Chapter 7

Modeling the Tourists Demand to Thailand and Singapore A Copula Based GARCH Approach

Komkrit Wongkhae[1] Songsak Sriboonchitta[2] Kanchana Chokethaworn[3] and Chukiat Chaiboonsri[4]

[1] *Faculty of Economics, Chiang Mai University, Thailand*
E-mail: komkrit_w@hotmial.com

[2]*E-mail: songsak@ econ.cmu.ac.th*

[3]*E-mail: kanchana@econ.cmu.ac.th*

[4]*E-mail: chukiat1973@gmail.com*

In this paper, we employ the new method to the area of tourism research. The copula estimation as well as GARCH model conveys the correlation of tourism growth between the two countries that posses the similarity in tourism endowments, Singapore and Thailand. The ARMA (12, 1) and ARMA (12, 6) are respectively offer the appropriate order of autoregressive model for Singapore and Thailand with selected marginal density for the series is student–t distribution. The results affirm the tail dependence correlation since parameter estimation by student-t in both static and dynamic copula is the selected candidate among the other types of copula. The negative dependence between Singapore and Thailand has verified the competitive situation of tourism sector of two countries.

1. Introduction

ASEAN or Association of South East Asian country is a region that favorite to foreign tourist from around the world every year. The attractive region boosts their economy by using the tourism revenue as the path way to both individually and regionally for decades. The cultural and natural tourism resources are both the stunning factors that the tourist always takes in to account for their choice of favorite. Each country itself has tried to promote its country's tourism sector as one of the main engine that stimulating economy. Therefore individual ASEAN country has attempted to enhance the arrival of tourist both internationally and locally. For decades, ASEAN country has emerged the tourism campaign that familiar to visitors worldwide, for instance, Thailand's "Amazing Thailand", Malaysia's "truly Asia" Vietnam's "Vietnam timeless charm", Indonesia's "Wonder Indonesia" and Singapore's "uniquely Singapore". Especially, for Thailand and Singapore, these two ASEAN countries have tried to beat each other in term of number of tourists and tourism activities. Thailand and Singapore define themselves as the hub for air transportation. Their both world class Star Alliance airlines, THAI and Singapore Airways have served the passengers cross the continent between the Down under and several destinations worldwide. Thus, the regional hub, in term of transportation, shopping, culinary as well as discovery of oriental styles are the crucial points that lead the two countries enjoy the benefits from tourism.

According to the World Tourism and Travel Council (WTTC), tourism sector provides the benefit gains to both Thailand and Singapore significantly. Table 1 present the importance of tourism to economy of Thailand and Singapore.

In table 1, Thailand's economy development measures by country's GDP has been added up by the contribution of tourism sector since 1988. The real growth of this contribution is mostly two digit growth. However there are few years that the negative real growth considerably negative. The same pattern as the contribution to employment, Thai labor also gains the payments from tourism related sector. The results also confirmed by the study of Wattanakuljarus and Coxhead (2008), Larsen et al (2011) and Ishii (2012). The same story for the island country, Singapore, tourism sector distribute the GDP for the country more than ten billion USD a year. The labor forces have been hired hundred thousand positions each year with the real growth rate of positive direction in majority. The latest study on Singapore tourism and economic development could be found by Lee (2010). To verify the co-movement between two countries' tourism demand, there have been a number of methodologies that examine the deviation of two variables that imply the preference choices of international tourists. The studies of Divino and McAleer (2009, 2010) are parts of the examples. The traditional studies were based on an assumption of normality, which leads to inconsistencies with real data. Suitable tools will provide the efficiency conclusion of the manners of two series of data — in this study, tourist arrivals of Singapore and Thailand.

TABLE 1. The distribution of tourism sector to economy of Thailand and Singapore

Year	Thailand				Singapore			
	Contribution to GDP		Contribution to Employment		Contribution to GDP		Contribution to Employment	
	2011 US$ bn	Real growth (%)	Number in thousand	Real growth (%)	2011 US$ bn	Real growth (%)	Number in thousand	Real growth (%)
1988	13.35	12.23	3331.70	-10.00	7.17	-2.55	119.70	-5.02
1989	15.90	19.00	3791.20	13.70	7.73	7.80	124.50	3.90
1990	18.10	13.70	4007.90	5.70	10.76	39.10	153.60	23.40
1991	17.76	-1.80	3637.90	-9.20	10.73	-0.30	126.00	-17.90
1992	19.76	11.20	3704.20	1.80	12.20	13.60	149.10	18.20
1993	21.54	9.00	3800.80	2.60	13.35	9.40	125.40	-15.80
1994	21.99	2.00	3622.10	-4.70	13.54	1.40	156.80	25.00
1995	25.38	15.40	3944.30	8.80	14.39	6.20	182.30	16.20
1996	30.56	20.40	3952.20	0.20	14.83	3.00	164.00	-10.00
1997	31.81	4.00	3965.10	0.30	16.39	10.50	180.30	9.90
1998	31.45	-1.10	3828.50	-3.40	16.40	0.00	191.10	5.90
1999	33.65	7.00	3800.10	-0.70	16.38	-0.10	184.00	-3.70
2000	38.24	13.60	4187.20	10.10	15.65	-4.40	183.40	-0.30
2001	39.35	2.90	4372.30	4.40	11.46	-26.70	129.00	-29.60
2002	43.29	10.00	4699.60	7.40	13.55	18.20	145.80	13.00
2003	44.39	2.50	4507.10	-4.00	12.40	-8.40	114.30	-21.60
2004	49.48	11.40	4957.80	9.90	16.26	31.00	156.20	36.60
2005	47.74	-3.50	4503.30	-9.10	17.02	4.70	164.70	5.40
2006	53.11	11.20	4920.90	9.20	16.95	-0.40	161.70	-1.80
2007	54.62	2.80	4933.10	0.20	20.58	21.40	196.80	21.60
2008	56.55	3.50	5105.20	3.40	20.05	-2.60	200.30	1.70
2009	51.26	-9.30	4873.60	-4.50	20.61	2.70	196.50	-1.90
2010	49.69	-3.00	4268.50	-12.40	25.32	22.80	234.10	19.10
2011	56.96	14.60	4468.40	4.60	28.15	11.10	266.30	13.70

