



Forecasting International Tourism Demand in Thailand

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Abstract : The aim of this study is to model and forecast the tourist arrivals from East Asia, namely China, Korea, and Japan, to Thailand for the period from 1991 to 2016. In order to achieve this, two forecast models are applied: the $AR(m)$ -GARCH(p,q), and the Kink AR-GARCH model (Kink $AR(m)$ -GARCH(p,q)) that combine the classical GARCH model of Bollerslev (1986) with the Kink model of Chan and Tsay (1998). The accuracy of the forecast models is evaluated in terms of the RMSE, the MAE and the MSPE. The empirical results show that the Kink $AR(1)$ -GARCH(1,1) produces forecast which perform (statistically) significantly better than $AR(1)$ -GARCH(1,1) in forecasting tourist arrivals from China and Korea to Thailand. However, $AR(1)$ -GARCH(1,1) is preferred for forecasting international tourism demand for Thailand from Japan.

Keywords : forecasting; international tourism demand; Thailand, Kink AR-GARCH.

2010 Mathematics Subject Classification : 62M10; 62P20; 91B42.

1 Introduction

Tourism in Thailand plays an important role in the Thai economic structure. Thailand has rich sources for travelling: mysterious temples, beautiful islands, nice beaches, delicious foods, marvelous cultural. All these elements profoundly attract visitors from all over the world especially from Europe, USA, South Asia, the Oceania, the Middle East, and Africa. In the last 20 years, tourism in Thailand has

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developed rapidly. According to the statistics data was collected by Immigration Bureau, Royal Thai Police [1], the number of international tourist arrivals to Thailand between 1997 and 2015 continuously increases as shown in Figure 1. Since 1997, by region, East Asia, led by China, provides the highest number of visitors. The number of international tourist arrivals from East Asia was about 14.6 million (58.9 percent of all foreign travelers) in 2014 and increased to 19.8 million (66.5 percent of all foreign travelers) in 2015.

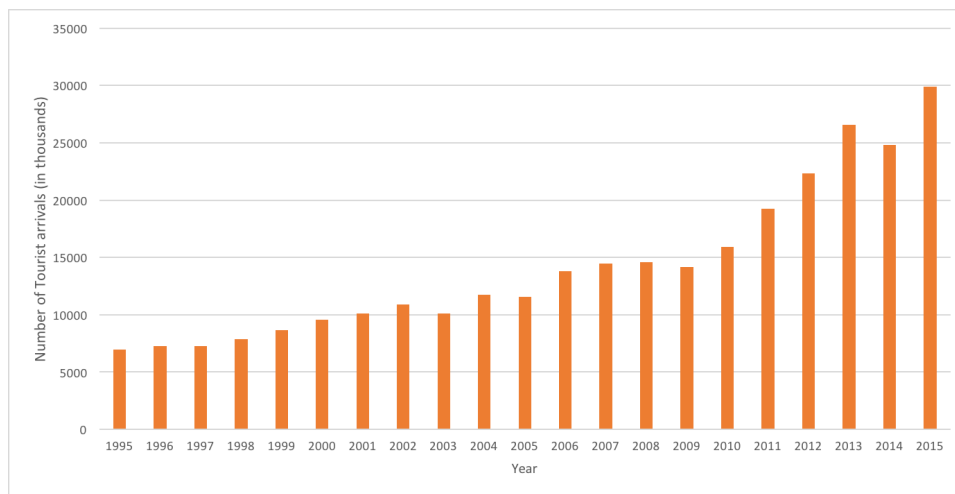


Figure 1: International tourist arrivals to Thailand 1997-2015 [1]

East Asia markets that contained good expansion rates were China, Malaysia, Japan, Korea and Laos, as shown in Figure 2. To a great extent the increase in visitors in 2015 was due to the significant increase in Chinese tourists. Roughly 7.9 million Chinese tourists arrived (26.6 percent of all foreign travelers), an increase of more than 3 million when compared with 2014. In 2015, there are 7.9 million Chinese, 3.4 million Malaysian, 1.38 million Japanese, 1.37 million Korean, and 1.2 million Laotian travelling to Thailand.

