Modeling Dependence and Contagion between East Asian Sovereign CDS Markets

: A Mixture of Time-varying Copulas Approach

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Abstract

Does sovereign risk contagion exist between East Asian economies? How did the Global Financial Crisis affect dependence structures between the sovereign risks of East Asian Economies? This paper aims to answer these questions 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 December 2004 to September 2015. We filter the CDS spreads using AR-GARCH-t models controlling for global and economy-specific factors and apply mixture of conditional (time-varying) Gaussian and symmetrized Joe-Clayton copulas for modeling dependence.

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

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dependence measures. Third, 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. Lastly, we also confirm that the GFC has structurally increased the linear dependence and the upper tail dependence in the pair of China and Korea and the pair of Japan and Hong Kong.

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

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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 CDS markets? How did the Global Financial Crisis affect dependence structures between the sovereign risks? 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 December 2004 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 during the Global Financial Crisis (GFC) in 2008-2009 and afterword.

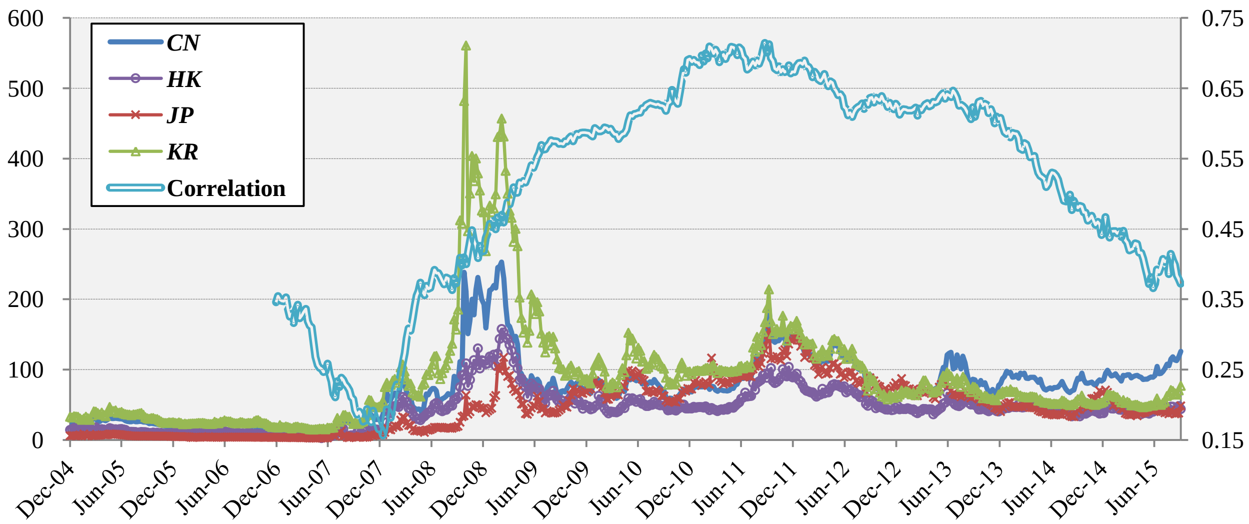

Figure 1. Weekly series of sovereign CDS spreads of China (*CN*), Hong Kong (*HK*), Japan (*JP*) and Korea (*KR*) in basis points (bps, left axis) and average of 2-year rolling Spearman correlation (left axis) between weekly changes of the CDS spreads for the period from December 2004 to September 2015. Correlations for the first 2-years are not plotted since our raw data starts from December 2004.

There are several sources of biases for testing financial contagion. Forbes and Rigobon (2002) report that heteroscedasticity biases tests for contagion based on the conventional correlation coefficients. Also, 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-GARCH-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 are assumed to follow dynamic processes conditional on the available information as in Patton (2006). To account for the linear dependence and the tail dependences together, 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' dependence due to an economy-specific 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 to the extant financial contagion literature. 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 sovereign risk contagion among Asian economies.[2] Most of 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 the upper 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 are a few studies analyzing financial markets' dependence using time-varying mixture copulas.[4] However, they only combined the upper and the lower tail

[1] Our definition of contagion is a slight modification of Forbes and Rigobon (2002) where financial contagion is defined as "a significant increase in cross-market linkage after a shock to one country". Metiu (2012) used a similar definition.

[2] There are studies on sovereign risk spillover or contagion among international markets including Asia, such as López-Espinosa et al. (2014) and Sasha et al. (2016). However, they do not analyze dependence and contagion structure between Asian markets in detail. To the best of our knowledge, Caceres and Unsal (2013) and Wong and Fong (2011) are the only sovereign risk contagion literature focusing on Asian economies.

[3] Afonso, A., Furceri, D., & Gomes, P. (2012), 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 for 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 between Asian currency markets, and Wu et al.

dependence and focus on dependence structure rather than contagion effect between financial markets. In addition, contagion studies using copulas have employed extensions of static copulas[5] or time-varying non-mixed copulas[6]. We combined the linear dependence and the tail dependence in a time-varying manner to explore contagion effect as well as dependence structure between the East Asian sovereign CDS markets. Our suggested model is probably the most general to analyze contagion using copulas.

