Comparison of Different Statistical Models for Forecasting Exchange Rate of Somali Shilling Against US Dollar

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Abstract:

The main goal of thispaper is to model and forecast the daily exchange rate of *Somali Shilling* (SOS) against *United States Dollar* (USD) over the period of 1st January 2009 to 31st December 2018 using Box-Jenkins models and *Autoregressive Conditional Hetroskedasticity* (ARCH) family models to compare between them and selected an appropriate one.Box-Jenkins models are employed for modeling and forecasting data using the steps of Box-Jenkins methodology.Additionally, non-normality, skewness, leptokurtosis, volatility clustering, and existence of ARCH effects in the residuals are observed in the data, therefore, ARCH family models which include ARCH, *Generalized* ARCH (GARCH), *Exponential*(EGARCH), and Threshold (TGARCH) are developed under three error distributions namely normal distribution, t-student distribution and*Generalized Error Distribution*(GED). The empirical analysis has shown that ARMA(0, 6) is the most appropriate model for the estimated models using *Akaike Information Criteria* (AIC) and *Schwarz Information Criteria* (SIC) as a selection criteria and also for the forecasted models using*Root Mean Square Error* (RMSE),*Mean Absolute Error* (MAE) and*Mean Absolute Percentage Error* (MAPE) as forecasting accuracywhile estimating and forecasting the conditional variance of volatility models, it was found that ARCH(6) under t-student is the best model. After comparing between the models, the result declared that ARCH family models are superior to Box-Jenkins. Moreover, Diebold Mariano(1995) test is applied and revealed that the ARMA models and ARCH family models have same predictive ability whichimplies that the DM (1995) test does not prefer any model over the other.

Keywords: Somali Shilling, Box-Jenkins, Volatility models, Conditional variance, Exchange rate return

1. Introduction

Foreign exchange rate is the price of one currency in terms of another currency and it has always been the interest of researchers in financial time series. Foreign exchange rate has a great impact on the international trade and investment, however, modeling and forecasting the exchange rate makes a crucial area forresearchers to determine the characteristics of the financial series using different statistical models like Box-Jenkins models and ARCHfamily models(Brooks 2014).Although the study of time series models began many years ago, the Box-Jenkins methodology was considered the most widely used in the theoretical and applied scientific circles and the main reference for judging the quality and suitability of many studies. Thus, Box-Jenkins presented methods for model building which are identifying, fitting and checking models for time series and dynamic system that make it possible finally to predict future values of a time series from current and past values (Box *et al.* 2016).

It is worth remembering that one of the assumptions of linear regression analysis is that the variance of the disturbance term (ε^2) is assumed to be constantwhich is called homoskedasticity (constant variance) while many time series data face another problem called heteroskedasticity , which implies that the variances of the error terms are not constant over time. The question here is how the models that accommodate heteroskedasticity be builttoobtain the estimated parameters for the variance of the error terms (Brooks 2014).

To answer the above question and model volatility of major asset classes including foreign exchange rate, subsequently, different scientific papers have been carried out. Robert F. Engle (1982) introduced a new class of stochastic process called ARCH process to estimate the means and variances of inflation in UK and he found that the ARCH effect is significant. Later, ARCH process was extended to be GARCH model by Bollerslev(1986). GARCH model imposed parameter restrictions and assumed that positive and negative shocks have the same impact on volatility. To overcome this restriction, many of the extensions to the GARCH model have been suggested. EGARCH model was proposed by

Nelson (1991). TGARCH model was introduced by Glosten*et al.* (1993).

In the context of Somalia, afteroverthrow of SiadBarre's government in 1991, all formal financial sectors of the country were collapsed such as*Central Bank of Somalia*(CBS), Commercial and Savings Bank of Somalia, Somali Commercial Bank, Cooperative Bank of Somalia, Somali Development Bank and the State Insurance Company of Somalia. However, it was replaced by informal financial sector like Somali remittance companies and some micro-finance institutions and became the providers of the financial services(CBS annual report 2012).

In the lack of a formal financial institution in Somalia, the value of SOS is depreciated and it is considered, de facto, as free floating (CBS annual report 2017). Additionally, the Somalia's economy is highly dollarized as a result of absence of CBS role and without issuing new bank notes since 1991. 95 percent of the local currency in circulation is believed to be counterfeit notes and it is used only for small transactions, thus, the only existing SOS denomination is 1,000 SOS worth $0.05 (CBS annual report 2017). The Somali currency has been selected as a result of the many changes witnessed by the Somali economy since the beginning of civil war in the nineties as a result of the repercussions of the wars and the economic problem over twenty years. The objective of this paper is to develop range of different statistical models to model and forecast daily exchange rate of SOS/USD over the period of 1st January 2009 until 31st December 2018 and then compare between them to selectan appropriate model to help decision makers improve their decision.

The rest of the study is organized as follows: Section 2 briefly summarizes literature review. Section3 describes data and methodologywhile Section 4gives the empirical results. Section 5shows conclusions and recommendations of this study.

2. Literature Review

Many researches about forecasting foreign exchange rate were carried out in the last four decades using different statistical models. However, the study exhibits variety of studies related to literature review.

Alshawadfi (2003) Presented artificial neural networks method for forecasting linear and nonlinear time series and then they compared the proposed method with the well-known Box Jenkins method through a simulation study. To achieve these objects, 16000 samples generated from different ARMA models were used for the network training.Thenthe systemtested the generated data.The accuracy of the neural networkforecasts(NNF) is compared with the corresponding Box-Jenkinsforecasts (BJF) by using three tools: MSE,MAD and the ratio ofcloseness from the true values (MPE). Finally, the artificial neural networks were found deliver a better forecasts than Box Jenkins technique.

Vee*et al.*(2011)evaluated volatility forecasts for the exchange rate of US Dollar against Mauritian Rupee. They use daily data for the period 30 June 2003 to 31 March 2008 by a GARCH (1,1) model under two distributional assumptions: GED and the Student’s t distribution. Results obtained show that GED gives better results for exchange rate out-of-sample forecasts.

Abdalla(2012)conducted paper to model daily exchange rate volatility in a panel of nineteen Arab countries using generalized autoregressive conditional heteroscedasticity over the period of 1st January 2000 to 19th November 2011. The paper also applies both symmetric and asymmetric models. Finally, EGARCH (1, 1) was used to capture leverage effects as GARCH models are poor in capturing these effects.

Sokhanvar (2013) attemptedin his thesis to forecast the exchange rate of Turkish Lira against US dollar and Euro using Naïve, Moving Averages, Simple Exponential Smoothing and Time Series Regression. The data for this study contains monthly and daily prices on the foreign exchange rate between the Turkish Lira, US dollar and Euro. The data set covers the time interval of June 2011 to June 2013.

Epaphra(2016)applied univariate nonlinear time series analysis to the daily exchange rate data of Tanzanian Shilling to US Dollar (TZS/USD) spanning from January 4, 2009 to July 27, 2015 to examine the behavior of exchange rate in Tanzania. The paper applied both ARCH and GARCH models and also employed exponential GARCH (EGARCH) model to capture the asymmetry in volatility clustering and the leverage effect in exchange rate.The paper concluded that the GARCH (1, 1) is adequate model and has a predictive power.

