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TIME SERIES ANALYSIS APPROACH TO STUDY THE TOURIST ARRIVAL IN SRI LANKA

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Abstract

Tourism has traditionally been the third foreign exchange earner in Sri Lanka. The collected international tourist's arrivals data from January 1970 to December 2019 are used for this study and it was obtained from the Sri Lanka Tourism Development Authority. The main aim of this study is to analyze and fit a model using the conditional variance of the logarithm of monthly, quarterly and annually international tourist arrivals data. This paper mainly focused on the time series models: Generalized Autoregressive Conditional Heteroscedastic (GARCH), Glosten, Jagannathan and Runkle (GJR) and Exponential GARCH (EGARCH) along with their estimation procedures for modelling international tourist arrivals and volatility. GARCH (1,1) and GJR-GARCH (1,1) are statistically significant for monthly arrivals of tourist whereas EGARCH (1,1) is statistically significant for annually arrivals of tourist.

Keywords: Conditional Volatility, EGARCH, GARCH, GJR-GARCH

Introduction

The main objective of this research study is to study and fit time series models GARCH, GJR-GARCH and EGARCH for the international tourist arrivals to Sri Lanka and check the volatility.

Sri Lanka is an island country located off the southern coast of India. Sri Lanka is surrounded by the Indian Ocean, Gulf of Mannar, the Pak Strait and lies in the vicinity of India and the Maldives. Tourism has traditionally been the third foreign exchange earner in Sri Lanka. The most well-known tourist attraction in Sri Lanka includes the Temple of the Tooth (Kandy), Mirissa (South Coast), Unawatuna (Galle), Nine Arch Bridge (Ella), Sigiriya Rock Fort & Sripada/Adam's Peak (Central Province).

The most important tourism source countries to Sri Lanka are Canada, USA, UK, India, France, Maldives, Germany, China, Australia and Russia. Europe countries to be the largest source of tourist traffic to Sri Lanka recording a share of 46.4%. Asia Pacific is the second major source market with a share of 43.9% (Tourism Industry Report - 2019). Volatility analysis for international tourist arrival was studied by Achal Lama, et, al. (2015), Bunnag (2014) and Fernando (2013).

The international tourist arrivals in Sri Lanka can help to promote economic stability in the country by providing jobs, generating income, diversifying the economy and promoting cross-cultural awareness. On an annual basis, the international tourist arrivals to Sri Lanka has shown an average growth rate of around 5% per annum from 1970 to 2019. The lowest growth rate was observed in 2015, with a decrease of 91% over the previous year, while the highest growth rate occurred in 2016, when there was a significant increase of 61% over 2015.

Review of Literature

Roshan and Jahufer (2018) studied "Forecasting Sri Lankan Arrivals: Time Series Approach". In this research study the authors mainly focused, Sri Lankan monthly tourist arrivals data from January 2000 to December 2017.

The approach of seasonal autoregressive integrated moving average (SARIMA) method was implemented to forecast tourist arrivals in Sri Lanka. They found that for the long-term (2000-2017) and post-war period (2010-2017), ARIMA (3,1,2)(1,0,1)12 and ARIMA (2,1,3)(1,0,0)12 are the suitable models respectively to sketch and to forecast the monthly tourist arrival pattern in Sri Lanka with a very precise extent by it satisfies the model assumptions as well as it indicates that forecasted and actual tourist arrivals are not much deviated from each other.

Kumudika (2017) analyzed tourist arrival in Sri Lanka data from 1986 to 2015. The data was analyzed using time series analysis, applying the ordinary least square linear regression method as well as 12-month moving average. The results of the data analysis revealed, that tourist arrivals in Sri Lanka has shown a moderate increasing trend during the period from 1986 to 2015. In seasonality of arrivals, the period from January to March and the month of December marked as a peak seasons while May and June as lean months.The overall picture showed that the tourists, especially younger tourists have demonstrated a decreasing trend and older tourists have demonstrated an increasing trend to visit Sri Lanka during the period of study. The study also revealed that the trends in percentage distribution of female and male representation were respectively positive and negative. The majority of the tourists who arrived in Sri Lanka during the period were gainfully occupied. At the regional level, tourist arrivals from South Asia, Eastern Europe, Middle East and Australasia regions have represented a remarkable increase.

“Modeling and predicting foreign tourist arrivals to Sri Lanka: A comparison of three different methods” research was studied by Diunugala and Mombeuil (2020). The results show that Winter’s exponential smoothing and ARIMA are the best methods to forecast tourist arrivals to Sri Lanka. Furthermore, the results show that the accuracy of the best forecasting model based on MAPE criteria for the models of India, China, Germany, Russia, and Australia fall between 5 to 9 percent, whereas the accuracy levels of models for the UK, France, USA, Japan, and the Maldives fall between 10 to 15 percent.

