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SUSTAINABLE INTERNATIONAL TOURISM DEMAND IN THAILAND: THE CASE OF CHINESE TOURISTS

This research serves two purposes. The first objective is to clarify the Chinese tourist arrivals role for Thailand tourism sustainable growth model. The second purpose is to reveal the factors affecting Chinese tourists' behaviors when macroeconomic explanatory variables are changed. Our quantitative research employed 6 seasonal time-series data such as Chinese tourist arrivals to Thailand, Chinese gross domestic product, prices for kerosene-type jet fuel, relative prices for goods and services between China and Thailand, relative exchange rates between Chinese Yuan and Thai Baht, and Thailand temperature indices during 2002 (q1) to 2016 (q1). Bayesian statistics and Markov chain Monte Carlo (MCMC) were applied in the ARDL model to reveal the needed relationship and parameters. The empirical results prove that Chinese tourism demand in Thailand has short-run linkage, and this is the evidence of unsustainable tourism model.

Keywords: *tourism demand; sustainable model; ARDL; Bayesian inference; Markov chain Monte Carlo; Chinese tourists.*

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СТІЙКИЙ МІЖНАРОДНИЙ ТУРИСТИЧНИЙ ПОПИТ В ТАЇЛАНДІ: НА ПРИКЛАДІ КИТАЙСЬКИХ ТУРИСТІВ

У статті переслідуються дві мети. Перша — пояснити роль китайського туризму для стійкого зростання сектору туризму в Таїланді. Друга мета — виявити фактори, що впливають на поведінку китайських туристів з урахуванням макроекономічних змінних. Проаналізовано часові ряди по 6 змінних: чисельність китайських туристів в Таїланді, ВВП КНР, ціни на авіапаливо, відносні ціни на товари та послуги в КНР та в Таїланді, відносний обмінний курс юаня до бату та коливання температури в Таїланді. Дані зібрано та проаналізовано за період з першого кварталу 2002 р. по перший квартал 2016 року. Для виявлення взаємозв'язку між цими параметрами використано Байєсовську статистику, метод Монте-Карло та авторегресивний розподільчий лаг. Результати аналізу довели, що китайський попит на Таїланд як дестинацію є короткотерміновим, таким чином, модель розвитку сектору туризму є нестійкою.

Ключові слова: *туристичний попит; стійка модель розвитку; авторегресивний розподільчий лаг; байєсівський висновок; аналіз Монте-Карло з використанням Марківських мереж.*

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УСТОЙЧИВЫЙ МЕЖДУНАРОДНЫЙ ТУРИСТИЧЕСКИЙ СПРОС В ТАИЛАНДЕ: НА ПРИМЕРЕ КИТАЙСКИХ ТУРИСТОВ

В статье преследуются две цели. Первая — пояснить роль китайского туризма для устойчивого роста сектора туризма в Таиланде. Вторая же цель — выявить факторы, влияющие на поведение китайских туристов с учётом макроэкономических переменных. Проанализированы временные ряды по 6 переменным: численность китайских туристов в Таиланде, ВВП КНР, цены на авиатопливо, относительные цены на товары и услуги в КНР и в Таиланде, относительный обменный курс юаня к бату и колебания температуры в Таиланде. Данные собраны и проанализированы за период с первого квартала 2002 г. по первый квартал 2016 года. Для выявления взаимосвязей между этими параметрами использованы Байесовская статистика, метод Монте-Карло и авторегрессивный рас-

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пределённый лаг. Результаты анализа доказали, что китайский спрос на Таиланд как дестинацию является краткосрочным, таким образом, модель развития сектора туризма является неустойчивой.
Ключевые слова: *туристический спрос; усточивая модель развития; авторегрессивный распределённый лаг; байесовский вывод; анализ Монте-Карло с использованием цепей Маркова.*

Introduction. Making tourism more sustainable is a crucial role in the new era of services industries. Previously, high volumes of tourism were in focus, but this concept proved it is not the greatest solution in fighting poverty and environmental impacts. For the relationship between tourism sectors and economic systems overall, sustainable tourism should ensure long-term economic operation and fair provision socioeconomic benefits for all stakeholders, including stable employments, income-earning opportunities as well as poverty alleviation (United Nations Environmental Programme, 2005). Undoubtedly, government must be the key performer here since it has all economic tools and political power. Hence, academic research of tourism trends can be an efficient instrument to activate tourism policies appropriately.

Worldwide China's outbound tourists are the largest source that flows to many countries. In 2014, nearly 92.5% of total Chinese outbound travel spending was received by major global cities – 44% excluding Hong Kong, Japan, South Korea, Macau, and Thailand. The largest urban tourism markets for Chinese tourists are located in the Asia-Pacific region (Oxford Economics Company, 2015). Most of China's outbound travelers are 15–29 y.o. – the so-called "millennials" group – which totally spent 229 bln USD in 2015. This Chinese millennials group is slightly less price sensitive than the previous generations of the Chinese and is the biggest purchaser of luxury goods in the Asia Pacific (Martin, 2016).

