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Modelling Thailand Tourism Demand: A Dual Generalized Maximum Entropy Estimator for Panel Data Regression Models

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Abstract : This study examines the factors that influence the behavior of international tourists to Thailand by using a dual generalized maximum entropy estimator for panel data regression models. The advantage of the entropy approach is its capability to deal with ill-prosed problem and the entropy approach for panel data has not yet been investigated in the tourism literature. The focus is on the tourists from 10 countries of origin having the highest number of international tourist arrivals to Thailand including Laos, Malaysia, Singapore, China, Japan, Korea, Russia, United Kingdom, USA, and India over the period of 22 years (1995−2016). A number of important economic factors, income, price, exchange rate, and number of population, are studied regarding international tourism demand. The study compares the results of two methods, namely ordinary least squared estimator and generalized maximum entropy estimator. According to minimum value of mean square error, the generalized maximum entropy estimator perform better than the ordinary least squared. The results of tourism demand estimation show that the growth in income of Thailands major tourists originating countries, exchange rate, and number of population in countries of origin have positive impact on international visitor arrivals to Thailand while relative price has a negative impact on international visitor arrivals to Thailand. The study also finds that per capita national income enjoy strong predictive power for Thailand tourism demand.

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1 Introduction

Travel and tourism is an important economic activity in most countries around the world including Thailand. Tourism industry has significant direct and indirect impacts on the Thai economy. The direct contribution of travel and tourism to Gross Domestic Product (GDP) of Thailand in 2016 was 1,292.5 billion baht or 9.2 percent of GDP. World Travel and Tourism Council [1] forecast that the direct contribution of travel and tourism to Thailands GDP will rise by 9.3 percent to 1,412.2 billion baht in 2017 and it is expected to grow by 6.7 percent to 2,708.0 billion baht or 14.3 percent of Thailand's GDP by 2027 (Figure 1).

Figure 1: Direct contribution of travel and tourism to Thailand's GDP

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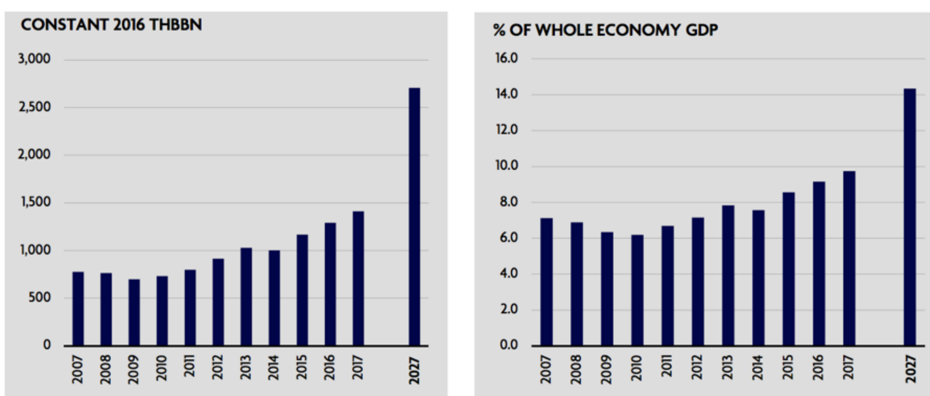

Source: World Travel and Tourism Council [1]

The tourism sector in total also generated 2,313,500 jobs directly in 2016, accounting for 6.1 percent of national employment and this is forecast to grow by 6.3 percent in 2017 to 2,458,500 jobs [1].

The growth of tourism in Thailand has been steady over the last two decades. In 1980, total international tourist arrivals were 7.8 million, increasing to 14 million in 2009 and 32 million in 2016.

Due to the importance of the tourism sector to the Thai economy, the Thai government has put much effort into stimulating the growth of the tourism industry including. The government also has been involved in marketing by launching several tourism promotional campaigns including community-based ecotourism[2] which has become one of the most popular practices throughout the country. With regard to the total tourist arrivals to Thailand, it seems that the number of foreign visitors has grown rapidly in the last decade. For these reasons, modelling and forecasting international tourism demand for Thailand is important for the government and policymakers. Despite the important role of the tourism demand in Thailand, so far little attention has been paid to quantitative analysis of this demand, and it is the intention of this study to model and analyze the international tourism demand using an econometric technique. This paper employed the dual generalized maximum entropy estimator for panel data regression models proposed by Lee and Cheon [2]. This study differs from previous empirical tourism studies in Thailand in that it employs the entropy approach with a panel data model of tourism demand, which has never been undertaken before. Moreover, this paper will benefit policymakers in terms of increasing the effectiveness of the strategic plan to develop the tourism industry and action plans to promote Thailand as a tourist destination.

