Chapter 2

Theory and Literature Review

2.1 Theory

2.1.1 Classical demand theory

Most of tourism demands studies have included elasticity of demand in the framework of demand theory because tourists maximize tourism products through demand function. More critical value beyond the neoclassical theory, the theoretical Lancastrian model explores the individual consumption of specific feature through the consumer attains satisfaction and utility; this model provides the demand approach to tourism. Tourism demand is basically influenced by income, tourism price, exchange rate, transportation cost, and many other external factors about the extent to which changes in the demand result from each of the variables; these changes are predominantly for policy to analyze the effects of these variables in details.

A lot of existing tourism demand studies using econometric models are demonstrated in the form of elasticity of demand, which is defined as the percentage changes of endogenous variable (number of tourist arrivals) with respect to the exogenous variables (the demand determinants). An elasticity is greater than one, meaning the demand is elastic, modifies that the demand for tourism goods and services respond fractionally more than the movement of each of the explanatory variables. Similarly, if the income rises, holding other variables constant, the effects of all the relevant tourism business activities and tourist destinations are likely positive. Hence, increasing income reflects to the increase of tourism purchasing power in the destination country, similar to the effect of increasing income on the demand for most goods and services, which are called the normal goods in the tourism demand study; that is positively related to income. However, it is possible for a rising income to bring a drop in demand in the tourism market destination based on the tourism inferior goods (Sookmark, 2011).

On the other hand, if the elasticity is less than one, it implies that demand is inelastic. It represents that the demand for tourism products responds fractionally less than the changes of manipulated variables (Sookmark, 2011).

1) Income Effect

Income represents all the amount of consumers' purchases goods and services at the targeted tourist destination, which is a matter of research seeking to measure the effect of income changes on tourism demand. The measure of the effect of the income changes is calculated in the form of income elasticity, which is the ratio of the percent change with respect to the change in disposal income as shown in the following equation (Sookmark, 2011):

$$E_y = \frac{\%\text{change in tourist demand}}{\%\text{ change in disposable income}}$$

The sign of income elasticity is expected to be positive for all goods and services because the demand for basic goods and services should be income inelasticity, while luxury items (an item that raises fractionally more with growing income) should be elasticity as the special case of foreign travel, see Divisekera and Kulendran (n.a) and Monoz (2007). This finding leads to conclude that the estimated income elasticity of demand is positive and greater than one in which is supported by Crouch (1994).

However, if the destination country is affected tremendously by cost factors, given the availability of many destinations from which to choose, international tourism arrivals can be sensitive to the price based on their personal income. Therefore, income elasticity is properly a negative, which denotes inferior tourism destination (Divisekera & Kulendran, n.a), and (Chadee & Miezkowski, 1987).

2) Price effect

The price effect is more complex than the income effect. Price in this study refers to tourism price, which is the amount of money the tourists pay in the destination country (such as on accommodation, recreation, entertainment, foods, transportation, and so on).

The tourism price/relative price is the price between destinations and/or the price differences between destination country and origin country. Moreover, international tourism demand, exchange rate is normally the leading of making the price of tourism product changes. If the income changes, the price of tourism products change; this can be measured as the price elasticity of demand formulated as the following (Sookmark, 2011):

$$E_p = \frac{\%\text{ change in quantity of tourism product demanded}}{\%\text{ change in tourism product price}}$$

According to the standard law of demand in microeconomics, the product will be diminished in the future, hence E_p will be negative; that it, there is an inversion relationship between product's price and the demand for that product. Elastic demand indicates that the demand is sensitively respond exceeding the percentages of any price changes, while price inelasticity implies the demand is relatively not respond to the demand. Cross price elasticity is defined by Sookmark (2011) as shown form below:

$$E_{pc} = \frac{\%\text{ change in demand for product A}}{\%\text{ change in price of product B}}$$

Where A and B are close substitutes and one might expect E_{pc} to be positive and probably> 1 (Sookmark, 2011).

2.1.2 International Tourism Demand

The concept of tourism demand and forecasting, almost all forecasts involve predicting the tourism demand at the same point in the future. In this neoclassical conception of demand, the tourism perspectives include age, education, tastes, and previous experience with the product, advertisement, product innovation, government policy or new technology. As a luxury good, the demand for tourism tends to be quite elastic while the income elasticity of different tourism products can differ considerably, as some recreation goods may actually show declining consumption with increasing income.

Demand forecasting in tourism research is reviewed from the perspective of method which is most appropriate to give research question, the time period specified and the information needs of managers. Factors which will govern the choice of method include the purpose, the time period being forecast, the degree of accuracy required, the availability of information, the forecasting environment and the cost of producing the forecast. Inaccuracies in forecasting result may result from five different factors: inappropriate model, incorrect use, error calculation in relationship in model, significant variables omitted and data used may have been inadequate or inappropriate. A review of quantitative, qualitative and technological forecasting of the techniques and the factors which influence tourism demand are also included.