Tourism sector of Thailand generates income and creates job for other related industries, especially for tourism services, transport, and the sale of food, drink and souvenirs to the tourists from all over the world. The total contribution of tourism sector to employment, including job indirectly supported by industry, was 14.1 percent of total employment (5,383,000 jobs)[2]. Thailand's tourism revenue was announced as 706,552.3 million baht (8.6 percent of Thailand's GDP) in 2015. While 53.6 percent of this income or 378,637.5 million baht was obtained from visitors from East Asia especially those from China (188,776.9 million baht), Malaysia (42,569.6 million baht), Japan (26,091.1 million baht), Korea (26,570.5 million baht) and Laos (11,486.0 million baht)[3].

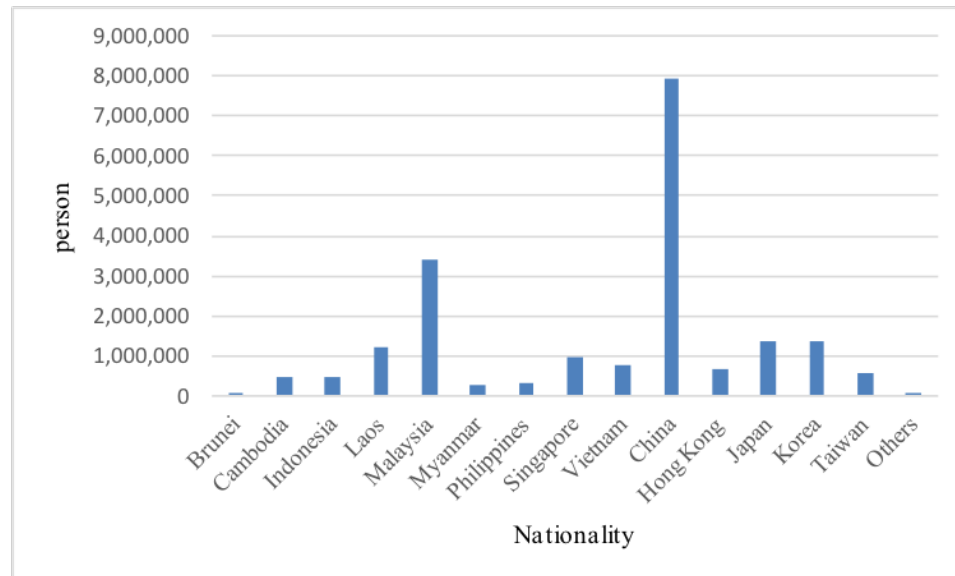


Figure 2: International tourist arrivals from East Asia to Thailand 2015 [1]

Since international tourism play important role to encourage Thai economy, tourism demand forecasts are of great economic value both for the public and private sector. In the last few decades, numerous researchers have studied international tourism demand and a wide range of the available forecasting techniques have been tested. This paper proposes the Kink Autoregressive GARCH model (Kink $AR(m)$ -GARCH(p,q)) which combines the classical GARCH model of Bollerslev [4] with the Kink model of Chan and Tsay [5], and we compare its result with those from AR-GARCH model. The objectives of this paper are to analyze the nonlinear behavior of international tourist arrivals espeacilly from East Asia to Thailand and to assess the forecasting performance of the model particularly when applied to tourist arrivals data.

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 for the Kink $AR(m)$ -GARCH(p,q) model are discussed in Section 5. Finally, Section 6 discusses the findings and draws conclusions.

2 Literature Review

The existing literature on forecasting tourism demand is wide ranging both in terms of the different techniques employed and in terms of the different countries

covered. The selection of the most accurate forecasting model for a particular destination is often based on the out-of-sample forecasting performance. The mean absolute percentage error (MAPE) or root mean squared percentage error (RMSPE) are computed and compared.

Song and Li [6] reviewed the published studies on tourism demand modeling and forecasting since 2000. They found that there is no single forecasting method had been found to be the best forecasting model across different situations.

