Chapter 4

Value at Risk of International Tourist Arrivals to Thailand

Value-at-Risk and tourism: Value-at-Risk is a procedure designed to forecast the maximum expected negative return over a target horizon, given a confidence limit. VaR measures an extraordinary loss on an ordinary or typical day. VaR is widely used to manage the risk exposure of financial institutions and is the requirement of the Basel Capital Accord. The central idea underlying VaR is that by forecasting the worst possible return for each day, institutions can prepare for the worst case scenario. In the case of Thailand where tourism revenue is a major source of income and foreign exchange reserve, it is important to understand the risk associated with this particular source of income and to implement adequate risk management policies to ensure economic stability and sustained growth.

The VaR forecast for the growth rate of tourist arrivals at any time t is given by, $VaR = E(Y_t | F_{t-1}) - \alpha\sqrt{h_t}$, where $E(Y_t | F_{t-1})$ is the forecasted expected growth rate of tourist arrivals, and h_t is the conditional volatility.

This chapter is a revised version from the original paper presented at the Third Conference of the Thailand Econometric Society, Chiang Mai, Thailand in Appendix B.

Abstract

This paper examines Value at Risk (VaR) of International Tourist Arrivals to Thailand using monthly time series data for the period 1976-2009. As Thailand has been a significant source of a substantial number of tourists, international tourist arrivals to Thailand needs to be analyzed and estimated for future planning. Being a major foreign exchange earner and an important source of job creation for Thailand, tourism is an important industry.

In this study we will consider the volatility of international tourist arrivals to Thailand by employing a VaR model. VaR is widely used to manage the risk exposure of financial institutions and is the requirement of the Basel Capital Accord. The central idea underlying VaR is that, by forecasting the worst possible return for each day, institutions can prepare for the worst case scenario. Forecasted VaR figures can be used to estimate the level of reserves required to sustain desired long-term government projects and foreign exchange reserves.

International tourists are divided into three types which are short haul, medium haul and long haul. Malaysian tourists represent short haul tourists. Japanese tourists represent medium haul tourists. And British and American tourists represent long haul tourists.

Finally, we can conclude that the VaR of short haul tourists are higher than medium haul and long haul tourists. And hence tourism tax revenue of short haul and medium haul tourists are higher than long haul tourists.

Keyword: Value at Risk (VaR), Tourism tax

4.1 Rational backgrounds and research question

4.1.1 Rational backgrounds

(see Table 4.1) The World Tourism Organization (WTO) estimated that the average growth of international tourists in 2005 would be 5.5% (lower than in 2004, when the growth of world tourism experienced a 10% expansion), with 808 million international tourists. However, the tourism industry saw a slowdown as a result of the world economic downturn. The region which was expected to grow at a higher rate was Asia Pacific (+10%) owing to the fact that tourists paid more attention to finding new attractions in this region, especially in Cambodia, Vietnam, India and China, where there was high growth in the number of visitors. Other regions at the lower ranks were Africa (+7%), the Americas (+6%), Europe (+4%), and the Middle East (+3%), respectively. (Tourism Authority of Thailand, 2007)

Table 4.1 Number of International tourist arrivals to Thailand 1997-2006

Year	International						
	Tourist		Average	Average Expenditure		Revenue	
	Number	Change	Length of Stay	/person/day	Change	Million	Change
	(Million)	(%)	(Days)	(Baht)	(%)	(Baht)	(%)
1997/1	7.22	+0.41	8.33	3,671.87	-0.92	220,754	+0.63
1998/1	7.76	+7.53	8.40	3,712.93	+1.12	2421177	+9.70
1999/1	8.58	+10.50	7.96	3,704.54	-0.23	253,018	+4.48
2000/1	9.51	+10.82	7.77	3,861.19	+4.23	285,272	+12.75
2001/1	10.06	+5.82	7.93	3,748.00	-2.93	299,047	+4.83
2002/1	10.80	+7.33	7.98	3,753.74	+0.15	323,484	+8.17
2003/1	10.00	-7.36	8.19	3,774.50	+0.55	309,269	-4.39
2004/1	11.65	+16.46	8.13	4,057.85	+7.51	384,360	+24.28
2005/1	11.52	-1.51	8.20	3,890.13	-4.13	367,380	-4.42
2006/1	13.82	+20.01	8.62	4,048.22	+4.06	482,319	+31.29

Source : Tourism Authority of Thailand: 19 December 2007
Note:/1 = actual

In Thailand, the tsunami and disturbance in the three southern provinces, as well as the increased market competition in new destinations (Vietnam, China, India) and tourism product creation (Japan, Hong Kong, and Korea) were key factors of Thailand's slow tourism growth in 2005, with 11.52 million inbound visitors, a 1.15 % decrease from the previous year. However, this slowdown is not that severe due to the attempt by the public and private sectors to stimulate markets and rebuild the tourist attractions affected by the disaster as fast as possible. This resulted in an only slight impact of the above-mentioned factors on the Thai tourism industry.

Considering the number of tourist arrivals and Thailand international tourism receipts, it was found that the majority of tourists are from Malaysia and Japan. This study can be used to compare with the USA and the UK for making policy because of the difference in tourism volatility. The sustainable tourism is also considered with regards to the policy for Thailand tourism future development.

Note: Malaysian tourists are "short haul" tourists, Japanese tourists are "medium haul" tourists as well as UK and American tourists are "long haul" tourists.

4.1.2 Research question

How the volatility of long haul, medium haul and short haul tourism affects the environment (eco-tourism) and determines tourism taxes.

4.2 Research methodology and literature review

4.2.1 Unit root tests

4.2.1.1 Augmented Dickey and Fuller tests

To test for the long run frequency, Dickey and Fuller (1979) proposed a procedure based on the following auxiliary regression:

$$\Delta y_t = \alpha + \beta t + \delta y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-k} + \varepsilon_t \qquad (4.1)$$

where $\Delta y_t = (1-L)$ designates the first different filter, ε_t is the error term and α , β and δ are the parameters to be estimated.

4.2.1.2 Phillips and Perron tests

The Phillips-Perron test is a unit root test. It is used in time series analysis to test the null hypothesis that a time series is 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 the test is based, the Phillips-Perron test makes a non-parametric correction to the t-test statistic to capture the effect of autocorrelation present when the underlying autocorrelation process is not AR(1) and the error terms are not homoscedastic.

For analyzing the volatility, we use econometrics as follows:

4.2.2 Volatility Analysis

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4.2.2.1 Conditional Mean Model

The conditional mean model is to the autoregressive moving average, or ARMA (p, q) model that is proposed by Box-Jenkins (1970) combining the AR (p) and MA (q). Such a model states that the current value of some series *y* depends linearly on its own previous values plus a combination of current and previous values of a white noise error term. The model could be written:

$$\beta(L) y_t = \mu + \theta(L) \mu_t \qquad (4.2)$$

where

$\beta(L) = 1 - \beta_1 L - \beta_2 L^2 - \cdots - \beta_p L^p$ and $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$

or

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \mu_t + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \cdots + \theta_q \mu_{t-q}, \quad (4.3)$$

with

$$E(\mu_t) = 0\,; E(\mu_t^{\,2}) = \sigma^2\,; E(\mu_t \mu_s) = 0,\ t \neq s$$

where $y_t, y_{t-1},..., y_{t-p}$ represent the current and lagged growth rate of tourist arrivals, p is the lag length of the AR error term, and q is the lag length of the MA error term.

If there are the seasonal effects, it will be the seasonal autoregressive moving average, or SARMA $(P,Q)_T$, model is given below:

$$y_t = \alpha + \beta_T y_{t-T} + \beta_{2T} y_{t-2T} + \cdots + \beta_{PT} y_{t-PT} + \mu_t + \theta_T \mu_{t-T} + \theta_{2T} \mu_{t-2T} + \cdots + \theta_{QT} \mu_{t-QT}, \quad (4.4)$$

where $y_t, y_{t-T},..., y_{t-PT}$ represent the current and lagged growth rate of tourist arrivals, P is the lag length of the SAR error term, and Q is the lag length of the SMA error term.

