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THE 1997 ASIAN FINANCIAL CRISIS: REVISITED WITH
A COPULA APPROACH †

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REVISITING THE 1997 ASIAN FINANCIAL CRISIS: A COPULA APPROACH

Abstract

This study is motivated by the stylized fact that the asymmetry in dependence usually exists in returns of financial data series. Owing to political and monetary reasons, this phenomenon may be present in daily changes of exchange rates. In this paper, we study the relationships between five currencies in Asia around the period of Asian Financial Crisis in 1997, including the Singapore Dollar, Japanese Yen, South Korea Won, Thailand Baht and Indonesia Rupiah. We employ various time-varying copula models to examine the possible structural breaks. The results indicate significant changes at the dependence level, tail behavior and asymmetry structures between returns of all permuted pairs from the five currencies before and after the crisis. Other methods for identifying structure changes are also explored to compare and contrast the findings using the copular models. The results show that the copular approach seems to have more explanatory power than the existing ones in identifying structure breaks.

I. Introduction:

The Asian financial crisis started in Thailand in July 1997 with the financial collapse of the Thai baht caused by the decision of the Thai government to float the baht, after exhaustive efforts to support it in the face of a severe financial overextension. As the crisis spread, most of East Asian economies were badly hit, a result of which have been the slumping currencies, devalued stock markets and other asset prices, and a precipitous rise in private debt. Indonesia, South Korea and Thailand were the countries most affected by the crisis. Hong Kong, Malaysia, Laos and the Philippines were also hurt by the slump. The People's Republic of China, India, Taiwan, Singapore, Brunei and Vietnam were less affected, although all suffered from a loss of demand and confidence throughout the region.

Although most of the Asian countries carried out sound fiscal interventions during the crisis, IMF provided a bailout package worth \$40 billion to stabilize the currencies in Thailand, Indonesia and South Korea. The financial crisis has eroded the credibility of unilateral fixed exchange rates and correspondingly renewed calls among politicians for tight monetary policy coordination and regional exchange rate stability in the East Asian region. In the wake of the financial crisis, exchange rate arrangements in East Asia have evolved considerably. Most of crisis-affected East Asian economies including Indonesia, Korea, the Philippines and Thailand shifted their exchange rate regimes from *de facto* US dollar pegs to floating ones. However, East Asian central banks have intervened heavily in foreign exchange rate markets in order to prevent the appreciation of their currencies for the pursuit of an 'export-led growth strategy' (Dooley, Folkerts-Landau, and Garber, 2003). The post-crisis exchange rate behavior in these economies may often resemble a managed float or even a *de facto* peg despite the declared regime being one of currency flexibility. McKinnon (2005) describes it as "fear of floating".

The financial crisis has recalled a tight monetary cooperation among the East Asian economies. The dependant relations between those Asian countries are expected to have a dramatic change during this period. After the crisis, many developing countries became more critical to global institutions rather they prefer more in bilateral trade agreement. This has motivated us to study the structural changes of several Asian currencies in terms of the dependence before and after the crisis. Before us, intensive research have been done relating to this crisis, such as Radelet and Sachs (1998), they argues that the crisis was caused by the shifts of market expectations and confidence. Allan and Gale (1999) reviewed a number of possible hypotheses about the process of financial contagion and related them to this crisis. Baig and Goldfajn (1999) looked at the change in correlation in currencies and equity markets in several Asian countries during the crisis where VARs were deployed. Some more recent literatures like Van Horen et al. (2006) managed to measure the contagion effects while controlling other external shocks through regression analysis. Baharumshah (2007) estimated the volatility before and after the crisis by using Exponential GARCH model (EGARCH) model. And the contagious effects were detected in terms of the volatility. Khalid and Rajaguru (2007) constructed Multivariate GARCH model and applied causality tests to study the inter-linkages among Asian foreign exchange markets. In this study, we attempt to study this crisis in terms of the dependence structure of exchange rates of currencies in Asia by some relatively new approaches.

The asymmetric structure of dependence between two financial returns has been documented in many literatures. In terms of dependence structure, there are many examples which provide evidence of multivariate distribution between financial returns differing from normal distribution in recent researches. For example, Erb et al. (1994), Longin and Solnik (2001), and Ang and Chen (2002) showed that the financial returns turn to have a higher dependence when the economy is at downturn than at the upturn. One

suggestion provided by Ribeiro and Veronesi (2002) is that the higher correlation between financial returns at bad time comes from the lack of confidence of the investors to the future economy trend. As a result, asymmetric property of the dependence would increase the cost of global diversification of the investment at bad times, and thus the analysis is valuable to risk control and portfolio management. In literatures like Patton (2006), the asymmetric dependence structure of different exchange rates is studied and the author proposed logic link between the government policies and the asymmetry in dependence. One objective of ours in this thesis will be to testify the asymmetric property of the currencies which are strongly affected in the financial crisis.

Inspired by some pioneer researches, we will apply the copula models to measure the imbalanced dependence structure and possible shifts of regimes of exchange rates. The copula approach has been used to study the dependence between random variables for the first time in Schweizer and Wolff (1981). Recently, there is an increasing popularity in researching risk management in financial market applying the copula model. The advantages of this approach in examining the multivariate dependence structures are: First, the copula approach is a great tool to connect margins and joint densities. Second, the measures of dependence provided by the copula models give a better description of the bivariate dependence when linear correlation doesn't work (i.e. nonlinear dependence). Thirdly, copula offers a flexible approach to model the joint distribution and dependence structures, such as parametric (both marginal distribution and copula used are parametric), semi-parametric (either marginal distribution or copula used are parametric) and nonparametric approaches (both marginal distribution and copula used are nonparametric). Flexibility of copula also is embodied in the way that marginal distributions need not come from the same family. Once we provide a suitable copula to marginal distributions from different families, we can still obtain a meaningful estimate of the joint distributions.

Finally, the estimations of the copula models can be based on standard maximum likelihood which can be handled by some desktop software.¹

Contagious effect during financial crisis is a special case of asymmetry dependence between financial returns. The financial returns seem to have a stronger connection when the economy is at bad time. Many studies on contagion are based on structure changes in correlations, for example, Baig and Goldfajn (1999) showed structural shifts in linear correlation for several Asian markets and currencies during the Asian crisis. Some other approaches also are used to address the issue, like Longin and Solnik (2001) applied extreme value theory to model the dependence structure on tails; Ang & Bekaert (2002) estimate a Gaussian Markov switching model for international returns with two regimes (low-return-high-volatility and high-return-low-volatility) identified. Some researchers applied copula approach to analyze the financial contagion in equity markets. Rodriguez (2007) applies Markov switching models to copula parameters to analyse the financial breakdown in Mexico and Asia, and finds evidence of increased correlation and asymmetry at the time of turmoil. Chollete (2008) studies the relation between VaR and various copula models and applies Markov switching on copula functional models to the G5 countries and Latin American regions.