In the mentioned region Thailand is one of the most popular destinations. According to the data from the InterContinental Hotels Group (IHG®), more than 2 mln Chinese tourists traveled to and spent at least 1 hotel night in Bangkok. This amount of hotel stay is the biggest number, larger than the same data for New York City and Tokyo, as of 2013 (Oxford Economics Company, 2015). In addition, all Chinese travelers can fly into Thailand with no visa (Ministry of Foreign Affairs of Kingdom of Thailand, 2016). Chinese tourist arrivals in Thailand have dramatically increased, by more than 200% during the past 9 years. As seen in Figure 1, 0.7 mln Chinese tourists came to Thailand in 2007. And in 2015 this number reached 18 mln persons (China National Tourism Administration, 2016). This leads us to pose two questions.

The first question concerns the relationship between Chinese travelers and Thailand tourism sector. Is it a short-run linkage, or a long-term connection? The second question how is Chinese tourists' behavior affected when macroeconomic factors are changed on many occasions?

This research aims to explain the factors affecting the Chinese tourism demand in Thailand from two positions. To answer the first question (whether it is short-run relation or a long-run linkage) Bayesian statistics and simulation analysis (Markov chain Monte Carlo – MCMC) are applied in the ARDL model. For the second answer (changing Chinese tourism trends when macroeconomic indices are fluctuating) the demand model and literature review are used to explain the outcomes from Bayesian parameters.

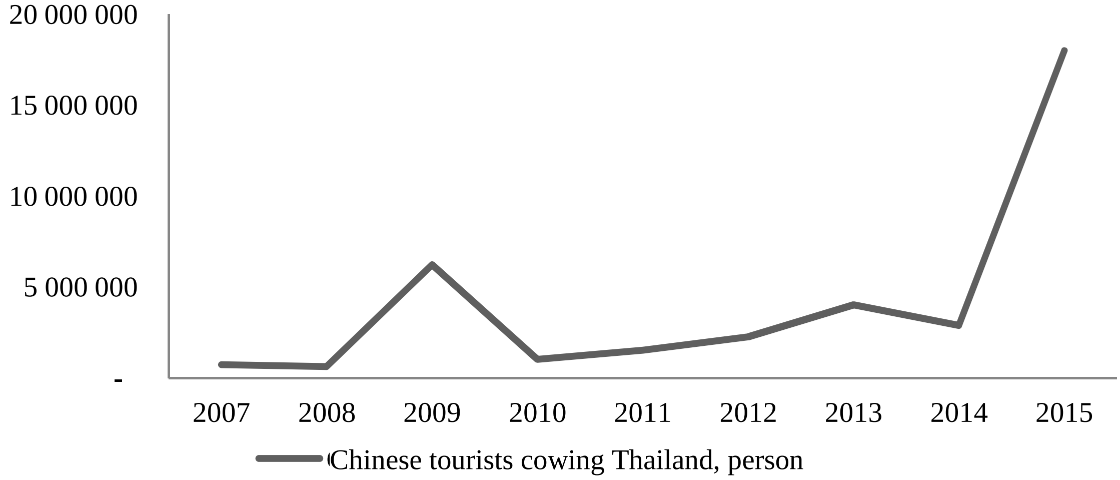

Figure 1. **The number of Chinese tourists visiting Thailand, 2007 to 2015,** *authors'*

The research scope. The intention of this paper is to explore the international tourist consumer behavior in Thailand during the period from 2002 (q1) till 2016 (q1). Information used in our research is quarterly time-series data, including that on Chinese tourist arrivals to Thailand (source: Tourism Authority of Thailand), Chinese GDP, world prices for kerosene-type jet fuel, relative price indices of China and Thailand, relative exchange rates between Chinese Yuan and Thai Baht, and finally seasonal temperatures in Thailand.

Literature review. Analyzing the relation between sustainable tourism and sustainable economic growth is an essential issue. The research paper of A. Freytag and C. Vietze (2010) stated that unsustainable mass tourism does not always growth in the long run. While C.M. Hall (2009) and C. Aall (2014) concluded that steady tourism is encouraging qualitative development without aggregating quantitative growth that unsustainably reduces natural capital.

In this paper, Bayesian statistics was applied to Markov Chain Monte Carlo (MCMC) simulation (Martin et al. 2016), a computationally intensive simulation method to replace exact integrals developed in the 1980s to extend the ability of two statistical models, including ADF unit root testing (Dickey and Fuller, 1979) and autoregressive distributed lag (ARDL) model (Shrestha, 2006). To clarify the stationary condition, the authors adjusted Bayesian inference to the ADF test referencing to R.E. Kass and A.E. Raftery (1995) and C.W.S. Chen et al. (2013) who studied the Bayesian factors for their hypotheses testing. To reach the objective of this research, the ARDL model based on Bayesian approach is adapted from P. Chaitip and C. Chaiboonsri (2009) who explored the long-run relationship of international tourism demands in Thailand using the ARDL model which integrates mixed-order variables. From the previous reviews, it is interesting to employ Bayesian statistics and statistical simulation to investigate the interdependences related to Chinese tourism demand in Thailand.

The conceptual framework of the research (Figure 2).