Most econometric analyses of tourism demand have used single equation models. Relatively few studies have used a complete demand system to describe the allocation of travel expenditures among various categories of goods in a particular destination, or among various groups of destinations/holiday types by a particular tourism market (Fujii et al 1985, 1987; O'Hagan and Harrison 1984; Divisekera 1993, 1994; Pyo et al 1991; Smeral et al 1992; Syriopoulos et al 1993; White 1985). Archer (1976), Crouch (1994), Walsh (1996), Lim (1997), Inclair (1998), Lise and Tol (2002), McAleer (2001,2003), Narayan (2004), Chaitip et al (2006). Growth in international tourism is closely aligned to economic variables, which at both the microeconomic and macroeconomic levels influences the consumer's decision to undertake overseas travel.

Empirical research on international tourism demand has overwhelmingly been based on aggregate time series data which permits the estimation of income and price elasticity on inbound tourism (Lim, 1997, McAleer (2000, 2001) and Chaitip, et al (2006)). A simple origin-destination demand model for international tourism can be represented as follows:

$$D_t = f(Y_t, TC_t, P_t) \qquad (2.1)$$

Where:

D_t = is a measure of travel demand at time t ;

Y_t = is a measure of income of the tourist-generating or origin country at time t

TC_t = is a measure of transportation costs from the origin to destination country at time t

P_t = is a measure of tourism price of goods and services at time t

And assume that (+Yt), (-TCt), (-Pt) and explain that when income at time t is increasing then the demand for international tourism is increasing simultaneously. When the measure of transportation costs from the origin to destination country at time t is increasing then the demand for international tourism decreases. And when the measure of tourism price of goods and services is increasing then the demand for international tourism is decreasing. Equation (3.1) can be expressed in log-linear (or logarithmic) form:

$$\ln D_t = \alpha + \beta \ln Y_t + \gamma \ln \{F1_t \text{ or } F2_t\} + \delta \ln \{RP_t, ER_t \text{ or } RER_t\} + \varphi \ln D_{t-1} + \theta \ln CP_t + u_t \qquad (2.2)$$

Where:

$\ln D_t$ = logarithm of short-term quarterly tourist arrivals (or demand) from the origin to destination country at time t

$\ln Y_t$ = logarithm of real GDP in origin country at time t

$\ln F1_t$ = logarithm of real round-trip coach, economy airfares, in Neutral Units of construction (NUC) between origin country and destination country at time t

$\ln F2_t$ = logarithm of real round-trip coach, economy airfares, in origin country currency between origin country and destination country at time t

$\ln RP_t$ = logarithm of relative prices (or CPI of destination country/CPI of origin country) at time t

$\ln ER_t$ = logarithm of exchange rate (origin country per destination country) at time t

$\ln RER_t$ = logarithm of real exchange rate [or CPI(destination country)/CPI(origin country)*1/ER] at time t

$\ln CP_t$ = logarithm of competitive prices [using CPI(destination country) /(other destination country)]

u_t = independently distributed random error term, with zero mean and constant variance at time t

And defined that α , β, γ, δ,φ,θ - parameters to be estimated; β > 0, γ < 0, δ < 0, 0 < φ < 1 , θ > 0 (substitutes) and θ < 0(complements).

2.2 Econometric Methods

2.2.1 Panel Data Analysis

A longitudinal, or panel data set is one that follows a given sample of individuals over time, and thus provides multiple observations on each individual in the sample (Hsiao, 2003). Panel data models have become increasingly popular among empirical studies due to the high capacity for capturing the complexity compared to cross-sectional or time-series data models. In other words, panel data can enrich empirical analysis in ways that may not be possible if we use only cross-sectional or time series data. A general linear panel model can be written as follows.

$$y_{it} = \alpha_i + x'_{it}\beta_{it} + \varepsilon_{it} \qquad i = 1,...,;\ t = 1,...,T \qquad (2.3)$$

Where the subscript *i* denotes the cross-sectional dimension *t* denotes the time-series dimension. y_{it} represents the dependent variable, α_i is a scalar, x'_{it} represents the independent variable, β_{it} is the coefficient term, and ε_{it} is residual term. If each cross-sectional unit has the same number of time series observations, then we call it balanced panel. If the number of observations differs among panel members, we call such a panel as unbalanced panel (Baltagi, 2008).

2.2.2 Panel Unit Root Tests

The study of panel cointegration or a long term relationship in the panel cointegration model is the test of stationary data or panel unit root test, there are many methods to test panel unit root test for example Levin, Lim and Chu (LLC) method, Pesaran and Shin (IPS) method and Fisher-.Type Tests using Fisher-ADF and Fisher-PP, which are detailed below.

Consider a following AR (1) process for panel

$$y_{it} = \rho_i y_{it-1} + X_{it}^{'}\delta_i + \varepsilon_{it} \tag{2.4}$$

Where i = 1,2,…..,N is cross section units

t = 1,2,…..,T_i is time series units

and $X_{it}^{'}$ = Exogenous Variables

ρ_i= Autoregressive coefficients

ε_{it} = error term

If $|\rho_i| < 1$ y_{it} Has no unit root. Or panel data are stationary.

