

Interdependence of International Tourism Demand and Volatility in Leading ASEAN Destinations*

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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 paper 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.

Keywords: Tourism demand, ASEAN, multivariate GARCH, volatility spillovers, interdependence, economic development.

JEL Classifications: C22, C32, F50, O53.

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. 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, 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. 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 1).

[Insert Table 1 here]

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 preceding 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 TSD (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 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%.

[Insert Table 2 here]

As given in Table 2, inbound tourism to South-East Asia has been distributed to four leading destinations, namely Malaysia, Thailand, Singapore, and Indonesia. The trend of international tourist arrivals to these countries has been relatively increasing over time. 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 1 and 2, the intra-ASEAN tourism is deemed to be important as extra-ASEAN 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 a unification among the nations of South-East Asia. These similarities seem to have 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 paper.

[Insert Figures 1 and 2 here]

Given the importance of understanding the dependence on tourism in ASEAN, this paper 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 paper 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 multivariate models. Some concluding remarks are given in Section 5.

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 paper 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 (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 (Hylleberg, Engle, Granger, and Yoo (1990)) framework was used as a pre-test for

seasonal unit root. 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 (2002) 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.

Goh and Law (2002) 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. In a similar study, Du Preez and Witt (2003) 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. The application of time-series method in tourism demand analysis can also be found in Lim and McAleer (2000, 2001), Cho (2001, 2003), Kulendran and Witt (2003a, 2003b), Gil-Alana et al. (2004), Coshall (2005, 2009), Gil-Alana (2005), Kulendran and Wong (2005), Oh and Morzuch (2005), Lim et al. (2008), and Chang et.al (2009).

Another extension of the time series analysis of tourism demand has been the application of the Generalized Autoregressive Conditional Heteroscedastic (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 (2005), Chang et al. (2009), Chang et al. (2009a, 2009b), McAleer et al. (2009), and Divino and McAleer (2009a, 2009b) 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. (2005) 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.

Shareef and McAleer (2007) 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.

Hoti et al. (2007) 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.

3. Econometric methodology

2.2.1 Univariate Conditional Volatility Models

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

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

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

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.

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. (1993) proposed the asymmetric (or threshold) GARCH, or GJR model, which is given by

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

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

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

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

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.

As noted in McAleer et al. (2007) and Chang et al. (2009b), 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); (iii) Shephard (1996) observed that $|\beta| < 1$ is likely to be a sufficient condition for consistency of QMLE for EGARCH(1,1); (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).

2.2.2 Multivariate Conditional Volatility Model

This section presents models of the volatility in tourism demand, namely the CCC model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003), and VARMA-AGARCH of 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:

$$y_t = E(y_t | F_{t-1}) + \varepsilon_t \quad (5)$$

$$\varepsilon_t = D_t \eta_t$$

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

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

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

where α_{ij} and β_{ij} represents the ARCH and GARCH effects, respectively. The conditional correlation matrix of CCC is $\Gamma = E(\eta_t \eta_t' | F_{t-1}) = E(\eta_t \eta_t')$, where $\Gamma = \{\rho_{ij}\}$ for $i, j = 1, \dots, m$. From (1), $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta_t' D_t$, $D_t = (\text{diag } Q_t)^{1/2}$, and $E(\varepsilon_t \varepsilon_t' | F_{t-1}) = Q_t = D_t \Gamma D_t$, where Q_t is the conditional covariance matrix. The conditional correlation matrix is defined as $\Gamma = D_t^{-1} Q_t D_t^{-1}$, 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 (2003) proposed a vector autoregressive moving average (VARMA) specification of the conditional mean in (5) and the following specification for the conditional variance:

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

where $H_t = (h_{1t}, \dots, h_{mt})'$, $\bar{\varepsilon} = (\varepsilon_{1t}^2, \dots, \varepsilon_{mt}^2)'$, and W , A_i for $i=1, \dots, r$ and B_j for $j=1, \dots, s$ 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. (2009) proposed the VARMA-AGARCH specification for the conditional variance, namely

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

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

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

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).

