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Modelling LKR/USD Exchange Rate Volatility: GARCH Approach

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Abstract:*Exchange Rate Volatility is a most prominent term in the financial econometrics. This Study aimed to estimate the changes in volatility of exchange rates focused on LKR/USD for the period of January 2000 to August 2018. Exchange rate return series were tested incorporating GARCH (Generalized Autoregressive Conditional Heteroscedasticity) family models with daily basis data. All the models are investigated using three different distributional approaches, Student t, Normal(Gaussian) and Generalized Error Distribution focusing on Mean variance and the conditional variance with the AR(2) effect. In-sample data were tested using forecast estimates of MASE, MAE and MAPE. Under the assumption generalized error distribution, best fitted model of measuring the LKR/USD daily exchange rate volatility is the AR(2)-GARCH(1,1) model. Final model is statistically significant at 5% confidence level and the residuals are deviate from the normality. This study reveals that the LKR/USD exchange rate returns are responding faster with the global Market fluctuations.*

Keywords*: ARMA Model, Exchange Rate Volatility, GARCH Model, Leverage Effect*

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I. Introduction

Exchange rates can be simply identified as the value of currency related to the value of other currency, which are changing as depreciation or devaluation as the global economic situation. Central Bank is authorized to manage the exchange rates. Floating exchange rates are economically efficient and more volatile while pegged exchange rates are opposite that way. When U.S. dollar values are strengths against the Sri Lankan rupee value, it is caused the diminishing international investment returns. Currently U.S. dollar value has been reached its optimal value, over Rs.160 and affected very badly in Sri Lankan economy. This will tend to increase the export demand while reduce the import demand. As the currency less strength, it will lead to the increased production; hence rice the employment opportunities of the country by increasing the demand for the goods and services [1].

Estimating exchange rate volatility, researchers have been developed very specific theoretical formulations as a result of addressing verities of research problems all over the world. As the examples, frequently used volatility models can be mentioned as the autoregressive conditional heteroscedastic (ARCH) model developed by Engle (1982), Bollerslev (1986) developed generalized ARCH (GARCH) model, Nelson(1991) proposed exponential ARCH(EGARCH) model and Zakoian (1994) developed the threshold GARCH(TGARCH) model. Across the world, there are number of empirical evidences related to modeling and forecasting exchange rate volatility which are compared with different kinds of microeconomic determinants. Few number of researches are been developed focusing on bilateral exchange rate movement. For examples, it can be included Pelinescu(2013), Selmi et al.(2012), Abdalla(2012), Bosnjak et al.(2016), Barunik(2015) and Miletic(2015) etc[2].

For the government policy makers, U.S. currency market was the main focus on exchange rate volatility; during the crisis it was expanded to the European market too as the exchange rate volatility is a key concern of establishing money market policies in Sri Lanka. Exchange Rate volatility is influenced by different factors as the focus on literature, including money supply, inflation, interest rates and trade openness etc. [3]. According to the study carried out by Rajakaruna[4] net official intervention, net foreign purchases and call money rates are the most affected indicators for the fluctuations of the exchange rates using multiple regression model, alternatively vector auto regression model was attached too. There are few studies focusing the volatility of Exchange rates related to the Sri Lanka rupee value against the U.S. dollar values. Plenty of Researches are focused on Exchange rate volatility which are affected the economic growth with different measurements. This study is specially attention with intervening the year 2009 (2000-2018), which is the end of terrorist war attack.

II. Exchange Rate Regimes in Sri Lanka

Evolution of the Sri Lanka's monetary policy framework with the foreign exchange market began from 1948 from the fixed exchange rate regime. With the gaining independence Sri Lankan rupee value against the Indian rupee value was managed by the currency board, which was replaced by the Central bank in Sri Lanka in 1950 for the economic growth and maintaining the rupee value against the global market. It was fixed as 4.77 rupees per one us dollar at the initial stage. In 1968, there was a dual exchange rate regime, with applying low rate to the essential imports and relatively high rate to the other imports and traditional exports. Thus it was affected until the end of 1977. In 1967, the rupee value was devalued by twenty per cent, and then it was reset as 15.56 rupee per US dollar which was devaluation of 120 percent with introducing managed floating regime [5], [6].

Fixed exchange rates were managed by Bretton Wood System in terms of fixing the rupee value against the sterling pound then shifted to US dollar, which was dropped down in1971, it was emerged the flexible exchange rate regime to be consistent with the new liberal regime. As introducing the central bank reports in 1982, it was attempted to use the private sector credit among the difference perspectives of the economy to maintain the balance between real and financial economic outputs. Central Bank allowed determining exchange rates to the Commercial Bank, starting with independently floating regime from 2001. With that central bank authorized to monitor the exchange rate movements and when it is necessary, ready to buy and sell exchange rates to the near market value. Central bank started to keep inflation rate in single digit since 2009, because it is too bed of maintaining the double digit inflation rate for the sustainable economic growth as the central bank only controlling the demand driven inflation rate in srilanka. Monetary policy frameworks are differs from country to country in the world, depending on the situation of the country's financial market situation with the global market. Currently central bank is attempting to conduct its monetary policy framework by adapting both monetary aggregate targets and flexible inflation targets [5],[6].

