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Analysis of appropriate forecasting models and dependence measures of exchange rates between People's Republic of China and Thailand

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ABSTRACT

This paper investigates the relationship between People's Republic of China's exchange rates and Thailand's exchange rates. The selection of several mixed forecasting consisting of linear model, nonlinear models and copulas approach was experimented of People's Republic of China's exchange rate return in percentage and Thailand's exchange rate return in percentage during 2006 to 2012. The mainly findings of this paper are: Firstly, the Self-Exciting Threshold Autoregressive Model (SETAR Model) and the Autoregressive-linear model (AR-linear Model) were suggested as the appropriate models for China's and Thailand's exchange rates during the specific period, respectively. Secondly, based on copulas approach, the dependence measures are not strong between returns in percentage of China's exchange rates and that of Thailand's exchange rates; different monetary policies and financial system in those two countries are the main reasons.

Keywords: Linear; Nonlinear; Copulas; Real Estate Sector Stock; Shenzhen Index

1. Introduction

Since the reform and opening of People's Republic of China in 1978, China's economy has developed dramatically. Thailand as one of the ASEAN members has very important economic status. In recently years, the international trade between China and Thailand shows the increase trend. In 2015, ASEAN target to be a single market and the corporation between ASEAN and China will become closer. Moreover, the research question is that how does a single foreign exchange market operation and based on the exchange rates how investors find themselves facing important financial opportunities. Therefore, analysis the forecasting models of each country's exchange rates and study the relationship between these two countries' exchange rates has the very vital practical meaning. It has already been the leading edge and hot spot of economics research with the nonlinear method to study internal regularity of exchange rate fluctuations.

Thus, this paper mainly has two purposes. First, in order to through the past data to calculate the future data, it will finds the appropriate forecasting models for People's Republic of China's exchange rates and Thailand's exchange rates. Second, it will analyze the dependence measures between these two countries' exchange rates which will help government modify monetary policies and guide investors to find the important financial opportunities in foreign exchange market.

The rest of the paper is organized as follows. Section 2 provides the literature review and highlights the contributions of this study. Section 3 introduces the econometric methodologies. Section 4 shows data sources and descriptions. Section 5 presents empirical results. Section 6 presents conclusions and discussions. Finally, Section 7 is concluding remarks.

2. Literature review

No matter foreign literature reviews or domestic literature reviews, more and more studies had focus on the dependence relationship between two or more countries' exchange rates and try to found an appropriate model which might explain the characteristic of exchange rates well.

Liew et al. (2002) shows that the exponential smooth transition autoregressive (ESTAR) model explained the adjustment behavior of nominal rates well that the exchange rates assumes as a symmetric distribution.

Liew et al. (2003) using the nonlinear methodology which based on Luukkonen et al. (1988) work paper and indicated that the nonlinear STAR model more effective than the linear AR model which captured the behaviors of real rates for 11 Asian countries.

Wu Zhenxiang, Ye Wuyi and Miao Baiqi (2004) using Archimedean Copula analysis two assets portfolio. The least VaR portfolio of two assets portfolio can be found by selecting proper copula.

Liu Wei (2008) a linear autoregressive model and two nonlinear regime switch model are selected as tool to analyzing real exchange rate theories and properties of RMB real exchange rate. The conclusion is that the smooth transition autoregressive model is the best one which describes the RMB real exchange rate behavior well.

Zhang Yuqin, Lin Guijun, Wang Shouyang (2011) focus on ASEAN-5 daily dollar exchange rates. They use surrogate data testing method to validate the test statistics.

Liu Qiongfang and Zhang Zongyi (2011) apply the copula theory to study the dependence structure between real estate and finance industries. Based on AIC and BIC minimum theories，the Gumbel Copula function shows that a correlation between these two markets exists in only upper tail for single parameter copulas.

Pisit Leeahtam, Chukiat Chaiboonsri, Prasert Chaitip, Kanchana Chokethaworn, Songsak Sriboonchitta (2011) aim to forecast Thailand's and Malaysia's single foreign exchange market and find itself facing important financial opportunities. The result of this study confirmed that the Autoregressive-linear model was suggested as appropriate model to both countries' exchange rate during the period of 2008-2011. And the relationship between these two countries' exchange rate return in percentage is not strong.

3. Methodology

This paper mainly has three steps. In the first step, adjust the each country's exchange rate data in form of the rate of return and test the data using unit root test and two-sample K-S test. In the second step, based on AIC, BIC and MAPE the appropriate forecasting models for People's Republic of China's exchange rates and Thailand's exchange rates will be selected and based on AIC and BIC we select the appropriate parametric copula. In the third step, combine Empirical Copula and the appropriate parametric copula the dependence measures of each country's exchange rates return in percentage will be examined.

3.1 Time series forecasting

Time series are data or a series of observations which have been changing along times. If time series explain or analyze the changes in the past capable, it means those time series can be used as a tool to predict or estimate the future.

