Chapter 2

Research designs and methods

2.1 Conceptual Framework

Tourism Demand

Empirical models of tourism demand have borrowed heavily from consumer theory which predicts that the optimal consumption level depends on the consumer's income level, the prices of goods, the prices of related goods (substitutes and complements goods) and other demand shifters.

For our tourism model, we use the number of tourist arrivals as the dependent variable because high frequency expenditure data is unavailable.

The model: the theory of demand suggests that for an individual location, the demand for tourism will be expressed as follows (C. Ouerfelli, 2008, 128-130):

$$\mathbf{N = N\ (GDP, RP, CP, EX, OC, \xi_i)} \qquad (2.1)$$

where

N = Number of Malaysian or Japanese tourist arrivals to Thailand

GDP = GDP per capita of Malaysian and Japanese tourists.

RP = Relative price of tourist goods and services in Thailand compared with the price level of Malaysia and Japan.

$$= \frac{CPI_{thailand}}{CPI_{japan} ER_{japan/thailand}} \text{ and } \frac{CPI_{thailand}}{CPI_{malaysia} ER_{malaysia/thailand}}$$

CP = Relative price of tourist goods and services in Thailand with respect to the price level observed in competing countries (Singapore, Indonesia and Philippines) (or the substitute prices).

$$= \frac{weighted\ CPI_{\sin g,indo,phillip}}{CPI_{japan}ER_{japan} / _{weighted\ \sin g,indo,phillip}} \text{ and } \frac{weighted\ CPI_{\sin g,indo,phillip}}{CPI_{malaysia}ER_{malaysia} / _{weighted\ \sin g,indo,phillip}}$$

EX = Nominal exchange rate, expressed in terms of the price of Thailand currency in the Malaysian currency unit and the Japanese currency unit.

OC = Occupancy rate of Malaysian and Japanese tourists.

Favorable natural and climate conditions and/or rich cultural heritage do not automatically guarantee the choice of destination. To assure client loyalty, tourist operators must guarantee an adequate infrastructure and most importantly hospitality. The Thai tourist package is essentially composed of accommodation and transport. Hotel capacity or occupancy rate is an important component of the tourist supply. It may affect the potential demand in two ways (i) it reflects the product's quality and expresses the destination's notoriety; and (ii) the quality and the quantity of this variable can be divided by the tourism professionals and managed according to tourist expectation.

ξ_i = other relevant factors pertaining to Thailand.

The following derivatives are expected to apply: income elasticity of demand (ε_{GDP}), own-price elasticity of demand (ε_{PR}), cross-price elasticity of demand (ε_{CP}), nominal exchange rate elasticity of demand (ε_{CP}) and occupancy rate elasticity of demand (ε_{OC}).

Assuming constant elasticity within the empirically relevant range, we may suppose that the functional form is log-linear. We can construct the tourism demand model which comprises demand determinants as follows:

$$NOM = \alpha_0 + \alpha_1 GDPM + \alpha_2 RPM + \alpha_3 CPM + \alpha_4 EXM + \alpha_5 OCM + \varepsilon_M \quad (2.2)$$
$$NOJ = \beta_0 + \beta_1 GDPJ + \beta_2 RPJ + \beta_3 CPJ + \beta_4 EXJ + \beta_5 OCJ + \varepsilon_J \quad (2.3)$$

Including British and American tourists demand model

$$NOUK = \gamma_0 + \gamma_1 GDPUK + \gamma_2 RPUK + \gamma_3 CPUK + \gamma_4 EXUK + \gamma_5 OCUK + \varepsilon_{UK} \quad (2.4)$$
$$NOUS = \phi_0 + \phi_1 GDPUS + \phi_2 LRPUS + \phi_3 LCPUS + \phi_4 LEXUS + \phi_5 LOCUS + \varepsilon_{US} \quad (2.5)$$