III. Literature Review

Pelinescu and Acatrinei[7] investigated the exchange rate volatility using daily data of Ron-Euro for five years, results showed that exchange rates are highly fractionally integrating, means fast process of mean reversion. Beside, Abdullah et al.[8] focused on the assumption of error distribution, concluding application of Student's t-distribution for errors in normal distribution is best suited for optimal accuracy of the model. Erdemlioglu et al[9] pointed out the rapid advances in modeling exchange rates volatility and jumps. They affirmed intraday periodicity, autocorrelation and allowance for discontinuities in prices are the three features of best fitted volatility model. According to Bauwens and Sucarrat[10], GETS derived models of observable volatility are better than the GARCH family comparison models for measuring forecast accuracy of out-of-sample volatility modeling. Implied volatility is upward biased due to errors of significant measurements, as the main reason positive volatility risk premium. In contrast Stock market returns and Brazil exchange rate returns are negatively correlated as mentioned by Andrade et al.[11].

Miletic[12] emphasized that global financial crisis has no influenced on exchange rate returns in selected CEEC countries, while European sovereign debt crisis has some negative effects. Miletic[13] further highlighted that emerging countries are more sensitive to the negative shocks of exchange rates than the positive shocks compared to the developed countries, addressing the problem with dummy variable. Barunik et al.[14] remarked that disentangling of jump variation from integrated variation is a significant feature of volatility forecasting in one day and multiday performance using high frequency data The Study, Griebeler[15] investigated the same and confirmed further using GARCH models, indicating there is no relationship between developed or emerging countries' exchange rate movements. Diebold and Nerlove[16] studied the temporal variability patterns by utilizing seven nominal dollar spot exchange rates for the period of 1973-1989. The model used for this analysis is ARCH model, concluding co-movements are having factor structure for the estimation of tractable parameters, further the identifying a martingale for the exchange rate movements. Exchange rate movements can be approximated by multivariate random work using ARCH.

As stated by Bosnjak[17] in microeconomics and finance, Exchange rate volatility plays a crucial role. By investigating EUR and USD against HRK, it is concluded that no leverage effect in exchange rate returns. Selmi et al.[18], in contrast shift level and the positive or negative intensity of shocks with jump intensity, the ARCH and GARCH effects are playing significant role in exchange rate volatility by analyzing the Oil prices of Tunizia. By the analysis of Pelinescu[19], stated that exchange rate returns are correlated with exchange rate volatility thus there is a high asymmetry in exchange rate evolution utilizing leu/euro exchange rates for the period of no of thirteen years data.

IV. Materials & Methodology

4.1 Unit Root Test

Testing Stationary is a powerful step to be satisfied for analyzing time series data. It is conducted by using both Augmented Dickey Fuller test (ADF) and the Philips-Perron test (PP). Ultimately, non-stationary time series are generally transformed into the Stationary Series.

ADF test can be written as follows:

$\Delta y_t = \varphi + \beta_t + \alpha y_{t-1} + \sum_{i=1}^{k} di\ \Delta y_{t-i} + \mu_t$

Augmented Dicky Fuller test can be modified as the Philips Perron equation which was introduced by Philips and Perron in 1988. PP test equation as follows:

$y_t = \delta_t + \gamma\ y_{t-1} + \gamma_1\ \Delta y_{t-1} + \ldots\ldots\ldots + \gamma_p \Delta y_{t-p} + \mu_t$

The Augmented Dickey Fuller (ADF) test is been used for testing the presence of a unit root by adding an unknown number of lagged first differences of the dependent variable to capture auto-correlated omitted variables that would otherwise, by default, enter the error term as in the regression [20]. Further H_0 as series is non-stationaryis rejected in favour of H_1if t-statistic is greater than the tabulated critical value. When using statistical software, this is equivalent to rejecting the null hypothesis when the p-value is less than the pre-selected level of significance as 1%, 5% & 10%.

4.2 ARIMA Model

To handle time series modeling with forecasting, and model Box & Jenkins, it has developed a systematic class of models called autoregressive integrated moving average (ARIMA) models.

Let $Y_t$be an ARIMA(p,d,q) model then,

$\Phi(\beta)(1 - \beta)^d\ (Y_t - \mu) = \theta(\beta)Z_t$

Where, $Z_t \sim WN(0, \sigma^2)$

ARIMA(1,1,0) defined as the differenced first order autoregressive model. This would yield the following equation:

$\acute{Y}_t = \mu + Y_{t-1} + \varphi_1 (Y_{t-1} - Y_{t-2})$

4.3 ARCH/GARCH Models

ARCH(Autoregressive Conditional Heteroskedasticity) and Generalized ARCH (GARCH) models are generally considered as the most attractive tools for estimating volatility. In financial and economic data series, ARCH/GARCH is adequate to capture the random movement. In financial data modeling, ARCH and GARCH models are being used to investigate the problem of volatility clustering and the persistence.

ARCH Model

When modeling financial time series data, heteroscedasticity and volatility clustering ARCH Model is used as very first model to analyze time series data. ARCH(q) is as follows :

$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \ldots\ldots\ldots + \alpha_q \varepsilon_{t-q}^2 = \omega + \sum_{i=1}^{q}(\alpha i\ \varepsilon_{t-1}^2)$

Where,

$\omega > 0$, $\alpha_i \geq 0$ for i=1,2,3,….,q and $\sum_{i=1}^{q}(\alpha i) < 1$

Let σ_t^2 denote as the Conditional Variance of Random Variable, then we can express the ARCH(1) Model as,

$\sigma_t^2 = \omega\ + \alpha_1{}_{t-1}^2$

It is known that,

$E(X_t) = E(E(X_t|F_{t-1})) = E(E(\sigma_t \varepsilon_t|F_{t-1})) = 0$

GARCH

The Generalized ARCH model(GARCH), is an extension of the ARCH model, which was developed by Bollerslev(1986). GARCH(p,q) can be expressed as:

$\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha i\ \varepsilon_{t-i}^2) + \sum_{j=1}^{p}(\beta j\ \sigma_{t-j}^2)$

Where,

$\omega > 0$, $\alpha_i \geq 0$ for i=1,2,3,….,q and $\beta_j \geq 0$ for i=1,2,3,….,p

$\sum_{i=1}^{q}(\alpha i) + \sum_{j=1}^{p}(\beta i) < 1$

In evaluating volatility clustering, the GARCH(1, 1) model is specified as follows:

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1\varepsilon_{t-1}^2$$

Where,

$\omega > 0$, $\alpha_1 > 0$, $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$

EGARCH Model

Non-negativity constraints and leverage effects are violated by the standard ARCH GARCH models. Therefore as a solution, EGARCH was proposed by Nelson in 1991. In Financial Time Series, to handle the asymmetric shocks to the exchange rate volatility EGARCH Model is used. Conditional Variance can be expressed as,

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{q}(\alpha i)\frac{|\varepsilon t-i|}{\sigma t-i} + \sum_{k=1}^{r}(\gamma k)\frac{\varepsilon t-k}{\sigma t-k} + \sum_{j=1}^{p}\beta j \log(\sigma_{t-j}^2)$$

Where,

γ_k– asymmetry parameter. Therefore, when $\gamma_k \neq 0$, there is a asymmetry effect, while $\gamma_k < 0$ indicates the volatility increases more after bad news, $\varepsilon_{t-1} < 0$ than after good news, $\varepsilon_{t-1} > 0$.

TGARCH Model

As an alternative to EGARCH model, In 1994, Zakoian was proposed the GARCH model with threshold effect called TGARCH model. In this model asymmetry of negative and positive shocks are incorporated. TGARCH is specified as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha i)\,\varepsilon_{t-i}^2 + \sum_{i=1}^{q}(\gamma i d(\varepsilon_{t-1} < 0)\,\varepsilon_{t-i}^2) + \sum_{j=1}^{p}\beta j\,(\sigma_{t-j}^2)$$

PGARCH Model

The Power-ARCH (PARCH) specification was introduced by Ding, Granger and Engle (1993). The PARCH specification is given by equation:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{p}\alpha i(|\varepsilon_{t-1}| - \gamma_i\,\varepsilon_{t-1})^\delta + \sum_{j=1}^{q}(\beta j)\,h_{t-j}^\delta$$

Where,

X $\omega > 0$, $\alpha_i \geq 0$ with at least one $\alpha_i > 0$, i = 1,2,3,….,q and $\beta_j \geq 0$, j = 1,2,3,…,p

4.4 Model Diagnostics

Analyzing the Time Series data, there are different types of Diagnostic Test to be performed for the accuracy of future forecasting. Those tests are focused on mainly to check the normality assumption and remove the serial correlation effect of the model for best fit of data.

JB test for normality is computed as:

$$JB = \frac{T}{6}(skew^2 + \frac{(kurt-3)2}{4})$$

4.5 Model Comparison Criteria

To determine the optimum statistical model for capturing the time series data, there are three tests to be applied, namely Akaike Information Criterion (AIC) test, the Schwarz Information Criterion (SC) test, the Hannan-Quinn Information Criterion (HQ) test with considering the Log-likelihood Ratio test.

The formulae of the information tests are:

$$AIC = \exp\left\{\frac{2k}{T}\right\}\frac{1}{T}\sum_{t=1}^{T}(e_t^2) = -2\ln(L) + 2k$$

$$SIC = T^{k/T}\frac{1}{T}\sum_{t=1}^{T}(e_t^2) = -2\ln(L) + k\ln(n)$$

Considering AIC and SIC criteria, model with lowest values are represented the best fit model comparing few number of models.

$HQ = -2\ln(L) + 2k\ln(n)$

Likelihood ratio test: $D = -2\ln(L_0) + 2\ln(L_1)$

The model with highest likelihood value of function is the best fit model.

where krepresents the number of free parameters to be estimated, nis the number of observations(sample size) and Lis the maximized likelihood function value[21].

4.6 Forecast Evaluation

Forecasting is an influential work application of time series data. It is important in determining the suitable model to use in the analysis of forecast evaluation. The Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are three of such evaluation statistics[20].

4.7 Data Description

This study utilizes 18 years daily frequency data was collected from the time period of January 2000 to August 2018 for the volatility forecasting. Data were obtained from the Fed online database.

First Difference of the Logarithm of the Exchange Rate Values was considered as the Exchange Rate Return. It is stated that,

Exchange_Rate_Return $= \ln\left[\frac{Rt}{Rt-1}\right] * 100$

Where R_t – Exchange Rates for day t, R_{t-1} – Exchange Rates for day t-1.

V. Estimation Results

5.1 Graphical Representation

Figure 1 plots monthly LKR/USD exchange rate for the January 2000 to August 2018 period of 18 years, for a total number of 4666 observations. It shows that nominal exchange rates have stochastic upward trends, that is, they are non-stationary. Further it shows that there are considerable ups and downs in the Exchange Rates over the selected sample period. Figure 2 illustrates the changes in the daily exchange rate returns. Figure 3, the Quantile-Quantile (*QQ*) plot for the LKR currency, graphically represent the similar evidence as the Figure 2. The normal QQ plot of Exchange Rate Returns, do not show strong deviation from normality for LKR/USD returns.