$|\rho_i| > 1$ y_{it} Has unit root. Or panel data are non-stationary

Assumptions of panel unit root test for the ρ_i, whit it different value. There are two assumptions underlying ρ_i = ρ for all i and all cross section units. Including the panel unit root test by Levin, Lin and Chu (LLC) Test. Breitung Test methods and procedures Hadri Test This is a Common Unit Root Process

1) Tests with Common Unit Root Process

Considering assumptions assigned to ρ_i cross section of all units are equal. However, testing by Levin, Lin and Chu (LLC) Test and Breitung Test the null hypothesis has unit root but Hadri Test the main hypothesis has no unit root. This paper will use LLC test which details method as follows:

LLC Test consider to procedures for the Augmented Dickey-Fuller (ADF) as follows:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{p_i} \beta_{it} \Delta y_{it-j} + X_{it}^{'}\delta + \varepsilon_{it} \tag{2.5}$$

Where Δy_{it} = difference term of y_{it}

y_{it} = panel data

α = $\rho - 1$

$X_{it}^{'}$ = exogenous variable

ε_{it} = error term

Hypothesis testing panel unit root is.

$H_0 : \alpha = 0$ Has unit root

$H_1 : \alpha < 0$ Has no unit root

A. Levin, Lin and Chu Test

The LLC Test (Levin, Lin and Chu, 2002) perform regression to estimate parameters α agents (Proxies) for Δy_{it} and y_{it}. At Lag Order level, estimates the equation by the two equations to test Δy_{it} and y_{it} at lag term and exogenous variable X_{it}, the parameters that are estimated from regression are $\left(\hat{\beta}, \hat{\delta}\right) and \left(\dot{\beta}, \dot{\delta}\right)$

For the first equation, find the value $\Delta \bar{y}_{it}$ and Δy_{it} of equation (2.5) to solve Autocorrelations problem then rewrite as follows.

$$\Delta \bar{y}_{it} = \Delta y_{it} - \sum_{j=1}^{p_i} \hat{\beta}_{it} \Delta y_{it-j} - X_{it}^{'} \hat{\delta} \tag{2.6}$$

Second equation find $\Delta \bar{y}_{it-1}$ from

$$\Delta \bar{y}_{it} = \Delta y_{it-1} - \sum_{j=1}^{p_i} \dot{\beta}_{it} \Delta y_{it-j} - X_{it}^{'} \dot{\delta} \tag{2.7}$$

Finding represents value of $\Delta \bar{y}_{it}$ and $\Delta \bar{y}_{it-1}$ divided by the standard error as follows:

$$\Delta \tilde{y}_{it} = \left(\Delta \bar{y}_{it} / s_i\right) \tag{2.8}$$

$$\tilde{y}_{it-1} = \left(\Delta \bar{y}_{it-1} / s_i\right) \tag{2.9}$$

Where: s_i Standard Error has estimated each value in the ADF equation (2.5). The estimate of the coefficient α obtained as follows.

$$\Delta \tilde{y}_{it} = \alpha \tilde{y}_{it-1} + \eta_{it} \quad (2.10)$$

t - Statistic of $\hat{\alpha}$ is normal distribution, it can be found as follows.

$$t_{\alpha}^{*} = \frac{t_{\alpha} - (N\tilde{T})S_N \hat{\sigma}^{-2} se(\hat{\alpha})\mu_{m\tilde{T}^*}}{\sigma_{m\tilde{T}^*}} \to N(0,1) \quad (2.11)$$

Where t_{α}^{*} = t-statistic for $\hat{\alpha} = 0$

$\hat{\sigma}^{-2}$ = (Error Term) η

$se(\hat{\alpha})$ = standard error of $\hat{\alpha}$ and $\tilde{T} = T - (\sum_i p_i / N) - 1$

S_N = Average Standard Deviation Ratio, which is average Standard Deviation of each cross section data, estimate using Kernel.

$\mu_{m\tilde{T}^*}$ and $\sigma_{m\tilde{T}^*}$ = Adjustment term of mean and standard deviation

2) Tests with Individual Unit Root Processes

Panel unit root test with Im, Pesaran and Shin (IPS) Test and Fisher-Type Tests using ADF-Test and PP-Test to test the unit root of each cross section are conducted so ρ_i of each cross-section has a different value. This method included unit root test results of cross-section each for use as the panel unit root test. Therefore, the panel unit root test with IPS Test and Fisher-Type Tests will be tested unit root of time series data of each cross section. Then the study summarizes the results for the test panel unit root of all countries.

A. Im, Pesaran and Shin Test

Im, Pesaran and Shin test, (2003) using the Augmented Dickey-. Fuller (ADF) considers separately the cross section units as follows.

$$\Delta y_{it} = \alpha y_{it-1} - \sum_{j=1}^{p_i} \beta_{it} \Delta y_{it-j} - X_{it}^{'} \delta + \varepsilon_{it} \quad (2.12)$$

Null and alternative hypothesis are defined as:

$H_0 : \alpha_i = 0$ for i

$H_1 : \alpha_i = 0$ for i = 1,2,….., N_1

$$H_1 : \alpha_i < 0 \text{ for } i = \text{N+1,N+2,…..,N}$$

t- Statistic for test α_i is:

$$\bar{t}_{NT} = \left(\sum_{i=1}^{N} t_{iT_i}(p_i) \right) / N \tag{2.13}$$

Where $\bar{t}_{NT}$ has normal distribution and rewrite new equation.