There are also several forecasting models for the international tourist arrivals to Thailand including those by Balogh et al.[7], Chokethaworn et al. [8], Sookmark [9], Chaitip et al. [10], and Min et al. [11]. Authors differ on the best method for tourism forecasting. For example, whereas, Sookmark [9] applied Seasonal Autoregressive Integrated Moving Average (SARIMA) and the Ordinary Least Square (OLS) techniques, Chaitip et al. [10] provided non-linear forecasting model which is Markov Switching Vector Autoregressive model (MS-VAR model) and Min et al. [11] applied the belief function approach to statistical forecasting of tourist arrivals to Thailand.

3 Methodology

3.1 Kink AR-GARCH Model

We consider the univariate specification of the growth of tourist arrivals to Thailand, which can be applied in forecasting purposes. In particular, we combine the classical GARCH model of Bollerslev[4] with the Kink model of Hansen [12] and propose the Kink Autoregressive GARCH model (Kink AR(m)-GARCH(p, q)). The model function is continuous but the slope has a discontinuity at a threshold point, hence a “Kink”[12]. The function splits the lag data into two (or more) groups based on indicator function. In the following, we model the mean equation as a Kink-AR process, and the innovations are generated from a Kink-GARCH process.

Kink-AR Mean Equation : The Kink-AR(m) process of autoregressive order m can be described as

$$y_t = \alpha + \sum_{i=1}^m \beta_{1i} y_{t-i} I(y_{t-d} \leq r) + \sum_{i=1}^m \beta_{2i} y_{t-i} I(y_{t-d} > r) + \epsilon_t, \quad (3.1)$$

where y_t is observed variable with mean α , lower regime autoregressive coefficients β_{1i} , and upper regime autoregressive coefficients β_{2i} . I is indicator variable with y_{t-d} is an observed variable determining the switching point and r is the threshold parameter or Kink point values defining the regime for both mean and variance equations through indicator function $I(y_{t-d} \leq r)$ for lower regime and $I(y_{t-d} > r)$ for upper regime. The ϵ_t term in the Kink-AR mean equation 3.1 are the innovations of the time series process. Engle [13] defined them as an autoregressive

conditional heteroscedastic process where all ϵ_t are of the form

$$\epsilon_t = h_t u_t, \tag{3.2}$$

where u_t is an *iid* process with zero mean and unit variance. Although ϵ_t is serially uncorrelated by definition its conditional variance equals h_t^2 and, therefore, may change over time.

Kink-GARCH Variance Equation: The variance equation of the Kink-GARCH(p,q) model can be expressed as

$$h_t^2 = \delta + \sum_{i=1}^p \zeta_{1i} \epsilon_{t-i}^2 I(y_{t-d} \leq r) + \sum_{i=1}^p \zeta_{2i} \epsilon_{t-i}^2 I(y_{t-d} > r) + \sum_{j=1}^q \theta_{1j} h_{t-j}^2 I(y_{t-d} \leq r) + \sum_{j=1}^q \theta_{2j} h_{t-j}^2 I(y_{t-d} > r), \tag{3.3}$$

Consider the variance equation of the GARCH(p,q) model, the conditional variance h_t^2 can be obtained from the variance equation 3.3. The estimated parameters δ , ζ_{1i} , ζ_{2i} , θ_{1j} , and θ_{2j} are restricted to be larger than zero in order to make a positive conditional variance.

3.2 MCMC Algorithm for the Parameters of Kink AR-GARCH Model

We wish to conduct Bayesian inference on our proposed model. In this section we construct Metropolis-Hastings (MH) algorithm, which was introduced by Metropolis et al. [14] and generalized by Hastings [15], for the parameters of the doubly truncated Kink AR-GARCH model. Let $\nu = (\alpha, \delta, \beta_{1i}, \beta_{2i}, \zeta_{1i}, \zeta_{2i}, \theta_{1i}, \theta_{2i}, r)$ be the Kink AR-GARCH parameters to be computed. First, we construct posterior density $p(\nu|y)$ via the Bayes' rule.

