of focus. Denoting $y_t^{(\varpi)}$ as Box-Cox transformed observations with the parameter ϖ, y_t is the observation at time t. De Livera et al (2010) extends equation (1) to (5) to contain Box-Cox transformation, $ARMA$ errors and T seasonal patterns ($BATS$) as follows:

$$y_t^{(\varpi)} = \begin{cases} \dfrac{y^{\varpi}{}_{t-1}}{\varpi}, \varpi \neq 0 \\ \log y_t, \varpi = 0 \end{cases} \qquad (7)$$

Where ,

$$y_t^{(\varpi)} = \iota_{t-1} + \phi\beta_{t-1} + \sum_{i=1}^{T} s^{(i)}{}_{t-p_i} + d_t \qquad (8)$$

$$\iota_t = \iota_{t-1} + \phi\theta_{t-1} + \alpha d_t \qquad (9)$$

$$\theta_t = (1-\phi) + \phi\theta_{t-1} + \beta d_t \qquad (11)$$

$$\theta_t^{(i)} = c^{(i)}{}_{t-p_i} + \gamma_i dt \qquad (12)$$

$$dt = \sum_{i=1}^{p} \varphi_i d_{t-1} + \sum_{i=1}^{q} \psi_i d_{t-i} + \varepsilon_t \qquad (13)$$

$p_1,.........p_T$ represents the seasonal periods, ι_t is the local level in period t , θ and θ_t stands for the long-run trend, and the short-run trend in period t, De Livera et at (2011) gives details of the models, De Livera et at (2010) introduced a more flexible and uncommon approach, which is takes advantage of trigonometric formulation of seasonal components, centered on Fourier series, adapting the work of (West & Harrison1997, Harvey 1989). By replacing the seasonal component $c_t^{(i)}$ in equation (8) by the trigonometric seasonal formulation, and it is measured by equation (14) below

$$y^{(\varpi)}{}_t = \iota_{t-1} + \phi\theta_{t-1} + \sum_{i=1}^{T} c_{t-i} + d_t \qquad (14)$$

with trigonometric T added to the model , we then have $TBATS$. The identifier is enhanced with relevant arguments gives $TBATS(\varpi, \phi, p, q, \{p, k_1\}, \{p_2, k_2\}, ...\{p_T, k_T\})$. The models above are exceptional cases of the linear innovations state space model adapted by De Livera et. al (2011) is by adding the Box-Cox transformation which is able to handle nonlinearities. It has the form:

$$y^{(\varpi)}{}_t = \varpi' x_{t-1} + \varepsilon_t \qquad (15)$$

$$x_t = F x_{t-1} + g\varepsilon_t \qquad (16)$$

2.1 TBATS Model

Introduction of trigonometry (T) part brings about the name $TBATS$ state vector model with a non-stationary growth term as stated by De Livera et at (2010) can be defined as $x_t = (\iota_t, \theta_t, c_t^{(1)}, ...c_t^{(T)}, d_t, d_{t-1}, ..., d_{t+p}, \varepsilon_t, \varepsilon_{t-1}, ...\varepsilon_{t-q+1})'$ where $c_t^{(i)}$ is the row vector $(c_{1,t}{}^{(i)}, c_{2,t}{}^{(i)} .....c_{k,t}{}^{(i)}, c_{1,t}{}^{(i)}, c^*{}_{2,t}{}^{(i)}, ...c_{k_i,t}{}^{(i)})$. Let $1_r = (1,1,....,1)$ and $0_r = (0,0,....,0)$ be row vectors of length r; let $\gamma^{(i)}{}_1 = \gamma_1{}^{(i)} 1_{k_i}, \gamma^{(i)}{}_2 = \gamma_2{}^{(i)} 1_{k_i}, \gamma^{(i)} = (\gamma^{(i)}{}_1, \gamma_2{}^{(i)})$, $\gamma = (\gamma^{(i)}{}_1, \gamma_2{}^{(T)}), \varphi = (\varphi_1, \varphi_2, ...\varphi_p)$, let $O_{u,v}$ be a $u \times v$ matrix of zeros, let $I_{u,v}$ $u \times v$ triangular diagonal matrix with element 1 on the diagonal, and let $a^{(i)} = (1_{k_i}, \theta_{k_i})$ and $a = (a^{(1)}, ...a^{(T)})$ matrix $M = \gamma'\varphi, N = \gamma'\theta$ is needed.

