East Asian financial crisis revisited: What does a copula tell?

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EAST ASIAN FINANCIAL CRISIS REVISITED: WHAT DOES A COPULA TELL?

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We construct a regime-switching model of copulas to capture observed asymmetric dependence in daily changes of exchange rates in five selected East Asian economies during the 1997 financial crisis era. In particular, we investigate the effects of the financial crisis on asymmetric dependence in exchange rates returns and assess the asymmetric relationships between five currencies, including the Singapore Dollar, Japanese Yen, South Korea Won, Thailand Baht and Indonesia Rupiah. Various time-varying copula models will also be applied to examine the possible structural breaks. The results confirm significant changes at the dependence level, tail behaviour and asymmetry structures between returns of all permuted pairs from the five currencies before and after the crisis. In comparison with other methods, it is found that the copular approach has more explanatory power than the existing ones in identifying structure breaks.

Keywords: *financial crises, asymmetric dependence, copulas, East Asia*

I. INTRODUCTION

The Asian financial crisis started in Thailand in July 1997 when the Thai government decided to float the Thai baht after exhaustive efforts to support it in the face of a severe financial overextension, which led to a 15 to 20% devaluation of the baht within two months. This was soon followed by the devaluations of the Philippine Peso, the Malaysian Ringgit, the Indonesian Rupiah and even the Singaporean Dollar and marked the beginning of the Asian financial crisis. 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.

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 the 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. Since then, these economies have intervened heavily in the foreign exchange rate markets to prevent the appreciation of their currencies for the pursuit of an "export-led growth strategy" (Dooley *et al.,* 2003). The post-crisis exchange rate behaviour in these economies may often resemble a managed float or even a *de facto* peg despite the

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declared regime being floating. McKinnon (2005) describes it as "fear of floating".

With the progress of the regional and monetary integration in East Asia, the dependant relations between those Asian countries are expected to change during this period. This has motivated us to study the structural changes of several Asian currencies in terms of asymmetric dependency before and after the crisis. The asymmetric structure of dependence between two financial returns has been well documented in the literature. For example, Erb *et al.* (1994), Longin and Solnik (2001), and Ang and Chen (2002) find that the financial returns tend 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 investors lack the confidence to invest in fear of the future economic uncertainty during the bad time period. As a result, asymmetric property of the dependence would increase the cost of global diversification of investment at bad times. This finding is important for risk control and portfolio management. However, there are a few studies on the asymmetric dependence of exchange rates. Patton (2006) studies the asymmetric dependence between Japanese Yen and D-Mark before and after the introduction of Euro using the time-varying copula approach with structure break identified. He suggests that the possible reason for asymmetric dependence between the two currencies are due to the two observations, namely, a country would depreciate its currency to match the depreciation of the rival country's currency while it would appreciate the home currency when there is an appreciation of the rival currency. This policy is meant to stabilise the domestic price level.

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 by applying the copula model. Nelsen (1999) defines copulas as "functions that join or couple multivariate distribution functions to their one-dimensional marginal distribution functions" (page 5). The advantages of this approach in examining the multivariate dependence structures are as follows. First, the copula approach is a great tool to connect margins and joint densities. Copulas contain all the information about the dependence structure of a vector of random variables, in particular, the joint behaviour of the random variables in the tails of the distribution, which is critical to the study of contagion of financial crises. 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 among random variables). This is because it takes the marginal property of random variables of interest into account, even when those margins are from different distribution families. Third, 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 is also embodied in the way that marginal distributions need not come from the same family. Finally, the estimations of the copula models can be based on the standard maximum likelihood which can be handled by some desktop software.[1]

Contagious effect during the financial crisis is a special case of asymmetry dependence between financial returns. Many studies on contagion are based on structure changes in correlations (see Baig and Goldfajn, 1999), and others apply the extreme value theory

[11] For details about applications and extensions of copula models, see Joe (1997) and Nelson (1999).

(Longin and Solnik, 2001) and Gaussian Markov switching model with two regimes (low-return-high-volatility and high-return-low-volatility) (Ang & Bekaert, 2002). Recently, 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.

In this study, we will examine the asymmetric property of the currencies strongly affected by the 1997 Asian financial crisis. In particular, we will employ the copula models with time-varying parameters to measure the asymmetric dependence structure and the possible shifts of regimes of exchange rates. 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 will be able to identify the possible structural change when the dependence structure of two currencies changes due to political or economical turmoil. We include five currencies in this study, namely, Singapore, Thailand, Japan, South Korea and Indonesia, and investigate the effects of the financial crisis and the sign of asymmetry in exchange rates returns. We will also shed light on the difference in the dominating tails which is implied by the time-varying tail dependence, and search for possible dynamic changes in dependence. By using the time-varying normal copulas, the finding of asymmetric dependence signals possible structure changes, which is confirmed by the structure break tests such as Andrews and Ploberger (1994) and Bai and Perron (2003). By using the time-varying SJC model, the asymmetric structure for tail dependence is found. In particular, the results show that in most cases a dominating tail change is found during the crisis from higher upper tail dependence to higher lower tail dependence and vice versa. The findings are important for studying the policy reaction patterns and correlations especially during the crisis period.

The rest of this paper is organised as follows. In Section II, we discuss the methodology and different models of copula, as well as the measures of dependence based on copula. Section III discusses the data issue and presents the results of empirical estimation. Section IV provides some concluding remarks.

II. METHODOLOGY

In this section we provide a brief review of the copulas and discuss the properties of the different copula models employed in this study. The definition of copula was first stated in Sklar's paper in 1959. Nelson (1999) defines copula as that, an n-dimensional copula is a multi-dimensional joint distribution function of margins with uniform distribution on [0,1]. Let F be an n-dimensional distribution function with marginal densities $F_1(y_1)$, $\ldots, F_n(y_n)$. Given $C:[0,1]^n \rightarrow [0,1]$, the n-dimensional multivariate distribution F can be associated with copula function C as follows:

$$F(y_1, y_2 ... y_n) = C(F_1(y_1)...F_n(y_n);\theta) \tag{1}$$

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 uniquely determined. Conversely, if C is an n-copula and are $F_1 ... F_n$ are distribution functions, the function F defined above is an n-dimensional distribution function with margins $F_1 \ldots F_n$.[2]

If F is a continuous multivariate distribution function, it is possible to separate the univariate margins from the dependence structure which is represented by the copula. If we assume the F_i's are differentiable, and C and F are n-times differentiable, the density of F can then be expressed as a product of the copula density and the univariate marginal densities. It is in this sense that we say that the copula has all the information about the dependence structure.

The copula models require all data 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. It is therefore very important first of all to determine the two "true" univariate marginal densities. In this study we first test the goodness of fit of the marginal density model by employing the Diebold *et al.* (1998) approach, and then conduct the Kolmogorov-Smirnov test to confirm if the transformed sequences are uniformly distributed.

Unconditional Copula Models

We now turn to the specification and the properties of the nine popular Archimedean copula models used in this study, which are unconditional with either symmetric or asymmetric properties. The first one is the Gaussian (Normal) copula (Lee, 1983) which is specified as:

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

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).

The second model is the Clayton copula which is proposed by Clayton (1978) and specified as:

$$C(u_1,u_2;\theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta}, \tag{3}$$

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.

The third one is called the rotated Clayton copula which is an extension of Clayton copula to capture the strong correlations on the right tail:

$$C_{RC}(u_1,u_2;\theta) = u_1 + u_2 - 1 + ((1-u_1)^{-\theta} + (1-u_2)^{-\theta} - 1)^{-1/\theta}, \tag{4}$$

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

[2] See Nelson (1999) for a proof.