Nor *et al*. (2020) investigated the volatility of Somalia's unregulated exchange rates using a monthly exchange rate of SOS against USD. Furthermore, the study examines whether macroeconomic factors have a significant effect on the unregulated exchange rate volatility of Somalia. GARCH, EGARCH, and TGARCH were utilized to model the volatility of Somalia's unregulated exchange rates. Finally, they concluded that the EGARCH model outperforms all other models.

3. Data and Methodology

3-1. Data

This paper used daily exchange rate series representing SOS/ USD in order to fit an appropriate model for forecasting the future data. The data was obtained from CBSfor the period of 1 January 2009 to 31 December 2018 (3110 observations). The Figure (1) is the plot of exchange rate of SOS/USD. As the Figure (1) revealsa rise in the plot shows strengthening of Shilling and weakening of Dollar while fall indicates strengthening of Dollar and weakening of Shilling.

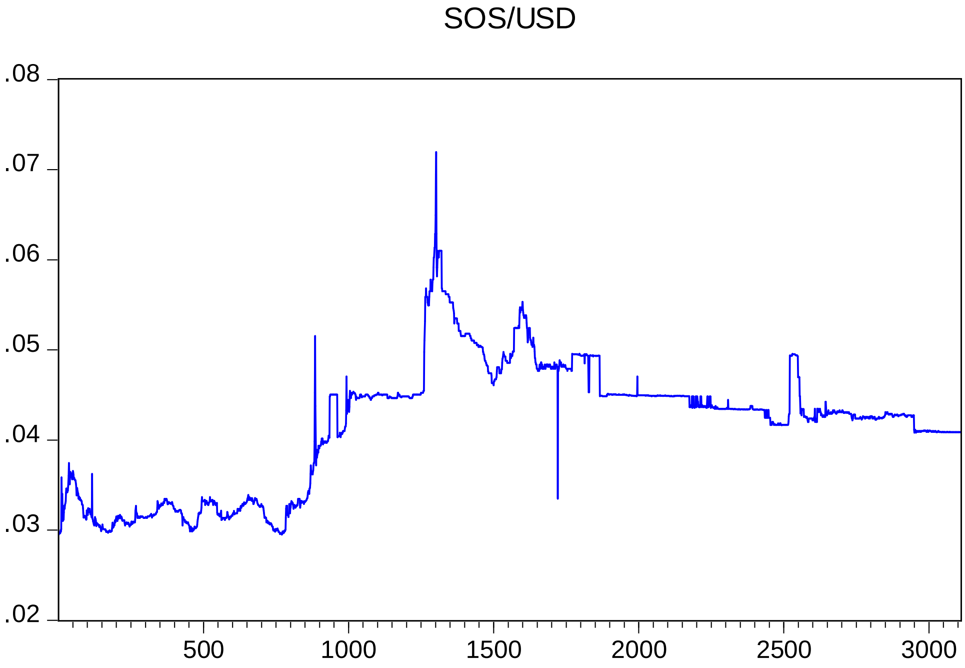


Figure (1) Exchange rate of SOS/USD from 1/1/2009 to 31/12/2018

3-2. Box-Jenkins Methodology

To achieve the goal of model building, practical three-step procedure for finding a good model was proposed by Box and Jenkins. The three steps are identification, estimation and diagnostic checking and they are applied repeatedly until a satisfactory model is obtained as it is seen inFigure (2). Brief details about the three steps are described below (Pankratz 1983, Box *et al.* 2016, Brooks 2014, Montgomery*et al.* 2008, Chattfield 1975).

Identification is the first step and it involves examining the given data to determine the number of autoregressive parameters (p), the degree of differencing (d), and the number of moving average parameters (q). The values are determined by using autocorrelation function (ACF) and partial autocorrelation function (PACF) and it also identify whether a series are Autoregressive(AR(p)), Moving Average(MA(q)), or Auto regressive Moving Average (ARMA (p,q)).

Estimation method leads to estimate simultaneously all the parameters of the process, the order of integration coefficient and parameters of an ARMA structure by using least squares method and maximum likelihood method.

*Diagnostic Check*is the third step and it involves assessing the residuals of the model whether to accept the model or reject. The residuals should be uncorrelated of each other which means the residuals is a white noise, in addition, Ljung-Box test or plotting ACF and PACF of the residuals can be considered helpful to identify misspecification.

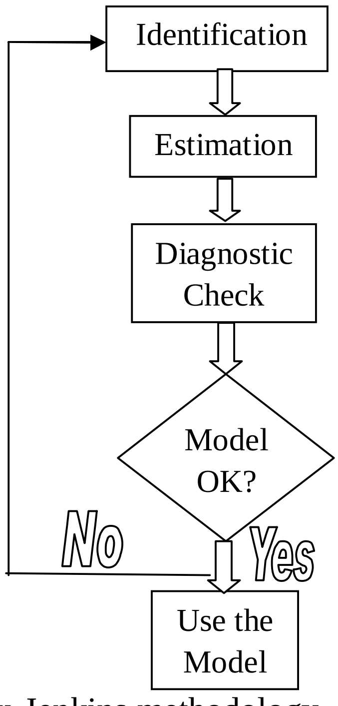


Figure (2)Box-Jenkins methodology

3-3. Box-Jenkins Models

Time series modeling has fundamental and specific significance to different practical domains. Many important models have been proposed in this sectionto improve the accuracy and efficiency of time series modeling. Some of popular time series models used in practice are described such asAR, MA, ARMA, and ARIMA (Chatfield 1975, Adhikari and Agrawal 2013, Box *et al.* 2016, Brooks 2014).

In AR model, the future value of a variable is assumed to be a linear combination of p past observations and a random error together with a constant term. MA model uses past errors as the explanatory variables while ARMA is considered as combination of AR model and MA model together.Thus, the mathematical formulation ofAR(p), MA(q) and ARMA(p,q)can be expressed as following equations respectively (Chatfield (1975):

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots\dots + \phi_p y_{t-p} + \varepsilon_t \quad (1)$$

$$y_t = \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots\cdots\cdots \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (2)$$

$$y_t = \phi_1 y_{t-1} \dots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots\cdots \theta_q \varepsilon_{t-q} \quad (3)$$

$\phi_i$representsparameters of the AR(p) model and θ_j are the parameters of the MA(q) model while ε_t represents random error at time t and it follows normal distribution with mean zero and variance σ^2. $\varepsilon_t \sim i.i.d\ N(0, \sigma^2)$, $E(\varepsilon_t) = 0$, $Var(\varepsilon_t) = \sigma^2$

Since ARMA model described above can only be used for stationary time series data, however, in practice many time series such as those related to economic show non-stationary behavior.In ARIMA(p,d,q) modelcan be converted from a nonstationaryseries to stationary by differencing the data and d represents the level of differencing(Adhikari and Agrawal, 2013).The mathematical formulation of the ARIMA(p,d,q) modelis given below (Box *et al*. 2016):

$$\phi(B)y_t = \phi(B)\nabla^d y_t = \theta_0 + \theta(B)\varepsilon_t \quad (4)$$

where

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots\cdots - \phi_p B^p \quad (5)$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots\cdots - \theta_q B^q \quad (6)$$

So, $\phi(B)$ is called the autoregressive operator and it is assumed to be stationary, $\phi(B) = \phi(B)\nabla^d$ is also called generalized autoregressive operator and it is a nonstationary operator. $\theta(B)$ is known as moving average operator and it is assumed to be invertible. When d=0 the model reduces to an ARMA(p,q) model.

