Sovereign Risk Contagion in East Asia

: A Mixture of Time-varying Copulas Approach

Yongwoong Lee[a)] KiHoon Hong[b)] Kisung Yang[c)]

June 15, 2017

Abstract

This paper examines sovereign risk dependence and contagion by measuring pair-wise dynamic dependences among weekly CDS spreads of four East Asian economies (China, Hong Kong, Japan and Korea) for the period from January 2005 to September 2015. We model marginals of the CDS spreads using AR-GARCH-t models controlling for global and economy-specific factors to prevent potential biases of testing for financial contagion. Then we apply mixture of conditional (time-varying) Gaussian and symmetrized Joe-Clayton copulas to the standardized residuals for modeling dependence. In this paper, contagion is defined as a significant increase in markets' dependence due to an economy-specific shock.

We first find that there exists contagion between the East Asian sovereign CDS markets. Second, the perceived impact of contagion could be different according to whether it is measured by linear (Gaussian) or tail dependence. Third, our mixture of copulas approach successfully reflects this heterogeneity of sovereign risk contagion and shows that the linear and the upper tail dependences

a) Assistant Professor, Department of International Finance, College of Economics and Business, Hankuk University of Foreign Studies, 81 Oedae-ro, Mohyeon-myeon, Cheoin-gu, Yongin-si, Gyeonggi-do, 449-791, Republic of Korea, Tel.: +82-31-330-4516, E-mail address: ywlee@hufs.ac.kr.

b) Assistant Professor, College of Business Administration, Hongik University, Seoul, 121-791, Republic of Korea, Tel.: +82-2-320-1757, E-mail address: khhong@hongik.ac.kr.

c) Corresponding Author. Ph.D. Candidate, Department of Financial Engineering, College of Political Science and Economics, Korea University, 145 Anam-ro, Seongbuk-gu, Seoul, 02841, Republic of Korea, Tel.: +82-2-3290-2238, E-mail address: akutrus@gmail.com, akutrus@korea.ac.kr.

trade off each other once contagion occurs. Lastly, our results indicate that Japan plays the most important role in the East Asian sovereign CDS market in terms of the linear dependence whereas China and Korea are crucial in terms of the upper tail dependence.

JEL classification: C51; F3; G01; G15; H63

Keywords: Contagion, Credit Default Swap, East Asian Economies, Mixture of Time-varying Copulas, Sovereign Risk

1. Introduction

Does sovereign risk contagion exist between East Asian economies? If so, how does it appear in terms of the co-movements between their markets? This paper aims to answer these questions by exploring pair-wise dependence between sovereign credit default swap (CDS) markets of four East Asian economies – China (CN), Hong Kong (HK), Japan (JP), and South Korea (KR) - for the period from January 2005 to September 2015. Figure 1 exhibits CDS spreads of these economies over the analyzed period. It shows that CDS spreads of the East Asian economies move together in general as well as the degree of the co-movements seems to be stronger for the periods of economic turmoils, such as the U.S. financial crisis in 2007-2008 and the Eurozone debt crisis in 2010.

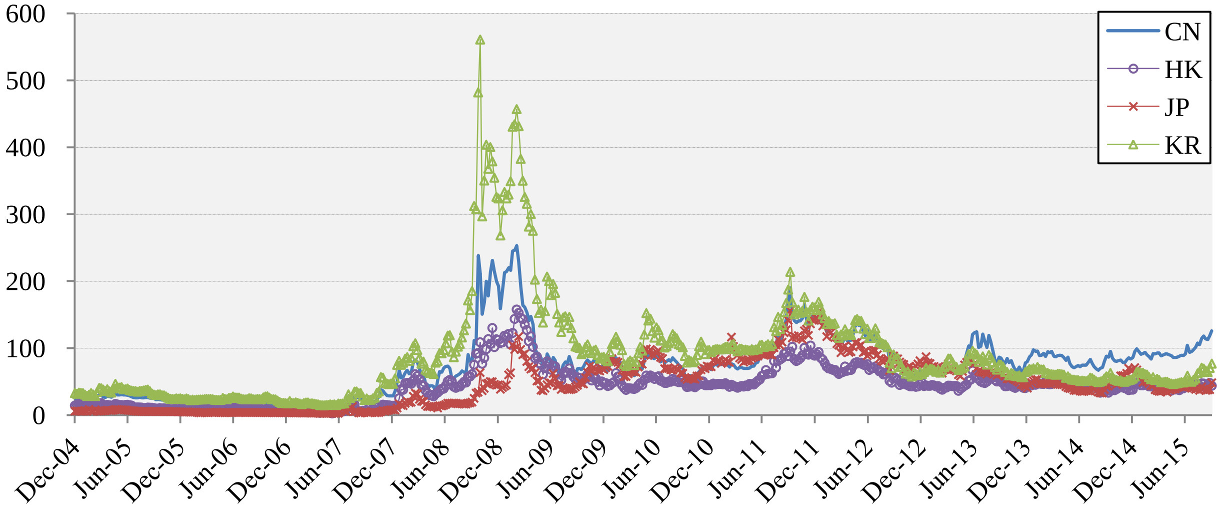

Figure 1. Weekly series of sovereign CDS spreads of China (CN), Hong Kong (HK), Japan (JP) and Korea (KR) in basis points for the period from December 2004 to September 2015.

There are several sources of biases, generally accepted in academic literatures, in testing for financial contagion. Forbes and Rigobon (2002) report that heteroscedasticity biases tests for contagion based on the conventional correlation coefficients. Corsetti et al. (2005) show that failing to distinguish between common and country-specific components of market returns induces a bias in testing for contagion. In this regard, we first filter out determinants of sovereign risk and heteroscedasticity from CDS spreads using AR-GARCH-t models to prevent these potential biases.

The mean equation of our AR-GRARCH-t filter has global and local variables affecting sovereign risk as regressors. We then apply time-varying bivariate copulas to the standardized filtered residuals for assessing dynamic pair-wise dependence structures. Parameters of copula functions are assumed to follow dynamic processes conditional on the available information as in Patton's (2006) study. To account for the linear and tail dependences simultaneously, we employ a mixture of the Gaussian and the symmetrized Joe-Clayton copulas.

Throughout the paper, we define contagion as a significant increase in markets's dependence due to an economy-specific (idiosyncratic) shock to one economy[1]. In order to identify contagion arose from economy-specific shocks, we introduce dummy variables in the dynamic processes of copula parameters.

Our study makes several contributions over the empirical literature on financial contagion. First, we focus on sovereign risk contagion between East Asian economies. Unlike studies on stock or currency market contagion, little attention has been paid to Asian economies in the discussion of sovereign risk contagion.[2] Most of the previous research on sovereign risk contagion analyzed contagion between Eurozone economies after the 2010 Eurozone debt crisis[3]. Second, we investigate contagion in terms of both the linear (Gaussian) and tail dependence using a time-varying mixture copula model. Time-varying mixture copulas are useful to analyze different kinds of dynamic dependence structures simultaneously. There have previously been a few studies analyzing financial markets' dependence using time-varying mixture copulas.[4] However, they only combined the upper

---

[1] Our definition of contagion is a slight modification of Forbes and Rigobon's (2002) where financial contagion is defined as "a significant increase in cross-market linkage after a shock to one country".

[2] To the best of our knowledge, Caceres and Unsal (2013) and Wong and Fong (2011) are the only previous literatures on sovereign risk contagion between Asian economies.

[3] Fong and Wong (2012), Giordano et al. (2013), Gómez-Puig and Sosvilla-Rivero (2014), Gorea and Radev (2014), Kalbaska and Gątkowski (2012), Metiu (2012) and Suh (2015).

[4] Chang (2012) used a time-varying mixture of the Gumbel and the Clayton copulas to model asymmetric dependence between crude oil spot and futures markets. Hsieh and Huang (2012) also adopted a time-varying mixture of the Gumbel and the Clayton copulas for asymmetric dependence modeling. Wu et al. (2012) employed a time-varying mixture of the Clayton and the Survival Clayton copulas to explore the asymmetric tail dependence structure between the oil prices and the U.S. dollar exchange rate.

and the lower tail dependences and examine dependence structure rather than contagion effect between financial markets. Our model combines the linear and the tail dependences in both sides together to explore not only dependence structure but also contagion effect. Furthermore, research on financial contagion using copulas have employed modifications of static copulas[5] or time-varying but non-mixed copulas[6]. Our suggested model is probably most general to investigate contagion using copulas. Lastly, we show that an economy with a contagious effect on other economies in terms of one dependence measure can be ineffective in terms of another dependence measure.

We have four main findings. First, our analysis shows that there exists contagion between East Asian sovereign CDS markets. That is, sovereign CDS shocks from one economy can spill over to others. As such, the pair-wise dependences are significantly changed even after controlling potential biases of testing for contagion. Second, the perceived impact of contagion could be different according to whether it is measured by linear or tail dependence. Third, our mixture of copulas approach successfully reflects this heterogeneity of sovereign risk contagion by combining linear and tail dependence measures and allowing the individual dependence measures to respond to shocks through their own dynamic processes. It shows that the linear dependence and the upper tail dependence trade off each other once contagion occurs: (1) shocks increasing the upper tail dependence will decrease the linear dependence and (2) shocks increasing the linear dependence will decrease the upper tail dependence. Lastly, our results indicate that Japan plays the most important role in the East Asian sovereign CDS market in terms of the linear dependence whereas China and Korea are crucial in terms of the upper tail dependence.

[5] Rodriguez (2007), Aloui et al. (2011), Abbara and Zevallos (2014), Weiß (2012), Ye et al. (2012), Loaiza-Maya et al. (2015) and many others.

