Analysis of seasonal tourism demand to economic growth in Thailand: Bayesian approach

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Abstract. This study investigates the dynamic empirical link between tourism demand (tourist arrivals, tourism revenues and tourism expenditures) and economic growth in the case of Thailand using a quarterly time-series data set from 2013q1 to 2018q4. The combination of Bayesian approach and Markov Chain Monte Carlo (MCMC) simulations can be applied and employed to estimate the parameters of tourism demand and economic growth. Stationary and correlative trends of variables datasets were examined by using Bayesian ADF unit-root testing (BADF), Bayesian seasonal unit-root testing (BHEGY) and Bayesian Auto Regressive Distributed Lag (BARDL) model respectively. BADF is applied in order to probe the stationary of the time-series data set. Moreover, BHEGY is utilized in order to examine the seasonally of the time-series data set. Furthermore, BARDL technique is used and implemented in order to analyse the long-run and short-run relationship between tourism demand and economic growth. Our empirical findings provide important policy implications for further study on Thailand tourism.

1. Introduction

Tourism has become an important origin of income for many countries. Most economies of many regions around the world rely on tourism. The revenues from tourism are the main factors that drive the country's economic improvement. The crucial economic development strategy in the most developing countries is about using promotion of the tourism industry to enhance economic growth. Therefore, a number of earlier studies have focused on investigating the relationships between tourism development and economic growth in many countries [1]. Many studies in the past have studied the significance of tourism to the economy of a country [2][3]. From most results confirm that tourism is one of the main determinants influencing the economic growth of that country. For Thailand, tourism is an important economic engine of Thailand in the last 3-4 years. In 2016, Thailand generated 12% of GDP from tourism sector. We can conclude that Revenue from overseas in tourism is increasing rapidly. Causing the GDP of Thailand to grow significantly and bringing in a large amount of foreign currency into the country each year.

2. Literature

There are many studies done on investigating the stationarity of data by employing ADF unit root test [4-7]. Realizing the fluctuation of tourism sector, we considered time-series dataset of tourism trends. Then, we believe that the trend of time-series tourism dataset has a seasonally structural movement.
The dissimilarity of this study from prior studies is that ADF was extended with Bayesian Seasonal unit-root testing in this study. Bayesian seasonal unit root testing, called BHEGY was employed to this study. There are various previous studies investigated and examined causal relationship by using ARDL approach to cointegration in many fields [8-12]. Some of them have done on causality analysis to identify the pattern of relationship between economic growths with tourism variables [13-16]. Bayesian ARDL approach was employed in this study. This paper examines the long-run and short-run relation between tourism demand variables and the economic growth. The goal of this paper is to diagnose that whether changes in the tourism demand variables brings variations in the economic growth and whether there is any interrelation between tourism time-series dataset and economic growth. In this study this index is compared also its interrelation with different tourism demand variables that include tourism expenditure, tourist arrivals and tourist revenues in Thailand.

3. Methodology

The quarterly time-series dataset was used in this paper such as tourism demand and economic growth during 2013q1 to 2018q4. Tourism demand can be seen in the form of tourist arrivals, tourism revenues and tourism expenditures (source: Department of Tourism, Ministry of Tourism and Sports, Thailand). While, economic growth can be seen in the form of Gross Domestic Product (GDP) (source: Bank of Thailand). In this paper, we used R software to construct the structure of the time-series dataset to analyze the results.

3.1. Bayesian inference approach

Basically, “inverse probability” was mentioned in Bayesian inference approach. The inverse probability is the posterior distribution denoted as \( p(\theta|x) \). Posterior distribution relies on a prior distribution and the likelihood function. Firstly, we have to determine a “prior distribution” which represents our “belief level” to solve the complicated model. Prior distribution is displayed in equation (1) as

\[
p(x|\theta) = \prod_{m=1}^{M} \left( \frac{\theta^{|x_m|}}{2\pi} \right)^{\frac{1}{2}} \exp\left( -\frac{\theta^2 x^2}{2} \right)
\]

After setting the prior, the prior and the likelihood are determined. Thus, we compute the “posterior distribution” over \( x \) via Bayes’ rule,

\[
p(x|t, \theta, \sigma^2) \propto \underbrace{p(t|x, \sigma^2)}_{\text{likelihood}} \cdot \underbrace{p(x|\theta)}_{\text{prior distribution}}
\]

Posterior can be considered as a result from the combination between the Gaussian prior and linear model within a Gaussian likelihood. So, the posterior is determined as \( p(x|t, \theta, \sigma^2) = N(\mu, \Sigma) \) with

\[
\mu = (\Phi^T \Phi + \sigma^2 I)^{-1} \Phi^T t
\]

\[
\Sigma = \sigma^2 (\Phi^T \Phi + \sigma^2 I)^{-1}
\]

where \( \Phi \) is the design matrix, \( T \) represents transpose of the design matrix \( \Phi \) and \((\Phi^T \Phi)^{-1}\) represents Moore-Penrose inverse.