We have five main findings. First, our analysis shows that there exists contagion between the 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 the linear or the upper tail dependence. In this regard, an economy having contagious effect on other economies in terms of one dependence measure can be ineffective in terms of another dependence measure. Third, our mixture of copulas approach successfully reflects this heterogeneity of sovereign risk contagion across different dependence measures by not only combining the linear dependence and the tail dependences but also allowing each measure to respond to shocks through its own dynamic processes. Our empirical study shows that contagion occurs exclusively either in the linear or the upper tail dependence. Fourth, our results indicate that *JP* is the most important in the East Asian sovereign CDS market in terms of the linear dependence whereas *CN* and *KR* are crucial in terms of the upper tail dependence. Lastly, the linear dependence has structurally increased after the GFC in general, which is related to the cluster of shocks after the GFC. On the other hand, the upper tail dependence has increased for (*CN*,*KR*) and

(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.

[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).

(JP, HK), but it decreased for the other economy pairs after the GFC. The structural change in the upper tail contagion is consistent with our findings about contagion.

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 East Asian sovereign CDS spreads. 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), their joint density of (*X*, *Y*) can be decoupled into marginal densities and their dependence density using a function $C(u,v):[0,1]^2 \to [0,1]$ called a "copula":

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

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

Patton (2006) extended Sklar's theorem in (Eq. 1) to 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 $C(u,v\,|\,\Omega_t)$ 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 dependences, which represent the probability of two random variables having upward or downward extreme co-movements together. From risk measurement and management perspectives, tail dependences play an important role to measure dependence between extreme events around the tails of a distribution. The upper and the lower tail dependence of two random variables *X* and *Y* are defined and obtained from copula functions as

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

, where $\lambda^U = 0$ ($\lambda^L = 0$) implies 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 stylized features of financial asset returns.

Let y_t^i be the change of CDS spread of economy *i* between week *t*-1 and week *t*, i.e. $y_t^i = CDS_t^i - CDS_{t-1}^i$ for *i* = *CN*, *HK*, *JP*, *KR*. For each *i*, we suppose that

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

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

To evaluate goodness-of-fit, we employed the Ljung-Box statistic for serial correlations 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. In our empirical analysis, *CN* and *KR* were fitted to the I-GARCH-M model with the existence of risk premium effect. For *JP* and *HK*, the I-GARCH models were chosen. But the GJR-GARCH model was not selected for any economy. [7]

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. Thus, we included various global and local variables as regressors in the mean equation for the individual filter of CDS spread. The variables were selected based on sovereign risk literature such as 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 by weekly changes of the VIX (%), funding liquidity in the banking sector proxied by weekly changes of the TED

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

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 the East Asian sovereign CDS markets. Among the various copula models, we chose the GA and the SJC copulas since they describe dynamic movements of linear dependence and the tail dependences in both sides, all together. The processes of time-varying dependence parameters are assumed to follow those suggested in Patton (2006) and we include additional dummy variables to test for the existence and the direction of contagion in the processes of dependences. More details of these dummies are presented in Section 2.3.2. Goodness-of-fit for the selected 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 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 in (Eq. 2) and $w_{GA}, w_{SJC} \in [0,1]$ satisfying $w_{GA} + w_{SJC} = 1$. Our mixture copula can reflect both the linear dependence and the 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 $c_{GA}(u,v;\rho) = \partial^2 C_{GA}(u,v;\rho)/\partial u \partial v$ and $c_{SJC}(u,v;\lambda^U,\lambda^L) = \partial^2 C_{SJC}(u,v;\lambda^U,\lambda^L)/\partial u \partial v$.

The upper and the lower tail dependence of the GASJC copula are calculated as

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

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

2.3.2. Dependence parameter specification

We employ time-varying dependence specification as in Patton (2006) with additional dummy variables to test for the existence and direction of sovereign risk contagion.

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

A shock to economy i is defined as a situation of $U_t^i \equiv \Pr[v_t^i \le \tilde{v}_t^i] > 95\%$, 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 economy-specific component of a CDS spread. Several recent studies report 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: 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

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

where $d_t^k = 1_{\{U_t^k > 0.95\}}$ for $i, j, k = CN, HK, JP, KR$. Here, d_t^i indicates shocks to economy i and $d_t^i \times \underset{k \ne i,j}{Max}\{d_t^k\}$ stands for shocks occurring to economy $k \ne i, j$ as well as to economy i contemporaneously. Thus, $D_{1,t}^{(i,j)}$ and $D_{2,t}^{(i,j)}$ denote the times of economy-specific shocks to economies i and j only not occurring to outside economies i and j.

Figure 2 shows a graphical example of these dummy variables. The four rectangles represent times of shocks to *CN*, *HK*, *JP* and *KR*. Assume that we are investigating contagion of (*CN*, *KR*) and consider the two points P_1 in the *CN* rectangle and P_2 in the intersection of the *CN* and the *KR* rectangles. P_1 gives $d_t^{CN}=1$. However, it gives $D_{1,t}^{(CN,KR)}=0$ since it lies in the rectangle for *HK* (that is, $d_t^{HK}=1$) as well. P_2 also produces $D_{1,t}^{(CN,KR)}=0$ since $d_t^{CN}=1$ and $d_t^{KR}=1$, but P_2 belongs to the rectangle for *JP* (that is, $d_t^{JP}=1$). In this way, the regions $A=\{t\,|\,D_{1,t}^{(CN,KR)}=1,\ D_{2,t}^{(CN,KR)}=0\}$ (blue colored), $B=\{t\,|\,D_{1,t}^{(CN,KR)}=0,\ D_{2,t}^{(CN,KR)}=1\}$ (red colored) and $C=\{t\,|\,D_{1,t}^{(CN,KR)}=D_{2,t}^{(CN,KR)}=1\}$ (violet colored) are considered as shocks to test contagion in the pair (*CN*, *KR*).

