Investigation on the Interconnectivity in Korean Financial Industry

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In this study, we investigate the interconnectivity in Korean financial system to find shock transmission routes from 1990 to 2016. The system includes financial firms in 6 sectors - commercial banking, insurance, securities, savings banking, merchant banking, credit financing. Using weekly rate of stock price returns, we estimate the size and direction of the pairwise connection by Granger causality test and principal component analysis. We analyze the dynamics in the degree and structure of this interconnectivity by detecting the changes in the average number of connections over time. We find that the link becomes strong during financial crises in 1997 and 2008. Our connectivity index provides statistically significant information in predicting the changes in CD rates and long−short spreads over the two crises. Accoridng to sector−based analysis, commercial and merchant banks have played a significant role in heightening the systemic risks during 1997 currency crisis whereas the securities and commercial banking sectors have led the increase in a financial crisis of 2008.

Key words: Cointegration; Granger causality; Interconnectivity; Princinpal Component Analysis; Systemic Risk

JEL Classification: G20, G21, G28

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Ⅰ. Introduction

A systemic risk, the risk from collapse of an entire financial system has been one of major topics in studying the effects of a financial crisis. The systemic risk represents the instability of a financial system, which can be caused by a risk associated with any one individual entity, or component of the system, and exacerbated by conditions in financial intermediaries. It, thus, refers to the risks imposed by interlinkages and interdependencies in a system or market, which critically determines the impact of a cascading failure triggered by the failure of a single component (Schwarcz, 2008). It is, however, hard to find a consensual measure of a systemic risk by the limited access to data on interlinkages and high costs in verifying every connections in a complex interdependent system. Bisias et al(2012), for instance, introduce thirty−one different quantitative measures of a systemic risk. Borio(2010)'s measure is one of them, discovering a systemic risk from both time−varying and cross−sectional dimensions of the market risk. A time−varying risk explains how an aggregate risk in the financial system varies over time. A cross−sectional risk, on the other hand, describes how the aggregate risk is shared within a financial system at a point of time. Most literature measures a systemic risk based on the connectivity within a financial industry, including Billio, et al. (2012), who have suggested that the degree of interconnectedness within a financial industry has significant implications on the degree of a systemic risk in an economy,

In this paper, we measure a systemic risk in Korean financial industry from the two perspectives: time−dimensional, and cross−sectional. In order to measure the systemic risk from a cross−sectional point of view, we investigate the average degree of interconnectivity among financial institutions from 1990 to 2016 using weekly stock returns of Korean financial institutions. Given a one−year−sized window, we find the average number of stocks that are in statistically significant Granger−causal relationships, referring to the approach of Billio et al. (2012). By applying stock returns of U.S. financial institutions, Billio et al (2012) have identified the increase in interconnectivity during the period of financial instability and an asymmetry in the degree of connectedness among financial sectors. We examine Granger causal relationships for a pair of stock returns after implementing Vector Autoregressive (VAR) model for a stationary pair and Vector error correction model (VECM) for a cointegrated pair.

It is also necessary to find the dynamic patterns in the interconnectivity because the market risks are procycal to help policy makers to predict the economic condition within a few periods(Borio(2010)). In finding time−varying features of a systemic risk, we complete a series of the interconnectivity from Jan. 1st, 1990 to Dec. 31st, 2016 by counting the number of significant interlinkages relative to the number of possible linkages in a window that is rolling over the sample period. We find a significant increase in the number of Granger−causal relations during major crises in comparison with the number of interlinkages during the (non−crisis) stable periods. When we use a one−month−window for the two crises periods - one in 1997 and the other in 2008 - we find that our interconnectivity has a statistically significant role in predicting the movements of CD rates and spreads between short and long−term bonds' yields.

In a closer look into leading components of the interconnectivity index, we find the difference between the structure of a systemic risk in 1997 and that in 2008: commercial and merchant banks were the most influential players the financial system in 1997 whereas commercial banks and the securities firms played a key role in 2008. We find the consistent results from a firm−level analysis that merchant banks and commercial banks are listed as institutions with the most connections in each crisis period.

The implications from empirical evidence in this paper are consistent with them suggested by previous studies including Billio et al, (2012), Suh (2014) and Rhee (2016), which have examined different sorts of financial data by Granger causality tests. Our study contributes to the current literature on a systemic risk in the following aspects. First, by analyzing Korean financial institutions in six sectors from 1990 to 2016, we show how the degree of interconnectivity in Korean financial system has evolved in and out of financial crises. Second, by implementing Granger causality test with VAR for stationary pairs and VECM for nonstationary pairs, respectively, we explicitly account for the existence of cointegration between firms. We avoid the misspecification problem by applying VECM to nonstationary but cointegrated data for using the long−run information without first−differencing. Third, we check robustness of the results by comparing the trends in the interconnectibity with that of the first components from the princiapal component analysis. The results after eliminating the common macro factors are also consistent with them before elimination.

The remainder of the paper is organized as follows: Section Ⅱ provides a brief review of the preceding literature. The data and empirical methodology are given in Section Ⅲ. Further details on the empirical analysis are provided in Section Ⅳ. Section Ⅴ provides the robustness check. In the last section, we conclude the paper.

Ⅱ. Literature review

Before a global financial crisis in 2007−2009, many studies focus on the intercontinental or international dependency in a crisis period. For example, Malliaris and Urrutia (1992) investigate the interlinkage between stock market indices in 1987. They find a significant increase in Granger−causality in the month (October) of the 1987's crisis. Yang et al. (2003) examine both long and short run interrelationships between different financial markets in 1997−1998 Asian financial crisis. They find that both interrelationships were statistically significant during the crisis period.

Since the Great Recession, a systemic risk, a risk measured to describe bank runs and currency crises, has received more attention. The systemic risk can be realized as individual institutions' exposure to a system and the interrelationships between financial institutions. The identification of individual firm−level exposure in real time, however, is so difficult that it has become important to manage aggregate risk by understanding the interlinkage between individual financial institutions in a system. Adrian and Brunnermeier (2016), for example, suggest to use conditional value−at−risk (CoVaR), the value at risk (VaR) of financial institutions conditional on the other institutions being in distress. Acharya et al. (2017) study systemic expected shortfall (in short, SES), a measure of the expected loss for each financial institution conditional on the entire set of institutions' poor performance. Huang, Zhou, and Zhu (2012) calculated the value of Distressed Insurance Premiums (DIP). In their study, DIP approximates distressed losses in the banking system by measuring the insurance premium required to cover distressed losses. Related studies on a systemic risk in Korea mostly apply the similar empirical tests for data of Korean financial market. Choi and Min (2010) and Kim and Kim (2010) estimate CoVaR meaure of Adrian Brunnermeier(2016) to analyze a systemic risk in Korean financial sectors. Chun (2011) applies the SES of Acharya et al.(2010) to measure systemic risk contribution by an individual institution in Korea. Lee, et al.(2013) estimate a systemic risk in the Korean banking sector by applying Vine Copula method.