The fourth model is the Plackett copula specified as:

$$C(u_1,u_2;\theta)=\frac{1}{2(\theta-1)}(1+(\theta+1)(u_1+u_2)-\sqrt{(1+(\theta-1)(u_1+u_2))^2-4\theta(\theta-1)u_1u_2}) \quad (5)$$

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

The fifth one is the Frank copula specified as (Trivedi, 2007):

$$C(u_1,u_2;\theta)=-\theta^{-1}\log\{1+\frac{(e^{-\theta u_1-1}-1)(e^{-\theta u_2-1})}{e^{-\theta}-1}\}, \quad (6)$$

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. The sixth model is the Gumbel copula:

$$C(u_1,u_2;\theta)=\exp(-((\log u_1)^{\theta}+(\log u_2)^{\theta})^{1/\theta}), \quad (7)$$

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.

The seventh one is the rotated Gumbel copula which can be specified as:

$$C(u_1,u_2;\theta)=u_1+u_2-1+\exp(-((\log(1-u_1))^{\theta}+(\log(1-u_2))^{\theta})^{1/\theta}), \quad (8)$$

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

The eighth one is the student *t*'s copula which can be specified as follows:

$$C(u_1,u_2;\theta_1,\theta_2)=\int_{-\infty}^{t_{\theta_1}^{-1}}\int_{-\infty}^{t_{\theta_2}^{-1}}\frac{1}{2\pi(1-\theta_2^2)^{1/2}}\times\{1+\frac{s^2-2\theta_2 st+t^2}{v(1-\theta_2^2)}\}^{-(\theta_1+2)/2}dsdt \quad (9)$$

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.

The last one is the symmetrised Joe-Clayton copula which is derived from Laplace transformation of the Clayton copula with special attention on tail dependence of the joint density (Joe, 1997):

$$C_{JC}(u_1,u_2\,|\,\tau^U,\tau^L)=1-(1-\{[1-(1-u_1)^k]^{-\gamma}+[1-(1-u_2)^k]^{-\gamma}-1\}^{-1/\gamma})^{1/k} \quad (10)$$

Where $\begin{matrix} k=1/\log_2(2-\tau^U) \\ \gamma=-1/\log_2(\tau^L) \end{matrix}$ and $\begin{matrix} \tau^U\in(0,1) \\ \tau^L\in(0,1) \end{matrix}$.

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

$$C_{SJC}(u_1, u_2 \mid \tau^U, \tau^L) = 0.5 \cdot (C_{JC}(u_1, u_2 \mid \tau^U, \tau^L) + C_{JC}(1-u_1, 1-u_2 \mid \tau^U, \tau^L) + u_1 + u_2 - 1). \quad (11)$$

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

Among the nine copula models described, we choose the best fit among these non-nested copula models by applying maximum likelihood method based on either AIC or BIC. BIC indicates a better fit when it gives the smallest value.

Conditional Copula Models

The extension of copula models with conditioning variables is very important when there is a need of modelling time series data. 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* be $F_{X|W}$ and $F_{Y|W}$ respectively, we then have:

$$F_{X|W}(x \mid w) = F_{XY|W}(x, \infty \mid w) \text{ and } F_{Y|W}(y \mid w) = F_{XY|W}(\infty, y \mid w) \quad (12)$$

The conditional bivariate distribution (*X, Y*|*W*) can be derived from unconditional distribution of (*X, Y, W*) as $F_{XY|W}(x, y \mid w) = f_w(w)^{-1} \cdot \dfrac{\partial F_{XYW}(x, y, w)}{\partial w}$ for $w \in \Omega$, where f_w is the unconditional density of *W*, and Ω is the support of *W*.

The extension of Sklar's theorem with conditional copula is defined as follows. Let $F_{X|W}(\bullet \mid w)$ be the conditional distribution of *X* conditioning on *W*, $F_{Y|W}(\bullet \mid w)$ be the conditional distribution of *Y* conditioning on *W*, and Ω be the support of *W*. Assume that $F_{X|W}(\bullet \mid w)$ and $F_{Y|W}(\bullet \mid w)$ are continuous in *X* and *Y* and for all $w \in \Omega$. Then there exists a unique conditional copula $C(\bullet \mid w)$, such that for each $w \in \Omega$:

$$F_{XY|W}(x, y \mid w) = C(F_{X|W}(x \mid w), F_{Y|W}(y \mid w)), \forall (x, y) \in \overline{R} \times \overline{R} \quad (13)$$

Conversely, if we let $F_{X|W}(\bullet \mid w)$ be the conditional distribution of X, $F_{Y|W}(\bullet \mid w)$ be the conditional distribution of Y, and $\{C(\bullet \mid w)\}$ be a family of conditional copulas that is measurable in w, then the function $F_{XY|W}(\bullet \mid w)$ defined above is a conditional bivariate distribution function of with conditional marginal distributions $F_{X|W}(\bullet \mid w)$ and

$F_{Y|W}(\bullet \mid w)$. 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 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.

Furthermore, to capture the asymmetric property of exchange returns, we adopt two conditional copula models, namely, the time-varying normal copula and time-varying symmetrised Joe-Clayton copula (SJC). Following Patton (2006), the time-varying normal copula model is specified as follows:

$$C(u,v;\theta) = \Phi_G(\Phi^{-1}(u),\Phi^{-1}(v);\theta)$$
$$= \int_{-\infty}^{\Phi^{-1}(u)}\int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi(1-\theta^2)^{1/2}} \times \{\frac{-(s^2-2\theta st+t^2)}{2(1-\theta^2)}\} dsdt \tag{14}$$

where θ is the dependence parameter and time varying, and defined as:

$$\theta_t = \tilde{\Lambda}(c+\beta\cdot\theta_{t-1}+\alpha\cdot\frac{1}{10}\sum_{j=1}^{10}(\Phi^{-1}(u_{t-j})\cdot\Phi^{-1}(v_{t-j})) \tag{15}$$

The modified logistic transformation function $\tilde{\Lambda}(x) = \frac{1}{(1-e^{-x})(1+e^{-x})}$ is used to keep θ_t lies between [-1, 1] all the time.

With the time-varying SJC copula model, we relate the dependence relation to upper and lower tail dependence 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. According to Patton (2006), the upper and lower tail dependence is defined as:

$$\tau_t^U = \Lambda(c_U+\beta_U\tau_{t-1}^U+\alpha_U\cdot\frac{1}{10}\sum_{j=1}^{10}|u_{t-j}-v_{t-j}|)$$
$$\tau_t^L = \Lambda(c_L+\beta_L\tau_{t-1}^L+\alpha_L\cdot\frac{1}{10}\sum_{j=1}^{10}|u_{t-j}-v_{t-j}|), \tag{16}$$

where $\Lambda(x) = \frac{1}{1+e^{-x}}$ is the logistic transformation function which can keep τ_t^U and τ_t^L within the interval (0,1) at all time.

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 find evidence of the asymmetric property of dependence on exchange rates data. Under financial context, more attention has been directed towards the extreme events, i.e. the correlation between extreme values in distributions. Exceedance correlation is able to capture the quality of the dependence of two random variables at extreme values (Longin and Solnik, 2001; Ang and Chen, 2002). The lower exceedance correlation is defined as:

$$Corr(x, y \mid x < \alpha, y < \beta) \tag{17}$$

which captures the dependence when two variables of x and y are below the threshold values. Quantile dependence is also used to measure the dependence on extreme values. Given two random variables X and Y with cdf F_X and F_Y, it can be defined as follows:

$$P(Y < F_Y^{-1}(\partial) \mid X < F_X^{-1}(\partial)) \tag{18}$$

When the 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. In particular, asymptotic tail dependence is a measure of the propensity of any two currencies move upward (depreciation) or downward (appreciation) at the same time.[3] The lower and upper tail dependence can be defined as:

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

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

We conduct several tests for structural change, including the Andrew and Ploberger (1994) test and the Bai and Perron (2003) test. The former is an asymptotical optimal test on identifying structure changes. The asymptotic distribution of the test depends on the number of parameters used to describe the system and the range of sample. The test can be used to identify the change point of the system with unknown single break point, which, however, cannot be easily identified near the two ends of the searching range. The Bai and Perron (2003) test is based on the principle of dynamic programming that computes the break points as a global minimiser of the sum of squared residuals. The method is computationally efficient and useful even when data range is small. The method can be used to estimate multiple number of structure changes in a linear regression system. Both methods track the changes in the parameters of regression models.