3-4. ARCH Family Models

To build volatility model of major asset classes including foreign exchange rate and obtain the estimated parameters for the variance of the error terms, subsequently, different scientific papers have been carried out. The original idea of the ARCH model was introduced in the initial paper by Engle(1982) to model inflation rates of UK. In the ARCH process, the conditional variance of the error term σ_t^2 is related to the previous value of the squared error. Bollerslev (1984)extended the ARCH model to be generalized version called GARCH model. In GARCH model,the conditional variance σ_t^2 depends on the squared error term in the previous time period and also on its conditional variance in the previous time period. Parameter restrictions imposed in GARCH model and assumed that positive and negative shocks have the same impact on volatility. To overcome this restriction, many of the extensions to the GARCH model have been suggested. Nelson (1991) proposed in his paper a new model called EGARCH and it is the extension of GARCH model; itis also more suitable for modeling conditional variances in financial series and ensures that σ_t^2 remains nonnegativeby making$\ln(\sigma_t^2)$. TGARCH is also extension of GARCH with an additional term added to account for possible asymmetries. The model named after the authors Glosten, Jagannathan and Runkle (1993).

Let $\varepsilon_t$denote the error terms of return residuals with respect to mean process and assume that

$$\varepsilon_t = \sigma_t Z_t \tag{7}$$

whereZ_t is independent and identically distributed with mean zero and variance 1. So, conditional variance of volatility modelsARCH(1), GARCH(1,1), EGARCH(1,1), and TGARCH(1,1) can be written as follows (Brooks 2014).

ARCH (1) $$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{8}$$

GARCH(1,1)

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{9}$$

EGARCH(1,1)

$$ln(\sigma_t^2) = \alpha_0 + \alpha_1 \left(\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right) + \gamma \left(\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right) + \beta\, ln(\sigma_{t-1}^2) \tag{10}$$

TGARCH(1,1)

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \qquad (11)$$

$$\mathrm{I}_{t-1} = 1 \; if \; u_{t-1} < 0$$
$$= 0 \; Otherwise$$

The non-negativity conditions of ARCH (1) and GARCH(1,1) would be $\alpha_0 \geq 0, \alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$, nevertheless, GARCH process can be reduced as ARCH process if p=0 and ε_t is a white noise when p and q are similar (Bollerslev 1986).EGARCH (1,1) model will not impose non-negativity constraints on the parameters unlike the other ARCH models, so σ_t^2 will always be positive even if the parameters of the model are negative.

In terms of GARCH family models, the error term is always considered to be identically distributed and independent with zero mean and unit variance but the main point here is the type of distribution that the error term should follow. In this study, three different types of the error distributions are utilized and they are normal distribution, t distribution and GED. Thus, the density function of each distribution is defined respectively.

4- Empirical Results

This Section classified basically into four Subsections and they are: Descriptive Statistics, ARMA model which demonstrate building ARIMA model through the steps of Box Jenkins approach, ARCH family models which present the estimation, diagnostic, and forecasting the volatility models and finally comparison between the models.

4-1. Descriptive Statistics

To evaluate the distributional properties of the daily exchange rate return, various descriptive statistics are displayed in Table (1). The number of observations consists of 3110, the mean of exchange rate return is 0.000105and close to zero with standard deviation of 0.017040. There is also evidence of negative skewness around -0.741697 indicating left tailed a little bit compared to the right side and also 289.1563 of kurtosis indicatingflat tail and its distribution is leptokurtic. In addition, the Jarque-Bera test shows that the hypothesis of normality of the data is rejected at a 5% significance level, which implies that the exchange rate return is thought to follow a non-normal distribution.

Table (1) Descriptive Statistics of SOS/USD return

Descriptive statistics	Result
Mean	0.000105
Median	0.000000
Maximum	0.358470
Minimum	-0.386425
Standard Dev	0.017040
Skewness	-0.741697
Kurtosis	289.1563
Jarque-Bera	10607864
Probability	0.000000
Number of observations	3110

4-2. ARMA Model

ARMA models can be built through Box Jenkins steps which are identification, estimation, diagnostic and forecasting.

4-2.1. Identification

The first thing is to visualize the data to determine whether the exchange rate data of SOS/USD is stationary or not. Thus, it is checked the stationarity of the series by plotting the data. The exchange rate series of SOS against USD is plotted as shown the Figure (1). The graphical analysis of exchange rate series of the Figure (1) shows trending upwards at the beginning then tends to be downwards suggesting that the mean of the exchange rates is changing during period of a time which implies that the exchange rate series is nonstationary. Moreover, outliers can also be observed in the Figure (1). Therefore, the outliers is removed and replaced by the average of the series and then the series is plotted again without outliers as exhibited in the Figure (3).

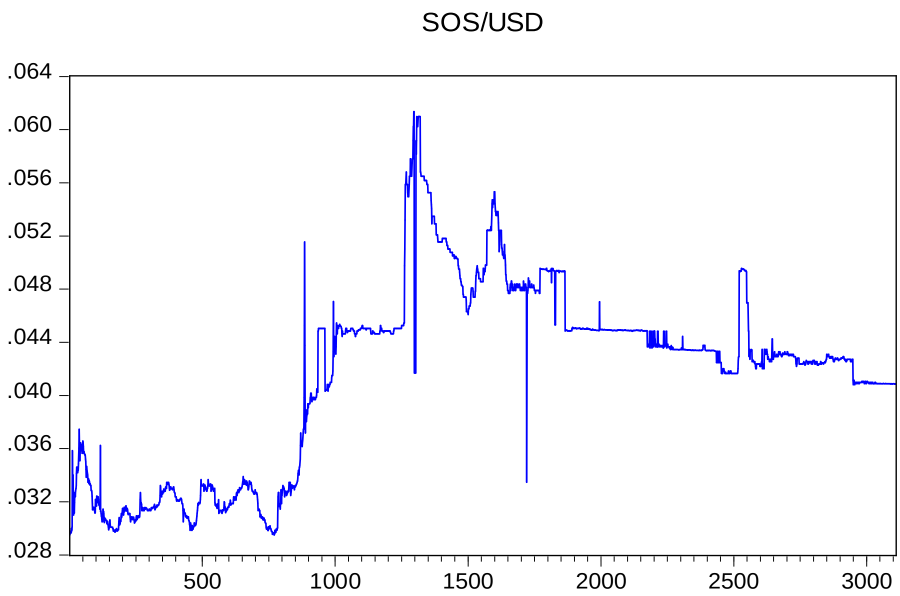


Figure (3) Exchange rate of SOS/USD after removing the outliers

In order to find the solution for the stationarityproblem and verify requirement of ARMA model, some transformationshould be doneby taking log of first difference of SOSUSD to be converted SOSUSD return as given in equation (12) below.

$$r_t = \ln\left(\frac{SOS_t}{SOS_{t-1}}\right) \qquad (12)$$

wherer_t represents daily exchange rate return, SOS_t and SOS_{t-1} denote the average exchange rate of SOS/USD.Thus, let us now check the stationarity of the series after transforming the data and make sure that there are different results as it did before.

Figure (4) is the plotting the time series data after transforming the data, as it is seen that SOS/USD return is totally differ from the SOS/USD. It is concluded that the data is finally constant about the mean and unchanged (stationary).

