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Forecasting Sudan's Exchange Rate Using Box-Jenkins Approach

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Abstract: *This paper attempts to perform an appropriate ARIMA model for forecasting Sudanese pound against USA dollar exchange rate. Both The Augmented Dickey Fuller (ADF) and correlogram tests were applied to exchange rate data. It is found that exchange rate series showed a unit roots (i.e. exchange rate series level is non stationary) however the first difference of exchange rate series is seristationary.Box-Jenkins approach through the stages of identification, estimation and diagnostic checking were applied to data representing exchange rate in the Sudan. The ACF and PACF indicates that ARIMA(1,1,0) an appropriate however, the diagnostic checking concluded that the error term of the model does not follow normal distribution. ARIMA(2,1,1) also estimated and checked however the error terms seems not normal, numerous ARIMA (p,d,q) models have been suggested with the objective of deciding which of these models is adequate to fit exchange rate data in the Sudan, ARIMA(1,1,0) model is selected as a greatest one according to corresponding AIC, SBC of model selection criteria.*

Key words*: Time series, exchange rate ADF test, Correlogram, Box-Jenkins, ARIMA models, AIC, SBC.*

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I. Introduction:

Exchange rate forecasts are necessary to evaluate the foreign denominated cash flows involved in international transactions, understanding and forecasting exchange rates behavior is important to monetary policy and international trade. Thus, exchange rate forecasting is very important to evaluate the benefits and risks attached to the international business environment. As a result, the appropriate prediction of exchange rate plays a very important role in financial risk management and economic activities of all sorts and crucial for the success of many businesses and financial managers.

II. Study problem and objective:

Modelling and forecasting exchange rate in the Sudan requires finding a model that reasonably represents it. In the literature Many academics and practitioners suggest a number of approaches for building a time series models are discussed however, the suitability of any of these methods to a given time – series data has to be judged on the basis of its fit to that data. In this study Box-Jenkins approach will applied to data representing exchange rate with the objective of identifying an appropriate model that provides an accurate predictions for modeling and forecasting exchange rate in the Sudan as well as to compare predictability performance among different competitive models to forecast the exchange rate of the Sudan pound.

III. The hypothesis:

The study hypothesizes that:
Exchange rate in the Sudan shows a global up word trend.ARIMA models with minimum value of parameters is when it used to model and forecast exchange rate in the Sudan.

IV. Methodology:

The study employs Augmented Dicky Fuller test, correlogram as well as the performance of ARIMA models to data representing exchange rate in the Sudan in order to fit an appropriate model for modeling and forecasting. Criteria used in the comparison among different models are such as mean absolute error and mean square error, AIC, BIC.

V. Literature review:

To model and forecast exchange rate a comprehensive empirical analysis of financial time series have been proposed using autoregressive integrated moving average models. Bellow a few literature review of these studies:

Appiah, S.T. and I.A. Adetunde (2011),they modeled monthly exchange rate between the Ghana Cedi and the US Dollar and forecast future rates using time series analysis, they used monthly data collected from January, 1994 to December 2010, the result showed that the predicted rates were consistent with the depreciating trend of the observed series. ARIMA (1,1,1) model was found as the most suitable model with least Normalized Bayesian information Criterion (BIC) of 9.111, Mean Absolute Percentage Error (MAPE) of 0.915, Root Mean Square Error of 93.873 and high value of R- Square of 1.000.

Aykan. A (2011) studied exchange rate forecasting. Official daily data of Central Bank of The Republic of Turkey (CBRT) are used for USD/TL ($/TL), EURO/TL (€/TL) and POUND/TL (£/TL) pars. Moving averages (MA) method, single exponential smoothing method, Holt's method, Winter's method and ARIMA models are applied to the each pars, Performance of the models are assessed with the performance criteria of mean absolute percentage error (MAPE), root mean square errors (RMSE) and mean square error (MAE). According to MAPE, RMSE and MAE criteria, the best results are obtained by Winter's method which means that Winter's method is the most appropriate method to forecast exchange rates for the given time interval in Turkey.

