Systemic Liquidity Risk and Measurement of Connectedness

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Abstract

Although insurance companies were believed to be less vulnerable to systemic risk compared to commercial banks and investment banks, we observed the simultaneous sharp increase of credit default swap spreads of insurance companies during the global liquidity squeeze. This study examines the determinants of CDS spreads of major financial institutions and explores the effect of the global liquidity squeeze on the financial institutions' creditworthiness. Specifically, the mutual interdependence across financial institutions is rigorously focused on.

Results show that the impact of the global liquidity squeeze on the CDS spreads of insurance companies, particularly those for which the main business is variable annuities with guaranteed minimum payments, was statistically significant. Secondly, worsened creditworthiness of banks were more influential to the global liquidity tightening than that of insurance companies. Although the development of systemic liquidity risk originating from insurance companies was not plausible, the aggravation of the creditworthiness of insurance companies might be influential to the same as that of banks.

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

Keywords: Liquidity squeeze, Interconnectedness, Credit Default Swap Spread

1. Introduction

Global systemic risk has been highlighted since the global financial crisis. Several measures intended to prevent global systemic 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 regulation for systemic reinforcement. Insurance companies identified as global systemically important insurers (G-SIIs) are also required to accumulate extra equity capital.

In actuality, insurance companies have been believed to be affected to only a negligible degree by systemic risk. However, the multinational insurance company American International Group (AIG) went to the verge of the bankruptcy in the midst of the financial turmoil, and the instability of financial markets was aggravated after the near-collapse of AIG. Several insurance companies such as Hartford Financial Services Group Inc. and Aegon N.V. were led to receive the financial bailout.

Since the global financial crisis, a growing body of literature has discussed whether insurance companies do pose systemic risk. For example, Billio et al. (2012) provide evidence that financial institutions including banks, insurance companies, hedge funds and broker/dealers have become higher interrelated during the years of the pre-crisis and the midst-crisis, likely increasing the level of systemic risk 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 during the global financial crisis. Berdin and Sottocornola (2015) investigate systemic risk across European financial institutions during the periods including

European sovereign crisis, and show that banks were always dominant and insurers played a subordinated role.

The methodology to identify G-SIIs was proposed in 2012 and the first list of G-SIIs was disclosed in 2013. The methodology cites several idiosyncratic characteristics which are regarded as possible drivers of systemic risk, that is, size, global activity, interconnectedness, non-traditional and non-insurance (NTNI) activities and substitutability. By employing indicators of potential sources of systemic risk, Weiss and Muhlnickel (2014) empirically test hypotheses that insurers could be susceptible and contribute to systemic risk. They find that insurers that were larger, relied more heavily on NTNI activities were highly exposed to the adverse effect of the financial turmoil, although the contribution of insurers to systemic risk is found to be only determined by insurer size. Billio et al. (2012) investigate the 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 one of the phenomena prominently seen during the global financial crisis. Two potential channels exist by which the fundraising liquidity crunch aggravates the creditworthiness of insurance companies: fundraising difficulties, and insolvency because of the depreciation of held assets caused by distress sales conducted during the liquidity shortage. Unlike AIG, which sold a huge amount of credit protection and was required to post additional collateral after the downgrading, insurance companies engaging in traditional insurance business tends to conduct short-term investment and long-term fundraising, which was regarded as a reason for them to avoid the effects of the liquidity crunch. However, securities held by insurance companies including those engaging in traditional insurance businesses are likely to be vulnerable to liquidity dry-up. Insurance companies across the world were damaged by the deterioration of the mortgage-backed securities (MBS) and the collapse of the asset-backed commercial paper (ABCP) as a result of the aggravation of the US housing markets. The damage of insurance companies for which the main business was variable annuities with guaranteed minimum payments was distinctly serious because their asset portfolios allocating a large percent of the total portfolio to higher-risk securities were considerably affected by liquidity tightening. Furthermore, those insurance companies were forced to raise additional funds to compensate for insufficient policy reserves due to the depreciation of the portfolio assets. They might increase probability of bankruptcy through the two channels of the liquidity squeeze.

Insurance companies might be exposed to systemic risk caused by fundraising liquidity crunch and contribute to systemic risk by worsening the availability of liquidity. In other words, there might be feedback effects, and the financial crisis caused by the liquidity crunch might aggravate the liquidity problem through a decline in financial institutions' soundness.

This study focuses on the effect of fundraising liquidity and explores whether insurance companies are relevant for the stability of the financial system. In this empirical study, the methodology proposed by Severo (2012) to create fundraising liquidity index is adopted to examine the relationship between liquidity squeeze and creditworthiness of financial institutions.

Unlike Billio et al. (2012) and Weiss and Muhlnickel (2014) which examine systemic risk by using stock returns of financial institutions, this study employs, as an indicator of creditworthiness, credit default swap (CDS) spreads of international financial institutions as a reference entity. During the financial turmoil, CDS spreads of almost all insurance companies including those mainly engaging in traditional insurance businesses exhibited an abrupt hike. A part of it might be explained by a decline in prices of securities held in their portfolios caused by the aggravation of risk appetite due to the liquidity squeeze and the worsened future perspectives.

A simultaneous increase in CDS spreads might be driven by not only common factors like fundraising liquidity, but also mutual interdependence across financial institutions via their investment and lending activities. Particularly during the global financial crisis, the worsening of banks' creditworthiness might strongly affect 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 the mortgage-backed securities, 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.

International financial markets again experienced turmoil after 2010 that was triggered by the Greek sovereign crisis. Although it is expected that the liquidity squeeze had diminished drastically because of the extremely easy monetary policies implemented by the major countries, rising borrowing interest rates were observed in European nations.

This paper adopts the structural vector autoregressive (SVAR) model to extract idiosyncratic shocks indicating fundraising liquidity tightness and financial institutions' soundness. A part of skyrocketing of CDS spreads during the crisis periods might be attributed to the excessive imbalance between demand and supply for the credit protection as a result of liquidity squeeze. Likewise, an increase in CDS spread of a financial institution might result from the aggravation of credit risk of another financial institution' instability. By identifying idiosyncratic shocks by using the methodology of SVAR, this study attempts to detect origins of systemic risk during the Lehman shock and the European sovereign crisis.

The remainder of this paper is organized as follows. Section 2 presents examination of the related literature. Section 3 and section 4 respectively present the econometric methodology and data used for the analyses. Section 5 reports the empirical results. Finally, the major findings and implications presented.

2. Literature Survey

During the global financial crisis and the European sovereign crisis, we observed the simultaneous skyrocketing of CDS spreads. Several studies have demonstrated that the hike in CDS spreads is explainable by factors other than credit risk. Ikeda et al. (2012), who attempted to decompose the sovereign CDS spreads into a component affected by credit risk and a component affected by other factors (the part including the risk premium), reported that the latter contributed to the hike of the sovereign CDS spreads to a marked degree during the European sovereign crisis, particularly those of nations outside of the Eurozone such as Japan.

The simultaneous increase in CDS spreads can reflect changes in market participants' attitudes. If investors rush into speculation related to the bankruptcy of a reference entity, and if sellers of protection evaporate for fear of loss, then its CDS spread can be expected to soar sharply. In this case, a factor related to changes in market participants' attitudes and their perception of uncertainty can become a common factor leading to the simultaneous increase in CDS spreads.

Since the global financial crisis, the risk appetite has been highlighted as a possible driving force of the downfall of asset prices across nations under stressful circumstances. Risk appetite indicators of various types have evolved. Illing and Aeron (2005) categorized those indicators as 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 those indexes were not highly correlated and that some were negatively correlated. They therefore concluded that the measurement of risk appetite is highly sensitive to the chosen methodology and underlying theory. What commonly holds in every index is that risk appetite is treated as a combination of attitudes and perceptions. For example, Gai and Vause (2006) emphasize that the risk appetite is not equivalent to a risk aversion although they have been often considered as the same. According to Gai and Vause (2006), irrespective of the asset, the risk premium must depend not only on the riskiness of the asset but also on the degree to which investors accept uncertainty (risk aversion) and the level of uncertainty itself (uncertainty about macroeconomic prospects) [1]. Therefore, CDS spreads can vary in accordance with changing risk appetites, even though the probability of bankruptcy of a reference entity does not

[1] The risk premium of any asset can be represented by two components: risk specific to an asset (beta risk) and risk common to all assets (price of risk), which can be regarded as risk appetite and which depends on the variance of the stochastic discount factor. Base on the Euler equation derived from the consumption-based capital asset pricing model applying the power-type consumption function, common risk can be regarded as a product of the variance of consumption and the magnitude of risk aversion. The risk appetite is then represented with the combination of the extent of uncertainty related to the instability of future consumption and the investors' willingness to accept risk.

change.

Since the global financial crisis, reports have been published of studies investigating the effects of a liquidity squeeze. As for papers employing CDS spreads, Frank et al. (2008) used the dynamic conditional correlation – generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model and estimated the conditional correlation coefficients between CDS spreads and the liquidity index. Eichengreen et al. (2009) applied a principal component analysis and suggested that the effect of liquidity as an influential common factor for CDS spreads during the Lehman shock. Ohno (2010) employed the SVAR model to assess the effects of the funding liquidity index as a common factor on the CDS spreads of financial institutions.

The risk appetite might be closely related to fundraising liquidity. The Bank of Japan (2008) asserts that the market average risk aversion can change as a reflection of market conditions, although individual investors' risk aversion does not change. A growing number of hedge funds and other less risk-averse players holding less equity capital participated in CDS markets as guarantors and underwrote credit risks during the easy money period. The entry of less risk-averse players probably lowered CDS spreads. When the crisis occurred and hedge funds faced fundraising problems, they were forced to exit from CDS markets. The remaining more risk-averse players such as banks and insurance companies became unwilling to bear risk and required higher risk premiums to offset the greater risk burdens.

Investors' perspectives can also produce changes in risk appetite. Hermosilo (2008) describes that periodic shifts in market sentiment witnessed over time are more likely to be driven by the macroeconomic environment than by changes in the risk aversion of investors. Uncertainty in the macroeconomic environment is therefore likely to affect

CDS spreads as a common factor.

This study chooses a world stock price index and an index of fundraising liquidity as proxies of risk appetite and adopts them as common determinants of CDS spreads. A world stock price is presumed to reflect investors' perspectives related to uncertainty of future macroeconomic conditions. An index of fundraising liquidity may represent the market average risk aversion and, perhaps, investors' perceptions for economic prospects.

It is not easy task to quantify the level of fundraising liquidity. Frank et al. (2008), Eichengreen et al. (2009), Boyson et al. (2010), and Ohno (2010) used as an indicator of fundraising liquidity the TED spread, the gap separating the LIBOR rate and the US Treasury Bill rate. Coffey et al. (2009), Fukuda (2009) and Severo (2012) proposed the deviation from the arbitrage parity. Among them, Severo (2012), which demonstrates that the magnitude of the deviation reflects the ability of investors to reallocate funds and to obtain positive excess returns quickly with small risks, created the systemic liquidity risk index (SLRI) by application of a common factor extracted from principal component analysis for series of deviations from the arbitrage conditions. Hui et al. (2011), on the other hand, proposed the gap separating LIBOR rate and OIS rate (designated herein as LO) as an indicator of fundraising liquidity and inferred the violation of the CIP during the global financial crisis as resulting from a liquidity squeeze from verification of the effects of LO on the deviation of the covered interest rate parity (CIP)[2]. Griffoli et al. (2010) confirmed the effects of a liquidity squeeze on the violation of the CIP using the TED spread and LO as indicators of fundraising liquidity. This study adopts LO and the index proposed by Severo as an indicator of

[2] Other studies using LO as an indicator of fundraising liquidity include that reported by Baba and Packer (2008).

fundraising liquidity and examines their causes to and receipts from changes in creditworthiness of financial institutions.

Since the Lehman shock, systemic risk has attracted growing interest, and various methodologies to explore systemic risk have been developed. The CoVAR approach used by Adrian and Brunnermeier (2011) and the Marginal Expected Shortfall (MES) approach of Acharya et al. (2010) track the association between individual stock price movements and overall market movements. Weiss and Muhlnickel (2014) estimate the MES and the conditional CoVAR of U.S. banks and insurers to see whether insurers were systematically relevant during the global financial crisis. Berdin and Sottocornola (2015) analyze systemic risk in the European financial sectors by conducting Granger causality test as well as the estimation of MES and CoVAR. Billio, et al. (2012) examine the connectedness across four financial sectors including insurers by applying Granger causality test and principal component analysis. Diebold and Yilmaz (2009, 2012), on the other hand, proposed a connectedness index derived from the decomposition analysis based on the VAR model as a methodology to measure connectedness at various levels from pairwise through system-wide. Contrary to Granger causality test, variance decomposition derived from SVAR can detect intrinsic contributions to instability of financial markets.