[6] Chen et al. (2014), Kenourgios et al. (2011), Manner and Candelon (2010), Philippas and Siriopoulos (2010), Samitas and Tsakalos (2013) and Wen et al. (2012).

The remainder of this paper is organized as follows. Section 2 introduces the econometric methodologies for our research. Section 3 deals with the data used in this paper. Section 4 explains the empirical results. Lastly, Section 5 concludes.

2. Econometric Methodology

We take advantage of a conditional (time-varying) copula to analyze time-varying co-movements between the CDS spreads. A main advantage of copulas is that they enable us to analyze dependence structures of random variables entirely separate from their marginal distributions.

Let *X*, *Y* be continuous random variables with marginal distributions (densities) F_X (f_X), F_Y (f_Y) respectively and the joint distribution (density) $F_{X,Y}$ ($f_{X,Y}$). According to Sklar's theorem (Sklar, 1959), the joint density of (*X*, *Y*) can be factored into marginals and a dependence density using a function $C(u,v):[0,1]^2 \rightarrow [0,1]$ called a "copula":

$$F_{X,Y}(x,y) = C(F_X(x), F_Y(y)) \text{ or } f_{X,Y}(x,y) = f_X(x) \times f_Y(y) \times c(F_X(x), F_Y(y)), \quad \text{(Eq. 1)}$$

where $c(u,v) = \dfrac{\partial^2 C(u,v)}{\partial u \partial v}$. Note that the above copula is unconditional and static.

Patton (2006) extended Sklar's theorem in (Eq. 1) into a conditional version:

$$F_{X,Y|\Omega_t}(x, y \mid \Omega_t) = C(F_{X|\Omega_t}(x \mid \Omega_t), F_{Y|\Omega_t}(y \mid \Omega_t) \mid \Omega_t)$$

or

$$f_{X,Y|\Omega_t}(x, y \mid \Omega_t) = f_{X|\Omega_t}(x \mid \Omega_t) \times f_{Y|\Omega_t}(y \mid \Omega_t) \times c(F_{X|\Omega_t}(x \mid \Omega_t), F_{Y|\Omega_t}(y \mid \Omega_t) \mid \Omega_t),$$

where Ω_t denotes a time-varying conditioning information set given at time *t*. The function $C(u, v \mid \Omega_t)$ is called a conditional (or time-varying or dynamic) copula. This extension allows us to apply copula theory to a dynamic dependence analysis.

Another advantage of copulas is that they allow tail dependence measures, which represent the probability of two random variables having upward or downward extreme co-movements together. If we are particularly interested in extreme events, the concept of tail dependences can be very useful for measuring dependence around the tails of a distribution. The upper and the lower tail dependences of two random variables *X* and *Y* are defined and obtained from copula functions as

$$\begin{aligned}\lambda^U &= \lim_{\varepsilon\to 1^-}\Pr[F_X \ge \varepsilon \mid F_Y \ge \varepsilon] = \lim_{\varepsilon\to 1^-}\Pr[F_Y \ge \varepsilon \mid F_X \ge \varepsilon] = \lim_{\varepsilon\to 1^-}\frac{1-2\varepsilon + C(\varepsilon,\varepsilon)}{1-\varepsilon} \in (0,1] \\ \lambda^L &= \lim_{\varepsilon\to 0^+}\Pr[F_X \le \varepsilon \mid F_Y \le \varepsilon] = \lim_{\varepsilon\to 0^+}\Pr[F_Y \le \varepsilon \mid F_X \le \varepsilon] = \lim_{\varepsilon\to 0^+}\frac{C(\varepsilon,\varepsilon)}{\varepsilon} \in (0,1]\end{aligned} \quad \text{(Eq. 2)}$$

If $\lambda^U = 0$ ($\lambda^L = 0$), then the copula $C(u,v)$ has no upper (lower) tail dependence.

2.1. Marginal distribution specification

It is well known that financial returns have some stylized facts such as serial correlation, fat tail, and volatility clustering. Ignoring heteroscedasticity can lead to misidentification of contagion (Forbes and Rigobon, 2002). Thus, we adopted "AR-GARCH-t" type models to control the stylize features of financial asset returns.

Let $y_t^i = CDS_t^i - CDS_{t-1}^i$, where CDS_t^i is the CDS spread of economy *i* at the t^{th} week for *i* = *CN*, *HK*, *JP*, *KR*. For each *i*, we suppose:

$$\begin{aligned} y_t^i &= \beta_0^i + \sum_{k=1}^{G}\beta_k^{g,i}x_{k,t}^g + \sum_{k=1}^{L}\beta_k^{l,i}x_{k,t}^i + \varepsilon_t^i \\ \varepsilon_t^i &= v_t^i - \varphi_1^i\varepsilon_{t-1}^i - \cdots - \varphi_m^i\varepsilon_{t-m}^i, \quad v_t^i = \sigma_t^i\sqrt{\frac{df^i-2}{df^i}}\eta_t^i, \end{aligned} \quad \text{(Eq. 3)}$$

where $x_{k,t}^g$ represents common (global) factors influencing sovereign risk of all East Asian economies, $x_{k,t}^i$ represents economy-specific factors of economy i's sovereign risk, and $(\sigma_t^i)^2$

represents conditional variances with heteroscedasticity. The standardized AR-GARCH-t filtered residual η_t^i is assumed to follow an *i.i.d.* student-*t* distribution with degrees of freedom, df^i.

The evaluation of goodness-of-fit for marginals is of great importance in copula modeling. We employed the Ljung-Box statistic for testing for serial correlations of the 1st – 4th moments of the $\{\eta_t^i\}$ series and the Engle's Lagrange multiplier (LM) statistic to examine heteroscedasticity of the $\{\eta_t^i\}$ series.

For GARCH specification, we considered various GARCH type models: the standard GARCH, the GJR-GARCH, the Integrated-GARCH (I-GARCH), the GARCH in Mean (GARCH-M) and the I-GARCH-M (Integrated GARCH in Mean) models.[7] In our analysis, CN and KR were fitted to the I-GARCH-M model because of the existence of risk premium effect in the conditional mean equation. For JP and HK, the I-GARCH models were chosen. The GJR-GARCH model was not selected for any economy.

2.2. Explanatory variables in the conditional mean equation

Corsetti et al. (2005) has pointed out that failing to distinguish between common and country-specific components of market returns can result in a bias for testing contagion. In this paper, we included various global and local factors as regressors in the mean equation for the individual CDS spread. These regressors were selected based on previous studies about sovereign risk such as Blaise Gadanecz et al. (2014), Erdem and Varli (2014), Longstaff et al. (2011), Hilscher and Nosbusch (2010) and many others.

2.2.1. Global variables. Five common risk factors ($x_{k,t}^g$) were considered: the global stock market proxied by weekly returns reported by MSCI World (%), global financial market sentiment proxied

[7] See Tsay (2010) for more details about GARCH models.

by weekly changes of the VIX (%), funding liquidity in the banking sector proxied by weekly changes of the TED spread (bp), term-structure of interest rates proxied by weekly changes of the US treasury 10-year and 3-month yield spread (bp), and commodity market proxied by weekly returns of the WTI spot price (%). Note that raw data of MSCI and WTI prices are denominated by USD.

2.2.2. Local variables. Five economy-specific risk factors ($x_{k,t}^{i}$) were considered: local stock markets proxied by weekly returns of the MSCI for each country (%), currency markets proxied by weekly appreciation of each currency against the USD (%), overall local economic conditions proxied by weekly changes of the annual growth rate of the quarterly GDP (%), government debt condition proxied by weekly changes of government debt divided by the annual GDP (%), and liquidity buffers proxied by weekly increasing rates of foreign reserve (%). Note that all raw data of GDP, government debt, and foreign reserve before normalizing are denominated by USD.

2.3. Copula function specification

In this paper, the conditional Gaussian (GA) and symmetrized Joe-Clayton (SJC) copula functions[8] and their mixture (GASJC) were used to explore the dynamic relationship between East Asian sovereign CDS markets. Among the various copula models, we chose the GA and the SJC copulas because they describe dynamic movements of linear dependence and tail dependences in both sides, respectively. The processes of time-varying dependence parameters are assumed to follow those suggested in Patton (2006), with additional dummy variables added to test for existence and direction of contagion. More details of these dummies are presented in Section 2.3.2. Goodness-of-fit for the copulas were evaluated by the joint hit test proposed by Patton (2006).

2.3.1. Mixture of the Gaussian and the SJC copulas

[8] See Patton (2006) for more details about the GA and the SJC copulas.

Based on the fact that a convex liner combination of a finite set of copulas is again a copula (Nelsen, 2013), we define the following mixture of the GA (C_{GA}) and the SJC (C_{SJC}) copulas as

$$C_{GASJC}(u,v;\rho,\lambda^U,\lambda^L) = w_{GA}C_{GA}(u,v;\rho) + w_{SJC}C_{SJC}(u,v;\lambda^U,\lambda^L),$$

where ρ is the Gaussian correlation, λ^U is the upper tail dependence, λ^L is the lower tail dependence and $w_{GA}, w_{SJC} \in [0,1]$ satisfying $w_{GA} + w_{SJC} = 1$. Our mixture copula can reflect both linear and tail dependences by combining the GA and the SJC copulas. The density of the GASJC copula can be written as

$$c_{GASJC}(u,v;\rho,\lambda^U,\lambda^L) = \frac{\partial^2 C_{GASJC}(u,v;\rho,\lambda^U,\lambda^L)}{\partial u \partial v} = w_{GA}c_{GA}(u,v;\rho) + w_{SJC}c_{SJC}(u,v;\lambda^U,\lambda^L),$$

where $c_{GA}(u,v;\rho) = \frac{\partial^2 C_{GA}(u,v;\rho)}{\partial u \partial v}$ and $c_{SJC}(u,v;\lambda^U,\lambda^L) = \frac{\partial^2 C_{SJC}(u,v;\lambda^U,\lambda^L)}{\partial u \partial v}$.