$$A_i = \begin{bmatrix} N^{(i)} & S^{(i)} \\ -c^{(i)} & N^{(i)} \end{bmatrix}, \quad \tilde{A}_i = \begin{bmatrix} \theta & 1 \\ I_{p_i-1} & \theta'_{p_i-1} \end{bmatrix},$$

and $A = \oplus^{T}{}_{i=1} A_i$, where $N^{(i)}$ and $c^{(i)}$ are $k_i \times k_i$ diagonal matrices with elements $\cos(\lambda^{(i)}{}_j)$ and $\sin(\lambda^{(i)}{}_j)$, and $j = 1, 2, ...k_i$ and $i = 1, ..., T$ where $\oplus$ denotes the direct sum of the matrices. Also let $\tau = 2\sum_{i=1}^{T} k_i$ then the matrices for the $TBATS$ model can be written as

$w = (1, \phi, a, \varphi, \theta)', g = (\alpha, \beta, \gamma, 1, 0_{q-1})'$ and

$$F = \begin{bmatrix} 1 & \phi & 0_\tau & \alpha\varphi & \alpha\theta \\ 0 & \phi & 0_\tau & \beta\varphi & \beta\theta \\ 0'_\tau & 0'_\tau & A & M & N \\ 0 & 0 & 0_\tau & \varphi & \theta \\ 0'_{p-1} & 0'_{p-1} & O_{p-1} & I_{p-1,p} & O_{p-1,q} \\ 0 & 0 & 0_\tau & 0_p & 0_q \\ 0'_{q-1} & 0'_{q-1} & 0'_{q-1,\tau} & 0'_{p-1,p} & I_{q-1,q} \end{bmatrix}$$

2.2 Evaluation Criteria for Time Series Forecast Model

There are several traditional statistical indices being used to evaluate financial time series forecasting models. Table 1 contains the criteria used in this study and their specifications. Chen et. al (2014) identifies that in practical terms, values of *MAE, MSE* are the most common evaluation criteria and Hyndman (2014) advises that the use of *MAE* or *RMSE* if all forecasts are on the same scale and *MAPE* if one needs to compare forecast accuracy on several series with unlike scales, provided that the data does not contain zeros or small values, or if they are not measuring the same quantity. Hyndman and Koehler (2006) recommend the Mean Absolute Scaled Error (*MASE*) as standard when comparing forecast accuracy. Franses (2015) showed that the MASE nicely fits within the standard statistical procedures to test equal forecast accuracy.

The traditional evaluation criterion is found to be limited hence; the Diebold-Mariano (DM) test is adopted in this study being modern evaluation criteria, because it offers a quantitative method to evaluate the forecast accuracy of time series forecasting models. The squared error (SE), and absolute error (AE) have moment properties which follow the assumptions underlying the asymptotic theory of the DM test, the same holds for the absolute scaled error (*ASE*).

3. DIEBOLD-MARIANO TEST

In this section, we discuss the DM test and steps taken to carry out the test. Steps taken in carrying out DM test are as follows:

Let $\{y_t\}$ denote the series to be forecast and let $\{\hat{y}_{i,t}\}$ denote ith $h-$forecasting horizon. Assuming that forecasting errors from ith competing models are $e_{i,t}{}^{h} (i = 1, 2, 3, ...n)$ where n is the number of forecasting models. The h-step forecasting error $e_{i,t}{}^{h}$ is:

$e_{i,t}{}^{h} = y_t{}^{h} - \hat{y}_{i,t}{}^{h} (i = 1,2,3,....n)$. The accuracy of each forecast is measure by a given loss function. Given actual values $\{y_t : t = 1,2,....T\}$ and two forecasts: $\{\hat{y}_{1,t} : t = 1,2,....T\}$ and $\{\hat{y}_{2,t} : t = 1,2,....T\}$. Forecast error is defined as $e_{i,t} = \hat{y}_{i,t} - y_t \quad i = 1,2$. The loss relating to forecast i is taken to be a function of the forecast error, $(e_{i,t})$ and $L(.)$ is the loss functions where $L(e_{i,t})$ is the square-error loss of the $e_{i,t}$ given as:

$$L(e_{i,t}) = e^2{}_{i,t}$$

$$L(e_{i,t}) = |e^2{}_{i,t}|, \; L(e_{i,t}) = \exp(\lambda e_{i,t}) - \lambda e_{i,t}$$

Where λ are some positive constants. The loss function between two forecasts is defined as

$$L(e_{i,t}) = L(e_{1,t}) - L(e_{2,t})$$

The alternative hypothesis is that no model is better than the other.