This study employs the SVAR methodology to investigate systemic risk though the effect of fundraising liquidity and mutual interdependence across financial institutions including insurance companies. First, we attempt to detect the impact of liquidity crunch on financial institutions soundness and the feedback effect of their creditworthiness on the liquidity condition. After the effect of common factors is extracted from CDS spreads, an idiosyncratic factor of a CDS spread can be regarded as a credit risk of the reference entity[3]. Secondly, spillover effects of credit risk across financial institutions are examined using the method of connectedness index proposed by Diebold and Yilmaz (2009, 2012). In this study, connectedness indices of three types are created; connectedness from common factors to financial institutions, connectedness from financial institutions to common factors, and connectedness across banks and insurance companies. Thirdly, unlike Diebold and Yilmaz (2009, 2012), historical decompositions are conducted to confirm the time-varying effect of liquidity and interdependence among financial institutions during the crisis which lasted for only a short period.

It is noteworthy that a decline of stock prices can affect CDS spreads of financial institutions through erosion of their equity capital as well as changing investors' risk appetites. Similarly, the worsening of fundraising liquidity conditions can raise CDS spreads of financial institutions through lowering of investors' risk tolerance as well as increasing the probability of bankruptcy related to fundraising difficulties. Although this study does not rigorously discriminate those two channels, we attempt to infer, by comparing the magnitude of reactions of CDS spreads to a change in common factors,

[3] A residual part of a CDS spread, which is regarded as a specific factor under the presumption presented above, might reflect not only credit risk of a reference entity but also market liquidity of the CDS market of the reference entity. It is noteworthy that fundraising liquidity risk is mutually and closely related to market liquidity risk as well as credit risk (Gonzalez-Hermosillo (2008), Brunnermeier (2009)). When a liquidity squeeze occurs and risk-tolerant guarantors with less equity capital are forced to exit from 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 guarantors' recognition of default risk of a reference entity might create a drastic decline in sales of protection, thereby shrinking market liquidity of the credit derivative market. 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 mid-term rates of CDS.

which financial institutions were more seriously damaged by the deterioration of stock markets as well as fundraising liquidity dry-up, under the assumption that CDS spreads react uniformly to changes in risk appetite.

3. Empirical Model

This section presents a structural VAR model to identify influential factors for CDS spreads of financial institutions during crisis periods. First, the following reduced form is estimated as

$$B(L)X_t = \varepsilon_t \quad , \tag{1}$$

where X_t is a N×1 vector of endogenous variables. $B(L)$ is matrix polynomials in the lag operator defined as

$$B(L) = B_0 - B_1 L - B_2 L^2 - \cdots - B_k L^k$$

Therein, X_0 represents the identity matrix; k signifies the maximum lag. Also, ε_t denotes a N×1 vector of the reduced-form residuals with a variance–covariance matrix $E[\varepsilon_t \varepsilon_t{}'] = \Sigma_t$.

One then assumes that the economy has a structural form as presented below.

$$A(L)X_t = u_t \tag{2}$$

$$A(L) = A_0 - A_1 L - A_2 L^2 - \cdots - A_k L^k$$

Therein, the variance–covariance matrix of the structural form disturbance u is the identity matrix.

The structural disturbances and reduced form residuals are related as shown below.

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

That equality implies that

$$\Sigma = E[\varepsilon_t \varepsilon_t{}'] = E[A_0^{-1} u_t u_t{}' (A_0^{-1})'] = A_0^{-1} (A_0^{-1})' \ .$$

To avoid an identification problem, restrictions of more than $N(N\text{-}1)/2$ should be imposed on the off-diagonal elements of matrix A_0. In this analysis, to elucidate the effects of the common factors and interdependence across financial institutions, the restrictions represented by the composition of the matrix A_0 and X_t are specified as the following form. Here is a case of two-country and two-sector as an example.

$$\mathrm{A}_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{21} & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{31} & -a_{32} & 1 & -a_{34} & 0 & 0 & 0 & 0 \\ -a_{41} & -a_{42} & -a_{43} & 1 & 0 & 0 & 0 & 0 \\ -a_{51} & -a_{52} & -a_{53} & 0 & 1 & -a_{56} & -a_{57} & 0 \\ -a_{61} & -a_{62} & -a_{63} & 0 & -a_{65} & 1 & 0 & -a_{68} \\ -a_{71} & -a_{72} & 0 & -a_{74} & -a_{75} & 0 & 1 & -a_{78} \\ -a_{81} & -a_{82} & 0 & -a_{84} & 0 & -a_{86} & -a_{87} & 1 \end{bmatrix} \tag{4}$$

$$X_t' = [LQ_t \quad MSCI_t \quad SOV_{1,t} \quad SOV_{2,t} \quad BANK_{1,t} \quad INS_{1,t} \quad BANK_{2,t} \quad INS_{2,t}]$$

In that example, *LQ* and *MSCI* respectively represent indicators of fundraising liquidity and the world stock index. Those two variables are used as worldwide common factors for the CDS spreads of financial institutions. Here, $BANK_i$ and INS_i (i =1 or 2), respectively denote CDS spreads of banks and insurance companies for which the headquarters were located in country i. SOV_i is the CDS spread of the country i government as a reference entity, which is regarded as a local common factor for CDS spreads of a bank and an insurance company of country i[4].

Under the restriction specified with matrix A_0, it is presumed that *LQ* is the most exogenous and that *SOV* is the least exogenous among the three common factors, with ordering determined according to the quoting time of data[5][6]. CDS spreads of banks and insurance companies are assumed to react simultaneously to a shock affecting those common factors[7]. It is also assumed that there is no contemporaneous reaction of the CDS spreads of a bank (or an insurance company) to a shock in the CDS spread of an insurance company (or a bank) in another country, although they contemporaneously respond to a shock in CDS spreads of another bank as well as a shock in CDS spreads of an insurance company in the same country

Equation (1) can be reformulated in a reduced-form vector moving average (VMA) representation as follows if variables used in these analyses satisfy stationarity.

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4 Local common factors are included to avoid the identification problem.

5 Data quoted at London time are used. The quoting times of data are as follows. MSCI World index (1:30 am). CDS spreads (7:30 am). 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 estimated with the data quoted at the previous data is applied for the first element of vector *X*.

6 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 to the liquidity index and the world stock index.

7 Under this supposition, disturbance terms of *BANK* and *INS* are regarded, respectively, as idiosyncratic shocks of banks and insurance companies.

$$X_t = D(L)\varepsilon_t \tag{5}$$

$$D(L) = I + D_1 L + D_2 L^2 + \cdots + D_k L^k + \cdots$$

Equation (5) can then be reformulated in a structural VMA representation.

$$X_t = \sum_{s=0}^{\infty} \Psi_s \, u_{t-s} \tag{6}$$

$$\Psi_0 = A_0^{-1}$$

In section 5, the estimation results of impulse response functions, $\Psi_0, \Psi_1, \dots, \Psi_k, \dots$ reportedly confirm the effect of the liquidity squeeze on financial institutions including insurance companies and confirm its feedback effect under stressful circumstances.

This study also analyzes credit risk spillovers across financial institutions during the financial turmoil by estimating the connectedness index developed by Diebold and Yilmaz (2009, 2012). The connectedness index measures the system-wide diffusion of shocks, which is derived from variance decompositions.

Consider *k*-step-ahead forecasting. The error in the *k*-step ahead forecast conditional on the information set at time *t* is the value shown below.

$$\sum_{s=0}^{k-1} \Psi_s u_{t-s} \tag{7}$$

Because structural shocks identified by equation (6) are uncorrelated both across time and contemporaneously, and because all the variables in vector *X* have stationarity, the forecast error variance of the *m*-th variable in vector *X* is represented as shown below. It is the sum of the variances of structural shocks.

$$\sum_{n=1}^{N}\left(\sum_{s=0}^{k-1}\Psi_{mn,s}^{2}\right)\sigma_n^2 \qquad (8)$$

In that equation, σ_n^2 stands for the variance of the *n*-th structural shock in vector *u*. Also, $\Psi_{mn,s}$ represents the coefficient of response of the *m*-th variable in vector *X* to the *n*-the structural shock at time *s*.

Variance decompositions are conducted in an attempt to evaluate the extent of the influence of one structural shock on a dependent variable by calculating the relative variance contribution of the shock. 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

$$C_{n\to m}^{s} = \frac{\left(\sum_{s=0}^{k-1}\Psi_{mn,s}^{2}\right)\sigma_n^2}{\sum_{n=1}^{N}\left(\sum_{s=0}^{k-1}\Psi_{mn,s}^{2}\right)\sigma_n^2} \qquad (9)$$

Next, one can 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 variables is defined as shown below.

$$C_{*\to m}^{s} = \sum_{n=1}^{N} C_{n\to m}^{s} \qquad (n \neq m) \qquad (10)$$

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

$$C^{s} = \frac{1}{N}\sum_{m=1}^{N}\sum_{n=1}^{N} C^{s}_{n\to m} \qquad (n \neq m) \tag{11}$$

The empirical model presented in this paper incorporates common factors as well as CDS spreads of financial institutions. Therefore, connectedness indices of three types are created: connectedness from common factors to financial institutions, connectedness from financial institutions to common factors, and connectedness across financial institutions. Furthermore, financial institutions are classified into two groups of banks and insurance companies to compare their relative mutual effects.

Diebold and Yilmaz (2012) identified structural shocks using the generalized variance decomposition (GVD) proposed by Pesaran and Shin (1998), which is independent of the ordering of variables. Diebold and Yilmaz (2012) also conducted the rolling estimation to evaluate the time-varying connectedness prevailing among financial institutions. The analyses reported in this paper adopt a different dynamic analysis because the effect of fundraising liquidity, which is particularly highlighted in this study, is expected to last during only a short period. This study conducted historical decompositions to confirm the time-varying effect of liquidity and interdependence among financial institutions.

By reformulating equation (6), the m-th element of vector X_{T+k} can be specified as shown below.

$$X_{m,T+k} = \sum_{n=1}^{N}\sum_{s=k}^{\infty} \Psi_{mn,s} u_{n,T+k-s} + \sum_{n=1}^{N}\sum_{s=0}^{k-1} \Psi_{mn,s} u_{n,T+k-s}. \tag{12}$$

The first sum of the right-hand-side of equation (12) is the forecast based on information available at time T. The second term represents the part of X_{T+k} attributable to innovations during periods $T+1$ through $T+k$. Fluctuations of dependent variables after time $T+1$ are traceable to the time path of the structural shocks generated from time $T+1$ to time $T+k$, as denoted by the second term.

4. Data

The analyses reported herein use daily data downloaded from *Datastream* and *EIKON*, Thomson Reuters. Here, two crisis periods are emphasized. The first crisis period is that including the Lehman shock, defined as the sample period from January 18, 2008 through October 31, 2009. The second crisis period is defined as a period from January 4, 2011 through September 30, 2012, when the European sovereign crisis was of prominent importance[8].

In this study, five-year CDS spreads of financial institutions in US, Japan, and European countries are selected, in which financial institutions defined as G-SIIs are also included[9][10].

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[8] The starting time of the first crisis period is the time at which data of CDS spreads are available from the database described above. The end point is selected at a time when the turmoil was believed to cease because of the disappearance of the hike in CDS spreads and the fundraising indicator. The second crisis period starts at a time when the sovereign risk triggered by the Greek budget deficit crisis became more prominent across the core nations in the eurozone, and ends at a time after the announcement of the outright monetary transactions implemented by the ECB for the purpose of the wipeout of the uncertainty regarding with sovereign risk prevalent across the Eurozone.

[9] Financial institutions are classified as either banks or insurance companies. In a case where both a bank and an insurance company belong to a financial group, the group is classified according to its core business.

[10] Commonly used names of financial institutions included in these analyses are the following.
Banks: JP Morgan Chase, Citigroup, Bank of America, Morgan Stanley, Goldman Sachs, Wells Fargo, Barclays, HSBC, Standard Chartered, Lloyds, BNP Paribas, Societe Generale, Credit Agricole, Deutsche Bank, Santander, BBVA, ING Bank, Mitsubishi UFJ, Mizuho, (defined as G-SIBs at 2014), American Express, Bank of Scotland, Credit Lyonnais, Banco Com. Portugues, Espirito Santo, Commerzbank, Bayerische Bank, LB Badenwuerttemberg, IKB dt Indstrbk, SNS Bank, KBC Bank, Intesa Sanpaolo, Mediobanca, Banca MDP di siena, BNL, BCA PPO Milano Soco, Nomura.