The series is described by an AR integrated MA model or ARIMA (p,d,q) when y_t is replaced by $\Delta_1^d y_t$ and an SAR integrated SMA model or SARIMA $(P,D,Q)_T$ when y_t is replaced by $\Delta_1^D y_t$.

When we already construct the conditional mean model, after that we will construct the conditional volatility model latter.

4.2.2.2 Conditional Volatility Model

We use value at risk (VaR) to measure risks from the growth in number of tourist arrivals that affect the environment. In this paper, the symmetric Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model of Bollerslev (1986), and the asymmetric GJR model of Glosten, Jagannathan and

Runkle (1992), which discriminates between positive and negative shocks to the tourist arrivals series will be used to forecast the required conditional volatilities.

The GARCH (p, q) model is given as $(i)\ Y_t = E(Y_t | F_{t-1}) + \varepsilon_t$ where $(ii)\ \varepsilon_t = h^{1/2}\eta_t$,

$$(iii)\ h_{it} = \omega_i + \sum_{l=1}^{p} \alpha_i \varepsilon_{i,t-1}^2 + \sum_{l=1}^{q} \beta_i h_{i,t-1} \tag{4.5}$$

The GJR (p, q) model is given as $(i)\ Y_t = E(Y_t | F_{t-1}) + \varepsilon_t$ where $(ii)\ \varepsilon_t = h^{1/2}\eta_t$,

$$(iii)\ h_{it} = \omega_i + \sum_{l=1}^{p} (\alpha_i \varepsilon_{i,t-1}^2 + \gamma I(\eta_{i,t})\varepsilon_{i,t-1}^2) + \sum_{l=1}^{q} \beta_i h_{i,t-1} \tag{4.6}$$

$$(iv)\ I(\eta_{i,t}) = 1, \varepsilon_{i,t} \le 0 \quad and \quad = 0, \varepsilon_{i,t} > 0$$

where F_t is the information set variable to time t, and $\eta : iid(0,1)$. The four equations in the model state the following : (i) the growth in tourist arrivals depends on its own past values; (ii) the shock to tourist arrivals has a predictable conditional variance component, h_t, and an unpredictable component, η_t; (iii) the conditional variance depends on its own past values and the recent shocks to the growth in the tourist arrivals series; and (iv) the conditional variance is affected differently by positive and negative shocks to the growth in tourist arrivals.

For the GARCH (1, 1) to be stationary, we need

$$\alpha_1 + \beta_1 < 1 \tag{4.7}$$

For the GJR (1, 1) to be stationary, we need

$$\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1 < 1 \qquad (4.8)$$

In equations (4.5) and (4.6), the parameters are typically estimated by the maximum likelihood method to obtain Quasi-Maximum Likelihood Estimators (QMLE) in the absence of normality of η_t, the conditional shocks (or standardized residuals). The conditional log-likelihood function is given as follows:

$$\sum_{t=1}^{n} \ell_t = -\frac{1}{2}\sum_{t=1}^{n}\left(\log h_t + \frac{\varepsilon_t^2}{h_t} \right)$$

The QMLE is efficient only if η_t is normal, in which case it is the MLE. When η_t is not normal, the adaptive estimation can be used to obtain efficient estimators, although this can be computationally intensive. Ling and McAleer (2003b) investigated the properties of adaptive estimators for univariate non-stationary ARMA models with GARCH (*r, s*) errors. The extension to multivariate processes is complicated.

Value-at-Risk and tourism: Value-at-Risk is a procedure designed to forecast the maximum expected negative return over a target horizon given a confidence limit. VaR measures an extraordinary loss on an ordinary day. VaR is widely used to manage the risk exposure of financial institutions and is the requirement of the Basel Capital Accord. The central idea underlying VaR is that by forecasting the worst possible return for each day, institutions can prepare for the worst case scenario. In the case of Thailand where tourism revenue is a major source of income and foreign exchange reserve, it is important to understand the risk associated with this particular source of income and to implement adequate risk management policies to ensure economic stability and sustained growth. Forecasted VaR figures can be used to estimate the level of reserves required to sustain desired long term government projects and foreign exchange reserves. Moreover, an understanding of the variability of tourist arrivals and tourism related revenue is critical for any investor planning to invest in or lend fund to supply side.

Normally, a VaR threshold is the lower bound of a confidence interval in terms of the mean. For example, suppose interest lies in modeling the random variable Y_t, which can be decomposed as $Y_t = E(Y_t|F_{t-1}) + \varepsilon_t$ .This decomposition suggests that Y_t is comprised of a predictable component, $E(Y_t|F_{t-1})$, which is the conditional mean, and a random component, ε_t. The variability of Y_t, and therefore its distribution, is determined entirely by the variability of ε_t. If it is assumed that ε_t follows distribution such that $\varepsilon_t : D(\mu_t, \sigma_t)$ where μ_t and σ_t are the unconditional mean and standard deviation of ε_t, respectively, these can be estimated using numerous parametric and/or non-parametric procedures. Therefore, the VaR threshold for Y_t can be calculated as $VaR_t = \mu_i - \alpha\sigma_i$ where α is the critical value from the distribution of ε_t that gives the correct confidence level.

4.2.3 Literature Review

In volatility analysis, Michael McAleer, Riaz Shareef and Bernardo da Veiga (2005) studied a risk management framework of daily tourist tax revenues for the Maldives, which was a unique SITE (Small Island Tourism Economies) because it relied almost entirely on tourism for its economic and social development. Daily international arrivals to Maldives and their associated growth rates were analyzed for the period 1994-2003. This seemed to be the first analysis of daily tourism arrivals and growth rates data in the tourism research literature.

The primary purpose for analyzing volatility was to model and forecast the Value-at-Risk (VaR) thresholds for the number of tourist arrivals and their growth rates. This would seemed to be the first attempt in the tourism research literature to apply the VaR portfolio management approach to manage the risks associated with tourism revenues. The empirical results based on two widely-used conditional volatility models showed that volatility was affected asymmetrically by positive and negative shocks, with negative shocks to the growth in tourist arrivals having a greater impact on volatility than previous positive shocks of a similar magnitude. The forecasted VaR threshold represented the maximum expected negative growth rate that could be expected given a specific confidence level. Both conditional volatility models led to the same average VaR at -6.59%, which meant that the lowest possible growth rate in daily tourists in residence, and hence in tourist tax revenues, was expected to be -6.59% at the 99% level of confidence. This should be useful information for the Maldivian government and private tourism service providers in the Maldives.

Riaz Shareef and Michael McAleer (2007) showed how the GARCH(1,1) model and the GJR (1,1) model could be used to measure the conditional volatility in monthly international tourist arrivals to six SITEs, namely Barbados, Cyprus, Dominica, Fiji, Maldives and Seychelles, and to appraise the implications of conditional volatility of SITEs for modeling tourist arrivals. For the logarithm of monthly international tourist arrivals, the estimates of the conditional volatility using GARCH (1, 1) and GJR (1, 1) were highly satisfactory. The sufficient conditions to ensure positivity of the conditional variance were met for all six SITEs, except for Maldives. It was worth noting that the empirical log-moment and second moment conditions were satisfied for both models and all six SITEs, which indicated model adequacy for policy analysis and formulation. The asymmetric effects were generally satisfactory, with the exception of Dominica. This implies that the effect of positive shocks on conditional volatility was greater than negative shocks in the short and long run. Thus, the results for Dominica suggested that an unexpected fall in monthly international tourist arrivals decreases the uncertainty about future monthly international tourist arrivals, which was contrary to the results for the other five SITEs.