The data \( t \) (the updating procedure) can provides estimated parameters. The estimated parameters can be existed from a distribution over all feasible values and provide up to date prior belief, with more posterior probability arranged to values that are both probable underneath the prior data.

Markov Chain Monte Carlo Method (MCMC) is the numerical methods which can be used for posterior estimation. It depends on pretending random samplers from \( p(x|t, \theta, \sigma^2) \). The task of MCMC is designing a Markov chain converging to target distribution. We can set up the transition function in order to converge to the target distribution by employing methods such as Metropolis-Hastings Sampling, Metropolis Sampling, and Gibb Sampling. The procedure for creating an order of \( T \) states from a Markov chain is the following
1. Define $t = 1$
2. Procreate an starting value $u$, and then define $X(t) = u$
3. Redo $t = t+1$

From the transition function $p(X(t)|X(t-1))$, we can sample a new value $u$

Determine $X(t) = u$

4. Until $t = T$ where $T$ in the MCMC procedure represents a stable state in the MCMC processes.

As shown in R.E. Kass and A.E. Raftery [17] and C.W.S. Chen et al. [18], Bayes factor comparisons can be used to consider hypotheses regarding multiple parameters in Bayesian statistics. Multiple hypotheses comparison can be done by employing the Bayes factors. The nested models are not compared [19]. Let $M_0$ is the model of the null hypothesis according to the parameters, $q_0$, and let $M_1$ is the model of the alternative hypothesis according to the parameters, $q_1$. Consequently, the posterior odds ratio of $M_0$ and $M_1$ is represented in equation:

$$\frac{pr(M_0|y)}{pr(M_1|y)} = \frac{\pi(M_0)}{\pi(M_1)} \cdot \frac{pr(y|M_0)}{pr(y|M_1)}$$ (5)

where $pr(y|M_0)$ is the marginal likelihood for model $M_0$

$\pi(M_1)$ is the prior probability for $M_1$

Thence, the marginal likelihood $pr(y|M_i)$ can be explained as

$$pr(y|M_i) = \int pr(y|\theta_i, M_i)pr(\theta_i|M_i) d\theta_i , i=0,1$$ (6)

Bayes factor was developed by H. Jeffreys [20]. The explanation in half-units on Jeffreys’ scales is explained as:

Bayesian factor | Premise against $M_0$
---|---
1/10 > BF | Extreme premise for $M_1$
1/10 < BF < 1/3 | Mediocre premise for $M_1$
1/3 < BF < 1 | Soft premise for $M_1$
1 < BF < 3 | Soft premise for $M_0$
3 < BF < 10 | Mediocre premise for $M_0$
10 < BF | Extreme premise for $M_0$

3.2. Bayesian ADF unit-root test

The purpose of the unit-root testing is to determine whether the stochastic component comprises a unit root or is stationary [21]. The existence of a unit root is assumed to occur in $H_0$. The alternative hypothesis ($H_1$) shows stationary. Normally, the time-series unit root testing approach can be demonstrated as the following equation.

$$Y_t = D_t + Z_t + \varepsilon_t$$ (7)

where $D_t$ is the deterministic component

$Z_t$ is the stochastic component

$\varepsilon_t$ is the stationary error process.

The ADF testing procedure can be written as:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_{p-1} \Delta Y_{t-p-1} + \varepsilon_t$$ (8)

where $\alpha$ is a constant

$\beta$ is the coefficient on a time trend

$p$ is the lag order of the autoregressive process.