As the world stock index, the logarithmic MSCI world index, denominated in US dollars, is used. Regarding the fundraising liquidity index, the deviation from arbitrage relations followed by Severe (2012) is used. This study collects 21 series of deviations from CIP and the swap spreads equivalent to the gaps between the OIS rate and the treasury-bill rate and extracts common factors for them by conducting principal component analysis[11][12][13]. The first principal component explains 73.3% of the total in-sample variation of the series. It constitutes the most important common source of fluctuations across all bases. Therefore, the first principal component is selected as the fundraising liquidity index.

All variables used in the empirical tests are converted in the first-order differential. Results obtained from the Augmented Dickey–Fuller test and Phillips–Perron test for unit root confirmed that they satisfy stationarity. In addition, a no-cointegration relation was detected using the Engle–Granger test[14].

Figure 1 depicts the estimated fundraising liquidity index derived from the deviation from the arbitrage conditions (DEV) and several LO series. The index shows a sharp increase during the first crisis period and restarted the upward trend during the second

Insurance companies: MetLife, Prudential Financial, Aviva, Prudential plc., AXA, Allianz, (defined as G-SIIs at 2014), Hartford, Berkshire Hathaway, Cigna, Aetna, Hannover, ING, Aegon, Tokio Marine, Sompo Japan, Sumitomo Mitsui Insurance.

[11] Severo (2012) uses the gap between the on-the-run versus off-the run spread of US treasuries and the gaps between corporate bonds 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 of the CIP and the swap spreads because of unavailability of the rest of variables.

[12] The CIP bases are derived from arbitrage strategies involving the U.S. dollar and five currencies including the euro, the Danish Krone, the Australian dollar, the Singapore dollar and the UK pound with maturities of 1, 3, 6, and 12 months. The deviations are calculated by applying the US and the five currencies' OIS rates. The swap spread involves data on the OIS rate and the yields on treasury bills for the US dollar, the UK pound and the euro for 1, 3, 6, and 12 month horizons.

[13] All of the series is normalized to have zero mean and standard deviation of 1. The calculation is based on the Rats procedure "Princomp".

[14] The results of those unit root tests and the results of the cointegration tests can be shown in response to a request from readers.

crisis period, implying that the global financial markets tightened severely in the autumn in 2008. Also liquidity tightening resurged slightly during spring in 2010 when Greece received its financial bailout package. It is noteworthy that the liquidity squeeze locally became prominent during the European sovereign crisis in spite of the coordinated liquidity provision among major countries. Figure 1 shows that, during the second crisis period, particularly in 2011 when the uncertainty for the sovereign risk diffused from peripheral countries to core nations, LO denominated in euros (EULO) increased more than any other index. In actuality, EULO reached a peak at the end of 2011 when the ECB announced the long-term refinancing operation (LTRO). It turned down thereafter. Therefore, EULO is used as an alternative fundraising liquidity indicator to elucidate the effects of the liquidity crunch during the second crisis period.

5. Empirical Results

5-1. Impulse Response Function Estimation

This subsection presents the estimation results of impulse response functions specified with equation (6). As reference data, a SVAR model constituting four variables in order of the fundraising liquidity index, the world stock index, sovereign CDS spread, CDS spread of a financial institution is used to elucidate the reactions of an individual financial institution to a shock in fundraising liquidity. The relations of four variables are represented with a recursive restriction on matrix A_0. The impulse responses are created by accumulating the estimated coefficients to present the effects of a shock to a level of dependent variables.

Figure 2-1 reveals the reactions of the CDS spreads of financial institutions to a shock in the fundraising liquidity indicator during the first crisis period. Financial institutions that present a prominently large reaction include Morgan Stanley and several insurance companies such as Metlife, Prudential Financial, Hartford, and AXA.

For this study, an idiosyncratic shock of a financial institution is defined as a representation of creditworthiness of a financial institution. Figure 2-2 presents the effects of financial institutions' idiosyncratic shocks on fundraising liquidity. Morgan Stanley, followed by US and UK banks such as Barclays and Goldman Sachs, presented a marked influence on the fundraising liquidity condition. In addition, insurance companies including ING, Metlife, Prudential Financial, Hartford, and Aegon also had a stronger effect.

Results showed that insurance companies received the effect of the liquidity squeeze. That evidence might result from either a change in investors' risk appetite, or the aggravation of creditworthiness caused by exacerbated fund-raising difficulties. Insurance companies for which the main insurance products were variable annuities combining characteristics of a fixed annuity with the benefits of owning mutual funds were required to undertake capital enhancement to reinforce their ability to absorb losses caused by the depreciation of risky assets and the cost of guarantees they provided to holders of annuities. The result, that their response to a shock in the fundraising liquidity index was exceptionally high, suggests that their CDS spreads increased sharply because the second channel worked intensively.

Next, the results of the impulse response function are reported for a case incorporating the mutual dependence of financial institutions. The results are derived from the two-country and two-sector VAR model represented with matrix (4). Here, equally weighted average indexes of CDS spreads of banks and insurance companies are used in order to explore the overall spillover effects between countries. Figure 3-1 depicts the impulse response functions of the fundraising liquidity index and CDS spreads of banks and insurance companies of US and France at the first crisis period. Black lines show point estimates of impulse responses. Blue lines show the confidence bands measured using two standard deviations with a Monte Carlo simulation. In this case, USINS (the averaged CDS spread of US insurance companies) is constructed with the three life insurance companies, which presented an exceptionally large reaction to the fundraising liquidity shock.

The effects of the fundraising liquidity index on USINS and FRINS as well as USBANK were confirmed, and the magnitude of the reactions of insurance companies was larger than banks. Regarding the reverse effect, the effect of credit risk of financial institutions on fundraising liquidity, however, only the effects from banks could be verified. When applying CDS spreads of other combinations of financial institutions in this empirical model, similar results were detected. An exceptional case is that including Japanese financial institutions where the Japanese banks did not have a significant influence on DEV (Figure 3-3).

The evidence implies a spiral effect of the liquidity crunch: financial institutions facing fundraising difficulties might intensify the aggravation of fundraising liquidity condition as a result of the increased credit risk. Results of analyses also show that banks, which are more influential in the interbank markets, contributed much more to severe liquidity tightening than insurance companies did, which is consistent with our expectations. It is also detected that Japanese financial institutions were less influential to the global liquidity squeeze, which is not against our expectations, too.

Regarding interdependence among financial institutions, the effects from banks on insurance companies were more prominent, although the reverse effect was also revealed. Similar results were obtained when CDS spreads of alternative banks and insurance companies were applied.

Banks and insurance companies are believed to be connected closely through money markets and derivative transactions. During the first crisis period, insurance companies were expected to receive a 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 is not so plausible.

Figure 3-2 reports results for the second crisis period. The effects of the fundraising liquidity index on CDS spreads of financial institutions as well as the reverse effects were not found in this case. When the European sovereign crisis occurred, major countries had already implemented radically eased 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 expected to halt aggravation of the liquidity crunch in a spiral course.

We also confirmed that the effects from banks were more prominent than those from insurance companies during the second crisis period as well.

5-2. Connectedness Index Analysis

This subsection presents the results of the connectedness index developed by

Diebold and Yilmaz (2009 2012), which utilizes the concept of the variance decomposition analysis. Table 1, which contains the result derived from the two-country and two-sector model specified with matrix (4), reports the three types of connectedness.

At the first crisis period, the connectedness from financial institutions (FIs) to DEV is estimated from 14.1 to 32.4. It is also verified that the worsened creditworthiness of UK and French financial institutions relatively strongly affected the liquidity tightening. At the second crisis period, however, the impact of a shock in financial institutions on liquidity drastically diminished. Although the connectedness from common factors to financial institutions increased at the second crisis period, it resulted from the increase in the relative contributions of MSCI shock to CDS spreads of financial institutions. The impact of liquidity shock on financial institutions sufficiently decreased. The connectedness across financial institutions (FIs) tends to increase at the second crisis period, although the results seem to be mixed.

Table 1 also presents that, 1) banks were likely to have a larger impact on the liquidity crunch, and 2) insurance companies have a larger impact than banks than vice versa in the second crisis period. Therefore, an alternative model is used to confirm the robustness of those results.

We take an example of four-country and single-country model. Vector X is composed of the two global common factors (LQ and $MSCI$), four country factors (sovereign CDS spreads of four countries) and banks' (or insurance companies') CDS spreads of those nations. The relationships between those ten variables are represented with a following matrix.

$$
A_0 = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-a_{21} & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-a_{31} & -a_{32} & 1 & -a_{34} & 0 & 0 & 0 & 0 & 0 & 0 \\
-a_{41} & -a_{42} & -a_{43} & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
-a_{51} & -a_{52} & -a_{53} & 0 & 1 & -a_{56} & -a_{57} & 0 & 0 & 0 \\
-a_{61} & -a_{62} & -a_{63} & 0 & -a_{65} & 1 & 0 & -a_{68} & 0 & 0 \\
-a_{71} & -a_{72} & 0 & -a_{74} & -a_{75} & 0 & 1 & -a_{78} & -a_{79} & -a_{710} \\
-a_{81} & -a_{82} & 0 & -a_{84} & 0 & -a_{86} & -a_{87} & 1 & -a_{89} & -a_{810} \\
-a_{91} & -a_{92} & 0 & 0 & -a_{95} & 0 & -a_{97} & -a_{98} & 1 & -a_{910} \\
-a_{101} & -a_{102} & 0 & 0 & 0 & -a_{106} & -a_{107} & -a_{108} & -a_{109} & 1
\end{bmatrix}
$$

$$
X_t' = [LQ_t \quad MSCI_t \quad SOV_{1,t} \quad SOV_{2,t} \quad SOV_{3,t} \quad SOV_{4,t} \quad BANK_{1,t} \quad BANK_{2,t} \quad BANK_{3,t} \quad BANK_{4,t}] \tag{13}
$$

Table 2-1 and 2-2 present the results in using the four-country and single-sector model. Here, too, we can also confirm that banks tended to be more influential than insurance companies on DEV in the first crisis period, which is consistent with the results shown in table 1. We can also confirm the connectedness from financial institutions to DEV dropped at the second crisis period. At the second crisis period, the connectedness across the European financial institutions increases although the connectedness across financial institutions including those outside the Eurozone decreases.

Table 3 presents results of four-country and two sector model, in which banks of two nations and insurance companies of the other two countries are considered. Table 3 reports the results at the first crisis period. In this case, too, the tendency that the worsened creditworthiness of banks was more influential on the liquidity squeeze than insurance companies is confirmed. Contrary to the results of table 1, it is suggested that the impact of banks on insurance companies was larger than that of insurance companies on banks.

5-3. Historical Decomposition Analysis

In the previous subsections, it was verified that the liquidity squeeze during the first crisis period resulted in the increase in CDS spreads of insurance companies, and some of them were severely affected by the fundraising liquidity problem. In the last subsection, the results of historical decomposition analysis are shown to confirm the time-varying impact of liquidity squeeze on insurance companies.

Figure 4-1 presents the result of historical decomposition for the CDS spread of the US life insurance companies in the first crisis period. We can confirm that the impact of fundraising liquidity shock on USINS increased in the autumn of 2008. According to Figure 4-1, the relative contribution of the liquidity tightening to USINS reached about twenty percent in the midst of October, which implies the 146 basis-point increase of the averaged CDS spread of the three life insurance companies caused by the severe liquidity squeeze. The impact of DEV ceased at the end of 2008, when the expansionary monetary policy of the major countries became more effective. Contrary to it, the effect of a shock in MSCI continued increasing under the stagnated market conditions in 2009. This may be interpreted as the increased risk appetite caused by the pessimistic perspectives for the future world economic activities. Alternatively, the aggravated creditworthiness of US insurance companies as a result of the downturn in the world-wide stock markets may be reflected to the sharp increase in their CDS spreads.

Figure 4-2 shows the historical decompositions for DEV at the first crisis period. Though a large part of the increase in DEV is explainable by its own shock until September 2008, the effect of a shock in MSCI and others enlarged afterward. This suggests that the investors' pessimistic perspective for the future macroeconomic conditions indicated by the decrease in the global stock prices led to the severe liquidity tightening. The possibility that the aggravated liquidity condition was wiped out by the drastic expansionary monetary policy is inferred.

