APPENDIX A

Dynamic copula-based GARCH model analysis China outbound tourism demand

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Dynamic Copula-Based GARCH Model Analysis China Outbound Tourism Demand

Jiechen Tang, Songsak Sriboonditta, Xinyu Yuan, and Berlin Wu

Abstract This paper used dynamic copula-GARCH model to analysis 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 high volatilities. Furthermore, the conditional dependence is time-varying and different copulas generate different the time path dependence structure. There is seasonal 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

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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 C China (2010). According to the WTO, China placed third position in international tourism spending in 2010 UNWTO Tourism Highlights 2011 Edition (2011). This information highlights that China has became one of most important tourism source country in the global tourism 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 four 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 et al. (2005); Shaeef and McAleer (2005, 2007); Seo et al. (2009); Kim and Wong (2006); Bartolom et al. (2009); Coşkun and Özer (2011); Daniel and Rodrigues (2010)). The univariate the autoregressive conditional heteroskedasticity (GARCH) model was applied in the Shaeef and McAleer (2005), Kim and Wong (2006), Bartolom et al. (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 has a drawback that it cannot examine the conditional correlation or dependence among destination. Hence, Chan et al. (2005), Shaeef and McAleer (2005), and Bartolom et al. (2009) developed multivariate GARCH model for researching tourism demand, based on the univariate GARCH model. For example, Chan et al. (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

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and the asymmetric effect of shocks in two of the four countries. Seo et al. (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 models 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 nonlinear 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, especially in financial (Patton 2006; Ane and Labidi 2006; Ning and Wirjanto 2009; Wang et al. 2011; Wu et al. (2011); 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-basedGARCH model to examine dependence among tourism demands.

3 Econometrics Models

3.1 The Model for the Marginal Distribution

The GARCH (1, 1) model can be described as follows:

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

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

$$h_{i,t} = \omega_{i,t} + \alpha_i e^2{}_{i,t-1} + \beta_i h_{i,t-1} \tag{3}$$

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 $\alpha_i + \beta_i < 1$. 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):

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

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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 then

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

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

$$C_t^T(a_t, b_t|\rho_t, n) = \frac{1}{\sqrt{1-\rho_t}} \left\{1 + \frac{-2\rho_t x_t y_t + x_t^2 + y_t^2}{n\left(1-\rho_t^2\right)}\right\}^{-\frac{n+2}{2}} \tag{6}$$

where $x_t = \phi^{-1}(a_t), y_t = \phi^{-1}(b_t)$, and $\phi^{-1}(.)$ denote 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

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

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where τ is the degree of dependence between a_t and b_t, and within $[1,+\infty)$, $\tau_t=1$, shows no dependent 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

$$C_t^{\text{Glay}}\left(a_t,b_t|\tau_t\right)=\left(\tau_t+1\right)\left(a_t^{-\tau_t}+-b_t^{-\tau_t}\right)^{-\frac{2\tau_t+1}{\tau_t}}a_t^{-\tau_t-1}b_t^{-\tau_t-1}, \tag{8}$$

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 dependent 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 paper, we follow Patton (2006) to use the historical information $\frac{1}{10},\sum_{i=1}^{10}|a_{t-1}-b_{t-1}|$. 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 model. The efficiency equation is as follows:

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

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

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4 Empirical Result

4.1 Descriptive Data

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 Fig. 1, 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).

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 $r_{i,t}$ is computed a continuous compounding basis as $y_{i,t} = \mathrm{Ln}(Y_t/Y_{t-1})$, where Y_t and Y_{t-1} are current and one-period lagged monthly tourist arrivals. $y_{i,t}$ is $y_{\mathrm{thai},t}$, $y_{\mathrm{sing},t}$, $y_{\mathrm{korea},t}$, and $y_{\mathrm{jap},t}$ as incremental rate of Chinese tourist arrivals in Thailand, Singapore, South Korea, and Japan, respectively. The tourist arrival incremental rates are plotted in Fig. 2, which show the GARCH model is appropriate for modeling the

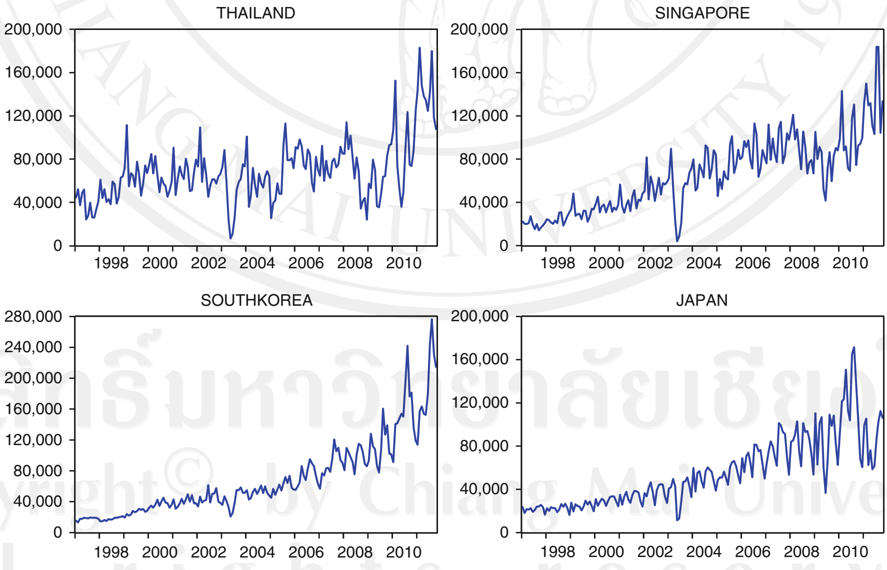

Fig. 1 Chinese tourist arrivals to each destination

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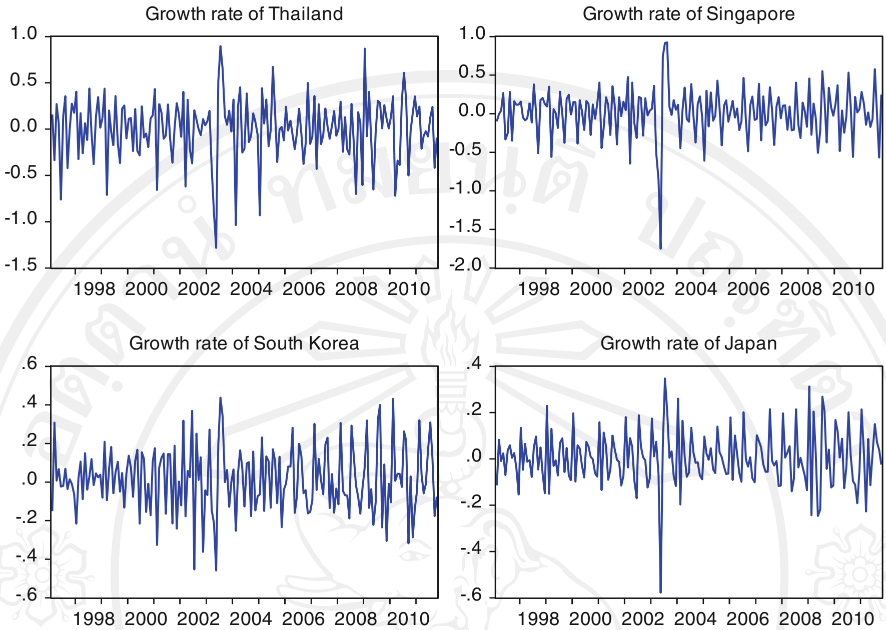

Fig. 2 Log Chinese tourist arrivals rate to four destinations

Table 1 Summary statistics for the incremental rate of Chinese tourist arrival

	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

tourist arrival return.[1] 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.

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 (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.

[1]The large (small) incremental rate is followed by a large (small) incremental rate. It implies that there is a conditional variance processes in the data.

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Table 2 Tests of hypotheses of unit-root

Variables	ADF Level	ADF Log of first difference	PP Level	PP Log of first difference
Thailand	−5.10972**	−12.04982**	−4.98858**	−28.3882**
Singapore	−0.30905**	−7.43598**	−3.77929**	−40.76052**
South Korea	2.71588**	−5.55876**	−0.09804**	−33.4513**
Japan	−0.8423**	−4.5195**	−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

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***	0.1352***
	(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

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4.2 Estimation Results

The estimated result of the GARCH model is reported in Table 3, using a maximum likelihood estimation method. The ARCH coefficient α_i is significant in Thailand 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 are highly significant. These results imply that a shock to the tourist arrival has long-run

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

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, respectively. 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.

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 $(x_{i,t}-\bar{x}_i)^k$ 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

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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*	−0.6991***	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	−0.5922134	−15.78694	−0.6484196	−13.59473
Panel B: Estimation of Student-t dependence structure						
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	3.3719*	1.8875	0.6130	−2.0530	2.2645
	(2.7799)	(1.8966)	(2.2273)	(0.7228)	(1.8814)	(2.6400)
n	141.2247***	21.1820***	26.653***	12.0641**	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
Panel C: Estimation of Gumbel dependence structure						
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	0.1823	−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

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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 every row (from 9 t0 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 Figs. 3–6. We can observe that different copula generates different dependence structure. From figure, we know 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. 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 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. 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.

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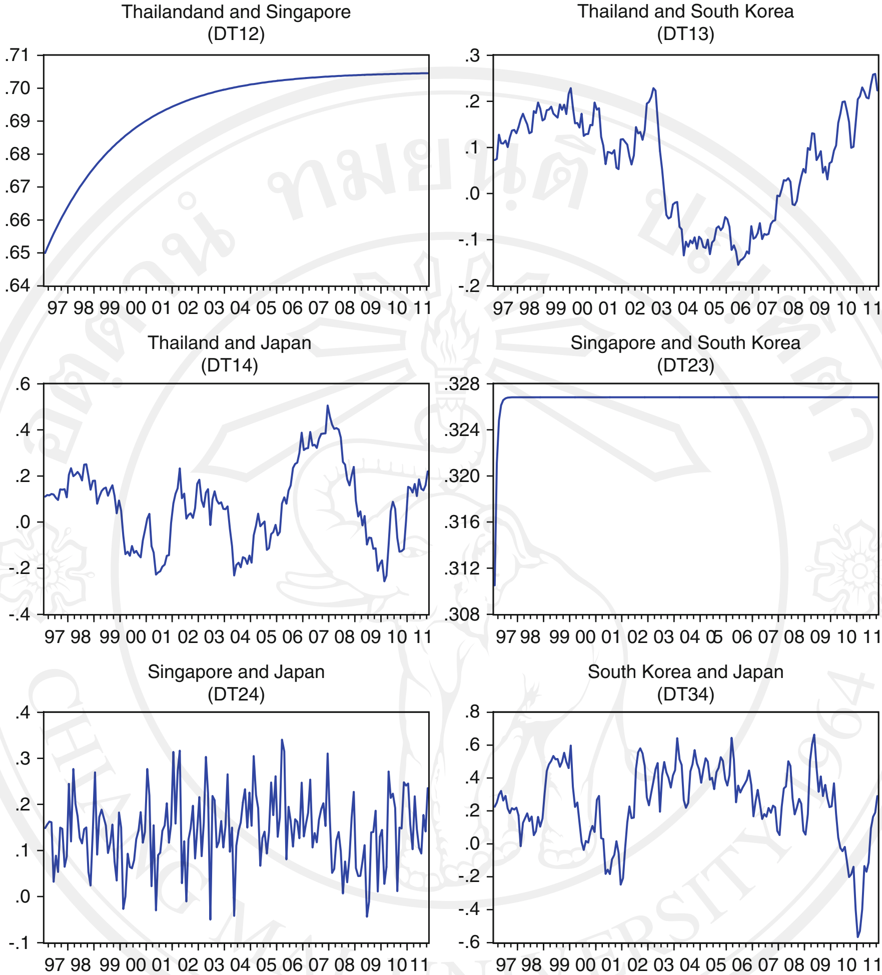

Fig. 3 Conditional dependence estimates between four destinations based on Guassian copula-GARCH

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 Genesta et al. (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 GOF for the copula. These tests revealed that the pair of Thailand and Singapore are not significant in the Gumbel copula at the 5% level, and the pair of 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 Tables 5 and 6, respectively, the Guassian dependence structure

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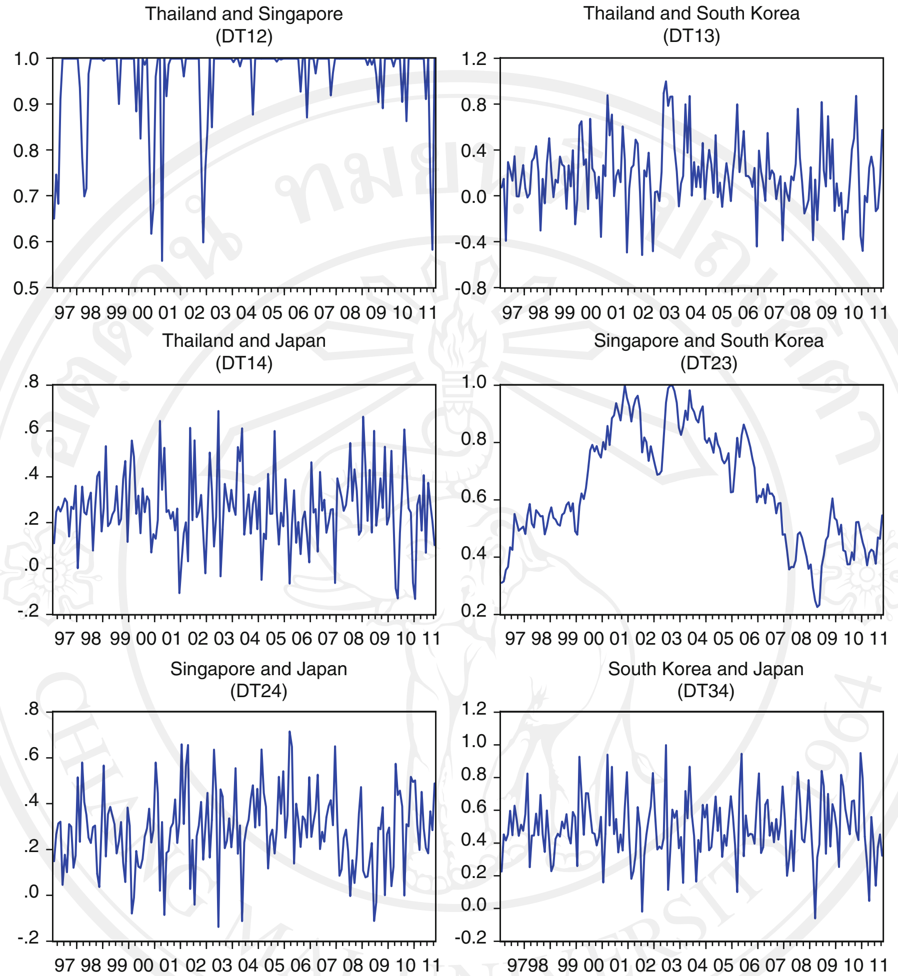

Fig. 4 Four conditional dependence estimates between four destinations based on Student-t copula-GARCH

between Thailand and Singapore, Thailand and Japan, and between Singapore and South Korea exhibits 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.