Five measures of systemic risk in the finance and insurance sectors in Billio et al. (2012) are different than the suggested measures on systemic exposure: Billio et al. (2012) measure the interlinkage between institutions directly and unconditionally. Their work is based on the statistical properties of the market returns of hedge funds, banks, brokers, and insurance companies. More specifically, Billio et al(2012) analyze systemic risk by using the monthly stock returns with Principle Component Analysis (PCA) and Granger causality test. The approaches by Suh(2014) and Rhee (2016) are similar with them of Billio et al. (2012). However, their works use different types of data that indicate the degree of connectivity in Korean financial industry. Suh (2014), for example implements Granger causality tests on the Expected Default Frequency (EDF) and Loss Given Default (LGD) that are calculated by the option pricing model of Black and Scholes (1973). Although Suh(2014)'s study provides the information about the systemic risk in a timely manner, the risk is measured according to the expected value based on the distributional assumption on the default probability, referring to the standard normal distribution and Merton's assumption on the process of a firm's asset - Brownian motion. On the other hand, Rhee (2016) analyzes the systemic risk of a financial industry including commercial banks, insurance and securities companies by using the ratios from the balance sheet in Granger causality test. Rhee(2016), however, has its limit in estimating the interlinkages or a systemic risk in a timely manner because Rhee(2016) is based on such low−frequency data: a balance sheet is published at a quarterly or yearly basis.

In this study, we use stock returns to measure the size and direction of pairwise connection for a given window to reflect the information from a current state of a stock market. In this study, we investigate the components of the market's firm−level interconnectivity. We believe that a realized market price of a firm's stock provides more information about the firm's timely contribution to a systemic risk than credit−debit exchange in an accounting book, by reflecting the market participants' perception, and decision on a firm's value relative to others. Billio, et al (2012) also argue more immediate and actionable measures of systemic risk from the forward−looking nature of equity markets. An appropriate econometric approach to stock returns show systemic risk, which is produced by the combination of correlation, illiquidity, and sudden changes in regime. An efficient stock price reflects the side effects from considerable leverage or the significant amount of collateral posted to support those positions when the market turns out to an adverse phase. Thus, the large price impact in the market is sufficient in measuring the systemic events lead by the reduction in the value of that collateral, and forced liquidations of large positions over short periods of time to reduce leverage (Billio et al. (2012)).

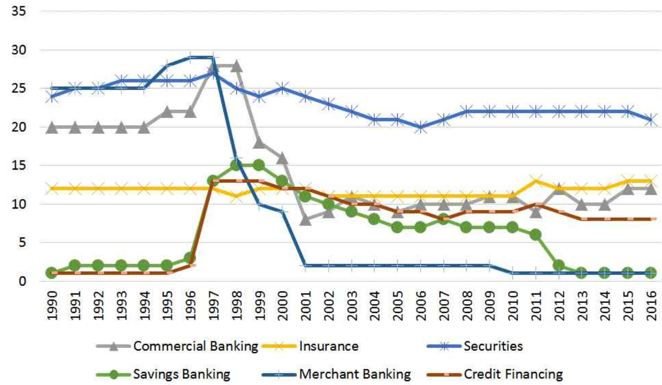
With the data, we examine the size and direction of links between financial institutions according to principal component analysis(PCA) and Granger causality test. PCA has been popularly used to anlayze a data table in which observations are decribed by sevral inter−correlated quantitative dependent variables. We exploit a set of orthogonal variables extracted from the data in estimating the pattern of similarity of the stock returns of financial firms. Billio, et al. (2012), Lee (2015), and Rhee (2016) use commonality among the asset returns and balance sheet data.

Granger(1969) introduces the notion of Granger causality test in terms of predictability in a set of non−cointegrated variables. Granger(1988) extends this notion further to a set of cointegrated variables by suggesting that in a set of cointegrated variables, the short−term causal relations among these variables should be examined within the framework of the error correction model(VECM). We refer to the estimation methods by Malliaris and Urrutia (1992), who used the two−step procedure of Engle and Granger (1987) to test the cointegrational relationships among price movements on six different markets during the market crash of October 1987. When the variables are not cointegrated, they conduct Granger causality test in the frame of Vector autoregressive model(VAR) after first−differencing. If the variables are cointegrated, Granger causality test is conducted in the frame of VECM by adding error correction terms in the equations. Sheng and Tu(2000) apply Johansen(1988)'s multivariate cointegration instead of Engle and Granger(1987) and error-correction tests to examine the linkages among the stock markets of twelve Asia-Pacific countries. Ratanapakorn and Sharma(2002) apply Johansen(1988)'s cointegration test and VECM for investigating the short and long run relationships among stock indices of five different markets before and after Asian financial crisis in 1997. Our focus is different than Malliaris and Urrutia (1992), Sheng and Tu (2000), and Ratanapakorn and Sharma(2002) by focusing on the interconnectivity between financial institutions and intraconnectivity of Korean financial system from 1990 to 2016. The investigation on the changes in the intraconnectivity of a financial system over time provides understanding on the structure behind a shock transmission mechanism according to a systemic environment in Korean financial industry.

Ⅲ. Data and Empirical methodology

We use weekly closing stock prices of financial institutions. The data is provided by 'Dataguide'. All prices are in Korean won and transformed to the differences in log prices. We refer to managerial information about firms to categorize them into six sectors: commercial banking, insurance, securities, savings banking, merchant banking, credit financing. The sample period is from January, 1990 to December, 2016. In each sector, we select financial firms that are publicly listed subject to external audit. Because there have been many M&A and bankruptcies over the 27 years, the number of firms in each sector varies according to the selected window. Figure 1 summaries the number of financial firms in the sample. The number tends to increase by the financial crisis in 1997. We find

<Figure 1> Number of firms in each sector



Source: Authors' calculation on the stock prices provided by Dataguide.
Notes: Each line indicates the number of firms in each sector. Grey triangles indicate commercial banking, yellow crosses indicate insurance, blue stars indicate securities, green solid circles indicate savings banking, dark blue pluses indicate merchant banking and red points indicate credit financing.

122 financial firms with full information in 1997. Since then, the number has steadily decreased. Particularly, we find a remarkable decrease in the number of merchant banks. Since 2011, the number of savings banks has decreased and the total number of financial firms as of 2016 is a half of that in 1997.

Over the entire sample period, we generate 27 panel-data-windows with an one-year-step size and 1362 panel-data-window with an one-week-step size. Within each window, we only include the returns of currently existing firms. In a window, the length of each stock's return is 52 weeks. In order to make a balanced panel for a window, we omitted a company without 52 number of observations in a window. In the investigation on the trends of interconnectivity between financial firms, The sample period includes two financial crises:

1. Jan.1, 1996 – Dec.31, 1998: the currency crisis of 1997
2. Jan.1, 2007 – Dec.31, 2009: the global crisis of 2008

For these periods, we estimate the VAR model by using monthly data for analyzing the index's cyclicality in comparison with some macroeconomic variables, CD rates and long–short spread (the rate spread between long–term government bond's rate and CD's rate). Finally, each crisis sample covering three years around a financial crisis is composed by 25 windows by rolling a window at one–month–step size.