The previous subsections show that the liquidity indicator was not influential on CDS spreads of financial institutions during the European sovereign crisis period. Figure 4-3 reports the result of historical decomposition for the CDS spread of the French insurance companies for the second crisis period, by replacing DEV with EULO as an indicator of local fundraising liquidity.

We can see that the relative contribution of EULO reached at the maximum level at the end of 2011, when the ECB announced the long-term refinancing operation (LTRO). According to Figure 4-3, the liquidity tightening in the European financial markets resulted in the 42 basis-point increase in the French insurance company, which corresponds to the thirty percent relative contribution of the increase in FRINS. The local worsening of the liquidity condition during the European sovereign crisis period might be partly reflected to CDS spreads of financial institutions in the Eurozone.

6. Conclusions

The following are the salient conclusions obtained from 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. This study also found that insurance companies engaging in NTNI activities more intensively were more vulnerable to the liquidity crunch, which is not inconsistent with our intuition. Insurance companies selling variable annuity products with minimum guarantees as a main product held portfolios, whose percentage share of risky securities was high in order to aim at higher investment yields. Under 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 for which the main business was traditional insurance business activities, however, were also affected by the liquidity squeeze because they also held risky assets to achieve a predicted interest rate required by insurance products[15].

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 and the amplification of worsened creditworthiness across financial institutions were detected. Those tendencies were more readily apparent for banks than they were for insurance companies.

Although insurance companies targeted for these analyses were susceptible to the liquidity crunch, the development of systemic risk originating from insurance companies was not highly plausible. It should be noted, however, that insurance companies might not play a dominant role but have a subordinate impact on instability of financial markets, and the degree of the impact might differ across them depending on the their scale in NTNI activities and so on.

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[15] It is almost impossible to achieve the predicted interest rate by holding only safe assets such as government bonds. Not only higher risk assets but also middle risk assets like corporate bonds and securitized products, which almost all insurance companies held plunged precipitously during the financial crisis.

Acknowledgements

The author wishes to thank Prof. Tsutomu Chano, Prof. Eiji Ogawa, Prof. Masaharu Hanasaki, Prof. Etsuro Shioji, Prof. Masataka Suzuki, Prof. Yoko Shirasu, Prof. Sadayoshi Takaya, and other participants at the 2016 Spring Meeting of the Japan Society of International Economics, for their valuable comments.

References

Baba, N., & Packer, F. (2008). Interpreting deviations from covered interest rate parity during the financial market turmoil of 2007-2008. *BIS Working Paper*, 267.

Bank of Japan (2008). Increased uncertainties about the economic and financial environment, and the turmoil in global financial markets. *Financial Market Report*, September 2008.

Berdin, E. & Sottocornola, M. (2015). Insurance activities and systemic risk. *SAFE Working paper*, 121.

Billio, M., Getmansky, M., Lo, A. & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104, 535-559.

Boyson, N. M., Stahel, C. W., & Stulz, R. M. (2010) Hedge fund contagion and liquidity shocks. *Journal of Finance*, 65, 1789-1816.

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives*, 23, 77-100.

Coffey, N., Hrung, W. B., & Sarkar, A. (2009). Capital constraints, counterparty risk, and deviations from covered interest rate parity. *Federal Reserve Bank of New York Staff Report*, 393.

Cossin, D., & Jung, G. (2005). Do Major Financial Crises Provide Information on Sovereign Risk to the Rest of the World? *FAME Research Paper*, 134.

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, 119, 158-171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28, 57-66.

Eichengreen, B., Mody, A., & Nedeljkovic, M. (2009). How the subprime crisis went global: Evidence from bank credit default swap spreads. *NBER Working Paper*, 14904.

Frank, N., Hermosillo, B. G., & Hesse, H. (2008). Transmission of liquidity shocks: Evidence from the 2007 subprime crisis. *IMF Working Paper,* WP/08/200.

Fukuda, S. (2012). Market specific and currency-specific risk during the global financial crisis: Evidence from the interbank market in Tokyo and London. *Journal of Banking and Finance*, 36, 3185-3196.

Gai, P., & Vause, N. (2006). Measuring investors' risk appetite. *International Journal of Central Banking*, 2, 167-188.

Gonzalez-Hermosillo, B. (2008). Investors' risk appetite and global financial market conditions. *IMF Working Paper,* WP/08/85.

Griffoli, T. M., & Ranaldo, A. (2010). Limits to arbitrage during the crisis: Funding liquidity constraints and covered interest parity. *Swiss National Bank Working Papers*, 2010-14.

Hui, C. H., Genberg, H., & Chung, T. K. (2011). Funding liquidity risk and deviations from interest-rate parity during the financial crisis of 2007–2009. *International Journal of Finance and Economics*, 16, 307-323.

Ikeda, K., Hiraki, K., & Yamada, K. (2012). Factorization of sovereign CDS premiums. Bank of Japan, *Working Paper Series*, 12-J-9, (in Japanese).

Illing, M., & Aaron, M. (2005). A brief survey of risk-appetite indexes. Bank of Canada, *Financial System Review*, June 2005.

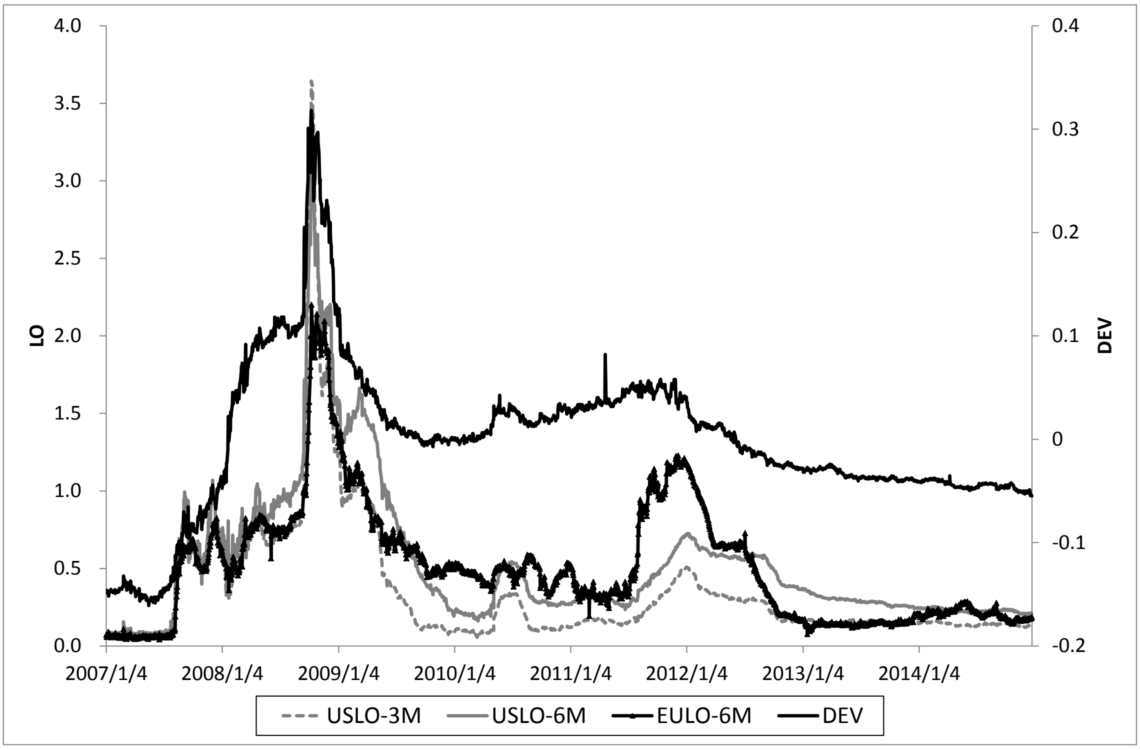
Ohno, S. (2010). Liquidity crunch and interdependence among major financial institutions during global financial turmoil: Evidence from credit default swap spreads. *Musashi University Discussion Paper,* 60.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58, 17-29.

Severo, T. (2012). Measuring Systemic Liquidity Risk and the Cost of Liquidity Insurance. *IMF Working Paper*, WP/12/194.

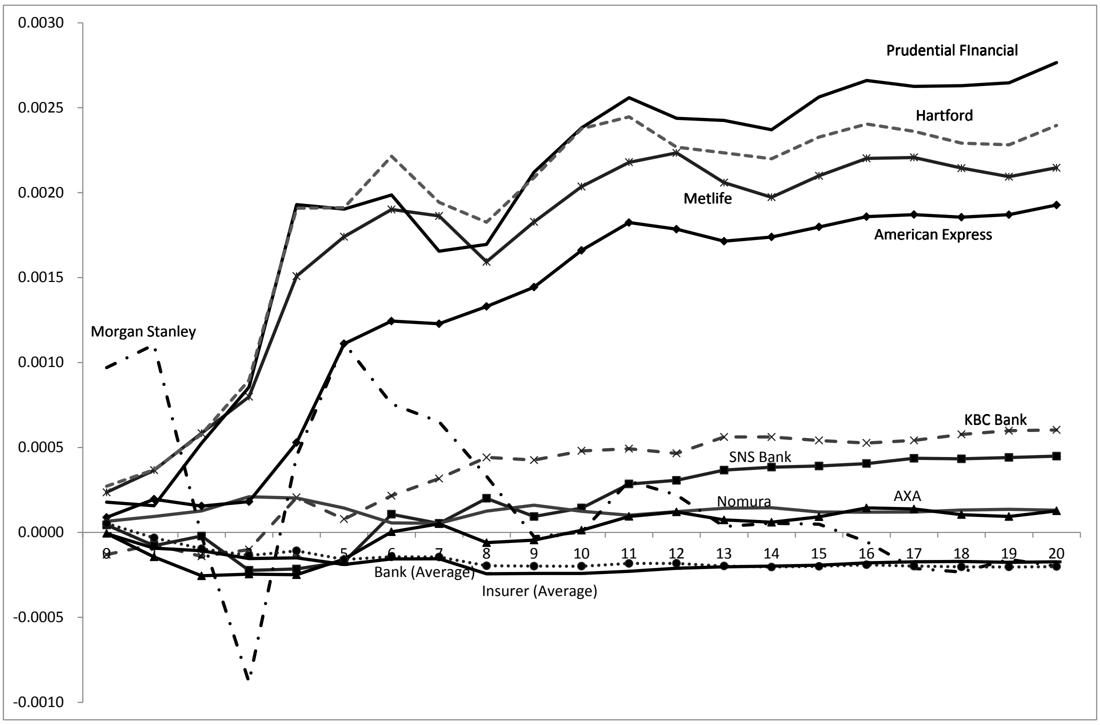
Weiss, G. & Muhlnickel, J. (2014). Why do some insurers become systemically relevant? *Journal of Financial Stability*, 13, 95-117.

Figure 1: Fundraising liquidity indicators



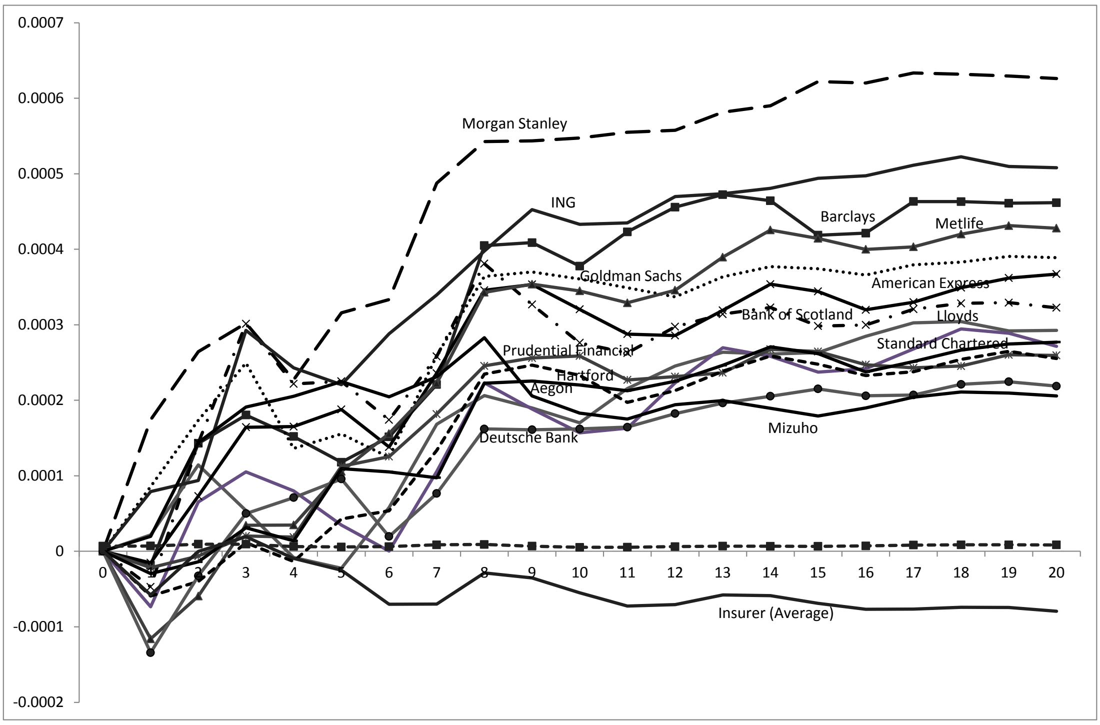
Note: The following abbreviations are used. DEV, the index of the deviation from the arbitrage conditions derived from the principal component analysis; USLO-3M, the differential between the three-month US dollar LIBOR rate and the three-month OIS rate; USLO-6M, the differential between the six-month US dollar LIBOR rate and the six-month OIS rate; EULO-6M, the differential between the six-month Euro LIBOR rate and the six-month OIS rate.

