Japanese Journal of Monetary and Financial Economics Vol. 7, No. 1, pp. 1-32, 2019

Are Insurers Susceptible to Systemic Liquidity Risk or do They Contribute to it?

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ABSTRACT

Although insurance companies were believed to be less vulnerable to systemic risk compared to banks, we have observed failures of insurance companies and the subsequent financial markets turmoil. During the global financial crisis, the severe liquidity shortage was also highlighted. This study employs connectedness indices to examine the relevance of systemic liquidity risk for financial institutions including insurance companies. Results show that the effect of the global liquidity squeeze on the CDS spreads of insurance companies, particularly those whose main business is variable annuities with guaranteed minimum payments, was significant. Secondly, banks were likely to have a larger responsibility for the global fundraising liquidity condition. Although the development of systemic liquidity risk originating from insurance companies does not seem plausible, we cannot ignore that the aggravation of the creditworthiness of insurance companies might be propagated and amplified to the rest of the financial system.

Key words: Liquidity squeeze, Interconnectedness, Credit default swap spread

JEL Classification: G01, G21, G22, G13, F65, E58

1. Introduction

The global financial crisis highlighted global systemic risk. Several measures for mitigating such risk, including the identification of global systemically important financial institutions (G-SIFIs), have been discussed. Not only banks, but also insurance companies have become targets of this wave of systemic reinforcement regulation. Insurance companies identified as global systemically important insurers (G-SIIs) are also required to accumulate extra equity capital.

It was generally believed that insurance companies are only negligibly affected by systemic risk. However, the multinational American International Group (AIG) went to the verge of bankruptcy in the midst of the financial turmoil, and financial market instability was aggravated after its near-collapse. Furthermore, several insurance companies such as Hartford Financial Services Group Inc., ING Group, and Aegon N.V. had to be bailed out.

Since the global financial crisis, several studies have discussed whether insurance companies do pose systemic risk. Billio et al. (2012) find that financial institutions including insurance companies, hedge funds, and brokers/dealers became more highly interrelated mid-crisis, likely increasing the systemic-risk level in the finance and insurance industries through a complex and time-varying network of relationships. Weiss and Muhlnickel (2014) reveal that insurers were more susceptible to systemic risk than banks. Berdin and Sottocornola (2015) investigate systemic risk across European financial institutions during the European sovereign crisis, and show that banks were always dominant and insurers played a subordinate role.

A G-SII identification method was proposed in 2012 and the first list was disclosed in 2013. The methodology cites several idiosyncratic characteristics regarded as possible systemic-risk drivers, that is, size, global activity, interconnectedness, non-traditional and non-insurance (NTNI) activities, and substitutability. Although the list of G-SIIs has been updated and published by the Financial Stability Board (FSB) annually based on new data, the FSB has decided not to publish a 2017 list. At this stage, the International Association of Insurance Supervisors (IAIS) has tentatively developed an Activities-Based Approach (ABA) to insurance sector systemic risk and is attempting to improve the assessment for identifying G-SIIs and for G-SII policy measures. Contrary to the existing entity-based approach (EBA), which focuses on whether the failure of an insurer poses a threat to the whole financial system, the ABA assesses how even solvent insurers, through their collective risk exposure, may propagate or amplify shocks to the rest of the financial system and the real economy.

By employing indicators of potential systemic risk sources, Weiss and Muhlnickel (2014) empirically test the hypothesis that insurers were susceptible and contributed to systemic risk. They found that insurers that were larger and relied more heavily on NTNI activities were highly exposed to the adverse effects of the financial turmoil, although their contribution to systemic risk was only determined by size. Billio et al. (2012) investigate connectedness across financial institutions and show that banks played a much more important role in transmitting shocks than other financial institutions.

Fundraising liquidity dry-up was prominent during the global financial crisis. Insurance companies were believed to be less affected by the liquidity crunch because the maturity of their liabilities, particularly of life insurance companies, is typically long. However, there might be several potential channels for fundraising liquidity to affect insurance companies' creditworthiness. The IAIS (2018) describes the association of liquidity risk with insurers and lists possible cases where insurers may face unexpected liquidity outflows, such as claims, expiration of funding sources, collateral calls, or policyholder withdrawals. Unlike AIG, which sold a huge amount of credit protection without sufficient hedging and was required to post additional collateral after the downgrading, ordinary insurance companies make asset investments to meet middle- or long-term liabilities which should have protected them from the adverse effects of the liquidity crunch. However, securities held by insurance companies, including those engaging in traditional insurance business, are likely to be vulnerable to liquidity dry-up[1]. Globally, insurance companies were damaged by the deterioration of mortgage-backed securities (MBS) and the collapse of the asset-backed commercial paper (ABCP) resulting from the aggravation of the US housing market. The liquidity shortage worsened the plummet of asset-backed securities' prices. The damage incurred by insurance companies whose core business was variable annuities with guaranteed minimum payments and had a portfolio with a larger portion of higher-risk securities was distinctly serious. Furthermore, they were forced to raise additional funds to compensate for insufficient policy reserves caused by the depreciation of portfolio assets. Insurers that faced sudden cash outflows from withdrawals and did not have sufficient liquidity assets were probably damaged more seriously.

Financial institutions might not only be exposed to fundraising liquidity crunch but also contribute to the aggravation of liquidity availability. In other words, feedback effects were a possibility, and the crisis caused by the liquidity crunch might worsen the liquidity problem through a deterioration of financial institutions' soundness.

Banks and insurance companies are closely related with each other via their investment and lending activities. Particularly during the global financial crisis, the worsening of banks' creditworthiness might have strongly affected insurance companies because they purchased ABCPs issued by structured investment vehicles (SIVs) sponsored by banks. Actually, SIVs have no explicit agreements with their sponsoring banks for committed back-stop liquidity lines covering all their short-term liabilities. As negative information about the real estate markets came to light in 2007, leading to the deterioration of MBSs, banks experienced difficulties in rolling over ABCPs. Therefore, institutional investors including insurance companies were adversely affected by the loss of the principal on the ABCP because of the collapse of SIVs under banks. Likewise, banks that made loans to and investments to insurers might be hurt because of the loss of the insurers' financial soundness.

In an EBA, counterparty exposure or cascading risk from a failing entity to others is a central element of systemic risk assessment. In an ABA, by contrast, counterparty exposure is regarded as a risk-enhancing factor and could amplify the domino effect among solvent financial institutions as well.

We focus on the effect of fundraising liquidity and explore whether insurance companies are relevant to the stability of the financial system. To investigate the relationship between fundraising liquidity condition and financial institution soundness as well as mutual interdependence simultaneously, we adopt Diebold and Yilmaz's (2009, 2012) connectedness indices. This approach applies the well-known econometric methodology of variance decomposition to explore directional as well as system-wide connectedness. We also create a fundraising liquidity index as suggested by Severo (2012) and examine the relationship between liquidity squeeze and financial institutions' creditworthiness.

Unlike Billio et al. (2012) and Weiss and Muhlnickel (2014) who examine systemic risk by using financial institutions' stock returns, we employ global financial institutions' credit default swap (CDS) spreads as an indicator of their creditworthiness. During the financial turmoil, almost all insurance companies' CDS spreads, including those mainly engaging in traditional insurance businesses, exhibited an abrupt hike. This might be partly explained by a decline in risk-appetite caused by the liquidity squeeze and worsened future perspectives. That is, a simultaneous increase in CDS spreads might be driven by a change in common factors like the fundraising liquidity condition. Alternatively, CDS spreads' co-movements might be a result of the intensified mutual interdependence across financial institutions via their investment and lending activities and financial institutions' worsened creditworthiness might be transmitted within the global financial markets.

This study adopts a structural vector autoregressive (SVAR) model to extract idiosyncratic shocks indicating fundraising liquidity tightness and financial institutions' soundness. Identifying idiosyncratic shocks using the SVAR methodology, we attempt to detect origins of systemic risk during the Lehman shock and European sovereign crisis.

The remainder of this paper is organized as follows. Section 2 reviews related studies. After the econometric methodology and data used for the analyses are presented in sections 3 and 4 respectively, empirical results are reported in section 5. Lastly, major implications are presented.

2. Related Literature

Systemic risk has attracted growing interest since the Lehman shock and various methodologies to explore it have been developed. The CoVAR approach proposed by Adrian and Brunnermeier (2016) and the Marginal Expected Shortfall (MES) approach of Acharya et al. (2017), who track the association between individual stock price movements and overall market movements, are often used. Weiss and Muhlnickel (2014) estimate the MES and the conditional CoVAR of U.S. banks and insurers to see whether insurers were systemically relevant during the crisis. Berdin and Sottocornola (2015) analyze systemic risk in the European financial sectors by conducting the Granger causality test as well as MES and CoVAR estimations. Billio et al. (2012) examine the connectedness across four financial sectors including insurers by applying the Granger causality test and principal component analysis.

Diebold and Yilmaz (2009, 2012), by contrast, propose a connectedness index utilizing the technique of variance decomposition analysis to measure connectedness at various levels. Contrary to the Granger causality test, variance decomposition derived from an SVAR extracting structural shocks can detect intrinsic causes of the instability of financial markets.

Reports have also been published of studies investigating the effects of a liquidity squeeze since the global financial crisis. As for papers employing CDS spreads, Frank et al. (2008) use the dynamic conditional correlation—generalized autoregressive conditional heteroskedasticity model and estimate the conditional correlation coefficients between CDS spreads and the liquidity index. Eichengreen et al. (2009) apply a principal component analysis and suggest the liquidity effect as an influential common factor for CDS spreads during the Lehman shock.

Quantifying liquidity availability is not an easy task. Frank et al. (2008), Eichengreen et al. (2009), and Boyson et al. (2010) use TED, the gap separating the LIBOR (London Interbank Offered Rate) and US Treasury Bill rates, and Baba and Packer (2008), Griffoli and Ranaldo (2010), and Hui et al. (2011) employ the gap separating the LIBOR and OIS (Overnight Index Swap) rates as an indicator. They may, however, be contaminated by the effect of the deteriorated soundness of financial markets, and may be inappropriate funding liquidity indicators. Severo (2012), who demonstrates that the extent of the deviation from the arbitrage parity reflects investor's ability to reallocate funds and obtain positive excess returns quickly with small risks, creates the systemic liquidity risk index (SLRI) by extracting a common factor from principal component analysis for series of deviations from the arbitrage conditions[2].

Fundraising liquidity might be closely related to market players' risk appetite. Risk-appetite indicators of various types have evolved[3]. What commonly holds in every index is that risk appetite is treated as a combination of the degree to which players accept uncertainty (risk aversion) and the level of uncertainty itself (uncertainty about macroeconomic prospects), and can affect risk premium of any kind of asset even though the riskiness of asset does not change. Market-average risk aversion can change with market conditions, although individual players' risk aversion does not change. A growing number of less risk-averse players holding less equity capital participated in CDS markets as guarantors and underwrote credit risks during the easy money period before the crisis. The entry of less risk-averse players probably lowered CDS spreads. When the crisis occurred they faced fundraising problems and were forced to exit CDS markets. The remaining more risk-averse players became unwilling to bear risk and required higher risk premiums to offset the greater risk burdens[4]. Players' perspectives for the future macroeconomic environment can also produce changes in risk appetite.

