Financial Stability Institute

FSI Award
2012 Winning Paper

Managing systemic risk from the perspective of the financial network under macroeconomic distress

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Foreword

The Financial Stability Institute is pleased to present the winning FSI Award paper for 2012. This award, announced every two years at the time of the International Conference of Banking Supervisors, was established to encourage thought and research on issues relevant to banking supervisors.

A jury of highly qualified individuals chose this year's winning paper. The group was chaired by Mr Jaime Caruana, General Manager of the Bank for International Settlements. It also included Mr Wayne Byres, Secretary General of the Basel Committee on Banking Supervision; Mrs Ruth de Krivoy, former President of the Central Bank of Venezuela; Mr Göran Lind, Advisor to the Executive Board, Sveriges Riksbank; and Mr Graeme Thompson, former CEO of the Australian Prudential Regulatory Authority.

The jury members and the FSI are pleased to announce that the paper authored by Mr Jae Hyun Jo of the Korean Financial Supervisory Service has been selected as the winner of the 2012 FSI Award. The author presents his study on the interconnectedness of financial institutions and provides a new analysis framework to facilitate contagion simulation. The analysis has implications for developing a supervisory framework for domestic financial institutions, including systemically important banks.

Congratulations to Mr Jae Hyun Jo and the other supervisors who submitted their work for consideration. Their interest in analysing financial markets and potentially improving supervisory techniques is an important contribution to the supervisory community.

Josef Tošovský
Chairman
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September 2012

Contents

1. Introduction

The recent global financial crisis has emphasized the importance of managing systemic risk, which disrupts the financial system and has a significant adverse impact on the real economy. Recently, the interconnectedness of financial institutions has been identified as a critical source of systemic risk. Financial sector supervisors realise that any systemic event carries contagion effects and conventional supervisory approaches at the level of an individual bank are insufficient. They now have initiated great efforts to assess financial system vulnerabilities arising from interconnectedness and to mitigate the impact of contagion.

This paper proposes an enhanced methodology to assess contagion risk arising from financial connections across financial firms. The methodology addresses the following three questions:

(1) How does the failure of some financial institutions impact other financial institutions?

(2) What are the key exposures that create systemic risk?

(3) How much must inter-financial institution exposures be reduced in order to prevent extensive spillovers and how much additional capital is needed for the same purpose?

Recently, various methods to measure and reduce systemic risk have been developed from the interconnectedness perspective. It is believed that the balance sheet-based network analysis can offer an intuitive and practical look in explaining default contagion effects arising from inter-connected financial linkages.

The network analysis has been used initially in Europe, where universal banking was developed. Sheldon and Maurer (1998) applied this analysis to Swiss interbank exposure data to measure system risk. Similar analyses have been attempted in many countries; Wells (2002) in the United Kingdom; Furfine (2003) in the United States; Upper and Works (2004), and

Memmel and Stein (2008) in Germany; Elsinger et al (2006) in Austria; and Degryse and Nguyen (2007) in Belgium. Most studies before the global financial crisis asserted that sufficient capital at individual banks in a country would protect them from exogenous failure of one or more banks and thus prevent the local failure from spreading to the whole financial system.

Recent network analysis studies, however, emphasize market and liquidity risk and incorporate them into macro-stress tests. They form a consensus that a high level of interconnectedness among financial institutions plays a key role in amplifying loss in the financial system during a global financial crisis. For example, Adrian and Shin (2008) asserted that financial market disruption and resultant devaluation of financial instruments affected the balance sheets of financial market players, which essentially became contagion channels. Chan-Lau (2010) suggested that not only credit shocks but also funding shocks should be modelled in network analysis. Amini et al (2010) conducted network analysis by subtracting losses caused by macroeconomic shocks from capital. Barnhill and Schumacher (2011) proposed a macro stress testing methodology emphasizing systemic liquidity risk and used network analysis to calculate credit losses from interbank exposures.

This paper refines the existing network analysis framework by linking liquidity risk and solvency risk by enhancing the network analysis of Chan-Lau (2010) and facilitates a more realistic default contagion simulation. First, a more elaborate model to measure liquidity risk is established. The size of cash outflow and funding costs, assumed to be constants in previous analyses, are associated with solvency ability of a financial institution in the model. In this way, the interaction between liquidity risk and solvency risk is explained. Second, the quality of assets and liabilities are considered in measuring contagion effects on top of direct exposures (in previous analyses, only bilateral exposures were taken into account). In this approach, the amounts of risky assets held and wholesale funding result in magnified losses in the case of default of other financial segments and in response to macroeconomic shocks. Third, the network analysis methodology is applied to balances related to households and corporates for a macro stress test. Based on the results of the analysis, a method for managing systemic risk is suggested from the perspective of a financial network under macroeconomic shocks.

In the simulation, it is found that domestic banks are crucial to the stabilization of the financial system. Default contagion is typically observed in three financial segments – securities firms, foreign bank branches and credit unions – only when domestic banks are set as a trigger failure. Other segments do not generate any significant knock-on effects. With macroeconomic shocks, however, extensive default contagion is witnessed. A trigger failure of securities firms or credit specialized financial companies[1] (hereafter CSFC) as well as domestic banks makes most financial segments default. This result is caused by inter-financial institution linkages among securities firms, CSFC and domestic banks and interaction between solvency risk and liquidity risk. Even though securities firms or CSFC hold only 6% of the total assets of the entire financial sector, the simulation indicates that, if their failure is triggered, they generate contagious defaults on up to 92% of total assets.

These results have policy implications for the maintenance of financial system stability. First, supervisors can simulate the spillover effects triggered by each financial sector's failure and consequently compare the systemic importance of each sector. The results can also be used to assess the contagion risk associated with domestic SIFIs. In addition, the model developed in this paper enables one to define critical bilateral exposures that can potentially cause extensive contagion. An investigation of the simulation runs leads to the conclusion that a 20 to 30% reduction of key bilateral exposures is sufficient to avoid extensive default contagion. It is also suggested that the

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[1] They deal with credit card, lease and venture capital business.

holding of additional capital would achieve the same result. For domestic banks as a money centre in the financial system, a 1.1% increase in the Basel ratio (ie 15.6% for domestic banks) is found to safeguard the financial system against default contagion under the stress scenario. Thus, the analysis in this paper can help to determine the level of additional capital requirement for systemically important financial institutions.