Figure 2-1: Impulse Response of CDS Spreads of Financial Institutions to a Shock in Fundraising Liquidity Index at the First Crisis Period



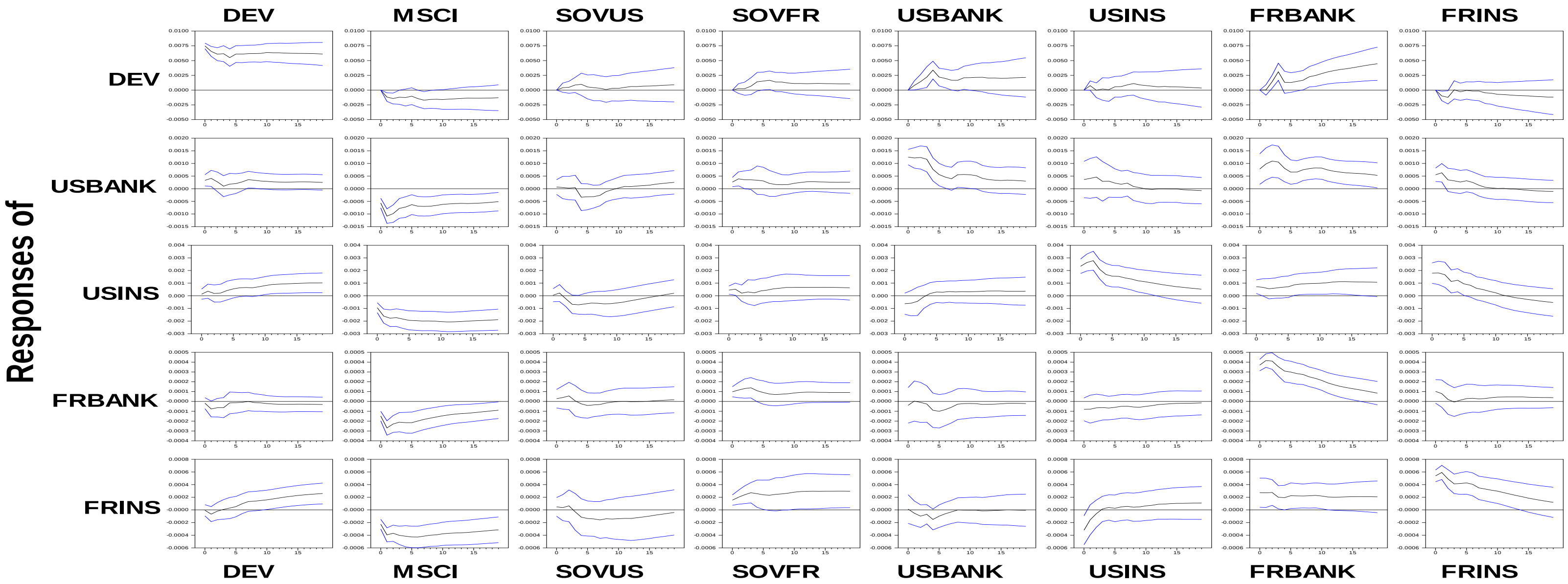
Note: The impulse responses reported in the figure above are derived from the four-variable SVAR model constituting DEV, MSCI, a sovereign CDS spread and CDS spread of a financial institution. The recursive-type restriction is imposed on the model. DEV and MSCI are applied as global common factors and the CDS spread of the nation where the headquarter of the financial institution adopted in the analysis is located is used as a local common factor. The impulse response of each financial institution is estimated by commonly using the three common factors.

Figure 2-2: Impulse Response of the Fundraising Liquidity Index to a Shock in CDS Spread of a Financial Institution at the First Crisis Period



Note: The impulse responses reported in the figure above are derived from the four-variable SVAR model constituted by DEV, MSCI, a sovereign CDS spread and a financial institution. The recursive-type restriction is imposed on the model. DEV and MSCI are applied as global common factors and the CDS spread of the nation where the headquarter of the financial institution adopted in the analysis is located is used as a local common factor. The impulse response of each financial institution is estimated by commonly using the three common factors.

Figure 3-1: Impulse Response Functions of the two-country model (US and France) at the first crisis period

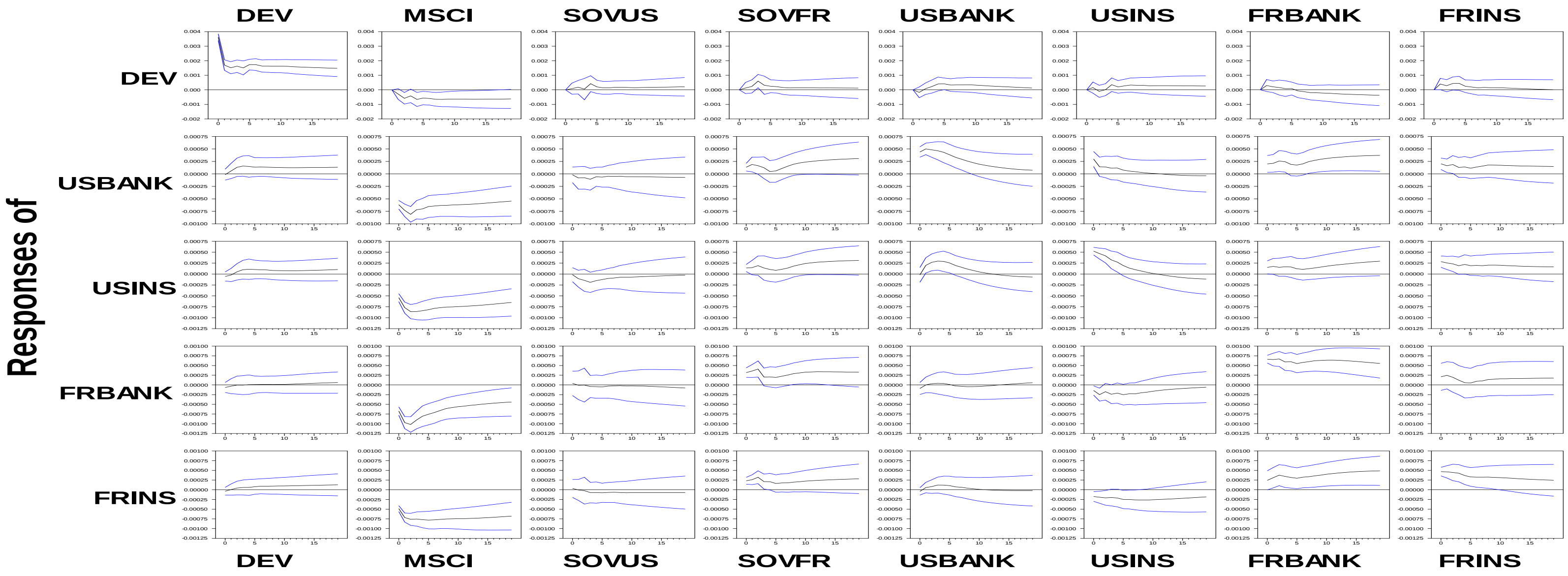


Note 1: The *i*-th row of the matrix in Figure 1 represents the *i*-th dependent variable in vector *X* in equation (1). The *j*-th column of the matrix signifies the *j*-th structural shock in vector u in equation (1).

Note 2: The following abbreviations were used: DEV: fundraising liquidity indicator represented with the deviation from the arbitrage conditions; MSCI, MSCI World Index; SOVUS and SOVFR, US and French sovereign CDS spread, respectively; USBANK and USINS, the averaged CDS spread of US banks (commercial banks and investment banks) and life insurance companies, respectively; FRBANK and FRINS, the averaged CDS spread of French banks and insurance companies, respectively.

Note 3: Black lines show point estimates of impulse responses. Blue lines show the confidence bands measured using two standard deviations with a Monte Carlo simulation.

Figure 3-2: Impulse Response Functions of the two-country model (US and France) at the second crisis period

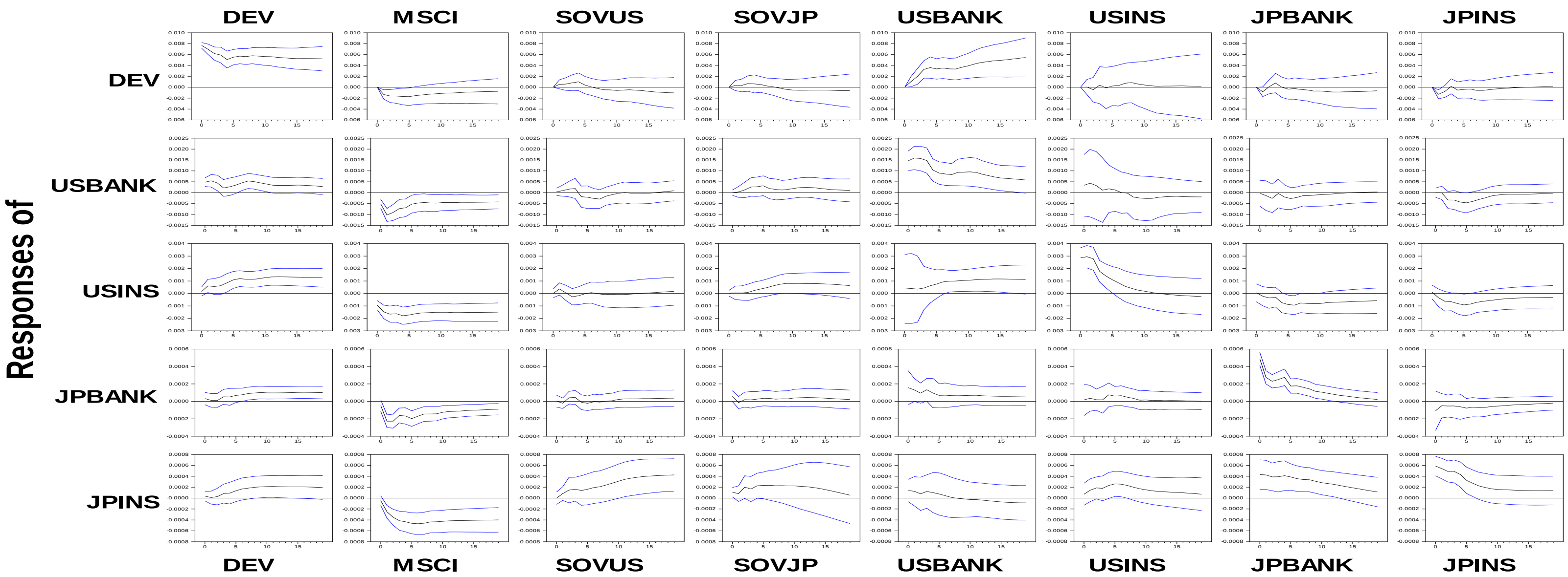


Note 1: The *i*-th row of the matrix in Figure 1 represents the *i*-th dependent variable in vector X in equation (1). The *j*-th column of the matrix signifies the *j*-th structural shock in vector u in equation (1).

Note 2: The following abbreviations were used: DEV: fundraising liquidity indicator represented with the deviation from the arbitrage conditions; MSCI, MSCI World Index; SOVUS and SOVFR, US and French sovereign CDS spread, respectively; USBANK and USINS, the averaged CDS spread of US banks (commercial banks and investment banks) and life insurance companies, respectively; FRBANK and FRINS, the averaged CDS spread of French banks and insurance companies, respectively.