3.2 Linear and Nonlinear Theory

In time series literature reviews, linear methods often run better than nonlinear methods and they often provide an adequate approximation for the object well. However, for the real economic situation linear methods could not capture the behaviors of data or observations accurately. Therefore using non-linear models will provide a potentially promising. And we also see linear model as one of the special nonlinear models.

3.2.1 CLS (Conditional Least Squares) method

Based on conditional expectations the minimization of a sum of squared deviations, we get "Conditional Least Squares" (CLS). This approach provides a unified standard of stochastic models estimation. In this paper, the linear and nonlinear models estimation based on this method.

3.2.2 Linear and Nonlinear Models

(1) Autoregressive-linear model (AR-linear Model)

The basic linear model AR-linear model explained as follows:

$$y_{ct+s} = \phi + \phi_0 y_{ct} + \phi_1 y_{1-d} + \ldots + \phi_m y_{ct-(m-1)d} + \varepsilon_{ct+s} \qquad (1)$$

$$y_{bt+s} = \phi + \phi_0 y_{bt} + \phi_1 y_{1-d} + \ldots + \phi_m y_{bt-(m-1)d} + \varepsilon_{bt+s} \qquad (2)$$

where y_{ct} is China's exchange rates at time t, y_{bt} is Thailand's exchange rates at time t ϕ is parameter and coefficient of y_t, ε is error term of this equation.

(2) Self-Exciting Threshold Autoregressive Model (SETAR Model)

The general Self-Exciting Threshold Autoregressive Model explained as follows:

$$y_{ct+s} = \begin{cases} \phi_1 + \phi_{10} y_{ct} + \phi_{11} y_{ct-d} + \ldots + \phi_{1L} y_{ct-(L-1)d} + \varepsilon_{ct+s} & Z_{ct} \le th \\ \phi_2 + \phi_{20} y_{ct} + \phi_{21} y_{ct-d} + \ldots + \phi_{2H} y_{ct-(H-1)d} + \varepsilon_{ct+s} & Z_{ct} > th \end{cases} \qquad (3)$$

$$y_{bt+s} = \begin{cases} \phi_1 + \phi_{10} y_{bt} + \phi_{11} y_{bt-d} + \ldots + \phi_{1L} y_{bt-(L-1)d} + \varepsilon_{bt+s} & Z_{bt} \le th \\ \phi_2 + \phi_{20} y_{bt} + \phi_{21} y_{t-d} + \ldots + \phi_{2H} y_{bt-(H-1)d} + \varepsilon_{bt+s} & Z_{bt} > th \end{cases} \qquad (4)$$

where y_{ct} is China's exchange rates at time t, y_{bt} is Thailand's exchange rates at time t, ϕ is the parameter and coefficient of equation, ε is error term of this equation and Z_{ct} and Z_{bt} are threshold variables in the model. The "L" is represented lower regime of model and "H" is represented the higher regime of the model.

(3) Logistic Smooth Transition Autoregressive Model (LSTAR model)

The general Logistic Smooth Transition Autoregressive Model explained as follows:

$$\begin{aligned} y_{ct+s} &= (\phi_1 + \phi_{10} y_{ct} + \phi_{11} y_{ct-d} + \ldots + \phi_{1L} y_{ct-(L-1)d})(1 - G(z_{ct}, \gamma, th)) + \\ &(\phi_2 + \phi_{20} y_{ct} + \phi_{21} y_{ct-d} + \ldots + \phi_{2H} y_{ct-(H-1)d}) G(z_{ct}, \gamma, th) + \varepsilon_{ct+s} \end{aligned} \qquad (5)$$

$$\begin{aligned} y_{bt+s} &= (\phi_1 + \phi_{10} y_{bt} + \phi_{11} y_{bt-d} + \ldots + \phi_{1L} y_{bt-(L-1)d})(1 - G(z_{bt}, \gamma, th)) + \\ &(\phi_2 + \phi_{20} y_{bt} + \phi_{21} y_{bt-d} + \ldots + \phi_{2H} y_{bt-(H-1)d}) G(z_{bt}, \gamma, th) + \varepsilon_{bt+s} \end{aligned} \qquad (6)$$

where y_{ct} is the China's exchange rates at time t, y_{bt} is the Thailand's exchange rates at time t, ϕ is the parameter and coefficient of equation, ε is error term of this equation and Z_{ct} and Z_{bt} are threshold variables in the model. The "L" is represented lower regime of model and "H" is represented the higher regime of the model. Moreover, "G" is the logistic function and ϕ, γ , th are the parameters to be computed.

(4) Neural Network Models (NNT Model)

The Neural Network Model explained as follows:

$$y_{ct+s} = \beta_0 + \sum_{j=1}^{D} \beta_j g(\gamma_{0j} + \sum_{i=1}^{m} \gamma_{ij} y_{ct-(i-1)d}) \tag{7}$$

$$y_{bt+s} = \beta_0 + \sum_{j=1}^{D} \beta_j g(\gamma_{0j} + \sum_{i=1}^{m} \gamma_{ij} y_{bt-(i-1)d}) \tag{8}$$

where y_{ct} is China's exchange rates at time t, y_{bt} is Thailand's exchange rates at time t, the β_0 is parameter of equation. In a hidden units and activation function g.