$H_1 : E[L(e_{1,t})] \neq E[L(e_{2,t})]$ that is, $E(d_t) \neq 0$

Let the same mean loss differential $\bar{d}$ be given as: $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t = \frac{1}{T} L(e_{i,t}) = L(e_{1,t}) - L(e_{2,t})$

DM test statistics is given as : $DM = \frac{\bar{d}}{\sqrt{\frac{2\pi \hat{f}_d(0)}{T}}} \xrightarrow{d} N(0,1)$

$$f_d(0) = \frac{1}{2\pi}\left(\sum_{k=-\infty}^{\infty} \gamma_d(k)\right)$$

Is the spectral density of loss differential at frequency 0, $\gamma_d(k)$ is the auto-covariance loss differential at lag k. The variance is used in the statistic as a result of the sample loss differential d_t are being serially correlated when $h > 1$.

If we have $h \geq 1$, then;

$$DM = \frac{\bar{d}}{\sqrt{\frac{\gamma_d(0) + 2\sum_{k=1}^{h-1}\hat{\gamma}_d(k)}{T}}}$$

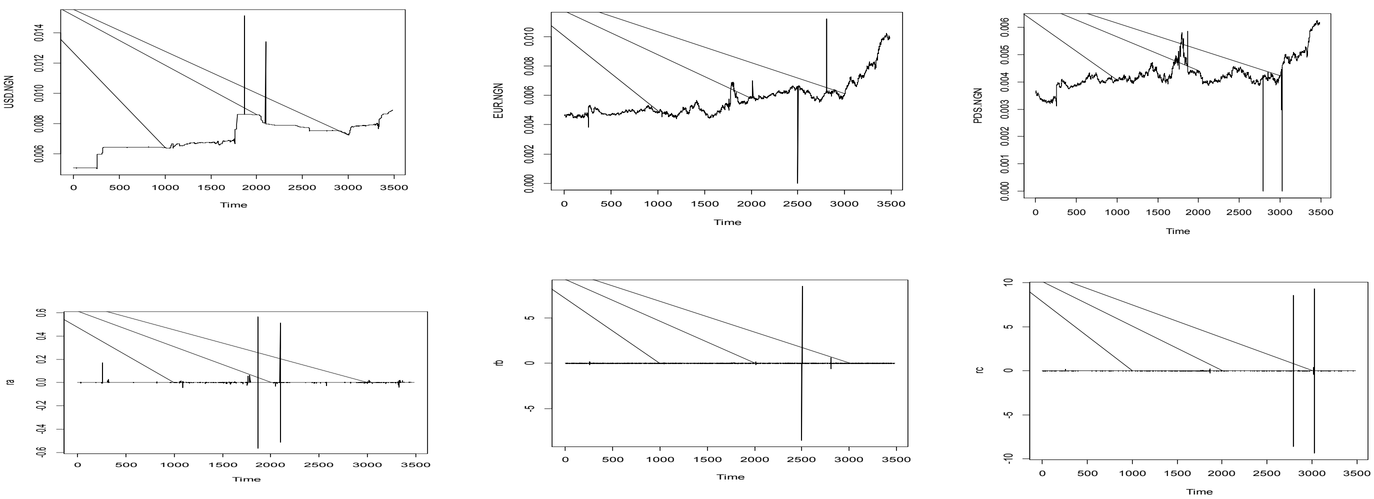
DM is standard normally distributed, that is $N(0,1)$. The null hypothesis of no difference will be rejected if the computed DM statistics falls outside the range -1.96 to 1.96.

