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VOLATILITY CO-MOVEMENT OF CHINA OUTBOUND TOURISM: DYNAMIC COPULA BASED GARCH MODEL

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ABSTRACT. *This paper used dynamic copula-GARCH model to analyze volatility and dependency of China outbound tourism to four leading countries, namely Thailand, Singapore, South Korea and Japan. It was found that Japan, South Korea and Thailand have a highly volatilities. Furthermore, the conditional dependence is time-varying and different copula generate different the time path dependence structure. Third, there is seasonal effect; the summer holiday and Chinese Spring Festival have positive effects on the all destinations. Finally, most of the time, Thailand and Singapore have the highest conditional dependence. The result indicates that Thailand and Singapore have a complementary relationship.*

Keywords: China Outbound Tourism; GARCH Model; Skewed Student-T Distribution; Dependency; Dynamic Copula

1. Introduction. Over the last decade, there has been strong growth in China's outbound tourism. The main factors that generally affect outbound travel are the confidence of continued and rapid economic growth, constant increasing income, furthermore the government's favorable policy framework, increased leisure time and RBM appreciation. According to the National Bureau of Statistics of China, the outbound tourism of China underwent a rapid growth from 2000 to 2010. Outbound travel has increased from around 10.5 million in 2000 to 57.4 million in 2010, the average annual growth rate is 18.5 (Tourism Flows Outbound China (2010)).According to the WTO, China placed third position in international tourism spending in 2010 (UNWTO Tourism Hightlights 2011 Edition (2011)).This information highlights that China has became one of most important tourism source country in the global touris market, and continuous growth of outbound tourism will bring tremendous business opportunities.

The purpose of this study is to examine the time-varying volatility and time-varying dependence structure among the destinations in China outbound tourism demand, we selected South Korea, Japan, Singapore, and Thailand as sample for this study (the top 4 tourism destinations for China mainland tourist). Based on the motivations discussed above, four research questions were formulated for this study: (1) Is the volatility high or low among the four destinations? (2) What is the conditional dependence among the four destinations? (3) Is the dependence between the four destinations time-varying over the study time horizon? (4) Is the dependence negative (substitute) or positive (complement) among the four destinations? The answer of these four questions can be used to help destination manager and policy makers

This paper is organized as follows. Section 2 provides a literature review of the tourism demand. Section 3 describes the econometrics models used in the paper, namely dynamic copula—GARCH. Section 4 discusses the data presented in the paper and also describes the estimate results of four kinds of copula-based GARCH. The last section provides implications for policy planning and destination management.

2. Literature Review. A large number of scholars have used the autoregressive conditional heteroskedasticity (GARCH) model as their tourism model (Chan, Lim and McAleer (2005); Shaeef and McAleer (2005); Shaeef and McAleer (2007); Seo, Park and Yu (2009); Kim and Wong (2006); Bartolom, McAleer, Ramos and Maquieira (2009); Coskun and Ozer (2011); and Daniel and Rodrigues (2010)).The univariate the autoregressive conditional heteroskedasticity (GARCH) model was applied in the Shaeef and McAleer (2005), Kim and Wong (2006),McAleer, Ramos and Maquieira (2009), and Daniel and Rodrigues (2010), which analyze tourism demand at different time series frequencies, ranging from monthly, weekly, and daily data. However,the univariate GARCH model have drawback that it cannot examine the conditional correlation or dependence among destination. Hence, Chan, Lim and McAleer (2005), Shaeef and McAleer (2005), and McAleer, Ramos and Maquieira (2009) developed multivariate GARCH model for researching tourism demand, based on the univariate GARCH model. For example, Chan, Lim and McAleer (2005) used the symmetric CCC-MGARCH, symmetric VARMA-GARCH, and asymmetric VARMA-GARCH to study Australia's tourism demand from the four leading source countries They examined the presence of interdependent effects in the conditional variance between the four leading countries and the asymmetric effect of shocks in two of the four countries. Seo, Park and Yu (2009) applied the multivariate GARCH model to analyses of the relationships in Korea outbound tourism demand. It found that conditional correlation among tourism demand was time-varying.

However, multivariate GARCH model such as the CCC-GARCH, DCC-GARCH, or VARMA-GARCH models are somewhat restrictive due to their requirements of normality for the joint distribution and linear relationships among variables. To account for non-linear and time-dependent dependence, the parameters of the copula functions were assumed to follow dynamic processes conditional to the available information. This study applied four kinds of copula-based GARCH to estimate the conditional dependence structure as a measure of analyzing the time-varying relationship of tourism demand for the leading destinations. Recently, the copula based GARCH model becomes popular in analyzing economic studies, especial in financialPatton (2006); Ane and Labidi (2006); Ning and Wirjanto (2009); Wang, Chen, and Huang (2011); Wang, Chen, and Huang (2011); Chung, and Chang (2012); Reboredo (2011)). As far as we know, there is no study applying copula based-GARCH model to investigate the dependence among tourism demands . Thus, in this study, we fill in the gap in literature by employing the copula-GARCH model to examine dependence amongtourism demands.