$$W_{\bar{t}_{NT}} = \frac{\sqrt{N}\left(\bar{t}_{NT} - N^{-1}\sum_{i=1}^{N} E(\bar{t}_{it}(p_i)) \right)}{\sqrt{N^{-1}\sum_{i=1}^{N} \operatorname{var}(\bar{t}_{it}(p_i))}} \to N(0,1) \tag{2.14}$$

B. Fisher-Type Tests using Fisher-ADF and Fisher-PP

Maddala and Wu (1999) using Fisher's ADF test which combine the p-value from unit root tests for each cross-section I to test for unit root in panel data

Where π_i (i =1,2,….,N) is p-value of testing the unit root of the cross section data i from all the cross section, N is a free variable U (0,1). - 2log π_i distribute by the chi-square and Degree of Freedom = 2, the statistical test was used.

$$p_\lambda = -2\sum_{i=1}^{N} \log \pi_i \to x^2 2N \tag{2.15}$$

In the case of Choi (2001) given p_i (i = 1,2, ..., N) is the p - value of the unit root test's the cross section data i from all cross sections.

$$p_\lambda = -2\sum_{i=1}^{N} \ln(p_i) \tag{2.16}$$

Statistical value test is:

$$Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} \Phi^{-1}(p_i) \tag{2.17}$$

Where Φ is the standard normal cumulative distribution function

$$L = \sum_{i=1}^{N} \ln\left(\frac{p_i}{1-p_i}\right) \tag{2.18}$$

Hypothesis testing panel unit root is.

$H_0 : p_i = 1$ Has unit root

$H_1 : p_i < 1$ Has no unit root

$H_1 : p_i = 1$ Has no unit root

2.3 Autoregressive Distribution Lags (ARDL)

Pesaran and smith (1998), Pesaran and Shin (1999) and Pesaran et al. (2001) studied and developed ARDL method based on two estimation methods used to analyze panel data model such as: Mean Group Estimator (MGE) and Pooled Mean Groups Estimator (PMGE), they are several methods such as first method, mean group estimator which contains averaging separate evaluation for each group in the panel data or panel model .Agreeing to the parameter's averages is provided consistence by estimator. In 1999, Pirotte shows that mean group estimator affords efficient long run estimates for big sample size. It lets the parameters to be generously independent across groups and does not show prospective homogeneity between groups. The second method estimate random effect, fixed effect and also GM methods. So these models force the parameters to be alike across countries and can inconsistent and misleading long run coefficient when the period is long that possible problem is exacerbated.

When imposing equality of the long term coefficient between countries, an intermediate estimator that allows the short term parameters to vary between groups proposed by Peraran et al. (1999).

2.3.1 Pooled Mean Group Estimator (PMGE).

A benefit of the Pooled mean group is that it can agree to the short-run dynamic specification to differ from country to country while making the long-run coefficients constrained to be the same. Additionally, unlike the Dynamic OLS (DOLS) and Fully Modified OLS (FMOLS), the PMG estimator highlights the modification dynamic between the short-run and the long-run. The causes for assuming that short-run dynamics and error variances should be the same trend to be less compelling. Not imposing equality of short-run slope coefficients allows the dynamic specification to differ across countries.

From Jamilah M. M, Normaz W. I and Law S. H. (2012), Suppose panel data denote t = 1,2,…..,T and data group I = 1,2,….,N with estimate by the Autoregressive Distributed lag (ARDL) (p,q,q,…q)

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \gamma_{ij}^{'} x_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (2.19)$$

where y_{it} is a scalar explained variable, x_{it} is the k × 1 vector of independent variables for group *i*, μ_i represents the fixed effects, λ_{ij} 's are scalar coefficients of the lagged explained variables, $y_{ij}^{'}$'s are k × 1 coefficient vectors. The re-parameterized form of Equation (2.19) can be formulated as follows:

$$\Delta y_{it} = \phi_i y_{i,t-1} + \beta_i^{'} x_{i,t-1} + \sum_{j=1}^{p-1} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q-1} \gamma_{ij}^{'} x_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (2.20)$$

The disturbance terms (ε_{it}) is explanatory distributed across i and t, with zero means and $\sigma_i^2 > 0$ variances. Additionally it is assumed that $\phi_i < 0$ for all *i*'s. Thus, there occurs a long-run relationship between y_{it} and x_{it} which is defined by:

$$y_{it} = \theta^{'} x_{it} + \eta_{it} i = 1,2,......N; t = 1,2,......T \qquad (2.29)$$

Where η_{it} 's are stationary with possibly non-zero means (including the fixed effects) and $\theta^{'} = -\beta_i^{'} / \theta_i$, is the k × 1 vector of the long-run coefficients. Hence, Equation (2.29) can be written as:

$$\Delta y_{it} = \phi_i \eta_{i,t-1} + \sum_{j=1}^{p-1} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q-1} \gamma_{ij}^{'} x_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (2.30)$$

Where ϕ_i is the error correction term coefficient measuring the speed of modification towards the long-run equilibrium and $\eta_{i,t-1}$ is the error correction term given by Equation (2.28) .This parameter is expected to be significantly negative, involving that variables return to a long-run stability.