1. Stationary test and Cointegration test

As a preliminary step, we test all stock prices' stationarity by Augmented Dickey–Fuller unit root test. The unit root test statistics reveal that each stock's log price is nonstationary in level. However, most first-differences of log prices are stationary at 5% level: all stock returns in the sample is I(1) series. The return for a firm A at t is

$$R_t^A = \ln(weekly\ closing\ price\ at\ t) - \ln(weekly\ closing\ price\ at\ t-1)$$

If each return series follow I(1) process and there is a linear combination of the returns of company A and company B that is stationary, the two returns are to be cointegrated. When the sample series are cointegrated, the simple application of Granger causality test after VAR can be misspecified. Granger (1988) suggested that in a set of cointegrated variables, the short–term causal relations among the variables should be examined by considering error correction terms. Referring to Granger (1988), we check the existence of cointegration for the two returns. If there is any cointegrating relationship, we apply the Vector Error Correction Moel (VECM) in estimating Granger causality. With statistical evidence on no cointegration, we apply Vector Autoregressive model (VAR) for first–differenced stock returns before the Granger causality test. For PCA, we use the level stock returns for all firms.

2. Principal Component Analysis, and Granger Causality Test after VAR and VEC Model

In PCA, we find four common factors that linearly reconstruct the p original stock returns in a window.

$$R_{ij} = z_{i1}b_{1j} + z_{i2}b_{2j} + \ldots + z_{i4}b_{4j} + e_{ij} \qquad (1)$$

where R_{ij} is the value of the ith observation on the jth return, z_{ik} is the ith observation on the kth common factor, b_{kj} is the set of linear coefficients called the factor loadings, and $e_{ij}$is similar to a residual but is known as the jth variable's unique factor. We examine the factors z_{ik} without rotating the loading matrix to retain some important properties of the original solution.

Granger causality test is one way to find statistical evidence of a variable's role in estimating another variable's conditional future value. If there is no cointegration, we construct VAR system before Granger causality such as:

$$R_t^A = \delta_0 + \sum_{i=1}^{4} \alpha_i R_{t-i}^B + \sum_{j=1}^{4} \beta_j R_{t-j}^A + \epsilon_t \qquad (2)$$

$$R_t^B = c_0 + \sum_{i=1}^{4} a_i R_{t-i}^A + \sum_{j=1}^{4} b_j R_{t-j}^B + e_t \tag{3}$$

where $\{R_t^A\}$ and $\{R_t^B\}$ are weekly stock returns of A and B; α_i, β_j, a_i, b_j are coefficients of the model; δ_0 and c_0 are constants; ϵ_t and e_t are white noise processes. In a pairwise setting, a time series $\{R_t^B\}$ Granger−causes $\{R_t^A\}$ if the conditional present value of R^A explained by the past values of R^A and R^B is significantly different than that of R^A by the past values of R^A only. The lag length is selected by four by the SIC and BIC criteria. In equation (1), the null hypothesis is $H_0: \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0$ and the rejection of the null hypothesis implies the B's returns Granger−cause the stock A's returns.

If the two returns $\{R_t^A\}$ and $\{R_t^B\}$, for example, are shown as nonstationary and cointegrated, we consider an error correction term[2] in testing Granger causality such as

$$R_t^A = \delta_0 + \sum_{i=1}^{4} \alpha_i R_{t-i}^B + \sum_{j=1}^{4} \beta_j R_{t-j}^A + \gamma(R_{t-1}^A - \rho R_{t-1}^B) + \epsilon_t \tag{3}$$

$$R_t^B = c_0 + \sum_{i=1}^{4} a_i R_{t-i}^A + \sum_{j=1}^{4} b_j R_{t-j}^B + d(R_{t-1}^A - \rho R_{t-1}^B) + e_t \tag{4}$$

where γ and d represent the short−term deviations from the long−term cointegrating relationships and these terms quantify the speed of adjustment to these errors. Failing to reject the $H_0: \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0$ and $\gamma = 0$ implies that the stock returns of company B do not Granger cause the stock returns of company A.

2) Equation (3) can be rewritten as

$$\triangle \ln P_t^A = \delta_0 + \sum_{i=1}^{4} \alpha_i \triangle \ln P_{t-i}^B + \sum_{j=1}^{4} \beta_j \triangle \ln P_{t-j}^A + \gamma(\triangle \ln P_{t-1}^A - \rho \triangle \ln P_{t-1}^B) + \epsilon_t$$

According to Billio, et al. (2012) it is highly likely to reject the Granger−causal relationship in an efficient market, in which all available information has influenced on the current level of stock returns. If there is additional information, arbitrage trading is possible against the efficient market hypothesis. However, transaction costs, borrowing constraints, and market frictions deters a market to achieve its efficiency, resulting in a Granger causal relationship. We often observe the market's inefficiency. Although major components from PCA imply the commonalities of many stock returns in a window, they cannot provide the directional or causal relationships between firms. Billio, et al. (2012) suggest that the Granger causal system indicates the shape of spillover effects between financial institutions because the Granger causal system informs the changes in directional interconnectivity. The interconnected network by Granger causal relationship can be made by dummy variables[3] such as

$$(j \rightarrow i) = \begin{cases} 1 \text{ if } \; j \; Granger\,causes\, i \\ 0 \text{ if } \; j \; otherwise \end{cases} \tag{5}$$

The interconnectivity matrix, in subsequence, is made by 1 for pairwise firms that are in a statistically significant Granger causal relationship, and 0 for those firms that are not in the relationship. It is worth minding that there is a possibility to find the twoway connectivity from the common latent factor that influences on both firms. In order to check the robusntess of the causal relationships without common factors, we conduct both PCA and Granger causality test with the residuals that are from the regression of the stock return on the value−weighted return in KOSPI and call rates. The results of robustness checks are provided in Section V.

3) We refer to the equation (5) in Billio, et al. (2012)

We define two measures for measuring connectedness in our Granger causal networks; the outward connections, the inward connections. When the total number of financial institution is n, the individual institution is denoted by i, j. We indexes sectors by α. Define following two measures where N represent the number of significant connections in the system:[4]

$$outward-connections: \frac{1}{N}\sum_{j\in\alpha}\sum_{i\neq j}^{n}(j\rightarrow i) \quad (6)$$

$$Inward-connections: \frac{1}{N}\sum_{j\in\alpha}\sum_{i\neq j}^{n}(i\rightarrow j) \quad (7)$$

Ⅳ. Empirical Results

1. Causal linkages from 1990 to 2016

In order to estimate the degree of interconnectivity in two given window, we have conducted Granger causality test for a pair of two stock returns. A window include 52 weekly returns of currently−existing companies. In order to find the dynamic patterns in the interconnectivity, we examine the 52−week−connectivity for 27 windows (one connecitivity in one year from 1990 to 2016). We also examine dynamics in interconnectivity made by one year with one−week−step size with 1362 one−year windows, by rolling a window at a weekly basis. This measure provides a denser picture of the dyanmic patterns.

If one pair has a significant Granger causal relationship to each

4) Referring to Billio et al. (2012), Suh (2014) has estimated sector−conditional indices to analyze the relationships between sectors. Our interconnectivity index counts all connections to one company including connections within the same sector in contrast to Suh (2014)'s indices, only counting the connections to other sectors' company.