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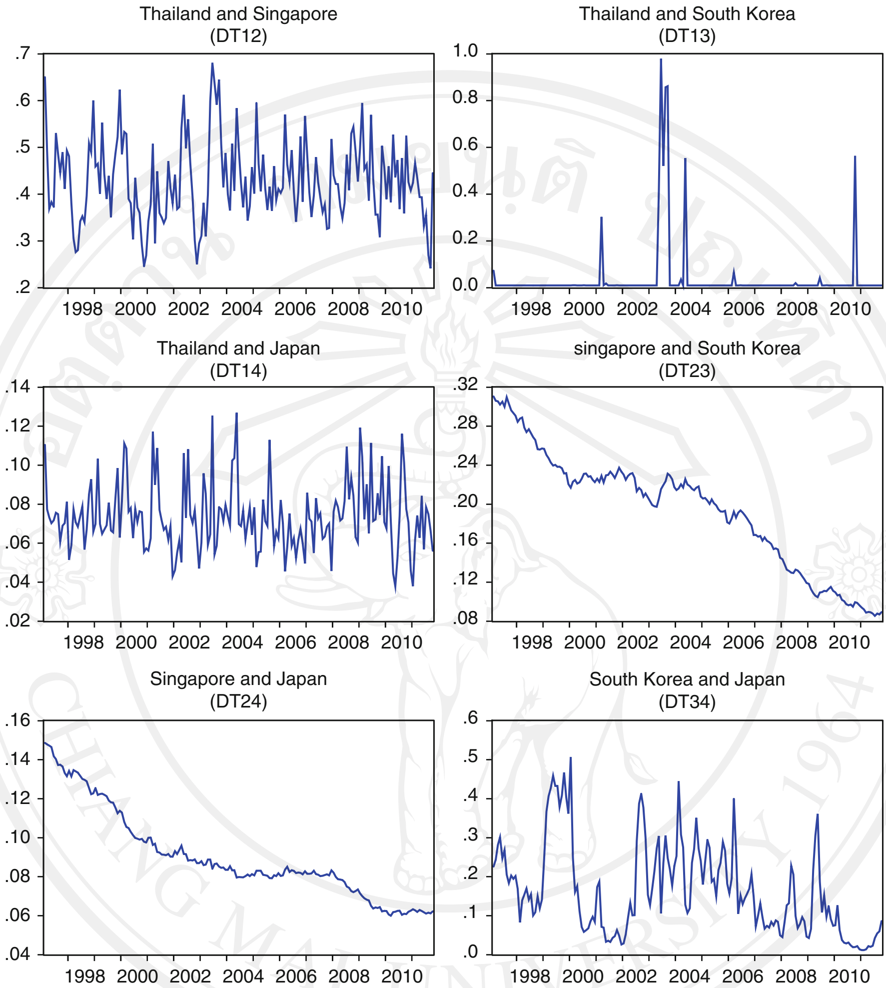

Fig. 5 Conditional dependence estimates between four destinations based on Gumbel copula-GARCH

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

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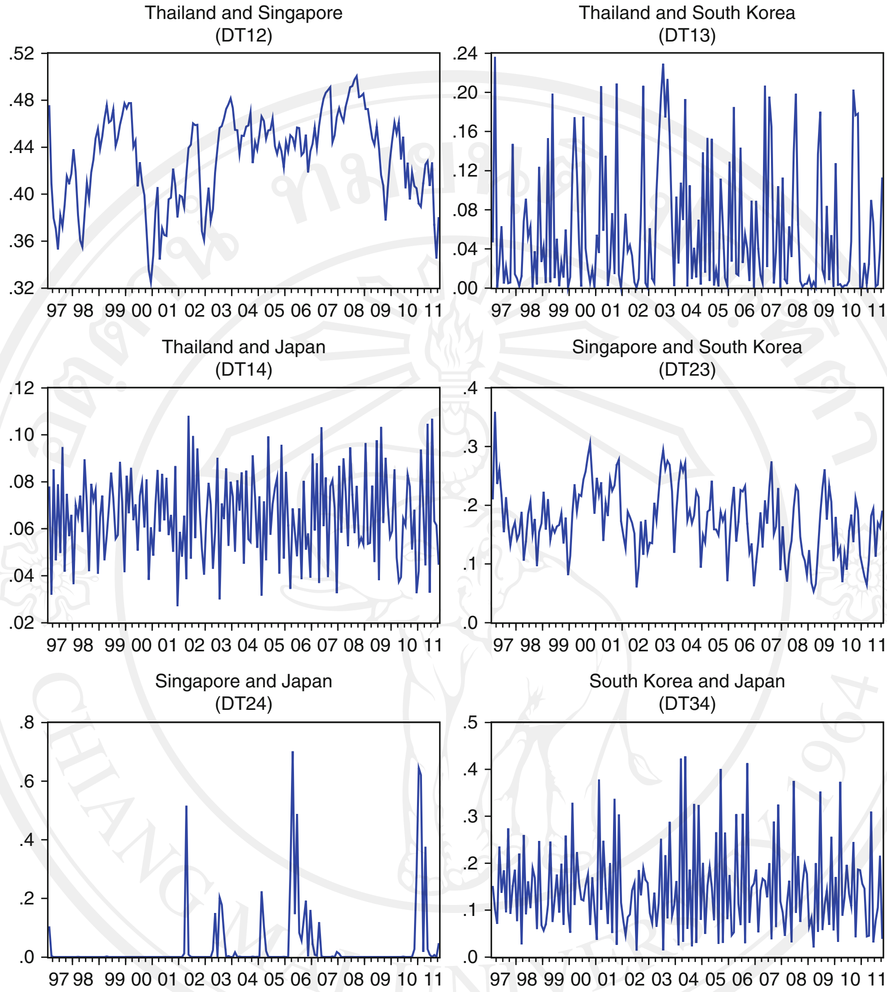

Fig. 6 Conditional dependence estimates between four destinations based on Clayton copula-GARCH

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

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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 indicates a rejection of the null hypothesis that the model is well specified

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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APPENDIX B

Modelling dependence between tourism demand and exchange rate using copula-based GARCH model

Jiechen Tang, Songsak Sriboonchitta, Vicente Ramos and Wing-Keung Wong

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Modelling dependence between tourism demand and exchange rate using copula-based GARCH model

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Modelling dependence between tourism demand and exchange rate using copula-based GARCH model

This paper investigates dependence between tourism demand and exchange rate, using the case of China, and from a new perspective by using copula-GARCH models. The empirical results show that the volatility of exchange rate is not a determinant factor in fluctuation of China's inbound tourism demand from the countries being studied. Furthermore, only Russia exhibit risk adverse behaviour with extreme SUR depreciation, or CNY appreciation associated with a extreme decline in arrivals. Third, introducing the tail dependence and dynamic dependence between growth rates of tourism demand and exchange rate add much to the explanatory ability of the model. The findings of this study have important implications for destination manager and travel agent as it helps to understand the impact of exchange rates on China inbound tourism demand and provide a complementary academic approach on evaluating the role of exchange rates in international tourism demand model.

Keywords: tourism demand; exchange rate; GARCH model; copula; dependence

1. Introduction

By continued development, expansion and diversification, tourism has become one of the world's largest and faster-growing economic sectors in the past few decades. International tourist arrivals reached a record of 1,035 million in 2012 (39 million more than in 2011).[1] According to Tourism Towards 2030, international tourist arrivals worldwide will reach 1.8 billion by 2030. Tourism is one of the most important driving forces of socio-economic development, through export revenues, the creation of jobs and enterprises, and infrastructure development to promote socio-economic progress. UNWTO Headlights (2012) reports that tourism contributes 5% to the worldwide gross domestic product (GDP), and the tourism revenue could be over one-fourth of GDP in some developing countries and small islands. This information highlights that continuous growth of tourism will bring tremendous business opportunities, and thus,

[1] World Tourism Barometer-Advance Release, January 2013.

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tourism market competition could become increasingly fierce.

Webber (2001) points out that tourism is one particular commodity, which is likely to be affected by the exchange rate volatility. Fluctuating exchange rates induce two different effects on the international tourism. First, exchange rate fluctuations may affect international tourist destination choice (Webber, 2001; Akar, 2012), as tourists tend to choose countries in which the exchange rate is more favourable (Wang et al, 2008). The second effect is that the variations of exchange rates are likely to alter visitors' intended length of stay and expenditure. When the destination's currency depreciates, international tourists have more money to spend, and thus, may prolong the length of stay and increase spending (Crouch, 1993). It is, therefore, interesting to study the dependence between exchange rates and international tourism demand.

Based on the motivations discussed above, this study aims to examine the dependence between tourism demand and exchange rates from a new perspective by using several copula-GARCH models. The conditional dependence of the standardized residuals describe show the variations in the exchange rate (destination country's currency with source country's currency) affect the international tourist arrivals from source country to destination country. As far as the authors are aware, no previous empirical paper studied dependence or co-movement between tourism demand and exchange rate and, by extension, no research on the asymmetry of that relation has been done. In order to fill in the gap in literature, this paper introduces both static and dynamic copula-GARCH models in this study. This methodological approach allows the paper to examine the static and dynamic dependence between tourism demand and exchange rate based on monthly data of the top six countries in terms of the number of tourist arrivals to China. Our study represents three main contributions. First, it captures the static and time-varying dependence between tourism arrivals and exchange rates, and investigates the asymmetric and symmetric dependence between these variables. The second contribution is to capture the tail dependence between growth rate of tourist arrivals and exchange rate. Third, there are no previous empirical papers studying dependence or co-movement between tourism demand and exchange rate, this paper will fill this gap.

This paper is organized as follows. Section 2 provides a literature review of the tourism demand and exchange rate. Section 3 describes the copula—GARCH models

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used in the paper. Section 4discusses the data and their properties and Section 5 presents the empirical results with inference. The last section provides some concluding remarks.

2. Literature review

A number of studies have been devoted to investigate the influence of exchange rate on international tourism demand. Crouch (1994a, 1994b) points out that the effect of the exchange rate on tourism demand change from study to study. Main findings can be divided in two groups. Firstly, some empirical studies have found that exchange rate doesn't have significant effects on tourism demand. Vanegas and Croes (2000) apply the linear and the double log linear models on the yearly data from 1975 to 1996 and find that exchange rate variable is not statistically significant for tourism demand from the United States to Aruba. In addition, Croes and Vanegas (2005) specify a dynamic econometric model on annual data from 1975 to 2000 and document that exchange rate had a positive effect on tourist arrivals to Aruba from the United States, the Netherlands and Venezuela, but the coefficient of exchange rate variables is not statistically significantly different from zero except for Venezuela. These two analyses focussed on the main determinants of the tourism demand, they do not greater insight and accuracy analyse the relationship between exchange rate and tourism demand. Quadri and Zheng (2010) apply a regression approach to examine relationship between exchange rates and international arrivals of 19 separate nations from February 2004 through July 2009. They find that exchange rates have no effect on 11 out of the 19 nations being examined. However, Quadri and Zheng use simple regression approach to research causal relationships between the exchange rates and the number of international tourist arrivals to Italy, without dynamic and asymmetric dependence between tourism demand and exchange rate considerations.

On the contrary, other empirical studies have found strong significant effects of the exchange rate on tourism demand. For example, Webber (2001) studies exchange rate volatility and cointegration in Australian outbound tourism demand applying both the Johansen and Engle and Granger procedures on the quarterly data from 1983 to 1997 on the quarterly data from 1983 to 1997. The paper documents that fluctuation in the exchange rate is a significant decisive factor that determines50% of the long-run

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tourism demand. This study is first time to use exchange rate volatility as an explanatory variable in an international context, but there is some drawbacks, for example time-varying and asymmetric dependence is not considered. Adopting a copula approach to study the correlation between tourism demand and exchange rates for some Asian Countries on monthly data from January 2001 to July 2007, Wang et al. (2008) observed that currency appreciation had a greater effect on tourism demand than the currency depreciation. They apply a new method to research tourism demand and exchange rate, , but without asymmetric and dynamic dependence considerations. Kuo et al. (2009) use panel data techniques to research the effect of the exchange rate on tourism demand in eight Asian countries, which monthly data is from January 2001 to July 2007. They find that currency of destination country depreciated relatively to currency of origin country is good for international tourism business of destination country, and vice versa. However, these papers juts focussed only linear relationships between the exchange rates and the number of international tourist arrivals to Italy. In addition, employing the DCC-GARCH and VEC models on monthly data from April 1980 to June 2006, Seo, Park, and Yu (2009) find that exchange rates yield positive or negative impact on conditional correlations. Using the bivariate GARCH approach, Akar (2012) uses DCC-GARCH model on monthly data from January 2001 to November 2010 and finds that tourism demands from the Euro zone and the USA to Turkey are positively related to exchange rates, and tourism destinations are more popular to people from countries where their currency is more valuable. Chan and McAleer (2012) apply the heterogeneous autoregressive model to daily tourist arrivals to Taiwan from January of 1990 to December. They find that the exchange rate has negative effect on tourist arrivals to Taiwan and exchange rate volatility have positive or negative impact on tourist arrivals to Taiwan. Saayman and Saayman (2013) use GARCH models and ADL models to study the relationship between exchange rate volatility and tourism. They find that the volatility of exchange rate is a deterrent for tourism to South Africa from countries such as China France, Brazil and Australia, while the UK, Germany and the USA volatility does not influence arrivals to South Africa. Although these empirical can capture time-invariant and time –varying correlation between in the growth rate of tourist arrivals-exchange rate as well as some of these stylized facts of growth rate distributions such as volatility persistence, but it

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still do not avoid the drawbacks of linear measures of dependence and asymmetric dependence. This is a critical drawback, since the nonlinear and asymmetric relations have become important issue in recent years.

In order to remedy the drawbacks mentioned above, this paper is from a new perspective by several copula-GARCH models to investigate conditional dependence between tourism demand and exchange rate, which can capture nonlinear, symmetric, asymmetric and dynamic dependence. The application of copula approach to analyse economic issues started at the beginning of the twenty-first century. For example, Patton (2001) is one of the earliest papers to use the copula based GARCH model to analyse exchange rate dependence. Later, Jondeaua and Rockingerb (2006) apply copula base GARCH-skewed Student-t model to international stock market and find that the conditional dependency between European markets changes over time and increases significantly and subsequently to movements in the same direction during a crash or boom.

Recently, the copula based GARCH model became popular for the analysis of economic issues, especially related with financial economics. For example, Ning and Wirjanto (2009) measure dependence in East-Asian stocks using copula approach. Wang, Chen, and Huang (2011) apply the dynamic copula based-GARCH model to examine the dynamic dependence between China's stock market and other international stock markets. Wu, Chung, and Chang (2012) study the co-movement between oil price and exchange rate by using copula based GARCH model. Reboredo (2011, 2012) also uses copula approach to study the co-movement between oil price and exchange rate. In addition, Zimmer (2012) applies six various copula specifications to measures conditional dependence between price changes at different geographic areas. He finds out that there is a stronger conditional dependence among housing prices in different states, and that the Clayton-Gumbel mixture copula fits the data better than the Gaussian copula. As far as the authors are aware, there is no previous published study applying copula based-GARCH model to investigate the dependence between tourism demands and exchange rates. The copula-GARCH model can capture the static and time-varying dependence between tourism demand and exchange rates, as well as investigate the asymmetric and symmetric dependence between these variables.

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3. Econometric model

This paper uses several static and dynamic copula models to study the relationship between China inbound tourism from six countries and their exchange rates variations. The models provide a flexible method to estimate multivariate distributions, the corresponding marginal distributions and the dependence structures. This section briefly reviews the basic properties of the copula based GARCH model.