The upper and lower tail dependences of the GASJC copula are calculated by using the following formulas:

$$\lambda^U = \lim_{\varepsilon \to 1^-} \frac{1 - 2\varepsilon + C_{GASJC}(\varepsilon,\varepsilon)}{1-\varepsilon} = w_{GA}\lambda^U + w_{SJC}\lambda^U = w_{SJC}\lambda^U$$
$$\lambda^L = \lim_{\varepsilon \to 0^+} \frac{C_{GASJC}(\varepsilon,\varepsilon)}{\varepsilon} = w_{GA}\lambda^L + w_{SJC}\lambda^L = w_{SJC}\lambda^L$$

respectively unless $\rho = 1$. Therefore, both the upper and lower tail dependences of the GASJC copula are inherited from the SJC copula.

2.3.2. Dependence parameter specification

We specified the processes of time-varying dependence parameters the same as Patton (2006) did with additional dummy variables included to test for the existence and direction of sovereign risk contagion.

2.3.2.1. Test for contagion. We tested the existence and direction of sovereign risk contagion by including dummy variables indicating economy-specific shocks in the copula parameter equations. Dummies are defined as follows:

A shock to economy *i* is defined as a situation of $U_t^i \equiv \Pr[v_t^i \leq \tilde{v}_t^i] > 95\%$, where v_t^i is the unstandardized residual in (Eq. 3) and $\tilde{v}_t^i$ is a realization of v_t^i for $i = CN, HK, JP, KR$. An occurrence of this type of shock can be interpreted as a situation of jump in the idiosyncratic component of a CDS spread. There are several recent studies reporting empirical evidence that jumps in asset prices are related to contagion between financial markets. Li and Zhang (2013) provided evidence of asymmetric contagion from jumps between international stock markets, with the US market typically having more influence on other markets than the reverse. Aït-Sahalia et al. (2015) found that cojump behavior of the US and the Chinese stock markets has been stronger since the subprime crisis, which is closely linked with contagion. Jawadi et al. (2015) reported asymmetric and nonlinear spillover effects between jumps in the US and the European stock markets.

To investigate the effect of shocks on dependence between CDS markets, we defined two dummy variables $D_{1,t}^{(i,j)}$ and $D_{2,t}^{(i,j)}$ for each pair (i, j) of economies, representing the time of economy-specific shocks to the economy *i* and *j*, respectively, as

$$D_{1,t}^{(i,j)} = d_t^i - d_t^i \times \underset{k \neq i,j}{Max}\{d_t^k\} \text{ and } D_{2,t}^{(i,j)} = d_t^j - d_t^j \times \underset{k \neq i,j}{Max}\{d_t^k\}, \qquad \text{(Eq. 4)}$$

where $d_t^k = 1_{\{U_t^k > 0.95\}}$ for $i, j, k = CN, HK, JP, KR$. Here, d_t^i stands for shocks to economy *i* and $d_t^i \times \underset{k \neq i,j}{Max}\{d_t^k\}$ stands for shocks occurring outside the economy pair (i, j). Thus, $D_{1,t}^{(i,j)}$ and $D_{2,t}^{(i,j)}$ respectively denote the time of economy-specific shocks in economies *i* and *j* that never overlaps with any other shocks outside economies *i* and *j*.

Note that we remove the effects of shocks occurring outside the pair (i, j) from d_t^i and d_t^j to define $D_{1,t}^{(i,j)}$ and $D_{2,t}^{(i,j)}$, respectively. This is why we want to explore the "pure" relationship between economies i and j without any interference from outside variables, such as possible systematic shocks remaining unfiltered in the mean and volatility equations. The remaining systematic effects could be incorporated through frailty factors, however, we just removed their possible impacts by defining $D_{1,t}^{(i,j)}$ and $D_{2,t}^{(i,j)}$ as (Eq. 4) for the sake of simplicity.

2.3.2.2. Specification of time-varying dependence parameters. Using the dummy variables defined in (Eq. 4), we slightly modified Patton's (2006) original specifications. We define the time-varying Gaussian dependence (ρ_t) and the time-varying upper and lower tail dependences (λ_t^U, λ_t^L) of each pair (i, j) of economies as

$$\begin{aligned}\rho_t &= \tilde{\Lambda}\left(\alpha_0 + \alpha_1 \rho_{t-1} + \alpha_2 \frac{1}{10}\sum_{s=1}^{10}\Phi^{-1}(u_{t-s})\Phi^{-1}(v_{t-s}) + \alpha_3 D_t\right)\\ \lambda_t^U &= \Lambda\left(\alpha_0^U + \alpha_1^U \lambda_{t-1}^U + \alpha_2^U \frac{1}{10}\sum_{s=1}^{10}|u_{t-s} - v_{t-s}| + \alpha_3^U D_t\right)\\ \lambda_t^L &= \Lambda\left(\alpha_0^L + \alpha_1^L \lambda_{t-1}^L + \alpha_2^L \frac{1}{10}\sum_{s=1}^{10}|u_{t-s} - v_{t-s}|\right),\end{aligned} \qquad \text{(Eq. 5)}$$

where $\Phi(\cdot)$ is the CDF of $N(0,1)$, $u_t = U_t^i$, $v_t = U_t^j$ and $D_t = D_{1,t}^{(i,j)}$ or $D_{2,t}^{(i,j)}$. The logistic transformations $\tilde{\Lambda}(x) \equiv \frac{(1-e^{-x})}{(1+e^{-x})}$ and $\Lambda(x) \equiv \frac{1}{(1+e^{-x})}$ are used to keep $-1 < \rho_t < 1$ and $0 < \lambda_t^U, \lambda_t^L < 1$ respectively.

We want to point out two observations here. First, we ran the regression twice for each pair (i, j) of economies: one with $D_t = D_{1,t}^{(i,j)}$, the other with $D_t = D_{2,t}^{(i,j)}$. Positive significance of $D_{1,t}^{(i,j)}$ ($D_{2,t}^{(i,j)}$) would imply existence of contagion from economy i (j) to economy j (i), whereas negative or insignificant estimates would be natural because our definitions of dummies are based on idiosyncratic shocks. The second point is that we applied dummy variables asymmetrically: they are included in the upper tail dependence, but not in the lower tail dependence.[9] The reason for this asymmetric modeling is to improve the identification of our mixture of copulas. Furthermore, our area of interest is with the impact of extreme "bad" news, related to a sharp increase in CDS spreads and the upper tail dependence.

2.4. Parameter estimation

Among the various estimation procedures of copula functions and marginal models, we applied the canonical maximum likelihood (CML) method. The CML method is a semi-parametric two-step estimation method, as a variation of the inference function for the marginal (IFM) method proposed by Joe and Xu (1996). The difference between the CML and the IFM is that the CML uses empirical marginal distributions instead of parametric margins.

Let $\{x_t, y_t\}_{t=1}^{T}$ be the observed paired data of two random variables *X* and *Y*. The joint probability density function of *X* and *Y* can be represented as

$$f_{X,Y}(x, y;\Theta) = c\left(F_X(x), F_Y(y);\Theta_C\right) f_X(x;\Theta_X) f_Y(y;\Theta_Y)$$

by using (Eq. 1), where Θ_C is the vector of parameters in a copula, Θ_X and Θ_Y denote the vector of parameters in the marginal distributions of *X* and *Y* respectively, and Θ is the union of Θ_X, Θ_Y and Θ_C. Hence, the log-likelihood function is decomposed into the sum of the log-likelihood functions of the marginals and the copula density:

$$L(\Theta) = \sum_{t=1}^{T} \ln c\left(F_X(x_t;\Theta_X), F_Y(y_t;\Theta_Y);\Theta_C\right) + \sum_{t=1}^{T} \left[\ln f_X(x_t;\Theta_X) + \ln f_Y(y_t;\Theta_Y)\right]. \qquad \text{(Eq. 6)}$$

The CML method is a two-step procedure using the decomposition in (Eq. 6), similar to the IFM method. As the first step, the margins are estimated by using the empirical distributions:

[9] Chen et al. (2014) measured the contagion effect between U.S. and Chinese stock markets during the financial crisis using a modified Clayton copula, which considers effects of contagion on the lower tail dependence only.

$$\hat{F}_X(x) = \frac{1}{T}\sum_{t=1}^{T} 1_{\{X_t \le x\}} \quad \text{and} \quad \hat{F}_Y(y) = \frac{1}{T}\sum_{t=1}^{T} 1_{\{Y_t \le y\}} .$$

In the second step, the copula parameters are conditionally obtained using the estimated empirical distributions $\hat{F}_X$ and $\hat{F}_Y$ by

$$\hat{\Theta}_C^{CML} = \max_{\Theta_C} \sum_{t=1}^{T} \ln c\left(\hat{F}_X(x_t), \hat{F}_Y(y_t); \Theta_C\right).$$

3. Data

We empirically examined all possible pair-wise dynamic dependence structures between the four East Asian sovereign CDS markets to analyze sovereign risk contagion due to extreme shocks. CDS spreads are probably the most popular market-based measure of sovereign credit risk because they reflect the change of both global and local economic conditions which have an effect on an economy (Longstaff et al., 2007). The CDS data collected covers every Wednesday from 29 December 2004 to 15 September 2015 which gives 561 weekly CDS spread differences. For missing data, we used the data on the previous trading date. Table 1 shows summary statistics of the weekly changes of the CDS spreads.