M.K. Newaz (2008),compared different time series models to forecast exchange rate, monthly exchange rate data of Indian rupee were collected from the International Financial covered the period September 1985 to June 2006, the result of this study shows that ARIMA models provides a better forecasting of exchange rates than exponential smoothing and Naïve models do.

VI. Arima Models:

Several models has been used to represent a time series depending on the underline process assumed to operate on the series. Below is a review of these models.

7.1 The Autoregressive Model:

In the autoregressive model the current value x_t in the time series is expressed as a linear combination of the previous values, and an unexplained portion e_t . A typical autoregressive model of order p takes the form:

$$\left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right) x_t = e_t$$

Or simply:

$$\emptyset(B)\, x_t = e_t$$

where the term is a constant which representing the mean of the process, $\emptyset_j$ (j=1,2,……,p) is the jth autoregressive parameter and e_t are the error term at time t .

The e_t are assumed to be independent normally distributed random variable with mean zero and variance one .

7.2 The Moving Average Model:

In the moving average model of order qdenoted by MA(q) the current observation x_t is expressed as a linear combination of the random disturbances going back q periods, it is equation is written as:

$$\left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^p\right) e_t = x_t$$

Or simply:

7.3 The Mixed Autoregressive – Moving Average Models:

For stationary time series $x_1, x_2, \ldots, x_n$ the mixed ARMA model is expressed as follows:

$$\emptyset(B)\, x_t = \theta(B) e_t$$

$\emptyset_j$ are the autoregressive part parameters.

θ_j are the moving average part parameters. e_t is the error term at time t .

7.4The ARIMA models:

ARIMA model takes the form:

$$\emptyset(B)(1 - B)^d\, x_t = \theta(B) e_t$$

Where $(1 - B)^d$ is the dth order difference.

this is the model that calls for the dth order difference of the time series in order to make it stationary.

7.5 The General Box-Jenkins model:

The general ARIMA model of orders $(p, d, q)(P, D. Q)^s$ can be written as:

$$\emptyset(B)\Phi(B^s)\Delta_d \Delta_s^D\, x_t = \theta(B)\Theta\,(B^s) e_t$$

Where (p, d, q) is the nonseasonal part of the model.

$(P, D. Q)^s$ is the seasonal part of the model. S is the number of periods.

VII. Empirical Results:

This section discuss the empirical analysis results of unit root, correlogram and the construction of an appropriate ARIMA models for modeling and forecasting exchange rate in the Sudan.

8.1 Database:

Monthly readings of Exchange Rate in the Sudan covered the period from 01/01/1999 to 10/11/2015. The data are obtained from Central Bureau of Statistics and Bank of Sudan.

Figure (1) shows monthly readings of exchange rate during the period 01/01/1999 to 10/11/2015.

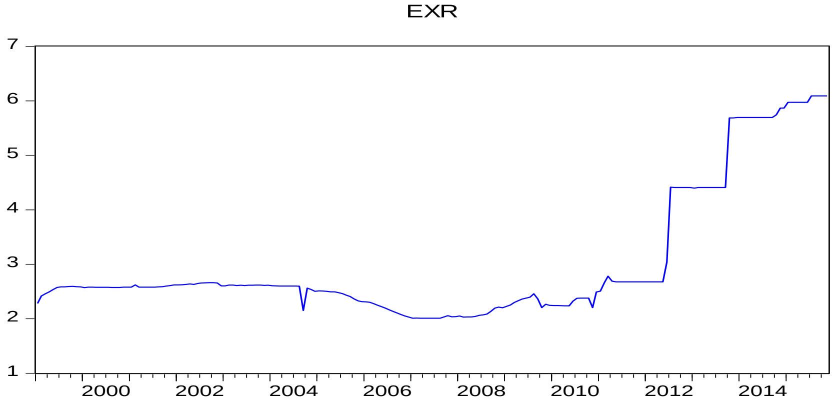


Figure (1) above shows the graph of monthly readings of exchange rates in the Sudan during the period 01/01/1999 to 10/11/2015, it can be seen that exchange rate series fluctuate around 2.00 pound to 2.50 from January 1999 to July2012 and then increased up to 6.02 till November 2015, which indicates that exchange rate has a global upward trend.