The results in table (2) showthatp-value of Augmented Dickey-Fuller (ADF) test and Phillip-Perron (PP) test aresmaller than 5%, therefore the null hypothesis is rejectedandalternative hypothesis is accepted. So the exchange rate returnhave not unit root which means that the data became stationary.

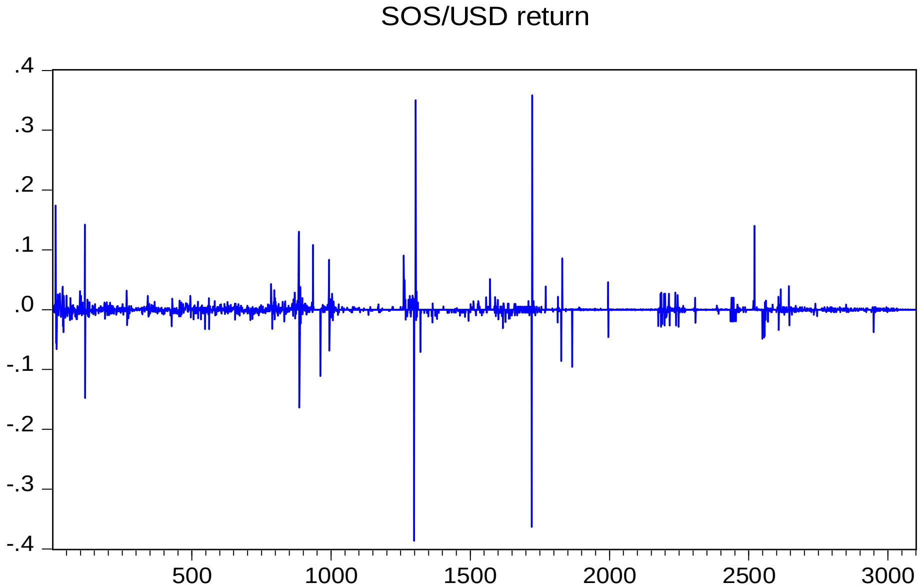


Figure (4) Exchange rate of SOS/USD return

Table (2)ADF and PP tests for stationarity of series

Variable	**ADF**	**p.vale**	**PP**	**P.value**
SOS/USD	0.065433	0.7036	0.182683	0.7393
SOS/USD return	-27.66404	0.0000	-77.68963	0.0001

After transforming the data, the daily time series data became stationary, now the values of p and q can be determined. Based on Box-Jenkins methodology, 49 tentative ARMA models were suggested to select later the best appropriate model for the data (see Appendix). ARMA(0,6) model is selected because it has the lowest AIC and SIC.

4-2.2. Estimation

In estimation process which consider the second step of the BJ methodology involves estimating the parameters of the ARMA(0,6) model. The Table (3) presents the estimation of the selected ARMA(0,6) model using maximum likelihood. According to the table, the parameters are significant at 5% except the constant, $\theta_4$andθ_5. Then it is time to check the diagnostic of the model as it will present the next step

Table (3) Estimation of ARMA(0,6) Model

Variable	Coefficient	t-Statistic	Prob.
μ	0.000100	0.520672	0.6026
θ_1	-0.177070	-66.21532	0.0000
θ_2	-0.054909	-6.251961	0.0000
θ_3	-0.061377	-5.552574	0.0000
θ_4	-0.028071	-1.641751	0.1007
θ_5	-0.017411	-0.967302	0.3335
θ_6	-0.149976	-25.69704	0.0000
SigmaSQ	0.000273	331.7444	0.0000
AIC	-5.363750		
SIC	-5.348203		

4-2.3. Diagnostic Checking of ARMA(0,6)

Since the model is determined and its parameters are estimated, now it is time to test the goodness of fit for the model. Ljung box test and ACF and PACF of the residuals of ARMA(0,6) were conducted. As shown in Figure (5) below, different correlations up to 24 lags were computed and the residual plots of ACF and PACF are examined. ACF and PACFof the residual indicate that none of 24 correlations is significantly different from zero at a reasonable level and then there is no information leftwhich the model does not capture. The Figure (6) shows the residual, actual and fitted of Somali exchange rate return which indicates clearly that the ARMA(0,6)model actually fits the data very well. Finally it is concluded that the ARMA(0,6) model is verified the goodness of fit, then it is checked the predictive power of the selected model.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.001	-0.001	0.0012	
		2	-0.002	-0.002	0.0203	
		3	-0.001	-0.001	0.0243	
		4	-0.004	-0.004	0.0786	
		5	-0.002	-0.002	0.0966	
		6	-0.006	-0.006	0.2012	
		7	-0.004	-0.004	0.2525	0.615
		8	0.010	0.010	0.5820	0.748
		9	-0.004	-0.004	0.6301	0.890
		10	0.017	0.017	1.5717	0.814
		11	-0.000	-0.000	1.5719	0.905
		12	0.015	0.015	2.2408	0.896
		13	0.018	0.018	3.2717	0.859
		14	0.014	0.014	3.8799	0.868
		15	0.016	0.016	4.6350	0.865
		16	0.022	0.022	6.1432	0.803
		17	-0.017	-0.016	7.0585	0.794
		18	0.002	0.002	7.0687	0.853
		19	-0.014	-0.013	7.6898	0.863
		20	-0.010	-0.010	7.9731	0.891
		21	0.001	0.001	7.9778	0.925
		22	0.004	0.003	8.0212	0.948
		23	0.045	0.044	14.244	0.650
		24	0.032	0.031	17.542	0.486

Figure (5) ACF and PACF of residuals of ARMA(0,6)

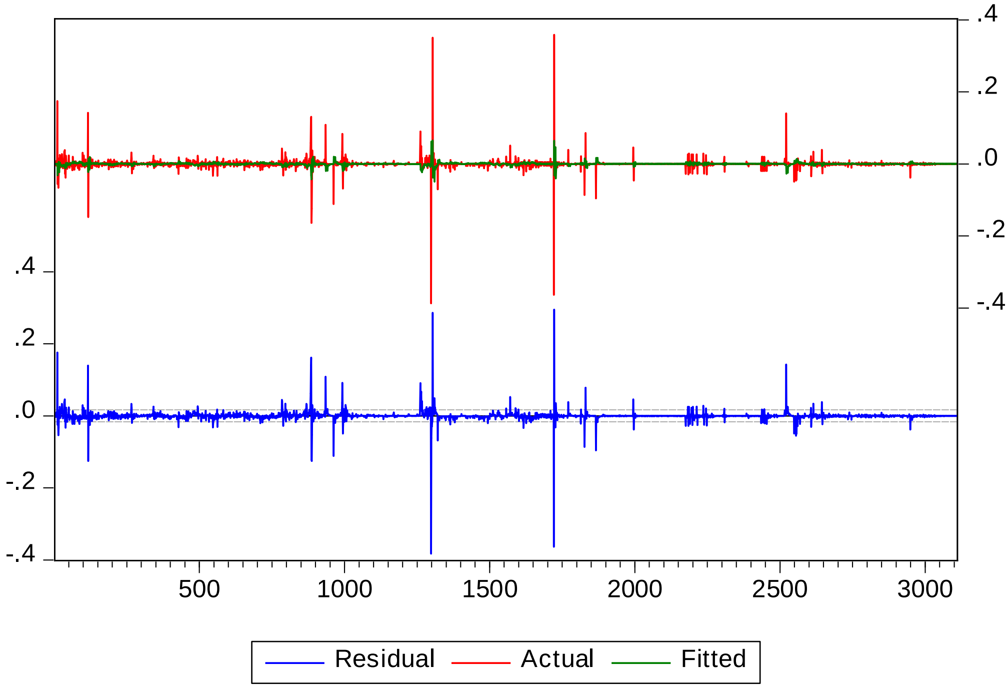


Figure (6) Residuals, actual, and fitted of ARMA(0,6)