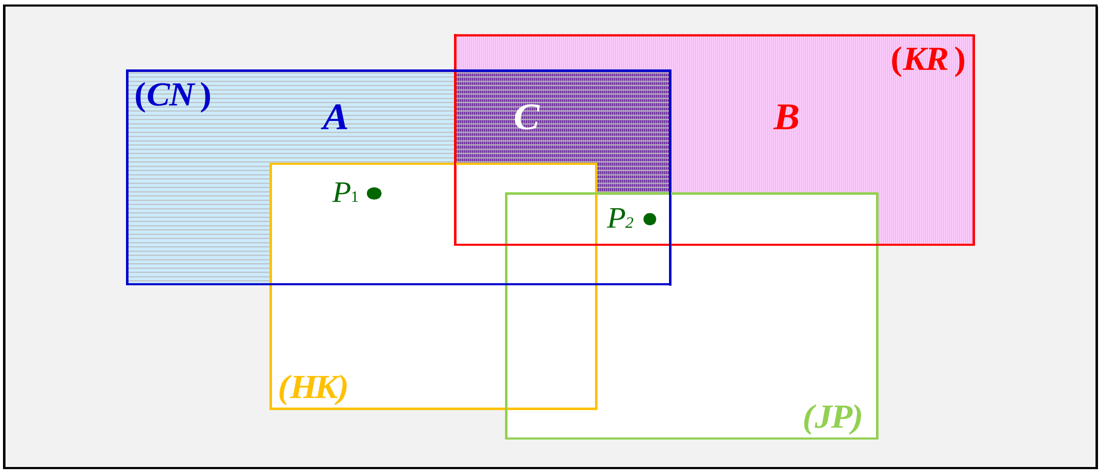

Figure 2. A graphical example of the dummy variables in (Eq. 4). The four rectangles represent times of shocks to *CN*, *HK*, *JP* and *KR*. The regions $A=\{t\,|\,D_{1,t}^{(CN,KR)}=1,\ D_{2,t}^{(CN,KR)}=0\}$ (blue colored), $B=\{t\,|\,D_{1,t}^{(CN,KR)}=0,\ D_{2,t}^{(CN,KR)}=1\}$ (red colored), $C=\{t\,|\,D_{1,t}^{(CN,KR)}=D_{2,t}^{(CN,KR)}=1\}$ (violet colored) are considered as shocks related to contagion of (*CN*, *KR*).

Note that we remove the effects of shocks occurring to outside the pair (i,j) by defining $D_{1,t}^{(i,j)}$ and $D_{2,t}^{(i,j)}$ from d_t^i and d_t^j, respectively. This is because we want to explore the "pure" contagion relationship between economies i and j without any interference from outside, such as possible systematic shocks remaining unfiltered in the conditional mean and volatility equations in the GARCH filters. 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 the lower tail dependence (λ_t^U and λ_t^L) of each pair of economies (i, j) as

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

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 of $\tilde{\Lambda}(x) = \frac{(1-e^{-x})}{(1+e^{-x})}$ and $\Lambda(x) = \frac{1}{(1+e^{-x})}$ are used to keep $-1 < \rho_t < 1$, $0 < \lambda_t^U < 1$ and $0 < \lambda_t^L < 1$, respectively.

It is worth to mention two comments on the dummies for better understanding as follows. First, we ran the regression twice for each pair (i, j) of economies: one with $D_t = D_{1,t}^{(i,j)}$, and 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 economy-specific 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. In addition, we are interested in analyzing the impact of extreme "bad" news related to a sharp "increase" in CDS spreads and the upper tail dependence.

[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.

2.4. Parameter estimation

We applied the canonical maximum likelihood (CML) method for estimation. 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

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

from (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. The log-likelihood function can be 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). As the first step, the margins are estimated by the empirical distributions:

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

In the second step, the copula parameters are obtained conditional on 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 (Longstaff et al., 2007). Our CDS data covers 561 Wednesday to Wednesday weekly differences of the CDS spreads from 29 December 2004 to 15 September 2015. For missing date, we used the previous trading date's data. 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 bps) of the four East Asian economies: *CN* (China), *HK* (Hong Kong), *JP* (Japan), and *KR* (Korea). The data covers from December 29, 2004 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. Volatilities are relatively low for developed economies (*HK* and *JP*) but high for emerging economies (*CN* and *KR*). The skewnesses of *HK* and *JP* are nearly zero whereas those of *CN* and *KR* are substantially different from zero (positive for *CN* but negative for *KR*), respectively. It is natural to expect a nonnegative skewness of CDS spread changes since financial asset prices are more sensitive to bad news than good news. The negative skewness of *KR* is caused by of the minimum value (-264.02 bp)[10] which happened for the period between 29 October 2008 and 05 November 2008[11]. All economies exhibit

[10] Skewness of *KR* without this minimum value became 6.8639 which is positive. Furthermore, when we exclude the minimum value and the maximum value (174.45 bps) together, the result became 3.8304 which is also positive.