Figure (2) descriptive statistics of US dolar vs sudanese pound exchange rate

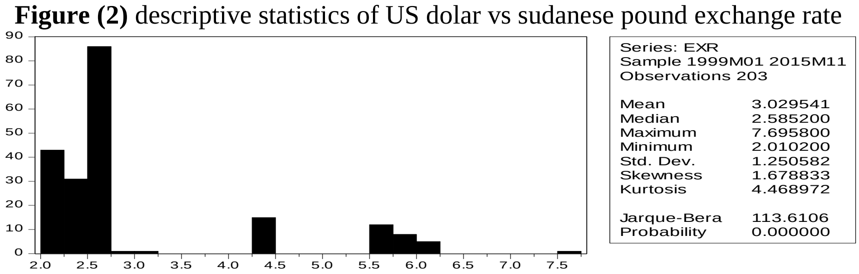


Figure (2) above illustrate the statistics of exchange rate in sudan the mean and standerdeviation of exchange rate are 3.03 and 1.25 respectively. The high value of jarque-bera test 113.6 with the significant value 0.000 indicates that the destribution of exchange rate in the sudan is not normal.

8.2 Augmented Dickey-fuller test on Exchange Rate Series result:

Figure (3) below shows the application of ADF test on exchange rate series level result, it is found that the ADF test value in absolute terms (0.9385) which is less than 1%, 5% and 10% critical values in absolute terms (3.470, 2.879 and 2.576) respectively, this result indicates that exchange rate series has a unit root which implies that exchange rate series is non stationary.

Figure (3) Augmented Dickey-Fuller Test on exchange rate series level

Null Hypothesis: EXR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

Prob.*	t-Statistic		
0.9959	0.938501	Augmented Dickey-Fuller test statistic	
	-3.462737	1% level	Test critical values:
	-2.875680	5% level	
	-2.574385	10% level	

*MacKinnon (1996) one-sided p-values.

Figure (4) below demonstrate the application of ADF test result on the difference of exchange rate series, it is found that the absolute value of the ADF test (19.391) is grater than 1%, 5% and 10% critical values in absolute terms (3.470, 2.879 and 2.576) respectively, this result confirmes that the first difference of exchange rate series is stationary.

Figure (4) Augmented Dickey-Fuller Test on first difference of exchange rate series

Null Hypothesis: D(EXR) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

Prob.*	t-Statistic		
0.0000	-19.39194	Augmented Dickey-Fuller test statistic	
	-3.462901	1% level	Test critical values:
	-2.875752	5% level	
	-2.574423	10% level	

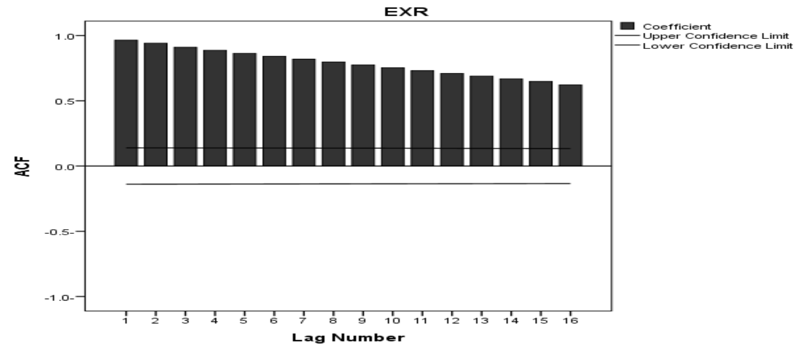
*MacKinnon (1996) one-sided p-values.