During the global financial and European sovereign crises, we observed the simultaneous skyrocketing of CDS spreads. CDS spread co-movements can be attributed to common factors and mutual dependencies. As an example of common factors, market players' attitudes probably bring about the simultaneous increases. The global crisis highlighted risk appetite as a possible driving force of the downfall of asset prices across nations under stressful circumstances, and several studies have demonstrated that the CDS spread hike can be explained by factors other than credit risk. Ikeda et al. (2012) attempted to decompose the sovereign CDS spreads into components affected by credit risk and by other factors (including the risk premium) and reported that the latter contributed to the hike of the sovereign CDS spreads to a marked degree during the European crisis, particularly of nations outside of the Eurozone such as Japan.

We apply the connectedness index proposed by Diebold and Yilmaz (2009, 2012) to investigate the relevance of financial institutions to systemic liquidity risk. Similarly to Ohno (2016), a funding liquidity indicator created by following Severo (2012), and the world stock price index as a proxy of perspectives for futures world macroeconomic conditions are chosen as global common factors[5], and the innovation accounting methodology based on the SVAR model is employed to extract financial institution's idiosyncratic shocks. The extracted shocks are regarded as changes in a reference entity's credit risk attributable to factors other than the common factors, and are used to explore financial institution interdependence. Similarly, the feedback effect is also analyzed by confirming the effect of the idiosyncratic shock on the fundraising liquidity indicator. This study creates a three-type connectedness index; connectedness from fundraising liquidity to financial institutions, from financial institutions to liquidity, and across financial institutions.

It is noteworthy that stock price declines can affect financial institutions' CDS spreads through erosion of their equity capital as well as changing investors' risk appetites. Similarly, the worsening of fundraising liquidity conditions can raise financial institutions' CDS spreads through lowering the market-average risk tolerance as well as increasing the probability of bankruptcy related to fundraising difficulties. The CDS spreads of financial institutions which were required to raise additional capital as a result of the deterioration of their balance-sheet soundness under the severe liquidity conditions were highly likely to increase drastically through these two channels. Although this study does not rigorously differentiate between these two channels, by comparing the magnitude of CDS spread reactions to the change in common factors, we attempt to infer which financial institutions were more seriously damaged by the deterioration of their creditworthiness as well as the aggravation of risk-appetite.

3. Empirical model

We use a structural VAR model to identify influential factors for financial institutions' CDS spreads as well as the feedback effect during crisis periods. This study uses a multiple-country and multiple-sector model to explore the interactions across financial institutions as well as the relationship between fundraising liquidity and creditworthiness of financial institutions. It should be noted that the time duration when the effect of liquidity crunch became dominant is not so long. Therefore, the sub-sample crisis periods in addition to the full-sample crisis periods are defined in the next section, and smaller- and larger-scale models are used for the estimation of the sub-sample and full-sample periods, respectively.

First of all, a two-country one-sector model comprising six variables, which is a smaller one, is specified. It is assumed that financial institutions' CDS spreads and their determinants are represented as follows.

$$A(L)X_t = u_t$$

$$\begin{aligned}
&A(L) = A_0 - A_1 L - A_2 L^2 - \cdots - A_k L^k \\
&A_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ -a_{21} & 1 & 0 & 0 & 0 & 0 \\ -a_{31} & -a_{32} & 1 & -a_{34} & 0 & 0 \\ -a_{41} & -a_{42} & -a_{43} & 1 & 0 & 0 \\ -a_{51} & -a_{52} & -a_{53} & 0 & 1 & -a_{56} \\ -a_{61} & -a_{62} & 0 & -a_{64} & -a_{65} & 1 \end{bmatrix} \\
&X_t' = \left[DEV_t \ MSCI_t \ SOV_{1,t} \ SOV_{2,t} \ BANK_{1,t} \ BANK_{2,t}\right] \\
&\qquad\qquad \text{or} \\
&X_t' = \left[DEV_t \ MSCI_t \ SOV_{1,t} \ SOV_{2,t} \ INS_{1,t} \ INS_{2,t}\right]
\end{aligned} \tag{1}$$

where X_t is a 6 × 1 vector of variables, $A(L)$ is the matrix polynomial in the lag operator, and k signifies the maximum lag. u denotes a 6 × 1 structural disturbance vector, and the off-diagonal elements of the variance-covariance matrix of structural disturbances Ω_u are zero.

Here, *DEV* and *MSCI* represent fundraising-liquidity indicators and the world stock index, respectively. They are used as worldwide common factors for financial institutions' CDS spreads. SOV_i is a CDS spread of country *i*'s government, which is a local factor for banking and insurance sector CDS spreads located in country *i*[6]. $BANK_i$ and INS_i (i = 1 or 2), respectively denote banking and insurance sector CDS spreads in country *i*. According to the specification, the structural shocks of $BANK_i$ and INS_i are idiosyncratic shocks, implying a change in banking and insurance sector creditworthiness attributed to factors other than common factors[7].

Matrix A_0 specified in (1) presumes that *DEV* is the most, and *SOV* the least, exogenous among the three common factors, with ordering determined according to the quoting time of data[8 9]. We assume that banking and insurance sector CDS spreads react simultaneously or late to a shock affecting these common factors, and banking or insurance sector CDS spreads in the two countries respond mutually to a shock affecting a counterparty country's sector.

Coefficients in matrix A_0 and the structural shocks are derived from the OLS estimation of each equation in the following reduced form system.

$$B(L)X_t = \varepsilon_t \qquad B(L) = B_0 - B_1L - B_2L^2 - \cdots - B_kL^k \tag{2}$$

where ε_t denotes a 6 × 1 vector of the residuals with a variance–covariance matrix Ω_ε.

The reduced form is derived by multiplying both sides of Equation (1) with matrix A_0 from the left. Accordingly, the relationship between the structural disturbances vector and the reduced form residuals vector is represented below.

$$\varepsilon_t = A_0^{-1}u_t \tag{3}$$

This equality implies $\Omega_u = A_0\Omega_\varepsilon A_0'$.

Matrix A_0 has 15 (= 6 × (6 − 1)/2) zeros, avoiding the under-identification problem. This analysis also adopts a two-country two-sector model and uses a variable combination, including the banking sector CDS spread in one country and that of an insurance sector in another country, to confirm the different financial sectors' mutual dependence.

In addition to the non-recursive type structural VAR model specified in Equation (1), we also adopt a recursive-type structural VAR model, considering the possibility that the non-recursive type model may produce unstable results.

Diebold and Yilmaz (2009) propose the connectedness index to measure the system-wide diffusion of shocks using the variance decomposition methodology, which are already well understood and widely applied. Diebold and Yilmaz (2012) extend Diebold and Yilmaz (2009) adopting the Cholesky factorization, to derive the measure of the directional and total spillovers by adopting the generalized VAR framework, making the results invariant to the ordering. We applied the non-recursive structural VAR model representing the simultaneous causality from common factors to CDS spreads as well as mutual dependencies across financial institutions to create orthogonal shocks.

If variables used in these analyses satisfy stationarity, then Equation (2) can be reformulated in a reduced-form vector moving average (VMA) representation as follows.

$$\begin{aligned} X_t &= D(L)\varepsilon_t \\ &\quad D(L) = I + D_1 L + D_2 L^2 + \cdots + D_k L^k + \cdots \end{aligned} \tag{4}$$

Equation (4) can then be reformulated in a structural VMA representation.

$$\begin{aligned} X_t &= \Psi(L)u_t \\ &\quad \Psi(L) = D(L)A_0 \end{aligned} \tag{5}$$

Consider a k-step-ahead forecasting error conditional on the information set at time t. Because structural shocks are cross-sectionally and serially uncorrelated, the forecast error variance of the m-th ($1 \leq m \leq 1$) variable in vector X is represented as shown below.

$$\sum_{n=1}^{6}\left(\sum_{s=1}^{k}\Psi_{mn,s}^2\right)\sigma_n^2 \tag{6}$$

In Equation (6), σ_n^2 stands for the variance of the n-th structural shock in vector u ($1 \leq n \leq 6$). Further, $\Psi_{mn,s}$ represents the coefficient of response of the m-th variable in vector X to the n-th structural shock at time s.

Variance decompositions evaluate the relative contribution of one structural shock on a dependent variable. The *pairwise directional connectedness* from the n-th shock to the m-th variable measured at the s-step forecast, as defined by Diebold and Yilmaz (2012) is

$$C_{n\to m}^{s} = \frac{\left(\sum_{s=1}^{k}\Psi_{mn,s}^2\right)\sigma_n^2}{\sum_{n=1}^{6}\left(\sum_{s=1}^{k}\Psi_{mn,s}^2\right)\sigma_n^2} \tag{7}$$

Next, consider the system-wide connectedness as the diffusion of shocks arising elsewhere within the system. The directional connectedness from every shock to the m-th variable is defined as shown below.

$$C^{s}_{*\rightarrow m} = \sum\nolimits_{n=1}^{6} C^{s}_{n\rightarrow m} \qquad (n \neq m) \tag{8}$$

Similarly, the opposite directional connectedness from the m-th variable to the rest are measured as follows.

$$C^{s}_{m\rightarrow *} = \sum\nolimits_{n=1}^{6} C^{s}_{m\rightarrow n}/5 \qquad (n \neq m) \tag{9}$$

Finally, the total connectedness, the diffusion of non-own-shocks within the system, is defined as

$$C^{s} = \frac{1}{6}\sum\nolimits_{m=1}^{6}\sum\nolimits_{n=1}^{6} C^{s}_{n\rightarrow m} \qquad (n \neq m) \tag{10}$$

This empirical analysis creates three types of connectedness indices: connectedness from a fundraising liquidity shock to financial institutions, from a shock in financial institutions to the fundraising liquidity indicator, and across financial institutions, to evaluate the effect of the fundraising liquidity squeeze on financial institutions' creditworthiness, the feedback effect, and the mutual dependence across financial institutions. They are created with reference to Equations (9), (8), and (10), respectively. Furthermore, financial institutions are classified into groups of banks and insurance companies to compare their relative effects.

The analysis targets are the financial institutions of six developed nations. Whereas the liquidity squeeze effect on global financial markets should be examined, the VAR model adopted here cannot include all nations. Therefore, we calculate a connectedness indices average derived from each model utilizing a combination of two nations selected from six to confirm the overall tendency observed across these nations.