3.1The model for the marginal distribution

The ARMA (p, q)—GARCH (1,1) model of $r_{s,t}$ for country s at time t can be described as follows:

$$r_{s,t} = c_s + \sum_{i=1}^{p} \phi_{s,i} r_{s,t-i} + \sum_{j=1}^{q} \theta_{s,j} e_{s,t-j} + e_{s,t},$$

$$e_{s,t} = \sqrt{h_{s,t}} z_{s,t}, z_{s,t} \sim SkT\left(z_{s,t} \middle| \xi_s, \lambda_s\right), \tag{1}$$

$$h_{s,t} = \omega_s + \alpha_s e^2{}_{s,t-1} + \beta_s h_{s,t-1},$$

where $r_{s,t}$ could be the growth rate of tourism demand or exchange rate, $\phi_{s,i}$ is the ith lag autoregressive (AR) parameter for $r_{s,t}$ to capture the impact of nonsynchronous effects, and $\theta_{s,j}$ is the jth lag moving average (MA) parameter. The restrictions in the variance equation include $\omega_s > 0$,$\alpha_s, \beta_s \geq 0$, and α_s+$\beta_s < 1$. The error term $e_{s,t}$is assumed to follow a skewed-t distribution. The skewed-t distribution (Fernandez and Steel, 1998) with λ_s degrees of freedom (DoF) has the following density:

$$skewed - t\left(z_{s,t} \middle| \xi_s, \lambda_s\right) = f\left(z_{s,t}\right) = \begin{cases} \frac{2}{\xi_s + \frac{1}{\xi_s}} f(\xi_s z_s), z_s < 0, \\ \frac{2}{\xi_s + \frac{1}{\xi_s}} f(\frac{z_s}{\xi_s}), z_s \geq 0, \end{cases} \tag{2}$$

where ξ_s is the skewness parameter. Whenξ_s is smaller (greater) than one, it is skewed to the left (right). If ξ_s=1, the skew-t distribution becomes the commonly used Student's t distribution.

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3.2The copula model for the joint distribution

This study will use several copula models to measure the dependence structure of growth rates between tourism demand and exchange rate. The paper uses six static specifications to capture dependence structure. These copula models and their statistical inference will be briefly described in this section.

From Jondeau and Rockinger (2002), the Gaussian copula is

$$C_{\rho}^{Gau}(u, v|\rho) = \Phi_{\rho}(\Phi^{-1}(u), \Phi^{-1}(v)\ ), \tag{3}$$

Where$\Phi_{\rho}$is the bivariate standard normal cumulative distribution function (CDF) with correlation ρ between u and v, $\Phi^{-1}(u)$ and $\Phi^{-1}(v)$are standard normal quantile functions, and $\rho \in (-1,1)$ measures the dependence between u and v.The Student-t copula is defined as

$$C_{\rho}^{Stu}(u, v|\rho, n) = t_{\rho,n}[t_n^{-1}(u), t_n^{-1}(v)], \tag{4}$$

where $t_{\rho,n}$ is the bivariate Student-t CDF with correlation$\rho \in (-1,1)$ and n (DoF), and $t_n^{-1}(u)$and $t_n^{-1}(v)$ are the univariate Student-t quantile functions. When $n \to \infty$, the Student-t copula converges to the Gaussian with zero dependence on both tails. Both Gaussian and Student-t copulas describe the symmetric dependence. But there is a different feature between them, as the Gaussian copula does not have either left tail or right tail ($\lambda_L = \lambda_R = 0$). While the characteristic of the Student-t copula is that it has non-zero dependence (or extreme-value dependence) in right and left tail, $\lambda_L = \lambda_R \neq 0$ (see Embrechts, Lindskog and McNeil, 2003).

In addition, the Plackett copula (Nelsen, 1999) given by

$$C_{\tau}^{Pla}(u, v|\tau) = \frac{1}{2(\tau-1)}\left(1 + (\tau-1)(u+v)\right)$$

$$-\sqrt{\left(1 + (\tau-1)(u+v)\right)^2 - 4\tau(\tau-1)uv}, \tag{5}$$

reflects symmetric dependence similar to what the Gaussian copula does. The degree of dependence τ belongs to $[0, +\infty)$. $\tau = 1$infers independence between u and v, $\tau \to 0$ represents perfectly negative dependence, and $\tau \to \infty$ indicates perfectly positive

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dependence.

The Frank copula (Nelsen, 1999) defined as

$$C_\tau^{Fra}(u,v|\tau) = -\frac{1}{\tau} ln\left(1 + \frac{(e^{-\tau u}-1)(e^{-\tau v}-1)}{e^{-\tau}-1}\right), \tag{6}$$

measures the symmetric dependence with $\tau \in [-\infty, +\infty)$.When $\tau = 0, u$ and v are independent; when $\tau > 0$, they are positively dependence; and when $\tau < 0$, they are negatively dependence.

On the other hand, both Gumbel and Clayton copulas are useful to model asymmetric dependence. To capture the right tail dependence (which is also called upper tail, it means upper side tail not equal to zero $\lambda_R \neq 0$, while low side tail equal to zero$\lambda_L = 0$).The Gumbel copula (Gumbel, 1960) is defined as

$$C_\tau^{Gum}(u,v|\tau) = exp\{-(\tilde{u}^\tau + \tilde{v}^\tau)^{1/\tau}\}, \tag{7}$$

where $\tilde{u} = -ln(u), \tilde{v} = -ln(v)$, and $\tau \in [1, +\infty)$ is the dependence between u and $v. \tau = 1$ shows no dependence, $\tau > 1$ shows positive dependence, and $\tau \to \infty$ represents a fully dependence relationship between$u$ and v.

Finally, to capture the left tail dependence(which is also called low tail, it means upper side tail equal to zero $\lambda_R = 0$, while low side tail not equal to zero $\lambda_L \neq 0$), the Clayton copula (Clayton, 1978) is defined as

$$C_\tau^{Clay}(u,v|\tau) = (u^{-\tau} + v^{-\tau} - 1)^{\ -1/\tau}, \tag{8}$$

where $\tau \in [0, +\infty)$ is the degree of dependence between u and $v. \tau = 0$ would indicate no dependence, while the increase of the value of τ indicates the increase of the dependence between u and v.

3.3 The Dependence parameters of the time-varying copula

As dependence for the copula described above is assumed to be time invariant, we considered dynamic dependence for Gaussian copula by assuming that the copula dependence parameters vary according on the lag-one dependence ρ_{t-1} and historical

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information $(u_{t-1} - 0.5)(v_{t-1} - 0.5)$(Wu, Chung, and Chang, 2012)[2]. The dependence process follows:

$$\rho_t = \Lambda(\alpha_c + \beta_c \rho_{t-1} + \gamma_c (u_{t-1} - 0.5)(v_{t-1} - 0.5)) \tag{9}$$

where ρ_t is determined from ρ_{t-1} to capture the persistence effect and $(u_{t-1} - 0.5)(v_{t-1} - 0.5)$ capture historical information. In the dynamic copula, $\Lambda = -ln[(1 - x_t)/(1 + x_t)]$ is the logistic transformation, which is used to ensure that the dependence parameter falls within the interval (-1, 1).

3.4 Estimation and calibration of the copula.

This paper follows Jeo and Xu (1996) and others in using the two-step ML procedure in the estimation (it is called inference function for marginal (IFM) method). The first step is to use equation (10) to obtain the maximum likelihood (ML) estimates of the parameters of the marginal distribution, and then the method applies equation (11) to estimate the parameters of copula. The efficiency equations are:

$$\hat{\theta}_{st} = argmax \sum_{t=1}^{T} lnf_{st}(z_{s,t}, \theta_{st}), \tag{10}$$

$$\hat{\theta}_{ct} = argmax \sum_{t=1}^{T} lnc_{st}(F_{st}(z_{1,t}), F_{st}(z_{2,t}), \theta_{ct}, \hat{\theta}_{st}). \tag{11}$$

4. Data Description

This study uses the case of China because China has become one of the most important tourism destinations in the world tourism. According to World Tourism Organization (UNWTO 2012), China is the third (3.4% worldwide market share) and fourth (5.86% worldwide market share) in inbound tourism arrivals and receipts in the world, respectively. The empirical analysis of dependence is applied to monthly data of

[2]If both $\mu_{t-1}$and v_{t-1} are either smaller or larger than 0.5, this infer that the dependence at time t is higher than previously. (see Wu, Chung, and Chang, 2012).If that is not the case, then the dependence at time t is lower than previously.

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tourism arrivals to China[3]from South Korea, Japan, Russia, USA, Malaysia, and Singapore and the corresponding exchange rates from January 1994 to December 2011.The exchange rate is defined as the amount of CNY per unit of foreign currency. Hence, a rise of the exchange rate, infers a depreciation of the CNY or an appreciation of the other currency.

The choice of the six countries is justified as those are the top countries in terms of the number of tourist arrivals to China, these source countries counting for the vast majority of China inbound tourism[4]. The monthly data of tourist arrivals are obtained from the National Bureau of Statistic of China, and the exchange rates are obtained from International Financial Statistics of the Federal Reserve Board. Figure 1 plots the monthly series of China inbound tourist arrivals from the six leading source countries. The figure exhibits that China inbound tourist arrivals increase over time in general, although it falls sharply around 2003 due to SARS, and the sub-prime crisis in 2008 and 2009. The figure also displays clear seasonal and cyclical movements. To measure the general trend of each series, seasonality is eliminated by employing X-12 ARIMA method[5]. Then, a logarithmic transformation of the data is applied to stabilize the increase of their volatility over time. Thereafter, this paper uses $r_{1,t} = Ln(Y_t/Y_{t-1})$ and $r_{2,t} = Ln(P_t/P_{t-1})$ to measure the growth rates of the monthly tourist arrivals and their exchange rates, respectively, in which Y_t and P_t are the seasonal adjusted tourist arrival and exchange rate at month t. The growth rates of the tourist arrivals and exchange rates are plotted in Figures 2 and 3, respectively. The figures suggest that there are

[3]China inbound tourism means non-residents travel to China for leisure, business, and other purposes.

[4] According National Bureau of Statistic of China, top six source countries in 2010 are South Korea, Japan, Russia, USA, Malaysia, Singapore, respectively.

[5]X-12ARMAmethod proposed by the U.S. Census Bureau is the most commonly used method for seasonal adjustment. Readers may refer to Findley, Monsell, Bell,Otto, and Chen (1998) for more methodological details about X-12 ARIMA.

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conditional variance processes in the data, and thus, the GARCH model is appropriate for analysing the growth rate of both tourist arrivals and their exchange rate.

[Figure 1 near here]

[Figure 2 near here]

[Figure 3 near here]

In additional, the descriptive statistics of monthly growth rates of tourist arrival and exchange rates are given in Table 1. The results show that the mean of South Korea (+0.0055), CNY/USD (-0.0027), CNY/MYR (-0.0034) and CNY/SGD (-0.0023) growth rates pass the 0.1 significant levels, which show these four series are significant in mean. The third column of Table 2shows that most of the series are significant and skew to the left, except CNY/JPY (+0.5711) and CNY/SGD (+0.3805) which are significant skew to the right. All series are significantly greater than 3 in kurtosis, inferring that all series are fat-tailed and sharp in their peaks. In addition, the normality hypothesis for all series is rejected at the 5% significant level based on the results of the JB test. All these result show all series do not follow normal distribution and support the use of the skewed-t distribution in our study.

[Table 1 near here]

Since it is necessary for the series to be stationary to conduct the GARCH analysis, the results of augmented Dickey-Fuller (ADF, Dickey and Fuller, 1979) and the augmented Dickey-Fuller generalized least squares (ADF-GLS test, Elliott, Rothenberg, and Stock ,1996) unit root tests are displayed in Table 2. The results suggest that most of the logarithms ($Ln(Y_t)$and $Ln(P_t)$) of the data contain unit roots while their growth rates ($r_{1,t} = Ln(Y_t/Y_{t-1})$ and $r_{2,t} = Ln(P_t/P_{t-1})$) are stationary. The ADF and ADF-GLS tests do not consider structural break in time series, so Zivot-Andrews (ZA, Zivot and Andrews,1992) test is used in this papers.[6] The test statistics are reported in Table 3. We can find that the unit root tests with structural breaks indicate growth rates ($r_{1,t} = Ln(Y_t/Y_{t-1})$ and $r_{2,t} = Ln(P_t/P_{t-1})$) are stationary,

[6] The ZA unit root test considers structural break(s) in the intercept, linear trend or both (Zivot and Andrews, 1992).

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which is consistent with the results based on previous ADF and ADF-GLS tests. Hence, the test results suggest that the use of growth rates in this analysis is appropriate.

[Table 2 near here]

5. Empirical result

5.1 Results of the marginal models

The empirical analysis starts with the estimation of the ARMA (p, q)—GARCH (1,1) models by using the maximum likelihood estimation method and by considering different combinations of the values of the parameters p and qranging from zero to a maximum of two lags. In addition, Akaike information criterion is adopted to select the most suitable models. Table 3 reports the parameters of ARMA (p, q)—GARCH (1,1) for growth rates of tourist arrivals from the six source countries and Table 4 reports parameters of ARMA (p, q)- GARCH (1,1) the growth rates of their exchange rates.

[Table 3 near here]

ARMA (0,1)—GARCH (1,1) specification is proven to be the best model for South Korea, Japan, and Malaysia, while ARMA (1,1)—GARCH (1,1) is more appropriate for Russia, USA, and Singapore. The results for the growth rates of tourist arrivals shown in Table 4 indicate that the estimate of the ARCH coefficient, α_s, is significant for all series except Russia, with South Korea attaining the highest value of 0.8279. On the other hand, the estimate of the GARCH coefficient, β_s, is not significant for South Korea and Japan, with Russia attaining the highest value of 0.9889. These results imply that there is short run persistency of shocks on tourist arrivals in all series except Russia and long run persistence in Russia, the USA, Malaysia, and Japan. The results of the conditional variance equations are $\hat{\alpha} + \hat{\beta} = 0.9990$ and 0.9408 for USA and Singapore, respectively, inferring that the volatilities of these two series are highly persistent. In general, the skewness parameter ξ_s and the degrees of freedom $\lambda_s$in the skewed-t distribution for all the series are significant, suggesting that the error terms are not normal and applying the Skew-t distribution is suitable. This is consistent with the evidence reported in Table 1.

[Table 4 near here]

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In addition, Table 4 exhibits the results for the growth rates of the exchange rates. The best model for all the series is ARMA (1,1)—GARCH (1,1) specification. The estimate of the GARCH coefficient, β_s, is significant in all series, while the estimates of the ARCH coefficient, α_s, are insignificant only for CNY/KRW and CNY/JPY. This information shows that an exchange rate growth rate shock has long run persistence in all series, while a shock to the growth rate of CNY/SUR, CNY/USD, CNY/MYR, and CNY/SGD has short run persistence. The conditional variance equations for almost all the series are nearly 1, except the exchange rate of CNY/KRW, inferring that the volatilities of these series are highly persistent. Furthermore, the skewness parameter ξ_s and the degrees of freedom λ_s are strongly significant, suggesting that the error terms are not normal and applying the Skew-t distribution is suitable. The results are also is consistent with the evidence report in Table 1.

[Table 5 near here]

The marginal distribution must be uniform (0, 1), otherwise the copula model may be mis-specified. Hence, the crucial step is to test the marginal distribution. Following Patton (2006) this paper uses two steps for this purpose. First, Ljung-Box (LB) test is used to examine the serial independence. Secondly, the Kolmogorow-Smirnov (KS) test is used to test whether the marginal distribution is uniform (0, 1). The result of LB and KS test summary in Table 5, which show all series are not rejected at the 5% significance level, which prove these are not mis-specified. Hence, the copula model can correctly capture the dependence between the growth rates of the tourist arrivals and the exchange rates.