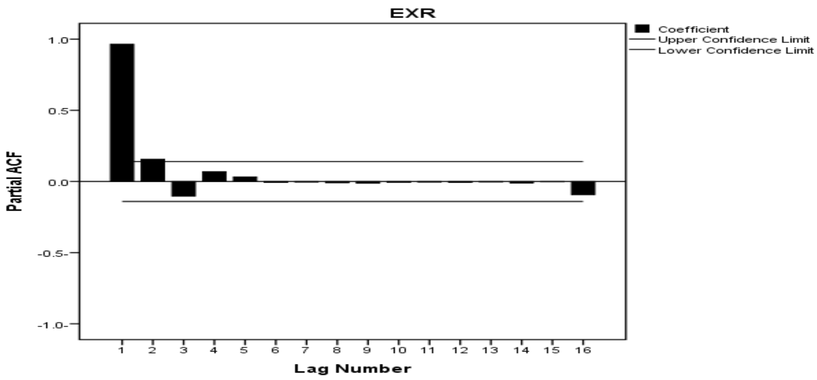
8.3 Correlogram of Exchange Rate Series:

This section employs the correlogram (autocorrelations and partial autocorrelations) on exchange rate series with the objective of determining whether the series is stationary as well as identifying the nature of adequate ARIMA model for modeling and forecasting exchange rate in the Sudan.

Figure (5) shows the autocorrelations and partial autocorrelations of exchange rate series level in the Sudan, the ACF starts out with large positive significant patterns decays gradually at increasing lags, while the partial autocorrelation function shows large positive peak at lag 1, this results confirms that the exchange rate series is non stationary as well as an autoregressive model is adequate in modelling and forecasting exchange rate data in the sudan.

Figure (5) The correlogram exchange rate series





8.4.1 Exchange Rate Model Identification:

Both ADF and correlogram tests result confirmed that the exchange rate series level is non stationary however, the first difference is stationary. Furthermore the ACF in figure (5) decays exponentially and the

PACF cut off to zero after lag of 1 this result confirmed that an autoregressive model of order (1,1,0) is an appropriate model for modeling exchange rate data in the Sudan.

8.4.2 ARIMA (1,1,0) Model Estimation:
After a tentative exchange rate model has been identified, model parameters can be estimated using least square method as follows:
Figure (6) shows the estimates of an ARIMA (1,1,0) of exchange rate data, the estimated equation of the above model is stated as follows:

$$(1 + 0.0556\mathrm{B})(1 - \mathrm{B})\mathrm{x_t} = 0.0182 + \mathrm{e_t}$$

A closer look to the above table, it can be seen that the constant as well as the autoregressive parameters are seems not significantly different from zero, R-square = 0.0031 . these findings encourage suggestion of comparing number of models and selecting an appropriate model among them to represent an exchange rate data and hence use for forecasting.

Figure (6) ARIMA (1,1,0) model Estimation of exchange rate series.

Dependent Variable: D(EXR)
Method: Least Squares
Date: 11/09/15 Time: 08:44
Sample (adjusted): 1999M03 2015M11
Included observations: 201 after adjustments
Convergence achieved after 3 iterations

Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.0959	1.673216	0.010903	0.018244	C
0.4316	0.788134	0.070666	0.055695	AR(1)

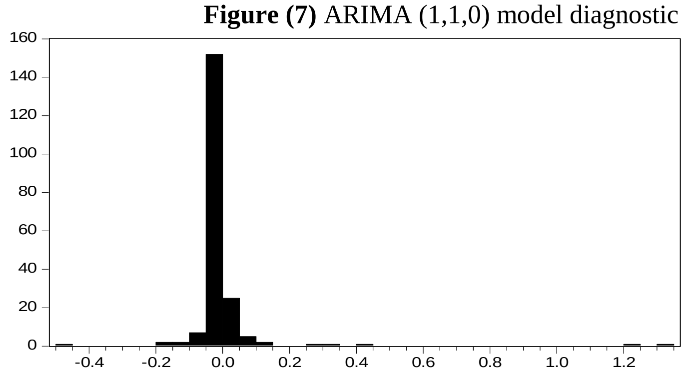
0.018284	Mean dependent var	0.003112	R-squared
0.145833	S.D. dependent var	-0.001898	Adjusted R-squared
-.9760919	Akaike info criterion	0.145971	S.E. of regression
-0.910050	Schwarz criterion	4.240192	Sum squared resid
-0.987619	Hannan-Quinn criter.	102.5923	Log likelihood
2.000139	Durbin-Watson stat	0.621156	F-statistic
		0.431556	Prob(F-statistic)

.06	Inverted AR Roots

8.4.3 ARIMA (1,1,0) Model Diagnostic Checking:

After a tentative exchange rate model has been identified and its parameters been estimated, diagnostic checking is then applied to the fitted model. It is necessary to supplement this approach by less specific checks applied to the residuals for the fitted model. The correlogram test is one of the most statistical tools used in testing whether the model ARIMA (1,1,0) model is adequate for exchange rate data.