3. Econometrics Models.

3. 1. The Model for the Marginal Distribution. The GARCH (1, 1) model can be described as follow:

$$y_{i,t} = c_0 + c_1 y_{i,t-1} + c_2 e_{i,t-1} + \sum_{i=1}^{2} \varphi_i D_{i,t} + e_{i,t} \tag{1}$$

$$e_{i,t} = \sqrt{h_{i,t}} x_{i,t}, x_{i,t} \sim SkT(x_i | \eta_i, \lambda_i) \tag{2}$$

$$h_{i,t} = \omega_{i,t} + \alpha_{ie_{i,t-1}^2} + \beta_i h_{i,t-1} \tag{3}$$

where $D_{i,t}$ are seasonal dummies ($D_{1,t}$ and $D_{2,t}$ are Chinese Spring Festival and summer holiday respectively) and capture the impact of the seasonal effects. The condition in the variance equation are $\omega_i > 0$, $\alpha_i, \beta_i \geq 0$ and$\alpha_i + \beta_i < 0$. In order to capture the possible asymmetric and heavy-tailed characteristics of the tourism demand returns, the error term of $e_{i,t}$ is assumed to be a skewed-t distribution. The density function is followed by Hansen (1994)

$$\text{skewed} - t(x|\eta, \lambda) = \begin{cases} nd\left(1 + \frac{1}{\eta - 2}\left(\frac{nx + m}{1 - \lambda}\right)^2\right)^{-(\eta+1)/2} & , x < -\frac{m}{n} \\ nd\left(1 + \frac{1}{\eta - 2}\left(\frac{nx + m}{1 - \lambda}\right)^2\right)^{-(\eta+1)/2} & , x \geq -\frac{m}{n} \end{cases} \tag{4}$$

The value of m; n, and d are defined as

$$m \equiv 4\lambda d \frac{\eta - 2}{\eta - 1}, n^2 \equiv 1 + 2\lambda^2 - n^2 \text{ and } d \equiv \frac{\daleth(\eta + 1/2)}{\sqrt{\pi(\eta - 2)\daleth(\eta/2)}}$$

where λ and η are the asymmetry kurtosis parameters and the degrees of freedom parameter, respectively. λ is restricted within $(-1,1)$.

3. 2. The Copula Model for Joint Distribution. In this paper we employed two families of copula model to describe the dependence structure between the four destinations that are two elliptical (Gaussian and Student-t copulas) and two Archimedean's copula model (Gumbel and Clayton copulas). The Gaussian copula and Student-t describe the symmetric dependence, while the Gumbel copula and Clayton copula reflect the asymmetric dependence. These copula models and the statistical inference derived from them are briefly discussed below.

The density of the time-varying Gaussian copula is

$$C_t^{Gau}(a_t, b_t|\rho_t) = \frac{1}{\sqrt{1 - \rho_t}} \exp\left\{\frac{2\rho_t x_t y_t - x_t^2 - y_t^2}{2(1 - \rho_t^2)} + \frac{x_t^2 + y_t^2}{2}\right\} \tag{5}$$

The density of the time-varying Student-t copula is

$$C_t^T(a_t, b_t|\rho_t, n) = \frac{1}{\sqrt{1 - \rho_t}} \exp\left\{1 + \frac{-2\rho_t x_t y_t + x_t^2 + y_t^2}{n(1 - \rho_t^2)}\right\}^{-\frac{n+2}{2}} \tag{5}$$

where $x_t = \emptyset^{-1}(a_t)$, $y_t = \emptyset^{-1}(b_t)$, and $\emptyset^{-1}(\cdot)$ denotes the inverse of the cumulative density function of the standard normal distribution. n is degrees of freedom and P_t is the degree of dependence between a_t and b_t, it belong to $(-1,1)$.

The density of the time-varying Gumbel copula is

$$C_t^{Gum}(a_t, b_t|\tau_t) = \frac{(-\ln a_t)^{\tau_t-1}(-\ln b_t)^{\tau_t-1}}{a_t b_t} \exp\left\{-[(-\ln a_t)^{\tau_t-1}+(-\ln b_t)^{\tau_t-1}]^{\frac{1}{\tau_t}}\right\}$$
$$\times\left\{-[(-\ln a_t)^{\tau_t-1}+(-\ln b_t)^{\tau_t-1}]^{\left(\frac{1-2\tau_t}{\tau_t}\right)^2}\right.$$
$$\left.+(\delta_t-1)\left[[(-\ln a_t)^{\tau_t-1}+(-\ln b_t)^{\tau_t-1}]^{\frac{1-2\tau_t}{\tau_t}}\right]\right\} \tag{7}$$

where τ is the degree of dependence between a_t and b_t, and within $[1,+\infty)$, $\tau_t = 1$, shows no dependence and if τ_t increase to infinity which represents a fully dependence relationship between a and b. The Gumbel copula can capture the right tail dependence.

The density of the time-varying Clayton copula is

$$C_t^{Gum}(a_t, b_t|\tau_t) = (\tau_t+1)(a_t^{-\tau_t} \pm b_t^{-\tau_t})^{-\frac{1+2\tau_t}{\tau_t}} a_t^{-\tau_t-1} b_t^{-\tau_t-1} \tag{8}$$

where $\tau_t \in [0,+\infty)$ is the degree of dependence between a_t and b_t, $\tau_t = 0$ implies no dependence and $\tau_t \to \infty$ represents a fully dependence relationship. The Clayton copula can capture the left tail dependence.

