Interconnectedness and Contagion Effects in Asian Sovereign CDS Markets

Daehyoung Cho[a]

Kyongwook Choi[b]

Keunsuk Chung[c]

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[a] National Assembly Research Service, 1 Uisadang-daero, Yeongdeungpo-gu, Seoul, 150-703, Korea. Tel.: +82-2-788-4585, fax: +82-2-788-4589, E-mail: dhcho@assembly.go.kr

[b] Department of Economics, University of Seoul, Jeonnong-dong, Dongdaemun-gu, Seoul 130-743, Korea. Tel.: +82-2-6490-2064, fax: +82-2-6490-2054, E-mail: kwchoi@uos.ac.kr

[c] School of Business Administration, Ulsan National Institute of Science and Technology, 50 UNIST-gil, Ulju-gun, Ulsan, 689-798, Korea , E-mail: chungk@unist.ac.kr

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Abstract

We investigate interconnectedness and the contagion effect of default risk in Asian sovereign credit default swap (CDS) markets since the global financial crisis. Using dynamic conditional correlation analysis, we find that there are significant co-movements in Asian sovereign CDS markets; that such co-movements tend to be larger between developing countries than between developed and developing countries; and that in the co-movements intra-regional nature is stronger than inter-regional nature. With the Spillover Index model, we measure contagion probabilities of sovereign default risk in CDS markets of seven Asian countries and find evidence of contagion effects among six of them; Japan is the exception. In addition, we find that these six countries are affected more by cross-market spillovers than by their own-market spillovers. Furthermore, a rolling-sample analysis reveals that contagion in the Asian sovereign CDS markets expands during episodes of extreme economic and financial distress, such as the Lehman Brothers bankruptcy, the European financial crisis, and the US-credit downgrade.

1. Introduction

Credit default swap (CDS) has been one of the fastest growing derivatives in global financial markets for the last decade. A sovereign CDS provides insurance by securing principal of the bond. For that reason, the sovereign CDS spread[1] proxies the risk of the country's financial market as well as its economic situation. From the protection seller's perspective, the CDS spread represents the expected loss from the swap contract. Therefore, a rise in the spread of sovereign CDS indicates a higher probability of expected loss or credit events; the CDS spread can be a useful indicator of a country's credit risk. A number of earlier studies have

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[1] A protection buyer pays a protection seller the risk premium or spread of CDS, with the premium or spread thus becoming the price of CDS. We shall employ the term "spread" in this paper.

focused on this aspect. For instance, Hull, Predescu and White (2004) report that changes in the CDS spread are useful in forecasting credit downgrade. Furthermore, it has been argued that CDS markets hold a dominant position over bond markets when it comes to price discovery function: See Blanco *et al*. (2005), Zhu (2006) and Ammer and Cai (2007).

In contrast, the negative aspects of sovereign CDS have been criticized because speculative transactions may generate sudden upward swings in the CDS spread of a particular country. In addition, it has been noted that naked CDS investors—who purchase CDSs only for speculative purposes without possessing the bond—may manipulate the market and cause excessive price increases. The EU has regarded them as one of the factors that provoked the European financial crisis and eventually, at the end of 2012, enforced a regulation to prohibit sovereign CDS trading by naked CDS investors.

Considering the economic fundamentals in some emerging economies in East and Southeast Asia, the sovereign CDS spreads in the region fluctuated significantly on the day following the Lehman Brothers bankruptcy: Korea (14.1bp), Philippines (14.7bp), Indonesia (15.2bp) and Malaysia (13.7bp); and on the day following the US credit downgrade: Korea (20.95bp), Philippines (29.99bp), Indonesia (27.09bp) and Malaysia (17.68bp). Dynamic and fast growing Asian emerging economies are susceptible to global variables with a larger volatility. Hence, we cannot rule out the possibility of contagion effects with which a sharp rise in the CDS spread in one nation may be transmitted to other countries, generating higher sovereign default risk in the entire region.

Previous literature on the CDS spread mainly analyzes the determinants of the CDS spread. For instance, Duffie (1999), Elton *et al*. (2001), Huang and Huang (2003) and Longstaff *et al*. (2005) analyze the relationship between the CDS spread and bonds. Alexander and Kaeck (2008) and Zang *et al*. (2009) find that the stock market risk is a determinant of the changes in the CDS spread.[2] In terms of systemic risk, Lown and Morgan (2006) analyze the impact of credit cycles on the business cycles. However, Gorton and He (2008) argue that credit cycles have their own dynamics separate from business cycles. Despite the plethora of studies on the determinants of

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[2] Alexander and Kaeck (2008), using a Markov regime-switching model, discover that the CDS spread is susceptible to stock market volatility during unstable periods, whereas it is more sensitive to the interest rate during stable periods. Zang *et al*. (2009) estimate the volatility and jump risk of individual stock prices to analyze the connectivity among these variables and the CDS spread, while Pires *et al*. (2009) find that the CDS spread could be described by the implied volatility of individual stock option, and analyze the impact of default risk and liquidity on the difference between the CDS spread and the corporate bond spread. There are ongoing efforts to find various factors of the CDS spread, including Fonseca and Gottschalk (2013).

the CDS spread—and as a part of such attempts, investigation on the relationship between the CDS spread and other financial markets such as the stock market or foreign exchange market—research on the interconnectedness among sovereign CDS spreads from different countries is rare. The only exception is the work by Gündüz and Kaya (2013), which discovers the co-movement of CDS spreads in ten Eurozone countries by using the Dynamic Conditional Correlation (DCC) model suggested by Engle (2002).