The unit-root testing can be accomplished by $H_0$: $\gamma = 0$, $H_1$: $\gamma < 0$

$$DF_t = \frac{\hat{\gamma}}{SE\hat{\gamma}}$$ (9)

Then, Dickey-Fuller testing can be employed to compare this value to the critical value. The null hypothesis of $\gamma = 0$ is rejected when the test statistic is less than the critical value. This means no unit root. The regression of the ADF test can be displayed as in equation (10).

$$\Delta y_t = c + \alpha D_t + \varphi y_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} + \varepsilon_t$$ (10)
Δy_t is I(0) for the null hypothesis. This demonstrates that the stationary model is φ=0. Therefore, the stationary model is

\[ Δy_t = c + αD_1 + φy_{t-1} + \sum_{i=1}^{p} γ_i Δy_{t-i} + ε_t \quad \text{where } φ = 0 \]  

The stationary model is

\[ Δy_t = c + αD_1 + \sum_{i=1}^{p} γ_i Δy_{t-i} + ε_t \]  

The non-stationary model is

\[ Δy_t = c + αD_1 + φy_{t-1} + \sum_{i=1}^{p} γ_i Δy_{t-i} + ε_t \]  

where ε_t is iid N(0,σ^2) for t=1,…,T and suppose that σ^2 is fixed, φ = (Ø,a^*), Ø = ∑_{i=1}^{q} Ø_i and a^* = (c, α, γ).

The prior density of φ is

\[ p(φ) = p(Ø) p(α^*) \]  

Marginal likelihood for Ø is

\[ l(Ø|D) \alpha |f(φ)|dφ \]  

where D is observation vector. The main composition applied by basic Bayesian steps to assess the unit root existence is a prior for φ. Principally, Bayes factors and posterior probabilities can be employed for all of them, as written in the following equation:

\[ B_{01} = \frac{l(Ø=0|D)}{l(Ø=1|D)} \]  

3.3. Bayesian ARDL approach to cointegration

The ARDL double-log model is outlined by equation as

\[ y_t = α + β_1 x_t + β_2 z_t + β_3 w_t + u_t \]  

where \( y_t \) is non-stationary model, \( D \) is the operator of first difference for variables. We split the ARDL model into two parts includes short-run and long-run model. For instance, the ARDL cointegration model is constructed with tourist arrivals and GDP. This can be displayed as

\[ ΔGDP_t = α_0 + \sum_{i=1}^{n-1} α_{1i} ΔGDP_{t-1} + \sum_{i=1}^{n-1} α_{2i} ΔΔGDP_{t-1} + \sum_{i=1}^{n-1} α_{3i} ΔΔGDP_{t-1} + \sum_{i=1}^{n-1} α_{4i} ΔΔGDP_{t-1} + β_1 ΔΔGDP_{t-1} + β_2 ΔΔGDP_{t-1} + β_3 ΔΔGDP_{t-1} + μ_t \]  

where \( α_0 \) is the deterministic drift parameter and \( Δ \) is the operator of first difference for variables. We discover that contains the long run relationship of cointegration among all time-series dataset such as GDP, tourist arrivals, tourism revenues and tourism expenditures respectively by employing the null hypothesis and alternative hypothesis testing such as:

- H0 : β1 = β2 = β3 = β4 = 0 (short-run model)
- H1 : β1 ≠ β2 ≠ β3 ≠ β4 ≠ 0 (long-run model)

Then, we estimate the unrestricted Error Correction Model (ECM). The equation (20) is the Error Correction Model (ECM).

\[ ΔGDP_t = α_0 + \sum_{i=1}^{n-1} α_{1i} ΔGDP_{t-1} + \sum_{i=1}^{n-1} α_{2i} ΔΔGDP_{t-1} + \sum_{i=1}^{n-1} α_{3i} ΔΔGDP_{t-1} + \sum_{i=1}^{n-1} α_{4i} ΔΔGDP_{t-1} + β_1 ΔΔGDP_{t-1} + β_2 ΔΔGDP_{t-1} + β_3 ΔΔGDP_{t-1} + μ_t + λECT_{t-1} + v_t \]  

The ratios of posterior probability with Bayes factors are described as:

\[ B_{01} = \frac{l(Ø=0|D)}{l(Ø=1|D)} \]  

The ARDL double-log model is constructed with tourist arrivals and GDP. This can be displayed as: 

\[ y_t = α + β_1 x_t + β_2 z_t + β_3 w_t + u_t \]  

where GDP, arrivals, revenues and expenditures are, respectively in natural logarithms. The model is designated as

\[ y_t = α + β_1 x_t + β_2 z_t + β_3 w_t + u_t \]  

The ratios of posterior probability with Bayes factors are described as:

\[ B_{01} = \frac{l(Ø=0|D)}{l(Ø=1|D)} \]  

where \( D \) is observation vector. The main composition applied by basic Bayesian steps to assess the unit root existence is a prior for φ. Principally, Bayes factors and posterior probabilities can be employed for all of them, as written in the following equation:

\[ B_{01} = \frac{l(Ø=0|D)}{l(Ø=1|D)} \]
\[ B_{02} = \frac{\int (|\beta| = 1) d\beta}{\int \int \int \int d\beta d\beta d\beta d\beta} \] (22)

Equation (21) is for the long-run model while equation (22) is for long-run model.