The PMG method of estimation allows short-run coefficients, intercepts and error variances to vary across countries but constrains the long-run coefficients to be equal. This implies that $\theta_i = 0$ for all *i's*, in order to estimate short-run coefficients and the common long-run coefficients.

2.3.2 Mean Group Estimator (MG)

Edward.,et al, (2007), Autoregressive Distributive Lag (ARDL) is an appropriate approach with the research that has less samples and this approach is very good to analysis the short run and long run relationship in one equation. Indeed, The form of panel dynamic specification of ARDL as follow

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} X_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (2.31)$$

Where number of group or cross section is i=1, 2,…, N and Time period t= 1,2, …, T

X_{it} are the vector of explanatory variables

δ_{it} are the coefficient vectors

λ_{it} are scalars, μ_i is the group specific effect

Time trends and other fixed repressors are included

Peasaran and Smith (1995), MG estimator allows differing across groups of the intercepts, slope of coefficients, and error variances.

$$\Delta y_{it} = \phi_i (y_{i,t-1} - \theta'_i X_{it}) + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta y_{i,t-1} + \sum_{j=0}^{q-1} \delta'^*_{ij} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (2.32)$$

Where $\phi_i = -(1-\sum_{j=1}^{p} \lambda_{ij})$

$$\theta_i = \sum_{j=0}^{q} \delta_{ij} / (1-\sum_{k} \lambda_{ik}),\ \delta^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im},\ \lambda^*_{ij} = -\sum_{m=j+1}^{p} \lambda_{im} \qquad (2.33)$$

j=1, 2,…, p-1

θ_i is error speed of adjustment term and if θ_i = 0, there is no long run cointegration

If θ_i > 0, there is no long run cointegration

If θ_i < 0, there has long run cointegration

Pesaran and Smith (1998), The Mean Group estimator (MG) is common to have the panel data in both *T* (the number of time series observation), and the number of group represent by *N* . MG estimate are quite large and of the same order of magnitude. The examine this model is either evaluation *N* separate regression and compute coefficient mean or pool the data and assume the slope coefficient and error variables are identical.

The MG estimators include mean of error correction coefficients and the other short run parameters, also it can be estimated consistently by the unweight average of individual coefficient

$$\hat{\phi}_{MG} = N^{-1}\sum_{i=1}^{N}\hat{\phi}_i, \hat{k}_{MG} = N^{-1}\sum_{i=1}^{N}\hat{k}_i \tag{2.34}$$

Pesaran, Smith and Im (1996) and Pesaran (1998) have recommenced the variance of these estimators can be consistently examined along the lines example, in the case of $\hat{\phi}_{MG}$, a consistent estimator of the variance of $\hat{\phi}_{MG}$ is follow by:

$$\hat{\Delta}_{\phi} = \frac{1}{N-1}\sum_{i=1}^{N}(\hat{\phi} - \hat{\phi}_{MG})^2$$

The MG estimators are asymptotic distribution of $\hat{\phi}_{MG}$ because asymptotically equivalent as $T \to \infty$ and $N \to \infty$ such that $\sqrt{N}/T \to 0$. Suggested by Hsiao, Pesaran and Tahmiscioglu (1998)

$$\sqrt{N}(\hat{\phi}_{MG} - \phi) \sim N(o, \Delta_{\phi})$$

Where ϕ = E(ϕ_i) and $\Delta_{\phi} = Var(\phi_i)$

2.4 Model Selection

(Pesaran et al., 1999) Hausman test is one of the best methods to choose or whether model reliable or effect in explain the best result or to do the judgment amount PMG and MG. The test of the method PMGE and MGE are familiar with Hausman test. If the true model is heterogeneity, PMGE is inconsistent; if the true model is homogeneity, MGE is inconsistent

$$H = (\hat{\beta}_b - \hat{\beta}_B)' D^{-1} (\hat{\beta}_b - \hat{\beta}_B) \tag{2.35}$$

Null hypothesis of Hausman Test

H_o: Difference in coefficients not systematic $\lambda^2 > 0.05$

H_a: other regression $\lambda^2 < 0.05$

Correction for endogeneity and serial correction in FMOLS

Pedroni (2000) suggested the group means Fully Modified OLS(FMOLS) estimator that incorporates the Phillips and Hansen (1990) semi-parametric correction to the OLS estimator to eliminate the bias due to the endogeneity of the repressors. Also adjusts for the heterogeneity is likely the dynamics based on x and y. specially, the FMOLS statistic is:

$$\hat{\beta}_{i,FMOLS} = N^{-1}\sum_{i=1}^{N}(\sum_{t=1}^{T}(x_{it}-\overline{x}_i)^2)^{-1}(\sum_{t=1}^{T}(x_{it}-\overline{x}_i)y_{it}^{*}-T\hat{\gamma}_i) \qquad (2.36)$$

Where

$$y_{it}^{*} = (y_{it}-\overline{y}_i)-\frac{\hat{\Omega}_{21i}}{\hat{\Omega}_{22i}}\Delta x_{it}$$

$$\hat{\gamma}_i = \hat{\Gamma}_{21i}+\hat{\Omega}_{21i}^{0}-\frac{\hat{\Omega}_{21i}}{\hat{\Omega}_{22i}}(\hat{\Gamma}_{21i}-\hat{\Omega}_{21i}^{0})$$