In the dynamic Gaussian copula and Student-t copula, we commonly use Pearson's correlation coefficient ρ_t to describe the dependence structure. On the other hand, we use the τ_t on the Gumbel and Clayton copula. The dependence process of the Gaussian and Student-t are

$$\rho_t = \Lambda\left(\alpha_c + \beta_c \rho_{t-1} + \gamma_c (a_{t-1} - 0.5)(b_{t-1} - 0.5)\right) \tag{9}$$

The dependence process of the Gumbel is

$$\tau_t = \Lambda\left(\alpha_c + \beta_c \tau_{t-1} + \gamma_c (a_{t-1} - 0.5)(b_{t-1} - 0.5)\right) \tag{10}$$

The conditional dependence, ρ_t and τ_t determined from its past level, ρ_{t-1} and τ_{t-1}, captures the persistent effect, and $(a_{t-1} - 0.5)(b_{t-1} - 0.5)$ captures historical information. In this aper we change the historical information to $\frac{1}{10}\sum_{i=1}^{10}|a_{t-1} - b_{t-1}|$. We proposed time-varying dependence processes for Clayton copula as

$$\tau_t = \Pi\left(\alpha_c + \beta_c \tau_{t-1} + \gamma_c \frac{1}{10}\sum_{i=1}^{10}|a_{t-1} - b_{t-1}|\right) \tag{11}$$

3. 3. Estimation and Calibration of the Copula. In this paper, we use IFM method to estimate the parameters of our copula-based GARCH mode. The efficiency equation is as followed.

$$\hat{\theta}_{it} = \arg\max \sum_{t=1}^{T} \ln f_{it}\left(x_{i,t}, \theta_{it}\right) \tag{12}$$

$$\hat{\theta}_{ct} = \arg\max \sum_{t=1}^{T} \ln c_{it}\left(F_{1t}(x_{1,t}), F_{2t}(x_{2,t}), \cdots, F_{nt}(x_{n,t}), \theta_{ct}, \hat{\theta}_{it}\right) \tag{13}$$

4. Empirical Result.

4. 1. Descriptive. In order to estimate the dynamic dependence structure of tourism demand in the top destination, this research designated the proxy variable the number of China's tourist arrivals to the following four destinations: Thailand, Singapore, South Korea, and Japan. China monthly tourist arrival data from Jan 1997 to Oct 2011 were used for this study, yielding a total of 178 observations. The data are obtained from Bank of Thailand, Singapore Tourism Board, Japan National Tourist Organization, and Korea Tourism Organization, respectively. China's monthly tourist arrival series are plotted in Figure1., which rises over time and along clear cyclical seasonal patterns, although tourist arrivals fell sharply around the time of SARS (2003) and the global financial crisis (2008 and 2009).