The remainder of the paper is organised as follows. Section 2 describes the new network analysis framework and illustrates a default contagion simulation process under macroeconomic shocks. Section 3 presents inter-financial linkage data and Section 4 gives the results of the simulation and identifies the key channels of default contagion. Finally, Section 5 concludes with policy implications.

2. A new network model

2.1 Data structure

The bilateral exposures among N financial sectors can be collected in a $N \times N$ matrix with entries x_{ij}, where x_{ij} denotes the liability of sector i to sector j. The sum of all the x_{ij} s in the i^{th} row of the matrix equal total intra-financial sector liabilities of the i^{th} sector. The sum of the elements x_{ij} in the j^{th} column equals total intra-financial sector assets. The x_{ij} s can be divided into short-term liabilities (x_{ij}^{S}) and long-term liabilities (x_{ij}^{L}). Denote by a_i^m total liquid assets (eg cash, stocks and bonds) and a_i^z total illiquid assets, mainly loans to households and corporations. Liabilities other than inter-financial sector liabilities are divided into wholesale funds

(L_i^w), deposits (L_i^d) and others. The capital of sector i is denoted by C_i . The asset and liability structure of the domestic financial system can be arranged as in Table 2–1.

Table 2–1

Bilateral exposure matrix of the domestic financial sector system

Creditor / Debtor		Sectors					Wholesale fund	Deposit	capital
		1	...	j	...	N			
Sectors	1	x_{11}	...	x_{1j}	...	x_{1N}	L_1^w	L_1^d	C_1
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\iddots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	i	x_{i1}	...	x_{ij}	...	x_{iN}	L_i^w	L_i^d	C_i
	$\vdots$	$\vdots$	$\iddots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	N	x_{N1}	...	x_{Nj}	...	x_{NN}	L_N^w	L_N^d	C_N
Liquid assets		a_1^m	...	a_j^m	...	a_N^m			
Illiquid assets		a_1^z	...	a_j^z	...	a_N^z			

What is important for implementing an effective network analysis is setting the scope of a trigger failure. Previous network simulation studies investigated default contagion effects that result from the hypothetical failure of a single financial institution. The impact that such a trigger failure can make on the whole financial system is so weak that the researchers therefore usually have had difficulty explaining systemic risk through contagion. As for this point, Elsinger et al (2006) referred that these studies are able to capture the effect of idiosyncratic bank failure.

Therefore, it is necessary to set up a trigger default that has a plausible but severe effect on the financial system. This paper assumes that all members in a financial sector are regarded as one institution and then implements network analysis. Since financial institutions in the same financial sector have similar asset portfolios and fund raising, they are likely to be exposed to a common shock and have a possibility of facing bankruptcy simultaneously. As herd behaviour within a financial sector became stronger recently, default of a few major members in the financial sector easily spread to other members. Moreover, it can be useful in the view of policy implementation that network analysis is applied to a financial sector composed of financial institutions under the same regulatory system.

Additionally, this paper makes use of statistical methods to examine financial similarity among members in the same financial sector. One simple method is to calculate correlation coefficients of stock prices between financial institutions. Furthermore, all financial institutions can be divided into several groups through cluster analysis. The similarity within a given sector can be identified by comparing these statistical groups with existing financial sectors.

2.2 Network analysis model

The basic framework adopted in this paper for modelling contagion risk is based on the balance sheet network analysis introduced by Chan-Lau (2010). It incorporated credit losses and funding losses originating from exposures to defaulted banks. In addition, it analyzed how trigger banks' default can cause the loss of other banks and how these losses were propagated through financial linkages. This paper enhances the existing model by utilising a more realistic default contagion simulation.

To begin, a definition of default is needed. Default is defined to be when a financial sector's capital, less loss caused by contagion, is smaller than the minimum regulatory capital plus some buffer. A set of defaulted financial sectors is as follows:

$$D = \{\ i : C_i - L_i < C_i^r (1 + b_i)\}$$

Where C_i is total regulatory capital held by sector *i*, L_i is the sector's loss, C_i^r is minimum regulatory capital and b_i is a buffer. For example, the regulatory capital of the banking sector is 8% of risk weighted assets but if one would like to regard the criteria of default as 10% from a supervisory perspective, a 25% buffer would need to be added. In what follows, b_i is set equal to zero.

Contagion risk arises from credit losses associated with counterparty defaults and funding loss – like Chan-Lau (2010). The former means losses from claims on the defaulted financial sectors. In the case of default by a given financial sector h, the exposure from i to h (x_{hi}) is regarded as credit loss. With a set of defaulted sectors, denoted by D, the credit loss (CL_i) of financial sector i is given by

$$CL_i = \sum_{h \in D} x_{hi} \delta$$

where the loss given default, δ, is assumed to be 100% for all financial sectors.[2]

[2] Some studies endogenously estimated LGD based on market clearing equilibrium, as suggested in Eisenberg and Noe (2001). However, Cont et al (2010) pointed out that, since bankruptcy procedures are usually slow, creditors write down their entire exposures in the short run. In practice, financial institutions in our country holding claims to Lehman have written down nearly 100% of the exposure.

Funding losses are calculated through a different, complex mechanism. To repay a claim from defaulted sectors, a particular sector must refinance from other creditors or sell a part of its assets. Under normal conditions, it can sell the asset at a regular price and easily find new creditors. However, under stressed conditions, the sector would probably have to sell marketable assets at fire sale prices or pay considerable funding costs for refinancing. This paper computes the funding losses through these two sources.

First, funding losses are generated by fire sales needed to cover cash outflow from defaulted sectors. Financial sector i has raised $\sum_{h \in D} x_{ih}$ from a set of defaulted sectors, D, and it is expected to be completely withdrawn. Sector i replaces a part of cash outflow with funds newly sourced from alternative creditors, and the replacement amount is $\gamma \sum_{h \in D} x_{ih}$ ($0 \le \gamma \le 1$), where γ is the replacement rate. Under the circumstance of liquidity shortage, it may be forced to liquidate its assets at fire-sale prices.

