Chapter 4

Interdependence of International Tourism Demand and Volatility in Leading ASEAN Destinations

Being one of the important areas in tourism research, tourism demand modeling and forecasting has attracted much attention of both academics and practitioners. Time-series models have been widely used for tourism demand forecasting with the dominance of the ARMA-based model. Another extension of the time-series analysis of tourism demand has been the application of the Generalized Autoregressive Conditional Heteroscadastic (GARCH) model. The GARCH model has been widely applied in financial econometrics to investigate the volatility of the time series. Recently, the volatility concept is highly popular in applications to tourism demand analysis.

The purpose of the third study is as followed - to estimate the conditional variance, or volatility, of monthly international tourist arrivals to four tourism leading South-East Asia countries, namely Indonesia, Malaysia, Singapore and Thailand, and to determine the interdependence of international tourism demand of leading ASEAN destinations for the period January 1997 to July 2009.

This chapter is a revised version of the original paper presented at the 2nd conference of the International Association for Tourism Economics, Chiang Mai, Thailand and was recently accepted for publication by the Tourism Economics Journal.

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Chia-Lin Chang, Thanchanok Khamkaew, Michael McAleer
and Roengchai Tansuchat

Abstract

International and domestic tourism are leading economic activities in the world today. Tourism has been known to generate goods and services directly and indirectly, attract foreign currency, stimulate employment, and provide opportunities for investment. It has also been recognized as an important means for achieving economic development. Substantial research has been conducted to evaluate the role of international tourism, and its associated volatility, within and across various economies. This study applies several recently developed models of multivariate conditional volatility to investigate the interdependence of international tourism demand, as measured by international tourist arrivals, and its associated volatility in the four leading destinations in ASEAN, namely Indonesia, Malaysia, Singapore and Thailand. Each of these countries has attractive tourism characteristics, such as significant cultural and natural resources. Shocks to international tourism demand volatility could affect, positively or negatively, the volatility in tourism demand of neighbouring countries. The empirical results should encourage regional co-operation in tourism development among ASEAN member countries, and also mobilize international and regional organizations to provide appropriate policy actions.

4.1 Introduction

Over the past six decades, the substantial growth in tourism activity has clearly marked tourism as one of the most remarkably important and rapidly growing sectors in the world economy. It is presently ranked fourth after fuels, chemicals and automotive products (UNWTO, 2009). For many developing countries, tourism is one of the main income sources that leads to exports of goods and services, generates employment, and creates opportunities for economic development.

According to the World Tourism Organization report 2009, international tourist arrivals have continued to grow from 438 million in 1990, to 534 million in 1995, to 684 million in 2000, reaching 922 million in 2008, with an average annual growth rate of 3.8% between 2000 and 2008 (UNWTO, 2009). While tourism has experienced continuous growth, it has nonetheless diversified world tourism destinations. Many new destinations have emerged alongside the traditional ones of Western Europe and North America, which are the main tourist-receiving regions. Both regions tend to have less dynamic growth in joint market shares, while Asia and the Pacific have outperformed the rest of the world in terms of an increasing share of international tourist arrivals, as well as market share of world international tourism receipts (see Table 4.1).

Despite the collapse of global financial markets and the subsequent recession that began in December 2007, and with much greater intensity since September 2008, international tourist arrivals in 2008 reached 922 million. This was a positive figure that had increased from 904 million in 2007, thereby representing a growth rate of 2%. This overall growth had been established on the strong results in the year proceeding the global economic recession. All regions had positive growth, except for

Europe. Asia and the Pacific saw a significant slowdown in arrivals when figures were compared to the previous bumper years, growing at just over 1% in 2008. The deceleration from 9.6% in 2007 to 1.2% in 2008 can be attributed principally to a rise in the price of tourism that was caused by an increase in aviation fuel prices. Growth in receipts in Asia outpaced that of arrivals. Year-on-year growth in receipts for the region was 2.7%, compared with 9.8% in 2007 (ASEAN, 2009).

South-East Asia and South Asia were the strongest performing sub-regions of Asia and the Pacific, growing at 3% and 2%, respectively, in 2008. In South-East Asia, countries such as Indonesia (13%), Cambodia (7%) and Malaysia (5%) grew at above average rates. Several Asia and Pacific sub-regions, especially in South-East Asia, are now reaping increasing benefits from tourism due to their own specific tourism resources, and an improvement in the supporting and facilitating factors of infrastructure and accommodation. The ASEAN tourism performance in 2006-2008 is given in Table 4.2. ASEAN attracted 61.7 million tourists in 2008, accounting for a market share of 6.7% and average annual growth rate of 6.9% (ASEAN, 2009).

As given in Table 4.2, inbound tourism to South-East Asia has been distributed to four leading destinations, namely Malaysia, Thailand, Singapore, and Indonesia. These destinations stimulate an interest since tourism data is available and very rich for the tourism demand volatility analysis, while Laos, Cambodia and Myanmar does not officially provide tourism data and Brunei does not have a rich tourism database. Therefore, this study only focuses on the study in tourism demand interdependency between Malaysia, Thailand, Singapore, and Indonesia instead of the whole ASEAN.

The trend of international tourist arrivals to these countries has been relatively increasing over time (see panel (a) in Figure 4.1). Whilst the data set illustrates the growing trends of tourism activity in the period 1998 to 2008, the impact of 'events', such as Severe Acute Respiratory Syndrome (hereafter SARS) epidemic in 2003 should not be underestimated. Although it is clear that such events are 'aberrations in the trend' the short term economic effect of such natural occurrences is of course high. After a sharp drop in tourist arrivals in 2003 due to SARS outbreak, the number of tourist arrivals was gradually recovered and continues to undergo rapid growth (see panel (b) in Figure 4.1). This favorable trend will continue forward as individuals with higher levels of disposable income and leisure time seek to visit the wonders of Asia. Other contributors to increased demand have been the aggressive marketing campaigns undertaken by many major ASEAN nations, the emergence of Low Cost Carrier Airlines and the currency leverage achieved in Asia by many Western Nation tourists.

In terms of North-East Asia, tourist arrivals to South-East Asia have accounted for over 30% of the market share in the Asia and the Pacific international tourist arrivals. In Figures 4.2 and 4.3, the intra-ASEAN[1] tourism is deemed to be important as extra-ASEAN[2] tourism in this sub-region as ASEAN member countries sustained their collaboration to increase intra-ASEAN travel and fortified the promotion of the ASEAN region as a major destination for intra-ASEAN and inter-ASEAN travel.

Sharing some similarities in climate, the archeological background and cultural influence brought from India, China, Muslim-nations and Europe have led to unification among the nations of South-East Asia. These similarities seem to have

[1] ASEAN arrivals
[2] Non-ASEAN arrivals

installed an influence on both regional tourism collaboration and regional tourism competitiveness. It is interesting to explore the interdependence between tourism in ASEAN, where each country could benefit and suffer from the shocks that occur in neighbouring countries. For example, negative shocks, which may capture political instability, terrorism, violent criminal behavior, and natural disasters, generally have the potential to generate volatility in tourism demand. Examining whether the impact of shocks to tourism demand in one destination would be volatile on the demand for international tourism in neighbouring destinations is a major aspect of the study.

Given the importance of understanding the dependence on tourism in ASEAN, this study estimates the conditional variance, or volatility, of monthly international tourist arrivals to four leading South-East Asian tourism countries, namely Malaysia, Thailand, Singapore and Indonesia. The estimates provide an indication of the relationship between shocks to the growth rate of monthly international tourist arrivals in each major destination in South-East Asia through the multivariate GARCH framework. The analysis of uncertainty in monthly international tourism arrivals to these major destinations has not been empirically investigated in the tourism literature. The results indicate the existence of tourism interdependence among these countries.

The structure of the remainder of the study is as follows. Section 2 reviews the tourism volatility research literature. Section 3 discusses the univariate and multivariate GARCH models to be estimated. Section 4 gives details of the data, descriptive statistics and unit root tests. Section 5 describes the empirical estimates and some diagnostic tests of the univariate and multivatiate models. Some concluding remarks are given in Section 5.

4.2 Literature Review

Tourism demand modelling and estimation rely heavily on secondary data. It can be divided broadly into two categories, based on non-causal time series models and causal econometric approaches. The primary difference between two is whether the forecasting model identifies any causal relationship between the tourism demand variable and its influencing factors. The focus in this study is on time series tourism modelling, which pays particular attention to exploring the historical trends and patterns in the time series ARMA-based models comprise one of the most widely used methods in time series analysis.

A recent example based on time series methods to analyze tourism demand is Lim and McAleer (Lim & McAleer, 1999), who used ARIMA models to explain the non-stationary seasonally unadjusted quarterly tourist arrivals from Malaysia to Australia from 1975(1) to 1996(4). HEGY framework was used as a pre-test for seasonal unit root (Hylleberg, Engle, Granger, & Yoo, 1990). The finding of seasonal unit root tests in international tourist arrivals from Malaysia shows evidence of a stochastically varying seasonal pattern. A deterministic seasonal model generated by seasonal dummy variables is likely to be a less appropriate univariate seasonal representation than the seasonally integrated process proposed by HEGY, and including deterministic seasonal dummy variables to explain seasonal patterns is likely to produce fragile results if seasonal unit roots are present. Lim and McAleer estimated Australian tourism demand from Asian source markets over the period 1975(1)-1984(4) by using various ARIMA models. As the best fitting ARIMA model is found to have the lowest RMSE, this model is used to obtain post-sample forecasts. The fitted ARIMA model forecasts tourist arrivals from Singapore for the period

1990(1)-1996(4) very well. Although the ARIMA model outperforms the seasonal ARIMA models for Hong Kong and Malaysia, the forecasts of tourist arrivals are not as accurate as in the case of Singapore (Lim & McAleer, 2002).