[11] For this period, there were economic and political events causing global CDS spreads to decrease. On 29 October 2008, FRB decided to lower the target 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* on 30 October 2008.

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. Moreover, the relatively high kurtosis for *CN* and *KR* may imply strong tail dependence between these two economies which will be tested in Section 4.4.

Our data source for weekly CDS spreads, MSCI's, VIX, U.S. 3-month LIBOR, U.S. 90-day T-bill rate and 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 provided by BIS.[16] Note that we ran our regressions on a weekly basis. To accommodate the data of different frequencies, we transformed monthly or quarterly data into weekly frequency using linear transformation similar to Gorea and Radev (2014).

4. Empirical Results

4.1. Estimation results of marginal distribution

The candidates of AR(m)-GARCH(p,q)-t models in Section 2.1 were evaluated for various combinations of (m, p, q) using maximum likelihood and the most suitable models are selected based on the AIC and SBC. Table 2 summarizes estimates for the conditional mean equation of the final AR(m)-GARCH(p,q)-t models for each economy.

[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

Table 2. Estimates 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*** **	0.013	**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 the 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 conditional mean equation are consistent with the previous literature on determinants of sovereign risk. 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, a result coincides with findings by Longstaff et al. (2011).

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 unfiltered CDS spreads has heteroscedasticity with infinite unconditional variance. Additionally, *CN* and *KR* fit the I-GARCH-M model with a risk premium effect. The results of negative risk premium parameters of *CN* and *KR* are consistent with the skewness values of *CN* and *KR* in Table 1.[17]

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

	Variable	*CN*	*HK*	*JP*	*KR*
Residual equation					
	AR(1)		0.1266***		-0.0739**
			(0.0404)		(0.0337)
	AR(2)	0.1266***	0.0720*		0.1801***
		(0.0400)	(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***	
		(0.0255)	(0.0237)	(0.0203)	
	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	1598	1363	1289	1677
	AIC	-3227	-2763	-2606	-3396
	SBC	-3297	-2841	-2667	-3487

Note: This table provides the estimates of residual and conditional variance equations. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively. *lnL* means a log likelihood value.

Table 4 reports the results of the goodness-of-fit tests for the filtered marginals, i.e. η_t^i's in (Eq. 3). All marginal distribution models passed the Ljung-Box tests at the 10% significance level,

[17] Negative sign of the risk premium parameter in the I-GARCH-M model means that a protection seller on a more volatile reference asset will expect higher profit from a larger decrease in the CDS spread. Also, see the footnote 10.

meaning that there are no serial correlations in the 1st – 4th moments of the standardized residuals. Also, all models passed the LM tests at the 10% significance level, indicating no heteroscedasticity in the standardized residuals. These results imply that the estimated models are well specified enough to describe the weekly changes of the CDS spreads and the standardized filtered residuals satisfy the *i.i.d.* assumptions.

Table 4. Goodness-of-fit test of 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.

**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.

4.2. Estimation results of static copulas

Table 5 reports the parameter estimates for the static copula functions of the GA, the SJC and their mixture. In the GA copula, all pairs of CDS markets have significant and positive static Gaussian correlations. In the static SJC copula, 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.

In Table 5, the static GASJC copula also shows overall positive Gaussian 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. In addition, the mixed model has higher p-values from the Hit tests than the non-mixed model, suggesting better goodness-of-fit. In conclusion, all results in Table 5 support our mixture of copulas approach.

Table 5. Estimates 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
	Hit Test	0.0283	0.3519	0.5398	0.9885	0.8972	0.6502
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
	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)
	lnL	69	242	81	53	37	73
	Hit Test	0.3199	0.7664	0.8007	0.9975	0.9168	0.7527

Note: This table presents parameter estimates of static copulas with standard errors in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively. *lnL* means a log likelihood value and *Hit Test* means a p-value from the Hit test.

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 sets $\{t \mid D_{1,t}^{(i,j)} = 1,\ 1 \le t \le 561\}$ and $\{t \mid D_{2,t}^{(i,j)} = 1,\ 1 \le t \le 561\}$ contain the times of extreme economy-specific shocks to economies i and j for the economy pair (i, j). Table 6 shows the number of the dummies equal to 1 for each pair of economies. Numbers in parentheses in Table 6 indicate sizes of the samples after the GFC.

Table 6. Number of the dummies equal to 1

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

Note: This table reports the number of samples where the values of dummy variables are equal to 1 for each economy pair (i, j). Numbers in parentheses indicate sizes of the samples after September 2008.