A research study was carried out by Konarasinghe (2016) to study and focus on pattern recognition of tourist arrivals to Sri Lanka from various regions in the world. Monthly time series data from January 2008 to December 2014 are used in this study. The regions selected for the study were the top four in market position. They are; Asia, Western Europe, Eastern Europe and the Middle East. Descriptive statistics, Time Series plots and Auto Correlation Functions (ACF) were used for pattern identification and one way Analysis of Variance (ANOVA) was used for mean comparison of tourist arrivals from selected regions. The average arrivals of Asia and Western Europe are the highest 29361 and 25982 respectively. There is no significant difference between these two regions. Eastern Europe and the Middle East have 5866 and 4300 of average respectively. Arrivals from Asia, Western Europe, and Eastern Europe were not normally distributed, all were positively skewed. Data series of all four regions were non stationary. There is a significant difference of tourist arrival from Asian and Western Europe compared to other regions. It is recommended to test Moving Average Methods, Exponential Smoothing techniques, Decomposition techniques, linear and non-linear trend models and Circular model for forecasting arrivals.

Kurukulasooriya and Lelwala (2014) did a comprehensive study of time series behavior of the postwar international tourist arrivals. The empirical study is carried out based on outbound tourist arrivals from all origins that create a demand for tourism in Sri Lanka. The time span is covers from July 2009 to June 2013. In the modeling exercise, classical time series decomposition approach is employed. Mann-Kendall test evidenced for existing linear trend while Kruskal-Wallis tests confirmed the seasonality in tourism. Thus, linear trend component and seasonal fluctuations are the two prominent components whereas multiplicative model is comparatively the most accurate model in forecasting. Tourism sector is booming after the war in Sri Lanka with an approximate increase of 1200 tourists per month. Seasonality accounts for over 85 percent of seasonal variation in arrivals and the seasonal pattern which prevailed within the war period has considerably changed to a new behaviour. According to the Gini coefficient, seasonality reached to an equilibrium after the war and hence June, July and October are tourism months. Since the seasonality is a prominent component in international tourist arrivals, the results of the study recommend necessary arrangements to minimize the negative impact of seasonality in arrivals in respective months. Therefore, different categories of travellers should be focused in low demand periods to alleviate negative impact of seasonality.

Methodology

Unit Root Tests

To test the stationarity of a time series data the unit root test is used. In this research paper ADF test and Phillips-Perron test are used to check the stationarity.

ADF Test

Augmented Dickey-Fuller test (ADF) is an augmented version of the Dickey-Fuller test(DF) developed by two American Statisticians, David Dickey and Wayne Fuller (Dickey and Fuller, 1979). There are more complex and dynamic structures in many economic and financial time series than can be grasped by a simple autoregressive model. In those cases, this test is very useful and valid. Basic differences between DF and ADF tests, is that ADF has the ability to handle large and complex time series in analytical processes.

Testing procedure;

$$y_t = c + \beta t + \gamma y_{t-1} + \delta_1 \Delta Y_{t-1} + \ldots.. + \delta_{p-1} \Delta Y_{t-p+1} + \varepsilon_t \quad (1)$$

where c is constant, β is the coefficient of the time trend, p is the lag order of autoregressive process.

In the analysis processes pay more attention to the negative values obtained from the test statistics of ADF test. If the negative value is too high, then it has more ability to reject the null hypothesis.

Phillips-Perron test

It is used in time series analysis to test the null hypothesis that a time series I(1). It builds on the Dickey-Fuller test, but unlike the Augmented Dickey–Fuller test, which extends the Dickey-Fuller test by including additional lagged variables as regressors in the model on which test is based, the Phillips-Perron test makes a non-parametric correction to the t-test statistic. The test is robust with respect to unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation.

Conditional Volatility Models

A process, such as the GARCH processes, the conditional mean is constant but the conditional variance is nonconstant is an example of an uncorrelated but dependent process. The dependence of the conditional variance of the past causes the process to be dependent. The conditional volatility is conditioned on past values of itself and of model errors.