Goh and Law introduced a multivariate SARIMA (MSARIMA) model, which includes an intervention function to capture the potential spillover effects of the parallel demand series on a particular tourism demand series. They showed that MSARIMA model significantly improved the forecasting performance of the simple SARIMA as well as other univariate time-series models (Goh & Law, 2002). In a similar study, Du Preez and Witt investigated the intervention effects of the time series models on forecasting performance within a state space framework. It was found that the multivariate state space time series model was outperformed by the simple ARIMA model (Preez & Witt, 2003). The application of time-series method in tourism demand analysis can also be found in Lim and McAleer (Lim & McAleer, 2000, 2001), Cho (Cho, 2001, 2003), Kulendran and Witt (Kulendran & Witt, 2003a, 2003b), Gil-Alana et al. (Luis A. Gil-Alana, Gracia, & CuÑado, 2004), Coshall (Coshall, 2005, 2009), Gil-Alana (L.A. Gil-Alana, 2005), Kulendran and Wong (Kulendran & Wong, 2005), Oh and Morzuch (Oh & Morzuch, 2005), Lim et al. (Lim, Min, & McAleer, 2008), and Chang et.al (Chang, Lim, & McAleer, 2009; Chang, McAleer, & Slottje, 2009; Chang, Sriboonchitta, & Wiboonpongse, 2009).

Another extension of the time series analysis of tourism demand has been the application of the Generalized Autoregressive Conditional Heteroscadastic (GARCH) model. The GARCH model has been used widely in financial econometrics to investigate the volatility of the time series. Univariate models of volatility in tourism demand have been used in, for example, Shareef and McAleer (Shareef & McAleer, 2005), Chang et al. (Chang, Lim et al., 2009; Chang, McAleer et al., 2009; Chang, Sriboonchitta et al., 2009), McAleer et al. (McAleer, Hoti, & Chan, 2009), and Divino and McAleer (Divino & McAleer, 2009, 2010) at different time series frequencies, ranging from monthly to daily data. Although the volatility concept is becoming increasingly popular in tourism research, few studies have yet applied multivariate models of volatility in tourism demand. In this respect, Chan et al. applied three multivariate GARCH models to examine the volatility of tourism demand for Australia and the effect of various shocks in the tourism demand models. The results suggested the presence of interdependent effects in the conditional variances between four leading countries, namely Japan, New Zealand, UK and USA, and asymmetric effects of shocks in two of the four countries (Chan, Lim, & McAleer, 2005).

Shareef and McAleer examined the uncertainty in monthly international tourist arrivals to the Maldives from eight major tourist source countries, namely Italy, Germany, UK, Japan, France, Switzerland, Austria and the Netherlands, from 1 January 1994 to 31 December 2003. Univariate and multivariate time series models of conditional volatility were estimated and tested. The conditional correlations were estimated and examined to ascertain whether there is specialization, diversification or segmentation in the international tourism demand shocks from the major tourism sources countries to the Maldives. The estimated static conditional correlations for monthly international tourist arrivals, as well as for the respective transformed series, were found to be significantly different from zero, but nevertheless relatively low (Shareef & McAleer, 2007).

Hoti et al. compared tourism growth, country risk returns and their associated volatilities for Cyprus and Malta. Monthly data were available for both international tourist arrivals and composite country risk ratings compiled by the International Country Risk Guide (ICRG) for the period May 1986 to May 2002. The time-varying conditional variances of tourism growth and country risk returns for the two Small Island Tourism Economies (SITEs) were analyzed using multivariate models of conditional volatility. The empirical results showed that Cyprus and Malta were complementary destinations for international tourists, such that changes to tourism patterns in Cyprus led to changes in tourism patterns in Malta (Hoti, McAleer, & Shareef, 2007).

4.3 Data

This study focuses on modeling conditional volatility and examining the interdependence of the logarithm of monthly tourist arrival rate (the difference of logarithm of monthly tourist arrivals or growth rates) of four leading South-East Asian countries, namely Indonesia, Malaysia, Singapore, and Thailand. The 151 monthly observations from January 1997 to July 2009 are obtained from Reuters, whereas Indonesia is obtained from Badan Pusat Statistik (Statistics Indonesia of The Republic Indonesia, 2009). The logarithm of monthly tourist arrival rate are calculated as $r_{ij,t} = \log\left(Y_{i,t}/Y_{i,t-1}\right)$, where $Y_{i,t}$ and $Y_{i,t-1}$ are the tourist arrivals of to country i in month t and t-1, respectively.

4.4 Methodology

4.4.1 Univariate Conditional Volatility Models

Following Engle (1982), consider the time series $y_t = E_{t-1}\left(y_t\right) + \varepsilon_t$, where $E_{t-1}\left(y_t\right)$ is the conditional expectation of y_t at time $t-1$ and ε_t is the associated error (Engle, 1982). The generalized autoregressive conditional heteroskedastity (GARCH) model of Bollerslev (1986) is given as follows:

$$\varepsilon_t = \sqrt{h_t}\eta_t \quad , \quad \eta_t \sim N(0,1) \tag{1}$$

$$h_t = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{2}$$

where $\omega > 0$, $\alpha_j \geq 0$ and $\beta_j \geq 0$ are sufficient conditions to ensure that the conditional variance $h_t > 0$. The parameter α_j represents the ARCH effect, or the short-run persistence of shocks to the log arrival rate, and β_j represents the GARCH effect, where $\alpha_j + \beta_j$ measures the long run persistence of shocks to the log arrival rate (Bollerslev, 1986).

Equation (2) assumes that the conditional variance is a function of the magnitudes of the lagged residuals and not their signs, such that a positive shock $(\varepsilon_t > 0)$ has the same impact on conditional variance as a negative shock $(\varepsilon_t < 0)$ of equal magnitude. In order to accommodate differential impacts on the conditional variance of positive and negative shocks, Glosten et al. proposed the asymmetric (or threshold) GARCH, or GJR model, which is given by (Glosten, Jagannathan, & Runkle, 1993);

$$h_t = \omega + \sum_{j=1}^{r} \left(\alpha_j + \gamma_j I\left(\varepsilon_{t-j} \right) \right) \varepsilon_{t-j}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \tag{3}$$

where $$I_{it} = \begin{cases} 0, & \varepsilon_{it} \geq 0 \\ 1, & \varepsilon_{it} < 0 \end{cases}$$

is an indicator function to differentiate between positive and negative shocks. When $r = s = 1$, sufficient conditions to ensure the conditional variance, $h_t > 0$, are $\omega > 0$,

$\alpha_1 \geq 0$, $\alpha_1 + \gamma_1 \geq 0$ and $\beta_1 \geq 0$. The short run persistence of positive and negative shocks are given by α_1 and $(\alpha_1 + \gamma_1)$, respectively. When the conditional shocks, η_t, follow a symmetric distribution, the short run persistence is $\alpha_1 + \gamma_1/2$, and the contribution of shocks to expected long-run persistence is $\alpha_1 + \gamma_1/2 + \beta_1$.

In order to estimate the parameters of model (1)-(3), maximum likelihood estimation is used with a joint normal distribution of η_t. However, when η_t does not follow a normal distribution or the conditional distribution is not known, quasi-MLE (QMLE) is used to maximize the likelihood function.

Bollerslev showed the necessary and sufficient condition for the second-order stationarity of GARCH is $\sum_{i=1}^{r}\alpha_i + \sum_{i=1}^{s}\beta_i < 1$ (Bollerslev, 1986). For the GARCH(1,1) model, Nelson obtained the log-moment condition for strict stationary and ergodicity as $E\left(\log\left(\alpha_1\eta_t^2\right) + \beta_1\right) < 0$, which is important in deriving the statistical properties of the QMLE (Nelson, 1991). For GJR(1,1), Ling and McAleer presented the necessary and sufficient condition for $E\left(\varepsilon_t^2\right) < \infty$ as $\alpha_1 + \gamma_1/2 + \beta_1 < 1$ (Ling & McAleer, 2002a, 2002b). McAleer et al. established the log-moment condition for GJR(1,1) as $E\left(\log\left(\alpha_1 + \gamma_1 I(\eta_t)\eta_t^2 + \beta_1\right)\right) < 0$, and showed that it is sufficient for consistency and asymptotic normality of the QMLE (McAleer, Chan, & Marinova, 2007).

In order to capture asymmetric behavior in the conditional variance with alternative model, Nelson (1991) proposed the Exponential GARCH (EGARCH) model, namely:

$$\log h_t = \omega + \sum_{i=1}^{r}\alpha_i\left|\eta_{t-i}\right| + \sum_{i=1}^{r}\gamma_i\eta_{t-i} + \sum_{j=1}^{s}\beta_j \log h_{t-j}\,, \qquad (4)$$

where $|\eta_{t-i}|$ and η_{t-i} capture the size and sign effects of the standardized shocks, respectively. If $\gamma = 0$, there is no asymmetry, while $\gamma < 0$ and $\gamma < \alpha < -\gamma$ are the conditions for a leverage effect, whereby positive shocks decrease volatility and negative shocks increase volatility (Nelson, 1991).