4. EMPIRICAL APPLICATION

4.1 Data Description

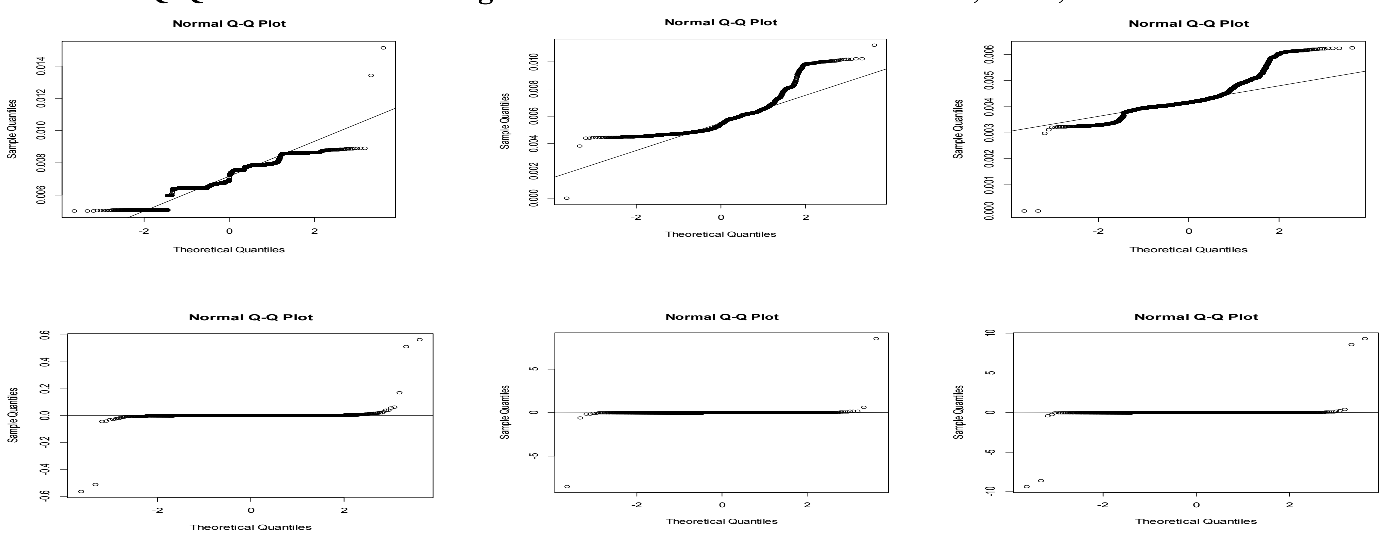
In this study, daily official central foreign exchange data were collected from Central Bank of Nigeria (CBN) official website, the sample period is from, October 12, 2001 to March 8 2016; this represents 3487. Data set for of three currency exchange rates against Nigeria Naira. Three foreign exchange rates were considered against the NGN which include US Dollars, Pounds Sterling, and Euro. According to Reiss & Thomas (2002), if S_t be the exchange rate of USD against NGN and let $r_t = \log\left(S_t / S_{t-1}\right)$, then the exchange rate of NGN against USD is $1/S_t$. This will yield the log returns $r_t = \log\left(\frac{1/S_t}{1/S_{t-1}}\right)$. Table 3 shows the descriptive statistics of the three raw exchange rates, and their corresponding log returns, it is observed from the skewness and kurtosis that the exchange rate is non-normal but it was closed to normal after the logarithm transformation. The normal Q-Q plots in session 4.3 attest to that. Also the exchange becomes stable after the logarithm transformation as seen in session 4.2

4.2 Plots of Raw and log returns of the Naira to US Dollars, Euro, and Pounds



Note: From left to right shows plots of raw exchange rate and log returns of Naira to US Dollars, Euro, and Pounds, it is observed that the data becomes stable after the logarithm transformation.

4.3 Q-Q Plots of Raw and log returns of the Naira to US Dollars , Euro, and Pounds



Note: From left to right shows Normal Q-Q plots of raw exchange rate and log returns of Naira to US Dollars, Euro, and Pounds, upper plots indicating raw exchange rate, while he lower indicate logarithm transformed of the exchange rate it is observed that the data is normalized (almost all the points' falls on the line after the logarithm transformation).

4.4 Estimation Results

In this study, we model the returns of exchange rates Nigeria naira with three world strong currencies (US Dollars, Euro and Pounds Sterling) respectively. The method adopted is the in-sample using software by R Core Team (2015), a language and environment for statistical computing. Also, "forecast" package in R by Hyndman (2016) was equally used to obtain the empirical results. The traditional criterion was computed for forecast accuracy; Diebold-Mariano (DM) test was equally computed. Basically, results for TBATS was compared with five other forecasting models which include (Arima, Auto.Arima, Box-Cox, Random walk Forecasting, and Exponential smoothing)

Table 4: result of descriptive of the Returns of US Dollars, Euro, and Pounds Sterling against Nigeria Naira

	US Dollars		Euro		Pounds	
	Raw	Log return	Raw	Log return	Raw	Log return
Min	0.005038	-0.56340	0.0000013	-8.53400	0.000004	-9.322000
Max	0.015130	0.56340	0.0112200	8.53900	0.006255	9.318000
Mean	0.007145	0.00016	0.0057140	0.00022	0.004272	0.000158
Std.dev	0.000963	0.19137	0.0011876	0.205347	0.000055	0.303702
Skewness	-0.06282	0.19137	1.667825	0.039130	0.977615	0.005283
Kurtosis	1.305108	800.516	3.344337	1712.428	4.459697	870.1968

Data Source: www.cenbank.org/*ExchangeRateByCurrency*

Table 5: DM-test statistics for model evaluation in forecasting Nigeria naira to US Dollars Alternative hypothesis: TBATS and other models have different level of accuracy.