Table 1. Summary statistics of weekly differences of the CDS spreads

Economy	Min	1Q*	Median	3Q*	Max	Mean	Stdev	Skew	Kurt
CN	-60.32	-2.44	-0.07	2.45	131.72	0.18	9.94	3.63	58.43
HK	-32.10	-1.38	-0.04	1.73	24.10	0.05	4.92	-0.34	8.48
JP	-40.98	-1.45	-0.03	1.43	41.44	0.08	5.58	0.59	16.53
KR	-264.02	-2.74	-0.26	2.65	174.45	0.08	18.48	-2.95	93.36

Note: This Table provides summary statistics of Wednesday-to-Wednesday weekly changes of CDS spreads (in basis points) of four East Asian economies: CN (China), HK (Hong Kong), JP (Japan), and KR (Korea). The data covers from January 3, 2005 to September 30, 2015, which corresponds to a sample of 561 observations.

*1Q and 3Q means 25% and 75% quartiles respectively.

In Table 1, the means of the weekly changes are close to zero for all economies. The skewnesses of HK and JP are nearly zero whereas those of CN and KR are substantially larger than and smaller than zero, respectively. It is natural to expect symmetry or positive skewness of CDS spread changes because financial asset prices are more sensitive to bad news than good news. The negative skewness of KR is a result of the minimum value (-264.02 bp)[10] which is a realization for the period between 29 October 2008 and 05 November 2008[11]. All data series exhibit excess kurtosis implying heavy tails for the unconditional distributions of the weekly changes. These observations are consistent with assumptions of the AR-GARCH-t models considered in Section 2.1.

Our data source for weekly CDS spreads, MSCI's, VIX, U.S. 3-month LIBOR, U.S. 90-day T-bill rate, as well as for monthly foreign reserves, is Bloomberg[12]. Weekly U.S. Treasury yields and WTI spot prices were obtained from the U.S. Department of Treasury[13] and the U.S. Energy Information Administration (EIA)[14] respectively. For weekly currency rates, we used the U.S. Board of Governors of the Federal Reserve System[15]. We collected quarterly GDP and government debt data from the General Government Debt to GDP data calculated by BIS[16]. Note that we ran our regression on a weekly basis. To accommodate the data of different frequencies, we transformed monthly or quarterly data into weekly frequency using linear transformation.[17]

4. Empirical Results

[10] Skewness of KR calculated excluding this minimum value is 6.8639 which is a positive value. Furthermore, if we calculate it excluding the minimum value as well as the maximum value (174.45 basis points) together, the result is 3.8304 which is also a positive value.

[11] For this period, there were economic and political events causing global CDS spreads to decrease. On 29 October 2008, FRB decided to lower its target for the federal funds rate 0.5% to 1.0% and the discount rate 0.5% to 1.25%. On 04 November 2008, Barack Obama was elected the 44th president of the United States. A relatively larger decrease in the CDS spread of KR might be due to the currency swap arrangement of up to 30 billion U.S. dollars between U.S. and KR that occurred on 30 October 2008.

[12] Ticker (Variable): "SOVR"(Sovereign CDS spreads), "MXWO Index" (MSCI World), "MXCN Index"/"MXHK Index"/"MXJP Index"/"MXKR Index" (MSCI's of CN/HK/JP/KR), "VIX Index" (VIX), "US0003M Index" (U.S. 3-month LIBOR), "USGB090Y Index" (U.S. 90-day T-bill rate), "WIRACHIN Index"/"532.055 Index"/"WIRAJAPA Index"/"542.055 Index" (Foreign reserve of CN/HK/JP/KR).

[13] https://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=yieldAll

[14] http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm

[15] https://www.federalreserve.gov/releases/h10/hist/

[16] http://www.bis.org/statistics/totcredit.htm

[17] Gorea and Radev (2014) employed a similar accommodation.

In this section, we present the results of estimation. First we present the results of the marginal models, then we discuss the results of the copula models.

4.1. Estimation results of marginal distribution

The AR(m)-GARCH(p,q)-t models mentioned in Section 2.1 were estimated by MLE for various combinations of (m, p, q). We selected the most suitable models based on the values of AIC and SBC among the model specifications satisfying *i.i.d.* assumptions on the standardized residuals. Table 2 shows the selected estimation results for the conditional mean equation of the marginal distributions of each economy.

Table 2. MLE results of marginal distributions : Conditional mean equations

Variable		*CN*	*HK*	*JP*	*KR*
Conditional mean equation					
	Constant	0.5427**	-0.0303	-0.0277	0.5398*
		(0.2635)	(0.0637)	(0.0260)	(0.2802)
Global factor	*Stock*	**-0.4217*****	**-0.1752****	-0.0314	**-0.7035*****
		(0.1018)	(0.0756)	(0.0219)	(0.1184)
	Vol	**0.1364****	0.0210	-0.0061	0.1690**
		(0.0595)	(0.0491)	(0.0183)	(0.0690)
	TED	**0.0332*****	0.0130	**0.0061*****	0.0023
		(0.0124)	(0.0101)	(0.0022)	(0.0124)
	10Y-3M	**-0.0288*****	-0.0106	-0.0022	**-0.0182***
		(0.0100)	(0.0072)	(0.0019)	(0.0110)
	WTI	0.0207	-0.0158	-0.0046	0.0166
		(0.0241)	(0.0168)	(0.0041)	(0.0263)
Economy-specific factor	*Stock*	0.0007	**-0.0705***	0.0099	-0.0725
		(0.0385)	(0.0418)	(0.0104)	(0.0518)
	FX	0.1303	1.1159	-0.0057	0.1076
		(0.4883)	(1.2866)	(0.0174)	(0.1097)
	GDP	-0.3850	**-1.0279***	-0.0871	1.8839
		(1.5272)	(0.5489)	(0.2813)	(1.4745)
	Debt	**4.6586****	0.7926	-0.1617	0.4947
		(2.1589)	(3.7488)	(0.3889)	(1.1810)
	Foreign reserve	**-0.5602***	0.0908	-0.0231	-0.7634
		(0.3322)	(0.2429)	(0.1005)	(0.5235)

Note: This Table provides parameter estimates of conditional mean equations in the marginal distribution models. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

In Table 2, the estimated coefficients of the regressors in the conditional mean equation show consistent results with previous literature on the determinants of sovereign risk.[18] Stock markets, term structure, GDP growth, and foreign reserve decrease the sovereign risk, whereas volatility, TED spread, currency rate, and government debt increase it. Furthermore, global variables play more important roles than local variables in determining the premium of sovereign credit risk, which is consistent with findings by Longstaff et al. (2011).

Table 3. MLE results of marginal distributions: Residual and conditional variance equations

Variable	*CN*	*HK*	*JP*	*KR*
Residual equation				
AR(1)	0.1266***	0.1266***		-0.0739**
	(0.0400)	(0.0404)		(0.0337)
AR(2)		0.0720*		0.1801***
		(0.0414)		(0.0286)
AR(3)		0.0730*		0.1004***
		(0.0393)		(0.0258)
AR(4)				0.1260***
				(0.0206)
AR(6)				0.0521*
				(0.0278)
AR(7)		0.0889**		
		(0.0376)		
AR(13)				-0.0790**
				(0.0326)
Risk premium	-0.1731*			-0.2460**
	(0.1049)			(0.1149)
Conditional variance equation				
Constant	0.1380**	0.0640*	0.0030**	1.5225***
	(0.0647)	(0.0337)	(0.0015)	(0.4539)
ARCH(1)	0.1703***	0.1417***	0.2231***	0.5470***
	(0.0255)	(0.0237)	(0.0203)	(0.0476)
GARCH(1)	0.8297***	0.8583***	0.7769***	-0.2460**
	(0.0255)	(0.0237)	(0.0203)	(0.1149)
GARCH(6)				0.4530***
				(0.0476)
Degree of Freedom	3.7850***	3.7693***	3.4200***	3.4014***
	(0.0254)	(0.0294)	(0.0210)	(0.0271)
lnL	1,598	1,363	1,289	1,677
AIC	-3,227	-2,763	-2,606	-2,606
SBC	-3,297	-2,841	-2,667	-2,667

Note: This Table provides parameter estimates of residual and conditional variance equations in the marginal distribution models. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

[18] Blaise Gadanecz et al. (2014), Erdem and Varli (2014), Hilscher and Nosbusch (2010), Longstaff et al. (2011) and many others.

Table 3 shows the estimated results for the residual and the conditional variance equations of the marginal distributions. All CDS markets are fitted to the I-GARCH model, meaning that each of the CDS spreads has heteroscedasticity with infinite unconditional variance. Additionally, CN and KR are revealed to have the risk premium effect and fit the I-GARCH-M model. The results of negative risk premium parameters[19] of CN and KR are consistent with the skewness values of CN and KR[20] in Table 1.

Table 4. Goodness of Fit Test for marginal distributions

Statistic	Variable	***CN***	***JP***	***KR***	***HK***
Q(6~24)*	*1st moment*	7.8000	21.5900	9.8500	6.2600
		[0.2532]	[0.6035]	[0.1311]	[0.3945]
	2nd moment	3.6000	0.2600	4.7600	2.1900
		[0.7303]	[0.9997]	[0.5752]	[0.9017]
	3rd moment	0.6200	0.0400	0.0200	4.3000
		[0.9961]	[1.0000]	[1.0000]	[0.6355]
	4th moment	0.6200	0.0300	0.0100	1.8100
		[0.9961]	[1.0000]	[1.0000]	[0.8519]
LM(1~12)**	*1st moment*	3.3102	0.0010	4.1228	0.2925
		[0.6523]	[0.9742]	[0.1273]	[0.5886]

*Q(6~24) stands for the Ljung-Box statistic with the minimum p-value among Q(6), Q(12), Q(18) and Q(24), where Q(m) represents the Ljung-Box statistic of order m. P-values (in brackets) indicate acceptance of the null hypothesis of no serial correlation at the 10% significance level.
**LM(1~12) stands for the Engle's LM statistics with the minimum p-value among LM(1)-LM(12), where LM(m) represents the LM statistic of order m. P-values (in brackets) indicate acceptances of the null hypothesis of no heteroscedasticity at the 10% significance level.