Source: World Tourism and Travel Council (WTTC)

To capture the observed time varying mean value and variance of growth rate in tourism data, the generalized autoregressive conditional heteroskedasticity (GARCH) model of Bollerslev (1986), which is usually adopted in financial series data, will be used to estimate the marginal distribution of two time series variables. Introduced by Skhla (1959), copula estimation will be cooperated into the GARCH model that is considered as the useful method in order to construct multivariate distribution to fit the tourism growth data series. Moreover, copula estimation can verify the extreme dependencies such as tail dependencies that are reported to be zero in normal distribution. This means that good and bad extreme events are not independent from each other, which normal distribution cannot report the correlation coefficients. Therefore the copula based GARCH model of tourism demand between Thailand and Singapore will reveal the dependency structure and be able to offer the tourism related policy for a pair of country or a region as a whole.

2. Literature review

Tourism demand studies starting with univariate time varying model of various types of Autoregressive Models. Deviating from financial data analysis and extending from the univariate study, the application of the GARCH model is put to the task of studying tourism data. The study by Chan, et al (2000) has examined the volatility of tourist arrivals in Australia. The results came up with the evidence of the conditional variance which is associated with Divino and McAleer (2009). After that, the study of Chen and Chiou-Wei (2009) also extended the application of EGARCH to study tourism flow and economic development in Korea and Taiwan and found the relation between international tourists and economic growth of the two countries. One who is interested in the application of GARCH model to tourism could find out the related researches of Seo, et al. (2009), Coshall (2009) and Divino and McAleer (2010).

For the study of copula, after the launching of Sklar's theorem of Sklar (1995), copula is one of the promising methodologies that deals with the dependency among variables that we use to distinct the marginal behavior and dependence structure from the joint distribution. Additionally, copula offers fewer restrictions for the common assumption of normal independence and constants, as well as time varying effects. There are some studies that continuously extend the application of copula estimation. The studies concentrate in the financial field. Most studies have been devoted to the study of the efficiency of copula estimation that one can explore from the studies of Hurlimann (2004), Biau and Wegkamp (2005), Chen and Fan (2006) and Haan, et al. (2008). The later studies have tried to put forward the efforts to expand the utilization of copula estimation. Several models are used corporately with the estimation of copula. In cooperating with the GARCH model, the copula GARCH model is able to find the evidence of whether the conditional dependent between two or more variables that are mostly related somehow exists. The majority of the studies of copula GARCH model are found in the financial data analysis.

Huang, et al. (2009) successfully offered the estimation of copula GARCH to describe the dependence structure of Value at Risk (VaR) of NASDAQ and TAIEX index. Zhang and Guegan (2008) also adopted copula GARCH to verify the relationship of Shanghai and Shenzhen Stock Composite Indexes, and pointed out the benefit of copula GARCH over the previous method. The latest examples of copula based GARCH estimation can be found in Ning (2010) and Wu, et al. (2012). However, from the recently investigation of tourism demand study, none of study has applied this useful methodology to study the tourism demand for the interesting destinations such as Singapore and Thailand.

3. Methodology

This study combines copula function to the GARCH-type model. The methodology to estimate is starting by using GARCH model to obtain the marginal distribution. After fit the model of growth rate of number of tourists' arrival, the study use the results to get the probability integral transform. The second step of estimation is using copula estimation to estimate the dependence in order to find the characters of the relationship between two data series of tourist arrival. This sector will present the theory and the estimation method of the copula GARCH model.

3.1 Theory of GARCH model

Initially with ARCH (Autoregressive Conditional Heteroskedasticity), Considering ARCH(q) model, the conditional variance is defined as the linear function. This linear function is only affected by the previous sample's variance.

Bollerslev (1980) has extended the Generalize ARCH or (GARCH) model. The process of GARCH (p,q) of any random variable is given by

$$\varepsilon_t|\psi_{t-1} \sim D(0, h_t) \qquad (1)$$
$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \qquad (2)$$
$$h_t = \alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t \qquad (3)$$

Where

$$p \geq 0, q > 0 \qquad (4)$$
$$\alpha_0 > 0, \alpha_i \geq 0, i = 1,2, \dots, q \qquad (5)$$
$$\beta_i \geq 0, i = 1,22, \dots, p \qquad (6)$$

ε_t representing the discrete-time stochastic process of real value. ψ_t refers to the information set of the time period of study. In the process of GARCH(p,q), the process is also impacted by the lag conditional variance. Therefore, if $B(L) = 0$, the process of GARCH(p,q) will be reduced to be ARCH effect. Additionally, if $(L) = B(L) = 0$, then is classified in to white noise.