The purpose of this paper is to investigate this rarely recognized phenomenon—the interconnectedness of sovereign CDS spreads and the contagion of default risk. To do that, we analyze the co-movements and spillovers in seven Asian sovereign CDS markets after the 2007 global financial crisis. We employ the *corrected* Dynamic Conditional Correlation (cDCC) model by Aielli (2013), an improved version the DCC model, and identify the correlation among the CDS spreads in our sample countries. The reason to use the cDCC model is, as Ang and Bekaert (2002) note, its superiority in identifying correlation among financial time series with time-varying features. Then, using the Spillover Index model by Diebold and Yilmaz (2012), we analyze the impact of a change in the CDS spread and volatility of one nation on the other nations along with the contagion effect in the entire Asian sovereign CDS market. After that, we examine time-varying features of the contagion effect in Asian sovereign CDS markets after the global financial crisis using rolling sample analysis.

The remainder of the paper is organized as follows. We review the trends of Asian sovereign CDS markets in Section 2, and introduce our research methodology in Section 3. Section 4 presents the data and estimation results, and reviews their significance. Section 5 summarizes the implications of our results and concludes.

2. Asian Sovereign CDS Market Trends

The CDS deals with credit risks of enterprises, financial institutions and sovereign nations. In such transactions, a protection buyer pays the spread until the underlying asset's maturity as a cost of risk, while a protection seller pays a predetermined amount of loss in case of a credit event before maturity.[3] Thus, the CDS spread is the price for the credit risk of the underlying assets, which rises as either the probability of credit event or the expected loss

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[3] According to the International Swaps and Derivatives Association (ISDA), credit events are divided into 6 categories: Bankruptcy, Failure to Pay, Obligation Acceleration, Obligation Default, Repudiation/Moratorium, and Restructuring.

increases.

===[Figure 1 about here]====

Trade of CDS underlying the sovereign's default risk is very active, especially when the sovereign government's issuance of foreign-currency denominated bonds increases. According to the data from the US Depository Trust and Clearing Corporation, as of May 3, 2013, the total balance of sovereign CDS transactions is USD 28.6 trillion. Among individual countries, Italy (USD 424.08 billion) has the highest volume, followed by Spain (USD 218.99 billion) and France (USD 179.68 billion). Korea is ranked ninth with USD 86.9 billion, and Japan is ranked tenth with USD 83.26 billion.[4]

==[Figure 2 about here]===

Figure 3 shows movements in the spreads of the seven most highly traded sovereign CDS, which depict significant similarities in changing patterns. Before 2007, the spreads were low with very small variations except for Indonesia and the Philippines. This pattern changes at the onset of the 2007 global financial crisis. The spreads began to rise with increasing volatilities after the second half of 2007. In particular, the bankruptcy of Lehman Brothers in September 2008 contributed to the Asian sovereign CDS spreads' record high increases, with the soaring rate of 1,256.7 basis points in Indonesia closely followed by the Philippines (870 bp) and Korea (700 bp). Such wide fluctuations continued for a while with concerns about an impending European financial crisis, and eventually tapered down until the US credit downgrade brought about the next volatility increases in August 2011.

===[Figure 3 about here]===

The general consensus about the timeline of the 2007 global financial crisis is that it began when BNP Paribas prohibited the repurchase of mortgage funds on August 9, 2007[5] and that it

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[4] Other Asian countries' balances are as follows: China (USD 74 billion; 12th), the Philippines (USD 45.88 billion; 19th), Indonesia (USD 40.09 billion, 23rd), Malaysia (USD 19.72 billion, 32nd) and Thailand (USD 12.86 billion, 38th).

[5] The Federal Reserve Board (FRB) and European Central Bank (ECB) released USD 130 billion and USD 84 billion, respectively, on August 9, 2007 in order to relieve the credit crunch facing financial institutions.

ended at the end of December 2009 when the recession ended according to the NBER business cycle. Therefore, we divide our sample period into three phases: pre-crisis (January 3, 2005-August 8, 2007), crisis (August 9, 2007-December 31, 2009) and post-crisis (January 1, 2010-May 31, 2013). Figure 4 exhibits correlations of the seven Asian sovereign CDS spreads during these phases. The correlations among the seven sovereign CDS spreads appear relatively low in the first phase (below 0.3), whereas most countries' spreads became significantly highly correlated in the second phase (mostly above 0.8 except for Japan). This tendency continues through the third phase when the global financial crisis is over.

These findings naturally motivate our investigation to identify the correlation among Asian sovereign CDS spreads and to analyze the contagion effect of the default risk in Asian sovereign CDS markets.