The difference between fire-sale prices and book values causes losses, which are calculated by the amount of liquid and illiquid assets, and their loss rates. Let us set q as the fire-sale loss rate for liquid assets and z the loss rate for illiquid assets. Naturally $q < z$ holds. The cash secured by the fire sale of a liquid asset (a_i^q) is $a_i^q(1-q)$. In case the cash outflow can be covered by selling liquid assets, ie $(1-\gamma)\sum_{h \in D} x_{ih} \le a_i^q(1-q)$, sector i should sell a part of its liquid assets accounting for $(1-\gamma)\sum_{h \in D} x_{ih} / (1-q)$ and then it takes $(1-\gamma)\sum_{h \in D} x_{ih} \cdot q / (1-q)$ as a loss. Therefore, fire sale losses (FSL_i) defined in this case are:

$$FSL_i = Min\left[(1-\gamma)\sum_{h \in D} x_{ih} \, , a_i^q \cdot (1-q) \right] \cdot \frac{q}{1-q} .$$

If the cash outflow cannot be covered by selling liquid assets ie $(1-\gamma)\sum_{h\in D} x_{ih} > a_i^q(1-q)$, sector i has no choice but to sell illiquid assets. Here, as in Cifuentes et al (2004), an illiquid asset is assumed to be liquidated after all liquid assets are sold off.[3] FSL_i equals:

$$FSL_i = Min\left[(1-\gamma)\sum_{h\in D} x_{ih}, a_i^q \cdot (1-q)\right] \cdot \frac{q}{1-q} + Max\left[(1-\gamma)\sum_{h\in D} x_{ih} - a_i^q \cdot (1-q), 0\right] \cdot \frac{z}{1-z} \quad (1)$$

Second, an increase in funding costs also causes funding losses in the process of refinancing. This paper assumes that inter-financial liabilities to be refinanced in the short term are composed of two sources: a part of funds raised by defaulted sectors, $\gamma\sum_{h\in D} x_{ih}$ and short-term debts from other sectors, $\sum_{k\notin D} x_{ik}^S$. Short term debts are included so that funding costs from financial markets are applied to all funds to be refinanced in the short term regardless of the state of existing debtors. In this respect, the more a financial sector relies on short term debt, the more it will be exposed to liquidity risk. When an incremental funding cost is denoted by μ , funding cost loss (FCL_i) is given by

$$FCL_i = \sum_{h\in D} x_{ih}\gamma\mu + \sum_{k\notin D} x_{ik}^S \mu \quad (2)$$

A key contribution of this paper is that the replacement rate (γ) and incremental funding cost (μ) of a financial sector are designed to be linked to its solvency ability, rather than assumed to be constant. It is believed that funding ability depends on an assessment of debtors' solvency ability from

3 It is reasonable to suppose that financial institutions sell liquid assets with low loss rates before selling illiquid assets in order to reduce losses.

market participants. The solvency ability is closely related with the future capital ratio and generally would be represented by a credit rating. Aikmen et al (2009) attempt to link funding costs with banks' credit ratings and suggests a "danger zone" approach where the possibility of refinancing is decided by a scoring system that focuses on solvency risk. In this regard, a replacement rate (γ) and an incremental funding cost (μ) are established as functions of the capital ratio.

The replacement rate first declines as the capital ratio falls. It is assumed that at a normal capital ratio (λ_0) a financial sector can completely rollover or find alternative creditors but below the regulatory capital ratio ($\bar{\lambda}$) refinancing is impossible. Between λ_0 and $\bar{\lambda}$, γ is designed to be inversely proportional to the square of the capital ratio.[4] In Figure 2–1(a), γ declines sharply near the regulatory capital level. A replacement rate can be expressed by

$$\gamma(\lambda) = \begin{cases} 1 & if\ \lambda_0 < \lambda \\ 1 - \dfrac{(\lambda_0 - \lambda)^2}{(\lambda_0 - \bar{\lambda})^2} & if\ \bar{\lambda} < \lambda \le \lambda_0 \\ 0 & otherwise \end{cases} \tag{3}$$

Next, an incremental funding cost adversely increases as a capital ratio falls. In a normal state (λ_0), replacement is possible at normal costs so μ is set to zero. Generally a funding cost can be approximately calculated by the relevant credit spread.[5] To empirically provide the relation between

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4 There is a similar function type in Lee (2010) where the amount of cash outflow is proportional to the square of decreasing amount of capital ratio.

5 In Schmieder et al (2012) the funding costs of large German banks are suggested by bond spreads above T-bill rates and they are associated with credit ratings.

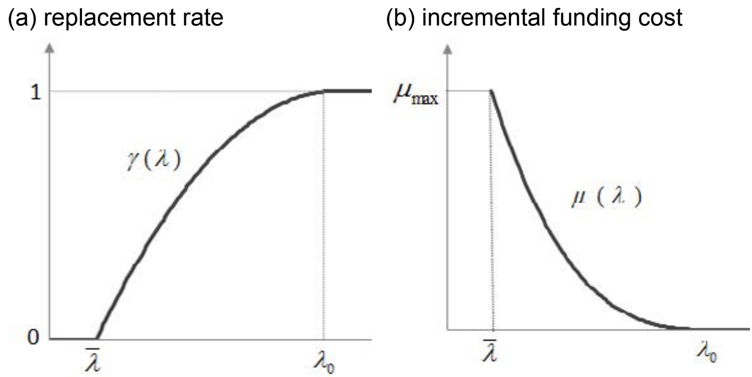
funding costs and solvency ability, it is a regression model that is estimated between credit spreads and capital ratios in Appendix 1. The results show that the credit spread is proportional to the cube of a decline in the capital ratio. Thus an incremental funding cost, $\mu(\lambda)$ is defined by

$$\mu(\lambda) = \begin{cases} 0 & \text{if } \lambda_0 < \lambda \\ a \cdot (\lambda_0 - \lambda)^3 & \text{if } \bar{\lambda} < \lambda \le \lambda_0 \end{cases} \tag{4}$$

where a is the proportional constant obtained by a regression coefficient. The upper bound of μ, $\mu_{\max}$ in Figure 2–1(b) is determined by forecast value at the regulatory capital ratio ($\bar{\lambda}$). Similarly to γ, μ changes abruptly near the minimum regulatory capital level.