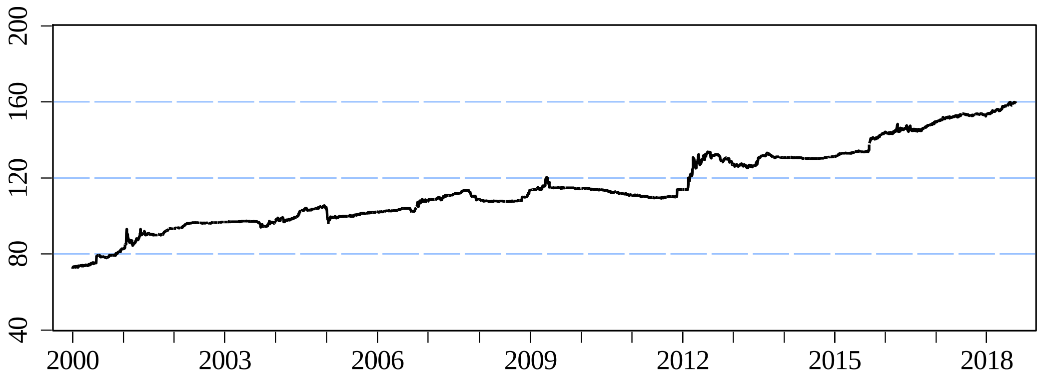


Figure 1: Daily Exchange Rates of LKR/USD

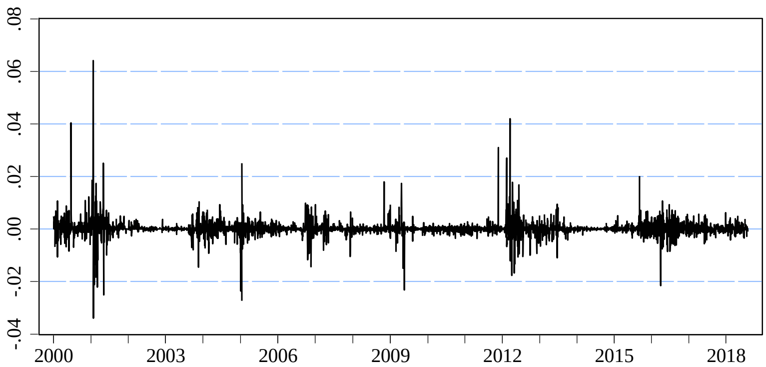


Figure 2: Daily Exchange Rate Returns LKR/USD

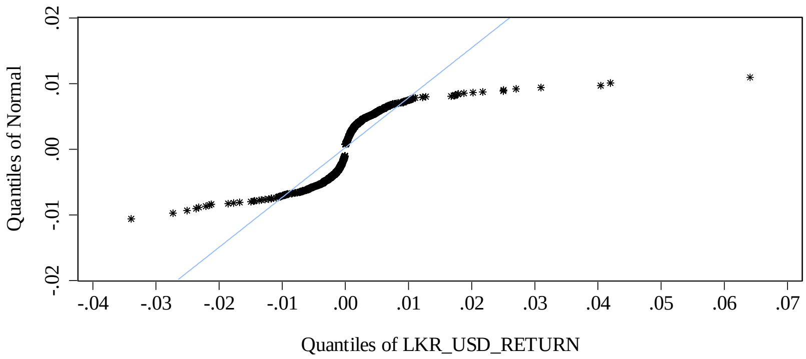


Figure 3: Q-Q plot of Exchange Rate Returns

5.2 Descriptive Statistics

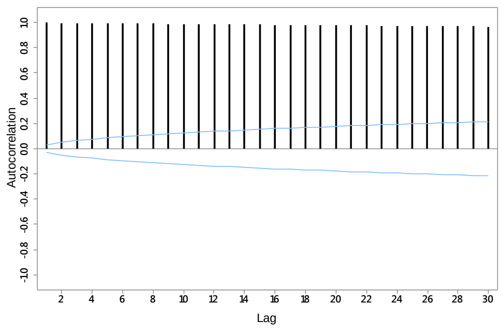
The descriptive statistics for the exchange rate are illustrated below in Table 1 and show a positive kurtosis, 2.4 for the LKR/USD daily exchange rate and also a positive skewness,0.33 indicates the distribution of Exchange Rate series is normally Distributed.

Table 1: Useful Statistical Indicators of Exchange Rate

Variable	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
LKR/USD	114.8333	110.7800	20.62460	0.328385	2.401512	153.5975

5.3 Serial Correlation and Unit Root Test

Figure 4 and Figure 5 plot the Auto Correlation Function(ACF) and Partial Auto Correlation Function(PACF) with 30 lags of the Exchange Rates LKR/USD.



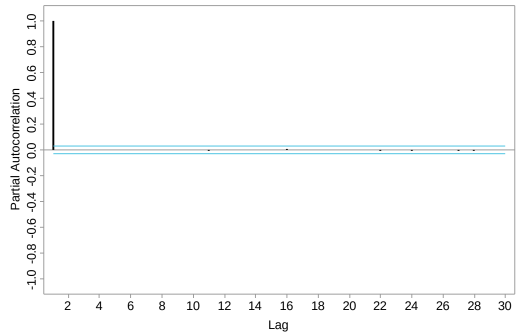


Figure 4: Autocorrelation of LKR/USD **Figure 5:** Partial Autocorrelation of LKR/USD (with 5% significance limits for the partial autocorrelations)

Figure 4 illustrates that exchange rates exhibit volatility clustering. That means volatility shows positive autocorrelation. It shows very high autocorrelation coefficients even up to lag of 30. Sample autocorrelations are decreasing with the increase of Lag. This is the typical Autocorrelation Function of a non-stationary series. In Figure 5 at lag one there is an extremely high coefficient while remaining part stays same.