III. EMPIRICAL RESULTS

Data

In order to identify the possible change of dependence structure during the Asian financial crisis in 1997, the data sample is confined to the period from 3 January 1994 to 31 December 2004. The data set is extracted 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

[3] Exchange rate is directly quoted in this study.

most severely affected by the crisis.[4] We assess the features of the series before estimation. Figure 1 reports the volatility of the daily exchange rates. We have also conducted unit roots test by employing the Augmented Dickey-Fuller methods, and found that the P-values for all the series are almost zero, thereby rejecting the null hypothesis that there exists a unit root. Thus, all the five series are weak stationary series, which 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 AGAINST USD (1994 ~ 2004)

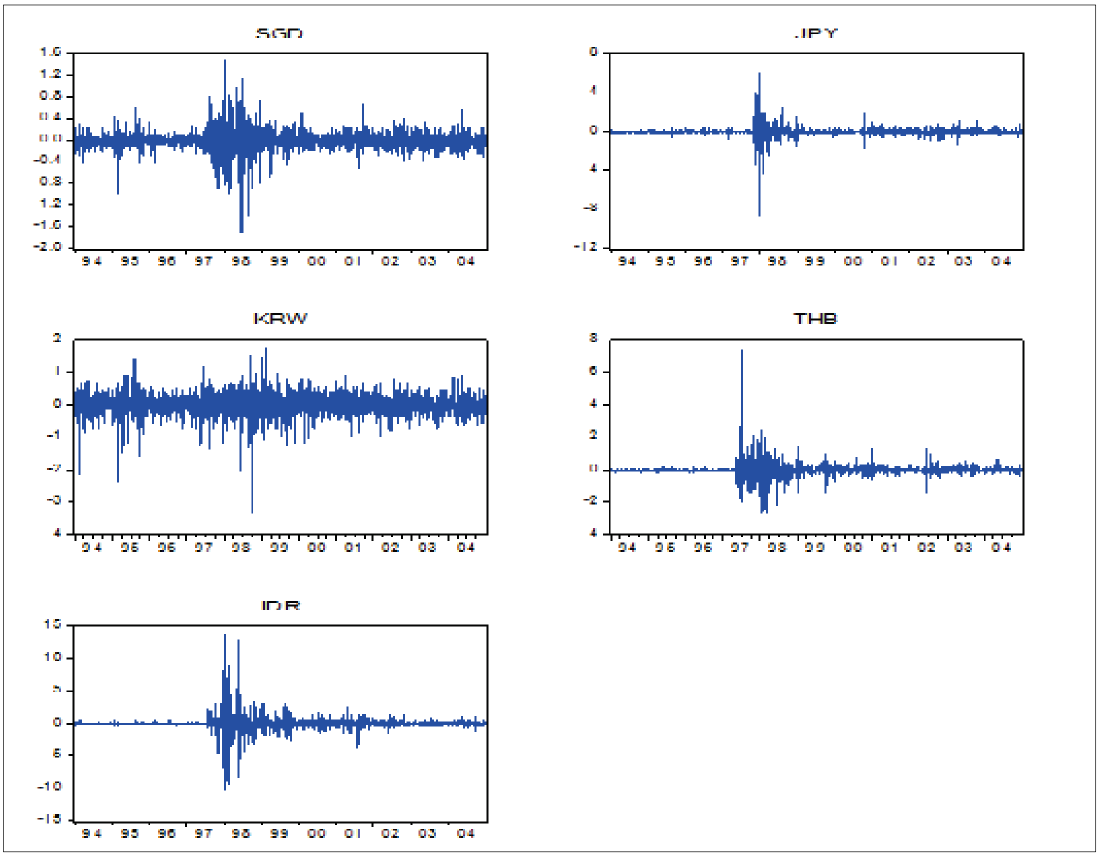


Table 1 displays the key descriptive statistics of the daily returns of the data sets used in this paper. As shown in Table 1, Jarque-Bera test rejects the normality of the data, and excess kurtosis is noted for all the series, with the Japanese yen and Thai baht having the highest kurtosis coefficients. Also, as measured by the standard deviation of the data sets, the Indonesian Rupiah is the most volatile, followed by the Japanese Yen and Thai Baht. The Singapore Dollar is the least volatile.

[4] Malaysia ringgit is not included in this study as the country was less vulnerable than its neighbours during the 1997 crisis, largely because of its earlier imposed limits on foreign borrowing and prudential regulations and supervision of the banking sector, and its orthodox adjustment program including the imposition of a short-term capital control regime. Similarly, the Philippine peso is also excluded as the Philippines was relatively left unscathed during the 1997 East Asian financial crisis, and more importantly the country was in fact the first in the region to recover from its contagion.

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	-10.30000
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

In order to investigate the dynamic changes over the crisis period, we divide the whole samples into two sub-periods. The pre-crisis period spans from 2 September 1991 to 10 January 1997 with 1400 observations, and the post-crisis period covers the period from 14 October 1998 to 24 February 2004 containing also 1400 observations. This partition is presumed by fitting the data into copula models by which location of the break is roughly known. We have examined the descriptive statistics of the five currencies during the two sub-periods, and the results are not reported but available upon request. It is found that the standard deviation of the exchange value of all the currencies against the US dollar has increased dramatically in the post-crisis period except the Korean Won. Excess kurtosis is noted for all the series during both periods.

Table 2 presents the pair-wise correlation coefficient between the concerned five exchange rates. It is noted that the exchange rates have become highly correlated after the crisis. This finding is consistent with our casual observation that there is an increasing trend of dependence between the movements of the exchange rates when the world economy is in downturn. This is especially true for the newly emerging economies.

TABLE 2: PAIR-WISE CORRELATIONS AMONG FIVE CURRENCIES

	Pre-Crisis period (2 September 1991 to 10 January 1997)					**Post-Crisis period** (14 October 1998 to 24 February 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

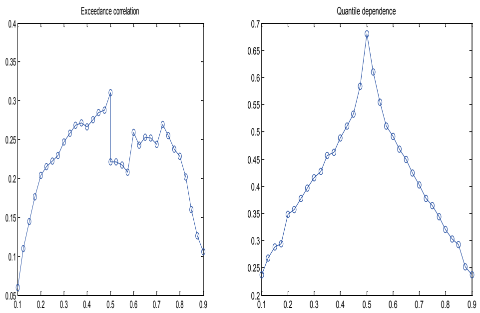
Results of Unconditional Copula Modelling

As we mentioned early, data required by copula models has to be uniformly distributed. Otherwise, probability integral transformation may lead to a misspecification in copula modelling. We first obtain uniformly distributed data for each exchange rate series after the probability integral transformation, and then apply the Kolmogorov-Smirnov test to testing the similarity of density specification of U and V to the standardised uniform distribution. The test statistics (not reported but available upon request) show that the p-value is close to 1 in each case, which supports the null hypothesis that the data set after being transformed has a uniform distribution on (0,1).