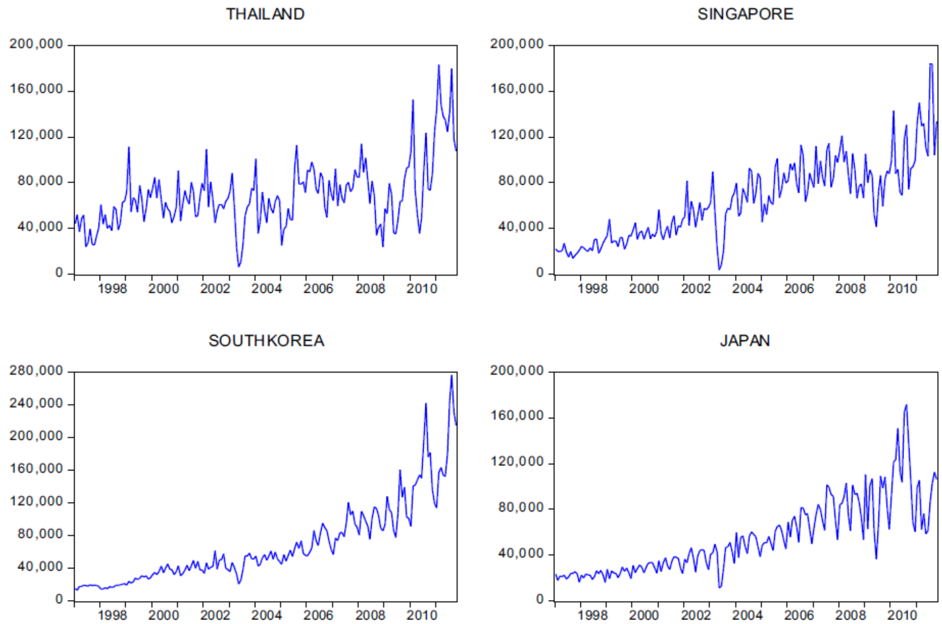

FIGURE 1. Chinese tourist arrivals to each destination

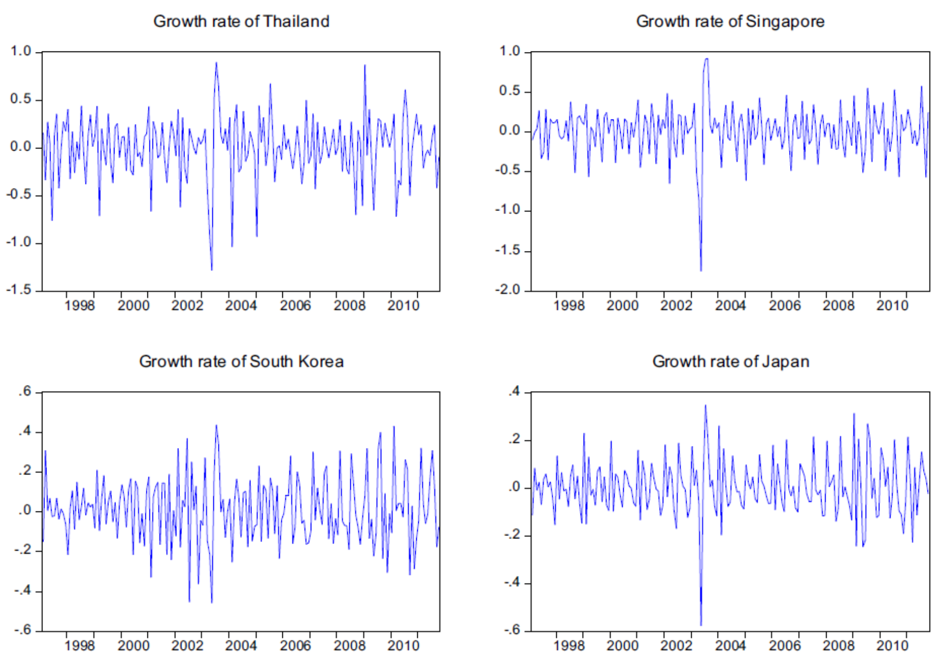

FIGURE 2. Log Chinese tourist arrivals rate

In building a model, most of the economic time series data are processed with the use of the logarithmic transformation. Hence, the monthly tourist arrival return $\mathbf{y_{i,t}}$ is computed a continuous compounding basis as $\mathbf{y_{i,t}} = \mathbf{Ln}(\mathbf{Y_t}/\mathbf{Y_{t-1}})$, where $\mathbf{Y_t}$ and $\mathbf{Y_{t-1}}$ are current and one-period lagged monthly tourist arrivals. $\mathbf{y_{i,t}}$ is $\mathbf{y_{thai,t}}, \mathbf{y_{sing,t}}, \mathbf{y_{korea,t}}$ and $\mathbf{y_{jap,t}}$ as incremental rate of Chinese tourist arrivals in Thailand, Singapore, South Korea, and Japan, respectively. The tourist arrival incremental rates are plot-ted in Figure 2., which show the GARCH model is appropriate for modeling the tourist arrival return. The descriptive statistics for the incremental rate of Chinese tourist arrival for each destination are reported in Table 1, which show that all series have heavy tail and they do not follow normal distribution. Hence, we introduced skewed-t distribution to this paper..

TABLE 1. Summary statistics for the Chinese tourist arrival returns.

	Thailand	Singapore	South Korea	Japan
Mean (%)	0.005006	0.010129	0.014975	0.003711
SD (%)	0.335940	0.315345	0.169541	0.119375
Skewness	-0.708892	-0.959877	0.042120	-0.231925
Excess Kurtosis	4.487008	8.061693	3.007216	5.611665
Max (%)	0.897066	0.923611	0.436791	0.347800
Min (%)	-1.281747	-1.750788	-0.459033	-0.578180
JB	31.13210	216.1332	0.052720	51.89012

The data should be stationary for modeling GARCH model, thus testing unit roots is essential. Augmented Dickey-Fuller (ADF, Dickey & Fuller, 1979) and Phillips-Perron (PP, Phillips & Perron, 1988) can perform the test for unit-root. Table 2 shows the results of unit-root tests. The tests strongly support the null hypothesis of unit-root for the first difference of log-transformed.

TABLE 2. Tests of hypotheses of unit-root.

Variables	ADF		PP	
	Level	Log of first difference	Level	Log of first difference
Thailand	5.1097**	-12.04982**	-4.9886**	-28.3882**
Singapore	-0.3091	-7.43598**	-3.7793**	-40.76052**
South Korea	2.7158	-5.55876**	-0.0980	-33.4513**
Japan	-0.8423	-4.1595**	-4.4855**	-32.9507**

Note: The critical values for the rejection of the null hypothesis of a unit-root are -3.451, and -2.870 for 1% and 5%, respectively. The symbol ** and * denote rejection of the null hypothesis at the 1% and 5% significance levels, respectively.

4. 2. Estimation Results. The estimated result of the GARCH model is reported in Table 3, using a maxi-mum likelihood estimation method. The ARCH coefficient α_i is significant in Thai-land and Japan. These results imply that a shock to the tourist arrival series has short run persistence in Thailand and Japan. All autoregressive coefficients β_i is highly significant. These results imply that a shock to the tourist arrival has long-run persistence in all series. The result of the conditional variance equations are $\hat{\alpha} + \hat{\beta} = 0.9626, 0.9007$ and

0.8027 for Japan, South Korea, and Thailand, respec-tively. The volatilities of these three destinations are highly persistent. However, Singapore does not have such persistence. As can be seen in the variance equation, the asymmetry parameters, λ_i, are significant and negative for Thailand, Singapore, and Japan, but no significance for South Korea, exhibiting that Thailand, Singapore and Japan are skewed to the left. For the seasonal effect, the summer holiday and the Chinese Spring Festival turn out to be quite significant and have positive effects at the all destination in the GARCH.