Comparing to a great deal of studies on international equity market returns, study of the dependence property on exchange rates has attracted less attention. One of the recent studies was Patton (2006) in which, he studied the asymmetric dependence between Japanese Yen and German Mark before and after the day of introduction of Euro. Evidence has been provided using the time varying copula approach with structure break identified. He suggested that the possible reason that asymmetry exists in the dependence between the two currencies comes from the imbalance of the two considerations. First consideration is that a government turns to depreciate the home currency in match with depreciation in the

¹ In monographs like Joe (1997) and Nelson (2006), details about applications and extensions of copula models can be found.

currency of the competing country. This is due to the consideration to maintain the competitiveness of the home currency in the global market. On the other hand, a country may want to appreciate the home currency when there is an appreciation of competing currency. This policy is meant to stabilize the domestic price level.

To check the possible asymmetry property between currencies in Asia, we will use copula models with time varying parameters to study the five currencies in Asia during the period of the Asian financial crisis, including Singapore, Thailand, Japan, South Korea and Indonesia. In particular, we investigate the effects that financial crisis brought to those countries and look for a sign of asymmetry in exchange rates returns. In addition, we will study the difference in the dominating tails which is implied by the time varying tail dependence and search for possible dynamic changes in dependence. We expect to see obvious changes in both tail dependence and conditional linear correlation during the financial crisis.

The rest of the study is organized as follows. In the next section we discuss the methodology and different models of copula, as well as the measures of dependence based on copula. In the third section, the data and the empirical results will be presented. Section 4 concludes.

2. Methodology

Copulas are very useful in modeling joint distributions among different data sets with various distributions. It is a better measure of the dependence structure than linear correlation as it takes the marginal property of random variables of interest into account, even when those margins are from different distribution families. Some existing copula models are capable of capturing asymmetric property that exchange rate and financial data often exhibit. By studying the time varying copula models, we can also observe the

possible structure change where the dependence structure of two currencies changes dramatically due to political or economical turnovers.

2.1 Definition of Copula

2.1.1 Sklar's Theorem

The definition of copula was first stated in Sklar's paper in 1959. They are functions that join multivariate distribution functions to their one-dimensional marginal distributions.

Sklar's theorem is the foundation of many recent empirical researches on two dimensional copulas. In Nelson (1999), it states that an n-dimensional copula is a multi-dimensional joint distribution function of margins with uniform distribution on [0,1]. Therefore, C is actually a mapping from n-cube $[0,1]^n$ to $[0,1]$, satisfying the following conditions,

- (1) $C(1 \dots 1, a_m, 1 \dots 1) = a_m$ for $m \leq n$ and a_m in $[0,1]$.
- (2) $C(a_1 \dots a_n) = 0$ if $a_m = 0$ for any $m \leq n$.
- (3) C is n-increasing. (2.1)

Property (1) shows that if the realizations for n-1 random variables are known each with marginal probability 1, the joint density of these n margins is just equal to the marginal probability of the remaining random variable. Property (2) states that if marginal probability is zero for one variable, then the joint probability of these n variables will be just zero. This property also refers to the grounded property of copula. Property (3) says that the C-volume of n dimensional interval is nonnegative which is equivalent to

$$\frac{\partial^n C}{\partial \alpha_1 \partial \alpha_2 \dots \partial \alpha_n} \geq 0. \text{ This is a general property for a multivariate cdf.}$$

For example, if we consider the case of multivariate cdf $F(y_1, y_2 \dots y_n)$ with all marginal densities being $F_1(y_1) \dots F_n(y_n)$ and the inverse functions of those margins are $F_1^{-1} \dots F_n^{-1}$. Then we have $y_1 = F_1^{-1}(u_1) \dots y_n = F_n^{-1}(u_n)$ where $u_1 \dots u_n$ are uniformly distributed on (0, 1) referring to probability transformation stated in the next section.

Hence we should have the transformation with continuous function F,

$$F(y_1, y_2, \dots, y_n) = F(F_1^{-1}(u_1) \dots F_n^{-1}(u_n)) = \Pr(U_1 < u_1, \dots, U_n < u_n) = C(u_1, \dots, u_n).$$

Copula is especially useful when we only have knowledge in marginal distributions as it can connect all those margins to find a reasonable fit for their joint distribution. In practice, sometimes the n-dimensional multivariate distribution F can be associated with copula function C as follows, given $C : [0,1]^n \rightarrow [0,1]$,

$$F(y_1, y_2, \dots, y_n) = C(F_1(y_1) \dots F_n(y_n); \theta),$$

where parameter θ is a measure of dependence between margins which can be a vector. If all margins are continuous functions, then the copula function of interest is unique. This is a starting point of applications of copula.

2.1.2 Probability Integral Transformation

For any random variables, given the cumulative distribution function, we can convert them into random variables that are uniformly distributed. Suppose X is a random variable with continuous cumulative function F, then a new random variable $Y = F(X)$ will have uniform distribution. This transformation is used to obtain uniformly distributed variables required by copula. Besides, this method can be used to generate random data from specified distribution which is also called inverse transform sampling.

2.2 Marginal density models

It is necessary to specify the two “true” univariate marginal densities first. Data required by copula models has to be uniformly distributed. If we misspecify marginal distributions for the data, probability integral transformation will not produce uniform distributed variables, and thereby leading to a misspecification in copula modelling. A test of fitness is then critical when we study the copula functions. A method proposed in Diebold et al. (1998) to test the goodness of fit of the marginal density model is often applied. We are suggested to test the independence of the transformed sequence U_t and V_t through a

regression of $(u_t - \bar{u})^k$ and $(v_t - \bar{v})^k$ on 20 lags of both $(u_t - \bar{u})^k$ and $(v_t - \bar{v})^k$, for $k=1, 2, 3, 4$. Then the Kolmogorov-Smirnov test is used to test the hypothesis that U_t and V_t are uniformly distributed on $(0, 1)$.