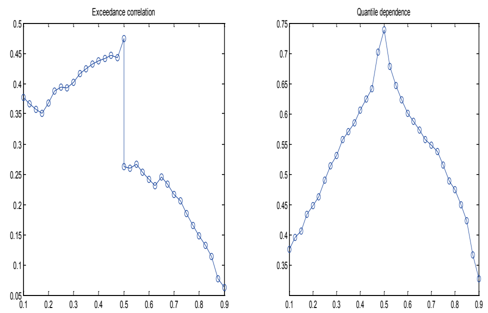
Once we have transformed the data required for copula, we are ready to estimate the proper model for each pair of margins. In this study we consider the bivariate copula models and examine a total of 10 combinations of the currency pairs. We estimate the eight unconditional copula models for each pair respectively, and assess the asymmetric dependence of the exchange rates data. Figure 2 presents the results from exceedance correlation and quantile distribution for all the pairs. Due to space limitation, we will only report the maximum likelihood estimation results for the SGD-JPY pair in Table 3, but make the rest available upon request.

FIGURE 2: EXCEEDANCE CORRELATION (LEFT PANEL) AND QUANTILE DEPENDENCE (RIGHT PANEL)

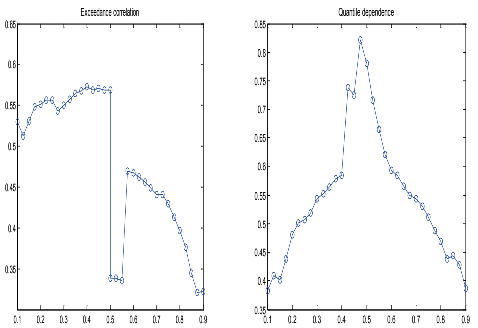
(a) SGD and JPY



(b) SGD and SKW



(c) SGD and THB



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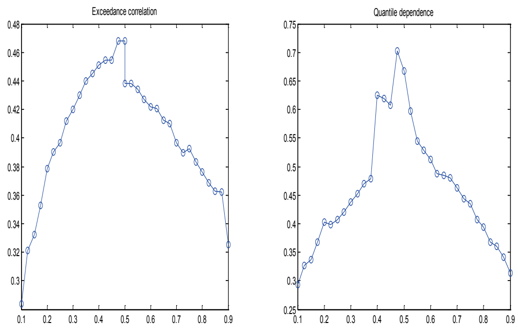
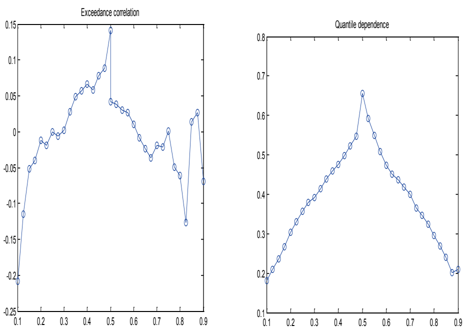
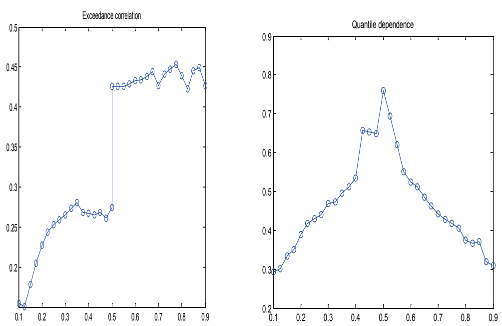


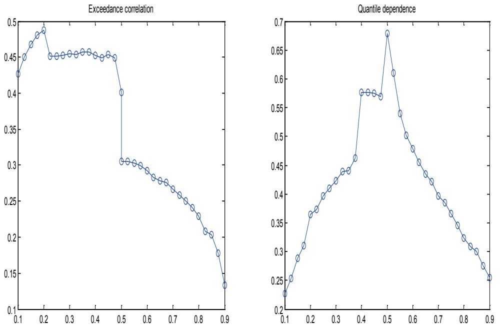
(e) JPY and SKW



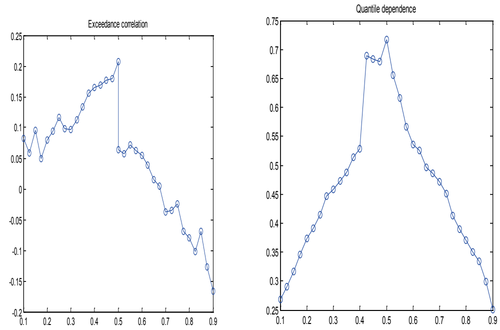
(f) JPY and THB



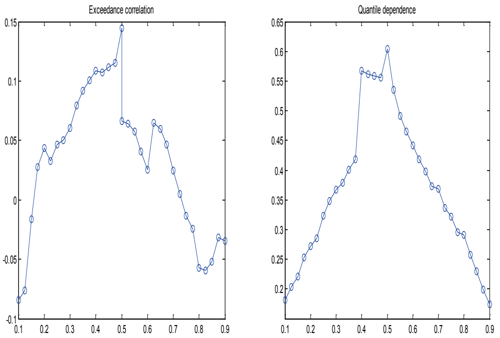
(g) JPY and IDR



(h) SKW and THB



(i) SKW and IDR



(j) THB and IDR

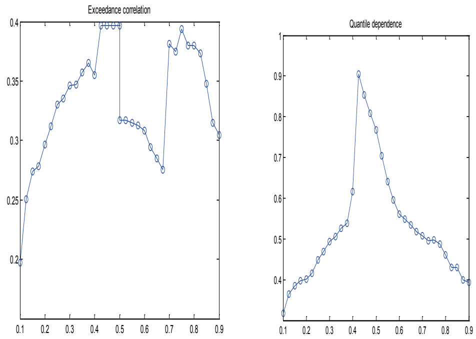


TABLE 3: LOG LIKELIHOOD AND AIC, BIC CRITERIONS (SGD AND JPY)

Models	Log likelihood	Number of parameters	AIC	BIC	Estimated parameters (s.e.)
Normal	42.81	1	-83.63	-77.66	0.1714
Clayton	44.24	1	-86.49	-80.52	0.2158 (0.0262)
Rotated Clayton	53.85	1	-105.69	-99.73	0.2356 (0.0261)
Plackett	59.21	1	-116.43	-110.46	2.0087 (0.1245)
Gumbel	73.11	1	-144.21	-138.25	1.1478 (0.0151)
Rotated Gumbel	69.77	1	-137.55	-131.59	1.1458 (0.0154)
Student T	157.54	2	-311.08	-299.16	0.1913 (0.0211) 3.0025 (0.2261)
Symmetrised Joe-Clayton	74.91	2	-145.82	-133.89	0.0833 (0.0236) 0.2261 (0.0228)

Given the size of the Japanese economy and JPY's importance as an invoicing currency in international business, asymmetric dependence would be expected between the Japanese Yen and the rest of the currencies. This also applies to other currency pairs. To confirm the asymmetric property of dependence, we conduct the symmetric test proposed by Hong *et al.* (2003) with the null hypothesis as that exceedance correlation plot is symmetric. Based on the estimated p-value, we reject the null hypothesis that the plot is symmetric for the pairs of SGD-JPY, JPY-SKW, SGD-THB, SKW-THB and THB-IDR. The results suggest that asymmetric dependence exists when the market moves up and down. However, the calibration of copula model is somewhat inconsistent with the results based on AIC or BIC criteria, where Student-*t* copula is shown to be the best fit (Table 3).

By employing a two-step maximum likelihood method, we separate the estimation of margins from the copula parameters. The results show that, for all the currency pairs, Student-*t* copula is dominating unconditional copula models according to AIC and BIC scores with the exception of two cases where Plackett copula is preferred. 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 outperforms the asymmetric models such as Clayton, Rotated Clayton, and Symmetrised Joe-Clayton copula models.