<Table 1> Summary statistics

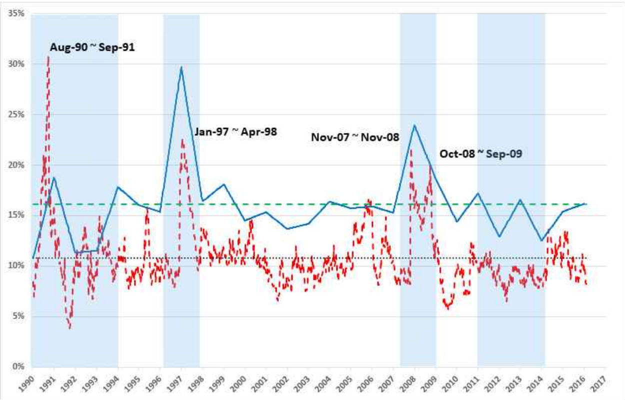
Year	No. of firms	No. of connections	No. of possible connections
1990	83	733	6806
1991	85	1342	7140
1992	85	808	7140
1993	86	843	7310
1994	86	1304	7310
1995	91	1314	8190
1996	94	1344	8742
1997	122	4391	14762
1998	108	1899	11556
1999	92	1516	8372
2000	87	1086	7482
2001	69	720	4692
2002	66	587	4290
2003	65	590	4160
2004	62	620	3782
2005	59	538	3422
2006	59	545	3422
2007	60	541	3540
2008	61	878	3660
2009	62	704	3782
2010	61	527	3660
2011	61	630	3660
2012	58	426	3306
2013	54	475	2862
2014	54	358	2862
2015	57	492	3192
2016	56	498	3080

Source: Authors' calculation.

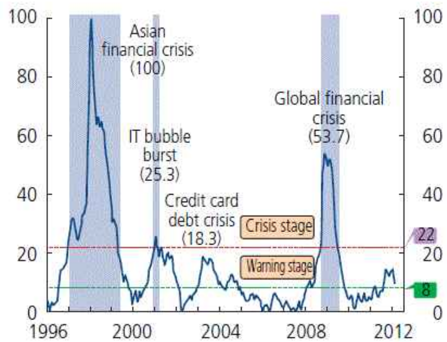
other, then we indicate a pair interconnected. Since each window has a different number of financial institutions, we have counted the number of pairs which share significant interconnectivity and then normalize the number by the number of all possible connections in each window. Table 1 summarizes i) the number of firms in a

<Figure 2>

a. Number of connections as a percentage of all possible connections. (The Degree of Granger causality) (Step size:one−year vs. one−week)



b. Financial Stability Index (FSI)



(a) Source: Authors' calculation. Notes: A blue solid line is drawn with the number of connections as a percentage of all possible connections. A green dashed horizontal line indicates the mean value over the sample period. The number of connections as a percentage of all possible connections in one−year window with one−week step size are in red dashed lines. A black dotted horizontal line indicates the mean value of result from 1362 one−year rolling windows. Shaded areas indicate major crises and volatile periods. (b) Source: Financial stability report, April 2012 by Bank of Korea(BOK). Notes: FSI is measured based on the values from 0(min) to 100(max). The closer it is to 100, the higher the level of instability <The level during the Asian financial crisis(Jan.1998) equals 100>

window; ii) the number of connections; iii) the number of possible pairwise connections.

In Figure 2a, we show the trends in the interconnectivity over 26 years – the number of connections as a percentage of all possible connections. Figure 2a shows the changes in a systemic interconnectivity according to the percentage of Granger−causal relationships in Korean financial system from 1990 to 2016. The number of connections as a percentage of all possible connections is in blue. The average number over the sample period is described by a green dashed horizontal line. The number of connections as a percentage of all possible connections in one−year window with one−week−step size are in red dashed lines. A black dotted horizontal line indicates the mean value of result from 1362 one−year rolling windows. According to Figure 2a, the interconnectivity in Korean financial system becomes intensive around 1991, 1997 and 2008: during these financial crises, the degree of interconnectivity increases significantly by two standard deviations greater than the macro average. With one week step sized rolling window, the peaks are more than three standard deviations away from the long run average. Suh (2014)'s empirical evidence is similar with ours to show the hike in the average Granger causality during the financial crisis. Moreover, Suh (2014) uses different window sizes over a different sample period, resulting that the degree of overall Granger causality tends to increase during financial crises. Rhee (2016)'s analysis on three financial sectors with two sample period such as before and after June of 2007 has the consistent implications.

The trends in the interconnectivity can be compared with them in the Financial Stability Index (FSI) calculated by Bank of Korea in

Figure 2b. The FSI is a weighted average of cyclical indicators[5] that particularly show the cyclical information in a financial industry. We observe that in 1997, the FSI is recorded at the highest. Another noteworthy increase in the FSI also corresponds to the peak of the interconnectivity index around 2008. This comparison confirms that our interconnectivity index contains the consistent information with the FSI. It is noteworthy because the interconnectivity index possibly substitutes the FSI, which is constructed based on 20 indicators including the average movements in a stock market index to macroeconomic indicators. The interconnectivity measure may provide the patterns in systemic risk for a longer term than the FSI, Furthermore, it can be extended to the time when Korean stock market is established and efficiently captures the degree of interconnetivity during 1990 with the financial instability.[6]

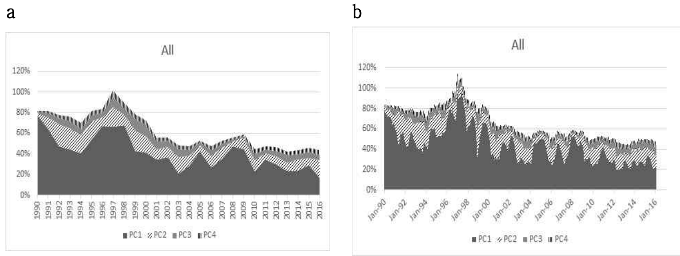
Our interconnectivity index is consistent with the trends in commonalities made by principal components analysis(PCA). The four components identify increased commonality during crisis periods and compare with previous literatures' results. As shown by the results in Billio et al. (2012), Rhee(2016) and Lee(2015), principal factors identify increased correlations among the financial institutions, In Figure 3, we show the trends of four principal

5) According to the financial stability report published by Bank of Korea, FSI consists of indicators for banks(delinquency rates, etc.), the stock, foreign exchange and bond markets(stock price and foreign exchage rate volatility, interest rate spread, etc.), foreign transactions and payments(current acccount, CDS premium, etc.), the real economy(growth rate, inflation rate, etc.) and the economic conditions of housefolds and business,(consumer survey index, business survey index, etc.)

6) In early 1990s, with financial liberalization, Korean stock market was volatile. Because of the financial instability in 1990, government raised four trillion won as financial stabilization funds. ("Four trillion won as financial stabilization funds", 1990)

7) We provide six-month rolling window result in the Appendix B.