In log-form

$$LNOM = \alpha_0 + \alpha_1 LGDPM + \alpha_2 LRPM + \alpha_3 LCPM + \alpha_4 LEXM + \alpha_5 LOCM + \varepsilon_M \quad (2.6)$$
$$LNOJ = \beta_0 + \beta_1 LGDPJ + \beta_2 LRPJ + \beta_3 LCPJ + \beta_4 LEXJ + \beta_5 LOCJ + \varepsilon_J \quad (2.7)$$
$$LNOUK = \gamma_0 + \gamma_1 LGDPUK + \gamma_2 LRPUK + \gamma_3 LCPUK + \gamma_4 LEXUK + \gamma_5 LOCUK + \varepsilon_{UK} \quad (2.8)$$
$$LNOUS = \phi_0 + \phi_1 LGDPUS + \phi_2 LRPUS + \phi_3 LCPUS + \phi_4 LEXUS + \phi_5 LOCUS + \varepsilon_{US} \quad (2.9)$$

2.2 Econometrics Framework

For analyzing the elasticity of demand and volatility, we use econometrics frameworks as follows:

2.2.1 Unit Root Test

When testing for unit roots, it is crucial to specify the null and alternative hypotheses appropriately to characterize the trend properties of the data. For example, if the observed data does not exhibit an increasing or decreasing trend, then the appropriate null and alternative hypotheses should reflect this. The trend properties of the data under the alternative hypothesis will determine the form of the test regression used. Furthermore, the type of deterministic terms in the test regression will have a larger influence; the type of deterministic terms in the test regression will influence the asymptotic distributions of the unit root test statistics. The two most common trend cases are summarized below.

Case I: Constant Only

The test regression is:

$$y_t = c + \phi y_{t-1} + \varepsilon_t \tag{2.10a}$$

and includes a constant to capture the non zero mean under the alternative. The hypotheses to be tested are:

$H_0: \quad \phi = 1 \Rightarrow y_t \sim I(1)$ without drift

$H_1: \quad |\phi| < 1 \Rightarrow y_t \sim I(0)$ with nonzero mean

This formulation is appropriate for non-trending time series.

Case II: Constant and Time Trend

The test regression is:

$$y_t = c + \delta t + \phi y_{t-1} + \varepsilon_t \tag{2.10b}$$

and includes a constant and deterministic time trend to capture the deterministic trend under the alternative. The hypotheses to be tested are:

$H_0: \quad \phi = 1 \Rightarrow y_t \sim I(1)$ with drift

$H_1: \quad |\phi| < 1 \Rightarrow y_t \sim I(0)$ with deterministic time trend

This formulation is appropriate for trending time series.

Augmented Dickey and Fuller Tests

The unit root tests described above are valid if the time series y_t is well characterized by an AR (1) with white noise errors. Many time series, however, have a more complicated dynamic structure than is captured by a simple AR (1) model.

Dickey and Said (1984) augment the basic autoregressive unit root test to accommodate general ARMA (p, q) models with unknown orders and their test is referred to as the augmented Dickey-Fuller (ADF) test. The ADF test tests the null hypothesis that a time series y_t is $I(1)$ against the alternative that it is $I(0)$, assuming that the dynamics in the data have an ARMA structure. The ADF test is based on estimating the test regression:

$$y_t = \beta' D_t + \phi y_{t-1} + \sum_{j=1}^{p} \psi_j \Delta y_{t-j} + \varepsilon_t \qquad (2.10c)$$

where D_t is a vector of deterministic terms (constant, trend etc.). The p lagged difference terms, Δy_{t-j}, are used to approximate the ARMA structure of the errors and the value of p is set so that the error ε_t is serially uncorrelated. The error term is also assumed to be homoskedastic. The specification of the deterministic terms depends on the assumed behavior of y_t under the alternative hypothesis of trend stationarity as described in the previous section. Under the null hypothesis, y_t is $I(1)$ which implies that $\phi = 1$. The ADF t-statistic and normalized bias statistic are based on the least squares estimates of (10c) and are given by:

$$ADF = t_{\phi=1} = \frac{\hat{\phi} - 1}{SE(\phi)}$$

$$ADF = \frac{T(\hat{\phi} - 1)}{1 - \hat{\psi}_1 - \cdots - \hat{\psi}_p}$$

Phillips and Perron Tests

Phillips and Perron (1988) developed a number of unit root tests that have become popular in the analysis of time series. The Phillips-Perron (PP) unit root tests differ from the ADF tests mainly in how they deal with serial correlation and heteroskedasticity in the errors. In particular, where the ADF tests use a parametric auto regression to approximate the ARMA structure of the errors in the test regression, the PP tests ignore any serial correlation in the test regression. The test regression for the PP tests is:

$$\Delta y_t = \beta' D_t + \pi y_{t-1} + \mu_t \tag{2.10d}$$

where μ_t is $I(0)$ and may be heteroskedastic. The PP tests correct for any serial correlation and heteroskedasticity in the errors μ_t of the test regression by directly modifying the test statistics $t_{\pi=0}$ and $T\hat{\pi}$. These modified statistics, denoted Z_t and Z_π, are given by:

$$Z_t = \left(\frac{\hat{\sigma}^2}{\hat{\lambda}^2}\right)^{1/2} \cdot t_{\pi=0} - \frac{1}{2}\left(\frac{\hat{\lambda}^2 - \hat{\sigma}^2}{\hat{\lambda}^2}\right) \cdot \left(\frac{T \cdot SE(\hat{\pi})}{\hat{\sigma}^2}\right)$$

$$Z_t = T\hat{\pi} - \frac{1}{2}\frac{T^2 \cdot SE(\hat{\pi})}{\hat{\sigma}^2}\left(\hat{\lambda}^2 - \hat{\sigma}^2\right)$$

Under the null hypothesis that $\pi = 0$, the PP Z_t and Z_π statistics have the same asymptotic distributions as the ADF t-statistic and normalized bias statistics. One advantage of the PP tests over the ADF tests is that the PP tests are robust to general forms of heteroskedasticity in the error term μ_t.

2.2.2 Seasonal Unit Root Test

There are several alternative ways to treat seasonality in a non-stationary sequence.

HEGY tests

The seasonal pattern of a series can change over time. Hence, the series exhibit non-stationary seasonality. A simple model that can describe the variation of the series is the seasonal random walk model given by:

$$y_t = y_{t-s} + \varepsilon_t$$

This model assumes s unit roots at seasonal frequencies. The series y_t is then an integrated seasonal process at the correspondent frequency $\omega_j = 2\pi j / s, j = 1,...., s/2,$ noted $I_{\omega_j}(1)$ where s is the number of time periods in a year. If s = 4, then the series has four roots with modulus one: one at a zero frequency, one at π (two cycles per year) and $\pi / 2$ (one cycle per year). Evidence of unit roots at seasonal frequencies implies that the stochastic seasonality is non-stationary. Hylleberg, Engle, Granger, and Yoo (1990) proposed a strategy that tests for unit roots in quarterly data (to deduce the appropriate different operators that must be applied to the series to achieve stationary status)

The test equation for the presence of seasonal unit roots is given by:

$$(1 - L^4) y_t = \pi_1 y_{1t-1} - \pi_2 y_{2t-1} - \pi_3 y_{3t-2} + \pi_4 y_{3t-1} + \mu_t + \varepsilon_t, \tag{2.11}$$

where:

$$y_{1t-1} = (1 + L + L^2 + L^3) y_{t-1} = y_{t-1} + y_{t-2} + y_{t-3} + y_{t-4}$$

$$y_{2t-1} = (1 - L + L^2 - L^3) y_{t-1} = y_{t-1} - y_{t-2} + y_{t-3} - y_{t-4}$$

$$y_{3t-1} = (1 - L^2) y_{t-1} = y_{t-1} - y_{t-3} \text{ so that } y_{3t-2} = y_{t-2} - y_{t-4}$$

The deterministic component μ_t includes seasonal dummies, a trend and a constant term, and ε_t is a normally and independently distributed error term with a zero mean and constant variance.

Testing for unit roots implies testing the significance of the estimated π_t. Form the t-statistics for the null hypothesis $\pi_1 = 0$; the appropriate critical values are reported in Hylleberg et al. (1990). If you do not reject the hypothesis $\pi_1 = 0$; conclude that $a_1 = 1$ so that there is a nonseasonal unit root. Next form the t-test for the hypothesis $\pi_2 = 0$. If you do not reject the null hypothesis, conclude that $a_2 = 1$ and there is root with a semiannual frequency. Finally, perform the F-test for the hypothesis $\pi_3 = \pi_4 = 0$. If the calculated value is less than the critical value reported in Hylleberg et al. (1990), conclude that π_3 and/or π_4 is zero so that there is a seasonal unit root. Be aware that the three null hypotheses are not the alternative; a series may have nonseasonal, semi-annual, and a seasonal unit root.