It is worth to mention two points about Table 6. First, the number of observations satisfying $D_{1,t}^{(i,j)} = 1$ or $D_{2,t}^{(i,j)} = 1$ is smaller than 28 which is the size of $\{t \mid d_t^k = 1,\ 1 \le t \le 561\}$, 5% of 561 observations, for all economy pairs. Furthermore, Sample sizes of $D_{1,t}^{(i,j)} = D_{2,t}^{(i,j)} = 1$ are also smaller than those of $d_t^i = d_t^j = 1$ for all economy pairs. These are because we removed shocks that occurred outside the pair (i, j) from d_t^i (d_t^j) to define $D_{1,t}^{(i,j)}$ ($D_{2,t}^{(i,j)}$) based on economy-specific shocks. Second, most of the economy-specific shocks appeared after the GFC. For example, total number of samples of $D_{1,t}^{(i,j)} = D_{2,t}^{(i,j)} = 1$ is 19 and 16 out of them lie after the GFC. This cluster of shocks after the GFC is related to the structural increase in the dependence after the GFC which will be tested in Section 4.5.

As mentioned 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 economy-specific shocks. Thus, we are only interested in the cases of dummies with positive coefficients which represent contagion.

4.3.1. Estimation results of the non-mixed dynamic copulas

4.3.1.1. Results of the dynamic GA copula. Tables 7 reports estimated results of the dynamic GA copula with dummy variables D_1 and D_2, respectively. Both dynamic GA copula models exhibit better goodness-of-fit than the static GA copula resulting in overall higher p-values of the Hit test.

Table 7. Estimates of dynamic GA copulas

	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
	Hit Test	0.0354	0.3628	0.5422	0.9981	0.9138	0.6713
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
	Hit Test	0.0346	0.3415	0.5349	0.9981	0.9149	0.6626

Note: This table provides parameter estimates of dynamic GA copulas with D_1. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively. *lnL* means a log likelihood value and *Hit Test* means a p-value from the Hit test.

In Table 7, only (JP, KR) has positive and significant D_1. This implies contagion from *JP* to *KR* meaning 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*. Also, (JP, KR) is the only pair having positive and significant D_2. This indicates that 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. Combining these results, we can infer that there exists a two-way sovereign risk contagion in terms of the linear dependence ("linear contagion") between *JP* and *KR*.

4.3.1.2. Results of dynamic SJC copulas. Tables 8-1 and 8-2 report estimated results of the dynamic SJC copula with dummy variables D_1 and D_2, respectively. Similar to the case of the GA copula, the dynamic model outperforms the static model in terms of goodness-of-fit in general.

Table 8-1. Estimates of dynamic SJC copulas with D_1

	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
	Hit Test	0.1984	0.8908	0.6125	0.9996	0.9578	0.7320

Note: This table provides parameter estimates of dynamic SJC copulas with *D*. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively. *lnL* means a log likelihood value and *Hit Test* means a p-value from the Hit test.

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 ("upper tail contagion"). For (CN, KR) as an example, the CDS market's expectation on the likelihood of the default of *KR* increases by $\Lambda(1.0123)$, on average, if a shock hits *CN*.[18] In

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

Table 8-2, however, no dummy has positive significance. All parameter estimates of D_2's are negative except one for (CN, KR), which is positive but insignificant.

Table 8-2. Estimates of dynamic SJC copulas with D_2

	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
	Hit Test	0.1864	0.8964	0.6051	0.9997	0.9547	0.7284

Note: This table provides parameter estimates of dynamic SJC copulas with D_2. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively. *lnL* means a log likelihood value and *Hit Test* means a p-value from the Hit test.

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 East Asian economies have sovereign risk contagion and its impact could be different according to whether it is measured by the linear or the upper tail dependence. Therefore, non-mixed copula models are not enough to fully describe this complex dependence structure. These results motivates simultaneous consideration of the linear dependence and the tail dependences to improve the ability of a model for investigating contagion effects 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

Tables 9-1 and 9-2 present estimated results of the dynamic GASJC copulas with dummy variables D_1 and D_2, respectively.

Table 9-1. Estimates of dynamic GASJC copulas with D_1

	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)
	lnL	78	254	100	67	42	84
	Hit Test	0.4173	0.8821	0.5551	0.9990	0.9624	0.7870

Note: This table provides parameter estimates of dynamic GASJC copulas with D_1. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively. *lnL* means a log likelihood value and *Hit Test* means a p-value from the Hit test.

Table 9-2. Estimates of dynamic GASJC copulas with D_2

	Regressor	(*CN*, *JP*)	(*CN*, *KR*)	(*CN*, *HK*)	(*JP*, *KR*)	(*JP*, *HK*)	(*KR*, *HK*)
Copula parameters with D_2 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)
	lnL	77	257	103	67	41	86
	Hit Test	0.3246	0.8777	0.5158	0.9992	0.9568	0.7487

Note: This table provides parameter estimates of dynamic GASJC copulas with D_2. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, and 10% significance levels respectively. *lnL* means a log likelihood value and *Hit Test* means a p-value from the Hit test.

The results in Tables 9-1 and 9-2 support usefulness of our mixture approach. The GASJC copula shows consistent results with non-mixed copulas: (1) the two-way linear contagion in (JP, KR) and (2) the one-way upper tail contagion in (CN, KR) and (CN, HK). In addition, our dynamic GASJC copulas identify further contagions that are not detected by the non-mixed copulas:

(1) the two-way linear contagion in (CN, JP) and (2) the one-way upper tail contagion from *KR* to *HK*. The pair (CN, JP) in Tables 9-1 and 9-2 has positive and significant D_1 and D_2 in ρ_t, which is negative in Table 7 for the dynamic GA copula. Also, (KR, HK) in Table 9-1 has positive and significant D_1 in λ_t^U, which is negative in Table 8-1 for the dynamic SJC copula. Therefore, these results confirm that our mixture of dynamic copulas approach reflects the complexity of sovereign risk contagion more comprehensively by incorporating the linear and the tail dependence measures together.