Where $\hat{\Omega}$ and $\hat{\Gamma}$ = covariance and sums of autocovariances obtained from the long run covariance

$\hat{\gamma}_i$ = term acts to correct for the effect of serial correlation

In contrast to the non parametric FMOLS estimators, Pedroni (2001) has also constructed a between – dimension, group-means panel Dynamic OLS(DOLS) estimator that incorporate corrections for endogeneity and serial correlation parametrically. This is done by modifying from the panel regression model to include lead and lag dynamics:

$$y_{it} = \alpha_i + \beta_i x_{it} + \sum_{j=-K_i}^{K_i}\Upsilon_{ik}\Delta x_{i,t-k} + e_{it} \qquad (2.37)$$

Where

$$\hat{\beta}_{iDOLS} = \left[N^{-1}\sum_{i=1}^{N}(\sum_{t=1}^{T}z_{it}z_{it}^{'})^{-1}(\sum_{t=1}^{T}z_{it}\tilde{y}_{it}) \right]$$

And z_{it} = 2(K+1) X 1 vector of regressors

2.5. Literature Review

In this study of international tourism demand for Lao PDR using structure equation model and also this research collected related research which consists of the econometric methodology and research on tourism demand model as tools to study the following:

2.5.1 Research on tourism demand model

NikoLao PDR Dritsakis (2003) investigate a research article on long-run demand for tourism to Greece by two countries as such German and British. Data was collected by secondary data (yearly data) ,it covered time period 1960-2000 and also using a number of primary macroeconomic variables, with income of the people in origin countries, tourism prices in destination country, transportation cost and exchanges rates are employed.

The method was used to test the stationary data in this study is Augmented Dickey–Fuller test. This method is scanned in the univariate structure and the method to test cointegration investing Long –Run relationship based on Johansen's maximum likelihood and to estimate the number of cointegrating vectors of VAR model, for the estimate the short rung relationship is Error correction model (ECM). The result showed a long-run equilibrium relationship among international tourism demand; income, transportation cost and real exchange rate appear to be supported by the data used for the examined period. An important finding from the dynamic models presented is that the error correction terms are negative and statistically significant. All repressors in the VEC models are statistically significant; there is no evidence of any problems associated with serial correlation, functional form, normality or heteroscedasticity. Suggests the existence of an equilibrium long-run relationship among important economic variables determining international tourism demand

Sarath Divisekera (2003) conducted research that check the model which is applied of tourism demand and chosen alternative destinations countries for Australia. The methodology used to predictable models are in conformity with the basic assumes of consumer theory, homogeneity, and symmetry. There were several methods to Derived elasticity reveal substantial cross-demand effects, reflecting the diversity of tourist preferences. The results of study indicate substantial new data on the effects and sensitivity of economic parameters on international tourism. Therefore, based on these findings should assist in formulating broad national policy measures directed towards maintaining and enhancing relative competitiveness enjoyed by individual destinations and in developing strategic policy initiatives to maximize gains from tourism.

Teresa Garın-Munoz (2006) studied tourism in the Balearic Islands. The purpose of this experimental research is to identify and measure the impact of the main determinants of international tourism flows. The data collected by the annual panel data set contains the number of tourists arrivals during the period time 1991–2003, and the main variable use which is a number of tourists arriving, the related price, price of crude oil and GDP. Methodology for estimate the dynamic model test for autocorrelation. This study found that estimated coefficient for the lagged dependent variable reflect to consumer loyalty to the destination and reflect to price of crude oil as a determinant of tourism demand arrival to Balearic Island. Several suggestion were made specially that the demand is heavily helpless on the progress of economic activity in each of the origin countries and heavily on the relative price when tourists living in the destination countries. This study also suggests that diversification of advertising and donation of high-quality services are some recommended measures of tourism policy.

Wanwasa Wirojanarome (2006) estimated foreign tourism demand in Thailand. There are various influences to tourists demand such as: account income level, transportation costs, relative prices level and exchange rate. The research uses a variety of methods to compare and analyze of panel unit root tests by the method of LLC test, Breitung test, Hardri test, IPS test, and Fisher-Type Tests using Fisher-ADF and Fisher-PP showed that the method of IPS test and Fisher-Type. The result of this study indicates panel cointegration tests by the method of Pedroni and Kao which showed that; first, the modeling of foreign tourism demand in Thailand had cointegration or relationship. Second the estimation of foreign tourism demand by the method of Group-Mean FMOLS showed that income level and exchange rate had the same direction with tourism demand, but relative price level and transportation costs had the opposite direction. The result of estimation of foreign tourism demand from individual country of origin by the method of FMOLS showed that income level was in the same direction with tourism demand of all countries, but transportation costs had the opposite direction only in the case of Singapore tourism demand. Meanwhile relative price level had effect on tourism demand in 2 cases, the opposite direction in the case of South Korea, Republic of China (Taiwan), People's Republic of China, Australia and The United State of America, and the same direction in the case of Singapore and Japan, and exchange had the same direction only with tourism demand of Republic of China (Taiwan).