At the five percent significance level, Hylleberg et al. (1990) report that the critical values using 100 observations are:

	$\pi_1 = 0$	$\pi_2 = 0$	$\pi_3 = \pi_4 = 0$
Intercept	-2.88	-1.95	3.08
Intercept plus Seasonal Dummies	-2.95	-2.94	6.57
Intercept plus Seasonal Dummies plus time	-3.53	-2.94	6.60

2.2.3 Cointegration analysis and error correction model

To investigate the long-term relationship between economic variables and the number of tourist arrivals, cointegration and error correction models will be employed. These models are useful because they provide long and short-term estimations for the purpose of long-term tourism planning and short-term business forecasting (Song and Witt, 2000).

The first step in testing cointegration is to ensure that all economic variables have the same order of integration. The order of integration can be tested using the unit root tests and the seasonal unit root tests.

Johansen's (1995) cointegration procedure will be employed in this study. To illustrate the procedure,

For Malaysian tourists, let $Z_t = \begin{bmatrix} LNOM_t \\ LGDPM_t \\ LRPM_t \\ LCPM_t \\ LEXM_t \\ LOCM_t \end{bmatrix}$ and Japanese tourists, let $Z_t = \begin{bmatrix} LNOJ_t \\ LGDPJ_t \\ LRPJ_t \\ LCPJ_t \\ LEXJ_t \\ LOCJ_t \end{bmatrix}$

For British tourists, let $Z_t = \begin{bmatrix} LNOUK_t \\ LGDUK_t \\ LRPUK_t \\ LCPUK_t \\ LEXUK_t \\ LOCUK_t \end{bmatrix}$ and American tourists, let $Z_t = \begin{bmatrix} LNOUS_t \\ LGDUS_t \\ LRPUS_t \\ LCPUS_t \\ LEXUS_t \\ LOCUS_t \end{bmatrix}$,

then, the vector autoregressive (VAR) can be written as:

$$Z_t = B_1 Z_{t-1} + B_2 Z_{t-2} + \ldots + B_p Z_{t-p} + U_t \qquad (2.12)$$

where p =number of lags, B_i = an $(m \times n)$ matrix of parameters, and U_t =error term.

To obtain the error-correction mechanism (ECM), equation (2.12) is transformed as follows:

$$\Delta Z_t = \sum_{i=1}^{p=1} \Phi_i \Delta Z_{t-i} + \Phi Z_{t-p} + U_t \qquad (2.13)$$

where $\Phi_i = -(I - B_1 - B_2 - ... - B_i)$, and $\Phi = -(I - B_1 - B_2 - ... - B_p)$. Φ_i and Φ are short-run and long-run adjustments to the changes in Z_t, respectively. Equation (2.13) is named as vector error-correction model (VECM). The equilibrium relationship can be expressed as:

$$\Phi = \alpha\beta',$$

where α is the speed of adjustment to disequilibrium , and β' is a set of co-integrating vectors. The existence of cointegration relationships can be determined by the rank of Φ, $r \le (m-1)$. To choose *r*, maximum eigenvalue and trace tests will be employed.

2.2.4 Volatility Analysis

It comprises two steps in volatility analysis: (i) the first step is to construct the conditional mean model. (ii) The second step is to construct the conditional volatility model.

2.2.4.1 Conditional Mean Model

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

$$\beta(L)y_t = \mu + \theta(L)\mu_t \qquad (2.14)$$

where

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

or

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \mu_t + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \cdots + \theta_q \mu_{t-q}, \quad (2.15)$$

with

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

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

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

$$y_t = \alpha + \beta_T y_{t-T} + \beta_{2T} y_{t-2T} + \cdots + \beta_{PT} y_{t-PT} + \mu_t + \theta_T \mu_{t-T} + \theta_{2T} \mu_{t-2T} + \cdots + \theta_{QT} \mu_{t-QT}, \quad (2.16)$$

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

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

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

2.2.4.2 Conditional Volatility Model

In this paper we use the symmetric Generalized Autoregressive Conditional Hetroskedasticity (GARCH) model of Bollerslev (1986) to measure the risk from growth of number of tourist arrivals and the asymmetric GJR model of Glosten, Jagannathan and Runkle (1992), which discriminates between positive and negative shocks to the tourist arrivals series, will be used to forecast the required conditional volatilities.