The remainder of the paper is organized as follows. Section 2 contains a brief literature review. In Section 3, we present a rigorous description of the methodology used in the analysis. Section 4 describes the data and presents the results of preliminary data analysis. The estimated models and empirical results are discussed in Section 5. Finally, Section 6 discusses the findings and draws conclusion.

2 Literature Review

Interest in the studies on tourism demand has grown remarkably in the decades after the second World War among academic researchers. Song and Li [3] reviewed 121 published studies on tourism demand modelling and forecasting since 2000. They found that the methods used are diverse in analyzing and forecasting the demand for tourism. Out of these 121 studies, at least four used panel data techniques to model demand for tourism. Ledesma-Rodríguez, et al. [4] used the panel data method to model the demand for Tenerife tourism and established both static and dynamic panel models. In addition, Naudé and Saayman [5] and Roget and Gonzalez [6] both employed the same panel data approach to examine demand for tourism in 43 African countries and the demand for rural tourism in Galicia, Spain. Similarly, Sakai, Brown, and Mak [7] used the panel data approach to analyze the effects of demographic change on Japanese peoples travel propensity. Most of them used static and dynamic panel data analysis with ordinary least squared (OLS) and generalized method of moments (GMM) estimation. However, the entropy approach has not yet been investigated in the tourism literature.

[2]community-based ecotourism refers to a form of tourism where the local community has substantial control over, and involvement in, its development and management, and a major proportion of the benefits remain within the community ([8]).

Panel data model has several advantages. Hsiao [9] and Serra, Correia, and Rodrigues [10] pointed out that panel data provides researchers with massive data sets, increases the degree of freedom, reduces the collinearity among explanatory variables, and improves efficiency of econometric estimation as well as is useful for examining a number of important economic questions that cannot be addressed by using cross-section and time series data sets.

Most recent studies that used panel data have examined both economic and non-economic factors that affect international tourism demand. These factors are Gross Domestic Product (GDP), relative price, exchange rate, substitute price, transaction cost, population growth, crisis, natural disaster, war, diseases, and social crisis. These have been seen in the previous works of researchers such as Massida and Etzo [11], Falk [12], Gormus and Gocer [13], Ouerfelli [14], Surugiu et al. [15], Seetanah [16], Boonmeesrisang et al. [17], Hor and Thaiprasert [18], Lomprakhon et al [19], Anyapornsuk [20], and Nootayasakul and Pasunon [21].

3 Methodology

3.1 Panel Data Regression Model

Consider the following panel data regression model [9, 22],

$$y_{nt} = x'_{nt}\beta + u_{nt}, \tag{3.1}$$

where $n = 1, \dots, N$,$t = 1, \dots, T$, y_{nt} is the observation on a dependent variable for the n^{th} cross sectional unit at the t^{th} time period, x_{nt} and β denote the $K \times 1$ vectors of independent variables and regression coefficients, respectively, and u_{nt} is the regression disturbance which is assumed to have no correlation with x_{nt}. The prime symbol also indicates the transpose of a matrix or vector.

The regression disturbance u_{nt} follows an error components structure

$$u_{nt} = \gamma_n + \varepsilon_{nt}, \tag{3.2}$$

where γ_n denotes the th individual specific effect assumed to be $i.i.d(0, \sigma_\gamma^2)$ and ε_{nt} is the remainder disturbance assumed to be $i.i.d(0, \sigma_\varepsilon^2)$ which is independent of γ_n.

The eqaution 3.1 can be rewritten in matrix notation as

$$y = X\beta + u \tag{3.3}$$

where y is now of dimension $NT \times 1$, X is $NT \times K$ where the constant is absorbed into X, β is $K \times 1$, and u is $NT \times 1$. The error term u can be rewritten in vector form as

$$u = (I_N \otimes i_T)\gamma + \varepsilon \tag{3.4}$$

with $u' = (u_{11}, \dots, u_{1T}, \dots, u_{N1}, \dots, u_{NT})$, $\gamma' = (\gamma_1, \dots, \gamma_N)$ and $\varepsilon' = (\varepsilon_{11}, \dots, \varepsilon_{1T}, \dots, \varepsilon_{N1}, \dots, \varepsilon_{NT})$, where I_N is $N \times N$ identity matrix, i_T is $T \times 1$ vector of ones, and $\otimes$ denotes the Kronecker product.