<Figure 3> Principal component analysis of the weekly returns with one-year rolling window [7]



Source: Authors' calculation.
Note: We consider the individual companies of three sectors (bank, securities, insurance); (a) Trend of four principal components with one-year rolling window with one-year step size; (b) Trend of four principal components with one-year rolling window with one-week step size

components over rolling windows with different time steps. We observe few principal components capture most of the variation of the stock returns. If we compare Figure 3 and Figure 2a, we observe that two have similar trends. This explains that the interconnectivity index contains the information of correlations between companies.

Furthermore, we provide the statistical evidence that verifies the interconnectivity index's role in forecasting the movements of variables that are related to the a business cycle. We particularly focus on the index's forecasting role around two crises: a financial crisis around 1997 (denoted by crisis 1) and 2008 (noted by crisis 2), respectively. In Table 2, we show the results from Granger causality test on the monthly connectivity measure, monthly CD rates, and monthly long-short spread (the yield from 3-year-bond issued by a government net the CD rate) statistically significant

<Table 2>

Dependent variable	Excluded independent variable	Chi-square	Degree of freedom	Probability
Crisis 1				
Connectivity				
	Spread	0.337	2	0.845
	CD rate	1.208	2	0.547
	All	3.419	4	0.490
Spread				
	Connectivity	41.969	2	0.000
	CD rate	0.780	2	0.677
	All	43.870	4	0.000
CD Rate				
	Connectivity	28.028	2	0.000
	Spread	4.725	2	0.094
	All	34.361	4	0.000
Crisis 2				
Connectivity				
	Spread	1.125	1	0.289
	CD rate	0.018	1	0.893
	All	1.297	2	0.523
Spread				
	Connectivity	8.071	1	0.004
	CD rate	8.254	1	0.004
	All	14.778	2	0.001
CD Rate				
	Connectivity	0.450	1	0.502
	Spread	1.778	1	0.182
	All	2.571	2	0.277

Source: Authors' calculation.

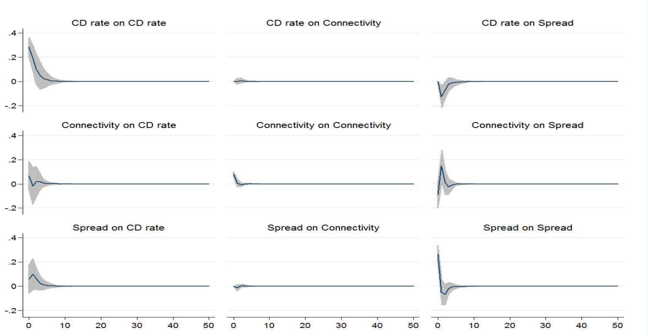
Note: Granger causality tests results are obtained after applying VAR model to three variables, the differences in CD rates, the differences in the spread, and the differences in the connectivity index. All data are at a monthly basis. We use a separate VAR analysis for the two crises: Crisis 1 and Crisis 2. The VAR system's coefficients estimates are available upon request. For more details about the data, see the text.

evidence on the forecastability during those two crises. We see the endogenous relationships between the interconnectivity index and the two macroeconomic variables. The results are based on the differenced variables because the three variables contain unit roots. According to the results, we find that the change in the interconnectivity index has a statistically significant role in forecasting the changes in CD rates and spreads in Crisis 1. In Crisis 2, the change in the interconnectivity index is significant in forecasting the movement of spreads, but not in informing that of CD rates. More interestingly, neither CD rates nor spreads helps in predicting the movement of the interconnetivity index.

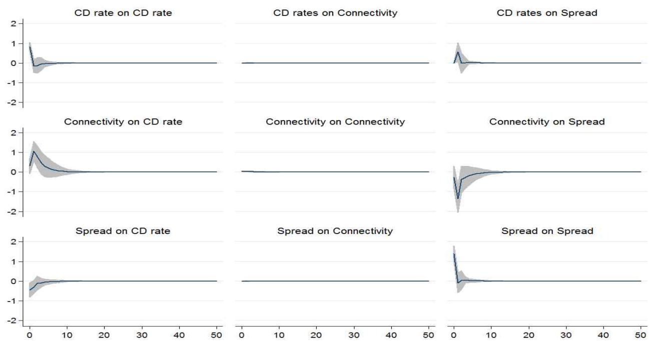
The responses of these endogenous variables by an impulse show a shock transmission mechanism when a shock arrives to the system exogenously. As shown by Figure 4, the response of the interconnectivity index by the external shocks to CD rates and spreads is not found. On the other hand, when there is an idiosyncratic shock to a financial system, resulting in the changes in the degree of interconnectivity, both CD rates, and government bonds' yield spreads react to the shocks: spread responds to a shock in a negative way corresponding to the initial increase in the CD rates despite the overshooting reaction of the spread realized after a initial few periods. According to the responses of key rates by the impulse on the financial interconnecitivity, the changes in the interconnetivity index represent the changes in a macroeconomic condition, resulting in responses of monetary policy makers, aiming at the stable economic growth. One interesting fact is that the responses of CD rates and the interconnectivity index according to the shocks to spread are different between two crises. It is related to the fundamental differences between two crises. This subject is

<Figure 4> Impulse response functions

Crisis 1



Crisis 2



Source: Authors' calculation.

Note: The impulse response functions are drawn after the VAR model applied to three variables, the differences in CD rates, the differences in the spread, and the differences in the connectivity index. All data are at a monthly basis. We use a separate VAR analysis for the two crises: Crisis 1 and Crisis 2. The VAR system's coefficients estimates are available upon request. For more details about the data, see the text.

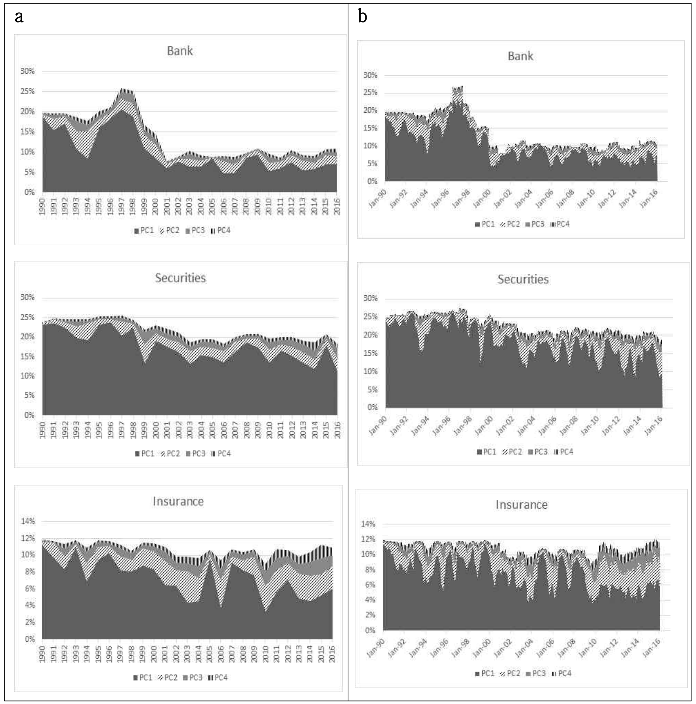
to be studied in an independent study with a microscope.