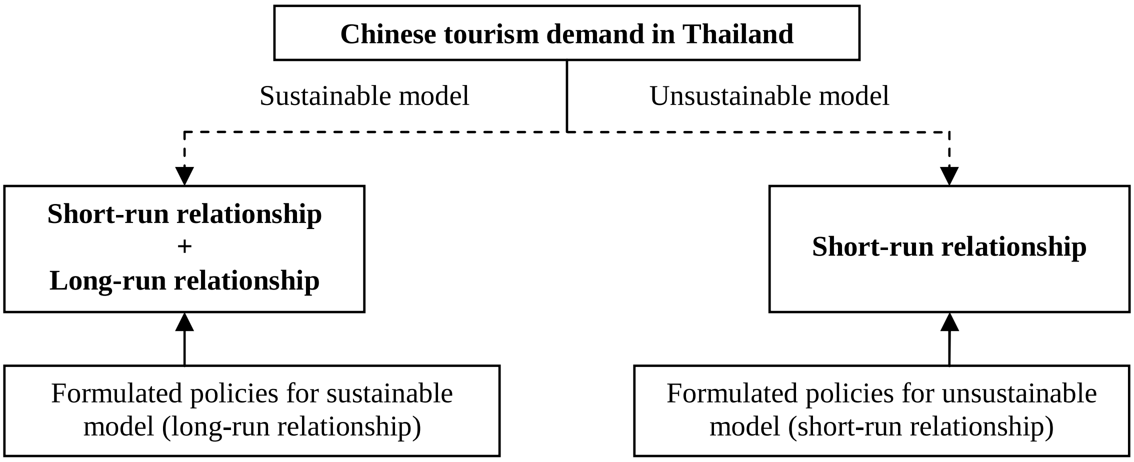

Figure 2. **The relationship of Chinese tourism demand in Thailand,** *authors'*

The methodology.

1. Background: the international demand model. The concept of tourism demand has been studied quite broadly. As seen in H. Song et al. (2003), M.C. Rodolfo et al. (2010), M.A. Ibrahim (2011), E.M. Ekanayake et al. (2012), and S. Guven and M. Mert (2016), statistical models and econometric tools are employed in estimating the demand function. Moreover, international tourism expansion is closely linked to economic parameters, which are at the microeconomic level affecting consumers' decision to travel. Empirically, the measurements of income, price elasticity, cost of travel, and time period are the essential components of the tourism demand function defined in equation:

$$D_t = f(Y_t, P_t, TC_t), \tag{1}$$

where D_t – the measure of tourism demand at time t; Y_t – the measure of international tourists' income (using real GDP in an origin country) at time t; P_t – the measure of goods and services cost at time t; TC_t – the measure of transportation cost between an origin country and a destination country at time t.

In this paper, the tourism demand function is expressed as a logarithm term, modified from equation (1) and shown in equation:

$$\ln D_t = \alpha + \beta \ln GDP_t + \delta \ln(PO_t) + \phi \ln(RP_t) + \gamma \ln(ER_t) + \rho \ln(TEM_t) + \varepsilon_t, \tag{2}$$

where $\ln D1_t$ – the logarithm of seasonal Chinese tourist arrivals to Thailand (tourism demands) at time t; $\ln GDP_t$ – the logarithm of seasonal real Chinese GDP at time t; $\ln PO_t$ – the logarithm of seasonal prices of jet fuel at time t; $\ln RP_t$ – the logarithm of seasonal relative prices (CPI of Thailand/CPI of China) at time t; $\ln ER_t$ – the logarithm of seasonal relative exchange rates (Yuan/Bath) at time t; $\ln TEM_t$ – the logarithm of seasonal temperature in Thailand at time t; ε_t – independently distributed random error term at time t (with $\bar{u} = 0$, $var = \sigma^2$); α, β, δ, ϕ, γ, ρ – parameters to be estimated; $\beta > 0$, $\delta < 0$, $\phi < 0$, $\gamma > 0$, $\rho < 0$.

2. Bayesian Inference Approach. The paper of Thomas Bayes (Rev.) "An Essay Towards Solving a Problem in the Doctrine of Chances" was the first to explore the theorem which currently praises his name. Bayes represented how "inverse probability" could be employed to estimate the probability of previous events from the occurrence of consequent situations. By the middle of XX century, Bayesian statistics had been revived by, among others (Bolstad, 2007).

Specifying a Bayesian prior, we give an identical solution for w as least-squares, maximum likelihood estimation will also display in overfitting. To solve the complex model, we early specify a "prior distribution" which explains our "belief level" over values that w might take before the weight penalty $E_w(w)$ is regularized. This is shown in equation:

$$p(w \mid \alpha) = \prod_{m=1}^{M} (\alpha/2\pi)^{\frac{1}{2}} \exp\left[-\frac{\alpha}{2} w_m^2\right]. \tag{3}$$

This is a zero-mean Gaussian prior expressed a preference for smoother models by declaring smaller weights to be more likely. The shared inverse variance hyperparameter α paralleled to λ moderates the intensity of belief, though the prior is independent for each weight (Tipping, 2006).