TABLE 3. Result for Garch model

	GARCH			
	Thailand	Singapore	South Korea	Japan
C_0	-0.0413***	-0.0352***	-0.0151**	-0.0211***
	(0.0134)	(0.0110)	(0.0061)	(0.0037)
C_1	-0.5842***	-0.5626***	-0.3403***	0.0626
	(0.0579)	(0.0583)	(0.1096)	(0.0868)
C_2	-0.7070***	0.6214***	0.2545*	-0.8697***
	(0.0759)	(0.0814)	(0.1449)	(0.0441)
D_1	0.1648***	0.1382***	0.0955***	0.1325***
	(0.0260)	(0.0203)	(0.0165)	(0.0220)
D_2	0.1406***	0.1786***	0.0996***	0.0815***
	(0.0223)	(0.0213)	(0.0140)	(0.0150)
ω_i	0.0028*	0.0040***	0.0004	0.0011
	(0.0017)	(0.0014)	(0.004)	(0.0008)
α_i	0.1916**	0.2331**	0.0456	0.3266
	(0.0941)	(0.1041)	(0.0452)	(0.3488)
β_i	0.6111**	0.3390*	0.8571***	0.6360*
	(0.1556)	(0.1975)	(0.1001)	(0.3332)
η_i	5.4558***	12.3850***	6.0185***	3.7896**
	(1.6542)	(3.5203)	(2.2835)	(1.5674)
λ_i	-0.3668***	-0.3223***	-0.0233	-0.2963**
	(0.1100)	(0.1140)	(0.1180)	(0.1236)

Note that ***, ** and * denote rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

TABLE 4. Test the skewed-t marginal distribution models

	Thailand	Singapore	South Korea	Japan
First moment LB test	0.4885	0.05867	0.06428	0.1185
Second moment LB test	0.2879	0.2119	0.6221	0.7778
Third moment LB test	0.09234	0.12079	0.08118	0.13408
Fourth moment LB test	0.754	0.3643	0.4616	0.91
K-S test	0.9883	0.9852	0.9924	0.9706

Note that this table reports the *p*-values from Ljung-Box tests of serial independence of the first four moments of the variables In addition we presents the *p*-values form the Kolmogorow-Smirnov (KS) tests for the adequacy of the distribution model.

When we model the conditional copula, if the marginal distribution models are mis-specified, then the probability integral transforms will not be uniform (0, 1) and the copula model will maybe automatically be mis-specified. Hence, the crucially important step is to test marginal distribution. In this paper, our test divides two steps. The first step is Ljung-Box test: Ljung-Box test is to examine serial independence, we regress $(x_{i,t} - \overline{x_i})^k$ on 5 lags of the variables for k = 1, 2, 3, 4. Second, Kolmogorow-Smirnov (KS) tests is used to test whether marginal distribution is uniform (0, 1). Table 4 presents the Ljung-Box tests and the Kolmogorow-Smirnov (KS) tests. The skewed-t marginal distribution of four destinations based on GARCH model passes the LB and KS tests at 0.05 level; hence, the copula model could correctly capture the dependency between tourist arrivals.

Table 5 reports the parameter estimates for four copula function-based on the GARCH model. The Table 5 result can be summarized as follows: (1) between Thailand and Singapore, the autoregressive parameter is close to 1, implying that a high degree of persistence pertaining to the dependence structure and the history information parameter is significant and displaying that the latest return information is a meaningful measure in all copula model (except Clayton copula); (2)between Thailand and South Korea, the autoregressive parameter is significant in Gaussian and Gumbel copula, indicating a degree of persistence pertaining to the dependence structure. The history information parameter is not significant in Clayton and implies that latest return information is a meaningful measure in Gaussian, Student-t and Gumbel copula; (3) between Thailand and South Korea, the autoregressive parameter is significant in Gaussian and Clayton copula, while history information parameter is only significant in Gaussian copula. These results show that the latest return information in Gaussian and Clayton copula and history information in Gaussian is a meaningful measure; (4) between Singapore and South Korea, the autoregressive parameter is only significant in Student-t copula, while history information parameter is not significant in all copula. These results show that the just latest return information in Student-t copula is a meaningful measure; (5) between Singapore and Japan, the autoregressive and history information parameter is only significant in Clayton copula. This result implies that the latest return information and history information is a meaningful measure in Clayton copula; (6) between Japan, and South Korea, the autoregressive parameter is significant in Gaussian, Gumbel, and Clayton copula, indicating a degree of persistence pertaining to the dependence structure. History information parameter is significant in Student-t and Clayton copula, indicating the latest return information is a meaningful measure; (7) the degree of freedom is significant in all destination and not very row (from 9 to 141) in the Student-t copula, indicating extreme dependence and tail dependence for all the tourist arrival return.

The dependence parameter estimates between the four destination returns are plotted in Figure 3, Figure 4, Figure 5 and Figure 6. We can observe that different copula generates different dependence structure.