(5) Additive Autoregressive Model (AAR Model)

The generalized non-parametric additive model (Generalized Additive Model) explained as follows:

$$y_{ct+s} = \mu + \sum_{i=1}^{m} s_i (y_{ct-(i-1)d}) \tag{9}$$

$$y_{bt+s} = \mu + \sum_{i=1}^{m} s_i (y_{bt-(i-1)d}) \tag{10}$$

where y_{ct} is China's exchange rates at time t, y_{bt} is Thailand's exchange rates at time t. S_i are smooth functions represented by penalized cubic regression.

3. 3 Copulas Theory

Copula connects a joint distribution to its marginal distributions. It will solve the high dimensional (equal or more than two dimensions) process, in this paper we will focus on bivariate case or two-dimensional process.

3.3.1 The Sklar's theorem

Sklar's theorem explains that if there is a joint distribution which will factor into two marginal distributions and a copula describes the dependence relationship between these distributions.

Suppose the multi-dimensional distribution function H is that $F_1(u_1),..., F_n(u_n)$, there is a copula function satisfies:

$$H(u_1,...u_n) = C(F_1(u_1),...F_n(u_n)) \tag{11}$$

If $F_1(u_1),..., F_n(u_n)$ is continuous, then the copula function is uniquely determined, and vice versa. If the marginal distribution function is not continuous, the copula function is not unique.

3.3.2 Two sample Kolmogorov-Smirnov test

K-S two-sample test is a distribution test of fitness; the purpose of this test is that test two observations come from the same distribution. It compares the cumulative distribution function with a specific distribution.

The K-S two sample test statistic explained as follows:

$$D = \left| E_1(d) - E_2(d) \right| \tag{12}$$

Where E_1(d) and E_2(d) are the two observations empirical distribution functions.

H_0: The two samples (one of them is specific distribution) come from a common distribution.

H1: The two samples (one of them is specific distribution) do not come from a common distribution.

3.3.3 Rank correlation

Rank correlation reflects the monotonic dependence structure between observations. The widely typical rank correlation coefficients we used are Kendall.tau and Spearman.rho.

(1) Kendall.tau

Suppose $(x_1, y_1), (x_2, y_2)$ are i.i.d vector, $x_1, x_2 \in x, y_1, y_2 \in y$.

τ is between [-1, 1], suppose the copula function of (x_1,y_1) is C (u, v), that the function τ explained as follows:

$$\tau = 4\iint_0^1 C(u,v)dC(u,v) - 1 \tag{13}$$

(2) Spearmam.rho

H(x, y) is the joint distribution of (x, y).

The copula function C (u, v) is given, where u=F(x), v=G (y), that the function ρ explained as follows:

$$\rho = 12\iint_0^1 C(u,v)dC(u,v) - 3 \tag{14}$$

3.3.4 The dependence of upper tail and lower tail

Joe in 1997 describes the dependence structure of the bivariate tails distribution between left lower quadrant and right upper quadrant which we called tail dependence.

F (x) and L (y) are the marginal distribution functions of continuous random variables X and Y respectively. The correlation coefficient of the distribution in upper tail and lower tail explained as follows:

$$\lambda^{up} = \lim_{u \to 1} P\{Y > L^{-1}(u) \mid X > F^{-1}(u)\} = \lim_{u \to 1} \frac{1 - 2u + C(u,v)}{1-u} \tag{15}$$

If $\lambda^{up} \in (0,1)$, the upper tail is dependent; if $\lambda^{up} = 0$, the upper tail is independent.

$$\lambda^{low} = \lim_{u \to 1} P\{Y < L^{-1}(u) \big| X < F^{-1}(u)\} = \lim_{u \to 1} \frac{C(u,v)}{1-u} \qquad (16)$$

If $\lambda^{low} \in (0,1)$, the low tail is dependent; if $\lambda^{low} = 0$, the lower tail is independent.

3.3.5 Maximum Likelihood estimation method

We suppose f(x, y) as the joint distribution F(x, y) density function; we do the partial derivative on both sides of equation (11) and get:

$$f(x,y) = C_\theta(F_x(x;\alpha), F_Y(y;\beta)) \cdot f_x(x;\alpha) \cdot f_Y(y;\beta) \qquad (17)$$

Where f(x; α), f(y; β) is the marginal density function of f(x, y), α, β are the parameters, θ is the copula parameter.

The copula density function explained as follows:

$$C_\theta(u,v) = \frac{\partial^2 C(u,v)}{\partial u \partial v} \qquad (18)$$

Using the maximum likelihood method, the log-likelihood function of equations (13) explained as follows:

$$l(v) = \sum_{t=1}^{T} \ln c(F_X(x_t;\alpha), F_Y(y_t;\beta);\theta) + \sum_{t=1}^{T} \ln f_X(x_t;\alpha) + \sum_{t=1}^{T} \ln f_Y(y_t;\beta) \quad (19)$$

Where α,β,θ, are the parameter vectors of marginal distribution and copula function, respectively.