After setting the prior, we give error measure and compute a single point estimate of W_{LS} for the weight. The likelihood and the prior are specified. Thus, we calculate the "posterior distribution" over w via Bayes' rule,

$$p(w \mid t, \alpha, \sigma^2) = \frac{likelihood \times prior}{nornalised \;\; factor} = \frac{p(t \mid w, \sigma^2) p(w \mid \alpha)}{p(t \mid \alpha, \sigma^2)}. \tag{4}$$

Considering the consequence of combining the Gaussian prior and linear model within a Gaussian likelihood, the posterior is defined as $p(w \mid t, \alpha, \sigma^2) = N(\mu, \Sigma)$ with

$$\mu = (\Phi^T \Phi + \sigma^2 \alpha I)^{-1} \Phi^T t; \tag{5}$$

$$\Sigma = \sigma^2 (\Phi^T \Phi + \sigma^2 \alpha I)^{-1}. \tag{6}$$

We infer a distribution over all possible values and bring our prior "belief" up to date for the estimated parameters provided by data t, with more posterior probability appointed to values that are both possible underneath the prior data (Tipping, 2006). For posterior estimation, the numerical methods of Monte Carlo integration rely on simulating random samples from distributions, which approximately calculate the posterior density function $p(w \mid t, \alpha, \sigma^2)$ for the random vector w of unknown parameters from Bayes' theorem. The method is known as Markov Chain Monte Carlo Method (MCMC). Basically, one simulates a Markov chain in the parameter space M for the unknown parameters w, and do not require a special distribution. Thus, the limitation of distributions of the chain is the posterior density function. The random samples of w are drawn sequentially, and the distribution of one sample relies on the previous selection so that the Makrov chain is assembled (Koch, 2007).

As shown in R.E. Kass and A.E. Raftery (1995) and C.W.S. Chen et al. (2013), Bayesian statistics considers hypotheses regarding multiple parameters by adapting Bayes factor comparisons. The Bayes factors are flexible allowing multiple hypotheses to be a synchronized comparison, and nested models are not used to make comparisons (Jeffrey, 1961). Let M_0 be the model devised in the term of null hypothesis, and let M_1 be the model of the alternative hypothesis. Two different models are set according to the parameters, θ_0 and θ_1. The posterior odds ratio of M_0 and M_1 is presented in equation:

$$\frac{pr(M_0\,|\,y)}{pr(M_1\,|\,y)}=\frac{pr(y\,|\,M_0)}{pr(y\,|\,M_1)}\times\frac{\pi(M_0)}{\pi(M_1)},\tag{7}$$

where $pr(y|M_i)$ is the marginal likelihood for model M_i; $\pi(M_i)$ is the prior probability for M_i. Hence, the marginal likelihood $pr(y|M_i)$ can be described as

$$pr(y\,|\,M_i)=\int pr(y\,|\,\theta_i,M_i)pr(\theta_i\,|\,M_i)d\theta_i,\ I=0,\ 1.\tag{8}$$

The Bayes factor is the summarization of evidence provided by a statistical model, as proposed by (Jeffrey, 1961). Interpretation in half-units on Jeffrey's scales is simply described as:

Bayesian factor	Evidence against M_0
BF < 1/10	Strong evidence for M_1
1/10 < BF < 1/3	Moderate evidence for M_1
1/3 < BF < 1	Weak evidence for M_1
1 < BF < 3	Weak evidence for M_0
3 < BF < 10	Moderate evidence for M_0
10 < BF	Strong evidence for M_0

3. ADF unit root test based on Bayesian inference. ADF test analyzes the null hypothesis that a time-series data y_t is I(1) against the alternative I(0), assuming that the dynamics in data have ARMA structure (Said and Dickey, 1984). The ADF test is based on the regression test, as presented in equation:

$$y_t=c+\alpha' D_t+(\phi-1)y_{t-1}+\sum_{j=1}^{p}\gamma_j\Delta y_{t-j}+\varepsilon_t,\tag{9}$$

where $\alpha`D_t$ is the vector of deterministic terms which are constant and trends. ADF test regression can be also written in an alternative formation, described in equation:

$$\Delta y_t=c+\alpha' D_t+\varphi y_{t-1}+\sum_{j=1}^{p}\gamma_j\Delta y_{t-j}+\varepsilon_t,\tag{10}$$

where $\varphi=\phi-1$. Considering the null hypothesis; Δy_t is I(0) which indicates that a stationary model is $\varphi=0$. In this research, the main Bayesian had been used to test unit roots. Considering the equation (10), ε_t is i.i.d. $N(0,\sigma^2)$ for t = 1, ..., T. Being $\varphi=(\phi,a^*)$ the parameter vector, $\phi=\sum_{i=1}^{\phi}\phi_i$ and $a^*=(c,\alpha,\gamma)$, and assuming σ^2 is fixed. The prior density of φ is factorized as in (Diniz et al., 2011)

$$p(\varphi)=p(\phi)p(a^*\,|\,\phi).$$

Marginal likelihood for ϕ is

$$l(\phi\,|\,D)\alpha\int l(\varphi\,|\,D)\phi(a^*\,|\,\phi)da^*,\tag{11}$$

where D is the observation vector. A prior for ϕ is the main ingredient used by standard Bayesian procedures to test the unit root existence. Basically, all of them employ Bayes factors and posterior probabilities, as described in equation:

$$B_{01} = \frac{l(\phi = 1 \mid D)}{\int_0^1 l(\phi \mid D)\phi(\phi)d\phi}. \tag{12}$$

4. ARDL approach to cointegration based on Bayesian inference. The autoregressive distributed lag (ARDL) model was developed by M.H. Pesaran et al. (2001). Outcomes obtained from the ARDL approach are unbiased and efficient (Narayan, 2004; Chaitip and Chaiboonsri, 2009). This method can be adapted for estimating long-run and short-run components in time series variables concurrently, removing the problem associated with omitted variables and autocorrelations, and analyzing irrespectively mixed-order variables that are I(0) and I(1). This is also supported by A. Mervar and J.E. Payne (2007) and S.B. Paudyal (2014). Furthermore, a dynamic error correction model (ECM) can be derived from the ARDL model, and it results as a simple linear transformation (Banerjee et al., 1993; Chaitip and Chaiboonsri, 2009). Demonstratively, the ARDL model is defined by equation:

$$Y_t = \alpha + \beta(X_t) + \delta(Z_t) + u, \tag{13}$$

where Y_t – dependent variables time series data at time t; X_t – first independent variables time series data at time t; Z_t – second independent variables time series data at time t; u_t – a vector of stochastic error terms; α, β, δ – parameters.