4. Data

In this paper, we focus on modelling conditional volatility and examining the interdependence of the logarithm of monthly tourist arrival rate of international tourist arrivals to 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 (BPS-Statistics, Indonesia).

Figure 3 presents the plots of the number of tourist arrivals in each country. Only three countries, namely Malaysia, Singapore and Thailand, exhibit upward trends in the number of tourist arrivals, with cyclical and seasonal patterns. Interestingly, in 2003 the numbers of

tourist arrivals in each country collapsed because of the Severe Acute Respiratory Syndrome (hereafter SARS) epidemic. These phenomena have been affirmed by the report of the 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. (2010)).

[Insert Figure 3 here]

Figure 4 presents the graphs of the logarithm of the monthly tourist arrival rate of the 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 monthly arrival rate, Indonesia and Malaysia exhibit greater volatility, with clustering. As in the plot of the number of tourist arrivals, SARS affected the log arrival rate significantly and negatively. Figure 5 displays the volatilities of the log arrival rate in the 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 5 are similar in all four countries, with volatility clustering and an obvious outlier due to the outbreak of SARS in 2003.

[Insert Figures 4 and 5 here]

Table 3 presents the descriptive statistics for the logarithm of the monthly tourist arrival rate of four countries. The averages of the log arrival rate of the 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 arrival rate in each country are statistically significant, thereby indicating that the distributions of these log arrival rates are not normal, which may be due to the presence of extreme observations.

[Insert Table 3 here]

The unit root tests for all logarithm of the monthly tourist arrival rate are summarized in Table 4, using the EViews6 econometric software package. 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 log arrival rate series reject the null hypothesis at the 5% level, thereby indicating that all log arrival rates are stationary. These test results are supported by the KPSS test (the results are available on request).

[Insert Table 4 here]

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 5, 6 and 7 report the estimated parameters using QMLE and the Bollerslev-Wooldridge (1992) robust t -ratios. 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 5. 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.

[Insert Table 5 here]

The results of two asymmetric GARCH(1,1) models, namely GJR(1,1) and EGARCH (1,1), are reported in Tables 6 and 7. 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.

[Insert Table 6 here]

For the EGARCH model in Table 7, 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.

[Insert Table 7 here]

Table 8 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 (1992) robust t -ratios. 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.

[Insert Table 8 here]

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 (1992) robust t -ratios, are

reported in Tables 9 and 10. In Table 9, 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.

[Insert Table 9 here]

Table 10 presents the VARMA-AGARCH estimates and corresponding Bollerslev-Wooldridge (1992) robust *t*-ratios. 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.

[Insert Table 10 here]

6. Concluding Remarks

The purpose of the paper 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 paper 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 medium to high range. The highest conditional correlation was between the pair Thailand and Singapore, which suggests that standardized shocks in the log of the monthly tourist arrival rate of both countries are moving in the same direction.

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.