Prasert Chaitip (2008) study how the factor influencing international tourist demand. The data used include GDP, transportation cost and exchange rate. The method used panel cointegration techniques to test long run relationship as well as both the OLS estimator and DOLS estimate are used the five standard method test for Panel Unit Root Tests such as Levin, Lin and Chu (2002), Breitung (2000), Im, Pesaran and Shin (2003), Maddala and Wu (1999) and Choi (2001) and Handri (1999). The long-run results indicate (GDP) of India's major tourist source markets has a positive relationship impact on international tourism demand arrivals to India, for the transportation cost has positive impact too, and then the currency value has negative impact. Furthermore, most findings were consistent with economic theory and the implications of the model which can be used for policy making.

Christine Lim & Michael McAleer (2010) The purpose of this study investigates actions in the long-run demand for tourist arriving from two origin countries to visit Australia. The variable uses in this paper include tourist demand, transportation cost and exchange rate all most variable are seasonal data. Methodology test the stationary data or test the unit root used augmented Dickey-Fuller test for unit roots to test in the univariate context, and Johansen's maximum likelihood technique was used to test for cointegration and to estimate the number of cointegrating vectors. Error correction models (ECM) explain quarterly tourism demand by Hong Kong and Singapore for Australia.

Chaiboonsri (2010) An application to international tourism demand of Thailand This paper sought to find the long-run relationships between international tourist arrivals in Thailand and economic variables such as GDP, transportation cost and exchange rates during period of 1986 to 2007. Also this paper used five standard panel unit root tests such as LLC (2002) panel unit root test, Breitung (2000) panel unit root test, IPS (2003) panel unit root test, Maddala and Wu (1999) and Choi (2001) panel unit root test and Handri (1999) panel unit root test. Moreover, the panel cointegration test based on Pedroni residual cointegration tests, Kao residual cointegration tests and Johansen fisher panel cointegration test were used to test in panel among the variables. The OLS estimator, DOLS estimator and FMOLS estimator were used to find the long-run relationship of the international tourism demand model for Thailand. The long-run results indicated that growth in income (GDP) of Thai's Asia major tourist source markets (Malaysia, Japan, Korea, China, Singapore and Taiwan) have a positive impact on international tourists arrival to Thailand. In addition, the transportation cost of these countries has negative impact on the number of international tourist arrivals to Thailand. Finally, Thailand's currency has positive impact on the number of international tourist arrivals to Thailand. Most of findings from this study were consistent with economic theory and the implications of the model can be used for policy making.

Ratanan Bunnag (2010) studied about Thailand's inbound tourism market is heavily dependent on Asia, in particular, Malaysia and Japan. These two countries have been and remain the two major sources of Thailand's international visitors. Therefore, a careful analysis of the demand and volatility of Malaysian and Japanese tourists is crucial to enhance Thailand's tourism policy. Various time series models will be used to construct univariate and multivariate tourism demand and volatility models for Malaysian and Japanese tourists to Thailand. This study can be used to compare with British and American markets. We can divide tourists into three groups (1) short haul such as Malaysian tourists (2) medium haul such as Japanese tourists (3) long haul such as British and American tourists. In the study of income elasticity of tourism demand in the long-run, we can conclude that (1) Malaysian tourism or short haul tourism is inelastic demand. (2) Japanese tourism or medium haul tourism, British and American tourism or long haul tourism are elastic demand. In this study, we will consider the volatility of international tourist arrivals to Thailand by employing a VAR model. VAR is widely used to manage the risk exposure of financial institutions and is the requirement of the Basel Capital Accord. Forecast VAR figures can be used to estimate the level of reserves required to sustain desired long term government projects and foreign exchange reserves. We can conclude that the VAR of Malaysian tourists are higher than Japanese, British and American tourists. Finally, in this study, we will consider the volatility of international tourist arrivals to Thailand by employing the GARCHX and GJR-X model. The real exchange rate is used because it has a pervasive effect on the tourist budget. For the GARCHX model and GJR-X, the change in the real exchange rate can impact on the volatility of Japanese tourist arrivals to Thailand. But this does not have an impact on the volatility of tourist arrivals from Malaysia, the UK and the USA to Thailand

Edwin Muchapondwa (2011) experimented Modeling International Tourism Demand for Zimbabwe. This paper purpose to test cointegration finding the long run relationship, this research study during 1998 – 2005. The methodology uses the autoregressive distributed lag (ARDL) approach to cointegration, The results show that transport costs, has positive and significant impact on tourism demand for Zimbabwe, it mean the transportation cost changes in global income. For the suggestion government should be improvement of international tourism by pay attention about infrastructure to reduce travel costs as well as support tourism formation for attract more international tourists arriving for Zimbabwe country. Additionally, the government or the related organization can potentially raise international tourism demand for the country by supporting pleasant events in the country.

Fateh Habibi and Hossein Abbasinejad (2011) estimate the impact of the factor determinants of the international tourist arrivals to the Malaysia. The data use annual panel data set includes the number of arrivals, a number of possible explanatory variables, during the period 1998–2007, the method was used a dynamic model is estimated the demand of tourist to arrival in this country, The results found that the income, accommodation capacity and political stability have positive effects on European tourism demand in Malaysia. One of the main conclusions of the study is the significant value of the lagged dependent variable (0.52), which may be interpreted as a major word-of-mouth effect on tourism demand in Malaysia. In addition, the dynamic panel data estimation highlights the importance of the accommodation capacity as the most important factor in attracting more tourism to Malaysia.