As a matter of fact, 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 (see, for instance, Bollerslev, 1987). Thus, it seems that the multivariate Student-*t* distribution would be a good candidate to model the bivariate exchange rates data. Breymann et al. (2003) also report that, 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. Also fatness of tails can be calibrated by using the Student-*t* copula. 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.

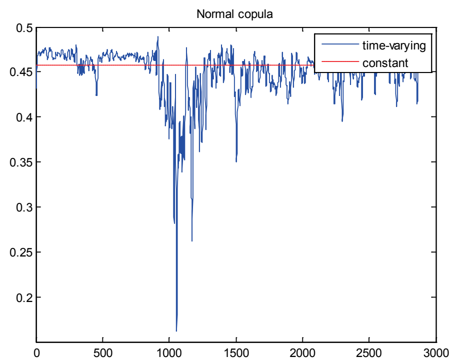
Structure Break at Asian Financial Crisis

We employ the time-varying normal copula to assess the dynamic changes of the conditional dependence. This will allow us to benchmark and compare with other copula models such as Student-*t* copula, and also to infer that the conditional dependence is time-varying, which will enable us to model the dynamic path of the dependence level. Figure 3 presents the conditional dependence parameters estimated from the time varying normal copula.

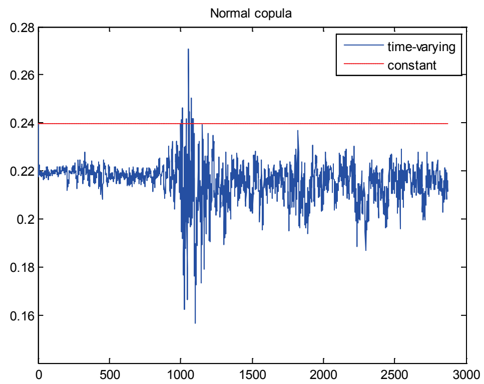
It is noted from Figure 3 that all the exchange rate series have shown visible spikes around the years 1997 and 1998 (matching observations roughly between 1000 and 1300), reflecting the spread effect of the crisis over time. In all the cases, the estimated time varying dependence parameters are always greater than zero. The results confirm that the conditional dependence is time-varying. An obvious lower dependence level in exchange rate can be observed in five out of 10 pairs during the crisis. There is also a clear sign of increasing correlation of the conditional dependence among the currencies in the post-crisis period.

FIGURE 3: CONDITIONAL CORRELATION GENERATED FROM TIME-VARYING NORMAL COPULA

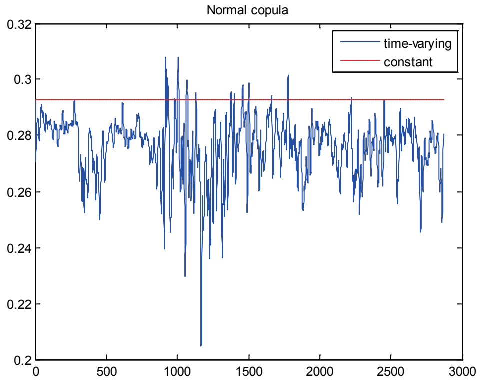
(a) SGD and THB



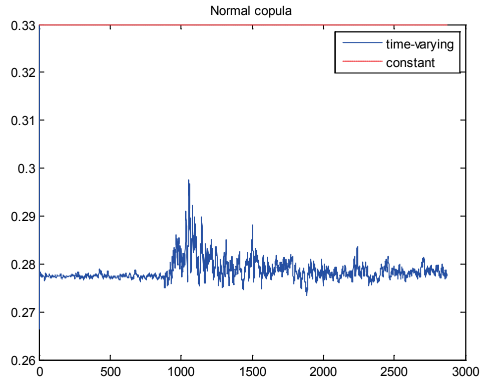
(b) JPY and THB



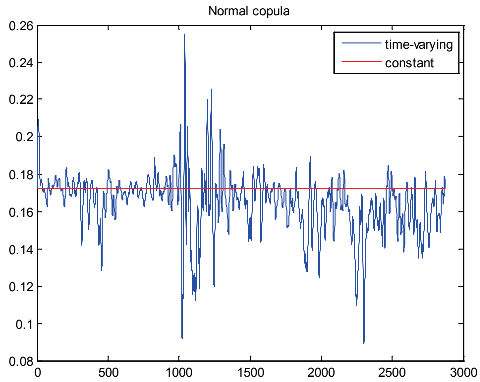
(c) SKW and THB



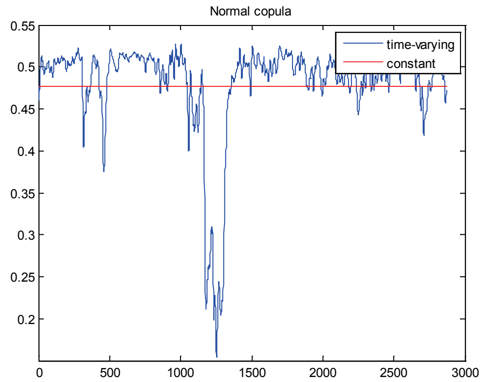
(d) IDR and THB



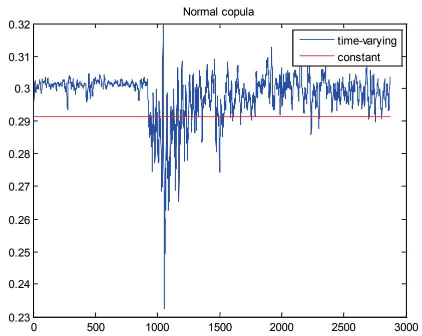
(e) SGD and JPY



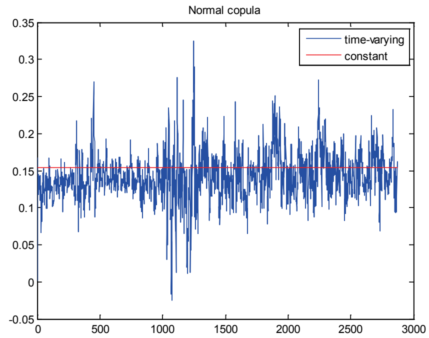
(f) SGD and SKW



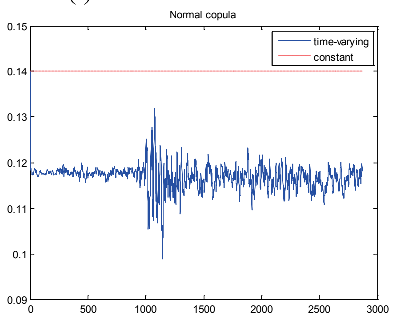
(g) SGD and IDR



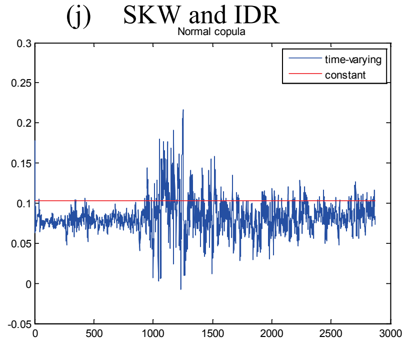
(h) JPY and SKW



(i) JPY and IDR



(j) SKW and IDR



We further evaluate the correlation estimates by conducting the Andrews and Ploberger (1994) test and the Bai and Perron (2003) test. The Andrews and Ploberger (1994) test helps locate the date of structural break by looking at the change of parameters in a regression, though it can only identify one break at the most. The Bai and Perron (2003) test, on the other hand, is capable of identifying multiple breaks. The p-values and bootstrap p-values proposed by Hansen obtained from the Andrews and Ploberger (1994) test reject the null hypothesis that there is no sign of structural change in nine cases out of ten at the 10% significant level (the test results are available upon request). The exact date of the estimated structural change varies across the different models, but mostly within the 1000-1300 daily range, which confirm the existence of the structural break during the Asian financial crisis. The Bai and Perron (2003) test and test statistics further confirm the existences of two structural breaks in the currency pairs of SGD-JPY, SGD-IDR, JPY-THB and JPY-IDR, and one break in the rest pairs.