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Table 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
<i>Northern Europe</i>	28.6	35.8	43.7	52.8	56.5	58.1	57.0	6.2	2.8	-1.9	3.4
<i>Western Europe</i>	108.6	112.2	139.7	142.6	149.6	154.9	153.3	16.6	3.6	-1.1	1.2
<i>Central/Eastern Europe</i>	33.9	58.1	69.3	87.5	91.4	96.6	99.6	10.8	5.6	3.1	4.6
<i>Southern/Mediter.Eu.</i>	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
<i>North-East Asia</i>	26.4	41.3	58.3	86.0	92.0	101.0	101.0	10.9	9.8	-0.1	7.1
<i>South-East Asia</i>	21.2	28.4	36.1	48.5	53.1	59.7	61.7	6.7	12.3	3.5	6.9
<i>Ocenia</i>	5.2	8.1	9.6	11.0	11.0	11.2	11.1	1.2	1.7	-0.9	1.8
<i>South Asia</i>	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
<i>North America</i>	71.7	80.7	91.5	89.9	90.6	95.3	97.8	10.6	5.2	2.6	0.8
<i>Caribbean</i>	11.4	14.0	17.1	18.8	19.4	19.8	20.2	2.2	1.6	2.0	2.1
<i>Central America</i>	1.9	2.6	4.3	6.3	6.9	7.8	8.3	0.9	12.0	7.0	8.4
<i>South America</i>	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
<i>North Africa</i>	8.4	7.3	10.2	13.9	15.1	16.3	17.2	1.9	8.5	4.9	6.7
<i>Subsaharan Africa</i>	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 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										
<i>China</i>	49,913	54,720	53,049	9.6	-3.1	28.8	33,949	37,233	40,843	19.8
<i>Hong Kong (China)</i>	15,822	17,154	17,320	8.4	1.0	9.4	11,638	13,754	15,300	7.4
<i>Japan</i>	7,334	8,347	8,351	13.8	0.0	4.5	8,469	9,334	10,821	5.3
<i>Korea, Republic of</i>	6,155	6,448	6,891	4.8	6.9	3.7	5,788	6,138	9,078	4.4
<i>Macao (China)</i>	10,683	12,942	10,605	21.2	..	5.8	9,829	13,612	13,382	6.5
<i>Taiwan (pr.of China)</i>	3,520	3,716	3,845	5.6	3.5	2.1	5,136	5,213	5,937	2.9
South-East Asia										
<i>Cambodia</i>	1,591	1,873	2,001	17.7	6.8	1.1	963	1,135	1,221	0.6
<i>Indonesia</i>	4,871	5,506	6,234	13.0	13.2	3.4	4,448	5,346	7,345	3.6
<i>Lao P.D.R.</i>	842	1,142	1,295	35.6	13.4	0.7	173	233	276	0.1
<i>Malaysia</i>	17,547	20,973	22,052	19.5	5.1	12.0	10,424	14,047	15,277	7.4
<i>Phillippines</i>	2,843	3,092	3,139	8.7	1.5	1.7	3,501	4,931	4,388	2.1
<i>Singapore</i>	7,588	7,957	7,778	4.9	-2.2	4.2	7,535	9,162	10,575	5.1
<i>Thailand</i>	13,822	14,464	14,584	4.6	0.8	7.9	13,401	16,669	17,651	8.6
<i>Vietnam</i>	3,584	4,229	4,236	18.0	0.2	2.3	3,200	3,477	3,926	1.9
Oceania										
<i>Australia</i>	5,532	5,644	5,586	2.0	-1.0	3.0	17,840	22,298	24,660	12.0
<i>New Zealand</i>	2,422	2,466	2,459	1.8	-0.3	1.3	4,738	5,400	4,912	2.4
<i>Fiji</i>	549	540	585	-1.6	8.4	0.3	480	497	568	0.3
South Asia										
<i>India</i>	4,447	5,082	5,367	14.3	5.6	2.9	8,634	10,729	11,832	5.7
<i>Maldives</i>	602	676	683	12.3	1.1	0.4	512	602	636	0.3
<i>Nepal</i>	384	527	500	37.2	-5.0	0.3	128	198	336	0.1
<i>Pakistan</i>	898	840	823	-6.6	-2.0	0.5	255	276	245	0.1
<i>Sri Lanka</i>	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 3: 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: 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 5: 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 6: 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	-1.469	-1.369
	-0.455			0.965	-0.336	1.456	2.769		
	-0.011	-0.211		0.001	-0.183	0.309	0.996	-1.469	-1.369
	-1.777	-3.428		4.278	-9.534	12.32	48.31		
	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	-1.153	-1.053
	0.356			2.301	-0.211	1.413	1.359		
	0.008	-0.206		0.012	-0.098	0.686	0.174	-1.160	-1.039
	0.842	-2.559		2.714	-1.094	1.437	1.508		
	0.010	0.579	-0.945	0.0005	0.607	-0.270	0.636	-1.375	-1.233
	9.412	4.309	-30.83	1.477	2.271	-0.943	5.289		
Singapore	-0.009			0.006	-0.122	2.310	0.278	-1.321	-1.220
	-1.244			6.567	-1.812	1.156	2.532		
	-0.016	-0.252		0.006	-0.250	2.030	0.416	-1.374	-1.253
	-2.434	-5.281		3.654	-5.734	0.900	1.933		
	-0.003	0.200	-0.582	0.004	-0.210	1.729	0.440	-1.468	-1.327
	-0.554	1.840	-8.628	4.592	-3.371	0.907	2.552		
Thailand	-0.016			0.003	-0.210	0.554	0.828	-1.158	-1.057
	-1.596			1.357	-2.870	2.071	5.978		
	-0.018	0.196		0.006	-0.178	0.612	0.577	-1.157	-1.036
	-1.247	3.200		2.543	-2.829	2.074	4.055		
	-0.011	-0.410	0.679	0.006	-0.149	0.430	0.572	-1.241	-1.100
	-0.843	-2.604	4.120	2.005	-2.001	1.481	3.010		