In the estimated model for GARCH, let X_t and Y_t be of Malaysia, Singapore and Thailand growth rate of tourist arrivals of interested countries, and $H(X, Y)$ is the joint probability distribution of pair of interested country, thus the marginal distribution of X_t is the distribution of $H(X, Y)$ when is not taken into account. We are able to present the marginal distribution for each model of X_t and Y_t as the following equations:

Marginal distribution of X_t

$$X_t = \mu_x + \emptyset_{1x} X_{t-1} + \varepsilon_t \qquad (7)$$
$$\sigma_{x,t}^2 = \omega_t + \beta_x \sigma_{x,t-1}^2 + \alpha_x \varepsilon_{t-1}^2 \qquad (8)$$

$$\varepsilon_t|\psi_{t-1} \sim D(0, \sigma_{xt}^2) \quad (9)$$
$$\varepsilon_t = z_t\sigma_{xt} \quad (10)$$
$$z_t \sim iid(0,1) \quad (11)$$

Marginal distribution of Y_t

$$Y_t = \mu_y + \emptyset_{1y}Y_{t-1} + \eta_t \quad (12)$$
$$\sigma_{y,t}^2 = \omega_t + \beta_y\sigma_{y,t-1}^2 + \alpha_y\eta_{t-1}^2 \quad (13)$$
$$\eta_t|\psi_{t-1} \sim D(0, \sigma_{yt}^2) \quad (14)$$
$$\eta_t = z_t\sigma_{yt} \quad (15)$$
$$z_t \sim iid(0,1) \quad (16)$$

3.2 Copula Function Theory

The pioneer of copula study, Sklar (1995) offers the copula theory without any formula. The p-dimension copula with all marginal distributions is considered as a uniform distribution. Sklar's theory is as follows:

Let F be a multivariate distribution function with marginal $F_1, \dots, F_p$, *there exist*s copula C that proposes the following property:

$$F(x_1, \dots, x_p) = C\{F_1(x_1), \dots F_p(x_p)\}, \quad x_1, \dots x_p \epsilon \mathbb{R}^+ \quad (17)$$

If F_i are continuous for $i = 1, \dots p$ then C is unique. Conversely, if C is copula and $F_1, \dots F_p$ are univariate distribution functions, then the above F function is a multivariate distribution function with margin $F_1, \dots, F_p$ and its copula function is defined as:

$$C(u_1, \dots, u_p) = F\{F_1^{-1}(u_1), \dots, F_p^{-1}u_p)\}, u_1, .. u_p \epsilon [0,1] \quad (18)$$

Where F_i^{-1} are inverse marginal distribution functions, then the uniform distribution of copula function is:

$$c(u_1, \dots, u_p) = \frac{\partial^p C(u_1, \dots u_p)}{\partial u_1, \dots, \partial u_p}, u_1, .. u_p \epsilon [0,1] \quad (19)$$

Associating with the Sklar theorem, the density function $f(.)$ of p-variate distribution F as the following:

$$f(x_1, \dots, x_p) = c\{F_1(x_1), \dots, F_p(x_p)\}\prod_{i=1}^{p} f_i(x_i), \quad x_1, \dots, x_p \epsilon \mathbb{R}^+ \quad (20)$$

Each of p dimension of copula, belongs to $2^p - 1$ which refers to associate copula. For instance if $p = 2$ and $U_1, U_2 \sim C$, the associated copula is able to explain the dependency between each pair of $(1-U_1, 1-U_2)$, $(U_1, 1-U_2)$ and $(1-U_1, U_2)$ therefore we can illustrate the equation as:

$$C'(u_1,u_2) = u_1 + u_2 + 1 - C(1-u_1, 1-u_2) \tag{21}$$

$$C''(u_1,u_2) = u_1 - C(u_1, 1-u_2) \tag{22}$$

$$C'''(u_1,u_2) = u_2 - C(1-u_1, u_2) \tag{23}$$

Where the copula C' is survival copula.

Classes of copula

The types of copula used to estimate the parameters are defined by the dimension of distribution F, p value. The distinctions of copula family are classified as Table 3.

TABLE 2. The classification of copula base on the size of p

Defined copula family	**Size of p**
Gaussian copula	$p \geq 2$
T copula	$p \geq 2$
Clayton copula	$p = 2$
SJC copula	$p = 2$

To define the class of copula, the log-likelihood function is used to estimate the copula parameters. The optimization of the function is as following:

$$\mathcal{L}(\xi; x) = \sum_{j=1}^{T}\left(\sum_{i=1}^{p} \log\left(f_i\left(x_{i,t}; \phi_i\right)\right) + \log\left(c\left(F_1\left(x_{1,t}\right), \dots, F_p\left(x_{p,t}\right); \theta\right)\right)\right) \tag{24}$$

Where ξ is (ϕ, θ) vector that consists of the marginal $\phi = (\phi_1, \dots, \phi_p)$ and the copula parameter θ, the optimization function can be separated into two parts, the marginal log likelihoods and copula log likelihood.

$$m\mathcal{L}(\phi; x) = \sum_{i=1}^{p} mll_i = \sum_{i=1}^{p}\sum_{j=1}^{T} \log\left(f_i\left(x_{i,t}; \phi_i\right)\right) \tag{25}$$

$$c\mathcal{L}(\theta; u, \emptyset) = \log\left(c\left(F_1\left(x_{1,t}\right), \dots, F_p\left(x_{p,t}\right); \theta\right)\right) \tag{26}$$

Each type of copula is presented by the function of log likelihood as follows:

Gaussian copula:

$$\mathcal{L}_{Gaussian}(R; u_t) = -\frac{1}{2}\sum_{t=1}^{T}(\log|R| + \epsilon_t'(R^{-1} - I)\epsilon_t) \qquad (27)$$

t copula:

$$\mathcal{L}_{St}(R, d, u_t) = -T\log\frac{\Gamma\left(\frac{d+p}{2}\right)}{\Gamma\left(\frac{d}{2}\right)} - pT\log\frac{\Gamma\left(\frac{d+1}{2}\right)}{\Gamma\left(\frac{d}{2}\right)} - \frac{d+p}{2}\sum_{t=1}^{T}\log\left(1 + \frac{\epsilon_t' R^{-1}\epsilon_t}{d}\right) - \sum_{t=1}^{T}\log|R| + \frac{d+1}{2}\sum_{t=1}^{T}\sum_{i=1}^{p}\log\left(1 + \frac{\epsilon_{it}^2}{d}\right)$$

(28)

Where ϵ_t *is* the vector of the transformed standardized residuals, the vector depends on the copula specification that we have made. If $\epsilon_t = \left(\Phi^{-1}(u_{1,t}), \ldots, \Phi^{-1}(u_t)\right)$, the normal copula is hold. However, in the case of t copula, the vector will be defined in the comparable of the inverse of student t distribution and is degree of freedom and ϵ_t is defined as $\epsilon_t = \left(t_d^{-1}(u_{1,t}), \ldots, t_d^{-1}(u_{p,t})\right).\Phi^{-1}$.

The Archimedean copulas are getting popular in the estimation of time series data in financial data analysis. The advantages of this class of copula that we take into account as the candidate to be selected is appropriate because this type of copula allows the dependencies of the model in the arbitrary high dimensions with the single of parameter. Moreover, Archimedean copula can detect the dependencies even in the extreme heavy tails. Archimedean copula family, including Clayton copula and Symmetrized Joe-Clayton (SJC) copula, are able to be formulate the log likelihood function as the following:

Clayton copula:

$$\mathcal{L}_{Clayton}(d; u_t) = \sum_{t=1}^{T}\log\left((1+d)(u_{1t}.u_{2t})^{-1-d}\left(u_{1t}^{-d} + u_{2t}^{-d} + 1\right)^{-2-\frac{1}{d}}\right) \qquad (29)$$

Symmetrized Joe-Clayton (SJC) copula:

$$\mathcal{L}_{SJC}(\tau^U, \tau^L; u_t) = \sum_{t=1}^{T}\log\left(\frac{\partial^2}{\partial u_1 \partial u_2}\left(\frac{1}{2}\left(C_{JC}(u_t|\tau^U, \tau^L) + C_{JC}(1 - u_t|\tau^L, \tau^U) + u_{1t} + u_t - 1\right)\right)\right)$$

(30)

Where $d = \frac{2\tau}{1-\tau}$ and τ is Kendall's tau.

3.2 Procedure of copula GARCH estimation

To estimate the copula GARCH of the growth rate of tourism data, there are plenty of tasks that one has to follow to get the results of desired parameters. However, the main examinations that are used to obtain the parameters are to estimate the marginal distribution from GARCH and to estimate the parameter under the copula estimation.

The possibility of heteroskedasticity of the time series may be correlated in the form of AR (q), GARCH (p,q) or AR(q), GJR(p,q). Additionally, the distribution of residuals also needs to be verified. Three choices of residual distributions, Gaussian, student t or skewed student t distribution are used to capture the excess of kurtosis and the excess of skewness.
The distinction between three types of distribution could be represented as the following Skew-T equation;

$$f(z;\upsilon,\lambda) = \begin{cases} bc\left(1+\frac{1}{\upsilon-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-(\upsilon+1)/2} & \text{if } z < -a/b \\ bc\left(1+\frac{1}{\upsilon+2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-(\upsilon+1)/2} & \text{if} z \geq -a/b \end{cases} \quad (31)$$

Where:

The degree of freedom parameter υ defined by $2 < \upsilon < \infty$ and the asymmetry parameter λ is, $-1 < \lambda < 1$.

The explanation of skew t distribution is the zero mean and one variance properties. However, if we extend the specific value of $\lambda = 0$, skew t distribution will become the student t distribution. Associating with $\lambda = 0$, if the value of υ approaches 2, the skew t distribution will be considered as normal distribution. After the selection of the GARCH or GJR have been made, by considering the criteria Akaike information criteria (AIC), the Schwarz's Bayesian information criteria (SBIC) and the maximum value of log likelihood (Lu, et al. 2010).

The third part of the study in copula GARCH is the selection of the fitting classes of copula. There are two types of copula that are used as the candidates of the copula to describe the relation between the growth rate in tourism demand of Thailand and Singapore: the elliptical and Archimedean copula. The elliptical copula types, Gaussian and student-t copula, are able to differentiate the degree of correlation, but only under the property of radial symmetry (Wu, et al., 2012). Archimedean copula, on the other hand, were originated by Ling (1965) and Schweizer and Skla (1961) with the properties of both upper and lower tail dependence that dominate the ability of elliptical copula. The families of copula that belong to Archimedean copula, including Gambel, Clayton and SJC copulas, are widely used in financial time series data. The application to tourism research will be useful to describe the tourism demand patterns to reveal the relation in ASEAN tourism market. Before getting the estimated parameters, the study needs to specify the variation of parameters over time. If parameter is assumed to be constant overtime, one has to estimate based on static approach. The theoretical model of static copula can be found in the study of Marshal and Zeevi (2002). If the parameter has changed according to time, the dynamic approach will be taken in to account.