Table 4 reports the results of the goodness-of-fit tests for the marginals. All marginal distribution models passed the Ljung-Box tests at the 10% significance level, meaning that there are no serial correlations in the 1^{st} – 4^{th} moments of the standardized residuals. Also, all models passed the LM tests at the 10% significance level, indicating no heteroscedasticity in the standardized residuals.

Hence, we can conclude that the estimated models are well specified enough to describe the weekly changes of the CDS spreads and satisfy the *i.i.d.* assumptions on the standardized filtered residuals.

[19] Negative sign of the risk premium parameter in the GARCH-M model means that a protection seller on a more volatile reference asset will expect more profit from a larger decrease in the CDS spread from the trade date.

[20] See the footnote 10.

4.2. Estimation results of static copulas

Table 5 reports the parameter estimates for the static copula functions. In the GA copulas, all pairs of CDS markets have positive static Gaussian correlations. In the static SJC copulas, all pairs of CDS markets except for (KR, HK) show $\lambda^U - \lambda^L > 0$, meaning they have asymmetric tail dependences with stronger co-movements in the upper tail than the lower tail, as expected.

Table 5. MLE results of static copulas

Regressor		(CN, JP)	(CN, KR)	(CN, HK)	(JP, KR)	(JP, HK)	(KR, HK)
Static non-mixed copulas							
GA	ρ	0.4387***	0.7513***	0.4631***	0.4115***	0.3378***	0.4638***
		(0.0013)	(0.0006)	(0.0013)	(0.0014)	(0.0015)	(0.0013)
	lnL	58	229	66	50	33	66
	AIC	-116	-458	-132	-101	-66	-132
	SBC	-116	-458	-132	-101	-66	-132
SJC	λ^U	0.3062***	0.5727***	0.3166***	0.2451***	0.2287***	0.2486***
		(0.0021)	(0.0009)	(0.0022)	(0.0022)	(0.0022)	(0.0025)
	λ^L	0.2296***	0.5453***	0.2659***	0.2051***	0.0946***	0.2954***
		(0.0024)	(0.0024)	(0.0024)	(0.0023)	(0.0023)	(0.0022)
	lnL	66	227	72	53	37	66
	AIC	-132	-454	-144	-106	-75	-132
	SBC	-132	-454	-144	-106	-75	-132
	Hit Test	0.2002	0.7084	0.7082	0.9979	0.9312	0.6564
Static GASJC copulas							
GA	ρ	0.1503***	0.8433***	0.2842***	0.4817***	-0.3881	0.6926***
		(0.0067)	(0.0009)	(0.0106)	(0.0093)	(0.3918)	(0.0066)
	Weight	0.4233***	0.7997***	0.6703***	0.2556***	0.0500*	0.6152***
		(0.5242)	(0.1773)	(0.7976)	(0.2450)	(0.2558)	(0.0100)
SJC	λ^U	0.5242***	0.1773***	0.7976***	0.2450***	0.2558***	0.0100
		(0.0053)	(0.0112)	(0.0004)	(0.0039)	(0.0038)	(0.0123)
	λ^L	0.4201***	0.2026***	0.5012***	0.1754***	0.1192***	0.0101
		(0.0061)	(0.0082)	(0.0031)	(0.0047)	(0.0050)	(0.0109)
	Weight	0.5767***	0.2003***	0.3297***	0.7444***	0.9500***	0.3848***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	lnL	69	242	81	53	37	73
	AIC	-137	-485	-161	-107	-75	-146
	SBC	-137	-485	-161	-107	-75	-146

Note: This Table provides parameter estimates of static copulas with standard errors in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

In Table 5, the static GASJC copulas also show overall positive GA dependences and asymmetric tail dependences skewed upward. These results are consistent with the non-mixed static copulas, implying that the static GASJC copula harmonizes the static GA with the static SJC copulas well. All dependence parameter estimates in Table 5 are used as initial guesses to estimate constant terms in parameter equations of the corresponding dynamic copulas. The weight estimates of static GASJC copulas are used as initial guesses to estimate weight parameters of GASJC copulas.

4.3. Estimation results of non-mixed dynamic copulas

As stated in (Eq. 5), the Gaussian and the upper tail dependence equations in our dynamic copulas have one of the dummies defined in (Eq. 4) to identify sovereign risk contagion. The set $\{t \mid D_{1,t}^{(i,j)}=1,\ 1\le t\le 561\}$ ($\{t \mid D_{2,t}^{(i,j)}=1,\ 1\le t\le 561\}$) stands for the times of an extreme idiosyncratic shock to economy i (j) for the economy pair (i, j). Table 6 shows sizes of the samples with values of the dummies equal to 1 for each pair of economies.

Table 6. Sizes of samples with the dummies equal to 1

Dummy	(CN,JP)	(CN,KR)	(CN,HK)	(JP,KR)	(JP,HK)	(KR,HK)
$D_1^{(i,j)}=1$	7	12	10	18	15	8
$D_2^{(i,j)}=1$	15	11	15	9	12	14
$D_1^{(i,j)}=D_2^{(i,j)}=1$	1	6	4	4	1	3

Note: This Table reports the number of samples where the values of dummy variables are equal to 1 for each pair (i, j) of economies. $D_1^{(i,j)}$ and $D_2^{(i,j)}$ stand for idiosyncratic shock on economy i and j in the pair (i, j), respectively.

In Table 6, note that the number of observations satisfying $D_{1,t}^{(i,j)}=1$ or $D_{2,t}^{(i,j)}=1$ is considerably smaller than 28 which is the size of $\{t \mid d_t^k=1,\ 1\le t\le 561\}$ for all economy pairs. This is because we removed effects of shocks that occurred outside of the pair (i, j) from d_t^i and d_t^j to define $D_{1,t}^{(i,j)}$ and $D_{2,t}^{(i,j)}$, respectively. Furthermore, the sizes of samples with $D_{1,t}^{(i,j)}=D_{2,t}^{(i,j)}=1$ are even smaller for all economy pairs. This is because dummies are defined based on idiosyncratic shocks.

As stated in Section 2.3.2, positive significance of $D_{1,t}^{(i,j)}$ ($D_{2,t}^{(i,j)}$) would imply the existence of contagion from economy i (j) to economy j (i), whereas negative or insignificant estimates would be natural because our definitions of dummies are based on idiosyncratic shocks. Thus, we are only interested in the cases of dummies with positive coefficients which represent contagion.

4.3.1. Estimation results of the dynamic non-mixed copulas

4.3.1.1. Results of dynamic GA copulas. Tables 7-1 and 7-2 report estimated results of the dynamic GA copulas with dummy variables D_1 and D_2, respectively. Both dynamic GA copula models exhibit better explanatory power than the static GA copulas in terms of the values of AIC and SBC.

Table 7-1. MLE results of dynamic GA copulas with D_1 as the dummy

	Regressor	**(*CN*, *JP*)**	**(*CN*, *KR*)**	**(*CN*, *HK*)**	**(*JP*, *KR*)**	**(*JP*, *HK*)**	**(*KR*, *HK*)**
Copula parameters with D_1 as a regressor							
ρ	*Constant*	0.0319***	5.6038***	0.3076***	0.3190***	0.9658***	2.0649***
		(0.0034)	(0.0015)	(0.0109)	(0.0156)	(0.0254)	(0.0143)
	AR(1)	1.9289***	-4.9079***	1.2817***	0.8579***	-0.7829***	-2.1236***
		(0.0115)	(0.0023)	(0.0287)	(0.0547)	(0.0678)	(0.0180)
	MA(10)	0.2205***	0.2014***	0.2669***	0.4948***	0.1059***	-0.0606***
		(0.0045)	(0.0015)	(0.0074)	(0.0172)	(0.0094)	(0.0129)
	D_1	-0.2728***	-0.0603***	-0.0937***	**0.0132****	-0.1633***	-0.4186***
		(0.0064)	(0.0011)	(0.0070)	(0.0061)	(0.0061)	(0.0082)
	lnL	67	235	69	58	34	70
	AIC	-134	-470	-139	-116	-67	-140
	SBC	-134	-470	-139	-116	-67	-140

Note: This Table provides parameter estimates of dynamic GA copulas with D_1 as the dummy. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

In Table 7-1, only (JP, KR) has positive and significant D_1. This means that the linear dependence of sovereign risks between *JP* and *KR* will increase by $\tilde{\Lambda}(0.0132)$, on average, if a shock hits *JP*. That is, contagion from *JP* to *KR* exists. Also, in Table 7-2, (JP, KR) is the only pair having positive and significant D_2 indicating a shock on KR will increase the linear dependence of sovereign risks between *JP* and *KR* as much as $\tilde{\Lambda}(0.3694)$, on average.