Furthermore, we conduct the estimation of a larger-scale model. Here, two types of matrix A_0 are specified as follows.

$$A_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{21} & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{31} & -a_{32} & 1 & -a_{34} & -a_{35} & -a_{36} & 0 & 0 & 0 & 0 \\ -a_{41} & -a_{42} & -a_{43} & 1 & -a_{45} & -a_{46} & 0 & 0 & 0 & 0 \\ -a_{51} & -a_{52} & -a_{53} & -a_{54} & 1 & -a_{56} & 0 & 0 & 0 & 0 \\ -a_{61} & -a_{62} & -a_{63} & -a_{64} & -a_{65} & 1 & 0 & 0 & 0 & 0 \\ -a_{71} & -a_{72} & -a_{73} & 0 & 0 & 0 & 1 & -a_{78} & -a_{79} & -a_{710} \\ -a_{81} & -a_{82} & 0 & -a_{84} & 0 & 0 & -a_{87} & 1 & -a_{89} & -a_{810} \\ -a_{91} & -a_{92} & 0 & 0 & -a_{95} & 0 & -a_{97} & -a_{98} & 1 & -a_{910} \\ -a_{101} & -a_{102} & 0 & 0 & 0 & -a_{106} & -a_{107} & -a_{108} & -a_{109} & 1 \end{bmatrix}$$

$$X_t' = \left[DEV_t \ MSCI_t \ SOV_{1,t} \ SOV_{2,t} \ SOV_{3,t} \ SOV_{4,t} \ BANK_{1,t} \ BANK_{2,t} \ BANK_{3,t} \ BANK_{4,t} \right]$$

or

$$X_t' = \left[DEV_t \ MSCI_t \ SOV_{1,t} \ SOV_{2,t} \ SOV_{3,t} \ SOV_{4,t} \ INS_{1,t} \ INS_{2,t} \ INS_{3,t} \ INS_{4,t} \right]$$

(11-1)

$$A_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{21} & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{31} & -a_{32} & 1 & -a_{34} & 0 & 0 & 0 & 0 \\ -a_{41} & -a_{42} & -a_{43} & 1 & 0 & 0 & 0 & 0 \\ -a_{51} & -a_{52} & -a_{53} & 0 & 1 & -a_{56} & -a_{57} & 0 \\ -a_{61} & -a_{62} & -a_{63} & 0 & -a_{65} & 1 & 0 & -a_{68} \\ -a_{71} & -a_{72} & 0 & -a_{74} & -a_{75} & 0 & 1 & -a_{78} \\ -a_{81} & -a_{82} & 0 & -a_{84} & 0 & -a_{86} & -a_{87} & 1 \end{bmatrix} \quad (11\text{-}2)$$

$$X_t' = \left[DEV_t \ MSCI_t \ SOV_{1,t} \ SOV_{2,t} \ BANK_{1,t} \ INS_{1,t} \ BANK_{2,t} \ INS_{2,t} \right]$$

(11-1) is the four-country, one-sector model and (11-2) is the two-country, two-sector model. These models examine the mutual interdependencies within as well as between the sectors and show the robustness of the results obtained from the six-variable models.

4. Data

These analyses use daily data downloaded from *Datastream* and *EIKON*, Refinitiv. We focus on two crisis periods. The first is defined as the sample period from January 18, 2008, through October 31, 2009, including the severe liquidity tightness triggered by the bankruptcy of Lehman Brothers. The second is defined as the period from January 4, 2011, through September 30, 2012, when the European sovereign crisis was of prominent importance[10]. It is expected, however, that the fundraising liquidity squeeze effect was only dominant for a limited time during both periods. We therefore conduct estimations of the six-variable models for the specified periods, during most of which the liquidity problem reached its peak[11]. We also investigate spillover effects using larger-scale models for the full sample periods.

We select five-year financial institution CDS spreads, some of which are defined as G-SIFIs. Countries where both banks and insurance companies have available CDS spread data are chosen and include the US, the UK, Japan, Germany, France, and the Netherlands. We create sectoral CDS spreads classifying individual spreads denominated in local currency for the protection of senior debts by country and then average them[12]. Five-year sovereign CDS spreads of these nations are also collected.

As the world stock index, we use the logarithmic MSCI world index denominated in US dollars and denoted here as *MSCI*. Regarding the fundraising liquidity index, we follow Severo (2012) and use the deviation from arbitrage relations. 21 series of the deviation from covered interest rate parity (CIP) and swap spreads equivalent to the gaps between the OIS and treasury-bill rates are collected and common factors are extracted by conducting principal component analysis[13 14 15]. The first principal component explains 73.3% of the total in-sample series variation. This constitutes the most important common source of fluctuations across all bases. Therefore, the first principal component, *DEV*, is selected as the fundraising liquidity index[16].

It is usual to test non-stationarity for individual variables and then estimate a VAR model. Because financial data are often revealed to be I (1), many estimation analyses use variable differences. Sims, Stock, and Watson (1990), by contrast, emphasize that the OLS estimator of the coefficients in a reduced form VAR containing level variables is consistent[17].

Perron (1989) shows that, when considering a structural break, most variables are trend stationary. While Perron (1989) exogenously determines the timing of a structural break, Zivot and Andrews (1992) develop a unit root test method (ZA test) to determine a structural break endogenously. This test can be conducted using three variants of the alternative hypotheses; 1) the series is trend-stationary with a break in the mean, 2) the series is trend-stationary with a break in the drift rate of the trend, 3) the series is trend-stationary with a break in both the mean and the drift rate of the trend. The ZA test is conducted based on the following equation.

$$x_t = \mu + \beta t + \gamma DU_t + \theta DT_t + \rho x_{t-1} + \sum\nolimits_{i=1}^{k} \lambda_i \Delta x_{t-i} + \nu_t$$
$$DU_t = \begin{cases} 0 & t \leq TB \\ 1 & t > TB \end{cases} \qquad DT_t = (t - TB)^* DU_t \tag{12}$$

where TB is the date of the endogenously determined break. The unit root hypothesis that $\rho = 1$ is considered. Models 1 and 2 are nested within model 3, a case of $\theta = 0$ and that of $\gamma = 0$ in

Equation (12), respectively. Detrended variables are created by extracting a residual term from Equation (12) based on a breaking time point endogenously determined in the unit root test.

Malliaropulos (2000) shows evidence that inflation, nominal, and real interest rates in the US are trend-stationary with a structural break in both the unconditional mean and the drift rate of a deterministic trend, and examines the Fisher effect, by applying the detrended variables[18]. The detrended data model estimation method is only appropriate if a structural break point is properly determined. We therefore utilize levels, first differences, and detrendings of all variables to estimate the SVAR model specified in the previous section, and to confirm whether consistent results can be obtained from the analyses using the three types of data.

Table 1 presents the Augmented Dickey-Fuller (ADF) test results using models with a constant and with a constant and a trend term. In the case excluding the trend term, two thirds of the variables employed in this empirical analysis do not satisfy stationarity. The unit root test incorporating the trend term reveals the possibility that three quarters of the variables are non-stationary[19 20]. Table 1 also contains the results of the ZA test, and reports that one fifth of the variables are still shown as non-stationary[21], although the ADF test rejected the hypothesis of non-stationarity for all of the created detrended variables.

Table 2-1 reports the summary of statistics for the level variables adopted in this study. It compares the results for the full periods of the first and second crises, and those obtained from the sub-periods of the two crises, which are highly likely to be periods of more serious fundraising tightness. As expected, the means of DEV calculated for the first and second crises are lower than those calculated for the sub-periods of the two crises, and DEV reaches the highest level during the sub-periods of both crises. The mean of the first crisis sub-period is about 3.5 times the mean of the second, suggesting that the severity of liquidity crunch was largely mitigated during the European sovereign crisis. Overall, the levels of sovereign CDS spreads are higher for the second crisis period, and the French sovereign CDS spread shows an exceptional hike.

Among banks, the CDS spread of Morgan Stanley is particularly high and reached 1251 basis points at the peak. Metlife, Prudential Financial, and Hartford also show a significant hike, and the maximum of Prudential Financial's CDS spread exceeded that of Morgan Stanley. Many of the banking sector's CDS spreads reached the highest level during the first sub-period, whereas only the US insurance sector's CDS spread experienced the highest level during that period. Among individual insurer's CDS spreads, the means for the first sub-period are the same as those of the first full period only for Prudential Financial, Cigna, Aetna, and Aegon. This implies that insurance companies were more vulnerable to the plunge in stock markets and many insurance companies' CDS spreads had updated to the highest level as a reflection of the aggravated

Table 1 ADF and ZA tests for the adopted variables

	t	lags	*tμ*	lags	*t* (*τ*)	lags	*TB*
(1) DEV	−1.858	1	−2.968	1	−5.747 *	1	12/01/08
(2) MSCI	−1.984	2	−2.092	2	−4.855	2	03/09/09
(3) Sovereign CDS spreads							
The United States	−2.382	1	−2.192	1	−5.448 *	1	03/12/09
The United Kingdom	−2.865 *	1	−2.969	1	−5.950 *	1	03/09/09
France	−2.001	3	−2.546	3	−4.840	3	07/02/11
Germany	−2.492	2	−2.402	2	−4.221	2	03/09/09
The Netherlands	−2.023	1	−2.039	1	−4.672	1	03/10/09
Japan	−2.595	4	−2.456	4	−4.171	4	10/28/08
(4) Sectoral CDS spreads							
(a) Banking Sectors							
The United States	−3.267 *	4	−3.219	4	−5.682 *	4	05/04/09
The United Kingdom	−3.364 *	1	−3.746 *	1	−5.086 *	1	04/29/09
France	−1.820	3	−3.086	3	−5.669 *	3	07/28/11
Germany	−2.780	1	−4.161 *	1	−6.281 *	1	07/28/11
The Netherlands	−1.821	3	−2.036	3	−4.850	3	04/29/09
Japan	−2.599	0	−3.060	0	−4.383	0	08/04/11
(b) Incurance sectors							
The United States	−2.694	5	−2.939	5	−5.669 *	5	04/06/09
The United Kingdom	−2.585	2	−2.629	2	−5.091 *	2	04/01/09
Germany	−3.630 *	1	−4.367 *	1	−5.959 *	1	05/04/09
The Netherlands	−2.736	1	−2.865	1	−4.835 *	1	04/29/09
Japan	−2.468	3	−2.701	3	−6.372 *	3	03/16/09
(5) CDS spreads of individual financial institutions							
(a) individual banks							
Morgan Stanley	−3.548 *	4	−3.528 *	17	−5.476 *	4	10/13/08
Goldman Sachs	−3.027 *	4	−3.006	4	−4.725	4	03/09/09
JP Morgan & Chase	−3.676 *	4	−3.627 *	4	−6.506 *	0	05/04/09
Bank of America	−2.905 *	1	−3.163	1	−5.558 *	1	08/03/11
Citigroup	−2.926 *	4	−2.989	4	−5.239 *	4	07/16/09
Wells Fargo	−3.856 *	4	−3.942 *	4	−6.544 *	4	05/01/09
Barclays	−3.548 *	1	−4.094 *	1	−5.943 *	1	05/04/09
HSBC	−3.103 *	0	−3.451 *	0	−5.308 *	0	05/04/09
Bank of Scotland	−4.648 *	1	−4.715 *	1	−5.585 *	1	08/01/11
Standard Chartered Bank	2.384	0	−2.287	0	−5.153 *	3	04/02/09
Lloyds	−2.349	0	−3.378	0	−5.314 *	0	08/01/11
BNP Paribas	−1.797	3	−2.885	3	−5.767 *	3	07/28/11
Societe Generale	−1.750	3	−2.709	3	−6.667 *	3	08/28/11
Credit Lyonnais	−1.907	3	−3.374	3	−5.210 *	3	07/28/11
Credit Agricole	−2.247	1	−3.979 *	1	−5.235 *	3	07/28/11
Deutsche Bank	−3.448 *	1	−4.409 *	1	−6.230 *	1	08/01/11
Commerzbank	−1.853	3	−3.291	3	−4.871 *	3	07/01/11
ING Bank	−2.176	1	−2.975	1	−4.569	1	04/15/09
SNS Bank	−1.944	0	−1.919	0	−5.582 *	0	04/29/09
Mitsubishi UFJ Bank	−2.503	0	−2.926	0	−4.535	0	08/04/11
Mizuho FG	−2.896 *	2	−3.137	2	−5.008 *	5	03/11/11
(b) individual insurance companies							
Metlife	−2.636	1	−2.867	1	−5.188 *	1	04/06/09
Prudential Financial	−2.397	5	−2.706	5	−5.876 *	5	04/07/09
Hartford	−2.616	4	−2.817	4	−5.397 *	4	04/07/09
Berkshire Hathaway	−2.518	1	−2.672	1	−4.826	1	03/05/09
Cigna	−2.620	2	−2.973	2	−4.492	2	03/09/09
Aetna	−3.438 *	2	−3.825	2	−5.270 *	5	03/09/09
Aviva plc.	−3.092 *	2	−3.073	2	−4.850	2	05/04/09
Prudential plc.	−2.131	3	−2.321	3	−5.853 *	3	03/18/09
AXA	−2.025	1	−2.377	1	−4.074	1	07/26/11
Allianz	−3.488 *	2	−3.814 *	2	−5.880 *	1	05/06/09
Hannover Re.	−2.985 *	1	−3.651 *	1	−4.776	1	04/20/10
ING	2.409	1	−3.345	1	−4.991	1	07/28/11
Aegon	−4.059 *	9	−4.045 *	9	−5.656 *	5	05/04/09
Tokio Marine	−2.615	2	−2.797	2	−6.247 *	2	03/13/09
Sompo Japan	−1.770	0	−2.092	0	−6.293 *	4	03/23/09
Mitsui Sumitomo Insurance	−2.254	0	−2.450	0	−6.293 *	0	03/18/09