From the above equation, the ARDL model has two parts. First, the dynamic short-run model is represented by the parameters such as α_i, β_i and δ_i. Second, the dynamic long-run model is represented by the parameters such as λ_1, λ_2 and λ_3. This full model is shown in equation:

$$\Delta Y_t = \alpha + \sum_{t=1}^{p} \beta_i \Delta Y_{t-1} + \sum_{t=1}^{p} \delta_i \Delta X_{t-1} + \sum_{t=1}^{p} \gamma_i \Delta Z_{t-1} + \lambda_t Y_{i-1} + \lambda_2 X_{t-1} + \lambda Z_{t-1} + u_t. \tag{14}$$

Modifying equation (14), the natural logarithm is taken into the equation. This can be displayed as in equation:

$$\begin{aligned} \Delta \ln Y_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta \ln(Y_{t-i}) + \sum_{i=1}^{p} \delta_i \Delta \ln(X_{t-i}) + \sum_{i=1}^{p} \gamma_i \Delta \ln(Z_{t-i}) + \\ + \lambda_1 \ln(Y_{i-1}) + \lambda_2 \ln(X_{t-1}) + \lambda_3 \ln(Z_{t-1}) + u_t. \end{aligned} \tag{15}$$

In this paper, real variables are set into the ARDL cointegration model for explaining Chinese tourism demand in Thailand. This can be shown as in equation:

$$\begin{aligned} \Delta \ln D1_{ij,t} = \alpha + \sum_{p=1}^{p} \beta_{pD1} \Delta \ln(D1)_{ij,t-p} + \sum_{p=1}^{p} \delta_{pD1} \Delta \ln(GDP)_{ij,t-p} + \sum_{p=1}^{p} \gamma_{pD1} \Delta \ln(PO)_{ij,t-p} + \\ + \sum_{p=1}^{p} \beta_{pD1} \Delta \ln(RP)_{ij,t-p} + \sum_{p=1}^{p} \delta_{pD1} \Delta \ln(RER)_{ij,t-p} + \sum_{p=1}^{p} \gamma_{pD1} \Delta \ln(TEM)_{ij,t-p} + \\ \lambda_{1D1} \ln(D1)_{ij,t-1} + \lambda_{2D1} \ln(GDP)_{ij,t-1} + \lambda_{3D1} \ln(RP)_{ij,t-1} + \lambda_{4D1} \ln(RER)_{ij,t-1} + \\ + \lambda_{4D1} \ln(TEM)_{ij,t-1} + u_t, \end{aligned} \tag{16}$$

while the null hypothesis is: $H_0 : \lambda_{1D1} = \lambda_{2D1} = \lambda_{3D1} = \lambda_{4D1} = \lambda_{5D1} = 0.$

Against the alternative hypothesis: $H_1 : \lambda_{1D1} \neq \lambda_{2D1} \neq \lambda_{3D1} \neq \lambda_{4D1} \neq \lambda_{5D1} \neq 0.$

Applying Bayesian inference, Bayes factors and posterior probability ratios are explained as:

- for the short-run model:

$$B_{01} = \frac{l[(\beta = 1),| D]}{\int_0^1 l[(\beta) | D)](\beta)[(\beta)d(\beta)]}; \tag{17}$$

- for the long-run model:

$$B_{02} = \frac{l[(\beta = 1),(\delta = 1) | D]}{\int_0^1 l[(\beta,\delta) | D)](\beta,\delta)[(\beta,\delta)d(\beta,\delta)]}. \tag{18}$$

The research results.

1. The results of the ADF unit root test based on Bayesian approach. Considering the empirical study of F.W. Ahking (2004), this paper concludes that the objective Bayesian test was biased in favor of trend-stationary models, and it is not better than the classical ADF approach in unit root tests. However, Y. Li and J. Yu (2011) and M. Diniz et al. (2011) who studied Bayesian alternatives based on the posterior density function for the unit root hypothesis testing stated that the posterior odds ratio is the product of Bayesian estimation and it can be easily computed by MCMC methods. This simulation method overcame the problems of the diverging "size" in the marginal likelihood estimation and improved the "power" of the unit root testing, while a mixed prior identification with random weights was employed. Ultimately, the authors applied the MCMC method based on Bayesian statistics to analyze the ADF unit root tests of macroeconomic variables, including Chinese tourist arrivals in Thailand ($Tour_{China,t}$) (tourism.go.th), China's GDP ($GDP_{China,t}$) (aric.adb.org), prices for kerosene-type jet fuel (PO_t) (www.forecasts.org), relative prices between Thailand and China (RP_t) (Bureau of Trade and Economic Indices, Ministry of Commerce, Thailand and the Federal Reserve Bank of St. Louis), relative exchange rates between Yuan and Baht (RER_t) (www2.bot.or.th), and temperatures in Thailand (TEM_t) (climateportal@worldbank.org). All needed information is displayed in Table 1.