Table 7-2. MLE results of dynamic GA copulas with D_2 as the dummy

	Regressor	**(*CN, JP*)**	**(*CN, KR*)**	**(*CN, HK*)**	**(*JP, KR*)**	**(*JP, HK*)**	**(*KR, HK*)**
Copula parameters with D_2 as a regressor							
ρ	*Constant*	1.1124***	0.4297***	0.4734***	0.2045***	0.5743***	0.5890***
		(0.0221)	(0.0292)	(0.0089)	(0.0067)	(0.0199)	(0.0116)
	AR(1)	-1.3079***	1.9975***	0.9893***	1.2065***	0.3335***	0.8630***
		(0.0527)	(0.0383)	(0.0203)	(0.0242)	(0.0599)	(0.0244)
	MA(10)	1.0123***	0.0952***	0.3177***	0.3904***	0.1203***	0.1381***
		(0.0136)	(0.0038)	(0.0060)	(0.0088)	(0.0087)	(0.0054)
	D_2	-0.1328***	-0.4762***	-0.3444***	**0.3694*** **	-0.1626***	-0.3724***
		(0.0069)	(0.0072)	(0.0053)	(0.0082)	(0.0059)	(0.0062)
	lnL	64	235	74	60	34	70
	AIC	-128	-470	-147	-120	-67	-140
	SBC	-128	-470	-147	-120	-67	-140

Note: This Table provides parameter estimates of dynamic GA copulas with D_2 as the dummy. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Combining these results, we can infer that there exists a two-way sovereign risk contagion in terms of the linear dependence (we call this "linear contagion" later on) between *JP* and *KR*.

4.3.1.2. Results of dynamic SJC copulas. Table 8-1 and 8-2 report estimated results of the dynamic SJC copulas with dummy variables D_1 and D_2, respectively. Similar to the case of the GA copulas, the dynamic SJC copulas are superior to the static SJC copulas in terms of AIC and SBC.

In Table 8-1, (CN, KR) and (CN, HK) exhibit positive and significant D_1's. This means that there exists one-way contagion from *CN* to *KR* and from *CN* to *HK* in terms of the upper tail dependence (we call this "upper tail contagion" from now on). That is, taking the case of (CN, KR) as an example, the CDS market's expectation on the likelihood of the default of *KR* given the near default of *CN* increases by $\Lambda(1.0123)$, on average, if a shock hits *CN*.[21] In Table 8-2, however, no dummy has positive significance. All parameter estimates of D_2's are negative except for (CN, KR). Although (CN, KR) has a positive dummy effect, it is insignificant.

[21] Recall that tail dependences are defined as limits of conditional probabilities from (Eq. 2).

Table 8-1. MLE results of dynamic SJC copulas with D_1 as the dummy

	Regressor	(*CN*, *JP*)	(*CN*, *KR*)	(*CN*, *HK*)	(*JP*, *KR*)	(*JP*, *HK*)	(*KR*, *HK*)
Copula parameters with D_1 as a regressor							
λ^U	*Constant*	0.7491***	5.5062***	5.6589***	7.8579***	0.3720***	2.8676***
		(0.1014)	(0.0052)	(0.0776)	(0.1185)	(0.0812)	(0.1194)
	AR(1)	1.6832***	-3.0794***	-2.4605***	-5.1118***	-3.0246***	2.1992***
		(0.1752)	(0.0144)	(0.0713)	(0.0585)	(0.1118)	(0.0841)
	MA(10)	-7.0494***	-17.0008***	-22.2439***	-27.2779***	-0.8929***	-19.1836***
		(0.2311)	(0.0799)	(0.2854)	(0.4920)	(0.2435)	(0.4974)
	D_1	-6.6845***	**1.0123*** **	**0.6943*** **	-13.0895***	-1.8394***	-6.5863***
		(0.1077)	(0.0039)	(0.0348)	(0.1904)	(0.0617)	(0.2115)
λ^L	*Constant*	2.4965***	8.4394***	3.9960***	0.9862***	4.9922***	1.0768***
		(0.0675)	(0.0247)	(0.0625)	(0.0920)	(0.0814)	(0.2517)
	AR(1)	-3.5336***	-6.2654***	-1.3806***	-2.6688***	-4.8488***	-2.3736***
		(0.1329)	(0.0157)	(0.0616)	(0.2857)	(0.0568)	(0.6410)
	MA(10)	-11.1605***	-26.9429***	-22.2471***	-6.2307***	-26.4740***	-3.9385***
		(0.2996)	(0.0144)	(0.3272)	(0.2268)	(0.2539)	(0.4053)
	lnL	72	243	95	64	41	79
	AIC	-145	-487	-190	-127	-83	-158
	SBC	-145	-487	-190	-127	-83	-157

Note: This Table provides parameter estimates of dynamic SJC copulas with D_1 as the dummy. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Table 8-2. MLE results of dynamic SJC copulas with D_2 as the dummy

	Regressor	(*CN*, *JP*)	(*CN*, *KR*)	(*CN*, *HK*)	(*JP*, *KR*)	(*JP*, *HK*)	(*KR*, *HK*)
Copula parameters with D_2 as a regressor							
λ^U	*Constant*	5.4366***	6.3979***	4.5820***	4.7254***	-0.4322***	1.3314***
		(0.0785)	(0.0108)	(0.0872)	(0.0846)	(0.0839)	(0.1030)
	AR(1)	-5.2551***	-4.0660***	-1.0536***	-1.5963***	-1.2437***	1.9115***
		(0.0376)	(0.0749)	(0.0744)	(0.0960)	(0.2608)	(0.0977)
	MA(10)	-16.5001***	-17.7788***	-18.6548***	-20.4246***	0.1006	-9.4080***
		(0.2968)	(0.3482)	(0.3107)	(0.2903)	(0.2338)	(0.3416)
	D_2	-1.0202***	**0.0157**	-17.1909***	-0.7285***	-1.1912***	-8.5013***
		(0.0332)	(0.0125)	(0.1312)	(0.0453)	(0.0486)	(0.1993)
λ^L	*Constant*	2.2781***	8.5959***	4.0866***	1.0275***	4.7885***	-1.4544***
		(0.0644)	(0.0483)	(0.0653)	(0.0677)	(0.1328)	(0.0248)
	AR(1)	-3.1054***	-6.8159***	-1.5422***	-3.0180***	-4.8618***	4.8615***
		(0.1189)	(0.0095)	(0.1048)	(0.1601)	(0.0576)	(0.0328)
	MA(10)	-11.3643***	-27.3753***	-22.9565***	-5.8050***	-24.9880	-2.3375***
		(0.2723)	(0.3716)	(0.1977)	(0.2210)	(0.6635)	(0.1042)
	lnL	73	244	96	63	41	80
	AIC	-145	-488	-193	-126	-81	-161
	SBC	-145	-488	-193	-125	-81	-161

Note: This Table provides parameter estimates of dynamic SJC copulas with D_2 as the dummy. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

4.3.1.3. Motivation for mixture of dynamic copulas. Note that the economy pairs with linear contagion and those with upper tail contagion are not only different but also separated completely. This implies that the perceived impact of sovereign risk contagion between East Asian economies could be different according to whether it is measured by linear or tail dependence. Therefore, non-mixed copula models are not enough to fully describe this complex dependence structure. Furthermore, the SJC copulas are superior to the Gaussian copula in terms of AIC and SBC for all pairs of economies. These results suggest that simultaneous introduction of the linear dependence and the tail dependences can improve the ability of a model to investigate effects of contagion on dependence structures between the East Asian sovereign CDS markets.

4.4. Estimation results of the mixture of dynamic copulas

4.4.1. Estimation results

Table 9-1 and 9-2 present estimated results of the dynamic GASJC copulas with dummy variables D_1 and D_2, respectively. The results imply usefulness of our mixture approach.

First, they fit better than the dynamic non-mixed copulas in terms of the values of AIC and SBC for all pairs of economies. Second, the dynamic GASJC copulas show consistent results with non-mixed dynamic copulas: the linear contagion ($JP \leftrightarrow KR$) in the dynamic GA copulas and the upper tail contagion ($CN \rightarrow KR$ and $CN \rightarrow HK$) in the dynamic SJC copulas still remain significant in the dynamic GASJC copulas. Third, our model can furthermore identify contagion that is not detected by the non-mixed copulas. In the GA dependence equations of Table 9-1 and 9-2, (CN, JP) has positive and significant D_1 and D_2, which is not the case of the dynamic GA copula. Also, (KR, HK) in Table 9-1 has positive and significant D_1 in the upper tail dependence equation meaning existence of one-way upper tail contagion from *KR* to *HK*, which is not the case of the dynamic SJC copula in Table 8-1. Therefore, we can conclude that our mixture of copulas approach successfully reflects the heterogeneity of sovereign risk contagion by combining linear and tail dependence measures and allowing the individual dependence measures to respond to shocks through their own dynamic processes.

