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Modeling to Forecast International Tourism Demand in Thailand

Suramase Hashim*

Department of Mathematics and Statistics, Faculty of Science and Technology, Thammasat University, Pathum Thani 12120, Thailand

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ABSTRACT

This study attempted to develop and certify a demand model to forecast international tourism demand in Thailand using 4 key macroeconomic variables which are foreign direct investment, exchange rate, inflation rate and openness of trade. This study examines Poisson regression and negative binomial regression. Overdispersion is encountered when fitting with the Poisson regression model. The study finds that the negative binomial regression model is the best model to develop for international tourism demand in Thailand. Exchange rate, inflation rate and openness of trade are three components in the model. The exchange rate and inflation rate have negative relationships with international tourism demand in Thailand. On the other hand, the openness of trade has a positive relationship with international tourism demand in Thailand.

Keywords: Forecasting; Negative binomial regression; Poisson regression; Tourism demand

1. Introduction

Recent decades have seen growing expansion in tourism demand in Thailand, as international tourism gradually has become key to Thailand economic development. Thailand's foreign revenue and current account mainly are from tourism and provide a significant contribution to the Gross Domestic Product (GDP). Tourism value has contributed more than 17% to the GDP since 2017. Moreover, the employees in the tourism sector number more than 4.26 million. The Ministry of Tourism and Sports has established a strategic plan covering the period 2017 to 2021 that includes a master plan to stimulate the economy by promoting tourism.

The government has been playing a very important role in stimulating the growth and development of the tourism industry. The forecasting of tourism demand is important for planning and managing resources to satisfy the coming tourists in the future. The accurate forecasting benefits both Thai entrepreneurs and foreign tourists. An under estimated forecast leads to an excess

*Corresponding author: suramase@mathstat.sci.tu.ac.th
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demand that can make tourists unhappy with their trips and not want to return to Thailand. On the other hand, an over estimated forecast leads to an excess supply and Thai investors will not have the return they expected.

In recent years, there has been a growing interest in analyzing and forecasting tourism demand in Thailand. Researchers have used different methods for forecasting. Time series methods are one of the common and useful methods which numerous studies have used. These methods consider historical patterns in data to forecast future values. They do not cover casual relationships [1]. Unlike other studies, this study considers macroeconomic variables such as Foreign Direct Investment (FDI), exchange rate, inflation and openness of trade to model the forecasting demand. This study uses a Poisson regression model and a negative binomial regression model to determine the drivers of international tourism demand in Thailand.

2. Materials and Methods

2.1 Materials

This study uses macroeconomic variables that might impact the demand of international tourists in Thailand. There are four independent variables: foreign direct investment (FDI), real exchange rate (RER), inflation (INF) and openness of trade (OT). The foreign direct investment is measured by the annual percentage change in GDP. The real exchange rate is calculated as an annual average based on the Thai baht relative to the U. S dollar. Inflation is measured by the consumer price index which reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services. The openness of trade is measured by the sum of imports and exports in the GDP. The dependent variable in this study is the number of international tourist arrivals to Thailand (TOU).

The data are obtained from the World Development Indicator database which is published by the World Bank. The data cover the period of 2000-2016.

2.2 Methodology

In generalized linear modelling, if y is a dependent variable and x is a collection of independent variables such that $x_1, x_2, ..., x_k$ are k different independent variables, a multivariate linear regression model is defined as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon, \quad (2.1)$$

where $\beta_0, \beta_1, \beta_2, ..., \beta_k$ are coefficients of their corresponding independent $x_1, x_2, ..., x_k$, and ε is the error term. This is a multiple linear regression model which has mainly 4 assumptions: (1) there exists a linear relationship between the dependent variables and the independent variables; (2) the error terms have constant variance at every level of independent variable or homoscedasticity; (3) the normally distributed between the error term and the independent variables, and (4) the independence of the error term and independent variables, i.e., there is no autocorrelation.

In the study of count data, such as the number of tourist arrivals, these assumptions may not always be satisfied. To satisfy the assumption requirements, some adjustments on the variables may be done. One possible method is to transform y into another variable by using a link function. Poisson regression and negative binomial regression are used in this study. These techniques have been widely used for count data [2]. The dependent variable is Poisson distributed.

