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A DAILY JAPANESE YEN – NIGERIAN NAIRA EXCHANGE RATES SIMULATION MODEL

Ette Harrison Etuk & Pius Sibeate
Department of Mathematics, Rivers State University of Science and Technology, Port Harcourt, Nigeria
Rivers State Ministry of Education, Port Harcourt, Nigeria
Email: ettetuk@yahoo.com

ABSTRACT

Daily Japanese Yen / Nigerian Naira exchange rates are modelled as a time series. A time plot of a realization of the series, which begins from 15th October 2015 to 8th April 2016, shows that relatively the Nigerian currency is depreciating. The exchange rates are adjudged to be non-stationary by the Augmented Dickey Fuller Test. A seven-point differencing of the series is not enough to render the series stationary according to the same unit-root test. Differencing of the seasonally differenced series finally renders the series stationary. The autocorrelation structure of this stationary series makes some seasonal autoregressive integrated moving average models suggestive. Such models include three with orders $(0,1,1)x(0,1,1)_7$, $(0,1,0)x(0,1,1)_7$ and $(1,1,1)x(1,1,1)_7$. The model selection criteria AIC, Schwarz criterion and Hannan-Quinn criterion unanimously adjudge the second model as the most adequate. Seven later values of the series from 9th to 15th April 2016 are used to compare with the forecasts. It is observed that this out-of-sample comparison shows the forecasts to be very close to the observations; in fact, they are not significantly different from them. Therefore forecasting and simulation of the series may be done using the proposed model.

Keywords: Japanese Yen, Nigerian Naira, Exchange Rates, SARIMA Modelling

INTRODUCTION AND LITERATURE REVIEW

International trade relations are invariably based on exchange rates of national currencies. It could therefore be helpful to predict on the basis of some model the exchange rates of two or more currencies. Many economic and financial time series often display some seasonal tendencies. Exchange rates are inclusive. There are approaches to the modelling of such seasonal series. One such approach is seasonal autoregressive integrated moving average (SARIMA) modelling proposed by Box and Jenkins, 1976. The study of the exchange rates of the Japanese currency and its Nigerian counterpart can help in the prediction of such rates. Economists, financial experts and administrators could get insight into probable future trends of such rates. This would go a long way to provide basis for sound commercial decisions. It is the aim of this study to fit a SARIMA model to daily Japanese Yen (JPY) and Nigerian Naira (NGN) exchange rates. Since its introduction in the 1970's, SARIMA modelling has been widely applied and very successfully, too, to model seasonal time series.

For instance, Linlin and Xiaorong (2012) observed the adequacy of the SARIMA modelling of expressway traffic flow. Khoei *et al.*, 2013, applied SARIMA modelling on Bluetooth data for short-term travel time prediction. A SARIMA $(0,1,0)x(2,0,0)_{12}$ has been fitted to Liberian monthly inflation rates (Fannoh *et al.*, 2014). Boaheng (2014) modelled monthly mean air temperature in the Ashanti region of Ghana as a SARIMA $(2,1,1)x(1,1,2)_{12}$. Kibunja *et al.*, 2014 proposed a SARIMA $(1,0,1)x(1,0,0)_{12}$ model for the forecasting of precipitation in Mount Kenya region. A SARIMA $(0,0,5)x(1,0,1)_{12}$ model has been fitted to rainfall drought for Sudanese Gadaref region by Hishan and Tariq (2014). Gikungu *et al.*, 2015, analysed Kenyan quaterly inflation rates and modelled them by a SARIMA $(0,1,0)x(0,0,1)_4$. Ibrahim *et al.*, 2016, fitted a SARIMA $(1,1,1)x(1,0,1)_4$ model to quarterly peads patients' attendance at Outpatients Medical Laboratory, Mayo Hospital, Lahore, Pakistan. These are just to mention but a few.