3.3.6 Generalized Pareto Distribution (GPD) models

The GPD distribution function explained as follows:

$$G_{\xi,\sigma}(y) = \begin{cases} 1-(1+\frac{\xi}{\sigma}y)^{-1/\xi} & if \xi \neq 0 \\ 1-\exp(-\frac{y}{\sigma}) & if \xi = 0 \end{cases} \qquad (20)$$

Where $\sigma > 0$. The function is defined for $y \geq 0$ when $\xi \geq 0$ and $0 \leq y \leq -\sigma/\xi$ when $\xi < 0$

Since the distribution of excesses can be estimated by a GPD, we are using the GPD function to estimate the tail of the original distribution F. We use GPD converse the exceed threshold sequence into the [0, 1] uniform distribution.

3.3.7 Copulas

(1) The empirical copula

Deheuvels in 1979 introduced Empirical copula theory. Suppose that the marginal distribution F is continuous, therefore the copula associated to F is unique.

Copula explained as follows:

$$C = \{(\frac{t_1}{T},\ldots,\frac{t_N}{T}); 1 \le n \le N, t_n = 0,\ldots,T\} \quad (21)$$

Through

$$\hat{C}(\frac{t_1}{T},\ldots,\frac{t_N}{T}) = \frac{1}{T}\sum_{t=1}^{T}\prod_{n=1}^{N} 1_{[\gamma_n^t \le t_n]} \quad (22)$$

We will get the empirical copula.

Suppose $\{x_k, y_k\}_{k=1}^{n}$ stand for the bivariate time series observation distribution and length of the observation is n, the Empirical copula C_n explained as follows:

$$C_n(\frac{i}{n},\frac{j}{n}) = \{\sum \text{ The sample which satisfied } x \le x_i \cap y \le y_j\}/\text{n} \quad (23)$$

(2) Gumbel Copula

$$C(u,v) = \exp(-[(-\ln u)\theta + (-\ln v)\theta]^{\frac{1}{\theta}} \quad (24)$$

When $\theta = 1$, the random variables u and v are independent; when $\theta = +\infty$, the random variables u and v are completely related. The density distribution shows "J" form which means that the upper tail dependence is high, and the copula reflects on the change of upper tail sensitively.

(3) Clayton Copula

$$C(u,v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta} \quad (25)$$

Where the parameters $\theta \in (0,+\infty)$, when $\theta \to 0$, the random variables u and v are independent, when $\theta = +\infty$, the random variables u and v tend to be perfect correlation. The density distribution shows "L" form which means that the lower tail dependence is high. This copula reflects the change of lower tail sensitively.

(4) Frank Copula

$$C(u,v) = -\frac{1}{\theta}\ln(1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1}) \quad (26)$$

Where the $\theta \ne 0$, if $\theta > 0$, the random variables u and v are positive correlation; if $\theta \to 0$ the random variables u and v are independent; if $\theta < 0$, the random variables u and v are negative correlated. The density distribution shows symmetric situation.

(5) Plackett Copula

The properties of Plackett copula are: first, for general marginal processes the density function is high elastic; second, a single parameter will explain the copula's two margins association.

Plackett copula (with $\theta > 0$) explained as follows:

$$C(u,v|\theta) = \{\frac{1}{2}(\theta-1)L - \sqrt{L^2 - 4uv(\theta-1)}\} \quad \text{if}\ \theta \neq 1 \tag{27}$$

$$= uv \quad \text{if}\ \theta = 1$$

Where $L = 1 + (\theta-1)(u+v)$. There is zero tail dependence.

(6) t Copula

Mashal & Zeevi (2002) and Breymann et al. (2003) in their paper showed the empirical t copula fit results. The t copula explains the dependence structure which the margins follow multivariate t distribution and we also call it Gaussian copula.

The t copula explained as follows:

$$C^t_{v,P}(u) = \int_{-\infty}^{t_v^{-1}(u_1)} \cdots \int_{-\infty}^{t_v^{-1}(u_d)} \frac{\Gamma(\frac{v+d}{2})}{\Gamma(\frac{v}{2})\sqrt{(\pi v)^d |P|}} (1 + \frac{x'P^{-1}x}{v})^{-\frac{v+d}{2}} dx \tag{28}$$

where t_v^{-1} is the standard univariate t_v distribution quantile function.

The density function of t copula explained as follows:

$$C^t_{v,P}(u) = \frac{f_{v,P}(t_v^{-1}(u_1),\ldots,t_v^{-1}(u_d))}{\Pi_{i=1}^d f_v(t_v^{-1}(u_i))}, u \in (0,1)^d \tag{29}$$

where $f_{v,p}$ is the joint density function and f_v is the density function of the univariate standard t distribution which freedom degree is v .