Figure 2–1

Replacement rate and funding cost associated with change of capital ratio



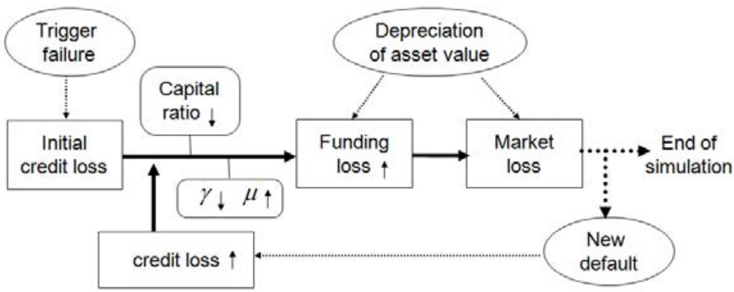
Finally, combining equations (1) and (2) with functions of γ, μ the funding loss (FL_i) of sector i is given by

$$
\begin{aligned}
FL_i &= FSL_i + FCL_i \\
&= Min\left[(1-\gamma(\lambda))\sum_{h\in D} x_{ih}\,, a_i^q(1-q)\right]\frac{q}{1-q} + Max\left[(1-\gamma(\lambda))\sum_{h\in D} x_{ih} - a_i^q(1-q)\,, 0\right]\frac{z}{1-z} \\
&\quad + \sum_{h\in D} x_{ih}\gamma(\lambda)\mu(\lambda) + \sum_{k\notin D} x_{ik}^S\mu(\lambda)
\end{aligned}
$$

Equations (3) and (4) establish a dynamic between credit risk and liquidity risk taking one step ahead from existing studies. A drop in the capital ratio leads to greater funding losses because funding costs increase and refinancing decreases. A greater funding loss might expand default contagion. Newly defaulted sectors cause an additional credit loss to non-defaulting sectors and their capital ratio decreases. Figure 2–2 shows the network analysis. Such an amplification process can keep going until no additional default occurs. This spiral structure indicates the possibility that even a small trigger default can cause huge financial system losses.

Figure 2–2

Dynamic linkage between credit risk and liquidity risk



2.3 Default contagion simulation

When network analysis is used for estimating systemic risk, macroeconomic shocks should be given consideration in addition to a trigger failure of a financial sector. Default contagion in financial systems has mostly been accompanied by macroeconomic shocks such as significant disruptions of financial markets, shortage of market liquidity, delinquency of loans and so on. Recent studies combining macro shocks with network analysis of financial linkages have become more active as a new approach to macro stress testing.[6]

Loans to households and corporates account for a considerable portion of credit risk. This credit risk is considered to be driven primarily by macroeconomic shocks that can lead to write-downs in the balance sheets of financial institutions. In this paper, macro credit loss is defined as the expected loss obtained by multiplying the PD of the loan portfolio by its LGD.

Depreciation of the market value for key assets has an adverse influence on capital in stressed situations. This paper differentiates a loss rate on account of fair value accounting (ie fair value loss rate) from the fire-sale loss rate in section 2.2. The reason is that financial institutions would pay a high cost when they are forced to sell their assets during a period of financial market stress and the price during a fire sale would likely be below the appraised price at reporting time. To specify the fair value loss rate, liquid assets are classified into cash, government bonds, corporate bonds, stocks and mutual funds and loss rates observed from historical data are applied to the relevant classes. By doing so, the quality of liquid assets is considered in calculating market loss.

Macroeconomic shocks can magnify the outflow of wholesale funds and deposits by households and corporates. As retail deposit run-off increases during financial crises, financial institutions could encounter liquidity shortages. To measure the extent of deposit withdrawal associated with

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6 See Castren and Kavonius (2009), Amini et al (2010), Barnhill, T. and Schumacher, L. (2011).

macroeconomic shocks, historical data is needed but obtaining detailed data is difficult. Alternatively, the paper utilizes the Net Stable Funding Ratio (NSFR) parameters in BCBS (2009) for calculating the amount of deposit run-off. The NSFR framework gives the extent of cash outflow according to the attributes of depositors in stress circumstances. For wholesale funds, the NSFR guidance is applied.

Finally, losses resulting from macroeconomic shocks arise from three kinds of risk: credit risk, market risk and liquidity risk. Additionally to reflect a regular operating net income, long-term average net income is added to capital at the last stage of simulation. The process discussed above can be summarized as follows:

1. Choose one financial sector, j as a trigger failure

2. For each $i\ (\neq j)$, compute CL_i by summing macro credit loss and credit loss by the trigger failure

3. Compute revised capital ratio by subtracting CL_i from the initial capital (First round).

3.1 Compute revised capital ratio by subtracting credit loss caused by newly defaulted sectors from the recent capital (Second round).

4. Update a replacement rate (γ) and an incremental funding cost (μ) according to revised capital ratio.

5. Compute FSL_i and FCL_i reflecting macroeconomic shocks by adding cash outflow of deposit and wholesale funds to $\sum_{h \in D} x_{ih}$ in equation (1) and (2).

6. Compute market loss (ML_i) by applying a fair value loss rate to the rest of liquid assets avoiding fire sale.

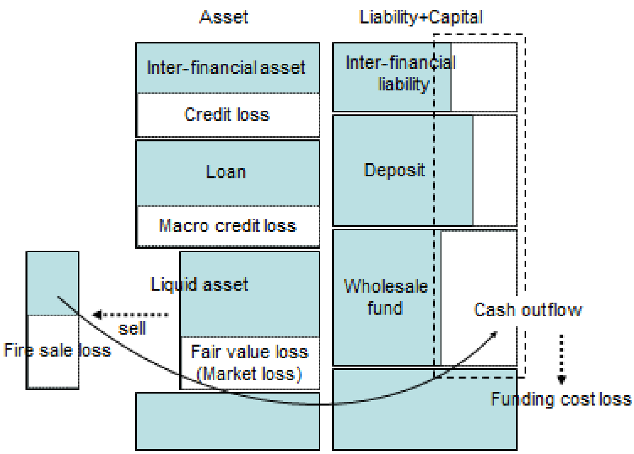
7. Update the capital ratio by subtracting CL_i, FL_i ($FSL_i + FCL_i$), ML_i and adding average net income on the capital.

8. Decide whether default or not by comparing minimum regulatory ratio and updated capital ratio for all i .

9. If there is a newly defaulted sector, repeat from 3.1 to 8 and the contagion process stops when no additional default occurs.

Figure 2–3

Losses on balance sheet in the default contagion simulation



Note: Fire-sale losses can be generated from illiquid assets when illiquid assets are sold to cover cash outflow.