Table 9-1. MLE results of dynamic GASJC copulas with D_1 as the dummy

	Regressor	*(CN, JP)*	*(CN, KR)*	*(CN, HK)*	*(JP, KR)*	*(JP, HK)*	*(KR, HK)*
Copula parameters with D_1 as a regressor							
ρ	*Constant*	-0.2315***	6.2258***	0.3608***	-0.5963***	2.2459***	2.5828***
		(0.0029)	(0.0731)	(0.0097)	(0.0115)	(0.0608)	(0.0325)
	AR(1)	2.5015***	-5.5146***	2.7109***	2.2061***	-2.1974***	-2.4240***
		(0.0076)	(0.0508)	(0.0147)	(0.0238)	(0.0319)	(0.0158)
	MA(10)	0.9839***	0.3579***	0.0189***	0.8717***	1.3053***	-1.0395***
		(0.0119)	(0.0179)	(0.0062)	(0.0176)	(0.1028)	(0.0258)
	D_1	**1.3753*** **	-0.0115	-2.0454***	**1.8503*** **	-5.1198***	-1.9621***
		(0.0723)	(0.0145)	(0.0269)	(0.0496)	(0.0450)	(0.0451)
	Weight	0.2010***	0.4703***	0.2442***	0.0990***	0.0963***	0.2912***
		(0.0125)	(0.0299)	(0.0129)	(0.0050)	(0.0062)	(0.0180)
λ^U	*Constant*	-0.2694***	7.4279***	5.9823***	8.7370***	-0.4385***	4.5594***
		(0.1042)	(0.1239)	(0.0830)	(0.0606)	(0.0884)	(0.0758)
	AR(1)	1.4574***	-2.6917***	-1.9363***	-5.4478***	-2.3979***	2.8500***
		(0.2044)	(0.1055)	(0.0352)	(0.0336)	(0.1912)	(0.0660)
	MA(10)	-1.8590***	-29.9853***	-29.9932***	-29.9965***	0.7644***	-29.9983***
		(0.2303)	(0.8210)	(0.2675)	(0.2352)	(0.2350)	(0.2942)
	D_1	-6.6830***	**1.5583*** **	**4.9611*** **	-13.0880***	-1.0093***	**0.9089*** **
		(0.0423)	(0.0870)	(0.0541)	(0.0423)	(0.0562)	(0.1140)
λ^L	*Constant*	2.4052***	8.6721***	4.2056***	0.8764***	5.5549***	3.8036***
		(0.0721)	(0.1820)	(0.0517)	(0.0452)	(0.1416)	(0.0570)
	AR(1)	-3.6085***	-6.5034***	-3.0991***	-3.0180***	-4.8448***	-4.5676***
		(0.1272)	(0.0491)	(0.0945)	(0.0783)	(0.0481)	(0.0733)
	MA(10)	-13.2509***	-29.9787***	-25.9827***	-3.8538***	-29.9956***	-10.7459***
		(0.3992)	(0.8295)	(0.1912)	(0.1564)	(0.6681)	(0.2322)
	Weight	0.7990***	0.5297***	0.7558***	0.9010***	0.9037***	0.7088***
		(0.0477)	(0.0315)	(0.0473)	(0.0557)	(0.0544)	(0.0431)
	lnL	78	254	100	67	42	84
	AIC	-156	-509	-200	-135	-85	-168
	SBC	-155	-509	-200	-135	-85	-168

Note: This Table provides parameter estimates of dynamic GASJC copulas with D_1 as the dummy. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Table 9-2. MLE results of dynamic GASJC copulas with D2 as the dummy

	Regressor	(*CN, JP*)	(*CN, KR*)	(*CN, HK*)	(*JP, KR*)	(*JP, HK*)	(*KR, HK*)
Copula parameters with D2 as a regressor							
ρ	*Constant*	4.2037***	2.1364***	7.4991***	-0.8891***	0.3199***	0.9435***
		(0.0883)	(0.1137)	(0.0477)	(0.0195)	(0.0437)	(0.0294)
	AR(1)	-2.6189***	0.7384***	-1.8078***	3.3219***	0.0926**	1.3111***
		(0.0638)	(0.0649)	(0.0387)	(0.0307)	(0.0418)	(0.0367)
	MA(10)	6.3427***	-0.3569***	-5.5858***	0.9464***	0.6349***	-0.0872***
		(0.0817)	(0.0711)	(0.0530)	(0.0183)	(0.0545)	(0.0227)
	D_2	**5.2611*** **	-3.0252***	-3.5329***	**6.5393*** **	-2.5954***	-1.5538***
		(0.1641)	(0.0356)	(0.0352)	(0.0649)	(0.0981)	(0.0312)
	Weight	0.0988***	0.4139***	0.1253***	0.0684***	0.0888***	0.4741***
		(0.0066)	(0.0267)	(0.0080)	(0.0049)	(0.0053)	(0.0244)
λ^U	*Constant*	5.2846***	5.9133***	5.3239***	5.1999***	-0.3536***	2.7074***
		(0.0590)	(0.0003)	(0.0292)	(0.0377)	(0.0250)	(0.1231)
	AR(1)	-5.0578***	-2.5728***	-1.6076***	-1.6990***	-1.3809***	5.6964***
		(0.0373)	(0.0001)	(0.0572)	(0.0848)	(0.0416)	(0.0756)
	MA(10)	-18.6757***	-22.8412***	-23.1027***	-22.4970***	0.1814***	-29.9994***
		(0.2213)	(0.0005)	(0.0579)	(0.0858)	(0.0418)	(0.6709)
	D_2	-1.4458***	**5.3406*** **	-17.1858***	-1.0434***	-0.8168***	-8.4946***
		(0.0440)	(0.0002)	(0.0423)	(0.0584)	(0.0429)	(0.0423)
λ^L	*Constant*	1.8014***	8.2824***	4.4490***	0.8303***	4.9787***	1.5634***
		(0.0367)	(0.0004)	(0.0259)	(0.0304)	(0.0409)	(0.0865)
	AR(1)	-2.3332***	-6.7026***	-1.3778***	-3.6813***	-4.8988***	5.7830***
		(0.0451)	(0.0007)	(0.0625)	(0.0516)	(0.0447)	(0.0530)
	MA(10)	-13.2470***	-27.3115***	-26.0719***	-3.9821***	-24.9103***	-29.9986***
		(0.1935)	(0.0006)	(0.0502)	(0.0528)	(0.0433)	(0.7426)
	Weight	0.9012***	0.5861***	0.8747***	0.9316***	0.9112***	0.5259***
		(0.0534)	(0.0351)	(0.0520)	(0.0552)	(0.0571)	(0.0359)
	lnL	77	257	103	67	41	86
	AIC	-154	-514	-205	-135	-82	-172
	SBC	-154	-514	-205	-135	-82	-172

Note: This Table provides parameter estimates of dynamic GASJC copulas with D2 as the dummy. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels respectively.

Notice that no pair of economies has linear and upper tail contagions simultaneously in the dynamic GASJC copula: if contagion exists between a pair of economies, the coefficient estimates of the corresponding dummies in ρ_t and λ_t^U have opposite signs. Furthermore, if a pair of economies have linear (upper tail) contagion not in the non-mixed models but in the mixture model, generally the coefficient estimate of the corresponding dummy in the λ_t^U (ρ_t) of the mixture model is smaller than that of the non-mixed model. Based on these results, we can infer that the linear dependence and the upper tail dependence trade off each other once contagion occurs: (1) shocks increasing the upper tail dependence will decrease the linear dependence and (2) shocks increasing the linear dependence will decrease the upper tail dependence.

Figure 2 summarizes our inferences about the existence and direction of sovereign risk contagion between East Asian economies based on the dynamic GASJC copula model. It shows that an economy with a contagious effect on other economies in terms of one dependence measure can be ineffective in terms of another dependence measure. *JP* plays the most important role in the East Asian sovereign CDS market in terms of linear contagion. In terms of upper tail contagion, however, *CN* and *KR* are crucial. Furthermore, *HK* is the most vulnerable to upper tail contagion among the four economies.

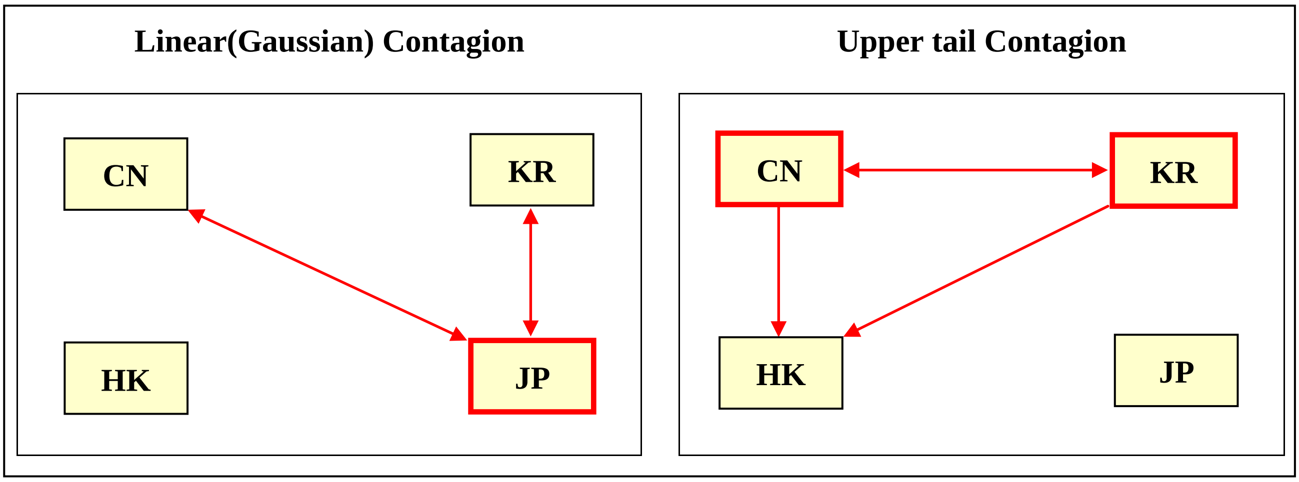

Figure 2. Existence and direction of contagion in the East Asian sovereign CDS market, where contagion is defined as a significant increase in market dependence due to an idiosyncratic shock to one economy.

4.4.2. Goodness of fit test. In Table 10, we present the results of the bivariate hit tests. We divided the support of the copulas into seven regions and tested whether the copula models are well specified in all regions for each economy pair.[22] A p-value less than 0.1 indicates a rejection of the null hypothesis that the model is well specified.