Note 3: Black lines show point estimates of impulse responses. Blue lines show the confidence bands measured using two standard deviations with a Monte Carlo simulation.

Figure 3-3: Impulse Response Functions of the two-country model (US and Japan) at the first crisis period

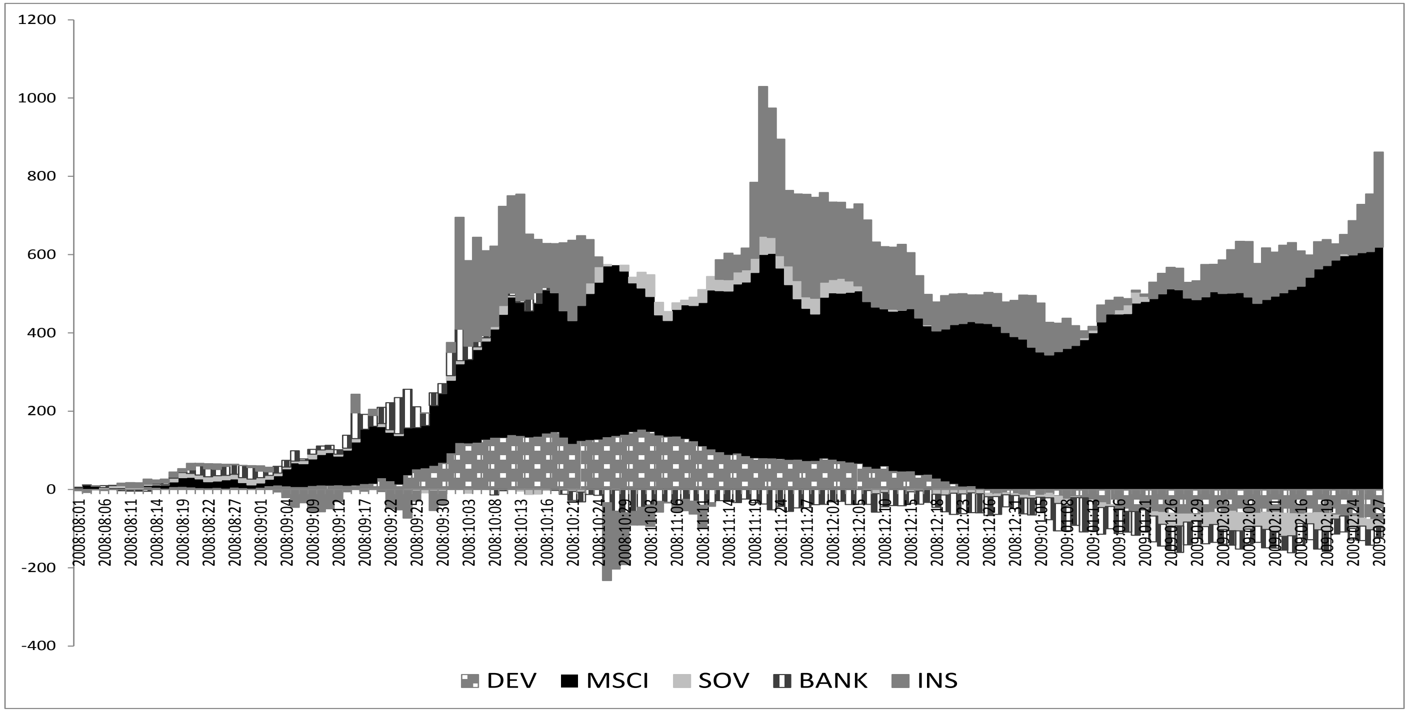


Note 1: The *i*-th row of the matrix in Figure 1 represents the *i*-th dependent variable in vector *X* in equation (1). The *j*-th column of the matrix signifies the *j*-th structural shock in vector u in equation (1).

Note 2: The following abbreviations were used: DEV: fundraising liquidity indicator represented with the deviation from the arbitrage conditions; MSCI, MSCI World Index; SOVUS and SOVFR, US and French sovereign CDS spread, respectively; USBANK and USINS, the averaged CDS spread of US banks (commercial banks and investment banks) and life insurance companies, respectively; JPBANK and JPINS, the averaged CDS spread of Japanese banks and insurance companies, respectively.

Note 3: Black lines show point estimates of impulse responses. Blue lines show the confidence bands measured using two standard deviations with a Monte Carlo simulation.

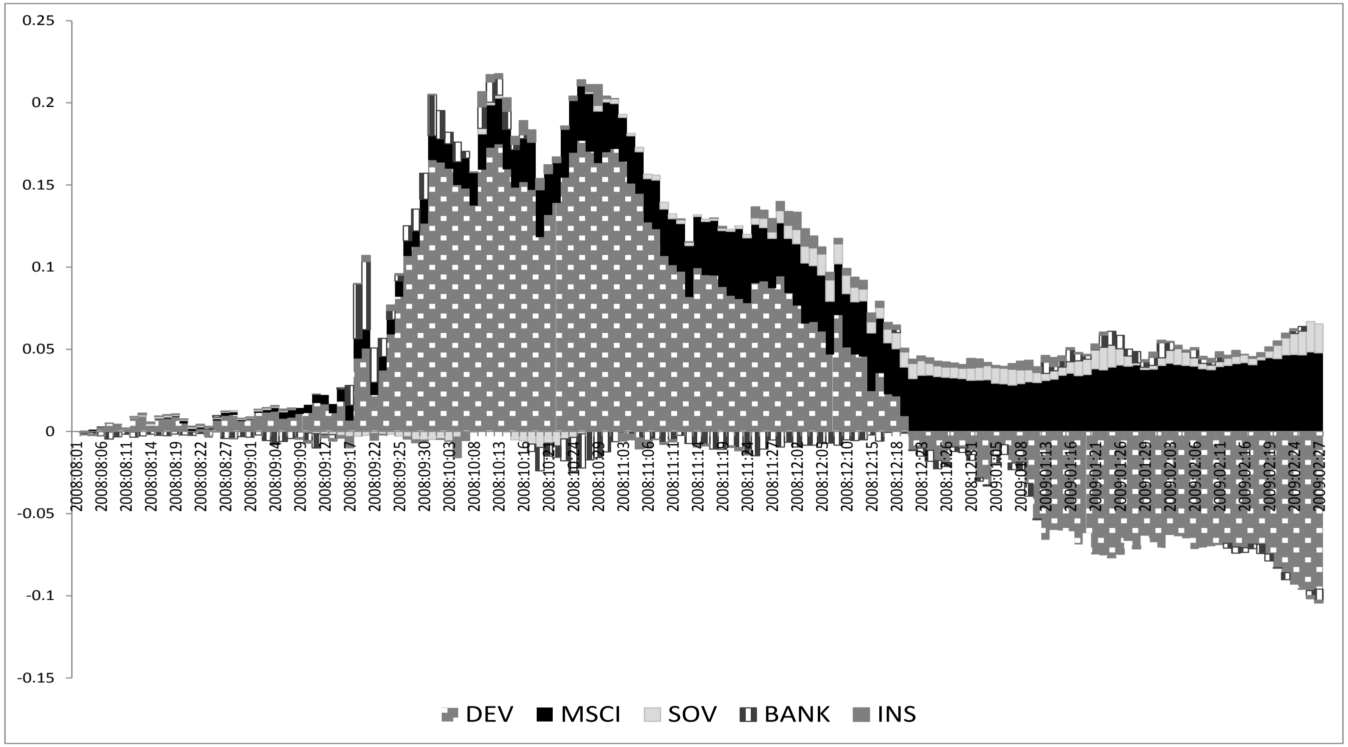
Figure 4-1: Historical Decomposition for the averaged CDS spreads of US life insurance companies during the first crisis period



Note1: Historical decompositions trace a relative contribution of each structural shock on a dependent variable. In Figure 4-1, each structural shock is accumulated to show its relative contribution on the level of USINS during the period after August 1, 2008.

Note 2: DEV, fundraising liquidity shock derived by using the deviation from the arbitrage conditions; MSCI, a shock in MSCI world index; SOV, the sum of the shocks of the US and French sovereign CDS spreads; BANK, the sum of the shocks in the CDS of the US and French banks; INS, the sum of the shocks in the CDS of the US and French insurance companies.

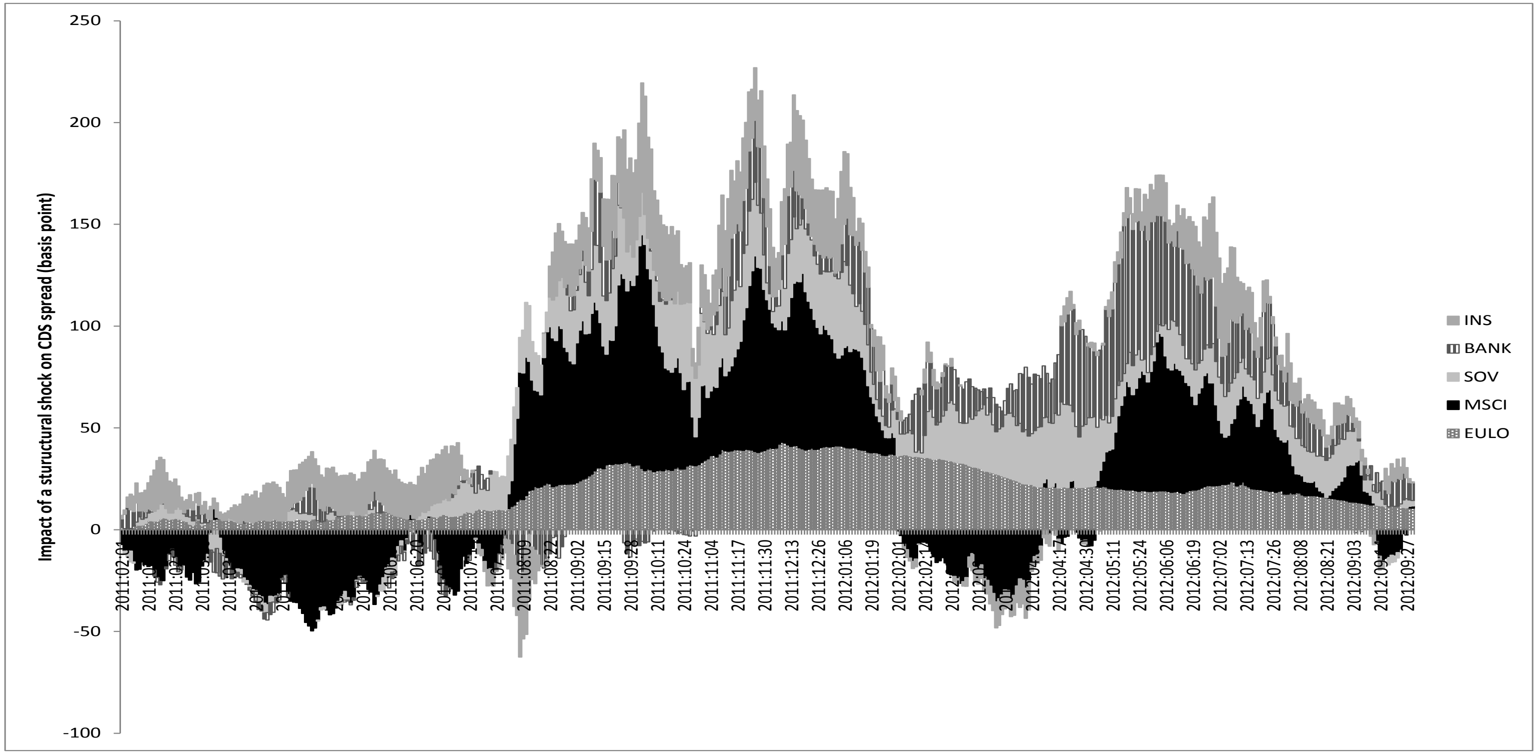
Figure 4-2: Historical Decomposition for DEV during the first crisis period



Note1: Historical decompositions trace a relative contribution of each structural shock on a dependent variable. In figure 4-2, each structural shock is accumulated to show its relative contribution on the level of DEV during the period after August 1, 2008.

Note 2: DEV, fundraising liquidity shock derived by using the deviation from the arbitrage conditions; MSCI, MSCI shock derived from MSCI world index; SOV, the sum of the shocks of the US and French sovereign CDS spreads; BANK, the sum of the shocks in the CDS of the US and French banks; INS, the sum of the shocks in the CDS of the US and French insurance companies.