Notes) The ADF tests are shown in the columns headed *t* (constant) and *tμ* (constant and trend). Column *t* (*τ*) reports the ZA tests, allowing for one break in both the mean and drift rate of the trend for variables except for Mizuho FG's and ING Bank's CDS spreads, and allowing for one break in the mean for these spreads. Column *TB* reports the estimated date of a structural break. * represents a 5% significant level. Lags denote the lag order determined according to the BIC criterion. Sample period is from January 18, 2008, to September 29, 2012.

Table 2-1 Summary of the level variable statistics

	1/18/08-10/31/09				1/4/11-9/28/12				6/1/08-1/31/09				6/1/11-1/31/12			
	mean	s.e.	maximum	minimum	mean	s.e.	maximum	minimum	mean	s.e.	maximum	minimum	mean	s.e.	maximum	minimum
(1) DEV	0.083	0.075	0.318	−0.023	0.024	0.023	0.058	−0.025	0.156	0.069	0.318	0.078	0.044	0.009	0.058	0.016
(2) MSCI	7.005	0.224	7.353	6.535	7.136	0.057	7.238	6.980	7.008	0.211	7.326	6.648	7.097	0.058	7.210	6.980
(3) Sovereign CDS spreads																
The United States	31.8	24.2	95.0	6.0	44.7	6.7	65.0	27.6	31.8	22.6	85.0	6.0	49.9	4.1	65.0	36.9
Germany	26.3	20.9	92.5	5.2	41.7	13.9	79.3	21.8	22.8	17.9	61.5	5.5	53.0	13.9	79.3	22.9
France	28.2	21.6	93.0	6.0	96.7	32.0	171.6	43.3	29.4	20.5	64.0	7.5	118.1	33.7	171.6	45.5
The United Kingdom	74.9	39.1	165.0	16.5	69.9	13.8	101.6	44.3	63.2	42.3	150.0	16.5	82.4	11.8	101.6	55.6
The Netherlands	44.2	34.8	130.0	6.3	80.6	31.0	133.8	28.1	38.4	35.1	115.0	6.8	84.9	30.1	133.8	28.3
Japan	39.7	25.3	120.0	13.9	58.8	10.8	96.4	34.8	26.4	15.4	58.0	13.9	66.2	9.6	96.4	49.3
(4) Sectoral CDS spreads																
(a) Banking sectors																
The United States	192.8	83.2	458.3	76.3	199.5	65.4	373.1	106.9	212.0	80.8	458.3	107.3	231.2	68.1	373.1	123.0
Germany	99.3	23.0	170.6	54.9	197.6	51.5	353.6	105.4	95.6	16.9	170.6	66.9	214.2	50.3	353.6	131.3
France	86.2	18.2	148.8	49.2	231.0	75.9	383.7	102.7	81.2	12.3	145.4	57.1	247.4	66.5	383.7	125.2
The United Kingdom	124.3	42.4	246.9	53.4	175.4	37.0	266.3	112.1	119.8	28.6	246.9	68.2	196.5	37.1	266.3	133.2
The Netherlands	193.8	95.2	398.8	67.1	254.5	63.4	362.9	157.5	194.3	87.8	319.5	77.0	254.8	53.6	350.3	164.0
Japan	88.3	28.3	152.5	45.3	137.6	29.5	214.8	71.9	101.0	23.5	152.5	50.0	157.5	24.8	214.8	114.6
(b) Insurance sectors																
The United States	409.8	275.7	1139.6	69.0	220.7	65.2	432.5	126.5	421.9	279.1	1139.6	92.9	261.3	69.8	432.5	146.2
Germany	80.3	24.9	167.4	43.2	116.8	14.9	162.1	86.7	82.6	19.8	128.6	57.5	124.7	12.0	162.1	99.2
The United Kingdom	219.1	141.9	719.7	66.7	154.4	24.0	214.6	110.1	201.7	114.3	427.5	80.0	166.1	21.3	214.6	131.2
The Netherlands	170.6	70.9	366.4	77.0	204.8	47.4	289.8	120.1	184.4	73.6	357.9	83.8	213.4	39.3	276.2	137.9
Japan	124.9	84.6	397.9	39.6	74.9	8.8	101.6	52.8	124.2	77.7	252.3	39.6	78.8	7.0	101.6	70.5
(5) CDS spreads of individual financial institutions																
(a) Banks																
Morgan Stanley	287.6	185.0	1251.0	105.3	288.3	114.1	619.0	132.5	398.9	238.7	1251.0	158.2	324.3	117.6	619.0	138.3
Goldman Sachs	202.1	104.0	630.8	81.8	232.2	85.5	443.8	102.0	262.1	117.9	630.8	104.1	265.3	86.9	443.8	134.8
JP Morgan & Chase	116.7	42.0	310.0	53.1	113.4	30.0	194.1	66.4	129.3	31.3	310.0	85.0	127.0	28.1	194.1	76.3
Bank of America	156.8	68.6	390.0	59.1	250.5	94.0	500.5	127.4	141.9	34.7	300.0	86.6	315.8	100.6	500.5	150.0
Citigroup	265.6	143.0	660.0	79.6	204.7	56.7	363.9	120.6	213.7	76.3	502.8	118.8	224.9	56.9	363.9	131.4
Wells Fargo	128.0	53.9	310.0	57.5	107.7	25.7	185.9	75.3	126.0	31.1	280.0	80.0	130.2	24.7	185.9	86.5
Barclays	129.7	46.5	252.0	52.7	181.5	46.0	277.8	103.9	139.7	35.4	252.0	72.8	196.4	43.1	277.8	122.6
HSBC	85.6	31.3	180.1	41.0	115.1	28.2	189.2	72.4	83.5	23.1	147.0	52.0	123.5	29.1	189.2	75.5
Standard Chartered Bank	134.1	74.2	358.8	47.2	136.7	33.1	215.6	82.3	119.8	47.1	225.5	57.0	154.7	32.4	215.6	96.2
Bank of Scotland	155.6	51.5	525.0	70.2	182.9	37.9	289.8	112.4	159.4	62.2	525.0	90.0	215.7	37.0	289.8	147.9
Lloyds	116.6	47.3	230.1	41.0	260.8	59.3	384.5	159.8	96.4	30.7	214.0	52.0	292.1	53.9	384.5	194.3
BNP Paribas	68.8	18.4	136.7	36.8	199.6	70.4	367.2	85.5	63.9	10.0	107.6	41.0	225.0	65.2	367.2	110.3
Societe Generale	92.6	19.7	158.0	46.8	256.1	91.2	436.4	108.1	90.6	16.8	158.0	53.6	291.4	89.0	436.4	128.9
Credit Lyonais	93.0	19.8	167.6	52.6	239.3	75.1	416.1	111.3	86.6	15.5	164.0	57.4	242.3	58.3	374.5	134.0
Credit Agricole	90.4	19.1	160.0	54.3	229.1	72.3	401.5	106.0	83.8	15.0	160.0	56.0	230.9	55.7	356.7	127.6
Deutsche Bank	105.0	26.8	178.5	53.5	160.8	47.1	327.6	86.4	107.7	25.5	178.5	63.0	177.6	48.8	327.6	100.9
Commerzbank	93.7	23.7	173.8	56.2	234.3	57.7	379.6	123.8	83.5	14.2	168.0	62.5	250.8	54.5	379.6	159.6
ING Bank	98.5	31.0	185.5	48.8	177.7	50.1	269.6	92.2	103.6	24.2	170.0	55.9	186.7	43.9	257.8	106.6
SNS Bank	289.0	170.9	632.5	62.4	331.3	80.3	465.3	217.9	285.1	159.7	495.0	98.1	322.9	66.2	465.3	221.3
Mitsubishi UFJ Bank	81.3	28.0	140.0	38.0	123.9	29.3	199.6	68.3	96.7	21.2	140.0	42.5	140.7	27.9	199.6	91.1
Mizuho FG	92.7	30.6	165.0	36.5	151.3	30.9	230.0	75.5	105.4	27.1	165.0	57.5	174.3	22.8	230.0	138.0
all individual banks	137.3	58.8	1251.0	36.5	198.9	57.9	619.0	66.4	141.8	50.4	1251.0	41.0	219.6	54.4	619.0	75.5
(b) Insurers																
Metlife	385.6	247.5	1047.4	66.1	224.0	67.0	408.7	121.6	398.9	247.0	966.9	95.1	261.5	70.6	408.7	144.1
Prudential Financial	436.7	306.8	1373.7	85.5	194.4	52.7	376.5	121.6	481.0	333.2	1373.7	105.0	225.5	55.6	376.5	132.8
Hartford	407.1	281.1	1161.2	48.5	243.6	78.3	512.3	136.2	385.7	263.7	1078.2	76.5	296.9	85.7	512.3	150.0
Berkshire Hathaway	200.0	116.9	525.0	41.5	142.0	35.9	284.6	87.1	203.8	115.2	500.0	60.5	169.0	39.4	284.6	108.0
Cigna	151.9	84.8	389.4	49.2	87.9	17.6	134.6	64.2	156.5	113.8	389.4	59.4	101.8	17.8	134.6	72.3
Aetna	88.5	33.5	185.0	45.0	66.4	10.0	94.0	44.9	92.7	41.4	185.0	49.0	74.3	8.0	94.0	57.3
Aviva	177.5	83.6	502.5	70.1	164.6	30.7	231.0	102.5	151.5	48.4	247.5	100.4	170.9	22.2	221.9	131.1
Prudential plc.	260.6	207.0	936.9	57.6	144.1	22.6	212.0	104.2	252.0	183.4	607.5	59.6	161.2	23.9	212.0	124.4
AXA	132.8	51.1	270.0	55.0	243.7	76.9	396.8	127.3	152.6	49.2	250.0	93.8	276.9	75.4	396.8	156.4
Allianz	88.5	29.0	194.8	44.6	111.5	23.6	181.8	70.2	90.8	28.4	153.8	56.5	118.2	24.9	181.8	78.2
Hannover Re.	72.2	23.0	147.1	32.0	122.1	15.9	159.7	88.4	74.4	12.6	120.0	55.0	131.2	16.3	159.7	98.2
ING Bank	99.7	31.1	184.0	47.0	177.8	49.9	271.6	92.2	105.2	26.8	182.0	56.0	186.3	43.3	251.8	106.9
Aegon	241.5	117.9	563.8	81.9	231.9	47.5	320.3	148.1	263.7	128.5	563.8	109.5	240.6	38.7	315.4	168.8
Tokio Marine	98.2	61.3	311.0	31.5	69.1	8.6	92.8	50.0	101.8	60.5	211.0	31.5	73.1	6.4	92.8	64.4
Sompo Japan	170.3	131.7	577.3	47.8	84.1	10.3	117.0	53.0	157.4	109.7	358.5	48.5	89.7	8.8	117.0	76.0
Mitsui Sumitomo Insurance	106.1	63.8	305.3	38.8	71.6	8.7	95.0	50.5	113.3	64.2	222.8	38.8	73.7	7.0	95.0	64.9
all individual insurers	194.8	116.9	1373.7	31.5	148.7	34.8	512.3	44.9	198.8	114.1	1373.7	31.5	165.7	34.0	512.3	57.3