The Poisson distribution models the probability of y events with the formula:

$$P(Y = y) = \frac{e^{-\mu} \mu^{y}}{y!}; y = 0,1,2,... \quad (2.2)$$

The Poisson distribution is specified with a single parameter μ. This is the mean incidence rate of an event per unit of exposure. The Poisson distribution has the property that its mean and variance are equal. In Poisson regression, we suppose that the Poisson incidence rate μ is determined by a set of k independent variables.

$$\mu = e^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k)}. \qquad (2.3)$$

The Eq. (2.3) can be transformed with natural logarithm

$$\ln(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k. \qquad (2.4)$$

The maximum likelihood estimation (MLE) is applied to estimate the β values. There are a couple of hypothesis tests for this model. The overall performance of the model can be measured by the changes in deviance. The deviance is -2 times the difference between the log-likelihood evaluated at the maximum likelihood estimate and the log-likelihood for a saturated model. The test statistic has a chi-squared distribution with d degree of freedom. While d is the difference in the degrees of freedom associated with the two models. If the null hypothesis is rejected, at least one of the independent variables has statistical significance with the dependent variable.

To test the significance of each independent variable and the dependent variable Wald statistics are used. The Wald statistics is the second power of the ratio between the estimated coefficient and its standard error which has a chi-squared distribution with degree of freedom of 1.

Using Poisson regression to make inference requires model assumptions: (1) the dependent variable is a count per unit of time or space, described by a Poisson distribution; (2) the observations must be independent of one another; (3) the mean of a Poisson random variable must be equal to its variance; and (4) the log of the mean rate must be a linear function of independent variables. According to reference [3] the assumption of equidispersion can sometimes not be met. Variance is sometimes greater than the mean (overdispersion), or smaller than the mean (underdispersion).

Underdispersion is rare in practice due to the presence of greater variance than the conditional mean of response variables [4].

Overdispersion results from the greater variance of dependent variables caused by other variables, unobserved heterogeneity, or the existence of excess zeros on dependent variable [5]. Overdispersion occurring in a Poisson regression model results in underestimated standard error and, consequently, an invalid conclusion [6]. If data with overdispersion are analyzed using Poisson regression, there will be some missing information. Dispersion parameters refer to parameters which appear as a result of the absence of equidispersion. The dispersion parameters can be estimated by dividing the model deviance by its corresponding degrees of freedom. If there is no overdispersion, this estimate should be close to one. It will be larger than one in the presence of overdispersion. Some regression models can be used to overcome overdispersion; two of which are the negative binomial regression model and the generalized Poisson regression model [7, 8].

Negative binomial regression is a generalization of Poisson regression which loosens the restrictive assumption that the mean is equal to the variance made by the Poisson regression. The negative binomial regression is based on the Poisson – gamma mixture distribution. The result of negative binomial distribution is

$$P(Y=y) = \frac{\Gamma(y+\alpha^{-1})}{\Gamma(y+1)\Gamma(\alpha^{-1})}\left(\frac{1}{1+\alpha\mu}\right)^{\alpha^{-1}}\left(\frac{\alpha\mu}{1+\alpha\mu}\right)^{y}. \qquad (2.5)$$

The parameter μ is mean incidence rate of y per unit of exposure. In negative binomial regression, the mean of y is determined by the exposure and a set of independent variables. Transform y into another variable by using natural logarithm as a link function, the negative binomial regression model can be shown as:

$$\ln(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k. \quad (2.6)$$

The maximum likelihood estimation (MLE) is applied to estimate the β values. The overall performance of the model can be measured by the changes in deviance and Wald statistics is used to test the significance of each independent variables and the dependent variable.

3. Empirical Results

A linear regression model is performed for estimating the ability of the model to forecast international tourism demand in Thailand. The stepwise method results with 0.05 level of significance can be seen in Table 1.

Table 1. Estimation result of multiple regression model.

	Coefficient	t-statistics	VIF
Const.	61,854.10		
RER	-1,131.15	-4.063*	1.015
INF	-1,660.72	-2.373*	1.015

Durbin – Watson = 0.854
Note: * indicate 5% level of significant

There are two explanatory variables in the regression model: real exchange rate and inflation. Both variables have negative relationship with the number of international tourist arrivals to Thailand. There is no multicollinearity between these two variables because VIF is less than 5 for both. However, the Durbin- Watson statistics is 0.854, which indicates the presence of autocorrelation. The regression model is not a fit model to forecast the international tourism demand in Thailand. Poisson regression and negative binomial regression models are considered.

3.1 Poisson regression model

Fitting the Poisson regression model to the number of international tourist arrivals to Thailand with foreign direct investment, real exchange rate, inflation and openness of trade as predictors, the estimated regression coefficients are shown in Table 2.

Table 2. Estimation result of Poisson regression model.