Notice that no pair of economies has linear and upper tail contagion simultaneously: if contagion exists, 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 contagion between two economies has only one type of contagion of either linear or upper tail dependence. Thus, shocks increasing the upper tail dependence will decrease the linear dependence and shocks increasing the linear dependence will decrease the upper tail dependence.

Figure 3 summarizes our inferences about the significant direction of sovereign risk contagion between East Asian economies based on Tables 9-1 and 9-2 for the dynamic GASJC copula model. It shows that a significant contagious effect between two economies in terms of one dependence measure become ineffective in terms of another dependence measure. For example, *CN* and *KR* have a significant two-way upper tail contagion but no linear contagion.

In Figure 3, *JP* plays the most important role in the East Asian sovereign CDS market in terms of linear contagion, but *CN* and *KR* are crucial in terms of upper tail contagion when economy-specific shocks are presented. The strongest upper tail contagion can be inferred by the fact that *CN* and *KR* have the highest kurtosis in Table 1 and share the most tail events in Table 6. Furthermore, *HK* is the most vulnerable but *JP* is the most robust to upper tail contagion among the four economies.

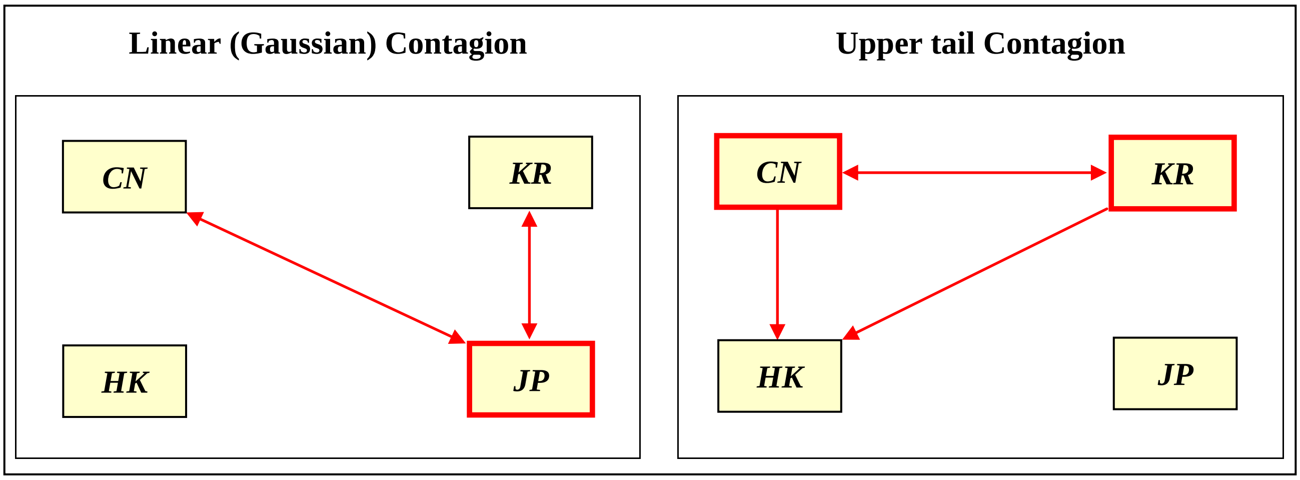

Figure 3. Existence and direction of contagion between the East Asian sovereign CDS market, where contagion is defined as a significant increase in market dependence due to an economy-specific shock to one economy.

Why is *JP* related to the linear contagion only and robust to tail events of other economies? First, the size of shocks to *JP* is not large enough to spillover to other economies as shown in skewness and kurtosis of Table 1. Second, *JP* has the least trade linkage to other economies. Table 10 exhibits ratios of foreign trade to GDP for the analyzed economies. As shown in Table 10, *JP* has the lowest Total Trade to GDP and Net Export to GDP ratios among the economies, meaning low economic linkage with other economies. Thus, shocks to *JP* could be less transmitted to other economies and thus, *JP*'s tail events may cause not upper tail contagion but at most linear contagion. Inversely, shocks to other economies such as *CN* and *KR* are also less transmitted to *JP* due to the same reason. Third, this is also related to the fact that *JP* is a developed markets regarded as a safe haven by global investors, resulting in a low vulnerability to outer shocks. Thus, *JP* is the most robust against tail events from other economies.

The importance of *CN* and *KR* in the upper tail contagion can be interpreted in a similar way. First, as shown in high kurtosis of Table 1 the size of shocks to *CN* and *KR* are fairly large which is feature of emerging markets. In fact, *CN* and *KR* are classified as emerging markets by global investors. Second, as shown in Table 10, *CN* and *KR* have large economic scales and strong trade linkages to other economies. Thus, their tail events can be easily transmitted and cause upper-tail contagion to each other and other economies.