As noted in McAleer et al. (McAleer et al., 2007) and Chang et al. (Chang, McAleer et al., 2009), there are some distinct differences between EGARCH and the previous two model: (1) as EGARCH uses the logarithm of conditional volatility, it is guaranteed that $h_t > 0$, so that no restrictions are required on the parameters in (4); (2) Nelson (1991) showed that $|\beta| < 1$ ensures stationarity and ergodicity for EGARCH(1,1) (Nelson, 1991); (iii) Shephard (1996) observed that $|\beta| < 1$ is likely to be a sufficient condition for consistency of QMLE for EGARCH(1,1) (Shephard, 1996); (iv) as the standardized residuals appear in equation (4), $|\beta| < 1$ would seem to be a sufficient condition for the existence of moments; (v) in addition to being a sufficient condition for consistency, $|\beta| < 1$ is also likely to be sufficient for asymptotic normality of QMLE for EGARCH (1,1); and (6) moment conditions are required for the GARCH and GJR models as they are dependent on lagged unconditional shocks, whereas EGARCH does not require moment condition to be established as it depends on lagged conditional shocks (or standardized residuals).

4.4.2 Multivariate Conditional Volatility Model

This section presents models of the volatility in tourism demand, namely the CCC model of Bollerslev (Bollerslev, 1990), VARMA-GARCH model of Ling and McAleer (Ling & McAleer, 2003), and VARMA-AGARCH of McAleer et al. (McAleer et al., 2009) in order to investigate the (inter) dependence of international tourism demand and volatility in leading ASEAN destinations. The typical specifications underlying the multivariate conditional mean and conditional variance in the log arrival rate are as follows:

$$y_t = E\left(y_t \middle| F_{t-1}\right) + \varepsilon_t \tag{5}$$

$$\varepsilon_t = D_t \eta_t$$

where $y_t = \left(y_{1t},\ldots,y_{mt}\right)'$, $\eta_t = \left(\eta_{1t},\ldots,\eta_{mt}\right)'$ is a sequence of independently and identically distributed (iid) random vectors, F_t is the past information available to time t, $D_t = diag\left(h_1^{1/2},\ldots,h_m^{1/2}\right)$.

The constant conditional correlation (CCC) model of Bollerslev (Bollerslev, 1990) assumes that the conditional variance for each log arrival rate, h_{it}, $i = 1,..,m$, follows a univariate GARCH process, that is

$$h_{it} = \omega_i + \sum_{j=1}^{r} \alpha_{ij}\varepsilon_{i,t-j}^2 + \sum_{j=1}^{s} \beta_{ij} h_{i,t-j} \ , \tag{6}$$

where α_{ij} and β_{ij} represents the ARCH and GARCH effects, respectively. The conditional correlation matrix of CCC is $\Gamma = E\left(\eta_t\eta_t' \middle| F_{t-1}\right) = E\left(\eta_t\eta'\right)$, where $\Gamma = \left\{\rho_{it}\right\}$ for $i, j = 1,\ldots,m$. From (1), $\varepsilon_t\varepsilon_t' = D_t\eta_t\eta' D_t$, $D_t = \left(\text{diag } Q_t\right)^{1/2}$, and $E\left(\varepsilon_t\varepsilon_t' \middle| F_{t-1}\right) = Q_t = D_t\Gamma D_t$, where Q_t is the conditional covariance matrix. The conditional correlation matrix is defined as $\Gamma = D_t^{-1}Q_tD_t^{-1}$, and each conditional correlation coefficient is estimated from the standardized residuals in (5) and (6). Therefore, there is no multivariate estimation involved for CCC, except in the calculation of the conditional correlations.

It is interesting that CCC does not contain any information regarding cross-country or asymmetric effect. In order to accommodate possible interdependencies, Ling and McAleer (Ling & McAleer, 2003) proposed a vector autoregressive moving average (VARMA) specification of the conditional mean in (5) and the following specification for the conditional variance:

$$H_t = W + \sum_{i=1}^{r} A_i \vec{\varepsilon}_{t-i} + \sum_{j=1}^{s} B_j H_{t-j} \ , \tag{7}$$

where $H_t = \left(h_{1t},...,h_{mt}\right)'$, $\vec{\varepsilon} = \left(\varepsilon_{1t}^2,...\varepsilon_{mt}^2\right)'$, and W, A_i for $i = 1,..,r$ and B_j for $j = 1,..,s$ are $m \times m$ matrices. As in the univariate GARCH model, VARMA-GARCH assumes that negative and positive shocks have identical impacts on the conditional variance.

In order to separate the asymmetric impacts of the positive and negative shocks, McAleer et al. (McAleer et al., 2009) proposed the VARMA-AGARCH specification for the conditional variance, namely

$$H_t = W + \sum_{i=1}^{r} A_i \vec{\varepsilon}_{t-i} + \sum_{i=1}^{r} C_i I_{t-i} \vec{\varepsilon}_{t-i} + \sum_{j=1}^{s} B_j H_{t-j} \ , \tag{8}$$

where C_i are $m \times m$ matrices for $i = 1,..,r$, and $I_t = \mathrm{diag}\left(I_{1t},...,I_{mt}\right)$, where

$$I_{it} = \begin{cases} 0, & \varepsilon_{it} > 0 \\ 1, & \varepsilon_{it} \le 0 \end{cases}$$

If $m = 1$, (7) collapses to the asymmetric GARCH, or GJR model. Moreover, VARMA-AGARCH reduces to VARMA-GARCH when $C_i = 0$ for all i. If $C_i = 0$ and A_i and B_j are diagonal matrices for all i and j, then VARMA-AGARCH reduces to CCC. The parameters of model (5)-(8) are obtained by maximum likelihood estimation (MLE) using a joint normal density. When η_t does not follow a joint multivariate normal distribution, the appropriate estimator is defined as the Quasi-MLE (QMLE).

Figure 4.4 presents the plots of the number of tourist arrivals to each country. Only three countries, namely Malaysia, Singapore and Thailand, exhibit upward trends with cyclical and seasonal patterns. Interestingly, in 2003 the numbers of tourist arrivals in each country collapsed because of SARS. These phenomena have been affirmed by the report of the World Travel and Tourism Council (World Travel and Tourism Council, 2003) that the outbreak of the SARS disease led to the collapse of the tourism industry in the most severely affected Asian countries (for an empirical analysis using panel data, see also McAleer et al. (McAleer, Huang, Kuo, Chen, & Chang, 2010).

Since each monthly tourist arrivals series clearly present the distinct seasonal pattern. The corresponding tests for seasonal unit root extended from Hylleberg et al. (1990) (or HEGY test) were discussed by Franses (Franses, 1991) based on the auxiliary regression:

$$\begin{aligned}\phi^*(B)y_{s,t} = \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_4 y_{3,t-2} + \pi_5 y_{4,t-1} + \pi_6 y_{4,t-2} + \pi_7 y_{5,t-1} + \\ \pi_8 y_{5,t-2} + \pi_9 y_{6,t-1} + \pi_{10} y_{6,t-2} + \pi_{11} y_{7,t-1} + \pi_{12} y_{7,t-2} + \mu_t + \varepsilon_t\end{aligned} \tag{9}$$

where $\phi^*(B)$ is a polynomial function of B and where

$$y_{1,t} = (1+B)(1+B^2)(1+B^4+B^8)y_t$$

$$y_{2,t} = -(1-B)(1+B^2)(1+B^4+B^8)y_t$$

$$y_{3,t} = -(1-B^2)(1+B^4+B^8)y_t$$

$$y_{4,t} = -(1-B^4)(1-\sqrt{3}B+B^2)(1+B^2+B^4)y_t$$

$$y_{5,t} = -(1-B^4)(1+\sqrt{3}B+B^2)(1+B^2+B^4)y_t$$

$$y_{6,t} = -(1-B^4)(1-B^2+B^4)(1-B+B^2)y_t$$

$$y_{7,t} = -(1-B^4)(1-B^2+B^4)(1+B+B^2)y_t$$

$$y_{8,t} = (1-B^{12})y_t$$

The μ_t might consist of constant, eleven seasonal dummies, and a linear deterministic time trend. The OLS is applied for (9) in order to estimate the π_i and the corresponding standard error. If π_2 through π_{12} differ from zero, there are no seasonal unit roots. Table 4.3 shows the seasonal unit tests on four tourist arrivals series, using EViews6 econometric software package. Under the null hypothesis $H_0 : \pi_2 = ... = \pi_{12} = 0$, the joint F ($\pi_2\ \pi_{12}$) value are larger than the critical values for testing for seasonal unit root in monthly data based on Franses (Franses & Hobijn, 1997) at 5% level, signifying every series rejects the presence of unit roots at all seasonal frequencies at conventional level. This means that seasonal pattern can be represented by deterministic dummies.

The characteristic of tourist arrivals series in Figure 4 may be due to the level shift or the structural break. If there is a shift in the level of tourist arrivals, it should be taken into account for unit root test because the traditional ADF test has very low power if the shift is ignored (Perron, 1989). One possible approach is to include the shift function denoted $f_t(\theta)'\gamma$ to the deterministic term μ_t (see (Lanne, Lütkepohl, & Saikkonen, 2002, 2003) for further details). Hence, a model is represented as follows;

$$y_t = \mu_0 + \mu_1 t + f_t(\theta)'\gamma + x_t \tag{10}$$

where θ and γ are unknown parameters or parameter vectors and the stochastic process x_t are generated by an AR(p) process $b(L)(1-\rho L)x_t = \varepsilon_t$ where

$\varepsilon_t \sim iid(0,\sigma^2)$ and $b(L) = 1 - b_1 L - ... - b_p L^p$ has all its zero outside the unit circle if $p > 1$, while $-1 < \rho \leq 1$. If $\rho = 1$, a unit root is present. The shift function may be (1) shift dummy variable with shift date or break date T_B (2) exponential distribution function or (3) rational function, as follows,

$$f_1^{(1)} = d_{1t} := \begin{cases} 0, & t < T_B \\ 1, & t \geq T_B \end{cases} \tag{11}$$

$$f_1^{(2)}(\theta) = \begin{cases} 0, & t < T_B \\ 1 - \exp\{-\theta(t - T_B + 1)\}, & t \geq T_B \end{cases} \tag{12}$$

$$f_1^{(3)}(\theta) = \left[\frac{d_{1,t}}{1-\theta L} : \frac{d_{1,t-1}}{1-\theta L} \right]' \tag{13}$$

Lanne et al. have defined $\hat{\omega}_t = \hat{\alpha}^*(L)\hat{x}_t$ and base the unit root test on the auxiliary regression model (Lanne et al., 2003);

$$\Delta\hat{\omega}_t = \upsilon + \phi\hat{\omega}_{t-1} + \left[\hat{\alpha}^*(L)\Delta f_t(\hat{\theta})'\right]\pi_1 + \left[\hat{\alpha}^*(L)\Delta F_t(\hat{\theta})'\right]\pi_2 + \sum_{j=1}^{p-1}\alpha_j \Delta\hat{x}_{t-j} + r_t \tag{14}$$

Based on OLS estimation of this model, the unit root test statistic is obtained as the usual t-statistic for the null hypothesis of a unit root $\phi = 1$. Table 4.4 presents the unit root tests with level shift for tourist arrivals, using JMulTi econometric software package. Based on the break date and the AR order p suggested from JMulTi (Lütkepohl & Kr¨atzig, 2006), the results show that the test statistic values of all country are not statistical significant at 5% level based on critical values for unit root with level shift of Lanne et al. (Lanne et al., 2002), meaning every tourist arrival series have unit root.