5.2 Copula estimates of dependence

The results for the static copulas report in panel A of Table 6 in which the dependence parameter is assumed to be constant over time. Examining the symmetric copulas in the panel A of Table 6, for the dependence parameters in the Gaussian, Student-t and Frank copulas are positive in South Korea-CNY/KRW, Russia-CNY/SUR, USA-CNY/USD and Singapore-CNY/SGD pairs and negative in Japan-CNY/JPY and Malaysia-CNY/MYR pairs, but all dependence are weak and not significant. The dependence varied across pairs of growth rates of tourist arrival and exchange rate. The degree of freedom for Student-t copula is lower in Russia-CNY/SUR pair, which suggests that

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only Russia-CNY/SUR have tail dependence. In the Plackett copula, the result is consist with result of Gaussian, Student-t and Frank copulas, while all the dependence parameters τ are significantly. In order to study the asymmetric dependence, Gumbel copula is applied to capture the right tail dependence and the Clayton copula to capture the left tail dependence. Note that there are no estimates of the dependence τ for Japan and Malaysia. This shows that there is not right tail dependence $\lambda_U$for Japan and Malaysia. The dependence parameters in Gumbel copula are significant in South Korea-CNY/KRW, Russia-CNY/SUR, USA-CNY/USD and Singapore-CNY/SGD pairs. The right tail dependence values for the Gumbel copula, $\lambda_U = 2 - 2^{1/\tau}$, are 0.0369 for South Korea-CNY/KRW, 0.0339 for Russia-CNY/SUR, 0.0781 for USA-CNY/USD, and 0.0188 for Singapore-SGD, respectively. Only the estimate for Russia is significant at 10% in Clayton copula, which shows that between Russia and CNY/SYR have a left tail dependence, $\lambda_L = 2^{-1/\tau}$, the values is 0.0033. Panel B of Table 6 reports the results of the application of the dynamic copula function based on the GARCH model. According to AIC criterion, the dynamic of the dependence parameter can improve the performance of the static copula for Japan-CNY/JPY, USA-CNY/USD, Malaysia-CNY/MYR and Singapore-CNY/SGD pairs in dynamic Gaussian copula. While the static Clayton is the best performer for South Korean-CNY/KRW and Russia-CNY/SUR.

[Table 6 near here]

Overall, the results from the copulas could draw the following interesting conclusions:1) the growth rates of inbound tourism demand and exchange rates are weak negative correlated for Japan and Malaysia and weak positive correlated for all other countries, but the coefficients of correlations are not statistically significantly. 2) There are not extreme dependence Japan-CNY/JPY, USA-CNY/USD, Malaysia-CNY/MYR and Singapore-CNY/SGD pairs, which imply extreme movements of CNY/JPY, CNY/USD, CNY/MYR and CNY/SGD, do not cause extreme movements of Japan, USA, Malaysia and Singapore outbound tourism demand to China, respectively.3) There are a lower tail dependence in Korean-CNY/KRW and Russia-CNY/SUR pairs, but the lower tail dependence is not significant and near zero in Korean-CNY/KRW pair. The significant lower tail dependence for Russia-CNY/SUR weak support that when the currency of tourists from south Russia depreciates, or CNY

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appreciates, tourists from Russia are less willing to choose China as their traveling destination. 4) The static Clayton for the South Korea-KRW/CNY and Russia-CNY/SUR and the dynamic Gaussian copula for Japan-JPY/CNY, USA-CNY/USD, Malaysia-MYR/CNY and Singapore-CNY/SGD perform better than the other models, which infer that introducing the tail dependence for South Korea-KRW/CNY and Russia-CNY/SUR and dynamic dependence for the remainder four pairs between growth rates of tourism demand and exchange rate add much to the explanatory ability of the model.

[Figure 4a near here]

[Figure 4a near here]

In order to get a better picture of the time-varying evolution, this paper plots the dynamic dependence parameter estimates between tourist arrivals and exchange rate growth rates over the sample period generated from GARCH-copula model in Figures4a and 4b. In addition, to check whether the estimates are significant, this paper plots the 10% significant level in the figures[7]. It can be observed that growth rates of tourist arrivals from different source countries and the related exchange rate have different conditional dependence structure. Interesting results from the figures of dynamic copula can be summarized as: 1) The conditional correlation of the tourist arrivals for different source countries with their corresponding exchange rate growth rates varies over time. 2) It is significantly positive in some periods, significantly negative in other periods, and not significant in some other time periods.

[Figure 4 near here]

5.3 Goodness-of-Fit for copula and comparisons

The last section of the empirical part of the paper presents the Goodness-of-Fit (GOF) tests to prove that the copula can fit well to the variables. The paper follows the

[7]Testing no correlation between *u* and *v*: $H_0: \rho = 0$: $H_1: \rho \neq 0$. With the $\alpha = 0.10$, we get the critical value of 10%$\pm t_{n-2} \times \sqrt{\frac{1}{n-2}}$. If the dynamic conditional dependence lie beyond critical value of 10%, the dynamic conditional dependence is significant at 10% level.

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approach recommended by Genest, Remillard and Beaudoin's (2009) by estimating the p-values of the bivariate Goodness-of-Fit for different copulas and exhibits it at Table 7. These tests reveal that all the growth rates' pairs are significant for all copulas used in our paper at the 5% level, inferring that all the copulas used in this paper can fit all the pairs very well.

[Table 7 near here]

6. Conclusion and implication

This study examines the dependence between exchange rates and tourism demand from a new perspective by applying the copula-GARCH model. To account for tail independence, tail dependence, time-invariant, and time-variant dependence, abroad family of copulas are applied to model the growth rate of the monthly exchange rate and tourist arrivals to China from the leading six tourism source countries, namely South Korea, Japan, Russia, USA, Malaysia, and Singapore, with a sample size of 216 observations from Jan 1994 to Dec 2011.

The dependence analysis shows that fluctuation of the exchange rate that has a negative effect on tourist arrivals on China from Japan and Malaysia and has a positive effect on tourist arrivals on China from South Korea, Russia, USA, and Singapore, but the coefficient of dependence is not statistically significant. The result indicates that the volatility of exchange rate is not a determinant factor in fluctuation of China's tourism demand from the countries being studied. Second, There are not extreme dependence Japan-CNY/JPY, USA-CNY/USD, Malaysia-CNY/MYR and Singapore-CNY/SGD pairs with , which imply extreme movements of CNY/JPY, CNY/USD, CNY/MYR and CNY/SGD, do not cause extreme movements of Japan, USA, Malaysia and Singapore outbound tourism demand to China, respectively. Third, there is weak support suggesting that when the currency of tourists from south Russia extremely depreciates, or CNY appreciates, tourists from Russia may extremely decrease. This suggests risk adverse behaviour of tourists from Russia. Furth, introducing the tail dependence and dynamic dependence between growth rates of tourism demand and exchange rate add much to the explanatory ability of the model.

Under those circumstances, government policies aimed to reduce tourist arrivals variability do not need to consider the exchange rate fluctuations effect since it is not

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possible to explain the volatility of tourism arrival on the basis of exchange rate fluctuations. This could be attributed to the purpose of tourists who travel to China. According China National Tourism Administration Statistics, travel for meeting and business, visiting relatives and friends, work and crew and others account for 57.23% in 2012. This indicates shows that most of tourists who travel China are price inelastic; they do not care about the change that the tour price changes due to fluctuations of exchange rate. Chinese tourism demand volatility may be caused by tourist preferences and economic conditions that originate from the tourism source countries, economic and cultural relationships between china and source countries, and promotional activities to China markets. If exchange rates influence tourists from some nations less than others in choosing China as a destination, then other price proxies may have more relevance than exchange rates, or the nature resource's attractiveness trumps exchange rate considerations. Hence, government and policy maker should diversify tourism products, strengthen tourism infrastructure (such as: hotels, restaurants, transportation and other and other services) and extend the tourism season. Moreover, the government should design the marketing promotion, increase Internet distribution channels, publicity, advertising and promotion. Second, travel agents do not need to worry about the reduction of competitiveness derived from exchange rate fluctuations. While they should design different tour package according traveller preferences, improve the quality of service, offer a diversity of attractions and provide a wide range of competitive tour packages to attract tourist and enhance its competitiveness. Last, this paper provides a complementary academic approach on evaluating the role of exchange rates in international tourism demand model.

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Table 1. Summary statistics for monthly logarithmic growth rates of tourist arrival and exchange rates.

	Mean	SD	Skewness	Kurtosis	Max	Min	JB
South Korea	0.0055 *	0.0485	-1.5751***	17.1537 ***	0.1694	-0.3552	1883.48 ***
CNY/KRW		0.0368	-4.0932***	38.2209***	0.0869	-0.3450	11713.25 ***
Japan	0.0028	0.0490	-1.8804***	27.0292 ***	0.2748	-0.3742	5299.28***
CNY/JPY	-0.0029	0.0272	0.5711***	4.4936***	0.1115	-0.0901	31.67 ***
Russia	0.0069	0.1007	0.3805**	18.5617***	0.6009	-0.5861	2174.58***
CNY/SUR	0.0013	0.0393	-6.7901***	75.9759 ***	0.0889	-0.4405	49359.58***
the USA	0.0032	0.0548	-3.0385***	46.0375 ***	0.3098	-0.5212	16923.66***
CNY/USD	-0.0027***	0.0069	-0.9841***	3.7514**	0.0114	-0.0260	39.76***
Malaysia	0.0037	0.0850	-2.1075***	27.1179***	0.4199	-0.7037	5369.97***
CNY/MYR	-0.0034**	0.0232	-0.1563				3937.02***
Singapore	0.0034	0.0667	-1.9659***	38.3263 ***	0.4265	-0.5895	11318.04**
CNY/SGD	-0.0023**	0.0150	0.0369	5.2138***	0.0558	-0.0653	43.95 **

Note: The total number of observations for each series is215. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Table 2. Tests of hypotheses of unit-root.

Variables	ADF		DF-GLS		ZA	
	Log	Growth rate	Log	Growth rate	Log	Growth rate
South Korea	-1.2075	-12.1463**	0.4537	-2.3744*	-4.1152	-5.0759*
CNY/KRW	-2.7772	-10.2561**	-0.0639	-10.2149**	-2.8775	-5.6882**
Japan	-1.9736	-11.2660**	-0.0763	-13.2626**	-5.0223	-5.6873**
CNY/JPY	-3.7303**	-10.8608**	-0.1158	-4.8343**	-4.4796	-5.0868*
Russia	-1.6282	-13.2456**	0.3745	-2.2955*	-5.5769**	-6.6398**
CNY/SUR	-1.5584	-10.2207**	-1.3327	-4.6624**	-4.1306	-6.4088**
the USA	-0.8884	-11.6289**	-0.0565	-2.1146*	-4.5248	-6.2310**
CNY/USD	-2.5291	-5.0542**	0.9176	-4.6624**	-4.3719	-6.4088**
Malaysia	-0.8582	-11.9389**	-0.0564	-2.7863**	-4.9255	-6.1694**
CNY/MYR	-3.3306**	-11.5559**	0.4192	-4.1877**	-6.7288**	-5.2995*
Singapore	-1.2199	-11.9387**	0.0004	-2.4900**	-5.2781*	-6.2317**
CNY/SGD	-4.5679**	-11.6084**	0.3652	-11.5786**	-4.9897	-5.7795**

Note: Lag orders of ADF, ADF-GLS and ZA tests are determined based on AIC. The ADF critical values for the rejection of the null hypothesis of a unit-root are -3.4626 and -2.8756 for 1% and 5%, respectively. The ADF-GLS critical values for the rejection of the null hypothesis of a unit-root are -2.5759 and -1.9423 for 1% and 5%, respectively. And ZA critical value for the rejection of the null hypothesis of a unit-root is -5.57 and -5.08 for 1% and 5%, respectively. The symbol ** and * denote rejection of the null hypothesis at the 1% and 5% significance levels, respectively.

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Table 3. Results of the ARMA-GARCH model for the growth rates of tourism demands.

	South Korea	Japan	Russia	the USA	Malaysia	Singapore
C_s	0.0072***	0.0035**	0.0039**	0.0031***	0.0034***	0.0037***
	(0.0019)	(0.0015)	(0.0020)	(0.0010)	(0.0015)	(0.0010)
$\phi_{s,1}$			0.6773***			
			(0.0715)			
$\theta_{s,1}$	-0.1726**	-0.2529***	-0.8634***	-0.5602**	-0.5698***	-0.6147***
	(0.0761)	(0.0789)	(0.0673)	(0.2294)	(0.0636)	(0.1325)
ω_s	0.0009***	0.0005*		0.0004*	0.0005*	0.0004**
	(0.0003)	(0.0003)		(0.0002)	(0.0003)	(0.0002)
α_s	0.8279**	0.6217*		0.6099*	0.2885*	0.5346*
	(0.3275)	(0.3503)		(0.3389)	(0.1438)	(0.2958)
β_s			0.9889***	0.3891**	0.1438***	0.4061**
			(0.0095)	(0.1669)	(0.1187)	(0.1786)
ξ_s	1.0420***	1.0959***	0.9206***	0.9318***	0.8296***	0.9026***
	(0.0979)	(0.0985)	(0.0838)	(0.0822)	(0.0884)	(0.0970)
λ_s	3.7186***	3.0871***	2.3696***	2.7539***	3.7981***	3.4895***
	(1.0602)	(0.7853)	(0.2788)	(0.5337)	(0.9216)	(0.8964)

Notes: The table shows the estimates and their standard errors (in parentheses) for the parameters of the marginal distribution model defined in equations (1) and (2).The lags p and qare selected by using the AIC criterion for different combinations of values ranging from 0 to 2. ***, ** and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Table 4. Results of the ARMA-GARCH model for the growth rates of the exchange rates.

	CNY/KRW	CNY/JPY	CNY/SUR	CNY/USD	CNY/MYR	CNY/SGD
C_s			0.0040*			
			(0.0021)			
$\phi_{s,1}$		0.3606*	0.5632***	0.9217***	0.7025***	-0.3552*
		(0.2045)	(0.0851)	(0.0472)	(0.3044)	(0.1910)
$\theta_{s,1}$	0.3940***			-0.3627*		0.6158***
	(0.1276)			(0.1656)		(0.1577)
ω_s	0.0001*		0.0000*		0.0000**	0.0000**
	(0.0000)		(0.0000)		(0.0000)	(0.0000)
α_s			0.4337***	0.1869**	0.4760***	0.2335**
			(0.1563)	(0.0882)	(0.1042)	(0.1082)
β_s	0.7830***	0.9931***	0.5653***	0.8057***	0.5230***	0.5486***
	(0.1514)	(0.0244)	(0.0899)	(0.0725)	(0.0756)	(0.1676)
ξ_s	0.7646***	1.2398***	0.8800***	0.9874***	1.1304***	1.1369***
	(0.1842)	(0.1225)	(0.0746)	(0.0987)	(0.0731)	(0.1156)
λ_s			3.3462***		4.0098***	
			(0.6269)		(0.8372)	

Notes: The table shows the maximum likelihood estimates and standard errors (in parentheses) for the parameters of the marginal distribution model defined in equations (1) and (2). The lags p and qare selected by using the AIC for different combinations of values ranging from 0 to 2. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

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Table 5. Tests for the skewed-t marginal distribution models.

	First moment LB test	Second moment LB test	Third moment LB test	Fourth moment LB test	K-S test
South Korea	0.5402	0.5376	0.1020	0.3776	0.8114
Japan	0.3955	0.8774	0.2725	0.6188	0.5830
Russia	0.3223	0.2513	0.2082	0.2619	0.9749
USA	0.1122	0.2930	0.1751	0.0528	0.7258
Malaysia	0.7049	0.7642	0.5150	0.5496	0.8974
Singapore	0.2035	0.8705	0.4805	0.9618	0.9579
CNY/KRW	0.0910	0.6596	0.0761	0.7888	0.7990
CNY/JPY	0.2223	0.3298	0.1193	0.3661	0.8796
CNY/SUR	0.9926	0.7823	0.6720	0.8380	0.6895
CNY/USD	0.1331	0.3634	0.2295	0.3156	0.4679
CNY/MYR	0.1216	0.6565	0.3779	0.6324	0.0560
CNY/SGD	0.2249	0.3911	0.3482	0.2821	0.7587

Note: This table reports the *p*-values from Ljung-Box (LB) tests for serial independence of the first four moments of the variables u or v. Regress $(u_t - \bar{u})^k and\ (v_t - \bar{v})^k$on the first 5 lags of the variables for k=1, 2, 3, 4. In addition, the *p*-values of the Kolmogorow-Smirnov (KS) tests for the adequacy of the distribution model are presented.