3.2 Generalized Maximum Entropy for Panel Data Regression Models

In this study, we used a dual generalized maximum entropy (dual GME) estimator for panel data regression models which was proposed by Lee and Cheon [2]. This estimator can solve ill-posed problems such as data limited, partial or incomplete. First, we describe the concept about the Generalized Maximum Entropy (GME) and then we explain the GME methodology for a panel data regression model, introduced by Song and Cheon [23].

The standard least square estimation of β vector of parameters is the solution of the following optimization problem:

$$min_{\beta} \sum u^2 \tag{3.5}$$

where $u = y - X\beta$.

The objective is to minimize the quadratic sum of squares function for β. The maximum entropy approach is based on the entropy objective function $H(p)$ instead of the quadratic sum of squares objective function. In order to be able to use entropy principle, the unknown parameter vector should be written in terms of probabilities.

Golan et al. [24] reparametrize β and u in 3.3 as follows:

$$\beta = Zp = \begin{bmatrix} z_1' & 0 & \dots & 0 \\ 0 & z_2' & \dots & 0 \\ \vdots & \vdots & \dots & 0 \\ 0 & 0 & \dots & z_K' \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_K \end{bmatrix} \tag{3.6}$$

where Z is a $K \times KM$ matrix, p is a $KM \times 1$ vector, $\beta_k = \sum_m z_{km} p_{km}$ for every k, $z_k' = (z_{k1}, \dots, z_{kM})$, and $p_k' = (p_{k1}, \dots, p_{kM})$.

Equation 3.4 can be rewritten as

$$\gamma = Fg = \begin{bmatrix} f_1' & 0 & \dots & 0 \\ 0 & f_2' & \dots & 0 \\ \vdots & \vdots & \dots & 0 \\ 0 & 0 & \dots & f_N' \end{bmatrix} \begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_N \end{bmatrix} \tag{3.7}$$

where F is a $N \times NR$ matrix, g is a $NR \times 1$ vector, $\gamma_n = \sum_r f_{nr} p_{nr}$ for every n, $f_n' = (f_{n1}, \dots, f_{nR})$, and $g_n' = (g_{n1}, \dots, g_{nR})$. Moreover

$$\varepsilon = Vw = \begin{bmatrix} v_{11}' & 0 & \dots & 0 \\ 0 & v_{12}' & \dots & 0 \\ \vdots & \vdots & \dots & 0 \\ 0 & 0 & \dots & v_{NT}' \end{bmatrix} \begin{bmatrix} w_{11} \\ w_{12} \\ \vdots \\ w_{NT} \end{bmatrix} \tag{3.8}$$

where V is a $NT \times NTJ$ matrix, w is a $NTJ \times 1$ vector, $\epsilon_{nt} = \sum_j v_{ntj} w_{ntj}$ for every n and t, $v_{nt}' = (v_{nt1}, \dots, v_{ntj})$ and $w_{nt}' = (w_{nt1}, \dots, w_{ntj})$. Then, we can rewrite equation 3.3 as a generic linear model

$$y = X\beta + u = XZp + (I_N \otimes i_T)Fg + Vw \tag{3.9}$$

Therefore, the generic GME problem selects p, g, w $(\epsilon(0,1))$ to maximize

$$H(p,g,w) = -p'log(p) - g'log(g) - w'log(w) \tag{3.10}$$

subject to $y = XZp + (I_N \otimes i_T)Fg + Vw$, $i_k = (I_K \otimes i'_M)p$, $i_N = (I_N \otimes i'_R)g$ and $i_{NT} = (I_{NT} \otimes i'_j)w$.
Then the Lagrangian function is

$$\begin{aligned} L = &- p'log(p) - g'log(g) - w'log(w) + \lambda'_1(y - XZp - (I_N \otimes i_T)Fg - Vw) \\ &+ \lambda'_2(i_k - (I_K \otimes i'_M)p) + \lambda'_3(i_N - (I_N \otimes i'_R)g) + \lambda'_4(i_{NT} - (I_{NT} \otimes i'_j)w) \end{aligned} \tag{3.11}$$