4-2.4. Forecasting

Forecast can be considered the final and the most important step of the Box- Jenkins methodology. It is interesting to remember that 22December 2018 to 31 December 2018 (10 observations) were used to examine predictive abilityof ARMA(0,6) model. The Figure (7) exhibited a graph of the forecast with ± 2 prediction error limits for ARMA(0,6). Furthermore, after it is acquired the forecasting exchange rate return of ARMA(0,6) model.It will compare the predicted return versus actual series of SOS against USD as shown in Figure (8).However, it is concluded that ARMA(0,6) model performs better in terms of forecasting daily exchange rate of SOS/USD having the lowest RMSE, MAE and MAPE

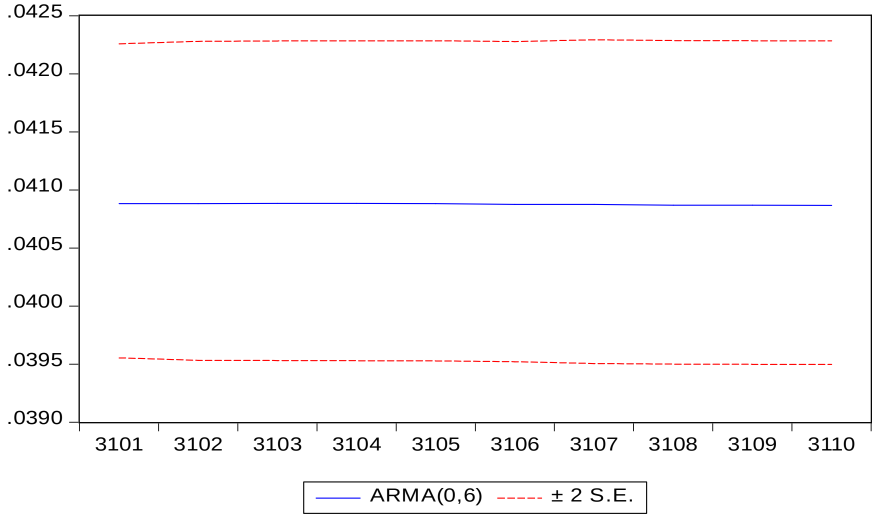


Figure (7) ARMA(0,6) forecast with prediction error limits

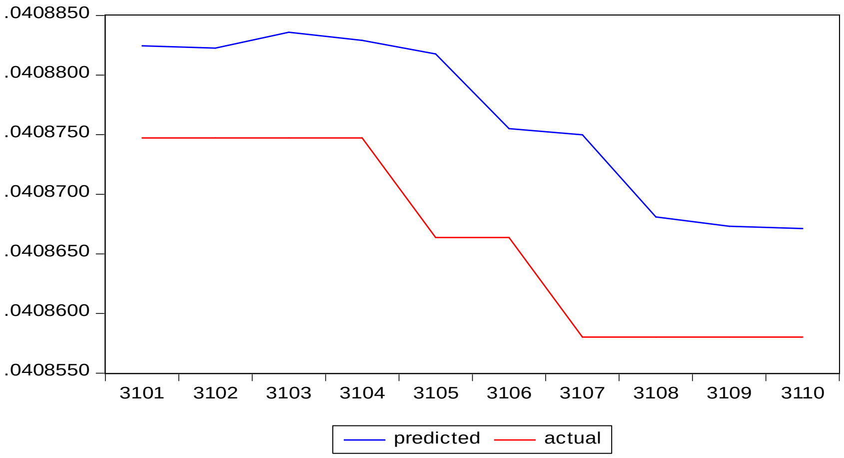


Figure (8) Actual and forecasted of ARMA(0,6)

4-3. ARCH Family Models

To construct ARCH family models for exchange rate return series, it is required to specify a mean equation first, then testing the presence of ARCH effects in the residuals, performing a joint estimation of the mean and volatility equations and then diagnostic check (Tsay 2010):

4-3.1. Testing for Heteroscedasticity

To test the presence of ARCH effect, Lagrange Multiplier (LM) test isutilized for exchange rate series. Thus, the results of LM test presented in Table (4) indicate thatthe p-value is less than 5%. Hence, the null hypothesis of absence of ARCH effect is rejectedwhich implies that there is ARCH effect in the residuals.

Table (4)Heteroskedasticity Test: ARCH effect for residuals

F-statistic	199.9687	Prob. F(1,3106)	0.0000
ObsR-squared	187.9941	Prob. Chi-Square(1)	0.0000

Since ARCH-LM test provide strong evidence for the existence of ARCH effects in the residuals series of the mean equation, therefore, the estimation of ARCH family models is developed. Econometric views(E-views) program especially version 10 is processed to estimate the parameters of the data.

4-3.2. Estimation of ARCH Models

As it clearly seen in Tables 5-7, the results of ARCH(6), GARCH(1,1), EGARCH(1,1), and TGARCH(1,1) under three different error distributions is summarized. According to the Tables5-7, coefficient of mean equation is statistically insignificant under the three error distributions while coefficients of variance equation are statistically significant under normal distribution, t student distribution and GED distribution. It is worth remembering that non-negativity condition of the estimated model is not violated. As it is seen, coefficients of ARCH model

are all strictly positive. Moreover, the results of GARCH(1,1) under three different error distributions is demonstrated. According to the tables, the mean coefficient$(\mu)$is statistically insignificant while the lagged squared residual(α_1) and the lagged conditional variance(β_1) in the conditional variance equation are positive and highlystatistically significant at standard level. The non-negativity condition of the GARCH(1,1) model is not violated since all parameters of the model are positive. It worth noting that the effect of shocks would increase over time since summation of theα_1 and β_1 in the conditional variance equation under t student is greater than one.
Tables 5-7 illustrate as well results ofEGARCH(1,1) model under three error distributions. According to tables, the asymmetry term γ for exchange rate return of SOS is calculated under normal, t student and GED with value of 0.221157, 0.437884and 0.053473 respectively. The p-value of asymmetry term is highly significant under normal distribution and GED distribution while it is insignificant under t student distribution. This explanation indicates that the exchange rate return of SOS did not have leverage effect. According to the results of TGARCH(1,1) model under three error distributions, the asymmetry term γ for exchange rate return is calculated under normal, t student and GED distributions with value of -1.971074, -0.169487 and 0.517006 respectively. The p-value of asymmetry term of TGARCH (1, 1) is highly significant under three error distributions and it has negative sign under normal distribution and t distribution while it has positive sign under GED distribution. This result reveals that negative shocks of exchange rate return tend to give a higher volatility in the future than positive shocks of same sign, therefore, the existence of leverage effect for exchange rate return is observed in TGARCH (1,1) model.