As proposed in many researches papers, two main approaches of handling the marginal series are stated below.

- (1) General ARMA-GARCH models with normal or generalized error distributed innovations are suggested to be used. Here we consider five margins of interest, where X_t is the log difference of the exchange rates for each time series,

$$\begin{aligned} X_t &= \mu_x + \sum_{i=1}^p \phi_i X_{t-i} + \sum_{j=1}^q \vartheta_j \varepsilon_{t-j} + \kappa_t \\ \delta_t^2 &= \omega_t + \sum_{i=1}^p \beta_i \delta_{t-i}^2 + \sum_{j=1}^q \alpha_j \kappa_{t-j}^2, \end{aligned} \quad (2.2)$$

where ε_{t-j} is white noise error, $\eta_t \delta_t = \kappa_t$ and η_t is i.i.d t distributed or generalized error distributed. GED can be used to capture the fatness of the tail distribution which is often observed in financial time series data. The random variable u_t following GED with zero mean and unit variance has a PDF,

$$\begin{aligned} f(u_t) &= \frac{\gamma \exp[-(1/2)(u_t / \lambda)^\gamma]}{\lambda \cdot 2^{(\gamma+1)/\gamma} \Gamma(1/\lambda)}, \\ \lambda &= \left[\frac{2^{-2/\gamma} \Gamma(1/\gamma)}{\Gamma(3/\gamma)} \right]^{1/2}, \end{aligned} \quad (2.3)$$

where γ is a positive parameter governing the behavior on tails. When $\gamma = 1$, the PDF becomes the PDF for double exponential distribution. When $\gamma = 2$, GED reduces to standard normal distribution. The distribution shows a thicker tail comparing to normal distribution when $\gamma < 2$ while a thinner tail when $\gamma > 2$.

- (2) Alternatively, we can compute the empirical CDF of the margins by using the following expression, which also refers to empirical CDF,

$$F_n = \frac{1}{T+1} \sum_{t=1}^T \mathbb{1}\{X_m < x\}, \text{ for } n=1, 2, \dots, d, \quad (2.4)$$

where X_m is the t element of n th data vector which contains T elements. We have

the term $\frac{1}{T+1}$ in order to keep cdf always less than 1. It is a semi-parametric

approach by applying this empirical cdf to copula models.

One good thing about this method is that the specification of copula models will be independent from the specification of marginal models which will save us some calculation time comparing to the first method when we want to estimate all parameters together using MLE. The data obtained after probability integral transformation will be truly uniformly distributed on $[0,1]$ which can be tested using Kolmogorov-Smirnov method. We will use this method for simplicity in the latter part.

2.3 Unconditional Copula models

Nine popular Archimedean copula models are listed in this thesis, and all of which are unconditional models with either symmetric or asymmetric properties. Maximum likelihood can be used to estimate the parameters of copula models and margins. Two approaches of estimation processes by maximum likelihood will be presented here. First, we can estimate all the parameters using the full maximum likelihood according to the log-likelihood function of copula, defined as follows, given n -copula $C : [0,1]^n \rightarrow [0,1]$ and n -dimensional multivariate distribution function F ,

$$\begin{aligned} f(y; \theta) &= \frac{\partial^n}{\partial y_1 \dots \partial y_n} F(y; \theta) = \frac{\partial^n}{\partial y_1 \dots \partial y_n} C(F_1(y_1; \theta_1), \dots, F_n(y_n; \theta_n)) \\ &= \prod_{i=1}^n f_i(y_i; \theta_i) \cdot \frac{\partial^n}{\partial u_1 \dots \partial u_n} C(F_1(y_1; \theta_1), \dots, F_n(y_n; \theta_n)) \\ &= \prod_{i=1}^n f_i(y_i; \theta_i) \cdot c(F_1(y_1; \theta_1), \dots, F_n(y_n; \theta_n)), \end{aligned} \quad (2.5)$$

and the joint density becomes the product of marginal density and copula density where

$$c(u_1, \dots, u_n) = \frac{\partial^n C(u_1 \dots u_n)}{\partial u_1 \dots \partial u_n}.$$

The log likelihood function of copula is then defined to be

$$L(\theta) = \ln c(F_1(y_1; \theta_1) \dots F_n(y_n; \theta_n); \theta) + \sum_{i=1}^n \ln f_i(y_i; \theta_i). \quad (2.6)$$

The other method adopts a two-step estimation process in which the marginal distributions are estimated in the first step and dependence parameter will be estimated after we substitute in the marginal distribution found. The 2-step maximum likelihood method exhibits an attractive property, as the estimate of dependence parameter is independent of marginal distributions chosen. We will use the 2-step method. After we adopt the empirical CDF and apply probability integral transformation, the uniformly distributed data u_1, \dots, u_n will be obtained and then the parameters of copula density will be

$$\text{identified according to the copula likelihood } L(\theta) = \sum_{t=1}^T \ln c(u_1 \dots u_n; \theta).$$

Among the 9 copula models described below, we choose the best fit among these non-nested copula models by applying maximum likelihood based method either Akaike or Bayesian information criterion. Akaike information is defined to be $AIC = -2K - \ln(L)$ while Bayesian information criterion (BIC) takes the form of $-2\ln(L) + K\ln(N)$ where $\ln(L)$ is the maximum of log-likelihood of copula likelihood and K is the number of parameters and N is the number of observations in both cases. BIC which gives the smallest value indicates a better fit.

(a) The Gaussian (Normal) copula (Lee, 1983) is specified as

$$\begin{aligned} C(u_1, u_2; \theta) &= \Phi_G(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \theta) \\ &= \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi(1-\theta^2)^{1/2}} \times \left\{ \frac{-(s^2 - 2\theta st + t^2)}{2(1-\theta^2)} \right\} ds dt \end{aligned} \quad (2.7)$$

where Φ is the cdf of the standard normal distribution, and parameter θ is a measure of correlation between two variables which is defined on $(-1, 1)$.

(b) The Clayton copula was first introduced in Clayton (1978), specified as

$$C(u_1, u_2; \theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta}, \quad (2.8)$$

where θ is a dependence parameter defined on $(0, +\infty)$. Clayton copula was widely used when modelling the case where two variables have strong correlations on the left tails.