Table 7. Goodness-of-fit tests for the copula model.

	Gaussian Copula	Student-t Copula	Gumbel Copula	Clayton Copula	Placket Copula	Frank Copula
South Korea and CNY/KRW	0.6558	0.2722	0.5410	0.7238	0.5519	0.5549
Japan and CNY/JPY	0.9915	0.9898	0.9935	0.9056	0.9975	0.9965
Russia and CNY/SUR	0.3171	0.6648	0.3022	0.3641	0.2592	0.2493
USA and CNY/USD	0.1500	0.1568	0.2823	0.0986	0.2139	0.1352
Malaysia and CNY/MYR	0.3931	0.2103	0.3911	0.5290	0.2632	0.2532
Singapore and CNY/SGD	0.3102	0.7177	0.7028	0.4378	0.7907	0.7328

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.

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Table 6. Result of the static and dynamic copula—GARCH model.

	South Korea CNY/KRW	Japan CNY/JPY	Russia CNY/SUR	the USA CNY/USD	Malaysia CNY/MYR	Singapore CNY/SGD
			Panel A : static copula			
			Gaussian Copula			
ρ	0.0776	-0.0187	0.0807	0.0727	-0.0089	0.0127
	(0.0611)	(0.0700)	(0.0580)	(0.060)	(0.0632)	(0.0646)
AIC	0.6655	1.9186	0.4396	0.7688	1.9778	1.9660
			Student-t Copula			
ρ	0.05720	-0.0070	0.0313	0.0660	-0.0202	0.0272
	(0.0923)	(0.0863)	(0.0800)	(0.0831)	(0.0820)	(0.0817)
T	21.8268	100.0000**	7.1064	12.3822	100.0000**	11.5134
	(36.1734)	(7.0711)	(5.3924)	(10.2795)	(7.7011)	(11.8836)
AIC	1.4854	10.0960	-3.2081	2.8192	14.9278	2.8530
			Frank Copula			
τ	0.2799	-0.0831	0.1581	0.4876	-0.1199	0.2462
	(0.4076)	(0.4054)	(0.4026)	(0.4050)	(0.4047)	(0.4032)
AIC	1.5260	1.9586	1.8497	0.5740	1.9029	1.6547
			Plackeet Copula			
τ	1.1498***	0.9591***	1.0833***	1.2759***	0.9445***	1.1359***
	(0.2334)	(0.1944)	(0.2176)	(0.2582)	(0.0191)	(0.2293)
AIC	1.5271	1.9584	1.8477	0.5725	1.9076	1.6426
			Gumbel Copula			
τ	1.0276***	_	1.0253***	1.0557***	_	1.0138***
	(0.0385)		(0.0391)	(0.0450)		(0.0434)
AIC	1.4624		1.5452	0.5121		1.9063
			Clayton Copula			
τ	0.0125	_	0.1214*	0.0476	0.0118	0.0102
	(0.0895)		(0.0632)	(0.0564)	(0.0558)	(0.0701)
AIC	-2.0849		-3.2367	1.1890	1.9467	1.9745
			Panel B: dynamic copula			
			Dynamic Gaussian copula			
α_c	0.0022	-0.0003	0.0020	0.0393	-0.0025	0.0054**
	(0.0755)	(0.0022)	(0.0011)	(0.0440)	(0.0467)	(0.0016)
β_c	0.9964***	0.9721***	0.9950***	0.3321	0.9856***	0.9345***
	(0.2647)	(0.0309)	(0.3359)	(0.3719)	(0.0414)	(0.2037)
γ_c	-0.4942	-0.7649**	-0.4799*	-2.0905**	-0.6803**	-1.2466***
	(0.3675)	(0.3587)	(0.2702)	(0.7172)	(0.1277)	(0.3045)
AIC	0.0624	1.2784	1.6552	-3.1908	0.9017	-4.6250

Note: This table reports the estimates of static and dynamic copula parameters defined in equations (3)-(9) and their corresponding standard errors (in brackets) for several copula specifications for each pair of growth rates of the tourist arrivals and exchange rates.***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

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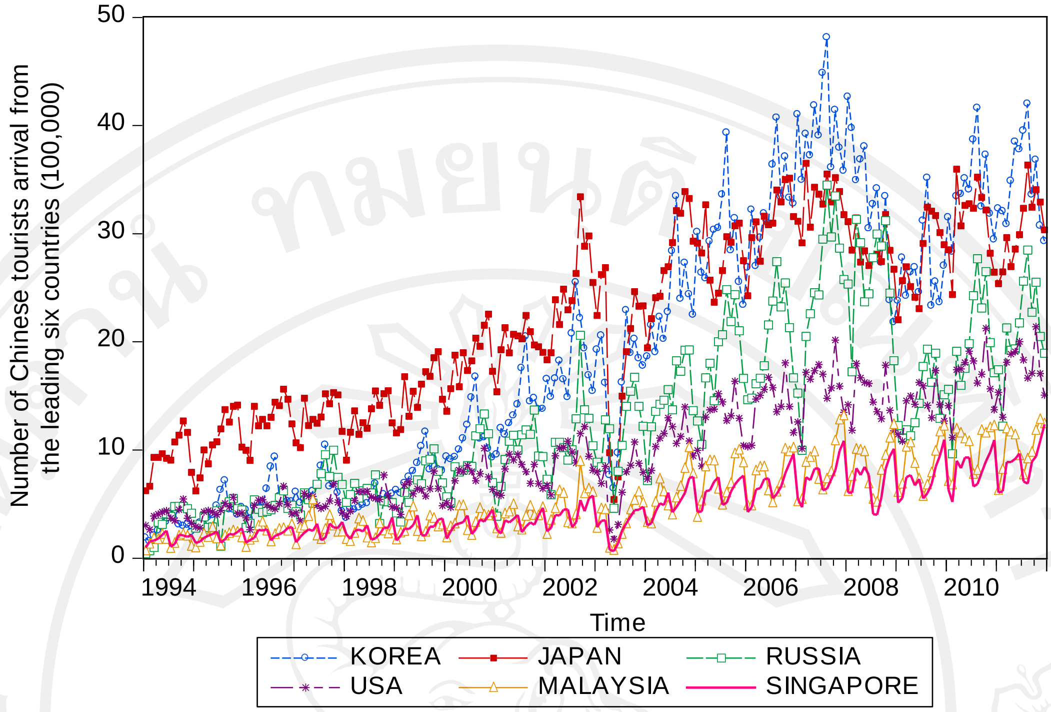

Figure 1.China inbound tourist arrival from the leading six countries

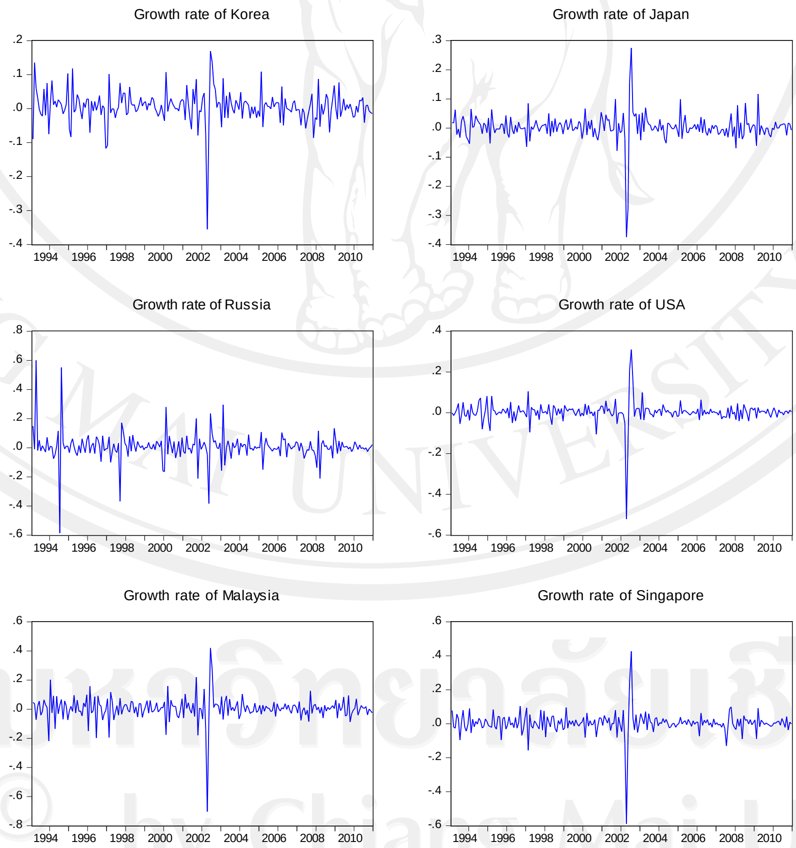

Figure 2. Monthly growth rates from tourist arrival of the leading six countries

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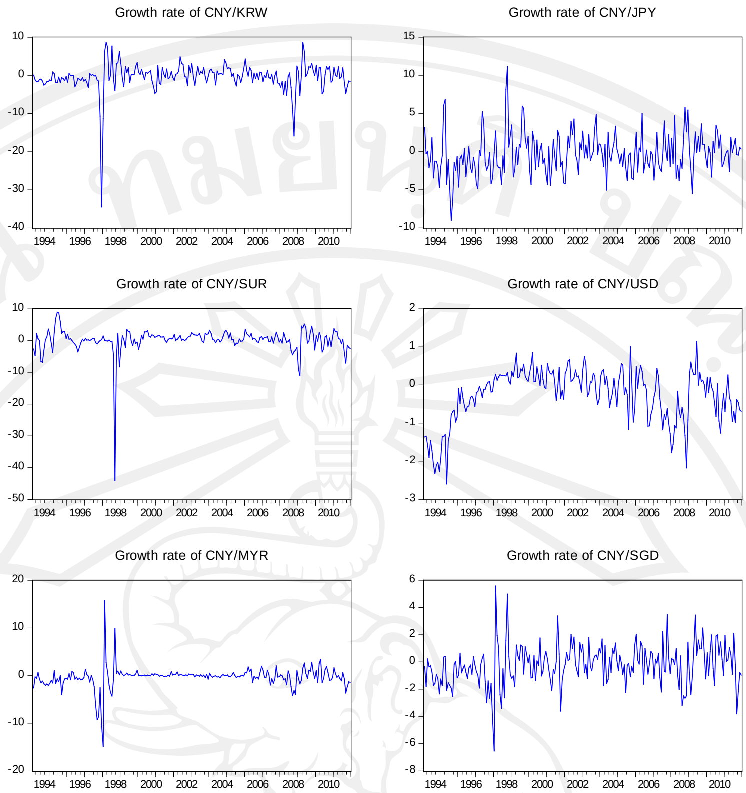

Figure 3. Monthly growth rates from exchange rate of the CNY

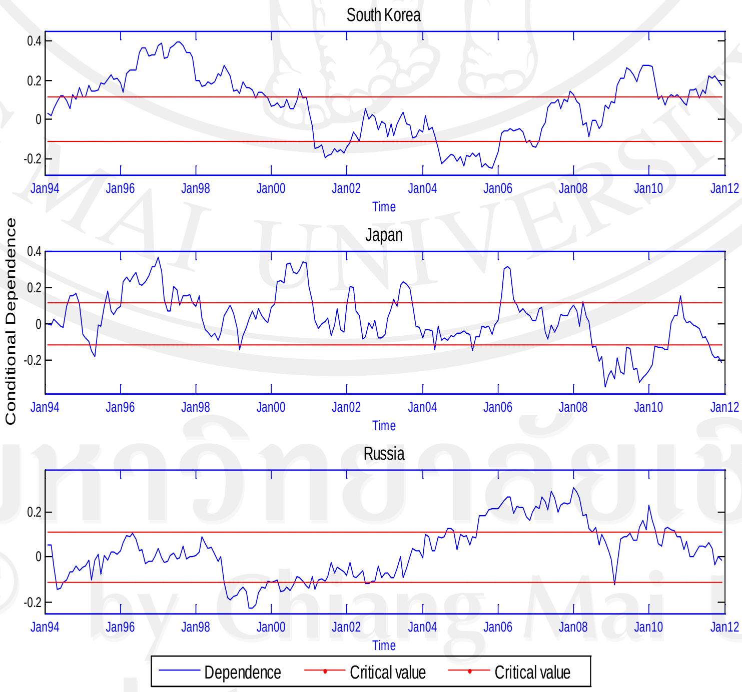

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Figure 4a. Conditional dynamic dependence estimates with critical value of 10% between tourist arrival and exchange rate growth rates from South Korea, Japan, and Russia

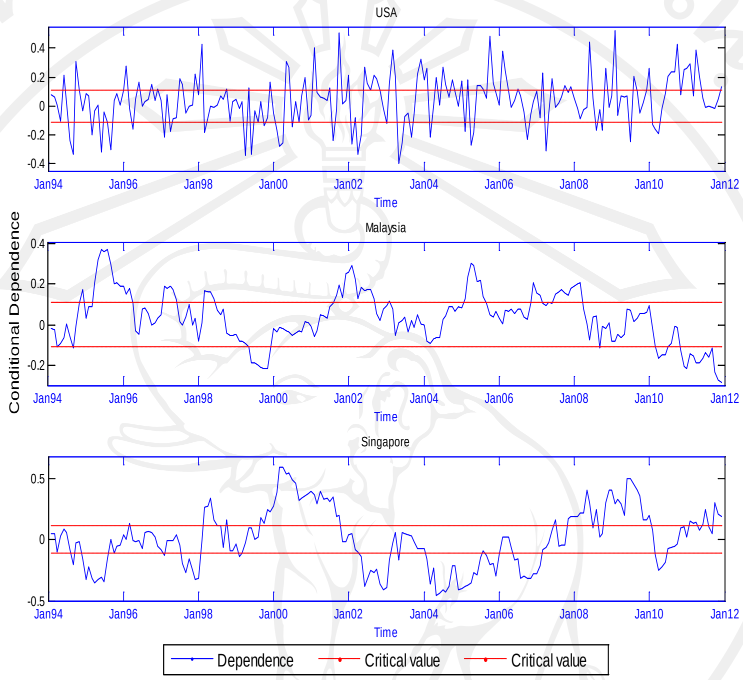

Figure 4b. Conditional dynamic dependence estimates with critical value of 10% between tourist arrival and exchange rate growth rates from USA, Malaysia and Singapore

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APPENDIX C

Co-movement of China outbound tourism demand: Singapore, Thailand and Malaysia

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Co-movement of China Outbound Tourism Demand: Singapore, Thailand and Malaysia

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ABSTRACT

This paper models the conditional volatility and co-movement (or dependence) of the growth rate of the monthly Chinese tourist arrival in Singapore, Thailand and Malaysia, using six kinds of copula-GARCH model. Monthly data from January 1998 to June 2012 are used in the empirical analysis. The empirical results suggest positive relationships exist between the conditional shocks in these three countries. Moreover, the variations in monthly Chinese tourist arrivals in Singapore market strong influence of Chinese tourist arrivals in Thailand, and vice-versa. This influence weakens in run between Singapore and Malaysia and between Thailand and Malaysia. Third, there is a strongly influence that an extremely high (low) growth rate in monthly Chinese Tourist arrivals in Singapore is likely to follow extremely high (low) growth rate in the monthly Chinese tourist arrivals in Thailand, and vice versa. But this decreases in run between Singapore and Malaysia and between Thailand and Malaysia probably. Forth, the dynamic conditional dependence between the conditional shocks of the three countries is not constant over time which is positive over the time.