Table 2 shows the results of unit root test for daily exchange rate series of both original series and the exchange rate return series. The Augmented Dickey-Fuller test and Phillips-Perron test statistics for all exchange rate are not significant in original series, while exchange rate return series is statistically significant 1%, 5% and 10% level, thereby suggesting the acceptance of null hypothesis of the presence of unit root in the series of original series.

Table 2: ADF and PP unit root tests

Test		Original Series		Return Series		Test critical values		
		Statistic	**Prob.***	***Statistic***	**Prob.***	***1%***	***5%***	***10%***
ADF Test	C	-0.328	0.919	-50.484	0.0001	-3.43	-2.86	-2.57
	T/C	-1.875	0.667	-50.489	0.0000	-3.96	-3.41	-3.13
PP Test	C	-0.322	0.9194	-67.437	0.0001	-3.43	-2.86	-2.57
	T/C	-1.877	0.666	-67.445	0.0000	-3.96	-3.41	-3.13

5.4 Estimating Models for the Conditional Mean

For the mean equation series of ARIMA models were tested. Few models were significant. Below, in Table 3, indicates the best models found for the conditional means of exchange rates and the selection criteria which are only significant on 5%. Based on the results, lowest AIC, SC and HQ with highest log likelihood, the model that best adjusted the exchange rates in Sri Lanka is an ARIMA (2 1 0).

Table 3: Summary Outputs of ARIMA Models

Model	P-value	Log likelihood	Akaike info criterion	Schwarz criterion	Hannan-Quinn criter.
ARIMA(0 0 0)	0.000	-20755.18	8.8911	8.8924	8.8915
ARIMA(0 0 1)	0.000	-17558.96	7.5224	7.5251	7.5233
ARIMA(1 1 1)	0.000	20640.89	-8.8442	-8.8400	-8.8427
ARIMA(0 1 2)	0.000	20643.79	-8.8440	-8.8412	-8.8430
ARIMA(2 1 0)	0.000	20636.50	-8.8446	-8.8419	-8.8437

5.5 Diagnostic Test of Residuals of ARIMA (2,1,0) Model

Diagnostic test of residuals are checked the model is with the serial correlation. It assumed to best fit the model that residuals are not normally distributed.

Figure 6 illustrates the histogram and skewness and kurtosis of the residuals of the fitted ARIMA (2 1 0) respectively. The normality test indicates that residuals of the ARIMA(2 1 0) model are not normally distributed as we are unable to reject the null hypothesis of normality using Jacque- Bera at 5 percent level.

Using Correlation LM test presented in Table 4 indicates that there is no serial correlation in the model since none of the lag is found to be significant at 5 percent level, confirming the explanatory power of the ARIMA (2 1 0) model. Errors are randomly distributed.

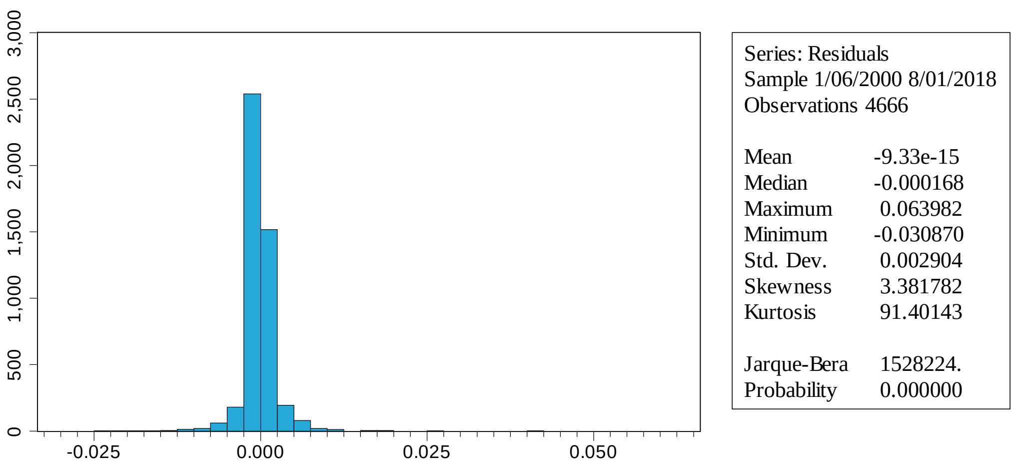


Figure 6: Histogram Normality Test of Residuals of ARIMA (2 1 0)

Table 4: Breusch-Godfrey Serial Correlation LM Test

F-statistic	1.564774	Prob. F(2,4662)	0.2092
Obs*R-squared	3.130132	Prob. Chi-Square(2)	0.2091

5.6 Estimation of Variance Equation

Table 5-7 summarizes variance equation estimates for the LKR/USD exchange rate return using Student t Distribution, Normal Distribution and Generalized Error Distribution respectively, fitted with different GARCH models. Test for presence of ARCH effects is done before the application of GARCH models. The test for the presence of ARCH effect is performed by first applying the least squares method in order to generate regression residuals.