3. Empirical data

3.1. Balance sheet data

The main sources of data are financial institutions' balance sheets, periodic reports to supervisory authorities and detailed data on flow of funds. In addition, stock prices of all listed financial institutions are utilized for cluster analysis and index of marketable securities such as bonds and stocks are necessary for measuring the fair value loss rate. Data from the central bank include key account balances, which are classified according to counterparty financial sectors. For some financial sectors with too many institutions, relevant data are estimated by combining information of specimen and aggregate data in the periodic report. The bilateral exposure matrix and asset and liability compositions are calculated based on these data.[7]

Table 3–1 gives data on assets, capital, liabilities, and inter-financial liabilities for selected financial sectors (as of end 2010). The liabilities of the nine sectors total $2,464.7 billion and the inter-financial liabilities total $331.4 billion, accounting for 13.4% of total liabilities. The total capital of the nine sectors equals $236.8 billion, which is equivalent to the level of 8.4% of total assets ($2,828.4 billion). The extent of inter-connectedness of each sector can be roughly measured by the ratio of the inter-financial liabilities of the sector to its total liabilities. Comparing the ratios among financial sectors studied, CSFC (credit specialized financial companies) recorded the highest ratio of 42.2% and foreign bank branches (FBs), securities firms, and domestic banks follow in that

[7] Especially for marketable securities such as bonds and stocks, issuing institutions have difficulty in finding final holders of these securities. Since inversely in asset side all financial institutions know issuer information of their holding securities, by transposing these data matrix, the final holders of marketable securities in liability can be identified.

order. The result of CSFC comes from a funding structure that CSFC should rely mainly on wholesale funds owing to prohibition on receiving deposits. Domestic banks, holding more than half of total assets and liabilities, have an inter-financial liability ratio of 17.2%.

Table 3–1

Asset, liability and inter-financial liability of financial sectors

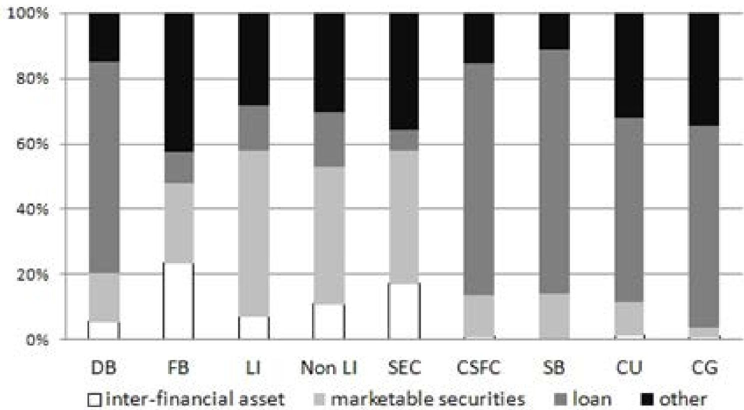
In USD billion, at 2010 end

Financial sectors	Number of institutions	Assets	Capital	Liabil-ities(A)		
					Inter-financial liability (B)	Liability Ratio (B/A,%)
Domestic banks	17	1,465.2	102.7	1,362.4	233.7	17.2
Foreign bank branches	37	171.1	11.2	160.0	33.9	21.2
Life insurance	23	430.9	32.8	327.7	1.6	0.0
Non-life insurance	30	90.5	12.9	74.3	0.2	0.0
Securities firms	62	175.4	32.7	142.8	22.8	16.0
CSFC	63	160.0	21.9	84.2	35.5	42.2
Savings banks	105	76.2	4.3	72.0	0.7	0.1
Credit unions	962	42.0	3.7	38.2	0.1	0.0
Credit guarantees	1,398	217.1	14.6	203.1	2.9	0.1
Total	2,697	2,828.4	236.8	2,464.7	331.4	13.4

Figure 3–1 shows the composition of assets for the nine sectors. The breakdown includes interfinancial assets, marketable securities and loans. Banking sectors such as domestic banks, saving banks, credit unions, and credit guarantees allocated a large amount of their assets to loans. The remaining sectors tended to show stronger preference for marketable securities. Under macroeconomic shocks, the former are likely to be exposed to credit risk from delinquent borrowers and the latter might be sensitive to market risk from a decline in bond or stock prices.

Figure 3–1

Asset composition[1]

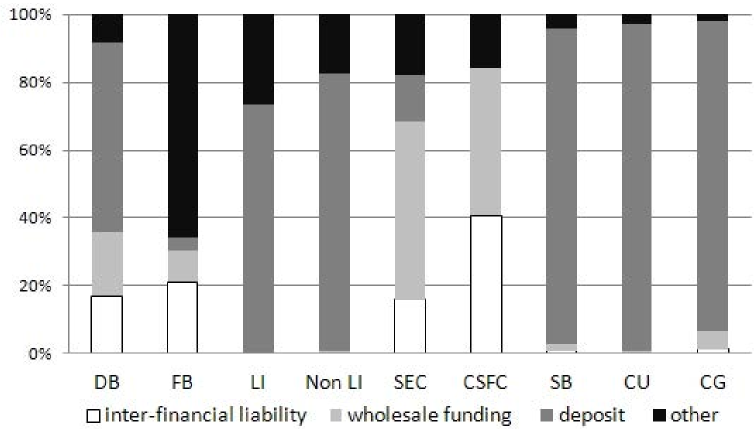


[1] DB: domestic banks, FB: foreign bank branches, LI: life insurance companies, Non LI: Non-life insurance companies, SEC: securities firms, CSFC: credit specialized financial companies, SB: saving banks, CU: credit unions, CG: credit guarantees.

To compare funding structure across sectors, Figure 3–2 divides total liabilities into four parts: inter-financial liabilities, wholesale funding, deposits, and other. The liability structure of each sector is closely related to liquidity risk. Banking and insurance sectors are mainly dependent on the behaviour of deposits and insurance premiums. In contrast, securities firms and CSFC show that the sum of inter-financial liabilities and wholesale funding occupies more than, respectively, 60% and 80% of total liabilities. From a interconnectedness point of view, the default of financial sectors with a high inter-financial liability ratio, such as domestic banks, FBs, securities firms and CSFC, can incur considerable credit loss to counterpart sectors.