Keywords: Tourism demand; GARCH model; Copula method; Co-movement

1. Introduction

International tourist arrivals grow year by year. According to the report of World Tourism Barometer [18], international tourist arrivals reach 1,035 million in 2012 (39 million more than in 2011), which is the first time in history. UNWTO's long-term outlook Tourism Towards 2030 is expected that international tourist arrivals will grow by 3.8% per year between 2010 and 2020 despite of ongoing economic challenges. The growth rate of Asian and the Pacific is relatively high comparing with other areas, and the growth rate is 6.8% and it reaches 232.9 million.

China outbound tourism industry is the most active and fastest growing tourism market in the world, and become the driving force and the rising star of global

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tourism industry. China outbound tourism occurred in the 80 years of the 20th century. In 1983, Hong Kong and Macau were considered the destinations a prelude to outbound tourism of the Chinese citizens; the main purpose of the route was to facilitate the mainland residents to visit relatives in Hong Kong and Macao.[1] China outbound tourism market was open for the Southeast Asian nations initially. In 1988, Thailand, besides Hong Kong and Macao, became the first of China's outbound tourism destination. Since 1990, China's authorities began to appoint Singapore, Malaysia, the Philippines, South Korea, Australia (Australia), New Zealand as China outbound tourism destination countries. China's outbound tourism industry rapidly grew in the last two decades. Until 2011, the tourist destination for Chinese citizens has reached 140 countries and regions. In additional, according the National Bureau of Statistics of China, outbound travel has increased from 3.74 million in 1993 to 70.3 million in 2011. This information highlights that the competition of China outbound tourism market could become increasingly fierce.

There is an extensive literature applying univariate and multivariate GARCH model to study tourism demand. Hoti, Leon and McAleer [8] study international tourist arrivals to the Canary Islands by CCC-GARCH model. They find that the conditional correlations are generally positive, varying from small negative to large positive correlations in the monthly tourist arrivals shocks. For example, Chan, Lim and McAleer [3] use the symmetric CCC-MGARCH, symmetric VARMA-GARCH and asymmetric VARMA-GARCH to study Australia's tourism demand from the four leading source countries. They examine 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. Shareef and McAleer [16] apply the symmetric VARMA-GARCH model to research international tourism demand and uncertainty in Maldives and Seychelles. This study points out there is spillover effects between Maldives and Seychelles. Shareef and McAleer [15] study the Maldives inbound tourism demand by CCC-GARCH and VARMA-GARCH model, which find that static conditional correlations and the respective transformed series are significantly different from zero, but also relatively low among eight major tourist source countries (Italy, Germany, UK, Japan, France, Switzerland, Austria and the Netherlands). Álvares, Hoti and McAleer [1] use CCC-GARCH model in Span domestic tourism market, it aims to research the correlation among five major Spanish destinations namely Canary Islands, Catalonia and the Community of Madrid. They find five destinations are substitutes and independent to shocks. Seo, Park and Yu [14] apply the multivariate GARCH model to analyses of the relationships in Korea outbound tourism demand. It finds that conditional correlations among tourism demand were time-varying. Coşkun and Özer [4] use BEKK-GARCH (1, 1) model to inbound tourism demand in Turkey. In this paper,

[1] Hong Kong and Macau did not return China in 1983, so Chinese traveled to Hong Kong and Macao is considered outbound tourism.

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authors get cross-country interdependent and dependent effects in the conditional correlations for Germany, France, United Kingdom and Netherlands. As far as we know, no study exists that study China outbound tourism demand market dependence or co-movements. In order to fill in the gap in literature, we introduce both static and dynamic copula-GARCH models in this study. The copula-GARCH model can capture the static and time-varying dependence (or co-movement) of China outbound tourism demand among Singapore, Thailand and Malaysia, as well as investigating the asymmetric and symmetric co-movement of China outbound tourism demand among three destinations. The application of copula to analyze economic issues begins at the beginning of the twenty first century, but recently, it has become popular in analyzing economic studies, especial in financial ([10-11, 13, 19-21]).

The purpose of the present study is to examine the volatility and conditional dependence structure (or co-movement) between tourism demands in three China outbound tourism markets. Where tourism demand is measured as the growth rate of monthly Chinese tourist arrivals, the conditional dependence of the standardized residuals make an accurate assessment how the variations in monthly Chinese tourist arrivals in one destination affect the monthly Chinese tourist arrivals in another tourist destination. To research volatility and dependence, we apply both marginal model (ARMAX-GARCH model) for Chinese tourist arrivals in each destination and a joint model (copula approach) for dependence. For the marginal model, we use ARMAX-GARCH model with error follow student-t distribution. For the joint model, we use several copula approach get different dependence structure: symmetric dependence (Gaussian copula with zero low and upper tail dependence; Student-t copula with low tail dependence equal to upper tail dependence); asymmetric dependence (Clayton copula with low tail dependence and zero upper tail dependence and Gumbel copula with upper tail dependence and zero low tail dependence); mixed dependence (symmetrized Joe-Clayton copula with asymmetric dependence and nest symmetry); dynamic dependence which can capture the time-varying dependence. The volatility and dependence structure can help the policy maker and tour operator.

This paper is organized as follows. Section 2 introduces copula function and describes the copula—GARCH models used in the paper. In additional, we discuss the data and their properties in Section 3, and present our empirical results with inference in Section 4. Finally, the last section summaries conclusions and suggest policy planning and destination management.

2. Econometrics models

2.1 The copula method

A copula function is a statistical tool which can capture enables a flexible

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dependence (or co-movement) between two (or more) random variables to be represented [13]. In 1959, Sklar [17] proved that a joint distribution can be separated into the marginal distribution and its dependence function, which called a copula. According to the Sklar's theorem, the copula can be constructed as follow:

$$F_{XY}(x,y) = C(F_X(x), F_Y(y)) \tag{1}$$

where $F_{X,Y}(x,y)$ a joint distribution of two continuous random variables X and Y, with marginal functions $F_X(x)$ and $F_Y(y)$. The copula is a multivariate cumulative distribution function with uniform marginal U[0, 1] and V[0, 1], which relates the quantiles of the marginal distributions rather than the original variables. And it is also defined by

$$c(u,v) = \Pr[U \le u, V \le v] \tag{2}$$

Where $u = F_X(x)$ and $v = F_Y(y)$.
Subsequently, Patton [11] presented the conditional copula function, which can be written as:

$$F_{XY|W}(x,y|w) = C(F_{X|W}(x|w), F_{Y|W}(y|w)|w) \tag{3}$$

where W is the conditioning variable, $F_{X|W}(x|w)$ is the conditional distribution of X|W = w, $F_{Y|W}(y|w)$ is the conditional distribution of Y|W = w and $F_{XY|W}(x,y|w)$ is the joint conditional distribution of (X,Y)|W = w.

Differentiate Equation (1) and Equation (3), the corresponding unconditional and conditional joint densities are obtained

$$f_{X,Y}(x,y) = f_X(x)\, f_Y(y) \frac{\partial^2 C(u,v)}{\partial u \partial v} = f_X(x)\, f_Y(y)\, c(u,v) \tag{4}$$

$$f_{XY|W}(x,y|w) = f_{X|W}(x|w)\, f_{Y|W}(y|w) \frac{\partial^2 C(u,v)|w}{\partial u \partial v} = f_{X|W}(x|w)\, f_{Y|W}(y|w)\, c(u,v|w) \tag{5}$$

where c(u,v) and c(u,v|w) are the densities of unconditional and conditional copula, respectively. Hence, the conditional joint density of the two variables X and Y is represented by the product of the conditional copula density and the two conditional

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marginal densities, $f_{X|W}(x|w)$ and $f_{Y|W}(y|w)$.

Copula method has an attractive characteristic, which is tail dependence. Tail dependence can measure the dependence of the probability that two variables are in the lower or upper joint tails of bivariate distributions. More straightforward say, tail dependence can capture the propensity of different tourism market to go up or down together. We express the coefficient of right (upper) and left (low) tail dependence in terms of the copula between X and Y as:

$$\lambda_R = \lim_{u\to 1} \Pr[X \geq F_X^{-1}(u)|Y \geq F_Y^{-1}(u)] = \lim_{u\to 1} \frac{1 - 2u + c(u,u)}{1 - u} \tag{6}$$

$$\lambda_L = \lim_{u\to 0} \Pr[X \geq F_X^{-1}(u)|Y \geq F_Y^{-1}(u)] = \lim_{u\to 0} \frac{1 - 2u + c(u,u)}{1 - u} \tag{7}$$

where λ_R and λ_L belong to [0, 1] and $F_X^{-1}(u)$ and $F_Y^{-1}(u)$ are the marginal quantile functions. If λ_R and λ_L are positive, then there are right and left tail dependence, otherwise there is right and left tail independence.

2.2 The model for the marginal distribution

The ARMA (p, q)—GARCH (1, 1) model of $r_{s,t}$ for country s at time t can be described as follows:

$$\begin{aligned} r_{s,t} &= c_0 + \sum_{i=1}^{p} \varphi_{s,i}\, r_{s,t-i} + \sum_{j=1}^{q} \theta_{s,j}\, e_{s,t-j} + \sum_{m=1}^{12} \varphi_{s,m}\, D_m + e_{s,t}\,, \\ e_{s,t} &= \sqrt{\frac{h_{s,t}\,(df_s - 2)}{df_s}}\; z_{s,t}\,,\ z_{s,t} \sim \text{iid}\ t_{df}\ s\,, \\ h_{s,t} &= \omega_s + \alpha_s\, e^2_{s,t-1} + \beta_s\, h_{s,t-1}\,, \end{aligned} \tag{8}$$

where $r_{s,t}$ could be the growth rates of tourism demand, $\varphi_{s,i}$ is the ith lag autoregressive (AR) parameter for $r_{s,t}$ to capture the impact of nonsynchronous effects, and $\theta_{s,j}$ is the jth lag moving average (MA) parameter. $\varphi_{s,m}$ denote coefficient of 12 month dummy variables. The restrictions in the variance equation include $\omega_s > 0$, $\alpha_s, \beta_s \geq 0$, and $\alpha_s + \beta_s < 1$. The error term $e_{s,t}$ is assumed to follow a student-t distribution to capture heavy tailed characteristic of the growth rates of tourism

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demand. $z_{s,t}$ represents the standardized residual from the first-stage estimation, and df_s is the degree of freedom.

2.3 The copula model for the joint distribution

The copula model is used to estimate the dependence or co-movement of the monthly growth rates of tourist arrival shocks between all pairs of destinations analyzed in this paper. We will use several copula models to measure the dependence to capture static tail independence, symmetric and asymmetric tail dependence, and time-varying dependence. We will briefly describe these copula models and their statistical inference in this section.

From Jondeau and Rockinger [9], the Gaussian copula is

$$C_{\rho}^{Gau}(u,v|\rho) = \Phi_{\rho}(\varphi^{-1}(u), \varphi^{-1}(v)), \tag{9}$$

Where Φ_ρ is the bivariate standard normal cdf with correlation ρ between u and v, $\varphi^{-1}(u)$ and $\varphi^{-1}(v)$ are standard normal quantile functions, and $\rho \in (-1, 1)$ measures the dependence between u and v. The Student-t copula is defined as

$$C_{\rho}^{Stu}(u,v|\rho,n) = T_{\rho,n}[t_n^{-1}(u), t_n^{-1}(v)], \tag{10}$$

where $T_{\rho,n}$ is the bivariate Student-t cdf with degree of freedom, correlation $\rho \in (-1, 1)$, and $t_n^{-1}(u)$ and $t_n^{-1}(v)$ are the univariate Student-t quantile functions. When $n \rightarrow \infty$, the Student-t copula converges to the Gaussian with zero dependence on both tails. Both Gaussian and Student-t copulas describe the symmetric dependence. But there is different feature. The feature of Gaussian copula does not have either left tail or right tail ($\lambda_L = \lambda_R = 0$). While the characteristic of the Student-t copula has non-zero dependence (or extreme-value dependence) in right and left tail, $\lambda_L = \lambda_R = 2t_{n+1}(-\sqrt{n+1}\sqrt{1-\rho}/\sqrt{1+\rho}$ (see [6]).

On the other hand, both Gumbel [7] and Clayton [2] copulas measure the asymmetric dependence. To capture the right tail dependence (is also called upper tail, it means upper side tail not equal to zero $\lambda_U = 2 - 2^{1/\tau}$, while low side tail equal to zero $\lambda_L = 0$), the Gumbel copula [7] is defined as

$$C_{\tau}^{Gum}(u,v|\tau) = \exp\{-(\tilde{u}^{\tau} + \tilde{v}^{\tau})^{1/\tau}\}, \tag{11}$$

where $\tilde{u} = -\ln(u), \tilde{v} = -\ln(v)$, and $\tau \in [1,+\infty)$ is the dependence between u and v.$\tau = 1$ shows no dependence, $\tau > 1$ shows positive dependence, and $\tau \rightarrow \infty$ represents a fully dependence relationship between u and v. Last, to captures the left (is also called

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low tail, it means upper side tail equal to zero $\lambda_U = 0$, while low side tail not equal to zero $\lambda_L = 2^{-1/\tau}$) tail dependence, the Clayton copula [6] is defined as

$$C_{\tau}^{Clay}(u,v|\tau) = (u^{-\tau} + v^{-\tau} - 1)^{-1/\tau} \quad , \tag{12}$$

where $\tau \in [0,+\infty]$ is the degree of dependence between u and v. $\tau = 0$ shows no dependence with the increase of the value of τ indicates the increase of the dependence between u and v.

We apply Gumbel (Clayton) copula to capture the behavior of Chinese's tourism arrival in different destination during extreme events, it measures the probability that extremely high (low) growth rate of monthly tourist arrivals in a country accompany extremely high (low) growth rate of monthly tourist arrivals in another country.

The last of copula we applied is the symmetrized Joe–Clayton copula which has two parameters, τ_R and τ_L, which are measures of dependence known as tail dependence. The symmetrized Joe-Clayton copula is a modification of Joe–Clayton copula. Joe–Clayton copula is defined as:

$$C_{\tau R\ \tau L}^{JC}((u,v|\tau_R,\tau_L) = 1 - (1\{[1-(1-u)^{\kappa}]^{-\xi} + [1-(1-v)^{\kappa}]^{-\xi} - 1\}^{-1/\xi^{1/\kappa}} \tag{13}$$

where $\kappa = 1/\log_2(2 - \tau_R)$, $\xi = 1/\log_2(2 - \tau_L)$ and $\tau_R \in (0.1)$, $\tau_L \in (0.1)$. But the Joe–Clayton copula has one major drawback.[2] Patton [11] proposes the symmetrized Joe–Clayton copula which is defined as:

$$C_{\tau R\ \tau L}^{SJC}((u,v|\tau_R,\tau_L) = 0.5(C_{\tau R\ \tau L}^{JC}(u,v|\tau_R,\tau_L) + C_{\tau R\ \tau L}^{JC}(1-u,1-v|\tau_R,\tau_L) + u + v - 1) \tag{14}$$

Tail dependence captures the behavior of the tourist demand during extreme events.

2.4 The dependence parameters of the time-varying copula

The above six copula method capture different dependence structures, but the dependence is assumed to be time invariant. In order to consider the time-varying dependence, we introduce the dynamic copula in this paper. In the dynamic Gaussian, the Pearson correlation coefficient ρ_t is commonly used to describe the dependence structure. Followed Wu, Chung and Chang [20], we assume that the dependence relies on the lag-one dependence ρ_{t-1} and historical information $(\mu_{t-1} - 0.5)(v_{t-1} - 0.5)$ in the dynamic Gaussian. The dependence process follows

[2] See [11].