TABLE 5. Result for dynamic Copula--GARCH

	Copula--GARCH					
	Thailand Singapore	Thailand South Korea	Thailand Japan	Singapore South Korea	Singapore Japan	Japan South Korea
Panel A: Estimation of Gaussian dependence structure						
α_c	0.1110**	0.0030	0.0075**	0.1538	0.1012	0.0264***
	(0.0542)	(0.0022)	(0.0030)	(0.1659)	(0.0855)	(0.0064)
β_c	0.7688***	0.9466**	0.9950***	0.4461	0.3704	0.9950***
	(0.0857)	(0.2697)	(0.00564)	(0.5093)	(0.4642)	（0.0775）
γ_c	0.8807***	-0.3037*	0.6691***	0.9643	-0.9462	-1.3039***
	(0.1543)	(0.1588)	(0.1913)	(0.7217)	(0.8911)	(0.1375)
Ln(L)	59.66281	1.384931	3.296107	10.89347	3.32421	9.797367
AIC	-113.3256	3.230139	-0.5922	-15.78694	-0.6484	-13.59473
α_c	0.2533	0.1358	0.2470	0.0232	0.2150	0.4526
	(0.1802)	(0.1419)	(0.3027)	(0.0476)	(0.1817)	(0.3487)
β_c	0.7585***	0.1804	0.0000	0.9413***	0.3410	0.0000
	(0.1347)	(0.2994)	(1.0233)	(0.0813)	(0.4801)	(0.7145
γ_c	3.3614	3.3179*	1.8875	0.6130	-2.0530	2.2645
	(2.7799)	(1.8966)	(2.2273)	(0.7228)	(1.8814)	(2.6400)
n	141.224***	21.1802***	26.653***	12.6041***	76.5050***	9.4572***
	(0.2253)	(1.3286)	(0.9473)	(4.7672)	(0.4491)	(1.1817)
Ln(L)	58.5307	2.385122	2.002171	11.13946	3.345037	7.025383
AIC	-109.0614	3.229756	3.995658	-14.27892	1.309926	-6.050765
α_c	-0.3598***	-18.4926***	-2.0646	-0.02558	-0.0152	0.0976
	(0.1358)	(2.3076)	(3.7409)	(0.75430)	(0.8252)	(0.0830)
β_c	0.5236***	0.2759***	0.2455	0.9955	0.9950	0.9950***
	(0.2201)	(0.0388)	(1.3960)	(0.2766)	(0.3588)	(0.1007)
γ_c	4.0572***	117.0893***	3.2423	0.3337	-0.2562	-6.0301
	(1.4765)	(13.8372)	(6.1443)	(0.3252)	(0.4728)	(6.2675)
Ln(L)	45.43125	10.45262	1.161393	9.427959	2.85591	7.447646
AIC	-84.86251	-14.90525	3.677214	-12.85592	0.2881799	-8.895292
Panel D: Estimation of Clayton dependence structure						
α_c	0.1832	-0.7780	-3.1137**	-0.0874	-5.4474**	-1.8565***
	(0.176)	(0.873)	(1.326）	(0.464)	(2.420)	(0.581)
β_c	0.7778***	0.0328	-0.4706*	0.5596	0.8830***	-0.6992*
	(0.161)	(0.041)	(0.281)	(0.417)	(0.017)	(0.077)
γ_c	-0.6479	-8.3803	-1.3047	-1.7920	13.5870**	-3.3375***
	(0.739)	(7.185)	2.107	(1.812)	(2.2972)	(1.696)
Ln(L)	55.424	3.332	1.345	10.471	5.110	10.362
AIC	-104.8472	-0.6638	3.3106	-14.9429	-4.2206	-14.7233

Note that ***, ** and * denote rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