4. Data

4.1 Sources of data

This study is mainly based on exchange rates, covered 7 years' daily data, from 2006 to 2012. The data are secondary data and return in percentage, which are derived from the official website, namely People's Republic of China's Exchange Rate (CEX) and Thailand's Exchange Rate (TEX).

All of the following results (tables and figures) are calculated by EViews; R; S-PLUS; MATLAB and Excel.

4.2 Data description

The description of the data are described and displayed in table 1 to table 6 and from figure 1 to figure 4 as follows:

TABLE 1: The descriptive statistics of People's Republic of China's exchange rates return in percentage from the period of 2006 to 2012.

Item	People's Republic of China's exchange rates return in percentage
Observations	1402
Mean	-0.000168
Median	-2.93e-05
Maximum	0.003638
Minimum	-0.004330
Std.Dev	0.000902
Skewness	-0.469677
Kurtosis	5.306592
JB	362.0875
Probability	0.000000

Source: Calculation

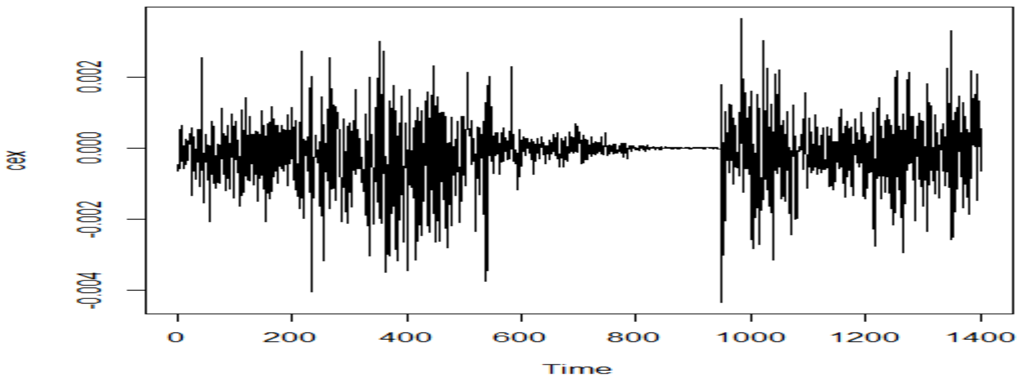

Figure 1: The historical daily data of People's Republic of China's exchange rates return in percentage during the periods of 2006 to 2012.

Source: Calculation

TABLE 2: Results of People's Republic of China's exchange rates return in percentage Unit Root test

Item	ADF Test	Item	PP Test
Data	cex	Data	cex
Dickey-Fuller	-9.9479	Dickey Fuller Z(alpha)	-1349.566
Lag order	11	Truncation lag Parameter	7
p-value	0.01	p-value	0.01
Alternative hypothesis	Stationary	Alternative hypothesis	Stationary
Result	Stationary	Result	Stationary

Note: Significant at 1% level
Source: Calculation

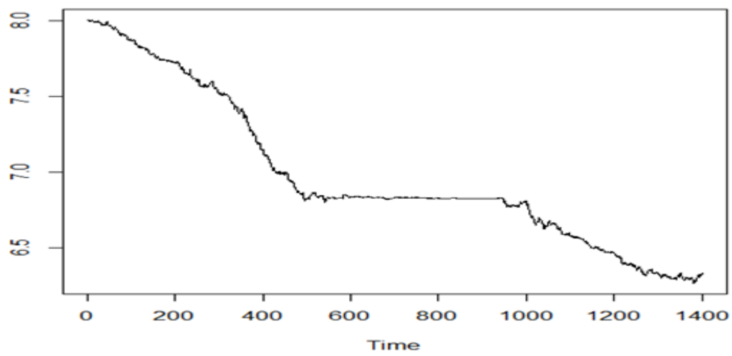

Figure 2: The People's Republic of China's nominal exchange rates from 2006 to 2012.

Source: Calculation

TABLE 3. The descriptive statistics of Thailand’s exchange rates return in percentage from the period of 2006 to 2012.

Item	Thailand's exchange rates return in percentage
Observations	1402
Mean	-0.000135
Median	0.000000
Maximum	0.044702
Minimum	-0.032345
Std.Dev	0.004895
Skewness	0.448775
Kurtosis	14.00870
JB	7121.581
Probability	0.000000