===[Figure 4 about here]===

3. Methodology

3.1. Dynamic Conditional Correlation (DCC) Results

To find the time-varying relationships among the seven Asian CDS markets, we estimate a corrected Dynamic Conditional Correlation (cDCC) multivariate GARCH model. Bollerslev (1990) proposes multivariate GARCH models for the case of constant conditional correlation over time. However, assuming a constant conditional correlation (CCC) is too restrictive for practical applications of empirical research. To tackle this problem, Engle (2002) develops the Dynamic Conditional Correlation (DCC) model that incorporates the time-dependent conditional correlation.[6] The DCC approach has a number of important advantages over the earlier versions of multivariate GARCH. It is parsimonious (compared to the multivariate GARCH models), theoretically sound and computationally flexible.

To understand the structure of the DCC model, first assume that there are m-dimensional, conditionally multivariate normal random vectors X_t with a covariance matrix H_t.

$$X_t \mid I_{t-1} \sim N(0, H_t), \tag{1}$$

$$H_t = D_t R_t D_t, \tag{2}$$

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[6] Tse and Tsui (2002) present a similar line of research as Engle (2002).

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where I_{t-1} is all the available information up to time $t-1$, R_t is a time-varying correlation matrix, D_t is an $N \times N$ diagonal matrix with the square root from the estimated univariate GARCH variances.

$$R_t = \left(diag\left(Q_t\right) \right)^{-1/2} Q_t \left(diag\left(Q_t\right) \right)^{-1/2}, \tag{3}$$

$$Q_t = \left(1-\alpha-\beta\right)S + \alpha u_{t-1} u_{t-1}^{'} + \beta Q_{t-1}, \tag{4}$$

where $S \equiv \left[s_{ij} \right]$ is positive definite, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta\ (< 1)$ measures the persistence of the correlation process. R_t and Q_t in the above equations are estimated by a multi-step procedure and will provide time-varying correlations.

Aielli (2013) notes that the process Q_t is, despite its appearance in equation (4), not a linear multivariate GARCH process because the conditional covariance matrix of u_t is R_t in equation (3), not Q_t. Furthermore, standard DCC models consider the location parameter S as the second moment of u_t and replace it with the sample second moment. However, Aielli (2003) shows that, treating Q_t as a linear MGARCH, $S = E[u_t u_t']$ does not hold in general.[7] To avoid these issues, he introduces the cDCC model. In its form, it is very similar to the original DCC model as shown in equation (5) below

$$Q_t = \left(1-\alpha-\beta\right)S + \alpha \left\{ Q_{t-1}^{*1/2} u_{t-1} u_{t-1}^{'} Q_{t-1}^{*1/2} \right\} + \beta Q_{t-1}, \tag{5}$$

where $Q_t^* \equiv diag\left(q_{11,t},\ldots,q_{NN,t}\right)$. He also provides an explicit representation of time-varying correlations, in which the relevant innovations and past correlations are combined together

$$\frac{\omega_{ij,t-1} + \alpha u_{i,t-1} u_{j,t-1} + \beta \rho_{ij,t-1}}{\sqrt{\left\{\omega_{ii,t-1} + \alpha u_{i,t-1}^2 + \beta \rho_{ii,t-1}\right\}} \sqrt{\left\{\omega_{jj,t-1} + \alpha u_{j,t-1}^2 + \beta \rho_{jj,t-1}\right\}}}, \tag{6}$$

where $\omega_{ij,t} \equiv \left(1-\alpha-\beta\right) s_{ij} / \sqrt{q_{ii,t} q_{jj,t}}$.

3.2. Spillover Index Model

To measure the spillover effect among the changes in the CDS spreads, we employ Yilmaz

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[7] He suggests that the only exception would be when the conditional correlations are constant ($\alpha = \beta = 0$).

and Diebold's spillover index model (2009), which is based on the variance decomposition via the *N*-variable Vector Autoregressive (VAR) model. Assume an *N*-variable first order VAR as follows:

$$X_t = \Phi X_{t-1} + \varepsilon_t, \tag{6}$$

where $X_t = (x_{1t}, K, x_{nt})$ and Φ is an $N \times N$ parameter matrix. Assuming that a moving average representation of the VAR exists, rewrite the above equation

$$X_t = \Psi(L)\varepsilon_t, \tag{7}$$

where $\Psi(L) = (1 - \Phi L)^{-1}$. Cholesky factorization makes the model easier to forecast as

$$X_t = A(L)u_t, \tag{8}$$

where $A(L) = \Psi(L)P_t^{-1}$, $u_t = P_t \epsilon_t$, $E(u_t u_t') = I$, and P_t^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix. Considering the one-step ahead forecast using equation (6), we obtain $X_{t+1,t} = \Phi X_t$. The one-step ahead forecast error and the covariance matrix are easily obtained:

$$e_{t+1,t} = X_{t+1} - X_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & \cdots & a_{0,1n} \\ \vdots & \ddots & \vdots \\ a_{0,n1} & \cdots & a_{0,nn} \end{bmatrix} \begin{bmatrix} u_{1t} \\ \vdots \\ u_{nt} \end{bmatrix}, \tag{9}$$