For volatility analysis, Michael McAleer et al. (2005) studied a risk management framework of daily tourist tax revenues for the Maldives using value at risk (VaR) to measure the risk from growth of the number of tourist arrivals affecting the environment. The GARCH (1, 1) and the GJR (1, 1) were used to forecast the required conditional volatilities. Riaz Shareef, et al. (2007) showed how the GARCH (1, 1) model and the GJR (1, 1) model could be used to measure the conditional volatility in monthly international tourist arrivals to six SITEs. Their results also show that the GARCH (1, 1) and the asymmetric GJR (1, 1) models provide an accurate measure of risk.

In studies from literature reviews we will estimate and forecast by using the GARCH (1, 1) and the asymmetric GJR (1, 1) in the conditional volatility model.

4.3 Objective of this Study

To analyze the volatility from the growth of the number of tourist arrivals that affects the environment (eco-tourism) and determines tourism taxes.

4.4 Data Collection

Based on the above methodology we can divide data collection as follows: we used the secondary data from 1976 to 2009. The data used to measure the independent and dependent variables are from the Tourism Authority of Thailand (TAT), the Bank of Thailand (BOT), and Immigration Bureau (Police Department).

Note the three important dips in the tourist activity for the periods 1991, 1997 and 2005, respectively. The first period is due to the negative impact of the Gulf War of 1991.The second is due to the "Tomyumkung" economics crisis of 1997 in which the Asian tourist market seemed to be the most affected. The third period is due to the Tsunami disaster of 2004.

Moreover, there exists a direct relationship between the monthly total tourist arrivals by residence and the government policy to keep tourism taxes in case of higher number of tourists exceed the maximum limit by using the outcome from VaR (Value at Risk), GARCH and GJR to find out the answer for the government to launch the direct tourism policy for earning the best results.

4.5 Unit Root Tests

Standard unit root test based on the methods of Augmented Dickey-Fuller (1979) and Phillips and Perron (1988) are reported in Table 4.2.

The ADF tests for a unit root are used for logarithmic variable series over the full sample period. Note that the ADF tests of the unit root null hypothesis correspond to the following one-sided test:

$$H_0 : \delta = 0$$

$$H_1 : \delta < 0$$

The ADF test results are confirmed by the Phillip-Perron test and the coefficient is significant at the 5% level. The results of the ADF unit root tests are that when the ADF test statistics are compared with the critical values from the nonstandard Dickey-Fuller distribution, the former for all of variable series are less than the critical value at 5% significance level. Thus, the null hypothesis of a unit root is rejected at the 5% level, implying that the series are stationary. By taking first differences of the logarithm of variables, the ADF tests show that the null hypothesis of a unit root is clearly rejected. The ADF statistics for the series are less than the critical value at the 5% significance level. Thus, the first differences of the logarithmic variables are stationary. These empirical results allow the use of this data to estimate conditional mean and conditional volatility model.

Table 4.2 the result of unit root tests

Variable	ADF Without trend		PP Without trend	
	level	1st difference	level	1st difference
DTN	-7.6671***	-14.9299***	-33.4911***	-30.6096***
DNM	-4.9960***	-12.9948***	-37.5955***	-277.6326***
DNJ	-5.8683***	-16.9183***	-31.2189***	-108.3260***
DNUK	-3.8053***	-13.1170***	-20.9481***	-61.4773***
DNUS	-4.4828***	-20.5141***	-31.2214***	-77.3335***

Notes:

1. DTN denotes the growth rate of total number of tourist arrivals, DNM denotes Malaysian tourist arrivals, DNJ denotes the growth rate of Japanese tourist arrivals, DNUK denotes the growth rate of United Kingdom tourist arrivals, and DNUS denotes the growth rate of American tourist arrivals

2. *** denotes the null hypothesis of a unit root is rejected at the 1% level.

4.6 Volatility Model

The number and graph for total monthly tourist arrivals, monthly Malaysian tourist arrivals, monthly Japanese tourist arrivals, monthly UK tourist arrivals, and monthly American tourist arrivals are given in figure 4.1-4.5 and table 4.3-4.5, respectively. All data displays degrees of variability and seasonality. The highest levels of tourism arrivals to Thailand occur during the winter season in East Asia, Europe and North America, while the lowest levels occur during the summer season in East Asia, Europe and North America. The descriptive statistics are given in table 4.4. The total amount of tourist arrivals have a mean of 498,513.9 arrivals per month, a maximum of 1,521,816 arrivals per month, and a low minimum of 74,611 arrivals per month. Furthermore, the monthly Japanese tourist arrivals display the greatest variability with the mean of 59,159.07 arrivals per month, a maximum of 127,334 arrivals per month, and a low minimum of 13,117 arrivals per month. The monthly Japanese tourist arrivals have a standard deviation of 33,953.08, which is the highest standard deviation of all.

As the focus of this paper is not concerned with behavior of international tourist arrivals to Thailand, but is on managing the risk associated with the variability in tourist arrivals and the policy to collect tourist taxes. The paper focuses on modeling the growth rate, namely the return in tourist arrivals. The graph for the returns in total monthly tourist arrivals, Malaysian tourist arrivals, Japanese tourist arrivals, UK tourist arrivals and American tourist arrivals are given in figures 4.6-4.10, respectively. The descriptive statistics for the growth rates are given in table 4.5. Total monthly tourist arrivals display the variability, with the standard deviation of 13.15%, a maximum of 46.12%, and a minimum of -45.32%. Furthermore, monthly

Malaysian tourist arrivals display the greatest variability, with a standard deviation 29.24%, a maximum of 126.61%, and a minimum of -59.65%. Each of the data is found to be non-normal distributed, based on the Jaque-Bera Lagrange multiplier statistics for normality.

Table 4.3 Accumulation of the number of tourist arrivals to Thailand

Accumulation of total number of tourist arrivals by residence (1976-2009)	Accumulation of Malaysian tourist arrivals (1979-2009)	Accumulation of Japanese tourist arrivals (1979-2009)	Accumulation of United Kingdom tourist arrivals (1979 -2009)	Accumulation of American tourist arrivals (1979-2009)
191,429,339	25,975,942	20,587,357	8,793,307	9,140,592

Table 4.4 Descriptive Statistics (monthly arrivals)

Statistics	Total number of tourist arrivals (1976-2009)	Malaysian (1979-2009)	Japanese (1979-2009)	UK (1979-2009)	American (1979-2009)
Mean	498,513.90	74,643.51	59,159.07	25,268.12	26,266.07
Median	444,007.00	70,933.50	54,765.50	21,083.50	24,014.50
Maximum	1,521,816	182,982	127,334	86,210	67,176
Minimum	74,611	11,465	13,117	2,958	5,927
Std. Dev.	332,358.20	32,983.87	33,953.08	18,968.30	14,399.76
Skewness	0.6648	0.5073	0.2621	0.8530	0.6653
Kurtosis	2.5176	3.1577	1.7428	2.8465	2.5916
Jarque Bera	32.0079	15.3127	26.9021	42.5431	28.0913
Probability	0.0000	0.000473	0.00001	0.0000	0.000001

Table 4.5 Descriptive Statistics for Growth Rate (monthly arrivals)

Statistics	Total number tourist arrivals (1976-2009)	Malaysian (1979-2009)	Japanese (1979-2009)	United Kingdom (1979-2009)	American (1979-2009)
Mean	1.5984	4.6727	2.5511	2.5459	2.3475
Median	2.3579	1.1012	2.5478	1.7017	-0.9065
Maximum	46.1240	126.6085	69.5582	69.9248	103.4871
Minimum	-45.316	-59.6502	-44.2007	-48.0263	-40.8867
Std. Dev.	13.1450	29.2423	20.5580	18.9440	19.5069
Skewness	-0.1465	0.7733	0.2195	0.5731	1.4645
Kurtosis	2.8757	4.1532	3.0172	3.6419	7.0056
Jarque-Bera	0.6180	53.8135	2.7900	24.9524	356.0243
Probability	0.4452	0.0000	0.2478	0.0000	0.0000