Figure 4-3: Historical Decomposition for FRINS during the second crisis period



Note1: Historical decompositions trace a relative contribution of each structural shock on a dependent variable. In figure 4-4, each structural shock is accumulated to show its relative contribution on the level of FRINS during the period after February 1, 2011.

Note 2: EULO, fundraising liquidity indicator represented by the gap between the six-month Euro LIBOR rate and the six-month Euro OIS rate; MSCI, MSCI shock derived from MSCI world index; SOV, the sum of the shocks of the US and French sovereign CDS spreads; BANK, the sum of the shocks in the CDS of the US and French banks; INS, the sum of the shocks in the CDS of the US and French insurance companies.

Table 1: Connectedness index derived from the two-country model

<First crisis period: 2008/1/18–2009/10/31>

①US–France

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	76.8	1.8	21.5	16.0	5.5
USBANK	18.7	7.4	36.1	24.2	6.0
USINS	13.7	6.4	31.7	3.7	24.4
FRBANK	18.3	7.7	14.2	5.4	4.4
FRINS	14.1	6.6	37.2	8.0	21.3
Bank	18.5	7.6	25.2	14.8	5.2
Insurance	13.9	6.5	34.5	5.8	22.9
Connectedness from common	16.2	7.0	29.8	10.3	14.0
Connectedness across FIs			38.8		

②US–Germany

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	82.8	3.0	14.2	6.5	7.7
USBANK	18.4	6.9	32.5	14.7	8.9
USINS	14.0	5.8	30.9	3.1	24.7
GEBANK	11.9	5.4	15.1	1.0	7.1
GEINS	15.5	5.9	25.3	6.8	11.7
Bank	15.2	6.2	23.8	7.9	8.0
Insurance	14.8	5.9	28.1	5.0	18.2
Connectedness from common	15.0	6.0	26.0	6.4	13.1
Connectedness across FIs			32.8		

③US–Japan

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	84.1	1.7	14.1	7.0	7.1
USBANK	19.6	6.1	21.5	5.5	8.0
USINS	13.8	3.5	10.2	2.9	4.5
JPBANK	10.4	6.6	11.4	6.4	2.5
JPINS	12.9	8.5	24.5	11.4	1.7
Bank	15.0	6.4	16.5	6.0	5.3
Insurance	13.4	6.0	17.4	7.1	3.1
Connectedness from common	14.2	6.2	16.9	6.5	4.2
Connectedness across FIs			21.2		

④US–Netherlands

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	77.4	4.8	17.8	12.4	5.4
USBANK	20.6	8.2	31.7	7.7	12.0
USINS	15.8	5.7	43.6	7.5	28.7
NEBANK	9.1	6.2	17.9	6.1	5.9
NEINS	16.4	8.0	23.5	6.7	10.2
Bank	14.9	7.2	24.8	6.9	9.0
Insurance	16.1	6.9	33.6	7.1	19.5
Connectedness from common	15.5	7.0	29.2	7.0	14.2
Connectedness across FIs			37.6		

⑤US–UK

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	59.3	8.3	32.4	27.2	5.2
USBANK	15.6	10.5	29.2	17.7	5.8
USINS	13.7	7.7	31.6	3.6	24.5
UKBANK	12.5	10.1	12.4	7.2	2.6
UKINS	13.1	9.5	25.2	7.5	10.3
Bank	14.1	10.3	20.8	12.5	4.2
Insurance	13.4	8.6	28.4	5.5	17.4
Connectedness from common	13.7	9.5	24.6	9.0	10.8
Connectedness across FIs			32.0		

⑥Germany–France

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	74.8	2.7	22.5	9.0	13.5
GEBANK	14.6	6.4	47.2	13.2	17.0
GEINS	17.3	6.5	51.4	3.9	43.7
FRBANK	19.4	6.0	66.7	34.3	16.2
FRINS	17.2	6.4	11.5	4.4	2.7
Bank	17.0	6.2	57.0	23.8	16.6
Insurance	17.3	6.5	31.5	4.1	23.2
Connectedness from common	17.1	6.3	44.2	13.9	19.9
Connectedness across FIs			57.7		

<Second crisis period: 2011/1/4–2012/9/30>

①US–France

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	90.2	5.7	4.2	1.7	2.5
USBANK	46.3	6.9	26.1	4.6	10.8
USINS	40.5	7.1	18.4	4.4	9.6
FRBANK	39.0	15.6	9.5	1.4	4.1
FRINS	36.8	14.5	15.9	6.1	3.7
Bank	42.7	11.3	17.8	3.0	7.4
Insurance	38.7	10.8	17.2	5.3	6.7
Connectedness from common	40.7	11.0	17.5	4.1	7.0
Connectedness across FIs			36.2		

②US–Germany

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	90.1	4.3	5.7	1.6	4.1
USBANK	45.4	5.7	24.4	2.0	11.2
USINS	38.4	6.6	45.3	4.4	36.5
GEBANK	37.9	8.0	24.7	2.4	11.2
GEINS	33.6	7.4	30.8	2.1	26.7
Bank	41.7	6.9	24.6	2.2	11.2
Insurance	36.0	7.0	38.1	3.2	31.6
Connectedness from common	38.8	6.9	31.3	2.7	21.4
Connectedness across FIs			57.6		

③US–Japan

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	90.1	3.5	6.4	2.6	3.8
USBANK	43.9	5.2	15.2	7.5	3.9
USINS	38.4	3.1	18.2	7.9	2.4
JPBANK	16.9	8.9	23.0	14.8	4.1
JPINS	8.0	10.4	13.0	5.2	2.6
Bank	30.4	7.1	19.1	11.2	4.0
Insurance	23.2	6.8	15.6	6.6	2.5
Connectedness from common	26.8	6.9	17.4	8.9	3.2
Connectedness across FIs			26.2		

④US–Netherlands

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	90.6	4.3	5.1	1.2	3.9
USBANK	41.5	8.8	35.8	11.0	12.4
USINS	37.6	7.2	27.1	7.3	12.6
NEBANK	10.0	5.1	26.1	5.2	10.5
NEINS	31.8	14.4	27.5	8.5	10.5
Bank	25.8	7.0	31.0	8.1	11.4
Insurance	34.7	10.8	27.3	7.9	11.6
Connectedness from common	30.2	8.9	29.1	8.0	11.5
Connectedness across FIs			47.7		

⑤US–UK

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	90.0	4.1	5.8	3.1	2.7
USBANK	44.2	7.2	20.5	2.4	9.1
USINS	38.2	7.5	28.6	4.5	19.6
UKBANK	39.9	14.5	13.1	1.4	5.9
UKINS	31.5	10.6	17.7	3.0	11.8
Bank	42.1	10.9	16.8	1.9	7.5
Insurance	34.9	9.1	23.2	3.7	15.7
Connectedness from common	38.5	10.0	20.0	2.8	11.6
Connectedness across FIs			38.7		

⑥Germany–France

	Common	Sovereign	Connectedness from Fis		
				Bank	Insurance
DEV	93.9	3.0	3.1	1.4	1.7
GEBANK	37.9	14.1	26.0	17.9	4.1
GEINS	33.2	16.0	42.3	9.6	23.1
FRBANK	40.1	17.8	3.5	0.5	1.5
FRINS	36.5	16.7	26.3	10.9	4.6
Bank	39.0	16.0	14.8	9.2	2.8
Insurance	34.9	16.4	34.3	10.2	13.9
Connectedness from common	36.9	16.2	24.5	9.7	8.3
Connectedness across FIs			52.3		

Note 1: DEV; fundraising liquidity indicator represented with the deviation from the arbitrage conditions. USBANK, UKBANK, GEBANK, FRBANK, NEBANK and JPBANK; the averaged CDS spread of banks in US, UK, Germany, France, Netherlands, and Japan, respectively. USINS, UKINS, GEINS, FRINS, NEINS and JPINS; the averaged CDS spread of insurance companies in US, UK, Germany, France, Netherlands, and Japan, respectively.

Note 2: The first column of the matrix represents the dependent variable including DEV and CDS spreads of four financial institutions. The seventh and eighth row report the result of the average of the two banks and two insurance companies, respectively. The second column of the matrix signifies the relative contribution of two global common factor shocks. The third column denoted as “connectedness from FIs (financial institutions)” is the relative contribution of a shock in CDS spreads of financial institutions. The value of connectedness from FIs to DEV is calculated as the sum of the contribution of the four financial institutions' shock. The value of connectedness from FIs to each financial institution is calculated as the sum of the contribution of non-own shocks of financial institutions. The connectedness from FIs is broken down into the part attributed to banks and that to insurance companies. The value in the fourth and fifth column is not the sum but the averaged relative contribution of banks and insurance companies.

Note 2: The connectedness across financial institutions (FIs) is calculated as a ratio of the sum of contributions of a shock from a financial institution to another to another relative to the total of contributions of a shock in CDS spreads of all financial institutions.

DEV: fundraising liquidity indicator represented with the deviation from the arbitrage conditions; USBANK, UKBANK, GEBANK, FRBANK, NEBANK and JPBANK, the averaged CDS spread of banks in US, UK, Germany, France, Netherlands, and Japan, respectively.

Table 2-1: Connectedness index derived from the four-country and singl- sector model (Banking sector)

<First crisis period: 2008/1/18-2009/10/3>

①US-UK-Germany-France

	Common	Sovereign	Connectedness from FIs
DEV	60.2	9.6	30.1
USBANK	17.0	15.5	37.6
UKBANK	11.6	12.6	35.0
GEBANK	13.8	12.8	59.5
FRBANK	14.6	18.4	20.8
Connectedness from common	14.3	14.8	38.2
Connectedness across FIs			53.5

②US-UK-Japan-France

	Common	Sovereign	Connectedness from FIs
DEV	60.3	8.9	30.8
USBANK	17.2	13.0	37.5
UKBANK	13.3	11.0	34.4
JPBANK	11.5	8.9	33.0
FRBANK	16.2	17.1	18.9
Connectedness from common	14.6	12.5	31.0
Connectedness across FIs			42.3

③US-UK-Germany-Japan

	Common	Sovereign	Connectedness from FIs
DEV	61.7	10.5	27.9
USBANK	21.1	12.7	19.3
UKBANK	12.4	9.8	22.9
GEBANK	13.8	9.1	29.2
JPBANK	11.0	10.3	21.3
Connectedness from common	14.6	10.5	23.2
Connectedness across FIs			30.9

④UK-Germany-France-Netherlands

	Common	Sovereign	Connectedness from FIs
DEV	63.9	8.6	27.5
UKBANK	12.1	11.2	29.9
GEBANK	12.4	12.4	65.7
FRBANK	16.6	14.3	23.3
NEBANK	10.3	5.6	33.2
Connectedness from common	12.9	10.9	38.0
Connectedness across FIs			49.8

<second crisis period: 2011/1/4-2012/9/30>

①US-UK-Germany-France

	Common	Sovereign	Connectedness from FIs
DEV	93.1	4.3	2.7
USBANK	46.3	7.7	10.4
UKBANK	42.1	15.5	14.2
GEBANK	37.5	14.5	35.2
FRBANK	40.1	16.9	8.8
Connectedness from common	41.5	13.7	17.2
Connectedness across FIs			38.3

②US-UK-Japan-France

	Common	Sovereign	Connectedness from FIs
DEV	92.0	3.8	4.2
USBANK	46.4	8.8	10.9
UKBANK	42.3	15.8	13.2
JPBANK	18.0	13.4	19.6
FRBANK	40.0	16.5	9.9
Connectedness from common	36.7	13.6	13.4
Connectedness across FIs			26.9

③US-UK-Germany-Japan

	Common	Sovereign	Connectedness from FIs
DEV	92.2	3.5	4.2
USBANK	44.6	9.2	11.6
UKBANK	39.8	17.4	4.7
GEBANK	35.6	14.5	26.9
JPBANK	17.0	16.0	9.7
Connectedness from common	34.3	14.3	13.2
Connectedness across FIs			25.7

④UK-Germany-France-Netherlands

	Common	Sovereign	Connectedness from FIs
DEV	95.6	2.8	1.5
UKBANK	41.3	19.1	31.5
GEBANK	35.6	15.8	33.5
FRBANK	39.3	20.2	25.9
NEBANK	9.4	13.2	47.3
Connectedness from common	31.4	17.1	34.6
Connectedness across FIs			67.0

Note 1: The row of the matrix represents the dependent variable including DEV and CDS spreads of four financial institutions. The first column of the matrix signifies the relative contribution of two global common factors shocks. The second column presents the relative contribution of sovereign CDS spread of the selected four countries. The third column is the relative contribution of a shock in CDS spreads of financial institutions excluding own.