- (c) Rotated Clayton copula is an extension of Clayton copula to capture the strong correlations on the right tail ,

$$C_{RC}(u_1, u_2; \theta) = u_1 + u_2 - 1 + ((1 - u_1)^{-\theta} + (1 - u_2)^{-\theta} - 1)^{-1/\theta}, \quad (2.9)$$

where $\theta \in [-1, +\infty) \setminus \{0\}$.

- (d) Plackett copula

$$C(u_1, u_2; \theta) = \frac{1}{2(\theta - 1)} (1 + (\theta + 1)(u_1 + u_2) - \sqrt{(1 + (\theta - 1)(u_1 + u_2))^2 - 4\theta(\theta - 1)u_1u_2})$$

where $\theta \in [0, +\infty) \setminus \{1\}$. (2.10)

- (e) Frank copula is specified as (Trivedi, 2007),

$$C(u_1, u_2; \theta) = -\theta^{-1} \log \left\{ 1 + \frac{(e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)}{e^{-\theta} - 1} \right\}, \quad (2.11)$$

where $\theta \in (-\infty, +\infty)$ and it represents independent case when $\theta = 0$. Frank copula allows negative relation between two marginal densities, and it is able to model symmetric property of joint distribution on both right and left tails. However, comparing to Normal copula, Frank copula is more suitable to model the structure with weak tail dependence.

- (f) Gumbel copula has the form,

$$C(u_1, u_2; \theta) = \exp(-((\log u_1)^\theta + (\log u_2)^\theta)^{1/\theta}), \quad (2.12)$$

where $\theta \in [1, +\infty)$ and it captures the independent case when $\theta = 1$. Gumbel copula doesn't allow negative correlation, and it is a good choice when two densities exhibit high correlation at right tails.

- (g) Rotated Gumbel copula is specified as,

$$C(u_1, u_2; \theta) = u_1 + u_2 - 1 + \exp(-((\log(1 - u_1))^\theta + (\log(1 - u_2))^\theta)^{1/\theta}), \quad (2.13)$$

where $\theta \in [1, +\infty)$. This model works for joint densities which show strong correlations on the left tails.

(h) Student t's copula is specified as follows,

$$C(u_1, u_2; \theta_1, \theta_2) = \int_{-\infty}^{t_{\theta_1}^{-1}} \int_{-\infty}^{t_{\theta_2}^{-1}} \frac{1}{2\pi(1-\theta_2^2)^{1/2}} \times \left\{ 1 + \frac{s^2 - 2\theta_2 st + t^2}{v(1-\theta_2^2)} \right\}^{-(\theta_1+2)/2} ds dt, \quad (2.14)$$

where $t_{\theta_1}^{-1}$ denotes the inverse distribution of student t's distribution with θ_1 degree of freedom. θ_1 and θ_2 here are two dependence parameters in which θ_1 controls the heaviness of the tails.

(i) Symmetrised Joe-Clayton copula is derived from Laplace transformation of the Clayton copula with special attention on tail dependence of the joint density (Joe, 1997). The Joe-Clayton copula takes the form,

$$C_{JC}(u_1, u_2 | \tau^U, \tau^L) = 1 - (1 - \{ [1 - (1 - u_1)^k]^{-\gamma} + [1 - (1 - u_2)^k]^{-\gamma} - 1 \}^{-1/\gamma})^{1/k}$$

where

$$\begin{aligned} k &= 1/\log_2(2 - \tau^U) & \tau^U &\in (0,1) \\ \gamma &= -1/\log_2(\tau^L) & \tau^L &\in (0,1) \end{aligned} \quad (2.15)$$

The two parameters τ^U, τ^L inside the function are measures of upper tail dependence and lower tail dependence respectively. The definitions of these two parameters are as following,

$$\begin{aligned} \lim_{\delta \rightarrow 1} \Pr[U_1 > \delta | U_2 > \delta] &= \lim_{\delta \rightarrow 1} \Pr[U_2 > \delta | U_1 > \delta] = \lim_{\delta \rightarrow 1} (1 - 2\delta + C(\delta, \delta)/(1 - \delta)) = \tau^U \\ \lim_{\varepsilon \rightarrow 0} \Pr[U_1 < \varepsilon | U_2 < \varepsilon] &= \lim_{\varepsilon \rightarrow 0} \Pr[U_2 < \varepsilon | U_1 < \varepsilon] = \lim_{\varepsilon \rightarrow 0} C(\varepsilon, \varepsilon)/\varepsilon = \tau^L. \end{aligned} \quad (2.16)$$

If τ^L exists and $\tau^L \in (0,1]$, the copula model will be able to capture the tail dependence of the joint density at the lower tail while no lower tail dependence if $\tau^L = 0$. Similarly, if the limit to calculate τ^U exists and $\tau^U \in (0,1]$, the copula model exhibits upper tail dependence.

The tail dependence exhibits the dependence relations between two events when they move together to extreme big or small values. However, the drawback is that when $\tau^L = \tau^U$, the model will still show some asymmetry as its structure shows. To overcome the problem, symmetrised Joe-Clayton copula was introduced in Patton (2006) which has the form,

$$C_{SJC}(u_1, u_2 | \tau^U, \tau^L) = 0.5 \cdot (C_{JC}(u_1, u_2 | \tau^U, \tau^L) + C_{JC}(1 - u_1, 1 - u_2 | \tau^U, \tau^L)) + u_1 + u_2 - 1. \quad (2.17)$$

This new model nests the original Joe-Clayton copula as a special case.

2.4 Conditional copula models

The extension of copula models on conditioning variables is very important when there is a need of modeling time series data. In this study, only bivariate case will be discussed. Following the notation in Patton (2006), let X and Y be the two time series random variables of interest, and W be the collection of the lag terms of two random variables. The joint distribution of X , Y and W is F_{XYW} , and the joint distribution of (X, Y) conditioning on W is $F_{XY|W}$. Let marginal density of X and Y conditioning on W to be $F_{X|W}$ and $F_{Y|W}$ respectively, we have

$$F_{X|W}(x | w) = F_{XY|W}(x, \infty | w) \text{ and } F_{Y|W}(y | w) = F_{XY|W}(\infty, y | w).$$

The conditional bivariate distribution $(X, Y|W)$ can be derived from unconditional distribution of (X, Y, W) as $F_{XY|W}(x, y | w) = f_w(w)^{-1} \cdot \frac{\partial F_{XYW}(x, y, w)}{\partial w}$ for $w \in \Omega$ where f_w is the unconditional density of W , and Ω is the support of W . As indicated in Patton (2006), given the marginal density of W , we can derive the conditional copula from unconditional copula of (X, Y, W) as $C[(X, Y) | W=w]$, where $X | W = w \sim F_{X|W}(\bullet | w)$ represents the conditional CDF of X and $Y | W = w \sim F_{Y|W}(\bullet | w)$ represents the conditional CDF of Y . The conditional joint

distribution function can be defined as $U \equiv F_{X|W}(X | w)$ and $V \equiv F_{Y|W}(Y | w)$ given $W=w$.