### 3.4. Bayesian seasonal unit-root testing (BHEGY)

The posterior density denoted as \( \pi(\theta | y) \) can be obtained from the Bayes’s theorem. A probability distribution of parameters \( \theta \) can be denoted as the posterior density in the form as

\[ \pi(\theta | y) \propto L(y | \theta) \pi(\theta) \] (23)

where \( \pi(\theta) \) refers the prior density of parameter \( \theta \).

\[ \{ \theta \} = \frac{1}{\int \pi(\theta | y) d\theta} \] (24)

and

\[ Z = \int \pi(\theta | y) d\theta \] (25)

\( \pi(\theta) \) can be supposed to be constant, which is shown in Equation (24) because the functional form of \( \pi(\theta) \) is unknown. From Equation (24) and (25), \( \{ \theta \} \) cannot be analytically operated. The complete data likelihood function is

\[ L(y | \theta) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi \sigma_i^2}} \exp\left(-\frac{y_i^2}{2\sigma_i^2}\right) \] (26)

where \( y \) represents the time-series data of \( n \) observations, \( y = (y_1, y_2, ..., y_n) \) and \( \theta \) stands for the parameters to be estimated. The estimated parameters in the log-likelihood function in equation (26) can be maximized expressed in Equation (27).

\[ \ln L(y | \theta) = -\frac{1}{2} \sum_{i=1}^{n} \ln(2\pi \sigma_i^2) - \sum_{i=1}^{n} \frac{y_i^2}{2\sigma_i^2} \] (27)

Since it is evident that time-series dataset has a seasonally structural movement from tourism trends, then the HEGY test can be utilized and Bayesian analysis can be applied to set the numbers of unit roots. BHEGY testing is depended on the following auxiliary regression,

\[ \Delta(B)y_{4,t} = \mu_t + \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-2} + \pi_4 y_{4,t-3} + \epsilon_t \] (28)

From Equation (28), \( \Delta(B) \) is an autoregressive polynomial in \( B \) with order \( r \) chosen to render the error terms in the white noise equation. \( \mu_t \) is an incorporation between seasonal dummies and a time trend. Expressly, the BHEGY method represents that the test for the appearance of non-seasonal prior and the amounts of seasonal unit roots to testing for the significance of the \( \pi \) terms in Equation (28). The explication of the different \( \pi_i \) is as follows:

1. there is no long-run (non-seasonal) unit root when \( \pi_1 < 0 \) and \( \pi_1 \) is depended upon \( W_{it} = S(B)Y_{1} \), which all of the seasonal roots are removed.
2. there is no semi-yearly unit root when \( \pi_2 < 0 \).
3. there is no unit root in the yearly cycle when \( \pi_3 < 0 \) and \( \pi_4 < 0 \).

### 4. Results

#### 4.1. Bayesian ADF unit-root testing

The results of Bayesian ADF unit-root testing are displayed in Table 1. The empirical results demonstrate that three quarterly time-series data sets including GDP, tourist arrivals and tourism revenues also found to be non-stationary at level and denoted as I(1) since we can saw the fluctuation of these time-series dataset during 2013q1 to 2018q4. On the other hand, the empirical results of
stationary conditions for tourism expenditures from the Bayesian unit-root testing are stationary at the zero level (I(0)).

Since these time-series data set occur mixed order variables, we can overcome this problem by choosing the method called the ARDL approach based on Bayesian inference. All these variables are used to investigate the interrelationship by employing the ARDL approach based on Bayesian inference between tourism demand and GDP because the ARDL approach based on Bayesian inference can solve the problem about the mixed order variables.