Table 5, according to the ARCH LM test statistics, there is no serial correlation of any GARCH family model. ARCH(1), p-value shows the effect of the serial correlation. According to Q-statistics with residuals and the squared residuals, all the models except ARCH(1) confirms the randomly distribution of residuals. Compared to variance estimate, lowest Akaike information criterion (AIC) and Schwarz Criterion (SC) values PGARCH(1,1) represents the most suitable model for LKR/USD volatility modeling. With Log likelihood criteria, (24676.09) confirm the result with the highest value among other ARCH family models. Considering mean equation, ARCH effect of the all the models are not significant in student t distribution. In the variance equation, ARCH and GARCH coefficients for all the GARCH family models are not statistically significant except the PGARCH model as the p-value shows the value less than zero. EGARCH is the only model that indicates the negative coefficients for the conditional variance, others represents the shocks of positive values in measuring the volatility of exchange rates of rupees against the U.S.dollars. When coefficients of PGARCH and EGARCH of mean equation are significant then ω is not significant for other models, indicates opposite direction.

According to the Table 6, coefficients of the conditional variance are statistically significant at 5% confident level for all the models which were tested for the best fit of LKR/USD exchange rate volatility while ARCH(1) and EGARCH are only shows the significant effect in the mean equation. As previous studies stated, significance of α and β is said to be having the explanatory power on current volatility from the previous period volatility. It is notable that constant is only significant in mean equation of PGARCH model. Comparing the AIC and SC values, the lowest value indicates with PGARCH mode, thus the highest log likelihood value confirms the result. As the Table 5 illustrated, except ARCH(1), residuals of other models are showed the effects of serial correlation. Coefficients of α and β are relatively very low value, compared to some values of student t distribution indicating that shocks to the conditional variance are not persistent. ARCH(1), GARCH(1,1) and TGARCH in the student t distribution indicates the volatility responding very quickly with the changes of the U.S. dollar values by indicating the higher α values of the coefficients of the three models. γ indicates the positive and significant effects on all the selected values.

Table 5: Parameter Estimates for the exchange rate return using Student t distribution

Parameter	ARCH(1)	GARCH(1,1)	TGARCH	EGARCH	PGARCH
C	4.27E-05	2.21E-05	2.00E-05	1.19E-05	6.00E-06
	[0.0001]	[0.0048]	[0.0114]	[0.1206]	[0.3213]
AR(2)	0.002398	-0.00038	0.000503	0.006738	0.001141
	[0.6853]	[0.9776]	[0.9702]	[0.5450]	[0.8892]
ω	0.001413	1.41E-05	1.09E-05	-0.33158	0.000326
	[0.9965]	[0.9925]	[0.9915]	[0.0000]	[0.0230]
α	2215.515	281.3485	201.9867	2.447371	0.54043
	[0.9965]	[0.9925]	[0.9915]	[0.0492]	[0.0007]
β		0.70196	98.51462	-0.849438	0.114966
		[0.0000]	[0.9915]	[0.0537]	[0.0131]
γ			0.712653	0.982906	0.858623
			[0.0000]	[0.0000]	[0.0000]
δ					0.695251
					[0.0000]
Log Likelihood	24282.92	24599.99	24604.25	24611.73	24676.09
AIC	-10.40631	-10.54179	-10.54318	-10.54639	-10.57355
SC	-10.3994	-10.5335	-10.53351	-10.53672	-10.56249
HQ	-10.40388	-10.53887	-10.53978	-10.54299	-10.56966
Q2(15)	[0.0000]	[1.0000]	[1.0000]	[1.0000]	[0.9060]
Q(15)	[0.0180]	[0.8310]	[0.8640]	[0.6590]	[0.3510]
Normality	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
ARCH LM(10)	[0.0000]	[1.0000]	[0.9999]	[0.9998]	[0.6687]

(P-values in the parenthesis)

Table 6: Parameter Estimates for the LKR/USD exchange rate return using Normal Distribution

Parameter	ARCH(1)	GARCH(1,1)	TGARCH	EGARCH	PGARCH
C	6.79E-05	-6.69E-06	6.74E-06	1.51E-05	4.56E-05
	[0.0000]	[0.5061]	[0.5855]	[0.0002]	[0.0000]
AR(2)	0.040191	-0.020624	-0.02509	0.061575	-0.01463
	[0.0000]	[0.1778]	[0.1107]	[0.0000]	[0.3054]
ω	2.90E-06	2.07E-08	2.25E-08	-0.429466	1.40E-05
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
α	2.475261	0.343719	0.432746	0.299303	0.223784
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
β		0.822644	-0.167265	0.020566	-0.213555
		[0.0000]	[0.0000]	[0.0000]	[0.0000]
γ			0.816584	0.978622	0.871467
			[0.0000]	[0.0000]	[0.0000]
δ					1.106662

(P-values in the parenthesis)

Table 6: Parameter Estimates for the LKR/USD exchange rate return using Normal Distribution(Cont.)

Parameter	ARCH(1)	GARCH(1,1)	TGARCH	EGARCH	PGARCH
δ					[0.0000]
Log Likelihood	21494.55	22802.4	22816.43	22800.75	22882.65
AIC	-9.211553	-9.77171	-9.777297	-9.770575	-9.805251
SC	-9.206025	-9.7648	-9.769005	-9.762284	-9.795577
HQ	-9.209609	-9.76928	-9.77438	-9.767659	-9.801848
Q2(15)	[0.0000]	[1.0000]	[1.0000]	[1.0000]	[1.0000]
Q(15)	[0.0010]	[0.4810]	[0.3300]	[0.4190]	[0.1110]
Normality	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
ARCH LM(10)	[0.0001]	[1.0000]	[1.0000]	[1.0000]	[1.0000]

(P-values in the parenthesis)