Figure 4.5 presents the graphs of the logarithm of the monthly tourist arrival rate of four countries. All countries show distinct seasonal patterns, but no time trend pattern exists. Surprisingly, while Singapore and Thailand display steady growth in the log of tourist arrival rate, Indonesia and Malaysia exhibit greater volatility, with clustering (periods of high volatility followed by periods of tranquility). Quite evidently, the volatility of tourism arrivals rate of Malaysia in the years before 2003 are higher than in subsequent years. As in the plot of the number of tourist arrivals, SARS affected the log arrival rate significantly and negatively. Figure 4.6 displays the volatilities of the log of tourist arrival rate in four countries, where volatility is calculated as the square of the estimated residuals from an ARMA(1,1) process. The plots of the volatilities in Figure 4.6 are similar in all four countries, with volatility clustering and an obvious outlier due to the outbreak of SARS in 2003.

Table 4.5 presents the descriptive statistics for the logarithm of the monthly tourist arrival rate of four countries. The averages of the log of tourist arrival rate of four countries are quite small and similar, while Malaysia has the largest average log arrival rate. The Jarque-Bera Lagrange Multiplier test statistics of the log of tourist arrival rate in each country are statistically significant, thereby indicating that the distributions of these log of tourist arrival rate are not normal, which may be due to the presence of extreme observations.

The unit root tests for all logarithm of the monthly tourist arrival rate are summarized in Table 4.6, using the EViews6. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used to test the null hypothesis of a unit root against the alternative hypothesis of stationarity. The tests provide large negative values in all cases, such that the individual logarithm of tourist arrival rate series rejects the null hypothesis at the 5% level, thereby indicating that all logarithm of tourist arrival rate are stationary. These test results are supported by the KPSS test (the results are available on request).

4.5 Empirical Results

This section models the conditional volatility of the logarithm of the monthly tourist arrival rate from the four leading ASEAN tourism countries, namely Indonesia, Malaysia, Singapore and Thailand, using the CCC, VARMA-GARCH and VARMA-AGARCH models. As the univariate ARMA-GARCH model is nested in the VARMA-GARCH model, and ARMA-GJR is nested in the VARMA-AGARCH model, with the conditional variances specified as in (2) and (3), the univariate ARMA-GARCH and ARMA-GJR models are also estimated.

The univariate conditional volatility models, GARCH(1,1), GJR(1,1) and EGARCH(1,1), were estimated with different mean equations. Tables 4.7, 4.8 and 4.9 report the estimated parameters using QMLE and the Bollerslev-Wooldridge robust t-ratios (Bollerslev & Wooldridge, 1992). The empirically satisfactory log-moment and second moment conditions were also calculated, and are available from the authors upon request.

The univariate GARCH estimates for the logarithm of the monthly tourist arrival rate are given in Table 4.7. The coefficients in the mean equation are statistically significant for ARMA(1,1) for the log arrival rate series. Surprisingly, the coefficients in the variance equation are statistically significant, both in the short run and long run, only for Malaysia, and for Singapore only in the short run.

The results of two asymmetric GARCH(1,1) models, namely GJR(1,1) and EGARCH (1,1), are reported in Tables 8 and 9. For GJR(1,1), only the coefficients in the mean equation for AR(1) are statistically significant, whereas the ARMA(1,1) coefficients are statistically significant only for Indonesia, Malaysia and Thailand. The estimates of the asymmetric effects of positive and negative shocks of equal magnitude on the conditional volatility in the GJR(1,1) model are not statistically significant, except for Indonesia and Thailand in the AR(1)-GJR(1,1) model. Therefore, the GJR model is preferred to GARCH only for Indonesia and Thailand.

For the EGARCH model in Table 4.9, the coefficient in the mean equation is statistically significant only for ARMA(1,1). The estimates of the asymmetric effects of positive and negative shocks on the conditional volatility are also not statistically significant, except for Singapore and Thailand. Therefore, the EGARCH (1,1) model is preferred to GARCH only for Indonesia and Thailand.

Table 4.10 presents the constant conditional correlations from the CCC model, with p = q = r = s = 1, using the RATS 6.2 econometric software package. The two entries corresponding to each of the parameters are the estimate and the Bollerslev-Wooldridge robust t-ratios (Bollerslev & Wooldridge, 1992). For the four country destinations, there are six pairs of countries to be analyzed. The lowest estimated constant conditional correlation is 0.301 between Malaysia and Thailand, while the highest is 0.716 between Singapore and Thailand. This suggests that the standardized shocks in the log of the monthly tourist arrival rate for both countries are moving in the same direction. However, the CCC model does not contain any information regarding cross-country spillover or asymmetric effects.

In order to examine the interdependent and dependent effects of volatility from one country on another, and to capture the asymmetric behaviour of the unconditional shocks on conditional volatility, the VARMA-GARCH and VARMA-

AGARCH models are also estimated. The corresponding multivariate estimates of the VARMA(1,1)-GARCH(1,1) and VARMA(1,1)-AGARCH(1,1) models for each pair of countries using the BHHH (Berndt, Hall, Hall and Hausman) algorithm, and the Bollerslev-Wooldridge robust t-ratios (Bollerslev & Wooldridge, 1992), are reported in Tables 4.11 and 4.12. In Table 4.11, the ARCH and GARCH effects are significant only for the pairs Thailand_Singapore, Singapore_Indonesia and Singapore_Malaysia, while the pairs Thailand_ Malaysia and Indonesia_Malaysia have only a significant GARCH effect. In addition, volatility spillovers are found in every pair of countries, except for Thailand_Indonesia. Interestingly, a significant interdependence in the conditional volatilities between the logarithms of the monthly tourist arrival rate is evident in the pair Thailand_Singapore.

Table 4.12 presents the VARMA-AGARCH estimates and corresponding Bollerslev-Wooldridge robust t-ratios (Bollerslev & Wooldridge, 1992). The ARCH and GARCH effects are significant only in the pairs Thailand_Indonesia, Singapore_Indonesia, Singapore_Malaysia and Indonesia_Malaysia, while the pair Thailand_Singapore only has a significant GARCH effect. In addition, volatility spillovers are found in all pairs of countries, except for Thailand_Indonesia and Thailand_Malaysia. Surprisingly, as in the case of VARMA-GARCH, there is significant interdependence in the conditional volatilities between the logarithms of the monthly tourist arrival rate between Thailand_Singapore. As the asymmetric spillover effects for each log of the tourist rate are not statistically significant, except for Thailand_Singapore, it follows that VARMA-AGARCH is dominated by VARMA-GARCH.

4.6 Concluding Remarks

The purpose of this study was to estimate the conditional variance, or volatility, of monthly international tourist arrivals to the four leading tourism countries in South-East Asia, namely Indonesia, Malaysia, Singapore and Thailand, and to determine the interdependence of international tourism demand of these leading ASEAN destinations, for the period January 1997 to July 2009. The modelling and econometric analysis of volatility in tourism demand can provide a useful tool for tourism organizations and government agencies concerned with travel and tourism. This is especially important for encouraging regional co-operation in tourism development among ASEAN member countries, and for mobilizing international and regional organizations to provide appropriate policy for the tourism industry.

This study applied several recently developed models of multivariate conditional volatility, namely the CCC model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003), and VARMA-AGARCH model of McAleer et al. (2009), to investigate the interdependence of international tourism demand, as measured by international tourist arrivals, and its associated volatility, in the leading tourism destinations. The constant conditional correlation between the log of the monthly tourist arrival rate from the CCC model were found to lie in the range of medium to high. The highest conditional correlation was between the pair of Thailand and Singapore.

The empirical results from the VARMA-GARCH and VARMA-AGARCH models also provided evidence of cross-country dependence in most country pairs. In addition, the results indicated that interdependent effects occur only between the pair

Thailand and Singapore. However, in the conditional variance between the different countries, there is no evidence of volatility spillovers between Thailand and Indonesia.