The variables U and V are obtained from conditional probability integral transform of X and Y condition on $W=w$. Following Diebold (1998), variables U and V are uniformly distributed on $(0, 1)$ regardless of the distributions of X and Y . The extension of Sklar's theorem on conditional copula is as below,

Theorem 1, Let $F_{X|W}(\bullet | w)$ be the conditional distribution of X conditioning on W , $F_{Y|W}(\bullet | w)$ be the conditional distribution of Y conditioning on W , and Ω be the support of W . Assume that $F_{X|W}(\bullet | w)$ and $F_{Y|W}(\bullet | w)$ are continuous in X and Y and for all $w \in \Omega$.

Then there exists a unique conditional copula $C(\bullet | w)$, such that

$$F_{XY|W}(x, y | w) = C(F_{X|W}(x | w), F_{Y|W}(y | w)), \forall (x, y) \in \bar{R} \times \bar{R} \quad (2.18)$$

for each $w \in \Omega$.

Conversely, if we let $F_{X|W}(\bullet | w)$ be the conditional distribution of X , $F_{Y|W}(\bullet | w)$ be the conditional distribution of Y , and $\{C(\bullet | w)\}$ be a family of conditional copulas that is measurable in w , then the function $F_{XY|W}(\bullet | w)$ defined above is a conditional bivariate distribution function of with conditional marginal distributions $F_{X|W}(\bullet | w)$ and $F_{Y|W}(\bullet | w)$. This theorem implies that for any two conditional marginal distributions, we can always link them with a valid copula function to get a valid conditional joint distribution. The application of this extended Sklar's theorem gives us more choices of selection of copula models as we can extract a copula function from any given multivariate distributions and use it independently of the original distribution.

However, there is one restriction when we apply this extended Sklar's theorem, which requires the conditioning set W of the two marginal distributions and copula function has to be the same. It is not difficult to prove that when we have different conditional variables, the equation (2.18) is not true as shown in Patton (2006). One

situation that (2.18) can hold is when the condition variables of X and Y are independent and it is the case when the lag terms of one variable do not affect the conditional marginal distributions of the other variable.

$$\begin{aligned} f_{XY|W}(x, y | w) &= \frac{\partial F_{XY|W}(x, y | w)}{\partial x \partial y} = \frac{\partial C(u, v | w)}{\partial x \partial y} \\ &= \frac{\partial F_{X|W}(x | w)}{\partial x} \times \frac{\partial F_{Y|W}(y | w)}{\partial y} \times \frac{\partial^2 C(F_{X|W}(x | w), F_{Y|W}(y | w) | w)}{\partial u \partial v}, \end{aligned} \quad (2.19)$$

So

$$\begin{aligned} \log[f_{XY|W}(x, y | w)] &= \log \frac{\partial F_{X|W}(x | w)}{\partial x} + \log \frac{\partial F_{Y|W}(y | w)}{\partial y} + \log \frac{\partial^2 C(F_{X|W}(x | w), F_{Y|W}(y | w) | w)}{\partial u \partial v} \\ &= \log f_{X|W}(x | w) + \log f_{Y|W}(y | w) + \log c(F_{X|W}(x | w), F_{Y|W}(y | w) | w) \end{aligned} \quad (2.20)$$

Some literatures have reported that unconditional copula models are not able to capture the asymmetric property of exchange returns, thus two conditional copula models are presented here, namely, the time varying normal and time varying symmetrised Joe-Clayton copula.

(1) Time varying normal copula: In order to capture the possible change in time variation and dependence level of the conditional copula, we have two main approaches. One is by allowing switching of regimes in function forms of copula, as in Rodriguez (2007) and Chollete (2008). And the alternative is to allow time variation in parameters of certain copula forms as in Patton (2006). Here we follow the time varying model as Patton proposed, given

$$\begin{aligned} C(u, v; \theta) &= \Phi_G(\Phi^{-1}(u), \Phi^{-1}(v); \theta) \\ &= \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi(1-\theta^2)^{1/2}} \times \left\{ \frac{-(s^2 - 2\theta st + t^2)}{2(1-\theta^2)} \right\} ds dt \end{aligned} \quad (2.21)$$

here we let the dependence parameter θ to be time varying,

$$\theta_t = \tilde{\Lambda}(c + \beta \cdot \theta_{t-1} + \alpha \cdot \frac{1}{10} \sum_{j=1}^{10} (\Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j}))),$$

which is a similar form to ARMA(1.10) process. The modified logistic transformation function which follows

$$\tilde{\Lambda}(x) = \frac{1}{(1-e^{-x})(1+e^{-x})} \quad (2.22)$$

is used to keep θ_t lies between [-1, 1] all the time.

(2) Time varying SJC copula: Using SJC model, we relate the dependence relation to upper and lower tail dependence which are denoted as τ^U and τ^L respectively. If we allow them to be time varying, it may capture the possible change in the tail dependence over time. The following is the model proposed by Patton (2006),

$$\begin{aligned} \tau_t^U &= \Lambda(c_U + \beta_U \tau_{t-1}^U + \alpha_U \cdot \frac{1}{10} \sum_{j=1}^{10} |u_{t-j} - v_{t-j}|) \\ \tau_t^L &= \Lambda(c_L + \beta_L \tau_{t-1}^L + \alpha_L \cdot \frac{1}{10} \sum_{j=1}^{10} |u_{t-j} - v_{t-j}|) \end{aligned}$$