The posterior density of our model is

$$p(\nu|y) = \frac{L(y|\nu) p(\nu)}{\int L(y|\nu) p(\nu) d\nu}, \tag{3.4}$$

where $y = (y_1, \dots, y_T)$, $L(y|\nu)$ is the likelihood function. $p(\nu)$ is the prior distribution of each parameter in the model, reflecting the prior beliefs before having observed the data. In order to compute the parameters of the model, we need to specify the likelihood function and specify the prior of the parameters.

The prior of the parameters is $p(\nu)$. Under the assumption of independence,

the prior density is chosen as

$$\begin{aligned}
 p(\nu) &= p(\alpha) p(\delta) p(\beta_{1i}) p(\beta_{2i}) p(\zeta_{1i}) p(\zeta_{2i}) p(\theta_{1i}) p(\theta_{2i}) p(r) \\
 &= N(\mu_\alpha, \Sigma_\alpha) \times N(\mu_\delta, \Sigma_\delta) \times N(\mu_{\beta_{1i}}, \Sigma_{\beta_{1i}}) \times N(\mu_{\beta_{2i}}, \Sigma_{\beta_{2i}}) \\
 &\times N(\mu_{\zeta_{1i}}, \Sigma_{\zeta_{1i}}) \times N(\mu_{\zeta_{2i}}, \Sigma_{\zeta_{2i}}) \times N(\mu_{\theta_{1i}}, \Sigma_{\theta_{1i}}) \times N(\mu_{\theta_{2i}}, \Sigma_{\theta_{2i}}) \\
 &\times Unif(0, 1),
 \end{aligned} \tag{3.5}$$

where $N(\cdot)$ is the normal density function, and $Unif(0, 1)$ is the uniform distribution.

The log likelihood function of Kink AR-GARCH or $L(y|\nu)$ is given by

$$L(y|\nu) = \ln \prod_t D_v(y_t, E(y_t|\Omega_{t-1}), u_t), \tag{3.6}$$

or the log-likelihood function of the Normal distribution is given by

$$L(\nu|y) = \ln \prod_t \frac{1}{\sqrt{2\pi h_t^2}} \exp\left\{-\frac{1}{2h_t^2} u_t^2\right\}, \tag{3.7}$$

where D_v is the conditional distribution function. The second argument of D_v denotes the mean, and the third argument the standard deviation. v is the distribution parameters in the case of a non-normal distribution function. Different types of conditional distribution functions D_v are discussed in literature. There are normal distribution, the standardized Student- t distribution and the generalized error distribution and their skewed versions [16]. Hence, in this study, we proposed six different error distributions consisting of normal, student- t , generalized error distribution (GED), skewed GED, skewed normal, and skewed student- t distributions.

Our MH algorithm consists of separate blocks for AR coefficients $\omega = (\alpha, \beta_{1i}, \beta_{2i})$, GARCH coefficients $\Theta = (\delta, \zeta_{1i}, \zeta_{2i}, \theta_{1i}, \theta_{2i})$, and threshold parameter r . We assume that the prior distribution on ω is normal distribution:

$$p(\hat{\omega}) \propto N(\hat{\omega}|y_t, \Theta, r, \Sigma_{\hat{\omega}}) \tag{3.8}$$

where $\Sigma_{\hat{\omega}}$ is the prior variance.

The prior distribution on Θ is also normal distribution:

$$p(\hat{\Theta}) \propto N(\hat{\Theta}|y_t, \omega, r, \Sigma_{\hat{\Theta}}) \tag{3.9}$$

where $\Sigma_{\hat{\Theta}}$ is the prior variance.

Lastly, the prior distribution on r is a uniform distribution:

$$r \sim Unif(0, 1) \tag{3.10}$$

Finally, a MH algorithm is employed using the following steps:

1. Establish a starting value from the Maximum Likelihood Estimation (MLE) for the first draw of sample and let them be denoted by ω_0 , Θ_0 , and r_0 and $i = 1$.
2. Then we generate a new value ω_i , Θ_i , and r_i from a certain probability distribution $g(\omega_i|\omega_{i-1})$, $g(\Theta_i|\Theta_{i-1})$ and $g(r_i|r_{i-1})$.
3. For AR coefficients, we accept the candidate ω_i with probability of $P_{MH}(\omega_{i-1}, \omega_i)$ where

$$P_{MH}(\omega_{i-1}, \omega_i) = \min \left[1, \frac{\pi(\omega_i)}{\pi(\omega_{i-1})} \frac{g(\omega_i|\omega_{i-1})}{g(\omega_{i-1}|\omega_i)} \right]. \quad (3.11)$$

When ω_i is rejected we keep ω_{i-1} i.e $\omega_i = \omega_{i-1}$.