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 7: 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	-1.457	-1.356
	0.495			-3.215	0.727	1.565	-1.027		
	0.003	-0.047		-6.520	0.107	0.174	-0.477	-1.440	-1.319
	0.357	-0.559		-2.958	0.551	1.420	-0.985		
	0.001	0.641	-0.983	-8.147	0.298	-0.012	-0.752	-1.580	-1.439
	1.647	10.27	-85.76	-16.45	2.623	-0.143	-6.325		
Malaysia	0.012			-0.307	0.302	0.135	0.978	-1.213	-1.112
	1.298			-1.779	4.810	0.498	28.03		
	0.012	-0.139		-2.726	0.061	-0.305	0.336	-1.124	-1.003
	1.266	-1.524		-1.369	0.270	-2.085	0.619		
	0.011	-0.938	0.984	-0.362	0.316	0.014	0.973	-1.283	-1.142
	1.315	-22.90	65.14	-2.812	4.841	0.094	42.34		
Singapore	-0.029			-0.217	-0.177	-0.560	0.896	-1.465	-1.365
	-3.180			-0.735	-0.842	-2.040	36.43		
	-0.026	-0.050		-0.130	-0.188	-0.556	0.919	-1.445	-1.324
	-2.603	-0.597		-1.413	-1.492	-2.458	51.79		
	0.003	0.495	-0.990	-7.225	0.185	-0.668	-0.482	-1.822	-1.681
	10.54	9.964	-333.8	-14.35	0.757	-3.545	-4.632		
Thailand	-0.017			-0.235	-0.001	-0.382	0.934	-1.150	-1.049
	-1.705			-0.687	-0.009	-2.714	12.04		
	-0.023	0.116		-0.428	0.076	-0.344	0.901	-1.143	-1.022
	-1.739	1.259		-0.787	0.581	-2.543	7.619		
	-0.018	-0.392	0.663	-0.269	0.044	-0.292	0.937	-1.192	-1.051
	-1.459	-1.950	3.782	-0.644	0.348	-2.144	10.53		

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 8: 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 9: 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