Note 2: The connectedness index is calculated as a ratio of the sum of contributions of a shock in CDS spread of a financial institution to another relative to the total of contributions of a shock in CDS spreads of all financial institutions.

Note 3: DEV: fundraising liquidity indicator represented with the deviation from the arbitrage conditions; USBANK, UKBANK, GEBANK, FRBANK, NEBANK and JPBANK, the averaged CDS spread of banks in US, UK, Germany, France, Netherlands, and Japan, respectively.

Table 2-2: Connectedness index derived from the four-country and single-sector model (Insurance sector)

<First crisis period: 2008/1/18-2009/10/3>

①US-UK-Germany-France

	Common	Sovereign	Connectedness from FIs
DEV	68.9	8.0	23.2
USINS	12.6	9.1	62.0
UKINS	9.5	11.0	64.4
GEINS	10.3	10.8	72.0
FRINS	11.9	8.6	23.7
Connectedness from common	11.1	9.9	55.5
Connectedness across FIs			70.3

②US-UK-Japan-France

	Common	Sovereign	Connectedness from FIs
DEV	72.8	6.9	20.3
USINS	10.5	7.4	31.9
UKINS	12.0	11.1	43.9
JPINS	13.6	10.1	30.9
FRINS	12.8	8.4	74.4
Connectedness from common	12.2	9.3	45.3
Connectedness across FIs			57.7

③US-UK-Germany-Japan

	Common	Sovereign	Connectedness from FIs
DEV	69.9	8.5	21.6
SOVJP	5.6	84.3	10.1
USINS	12.2	8.1	14.5
UKINS	10.1	10.8	45.1
GEINS	10.1	9.4	64.6
JPINS	12.5	10.9	22.6
Connectedness from common	11.2	9.8	36.7
Connectedness across FIs			46.2

④UK-Germany-France-Netherlands

	Common	Sovereign	Connectedness from FIs
DEV	66.1	8.4	25.4
MSCI	80.9	4.5	14.7
UKINS	8.6	13.6	63.0
GEINS	12.4	9.6	69.7
FRINS	11.2	7.7	39.1
NEINS	12.8	7.7	40.5
Connectedness from common	11.3	9.7	53.1
Connectedness across FIs			67.1

<second crisis period: 2011/1/4-2012/9/30>

①US-UK-Germany-France

	Common	Sovereign	Connectedness from FIs
DEV	90.2	4.3	5.5
USINS	38.8	10.8	37.0
UKINS	31.9	15.1	29.9
GEINS	34.3	16.0	42.7
FRINS	37.1	16.1	18.3
Connectedness from common	35.5	14.5	32.0
Connectedness across FIs			63.9

②US-UK-Japan-France

	Common	Sovereign	Connectedness from FIs
DEV	91.1	4.2	4.6
USINS	39.1	10.8	37.0
UKINS	32.1	13.8	24.5
JPINS	6.5	12.0	6.4
FRINS	37.8	15.6	22.4
Connectedness from common	28.9	13.1	22.6
Connectedness across FIs			38.9

③US-UK-Germany-Japan

	Common	Sovereign	Connectedness from FIs
DEV	91.2	3.7	5.2
SOVJP	6.5	88.3	5.3
USINS	38.8	9.6	28.3
UKINS	30.9	15.0	24.1
GEINS	32.5	17.0	44.9
JPINS	5.9	13.2	10.7
Connectedness from common	27.0	13.7	27.0
Connectedness across FIs			45.5

④UK-Germany-France-Netherlands

	Common	Sovereign	Connectedness from FIs
DEV	93.4	2.7	3.8
MSCI	89.8	3.8	6.4
UKINS	29.9	17.3	48.9
GEINS	33.8	19.2	42.7
FRINS	35.6	19.4	38.0
NEINS	32.5	15.4	45.0
Connectedness from common	33.0	17.8	43.7
Connectedness across FIs			88.8

Note 1: The row of the matrix represents the dependent variable including DEV and CDS spreads of four financial institutions. The first column of the matrix signifies the relative contribution of two global common factors shocks. The second column presents the relative contribution of sovereign CDS spread of the selected four countries. The third column is the relative contribution of a shock in CDS spreads of financial institutions excluding own.

Note 2: The connectedness index is calculated as a ratio of the sum of contributions of a shock in CDS spread of a financial institution to another relative to the total of contributions of a shock in CDS spreads of all financial institutions.

Note 3: DEV: fundraising liquidity indicator represented with the deviation from the arbitrage conditions; USINS, UKINS, GEINS, FRINS, NEINS and JPINS, the averaged CDS spread of insurance companies in US, UK, Germany, France, Netherlands, and Japan, respectively.

Table 3 Connectedness index derived from the revised two-sector model at the first crisis period

(1-1) BANK; UK, France INSURANCE; US, Germany

	Common	Sovereign	Connectedness from FIs		
				BANK	INSURANCE
DEV	62.1	9.5	28.4	26.1	2.3
USINS	12.0	13.0	51.1	21.2	8.7
UKBANK	11.2	10.5	36.8	27.8	4.5
GEINS	12.4	10.3	64.3	26.8	10.7
FRBANK	14.0	17.4	25.3	10.6	7.4
BANK	12.6	14.0	31.1	19.2	5.9
INSURANCE	12.2	11.7	57.7	24.0	9.7
Connectedness from common	12.4	12.8	44.4	21.6	7.8
Connectedness across FIs			59.4		

(1-2) BANK; UKS Germany INSURANCE; UK, France

	Common	Sovereign	Connectedness from FIs		
				BANK	INSURANCE
DEV	71.5	9.5	18.9	4.9	14.0
USBANK	18.6	13.1	29.7	4.0	12.9
UKINS	11.6	12.6	51.8	12.0	27.9
GEBANK	14.5	11.4	64.5	2.0	31.3
FRINS	13.6	9.1	20.4	5.0	17.8
BANK	12.6	10.9	36.1	3.0	22.1
INSURANCE	16.6	12.3	47.1	8.5	22.9
Connectedness from common	14.6	11.6	41.6	5.7	22.5
Connectedness across FIs			56.3		

(2-1) BANK; UK, Netherlands INSURANCE; US, Germany

	Common	Sovereign	Connectedness from FIs		
				BANK	INSURANCE
DEV	60.8	10.5	28.7	25.9	2.8
USINS	12.8	12.2	64.2	30.3	3.6
UKBANK	10.1	9.5	16.0	10.2	2.9
GEINS	11.2	10.6	59.7	25.1	9.5
NEBANK	10.0	8.9	54.2	11.4	21.4
BANK	10.1	9.2	35.1	10.8	12.2
INSURANCE	12.0	11.4	62.0	27.7	6.6
Connectedness from common	11.0	10.3	48.5	19.3	9.4
Connectedness across FIs			61.7		

(2-2) BANK; US, Germany INSURANCE; UK, Netherlands

	Common	Sovereign	Connectedness from FIs		
				BANK	INSURANCE
DEV	70.9	12.0	17.1	10.7	6.4
USBANK	20.5	12.9	21.6	9.4	6.1
UKINS	10.1	13.4	62.0	5.2	51.7
GEBANK	12.5	9.5	6.4	1.9	2.3
NEINS	13.3	12.2	29.6	5.4	1.3
BANK	11.7	12.8	45.8	5.7	4.2
INSURANCE	16.5	11.2	14.0	5.3	26.5
Connectedness from common	14.1	12.0	29.9	5.5	15.3
Connectedness across FIs			40.5		

(3-1) BANK; UK, Japan INSURANCE; US, Germany

	Common	Sovereign	Connectedness from FIs		
				BANK	INSURANCE
DEV	61.8	9.2	29.0	25.3	3.7
USINS	12.1	11.0	34.2	3.8	26.7
UKBANK	12.0	9.6	17.5	11.1	3.2
GEINS	13.1	7.9	64.9	26.2	12.6
JPBANK	12.2	9.8	17.1	3.4	6.9
BANK	12.1	9.7	17.3	7.3	5.0
INSURANCE	12.6	9.5	49.6	15.0	19.7
Connectedness from common	12.4	9.6	33.4	11.1	12.3
Connectedness across FIs			42.8		

(3-2) BANK; US, Germany INSURANCE; UK, Japan

	Common	Sovereign	Connectedness from FIs		
				BANK	INSURANCE
DEV	73.7	9.0	17.3	4.3	13.0
USBANK	18.5	13.6	21.8	3.9	9.0
UKINS	12.5	10.3	44.4	20.9	2.6
GEBANK	12.6	10.1	68.2	1.5	33.4
JPINS	12.8	9.2	16.7	6.2	61.6
BANK	12.7	9.8	30.6	2.7	21.2
INSURANCE	15.6	11.9	45.0	13.6	32.1
Connectedness from common	14.1	10.8	37.8	8.1	26.6
Connectedness across FIs			50.3		

(4-1) BANK; UK, Netherlands, INSURANCE; US, France

	Common	Sovereign	Connectedness from FIs		
				BANK	INSURANCE
DEV	60.1	9.2	30.7	27.1	3.6
USINS	13.6	10.9	56.4	27.9	0.6
UKBANK	11.1	8.4	22.6	5.1	8.8
FRINS	13.9	10.6	20.0	9.3	1.5
NEBANK	9.8	8.5	46.0	13.1	16.5
BANK	10.5	8.5	34.3	9.1	12.6
INSURANCE	13.8	10.8	38.2	18.6	1.1
Connectedness from common	12.1	9.6	36.3	13.8	6.8
Connectedness across FIs			46.3		

(4-2) BANK; US, France, INSURANCE; UK, Netherlands

	Common	Sovereign	Connectedness from FIs		
				BANK	INSURANCE
DEV	68.6	9.9	21.5	12.8	8.7
USBANK	17.6	13.9	29.4	23.1	3.2
UKINS	10.7	15.2	61.6	13.5	34.7
FRBANK	14.7	18.2	23.0	2.6	10.2
NEINS	13.5	11.7	27.8	6.3	16.4
BANK	12.1	13.5	44.7	12.9	6.7
INSURANCE	16.2	16.1	26.2	9.9	25.6
Connectedness from common	14.1	14.8	35.5	11.4	16.1
Connectedness across FIs			49.8		

(5-1) BANK; Germany, Netherlands INSURANCE; UK, France

	Common	Sovereign	Connectedness from FIs		
				BANK	INSURANCE
DEV	70.8	8.6	20.6	7.1	13.5
UKINS	12.4	12.4	53.6	17.0	19.7
GEBANK	13.2	10.1	63.6	7.9	27.9
FRINS	14.5	8.2	28.1	7.8	12.5
NEBANK	10.1	5.5	56.8	4.9	26.0
BANK	11.7	7.8	60.2	6.4	26.9
INSURANCE	13.5	10.3	40.9	12.4	16.1
Connectedness from common	12.6	9.1	50.5	9.4	21.5
Connectedness across FIs			64.4		

(5-2) BANK; UK, France INSURANCE; Germany, Netherlands

	Common	Sovereign	Connectedness from FIs		
				BANK	INSURANCE
DEV	64.8	9.3	25.9	21.4	4.5
UKBANK	12.2	10.0	39.3	26.8	6.3
GEINS	13.6	8.8	72.9	20.8	31.3
FRBANK	16.7	15.3	22.4	3.9	9.3
NEINS	13.3	10.1	41.1	7.5	13.3
BANK	13.5	9.5	57.0	15.4	7.8
INSURANCE	14.5	12.7	30.9	14.2	22.3
Connectedness from common	14.0	11.1	43.9	14.8	15.0
Connectedness across FIs			58.6		

Note 1: The row of the matrix represents the dependent variable including DEV and CDS spreads of four financial institutions. The sixth and seventh rows represent the average for the two banks and two insurance companies, respectively. The second column of the matrix signifies the relative contribution of two global common factors shocks. The second column presents the relative contribution of sovereign CDS spread of the selected two countries. The third column is the relative contribution of a shock in CDS spreads of financial institutions excluding own. Its contribution for DEV is divided into the part attributed to banks and that to insurance companies. The values in the part from the second to fifth row and from the fourth to fifth column report the averaged contribution of banks (or insurance companies) to a financial institution.

Note 2: The connectedness index is calculated as a ratio of the sum of contributions of a shock in CDS spread of a financial institution to another relative to the total of contributions of a shock in CDS spreads of all financial institutions.