Figure (7) ARIMA (1,1,0) model diagnostic checking.



Series: Residuals	
Sample 1999M03 2015M11	
Observations 201	
Mean	-2.14e-10
Median	-0.014635
Maximum	1.341150
Minimum	-0.459020
Std. Dev.	0.145348
Skewness	7.164992
Kurtosis	64.95622
Jarque-Bera	33867.85
Probability	0.000000

A closer look to figure (7) above. it can be seen that the distribution of the error term of ARIMA (1,1,0) is not normal, this result confirmed that ARIMA (1,1,0) model is not adequate in modelling and forecasting exchange rate data in the Sudan. Hence, numerous ARIMA models are suggested to fit exchange rate data in the Sudan, table (1) bellow shows the suggested models and their corresponding AIC and BIC criteria.

ARIMA (p,d,q) model	AIC	SBC
ARIMA (1,1,0)	**-.976**	**-0.910**
ARIMA (1,1,1)	-.990	-.941
ARIMA (2,1,1)	-1.000	-.968
ARIMA (1,1,2)	-.981	-.915
ARIMA (2,1,2)	-1.035	-.952

A closer look to table (1) it can be shown that ARIMA (2,1,1) model have smallest value of AIC and BSC criteria in absolute terms. In this model it is assumed that exchange rate data is subject to autoregressive of order2, moving average of order 1 and difference of order 1.

8.4.5 ARIMA (2,1,1) Model Estimation:

The estimation of the selected ARIMA (2,1,1) is given below:

Dependent Variable: D(EXR)
Method: Least Squares
Date: 11/09/15 Time: 09:27
Sample (adjusted): 1999M04 2015M11
Included observations: 200 after adjustments
Convergence achieved after 13 iterations
MA Backcast: 1999M03

Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.0957	1.674090	0.010719	0.017944	C
0.0322	0.342646	2.069211	0.709006	AR(1)
0.6502	-0.454145	0.109096	-0.049545	AR(2)
0.7526	-0.315650	2.070180	-0.653453	MA(1)
0.018165	Mean dependent var		0.003471	R-squared
0.146189	S.D. dependent var		-0.011782	Adjusted R-squared
-1.002325	Akaike info criterion		0.147047	S.E. of regression
-0.968359	Schwarz criterion		4.238099	Sum squared resid
-0.949630	Hannan-Quinn criter.		101.6325	Log likelihood
2.000906	Durbin-Watson stat		0.227580	F-statistic
			0.877127	Prob(F-statistic)
	.08		.63	Inverted AR Roots
		.65		Inverted MA Roots

AR(1) is significant however, AR(2) and moving average A closer look to the above figure, it can be seen that the autoregressive parameter parameter MA(1) are seems not significantly different from zero.