creditworthiness caused by the worldwide stock price plummet after February 2009. For the second crisis, most of the financial institutions experienced the highest level of their CDS spreads during the sub-period.

Tables 2-2 and 2-3 show summaries of the statistics for the differences and detrendings of the variables employed in the empirical analyses and omit the results for individual sectors' and financial institutions' CDS spreads. In addition, these tables only focus on the two sub-periods'

Table 2-2 Summary of statistics for the difference of variables

	6/1/08-1/31/09				6/1/11-1/31/12			
	mean	s.e.	maximum	minimum	mean	s.e.	maximum	minimum
(1) DEV	−0.005%	1.250%	6.913%	−5.914%	−0.012%	0.346%	1.154%	−1.349%
(2) MSCI	−0.347%	2.437%	9.097%	−7.325%	−0.050%	1.540%	4.112%	−5.256%
(3) Sovereign CDS spreads All countries	0.43	2.60	43.60	−16.00	0.17	4.60	29.10	−29.50
(4) Sectoral CDS spreads								
(a) All banking sectors	0.51	13.01	179.90	−260.50	0.38	10.22	51.50	−46.50
(b) All insurance sectors	1.23	17.70	319.90	−237.00	0.23	6.58	47.00	−52.80
(5) CDS spreads of individual financial institutions								
(a) all individual banks	0.52	17.62	382.50	−831.00	0.41	11.61	127.40	−89.10
(b) all individual insurers	1.22	18.34	344.80	−286.00	0.24	6.77	54.90	−59.50

Table 2-3 Summary of statistics for the detrended variables

	6/1/08-1/31/09				6/1/11-1/31/12			
	mean	s.e.	maximum	minimum	mean	s.e.	maximum	minimum
(1) DEV	1.69%	6.26%	17.98%	−7.02%	2.65%	0.86%	4.26%	0.22%
(2) MSCI	2.81%	9.97%	16.41%	−23.96%	−2.90%	6.65%	10.20%	−14.65%
(3) Sovereign CDS spreads All countries	−0.04%	0.12%	0.37%	−0.32%	0.08%	0.15%	0.54%	−0.72%
(4) Sectoral CDS spreads								
(a) All banking sectors	−0.10%	0.32%	1.56%	−1.61%	0.14%	0.38%	1.39%	−1.01%
(b) All insurance sectors	−0.28%	0.73%	5.70%	−2.45%	0.18%	0.33%	2.12%	−0.90%
(5) CDS spreads of individual financial institutions								
(a) all individual banks	−0.02%	0.42%	7.31%	−2.33%	0.14%	0.41%	3.50%	−2.00%
(b) all individual insurers	−0.21%	0.76%	7.39%	−2.87%	0.18%	0.33%	2.72%	−1.36%

results. In Table 2-2, both the mean and the standard error of DEV are lower in the second crisis sub-period, indicating that liquidity conditions under the European sovereign crisis were more stable than that of the period including the Lehman shock. MSCI also indicates that the world stock markets went into havoc and experienced a sharper decline during the first crisis sub-period. The daily change rate of MSCI for that period is −0.327%, interpreted as more than an 8% decline per month.

The fourth row in Table 2-2 shows the average of the mean and standard error for the sectoral CDS spreads of the six countries, and the maximum and minimum values among them. Both the banking and insurance sectors' CDS spreads reveal higher mean values and larger standard errors during the first sub-period. The increase in the US banking sector's CDS spreads is the highest among the six countries. On September 16, 2008, it rose by 179.9 basis points. The US insurance sector also reveals the highest increase and rose by 319.9 basis points on October 2, 2008. The fifth row in the table reports the average of the mean and standard error for individual financial institutions, and the maximum and minimum value among them. As for banks, the CDS spread of Morgan Stanley presents the highest increase for the two sub-periods and jumped by 382.5

basis points on September 16, 2008, and by 127.4 basis points on October 3, 2011. Among insurance companies, Prudential Financial increased the most and rose by 344.8 basis points on October 2, 2008. On the same day, the CDS spread of Metlife and Hartford increased by 326 and 289 basis points, respectively. During the second period, these three US insurance companies also revealed a particularly higher increase, the maximum being Hartford, by 54.0 basis points on October 3, 2011.

Lastly, Table 2-3 presents a summary of the statistics for the detrended variables for the two sub-sample periods. Although the mean of DEV is lower and that of MSCI is higher during the first crisis sub-period, the standard errors of the two variables are larger, which also suggests that the global financial markets suffered more seriously from instability during the period.

The third row in Table 2-3 shows the average of the mean and standard error for the sovereign CDS spreads of the six countries and the maximum and minimum values among them. The mean and standard error are higher in the second sub-period. Because the standard errors of the sovereign CDS spreads of Germany, France, and the Netherlands largely increase, the averaged standard error also increases in spite of the decline in the standard error of the US sovereign CDS spread. The fourth and fifth rows of the table show the results of the sectoral and individual CDS spreads. The maximums of the two periods of the banking sectors are of the US banking sector at 1.56% and 1.39%, respectively. The maximums of the insurance sectors are also of the US insurance sector, and are 5.7% for the first crisis sub-period and 2.12% for the second sub-period. Among the CDS spreads of individual banks, Morgan Stanley also reveals the highest value for the two sub-periods. As for insurers, Prudential Financial presents the highest value for the first period and Hartford for the second. The standard errors of the CDS spreads of the three insurance companies, including Metlife, are exceptionally high.

5. Empirical results

5.1. Connectedness indices derived from using sectoral CDS spreads

This subsection presents the results of the connectedness index developed by Diebold and Yilmaz (2009, 2012). The three types of connectedness are shown; that is, the connectedness 1) from financial institutions (FIs) to DEV representing the effect of FIs' aggravated creditworthiness on fundraising liquidity condition, 2) from DEV to FIs indicating the effect of the tightened liquidity on FIs' creditworthiness and 3) across FIs showing the amplified turmoil caused by the domino effect across FIs caused by factors other than common factors.

Table 3 reports the results derived from the six-variable SVAR model specified in Equation (1) estimated for the two crisis sub-periods. The lag order is determined according to the AIC criterion. Numbers are the relative contributions of shocks calculated based on the 25 step-ahead

Table 3-1 Connectedness derived from the two-country one-sector model with six variables

<Detrendings>

	Frist Crisis Period				Second Crisis Period			
	Banks		Insurers		Banks		Insurers	
Connectedness from FIs to DEV	21.77		21.01		9.91		14.75	
Connectedness from DEV to FIs	7.08		9.77		5.72		3.39	
Connectedness across FIs	21.99	(33.76)	16.07	(31.53)	16.58	(41.58)	9.37	(34.94)

<Levels>

	Frist Crisis Period				Second Crisis Period			
	Banks		Insurers		Banks		Insurers	
Connectedness from FIs to DEV	37.35		18.87		13.39		17.00	
Connectedness from DEV to FIs	5.41		15.04		4.61		3.81	
Connectedness across FIs	22.32	(31.79)	14.93	(33.23)	6.91	(29.95)	11.22	(39.71)

<Differences>

	Frist Crisis Period				Second Crisis Period			
	Banks		Insurers		Banks		Insurers	
Connectedness from FIs to DEV	23.70		21.21		8.28		6.98	
Connectedness from DEV to FIs	3.02		2.60		3.49		3.22	
Connectedness across FIs	20.14	(26.93)	23.60	(30.65)	9.95	(22.89)	14.36	(34.01)

Notes) The first crisis period is from June 1, 2008, to January 31, 2009, and the second is from June 1, 2011, to January 31, 2012. Connectedness from FIs to DEV is calculated as the sum of the relative contributions of two financial sectors' idiosyncratic shocks to DEV. Connectedness from DEV to FIs is derived by taking an average of the relative contribution of DEV to each financial sector's CDS spread. Connectedness across FIs signifies the average of the relative contribution of the idiosyncratic shock of each financial sector to another (the average of numbers in (5, 6) element and in (6, 5) element in the 6 × 6 variance decomposition matrix). The numbers in parentheses are the ratio of the sum of the off-diagonal contributions of idiosyncratic shocks to the sum of all the idiosyncratic shocks contributions (the ratio of the sum of numbers in (5, 6) element and in (6, 5) element in the variance decomposition matrix relative to the sum of numbers in elements of (5, 5), (5, 6), (6, 5), and (6, 6) in the matrix).

forecasting error's variance. Table 3-1 contains the results of the two-country one-sector model and Table 3-2 the results of the two-country two-sector model. Connectedness indices are calculated by averaging the connectedness obtained from a model of a combination of two nations chosen from the six countries. In taking two out of the six countries, 15 combinations can be made. Table 3-1 shows the average of the 15 connectedness indices derived from each estimation for each industry, in using the detrendings, the levels, and the differences of the variables, respectively. Table 3-2 also includes the results of using and replacing the banking and insurance sectors' CDS spreads for the two-country pair. In taking a pair of the US and Germany as an example, two models can be made; one adopting the US banking and German insurance sectors' CDS spreads, and the other adopting the German banking and US insurance sectors' CDS spread. Table 3-2 shows the averaged connectedness of 30 combinations of two-country and two-industry.