Table 1 presents the unit root testing of stationary conditions for macrotourism variables. 4 quarterly time-series facts such as PO_t, RP_t, RER_t, and TEM_t are stationary at the zero level (I(0)). On the other hand, other two factors such as $Tour_{China,t}$, and $GDP_{China,t}$ are not stationary at the zero level (I(d)) since these two time-series data fluctuated enormously during 2002 to 2016 (Figures 3 and 4). However, the advantage of the ARDL approach is that it can overcome the problem of mixed order variables. As a result, all these variables are employed to investigate the interdependent category between the numbers of Chinese tourists in Thailand and Thailand tourism.

2. The results of ARDL approach to cointegration based on Bayesian computing. Empirical results of Chinese tourism demand model for Thailand are presented in Table 2.

In Table 2, hypothesis testing for the ARDL model and cointegration was solved by applying MCMC and Bayesian factors. The empirical results found that the interdependence between Chinese tourism demand and Thailand tourism is of short-run nature. Thus, we are accepting the null hypothesis (H_0) that Chinese tourism demands in Thailand follows the unsustainable model. In other words, the matrix of Bayesian factors based on Jeffrey's scales indicated that evidence supported the null hypothesis was intensively weighted, while the posterior odds ratios are 9.09e+13 and 1.1e-14 respectively.

Table 1. **ADF unit root test based on Bayesian inference in quarterly macrotourism variables between 2002 (q1) and 2016 (q2),**
authors' computing

Variables	Bayesian factor model	Hypothesis	Number of MCMC iterations	Posterior odds ratio (POR)	Interpretation of the Bayesian factor	Result
$Tour_{China,t}$	Model 1	H_0 (M_i): Non-stationary data	3,500	0.891	Weak evidence for *Mj*	*I(1)*
	Model 2	H_1 (M_j): Stationary data	1,600	1.120		
$GDP_{China,t}$	Model 1	H_0 (M_i): Non-stationary data	6,000	4.280	Moderate evidence for *Mi*	*I(1)*
	Model 2	H_1 (M_j): Stationary data	20,500	0.234		
PO_t	Model 1	H_0 (M_i): Non-stationary data	80,000	0.023	Strong evidence for *Mj*	*I(0)*
	Model 2	H_1 (M_j): Stationary data	21,000	43.2		
RP_t	Model 1	H_0 (M_i): Non-stationary data	50,000	0.000	Strong evidence for *Mj*	*I(0)*
	Model 2	H_1 (M_j): Stationary data	6,000	1.460		
RER_t	Model 1	H_0 (M_i): Non-stationary data	55,000	0.003	Strong evidence for *Mj*	*I(0)*
	Model 2	H_1 (M_j): Stationary data	16,000	366		
TEM_t	Model 1	H_0 (M_i): Non-stationary data	48,000	0.011	Strong evidence for *Mj*	*I(0)*
	Model 2	H_1 (M_j): Stationary data	37,000	93.9		

Next, the parameters of sustainable and unsustainable model are displayed in Table 3. As we see, Chinese tourism demand in Thailand has a short-run linkage, the estimated parameters of unsustainable model are specifically considered. In this paper, 6 variables were considered to investigate the factors affecting Chinese tourism demand in Thailand.

The first variable is seasonal economic growth of China (ΔlnGDP (lag_{t-1})). Interestingly, this factor has a negative effect on Chinese tourism in Thailand (see the negative trend of the parameter (δ), Table 3). This implies that positive expansion of GDP rates in China decreases the numbers of Chinese arrivals in Thailand. In other words, Thailand tourism serves as "subordinate goods", that is the place to which Chinese tourists prefer to travel second chance, as compared with Japan and South

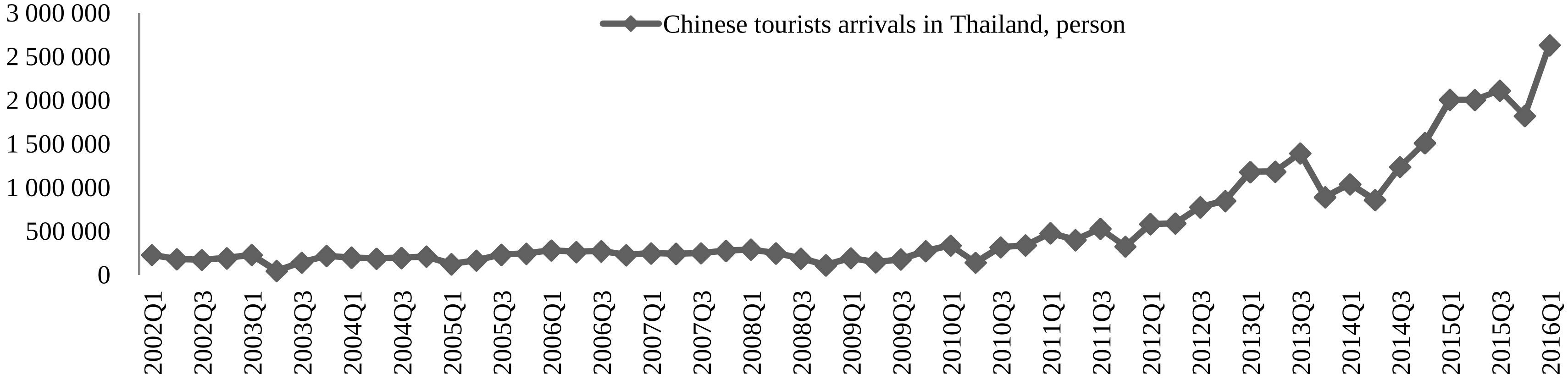

Figure 3. **Chinese tourist arrivals in Thailand, 2002 (q1) to 2016 (q1),** *authors'*