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$$\rho_t = \Lambda(\alpha_c + \beta_c \rho_{t-1} + \gamma_c(\mu_{t-1} - 0.5)(v_{t-1} - 0.5)) \quad , \tag{15}$$

where ρ_t is determined from ρ_{t-1} to capture the persistence effect and $(\mu_{t-1} - 0.5)(v_{t-1} - 0.5)$ capture historical information. In the dynamic copula, $\Lambda = -\ln[(1 - x_t)/(1 + x_t)]$ is the logistic transformation, which is used to ensure the dependence parameter falls within the interval (–1, 1). In this paper, we use a constant, α_c, an autoregressive term, β_c, and historical information, γ_c to explain the dependence parameter .The autoregressive parameter β_c measure the degree of persistence, where $0 \le \beta_c < 1$. The parameter β_c is large, which shows that a high degree of persistence pertaining to the dependence structure. The parameter γ_c measures their variations in the dependences.[3]

2.5 Estimation and calibration of the copula

We use standard maximum likelihood estimation CML (Canonical Maximum Likelihood method) in our study. In the procedure, the first step is to use Equation (16) to transform the standardized innovations series z_t into uniform variate u_t. The second step is to use Equation (17) to estimate the parameters of copula. The efficiency equations are

$$\hat{u}_t = F(z_t) = \frac{1}{T+1} \sum_{t=1}^{T} 1_{z_{s,t \le z}} \tag{16}$$

Where 1 denotes the indicator function: 1 (expression) = $\begin{cases} 1, \text{ If expression is true} \\ 0, \text{ If expression is false} \end{cases}$
and T is the number of observations.
and

$$\theta_{ct} = \operatorname{argmax} \sum_{t=1}^{T} \ln c_{st}(F_{st}(z_{1,t}), F_{st}(z_{2,t}), \theta_{ct}, \theta_{st}). \tag{17}$$

3. Data description

In this paper, we use the monthly data of China outbound tourism to estimate the co-movement of China outbound tourism demand. The sample period is from January 1998 to June 2012, which gives 174 observations for each country. China

[3] If both μ_{t-1} and v_{t-1} are either smaller or larger 0.5, this infer the dependence is higher than previously (see [20]).

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outbound tourism[4] demand is the number of Chinese tourist arrivals to destinations: Singapore, Thailand, and Malaysia. The monthly data of tourist arrivals are obtained from the Singapore Tourism Board, Thailand office of Tourism development, and Tourism Malaysia, respectively. We plot the monthly series of China outbound tourist arrivals for the three destinations in Figure 1. The figure exhibits that China outbound tourist arrivals increase over time in general, although it falls sharply around the time of SARS in year 2003 and the sub-prime crisis in year 2009. The figure also displays clear seasonal and cyclical movements. To measure the seasonality, we apply twelve month seasonal dummy variable in the ARMA-GARCH model. The data should be stationary for modeling time series, thus testing for unit roots is essential for time series analysis with ARMA-GARCH models. So the augmented Dickey-Fuller [5] and Phillips-Perron [12] are used unit root tests to test whether the data are stationary and present the results in Table 1. The Table 1 shows that all of the levels of the series have unit roots at the 5% significance, there is strong evidence all of the levels of the series are not stationary. This demonstrates that all series need to be transformed to stationary processes to enable valid empirical estimates and inferences. Therefore, we conduct the logarithmic transformation of the data so that all series are stationary. Thereafter, we use $r_{s,t} = Log(Y_{s,t}/Y_{s,t-1})$ to measure the growth rate of the monthly tourist arrivals, in which $Y_{s,t}$ is the tourist arrival at month t. We also use the augmented Dickey-Fuller and Phillips-Perron unit root tests to test whether the logarithmic transformation of the data are stationary and display the results in Table 1. The Table 1 shows the logarithm of the monthly arrival rate ($r_{s,t} = Log(Y_{s,t}/Y_{s,t-1})$) are denote rejection of the null hypothesis at the 1% and 5% significance levels, which suggest that all series are stationary after transformation by logarithm. This show the logarithm of the monthly arrival rate can be conducted by ARMA-GARCH model.

Table 1. Tests of hypotheses of unit-root.

Variables	ADF		PP	
	Level	Difference	Level	Difference
Singapore	1.5396	-7.7844**	-1.8698	-24.4867**
Thailand	0.5787	-11.6388**	-1.6580	-26.9376**
Malaysia	0.0331	-19.4570**	-0.1231	-27.8142**

Note: Lag orders of ADF and PP tests are determined based on AIC. The critical values for the rejection of the null hypothesis of a unit-root are -2.5795 and -1.9428 for 1% and 5%, respectively. The symbol ** and * denote rejection of the null hypothesis at the 1% and 5% significance levels, respectively. The total number of observations for each series is 174. Levels refer to $Y_{s,t}$, while differences refer to $r_{s,t} = Log(Y_{s,t}/Y_{s,t-1})$.

[4] China outbound tourism means China residents travel to another country for leisure, business, and other purposes.

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Plot the growth rates of the tourist arrivals are given in Figures 2. After transformation, the three series do not present trends and they all vary around zero. The growth rate of tourist arrival series to the three destinations vary substantially, with noticeable peaks over the sample period. The figures suggest that there are conditional variance processes in the three series, and thus, the GARCH model is appropriate for modeling the growth rate of tourist arrivals.

The descriptive statistics of the growth rates of monthly arrivals are given in Table 2. From the table, we find that the mean of Singapore (+0.0040), Thailand (+0.0027), and Malaysia (+0.0045) are positive, which show these all series are a positive trend of tourist growth for all three destinations. We also notice that the series of Singapore and Thailand's skewness are -0.9043 and -0.6930, respective, which indicates that the series of Singapore and Thailand are skew to the left. And the series of Malaysia's skewness is 0.0878, which shows it is skew to the right. All series are more than 3 in kurtosis, inferring that all series are fat-tailed and sharp in their peaks. In addition, the null hypothesis that the series are normally distributed is tested at the 1% level of significance; and the normality hypothesis for all series is rejected at the 1% significant level base on the statistic of the Jarque-Bera Lagrange multiplier test. These results make clear that the empirical of growth rates display fatter tails than normal distribution. Therefore, we introduce the student-t distribution in our study.

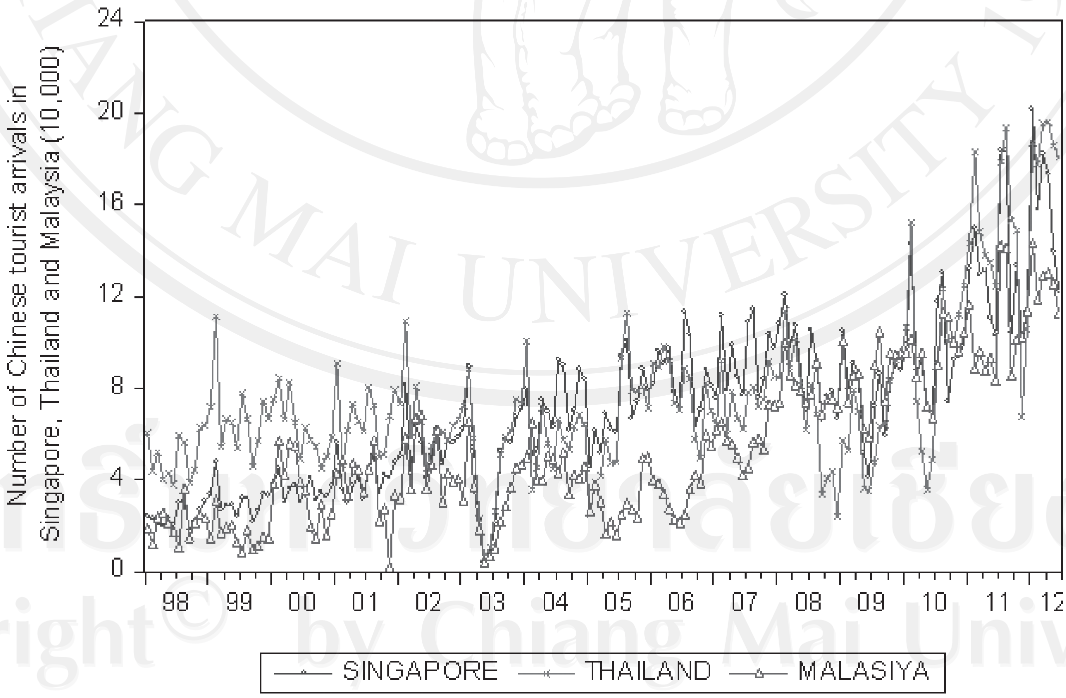

Figure 1. China outbound tourist arrival in Singapore, Thailand, and Malaysia.

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Table 2. Summary statistics for the logarithm of the monthly arrival rate.

	Mean	SD	Skewness	Kurtosis	Max	Min	JB	Obs
Singapore	0.0040	0.1387	-0.9043	7.8793	0.4011	-0.7604	195.1928***	173
Thailand	0.0027	0.1452	-0.6930	4.6871	0.3896	-0.5567	34.3663***	173
Malaysia	0.0045	0.2053	0.0878	15.3075	1.2373	-1.1490	1092.1040***	173

Note: The total number of observations for each series 4 is 174. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

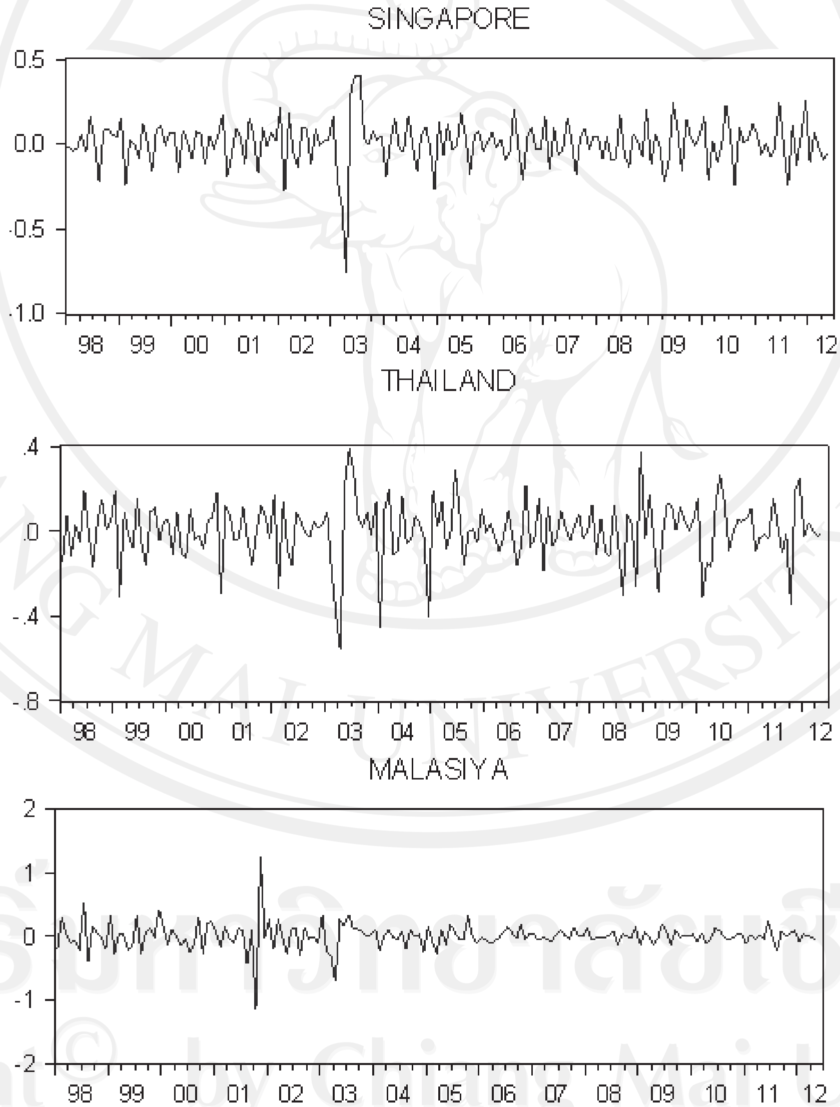

Figure 2. The logarithm of the monthly arrival rate for Singapore, Thailand and Malaysia.

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4. Empirical results

4.1 Results for the marginal models

In this study, we estimate the ARMA (p, q)—GARCH (1, 1) models with student-t of error distribution by using the maximum likelihood estimation method and considering different combinations of the values of parameters p and q ranging from zero to maximum lags of two. In addition, we adopt the AIC criterion to select the most suitable models. We report the result of the ARMA-GARCH model for the growth rate of tourist arrivals in Singapore, Thailand, and Malaysia in Table 3. From the conditional mean estimates, we notice that the ARMA (1, 0)—GARCH (1, 1) specification is the best model for Singapore and Malaysia, while ARMA (2, 1)—GARCH (1, 1) is more appropriate for Thailand. All of $\varphi_{s,1}$ are high significant and the negative values of $\varphi_{s,1}$ demonstrate that all tourism demand is negatively related with the previous one. Only Thailand tourism demand is significantly negatively related with the previous two implying by the significantly negative values of $\varphi_{s,2}$. From the conditional variance estimates, it is observed that the estimate of the ARCH coefficient, α_s, is significant for Singapore and Thailand. This implies that, in general, given any unanticipated shocks to monthly growth rate of Chinese tourist arrivals to the Singapore and Thailand, the effect of that shock will last for a short period of time. On the other hand, the estimate of the GARCH coefficient, β_s, is not significant for Thailand, while it is significant for Singapore and Malaysia. This demonstrate that, in general, given any unanticipated shocks to monthly growth rate of Chinese tourist arrivals to the Malaysia, the effect of that shock will last for a considerable period of time. The results of the conditional variance equations are $\hat{\alpha} + \beta = 0.9383$ and 0.9829 for Singapore and Malaysia, inferring that the volatilities of these two series are highly persistent. However, only Thailand does not have such persistence. There is strong evidence to suggest that China outbound tourism to the Singapore, Thailand and Malaysia are highly seasonal, with tourist arrivals being significantly concentrated in the peak tourist season. The degrees of freedom λ_s in the student-t distribution for all the series are significant, suggesting the error terms are not normal. This is consistent with the evidence reported in Table 2.

The probability integral transforms should be Uniform (0, 1) for modeling the marginal distribution, thus the marginal distribution test is essential and the copula model could be correctly specified. Hence, followed Patton test the marginal distribution in this paper. Test is divided into two steps. First, we use Ljung-Box (LB) test to examine the serial independence. To do so, we regress $(u_{s,t} - u_i)^k$ on the first 10 lags of the variables. The results of LB test are given in Table 4. From the table 4, we know that that all series are not rejected at the 5% level significant which show all of them are serial independent at 5% level. Secondly, we use the Kolmogorow-Smirnov (KS) test to test whether the marginal distribution is from uniform (0, 1). The p-values of Kolmogorow-Smirnov (KS) tests are also given in Table 4. Overall,

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Table 3. Results of the ARMA-GARCH model for the logarithm of the monthly arrival rate.