Table 4.1 International Tourist Arrivals by Region

Regions	International Tourist Arrivals (million)							Market share (%)	Change (%)		Average annual growth (%)
	1990	1995	2000	2005	2006	2007	2008		07/06	08/07	
Europe	**265.0**	**309.5**	**392.6**	**441.8**	**468.4**	**487.9**	**489.4**	**53.1**	**4.1**	**0.3**	**2.8**
Northern Europe	28.6	35.8	43.7	52.8	56.5	58.1	57.0	6.2	2.8	-1.9	3.4
Western Europe	108.6	112.2	139.7	142.6	149.6	154.9	153.3	16.6	3.6	-1.1	1.2
Central/Eastern Europe	33.9	58.1	69.3	87.5	91.4	96.6	99.6	10.8	5.6	3.1	4.6
Southern/Mediter.Eu.	93.9	103.4	139.9	158.9	170.9	178.2	179.6	19.5	4.3	0.8	3.2
Asia and the Pacific	**55.8**	**82.0**	**110.1**	**153.6**	**166.0**	**182.0**	**184.1**	**20.0**	**9.6**	**1.2**	**6.6**
North-East Asia	26.4	41.3	58.3	86.0	92.0	101.0	101.0	10.9	9.8	-0.1	7.1
South-East Asia	21.2	28.4	36.1	48.5	53.1	59.7	61.7	6.7	12.3	3.5	6.9
Ocenia	5.2	8.1	9.6	11.0	11.0	11.2	11.1	1.2	1.7	-0.9	1.8
South Asia	3.2	4.2	6.1	8.1	9,8	10.1	10.3	1.1	2.6	2.1	6.8
Americas	**92.8**	**109.0**	**128.2**	**133.3**	**135.8**	**142.9**	**147.0**	**15.9**	**5.2**	**2.9**	**1.7**
North America	71.7	80.7	91.5	89.9	90.6	95.3	97.8	10.6	5.2	2.6	0.8
Caribbean	11.4	14.0	17.1	18.8	19.4	19.8	20.2	2.2	1.6	2.0	2.1
Central America	1.9	2.6	4.3	6.3	6.9	7.8	8.3	0.9	12.0	7.0	8.4
South America	7.7	11.7	15.3	18.3	18.8	20.1	20.8	2.3	6.5	3.6	3.9
Africa	**15.1**	**20.0**	**27.9**	**37.3**	**41.5**	**45.0**	**46.7**	**5.1**	**8.4**	**3.7**	**6.7**
North Africa	8.4	7.3	10.2	13.9	15.1	16.3	17.2	1.9	8.5	4.9	6.7
Subsaharan Africa	6.7	12.7	17.6	23.4	26.5	28.7	29.5	3.2	8.3	3.1	6.7
Middle East	**9.6**	**13.7**	**24.9**	**37.9**	**40.9**	**46.6**	**55.1**	**6.0**	**14.0**	**18.1**	**10.5**
World	**438**	**534**	**684**	**804**	**853**	**904**	**922**	**100**	**6.1**	**2.0**	**3.8**

Source: World Tourism Organization (UNWTO), 2009.

Table 4.2 International Tourist Arrivals to Asia and the Pacific

Major destinations	International Tourist Arrivals (million)						International Tourism Receipts (%)			
	(1000)			Change (%)		Share(%)	(US$ million)			Share (%)
	2006	2007	2008	07/06	08/07	2008	2006	2007	2008	2008
North-East Asia										
China	49,913	54,720	53,049	9.6	-3.1	28.8	33,949	37,233	40,843	19.8
Hong Kong (China)	15,822	17,154	17,320	8.4	1.0	9.4	11,638	13,754	15,300	7.4
Japan	7,334	8,347	8,351	13.8	0.0	4.5	8,469	9,334	10,821	5.3
Korea, Republic of	6,155	6,448	6,891	4.8	6.9	3.7	5,788	6,138	9,078	4.4
Macao (China)	10,683	12,942	10,605	21.2	..	5.8	9,829	13,612	13,382	6.5
Taiwan (pr.of China)	3,520	3,716	3,845	5.6	3.5	2.1	5,136	5,213	5,937	2.9
South-East Asia										
Cambodia	1,591	1,873	2,001	17.7	6.8	1.1	963	1,135	1,221	0.6
Indonesia	4,871	5,506	6,234	13.0	13.2	3.4	4,448	5,346	7,345	3.6
Lao P.D.R.	842	1,142	1,295	35.6	13.4	0.7	173	233	276	0.1
Malaysia	17,547	20,973	22,052	19.5	5.1	12.0	10,424	14,047	15,277	7.4
Phillippines	2,843	3,092	3,139	8.7	1.5	1.7	3,501	4,931	4,388	2.1
Singapore	7,588	7,957	7,778	4.9	-2.2	4.2	7,535	9,162	10,575	5.1
Thailand	13,822	14,464	14,584	4.6	0.8	7.9	13,401	16,669	17,651	8.6
Vietnam	3,584	4,229	4,236	18.0	0.2	2.3	3,200	3,477	3,926	1.9
Ocenia										
Australia	5,532	5,644	5,586	2.0	-1.0	3.0	17,840	22,298	24,660	12.0
New Zealand	2,422	2,466	2,459	1.8	-0.3	1.3	4,738	5,400	4,912	2.4
Fiji	549	540	585	-1.6	8.4	0.3	480	497	568	0.3
South Asia										
India	4,447	5,082	5,367	14.3	5.6	2.9	8,634	10,729	11,832	5.7
Maldives	602	676	683	12.3	1.1	0.4	512	602	636	0.3
Nepal	384	527	500	37.2	-5.0	0.3	128	198	336	0.1
Pakistan	898	840	823	-6.6	-2.0	0.5	255	276	245	0.1
Sri Lanka	560	494	438	-11.7	-11.2	0.3	410	385	342	0.2
Asia and the Pacific	**165,989**	**181,984**	**184,104**	**9.6**	**1.2**	**100**	**157,067**	**186,789**	**206,022**	**100**

Source: World Tourism Organization (UNWTO), 2009

Table 4.3 Seasonal Unit Root Tests

	Auxiliary Regression			
***t* -Statisitics**	**Indonesia**	**Malaysia**	**Singapore**	**Thailand**
π_1	**-0.044**	**-0.031**	-0.015	-0.030
π_2	**-0.202**	-0.132	**-0.193**	**-0.241**
π_3	-0.013	-0.128	**-0.182**	-0.098
π_4	**-0.172**	**-0.252**	-0.076	**-0.248**
π_5	**-0.222**	-0.199	**-0.255**	**-0.441**
π_6	**-0.272**	**-0.277**	**-0.288**	**-0.327**
π_7	0.037	0.020	0.041	0.062
π_8	**-0.106**	**-0.062**	**-0.077**	**-0.094**
π_9	**-0.233**	-0.138	-0.094	**-0.301**
π_{10}	**-0.238**	**-0.184**	**-0.241**	**-0.560**
π_{11}	0.022	-0.048	-0.020	0.002
π_{12}	**-0.108**	-0.080	**-0.103**	-0.115
***F* -Statisitics**				
π_3, π_4	2.706	4.808	3.880	3.236
π_5, π_6	3.626	2.977	5.073	**7.554**
π_7, π_8	**7.036**	5.506	5.742	5.539
π_9, π_{10}	4.058	2.586	3.778	**8.539**
π_{11}, π_{12}	3.090	3.375	4.481	2.637
π_2, π_{12}	**5.241**	**5.413**	**5.641**	**6.102**
π_1, π_{12}	**5.582**	**5.600**	**5.858**	**6.492**

Notes: (1) The auxiliary regression contains constant, seasonal dummies and trend.

(2) Entries in bold are significant at 5%.

(3) The critical value for testing unit root with level shift are based on Franses (2002)

Table 4.4 Unit Root Tests with Level Shift

	Shift Function			Critical Value	
	$f_1^{(1)}\gamma$	$f_1^{(2)}(\theta)\gamma$	$f_1^{(3)}(\theta)\gamma$	1%	5%
Indonesia	-1.580	-1.678	-1.714	-3.48	-2.88
Malaysia	-2.202	-2.622	-2.180		
Singapore	-2.497	-2.553	-2.455		
Thailand	-0.663	-1.346	-0.540		

Notes: (1) The auxiliary regression contains constant and seasonal dummies.

(2) Shift functions are $f_1^{(1)} = d_{1t} := \begin{cases} 0, & t < T_B \\ 1, & t \geq T_B \end{cases}$, $f_1^{(2)}(\theta) = \begin{cases} 0, & t < T_B \\ 1 - \exp\{-\theta(t - T_B + 1)\}, & t \geq T_B \end{cases}$

and $f_1^{(3)}(\theta) = \left[\frac{d_{1,t}}{1-\theta L} : \frac{d_{1,t-1}}{1-\theta L} \right]'$.

(3) Entries in bold are significant at 5%.