$$E\left(e_{t+1}, e_{t+1,t}^{'}\right) = A_0 A_0^{'} \tag{10}$$

The above results are basically the same as in the variance decomposition in the standard VAR literature. However, Yilmaz and Diebold (2009) further introduce "own-variance shares" and "cross-variance shares (or spillovers)." The former is defined as a fraction of the *H*-step ahead error variance in forecasting x_i, due to shocks to x_i $(i = 1, 2, K, n)$ while the latter is defined as the fraction of the *H*-step ahead error variance in forecasting x_i, due to shocks to x_j $(i \neq j)$. With two variables, we are able to have two possible spillovers that are calculated from $a_{0,21}^2$ (x_{1t} shocks that affect the forecast error variance of x_{2t}) and $a_{0,12}^2$ (x_{2t} shocks that affect the forecast error variance of x_{1t}) for the one-step ahead forecast. Our spillover index is the fraction of the total forecast error variance $(tr(A_0 A_0'))$ relative to the sum of two possible spillovers. We can easily extend it to an *N*-variable *p*-th order VAR using a *H*-step ahead forecast and expressing the ratio in percent:

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$$S = \frac{\displaystyle\sum_{h=0}^{H-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{h,ij}^2}{\displaystyle\sum_{h=0}^{H-1} \text{trace}(A_h A_h')} \times 100 \tag{11}$$

It should be noted, however, that there are several well-known ordering issues when we use Cholesky decomposition in solving identification problems in a VAR model. Yilmaz and Diebold (2012) provide a generalized VAR framework that yields variance decomposition invariant to ordering.[8]

To define the generalized spillover index, we first define the generalized forecast error variance decomposition as

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \displaystyle\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\displaystyle\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)} \tag{12}$$

where Σ is the variance matrix of the error vector u, $\sigma_{jj}^2 = Var(u_{jt})$ and e_i is a vector with zeroes except for the i-th element. As $\Sigma_{j=1}^{N} \theta_{ij}^g(H) \neq 1$ in general, we further normalize it as

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\displaystyle\sum_{j=1}^{N} \theta_{ij}^g(H)}. \tag{13}$$

Using the normalized variance decomposition, we can construct the total volatility spillover index as follows:

$$S^g(H) = \frac{\displaystyle\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{N} \times 100 \tag{14}$$

We measure and report the spillover effects among changes in the Asian sovereign CDS spreads with our generalized spillover index from equation (14).

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[8] The generalized framework was originally developed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998).

4. Results

4.1. Data

Our data, obtained from Credit Market Analysis (CMA), comprise USD-denominated sovereign CDS spreads with 5-year maturity from seven Asian countries: China, Indonesia, Japan, Korea, Malaysia, Philippines and Thailand. These seven countries were selected based on the top 50 transaction balances as of May 3, 2013 as per the Depository Trust and Clearing Corporation (DTCC). The data span from August 9, 2007 to May 31, 2013[9] on a daily basis, and we eliminated observation values for the days without CDS spread bid submission in any of the above nations to minimize non-synchronous trading problems.

Table 1 displays descriptive statistics of CDS spreads and the CDS spread changes[10] in our sample countries. The average CDS spread (Panel A) is the lowest in Japan (70.91 bp) and the highest in Indonesia (229.01 bp). Japan and China have relatively lower spreads with smaller volatilities while Indonesia and the Philippines have relatively higher spreads with greater volatilities. However, with regard to the CDS spread changes (Panel B), there is no significant difference in average CDS spread changes among the seven countries. Furthermore, the minimum and the maximum spread changes, together with the standard deviations, are similar in six nations except for Japan. Normality is not observed in skewness or kurtosis while time series show a strong autocorrelation, spread and spread change in all seven countries according to the Ljung-Box test result, which indicates that the time series follow the GARCH process.

===[Table 1 about here]===

4.2. Interconnectedness in Asian Sovereign CDS Markets

Table 2 provides the dynamic conditional correlation result analyzed by the cDCC model. The AR(1)-cDCC-MGARCH (1, 1) model is adopted by Akaike Information Criterion (AIC) and Schwarz's Criterion (SC) for appropriate parallax. Both α and β are estimated as statistically significant by the cDCC model. The estimated β is 0.8620, representing the mean reversion

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[9] Figure 3 shows that the CDS spreads hardly changed in most countries (except for Indonesia and the Philippines) before August 9, 2007. For that reason we set our sample period after August 9, 2007—generally recognized as the beginning of the 2007 global financial crisis—because the entire data from all seven countries could distort the result and it is not significant to compare the pre- and the post-crisis periods.

[10] The CDS spread change is calculated by log(CDS spread$_t$ /CDS spread$_{t-1}$). We use the term 'spread change' or 'change in the spread' in order to distinguish it from stock profit ratio.

speed by the dynamic conditional correlation, *i.e.*, the time required for the extinction of the impact. The correlation persistence is very large as the sum of α + β is close to 1, indicating that the seven sovereign CDS markets are highly correlated.

Conditional correlation shows very high co-movements among Asian sovereign CDS spread changes, in the order of Indonesia-Philippines (0.9195), Korea-China (0.8157) and Thailand-Malaysia (0.8121). It is noteworthy that conditional correlation among the six countries excluding Japan is high, ranging from 0.7458 to 0.9195 whereas the values between Japan and the other six nations are comparably lower, ranging from 0.3238 to 0.3543.