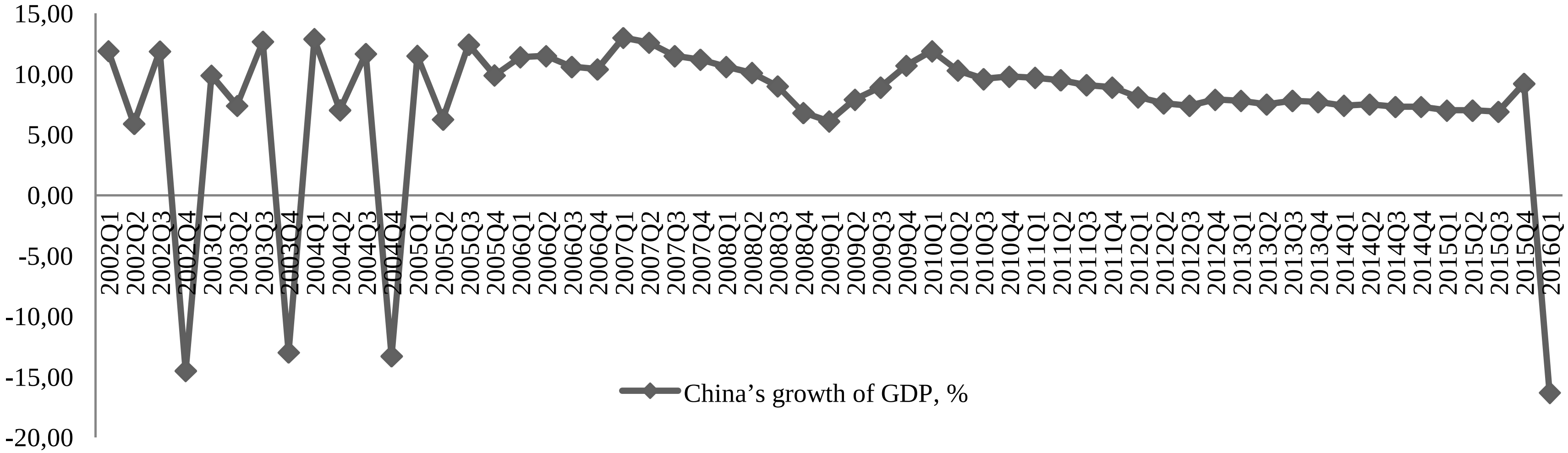

Figure 4. **China's GDP growth rates, 2002 (q1) to 2016 (q1),** *authors'*

Korea (China National Tourism Administration, 2016). Thus, it is reasonable to hint that Chinese tourism demand is probably not the best choice for Thailand's economy.

Table 2. **ARDL approach to cointegration based on Bayesian computing of Chinese tourism demands in Thailand between 2002 (q1) and 2016 (q1),** *authors' computing*

1. Hypothesis testing	Parameter	Model 1	Model 2
Hypothesis		H_0 : The model has only short-run relationship (unsustainable model)	H_1 : The model has short-run relationship and long-run connection (sustainable model)
Number of MCMC regression iterations for estimating the stable distribution function		2,250	11,000
2. Bayesian factors			
Posterior odds ratios (POR)	$\frac{M_i}{M_j}$	$M_i(H_0)/M_j(H_1)$ = 9.09e+13	$M_i(H_1)/M_j(H_0)$ = 1.1e-14
Interpretation of Bayesian factor		Strong evidence for M_i	Strong evidence for M_j
Result		The model has short-run relationship (Unsustainable model)	The model has only short-run relationship (Unsustainable model)

Table 3. **MCMC regression simulation,** *authors'*

Parameters in MCMC simulation	Parameter	Unsustainable tourism model	Sustainable tourism model
Constant	α	0.0678	-0.0909
Δ lnGDP (lag_{t-1})	δ	-0.0136	-0.0132
Δ lnPO (lag_{t-1})	γ	0.5962	0.6187
Δ lnRP (lag_{t-1})	ϕ	-3.0724	-0.6967
Δ lnRER (lag_{t-1})	φ	0.5046	0.1423
Δ lnTEM (lag_{t-1})	ρ	0.7927	0.3756
lnD1 (lag_{t-1})	λ_1		0.3038
lnGDP (lag_{t-1})	λ_1		0.0006
lnPO (lag_{t-1})	λ_2		-0.2571
lnRP (lag_{t-1})	λ_3		2.9435
lnRER (lag_{t-1})	λ_4		-3.4493
lnTEM (lag_{t-1})	λ_5		-0.2837
U_t (the error term)	ε	0.1422	0.1181
Log-marginal likelihood		-87.0013	-54.8605
Log-likelihood		-19.4686	-25.7193
Log-prior		-56.8484	-23.9520
Log-beta		7.9260	2.5972
Log-sigma		2.7582	2.5921

Considering seasonal prices for kerosene-type jet fuel index (ΔlnPO (lag$_{t-1}$)), it is interesting that the parameter (γ) is positive (see Table 3). This implies that the increment of the world jet fuel prices increases the numbers of Chinese arrivals in Thailand. In other words, Thailand tourism is sort of a "a second choice" for Chinese tourists when the cost of air transportation is raised.