	$h=1$		$h=10$		$h=100$	
	DM	p-value	DM	p-value	DM	p-value
Arima	1.2519	0.2107	1.1983	0.2309	1.2519	0.2107
Auto.arima	-0.9715	0.3314	-1.0591	0.2896	-1.0233	0.1877
Box-Cox	4.9978	0.3314	8.2797	2.2×10^{-16}	-0.00416	0.0004
RWF	1.4478	0.09355	1.4032	0.1607	20.53	0.3166
ES	1.2519	0.1478	1.1984	0.2308	-0.92801	0.3292

Table 6: Indicating models fitted to Naira- US Dollars

	$Arima(0,0,0)$	$Auto.arima(1,1,0)$	Box-Cox	RWF	ES	$TBATS$
AIC	-18536.8	-19973.7	1171.62	-	4.34762	-1427.057
AIC_c	-1836.75	-19973.7	1171.63	-	4.35106	-
BIC	-18524.4	-19961.4	1190.08	-	16.6606	NA
ME	3.873×10^{-16}	-1.725×7^{-7}	9.497×10^{-5}	4.23×10^{-20}	-2.88×10^{-6}	0.000250
$RMSE$	0.016937	0.013787	0.016937	0.029110	0.01693	0.013786
MAE	0.001146	0.002079	0.00108	0.002022	0.00114	0.001939

MPE	100	247.673	30.4711	-32.9145	102.7594	83.73163
$MAPE$	100	835.655	69.0617	449.6735	102.7594	721.3306
$MASE$	0.56706	1.02807	0.53556	1.00000	0.56849	0.959124
$ACF1$	-0.47661	-0.0078	-0.47672	-0.66229	-0.476607	-0.00829
σ^2	0.000287	0.00018	0.008018	-	0.0002856	0.000189

Note: MA coefficient and Alpha for TBATS is -0.706092 and 0.0002977 respectively.

Table 7: Indicating models fitted to Naira-EURO

	$Arima(0,0,0)$	$Auto.arima(1,1,0)$	Box-Cox	RWF	ES	$TBATS$
AIC	-18511.48	-20750.32	-8327.81	-	4.348987	-2217.012
AIC_c	-18511.48	-20750.31	-8327.81	-	4.348987	-
BIC	-18499.17	-20738	-8309.36	-	16.659712	-
ME	-1.225×10^{-20}	-1.799×10^{-6}	2.18×10^{-6}	-6.90844	9.8×10^{-6}	5.406×10^{-5}
$RMSE$	0.0169467	0.012283	0.016947	0.029351	0.016947	0.012311
MAE	0.0087088	0.001891	0.000869	0.001531	0.000870	0.001941
MPE	100	-6389.36	100.6026	2070.201	125.5574	-4227.73
$MAPE$	100	8496.12	103.7983	2463.522	131.3278	6346.153
$MASE$	0.508688	1.234577	0.567637	1.00000	0.568709	1.267523
$ACF1$	-0.499502	-0.00390	-0.49950	-0.66655	-0.49950	0.004613

Note: MA coefficient for TBATS is -0.9901 while and alpha for Exponential smoothing and TBATS are 1×10^{-4} and 0.03961

Table 8: DM-test statistics for model evaluation in forecasting Nigeria naira to EURO
Alternative hypothesis: TBATS and other models have different level of accuracy.