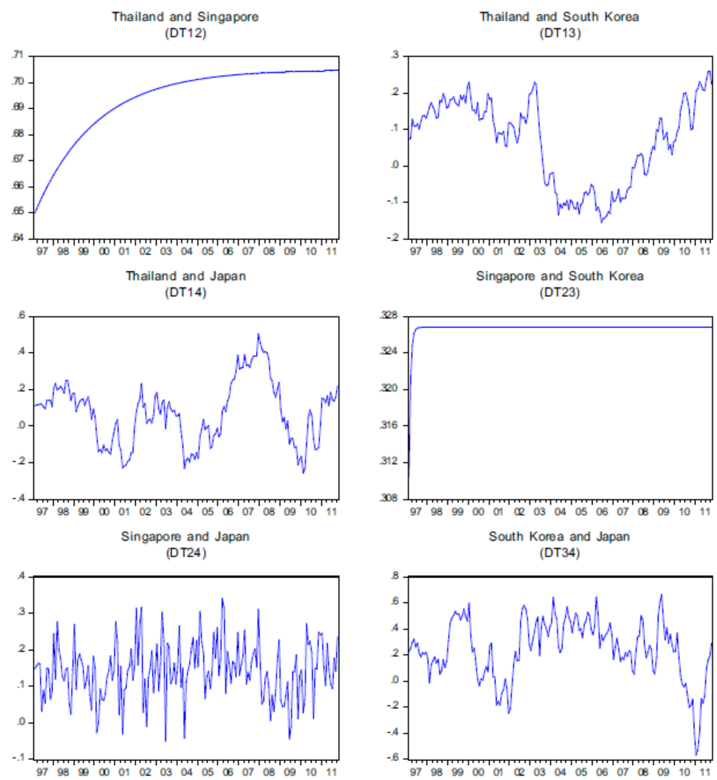

FIGURE 3. Conditional Dependence based estimates Student-t copula-GARCH

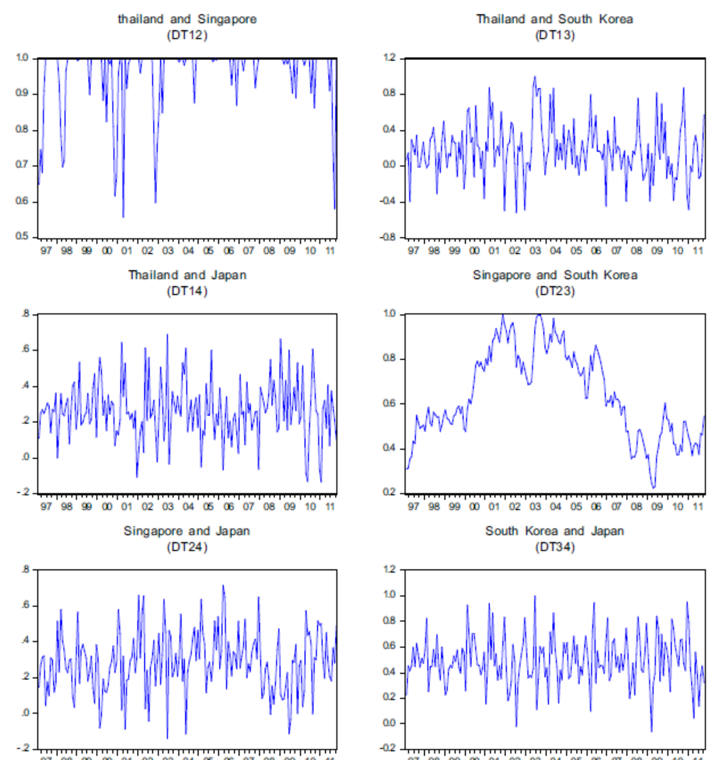

FIGURE 4. Conditional Dependence estimates based Guassian copula-GARCH

The Figure 3 shows the conditional dependence estimates (Pearson's ρ_t) between four destinations based on Guassian copula-GARCH. DT12 and DT23 have the same structure, increasing and stabling at 0.70 and 0.326, respectively. All the dependence structure for tourism demand among four destinations has shown increasing patterns, implying that a positive relationship tends to increase as time progresses. The Figure 4 plots the conditional dependence estimates (Pearson's ρ_t) between the four destinations based on Student-t copula-GARCH. DT12 is higher than other dependence structures and close to 1 at some times, dictating that Thailand and Singapore have a higher correlation and could be recognized as the "complement effect." The reason is their geographic position and the large number of groups of tourists traveling to Thailand and Singapore at the same time. DT13, DT14, DT24 and DT34 have the same structure and shock in 0.05, 0.2, 0.2, and 0.4, respectively. DT23 has a higher relationship from 2000 to 2006.

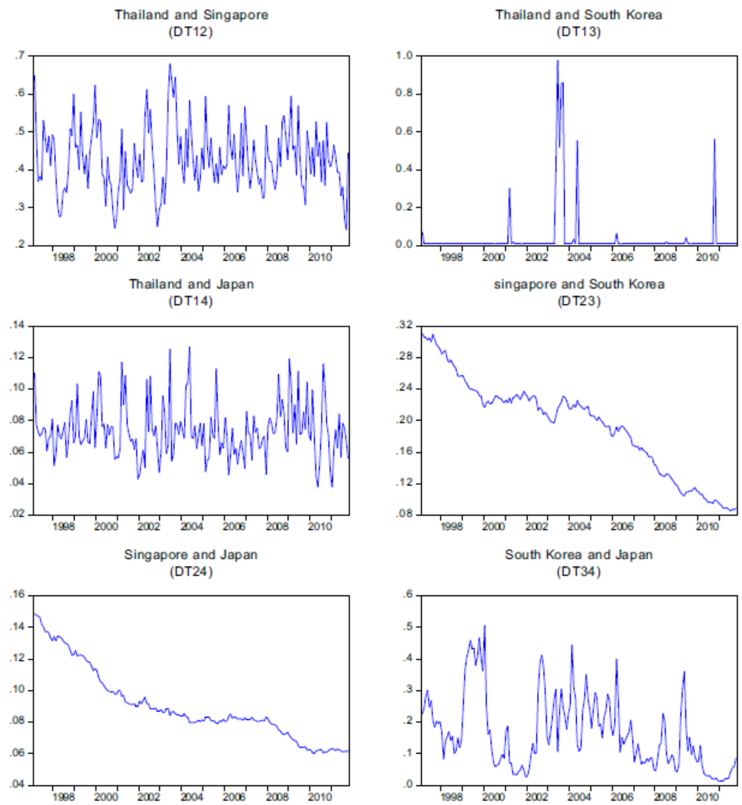

FIGURE 5. Conditional Dependence estimates Gumbel copula-GARCH

The Figure 5 illustrates the implied time paths of the conditional dependence estimates (Kendall's tau) between the four destinations, based on the Gumbel copula-GARCH. The Gumbel copula captures the right tail dependence. All of the conditional dependence changes over time. DT13 is very low and nearly 0.01; it dictates that Thailand and South Korea have a lower correlation. It means that the improbability of Thailand and South Korea tourist market booms at the same time.DT23 and DT24's conditional dependence obviously exhibited negative trends, implying that negative relationship tends to increase as time progresses. The Figure 6 plots the conditional dependence estimates (Kendall's tau) between the four destinations based on the Clayton copula-GARCH. The Clayton copula captures the left tail dependence. DT24 is very low and nearly 0.0001; it dictates that Singapore and Japan have a lower correlation. It means that the improbability of Thailand and South Korea tourist market crashes at the same time.DT13 jumps from 0.01 to 0.24, and DT14 and DT34 shock around at 0.6 and 0.15, respectively.