Table (5) Estimation of Volatility Models Normal

Coefficient	**ARCH(6)**	**GARCH(1,1)**	**EGARCH(1,1)**	**TGARCH(1,1)**
μ	-2.30E-05 (0.9584)	-0.000891 (0.0000)	0.000217 (0.0000)	-0.000172 (0.0000)
α_0	0.000226 (0.0000)	-3.79E-08 (0.4956)	-0.407305 (0.0000)	5.04E-07 (0.0000)
α_1	0.122882 (0.0000)	1.063804 (0.0000)	0.378586 (0.0000)	2.050579 (0.0000)
α_2	0.022512 (0.1560)			
α_3	0.032192 (0.0000)			
α_4	-0.001591 (0.0000)			
α_5	0.075282 (0.0000)			
α_6	0.033803 (0.0000)			
β_1		0.849461 (0.0000)	0.965727 (0.0000)	0.847787 (0.0000)
γ_1			0.221157 (0.0000)	
γ_2				-1.971074 (0.0000)

Note: the p-values are shown in parentheses

Table (6) Estimation of Volatility Models t-student

Coefficient	ARCH(3)	GARCH(1,1)	EGARCH(1,1)	TGARCH(1,1)
μ	5.83E-09 (0.9265)	-1.34E-08 (0.9982)	6.75E-08 (0.9984)	-2.62E-08 (0.9967)
α_0	2.93E-14 (0.0002)	1.12E-12 (0.1328)	-4.514169 (0.0000)	1.85E-12 (0.1202)
α_1	0.574805 (0.0000)	0.636231 (0.0000)	1.401499 (0.2461)	0.621930 (0.0000)
α_2	0.445007 (0.0000)			
α_3	0.324776 (0.0000)			
α_4	0.202562 (0.0000)			
α_5	0.066429 (0.0000)			
α_6	0.233509 (0.0000)			
β_1		0.514741 (0.0000)	0.526660 (0.0000)	0.525280 (0.0000)
γ_1			0.437884 (0.2465)	
γ_2				-0.169487 (0.0001)

Note: the p-values are shown in parentheses

Table (7) Estimation of Volatility Models GED

Coefficient	ARCH(3)	GARCH(1,1)	EGARCH(1,1)	TGARCH(1,1)
μ	-4.03E-05 (0.9078)	2.19E-06 (0.9859)	3.60E-05 (0.8318)	-7.74E-08 (0.9994)
α_0	0.000120 (0.0000)	2.13E-05 (0.0000)	-9.661930 (0.0000)	1.86E-05 (0.0000)
α_1	0.160152 (0.0000)	0.020094 (0.0000)	0.052361 (0.0000)	0.067339 (0.0000)
α_2	0.033782 (0.0005)			
α_3	0.028360 (0.0000)			
α_4	0.027349 (0.0048)			
α_5	-0.000802 (0.0000)			
α_6	0.025805 (0.0000)			
β_1		0.456075 (0.0000)	0.020190 (0.3427)	0.354743 (0.0000)
γ_1			0.053473 (0.0000)	
γ_2				0.517006 (0.0000)

Note: the p-values are shown in parentheses

4-3.3. Diagnostic Checking of ARCH Models

According to the results presented in Table (8), Ljung-Box of standardized and squared standardized residuals up to 12 lags are statistically insignificant since the p-value is greater than 5%. Furthermore, LM test for ARCH effect indicates that there is no ARCH effect left in the residuals. GARCH(1,1) under GED, EGARCH(1,1) under t and EGARCH(1,1) under GED may exclude because it’s p-value is less than at standard level in terms of standardizedresiduals, squared standardized residualswhile the p-value of LM test of EGARCH(1,1) under GED is less than at 5% . Finally, according to the results and explanations summarized above, it is concluded that the models are specified and estimated correctly.

Table (8)Diagnostic check of the models

Model	DIST	Ljung-Box(Res) Lag(10)	Ljung-Box(Res^2) Lag(10)	ARCH-LM
ARCH(6)	Normal	13.752 (0.185)	1.0696 (1.000)	0.159286 (0.6898)
	T	0.0487 (1.000)	0.0126 (1.000)	0.001262 (0.9717)
	GED	9.8074 (0.458)	0.4510 (1.000)	0.009314 (0.9231)
GARCH(1,1)	Normal	7.4279 (0.685)	0.1131 (1.000)	0.003134 (0.9554)
	T	0.0011 (1.000)	0.0076 (1.000)	0.000757 (0.9780)
	GED	64.848 (0.0000)	82.366 (0.0000)	0.116065 0.7333
EGARCH(1,1)	Normal	5.5504 (0.852)	0.2103 (1.000)	0.045071 (0.8319)
	T	51.218 (0.0000)	37.393 (0.0000)	0.012236 (0.9119)
	GED	152.20 (0.0000)	357.00 (0.0000)	178.0601 (0.0000)
TGARCH(1,1)	Normal	4.3748 (0.929)	0.3451 (1.000)	0.239221 (0.6248)
	T	0.0018 (1.000)	0.0081 (1.000)	0.000801 (0.9774)
	GED	12.653 (0.244)	1.8668 (0.997)	0.003746 (0.9512))

4-3.4. Forecasting Volatility

After the estimating and checking models are completed, it is going to predict 10 observations starting from 22nd December of 2018 and finishing in 31st December of 2018 using static forecast in E-views. Table (9) presents the results of RMSE, MAE and

MAPE. According to the Table (9), it is found that ARCH(6) under t distribution is the best model for predicting volatility of SOS against USD because it has the lowest RMSE, MAE and MAPE.

Table (9) Criterion of forecast evaluation

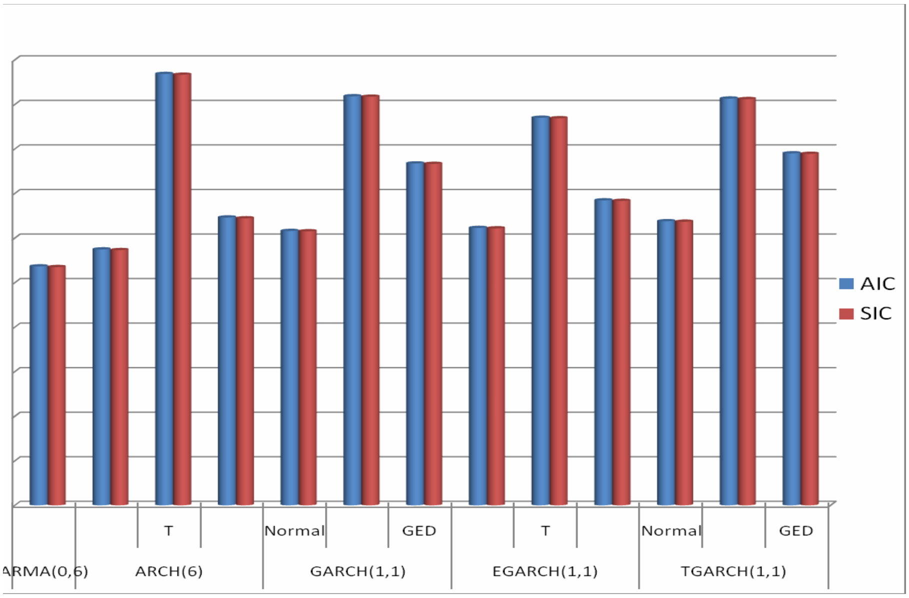
Model	**DIST**	**RMSE**	**MAE**	**MAPE**
ARCH(6)	Normal	3.42E-06	2.23E-06	0.005469
	T	3.73E-06	**1.67E-06**	**0.004087**
	GED	**3.34E-06**	2.66E-06	0.006505
GARCH(1,1)	Normal	3.49E-05	3.47E-05	0.084980
	T	3.73E-06	1.67E-06	0.004088
	GED	3.78E-06	1.76E-06	0.004306
EGARCH(1,1)	Normal	1.11E-05	1.05E-05	0.025812
	T	3.74E-06	1.67E-06	0.004094
	GED	4.58E-06	3.14E-06	0.007686
TGARCH(1,1)	Normal	6.30E-06	5.88E-06	0.014377
	T	3.73E-06	1.67E-06	0.004088
	GED	3.73E-06	1.67E-06	0.004092