===[Table 2 about here]===

The result signifies that the interconnectedness of the CDS spread is larger among developing countries than between the developed and developing ones. It is specifically higher between Indonesia and the Philippines showing an unstable spread, which is consistent with the finding of Gündüz and Kaya (2013).[11] It is also important that Korea is most highly correlated with China than with any other countries, and vice versa. The other four countries are also highly correlated with the other countries in our sample. Furthermore, the Asian sovereign CDS spread changes tend to co-move more strongly within the region than across the regions. It is similar to the currency contagion introduced by Glick and Rose (1988) and Antonakakis (2012).

We conduct an additional examination on the dynamic conditional correlation by using the cDCC model and incorporate the time-varying correlation changes into our investigation. Figure 5 illustrates the progress of dynamic conditional correlation progress among Asian sovereign CDS spread changes during our sample period.

===[Figure 5 about here]===

Most countries are highly correlated particularly between 2007 and 2008 with an increasing probability of a global financial crisis; and between 2011 and 2012 along with the higher volatility in global financial markets, triggered by the US credit downgrade. However, the correlations tend to decline in 2009—2010 and 2012—2013 as the crises calm down.

Our finding is consistent with the earlier literature in that the correlation increases during

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[11] Gündüz and Kaya (2013) analyze 10 countries in Europe using the DCC model and report stronger co-movements in countries with higher CDS spreads and unstable economies, such as Greece, Italy, Ireland, Portugal and Spain.

periods of increasing economic and financial instability.[12] Compared to the other six countries, Japan's correlation coefficients with the others remain relatively low. Also note that its correlations, once negative before the 2007 global financial crisis, turn positive during and after the crisis. It provides partial, if not all, evidence of intensifying co-movements in Asian CDS markets since the global financial crisis.

4.3. Contagion Effects in Asian Sovereign CDS Markets

In this subsection, we first measure contagion effects in Asian sovereign CDS markets by using Diebold and Yilmaz's (2012) Spillover Index model. We then proceed to additional analysis on the contagion effects, first by CDS spread change then by CDS spread volatility. For the CDS spread volatility, we employ Squared Spread Change and Absolute Spread Change equivalent to the squared profit ratio and the absolute profit ratio, respectively, the usual proxy for volatility index of financial time series. We obtain the Spillover Index using the formula in equation (18) for the sample period and review variation factors for the individual sovereign CDS spread changes and volatilities. Then, via rolling-sample analysis, we calculate the three Spillover Indices and plot them in Figure 6, with which we can examine the time-varying features of the contagion effects generated by significant economic events such as financial crises.

Table 3 presents the estimated contagion effects of CDS spread changes. For computation, we measure the `spread changes` over ten days according to the generalized forecast error variance decomposition method and adopt the VAR(12) model by Akaike Information Criterion (AIC) and Schwarz's Criterion (SC).

===[Table 3 about here]===

The implied Spillover Index is 67.2% according to the estimated result, which signifies that 67.2% of the forecast error variance for the seven Asian sovereign CDS spread changes can be explained as impacts from other countries. Thus, we can see the contagion effect is quite high among Asian sovereign CDS spread changes. If we look into individual variation factors, own-market spillovers tend to take the greatest proportions among all spillovers from other countries. In particular, Japan has the highest own-market spillover (93.8%), indicating that the country is barely affected by other Asian nations. Similar to the estimated result by the cDCC model, the

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[12] Kolb (2011) also finds that variance, covariance or correlation increase during extreme events, such as political turmoil, currency and debt crises.

contagion effect is not very large between Japan and the other six countries. In contrast, the other nations have much milder own-market spillovers ranging from 18.4% to 38.5%, implying greater spillovers from/to other nations. Indonesia in particular has the highest contagion effect to the others (111%). In the Philippines and Thailand, for example, CDS spreads are affected more by spillovers from Indonesia than from their own markets. And in China and Korea, the influence from Indonesia is almost as large as their own-market spillovers. The Indonesian CDS spread, the most unstable in Asia, greatly influences other developing Asian countries.

Table 4 summarizes the estimated contagion effects of CDS spread volatility. Spillover Indices are 65.7% and 66.8% by Squared Spread Change and by Absolute Spread Change, respectively, similar to the Spillover Indices by the CDS spread change. Therefore, the contagion effects based on CDS spread volatility are also very high in our sample Asian countries. For variation factors of CDS spread volatility the own-market spillovers are again the highest in Japan (93.4% by squared spread change and 99.6% by the absolute spread change), while the numbers are considerably lower in the other six nations (ranging from 23.0% to 25.9% by squared spread change and from 20.5% to 25.8% by absolute spread change), similar to the case of CDS spread change. The only difference between our estimated Spillover Indices—one by the spread change and the ones by the volatility—is that, in the latter case, the own-market spillovers are larger than the cross-market spillovers in all seven countries.

===[Table 4 about here]===

Next, we examine the time-varying nature of contagion effects in Asian sovereign CDS markets after the global financial crisis. We apply the rolling sample (over 250 days) analysis and calculate the first Spillover Index with initial data over the first 250 days, then calculate the second Index by repeating the same procedure with an updated subsample ranging from day 2 to day 251. Progression of our Spillover Indices based on the CDS spread change and the ones based on the two measures of volatility (squared and absolute spread change) are plotted in Figure 6. The time-varying nature of contagion effect is very clear in all the Spillover Indices we measure.