(4) The critical value for testing unit root with level shift are based on Lanne et al. (2002)

Table 4.5 Descriptive Statistics

Commodity	Mean	Max	Min	S.D.	Skewness	Kurtosis	Jarque-Bera
Indonesia	0.003	0.323	-0.349	0.115	-0.416	3.504	5.915
Malaysia	0.012	0.284	-0.637	0.138	-1.257	7.666	175.534
Singapore	0.002	0.577	-0.011	0.141	-1.653	21.740	2263.38
Thailand	0.004	0.454	-0.608	0.141	-0.509	5.327	40.331

Table 4.6 Unit Root Tests

Country	Augmented Dicky-Fuller			Phillip-Peron			KPSS	
	N	C	C&T	N	C	C&T	C	C&T
Indonesia	**-11.660**	**-11.626**	**-11.610**	**-16.955**	**-16.952**	**-17.158**	**0.102**	**0.067**
Malaysia	**-13.170**	**-13.234**	**-13.190**	**-14.737**	**-16.399**	**-16.355**	**0.071**	**0.068**
Singapore	**-8.179**	**-8.159**	**-8.143**	**-23.739**	**-31.210**	**-37.388**	**0.500**	0.500
Thailand	**-8.446**	**-8.626**	**-8.626**	**-15.718**	**-16.243**	**-16.143**	**0.111**	**0.095**

Table 4.7 GARCH(1,1), AR(1)-GARCH(1,1) and ARMA(1,1)-GARCH(1,1) Estimates

Country	Mean equation			Variance equation			AIC	SIC
	c	AR(1)	MA(1)	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\beta}$		
Indonesia	0.002			0.004	0.107	0.577	-1.463	-1.383
	0.268			0.719	0.941	1.097		
	0.003	-0.111		0.004	0.105	0.597	-1.455	-1.354
	0.305	-1.300		0.652	0.923	1.091		
	0.001	**0.682**	**-0.983**	0.002	0.077	0.728	-1.566	-1.445
	1.056	**11.01**	**-91.50**	0.575	0.978	1.781		
Malaysia	0.003			0.0004	**0.285**	**0.769**	-1.195	-1.115
	0.228			1.457	**3.392**	**17.96**		
	0.005	**-0.309**		0.0002	**0.450**	**0.713**	-1.243	-1.142
	0.612	**-2.442**		0.700	**2.925**	**13.63**		
	0.010	**0.555**	**-0.934**	0.0004	**0.485**	**0.628**	-1.243	-1.142
	10.286	**3.544**	**-31.53**	1.496	**2.145**	**6.374**		
Singapore	0.007			**0.006**	0.166	**0.511**	-1.171	-1.090
	0.899			**2.275**	1.721	**3.477**		
	0.017	**-0.254**		**0.009**	0.849	0.017	-1.209	-1.108
	1.960	**-2.921**		**4.610**	0.907	0.125		
	0.016	**-0.576**	**0.891**	**0.005**	**0.791**	0.063	-1.460	-1.339
	1.818	**-7.347**	**37.91**	**3.265**	**2.199**	0.621		
Thailand	-0.002			0.009	0.227	0.295	-1.112	-1.032
	-0.181			1.178	1.175	0.625		
	-0.004	0.102		0.008	0.227	0.369	-1.108	-1.008
	-0.380	0.970		1.290	1.206	0.955		
	-0.005	**-0.451**	**0.737**	0.007	0.266	0.332	-1.187	-1.067
	-0.396	**-2.700**	**6.021**	1.665	1.306	1.077		

Note: The two entries for each parameter are their respective parameter estimate and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level.

Table 4.8 GJR(1,1), AR(1)-GJR(1,1) and ARMA(1,1)-GJR(1,1) Estimates

Country	Mean equation			Variance equation				AIC	SIC
	c	AR(1)	MA(1)	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\beta}$		
Indonesia	-0.004			0.002	-0.063	0.247	**0.766**	-	-1.369
	-0.455			0.965	-0.336	1.456	**2.769**	1.469	
	-	**-0.211**		**0.001**	**-0.183**	**0.309**	**0.996**	-	-1.369
	0.011	**-3.428**		**4.278**	**-9.534**	**12.32**	**48.31**	1.469	
	-								
	1.777								
	0.001	**0.672**	**-0.984**	**0.020**	0.132	-0.087	**-0.859**		
	1.586	**11.25**	**-106.1**	**4.452**	1.194	-0.706	**-4.514**		
Malaysia	0.004			**0.011**	-0.030	0.587	0.182	-	-
	0.356			**2.301**	-0.211	1.413	1.359	1.153	1.053
	0.008	**-0.206**		**0.012**	-0.098	0.686	0.174	-	-1.039
	0.842	**-2.559**		**2.714**	-1.094	1.437	1.508	1.160	
	0.010	**0.579**	**-0.945**	0.0005	**0.607**	-0.270	**0.636**	-	-1.233
	9.412	**4.309**	**-30.83**	1.477	**2.271**	-0.943	**5.289**	1.375	
Singapore	-			**0.006**	-0.122	2.310	**0.278**	-	-1.220
	0.009			**6.567**	-1.812	1.156	**2.532**	1.321	
	-								
	1.244								
	-	**-0.252**		**0.006**	**-0.250**	2.030	0.416	-	-1.253
	0.016	**-5.281**		**3.654**	**-5.734**	0.900	1.933	1.374	
	-								
	2.434								
	-	0.200	**-0.582**	**0.004**	**-0.210**	1.729	**0.440**	-	-1.327
	0.003	1.840	**-8.628**	**4.592**	**-3.371**	0.907	**2.552**	1.468	
	-								
	0.554								
Thailand	-			0.003	**-0.210**	**0.554**	**0.828**	-	-1.057
	0.016			1.357	**-2.870**	**2.071**	**5.978**	1.158	
	-								
	1.596								
	-	**0.196**		**0.006**	**-0.178**	**0.612**	**0.577**	-	-1.036
	0.018	**3.200**		**2.543**	**-2.829**	**2.074**	**4.055**	1.157	
	-								
	1.247								
	-	**-0.410**	**0.679**	**0.006**	**-0.149**	0.430	**0.572**	-	-1.100
	0.011	**-2.604**	**4.120**	**2.005**	**-2.001**	1.481	**3.010**	1.241	
	-								
	0.843								

Note: The two entries for each parameter are their respective parameter estimate and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level.

Table 4.9 EGARCH(1,1), AR(1)- EGARCH(1,1) and ARMA(1,1)-EGARCH(1,1) Estimates

Country	Mean equation			Variance equation				AIC	SIC
	c	AR(1)	MA(1)	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\beta}$		
Indonesia	0.004			-6.425	0.136	0.191	-0.448	-	-
	0.495			-3.215	0.727	1.565	-1.027	1.457	1.356
	0.003	-0.047		**-6.520**	0.107	0.174	-0.477	-	-
	0.357	-0.559		**-2.958**	0.551	1.420	-0.985	1.440	1.319
	0.001	**0.641**	**-0.983**	**-8.147**	**0.298**	-0.012	**-0.752**	-	-
	1.647	**10.27**	**-85.76**	**-16.45**	**2.623**	-0.143	**-6.325**	1.580	1.439
Malaysia	0.012			-0.307	**0.302**	0.135	**0.978**	-	-
	1.298			-1.779	**4.810**	0.498	**28.03**	1.213	1.112
	0.012	-0.139		-2.726	0.061	**-0.305**	0.336	-	-
	1.266	-1.524		-1.369	0.270	**-2.085**	0.619	1.124	1.003
	0.011	**-0.938**	**0.984**	**-0.362**	**0.316**	0.014	**0.973**	-	-
	1.315	**-22.90**	**65.14**	**-2.812**	**4.841**	0.094	**42.34**	1.283	1.142
Singapore	**-0.029**			-0.217	-0.177	**-0.560**	**0.896**	-	-
	-3.180			-0.735	-0.842	**-2.040**	**36.43**	1.465	1.365
	-0.026	-0.050		-0.130	-0.188	**-0.556**	**0.919**	-	-
	-2.603	-0.597		-1.413	-1.492	**-2.458**	**51.79**	1.445	1.324
	0.003	**0.495**	**-0.990**	**-7.225**	0.185	**-0.668**	**-0.482**	-	-
	10.54	**9.964**	**-333.8**	**-14.35**	0.757	**-3.545**	**-4.632**	1.822	1.681
Thailand	-0.017			-0.235	-0.001	**-0.382**	**0.934**	-	-
	-1.705			-0.687	-0.009	**-2.714**	**12.04**	1.150	1.049
	-0.023	0.116		-0.428	0.076	**-0.344**	**0.901**	-	-
	-1.739	1.259		-0.787	0.581	**-2.543**	**7.619**	1.143	1.022
	-0.018	-0.392	**0.663**	-0.269	0.044	**-0.292**	**0.937**	-	-
	-1.459	-1.950	**3.782**	-0.644	0.348	**-2.144**	**10.53**	1.192	1.051

Note: The two entries for each parameter are their respective parameter estimate and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level.

Table 4.10 Constant Conditional Correlations

Country	Indonesia	t-ratio	Malaysia	t-ratio	Singapore	t-ratio	Thailand
Indonesia	1						
Malaysia	**0.318**	(3.429)	1				
Singapore	**0.534**	(6.420)	**0.405**	(3.468)	1		
Thailand	**0.455**	(5.062)	**0.301**	(3.389)	**0.716**	(11.195)	1

Note: The two entries for each parameter are their respective parameter estimate and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level.

Table 4.11 VARMA-GARCH Estimates

Panel 9a Thailand_Indonesia

Country	ω	α_{Thai}	α_{Indo}	β_{Thai}	β_{Indo}
Thailand	-0.008	0.184	-0.017	0.191	1.489
	-0.941	1.065	-0.125	0.494	1.619
Indonesia	**0.005**	0.088	0.096	-0.224	0.753
	2.261	1.271	1.026	-0.863	1.828

Panel 9b Thailand_Malaysia

Country	ω	α_{Thai}	α_{Malay}	β_{Thai}	β_{Malay}
Thailand	0.007	0.266	0.015	0.336	-0.012
	1.724	1.346	0.441	1.125	-0.391
Malaysia	**0.016**	**0.418**	0.072	**-1.215**	**0.907**
	2.402	**2.034**	1.455	**-2.289**	**12.84**

Panel 9c Thailand_Singapore

Country	ω	α_{Thai}	α_{Sing}	β_{Thai}	β_{Sing}
Thailand	**0.012**	**0.535**	**-0.129**	-0.069	**0.115**
	3.137	**2.483**	**-2.740**	-0.401	**2.573**
Singapore	**0.020**	**0.312**	**0.064**	**-1.404**	**1.014**
	320.4	**3.641**	**2.191**	**-35.73**	**17.04**

Panel 9d Singapore_Indonesia

Country	ω	α_{Sing}	α_{Indo}	β_{Sing}	β_{Indo}
Singapore	-0.001	0.631	-0.019	0.088	0.630
	-0.222	1.305	-0.154	0.432	1.179
Indonesia	**0.012**	**0.244**	**0.133**	**0.198**	**-0.762**
	4.672	**2.472**	**2.657**	**3.006**	**-14.95**

Panel 9e Singapore_Malaysia

Country	ω	α_{Sing}	α_{Malay}	β_{Sing}	β_{Malay}
Singapore	**0.009**	0.315	0.345	**0.413**	**-0.150**
	4.388	1.496	1.695	**2.339**	**-2.650**
Malaysia	0.003	**-0.059**	**0.136**	0.022	**0.833**
	1.443	**-2.746**	**2.161**	1.835	**8.547**

Panel 9f Indonesia_Malaysia

Country	ω	α_{Indo}	α_{Malay}	β_{Indo}	β_{Malay}
Indonesia	0.002	0.075	-0.011	**0.750**	-0.001
	0.648	0.999	-0.681	**2.114**	-0.065
Malaysia	0.002	**-0.247**	0.033	0.395	**0.836**
	0.113	**-5.112**	1.136	0.625	**3.318**

Note: The two entries for each parameter are their respective parameter estimate and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level.