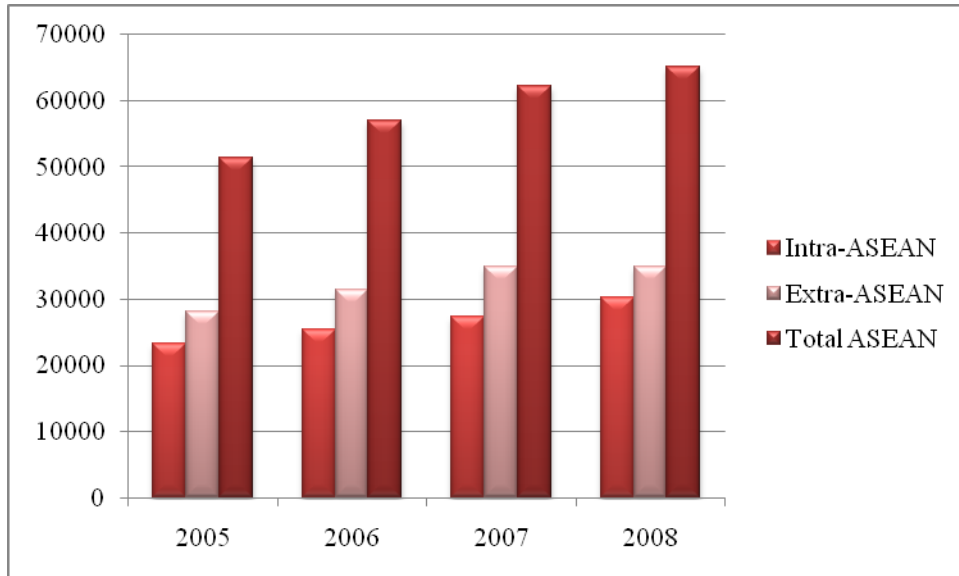
Note: The two entries for each parameter are their respective parameter estimate and Bollerslev and Wooldridge (1992) robust t -ratios. Entries in bold are significant at the 5% level.

Table 10: 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

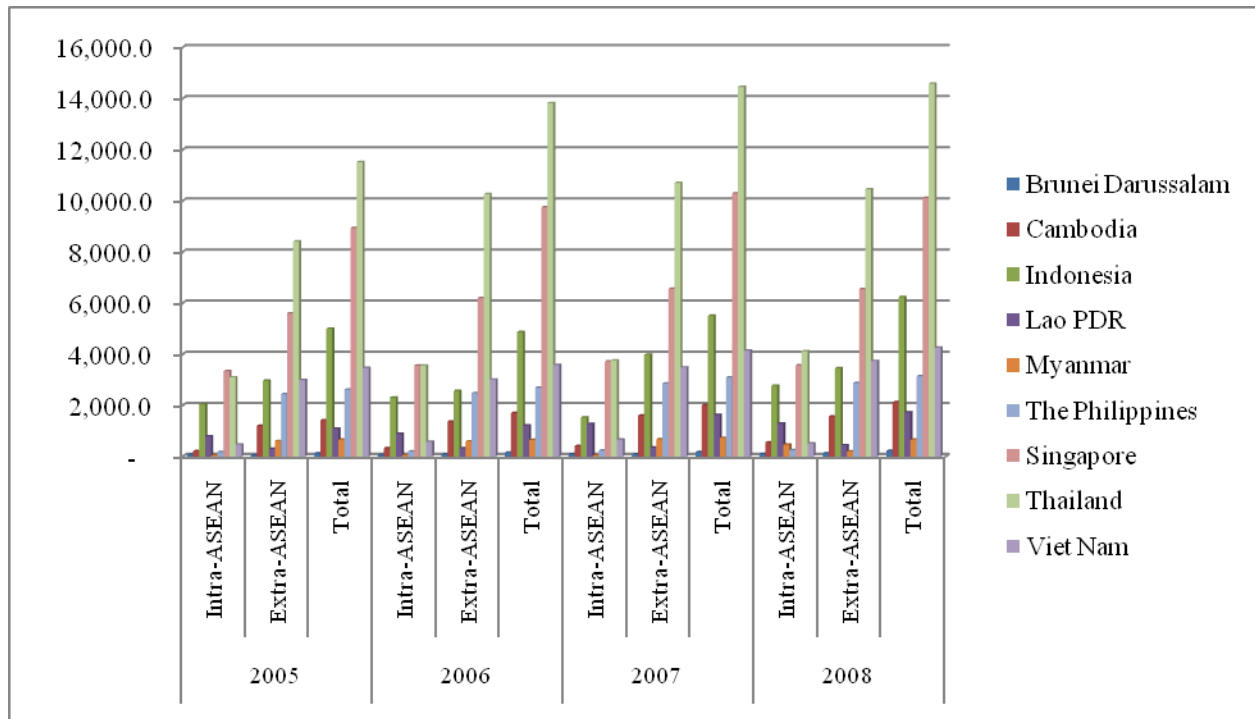
Note: The two entries for each parameter are their respective parameter estimate and Bollerslev and Wooldridge (1992) robust t -ratios. Entries in bold are significant at the 5% level.