We can confirm that the influence of the liquidity squeeze on the financial institutions' creditworthiness as well as the feedback effect observed during the first crisis period were more in evidence compared with those during the second, which is consistent with our expectation. Whereas the international financial markets again experienced turmoil after 2010 that was triggered by the Greek sovereign crisis, major countries had already implemented radically eased

Table 3-2 Connectedness derived from the two-country two-sector model with six variables

<Detrendings>

	First Crisis Period		Second Crisis Period	
	Banks	Insurers	Banks	Insurers
Connectedness from FIs to DEV	12.10	10.15	5.72	6.38
Connectedness from DEV to FIs	7.14	9.67	5.71	2.84
Connectedness across FIs	17.53	(30.98)	11.85	(35.04)
Banks		21.07		14.13
Insurers	13.99		9.57	

<Levels>

	First Crisis Period		Second Crisis Period	
	Banks	Insurers	Banks	Insurers
Connectedness from FIs to DEV	20.74	12.36	5.94	8.82
Connectedness from DEV to FIs	6.13	12.22	6.05	3.67
Connectedness across FIs	18.38	(30.73)	8.53	(33.94)
Banks		19.39		9.41
Insurers	17.36		7.65	

<Differences>

	First Crisis Period		Second Crisis Period	
	Banks	Insurers	Banks	Insurers
Connectedness from FIs to DEV	11.99	9.08	4.65	2.82
Connectedness from DEV to FIs	3.03	2.26	2.93	3.32
Connectedness across FIs	21.41	(27.99)	11.39	(26.42)
Banks		22.99		10.45
Insurers	19.84		12.32	

Notes) The first crisis period is from June 1, 2008, to January 31, 2009, and the second is from June 1, 2011, to January 31, 2012. Connectedness from FIs to DEV is calculated as the sum of the relative contributions of two financial sectors' idiosyncratic shocks to DEV. Connectedness from DEV to FIs is derived by taking an average of the relative contribution of DEV to each financial sector's CDS spread. Connectedness across FIs signifies the average of the relative contribution of the idiosyncratic shock of each financial sector to the other (the average of numbers in (5, 6) element and in (6, 5) element in the 6 × 6 variance decomposition matrix). The numbers in parentheses are the ratio of the sum of the off-diagonal contributions of idiosyncratic shocks to the sum of all idiosyncratic shock contributions (the ratio of the sum of numbers in (5, 6) element and in (6, 5) element in the variance decomposition matrix relative to the sum of numbers in elements of (5, 5), (5, 6), (6, 5), and (6, 6) in the matrix). Connectedness across FIs also include the relative contribution of the banking (insurance) sector's idiosyncratic shock in a country to the insurance (banking) sector's CDS spread in another country.

monetary policies to provide extraordinarily abundant liquidity to international financial markets. In the Eurozone, the ECB decided to introduce a series of untraditional measures in response to the domino effect of sovereign risks toward the core nations, which was inferred to halt aggravation of the liquidity crunch in a spiral course[22].

We can also see, in tests using the level variables in both Tables 3-1 and 3-2, that the connectedness from the banking sectors' idiosyncratic shocks to DEV is much higher than that of insurance sectors to DEV, suggesting that banks have more effect on the liquidity condition. This is also consistent with our expectation, and the severe global liquidity crunch might largely be attributed to the aggravated soundness of global banks. The connectedness from DEV to insurance sectors, by contrast, is significantly larger than that from DEV to banking sectors. Except for the result obtained from the estimation using the differences indicating that banking sectors were slightly more susceptible to the liquidity squeeze than insurance sectors, similar results are obtained from tests using the detrendings and the differences.

These results imply that banks had a larger responsibility for the global liquidity tightening and insurers played a susceptible role. The extent that insurers were affected by the liquidity squeeze was, however, by no means small. Insurers have been considered to be less affected by liquidity pressures because most insurers' liabilities are long-term debt. This study suggests that insurers are not isolated from the fundraising liquidity problem.

Connectedness across FIs represents the magnitude of the transmission effect of one financial institution's idiosyncratic shock to another. While banks seem to be more vulnerable to a shock happening within their own industry in the tests using the detrendings and the levels shown in Table 3-1, it is not clear which sector is more interdependent. The two-country two-sector model, which suggests a transmission from one sector to the other, indicates that insurers are likely to be more influential than banks.

To see the robustness of the results, connectedness indices calculated from a recursive-type SVAR are shown in Table 4. Here, we only focus on the connectedness for the first crisis period. Because the result of a recursive-type model depends on the ordering of variables, we also conduct an analysis in which the order of the first and second countries is reversed. Therefore, we show the average of the 30 connectedness indices obtained from the 15 country combinations

Table 4 Connectedness derived from the six-variable recursive model of two-country one-sector for the first crisis period

<Detrendings>

	Banks		Insurers	
Connectedness from FIs to DEV	21.71		20.85	
Connectedness from DEV to FIs	7.14		9.77	
Connectedness across FIs	16.06	(24.57)	14.75	(29.43)

<Levels>

	Banks		Insurers	
Connectedness from FIs to DEV	37.80		17.49	
Connectedness from DEV to FIs	5.35		14.83	
Connectedness across FIs	17.51	(25.22)	12.57	(27.54)

<Differences>

	Banks		Insurers	
Connectedness from FIs to DEV	23.50		20.87	
Connectedness from DEV to FIs	3.03		2.60	
Connectedness across FIs	15.62	(20.89)	15.33	(19.98)

Notes) The sample is from June 1, 2008, to January 31, 2009. Connectedness from FIs to DEV is calculated as the sum of the relative contributions of two financial sectors' idiosyncratic shocks to DEV. Connectedness from DEV to FIs is derived by taking an average of the relative contribution of DEV to each financial sector's CDS spread. Connectedness across FIs signifies the average of the relative contribution of each financial sector's idiosyncratic shock to the other (the average of numbers in (5, 6) element and in (6, 5) element in the 6 × 6 variance decomposition matrix). The numbers in parentheses are the ratio of the sum of the off-diagonal contributions of idiosyncratic shocks to the sum of all idiosyncratic shocks' contributions (the ratio of the sum of numbers in (5, 6) element and in (6, 5) element in the variance decomposition matrix relative to the sum of numbers in elements of (5, 5), (5, 6), (6, 5) and (6, 6) in the matrix).

Table 5-1 Connectedness derived from the ten-variable four-country one-sector model for the first crisis period

<Detrendings>

	Banks		Insurers	
Connectedness from FIs to DEV	19.65		15.96	
Connectedness from DEV to FIs	3.36		1.32	
Connectedness across FIs	40.22	(60.37)	35.52	(64.53)

<Levels>

	Banks		Insurers	
Connectedness from FIs to DEV	42.21		23.14	
Connectedness from DEV to FIs	2.99		9.90	
Connectedness across FIs	33.24	(57.60)	26.06	(64.45)

<Differences>

	Banks		Insurers	
Connectedness from FIs to DEV	26.96		23.51	
Connectedness from DEV to FIs	2.16		1.60	
Connectedness across FIs	34.75	(46.09)	45.50	(58.84)

Notes) The sample period is from January 18, 2008, to October 31, 2009. Connectedness from FIs to DEV is calculated as the sum of the relative contributions of four financial sectors' idiosyncratic shocks to DEV. Connectedness from DEV to FIs is derived by taking an average of the relative contribution of DEV to each financial sector's CDS spread. Connectedness across FIs is calculated by adding the relative contributions of the financial sectors' idiosyncratic shocks, except for an own shock, for each financial sector's CDS spread, and averaging them. The numbers in parentheses are calculated by adding the relative contributions of the financial sectors' idiosyncratic shocks, except for own shocks, for all the four countries and then dividing it by the sum of the relative contributions of the financial sectors idiosyncratic shocks including own shocks.

in Table 4. We can confirm similar results.

Tables 5-1 and 5-2 report the results using the ten-variable four-country one-sector model specified in Equation (11-1), and the eight-variable two-country two-sector model specified in Equation (11-2). Because the number of coefficients estimated increases, the sample period is extended and is determined as the full period from January 18, 2008, to October 31, 2009.

Compared with the results presented in Tables 3 and 4, connectedness from DEV to FIs shown in Table 5 decreases sharply, implying that the effect of the liquidity squeeze only lasted for a limited period. Ohno (2016) conducts historical decompositions to explore the effect of liquidity squeeze on insurance companies, and revealed that one third of the sharp increase in US insurance companies' CDS spreads in October 2008 was attributed to the liquidity dry-up and its effect had almost ceased by the end of December. We can again see the tendency that banks had more influence in the liquidity squeeze than insurance companies.

While mutual interdependence within the global banking markets seems to be more prominent according to the connectedness across FIs' indices, insurance sectors reveal higher connectedness when excluding the contributions of common factors. This is because insurance sectors were likely to receive a larger effect from common factors. Table 5-2 reports that intra-industry interdependencies were more prominent than inter-industry interdependencies, which may be consistent with our intuition. No clear results have been obtained as to which of the banking and insurance sectors were more influential[23].

Table 5-2 Connectedness derived from the eight-variable two-country two-sector model for the first crisis period

<Detrendings>

	Banks	Insurers
Connectedness from FIs to DEV	9.63	6.13
Connectedness from DEV to FIs	3.82	1.01
Connectedness across FIs	27.16	(43.34)
Banks	10.69	8.23
Insurers	6.57	14.04

<Levels>

	Banks	Insurers
Connectedness from FIs to DEV	26.27	11.55
Connectedness from DEV to FIs	3.72	5.05
Connectedness across FIs	30.49	(54.15)
Banks	12.14	9.61
Insurers	9.61	10.39

<Differences>

	Banks	Insurers
Connectedness from FIs to DEV	13.18	9.04
Connectedness from DEV to FIs	2.08	1.28
Connectedness across FIs	34.10	(43.22)
Banks	11.17	9.98
Insurers	11.52	14.04

Notes) The sample period is from January 18, 2008, to October 31, 2009. Connectedness from FIs to DEV is calculated as the sum of the relative contributions of two financial sectors' idiosyncratic shocks to DEV. Connectedness from DEV to FIs is derived by taking an average of the relative contribution of DEV to each financial sector's CDS spread. Connectedness across FIs is calculated by adding the relative contributions of the financial sectors' idiosyncratic shocks, except for an own shock, for each financial sector's CDS spread, and averaging them. The numbers in parentheses are calculated by adding the relative contributions of the financial sectors' idiosyncratic shocks, except for own shocks, for all four countries and then dividing it by the sum of the relative contributions of the financial institutions idiosyncratic shocks including own shocks. The matrix described from the fifth to sixth lines in each sub-table presents connectedness indicating intra-industry (diagonal elements) and inter-industry (off-diagonal elements) interdependencies.