Table 4.12 VARMA-AGARCH Estimates

Panel 10a Thailand_Indonesia

Country	ω	α_{Thai}	α_{Indo}	γ	β_{Thai}	β_{Indo}
Thailand	-0.005	**-0.144**	0.069	**0.635**	0.303	1.158
	-0.855	**-2.480**	0.562	**2.222**	1.508	1.740
Indonesia	0.001	0.040	**-0.195**	0.257	-0.046	**0.975**
	0.634	1.101	**-2.746**	1.740	-0.361	**16.61**

Panel 10b Thailand_Malaysia

Country	ω	α_{Thai}	α_{Malay}	γ	β_{Thai}	β_{Malay}
Thailand	0.008	-0.126	0.039	0.562	0.374	0.012
	2.095	-1.882	0.858	1.862	1.329	0.416
Malaysia	0.004	0.193	-0.112	0.898	0.730	-0.074
	0.422	1.238	-1.542	1.647	1.125	-0.835

Panel 10c Thailand_Singapore

Country	ω	α_{Thai}	α_{Sing}	γ	β_{Thai}	β_{Sing}
Thailand	**0.009**	-0.036	**-0.172**	**-0.722**	-0.039	**0.409**
	2.509	-0.722	**-2.595**	**2.480**	-0.190	**3.661**
Singapore	**0.017**	**0.157**	-0.155	**0.385**	**-1.044**	**0.972**
	0.017	**2.716**	-1.459	**2.472**	**-1.044**	**19.63**

Panel 10d Singapore_Indonesia

Country	ω	α_{Sing}	α_{Indo}	γ	β_{Sing}	β_{Indo}
Singapore	**0.016**	0.164	0.110	1.228	0.132	**-0.934**
	5.086	1.781	1.461	1.378	1.783	**-4.728**
Indonesia	0.001	0.012	**-0.178**	-2.565	-0.008	**0.999**
	1.915	0.430	**-2.565**	1.690	-0.260	**25.02**

Panel 10e Singapore_Malaysia

Country	ω	α_{Sing}	α_{Malay}	γ	β_{Sing}	β_{Malay}
Singapore	**0.006**	**-0.149**	0.089	1.307	**0.369**	-0.045
	5.927	**-2.374**	1.449	1.297	**2.831**	-2.424
Malaysia	**0.021**	**-0.035**	**-0.285**	0.913	**-0.030**	0.150
	5.174	**-5.033**	**-5.581**	1.840	**-2.974**	1.440

Panel 10f Indonesia_Malaysia

Country	ω	α_{Indo}	α_{Malay}	γ	β_{Indo}	β_{Malay}
Indonesia	**0.002**	-0.149	-0.031	**0.322**	**0.891**	0.013
	2.107	-1.809	-1.267	**2.834**	**12.031**	0.611
Malaysia	**0.038**	**-0.194**	**-0.324**	0.838	**-1.067**	0.223
	4.062	**-3.071**	**-5.352**	1.997	**-2.207**	1.816

Note: The two entries for each parameter are their respective parameter estimate and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level.

Figure 4.1 Annual Tourism Arrivals and Annual Growth Rates of Leading Four

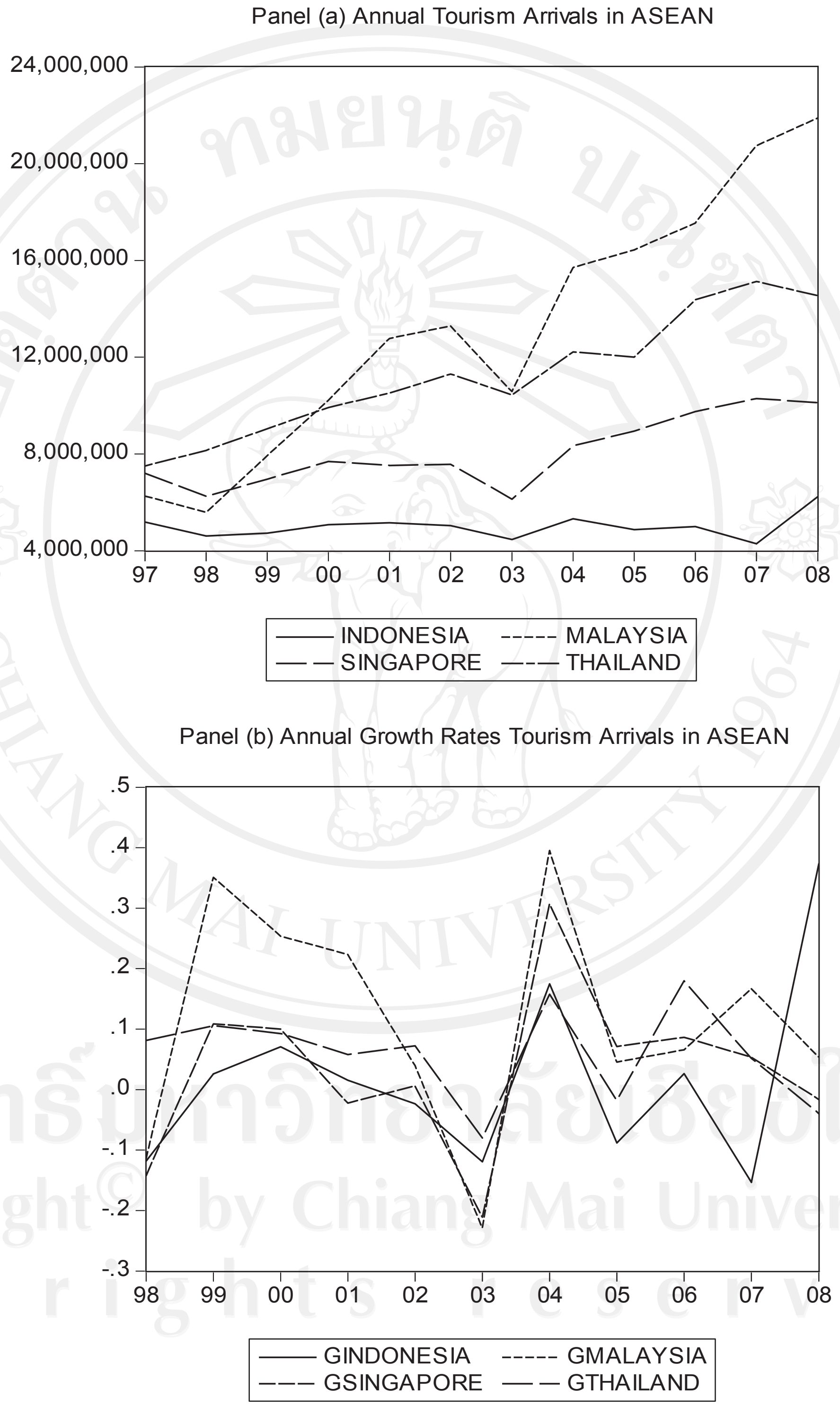
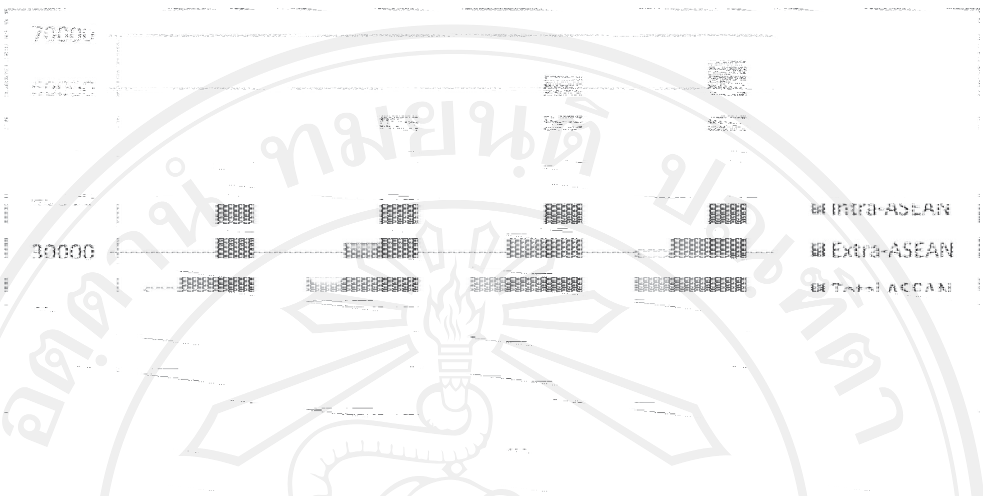
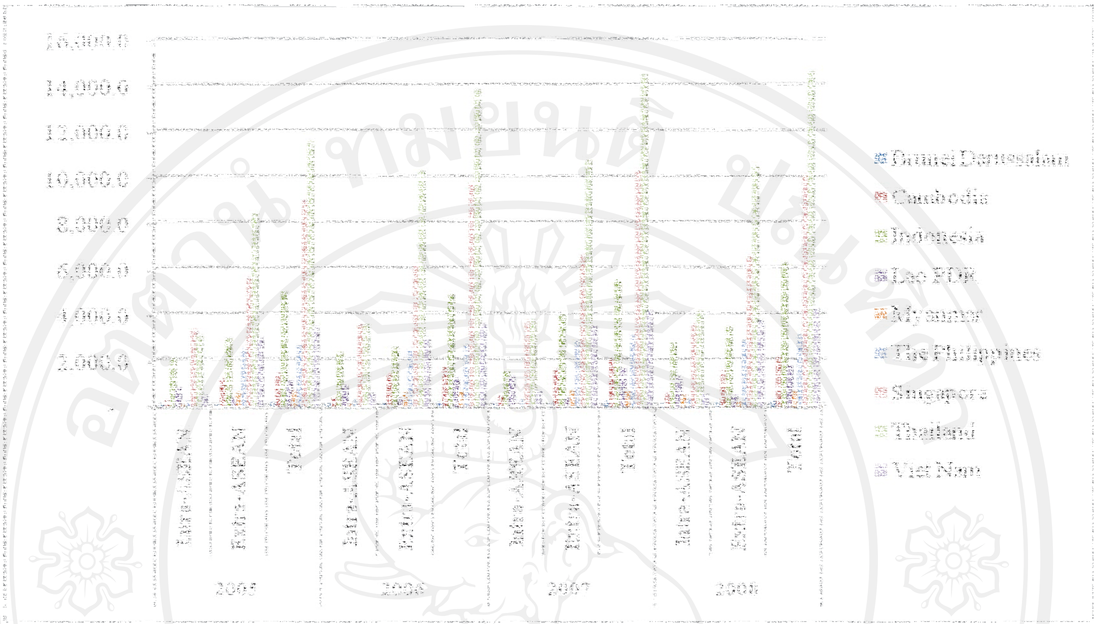