Table 10. Joint hit test results for the copula models

	Model	(*CN*, *JP*)	(*CN*, *KR*)	(*CN*, *HK*)	(*JP*, *KR*)	(*JP*, *HK*)	(*KR*, *HK*)
Static	*GA*	0.0283	0.3519	0.5398	0.9885	0.8972	0.6502
	SJC	0.2002	0.7084	0.7082	0.9979	0.9312	0.6564
	GASJC	0.3199	0.7664	0.8007	0.9975	0.9168	0.7527
Dynamic	$GA(D_1)$	0.0354	0.3628	0.5422	0.9981	0.9138	0.6713
	$SJC(D_1)$	0.1984	0.8908	0.6125	0.9996	0.9578	0.7320
	$GASJC(D_1)$	0.4173	0.8821	0.5551	0.9990	0.9624	0.7870
	$GA(D_2)$	0.0346	0.3415	0.5349	0.9981	0.9149	0.6626
	$SJC(D_2)$	0.1864	0.8964	0.6051	0.9997	0.9547	0.7284
	$GASJC(D_2)$	0.3246	0.8777	0.5158	0.9992	0.9568	0.7487

Note: This Table reports the p-values from joint hit tests. A p-value less than 0.1 indicates a rejection of the null hypothesis that the model is well specified.

GA copulas passed the test at the 10% significance level for all economy pairs except (*CN*, *JP*). SJC and GASJC copulas passed the test at the 10% significance level for all economy pairs. Furthermore, the overall p-values are the largest for GASJC copulas whereas the smallest for GA copulas. These results imply that introducing tail dependences and mixing them with the Gaussian dependence would enhance the explanatory power of a model for dependence structure and contagion.

5. Conclusion

This paper examined sovereign risk contagion between East Asian economies using a mixture of dynamic GA and SJC copulas based on the sovereign CDS spreads of *CN*, *HK*, *JP* and *KR*. Throughout the paper, contagion is defined as a significant increase in markets' dependence due to an economy-specific shock. In order to identify contagion that arose from this type of shock, we

[22] All detailed settings of the test are the same as in Patton's (2006) study.

introduced dummy variables into parameter equations of the dynamic copulas. We filtered the CDS spreads using AR-GARCH-t models controlling for global and economy-specific factors to prevent potential biases of testing for financial contagion reported in by Forbes and Rigobon (2002) and Corsetti et al. (2005). Then we applied mixture of conditional (time-varying) Gaussian and symmetrized Joe-Clayton copulas to the standardized residuals for modeling pair-wise dependence between economies.

The main findings of our study are as follows. First, we found evidence that contagion exists between the East Asian sovereign CDS markets. Second, the perceived impact of contagion could be different according to whether it is measured by linear or tail dependence. Third, our mixture of copulas model successfully reflects this heterogeneity of sovereign risk contagion by combining linear and tail dependence measures and allowing the individual dependence measures to respond to shocks through their own dynamic processes. It showed that the linear dependence and the upper tail dependence trade off each other once contagion occurs. Lastly, Japan plays the most important role in the East Asian sovereign CDS market in terms of linear dependence, whereas *CN* and *KR* are crucial in terms of upper tail dependence.

- References –

Abbara, O., & Zevallos, M. (2014). Assessing stock market dependence and contagion. Quantitative Finance, 14(9), 1627-1641.

Aït-Sahalia, Y., Cacho-Diaz, J., & Laeven, R. J. (2015). Modeling financial contagion using mutually exciting jump processes. Journal of Financial Economics, 117(3), 585-606.

Aloui, R., Aïssa, M. S. B., & Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? Journal of Banking & Finance, 35(1), 130-141.

Caceres, C., & Unsal, D. F. (2013). Sovereign spreads and contagion risks in Asia. Asian Economic Journal, 27(3), 219-243.

Chang, K. L. (2012). The time-varying and asymmetric dependence between crude oil spot and futures markets: Evidence from the mixture copula-based ARJI–GARCH model. Economic Modeling, 29(6), 2298-2309.

Chen, W., Wei, Y., Zhang, B., & Yu, J. (2014). Quantitative measurement of the contagion effect between US and Chinese stock market during the financial crisis. Physica A: Statistical Mechanics and its Applications, 410, 550-560.

Erdem, O., & Varli, Y. (2014). Understanding the sovereign credit ratings of emerging markets. Emerging Markets Review, 20, 42-57.

Fermanian, J. D. (2005). Goodness-of-fit tests for copulas. Journal of Multivariate Analysis, 95(1), 119-152.

Fong, T. P. W., & Wong, A. Y. (2012). Gauging potential sovereign risk contagion in Europe. Economics Letters, 115(3), 496-499.

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. The Journal of Finance, 57(5), 2223-2261.

Gadanecz, B., Miyajima, K., & Shu, C. (2014). Exchange rate risk and local currency sovereign bond yields in emerging markets. BIS Working Paper, No 474.

Genest, C., Kojadinovic, I., Nešlehová, J., & Yan, J. (2011). A goodness-of-fit test for bivariate extreme-value copulas. Bernoulli, 17(1), 253-275.

Giordano, R., Pericoli, M., & Tommasino, P. (2013). Pure or wake-up-call contagion? Another look at the EMU sovereign debt crisis. International Finance, 16(2), 131-160.

Gómez-Puig, M., & Sosvilla-Rivero, S. (2014). Causality and contagion in EMU sovereign debt markets. International Review of Economics & Finance, 33, 12-27.

Gorea, D., & Radev, D. (2014). The euro area sovereign debt crisis: Can contagion spread from the periphery to the core? International Review of Economics & Finance, 30, 78-100.

Hilscher, J., & Nosbusch, Y. (2010). Determinants of sovereign risk: Macroeconomic fundamentals and the pricing of sovereign debt. Review of Finance, 14 (2), 235-262.

Hsieh, C. H., & Huang, S. C. (2012). Time-varying dependency and structural changes in currency markets. Emerging Markets Finance and Trade, 48(2), 94-127.

Hu, L. (2006). Dependence patterns across financial markets: A mixed copula approach. Applied Financial Economics, 16(10), 717-729.

Jawadi, F., Louhichi, W., & Cheffou, A. I. (2015). Testing and modeling jump contagion across international stock markets: A nonparametric intraday approach. Journal of Financial Markets, 26, 64-84.

Joe, H., & Xu, J. J. (1996). The estimation method of inference functions for margins for multivariate models. Dept. of Statistics, University of British Columbia, Technical Report, 166.

Kalbaska, A., & Gątkowski, M. (2012). Eurozone sovereign contagion: Evidence from the CDS market (2005–2010). Journal of Economic Behavior & Organization, 83(3), 657-673.

Kenourgios, D., Samitas, A., & Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. Journal of International Financial Markets, Institutions and Money, 21(1), 92-106.

Li, X., & Zhang, B. (2013). Spillover and cojumps between the US and Chinese stock markets. Emerging Markets Finance and Trade, 49(sup2), 23-42.

Loaiza-Maya, R. A., Gómez-González, J. E., & Melo-Velandia, L. F. (2015). Exchange rate contagion in Latin America. Research in International Business and Finance, 34, 355-367.

Longstaff, F. A., Pan, J., Pedersen, L. H., & Singleton, K. J. (2011). How sovereign is sovereign credit risk? American Economic Journal: Macroeconomics, 3(2), 75-103.

Manner, H., & Candelon, B. (2010). Testing for Asset Market Linkage: A New Approach based on Time-varying Copulas. Pacific Economic Review, 15(3), 364-384.

Metiu, N. (2012). Sovereign risk contagion in the Eurozone. Economics Letters, 117(1), 35-38.

Nelsen, R. B. (2013). An introduction to copulas (Vol. 139). Springer Science & Business Media.

Patton, A. J. (2006). Modeling asymmetric exchange rate dependence. International Economic Review, 47(2), 527-556.

Philippas, D., & Siriopoulos, C. (2013). Putting the “C” into crisis: Contagion, correlations and copulas on EMU bond markets. Journal of International Financial Markets, Institutions and Money, 27, 161-176.

Reboredo, J. C. (2011). How do crude oil prices co-move?: A copula approach. Energy Economics, 33(5), 948-955.

Reboredo, J. C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Economics, 48, 32-45.

Rodriguez, J. C. (2007). Measuring financial contagion: A copula approach. Journal of Empirical Finance, 14(3), 401-423.

Samitas, A., & Tsakalos, I. (2013). How can a small country affect the European economy? The Greek contagion phenomenon. Journal of International Financial Markets, Institutions and Money, 25, 18-32.

SAS. (2011). SAS User's Guide, Version 9.3.

Sklar, M. (1959). Fonctions de répartition à n dimensions et leurs marges. Université Paris 8, 229-231.

Suh, S. (2015). Measuring sovereign risk contagion in the Eurozone. International Review of Economics & Finance, 35, 45-65.

Tsay, R. S. (2010). Analysis of financial time series, 3rd Edition. John Wiley & Sons.

Weiß, G. N. (2012). Analysing contagion and bailout effects with copulae. Journal of Economics and Finance, 36(1), 1-32.

Wen, X., Wei, Y., & Huang, D. (2012). Measuring contagion between energy market and stock market during financial crisis: A copula approach. Energy Economics, 34(5), 1435-1446.

Wong, A. Y., & Fong, T. P. W. (2011). Analysing interconnectivity among economies. Emerging Markets Review, 12(4), 432-442.

Wu, C. C., Chung, H., & Chang, Y. H. (2012). The economic value of co-movement between oil price and exchange rate using copula-based GARCH models. Energy Economics, 34(1), 270-282.

Ye, W., Liu, X., & Miao, B. (2012). Measuring the subprime crisis contagion: Evidence of change point analysis of copula functions. European Journal of Operational Research, 222(1), 96-103.