===[Figure 6 about here]===

All three Spillover Indices reach their peaks on the collapse of Lehman Brothers and start to rise again as another financial crisis from Europe looms with the bailout in Greece. The

contagion effect significantly increases once again with the US credit downgrade and then declines as the Federal Reserve launches the 3rd round of quantitative easing (QE3) in September 2012. These findings provide support to the literature documenting that cross-country correlation increases in the time of growing economic and financial instability.

5. Conclusion

We have examined the interconnectedness of Asian sovereign CDS markets and the contagion of sovereign default risk after the 2007 global financial crisis. We have applied the cDCC model by Aielli (2013) and the Spillover Index model by Diebold and Yilmaz (2012) to provide a better understanding of the correlation among financial markets with time-varying features. We have several noteworthy findings.

Co-movements of CDS spread change are larger among developing countries than between developed and developing countries. This is similar to the case of currency contagion in which the intra-regional nature is stronger than the inter-regional nature. It is also found that co-movements among Asian nations tend to intensify during periods of growing financial instability.

Using the Spillover Index model by Diebold and Yilmaz (2012), we find high contagion effects in Asian sovereign CDS markets to be particularly higher among six nations, with Japan being the exception. The CDS spread change is influenced both by cross-market spillovers and by own-market spillovers. Our rolling-sample analysis reconfirms one of the findings obtained by the cDCC model that the contagion effect increases during unstable periods, such as Lehman Brothers bankruptcy, looming financial crisis in Europe and the US credit downgrade.

Evidence of interconnectedness and contagion effects, which we found through analysis on co-movements and default risk spillovers in Asian sovereign CDS markets, is rarely acknowledged so far. Our findings show the importance of policy countermeasure in reference to global economic and financial crises. Investigating the default risks in Asian sovereign CDS markets and their connectivity to the region's stock, bond or currency markets would be a natural way to extend our current work.

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Appendix A. Figures

<Figure 1> Credit Default Swap
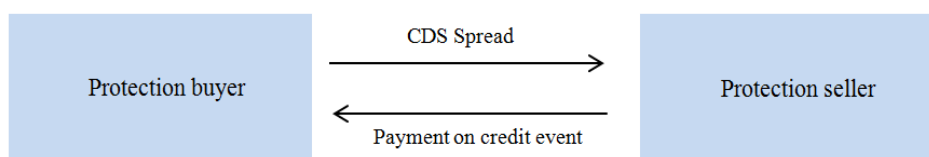
<Figure 2> Sovereign CDS Ranking (billions of USD)
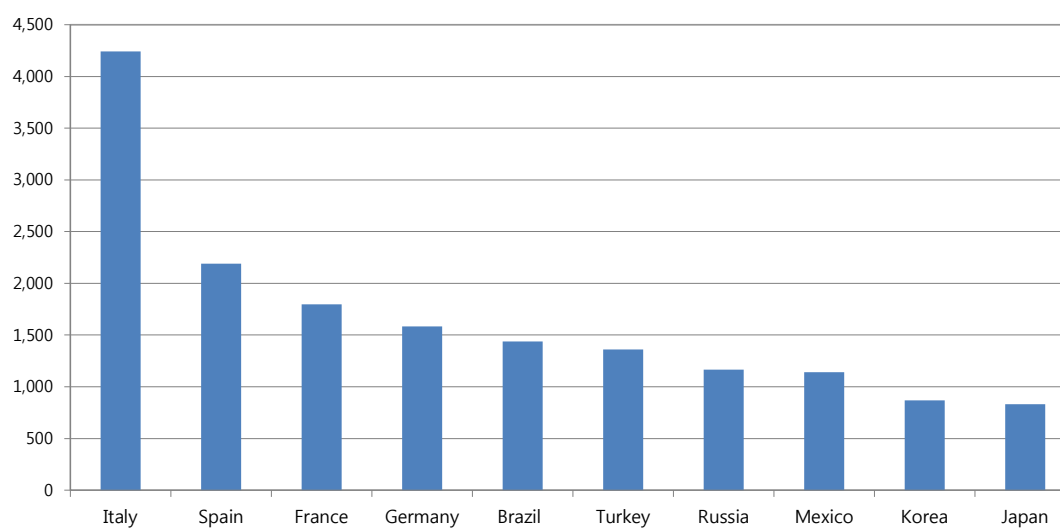
<Figure 3> Asian Sovereign CDS Spread
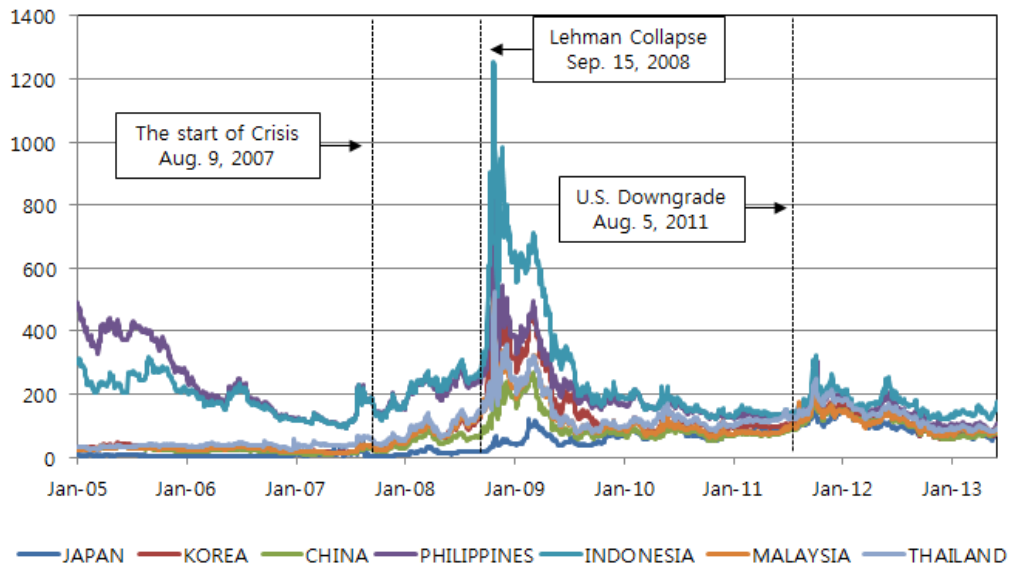
<Figure 4> Comparison of Correlation Coefficients
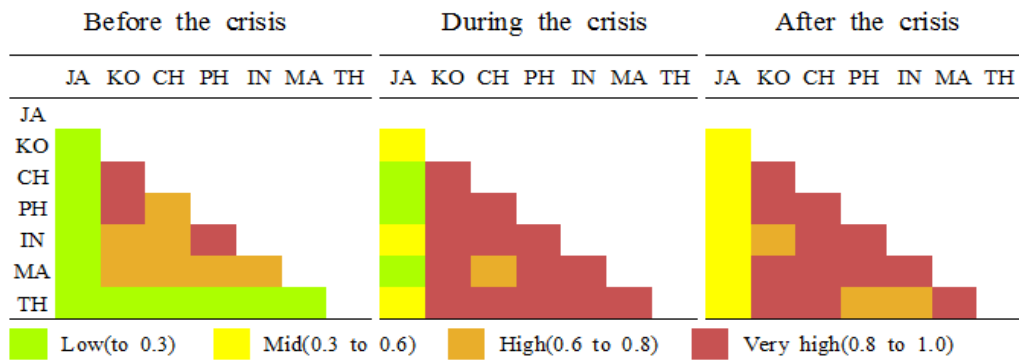
Note: JA, KO, CH, PH, IN, MA, and TH denote Japan, Korea, China, Philippines, Indonesia, Malaysia, and Thailand respectively.