Figure 4.1 Total monthly international tourist arrivals from 1976-2009

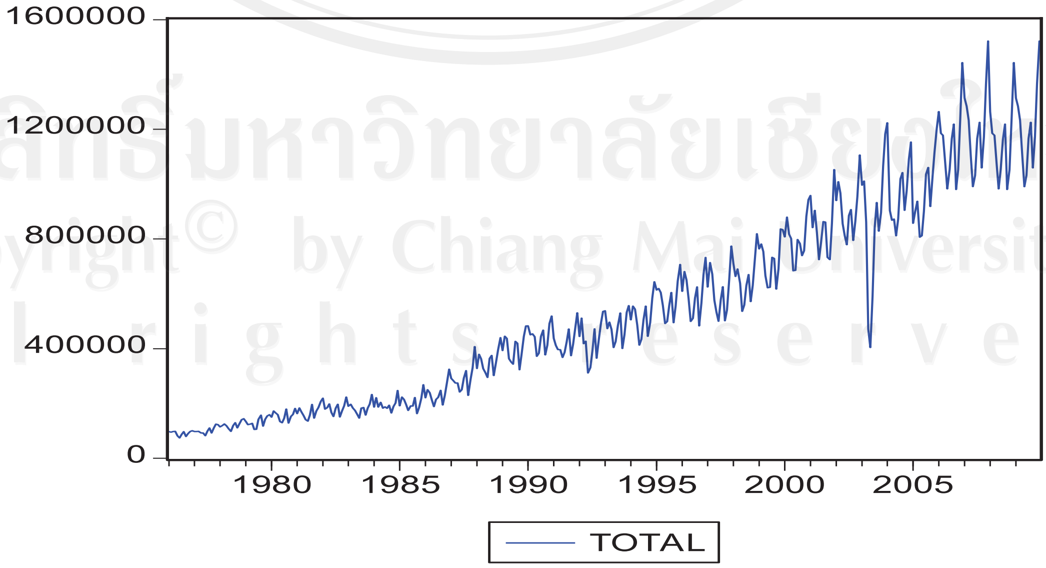


Figure 4.2 Monthly Malaysian tourist arrivals from 1979-2009

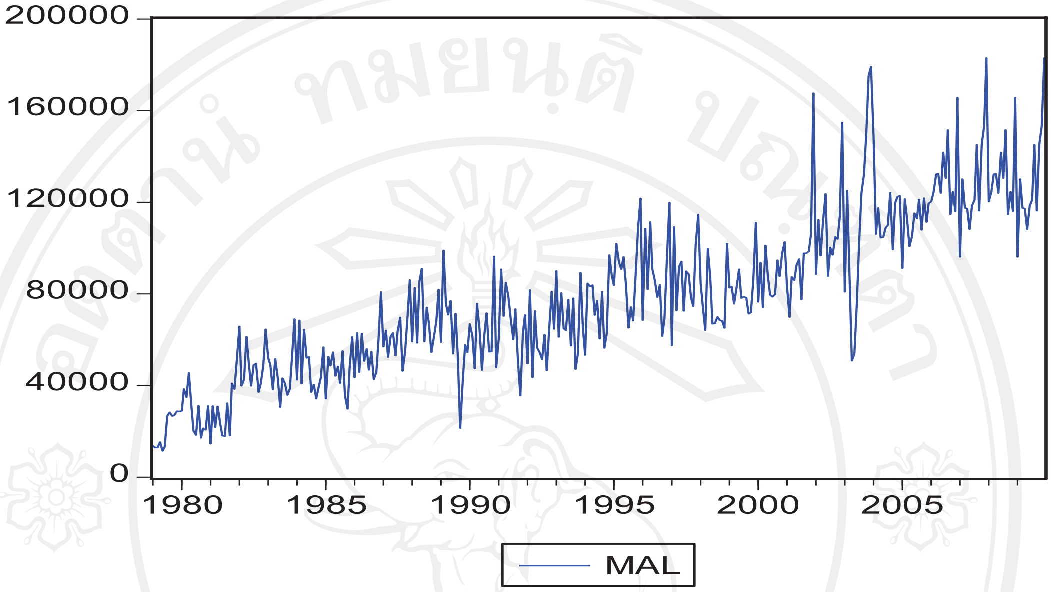


Figure 4.3 Monthly Japanese tourist arrivals from 1979-2009

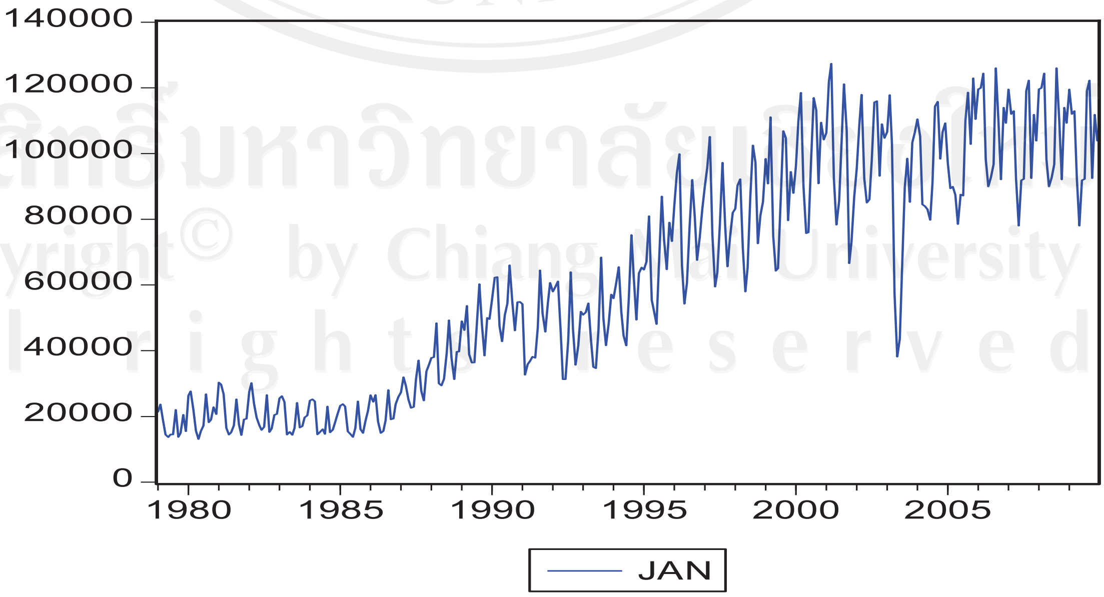


Figure 4.4 Monthly UK tourist arrivals from 1979-2009

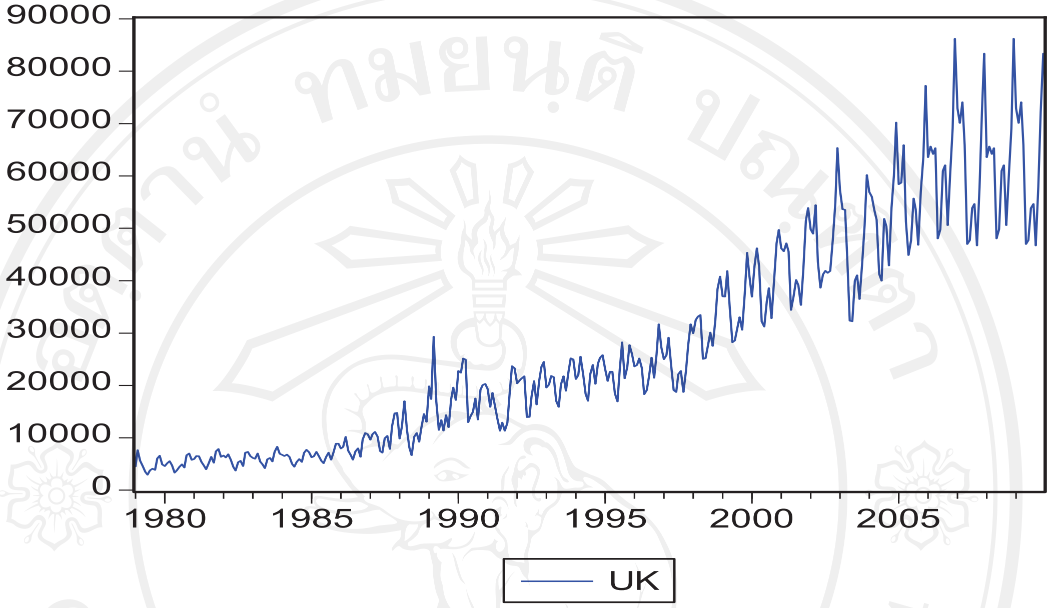


Figure 4.5 Monthly American tourist arrivals from 1979-2009