The dynamic conditional correlation (DCC) is explained by the evolving of correlation, as in the following equation:

$$Q_t = (1-\alpha-\beta).\bar{Q} + \alpha\epsilon_{t-1}.\epsilon'_{t-1} + \beta Q_{t-1} \quad (32)$$

$$\text{Where } R_t = \tilde{Q}_t^{-1} Q_t \tilde{Q}_t^{-1}$$

$\bar{Q}$is sample covariance of ϵ_t, $\tilde{Q}_t$, is square matrix. The parameters constraint for the model is $\alpha + \beta < 1$ and $a, \beta \in (0,1)$. Patton (2006) explains the equation to compute the value of Kendal's tau that describes the overtime changing of the dependency parameter in Clayton copula and the upper and lower tail dependence coefficient in the case of SJC copula.

$$\tau_{tClayton} = \Lambda\left(\omega + \beta\tau_{t-1} + \alpha.\frac{1}{10}\sum_{i=1}^{10}|u_{1,t-i} - u_{2,t-i}|\right) \quad (33)$$

and

$$\tau_{tSJC} = \Lambda(\omega + \beta\tau_{t-1} + \alpha.|u_{1,t-i} - u_{2,t-i}|) \quad (34)$$

Λ is logistic transformation that limits Clayton and SJC copula in the interval of as defined by the follow equation:

$$\Lambda(x) = (1 + e^{-x})^{-1} \quad (35)$$

The model selection of copula

This thesis will present two concepts of goodness of fit test for copula, according to the study of Lu, et al. (2010). Patton (2006) also presented the Akaike information criteria (AIC), the Schwarz's Bayesian information criteria (SBIC) and the log likelihood value of optimum (LL). Each indicator can be calculated as following equation:

Akaike information criteria (AIC)

$$AIC = -2\sum_{i=1}^{N} \ln[C(u,v|\theta)] + 2k \quad (36)$$

Where k is number of copula parameters which need to be estimated. Similar to SBIC, one can obtain the value of SBIC from the following:

$$SBIC = -2\sum_{i=1}^{N} \ln[C(u,v|\theta)] + \ln(N)k \quad (37)$$

Another concept of model collection base on the goodness of fit test, the Kendell's test which was successively explored by Genest,et al (1995), and also utilized in the studies of Genest, et al. (2006) and Wang and Wells (2000). The theoretical Kendell's test was offered in the study of Genest, et al. (2009). The Kendell's test is based on the probability integral transformation of the data. Let K is the distribution function of V, Genest and Rivest (1995) showed that we can estimate K via the nonparametric method by using the empirical distribution of a rescale version of the pseudo observation, $V_1 = C_n(\mathcal{U}_1), \dots, V_n = C_n(\mathcal{U}_n)$. The estimator of Kendell statistic can be obtained from:

$$K_n(v) = \frac{1}{n}\sum_{i=1}^{n} 1(V_i \leq \upsilon), \quad \upsilon \in [0,1] \tag{38}$$

Under , H_0, the vector $\mathcal{U} = (\mathcal{U}_1, \dots, \mathcal{U}_d)$ has a distribution of C_θ for $\theta \in \varphi$. Then we will imply that the Kendell transformation $C_\theta(\mathcal{U})$has the distribution of K_θ. The goodness of fit can be measured as the distance between K_n and a parametric estimation of K_{θ_n}will be tested by the hypothesis of $H_0'': K \in \mathcal{K}_0 = \{K_\theta : \theta \in \varphi\}$. Since H_0 is the part of H_0'', therefore if the test does nonreject for H_0'', the acceptance of H_0 could not be concluded. Genest, et al. (2006) have offered the testing statistic of Cram'er–von Mises and Kolmogorov–Smirnov statistics:

$$S_n^{(K)} = \int_0^1 \mathbb{K}_n(\upsilon)^2 dK_{\theta_n}(\upsilon) \tag{39}$$

$$T_n^{(K)} = \sup|\mathbb{K}_n(\upsilon)|, \quad \upsilon \in [0,1] \tag{40}$$

Where $\mathbb{K}_n = \sqrt{n}\left(K_n - K_{\theta_n}\right)$

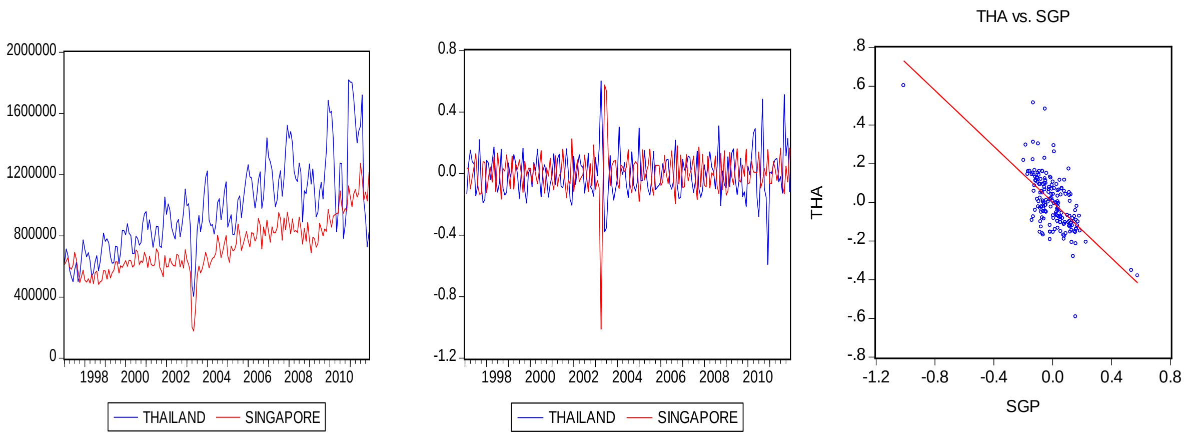
Utilizing the goodness of fit according to AIC, SBIC and LL associating with the Cram´er–von Mises and Kolmogorov–Smirnov test will confirm the suitability of copula model that leads to the resultant of parameters estimation and the concrete behavior of the tourism variables included in the study.