Source: Calculation

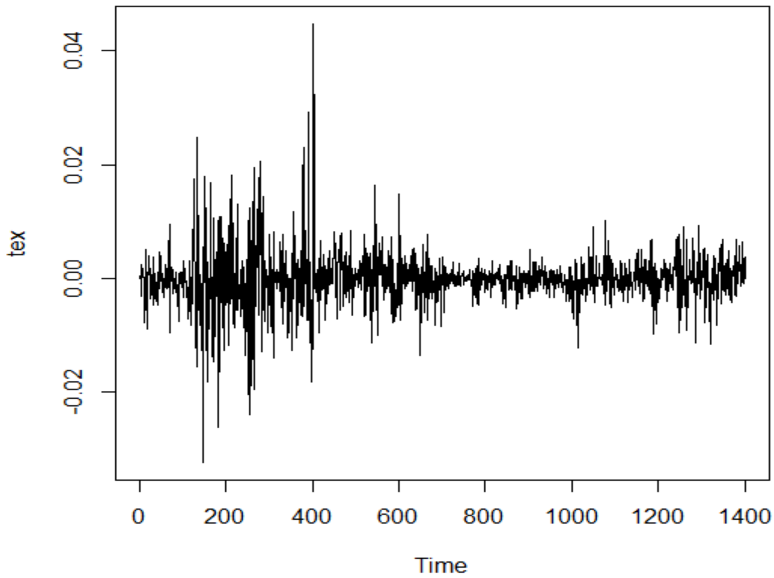

Figure 3: The historical daily data of Thailand’s exchange rates return in percentage during the periods of 2006 to 2012.

Source: Calculation

TABLE 4: Results of Thailand's exchange rates return in percentage Unit Root test

Item	ADF Test	Item	PP Test
Data	tex	Data	tex
Dickey-Fuller	-9.0724	Dickey Fuller Z(alpha)	-1314.37
Lag order	11	Truncation lag Parameter	7
p-value	0.01	p-value	0.01
Alternative hypothesis	Stationary	Alternative hypothesis	Stationary
Result	Stationary	Result	Stationary

Note: Significant at 1% level
Source: Calculation

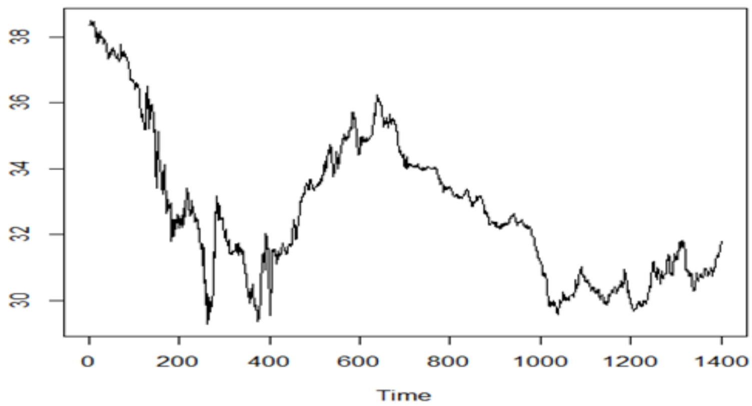

Figure 4. Thailand's nominal exchange rates from 2006 to 2012.

Source: Calculation

TABLE 5: Two sample Kolmogorov-Smirnov test for People's Republic of China's exchange rates return in percentage

Item	value
h	0
p	0.9765
ks2stat	0.0180
Result	Uniform Distribution

Note: Significant at 1% level
Source: Calculation

Table 6: Two sample Kolmogorov-Smirnov test for Thailand's exchange rates return in percentage

Item	value
h	0
p	0.8937
ks2stat	0.0217
Result	Uniform Distribution

Note: Significant at 1% level
Source: Calculation

Table 5 and Table 6 show the two sample KS test, the null hypothesis is that People's Republic of China's exchange rates return in percentage distribution or Thailand's exchange rates return in percentage distribution and a random uniform distribution which based on these two countries' real exchange rates return in percentage are from the same continuous uniform distribution. The alternative hypothesis is that they are not from the same continuous uniform distributions. The result h is 0 means the test accepts the null hypothesis at the 5% significance level. These results indicate that we can use copulas to describe the dependencies between the two sample data.

5. Empirical Results

5.1 The appropriate model of People's Republic of China's exchange rates return in percentage

We use AIC, BIC and MAPE (%) (Mean Absolute Percent Error) help us to select the appropriate model for People's Republic of China's exchange rates return in percentage.

TABLE 7: The model selection of People's Republic of China's exchange rates return in percentage based on AIC, BIC and MAPE (%)

Items	Autoregressive Linear Model	Self-Exciting Threshold Autoregressive Model	Logistic Smooth Transition Autoregressive Model	Neural Network Model	Additive Autoregressive Model
AIC	-19659.59	-19674.13	-19656.06	-19639.53	-19643.96
BIC	-19643.85	-19637.42	-19614.10	-19571.33	-19544.29
MAPE(%)	2.073917	1.613032	1.932661	2.065262	1.673697

Source: Calculation

From Table 7, the forecasting evaluation statistics indicated that Self-Exciting Threshold Autoregressive Model (SETAR Model) is the best model to forecast the People's Republic of China's exchange rates return in percentage of exploration period, which minimizes AIC and MAPE (%) among all candidate models.

5.2 The appropriate model of Thailand's exchange rates return in percentage

The function AIC, BIC and MAPE (%) can be used to compare all models fitted to the same data. Therefore AIC, BIC and MAPE (%) will help us find the appropriate model for Thailand's exchange rates return in percentage.