	Coefficient	Wald statistics	Exp(b)
Const	8.119		
FDI	-0.055	961.83*	0.946
RER	-0.039	2,750.64*	0.960
INF	-1.161	6,087.14*	0.848
OT	0.027	2,226.20*	1.027

Deviance Residual = 34,456.47*
Dispersion = 1,072.75
Note: * indicate 5% level of significant

The Poisson regression model is:

$$\ln(TOU) = 8.119 - 0.055FDI$$
$$- 0.039RER - 1.161INF + 0.027OT.$$

All the independent variables are statistically significant to forecast the number of tourist arrivals to Thailand. The foreign direct investment, real exchange rate, and inflation have negative relationship with international tourism demand in Thailand. Inflation has the highest impact on the number of tourist arrivals to Thailand. An increase of 1% in inflation leads to a 15.2% decrease in the number of tourist arrivals when other variables are held constant. The openness of trade has a positive relationship with international tourism demand in Thailand. A 1% increase in openness of trade leads to a 2.7% increase in the number of tourist arrivals when other variables are held constant.

The overall performance of the model is tested by the deviance residual. The deviance residual is 34,456.47 with p-value less than 0.05. The null hypothesis is rejected, at least one of the independent variables has statistical significance with the number of tourist arrivals to Thailand. The Wald statistics test for each independent variable associated with their p-value indicates that each independent variable is statistically significant to forecast the number of tourist arrivals to Thailand.

The assumption of Poisson regression model is equidispersion. The dispersion parameter is 1072.75 which is apart from one. The presence of overdispersion appears to be in the Poisson regression model.

3.2 Negative binomial regression model

The overdispersion violates the Poisson regression' s assumption. One approach that addresses this issue is the negative binomial regression model. The negative binomial regression is for modeling count variables, usually for over-dispersed count outcome variables. The estimated regression coefficients can be shown in table 3.

Table 3. Estimation result of negative binomial regression model.

	Coefficient	Wald statistics	Exp(b)
Const	8.055		
RER	-0.044	6.418*	0.957
INF	-0.176	11.011*	0.839
OT	0.028	3.845*	1.029

Deviance Residual = 23.531*
Dispersion = 1.426
Note: * indicate 5% level of significant

The negative binomial regression model is:

$$\ln(TOU) = 8.055 - 0.044RER \\ - 0.176INF + 0.027OT.$$

The deviance residual associated with its p-value indicate that the overall performance of the model is adequate. The Wald statistics test shows that real exchange rate, inflation and the openness of trade are statistically significant to forecast the number of tourist arrivals to Thailand. This conclusion is different from the Poisson regression model, which includes the foreign direct investment. However, interpretation is not majorly different. Real exchange rate and inflation have negative relationships with international tourism demand in Thailand while the openness of trade has a positive relationship. Inflation has the highest impact on the number of tourist arrivals to Thailand. A 1% increase in inflation leads to a 16.1% decrease in the number of tourist arrivals when other variables are held constant. Similarly, a 1% increase in the real exchange rate leads to a 4.3% decrease in the number of tourist arrivals when other variables are held constant, and a 1% increase in openness of trade causes a 2.9% increase in the number .of tourist arrivals when other variables are held constant.

The dispersion parameter is 1.426 which indicate an overdispersion in the model. However, the overdispersion is not a concern in negative binomial regression models.

4. Discussion and Conclusions

Tourism is one of the main industries in Thailand which generated revenue of more than 3 billion baht in 2019. The growth is more than 2% from the previous year. Meanwhile, two-thirds of the revenue was generated from international tourism. Therefore, an accurate model to forecast international tourism demand is important for government and investors. This study indicates that a negative binomial regression model is the most effective model in line with the study of number of tourist arrivals in India [9] and the forecasting model of tourism demand in ASEAN countries [10]. The recent study on tourism demand in Thailand mainly focus on the forecasting models. Multiplicative decomposition model [11] and AR(1)-GARCH(1,1) model [12] were recommended to forecast the international tourism demand in Thailand. However, those models did not present variables impact to the tourism demand in Thailand.

Based on this study, there are three macroeconomic variables that impact the demand of international tourists in Thailand: real exchange rate, inflation and openness of trade. This is in contrast to the studies in the literature on international tourism demand in African [13] and ASEAN [10]. These studies found that foreign direct investment, real exchange rate, inflation and openness of trade have relationships with the demand of international tourism.

The real exchange rate and inflation have negative relationships with the international tourism demand. Based on previous studies, exchange rate fluctuation is an important factor in the tourism industry [14]. Previous research has reported that exchange rate has an adverse interaction with tourism demand [15]. Meanwhile, Chatziantoniou et al. [16], found that there is reverse causality and negative effect between inflation and tourism. In contrast, there is a positive relationship between openness of trade and international tourism demand in line with the study of tourism demand in ASEAN countries [17].

In conclusion, a negative binomial regression model is the best model to forecast international tourism demand in Thailand. Real exchange rate, inflation and openness of trade are three factors in the model. Real exchange rate and inflation have negative relationships with tourism demand while the openness of trade has a positive relationship.

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