<Figure 5> Dynamic Conditional Correlation

Korea and Japan

China and Japan

Philippines and Japan

Indonesia and Japan

Malaysia and Japan

Thailand and Japan

China and Korea

Philippines and Korea

Indonesia and Korea

Malaysia and Korea

Thailand and Korea

Philippines and China

Indonesia and China

Malaysia and China

Thailand and China

Indonesia and Philippines

Malaysia and Philippines

Thailand and Philippines

Malaysia and Indonesia

Thailand and Indonesia

Thailand and Malaysia

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<Figure 6> Spillover Index of Asian CDS Markets
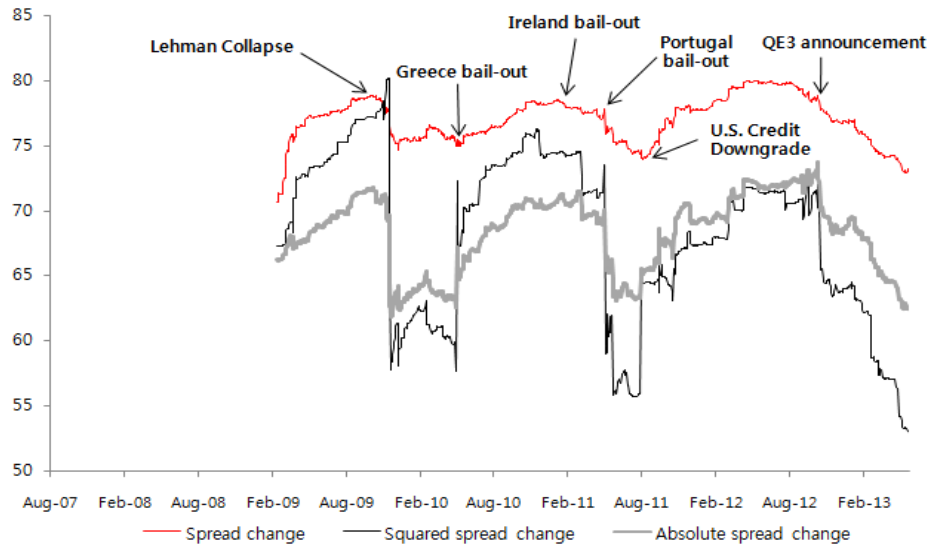
Appendix B. Tables