where λ'_1, λ'_2, λ'_3, and λ'_4 are the vectors of Lagrangian multiplier.
Taking the gradient of L to derive the first-order conditions, we have

$$\begin{aligned} \frac{\partial L}{\partial p} &= -log(p) - i_{KM} - Z'X'\lambda_1 - (I_K \otimes i'_M)\lambda_2 = 0 \\ \frac{\partial L}{\partial g} &= -log(g) - i_{NR} - F'(I_N \otimes i_T)\lambda_1 - (i_N - (I_N \otimes i'_R)\lambda_3 = 0 \\ \frac{\partial L}{\partial w} &= -log(w) - i_{NTJ} - V'\lambda_1 - (I_{NT} \otimes i'_j)\lambda_4 = 0 \\ \frac{\partial L}{\partial \lambda_1} &= y - XZp - (I_N \otimes i_T)Fg - Vw = 0 \\ \frac{\partial L}{\partial \lambda_2} &= i_k - (I_K \otimes i'_M)p = 0 \\ \frac{\partial L}{\partial \lambda_3} &= i_N - (I_N \otimes i'_R)g = 0 \\ \frac{\partial L}{\partial \lambda_4} &= i_{NT} - (I_{NT} \otimes i'_j)w = 0 \end{aligned} \tag{3.12}$$

After some algebra, we obtain

$$\begin{aligned} p &= exp(-Z'X'\lambda_1) \odot exp(-i_{KM} - (I_K \otimes i_M)\lambda_2) \\ g &= exp(-F'(I_N \otimes i'_T)\lambda_1) \odot exp(-i_{NR} - (I_N \otimes i_R)\lambda_3) \\ w &= exp(-V'\lambda_1) \odot exp(-i_{NTJ} - (I_{NT} \otimes i_J)\lambda_4) \end{aligned} \tag{3.13}$$

where $\odot$ denotes the Hadamard product.

Furthermore, since $exp(-i_{KM} - (I_K \otimes i_M)\lambda_2) = (I_K \otimes J_M)exp(-Z'X'\lambda_1)^{\odot(-1)}$ where $\odot(-1)$ means the Hadamard inverse; that is, the elementwise reciprocation.

Equation 3.13 can be rewritten as

$$\begin{aligned} p &= exp(-Z'X'\lambda_1) \odot (I_K \otimes J_M)exp(-Z'X'\lambda_1)^{\odot(-1)} \\ g &= exp(-F'(I_N \otimes i'_T)\lambda_1) \odot (I_N \otimes J_R)exp(-F'(I_N \otimes i'_t)\lambda_1)^{\odot(-1)} \\ w &= exp(-V'\lambda_1) \odot (I_{NT} \otimes J_J)exp(-V'\lambda_1)^{\odot(-1)} \end{aligned} \tag{3.14}$$

3.3 A Dual Generalized Maximum Entropy Estimator

Golan et al. [24] developed this class of estimation methods which can be solved with simpler and more widely available unconstraint numerical methods. They discuss different ways to incorporate the sample data in the GME optimization. Building on the Lagrangean function 3.11 and the solutions from 3.14, the dual unconstraint GME is:

$$
\begin{aligned}
L &= -p'log(p) - g'log(g) - w'log(w) + \lambda_1'(y - XZp - (I_N \otimes i_t)Fg - Vw) \\
&= -p'[-Z'X'\lambda_1 - log((I_K \otimes J_M)exp(-Z'X'\lambda_1))] \\
&\quad - g'[-F'(I_N \otimes i_T')\lambda_1 - log[(I_N \otimes J_R)exp(-F'(I_N \otimes i_t')\lambda_1)]] \\
&\quad -w'[-V'\lambda_1 - log[(I_{NT} \otimes J_J)exp(-V'\lambda_1)]] + [y' - p'Z'X' - g'F'(I_N \otimes i_t') - w'V']\lambda_1 \\
&= y'\lambda_1 + p'log((I_K \otimes J_M)exp(-Z'X'\lambda_1)) + g'log[(I_N \otimes J_R)exp(-F'(I_N \otimes i_t')\lambda_1) \\
&\quad + w'log[(I_{NT} \otimes J_J)exp(-V'\lambda_1)]
\end{aligned} \tag{3.15}
$$

The dual GME estimator of is defined as

$$\hat{\beta_{GME}} = Z\hat{p} \tag{3.16}$$

where $\hat{p} = exp(-Z'X'\lambda_1) \odot (I_K \otimes J_M)exp(-Z'X'\lambda_1)^{\odot(-1)}$ from 3.14 and $\hat{\lambda_1} = min_{\lambda_1} L$ from 3.15.