MATERIALS AND METHODS

DATA

The data for this study are daily JPY/NGN exchange rates from 15th October 2015 to 15th April 2016 obtained from the website www.exchangerates.org.uk/JPY-NGN-exchange-rate-history.html . The 177-point sample spans from 15th October 2015 to 8th April 2016. The rest from 9th to 15th April 2016 are out-of-sample rates to be used for out-of-sample forecast comparison. The website was accessed on 9th April 2016 for the sample and 16th April for the out-of-sample data. These data are to be interpreted as the amounts of NGN in one JPN.

SARIMA MODELLING

A time series $\{X_t\}$ in order to be modelled must be stationary. If not, it could be differenced non-seasonally and/or seasonally to make it stationary. Before and after being differenced the time series shall be tested for stationarity by the Augmented Dickey Fuller (ADF) Test.
Box and Jenkins, 1976 proposed that a seasonal time series $\{X_t\}$ of period s might be modelled by a SARIMA $(p,d,q)x(P,D,Q)_s$ model defined by

$$A(L)\Phi(L^s)\nabla_s^D\nabla^d X_t = B(L)\Theta(L^s)\varepsilon_t \qquad (1)$$

where A(L) is the non-seasonal autoregressive operator, a polynomial in L of degree p; B(L) is the non-seasonal moving average operator, a polynomial in L of degree q; Φ(L) the seasonal autoregressive operator, a polynomial in L of degree P; Θ(L) the seasonal moving average operator, a polynomial in L of degree Q; L the backshift operator defined by $L^kX_t = X_{t-k}$; ∇ the non-seasonal difference operator defined by $\nabla = 1 - L$; ∇_s the seasonal difference operator given by $\nabla_s = 1 - L^s$; $\{\varepsilon_t\}$ a white noise process.

Model selection shall be done by the use of Akaike Information Criterion (AIC), Schwarz Criterion and Hannan- Quinn criterion.

STATISTICAL SOFTWARE

The analysis of data of this work was done using the statistical and econometric package reviews 7.

RESULTS AND DISCUSSION

The time plot of the original series in Figure 1 shows an overall positive secular trend which indicates a comparative depreciation of the Naira within the time of interest, that is, between October 2015 and April 2016. Expectedly the exchange rates are non-stationary. The ADF test statistic is equal to 0.73. With the 1%, 5% and 10% critical values of -3.47, -2.88 and -2.58 respectively, this original series is adjudged non-stationary. A seasonal (i.e. seven-point) differencing of the original series yields a series with a slightly overall positive trend (See Figure 2). With an ADF test statistic of -2.59, it is adjudged non-stationary too. A non-seasonal differencing of the seasonal differences yields a series with an overall horizontal trend (See Figure 3). An ADF test statistic value of -8.32 is an indication of stationarity of series, given the above critical values. The correlogram of the series in Figure 4 gives an indication of some SARIMA models which include a SARIMA$(0,1,1)x(0,1,1)_7$ model and a SARIMA$(1,1,1)x(1,1,1)_7$ model. Estimation of the SARIMA $(0,1,1)x(0,1,1)_7$ model as summarized in Table 1 yields

$$X_t = \underset{(\pm 0.0767)}{0.1047\varepsilon_{t-1}} - \underset{(\pm 0.0145)}{0.9395\varepsilon_{t-7}} - \underset{(\pm 0.0732)}{0.0849\varepsilon_{t-8}} + \varepsilon_t \qquad (2)$$

Clearly it is only the ε_{t-7} coefficient that is significantly different from zero. Hence a SARIMA $(0,1,0)x(0,1,1)_7$ is proposed. Estimation of this model as summarized in Table 3 yields the model

$$X_t = \underset{(\pm 0.0139)}{-0.9371\varepsilon_{t-7}} + \varepsilon_t \qquad (3)$$

Estimation of the SARIMA $(1,1,1)x(1,1,1)_{12}$ model as summarized in Table 3 yields

$$X_t + 0.1804X_{t-1} + 0.3161X_{t-7} + 0.3396X_{t-8} = \varepsilon_t + 0.3323\varepsilon_{t-1} - 0.3019\varepsilon_{t-7} + 0.3656\varepsilon_{t-8} \quad (4)$$