8.4.6 ARIMA (2,1,1) Model Diagnostic Checking:

Figure (7) histogram of residuals of ARIMA (1,1,2) for exchange rate model

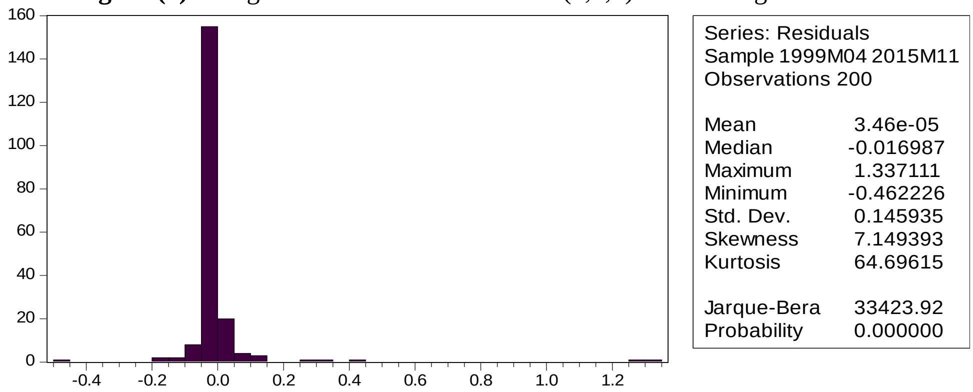


Figure (7) shows residuals histogram of an ARIMA (1,1,2) model of exchange rate data, it can be shown that the distribution of the residuals is not normal.

Figure (8) shows exchange rate forecasting

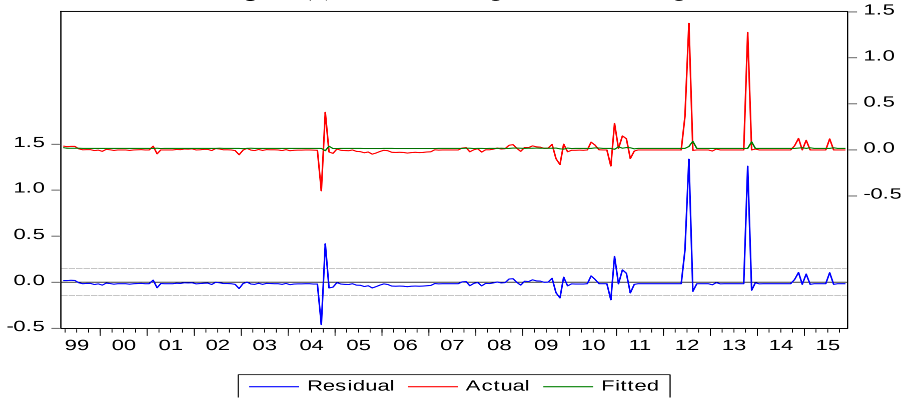
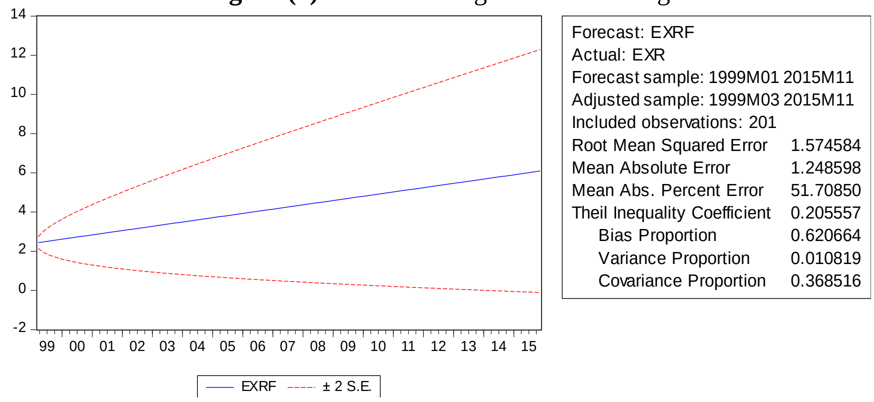


Figure (9) shows exchange rate forecasting



VIII. Conclusion:

This paper provided the performance of ARIMA models to obtain an appropriate model for modeling and forecasting USA dollar versus Sudanese pound exchange rate using Box-Jenkins approach. The empirical analysis reveals that both Augmented Dickey Fuller (ADF) and correlogram tests conclude that the original series of exchange rate data are not stationary, while the first difference is stationary. More over ARIMA (1,1,0) model is identified as a suitable model that provides an accurate predictions for forecasting exchange rate data, however, the distribution of the error terms is not normal. ARIMA (1,1,2) is also estimated and checked, however, the error term is not normally distributed . Numerous ARIMA models have been suggested to fit exchange rate data, among these models the model which has smallest value of AIC and BIC is adequate, hence according to models selection criteria, ARIMA (1,1,0) model is appropriate in modeling ad forecasting exchange rate data in the Sudan, there for this particular type of data Box-Jenkins approach is highly recommended.

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