E. M. Ekanayake (2012) analyzed the demand for tourist arrivals to the United States, using the panel cointegration technique. The study attempts to identify and measure the impact of the main determinants of inbound international tourism flows to the United States. The study uses annual data from 1986 to 2011 for tourist arrivals from 50 major countries of tourist origin. The panel unit root tests indicate all the variables are integrated of order one. The panel cointegration tests show that all seven test statistics reject the null hypothesis of no cointegration at the 1% significance level, indicating that the five variables are cointegrated. The results suggest that tourism demand to the United States must be considered as a luxury good and is highly dependent on the evolution of relative prices and cost of travel between origin and destination country. The results also show that tourism demand is elastic with respect to income but inelastic with respect to tourism price, real exchange rate, and travel costs.

2.5.2 Related research on econometric methodology

Pesaran (1997) tested an Autoregressive Distributed Lag Modeling Approach to Cointegration Analysis. This paper examinations the practice of autoregressive distributed lag (ARDL) models for the analysis both long-run relationship and short run relationship zide. The method used in this study major variables of the order of the ARDL model, the OLS estimators of the short-run parameters are $\sqrt{T}$ -consistent with the asymptotically singular covariance matrix. These outcomes of this paper exposed strong evidence in favors of a reintegration of the traditional ARDL approach to time series econometric modeling. The ARDL approach has estimates of the long-run coefficients that are asymptotically normal nevertheless of whether the basic regressive are I(1) or I(0).

Nowak-Lehmann, et al (2006) studied the applicability of a commonly used dynamic model, the autoregressive distributed lag model (ARDL), is examined in a panel data setting. Second, Chile's advance of market shares in the EU market during time period of 1988 until 2002 is then investigated in this dynamic framework, testing for the effect of price competitiveness on market shares and finding for estimation methods that agree distributing with the problem of inter-temporal and cross-section correlation of the disturbances. To evaluation or examined to find out the coefficients of the ARDL model, FGLS is utilized within the Three Stage Feasible Generalized

Least Squares (3SFGLS) and the system Generalized Method of Moments (system GMM) methods. A calculation of errors is extra to climax the weakness of the model to problems related to fundamental model assumptions.

Zaidi, M. A. S, et al (2012) explore the role of recognized variables upon the inflow of foreign direct investment (FDI) in selected Middle East and North Africa countries (MENA). Used a panel ARDL model, or Pooled Mean Group Estimator (PMGE) offered by Pesaran et al. (1999), in which it allows to apprehension the long-run and short-run relationship between the variables of interest. This study focuses on some foundation variables that is the investment profile, internal conflict, democratic accountability, administration quality and military in politics. The empirical findings exposed that the investment profile, internal conflict, and government are positively and statistically significant in effecting the inflow of FDI. Therefore, in attracting foreign investors, the policy maker in MENA countries should device a FDI-friendly policies by supporting and continuing the quality of domestic institutions.

Goswami, G. G., & Junayed, S. H. (2006) utilized Autoregressive Distributed Lag Model (ARDL) even though differentiates between the short run and the long run effect lets both the intercepts and slopes to vary across countries. Additionally, the static panel estimation such as fixed-effects estimation (FE) cannot differentiate among the short run and the long run performance. To address the issue of short run heterogeneity and long run homogeneity of the estimated coefficients in a panel outline the pooled mean group estimator (PMGE), Pesaran, Shin, & Smith, 1999 has extended attractiveness in current days. In this study, we approximation the bilateral trade balance model for the US vis-à-vis her nineteen OECD trading partners for the period 1973q1-2004q4 using PMGE and discover that PMG achieves better than ARDL, FE, and MG estimators and offers significant and theoretically consistent result.

While all above studies use the time series data analysis, there are a lot of research papers using econometric methods based on panel data analysis due to its several advantages over time series data, such as 1) it provides researchers a massive data sets; 2) it increases the degree of freedom which properly avoid the spurious result; 3) it reduces the collinearity among explanatory variables; 4) it improves the efficiency of econometric estimation; 5) it specially permits researchers to examine a number of important economic questions that cannot be addressed using cross-section or time series data and also from the previous study there is not researcher using Panel ARDL approach under PMG and MG model.

Many previous papers have surveyed the international tourism demand in various countries but for Lao PDR have been done only Phakdisoth and Kim, (2007). However, the author looked at the aggregate data instead of Thai tourists only but this paper would like to fill the gap to explore the demand of Thai tourists to Lao PDR both in the short and long runs. This paper applies an economic model for tourism demand, especially in solution with method panel data which will be useful for decision policies of different strategies as tourism increase. Accordingly, in order to investigate the determinants of the international tourism demand in Lao PDR and to measure and detect the most significant factors affecting the flow of international tourists by country of origin to Lao PDR, the technique is used based on Panel ARDL (Pooled mean group) approach to find the long-run relationship of the international tourism demand model.