TABLE 8: The model selection of Thailand's exchange rates return in percentage based on AIC, BIC and MAPE (%)

Items	Autoregressive Linear Model	Self-Exciting Threshold Autoregressive Model	Logistic Smooth Transition Autoregressive Model	Neural Network Model	Additive Autoregressive Model
AIC	-14921.36	-14926.78	-14918.40	-14901.47	-14911.08
BIC	-14905.62	-14890.06	-14876.44	-14833.28	-14811.41
MAPE(%)	1.016519	1.016747	1.016734	1.016385	1.036549

Source: Calculation

From Table 8, the forecast evaluation statistics found that Autoregressive Linear Model (AR model) is the best model to forecast the Thailand's exchange rates return in percentage during exploration period because this model has minimize value of BIC and MAPE (%).

These results indicate that the exchange rates data's characteristic of People's Republic of China is different with that of Thailand. These two countries took the different monetary policies are the main reason of these results. From Bank of Thailand, we found that Thailand has adopted the managed-float exchange rates policy in 1997, which is also compliance with the inflation targeting policy that has adopted in 2000. Since 2005, Chinese government took the similar monetary policies, and switch to more flexibility exchange rates regime near 2010. Notice that, for Thailand's exchange rates the linear model used perhaps due to the world's financial crisis which affect Thailand's economy seriously.

From micro aspect, these appropriate models will help us to catch the data behaviors and operation rules which will help us to forecast each country's exchange rates in the future. From macro aspect, it provides some suggestions for government monetary policies. If the exchange rates expected decrease or increase rapidly, the government should use an appropriate economic leverage to modify the foreign exchange market and let their own currency value keep a healthy development.

5.3 Copula modeling

The function AIC, BIC can be used to compare all copulas fitted to the same data. Therefore AIC, BIC will help us to find the appropriate parametric copula. We should notice that different copulas measure the different dependence structures that the Normal copula has zero tail dependence, Clayton copula has zero upper tail dependence, Rotated Clayton copula has zero lower tail dependence, Plackett copula has zero tail dependence, Frank copula has zero tail dependence, Gumbel copula has zero lower tail dependence, Rotated Gumbel copula has zero upper tail dependence, Student's t copula has symmetric tail dependence and SJC copula parameters are the tail dependence coefficients, but in reverse order.

TABLE 9: Copula selection based on AIC and BIC

Copulas	Param	Param Value	St.Error	LL	AIC	BIC
Normal Copula	ρ	0.0946		-6.2952	-12.58897	-12.58816
Clayton's copula	θ	0.0918	8.81E-04	-4.527	-9.052573	-9.051756
Rotated Clayton copula	θ	0.1449	9.24E-04	-11.236	-22.47057	-22.46976
Plackett copula	θ	1.5161	0.0036	-10.8182	-21.63497	-21.63416
Frank copula	θ	0.7299	0.0045	-9.4432	-18.88497	-18.88416
Gumbel copula	θ	1.1	8.74E-04	-15.2614	-30.52137	-30.52056
Rotated Gumbel copula	θ	1.1	8.86E-04	-7.2754	-14.54937	-14.54856
Student's t copula	ρ	0.1198	0.71	-30.357	-60.71115	-60.70951
	DOF	4.5335				
Symmetrised Joe-Clayton copula	τ^U	0.061	2.02E-12	-13.5667	-27.13055	-27.12891
	τ^L	6.98E-10	0			

Source: Calculation

Table 9 presents the Student’s t copula is the best copula to measure the dependence coefficient, which minimizes AIC and BIC among all candidate copulas. This result indicates that the relationship between these two countries’ exchange rates return in percentage shows the symmetric tail dependence correlations.

Therefore we will use Empirical Copula which is non-parametric copula and the Student’s t Copula which we selected from all candidate parametric copulas to measure dependence relationship between People’s Republic of China’s exchange rates return in percentage and that of Thailand’s exchange rates.

5.4 The dependence measures based on copulas approach

5.4.1 Empirical copula approach

TABLE 10: The dependence measure of People's Republic of China's exchange rates and Thailand's exchange rates based on Empirical Copula, 2006-2012

Correlation items	Dependence Coefficients
Kendall's tau	0.07931982
Spearman's rho	0.1102664

Source: Calculation

From Table 10 we will get that based on Empirical Copula the Kendall's tau statistics of dependence measure between People's Republic of China's currency and Thailand's currency is 0.07931982. In addition, the Spearman's rho statistics of dependence measure between People's Republic of China's currency and Thailand's currency is 0.1102664. (See more details in Appendix)

5.4.2 Student's t copula approach

TABLE 11: The dependence measure of People's Republic of China's exchange rates and Thailand's exchange rates based on Student's t Copula, 2006-2012

Correlation item	Dependence Coefficients
Kendall's tau	0.0573

Source: Calculation

Table 11 shows that based on Student's t Copula the Kendall's tau statistics of dependence measure between People's Republic of China's currency and Thailand's currency is 0.0573.

All the copula approach dependence coefficients results indicate that the dependence measure between these two countries' exchange rates return in percentage is not strong.