2. Sector level analysis

In this section, we analyzes inter–and intra– sector correlations with PCA and Granger causal relations. Figure 5 shows the trends of principal components analysis in each sector. As the number of individual companies in each sector varies every week, we confine the analysis to three main sector; commercial banks, securities, insurances. We conduct one–year rolling window analysis with one–year step and one–week step. Both graph show similar trends of principal components and few principal components(PCs) explains most of variations. In commercial banking sector, PC1 varies from 5% to 23% and in securities sector, it varies from 10% to 25%. Although commercial banking sector's PC1 explains total return variation less than before, securities sectors' still explains considerable amount. In insurance sector, PC1 varies from 4% to 11%. When the market becomes more intense than usual time, we find the stronger links for easy transmission of shocks across the market. As commercial banks and securities have larger PCs than insurance companies, these sectors are more intense than insurance sector. It means these sectors have higher systemic risk than the insurance sector. In this section, we particularly focus on the direction of the link between institutions and shows how individual company affects each others every moment explicitly.

We delve into the structure of a financial network during financial crises, 1997 and 2008. We rearrange the aggregate interconnectivity

<Figure 5> Principal component analysis of the weekly returns with one-year rolling window (Sectors)



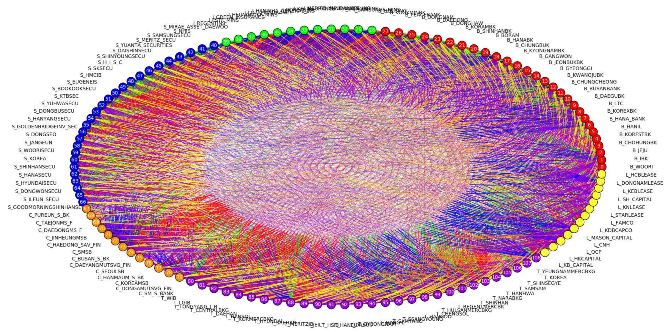
Source: Authors' calculation.

Notes: We apply princial components analysis for the each sector of bank, securities, insurance; (a) Trend of four principal components with one-year rolling window with one-year step size; (b) Trend of four principal components with one-year rolling window with one-week step size

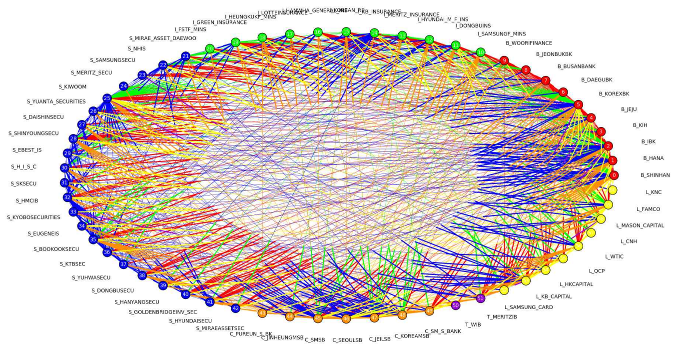
into group-wise networks by sectors in a financial industry: commercial banking, insurance banking, securities, savings banking, merchant banking, credit financing. In Figure 6a and 6b,

<Figure 6> Network Structure by the Interconnectivity Test

a. 1997



b. 2008



Source: Authors' calculation.

Notes: Granger-causal relations with 5% significance level during 1997 and 2008 are drawn as lines with connecting two institutions. The arrow "→" is denoted by the line with thicker stubs at one end of it such as "—━". Red indicates a commercial bank, green indicates an insurance company, blue indicates a securities company, orange indicates a savings bank, violet indicates a merchant bank and yellow indicates a credit finance company.

interconnectivity is based on Granger-causal pairwise relations which are significant at 5% level. The arrow “→” is denoted by the line with a thicker stub at one end of it such as “——”. For example, when one red line is connecting a red node (a commercial bank) and a blue node (a security company), there is a thicker stub at blue node side and it means a commercial bank influences a security company.

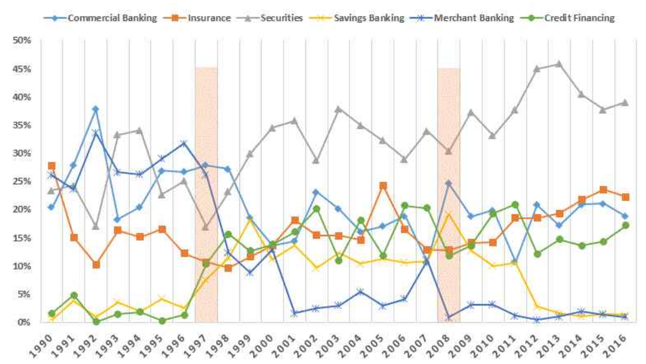
Figure 6b shows the network structure in the most recent financial crisis in 2007-2009. In comparison with the structure in 1997 of Figure 6a, it contains fewer number of financial institutions. We find that the role of securities firms in 2008 is different than that in 1997 by observing a lot of statistically significant connections from other institutions to securities firms (in blue). By comparing both networks, blue lines are more dominate in 2008 than in 1997. There are more significant relations from securities firms to other firms. Commercial banks highlighted in red have retained their leading power since the 1990s, implying their roles in transmitting a systemic risk to other institutions. Their roles are noteworthy because many economic decisions on the flow of funds are made with loans and savings through these commercial banks: a commercial bank intensifies the systemic risk by linking a financial street with a main one. In summarizing the changing shape of the network structure in a financial system, we calculate the outward and inward connections which are defined with equation (6) and (7).

The outward connections are estimated by the number of stock returns that explain them in other sectors whereas the inward ones are by the number of returns that are explained by them in other sectors. If a sector's stock returns Granger-cause another sector's returns, it contributes to outward connectivity of a sector. In Figure

<Figure 7>

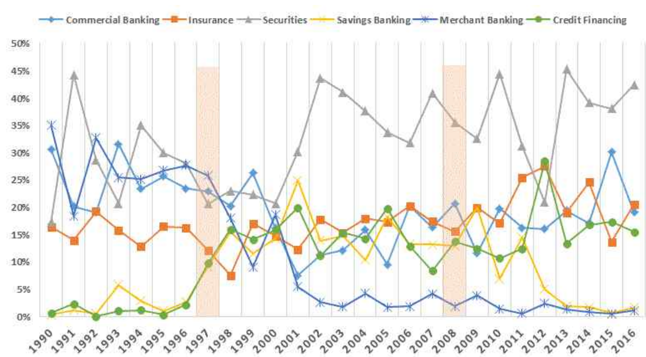
a. Number of connections

from a sector to other financial institutions



b. Number of connections

from other financial institutions to a sector



Source: Author's calculation.

Notes: Normalized by as a percentage of total possible connections. Calculated by significant Granger-causal relations at 5% significance level. ;(a) The normalized number of causal relations that each sector Granger causes the other institutions are calculated for each year. ;(b) The normalized number of causal relations that the other institutions Granger causes each sector are calculated for each year. ; Light blue diamonds indicate commercial banking, orange squares indicate insurance, grey triangles indicate securities, yellow crosses indicate savings banking, dark blue stars indicate merchant banking and green solid circles indicate credit financing.