For GARCH coefficients, we accept the candidate Θ_i with probability of $P_{MH}(\Theta_{i-1}, \Theta_i)$ where

$$P_{MH}(\Theta_{i-1}, \Theta_i) = \min \left[1, \frac{\pi(\Theta_i)}{\pi(\Theta_{i-1})} \frac{g(\Theta_i|\Theta_{i-1})}{g(\Theta_{i-1}|\Theta_i)} \right]. \quad (3.12)$$

When Θ_i is rejected we keep Θ_{i-1} i.e $\Theta_i = \Theta_{i-1}$.

For r parameters, we accept the candidate r_i with probability of $P_{MH}(r_{i-1}, r_i)$ where

$$P_{MH}(r_{i-1}, r_i) = \min \left[1, \frac{\pi(r_i)}{\pi(r_{i-1})} \frac{g(r_i|r_{i-1})}{g(r_{i-1}|r_i)} \right]. \quad (3.13)$$

When r_i is rejected we keep r_{i-1} i.e $r_i = r_{i-1}$.

- 4 Go back to 2) with an increment of $i = i + 1$.

We make 10,000 draws of the parameters in each of the three blocks, and we burn the first 2,000 draws. Out of the remaining 8,000 draws, the estimated Bayesian parameters are obtained by mean of each parameter.

3.3 Forecasting

In this study, the recursive forecast is conducted to generate the k -step forecast series: an initial sample using data from $t = 1, \dots, T$ is used to estimate the Kink AR-GARCH model and forecast the in-sample forecast, and k -step ahead out-of-sample forecasts are produced from starting at time T . To forecast the out-sample data, we estimate recursively to forecast for one step ahead and so on. The sample is increased by one, the model is re-estimated, and k -step ahead forecasts are produced starting at $T + 1$, for example

$$\begin{aligned}
[1, \dots, T] &\rightarrow T + k \\
[1, \dots, T + k] &\rightarrow T + k + 1 \\
&\vdots \\
[1, \dots, T + K] &\rightarrow T + K + 1.
\end{aligned}$$

For the in-sample forecasting performance, Mean Squared Error (MSE) and Mean Absolute Error (MAE) are conducted.

$$MSE = \frac{1}{n} \sum_{t=1}^T (y_t - \hat{y}_t)^2 \quad (3.14)$$

$$MAE = \frac{1}{n} \sum_{t=1}^T |y_t - \hat{y}_t| \quad (3.15)$$

The out-of-sample one-step-ahead prediction errors are obtained as follows: given a sample of size $T+K$, we first remove K observations at the end of the sample and that correspond to the forecast horizon considered. The model is then estimated on the remaining sample the dependent variable's value is forecast for period $T+1$ and denoted $\hat{y}_{T+1|T}$. The $T+1$ forecast error resulting from the comparison of $\hat{y}_{T+1|T}$ and y_{T+1} is computed. Next, the $T+1$ observed value of the dependent variable is added to our sample, and the model is re-estimated. The $T+2$ observation is then forecast and denoted $\hat{y}_{T+2|T+1}$. The $T+2$ forecast error is computed, and so on, until all K observations are covered. The MSPE is then defined as:

$$MSPE = \frac{1}{K} \sum_{k=1}^K [\hat{y}_{T+k|T+k-1} - y_{T+k}]^2 \quad (3.16)$$

4 Data

In the study of international tourism demand for visiting Thailand from three major countries, comprising China, Korea, and Japan, the number of tourist arrivals from these origins is used to forecast the demand for tourism in Thailand. The data are monthly time series for the period from January 1991 to February 2016. All data for this study were collected from CEIC [17]. Additionally, we transform these time-series variables into growth rate before estimation.