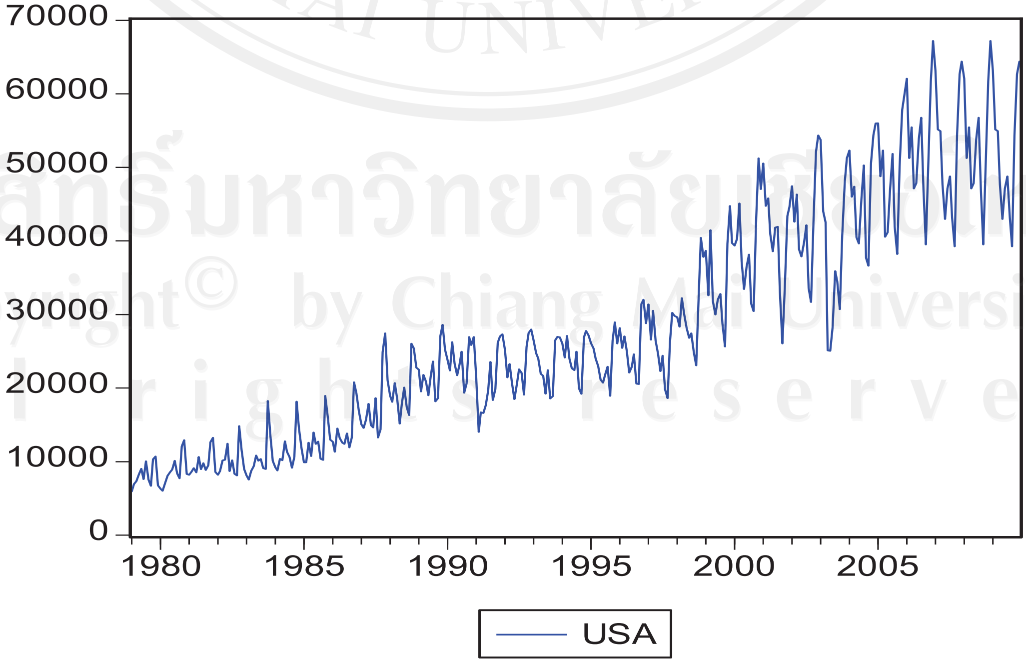


Figure 4.6 Total monthly tourist arrival growth rates from 1976-2009

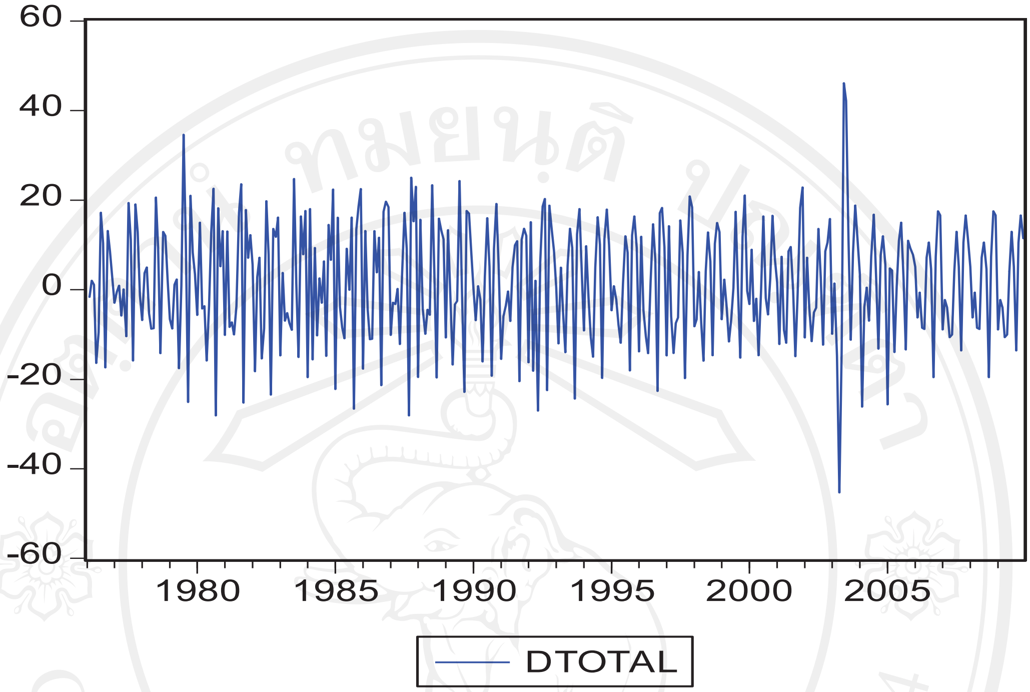


Figure 4.7 Monthly Malaysian tourist arrival growth rates from 1979-2009

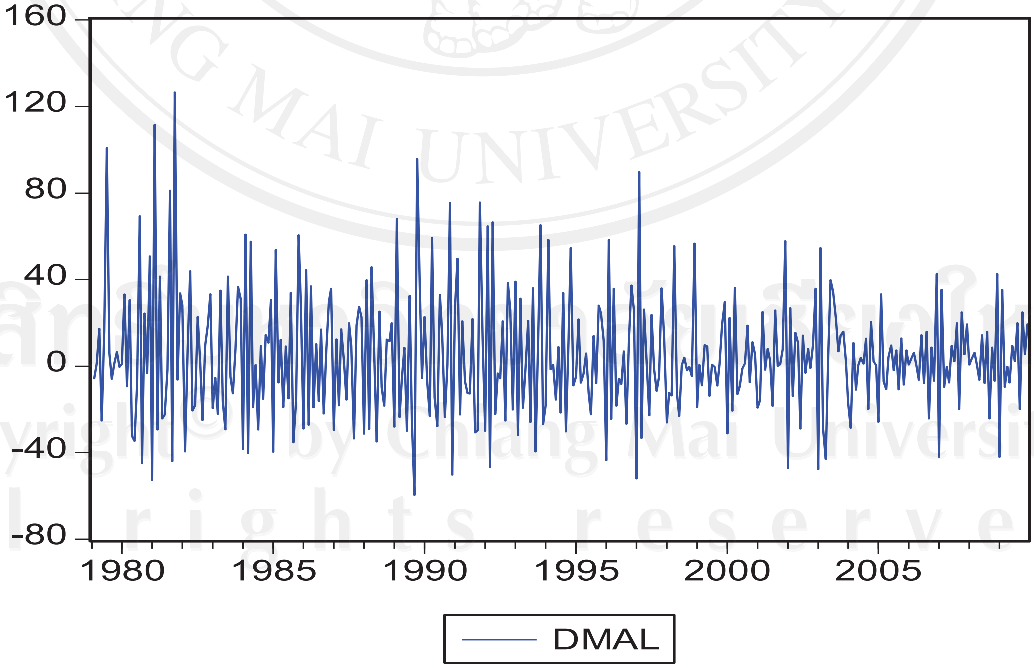


Figure 4.8 Monthly Japanese tourist arrival growth rates from 1979-2009

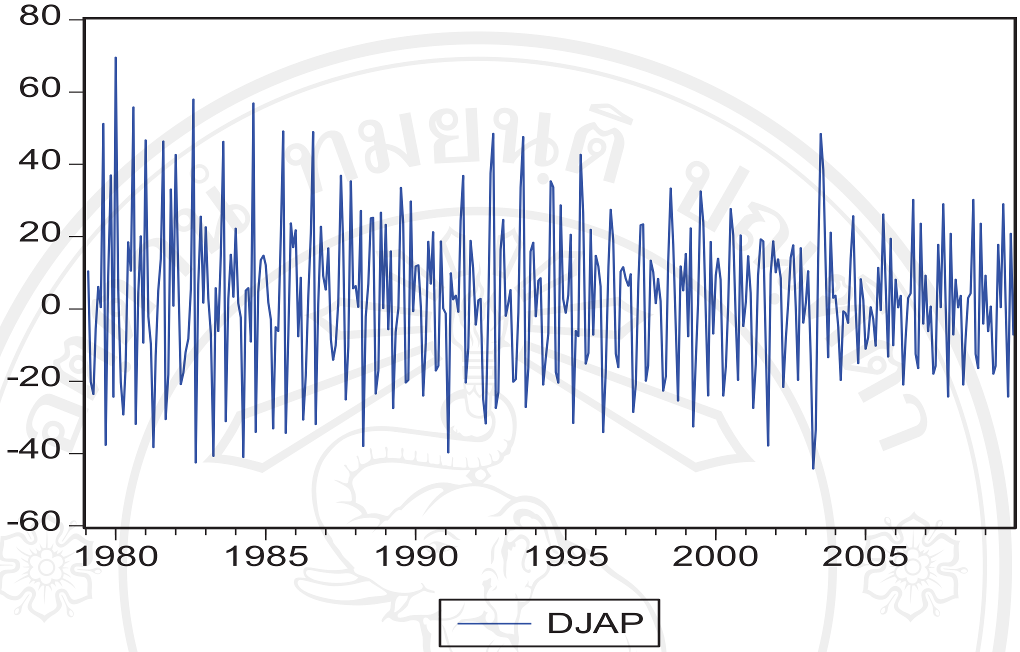


Figure 4.9 Monthly UK tourist arrival growth rates from 1979-2009

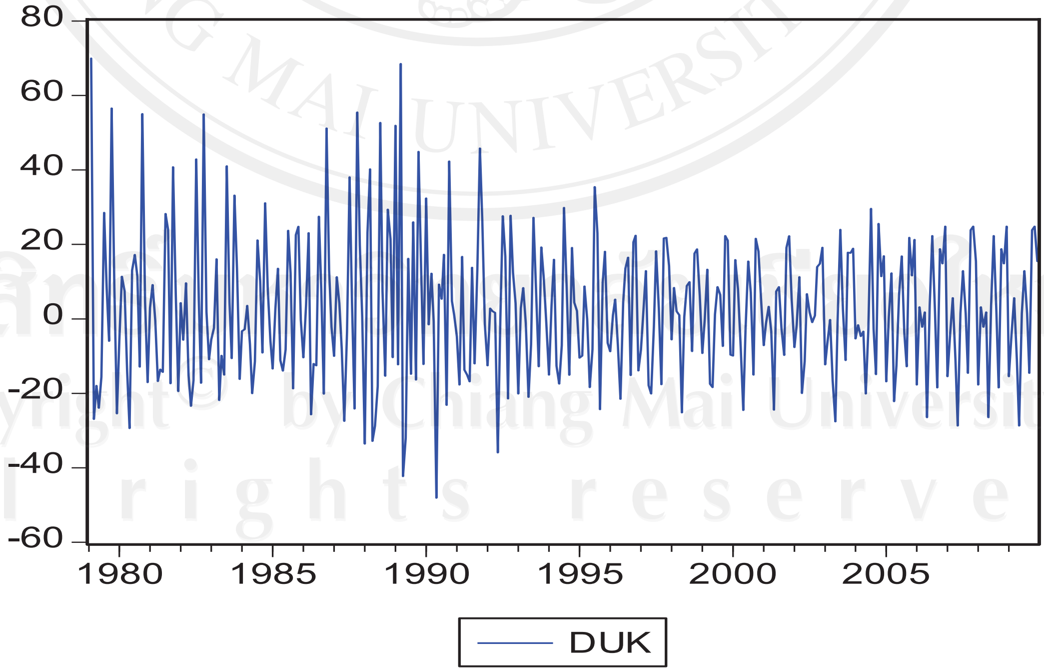