	Singapore		Thailand		Malaysia	
	Par.	S.E.	Par.	S.E.	Par.	S.E.
Conditional mean						
$\varphi_{s,1}$	-0.1572*	0.0855	-1.0309***	0.1037	-0.3785***	0.0613
$\varphi_{s,2}$			-0.1133	0.0973		
$\theta_{s,1}$			0.9858***	0.0026		
Seasonal dummies						
$\varphi_{s,1}$	0.0513***	0.0147	0.0244	0.0243	0.0357	0.0225
$\varphi_{s,2}$	0.0746***	0.0152	0.0600**	0.0249	0.0053	0.0212
$\varphi_{s,3}$	-0.0996***	0.0147	-0.0737***	0.0226	-0.0362	0.0258
$\varphi_{s,4}$	0.0499***	0.0186	0.0414	0.0302	0.0020	0.0250
$\varphi_{s,5}$	-0.0577***	0.0148	-0.0600*	0.0371	-0.0411*	0.0218
$\varphi_{s,6}$	-0.0541***	0.0197	-0.0525*	0.0298	-0.0554*	0.0327
$\varphi_{s,7}$	0.1691***	0.0143	0.1423***	0.0303	0.1008***	0.0216
$\varphi_{s,8}$	0.0134	0.0160	0.0169	0.0254	0.0900***	0.0272
$\varphi_{s,9}$	-0.1787***	0.0154	-0.1023***	0.0229	-0.1195***	0.0218
$\varphi_{s,10}$	0.0688***	0.0177	0.0301	0.0285	0.0363	0.0286
$\varphi_{s,11}$	0.0562***	0.0116	0.0642**	0.0300	0.0360	0.0239
$\varphi_{s,12}$	-0.0034	0.0153	0.0132	0.0263	0.0163	0.0305
Conditional variance						
ω_s	0.0022**	0.0010	0.0064**	0.0025	0.0003	0.0003
αs	0.6751*	0.3490	0.6599**	0.3161	0.0974	0.0611
β_s	0.2632*	0.1588	0.1274	0.1966	0.8855***	0.0457
n	3.4410***	0.9806	5.2700***	0.8630	3.2706***	0.7857
LL	204.8641		149.7725		117.6426	
AIC	-2.1972		-1.5503		-1.1771	
BIC	-1.8849		-1.2182		-0.8648	

Notes: The table shows the estimates and their standard errors for the parameters of the marginal distribution model defined in Equations (8) The lags were selected by using the AIC criterion for different combinations of values ranging from 0 to 2. ***, ** and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. The total number of observations for each series is 173.

the LB test and KS test for our marginal distribution model show that these are not mis-specified. Hence, the copula model can correctly capture the dependence of growth rate of monthly tourist arrivals in three countries.

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Table 4. Test the student-t marginal distribution models.

	First Moment	Second Moment	Third Moment	Fourth Moment	K-S test
Singapore	0.3142	0.1466	0.1674	0.1443	0.8967
Thailand	0.5035	0.3305	0.1518	0.5066	0.7563
Malaysia	0.1599	0.2204	0.1201	0.0984	0.9851

Note: This table reports the p-values from Ljung-Box (LB) tests for serial independence of the first four moments of the variables $U_{s,t}$. We regress $(\bar{u}_{s,t} - \bar{u}_s)^k$ on the first 10 lags of the variables for k = 1, 2, 3, 4. In addition, we present the *p*-values of the Kolmogorow-Smirnov (KS) tests for the adequacy of the distribution model. The total number of observations for each series is 174.

4.2 Results for the copula models

The results for the static copulas are given in Table 5 in which the dependency parameters are assumed to be constant over time. In the Gaussian copula, all the dependence parameters ρ are significantly and the dependence values of ρ are 0.7060, 0.4314, and 0.2493 for between Singapore and Thailand, between Singapore and Malaysia and between Thailand and Malaysia, respectively. In additional, the dependence parameters in the Student-t copulas are also significant and consistent close to the dependence values in Gaussian copula. These figures provide clear evidence that positive relationships exist between the conditional shocks in three destination countries. In three pairs, between Singapore and Thailand has the highest relationship. These results imply that the variations in monthly Chinese tourist arrivals in Singapore market strong influence of Chinese tourist arrivals in Thailand, and vice-versa. This influence weakens in run between Singapore and Malaysia and between Thailand and Malaysia. These results are mainly due to the following factors. First, Singapore, Thailand and Malaysia are in Southeast Asia and share similar geographical and environmental characteristics. But Singapore-Thailand and Singapore-Malaysia have different tourism resources. Hence, Singapore-Thailand and Singapore-Malaysia have complement effect in tourism market. Second, Singapore has a well-developed transportation conditions. Singapore holds tourism resources of neighboring countries in Southeast Asia as a favorable condition to develop his tourism, making it to develop into a transit point for Southeast Asia. For this reason, the tourist may travel Singapore first, after to travel Malaysia, Thailand or Indonesia and so on. The degrees of freedom for the Student-t range from 5 to 17, which are reasonably low. However, the degree of freedom is only significant in between Singapore and Thailand, indicating substantially extreme co-movements and tail dependence for between Singapore and Thailand. Tail dependence values for the Student-t copula, $\lambda_L = \lambda_R = 2t_{n+1}(-\sqrt{n+1}\sqrt{1-\rho}/\sqrt{1+\rho}$, are 0.1643, 0.0554 and 0.0016 for the Singapore-Thailand, Singapore-

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Table 5. Result of the static copula—GARCH model.

	Gaussian Copula	Student-t Copula		Gumbel Copula	Clayton Copula		SJC copula
Singapore and Thailand							
ρ	0.7060*** (0.0364)	0.7055*** (0.0443)	τ	1.8440*** (0.1176)	1.6751*** (0.2439)	τ^L	0.3520*** (0.1108)
n	-	5.4628* (3.1594)	-	-	-	τ^U	0.6336*** (0.0433)
AIC	55.7790	57.9289	AIC	47.5802	57.4019	AIC	126.6766
Singapore and Malaysia							
ρ	0.4314*** (0.0550)	0.4369*** (0.0656)	τ	1.3602*** (0.0705)	0.6547*** (0.1212)	τ^L	0.1625 (0.1276)
n	-	7.1568 (5.3346)	-	-	-	τ^U	0.3286*** (0.0866)
AIC	16.1453	17.0816	AIC	14.2114	15.4876	AIC	38.2790
Thailand and Malaysia							
ρ	0.2493*** (0.0692)	0.2492*** (0.0834)	τ	1.1702*** (0.0629)	0.2983*** (0.1056)	τ^L	0.0799 (0.1103)
n	-	17.9622 (27.6832)	-	-	-	τ^U	0.1000 (0.1076)
AIC	4.9469	4.5142	AIC	4.2669	3.9591	AIC	13.7842

Note: This table reports the estimates of static copula parameters defined in Equations (9-14) and their corresponding standard errors (in brackets) for several copula specifications for each pair of growth rate of the tourist arrivals. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels respectively. The total number of observations for each series is 174.

Malaysia and Thailand-Malaysia, respectively. This result shows that larger symmetric tail dependence or co-movement for the Singapore and Thailand tourism market, which is more tai dependence value than for the between Singapore and Malaysia tourism market and between Thailand and Malaysia tourism market which have lower tail dependence.

In order to study the asymmetric tail dependence, we use the Gumbel copula to capture the upper tail dependence and the Clayton copula to capture the low tail dependence. We note that there are the estimates of τ for the Gumbel copulas are significant and the dependence values are 1.8440, 1.3602, and 1.1702 for Singapore-Thailand, Singapore-Malaysia and Thailand-Malaysia, respectively. For the same pairs, the upper tail dependence values for the Gumbel copula, $\lambda_U = 2 - 2^{1/\tau}$, are 0.5437, 0.3354 and 0.1918, respectively. This show that there is a more probably that an extremely more Chinese tourist arrivals in Singapore is likely to accompany extremely more Chinese tourist arrivals in Thailand, and vice versa. But this

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probably decreases in run between Singapore and Malaysia and between Thailand and Malaysia. Moreover, in the Clayton copula, the dependence parameters τ are significantly and the dependence values of τ are 1.6751, 0.6547 and 0.2983 Singapore-Thailand, Singapore-Malaysia and Thailand-Malaysia, respectively, which low tail dependence values for the Clayton copula, $\lambda_L = 2^{-1/\tau}$, are 0.6611, 0.3469 and 0.0979 for the same pairs, respectively. Especially between Thailand and Malaysia, this probably is very low. This show that there is a more probably that an extremely less Chinese tourist arrivals in Singapore is likely to accompany extremely less Chinese tourist arrivals in Thailand, and vice versa. But this probably decreases in run between Singapore and Malaysia and between Thailand and Malaysia. Moreover, we also estimated the SJC copula which has different upper and lower tail dependence values. The estimated values of λ_L and λ_U are only significant in the pair of Singapore-Thailand.

In additional, assumed the dependence is time varying, we turn to apply the dynamic copula function to examine the issue. The parameter estimates for the Student-t dependence structure are given in the Table 6. From the Table 6, we first find that α_c is positive but only significantly between Singapore and Thailand, inferring that there is intercept for ρ_t only between Singapore and Thailand. Secondly, the autoregressive parameter β_c is strongly significant at the 0.01 level for all pairs except Singapore-Malaysia. Our finding of high and significant β_c in the Student-t dependence structure infers that the dependence between Singapore and Thailand and between Thailand and Malaysia have high degree of persistence pertaining to the dependence from time t-1 to time t. Third, the latent parameter γ_c is not significant in three pairs being studied in our paper. The degrees of freedom n are significant and not very low (from 6 to 17), indicate extreme co-movement and tail dependence for all pairs.

In order to get a better picture of the dynamic dependence parameter estimates, we plot the dynamic dependence parameter estimates among three destinations,

Table 6. Result of the dynamic student-t copula—GARCH model.

	Singapore and Thailand		Singapore and Malaysia		Thailand and Malaysia	
	Par.	S.E.	Par.	S.E.	Par.	S.E.
α_c	0.5215	0.4225	0.8783*	0.4312	0.2278	0.2275
β_c	0.6408***	0.2455	0.0001	0.0392	0.5077***	0.2171
γ_c	2.3539	1.5016	3.4692	2.2474	2.0116	1.7523
n	6.6602***	1.3960	6.6907***	2.5058	17.2807***	1.5313
AIC	-108.7766		-4.5090		-30.4837	

Note: This table reports the estimates of dynamic copula parameters defined in Equation (15) for each pair of growth rates of the tourist arrivals. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. The total number of observations for each series is 173.

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namely Singapore, Thailand and Malaysia over the sample period generated from GARCH-student-t copula model in Figure 3. From the Figure 3, we can find that different pairs have different conditional dependence structure. The dynamic conditional dependence between the conditional shocks of the three countries is not constant over time. All conditional dependence between the selected countries is positive over the time, which implies the destinations are positive dependent on one or the other. Moreover, the conditional dependence between Singapore and Thailand is highest among three pairs,[5] followed by Singapore and Malaysia. This result is consistent with the static copula result. From the figure, we find the dependence between we selected countries is higher during 2003 SARs and 2008 World Financial Crisis. Natural disasters and Financial Crisis have an impact on dependence.

5. Conclusion and implication

This study examines the conditional volatility and dependence (or co-movement) among Singapore, Thailand and Malaysia from a new perspective by copula-GARCH model. To account for tail independence, tail dependence, time-invariant, and time-

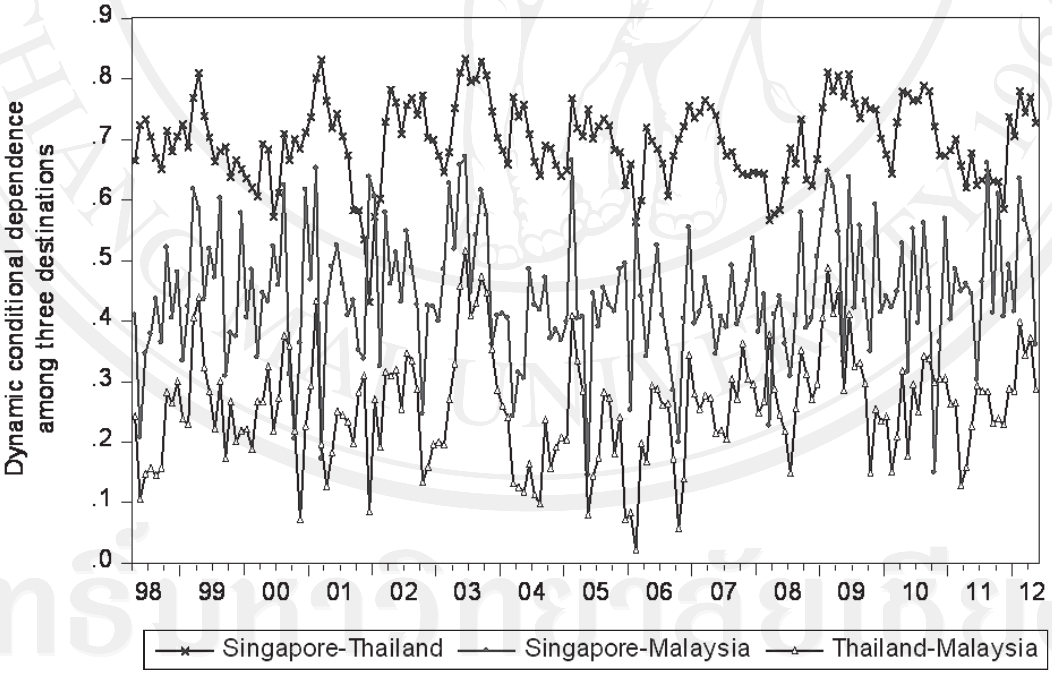

Figure 3. Dynamic conditional dependence among Singapore, Malaysia and Thailand.

[5] Three pairs are Singapore and Thailand, Singapore and Malaysia, and Thailand and Malaysia, respectively.

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variant dependence, we apply the abroad family of copulas to model the logarithm of the monthly China tourist arrivals in three destinations, namely Singapore, Thailand and Malaysia, with a sample size of 174 observations from January 1998 to June 2012.

The empirical results provided evidence of volatility and dependence in the conditional variances among three countries. The volatility analysis show that given any unanticipated shocks to monthly growth rate of Chinese tourist arrivals to the Singapore and Thailand, the effect of that shock will last for a short period of time, while given any unanticipated shocks to monthly growth rate of Chinese tourist arrivals to the Malaysia, the effect of that shock will last for a considerable period of time. The static symmetric dependence analysis infers that positive relationships exist between the conditional shocks in tourist destination countries. In three pairs, between Singapore and Thailand has the highest relationship. These results imply that the variations in monthly Chinese tourist arrivals in Singapore market strong influence of Chinese tourist arrivals in Thailand, and vice-versa. This influence weakens in run between Singapore and Malaysia and between Thailand and Malaysia. The empirical of the asymmetric tail dependence result show there is a more probably an extremely more (less) Chinese tourist arrivals in Singapore is likely to accompany extremely more (less) Chinese tourist arrivals in Thailand, and vice versa. But this probably decreases in run between Singapore and Malaysia and between Thailand and Malaysia. But this probably decreases in run between Singapore and Malaysia and between Thailand and Malaysia. The dynamic dependence analysis infers that the dynamic conditional dependence between the conditional shocks of the three countries is not constant over time. All conditional dependence between the selected countries is positive over the time, which implies the destinations are positive dependent on one or the other. The empirical results of this study have important implications for policy makers in this three countries and tour operator who sell holiday to these three countries to make o make an accurate assessment about how the variations in Chinese tourist arrivals to one country affect Chinese tourist arrivals to the other countries.

The empirical result also show that China outbound tourism to the Singapore, Thailand and Malaysia are highly seasonal, with tourist arrivals being significantly concentrated in the peak tourist season. Specially, summer holiday and the spring festival are the Chinese tourism seasons; the competition is fierce. Therefore, policy makers and destination manager in these three countries should take some measure to attract more tourists during the tourist season. For example, providing a wide range of competitive tour packages; reducing transportation cost and regulating real exchange rates to attract Chinese tourists. The finding of this study have important implications for policy makers in this three countries and tour operator who sell holiday to these three countries to make o make an accurate assessment about how the variations in Chinese tourist arrivals to one country affect Chinese tourist arrivals to the other countries.

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