	$h=1$		$h=10$		$h=100$	
	DM	p-value	DM	p-value	DM	p-value
Arima	0.95296	0.3407	0.96543	0.3344	0.97587	0.3292
Auto.arima	-6.0231	1.88×10^{-16}	-1.7371	0.08245	-1.0233	0.1877
Box-Cox	4.0388	5.48×10^{-5}	2.8660	0.00418	-0.00416	0.0004
RWF	1.2083	0.227	0.99862	0.3180	20.53	0.3166
ES	1.0862	0.2775	0.9654	0.3344	-0.92801	0.3292

Table 9: Indicating models fitted to Naira- Pounds Sterling

	$Arima(0,0,0)$	$Auto.arima(1,1,0)$	Box-Cox	RWF	ES	$TBATS$
AIC	1586.26	-717.93	12095.8	-	20127.4	--17835.1
AIC_c	1586.26	-717.93	12095.8	-	20127.4	-
BIC	1598.57	-705.62	12114.28	-	20139.7	-
ME	5.71×10^{-15}	0.00457	0.001230	-8.6×10^{-7}	-1.50×10^{-5}	0.001849
$RMSE$	0.30362	0.21808	0.33910	0.52590	0.30363	0.218429

MAE	0.01539	0.03088	0.05587	0.02830	0.01538	0.031682
MPE	-	-	-	-	-	-
MAPE	-	-	-	-	-	-
MASE	0.54338	1.09113	1.97426	1.0000	0.54343	1.11948
*ACF*1	-0.49975	-0.00267	-0.49973	-0.66667	-0.49974	0.002057
σ^2	0.09218	0.04756	1.865	-	0.092173	0.004771

Note: *MA* coefficient for TBATS is -0.99009, Alpha for TBATS and Exponential Smoothing are -0.706092 and -1.50×10^{-5} respectively.

Table 10: DM-test statistics for model evaluation in forecasting Nigeria naira to Pounds Sterling
Alternative hypothesis: TBATS and other models have different level of accuracy.

	$h=1$		$h=10$		$h=100$	
	DM	p-value	DM	p-value	DM	p-value
Arima	-2.7743	0.0056	-1.3651	0.1723	-1.4304	0.1527
Auto.arima	-2.7743	0.0056	-1.7056	0.0882	-1.5618	0.1184
Box-Cox	1.9735	0.0485	1.3993	0.1618	1.4393	0.1502
RWF	1.7021	0.0889	1.4048	0.1602	14516	0.1467
ES	1.3645	0.1725	1.3649	0.1724	1.4302	0.3292

5. DISCUSSION AND CONCLUSION

Various foreign exchange forecast techniques were evaluated in this study using central Nigeria foreign exchange market against three world leading currencies, the US Dollars, Pounds Sterling and the Euro. The data were found not to be normally distributed and logarithm transformation was made to make the data normal and stable (fig 5.2 and fig 5.3). In the empirical analysis, the TBATS time series forecast technique was compared to five other forecast techniques, findings are contained in tables 5-10. Simulation study, arima outperforms other techniques with *ME* criteria, Auto.arima outperforms other techniques with *BIC, RMSE, MAE, MAPE, MASE, and ACF1,* Box-Cox outperforms other techniques with AIC_c Criteria *TBATS* outperforms other techniques with *AIC* and *ACF1* criteria and Auto.arima. The DM-test statistics shown in table 3 reveals that *TBATS* forecasting have different level of accuracy with Arima and Random Walk forecasting irrespective of the forecast horizons. Forecasting the Nigeria Naira against the US Dollars; Arima outperforms other forecasting techniques using the *MAPE* criteria, Auto.arima outperforms other techniques with *AIC,* AIC_c *and BIC*, Box-cox outperforms with *MAE* and *MASE*, Random work Forecast (*RWF*) outperforms with *ME, MAPE* and *ACF1, TBATS* outperforms with *RMSE*, least variance is recorded for the *TBATS* among other forecasting techniques. Forecasting the Nigeria Naira against Euro; Arima outperforms other techniques with BIC, ME and MASE criteria, Auto.arima outperforms other techniques with AIC_c , *RMSE* and *MPE*. Box-cox outperforms other techniques with *AIC, MAE,* and *MAPE* as shown in table7. DM-test statistics in table 8 reveals that *TBATS* forecast differs from auto.Arima and Box-Cox forecasting techniques when from a short horizon of $h=1$, but less than 10. Forecasting the Nigeria Naira against Pounds Sterling; Arima outperforms other techniques with *ME* and *MASE*, auto.arima outperforms other technique other technique using AIC_c , *BIC* and *RMSE, ES* outperforms other technique using *MAE* technique, Box-Cox outperforms with *ACF1, TBATS* outperforms with AIC as seen in table 9. DM-Test statistics reveals that *TBATS* forecast techniques differs from that of Arima, Auto.arima, and Box-Cox technique when forecasting is done on very small horizon of $h=1$, but less than 10.

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