(±0.1808) (±0.1002) (±0.1100) (±0.1505) (±1036) (±0.1557)

where in (2) , (3) and (4), X_t refers to the difference of the seasonal differences series. Clearly the model (3) is the most adequate of the three on the basis of the model selection criteria AIC, Schwarz criterion and Hannan-Quinn criterion. The residuals of this model are mostly uncorrelated (See Figure 5) and normally distributed at 0.1% level of significance (See Figure 6). Finally out-of- sample forecast comparison in Table 4 shows the closeness of the forecasts to the real observations. The goodness-of-fit of the model is evident.

CONCLUSION

It may be inferred that the model (3) which is a SARIMA $(0,1,0)x(0,1,1)_7$ is adequate for the forecasting and the simulation of daily JPY-NGN exchange rates. Economists, planners, managers and financial experts may use this model in short-term forecasting and simulation of the series.

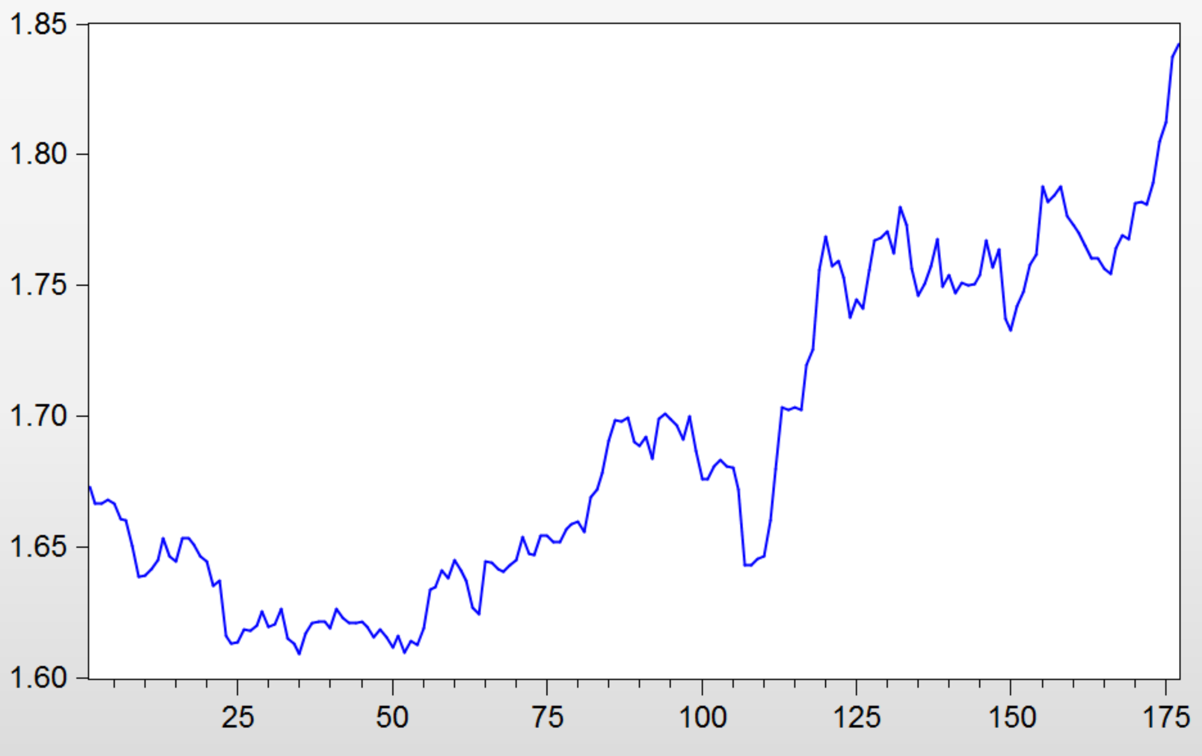

FIGURE 1: THE EXCHANGE RATES

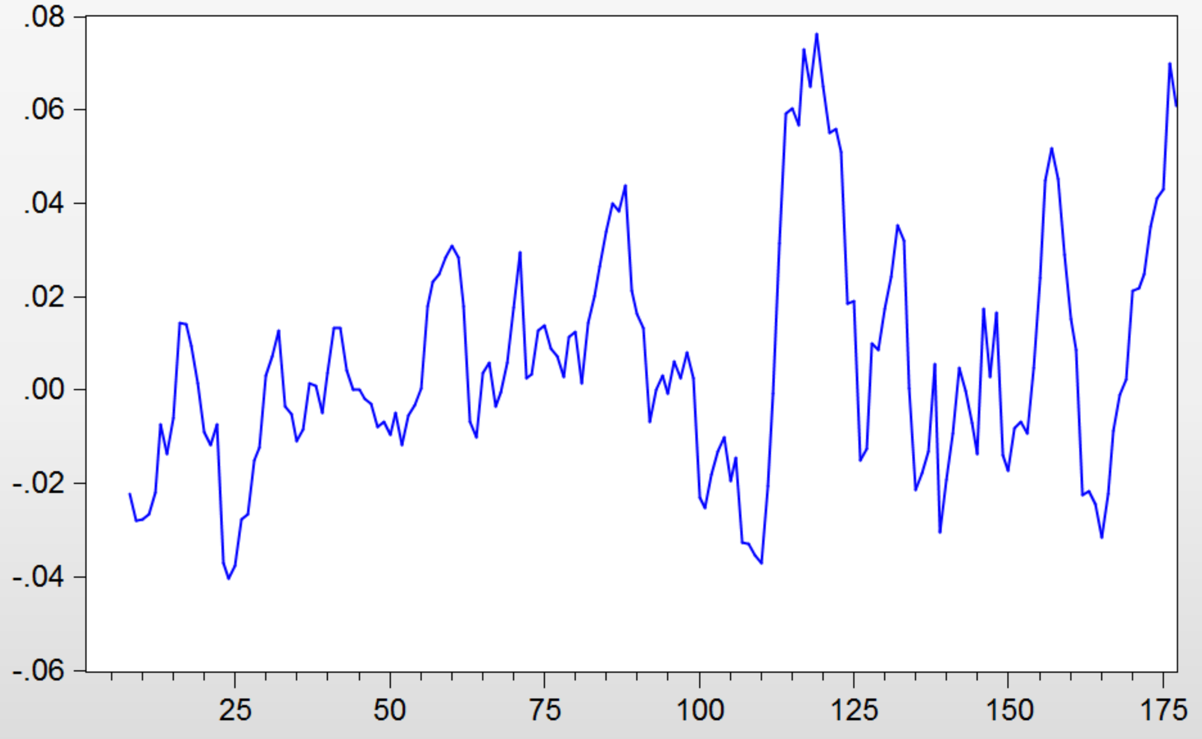

FIGURE 2: SEASONAL (I.E. 7-POINT) DIFFERENCES

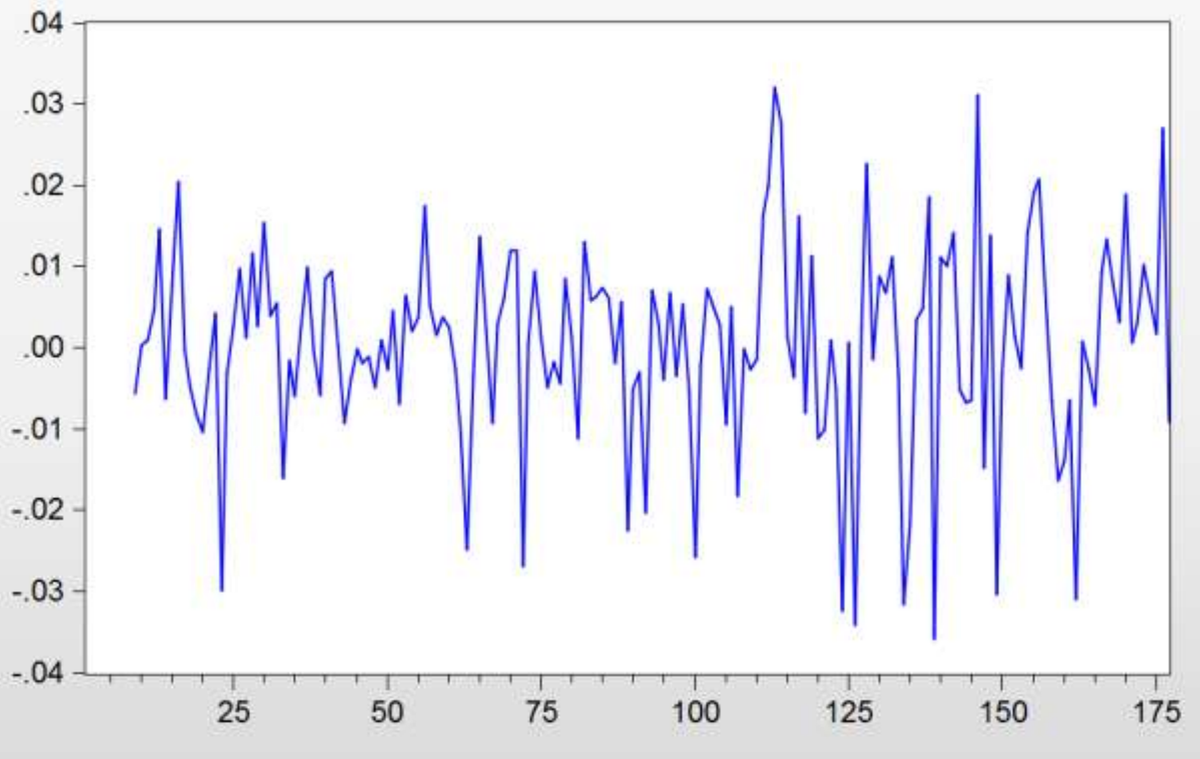

FIGURE 3: DIFFERENCES OF THE SEASONAL DIFFERENCES

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.104	0.104	1.8583	0.173
		2	0.079	0.069	2.9380	0.230
		3	-0.013	-0.028	2.9678	0.397
		4	-0.036	-0.038	3.1887	0.527
		5	-0.008	0.003	3.1990	0.669
		6	-0.106	-0.102	5.1830	0.521
		7	-0.451	-0.444	41.501	0.000
		8	-0.027	0.070	41.633	0.000
		9	0.030	0.120	41.800	0.000
		10	0.110	0.085	43.998	0.000
		11	-0.065	-0.162	44.776	0.000
		12	-0.167	-0.216	49.899	0.000
		13	0.033	0.022	50.101	0.000
		14	0.004	-0.195	50.104	0.000
		15	0.174	0.277	55.796	0.000
		16	-0.020	0.052	55.870	0.000
		17	-0.045	-0.015	56.250	0.000
		18	0.035	-0.182	56.491	0.000
		19	0.081	-0.127	57.751	0.000
		20	-0.076	-0.057	58.874	0.000
		21	-0.157	-0.235	63.661	0.000
		22	-0.282	-0.005	79.305	0.000
		23	0.011	0.073	79.327	0.000
		24	0.056	0.073	79.950	0.000
		25	0.059	-0.096	80.646	0.000
		26	0.092	0.059	82.370	0.000
		27	0.065	0.025	83.231	0.000
		28	0.118	-0.206	86.105	0.000
		29	0.174	0.101	92.374	0.000
		30	-0.058	-0.014	93.075	0.000
		31	-0.127	-0.043	96.453	0.000
		32	-0.043	-0.063	96.850	0.000
		33	-0.069	-0.041	97.862	0.000
		34	0.088	0.106	99.505	0.000
		35	0.018	-0.066	99.576	0.000
		36	-0.103	-0.021	101.86	0.000