4-4. Comparison between the Models

It is compared between the Box-Jenkins model and volatility models to obtain anappropriate model using different information criterion like AIC and SIC. Therefore, the appropriate model will be the one with lowest AIC and SIC. According to the Table (10) and Figure (9), ARCH (6) under t is the most appropriate model having lowest AIC and SIC and it followed by GARCH(1,1) under t-student. Moreover, the Figure 1A-3A in the Appendix demonstrates the predictive ability among the models using the forecast evaluation criterion. According to RMSE, ARCH(6) under GED distribution is the fittest model while MAE suggests that none of the models can dominate the others and ARCH(6) under t student distribution is superior to the others in terms of MAPE.

Table (10) Comparison of estimated Models

Model	DIST	AIC	SIC
ARMA(0,6)		-5.577965	-5.567350
ARCH(6)	Normal	-5.745403	-5.729856
	T	**-9.684179**	**-9.666688**
	GED	-6.461325	-6.443834
GARCH(1,1)	Normal	-6.159841	-6.152067
	T	-9.182900	-9.173183
	GED	-7.675335	-7.665618
EGARCH(1,1)	Normal	-6.227412	-6.217695
	T	-8.700728	-8.689068
	GED	-6.846027	-6.834366
TGARCH(1,1)	Normal	-6.377115	-6.367398
	T	-9.132105	-9.120413
	GED	-7.902168	-7.890507



Figure(9) Comparison of estimated Models

The DM (1995) test is applied to each model of exchange rate returns to compare whether the models have the same predictive ability or not. The null hypothesis of this test is that the models have the same forecast accuracy against the alternative hypothesis that the second model is less accurate than the first model. The results are displayed below in Table (11). According to the Table (11), it is failed to reject the null hypothesis since the p-values are approximatelylarger than 5%.Thus, it is suggested that the forecast accuracy of the ARMA(0,6) and all types of ARCH family models in predicting volatilities of daily exchange rate return of Somali currency against US currency have same predictive ability. The resultimplies that the DM test does not prefer any model over the other.

Table (11) DM test for forecast evaluation

Model	DIST	DM statistic	P-value
ARMA(0,6)		-1.320234	0.186757
ARCH(6)	Normal	1.316226	0.188098
	T	****	****
	GED	-1.322948	0.185853
GARCH(1,1)	Normal	1.316373	0.188049
	T	-1.322944	0.185854
	GED	1.322921	0.185862
EGARCH(1,1)	Normal	-1.332976	0.182540
	T	1.322941	0.185855
	GED	1.322221	0.186094
TGARCH(1,1)	Normal	-1.323916	0.185531
	T	-1.322945	0.185854
	GED	1.322741	0.185921

**** represents that ARCH(6) is the best one

5- Conclusions and Recommendations

The main goal of the study is to model and forecast the daily exchange rate of SOS against USD using Box Jenkins models and ARCH family models and then compare between them to select an appropriate model. The data used in this study is obtained from CBS and it is covered from 1st January 2009 to 31st December 2018 with a total of 3110 observations. Box-Jenkins models are employed for modeling and forecasting daily exchange rate data using four steps of Box Jenkins methodology which includes identification, estimation, diagnostic checking and forecasting.Additionally,Identifyingsuitable volatility model for capturing fluctuations in exchange rate return, ARCH family models which include ARCH, GARCH, EGARCH, and TGARCH are developed under three error distributions namely normal distribution, t-student distribution and generalized error distribution.

According to the empirical results demonstrated in Section4, these conclusions can be summarized as follows:

1. Based on Box Jenkins models, ARMA (0, 6) is the most appropriate model for the estimated models using AIC and SIC as a selection criteria.
2. The coefficients of variance equation of ARCH(6) are statistically significant under normal distribution, t student distribution and GED distribution. Also non-negativity

condition of the ARCH(6) model is not violated since the most of parameters are all strictly positive.

3. The estimation of GARCH(1,1), α_1 and β_1 in the variance equation are positive and highlystatistically significant. Furthermore, the sum of $\alpha_1$and β_1 $(\alpha_1 + \beta_1 > 1)$is greater than one under t distribution implying that the conditional variance of GARCH(1,1) is explosive.
4. The asymmetry term γ of EGARCH(1,1) is positive under all three error distributions and highly significant under normal distribution and GED distribution while it is insignificant under t student distribution. This explanation indicates that the exchange rate return of SOS did not have a leverage effect.
5. The Asymmetry term γ of TGARCH(1,1) is highly significant under three error distributions and it has negative sign under normal distribution and t distribution while it has positive sign under GED distribution. Consequently, the existence of leverage effect can be observed in SOS/USD return.
6. As comparing volatility models of conditional variance of the return, it was found that ARCH (6) under t-student is the most appropriate model having the lowest AIC and SIC and followed by GARCH(1,1) under t-student.

7. Forecasting the volatility, the result reveals that ARCH family model is better than Box Jenkins models.
8. It is also found that the t-student and GED distribution outperform than the normal distributionfor modeling and forecasting exchange rate return volatility.
9. According to DM(1995) test, the papersuggests that the forecast accuracy of the ARMA(0,6) and all types of ARCH family models in predicting the volatility of daily exchange rate return of SOS/USD have a same predictive ability whichimplies that the DM test does not prefer any model over the other.

The study suggested theserecommendations for further research can and presented as follows:

1. The Somali economy, like other countries, needs more in-depth study of its data and the use of scientific methods in decision-making
2. Recommended the establishment of specialized information centers for supporting decision-making activities
3. Providing scientific studies and recommendations necessary for decision-makers

Further research can be recommended as the following below:

1. The study suggests the possibility of modeling macroeconomic factors such as inflation rate, interest rate, exports and imports to discover its effects on exchange rate series of SOS
2. To model and predict time series data of Somali currency, ARMA models and ARCH family models were applied using daily data. Thus, the studyrecommends utilizing other time periods like monthly, weekly, quarterly and annually.
3. It is interesting to note that the static forecasting is applied in forecasting the data. Therefore, it is suggested to use multi-step ahead forecasting
4. Since the sum of α_1 and β_1 in the variance equation of GARCH(1,1) under t distribution is greater than one $(\alpha_1 + \beta_1 > 1)$, therefore, Integrated GARCH (IGARCH) can be recommended
5. Hybrid method, especially combining ARMA with GARCH, multivariate GARCH as well as artificial neural network (ANN) models can be employed in modeling and forecasting exchange rate data of SOS versus USD.