7a, the trends in group–wise outward connection from a sector to others. Figure 7b shows the inward connection based on Granger causality drawn by others to explain the trends in a sector.

Figure 7a and 7b show the time–varying role of each sector in transmitting a shock by showing the outward, and inward connectivity, respectively. In 1997, commercial banking and merchant banking sectors played a critical role in the exchange of information on stock returns: according to the outward connectivity in Figure 7a, commercial banks Granger–caused 28% of the total connections and merchant banks made 26% of the total. Their inward connectivity is also significant than other sectors (see Figure 7b). Specifically, 26% of stock return movements in a merchant banking sector were Granger–caused by them in other sectors.

According to the trends in the early 1990s, the stock returns of firms in merchant banking and commercial banking sectors in those years explain the movements in returns of firms in other institutions. Their role have become obsolete since 1997, in which many merchant banks and commercial banks were merged and acquired by another. On the other hand, in 2008, securities firms and commercial banks were a network leader: securities firms Granger–cause 30% of the total connections; a commercial banking sector Granger–causes 25% of the total. Additionally, they have been active in absorbing the influences from others by inward connections such that 36% were Granger–caused by securities sector and 21% were Granger–caused by a commercial banking sector.

3. Firm–level analysis

In our sector–level analysis, we identify commercial and merchant banking sectors as a main transmitter of an idiosyncratic shock to institutions even in other sectors in 1997 and securities and commercial banking sectors as the one in 2008. In the sector–level analysis, we find that it is necessary to consider the relative size of a sector according to the number of firms in the sector such that the more number of firms in the sector, the easier the sector affects others. However, as the market share of each firms in the each sector varies over a window, it is hard to estimate the size according to the market share of a firm. As a robustness check on the implications from the sector–level analysis, we conduct similar analysis at a firm–basis.

In Table 3 and 4, we tabulate the number of connections from the company to the other and the number of connections from the other to the company in 1997 and 2008, respectively. In 1997, in the list of firms having outward causality, there are 4 merchant banks and 3 commercial banks and 1 savings bank and 1 insurance firm and 1 credit financing company in a top 10 list. On the list of top inward–connected firms, we find 3 merchant banks, 2 credit financing companies, 2 insurance companies, 1 commercial bank, 1 securities firm, 1 savings bank in the list. Looking into the list of firms in 1997, we find that the results are related to the cause of a financial crisis in 1997. Numerous ex–post analysis on 1997 currency crisis (Choi, 2006; Kim, 2006; Yoon, 2007) argue that one of the main cause of a crisis was the excessive use of short–term debt by merchant banks and commercial banks. This argument is consistent with our result of the firm level analysis

<Table 3> Top 10 listed firms according to the number of connections (1997.1.1. ~ 1997.12.31.)

No. of connections from the company to the other		
Rank	Company name	Number
1	Han Kook Capital Co., Ltd.	87
2	Nara Banking Corporation	80
3	Kookmin Bank	77
4	Samsung Fire & Marine Insurance Co., Ltd.	64
4	Korea Housing & Commercial Bank	62
6	Hana Bank	56
6	Dae Dong Mutual Savings & Finance CO,LTD.	56
6	Samyang Merchant Bank	56
6	H & S Investment Bank	55
10	Samsam Merchant Bank	53

No. of connections from the other to the company		
Rank	Company name	Number
1	Busan Mutual Savings bank CO., LTD.	79
2	Saehan Merchant Banking Corporation	72
3	KTB Investment & Securities Co., Ltd.	68
4	Samsung Fire & Marine Insurance Co., Ltd.	66
5	Korean Reinsurance Company	63
6	Dongnam Leasing CO., LTD.	63
7	Hana Bank	57
8	Yeungnam Merchant Banking Corporation	57
8	Q Capital Partners Co., Ltd.	57
10	Daehan Investment Banking Corporation	55

Source: Authors' calculation.

<Table 4> Top 10 listed firms according to the number of connections (2008.1.1. ~ 2008.12.31.)

No. of connections from the company to the other		
Rank	Company name	Number
1	Daegu Bank	39
2	Fine Asset Management Corporation	36
3	Solomon Savings Bank	33
4	Busan Bank	29
5	Seoul Mutual Savings Bank	29
6	Jeil Savings Bank	29
6	Industrial Bank Of Korea	22
6	Pureun Mutual Savings Bank Co., Ltd.	21
9	Hana Financial Group Inc.	19
10	Korea Exchange Bank	19

No. of connections from the other to the company		
Rank	Company name	Number
1	Shinhan Financial Group Co., Ltd.	29
2	Korea Exchange Bank	29
2	Hana Financial Group Inc.	26
4	Kiwoom Securities Co., Ltd.	26
5	KB Capital CO.,LTD.	22
6	Jeil Savings Bank	21
6	KB Insurance Co., Ltd.	18
8	Solomon Savings Bank	18
9	Shinyoung Securities Co., Ltd.	17
10	Woori Technology Investment Co., Ltd.	17

Source: Authors' calculation.

In 2008, 5 commercial banks and 4 savings banks, 1 credit financing company are listed on the top 10 firms, having Granger causality to others. On the list of companies that have serious inward connectivity, 3 commercial banks, 2 securities companies, 2 savings banks, 1 insurance firm, 1 credit finance company are listed. While securities firms played the most significant role in a sector level analysis, there are only few securities firms because many securities firms are usually sized smaller than others. During this period, the firm−level analysis shows that the stock returns of commercial and savings banks contain much information on the returns of other institutions.

The results from our micro study is comparable with them from the study of Rhee (2016) on individual commercial banks. His study shows that the number of connections from regional commercial banks to other firms tends to higher than the number of connections from major commercial banks. In both analyses in this paper, sector and firm−level, commercial banks are a main transmitter of a shock in a financial system while intensifying a systemic risk. The implications from Korean financial industry is also consistent with the following argument in Billio et al (2012):

> *"one obvious explanation for this asymmetry is the fact that banks lend capital to other financial institutions, hence, the nature of their relationships with other counter−parties is not symmetric."*

On the other hand, Cho(2012) suggests that Korea has accumulated short−term foreign debts since 2005 and this made Korean banking sector be susceptible to the liquidity shock in 2008. the second explanation is also related to the nature of banking, borrowing at short−term and lending for long−run investment.

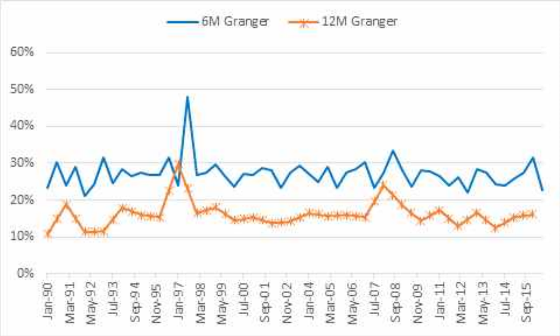
V. Robustness check

In figure 8, Blue solid line indicates results for 54 six−month rolling windows. Orange stars indicate results for 27 one−year rolling windows. As the rolling window size is smaller, the interconnectivity index is more volatile and capture more connectedness among institutions. For eliminating market factors from the data, we regress stock returns on the macro data (KOSPI index, Financial sector index, call rate) and conduct Granger causality test and PCA on the residuals. Figure 9 shows the comparison between the interconnectivity index with raw data and that with the residuals. We find that the trends remain with the residuals. Furthermore, the interconnectivity index without market common factors shows its feature during the crisis period with a higher volatility. In Figure 10, we provide the PCA results with raw data and residuals. The figure shows that there is the interconnectivity is consistent regardless of a market factor, which may drive the stock returns into the same direction.