Compared to the primal GME problem, the dual unconstrained GME estimation is computationally more efficient since the number of estimated parameters in dual problem is less than primal problem [24]. For the large sample properties of a dual GME estimator for panel regression, refer to Lee and Cheon [2].

4 Data

The demand for tourism in Thailand by tourists originated from 10 major countries are analyzed by using panel data set, consisting of tourist arrivals from Laos, Malaysia, Singapore, China, Japan, Korea, Russia, United Kingdom, USA, and India. Based on the sample period of 22 years, from 1995 to 2016, the data for the study are obtained from CEIC database.

The model constructed in this study is based on consumer behavior theory, which postulates that income and price type factors are likely to play a central role in determining the demand for international tourism.

Number of tourist arrivals to Thailand are used as a measurement of tourism demand, determined by Gross Domestic Product per capita ($GDPpc_{nt}$), relative price of tourism in Thailand (RP_{nt}), exchange rate (ER_{nt}), and population (POP_{nt}).

The following model is used to estimate tourism demand to Thailand from 10 major countries:

$$lnTA_{nt} = \alpha_0 + \alpha_1 lnGDPpc_{nt} + \alpha_2 lnRP_{nt} + \alpha_3 lnER_{nt} + \alpha_4 lnPOP_{nt} + \epsilon_{nt}, \tag{4.1}$$

where

$lnTA_{nt}$=Log of the number of tourist arrivals from country of origin n to Thailand in year t.

$lnGDPpc_{nt}$=Log of the Gross Domestic Product per capita of country n(in USD dollars) in year t.

$lnRP_{nt}$=Log of the price in Thailand relative to the price in the origin country n at time t. The is measured by the ratio of CPI in Thailand over the CPI in origin n at time t.

$lnER_{nt}$=Log of the bilateral exchange rate between Thailand and the origin country n at time t.

$lnPOP_{nt}$=Log of population of country n.

ϵ_{nt}=The stochastic error term.

α_0=constant term.

α_1,α_2,α_3,α_4=coefficients.

For the model estimation, a dual generalized maximum entropy (dual GME) estimator for panel data regression models was employed.The sample statistics for the data used in this paper was shown in Table 1.

Table 1: Descriptive statistics.

Variable	Mean	Std.Dev	Maximum	Minimum	Obs
$lnTA_{nt}$	13.329	0.989	15.985	10.023	220
$lnGDPpc_{nt}$	8.995	1.640	10.959	5.516	220
$lnRP_{nt}$	4.516	0.692	6.921	2.740	220
$lnER_{nt}$	−0.493	2.942	5.625	−4.358	220
$lnPOP_{nt}$	18.238	1.847	21.044	15.075	220

Source:Calculation.

5 Empirical Results

In this section the comparison of the selected techniques in modelling international tourism demand in Thailand is made and the obtained results are discussed. This section presents the estimation using a dual generalized maximum entropy (dual GME) estimator for panel data regression models proposed by Lee and Cheon [2] compare with the result of the ordinary least squared estimator.

Since the maximum entropy estimator allows us to include the prior information on parameters by modifying the support values of the parameters to be estimated; in this study, before estimation, four different support spaces are specified for the estimated models.