Table 10. Economic scale and openness of East Asian economies

Economic Characteristic	***CN***	***HK***	***JP***	***KR***	***World***
GDP (in $tri)	6,062	237	5,214	1,117	64,970
Export / GDP	29.08	198.93	15.53	47.63	29.68
Import / GDP	24.17	192.56	15.49	44.96	28.93
Total Trade / GDP	53.25	391.49	31.02	92.59	58.61
Net Export / GDP	4.91	6.38	0.04	2.67	0.74

Note: This table exhibits GDP's and ratios of foreign trade to GDP for analyzed East Asian economies. Larger GDP means larger economic scale and higher ratio means higher economic openness. *World* in the last column represents global average. All values are calculated using statistics from World Bank and averaged from 2005 to 2014.

Lastly, *HK* does not cause upper tail contagion but receives impacts of tail events of other economies. This vulnerability of *HK* basically seems to be related with its high economic openness and the small economic scale. Especially, the upper tail contagion from *CN* to *HK* is a result of the heavy economic dependence of *HK* on *CN*. Thus, *HK* is vulnerable to *CN*-specific shock. On the other hand, the upper tail contagion from *KR* to *HK* seems to be related with not only *KR*-specific shocks but also the high systemic risk during the GFC period. Actually, shocks related to the tail contagion from *KR* to *HK* satisfying $D_{1,t}^{(HK,KR)} = D_{2,t}^{(HK,KR)} = 1$ clustered between March 2009 and August 2009.[19] For this period, investors were still worrying about the ability of repayment of *KR* although the peak of the GFC crisis already passed and thus, the upper tail contagion from *KR* to *HK* can be interpreted as investors in the *HK* sovereign CDS market were sensitive to *KR* because *HK* was a representative international financial center in Asia having various financial linkage with other economies.[20]

The vulnerability of *HK* to the upper tail dependence can also be understood with respect to spillover from lower rated economies to higher rated economies. Afonso et, al (2012) showed

[19] The 1st week of March, the 2nd week of June, and the 2nd week of August in 2009.

[20] Complex financial products such as derivatives played an important role in amplifying and propagating the systemic risk for the GFC period.

spillovers in the government bond markets from lower rated countries to higher rated countries in the case of negative announcements on credit ratings, especially among EMU countries. In this regard, tail events on the *CN* and *KR*, lower rated economies, could spill over to *HK*, a higher rated economy. Of course, there are limitations in this aspect because Afonso et, al (2012)'s finding is obtained from the sovereign bond yields of the EU countries, whereas we are analyzing the sovereign CDS spreads of the Asian economies.

4.4.2. Goodness-of-fit test

In Table 11, we present the results of the bivariate hit tests for all estimated copulas. 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.[21] A p-value less than 0.05 indicates a rejection of the null hypothesis that the model is well specified.

Table 11. 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 the joint Hit tests. A p-value less than 0.05 rejects the null hypothesis that the model is well specified.

Regardless of static or dynamic in Table 11, none of GA copulas passed the test at the 5% significance level for the pair (*CN*, *JP*), but SJC and GASJC copulas passed the test for all economy pairs. This implies the strong tail contagion existence between four Asian economies. Furthermore,

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

the highest p-values for GASJC copulas across all economy pairs imply that the mixture approach combining the tail and the Gaussian dependence is more appropriate for studying dependence structure and contagion.

4.5. Effect of the GFC on dependence structure

Our sample period covers the GFC and EDC which are regarded as the two most important events in the financial markets in the past decade. Remolona et al. (2015) report the GFC has structurally changed the sovereign credit risks and their relationships. In this regard, this section explores how the dependence changed after the GFC.

In order to test whether the dependences have increased or decreased after the GFC, we define a new dummy variable D_t^{GFC} whose value is equal to 1 for the period from October 2008[22] and substitute D_t in (Eq. 6) to D_t^{GFC} as following:

$$
\begin{aligned}
\rho_t &= \tilde{\Lambda}\left(\alpha_0 + \alpha_1 \rho_{t-1} + \alpha_2 \frac{1}{10}\sum_{s=1}^{10} \Phi^{-1}(u_{t-s})\Phi^{-1}(v_{t-s}) + \alpha_3 D_t^{GFC}\right) \\
\lambda_t^U &= \Lambda\left(\alpha_0^U + \alpha_1^U \lambda_{t-1}^U + \alpha_2^U \frac{1}{10}\sum_{s=1}^{10} |u_{t-s} - v_{t-s}| + \alpha_3^U D_t^{GFC}\right) \qquad \text{(Eq. 7)} \\
\lambda_t^L &= \Lambda\left(\alpha_0^L + \alpha_1^L \lambda_{t-1}^L + \alpha_2^L \frac{1}{10}\sum_{s=1}^{10} |u_{t-s} - v_{t-s}|\right)
\end{aligned}
$$

Positive significance would imply structural increase in dependence after the GFC whereas negative significance would imply structural decrease in dependence.

Table 12 reports estimation results for testing structural breaks in time-varying dependences. It gives consistent results with the inferences about contagion based on GASJC copula in a sense that all the economy pairs with two-way contagion have structural increase in the corresponding dependence.

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[22] Lehman Brothers collapsed on Sep 2008.