**Table 1. The Bayesian ADF unit root-testing results for four quarterly time-series data set.**

| Variables          | Bayesian factor model | Hypothesis               | Number of MCMC iterations | Posterior odds ratio (POR) | Interpretation of Bayesian factor | Result       |
|-------------------|----------------------|--------------------------|---------------------------|---------------------------|----------------------------------|--------------|
| GDP               | Model1               | $H_0(M_i)$: Non-stationary data | 1000                      | 52                        | Strong evidence for Model1       | Non-Stationary data I(1)          |
|                   | Model2               | $H_1(M_j)$: Stationary data | 1000                      | 0.0192                    |                                  |              |
| Tourist Arrivals  | Model1               | $H_0(M_i)$: Non-stationary data | 1000                      | 182                       | Strong evidence for Model1       | Non-Stationary data I(1)          |
|                   | Model2               | $H_1(M_j)$: Stationary data | 1000                      | 0.00549                   |                                  |              |
| Tourism Revenues  | Model1               | $H_0(M_i)$: Non-stationary data | 1000                      | 24.8                      | Strong evidence for Model1       | Non-Stationary data I(1)          |
|                   | Model2               | $H_1(M_j)$: Stationary data | 1000                      | 0.0403                    |                                  |              |
| Tourism Expenditures | Model1           | $H_0(M_i)$: Non-stationary data | 1000                      | 0.36                      | Weak evidence for Model2         | Stationary data I(0)              |
|                   | Model2               | $H_1(M_j)$: Stationary data | 1000                      | 2.78                      |                                  |              |

Noted: We used number as 1,000 is the considered number of MCMC iterations because we need to set the same standard of the observations. This number is applied to examine that under the same observation, the variable will reject null-hypothesis or accept null-hypothesis.

### 4.2. Bayesian seasonal unit-root testing (BHEGY)

The empirical results from Bayesian Seasonal unit-root testing are displayed in Table 2. Estimating the Bayesian seasonal unit-root testing (BHEGY) model, the quarterly data sets were investigated to ensure that the theses contains the seasonally structural trends. Clearly, the results can be estimated and displayed in Table 2 strongly represent that the BHEGY approach is the most suitable method for interpreting theses quarterly trends since from the BADF unit-root testing proved that time-series data sets are not stationary.

Furthermore, BHEGY was employed to check whether these all variables were seasonal in long-run period or not. The empirical results found that GDP follows the long-run seasonal model. Whereas, tourist arrivals, tourism revenues and tourism expenditures follow seasonal model but not for long-run period. The results are demonstrated in Table 3.
### Table 2. The results of the Bayesian Seasonal unit-root testing (BHEGY).

| Variables      | Bayesian factor model | Hypothesis                        | MCMC iterations | Posterior odds ratio (POR) | Bayesian factor explanation | Result                      |
|----------------|-----------------------|-----------------------------------|-----------------|---------------------------|------------------------------|-----------------------------|
| GDP            | Model 1               | H₀(Mᵢ): Normally structural unit root | 1000            | 6.05e-19                  | Strong evidence for Model 2  | The data has seasonally structural unit root |
|                | Model 2               | H₁(Mᵢ): Seasonally structural unit root | 1000            | 1.65e+18                  |                              |                             |
| Tourist Arrivals | Model 1               | H₀(Mᵢ): Normally structural unit root | 1000            | 2.5e-19                   | Strong evidence for Model 2  | The data has seasonally structural unit root |
|                | Model 2               | H₁(Mᵢ): Seasonally structural unit root | 1000            | 4e+18                     |                              |                             |
| Tourism Revenues | Model 1               | H₀(Mᵢ): Normally structural unit root | 1000            | 4.32e-19                  | Strong evidence for Model 2  | The data has seasonally structural unit root |
|                | Model 2               | H₁(Mᵢ): Seasonally structural unit root | 1000            | 2.32e+18                  |                              |                             |
| Tourism Expenditures | Model 1               | H₀(Mᵢ): Normally structural unit root | 1000            | 5.31e-19                  | Strong evidence for Model 2  | The data has seasonally structural unit root |
|                | Model 2               | H₁(Mᵢ): Seasonally structural unit root | 1000            | 1.88e+18                  |                              |                             |

Noted: We used number as 1,000 is the considered number of MCMC iterations because we need to set the same standard of the observations. This number is applied to examine that under the same observation, the variable will reject null-hypothesis or accept null-hypothesis.