Where

$$\Lambda(x) = \frac{1}{1+e^{-x}} \quad (2.23)$$

is the logistic transformation function which can keep τ_t^U and τ_t^L within interval (0,1) at all

time. 2.5 Dependence measurement

Asymmetric dependence of financial data is very important and often observed, thus we will also look into some dependence measures such as Exceedance Correlation, Quantile dependence and tail dependence which can help us find evidence of the asymmetric property of dependence on exchange rates data. Under financial context, more attention has been directed at the extreme events, i.e. the correlation between extreme values in distributions. Exceedance correlation, proposed by Longin & Solnik (2001), Ang & Chen (2002), is able to capture the quality of the dependence of two random variables at extreme values. The lower exceedance correlation is defined as

$$Corr(x, y | x < \alpha, y < \beta),$$

It captures the dependence when two variables of x and y are below some threshold values. Quantile dependence, which is also used to measure the dependence on extreme values, is defined using the form as followed, given two random variables X and Y with CDF F_X and F_Y ,

$$P(Y < F_Y^{-1}(\partial) | X < F_X^{-1}(\partial)) .$$

Whenever this probability is greater than zero, we can find the quantile dependence for different quantile thresholds ∂ . Tail dependence is defined based on the definition of quantile dependence and it represents the correlation between two series to the extreme of both ends of the distribution. The lower and upper tail dependence are defined as,

$$\lambda_L = \lim_{\partial \rightarrow 0^+} [P(Y < F_Y^{-1}(\partial) | X < F_X^{-1}(\partial))] = \lim_{u \rightarrow 0^+} C(u, u) / u ,$$

$$\lambda_U = \lim_{\partial \rightarrow 1^-} [P(Y > F_Y^{-1}(\partial) | X > F_X^{-1}(\partial))] = \lim_{u \rightarrow 1^-} (1 - 2u + C(u, u)) / (1 - u) .$$

The tail dependence is referred to the probability that two currencies of interest move upward (depreciation) or downward (appreciation) at the same time, as we are using direct quote (home currency/USD) for the exchange rates here.

2.5.1 Structural change test

By using conditional copula models, we want to capture the asymmetric dependence structure amongst those exchange rates data. For the sake of verification and comparison, we will also apply the structural change tests proposed by Andrew & Ploberger (1994), and Bai and Perron (2003). Andrew and Ploberger's test is a single break test while Bai and Perron's test is a multi break tests. Both methods track the changes in the parameters of regression models. The asymptotic P-value which is presented in Hansen (1997) of Andrew & Ploberger method will be reported in the later chapter. The null hypothesis that there is no structural change in the parameters will be tested. In the Bai and Perron test, the

sequential procedure to identify the location of breaks, Dmax test on hypothesis that no breaks against unknown number of breaks and $F_i(m+/m)$ test on the existence of $m+1$ structure break again m breaks will also be reported.

3. Empirical Results

3.1 Data

In order to identify the possible change of dependence structure during Asian financial crisis around year 1997, the data sample is confined to the period from 3rd Jan 1994 to 31st Dec 2004. The data set is downloaded from DATASTREAM, containing 2870 daily exchange rates of five currencies against US dollars, i.e. SGD-USD, JPY-USD, KRW-USD, THB-USD, and IDR-USD. Those countries are identified to be most severely affected by the crisis. We assess the features of the series before estimation. Figure 1 reports the volatility of the daily exchange rates.

As can be seen from Figure 1, there are obvious deviations from a normal level since the Asian financial crisis begun in July 1997. Before 1997, Thai Baht was pegged to USD which explains the low volatility of data. In the same period, some empirical studies suggest that Indonesia central bank also controlled rupiah against USD to maintain the competitiveness. In Japan, after the huge appreciation period against USD from early 80s to early 90s, Yen came through a relative quiet period before the Asian Financial Crisis. However, for Singapore and South Korea case, there is no obvious change after the crisis in mean and variance relative to other countries. We use Augmented Dickey-Fuller methods to test for the existence of unit roots, and found all five P-values are almost zero, thereby rejecting the null hypothesis that there exists a unit root. Thus all the 5 series are weak stationary series and this is a necessary condition for applying the structural change test by Andrews and Ploberger (1994) to identify the date that structural change occurs.

Figure 1, log difference of exchanges to USD (1994 ~2004)

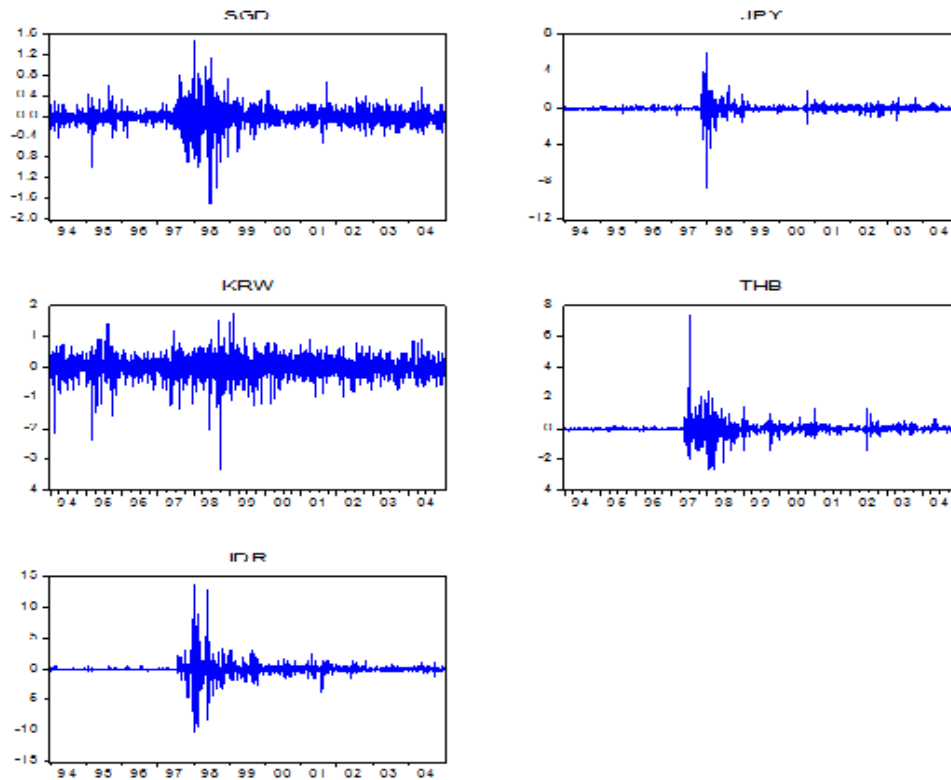


Table 1 shows key descriptive statistics of the data. Jarque-Bera test strongly rejects the normality of the data and all five series exhibit excess kurtosis. In order to have a clearer view of what has been changed before and after crisis, the data will be cut into two sub samples with a reasonable expansion of data in each to get a larger group of observations. The pre-crisis data of 1400 observations ranges from 2nd Sep 1991 to 10th Jan 1997 and the post crisis data contains 1400 observations from 14th Oct 1998 to 24th Feb 2004. This partition is presumed by fitting the data into copula models by which location of the break is roughly known. Tables 2 and 3 present the descriptive statistics of these two data series.