$GME1$:$z = (-1, 0, 1), f = (-1, 01), v = (-1, 0, 1)$

$GME2$:$z = (-2, 0, 1), f = (-1, 01), v = (-1, 0, 1)$

$GME3$:$z = (-3, 0, 1), f = (-1, 01), v = (-1, 0, 1)$

$GME4$:$z = (-4, 0, 1), f = (-1, 01), v = (-1, 0, 1)$

Table 2: Results of Thailand tourism demand estimated by a dual general maximum entropy estimator for panel data

variable	$GME1$	$GME2$	$GME3$	$GME4$	OLS
$lnGDPpc_{nt}$	0.999	0.549	0.365	0.273	0.131
	(0.103)	(0.162)	(0.195)	(0.1033)	(0.033)
$lnRP_{nt}$	−0.001	−0.001	−0.001	−0.001	−0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
$lnER_{nt}$	0.369	0.199	0.136	0.103	−0.009
	(0.242)	(0.382)	(0.459)	(0.500)	(0.017)
$lnPOP_{nt}$	0.259	0.021	0.019	0.008	0.021
	(0.658)	(1.031)	(1.247)	(1.358)	(0.025)
Max Entropy	−229.993	−231.440	−231.592	−231.646	
MSE	1.695	6.549	9.845	11.946	14.859

Note : () is standard error

Table 2 shows the estimated coefficients of the international tourist arrivals to Thailand from Laos, Malaysia, Singapore, China, Japan, Korea, Russia, United Kingdom, USA, and India.

The empirical results show $GME1$ is the most appropriate model to describe international tourist arrivals to Thailand patterns as it has the maximum Max Entropy value and minimum value of mean square error (MSE).

The results also show that Thailand tourism demand is positively determined by GDP per capita ($lnGDPpc_{nt}$), Exchange Rate ($lnER_{nt}$) and population ($lnPOP_{nt}$), while relative price ($lnRP_{nt}$) has negative impact on Thailand tourism demand.

The results imply that when GDP per capita ($lnGDPpc_{nt}$) increases by 1 percent then the number of international tourists arriving in Thailand will increase by 0.999 percent. The estimated elasticity value implies that international tourism demand to Thailand is a normal goods; its income elasticity is less than 1. The results of Exchange Rate ($lnER_{nt}$) and population ($lnPOP_{nt}$) imply that the increases by 1 percent of Exchange Rate ($lnER_{nt}$) will increase the number of international tourists arriving in Thailand by 0.369 percent and when population ($lnPOP_{nt}$) increases by 1 percent then the number of international tourists arriving in Thailand will increase by 0.259 percent.

The result of relative price indicates its negative impact on international tourist arrivals to Thailand, implying that when relative price ($lnRP_{nt}$) increases by 1 percent then the number of international tourists arriving in Thailand will decrease by 0.001 percent. Meanwhile, the international tourism demand to Thailand is not very sensitive to destination price changes, with an absolute value of price elasticity lower than 1.

6 Conclusion

This study aims to measure the determinants of international tourism demand from ten major origin countries (Laos, Malaysia, Singapore, China, Japan, Korea, Russia, United Kingdom, USA and India) to Thailand over a period of 22 years (1995−2016). A dual generalized maximum entropy (dual GME) estimator for panel data regression models proposed by Lee and Cheon [2] is employed. There are several researches used static and dynamic panel data for analysis with ordinary least squared (OLS) and generalized method of moments (GMM) estimation. However, the entropy approaches for panel data has not yet been investigated in the tourism demand analysis. The primary advantage of the entropy approach is helping to solve problem of limited, partial, or incomplete data, known as ill-posed problem.

Important economic factors such as income, price, exchange rate, and the number of population included as independent variables in model have been studied. The empirical results indicate that international tourist arrivals to Thailand is positively determined by GDP per capita ($lnGDPpc_{nt}$), Exchange Rate ($lnER_{nt}$) and population ($lnPOP_{nt}$), while relative price ($lnRP_{nt}$) has negative impact on international tourist arrivals to Thailand.

The research results shown that, the estimation using a dual generalized maximum entropy (dual GME) estimator performed the best modelling of tourism demand in Thailand for the tested period.

Based on our finding, income of origin country plays important role in determining international tourist arrivals to Thailand because the estimated income elasticity is the highest of all factors. Income elasticity closer to 1 indicates that tourism to Thailand is considered by foreigners as a non-luxury good and service. This also suggests that tourism is very much dependent on the economic conditions of the origin countries. Moreover, High values of income elasticity mean that demand for tourism increases significantly as income in the origin countries increases. Therefore Thailand will benefits from the long run growth of income in other countries.

For further research, there are other influences on tourism demand that have not been included in the model, such as trends in fashion and tastes, or advertising expenditure. Including these variables would increase the estimates gained from this form of modelling methodology.

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