Asymmetric Dependence during Pre- and Post-crisis

Given these results we can confirm the existence and the location of structural breaks. We now move to further evaluate the asymmetric dependence of exchange returns in both the pre- and post-crisis periods using the two conditional copula models, i.e. the time varying normal copula and time varying symmetrised Joe-Clayton copula. The time varying symmetrised Joe-Clayton copula is used to capture the changes on both tails, which enables the analysis of possible asymmetric change at extreme values, given that the upper and lower tail dependence variables are time varying. We define the difference of upper and lower dependence as ($\lambda_u - \lambda_L$) and the average of the two tail dependences as ($\frac{\lambda_u + \lambda_L}{2}$). The difference of the two tail dependence parameters should be equal to zero if the data of both currencies exhibits symmetric dependence, and we will then be able to determine the effect of the structure change on the tail dependence by comparing the values from the two periods. We estimate the dependence parameters using maximum likelihood method, and report the estimation results in Table 4. Figure 4 presents the conditional correlation estimated from the time varying normal copula and Figure 5 presents the average of the two tail dependences in the pre-and post-crisis period.

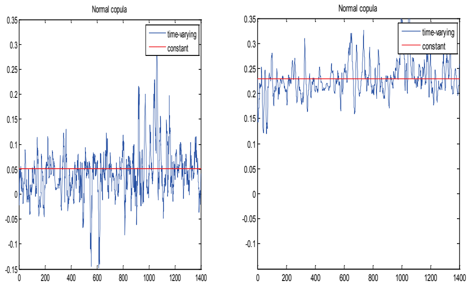
TABLE 4: COMPARISON OF MAIN RESULTS BETWEEN PRE- AND POST-CRISIS (SGD AND JPY)

	Time-varying normal copula			Time-varying SJC copula					
	C	α	β	C_U	α_U	β_U	C_L	α_L	β_L
(a) Pre-crisis									
SGD-JPY	0.0804	0.2697	-0.1922	-18.1878	-17.0307	-0.0028	-1.1217	-25.01	3.1767
	(0.018)	(0.0037)	(0.0256)	(0.1059)	(0.1783)	(0.0267)	(0.0281)	(0.2784)	(0.0325)
SGD-SKW	1.6075	0.3209	-1.7284	0.5476	-4.0504	-1.3488	1.9512	-9.2531	-5.897
	(0.0115)	(0.0028)	(0.0284)	(0.0149)	(0.0578)	(0.0079)	(0.0099)	(0.0324)	(0.0131)
SGD-THB	0.0066	0.0383	1.9731	2.1264	-18.2277	-1.2263	0.6078	-5.0483	-8.8117
	(0.0005)	(0.0007)	(0.0027)	(0.0395)	(0.1731)	(0.0504)	(0.0092)	(0.0185)	(0.0365)
SGD-IDR	0.0222	0.1398	0.4522	-10.8022	-0.0026	0.0000	-13.879	-0.0001	0.0000
	(0.0014)	(0.0031)	(0.0297)	(0.0267)	(0.0267)	(0.0267)	(0.0267)	(0.0267)	(0.0267)
JPY-SKW	0.233	0.4175	-1.4982	-11.9003	-0.1155	-0.0003	1.8634	-21.2111	-3.6676
	(0.002)	(0.0044)	(0.0166)	(0.0269)	(0.0268)	(0.0267)	(0.0555)	(0.2648)	(0.1431)
JPY-THB	0.2183	0.1059	-0.6739	-0.1743	-8.6711	-11.7674	-2.9235	-7.2795	-0.8242
	(0.0065)	(0.0044)	(0.0812)	(0.0434)	(0.1903)	(0.2207)	(0.1051)	(0.4438)	(0.1004)
JPY-IDR	0.0774	-0.019	-0.0044	-0.5538	-9.7492	0.217	-24.9999	0 .0000	0 .0000
	(0.0018)	(0.0032)	(0.0267)	(0.03)	(0.1349)	(0.0286)	(0.0267)	(0.0267)	(0.0267)
SKW-THB	0.8913	0.7796	-1.8731	1.8318	-13.7815	-0.3077	0.9023	-11.3056	-0.1391
	(0.0026)	(0.0032)	(0.0057)	(0.0453)	(0.1534)	(0.0541)	(0.0273)	(0.079)	(0.0548)
SKW-IDR	0.0329	-0.3946	-1.9324	-13.8633	-0.0001	0.0000	-13.8636	-0.0002	0
	(0.0005)	(0.005)	(0.0019)	(0.0267)	(0.0267)	(0.0267)	(0.0267)	(0.0267)	(0.0267)
THB-IDR	0.0329	-0.3946	-1.9324	-13.8633	-0.0001	0	-13.8636	-0.0002	0
	(0.0005)	(0.005)	(0.0019)	(0.0267)	(0.0267)	(0.0267)	(0.0267)	(0.0267)	(0.0267)
(b) Post-crisis									
SGD-JPY	0.1067	0.0891	1.2556	0.4539	-7.1674	-6.25	1.1723	-17.2974	1.844
	(0.0051)	(0.0022)	(0.0247)	(0.0285)	(0.1073)	(0.0714)	(0.0211)	(0.0997)	(0.0241)
SGD-SKW	1.0614	-0.0284	-0.0252	-1.7038	-1.9089	3.9872	-0.7447	-3.4509	2.1246
	(0.0116)	(0.0027)	(0.0242)	(0.0035)	(0.022)	(0.0032)	(0.0302)	(0.0615)	(0.0558)
SGD-THB	1.9591	0.2099	-2.106	1.997	-7.9233	-3.6317	1.6904	-9.9857	-1.5026
	(0.0061)	(0.0038)	(0.0115)	(0.0216)	(0.0844)	(0.0227)	(0.0398)	(0.1267)	(0.0544)
SGD-IDR	0.8579	0.3683	-2.084	1.2753	-10.1248	-3.7824	1.7766	-17.854	-3.9119
	(0.0027)	(0.0029)	(0.001)	(0.0304)	(0.0938)	(0.1023)	(0.0238)	(0.1428)	(0.0675)
JPY-SKW	0.7383	0.6498	-2.0789	-0.8441	-6.7139	0.0065	-2.1942	-2.3706	0.0368
	(0.0029)	(0.0048)	(0.001)	(0.0573)	(0.2394)	(0.0279)	(0.031)	(0.0811)	(0.0267)
JPY-THB	0.6894	-0.0222	-0.0136	2.3646	-11.3666	-3.7275	-1.9196	-1.0914	-1.3486
	(0.0085)	(0.0026)	(0.0254)	(0.0573)	(0.0837)	(0.02)	(0.0258)	(0.1339)	(0.1025)
JPY-IDR	0.1534	-0.066	1.2095	-1.3756	-8.9627	4.5918	0.2756	-13.6538	2.8613
	(0.0123)	(0.0045)	(0.0662)	(0.0121)	(0.1178)	(0.0152)	(0.0271)	(0.1423)	(0.0243)
SKW-THB	0.2209	-0.048	1.3487	-0.9469	-4.9868	3.3612	-1.9436	-1.7242	-0.1036
	(0.0061)	(0.0015)	(0.0203)	(0.0162)	(0.0679)	(0.0154)	(0.0139)	(0.0352)	(0.0266)
SKW-IDR	0.1437	0.029	1.3487	-14.6796	-8.7335	-0.0096	2.5945	-24.0506	-2.2236
	(0.0025)	(0.0026)	(0.0268)	(0.1178)	(0.1406)	(0.0267)	(0.0839)	(0.3946)	(0.1358)
THB-IDR	0.1437	0.029	1.3487	-14.6796	-8.7335	-0.0096	2.5945	-24.0506	-2.2236
	(0.0025)	(0.0026)	(0.0268)	(0.1178)	(0.1406)	(0.0267)	(0.0839)	(0.3946)	(0.1358)