Dependent Variable: DSDJPNG
Method: Least Squares
Date: 04/14/16 Time: 07:06
Sample (adjusted): 9 177
Included observations: 169 after adjustments
Convergence achieved after 10 iterations
MA Backcast: 1 8

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	0.104720	0.076686	1.365576	0.1739
MA(7)	-0.939464	0.014491	-64.82996	0.0000
MA(8)	-0.084872	0.073161	-1.160072	0.2477

R-squared	0.485223	Mean dependent var	0.000491
Adjusted R-squared	0.479021	S.D. dependent var	0.012254
S.E. of regression	0.008845	Akaike info criterion	-6.600344
Sum squared resid	0.012987	Schwarz criterion	-6.544783
Log likelihood	560.7290	Hannan-Quinn criter.	-6.577796
Durbin-Watson stat	1.995877		

Inverted MA Roots	.99	.62-.77i	.62+.77i	-.09
	-.22-.97i	-.22+.97i	-.90+.43i	-.90-.43i

Dependent Variable: DSDJPNG
Method: Least Squares
Date: 04/15/16 Time: 08:23
Sample (adjusted): 9 177
Included observations: 169 after adjustments
Convergence achieved after 7 iterations
MA Backcast: 2 8

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(7)	-0.937091	0.013859	-67.61613	0.0000

R-squared	0.476423	Mean dependent var	0.000491
Adjusted R-squared	0.476423	S.D. dependent var	0.012254
S.E. of regression	0.008867	Akaike info criterion	-6.607062
Sum squared resid	0.013209	Schwarz criterion	-6.588542
Log likelihood	559.2967	Hannan-Quinn criter.	-6.599546
Durbin-Watson stat	1.766513		

Inverted MA Roots	.99	.62+.77i	.62-.77i	-.22+.97i
	-.22-.97i	-.89-.43i	-.89+.43i	

Dependent Variable: DSDJPNG
Method: Least Squares
Date: 04/13/16 Time: 19:09
Sample (adjusted): 17 177
Included observations: 161 after adjustments
Convergence achieved after 18 iterations
MA Backcast: 9 16

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.180380	0.180819	-0.997571	0.3200
AR(7)	-0.316074	0.100179	-3.155095	0.0019
AR(8)	-0.339587	0.109998	-3.087201	0.0024
MA(1)	0.332307	0.150461	2.208590	0.0287
MA(7)	-0.301889	0.103559	-2.915151	0.0041
MA(8)	0.365624	0.155701	2.348246	0.0201

R-squared	0.326140	Mean dependent var	0.000288
Adjusted R-squared	0.304403	S.D. dependent var	0.012367
S.E. of regression	0.010315	Akaike info criterion	-6.273976
Sum squared resid	0.016490	Schwarz criterion	-6.159141
Log likelihood	511.0550	Hannan-Quinn criter.	-6.227348
Durbin-Watson stat	1.922912		

Inverted AR Roots	.84-.38i	.84+.38i	.27-.87i	.27+.87i
	-.44-.76i	-.44+.76i	-.76+.24i	-.76-.24i
Inverted MA Roots	.72+.26i	.72-.26i	.37+.77i	.37-.77i
	-.34+.87i	-.34-.87i	-.92-.38i	-.92+.38i