Figure 4.2Tourist Arrivals to ASEAN by Source



Source: ASEAN Tourism Statistical Database 2009.

Figure 4.3 Tourist Arrivals to ASEAN by Country and Source



Source: ASEAN Tourism Statistical Database 2009.

Figure 4.4Tourist Arrivals of Leading Four Countries

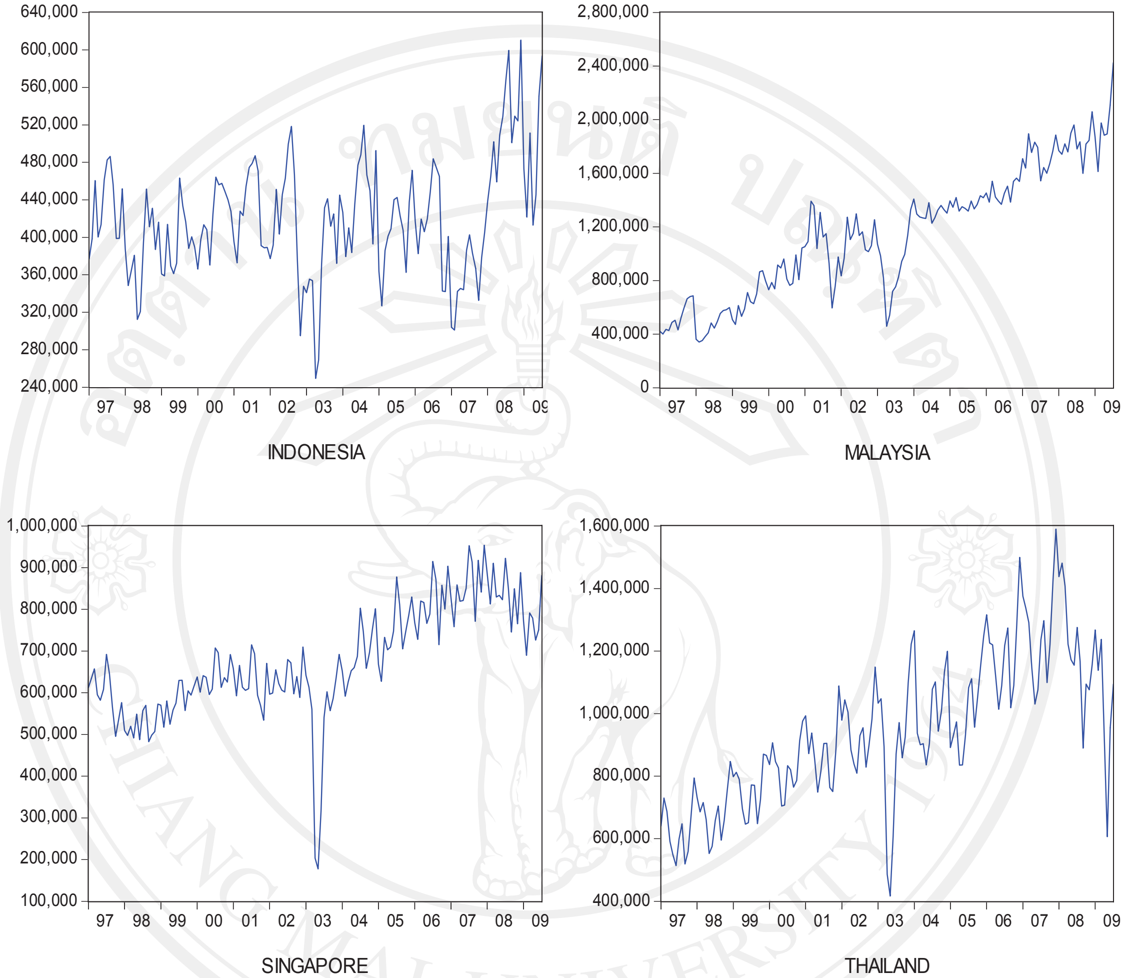


Figure 4.5 Logarithm of Tourist Arrival Rate of Leading Four Countries

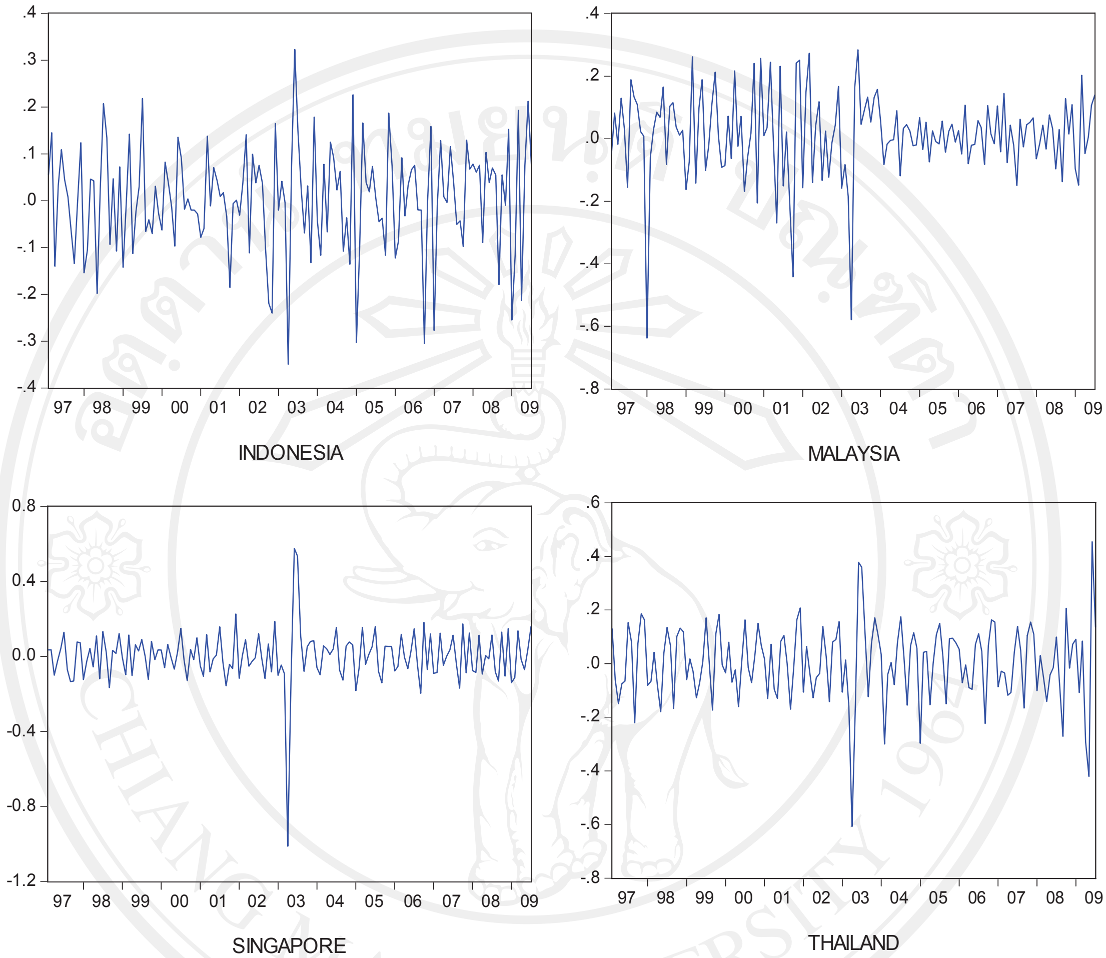


Figure 4.6 Volatility of Log Arrival Rate of Leading Four Countries