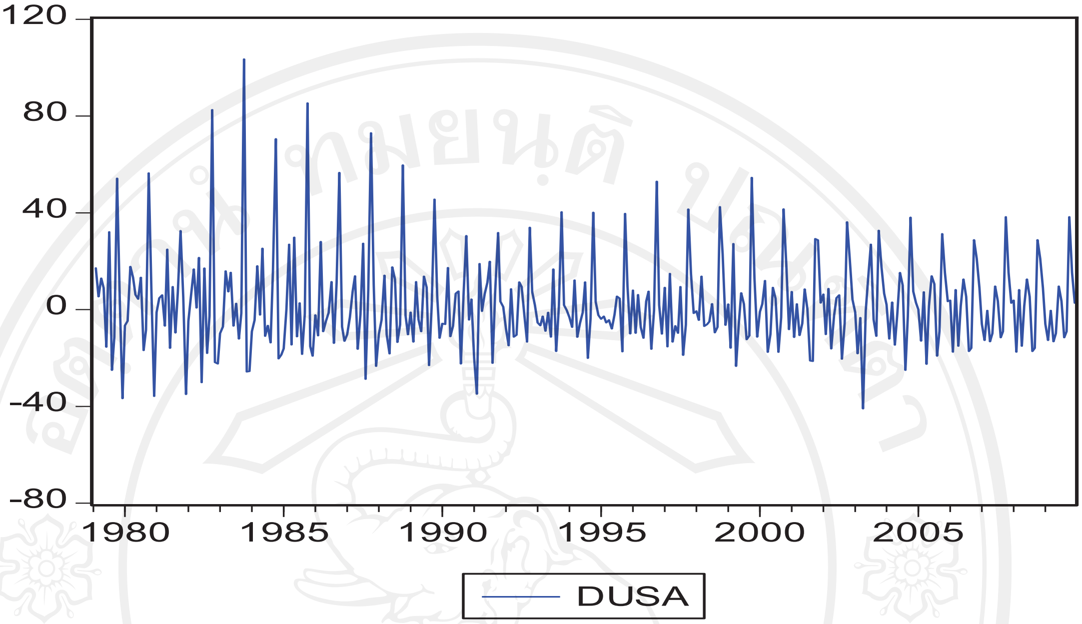


Figure 4.10 Monthly American tourist arrival growth rates from 1979-2009



4.7 SARMA models for conditional mean model

Since the ADF test procedures show that the tourist arrival growth rate series are integrated of order zero, $I(0)$ the latter is used to estimate the Box-Jenkins models. The autoregressive moving average, or ARMA(p,q) model and the seasonal autoregressive moving average, or SARMA $(P,Q)_T$ are used in conditional mean estimation.