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.111	0.111	2.1061	
		2	0.109	0.098	4.1491	0.042
		3	0.009	-0.013	4.1632	0.125
		4	-0.088	-0.100	5.5199	0.137
		5	-0.025	-0.006	5.6305	0.228
		6	-0.080	-0.058	6.7657	0.239
		7	-0.043	-0.026	7.0887	0.313
		8	0.074	0.090	8.0713	0.326
		9	0.075	0.067	9.0805	0.336
		10	0.116	0.076	11.528	0.241
		11	-0.115	-0.166	13.962	0.175
		12	-0.144	-0.144	17.800	0.086
		13	-0.082	-0.022	19.034	0.088
		14	-0.111	-0.040	21.324	0.067
		15	0.085	0.127	22.691	0.065
		16	-0.013	-0.019	22.725	0.090
		17	0.010	-0.044	22.744	0.121
		18	0.020	-0.055	22.820	0.155
		19	0.096	0.105	24.609	0.136
		20	-0.078	-0.086	25.803	0.136
		21	-0.153	-0.113	30.398	0.064
		22	-0.207	-0.156	38.862	0.010
		23	-0.030	0.017	39.045	0.014
		24	0.040	0.065	39.364	0.018
		25	0.042	-0.008	39.710	0.023
		26	0.135	0.122	43.398	0.013
		27	0.034	-0.023	43.636	0.017
		28	0.048	-0.029	44.101	0.020
		29	0.030	0.009	44.287	0.026
		30	-0.102	-0.033	46.443	0.021
		31	-0.068	-0.000	47.419	0.023
		32	-0.035	-0.009	47.676	0.028
		33	0.034	-0.000	47.923	0.035
		34	0.080	-0.043	49.277	0.034
		35	0.054	0.035	49.911	0.038
		36	-0.054	-0.103	50.546	0.043

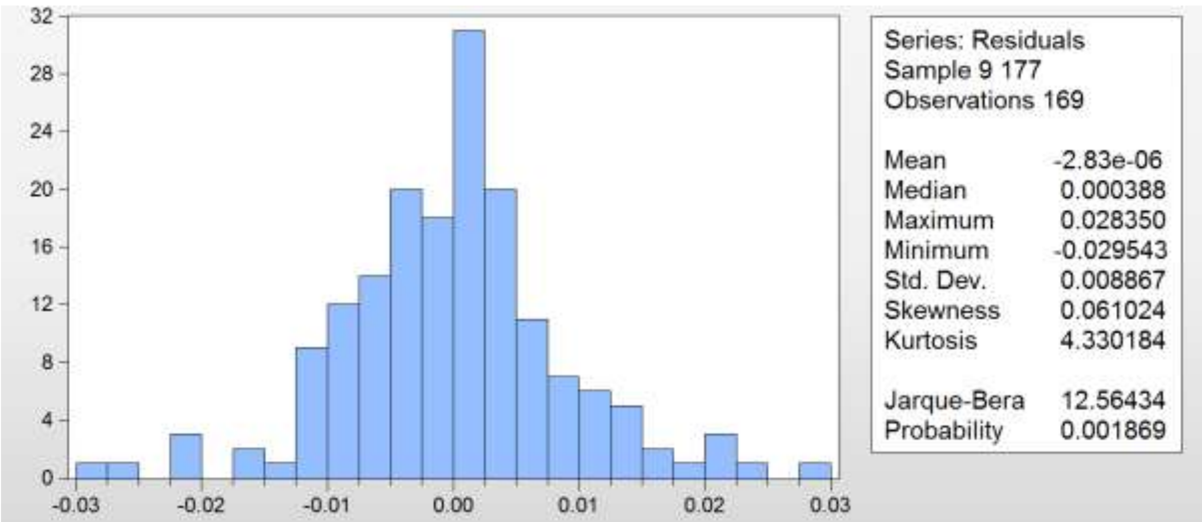

TABLE 4: OUT-OF-SAMPLE FORECAST COMPARISON

Day	Forecasted Rate	Observed Rate
9th April 2016	1.8425	1.8433
10th April 2016	1.8439	1.8400
11th April 2016	1.8441	1.8452
12th April 2016	1.8485	1.8318
13th April 2016	1.8510	1.8207
14th April 2016	1.8557	1.8202
15th April 2016	1.8541	1.8302

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