4. Data

To verify the patterns of tourist arrivals between Thailand and Singapore, the research employs the monthly data of international tourists during January 1997 to December 2011. To eliminate the problem of stationary of data, the monthly data is taken into growth rate of number of arrivals for each country, thus,

$$\text{Arrival}_{\text{Growth}} = \log \frac{\text{Arrival}_t}{\text{Arrival}_{t-1}} \tag{41}$$

The natures of data for raw, growth and correlation between data are depicted in figure 1 a), b) and c) respectively. The main characteristics of data series reveal that tourist arrival come to Thailand rather than to Singapore almost the whole series data set. The variation of number of tourist can be observed in 2003 for both raw and growth data due to the effect of SARs to all over Asian countries. The empiric results can be found in Kuo, et al (2008) and McAleer, et al (2010).



(a) (b) (c)

Figure 1 International arrivals of Thailand and Singapore for raw data (a) and growth (b) and correlation (c)

Table 3 summarizes the descriptive statistic of tourism data of Singapore and Thailand. The growth rate of tourism arrival show the negative growth in Thailand but in positive sign in Singapore implies the preference is higher in the small island. The negative skewness does present in Singapore data. The Jargue-Bera (1980) of normality tests are rejected in all of series data.

TABLE 3. The summary descriptive statistic of Thailand and Singapore tourist arrivals

Statistics	THAILAND		SINGAPORE	
	Raw data	Growth data	Raw data	Growth data
Mean	976992.804	-0.016	729011.503	0.004
Median	921510.003	-0.014	694934.501	0.001
Maximum	1819751.000	0.604	1273870.000	0.577
Minimum	404563.000	-0.591	177808.000	-1.012
Std. Dev.	289432.602	0.147	177576.609	0.133
Skewness	0.722	0.458	0.365	-1.630
Kurtosis	3.334	6.027	3.573	22.816
Jarque-Bera	16.545	74.574	6.331	3008.006
Probability	0.000***	0.000***	0.039**	0.000***
Observations	180.000	179.000	180.000	179.000

Table 4 presents unit root test in growth data series. Adopting the ADF-test (Dickey, Fuller, 1979) and PP-test (Phillips and Person, 1988), all indexes imply the neglect of unit root in every manner of data.

TABLE 4. Unit root test of tourist variables

Statistics	Unit root test at I(0)					
	Thailand			Singapore		
	With intercept	Trend and intercept	None	With intercept	Trend and intercept	None
ADF-test	-9.020***	-9.043***	-8.874***	-5.052***	-5.077***	-4.891***
PP-test	-16.498***	-16.686***	-16.463***	-29.937***	-43.283***	-19.506***

5. Results

5.1 The results of marginal estimation

To achieve the appropriate lag of ARMA model, the testify has been attempted to use various of order of ARMA (p,q) model. Follow Hannan and Risanan (1982), after minimizing the conditional sum of square error, the fit order are ARMA(12,1) and ARMA(12,6) for Singapore and Thailand respectively. The full detail of results is presented in table 5.

TABLE5. ARMA model of Singapore and Thailand

Parameter	**Singapore ARMA(12,1)**				**Thailand ARMA(12,6)**			
	Coef.	**std err**	**t-stat**	**p-value**	**Coef.**	**std err**	**t-stat**	**p-value**
ar(1)	-0.396	0.020	-19.796	0.000***	0.631	0.001	1006.042	0.000***
ar(2)	-0.389	0.006	-60.887	0.000***	-0.801	0.000	-6028.507	0.000***
ar(3)	-0.323	0.011	-30.547	0.000***	-0.338	0.001	-296.237	0.000***
ar(4)	-0.336	0.008	-41.935	0.000***	0.459	0.000	2085.003	0.000***
ar(5)	-0.099	0.010	-9.529	0.000***	-0.616	0.000	-20656.650	0.000***
ar(6)	-0.265	0.009	-30.748	0.000***	0.080	0.001	94.724	0.000***
ar(7)	-0.101	0.012	-8.684	0.000***	-0.019	0.001	-19.057	0.000***
ar(8)	-0.107	0.009	-12.167	0.000***	-0.024	0.001	-19.599	0.000***
ar(9)	-0.037	0.010	-3.862	0.000***	-0.609	0.001	-1073.720	0.000***
ar(10)	-0.075	0.007	-10.195	0.000***	0.191	0.001	208.308	0.000***
ar(11)	-0.117	0.007	-15.898	0.000***	-0.284	0.000	-783.852	0.000***
ar(12)	0.306	0.006	52.261	0.000***	0.032	0.000	64.664	0.000***
ma(1)	0.511	0.019	27.010	0.000***	-0.849	0.002	-482.416	0.000***
ma(2)					1.000	0.008	130.762	0.000***
ma(3)					0.159	0.006	24.645	0.000***
ma(4)					-0.694	0.004	-171.387	0.000***
ma(5)					0.940	0.010	92.276	0.000***
ma(6)					-0.897	0.005	-180.630	0.000***

After testing for the order of ARA model, the next step is to select the suitable distribution. The candidates are normal or Gaussian which implies the continuous probability distribution. Student-t or t distribution arises when the sample size is small and possesses the heavier tail than the normal one. And skew-T distribution which proposed by Hanson (1994) and usually utilized in the financial data estimation due to the requiring of large observations and considered as the advantage one in Value-at-Risk study (Demarta and McNeil, 2005). Considering the satisfaction of i.i.d. and uniform distribution assumption, the K-S test or Kolmogorov-Smirnov goodness of fit test (Conover, 1980) is used to verify the uniform distribution of data. With the null hypothesis of the sample data is drawn from uniformly distribution, the testing result is shown in table 6 and does reveal the unable rejection of the null in both Singapore and Thailand data.