Table 7: Parameter Estimates for the LKR/USD exchange rate return using GED

Parameter	ARCH(1)	GARCH(1,1)	TGARCH	EGARCH	PGARCH
C	7.04E-07	1.22E-06	2.09E-07	-7.57E-08	1.95E-06
	[0.9327]	[0.8898]	[0.9898]	[0.9921]	[0.8817]
AR(2)	0.055211	-0.004888	0.020109	-1.51E-05	0.00035
	[0.0000]	[0.6344]	[0.1046]	[0.9983]	[0.9771]
ω	1.04E-06	2.62E-07	4.78E-07	-3.334677	2.30E-06
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0531]
α	0.575619	0.39303	0.179985	0.510913	0.392467
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
β		0.405075	0.667479	-0.140577	0.310302
		[0.0000]	[0.0000]	[0.0000]	[0.0000]
γ			0.439809	0.775753	0.53316
			[0.0000]	[0.0000]	[0.0000]
δ					1.673415
					[0.0000]
Log Likelihood	24133.02	24310.26	23863.17	24431.27	23969.41
AIC	-10.34206	-10.4176	-10.22553	-10.46904	-10.27064
SC	-10.33515	-10.40931	-10.21586	-10.45937	-10.25959
HQ	-10.33963	-10.41468	-10.22213	-10.46564	-10.26675
Q2(15)	[0.0020]	[1.0000]	[1.0000]	[0.9970]	[1.0000]
Q(15)	[0.0000]	[0.8070]	[0.8090]	[0.8130]	[0.8140]
Normality	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
ARCH LM(10)	[0.0010]	[1.0000]	[0.9967]	[0.9727]	[0.9994]

(P-values in the parenthesis)

As illustrated in Table 7, EGARCH is being selected as the best fitted model of the generalized error distribution as the lowest AIC and SIC values and the highest log likelihood value. Residuals are illustrating the same behavior as the student t distribution and the normal distribution indicated in above two tables. Conditional variance α and β indicate the significant positive coefficients except EGARCH model which is having negative significant shock.The PGARCH is not the most suitable model form to describe the LKR/USD exchange rate volatility, since this form still shows heteroscedasticity effect in variance. In order to capture the LKR/USD exchange rate volatility pattern, the model needs to be extended up to the highest level forms. Forecast estimates are taken for the in-sample data for the period of January 2016 to August 2018 to identify the best fitted model for the volatility of exchange rates.

Comparison of Table 5, Table 6 and Table 7, the model representing the variance equation for the Student t distribution of exchange rate returns takes the AR(2)-PGARCH (1, 1) form, equation for the generalized error distribution takes AR(2)-EGARCH(1,1) model while the equation for the normal distribution of exchange rate returns takes the AR(2)-PGARCH (1, 1) form again.

It considered that the lowest values of forecast estimates of RMSE, MAE and MAPE are indicated the best fit of model for the exchange rate volatility forecasting. Irrespective of the methods student t distribution, normalized error distribution and the generalized error distribution, as the best model we can emphases as the AR(2)-GARCH(1,1) model, as illustrated the forecast estimate results in Table 8. Conditional variance estimates are confirmed the AR(2)-PGARCH(1,1) is the most suitable model for the investigating the Sri Lankan rupee value against the U.S. dollar value using the information criteria and log likelihood value under the generalized error distribution.

Table 8: Model Comparison Forecast Estimates

	Method	ARCH (1)	GARCH (1,1)	TGARCH	EGARCH	PGARCH
RMSE	Student t'	0.00229	0.00229	0.00229	0.00229	0.00229
	Normalized Error	0.00229	0.00229	0.00229	0.00229	0.00229
	Generalized Error	0.00229	0.00229	0.00229	0.00229	0.00229
MAE	Student t'	0.00140	0.00139	0.00139	0.00139	0.00139
	Normalized Error	0.00140	0.00139	0.00139	0.00139	0.00140
	Generalized Error	0.00139	0.00139	0.00139	0.00139	0.00139
MAPE	Student t'	78.7032	78.7023	78.7030	78.7080	78.7042
	Normalized Error	78.7292	78.6888	78.6849	78.7480	78.6907
	Generalized Error	78.7442	78.7000	78.7185	78.7037	78.7039
Rank		5	1	2	4	3

VI. Conclusion

This study was focused on the currency of Sri Lanka against United States dollar, behavior of the exchange rates according to the international market condition with analysis of daily data collected from Fred Online Database. The starting point of the analysis is evaluating the ARIMA model towards the selected GARCH family models as the first part of the analysis, which is considered to be one of the most efficient models for modelling financial time series data. The model is applied to the daily data basis from January 2000 to August 2018. As the confidence interval for the parameters of the selected ARIMA(2,1,0) model included 95%, and thus was significant among other utilized models.