Table 1: Statistics of the whole data set

	SGD	JPY	KRW	THB	IDR
Mean	0.000282	0.003746	-0.001277	0.006384	0.022466
Median	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	1.480000	5.920000	1.720000	7.410000	13.70000

Minimum	-1.720000	-8.760000	-3.340000	-2.680000	-10.300000
Std. Dev.	0.165779	0.425882	0.315054	0.327796	0.927596
Skewness	-0.650984	-1.264123	-0.937820	3.682000	2.419196
Kurtosis	19.62365	109.7226	11.95405	108.4277	70.65689
Jarque-Bera	33249.04	1362785.	10008.30	1335654.	550186.8
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.809713	10.75111	-3.665970	18.32196	64.47739
Sum Sq. Dev.	78.84802	520.3654	284.7745	308.2748	2468.587
Observations	2870	2870	2870	2870	2870

Table 2: statistics of the pre-crisis period

Table 2	SGD	JPY	SKW	THB	IDR
Mean	-0.006248	0.004513	-0.005095	-9.67E-05	0.005770
Median	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.589584	1.950852	1.797625	0.379751	0.639419
Minimum	-0.977211	-1.711598	-2.355228	-0.568389	-0.338769
Std. Dev.	0.105525	0.125175	0.293003	0.050343	0.055325
Skewness	-0.574818	1.482744	-0.700633	-0.393715	3.090625
Kurtosis	12.56803	83.04216	11.59123	23.81487	39.51802
Jarque-Bera	5417.355	374240.0	4420.083	25309.59	80020.11
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-8.747321	6.317676	-7.132873	-0.135347	8.078585
Sum Sq. Dev.	15.57859	21.92066	120.1053	3.545621	4.282198
Observations	1400	1400	1400	1400	1400

Table 3: statistics of the post-crisis period

	SGD	JPY	SKW	THB	IDR
Mean	0.001147	-0.004287	-0.002930	0.000797	-0.001963
Median	0.000000	-0.001887	-0.004048	0.000000	0.000000
Maximum	0.768405	1.882332	1.717245	1.397850	3.420768
Minimum	-0.807977	-1.769776	-1.237526	-1.447327	-3.901245
Std. Dev.	0.125029	0.236423	0.287067	0.193913	0.560325
Skewness	-0.062406	0.247429	0.018834	0.179232	-0.178023
Kurtosis	7.344254	12.66043	5.641693	16.28776	12.45391
Jarque-Bera	1101.807	5458.177	407.1645	10307.10	5221.016
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1.606374	-6.002180	-4.101678	1.116443	-2.748864
Sum Sq. Dev.	21.86954	78.19801	115.2883	52.60531	439.2352
Observations	1400	1400	1400	1400	1400

Table 4: pair wise correlations among 5 currencies

	PreCrisis period (2 nd Sep 1991 to 10 th Jan 1997)					PostCrisis period (14 th Oct 1998 to 24 th Feb 2004)				
	SGD	JPY	SKW	THB	IDR	SGD	JPY	SKW	THB	IDR
SGD	1.00	0.04	0.46	0.28	0.08	1.00	0.21	0.46	0.42	0.20
JPY	0.04	1.00	0.05	0.03	0.04	0.21	1.00	0.20	0.30	0.11
SKW	0.46	0.05	1.00	0.31	0.00	0.46	0.20	1.00	0.25	0.06

THB	0.28	0.03	0.31	1.00	0.12	0.42	0.30	0.25	1.00	0.24
IDR	0.08	0.04	0.00	0.12	1.00	0.20	0.11	0.06	0.24	1.00

Table 4 presents the pair wise correlation coefficient between any combinations of the five exchange rates. There is an obvious rise in every correlation after the crisis, which is consistent with our intuition that there is a rise in dependence between different currency exchange rates when the economic situation is getting worse.

We have applied the empirical CDF to copula models. After the probability integral transformation is done, uniformly distributed data are obtained for each exchange rate series. We then apply the Kolmogorov-Smirnov test to testing the similarity of density specification of U and V (data after integral probability transformation) to the standardized uniform distribution. The test statistics show that the p-value is close to 1 in each case, which strongly supports the null hypothesis that the data set after being transformed has a uniform distribution on (0,1).

3.2 Results of unconditional copula modelling

Once we manage to transfer the data required for copula, we are ready to estimate the proper model for each pair of margins as we are only considering the bivariate copula models here. In this case, we will examine a total of 10 combinations from the currencies data. Among eight stated unconditional copula models, we ranked them for each case according to the magnitude of the copula likelihood. The tables below summarizing the results from exceedance correlation, quantile distribution and parameter estimations for all copula models of interest will be presented as followed. Due to space limitation, we will not report the results but make them available upon request.

The results show that, for all the 10 cases, student t copula is dominating unconditional copula models according to AIC and BIC scores except for two cases where Plackett copula is more preferred according to BIC scores. Although, the exceedance correlation shows some level of asymmetry in some cases between lower and higher

quantile dependence, student t copula as a symmetric mode still beats the asymmetric models that we expect to perform better like Clayton, Rotated Clayton, and Symmetrised Joe-Clayton copula models.

Actually our calibration result is not totally a surprise. Some studies on student t distribution show it is a reasonable fit to conditional daily exchange rates, as in Bollerslev (1987). Thus, it seems that the multivariate student t distribution would be a good candidate to model the bivariate exchange rates data. However, the difficulty in applying the bivariate student t distribution is that both exchange rates need to have the same degree of freedom which is not always the case in empirical research. Student t copula obtained from multivariate student t distribution, on the other hand, has weak restrictions on marginal densities with which we can join any two marginal densities together with student t copula to find a reasonable estimation of multivariate distribution.

As observed by Breymann et al. (2003), for the empirical fit of financial data, student T model does a better job than Gaussian copula or normal copula, as it can capture the property of dependence at the extreme values which is considered very important for the analysis of financial data. Also fatness of tails can be calibrated by using the student t copula.