Figure 3–2

Liability composition

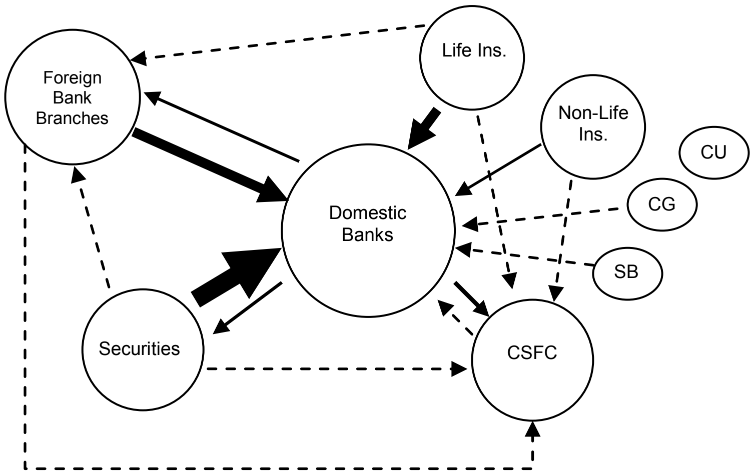


3.2. Inter-financial linkage structure

The calculated bilateral exposure matrix explains characteristics of the inter-financial linkage structure. Major counterparties consisting of inter-financial liabilities of domestic banks include securities firms, life insurance companies, non-life insurance companies and FBs. Also, domestic banks have considerable claims on other sectors. Figure 3–3 illustrates that domestic banks play a key role as a money centre. In particular, considerable funds of securities firms have flowed into domestic banks. And CSFC have raised necessary funds by issuing bonds that have been utilized as a tool of investment in various sectors. It is believed that large exposures between financial sectors are so volatile that they would likely be sharply reduced under macroeconomic shocks.

Figure 3–3

Inter-financial linkage structure



Note: The arrows indicate the flow of funds and their thickness is proportional to the amount. The dotted lines mean relatively small amounts of funds (under $10 billion).

Meanwhile, to check whether the given financial sectors are plausible as a unit of network analysis, cluster analysis is applied to the stock price data of individual financial institutions. The results in Appendix 2 show the similarity between financial institutions belonging to the same financial sector. It can be regarded that financial sector groups have validity as a unit of network analysis. Most savings banks and a few domestic banks are included in Cluster 1 and other domestic banks are allocated to Cluster 2. More than 60% of securities firms are classified in Cluster 3. Other securities tend to be included in the cluster of the primary company of their consolidated group. Major non-life insurance institutions are included in Cluster 6.

4. Simulation results

4.1. Parameter calibration

The feasibility of the parameter settings is an important factor in determining how realistic the network simulation is. Basically, the extent of liquidity shortage assumed in this paper is more or less equivalent to the level of the NSFR framework. Two parameters for fire-sale loss rates of liquid and illiquid assets, q and z, are based on the required factor for Required Stable Funding (RSF) in NSFR. After liquid assets are classified according to RSF categories, the fire-sale loss rate for liquid assets is calibrated by a weighted average of the RSF factor.[8] Thus the more a portfolio of a given financial sector has risky assets, the larger is the fire-sale loss it suffers. Meanwhile, the fire-sale loss rate for illiquid assets is determined to be 70%, considering the RSF factor for loans.

This paper represents the impact of macroeconomic shocks on credit losses, market risk losses and funding losses as have recent approaches to macro stress testing.[9] For example Elsinger et al (2006) used the Merton-type sub-modules for generating credit and market risk losses and implemented thousands of simulations. In contrast, this paper adopts a

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8 This paper applied 0% for cash and marketable securities with remaining maturity < 1 year, 5% for government bonds, 35% for corporate bonds and 50% for equity, and then computed a weighted average according to the amount of each category.

9 See Borio et al (2012).

stress scenario based on data for historical periods of financial market distress. This scenario approach has the advantage of highlighting the mechanism of this model and finding policy implications that are obtained in the middle of the simulation process.

First, macro credit losses are calculated by an empirical loss rate from provisions for impairment of household and corporate loans in distress periods.[10] For domestic banks, FBs, insurance companies and securities firms targeting relatively creditworthy counterparties, 3% of household and corporate loans is disposed of credit loss and for the other sectors 5% is applied.[11] Second, a fair value loss rate for market loss is estimated through domestic bond and stock indexes ranging from 2001 to 2010. The bond yields during the global financial crisis were 3.5 percentage points lower than their long-run average and the rates of stock returns about 30 percentage points. Third, wholesale funds are assumed to be drained by 50% according to the capital ratio. A deposit run-off rate of 5% is reasonable for household deposits, 10% for small and medium enterprises, and 50% for large corporates. Besides these losses, the average net income during the most recent five-year period is added to capital in order to reflect a regular operating net income. Table 4–1 presents credit loss, market loss and average net income for each sector. It can be easily inferred from this table that savings banks and credit unions fall into default only with macroeconomic shocks.

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[10] When supervisory authorities apply this methodology, they can get credit loss estimated from financial institutions through a bottom-up approach.

[11] Three per cent came from the loan to provisions ratio (2.3%) of domestic banks during the 2003–04 crisis and 5% from the loan to provisions ratio (4.3%) of saving banks during the 2008–09 crisis.

Table 4–1

Capital, loss and macro loss ratio of financial sectors

In USD billion, %)

Financial sectors	Capital		Loss		Net income(D)	Macro loss ratio (B+C-D)/A
	Buffer (A)	Regula-tory capital	Credit loss (B)	Market loss(C)		
Domestic banks	62.2	75.5	27.1	15.5	9.2	53.6
Foreign bank branches	14.7	3.1	0.3	1.0	1.2	1.0
Life insurance companies	27.8	14.4	1.7	19.4	1.9	69.0
Non-life insurance companies	12.0	5.4	0.4	3.6	1.3	22.1
Securities firms	18.6	7.2	0.3	7.0	2.5	25.9
CSFC	16.3	7.4	3.9	3.1	2.8	25.8
Savings banks	3.0	3.6	2.8	1.2	0	133.3
Credit unions	0.6	0.8	1.1	0.2	0.2	194.0
Credit guarantees	13.3	4.7	6.7	0.5	1.2	45.8

4.2. Simulation results

The simulation results show that in normal times default contagion is observed only when domestic banks are set as trigger failure. Other sectors do not generate any significant knock-on effects. This is because of domestic banks' role as a money centre in inter-financial linkage structure. The trigger failure of domestic banks incurs default contagion in FBs, securities firms and credit unions. Exposures from these sectors to domestic banks are regarded as credit loss and then the loss exhausts their capital buffer. Funding losses also arise but they are much lower than credit losses. These results are obtained from pure balance sheet contagion, ignoring macroeconomic stress.[12]

With macroeconomic shocks, however, an extensive default contagion is witnessed in the case of a trigger failure of securities firms or CSFC, as well as domestic banks as seen in Table 4–2. A hypothetical failure of domestic banks combining macroeconomic shocks leads seven sectors to default, which accounts for 84% of total assets except for domestic banks. In the first round, FBs, insurance companies and securities firms fall into default by direct exposures from domestic banks and in the second round CSFC are sequentially contaminated by pre-defaulted sectors from the previous round. As mentioned above, macroeconomic shocks have already led to the failure of savings banks and credit unions.[13] But credit guarantees avoid default contagion because this sector has only a relatively small bilateral exposure as well as sufficient capital.