TABLE 6. Komorgorov uniformly distribution test

Data	Kolmorgorov-statistic	p-value
Singapore(u)	0.006	1.000
Thailand (v)	0.006	1.000

To ensure the lack of autocorrelation, the testing is conducted for both Singapore and Thailand data. The results are illustrated in table 7 and 8. The testing statistics offer the evidence of no-autocorrelation from 1st moment to 4th moment.

TABLE7. Autocorrelation test of growth rate of tourism arrival to Singapore

Lag	1st Moment		2nd Moment		3rd Moment		4th Moment	
	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value
Lag(1)	0.851	0.356	15.842	0.000***	0.596	0.440	6.648	0.010***
Lag(2)	1.634	0.442	16.768	0.000***	0.967	0.617	8.916	0.012**
Lag(3)	2.719	0.437	17.258	0.001***	1.286	0.733	8.839	0.032**
Lag(4)	1.993	0.737	17.284	0.002***	1.125	0.890	9.010	0.061*
Lag(5)	2.335	0.801	14.868	0.011**	2.457	0.783	7.106	0.213
Lag(6)	2.522	0.866	14.418	0.025**	2.710	0.844	7.767	0.256
Lag(7)	2.717	0.910	14.351	0.045**	2.934	0.891	7.975	0.335
Lag(8)	10.068	0.260	14.454	0.071*	6.948	0.542	8.396	0.396
Lag(9)	9.911	0.358	15.886	0.069*	7.256	0.611	10.679	0.298
Lag(10)	10.117	0.430	17.592	0.062*	7.545	0.673	10.906	0.365
Lag(11)	11.718	0.385	17.584	0.092*	7.527	0.755	11.124	0.433
Lag(12)	11.572	0.481	18.050	0.114	7.793	0.801	11.065	0.523
Lag(13)	13.070	0.442	17.886	0.162	8.632	0.800	11.609	0.560
Lag(14)	13.664	0.475	22.433	0.070*	9.117	0.824	15.447	0.348
Lag(15)	13.306	0.579	22.251	0.101	9.545	0.847	15.543	0.413
Lag(16)	14.099	0.591	22.753	0.121	10.194	0.856	16.155	0.442

Lag	1st Moment		2nd Moment		3rd Moment		4th Moment	
	t-stat	**p-value**	**t-stat**	**p-value**	**t-stat**	**p-value**	**t-stat**	**p-value**
Lag(17)	14.015	0.666	22.442	0.168	10.406	0.886	16.021	0.522
Lag(18)	15.338	0.639	23.034	0.189	11.253	0.883	16.379	0.566
Lag(19)	15.729	0.675	23.647	0.210	12.834	0.847	17.637	0.547
Lag(20)	16.204	0.704	24.993	0.202	13.205	0.868	18.560	0.551

TABLE8. Autocorrelation test of growth rate of tourism arrival to Thailand

Lag	1st Moment		2nd Moment		3rd Moment		4th Moment	
	t-stat	**p-value**	**t-stat**	**p-value**	**t-stat**	**p-value**	**t-stat**	**p-value**
Lag(1)	0.585	0.444	0.000	0.986	0.071	0.790	0.003	0.954
Lag(2)	1.319	0.517	0.770	0.680	0.449	0.799	0.169	0.919
Lag(3)	1.457	0.692	0.996	0.802	1.159	0.763	0.727	0.867
Lag(4)	1.570	0.814	1.008	0.909	1.219	0.875	0.724	0.948
Lag(5)	6.734	0.241	5.496	0.358	3.134	0.679	5.149	0.398
Lag(6)	8.267	0.219	5.914	0.433	4.684	0.585	5.321	0.503
Lag(7)	8.220	0.314	5.848	0.558	5.163	0.640	5.637	0.583
Lag(8)	7.615	0.472	5.902	0.658	6.658	0.574	5.550	0.697
Lag(9)	7.325	0.603	5.860	0.754	6.786	0.659	5.831	0.757
Lag(10)	8.660	0.565	6.594	0.763	6.873	0.737	6.733	0.750
Lag(11)	9.648	0.562	7.250	0.778	7.617	0.747	8.660	0.653
Lag(12)	10.072	0.610	21.861	0.039	7.628	0.814	22.695	0.030
Lag(13)	11.330	0.583	22.056	0.055	9.175	0.760	22.802	0.044
Lag(14)	13.021	0.525	22.053	0.078	11.450	0.650	22.778	0.064
Lag(15)	12.140	0.668	21.338	0.126	11.016	0.751	22.159	0.104
Lag(16)	12.212	0.729	22.575	0.126	11.952	0.747	22.981	0.114
Lag(17)	12.474	0.771	23.112	0.146	12.335	0.779	23.334	0.139
Lag(18)	12.697	0.809	26.090	0.098	12.866	0.799	24.387	0.143
Lag(19)	13.034	0.837	26.980	0.105	12.922	0.843	25.256	0.152
Lag(20)	12.744	0.888	28.095	0.107	14.990	0.777	26.023	0.165

Before estimating copula, we separately estimate marginal distribution. After fit the model of ARMA(p,q), we obtain the probability transformation integral u and v for Singapore and Thailand respectively. The coefficients estimation by Student- t estimation of ARMA (p,q) GARCH (1,1) model of tourism growth data of Singapore and Thailand have been proved to be are confirmed the significant level in table 9. The similar specifications are detected in the results of both Singapore and Thailand model. The p-values are significantly at least 9.0 level found in all parameters.