Banks and insurance companies are believed to be closely connected through money markets and derivative transactions. During the first crisis period, insurance companies possibly received sufficient influence from banks through the trades of ABCP issued by a SIV under banks, which might be one cause for the transmission of credit risks of banks to insurance companies. This evidence suggests that the development of systemic risk originating from insurance companies cannot be ignored.

5.2. Connectedness indices derived from using individual CDS spreads

In this subsection, connectedness indices calculated by using individual financial institutions' CDS spreads are shown. A recursive-type SVAR model constituting four variables with the ordering of DEV, MSCI, the sovereign CDS spread of a nation, and the CDS spread of a financial institution located in the country is used to elucidate the reactions of an individual financial institution to a shock in fundraising liquidity as well as the feedback effect. Connectedness from DEV to FIs denoted as "DEV⇒FI" is the relative contribution of a shock in DEV to each financial institution's CDS spread, and connectedness from FIs to DEV designated as

"FI⇒DEV" is the relative contribution of a shock in a financial institution's CDS spread to DEV. Numbers are calculated based on the variance of a 25 step-ahead forecast error. Models are estimated for the period from June 1, 2008, to January 31, 2009.

The evidence shown in Table 6 is consistent with that obtained in the previous subsection. Indices representing connectedness from a financial institution to DEV are higher for banks than insurance companies, and the hypothesis that banks have a larger responsibility for the stability of liquidity conditions is plausible. It should be noted, however, that several insurance companies such as Metlife and Prudential Financial, which are defined as a G-SII, and ING also presented a prominent influence on liquidity conditions. Indices for the connectedness from DEV to a financial institution, on the other hand, are higher for insurance companies except for the tests in using the differences of variables. US insurance companies including Metlife, Prudential Financial, and Hartford show a particularly large reaction to a shock in the fundraising liquidity indicator.

Table 7 shows numbers taken from the matrix of variance decompositions, selecting three US insurance companies as an example. The contribution of DEV to MSCI obtained in the three tests is almost the same. The contribution of DEV to Hartford's CDS spread is evidently larger than that of Cigna and Aetna. Table 7 also reveals that all of the three insurers' CDS spreads were largely affected by MSCI.

Hartford, which sold variable annuity products with minimum guarantees as a core business, suffered severely from the financial turmoil and was forced to accept the public financial bailout. The large influence of DEV on Hartford may reflect the situation where Hartford was required to raise additional capital in order to compensate for the loss in the value of the assets caused by the distress sales of securities. The decline in securities prices, partly as a result of the severe liquidity squeeze, may also hurt other insurance companies including those engaging in traditional insurance businesses, because they invest in securities to meet the required liabilities reserve in preparation for insurance payment[24].

Fig. 1 reports the relative contribution of a shock in DEV to Aetna's and Hartford's CDS spreads derived from historical decompositions for the four-variable recursive model including the two insurers's CDS spreads, respectively. It is confirmed that the timing that the shock in DEV becomes dominant is almost the same and the magnitude of its contribution abruptly increases after September 16, 2008. On October 7, 2008, Aetna's CDS, who was hardly believed to suffer from the liquidity problem, increased to 62.5 basis points and 26.5% of it was attributed to the liquidity squeeze. A possible cause of it is the aggravation of the market risk appetite. The increase in Hartford's CDS spread, by contrast, might be intensified because of the change in the market risk appetite as well as the deterioration of its creditworthiness. The relative contribution

Table 6 Connectedness derived from the four-variable recursive model in using individual financial institutions' CDS spreads

	Detrendings		Levels		Differences	
	DEV ⇒ FI	FI ⇒ DEV	DEV ⇒ FI	FI ⇒ DEV	DEV ⇒ FI	FI ⇒ DEV
<Banks>						
Morgan Stanley	15.88	23.74	12.12	30.87	15.47	4.30
Goldman Sachs	7.47	9.41	8.52	34.47	7.77	3.84
JP Morgan & Chase	2.21	6.40	2.98	15.48	4.39	14.63
Bank of America	1.03	11.10	3.07	10.28	7.99	12.21
Citigroup	0.82	1.08	4.56	16.38	5.62	4.71
Wells Fargo	8.89	2.54	4.82	9.61	5.43	13.70
Barclays	4.93	6.54	0.98	28.53	3.30	21.59
HSBC	3.74	4.37	1.00	47.75	0.96	17.38
Scotland Bank	10.20	8.13	10.45	43.90	2.12	28.27
Standard Chartered	0.57	4.12	3.99	20.77	2.10	14.62
Lloys	14.79	18.61	8.36	65.11	3.22	8.14
BNP Paribas	1.39	4.27	6.87	44.73	5.39	10.75
Societe Generale	10.92	4.77	6.66	37.46	8.23	5.02
Credit Lyonais	4.97	3.36	8.13	27.23	2.57	3.23
Credit Agricole	4.95	3.25	9.05	28.62	3.72	5.44
Deutschebank	12.12	9.79	1.84	35.70	3.69	6.89
Commerzbank	9.92	3.90	0.78	20.24	1.67	14.92
ING Bank	10.13	11.99	0.93	45.04	2.05	12.90
SNS Bank	9.36	18.94	11.00	3.28	0.41	8.40
Mitsubishi UFJ	0.77	7.57	9.19	0.86	0.51	6.37
Mizuho FG	2.64	14.23	11.96	2.29	4.96	4.94
Average	6.56	8.48	6.06	27.07	4.36	10.58
Maximum	15.88	23.74	12.12	65.11	15.47	28.27
Minimum	0.57	1.08	0.78	0.86	0.41	3.23
<Insurers>						
Metlife	18.73	22.15	13.55	13.28	4.23	5.68
Prudential Financial	12.75	15.71	22.83	2.17	3.15	1.81
Hartford	22.81	5.73	37.40	1.00	5.26	2.88
Berkshire Hathaway	6.69	2.03	13.27	0.37	1.08	2.16
Cigna	2.38	3.10	20.11	3.18	0.39	0.77
Aetna	4.60	2.31	29.72	4.90	6.42	2.55
Aviva	0.30	2.42	3.81	1.02	1.90	12.17
Prudential	27.25	8.47	6.60	1.60	1.05	4.20
AXA	5.90	9.46	36.83	0.87	1.06	5.24
Allianz	2.82	5.05	8.88	1.37	6.46	11.48
Hannover Re	2.96	1.91	2.66	8.90	1.53	23.11
ING	5.76	15.44	1.72	57.15	2.68	13.00
Aegon	29.17	11.90	30.27	5.59	2.50	4.75
Tokyo Marine	6.97	2.38	10.50	0.44	0.90	13.15
Sompo Japan	1.87	0.80	4.17	1.18	1.05	11.98
Mitsui Sumitomo	4.70	2.63	11.29	0.38	0.19	14.52
Average	9.73	6.97	15.85	6.46	2.49	8.09
Maximum	29.17	22.15	37.40	57.15	6.46	23.11
Minimum	0.30	0.80	1.72	0.37	0.39	0.77

Notes) The sample period is from June 1, 2008, to January 31, 2009. Column "DEV ⇒ FI" reports connectedness from DEV to FIs and column "FI ⇒ DEV presents connectedness from FIs to DEV.

Table 7 Relationship between DEV, MSCI, and US insurance companies' CDS spread

<Hartford>

DEV ⇒ MSCI	19.7
DEV ⇒ Hartford	22.8
MSCI ⇒ Hartford	11.3

<Cigna>

DEV ⇒ MSCI	18.3
DEV ⇒ Cigna	2.4
MSCI ⇒ Cigna	25.4

<Aetna>

DEV ⇒ MSCI	18.6
DEV ⇒ Aetna	4.6
MSCI ⇒ Aetna	43.8

Notes) Models are estimated using the detrended variables. The sample period is from June 1, 2008, to January 31, 2009. The CDS spreads of Hartford, Cigna, and Aetna are selected as the fourth variable in the VAR model. Common factors including DEV, MSCI, and the US sovereign CDS spreads are included as the first, second, and third variables of the model in the three tests. Row "DEV ⇒ MSCI" denotes the relative contribution of a shock in DEV to MSCI. Row "DEV ⇒ insurer" reports the relative contribution of a shock in DEV to an insurer's CDS spread. Row "MSCI ⇒ insurer" shows the relative contribution of a shock in MSCI to an insurer's CDS spread.

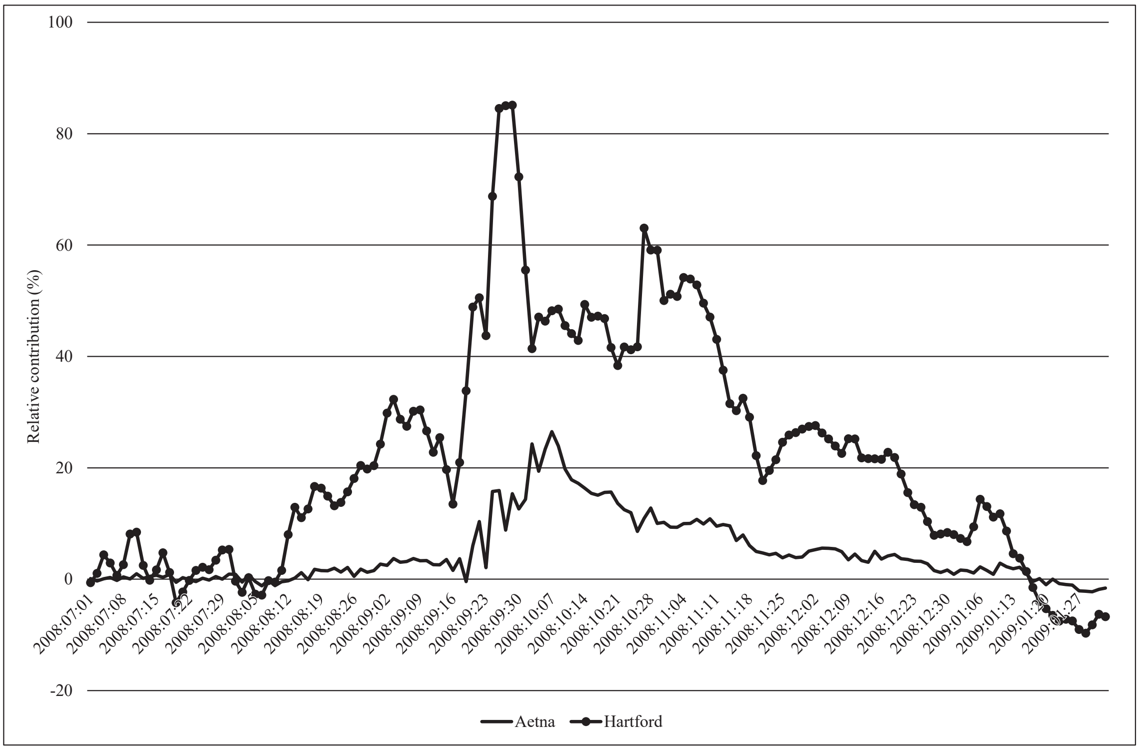

Fig. 1 Relative contribution of a shock in DEV to Aetna's and Hartford's CDS spreads

Note) The relative contribution is derived by accumulating a shock of DEV produced from historical decomposition and then dividing it by an insurer's CDS spread.

of DEV for Aetna exceeds 10% only for the period from the middle of September to the middle of November and continues to decline afterward. The result infers that insurers engaging in traditional insurance businesses might also be influenced by the severe liquidity squeeze for an extremely short period[25].