Figure 1
Tourist Arrivals to ASEAN by Source



Source: ASEAN Tourism Statistical Database 2009.

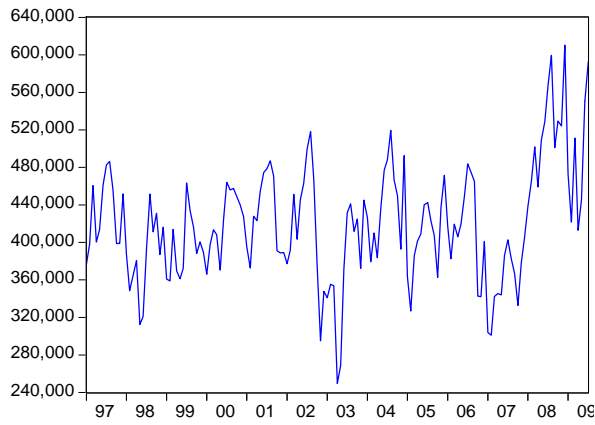
Figure 2
Tourist Arrivals to ASEAN by Country and Source



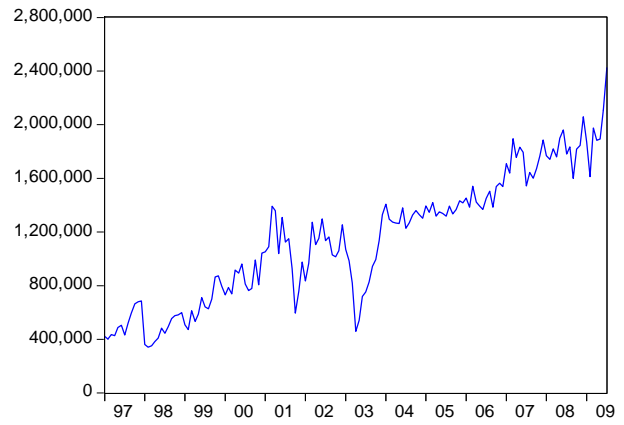
Source: ASEAN Tourism Statistical Database 2009.