The GARCH (p, q) model is given as $(i) Y_t = E(Y_t | F_{t-1}) + \varepsilon_t$

where $(ii) \varepsilon_t = h^{1/2} \eta_t$,

$$(iii) h_{it} = \omega_i + \sum_{l=1}^{p} \alpha_i \varepsilon_{i,t-1}^2 + \sum_{l=1}^{q} \beta_i h_{i,t-1} \tag{2.17}$$

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

$(ii) \varepsilon_t = h^{1/2} \eta_t$,

$$(iii) h_{it} = \omega_i + \sum_{l=1}^{p} (\alpha_i \varepsilon_{i,t-1}^2 + \gamma I(\eta_{i,t}) \varepsilon_{i,t-1}^2) + \sum_{l=1}^{q} \beta_i h_{i,t-1} \tag{2.18}$$

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

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

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

$$\alpha_1 + \beta_1 < 1 \qquad (2.19)$$

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

$$\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1 < 1 \qquad (2.20)$$

In equations (2.17) and (2.18), the parameters are typically estimated by the maximum likelihood method to obtain Quasi-Maximum Likelihood Estimators (QMLE) in the absence of normality of η_t, the conditional shocks (or standardized residuals). The conditional log-likelihood function is given as follows:

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

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

This study covers conditional volatility of all tourist groups. We use value at risk (VaR) to measure the risk from growth of the number of tourist arrivals affecting the environment.

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

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

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

Finally, this study covers conditional volatility of all tourist groups by taking changes in the real exchange rate into consideration. The reason is that the real exchange rate has a great effect upon international tourism demand. Therefore, we use the GARCHX model and GJR-X model.

For the GARCHX model we added an external factor such as the real exchange rate, therefore:

$$h_{it} = \omega_i + \sum_{l=1}^{p} \alpha_i \varepsilon_{i,t-1}^2 + \sum_{l=1}^{q} \beta_i h_{i,t-1} + \delta X_i \quad (2.21)$$

where X_i denotes external variables i.e. the real exchange rate

For the GARCHX (1, 1) to be stationary, we need:

$$\alpha_1 + \beta_1 < 1 \quad (2.22)$$

This model is called the GARCHX model since the constant in the GARCH models is replaced by an extra variable or extra term, for example the real exchange rate. The GARCHX model is also a generalized version model by Braun, Nelson, and Sunier (1995) and Glosten, Jagannathan, and Runkle (1993). The GARCHX model may be considered a simplified version of Connor and Linton (2001).

For the GJR-X (p, q) model, we added an external factor such as real exchange rate, therefore:

$$h_{it} = \omega_i + \sum_{l=1}^{p} (\alpha_i \varepsilon_{i,t-1}^2 + \gamma I(\eta_{i,t}) \varepsilon_{i,t-1}^2) + \sum_{l=1}^{q} \beta_i h_{i,t-1} + \delta X_i \tag{2.23}$$

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

where X_i denotes external variables i.e. the real exchange rate

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

$$\alpha_1 + \frac{1}{2}\gamma_1 + \beta_1 < 1 \tag{2.24}$$

In equations (2.21) and (2.23), the parameters are typically estimated by the maximum likelihood method to obtain Quasi-Maximum Likelihood Estimators (QMLE) in the absence of normality of η_t, the conditional shocks (or standardized residuals). The conditional log-likelihood function is given as follows:

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

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

For more details, we will revise from the three presented papers in the conferences which are found in chapters 3, 4 and 5 as follows:

1. Modeling and analysis of demand by Malaysian and Japanese tourists to Thailand

2. Value at Risk of international tourists arrivals to Thailand

3. The impacts of the real exchange rate on the volatility of international tourist arrivals to Thailand