Table 9: Heteroskedasticity Test: ARCH

F-statistic	0.058925	Prob. F(2,4662)	1.0000
Obs*R-squared	0.590572	Prob. Chi-Square(2)	1.0000

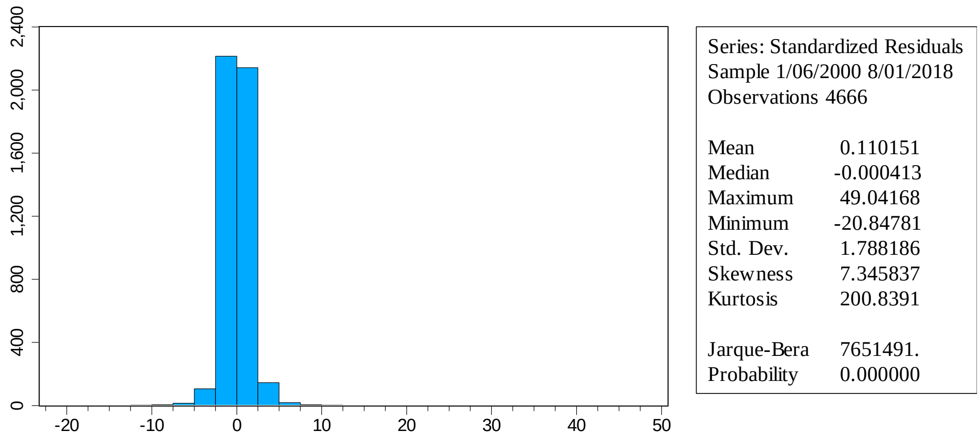


Figure 7: Histogram Normality Test of Residuals of AR(2)-GARCH (1,1)

Finally the study, reached to the conclusion that the AR(2)-GARCH(1,1) under GED is the most appropriate model for the volatility forecasting. Implementing the model, only LKR/USD was considered for the volatility behavior of individual selection. For the best fit of models, analysis of data using different types GARCH models provided the maximum error free results at the end. Limited time frame, this study focused only on the five types of GARCH family models with three types of methods. At the end of the analysis the model was significant with no serial correlation and residuals are significantly deviate from the normality.

References

[1] Banda, H.M.N., Rupee devaluation and economy of Sri Lanka, *Repository of University of Kelaniya, Sri Lanka*, 391-406

[2] Abdalla, S.Z.S.(2012), Modelling Exchange Rate Volatility using GARCH Models: Empirical Evidence from Arab Countries, *International Journal of Economics and Finance*, 216-229

[3] Wanaguru, S.T,From Where Does it Come? An Analysis of Currency Market Volatility in Sri Lanka, *Staff Studies: Central Bank of Sri Lanka*, 75-97

[4] Rajakaruna, S.H.I, An Investigation on Factors affecting Exchange Rate Fluctuations in Sri Lanka, *Staff Studies: Central Bank of Sri Lanka*, 69-100

[5] Exchange Rate: Central Bank of Sri Lanka, April 2016, *Pamphlet Series* No.03

[6] Agrawal, A. (2018), Evolution of Monetary and Exchange Rate Policy in Sri Lanka and the Way forward: wordpress, Received from: https://mostlyeconomics.wordpress.com/2018/01/25/evolution-of-monetary-and-exchange-rate-policy-in-sri-lanka-and-the-way-forward/

[7] Pelinescu, E. and Acatrinei, M.(2014), Modelling the high frequency exchange rate in Romania with FIGARCH, *Procedia Economics and Finance*, 1724-1731

[8] Abdullah, S.M. Siddiqua, S. Siddiquee, M.S.H. and Hossain, N.(2017), Modeling and forecasting exchange rate volatility in Bangladesh using GARCH models: a comparison based on normal and Student's t-error distribution, *Financial Innovation*, 3:18

[9] Erdemlioglu, D. Laurent, S. and Neely, C.J.(2012), Econometric Modeling of Exchange Rate Volatility and Jumps, *Handbook of Research Methods and Applications in Empirical Finance,* 2012-008A

[10] Bauwens, L. and Sucarrat, G. (2005), General to Specific Modelling of Exchange Rate Volatility: A Forecast Evaluation, *3rd Oxmetrics Conference in London*, 2002-00232

[11] Andrade, S.C.D. Chang, E.J. and Tabak, B.M.(2003), Tracking Brazilian Exchange Rate Volatility,

[12] Miletic, S.(2015), Modeling Exchange Rate Volatility in CEEC Countries: Impact of Global Financial and European Sovereign Debt Crisis, *Expert Article*, 105-122

[13] Miletic, S.(2015), Modeling and forecasting exchange rate volatility: comparison between EEC and Developed countries, *Expert Article*, 4-11

[14] Barunik, J. Krehlik, T. and Vacha, L.(2015), Modeling and forecasting exchange rate volatility in time-frequency domain, *European Journal of Operational Research*, 329-340

[15] Griebeler, M.D.C.(2010), Models for Forecasting Exchange Rate Volatility: A Comparison between Developed and Emerging Countries

[16] Diebold, F.X. and Nerlove, M.(1989), The Dynamics of Exchange Rate Volatility: A Multivariate Latent Factor ARCH Model, *Journal of Applied Econometrics*, 1-21

[17] Bošnjak, M. Bilas, V. and Novak, I.(2016), Modeling Exchange Rate Volatilities in Croatia, *EkonomskiVjesnik*, 81-94

[18] Selmi, R. Bouoiyour, J. and Ayachi, F.(2012), Another look at the interaction between oil price uncertainty and exchange rate volatility: The case of small open economies, *International Conference On Applied Economics*, 346-355

[19] Pelinescu, E.(2013), Volatility analysis of the Romanian exchange rate, *Procedia Economics and Finance,* 543-549

[20] David, R.O. Dikko, H.G.andGulumbe, S.U. (2016), Modelling Volatility of the Exchange Rate of the Nairato major Currencies, *CBN Journal of Applied Statistics*, Vol 07

[21] Phoong, S.W. Ismail, M.T. and Sek, S.K. (2014), Linear Vector Error Correction Model Versus Markov Switching Vector Error Correction Model to Investigate Stock Market Behavior, *Asian Academy of Management Journal of Accounting and Finance,* Vol 10, 133-149

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