Figure 3

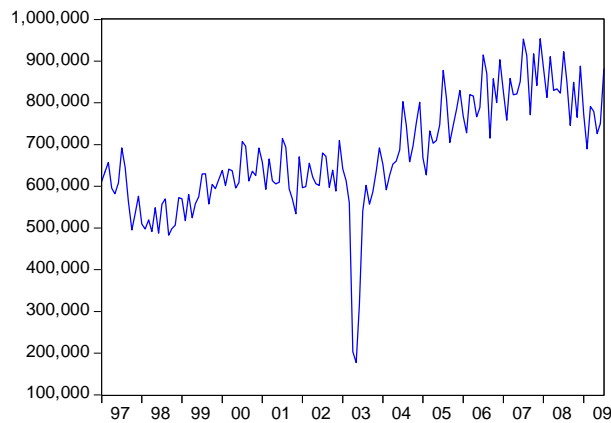
Tourist Arrivals in ASEAN



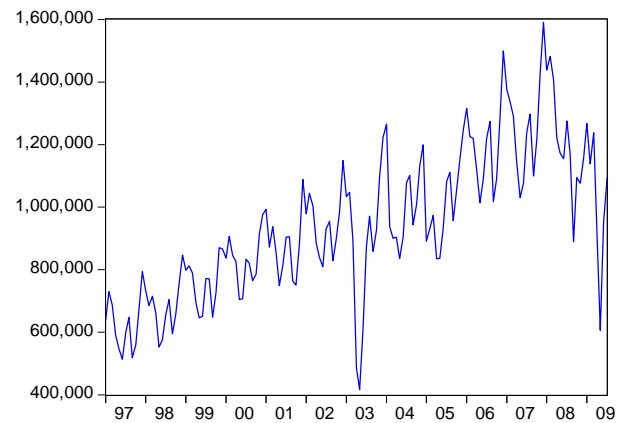
INDONESIA



MALAYSIA



SINGAPORE



THAILAND

Figure 4

Log Arrival Rate of Leading Four Countries

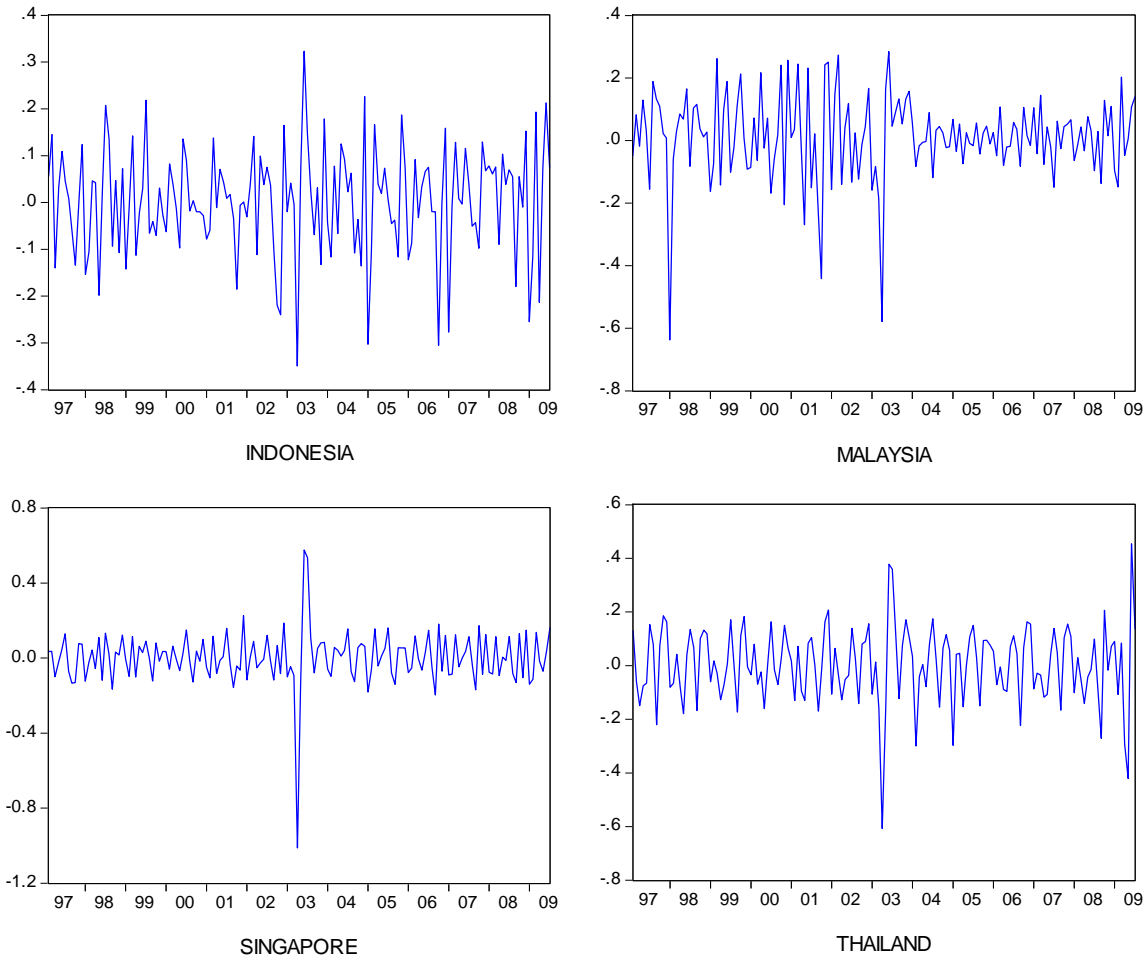
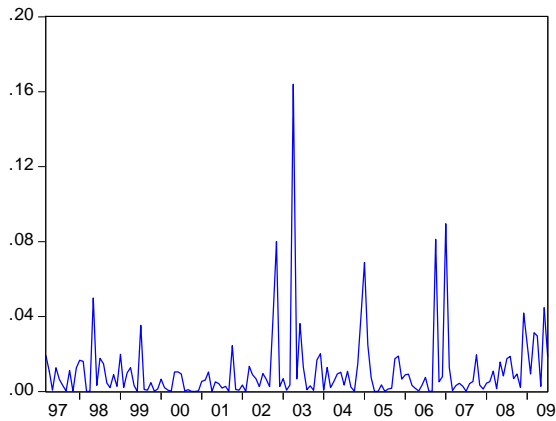
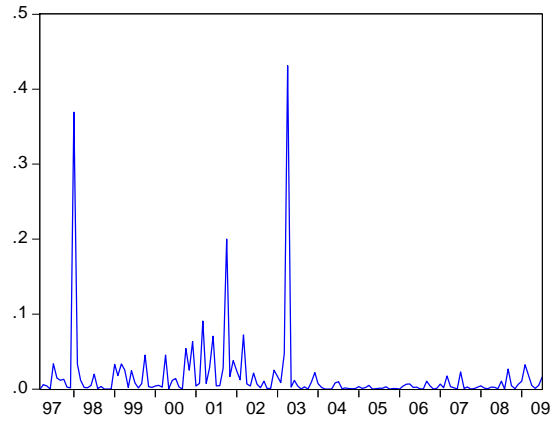