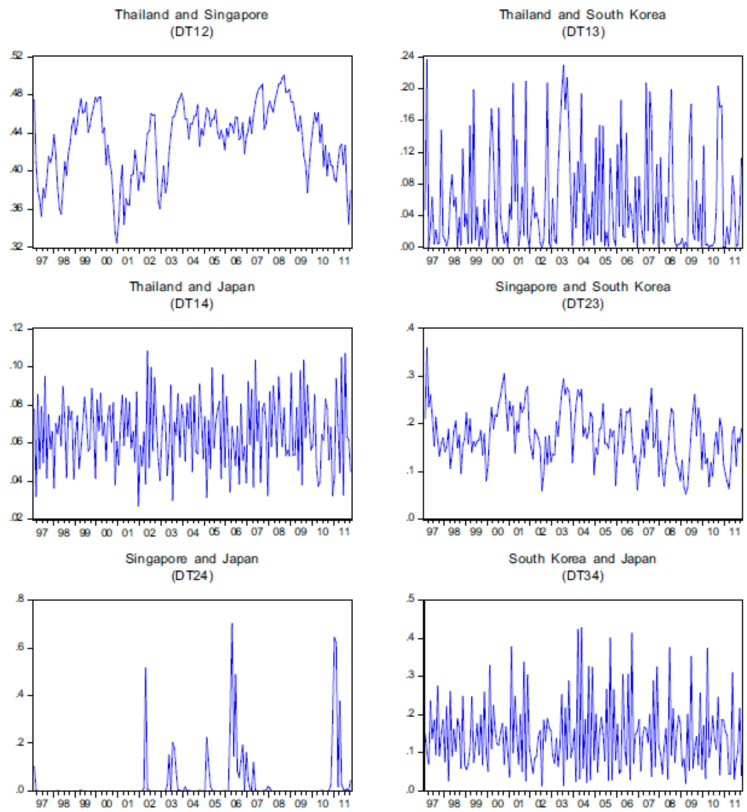

FIGURE 6. Conditional Dependence estimates between four destinations based on Clayton copula-GARCH

TABLE 6. Goodness-of-fit tests for the copula model

	Guassian Copula	Student-t Copula	Gumbel Copula	Clayton Copula
Thailand and Singapore	0.5779	0.7308	0.0034	0.0574
Thailand and South Korea	0.1024	0.1154	0.1414	0.0634
Thailand and Japan	0.6658	0.6778	0.8237	0.2972
Singapore and South Korea	0.5609	0.6449	0.5160	0.6439
Singapore and Japan	0.0365	0.0324	0.0724	0.0045
Japan and South Korea	0.4830	0.6039	0.1743	0.5270

Note: We report the *p*-value from the Goodness of fit tests. A *p*-value less than 0.05 indicate a rejection of the null hypothesis that the model is well specified.

The evaluations of the copula model have become a crucially important step. Therefore, goodness of Fit (GOF) was applied to the copula. This paper used Genest, Remillard, and Beaudoin’s (2009) way to compute approximate P-values for statistics derived from this process consisting of using a parametric bootstrap procedure. Table 6 presents the results of the bivariate Goodness-of-Fit for the copula. These tests revealed that between Thailand and Singapore are not significant in the Gumbel-copula at the 5% level, and between Singapore and Japan is just significant in the Gumbel copula at 5% the level. The others pass the test at 5% level. In terms of the values AIC and the P-value in the table 5 and table 6,respectively, the Guassian dependence structure between Thailand and Singapore, Thailand and Japan and between Singapore and South Korea exhibit better explanatory ability than other dependence structure, the Gumbel dependence structure between Thailand and South Korea, and Singapore and Japan exhibits better explanatory ability than other dependence structure; while the Clayton dependence structure between Japan, and South Korea exhibits better explanatory ability than other dependence structures. These results imply that introducing the tail dependence between the four destinations adds much to the explanatory ability of the model.

5. Implications for Policy Planning and Destination Management. The empirical findings of this study imply that each of the conditional correlation is different between each two destinations and all of the conditional dependence changes over time. Evidently, Thailand and Singapore have the highest conditional dependence. The result indicates that Thailand and Singapore have a complementary relationship. Therefore, the policy makers and destination managers in Thailand and Singapore need to consider forming strategic alliances to develop jointly products and Thailand and Singapore can complement one another to attract China's outbound tourists. They can also consider signing an agreement on visas, like the Schengen visa. It is recommended that they consider signing the Southeast Asian agreement about visa to improve competitiveness.

The results also found that the summer holiday and the Chinese Spring Festival turned out to be quite significant and have positive effects on the all destination. The summer vacation and the spring festival are the Chinese tourism seasons; the competition is fierce between destinations. Therefore, policy makers and destination manager should take some measure, for example, providing a wide range of competitive tour packages; reducing transportation cost and regulating real exchange rates to attract Chinese tourists.

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