### Table 3. The results of the Bayesian Seasonal unit-root testing (BHEGY).

| Variables      | Bayesian factor model | Hypothesis                        | MCMC iterations | Posterior odds ratio (POR) | Bayesian factor explanation | Result                      |
|----------------|-----------------------|-----------------------------------|-----------------|---------------------------|------------------------------|-----------------------------|
| GDP            | Model 1               | H₀(Mᵢ): Long-run seasonal model  | 1000            | 1.11                      | Weak evidence for Model 1    | Long-run seasonal model     |
|                | Model 2               | H₁(Mᵢ): Only seasonal model      | 1000            | 0.898                     |                              |                             |
| Tourist Arrivals | Model 1               | H₀(Mᵢ): Long-run seasonal model  | 1000            | 0.406                     | Weak evidence for Model 2    | Seasonal model              |
|                | Model 2               | H₁(Mᵢ): Only seasonal model      | 1000            | 2.46                      |                              |                             |
| Tourism Revenues | Model 1               | H₀(Mᵢ): Long-run seasonal model  | 1000            | 0.524                     | Weak evidence for Model 2    | Seasonal model              |
|                | Model 2               | H₁(Mᵢ): Only seasonal model      | 1000            | 1.91                      |                              |                             |
| Tourism Expenditures | Model 1               | H₀(Mᵢ): Long-run seasonal model  | 1000            | 0.932                     | Weak evidence for Model 2    | Seasonal model              |
|                | Model 2               | H₁(Mᵢ): Only seasonal model      | 1000            | 1.07                      |                              |                             |
4.3. Bayesian ARDL approach to cointegration

MCMC and Bayesian factors were applied and employed to examine the hypothesis for the ARDL model and cointegration. The evidence results found that there is the short-run mutuality between tourism demand in Thailand and GDP. Therefore, the null hypothesis (H₀) is reject that the interrelation between demands of tourism sector and GDP pursue the unsustainable model. Table 4 are displayed the empirical results of tourism demand to GDP.

Table 4. The Bayesian ARDL approach results.

| Variables        | Bayesian factor model | Hypothesis          | Posterior odds ratio (POR) | Interpretation of Bayesian factor | Result                  |
|------------------|-----------------------|---------------------|-----------------------------|----------------------------------|-------------------------|
| GDP-Tourist Arrivals Model1 | H₀(M₁): Sustainable model | 6.44e-05             | Extreme evidence for Mj      | Short-run relationship model     |
| Model2           | H₁(M₁): Unsustainable model | 15529               |                             |                                  |
| GDP-Tourism Revenues Model1  | H₀(M₁): Sustainable model | 0.000108            | Extreme evidence for Mj      | Short-run relationship model     |
| Model2           | H₁(M₁): Unsustainable model | 9238                |                             |                                  |
| GDP-Tourism Expenditures Model1  | H₀(M₁): Sustainable model | 0.000129            | Extreme evidence for Mj      | Short-run relationship model     |
| Model2           | H₁(M₁): Unsustainable model | 7776                |                             |                                  |

5. Conclusions

This paper has successfully imposed the mutuality between economic growth in form of GDP (dependent variable) and tourism demand in the form of tourist arrivals, tourism revenues and tourism expenditures (independent variables) respectively. As we see, the results from Bayesian ARDL approach found that tourist arrivals, tourism revenues and tourism expenditures had only a short-run connection (the unsustainable tourism model) to GDP. These results confirm that economic growth and tourism demand has only short-run relationship between them. Moreover, we realize about the fluctuation of tourism sector during that time period. This can be proved by examining the results from Bayesian ADF unit root test. The results from BADF showed that all time-series dataset are non-stationary. Then, Bayesian Seasonal unit-root test (BHEGY) can be used in order to check seasonally of the time-series data set. The result from BHEGY showed that tourist arrivals, tourism revenues and tourism expenditures follow the seasonal model but not for long-run period. On the other hand, GDP follows the long-run seasonal model. From the results, we conclude our empirical evidence that tourist arrivals, tourism revenues and tourism expenditures are the variables that can be advocated and designated most to the economic growths in the short-run period. From the results, the suggestion is that both government authorities and private sectors should aware about the sustainable tourism which can be contributed to the economy of country in the longer period. The suggestion is about that the tourism industry should be massively motivated by suitable advocates incessantly from government authorities and private sectors to supporting and expanding Thailand’s tourism in sustainable ways. Moreover, we must make Thailand as Asia’s premier tourism destination since the tourism industry is fast growing segment.
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