3.3 Structure break at Asian Financial Crisis

However, there is time when unconditional model is not perfect to describe the data. For example, to investigate the property of data during a crisis, it is necessary to check for possible structure breaks first and unconditional models are not good choices including student t model. As showed in Patton (2006), this is when conditional models have their appearance, to identify the point of time where changes of dependence structure, the dependence level and structure dynamics take place.

Table 6: estimated parameters from time varying normal copula

Time varying normal Copula	Constant	α	β	Loglikelihood
SGD and JPY	0.0575 (0.001)	-0.0192 (0.0003)	1.7234 (0.0054)	43.8869
SGD and SKW	-0.0435 (0.2292)	-0.0205 (0.0373)	2.3043 (0.9685)	383.0047
SGD and THB	0.3466 (0.0038)	-0.0667 (0.0006)	1.5524 (0.0072)	358.7756
SGD and IDR	0.6622 (0.0056)	-0.0283 (0.0007)	-0.1294 (0.0185)	127.6949
JPY and SKW	0.4852 (0.0024)	0.2765 (0.0022)	-1.4217 (0.0151)	37.5035
JPY and THB	0.4367 (0.0098)	-0.0599 (0.0014)	0.3798 (0.0375)	88.7508
JPY and IDR	0.2408 (0.0072)	-0.0179 (0.0009)	0.3692 (0.0491)	29.315
SKW and THB	0.1748 (0.0028)	-0.0392 (0.0005)	1.528 (0.009)	132.1248
SKW and IDR	0.3459 (0.002)	0.1661 (0.0017)	-1.6239 (0.0167)	17.483
THB and IDR	0.0816 (0.0012)	-0.017 (0.0002)	1.8916 (0.0031)	179.0109

*It shows all of our estimators are significant in 5% confidence interval.

As can be seen from Table 6, for all the cases, the time varying dependence parameters are always greater than zero which suggests the crisis was dragging down the Asian economies and no country among these five could survive at that time. To further convince ourselves, we apply a structure change test proposed by Andrews and Ploberger (1994) to locate the date of structure change by looking at the change of parameters in a regression. The results show that in nine out of ten cases, the null hypothesis that there is no sign of structure change can be rejected at 10% level. The only combination that we are unable to reject the null hypothesis is between South Korea Won and Thailand Baht. The dates of estimated structure change are different among different models but mostly are within 1000 to 1300 daily intervals which are consistent to our expectation. By this method, only one specific date can be found even the actual period may be more accurate to

describe the structure change for this financial crisis. But it provides evidence of the structure break during the Asian financial crisis.

3.4 Dominating tails

With the help of time varying SJC models, we are able to depict the difference of upper and lower tail dependence. This difference is zero when the exchange rates exhibit symmetric structure and nonzero when the dependence structure is asymmetric. As can be seen from Table 7, the result of conditional difference of the tail dependence show the change before and after the crisis. If the change sign is <0 , it means the lower dependence is dominating the upper tail dependence with frequency which represents the percentage of the total days in each period. This shows that the government at this point of time tends to pay more attention to price stabilization. If the change is positive sign (>0), it shows that upper dependence is the dominating tail, and the government tends to focus on the policy to maintain price competitiveness. With this comparison between pre-crisis and post-crisis periods, we can analyse the possible structure break from the government policy side.

Table 7: change of dominating tails of pre and post crisis periods

Difference of upper and lower dependence	Pre-crisis	Frequency	Post-crisis	Frequency
SGD and JPY	<0	100%	>0	85%
SGD and SKW	>0	94.50%	<0	80.90%
SGD and THB	<0	87%	>0	66.50%
SGD and IDR	≈ 0	100%	>0	99.80%
JPY and SKW	<0	100%	>0	63.90%
JPY and THB	>0	100%	>0	97.20%
JPY and IDR	>0	100%	<0	75.70%
SKW and THB	>0	90.20%	>0	91.90%
SKW and IDR	≈ 0	100%	<0	100%
THB and IDR	>0	100%	>0	100%

The parameters of the two models have significant changes in both time varying models we used which represent dynamic changes in the dependence structure. In 9 out of 10 cases, the dependence level suggested by the constant normal which is equivalent to linear correlation increased and the conditional correlation from time varying normal model also increased. In 7 out of 10 cases, the average value of tail dependence increases after the crisis.

Through the time varying tail dependence parameters, we find that 5 out of 10 cases that in both periods, more days are found to have an asymmetric returns than symmetric returns. Apart from that, the obvious change in the structure also observed by means of changing in as the dominating tail is different in the two periods. For another 3 cases, although the tail dependence parameter would show asymmetry in the most days, there is no change in the dominating tail. In the rest 2 cases, the dependence structure changes from symmetric before the crisis to asymmetric after the crisis. Thus this can be evidence that the crisis does affect the decision of the government and the dependence structure changes.

4. Conclusion

In this paper, we have studied different copula models using time series data of exchange rates from five Asian countries during the financial crisis in 1997. We obtained the most appropriately fitted unconditional copula models in terms of SIC and BIC. Under the category of unconditional copula models, the student-t distribution was found to be adequate for most pairs and our results are consistent with earlier findings. In order to study the dynamics of both nonlinear and linear dependence structures between pair of the five currencies, we adopted the time-varying normal and symmetrised Joe-Clayton copulas to capture the conditional linear correlation and conditional tail dependence. The results

showed a higher level of dependence after the crisis in most of the pairs for both conditional linear correlation and conditional tail dependence. This is consistent with findings in other literatures. And parameters of fitted models changed for each period in all of the 10 pairs. The structure break is thus identified by the change of the dependence structure indicating the period of crisis. The structural break periods identified by copula models match with those structural break points identified using Andrews & Ploberger and Bai & Perron tests.

In addition, we find that the average of the two tail dependence changed to a higher level. This shows that governments of the five countries of interest became more sensitive and alert to changes of other currencies at extreme events after the crisis. From the difference of the upper tail and lower tail dependence, the dominating tails changed for most pairs of currencies. This shows a change of policies after the crisis. A greater upper tail indicates more attention on achieving the international competitiveness of the currency while a greater lower tail indicates more emphasis on maintaining price stability.

We have also used other two methods to detect the structure breaks. Indeed, copula models are able to specify periods of breaks rather than a single break point. They are more valuable in identifying structure breaks in nonlinear dependence structures. However, our findings are confined to bivariate models. Future research should extend the study to multidimensional copula models, thereby incorporating co-movements of exchange rates among various countries.

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