Table 4.6 presents the results of the SARMA model for total tourist arrival growth rates, model is given below:

Table 4.6 SARMA model for growth rates in total monthly tourist arrivals

Variable	Coefficient	t-Statistic	AIC/BIC	LM(SC)
C	1.660	1.103	AIC=7.241	*F*=1.282
AR(1)	-0.190	-3.694	BIC=7.273	*p*=0.076
SAR(12)	0.739	20.913		

Table 4.7 presents the results of the SARMA model for Malaysian tourist arrival growth rates, model is given below:

Table 4.7 SARMA model for growth rates in monthly Malaysian tourist arrivals

Variable	Coefficient	t-Statistic	AIC/BIC	LM(SC)
C	4.252	2.983	AIC=9.170	*F*=2.473
AR(1)	-0.474	-9.805	BIC=9.204	*p*=0.062
SAR(12)	0.385	7.818		

Table 4.8 presents the results of the SARMA model for Japanese tourist arrival growth rates, model is given below:

Table 4.8 SARMA model for growth rates in monthly Japanese tourist arrivals

Variable	Coefficient	t-Statistic	AIC/BIC	LM(SC)
C	0.098	0.025	AIC=7.461	*F*=3.303
AR(1)	-0.173	-3.181	BIC=7.506	*p*=0.070
SAR(12)	0.958	86.397		
MA(12)	-0.676	-16.551		

Table 4.9 presents the results of SARMA model for UK tourist arrival growth rates, model is given below:

Table 4.9 SARMA model for growth rates in monthly UK tourist arrivals

Variable	Coefficient	t-Statistic	AIC/BIC	LM(SC)
C	2.423	6.005	AIC=8.282	*F*=1.217
AR(1)	-0.275	-5.285	BIC=8.315	*p*=0.125
SAR(6)	-0.596	-13.675		

Table 4.10 presents the results of SARMA model for American tourist arrival growth rates, model is given below:

Table 4.10 SARMA model for growth rates in monthly American tourist arrivals

Variable	Coefficient	t-Statistic	AIC/BIC	LM(SC)
C	2.078	0.711	AIC=7.418	*F*=1.689
AR(1)	-0.276	-5.241	BIC=7.452	*p*=0.075
SAR(12)	0.856	31.625		

We use the two most commonly model selection criteria are the Akaike Information Criterion (AIC) and the Schwarz Baysian Criterion (BIC), with the decision to base the model choice being to select the model for which the appropriate criterion smallest.

For ensuring that the estimated residuals do not have serial correlation at the 5% significance level, we use the Breusch-Godfrey Lagrange multiplier test of serial correlation, LM (SC). It can be used to test for higher-order ARMA or SARMA errors, and is applicable in the presence of lagged dependent variables. Using the Lagrange multiplier test, if the computed F statistic exceeds the critical value at 5% level, this leads to the rejection of the null hypothesis of no serial correlation.

Furthermore, the computed F statistics for the LM (SC) test are all less than the critical value. Thus, the null hypothesis of no serial correlation is not being rejected for these models.

4.8 GARCH and GJR for conditional volatility model

The variable of interest for the Thailand government is the number of tourist arrivals at any given month as this figure is directly related to tourism revenue. In this section, the tourist arrivals are used to estimate the GARCH (1, 1) and GJR (1, 1) model. All estimation was conducted using Eviews 5.1. The models are estimated using QMLE for the case p=q=1 in Table 4.11-4.12.

The estimated GARCH (1, 1) equation for monthly growth rates in the total number of tourist arrivals is given as follows:

$$h_t = \underset{(1.615)}{5.832} + \underset{(0.028)}{0.138}\,\varepsilon_{t-1}^{\;2} + \underset{(0.029)}{0.786}\,h_{t-1}$$

The estimated GARCH (1, 1) model of monthly growth rates in total number of international tourist arrivals to Thailand for the short run persistence lies at 0.138, whilst the long run persistence lies at 0.924. As the respective estimate of the second moment conditions, $\alpha_1 + \beta_1 < 1$ for GARCH (1, 1), are satisfied. The QMLE are consistent and asymptotically normal. This means that the estimates are statistically adequate and sensible for the purpose of interpretation.

The estimated GJR (1, 1) equation for monthly growth rates in the total number of tourist arrivals is given as follows:

$$h_t = \underset{(1.611)}{5.829} + \underset{(0.048)}{0.123}\,\varepsilon_{t-1}^{\;2} + \underset{(0.059)}{0.025}\,I\varepsilon_{t-1}^{\;2} + \underset{(0.030)}{0.789}\,h_{t-1}$$

The asymmetry coefficient is found to be positive and significant for the GJR (1, 1) model, namely 0.123, which indicates that decreases in total number of tourist arrivals to Thailand increase volatility. As the respective estimates of the second moment conditions, $\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1 < 1$ for GJR (1, 1) and where the figures in parentheses are standard errors, which indicates that the model provides an adequate fit to the data. As γ_1 is estimated significant and $\alpha_1 + \gamma_1 > \alpha_1$, it appears that volatility is affected asymmetrically by positive and negative shock, with previous negative shocks having a greater impact on volatility than previous positive shocks of similar magnitude.

The estimated GARCH (1, 1) equation for monthly growth rates in Malaysian tourist arrivals is given as follows:

$$h_t = \underset{(15.645)}{33.132} + \underset{(0.042)}{0.118}\,\varepsilon_{t-1}{}^2 + \underset{(0.059)}{0.818}\,h_{t-1}$$

The estimated GARCH (1, 1) model of monthly growth rates in Malaysian tourist arrivals shows the short run persistence lies at 0.118, while the long run persistence lies at 0.936. As the respective estimate of the second moment conditions, $\alpha_1 + \beta_1 < 1$ for GARCH (1, 1), are satisfied. The QMLE are consistent and asymptotically normal. This means that the estimates are statistically adequate and sensible for the purpose of interpretation.

The estimated GJR (1, 1) equation for monthly growth rates in Malaysian tourist arrivals is given as follows:

$$h_t = \underset{(15.719)}{26.257} + \underset{(0.050)}{0.071}\,\varepsilon_{t-1}{}^2 + \underset{(0.080)}{0.100}\,I\varepsilon_{t-1}{}^2 + \underset{(0.060)}{0.835}\,h_{t-1}$$

The asymmetry coefficient is found to be positive and significant for the GJR (1, 1) model, namely 0.071, which indicates that decreases in monthly Malaysian tourist arrivals to Thailand increase volatility. As the respective estimates of the second moment conditions, $\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1 < 1$ for GJR (1, 1) and where the figures in parentheses are standard errors, which indicates that the model provides an adequate fit to the data. As γ_1 is estimated significant and $\alpha_1 + \gamma_1 > \alpha_1$, it appears that volatility is affected asymmetrically by positive and negative shock, with previous negative shocks having a greater impact on volatility than previous positive shocks of similar magnitude.

The estimated GARCH (1, 1) equation for monthly growth rates in Japanese tourist arrivals is given as follows:

$$h_t = \underset{(10.738)}{32.064} + \underset{(0.065)}{0.293}\,\varepsilon_{t-1}^{\;2} + \underset{(0.134)}{0.398}\,h_{t-1}$$

The estimated GARCH (1, 1) model of monthly growth rates in Japanese tourist arrivals shows the short run persistence lies at 0.293, while the long run persistence lies at 0.691. As the respective estimate of the second moment conditions, $\alpha_1 + \beta_1 < 1$ for GARCH (1, 1), are satisfied. The QMLE are consistent and asymptotically normal. This means that the estimates are statistically adequate and sensible for the purpose of interpretation.

The estimated GJR (1, 1) equation for monthly growth rates in Japanese tourist arrivals is given as follows:

$$h_t = \underset{(73.385)}{145.296} + \underset{(0.132)}{0.038}\,\varepsilon_{t-1}^{\;2} - \underset{(0.124)}{0.115}\,I\varepsilon_{t-1}^{\;2} + \underset{(0.452)}{0.148}h_{t-1}$$

The asymmetry coefficient is found to be positive and significant for the GJR (1, 1) model, namely 0.038, which indicates that decreases in monthly Japanese tourist arrivals to Thailand increase volatility. As the respective estimates of the second moment conditions, $\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1 < 1$ for GJR (1, 1) and where the figures in parentheses are standard errors, which indicates that the model provides an adequate fit to the data. As γ_1 is estimated significant and $\alpha_1 + \gamma_1 < \alpha_1$, it appears that volatility is affected asymmetrically by positive and negative shock, with previous positive shocks having a greater impact on volatility than previous negative shocks of similar magnitude.