Table 12. Estimates of dynamic GASJC copulas with D^{GFC}

	Regressor	(*CN*, *JP*)	(*CN*, *KR*)	(*CN*, *HK*)	(*JP*, *KR*)	(*JP*, *HK*)	(*KR*, *HK*)
ρ	*Constant*	-0.2800***	7.8918***	2.1894***	-5.7725***	-3.6861***	-0.1660***
		(0.0078)	(0.0404)	(0.0874)	(0.0545)	(0.0556)	(0.0025)
	AR(1)	2.2833***	-6.8915***	-2.0916***	-2.6442***	-2.3028***	2.5259***
		(0.0133)	(0.0370)	(0.0095)	(0.0403)	(0.0107)	(0.0040)
	MA(10)	0.7864***	0.6876***	-1.7393***	2.7419***	3.2018***	0.0852***
		(0.0149)	(0.0114)	(0.0632)	(0.0296)	(0.0242)	(0.0024)
	D^{GFC}	**0.6283*** **	**0.0667*** **	**0.1593** **	**7.9891*** **	**4.4125*** **	-0.0171***
		(0.0172)	(0.0055)	(0.0639)	(0.1052)	(0.0699)	(0.0016)
	Weight	0.2185***	0.5565***	0.3555***	0.1086***	0.0938***	0.2704***
		(0.0139)	(0.0342)	(0.0185)	(0.0064)	(0.0060)	(0.0167)
λ^U	*Constant*	6.7616***	1.3182***	8.3274***	5.1128***	0.0798***	5.4497***
		(0.0786)	(0.1321)	(0.2038)	(0.0385)	(0.0306)	(0.0434)
	AR(1)	-6.0993***	0.8141***	0.6139***	-1.1075***	-6.5597***	1.4178***
		(0.0215)	(0.2042)	(0.0834)	(0.0634)	(0.0429)	(0.0659)
	MA(10)	-18.7392***	-12.3805***	-29.9962***	-22.2352***	1.0853***	-29.9845***
		(0.2781)	(0.4968)	(0.5798)	(0.1129)	(0.0656)	(0.0847)
	D^{GFC}	-2.4590***	**1.0894*** **	-1.2852***	-0.5307***	**0.2456*** **	-0.3501***
		(0.0559)	(0.0499)	(0.0582)	(0.0368)	(0.0097)	(0.0349)
λ^L	*Constant*	1.4051***	6.9894***	2.5877***	0.4927***	4.4175***	0.4861***
		(0.0988)	(0.0745)	(0.1041)	(0.0322)	(0.0851)	(0.0408)
	AR(1)	-2.9495***	-6.3254***	6.2758***	-3.8824***	-4.8043***	-0.7477***
		(0.2332)	(0.0354)	(0.0633)	(0.0634)	(0.0641)	(0.0815)
	MA(10)	-9.4425***	-29.9998***	-29.9942***	-2.5729***	-22.8452***	-4.0534***
		(0.4211)	(0.4859)	(0.7258)	(0.0620)	(0.2457)	(0.2240)
	lnL	77	253	100	67	41	83
	Hit Test	0.4086	0.8969	0.7975	0.9993	0.9396	0.7664

Note: This table provides parameter estimates of dynamic GASJC copulas with D^{GFC} as the dummy. Values in parentheses are standard errors. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively. *lnL* means a log likelihood value and *Hit Test* means a p-value from the Hit test.

We mention two inferences from these results. First, Gaussian dependence generally increased after the GFC including economy pairs without two-way contagion. This means overall dependence of sovereign risk between East Asian economies perceived in their CDS markets structurally increased after the GFC, regardless of their contagion in linear dependence. This result is consistent with Table 6, where most of economy-specific shocks are located in the period after the GFC.

Second, the upper-tail dependence structurally increased after the GFC for the cases of (*CN*, *KR*) and (*JP*, *HK*) only. Global investors usually classify *JP* and *HK* as advanced markets whereas *CN* and *KR* are regarded as emerging markets. Thus we can summarize this result that the upper tail dependences between economies of similar economic development status structurally increased after the GFC whereas the upper tail dependences between economies of different economic development status structurally decreased among the East Asian sovereign CDS markets. The case of (*CN*, *KR*) is also related to their two-way tail contagion. Note that other economy pairs with one-way contagion such as *CN*→*HK* and *KR*→*HK* do not show structural increases in their upper-tail dependences. This implies that impact of one-way upper tail contagion is temporary whereas that of two-way upper tail contagion lasts for a longer period of time.

5. Conclusion

This paper examined sovereign risk contagion and the impact of the GFC on dependence 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 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 the linear or the tail dependence. That is, an economy with a contagious effect in terms of one dependence measure can be ineffective in terms of another dependence measure. Third, our mixture of copulas model successfully reflects this heterogeneity of sovereign risk contagion across different dependence measures by combining the linear and the tail dependences together and allowing the individual dependence measures to respond to shocks through their own dynamic processes. It showed that the linear and the upper tail dependence trade off each other once contagion occurs. Fourth, *JP* plays the most important role in the East Asian sovereign CDS market in terms of the linear dependence, whereas *CN* and *KR* are crucial in terms of the upper tail dependence. Lastly, the linear dependence has structurally increased after the GFC in general, which is related to the concentration of shocks after the GFC. On the other hand, the upper tail dependence has increased for (CN, KR) and (JP, HK), but it decreased for the other economy pairs after the GFC. The structural change in the upper tail contagion is consistent with our findings about contagion.

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