Table 1 gives the summary statistics for the growth rate of international tourism demand for Thailand from three major countries. We present statistics that are calculated using the observations in the samples of 3 countries including Skewness, Kurtosis, Jarque-Bera, and the probability corresponding to the Jarque-Bera normality test.

Table 1: Descriptive statistics.

	China	Korea	Japan
Mean	0.058	0.019	0.044
Median	0.039	0.012	0.052
Maximum	1.452	0.543	1.164
Minimum	-0.722	-0.434	-0.721
Std. Dev.	0.297	0.180	0.271
Skewness	0.834	0.232	0.192
Kurtosis	5.835	2.800	3.515
Jarque-Bera	135.243	3.198	5.166
Probability	0.000	0.202	0.076
ADF	-11.740	-14.348	-4.256
Probability	0.000	0.000	0.005

Source: Calculation.

As can be seen above, Table1 gives some standard summary statistics along with the Jarque-Bera (JB) test for normality. Under the null that the data are iid normal, JB is asymptotically distributed as chi-square with 2 degrees of freedom. The distribution of the growth rate of international tourism demand for Thailand from China and Japan is clearly normal.

In this study, we employ the Augmented Dickey-Fuller (ADF) [18] test statistic to analyze the order of integration of our variables. The null hypothesis tested is that the variable under investigation has a unit root against the alternative that it does not. Since the null hypothesis are rejected for all series, it implies that the tourism growth of China, Korea, and Japan are stationary which makes it reasonable to model with AR and GARCH.

5 Empirical Results

5.1 Identifying the Order of AR

First of all, we have to identify the order of AR. Bayesian information criterion (BIC) [19] is the standard commonly used for selecting statistical model. The autoregressive (AR) order of mean equation is determined by way of minimizing BIC. According to Table 2, for all countries, AR(1) is identified.

Table 2: Lag length criteria

	BIC				
	lag1	lag2	lag3	lag4	lag5
China	- 731.135	-730.628	-724.959	-729.121	-724.971
Korea	- 799.997	-790.008	-785.754	-796.619	-798.111
Japan	- 967.098	-966.125	-961.833	-957.077	-954.426

Source: Calculation.

Note:smallest BIC in **bold**

5.2 Selecting the Number of Regime

Before we estimate the model, the Bayesian information criterion (BIC) [19] is employed to select the number of regime. According to minimizing BIC, the result from Table 3 suggests the movement of the growth rate of tourist arrivals from China and Korea to Thailand can be approximated by a two-regime model. However, the movement of the growth rate of tourist arrivals from Japan to Thailand can be approximated by a one-regime model. Therefore, we employ Kink AR(1)-GARCH(1,1) with 2 regime for forecasting tourist arrivals from China and Korea to Thailand and AR(1)-GARCH(1,1) is used to forecast international tourism demand for Thailand from Japan.

Table 3: Number of Regime Selection

China	BIC
1 regime	135.305
2 regimes	133.857
3 regimes	385.494
Korea	BIC
1 regime	77.677
2 regimes	76.129
3 regimes	374.937
Japan	BIC
1 regime	-98.003
2 regimes	-86.619
3 regimes	375.214

Source: Calculation.

Note: preferred model of each countries in **bold**

Table 4 shows the model selection results and the smaller the deviance information criterion (DIC) [20] the better the fit. For China, the DIC selects the 2-regimes Kink AR(1)-GARCH(1,1) with generalized error distribution (GED) model as the preferred one.

Table 4: Model Selection

DIC	China	Korea	Japan
innovation	Kink AR(1)	Kink AR(1)	AR(1)
	-GARCH(1,1)	-GARCH(1,1)	-GARCH(1,1)
	2 regimes	2 regimes	
normal	515.861	9707.079	-5.645
student- <i>t</i>	179.546	94.917	-5.978
GED	137.873	132.079	-6.252
skewed normal	376.792	105.039	-6.324
skewed GED	3102.172	9737.298	-6.301
skewed student- <i>t</i>	240.564	12927.450	-6.037

Source: Calculation.