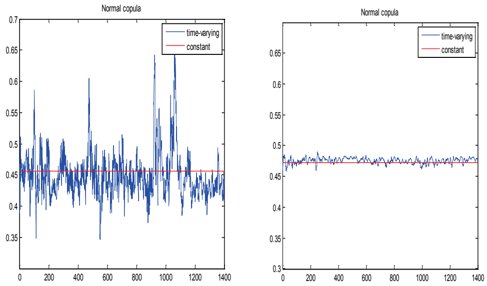
Note: The standard errors presented in the table are the asymptotic standard errors derived from Hessian matrix. The square roots of diagonal entries of the inverse of the information matrix are used as standard errors.

FIGURE 4: CONDITIONAL CORRELATION BY TIME-VARYING COPULA
(Pre-Crisis: Left panel and Post-Crisis: Right panel)

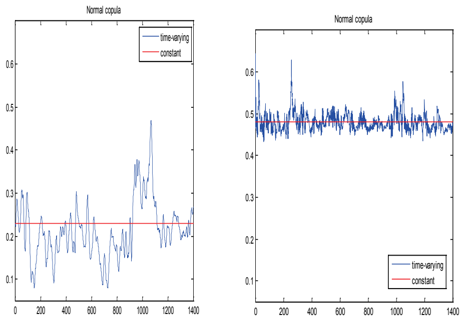
(a) SGD-JPY



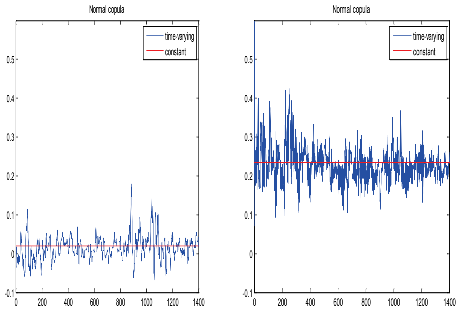
(b) SGD-SKW



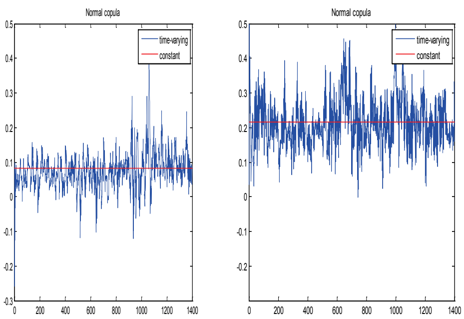
(c) SGD-THB



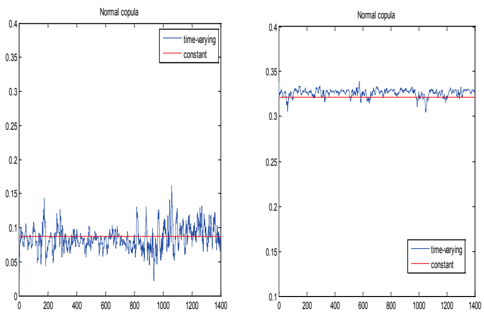
(d) SGD-IDR



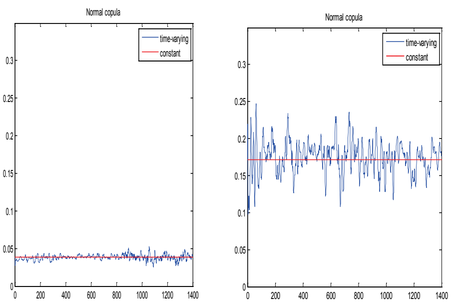
(e) JPY-SKW



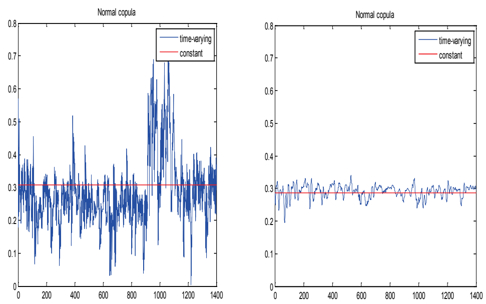
(f) JPY-THB



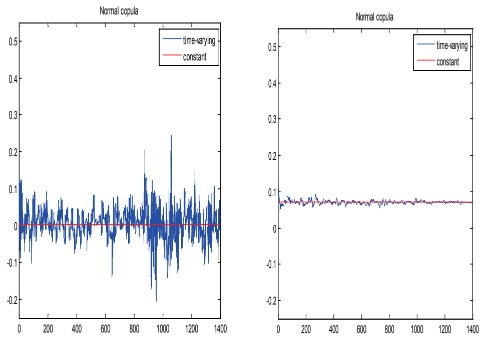
(g) JPY-IDR



(h) SKW-THB



(i) SKW-IDR



(j) THB-IDR

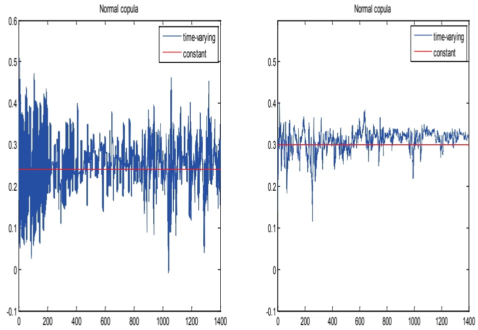
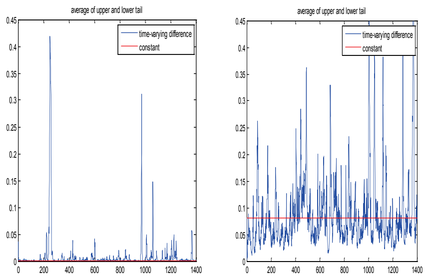
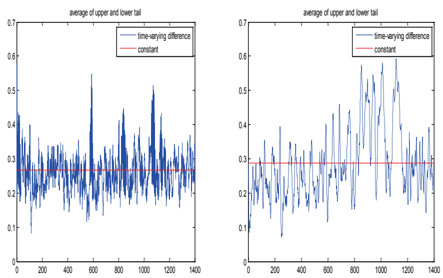


FIGURE 5: AVERAGE OF UPPER AND LOWER TAIL DEPENDENCE (Pre-Crisis: Left panel and Post-Crisis: Right panel)