The default contagion round in Table 4–2 reveals that the trigger failure of securities firms or CSFC can lead most other sectors to default, although they account for only 6.2% and 5.6%, respectively, of the assets of the entire financial sector. It is an important feature of contagion that a failure of even a small sector would spread over the whole financial system by interconnectedness between financial institutions and common economic shocks. The reason why trigger failure of the two sectors can spread across the entire system is that their

[12] Cont et al (2010) suggest that ignoring macroeconomic shocks like market shocks in analyses of contagion effects can lead to a serious underestimation of contagion risk.

[13] However, it is expected that the two sectors will experience contagion default even though they avoid default by macroeconomic shocks.

failures lead domestic banks into default.[14] In other words, the evolution of a failure of some financial institutions into a systemic event always involves the default of domestic banks.

In particular, the large exposure between securities firms and domestic banks enables the trigger failure of securities firms to expand to most sectors. Since securities firms allocate a considerable amount of assets to domestic banks as shown in Figure 3–3, funding outflow of domestic banks by securities firms makes domestic banks sell off large amounts of their assets. Consequently, the fire-sale losses become the main cause of banks' default. Also, a trigger failure of CSFC cause credit losses to most sectors. In particular, CSFC attract a relatively large exposure from domestic banks. Therefore, domestic banks experience considerable credit losses from the failure of CSFC and it is largely responsible for the default of domestic banks.

A recapitalization plan for domestic banks can prevent the extensive spread of contagious defaults triggered by either securities firms or CSFC. Table 4–3 shows the size of three types of losses on the round just when domestic banks are contaminated. The amount of additional capital required for blocking domestic banks' default is suggested as the difference between the loss absorbing buffer and total loss. For example, under the macro stress scenario, domestic banks should increase their capital by $6.5 billion for preventing contagion from securities firms and increase by $10.7 billion for CSFC. These recapitalization amounts account for 0.7% and 1.1% in the Basel ratio, respectively. Therefore, under the given scenario, a 1.1% increase in the Basel ratio (ie 15.6% for domestic banks) prevents the extensive contagion triggered by either securities firms or CSFC.

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[14] Cont et al (2010) demonstrate that network structure as well as size of interbank liability matter when assessing systemic importance and connectivity, and the concentration of exposures across counterparties is shown to contribute significantly to systemic importance.

Table 4–2

Default contagion round

Contagion / Trigger	Domestic banks	Foreign bank branches	Life insur-ance comp-anies	Non-life insurance companies	Securities firms	Credit-specialized financial companies	Savings banks	Credit unions	Credit cooperatives	# of contagion
Domestic banks		1	1	1	1	2	–	–		5
Foreign bank branches							–	–		
Life insurance companies							–	–		
Non-life insurance companies							–	–		
Securities firms	1	2	2	2		2	–	–		5
Credit-specialized financial companies	1	2	2	2	2		–	–		5

Table 4–2

Default contagion round (cont)

Contagion / Trigger	Domestic banks	Foreign bank branches	Life insur-ance comp-anies	Non-life insurance companies	Securities firms	Credit-specialized financial companies	Savings banks	Credit unions	Credit cooperatives	# of contagion
Savings banks								–		
Credit unions							–			
Credit cooperatives							–	–		

Note: With the exception of the last column, figures in cells indicate the default round. Savings banks and credit unions are already contaminated by macroeconomic shocks before contagion effects.

Table 4–3

Total loss of domestic banks on default round under the stress scenario

In USD billion

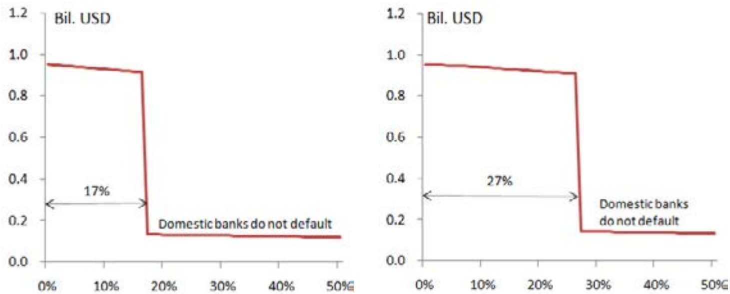
Loss type / Trigger	Credit loss	Funding loss	Market loss	Total loss (A)	Loss absorbing buffer (B)	Additional required capital (A-B)
Securities firms	33.8	32.3	11.2	77.6	71.4	6.2
Credit-specialized financial companies	36.7	30.9	14.2	81.8	71.4	10.4

Moreover, reduction of key bilateral exposures can be another effective tool that restrains the extensive contagion ex-ante. Figure 4–1(a) shows the simulation results that only a 17% reduction in exposures between securities firms and domestic banks can block contagion default of domestic banks from the failure of securities firms. If the exposures between CSFC and domestic banks decrease by 27%, the far-reaching contagion by CSFC does not happen (see Figure 4–1(b)). This solution would be inexpensive compared to the recapitalization remedy.

Figure 4–1

Total loss in entire financial sector according to reduction rate of bilateral exposure

(a) Securities firms trigger case (b) CSFC trigger case



Note: The horizontal axis is the reduction of the bilateral exposure and the vertical axis measures total loss amount after network simulation.

5. Conclusions and policy recommendations

Shortly after Lehman Brothers' bankruptcy, domestic banks and asset management companies in Korea sharply cut down call loans to securities firms because they worried that such companies holding a claim on Lehman would default. Securities firms that had been used to raising funds mainly in the call money market sold off their marketable securities quickly to secure adequate liquidity. Consequently, market interest rates spiked. Such turmoil in the bond market led to a devaluation of other financial institutions. The Korean experience showed the possibility that when some institutions are brought to default under economic distress, other institutions with a similar balance sheet structure are affected, and eventually the contagion plagues other parts of the financial sector and even the entire financial system. The model in this paper has much to do with the situation after the Lehman debacle.