6. Conclusions

The following are the salient conclusions obtained from the empirical analyses of this study.

First, results show that not only banks but also insurance companies sustained serious adverse effects from the liquidity squeeze. In actuality, AIG and monoline companies, which were not included in this analysis, might have been severely affected by the liquidity crunch. This finding implies that insurance companies, including those mainly engaged in traditional insurance business activities, were susceptible to liquidity dry-up. We also found that insurance companies engaging more intensively in NTNI activities were more vulnerable to the liquidity crunch, which is consistent with our intuition. Insurance companies selling variable annuity products with minimum guarantees as a main product held a portfolio with a higher percentage of risky securities to aim at higher investment yields. Under the stressful conditions, where risky asset prices plunged because of the liquidity squeeze, they were required to raise additional funds to compensate for insufficient policy reserves. Insurance companies whose main business was traditional insurance activities, however, were also affected by the liquidity squeeze because they also held risky assets to achieve the predicted interest rate required by insurance products. The result infers that insurers that are collectively forced to liquidate assets in a stressful environment to meet the withdrawals from policyholders who become skeptical about the soundness of held assets and the viability of a specific business model are significantly damaged. The requirement to hold additional equity capital as a risk buffer can partially help to isolate insurers from the spirally aggravating liquidity problem.

Secondly, not only financial institutions were affected by the liquidity crunch. The feedback effect from the aggravated credit risk of financial institutions on further liquidity availability problem was also detected, and this tendency was more readily apparent for banks than insurance companies. We can interpret that banks had a larger responsibility for the stability of liquidity conditions and insurers possibly played a subordinate role.

Although insurance companies targeted for these analyses were susceptible to the liquidity crunch, the development of systemic fundraising liquidity risk originating from insurance companies was not highly plausible. It should be noted, however, that the degree of the effect might differ across insurers depending on their size and the extent of their involvement in NTNI activities. With regard to the mutual dependence across financial institutions, whether banks or insurers were more dominant has not been clearly determined. The possibility that the deterioration of financial soundness of an insurance company negatively affected money markets and derivatives markets through lending relationships cannot be ignored and should be examined in more depth in the future. The effect of the erosion of insurance companies' soundness as a result of their borrowers' bankruptcy, for example, might also be propagated to the rest of the financial system via cross-holdings and other activities with other financial institutions.

The IAIS has determined to focus the development of ABA policy measures on liquidity and macroeconomic risk exposures as the underlying exposures could be strongly correlated across institutions and have the potential to cause a number of correlated cases of distress responses. To the degree that insurers are investing in assets issued by other financial institutions, the systemic effect could also be magnified. Additional buffer resources required for insurers may reinforce their ability to protect themselves from losses and avoid further domino effects across financial institutions.

NOTES

1. It is almost impossible to achieve the predicted interest rate by holding only safe assets such as government bonds. Not only higher- but also middle-risk assets like corporate bonds and securitized products, which almost all insurance companies held, plunged precipitously during the financial crisis.
2. Fukuda (2012) estimates the effects of the Federal Reserve Bank (FRB)'s Foreign Exchange swap Lines with the central banks of major nations to analyze how the liquidity risk was related to the difference between the Tokyo Interbank Offered Rate (TIBOR) and the LIBOR.
3. Illing and Aeron (2005) categorized two types: atheoretic indexes which aggregate information from various financial markets using statistical methods, and theory-based indexes which originate from economic or financial models. They confirmed that the indexes were not highly correlated and that some were negatively correlated, and therefore concluded that risk-appetite measurement is highly sensitive to the chosen methodology and underlying theory.
4. It is worth noting that fundraising liquidity risk is mutually and closely related to market liquidity as well as credit risks (Hermosillo, 2008; Brunnermeier, 2009). When a liquidity squeeze occurs and risk-tolerant guarantors with less equity capital are forced to exit markets, the remaining guarantors are more risk-averse players. When sellers of protection disappear and the demand for protection extremely exceeds the extent to which sellers are

willing to bear risks, CDS spreads hike sharply. Consequently, an increase in funding liquidity risk might lead to an increase in market liquidity risk. In addition, a change in the guarantors' recognition of the default risk of a reference entity might create a drastic decline in sales of protection, thereby shrinking the credit derivative's market liquidity. The effect of market liquidity on CDS premiums can be explored if an indicator of market liquidity such as bid–ask spreads is available. Cossin and Jung (2005) explored the CDS markets around the Russian and the Latin American crises using an original dataset of transactions and quotes, and reported a readily observable "flight to quality" accompanied by a drastic increase in the purchase of protection relative to sale, creating an imbalance in the markets, which might translate not only into the widening of bid-ask spreads but also into the skyrocketing of CDS mid-term rates.

5. There may be other alternative indicators of fundraising liquidity and investors' perspectives for future world macroeconomic conditions. This study conducted additional empirical analyses by replacing those indicators with another proxies, namely, the gap between the LIBOR and the OIS rate and the gap separating the US long-term and short-term government bond yields, respectively. Similar findings were confirmed.
6. Local factors are included to avoid the identification problem.
7. The residual part of a CDS spread may reflect not only credit risk of a reference entity but also market liquidity of the reference entity's CDS market. Although the effect of market liquidity risk should be noted, this study regards the residual as credit risk because of the unavailability of a proxy of market liquidity risk such as a bid-ask spread.
8. Data quoted at London time are used. The quoting times of MSCI world index and CDS spreads are 1:30 am and 7:30 am, respectively. Several data used to estimate the fundraising liquidity index are quoted at different times, but all are quoted after 7:30 am. Therefore, the fundraising liquidity index calculated with the data quoted at the previous date is applied for the first element of vector X.
9. A change in the world stock index includes shocks attributed to a change in the liquidity index as well as world stock specific shock. Here, MSCI shock is defined as a change in the world stock index extracted with the effect of the liquidity index. Likewise, SOV shock is defined as a change in sovereign CDS spreads which are not explainable by the liquidity index and the world stock index.
10. The first crisis period starts when the data of CDS spreads are available from the database described above. The end point is when the turmoil was believed to cease because of the disappearance of the hike in CDS spreads. The second crisis period starts when the sovereign risk triggered by the Greek budget deficit crisis became more prominent across

the core nations in the Eurozone, which are the targeted countries in this study, and ends after the announcement of the outright monetary transactions implemented by the ECB for the purpose of the wipeout of the uncertainty regarding sovereign risk prevalent across the Eurozone.

11. Diebold and Yilmaz (2009, 2012) also conduct a rolling estimation to evaluate the time-varying connectedness prevailing among financial institutions. Because it is presumed that fundraising liquidity had a dominant effect for a short period, we focus on the period when the liquidity squeeze was particularly highlighted. Ohno (2016) conducts historical decompositions to confirm the time-varying effect of fundraising liquidity.
12. Although the CDS spreads of all six US insurance companies are available, three among them are used to create the US sectoral CDS spread. These include Metlife, Prudential Financial, and Hartford, which are expected to be largely affected by the liquidity squeeze.
13. Severo (2012) uses the gap between the on-the-run versus the off-the run spread of US treasuries and the gaps between corporate bond yields and CDS spreads as well as the deviation from the CIP and the swap spreads to create the fundraising liquidity index. This analysis uses only the deviations from the CIP and the swap spreads because of unavailability of the rest of variables.
14. The deviations from the CIP are calculated by defining the U.S. dollar as a benchmark currency and five currencies including the Euro, the Danish Krone, the Australian dollar, the Singapore dollar, and the UK pound as investment currencies. The forward exchange rate maturities of these currencies are 1, 3, 6, and 12 months, and the OIS rates of the US dollar and the five currencies with these maturities are also collected. The swap spread involves data on the OIS rate and the yields on treasury bills for the US dollar, UK pound, and Euro for 1, 3, 6, and 12-month horizons.
15. All of the series is normalized to have a zero mean and a standard deviation of 1. The calculation is based on the Rats procedure “Princomp.”
16. Considering the possibility that financial institutions lost the ability to participate in markets because of their loss of creditworthiness, DEV can be also contaminated with the aggravation of financial institutions’ soundness. In the estimation of a VAR model, an alternative ordering of variables was also applied to extract the contemporaneous impact of credit risk of financial institutions on fundraising liquidity condition. Results are almost consistent with the results shown in this paper.
17. One of the alternative reasons that Sims et al. (1990) recommend using levels of variables is that the estimation of a cointegrated VAR model has the possibility of a specification error unless the cointegrating vector is correctly estimated.

18. Atkins and Chan (2004), who find that nominal interest and inflation rates in Canada and the US are stationary around a deterministic trend with two breaks, investigate the Fisher effect. Contrary to Atkins and Chan (2004), this study, focusing on the shorter sample period, conducts the filtering out by considering a structural break in the mean and the drift.
19. The null hypothesis of the unit root is rejected for all variables when taking the first difference.
20. Phillip-Perron tests lead to similar results.
21. For all variables except for the CDS spread of INB Bank and Mizuho FG, the unit root hypothesis can be rejected at the 5% level against the alternative of stationarity with a shift in the mean and the drift rate of the deterministic trend. For the CDS spread of ING Bank and Mizuho FG, the unit root hypothesis can be rejected at the same significance level against the alternative of trend–stationary with a break in the mean.
22. Considering the rising borrowing interest rates observed in European nations, the possibility that a fundraising liquidity problem happened locally during that period cannot be ignored.
23. Table 5-2 reports the results in using matrix A_0 represented with equation (11-2), which supposes that a shock in one industry in one country is not contemporaneously transmitted and is spilled over with lags to the other industry in the other country. Although the finding that intra-industry interdependencies were more prominent than inter-industry interdependencies can be derived from the specification even though the result is consistent with our expectations, it is not plausible that the procedure produces some biases as to which industry is more dominant. From the six countries targeted in this study, 15 pairs of two nations are created. The numerical values in Table 5-2 are the averages of connected indices obtained from the 15 estimations of two nations selected from the six countries.
24. Although insurance companies engaging in traditional insurance businesses mainly hold fixed income securities rather than stocks, prices of those with credit risk or market liquidity risk are tempted to be correlated with stock prices and are likely to decline caused by funding liquidity tightness. The impact of the MSCI world stock index can also reflect a change in risk appetite resulting from the pessimistic perspectives for the future economic conditions.
25. Although this paper does not contain results of impulse response estimations because of space limitations, they also showed findings inferring the influence of liquidity crunch on insurance companies which have been believed to be less vulnerable to liquidity shortage, and the dominant responsibility of banks for the fundraising liquidity conditions during the autumn in 2008.

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