The Generalized ARCH(GARCH) model in which conditional variance is also a linear function of its own lags and has the following form and to be stationarity $\alpha + \beta < 1$,

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

The 'GJR' stands for Glosten, Jagannathan and Runkle. It is an asymmetric GARCH model. This means it allows for the variance to react differently depending on the sign or size of the shock it receives. The GJR model to be stationarity $\alpha + \frac{1}{2}\gamma + \beta < 1$. The GJR model is given as:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} [\alpha_i + \gamma_j I, \varepsilon_{t-i>0.1}] \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j} \quad (3)$$

The EGARCH model was developed to allow for asymmetric effects between positive and negative shocks on the conditional variance of future observations. In the EGARCH model, the conditional variance σ_t^2, is an asymmetric function of lagged disturbances.

The EGARCH model can be represented in the logarithm of conditional variance as:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{q} \left(\alpha_i \left| \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}} \right) + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2) \quad (4)$$

Results and Discussion

Unit Root Test Results

Standard unit root test based on the method of Augmented Dickey-Fuller and Phillips Perron are reported in Table 1.

Table 1: The result of unit root tests

	ADF		Phillips-Perron	
	level	1st difference	level	1st difference
Monthly arrivals	0.9558	0.0000***	0.6886	0.0000***
Quarterly arrivals	0.9794	0.0013***	0.0200	0.0001***
Annually arrivals	1.0000	0.0000***	0.9501	0.0000***

Notes:***denotes the null hypothesis of a unit root is rejected at the 5%significance level

The ADF test results and the Phillip-Perron test results for the coefficient is significant at the 1% level. Therefore, it can be confirmed that the series are stationary at first difference.

Volatility Model

The time series plot for the monthly international tourist arrivals in Sri Lanka from 1970 January to 2019 December is given in Figure 1. The largest number of tourists have arrived in 2018 December and the smallest number of tourists have arrived in 1971 May.

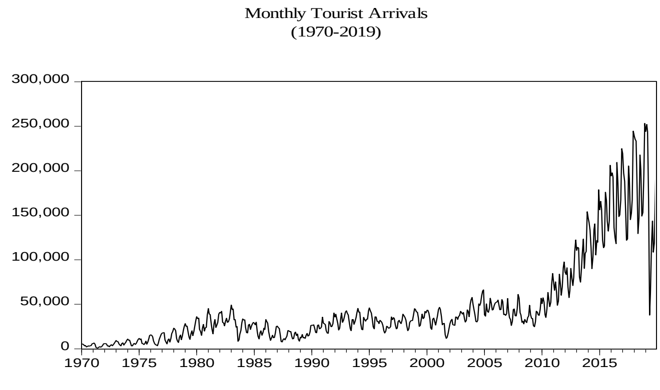

Figure 1: Monthly international tourist arrivals in Sri Lanka from 1970 to 2019

Descriptive statistics for monthly, quarterly and annually arrivals of international tourist in Sri Lanka from 1970 January to 2019 December is given in table 2.

Table 2: Descriptive Statistics - International tourist arrivals in Sri Lanka from 1970 to 2019

Statistics	Monthly arrivals (1970-2019)	Quarterly arrivals (1970-2019)	Annually arrivals (1970-2019)
Mean	46361.50	137220.7	536530.3
Median	30819.00	92481.00	386656.5
Maximum	253169.0	740600.0	2333796.
Minimum	952.0000	3452.000	39654.00
Std. Dev.	50336.79	147701.8	549834.4
Skewness	2.158909	2.093363	2.016308
Kurtosis	7.299688	6.839962	6.218382
Jarque Bera	928.6604	268.9499	55.45827
Probability	0.000000	0.000000	0.000000

Volatility clustering refers to the observation, Mandelbrot (1963), that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes". Volatility period tends to be followed by another volatile period that is volatile period that is volatile periods are usually clustered. Volatility cluster exist in Monthly, Quarterly and Annually volatility clusters in Figure 2.

GARCH (1,1), GJR (1,1) And EGARCH (1,1) For Conditional Volatility Model

The international tourist arrivals are used to estimate the GARCH (1,1), GJR (1,1) and EGARCH (1,1) model. All estimation was conducted using EViews-10. The parameters were estimated using QMLE for the case p=q=1 and the test results are in Table 2 to 5.

Table 3: Estimated GARCH(1,1) Model

	GARCH		
Parameters	Monthly arrivals	Quarterly arrivals	Annually arrivals
ω	1.44E+08***	26144315	5.56E+08
	(15639550)	(23962789)	(7.08E+08)
α	0.707***	0.474***	0.562**
	(0.106)	(0.180)	(0.235)
β	0.089***	0.586***	0.534**
	(0.032)	(0.136)	(0.239)
Second moment	0.796	1.06	1.096
AIC	21.698	23.720	25.800
BIC	21.735	23.802	25.994
Jarque Bera	8.628	21.364	1.978
P value	0.013	0.000	0.372

Notes: Numbers are parentheses are standard error. AIC and BIC denote the Akaike Information Criterioand Schwarz Criterion, respectively; *** denotes the estimated coefficient is statistically significant at 1%. **denotes the estimated coefficient is statistically significant at 5%. * denotes the estimated coefficient is statistically significant at 10%.