TABLE 9. Student t estimation of ARMA (p,q) GARCH (1,1) model

Parameter	Singapore, ARMA(12,1) GARCH (1,1)				Thailand, ARMA(12,6) GARCH (1,1)			
	Coef.	std err	t-stat	p-value	Coef.	std err	t-stat	p-value
cons	0.002	0.000	2158.786	0.000***	0.001	0.000	3560.096	0.000***
α	0.468	0.060	7.783	0.000***	0.070	0.002	31.317	0.000***
β	0.324	0.037	8.830	0.000***	0.842	0.005	168.514	0.000***
d. f.	5.030	2.416	2.082	0.019**	5.181	4.029	1.286	0.100*

Note: Log Likelihood of Singapore = -23.051 and for Thailand =-32.014

5.2 Copula based GARCH model

To study the dependence structure of variables, the paper has employed two types of manners, static and time varying copula. The estimated results are presented in table 10.

1) Static copula

The candidate for classes of copula family include in the study are Gaussian, Clayton, Rotated Clayton, Frank, Gambel and student –t copulas. Trivedi and Zimmer (2005) has emphasized that Clayton and Gambel copula do not account for the negative dependence variable as the original nature of these two growth series variable. Therefore, these two classes of copula are eliminated. The rest nominees are Gaussian, Frank and Student-t copula. According to the goodness of fit statistics that used to determine the choice of selection which are Akaike's Information Criterion (AIC) of Akaike (1974), the Bayesian information criterion (BIC) or Schwarz criterion (also SBC, SBIC) of Schwarz (1978), Log Likelihood statistic (LL), Kolmogorov–Smirnov statistics (KS) and Cram'er–von Mises (CVM) of Anderson (1962) with the extension of Genest, et al. (2006). The main idea behind KS and CVM test is to examine the null hypothesis that the given u and v are uniform (0,1). The results in table 10, the level of signification reveals the preference to student-t copula rather than Gausian and Frank copula. This result supports the study of Jondeau and Rockinger (2006), Wu, et al (2012) and Zhang (2008).

TABLE 10. The estimation of static copula with goodness of fit test

Copula	Parameter	std err	t-stat	p-value	AIC	BIC	LL	KS	CVM
Gaussian	-0.183	0.022	-8.222	0.000***	-5.698	-5.680	-2.855	0.814 (0.430)	0.100 (0.490)
Clayton	0.0001	0.011	0.009	0.496	0.017	0.036	0.003	Na	Na
Frank	0.0001	0.037	0.003	0.499	0.013	0.031	0.000	0.739 (0.400)	0.101 (0.200)
Gambel	1.100	0.008	134.398	0.000***	9.965	9.983	4.976	Na	Na
Student-t	-0.184	0.000	-2.6E+8	0.000***	-5.796	-5.759	-2.190	0.835 (0.601)	0.113 (0.630)
	26.670	0.000	7.8E+5	0.000***					

2) Time varying copula

The results of time varying copula also confirm the result from static copula, student –t copula offers the minimum AIC and BIC. The correlation parameters exhibit negative relation between growth rate of tourist arrival to Singapore and Thailand.

TABLE 11. Time varying copula estimation

Copula	Parameter	std err	t-stat	p-value	AIC	BIC	LL
Gaussian	-0.090	0.279	3.100	0.088*			
	0.935	0.152	6.153	0.000***	-5.770	-5.773	-2.287
Student-t	-23.061	0.245	94.202	0.000***			
	0.011	0.223	4.901	0.041**			
	0.938	0.134	7.025	0.000***	-5.915	-5.859	-2.176

6. Concluding remarks

In this paper, we employ the new method to the arena of tourism research. The copula estimation as well as GARCH model conveys the correlation of tourism growth between the two countries that posses the similarity in tourism endowments, Singapore and Thailand. The ARMA (12, 1) and ARMA (12, 6) are respectively offer the appropriate order of autoregressive model for Singapore and Thailand with selected marginal density for the series is student – t distribution. The results affirm the tail dependence correlation since parameter estimation by student-t in both static and dynamic copula is the selected candidate among the other types of copula, the lower tail Clayton, the upper tail Gambel, the symmetry with no tail dependence of Gaussian and Frank copula. The negative dependence between Singapore and Thailand has verified the competitive situation of tourism sector of two countries.

From the direction of correlation, Singapore and Thailand may be considered as the substitute goods for each other, tourists who come to Singapore will not continue their journey to Thailand, vice versa. The policy recommendation from this research is to advice the tourism authority of two countries to realize the important of launching policy that is able to overcome the neighbor country. In the other hand, the cooperative policy also can be also considered. To enhance the tourist to extend their travelling and continue the rest of the trip to another country, Singapore and Thailand should provide the tourism campaign or tourism package promotion, for i.e. the special event or discount air fair or other mode of transportation if the tourist visits two countries in the same time of their holiday. This policy will be fruitful for Singapore and Thailand tourism sector and their economy as a whole.

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