The estimated GARCH (1, 1) equation for monthly United Kingdom tourist arrivals is given as follows:

$$h_t = \underset{(2.781)}{3.273} + \underset{(0.038)}{0.092}\,\varepsilon_{t-1}{}^2 + \underset{(19.825)}{0.890}\,h_{t-1}$$

The estimated GARCH (1, 1) model of monthly growth rates in United Kingdom tourist arrivals shows the short run persistence lies at 0.092, while the long run persistence lies at 0.982. As the respective estimate of the second moment conditions, $\alpha_1 + \beta_1 < 1$ for GARCH (1, 1), are satisfied. The QMLE are consistent and asymptotically normal. This means that the estimates are statistically adequate and sensible for the purpose of interpretation.

The estimated GJR (1, 1) equation for the United Kingdom tourist arrivals is given as follows:

$$h_t = \underset{(3.092)}{3.051} + \underset{(0.049)}{0.084}\,\varepsilon_{t-1}{}^2 + \underset{(0.094)}{0.040}\,I\varepsilon_{t-1}{}^2 + \underset{(0.047)}{0.883}\,h_{t-1}$$

The asymmetry coefficient is found to be positive and significant for the GJR (1, 1) model, namely 0.084, which indicates that decreases in monthly United Kingdom tourist arrivals to Thailand increase volatility. As the respective estimates of the second moment conditions, $\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1 < 1$ for GJR (1, 1) and where the figures in parentheses are standard errors, which indicates that the model provides an adequate fit to the data. As γ_1 is estimated significant and $\alpha_1 + \gamma_1 > \alpha_1$, it appears that volatility is affected asymmetrically by positive and negative shock, with previous negative shocks having a greater impact on volatility than previous positive shocks of similar magnitude.

The estimated GARCH (1, 1) equation for monthly growth rates in American tourist arrivals is given as follows:

$$h_t = \underset{(12.227)}{93.615} + \underset{(0.051)}{0.181}\,\varepsilon_{t-1}^{\;2} + \underset{(0.073)}{0.230}\,h_{t-1}$$

The estimated GARCH (1, 1) model of monthly growth rates in American tourist arrivals shows the short run persistence lies at 0.181, while the long run persistence lies at 0.411. As the respective estimate of the second moment conditions, $\alpha_1 + \beta_1 < 1$ for GARCH (1, 1), are satisfied. The QMLE are consistent and asymptotically normal. This means that the estimates are statistically adequate and sensible for the purpose of interpretation.

The estimated GJR (1, 1) equation for American tourist arrivals is given as follows:

$$h_t = \underset{(39.935)}{114.467} + \underset{(0.029)}{0.114}\,\varepsilon_{t-1}^{\;2} + \underset{(0.065)}{0.024}\,I\varepsilon_{t-1}^{\;2} + \underset{(0.390)}{0.326}\,h_{t-1}$$

The asymmetry coefficient is found to be positive and significant for the GJR (1, 1) model, namely 0.114, which indicates that decreases in monthly American tourist arrivals to Thailand increase volatility. As the respective estimates of the second moment conditions, $\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1 < 1$ for GJR (1, 1) and where the figures in parentheses are standard errors, which indicates that the model provides an adequate fit to the data. As γ_1 is estimated significant and $\alpha_1 + \gamma_1 > \alpha_1$, it appears that volatility is affected asymmetrically by positive and negative shock, with previous negative shocks having a greater impact on volatility than previous positive shocks of similar magnitude.

Table 4.11 Estimated GARCH Model

Parameters	GARCH				
	Total	**Malaysian**	**Japanese**	**UK**	**American**
ω	5.832***	33.132***	32.064***	3.273*	93.615***
	(1.615)	(15.645)	(10.738)	(2.781)	(12.227)
α	0.138***	0.118***	0.293***	0.092**	0.181***
	(0.028)	(0.042)	(0.065)	(0.038)	(0.051)
β	0.786***	0.818***	0.398***	0.890***	0.230***
	(0.029)	(0.059)	(0.134)	(0.045)	(0.073)
Diagnostics					
Second moment	0.924	0.936	0.691	0.982	0.411
AIC	7.054	9.073	7.386	8.128	7.386
BIC	7.118	9.142	7.466	8.196	7.456

Notes:

Numbers in parentheses are standard error.

The log-moment condition is necessarily satisfied as the second the moment condition is satisfied.

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 4.12 Estimated GJR Model

Parameters	GJR				
	Total	**Malaysian**	**Japanese**	**UK**	**American**
ω	5.829***	26.257*	145.296**	3.051*	114.467***
	(1.611)	(15.719)	(73.385)	(3.092)	(39.935)
α	0.123***	0.071*	0.038*	0.084*	0.114***
	(0.048)	(0.050)	(0.131)	(0.049)	(0.029)
γ	0.025*	0.100*	-0.115*	0.040*	0.024*
	(0.059)	(0.080)	(0.124)	(0.094)	(0.065)
β	0.789***	0.835***	0.148*	0.883***	0.326*
	(0.030)	(0.060)	(0.452)	(0.047)	(0.390)
Diagnostics					
Second moment	0.925	0.956	0.128	0.987	0.452
AIC	7.060	9.074	7.649	8.134	7.412
BIC	7.118	9.153	7.740	8.212	7.792

Notes:

Numbers in parentheses are standard error.

The log-moment condition is necessarily satisfied as the second the moment condition is satisfied.

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%.

4.8.1 Forecasting

We used the sample for the total number of international tourist arrivals ranging from January 1976 to December 2009 and number of tourist arrivals ranging from January 1979 to December 2009 for each country. In order to strike a balance between the efficiency in estimation and a variable number of rolling regressions, the rolling window size is set for forecasting the period from January 1991 to December 2009 for total number of international tourist arrivals and from January 1994 to December 2009 for number of international tourist arrivals for each country. Using the notation developed in the previous section, the VaR forecast for the growth rate of tourist arrivals at any time t is given by, $VaR = E(Y_t|F_{t-1}) - \alpha\sqrt{h_t}$, where $E(Y_t|F_{t-1})$ is the forecasted expected growth rate of tourist arrivals, and h_t is the conditional volatility.

The forecasted VaR thresholds represent the maximum expected negative growth rate that could be expected given a specific confidence level. This paper uses 1% to calculate the VaR. Based on the Likelihood Ratio test; both models (GARCH and GJR) display the correct conditional coverage. In addition, the second moment additions for each rolling window of both models are satisfied for every rolling window which provides greater confidence in the statistic adequacy of the two estimated models. Finally, both models lead to the same average VaR at -91.09% which means that, on average, the lowest possible monthly growth rate in total tourist arrivals, and hence in tourist tax revenue, is -91.09%, given a 99% level of confidence. Monthly growth rate in Malaysian, Japanese, United Kingdom and American tourist arrivals have an average VaR at -647.71%, -132.95%, -329.83% and -213.67%, respectively. And hence in tourism tax revenue, are -647.71%, -132.95%, -329.83% and -213.67%, respectively, given 99% level of confidence.

4.9 Conclusion

The empirical study based on two widely-used conditional volatility models shows that the volatility is affected symmetrically by positive and negative shocks, with the previous positive shocks to the growth in tourist arrivals to Thailand having a greater impact on volatility than previous negative shocks of similar magnitude. The forecasted VaR threshold represents the maximum expected negative growth rate that could be expected given a specific confidence level. Both conditional volatility models leads to the same average VaR at -91.09% which means that, on average, the lowest possible monthly growth rate in total tourist arrivals, and hence in tourist tax revenue, is -91.09%, given a 99% level of confidence. The monthly growth rates in Malaysian, Japanese, United Kingdom and American tourist arrivals have an average VaR at -647.71%, -132.95%, -329.83% and -213.67%, respectively. VaR of short haul tourists are higher than medium haul and long haul tourists. And hence tourism tax revenue, are, -647.71%, -132.95%, -329.83% and -213.67%, respectively, given 99% level of confidence.

This should be useful information for both private and public tourist providers to manage sustainable tourism in Thailand.