<Table 1> Summary Statistics

	Mean	Min	Max	SD	Skewness	Kurtosis	Q(20)	ADF
Panel A. CDS Spread								
Japan	70.91	2.3	154.75	32.68	-0.09	2.78	23472**	-2.629
Korea	130.48	22.1	700.0	86.05	2.48	10.31	20628**	-3.068
China	93.30	17.8	296.7	44.26	1.52	5.56	21192**	-2.557
Philippines	187.28	80.5	870.0	88.59	2.48	11.91	20573**	-2.992
Indonesia	229.01	117.8	1256.7	154.97	2.84	11.86	21596**	-2.467
Malaysia	110.81	23.0	520.2	56.35	2.31	10.24	20058**	-2.646
Thailand	130.42	38.0	524.2	54.98	1.97	8.86	19265**	-2.399
Panel B. CDS Spread Change								
Japan	0.0009	-2.466	1.609	0.121	-5.49	176.20	190.15**	-7.655**
Korea	0.0008	-0.428	0.835	0.057	2.01	43.59	76.02**	-23.510**
China	0.0009	-0.325	0.657	0.053	1.43	25.72	69.11**	-23.232**
Philippines	-0.0004	-0.413	0.367	0.044	-0.26	18.60	74.50**	-36.361**
Indonesia	-0.0001	-0.327	0.401	0.045	0.59	18.21	110.94**	-22.559**
Malaysia	0.0008	-0.432	0.775	0.054	1.83	41.47	83.19**	-23.006**
Thailand	0.0003	-0.498	0.541	0.049	0.49	26.49	126.54**	-22.107**

Note: Q(20) is the Ljung-Box portmanteau test, ADF is the Augmented Dickey Fuller test. * and ** denote significance at the 5% and 1% level, respectively.

<Table 2> Estimation Results of cDCC Model

	Japan	Korea	China	Philippines	Indonesia	Malaysia
Panel A: Correlation estimates						
Korea	0.3528					
China	0.3529	0.8157				
Philippines	0.3238	0.7640	0.7998			
Indonesia	0.3248	0.7458	0.7870	0.9195		
Malaysia	0.3543	0.8024	0.8045	0.7868	0.7762	
Thailand	0.3286	0.7638	0.7790	0.7639	0.7605	0.8121
Panel B: Parameter estimates						
α	0.0496 (4.095)**					
β	0.8620 (17.52)**					

Note: Numbers in the parentheses are t-values. * and ** denote significance at the 5% and 1% level, respectively.

<Table 3> CDS Change Spillover

To	From							
	China	Japan	Korea	Thailand	Indonesia	Malaysia	Philippines	Contribution from others
China	19.6	0.1	15.8	15.8	19.1	16.6	13.0	80
Japan	1.5	93.8	1.8	0.5	0.2	1.8	0.2	6
Korea	17.5	0.1	18.6	15.9	18.0	18.1	11.8	81
Thailand	13.6	0.0	12.3	18.4	27.4	13.9	14.4	82
Indonesia	12.3	0.0	9.4	12.9	38.5	10.3	16.6	61
Malaysia	17.7	0.1	18.3	17.2	15.2	19.7	11.8	80
Philippines	13.1	0.0	9.3	15.0	30.9	10.4	21.1	79
Contribution to others	76	0	67	77	111	71	68	470
Contribution including own	95	94	86	96	149	91	89	Spillover Index 67.2%

Note: The underlying variance decomposition is based on 10-day-ahead forecast errors from VAR of order 12. The numbers in the table are in percent.

<Table 4> CDS Volatility Spillover

To	From							Contribution from others
	China	Japan	Korea	Thailand	Indonesia	Malaysia	Philippines	
Panel A. Squared spread change								
China	24.8	0.3	15.7	15.2	13.1	16.5	14.5	75
Japan	1.0	93.4	1.2	1.5	1.1	0.9	0.9	7
Korea	15.2	0.3	23.6	15.6	13.8	17.5	14.0	76
Thailand	14.5	0.3	15.0	24.6	13.1	18.1	14.4	75
Indonesia	13.0	0.2	13.8	13.5	25.9	13.8	19.9	74
Malaysia	15.2	0.2	16.7	17.8	13.1	23.0	14.1	77
Philippines	14.0	0.2	13.5	14.2	19.0	14.3	24.8	75
Contribution to others	73	1	76	78	73	81	78	460
Contribution including own	98	95	100	103	99	104	102	Spillover Index 65.7%
Panel B. Absolute spread change								
China	21.3	0.0	18.0	16.9	12.2	18.5	13.0	79
Japan	0.0	99.6	0.0	0.1	0.1	0.0	0.1	0
Korea	17.8	0.0	20.9	17.6	11.9	19.8	12.0	79
Thailand	15.8	0.0	16.0	20.5	15.4	17.0	15.3	80
Indonesia	13.5	0.0	12.8	15.9	25.8	13.2	18.8	74
Malaysia	18.1	0.0	19.4	18.1	12.0	20.6	11.8	79
Philippines	14.3	0.0	12.7	17.0	19.3	12.8	23.9	76
Contribution to others	79	0	79	86	71	81	71	467
Contribution including own	101	100	100	106	97	102	95	Spillover Index 66.8%

Note: The underlying variance decomposition is based on 10-day-ahead forecast errors from VAR of order 12. The numbers in the table are in percent.