Fitting Of GARCH Model

The estimated GARCH (1,1) equation for monthly tourist arrivals is given in equation (5):

$$\sigma_t^2 = 1.44E{+}08 + 0.707\,\varepsilon^2_{t-1} + 0.089\,\sigma^2_{t-1} \quad (5)$$

The estimated GARCH (1,1) model of monthly tourist arrivals shows the short run persistence lies at 0.707, while the long run persistence lies at 0.796. In the monthly tourist arrivals, the respective estimate of the second moment conditions $\alpha_1+\beta_1 < 1$ for GARCH (1,1) are satisfied and the QMLE are consistent and asymptotically normal. But quarterly and annually arrivals not satisfied the second moment condition.

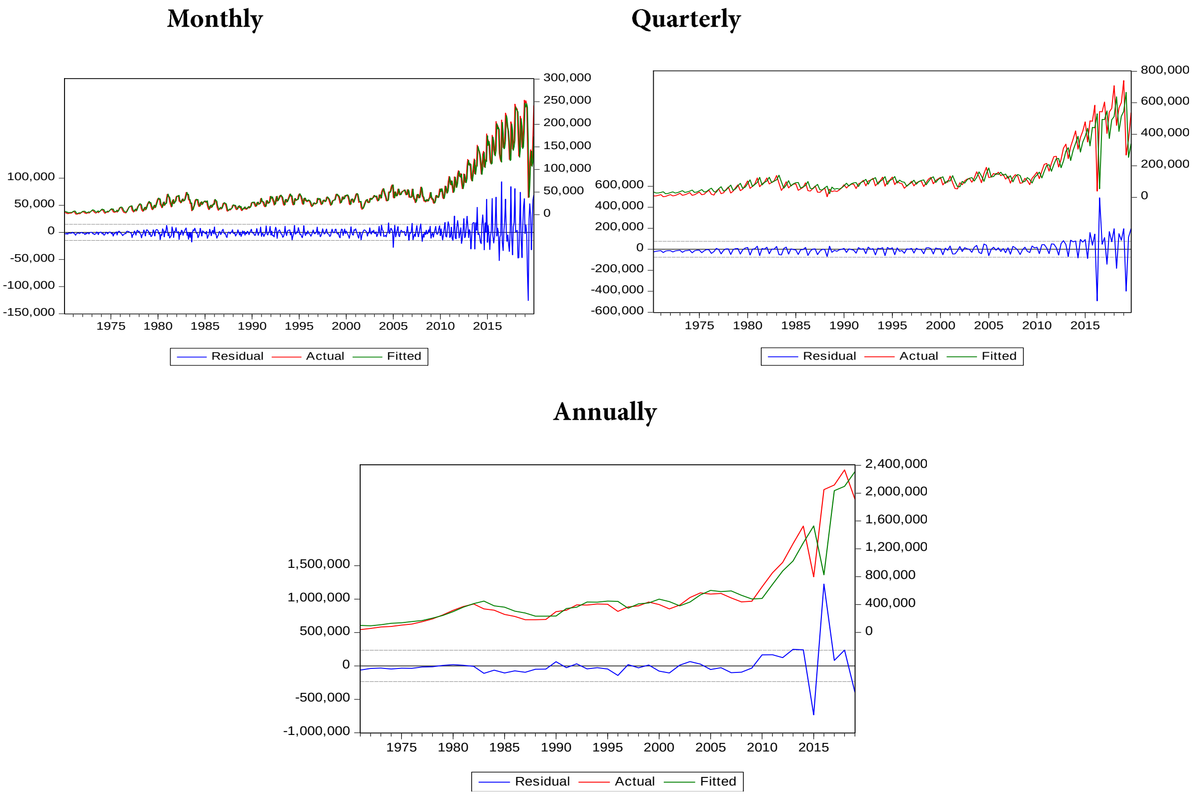

Figure 2: Volatility Clustering

Table 4: Estimated GJR(1,1) model

	GJR		
Parameter	Monthly arrivals	Quarterly arrivals	Annually arrivals
ω	1.43E+08***	3.73E+09***	4.14E+08
	(15700109)	(7.32E+08)	(5.75E+08)
α	0.164*	1.594*	0.528**
	(0.099)	(0.832)	(0.389)
β	0.122***	-0.002	0.522
	(0.028)	(0.024)	(0.228)
γ	1.118***	-1.361	0.242
	(0.306)	(0.897)	(0.728)
Second moment	0.286	1.592	0.764
AIC	21.670	24.618	25.817
BIC	21.714	24.718	26.049
Jarque Bera	19.613	4.381	2.115
P value	0.000	0.111	0.347