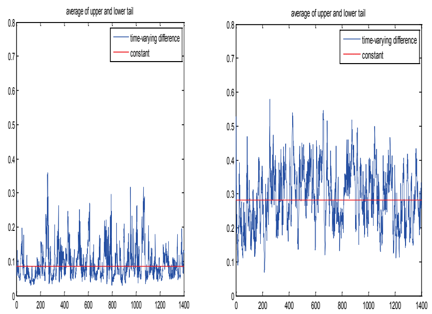
(a) SGD-JPY



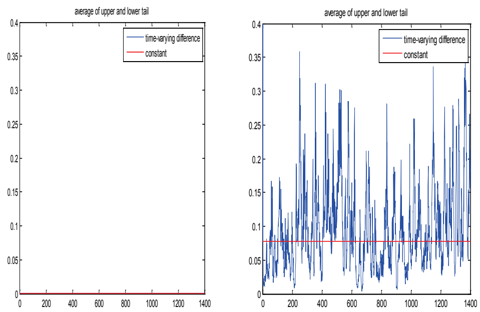
(b) SGD-SKW



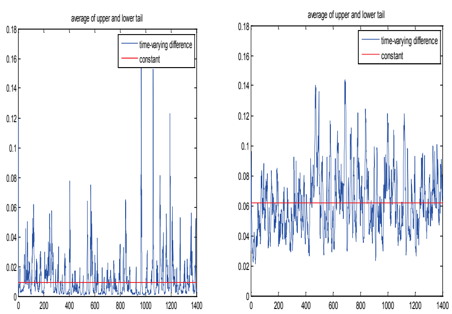
(c) SGD-THB



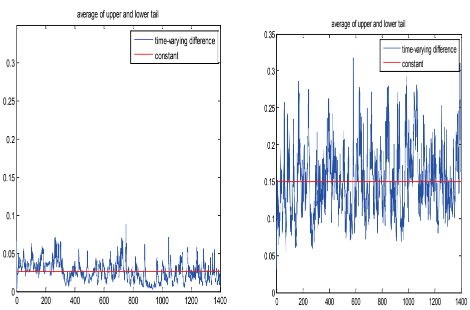
(d) SGD-IDR



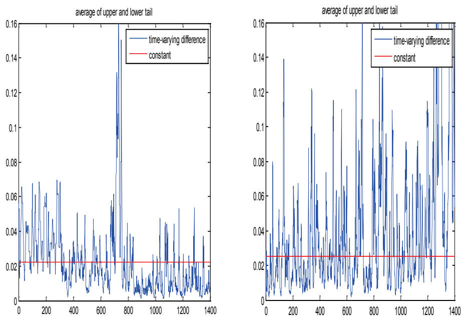
(e) JPY-SKW



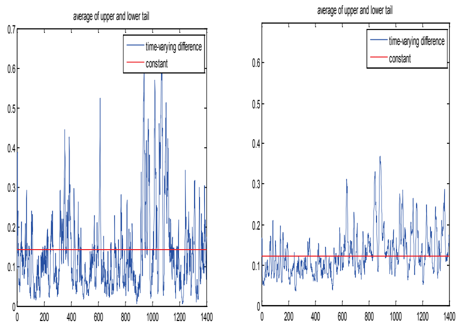
(f) JPY-THB



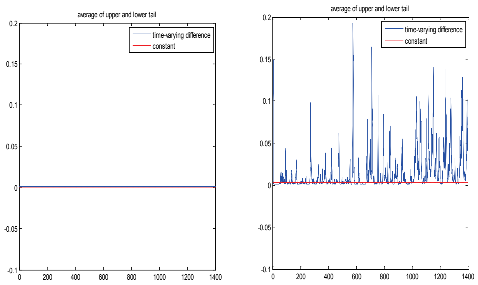
(g) JPY-IDR



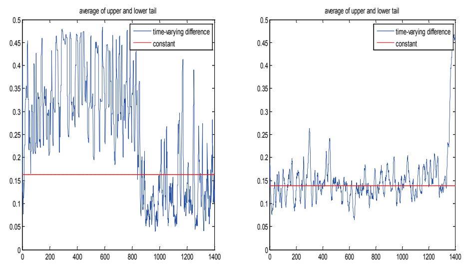
(h) SKW-THB



(i) SKW-IDR



(j) THB-IDR



It can be seen from Table 4 and Figure 4 that all the dependence parameters have increased in the post-crisis period in comparison with the pre-crisis level, with the exception of the SKW-THB pair. In particular, the constant dependence level for the pairs of SGD-JPY, SGD-THB, SGD-IDR and SGD-SKW rose from the lowest 0.02 before the crisis to as high as 0.48 after the crisis. A similar pattern of changes is observed with the pairs of JPY-IDR, JPY-THB, JPY-SKW, THB-IDR and SKW-IDR even though the level change over the crisis period is not as great as the rest of the pairs. These represent the dynamic changes in the dependence structure. Furthermore, in 7 out of 10 cases the average values of tail dependence have increased after the crisis. In most cases, the difference of the time varying upper and lower dependence shows an increase in value after the crisis, indicating the upper tail dependence parameter in the post-crisis period has become greater than that of the lower tail dependence. As the upper dependence represents the correlation on dates that both currencies depreciate against the USD, the result seems to suggest that the pair countries have become more sensitive to each other’s currency depreciation after the crisis. It is also found that over half of all the pairs have more days with asymmetric returns than with symmetric returns.

To confirm the impact of the crisis on policy changes and asymmetric dependence, we assess the changes of dominating tails in the pre- and post-crisis periods based on the differences between the upper and lower dependences. When the exchange rates exhibit symmetric structure, the difference between the upper and lower dependences is zero, and vice versa when the dependence structure is asymmetric. When the lower tail dependence dominates, the governmental policy tends to focus on internal price stabilisation. When the upper tail dependence prevails, the governmental policy tends to emphasise the price competitiveness. We report the results in Table 5. As can be seen in Table 5, there are clear cases where the dominating tail dependence changes status over the crisis period. It implied that the 1997 East Asian crisis has changed the original mechanism between any of two countries, largely due to the process of self-correction of policy makers after the crisis. This provides additional evidence to confirm the possible structural break over the crisis period.

TABLE 5: DOMINATING TAIL DEPENDENCE DURING THE PRE- AND POST-CRISIS PERIODS

Difference of upper and lower dependence	Dominating tail in pre-crisis period	Frequency	Dominating tail in post-crisis period	Frequency
SGD and JPY	Lower	100%	Upper	85%
SGD and SKW	Upper	94.50%	Lower	80.90%
SGD and THB	Lower	87%	Upper	66.50%
SGD and IDR	Symmetric	100%	Upper	99.80%
JPY and SKW	Lower	100%	Upper	63.90%
JPY and THB	Upper	100%	Upper	97.20%
JPY and IDR	Upper	100%	Lower	75.70%
SKW and THB	Upper	90.20%	Upper	91.90%
SKW and IDR	Symmetric	100%	Lower	100%
THB and IDR	Upper	100%	Upper	100%

Note: Frequency is defined as the percentage of the total days of the dominating tail in the period.

IV. CONCLUSION

In this paper, we developed a regime-switching model of copulas to capture observed asymmetric dependence in daily changes of exchange rates in five selected East Asian economies during the 1997 financial crisis era, and also applied various time-varying copula models to examining possible structural breaks. The AIC and BIC values obtained allow us to rank these models. As regard of the unconditional copula models, the Student-*t* copula is found to be the best fit for most currency pairs.

The results from the time-varying normal copula and symmetrised Joe-Clayton copula confirm a higher level of dependence after the crisis for most currency pairs with respect to both conditional linear correlation and conditional tail dependence, and imply significant changes at the dependence level, tail behaviour and asymmetry structures between returns of all the currency pairs from the five currencies before and after the crisis. The structural break periods identified by copula models match those identified with the Andrews and Ploberger test and the Bai and Perron test. Furthermore, the results show that in most cases the average values of tail dependence have increased after the crisis, and the difference between the time-varying upper and lower dependences increases in value after the crisis, indicating the upper tail dependence parameter in the post-crisis period has become greater than that of the lower tail dependence. There are clear changes in the dominating tail dependence over the crisis period. These findings confirm the impact of the crisis on policy changes and asymmetric dependence. However, this study is limited to a bivariate model framework. It can be further extended in the future study to multidimensional copula models in order to incorporate the co-movements of exchange rates among various countries.

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