6. Discussions

This paper investigates the relationship between People's Republic of China's exchange rates and Thailand's exchange rates during 2006 to 2012.

Moreover, in this paper we use statically copulas to measure the dependence structures. But if we switch to the time-varying copulas, we will find that the dependence measures will not constant. We will show part of the time-varying copulas results. And the related theories and the results we will no longer to explain in this paper.

TABLE 12: Time-varying copulas parameters and its values

Copulas	ω	β	α			
Time-varying normal Copula	0.084 (0.0022)	-0.0434 (0.0018)	1.1753 (0.0216)			
Time-varying rotated Gumbel Copula	0.7921 (0.0028)	0.2732 (8.2162e-04)	-2.7488 (0.0068)			
Copula	ω_U	β_U	α_U	ω_L	β_L	α_L
Time-varying SJC Copula	1.8103 (0.0472)	-15.2704 (0.1687)	1.5520 (0.0405)	-21.0822 (0.0267)	-6.78E-05 (0.0267)	9.61E-06 (0.0267)

Source: Calculation

Table 13: Time-varying copulas selection based on AIC and BIC

Copulas	LL	AIC	BIC
Time-varying normal Copula	-6.6763	-13.3483204	-13.34586659
Time-varying rotated Gumbel copula	-38.6207	-77.2371204	-77.23466659
Time-varying SJC Copula	-46.53	-93.0514408	-93.04653318

Source: Calculation

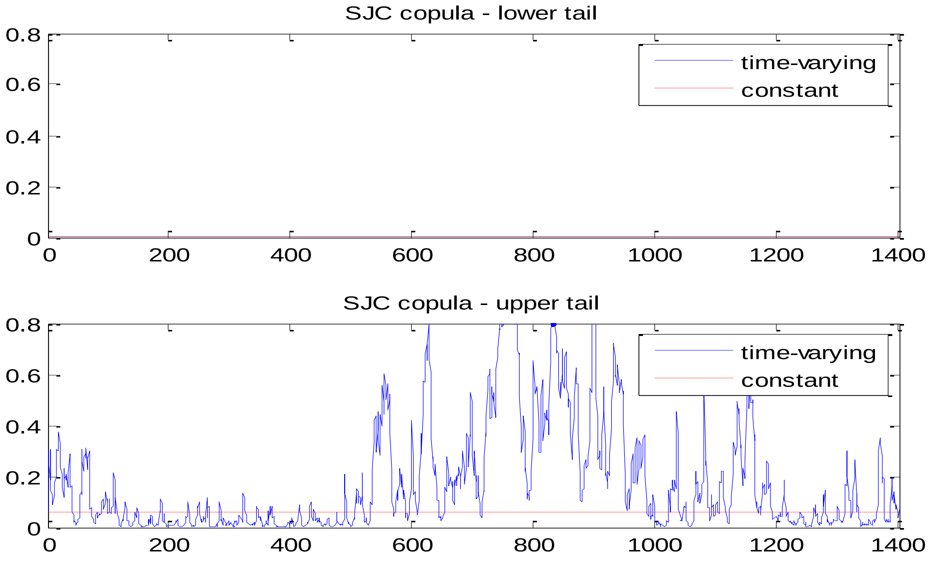

Figure 5: Dependence measures based on Time-varying SJC Copula

Source: Calculation

From Table 12 and Table 13 based on AIC and BIC minimum theory, the Time-varying SJC copula is the appropriate copula which among all candidate Time-varying copulas. Figure 5 will shows the Time-varying dependence relationship between People's Republic of China's exchange and Thailand's exchange.

7. Concluding remarks

The results of this study confirmed that the Self-Exciting Threshold Autoregressive Model (SETAR Model) and the Autoregressive-linear model (AR-linear Model) were suggested as the appropriate models for China's and Thailand's exchange rates during 2006 to 2012, respectively. Based on the Empirical Copula approach and Student's t Copula approach, the dependence measures are very small between returns in percentage of People's Republic of China's exchange and Thailand's exchange.

The results indicate that, on one hand, the behaviors of these two countries' exchange rates are different. Thailand's exchange rates show the linear feature because its economy affected by world's financial crisis serious. On the other hand, it means that the currency of both countries' did not strong enough to challenge. From macro aspect different monetary policies and financial system took in those two countries are the main reasons. From micro aspect, in the foreign exchange market investors' expectations are different. Therefore, government based on their own exchange rates expectation should take a series of workable monetary policies and financial leverage tools to keep their currency value growth healthy. And currency investors should take reasonable to avoid risks.

For the further research, on the one hand the time-varying copulas can be improved to analysis the relationship between People's Republic of China's exchange rates and Thailand's exchange rates by adding each country's interest rates or other variables. On the other hand, some further researches on the VaR analysis, and find the reasonable portfolio for foreign exchanges.

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APPENDIX

Empirical Copulas for People's Republic of China's exchange rates (x) and Thailand's exchange rates (y).