The third variable is seasonal relative prices for goods and services between China and Thailand (ΔlnRP (lag$_{t-1}$)). The parameter (ϕ) shows a negative effect of Chinese tourism demand in Thailand (Table 3). This result indicates that the increasing prices for goods and services can drop the numbers of Chinese tourist arrivals in Thailand. On the other hand, the increment of relative exchange rates between Yuan and Baht (ΔlnRER (lag$_{t-1}$)) has the positive parameter (φ) (Table 3). This implies that weakening of Baht can increase the number of Chinese tourists in Thailand. However, these numbers are just a temporary rise in this rather unsustainable relationship. Lastly, the parameter (ρ) of temperatures in Thailand (ΔlnTEM (lag$_{t-1}$)) has positive impact on the numbers of Chinese tourist arrivals (Table 3). This means that hotter weather in Thailand can be a reasonable factor in attracting the increasing numbers of Chinese tourists in the short run.

Conclusion and recommendations. This study has successfully identified the interdependence types of Chinese demand and Thailand tourism. With 6 seasonal macroeconomic explanatory variables such as Chinese tourist arrivals to Thailand (classifying as a dependent variable), Chinese gross domestic products, prices of kerosene-type jet fuel, the relative prices for goods and services between China and Thailand, relative exchange rates between Chinese Yuan and Thai Baht, and Thailand temperature indices, we have simulated the MCMC regression in order to get some information on future trends of Chinese tourism demand in Thailand. In this paper, MCMC simulation package (Martin et al., 2016) was based on the alternative statistical method called Bayesian inference used for analyzing two hypotheses, including also testing the ADF unit root test and ARDL approach to cointegration.

In the section on the ADF unit root test (Dickey and Fuller, 1979), the results showed that mixed order variables between I(0) and I(1) were obtained from the Bayesian factor estimation. However, both non-stationary and stationary variables were employed in the ARDL cointegration hypothesis test, which can concurrently estimate long-run and short-run components in time series variables and irrespectively analyze mixed-order variables that are I(0) and I(1). Interestingly, the empirical results of the ARDL model based on the Bayesian factor comparison (Kass and Raftery, 1995) found that Chinese tourism demands in Thailand had only a short-run linkage (the unsustainable tourism model).

As we see, the ARDL hypothesis testing result shows that the number of Chinese tourist arrivals in Thailand is not sustainable, and this empirically confirms that Chinese tourists are not the best solution for Thailand's tourism in the long run, even though they indeed from an enormous tourist group in Thailand. This is supported by A. Freytag and C. Vietze (2010) who stated that unsustainable mass tourism is not growth enhancing in the long run. The parameter outcomes estimated from Bayesian calculations indicate that tourism in Thailand can be tilled as "inferior tourism goods", that is this is the place that Chinese tourists choose only once. This is confirmed by the parameter of Chinese economic expansions. The increment of this parameter negatively impacts Chinese tourist arrivals in Thailand. The solution for this issue is suggested by the World Tourism Cities Federation (2014). Because Chinese millennials group is slightly less price sensitivite and is the biggest buyer of luxury goods in Asia Pacific (Martin, 2016), the suggestion insistently mentions improving mid- and high-range hotels, luxury shopping, touring security situation (Wong and Lau, 2001). Moreover, Chinese brands and staff who can speak Chinese are required.

Another interesting result is the parameter of kerosene-type jet fuel price. This parameter displays that increasing air fuel cost has a positive effect on the number of Chinese tourists in Thailand. This implies that Thailand tourism is not the primary choice for Chinese tourists' travel (again, more of "a second choice"). This can be solved by improving land infrastructure for mass transportation between significant places in Thailand, especially railway system (Albalate, 2009). This improvement can help tourists have more choice in reducing their transportation cost.

Other crucial parameters are the relative goods and services price between China and Thailand and the relative exchange rates between Yuan and Baht. The former parameter has a negative impact on the number of Chinese tourists in Thailand. This can suggest that the fair price of goods and services for foreign tourists and domestic travelers should be continuously controlled by government authorities. On the other hand, the later parameter has a positive effect on Chinese tourism demands in Thailand. This also gives a hint that the currency rates of Yuan/Baht should be carefully adjusted. Also, both upper and lower bounds in exchange rates should be statistically investigated for launching an appropriate tourism policy.

Ultimately, this paper recommends two solutions to conclude on the question of what should we do when we already proved that Chinese tourism demand in Thailand is not sustainable enough. The first suggestion is that all tourism areas in Thailand should be creatively renovated, attracting private-sector investments which today are reluctant to enter (United Nations, 2013). The second option is that Thailand tourism should be promoted by authorities at the new market, for instance, ASEAN countries or in Central Asia.

Also, this idea to explore the sustainable tourism demand for Thailand as applied to other countries will be a focus of further studies of the authors.

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