The approach in this paper highlights the spiral relationship between future solvency risk and liquidity risk. Key factors such as measuring liquidity risk, replacement rates and funding costs are driven by a capital ratio reflecting future solvency risk. The empirical estimation covers funding costs based on the relationship of bank bond spreads and a Basel ratio. Two types of market loss due to depreciation of marketable asset values are computed. One is a fire-sale loss rate for assets sold off in markets. The other is a fair value loss rate for assets remaining on the balance sheet. Since macroeconomic shocks are assumed in a scenario using variables such as NSFR and financial instruments index data, the model in this paper is easily applicable to other countries. The simulation results under this scenario enable one to explain in detail the process of default contagion and propose policy actions that can be obtained in the middle of the simulation.

Empirical data of inter-financial exposures reveal that domestic banks play a key role as a money centre. The simulations show that under macroeconomic shocks, a trigger failure of securities firms, CSFC, or domestic banks can bring most financial sectors down through transaction channels for transferring three types of loss: credit loss, market loss, and liquidity loss. To prevent this extensive default contagion, and in order to safeguard the financial system under a given stress scenario, key bilateral exposures (domestic banks↔securities firms, domestic banks↔CSFC) have to be reduced by at least 20–30% or the Basel ratio of domestic banks should increase 1.1%. In practice, during the global financial crisis of 2008–09, the supervisory authorities in Korea urgently conducted capital injections into domestic banks to limit systemic risk. They thereby reduced a key channel of default contagion by prohibiting call money inflow to securities firms.

It is necessary that the bilateral exposures to financial institutions be periodically investigated. At the time of the Lehman bankruptcy, it was difficult to find out the inter-financial exposure between large financial institutions. Uncertainties rose in financial markets and irrational responses, such as a high run-off of funds and asset fire sales, was observed. If supervisory authorities had accurate data on the intricate financial linkages among financial institutions, they could have estimated the impact of the upcoming default contagion and successfully helped reduce the uncertainties. Moreover, if this network analysis was available, those supervisors could have detected and restrained the bilateral exposure, which could be critical channels of contagion. Also simulation results would have helped select domestic SIFIs and impose an adequate level of additional capital on them as they have the possibility of incurring systemic risk. Fortunately, international institutions like the Bank for International Settlements and the Financial Stability Board (FSB) have already realised the criticality of bilateral exposure data and the Data Gap Working Group of the FSB has a plan to aggregate these data across major large banks.

But there are more things to be done. Empirical studies need to be conducted to identify functions of replacement rates and funding costs, but procurement of sufficient data remains difficult until now. While this paper shares an improved method of measuring funding loss, it does not adequately reflect the maturity structure of liabilities, one of the important factors for liquidity risk. If the run-off of funds can be measured by subdivided maturity, a more elaborate and dynamic model for liquidity risk can be constructed in the future. Such effort will be especially useful for money market and derivative instruments. Lastly, further research will need to look at the impact of overseas shocks on domestic financial institutions through contagion channels due to foreign currency shortages and inter-financial linkages with foreign financial institutions.

Appendix 1

Empirical study investigates the relationship between capital ratios and bank bond spreads above government bonds (1year). With the data before and after the Lehman bankruptcy (2007Q3 to 2010Q3), a cube model is fitted with high performance (an R-square 0.92) in Figure A1(a) and is denoted by

$$spread_t = 0.04(14.62 - Basel\,ratio_t)^3 + 0.50$$

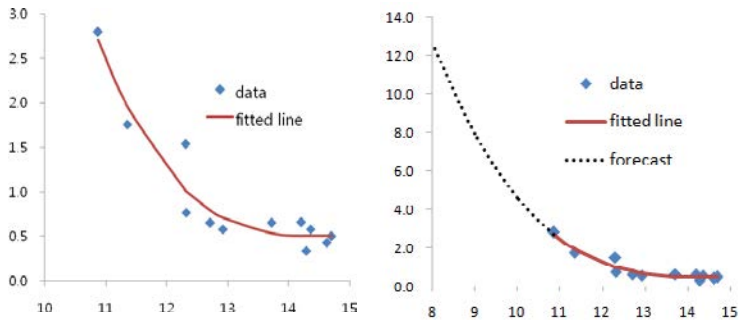
An incremental funding cost, μ is represented by the equation above without intercept i.e. $\mu(\lambda) = 0.04(14.62 - \lambda)^3$. Intercept in the equation above means a spread in normal state (λ_0). At regulatory Basel ratio ($\bar{\lambda}$, 8%), the upper bound of μ, $\mu_{\max}$, is calculated as $0.04(14.62 - \bar{\lambda})^3$ in Figure A1(b). Incremental funding costs for other financial sectors are decided considering spreads of bonds issued by the sector or differences in deposit interest rates with domestic banks and so on.

Figure A1

Scatter plot between capital ratio and bank bond spread and out of sample forecast

(a) capital ratio and bank bond spread

(b) forecast by regulatory Basel ratio (8%)



Note: The horizontal axis is the Basel ratio and the vertical axis is the bank bond spread.

Appendix 2

The paper applies cluster analysis to stock price data as a comprehensive indicator that can reflect idiosyncratic risk of individual institutions and a common economic cycle. First the author standardized the stock prices of all listed financial institutions from 2006 to 2010 and computed correlation coefficients between all stock prices. K-means cluster analysis based on correlation relation is implemented.

Cluster analysis results

Sector	Institution	Clusters	Sector	Institution	Clusters
Domestic banks	DB1	1	Securities	Sec1	3
DB	DB2	2	Securities	Sec2	1
DB	DB3	1	Securities	Sec3	3
DB	DB4	2	Securities	Sec4	3
DB	DB5	2	Securities	Sec5	3
DB	DB6	2	Securities	Sec6	5
DB	DB7	1	Securities	Sec7	1
DB	DB8	3	Securities	Sec8	3
Savings banks	SB1	1	Securities	Sec9	1
SB	SB2	1	Securities	Sec10	1
SB	SB3	3	Securities	Sec11	3
SB	SB4	1	Securities	Sec12	3
SB	SB5	1	Securities	Sec13	3
SB	SB6	1	Securities	Sec14	3
SB	SB7	1	Securities	Sec15	1
Non-life insurance companies	NL1	6	Securities	Sec16	3
Non-Life	NL2	6	Securities	Sec17	3
Non-Life	NL3	6	Securities	Sec18	4
Non-Life	NL4	6	Securities	Sec19	3
Non-Life	NL5	3	Securities	Sec20	3
Non-Life	NL6	1	Securities	Sec21	1
Non-Life	NL7	5	Total	44	
Non-Life	NL8	3			

Note: At the end of 2010, stock price data of 44 listed financial institutions from four sectors with sufficient time series, are utilized in cluster analysis. Members in a sector are sorted by asset size.

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