Notes: Numbers are parentheses are standard error. AIC and BIC denote the Akaike Information Criterion and Schwarz Criterion, respectively; *** denotes the estimated coefficient is statistically significant at 1%. **denotes the estimated coefficient is statistically significant at 5%. * denotes the estimated coefficient is statistically significant at 10%.

Table 5: Estimated EGARCH(1,1) Model

	EGARCH		
Parameter	Monthly arrivals	Quarterly arrivals	Annually arrivals
ω	-0.102**	-0.064	29.217***
	(0.041)	(0.595)	(4.308)
α	0.132***	0.494***	1.728***
	(0.035)	(0.157)	(0.327)
γ	0.066	0.212*	-0.262*
	(0.0411)	(0.188)	(0.197)
β	1.000***	0.983***	0.320*
	(0.002)	(0.032)	(0.183)
AIC	20.479	23.678	26.152
BIC	20.522	23.777	26.384
Jarque Bera	7.097	25.416	4.321
P value	0.028	0.000	0.115

Notes: Numbers are parentheses are standard error. AIC and BIC denote the Akaike Information Criterion and Schwarz Criterion, respectively; *** denotes the estimated coefficient is statistically significant at 1%. **denotes the estimated coefficient is statistically significant at 5%. * denotes the estimated coefficient is statistically significant at 10%.

Fitting Of GJR-GARCH Model

The estimated GJR-GARCH (1,1) equation for monthly tourist arrivals is given in equation (6):

$$\sigma_t^2 = 1.43E{+}08 + 0.164\, \varepsilon^2_{t-1} - 1.182\, I\varepsilon^2_{t-1} + 0.122\, \sigma^2_{t-1} \tag{6}$$

The GJR-GARCH (1,1) model in monthly tourist arrivals shows the asymmetry coefficient is found to be positive and significant, namely 0.164 which indicates that decreases in monthly international tourist arrivals to Sri Lanka increase volatility, and namely 0.528 which indicates that decreases in annually international tourist arrivals to Sri Lanka increase volatility. As the respective estimates of the second moment conditions, $\alpha_1+\frac{1}{2}\gamma_1+\beta_1 < 1$ for GJR-GARCH(1,1). In monthly tourist arrivals long run persistence lies at 0.286 and in annually tourist arrivals long run persistence lies at 0.764 thus, second moment conditions for GJR-GARCH (1,1) are satisfied for monthly and annually tourist arrivals. In monthly tourist arrivals, as γ_1 is estimated significant and $\alpha_1+\gamma_1 > \alpha_1$, volatility is affected asymmetrically.

Fitting Of EGARCH Model

The estimated EGARCH (1,1) equation for annually tourist arrivals is given in equation (7):

$$\log(\sigma_t^2) = 29.217 + 1.728\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - 0.262\,\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + 0.320\log(\sigma_{t-1}^2) \tag{7}$$

For international tourist arrivals, EGARCH (1,1) estimates statistically significant for annually arrivals, with the size of effect α=1.728 being positive which shows there is a positive relation between past variance and current variance in absolute value. This means the bigger the magnitude of the shock to the variance, then higher the volatility. γ =-0.262 being negative which indicates that bad news will increase volatility more than good news of the same size evidence of leverage effect $\gamma<0$ it implies that bad news generates larger volatility. The coefficient of the lagged dependent variable β, is estimated to be 0.320, which suggest that the statistical properties of the QMLE for EGARCH (1,1) will be consistent and asymmetrically normal.

Conclusions

Models GARCH (1,1) and GJR-GARCH (1,1) are statistically significant for monthly arrivals and QMLE are consistent and asymptotically normal. The model EGARCH (1,1) is statistically significant for annually arrivals data and QMLE are consistent and asymptotically normal. According to the GJR-GARCH model 0.164 decrease in international tourist arrivals to Sri Lanka increase volatility. The models GARCH (1,1) and GJR-GARCH (1,1) are conditional volatility in the international tourist arrivals to Sri Lanka and sensitive to the long memory nature. Moreover, EGARCH (1,1) model is conditional volatility and sensitive to the short memory nature.

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