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Appendix A

Table (A1) Model Selection Criteria Table

ARMA	AIC	SIC
(0,6)	**-5.360512**	**-5.344923**
(6,1)	-5.360047	-5.342509
(1,6)	-5.359881	-5.342343
(6,2)	-5.359680	-5.340194
(6,3)	-5.359493	-5.338058
(2,6)	-5.359421	-5.339934
(6,4)	-5.358984	-5.335600
(3,6)	-5.358783	-5.337348
(4,6)	-5.358540	-5.335157
(6,5)	-5.358448	-5.333116
(5,6)	-5.357918	-5.332586
(6,6)	-5.357854	-5.330573
(6,0)	-5.355144	-5.339554
(5,5)	-5.351824	-5.328440
(2,5)	-5.350314	-5.332777
(5,4)	-5.349774	-5.328339
(3,3)	-5.349561	-5.333972
(4,5)	-5.349516	-5.328081
(5,3)	-5.348936	-5.329450
(3,2)	-5.348619	-5.334979
(4,4)	-5.348334	-5.328848
(2,3)	-5.347885	-5.334245
(3,4)	-5.347352	-5.329814
(4,3)	-5.347345	-5.329807
(3,5)	-5.346799	-5.327313
(1,5)	-5.346127	-5.330537
(5,1)	-5.345839	-5.330250
(4,2)	-5.345482	-5.329893
(2,1)	-5.345243	-5.335499
(1,2)	-5.345109	-5.335366
(1,3)	-5.345037	-5.333345
(3,1)	-5.345019	-5.333327
(2,4)	-5.344995	-5.329406

ARMA	AIC	SIC
(5,2)	-5.344891	-5.327353
(2,2)	-5.344832	-5.333140
(4,1)	-5.344769	-5.331129
(1,4)	-5.344644	-5.331003
(1,1)	-5.344008	-5.336213
(0,5)	-5.338267	-5.324627
(0,4)	-5.336975	-5.325283
(0,3)	-5.334808	-5.325065
(4,0)	-5.330935	-5.319243
(5,0)	-5.330344	-5.316704
(3,0)	-5.329935	-5.320192
(0,2)	-5.329818	-5.322023
(2,0)	-5.327109	-5.319315
(0,1)	-5.326982	-5.321136
(1,0)	-5.324017	-5.318172
(0,0)	-5.302347	-5.298450

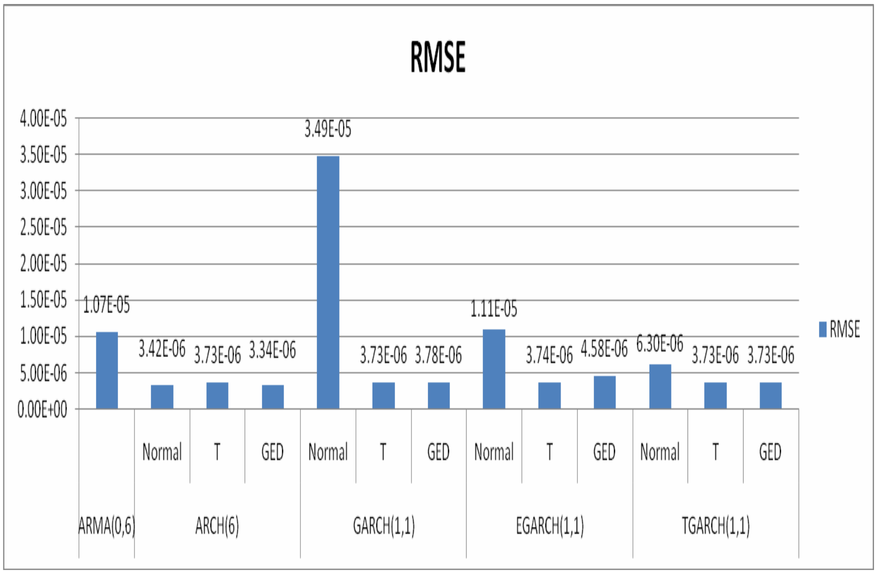

Figure (1A)Forecast evaluation: RMSE

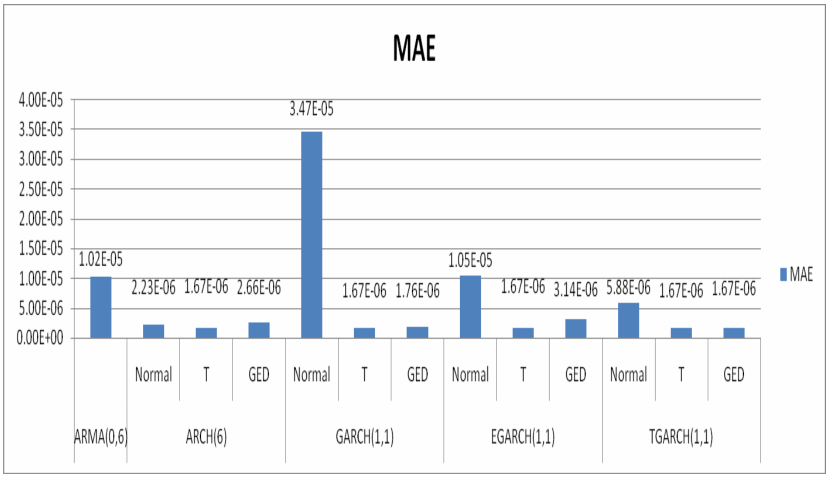

Figure (2A)Forecast evaluation: MAE

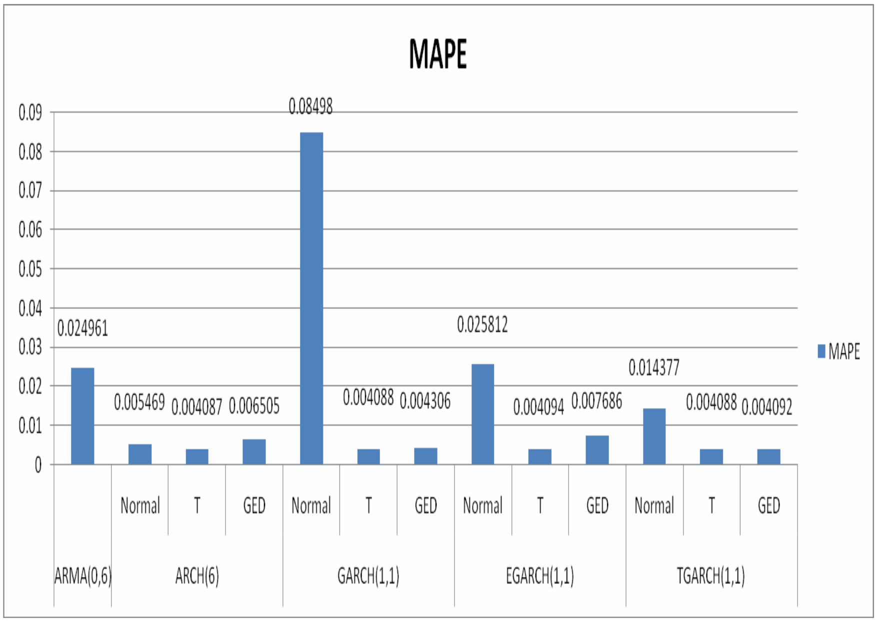

Figure (3A)Forecast evaluation: MAPE