Figure 5

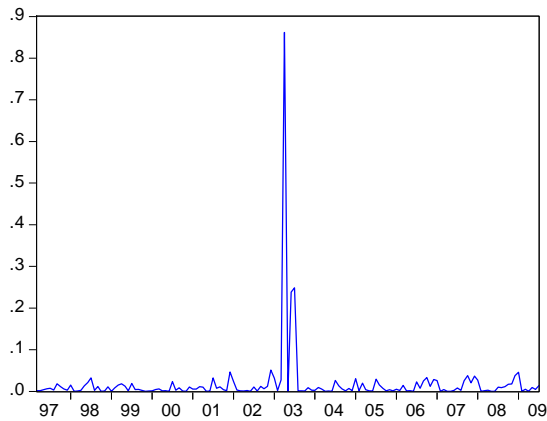
Volatility of Log Arrival Rate of Leading Four Countries.



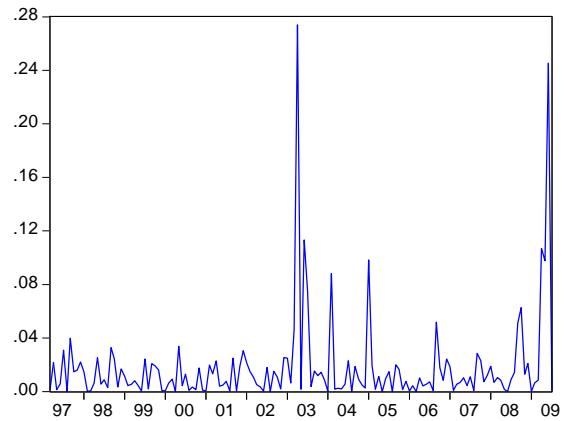
VOLATILITY_INDONESIA



VOLATILITY_MALAYSIA



VOLATILITY_SINGAPORE



VOLATILITY_THAILAND