Note: preferred model of each countries in **bold**

For Korea, the DIC selects the 2-regimes Kink AR(1)-GARCH(1,1) with student-*t* model as the preferred one and, for Japan, the DIC selects the AR(1)-GARCH(1,1) with skewed normal model as the preferred one.

Table 5: In-sample forecasting performance

China			
	AR(1) -GARCH(1,1)	Kink AR(1) -GARCH(1,1) 2 regimes	Kink AR(1) -GARCH(1,1) 3 regimes
	GED	GED	GED
MAE	0.214	0.213	0.213
RMSE	0.264	0.260	0.290
Korea			
	AR(1) -GARCH(1,1)	Kink AR(1) -GARCH(1,1) 2 regimes	Kink AR(1) -GARCH(1,1) 3 regimes
	student- <i>t</i>	student- <i>t</i>	student- <i>t</i>
MAE	0.213	0.211	0.212
RMSE	0.267	0.260	0.268
Japan			
	AR(1) -GARCH(1,1)	Kink AR(1) -GARCH(1,1) 2 regimes	Kink AR(1) -GARCH(1,1) 3 regimes
	skewed normal	skewed normal	skewed normal
MAE	0.142	0.213	0.142
RMSE	0.176	0.290	0.177

Source: Calculation.

Note:smallest MAE and RMSE in **bold**

Table 6: Out-sample forecast error MSPE

	China	Korea	Japan
	Kink AR(1) -GARCH(1,1)	Kink AR(1) -GARCH(1,1)	AR(1) -GARCH(1,1)
<i>k</i> -steps	2 regimes	2 regimes	
1	0.015	0.168	-0.184
2	-0.079	0.006	-0.175
3	0.010	0.185	0.170
4	0.234	0.186	0.069
5	0.139	-0.170	-0.042

Source: Calculation.

5.3 In-Sample and Out-Sample Forecasting

After modeling and forecasting of tourist arrivals from China, Korea, and Japan to Thailand, the in sample mean absolute error (MAE) and root mean squared error (RMSE) of the three different regime models, namely a linear ARMA-GARCH, two-regime Kink AR-GARCH and three-regime Kink AR-GARCH, were calculated and were shown in Table 5

For China and Korea, the smallest mean absolute error and root mean squared error are performed by Kink AR(1)-GARCH(1,1) with 2 regimes. However, the smallest mean absolute error and root mean squared error are performed by AR(1)-GARCH(1,1) for Japan. To examine the forecasting accuracy of each model, 5-step-ahead ex-post forecasts are generated for each country. In this study, the out-of-sample mean squared percent error (MSPE) is used to measure accuracy. The results are shown in Table 6.

6 Conclusions

Tourism can play a greater role in economic growth of a developing country like Thailand. Therefore, accurate forecast of tourism demand is important for investors, tourism business managers and policy makers. Considering the forecasting accuracy, Song and Li [6] reviews 121 studies on tourism demand modelling and forecasting published since 2000. They suggested that although recent studies show that the newer and more advanced forecasting techniques tend to result in improved forecast accuracy under certain circumstances, no clear-cut evidence shows that any one model can consistently outperform other models in the forecasting competition. This paper proposes the Kink AR-GARCH model (Kink AR(m)-GARCH(p,q)) that combines the classical GARCH model of Bollerslev [4] with the Kink model of Chan and Tsay [5]. To examine the performance of Kink AR(m)-GARCH(p,q) forecasts, this study forecasts tourist arrivals to Thailand from three East Asian countries, namely, China, Korea and Japan. Monthly data over the period 1991 to 2016 are employed. The Kink AR(m)-GARCH(p,q) forecasts are compared to the results of AR(m)-GARCH(p,q). The empirical findings show that the 2-regimes Kink AR(1)-GARCH(1,1) with generalized error distribution (GED) produces forecast statistically significantly more accurate than the AR(1)-GARCH(1,1) in forecasting tourist arrivals from China to Thailand. The 2-regimes Kink AR(1)-GARCH(1,1) with student- t model is preferred to forecast growth rate of tourist arrivals from Korea to Thailand. However, AR(1)-GARCH(1,1) is preferred for forecasting international tourism demand for Thailand from Japan.

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