We present the number of firms in each sector out of top 10, top 15 and top 20 in Table 5. According to the list in the table, merchant banks and commercial banks affected other sectors' firms more than others in 1997 and commercial banks and saving banks played the most significant role in 2008.

VI. Summary and conclusion

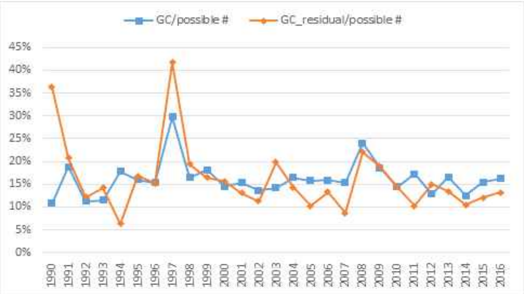
<Figure 8> Comparision of
six-month window and 12-month window



Source: Author's calculation.

Notes: Blue solid line indicates results for 54 six-month rolling windows. Orange stars indicate results for 27 one-year rolling windows.

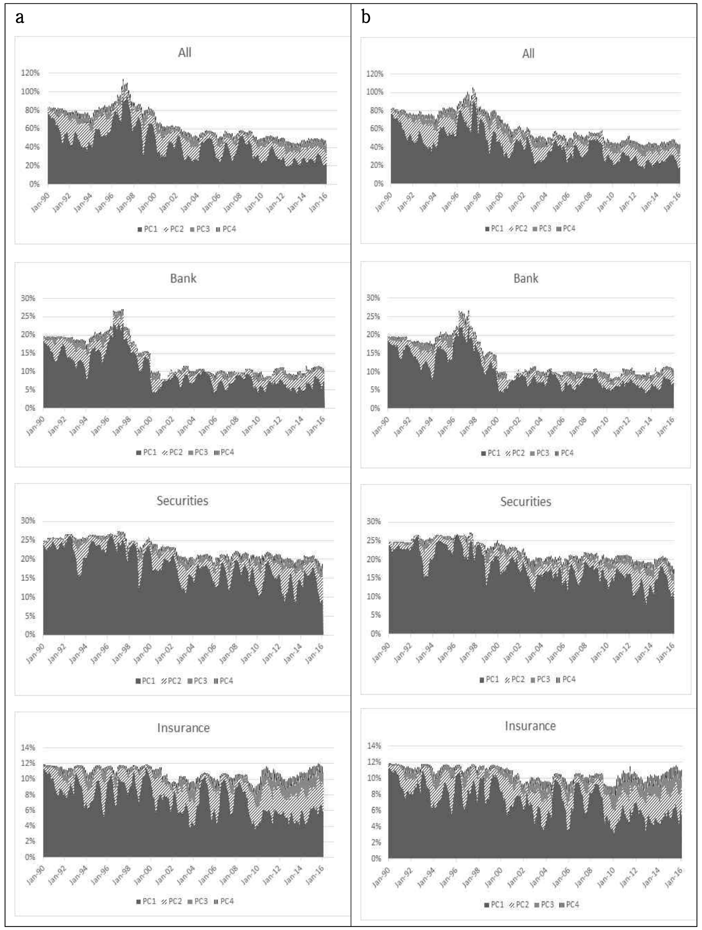
<Figure 9> Comparision of
raw data and residual with one-year window



Source: Author's calculation.

Notes: Blue squares are drawn with the number of connections as a percentage of all possible connections. Orange diamonds indicates the number of connections as a percentage of all possible connections but is calculated with the residuals after regression on macro data.

<Figure 10> Principal component analysis of the weekly returns
with one-year rolling window



Source: Author's calculation.

Notes: (a)Calculation with raw data; (b)Calculation with residuals after regression on macro data

<Table 5> Number of firms in each sector out of Top 10, Top 15, Top 20 listed firms

1997					
Top 10		Top 15		Top 20	
Outward	#	Outward	#	Outward	#
Merchant banks	4	Merchant banks	5	Merchant banks	6
Commercial banks	3	Commercial banks	4	Commercial banks	6
savings banks	1	Credit financing	3	Credit financing	5
Insurance	1	savings banks	2	Insurance	4
Credit financing	1	Insurance	1	savings banks	2
Inward	#	Inward	#	Inward	#
Merchant banks	3	Merchant banks	5	Merchant banks	8
Credit financing	2	Insurance	4	Insurance	5
Insurance	1	Credit financing	2	Commercial banks	2
Commercial banks	1	Commercial banks	2	savings banks	2
Securities	1	Securities	1	Credit financing	2
savings banks	1	savings banks	1	Securities	1
2008					
Top 10		Top 15		Top 20	
Outward	#	Outward	#	Outward	#
Commercial banks	5	Commercial banks	6	Commercial banks	8
savings banks	4	savings banks	5	savings banks	6
Credit financing	1	Securities	2	Credit financing	3
		Credit financing	2	Securities	2
		Insurance	2	Insurance	2
Inward	#	Inward	#	Inward	#
Commercial banks	3	Commercial banks	5	Commercial banks	5
Securities	2	Securities	3	savings banks	4
savings banks	2	Credit financing	3	Credit financing	4
Insurance	1	savings banks	3	Insurance	4
Credit financing	1	Insurance	2	Securities	3

Source: Author's calculation.

In this paper, we estimate the interconnectivity among Korean financial firms from 1990 to 2016 by using the weekly stock prices. We discretize the window at a yearly basis to analyze the components contributing to the notable features of interconnectivity within a window. Within each window, we conduct the Granger causality test by VECM for nonstationary and cointegrated pairs and VAR for stationary pairs. We also conduct the PCA for finding the commonalities among the stock returns in a financial sector. After finding the degree of commonality and interconnectivity for each window, we find the trends in those measures. Both trends show a significant increase in the interconnectivity in 1997 and 2008, implying the increase in a systemic risk for those periods. In a sector-level analysis, we find that commercial and merchant banking sectors were intensifying the systemic risk by explaining 30% of both inward and outward causal relationships in 1997. In 2008, securities and commercial banking sectors played a similar role. In an firm-level analysis, we find the consistent results with our macro analysis by showing that the causal links from the merchant banks and the commercial banks to other institutions were significant in each crisis period. These findings help identifying the significant financial firms which are transmitting the risks and information to others, intensifying the systemic risk. The interconnectivity index can be one indicator to consider when determining the Systemically Important Financial Institutions (SIFIs) or Domestically-Systemically Important Banks(D-SIBs). If the analysis is conducted on the stock return in every minutes, we can measure the systemic risk in time. Additionally, the interconnectivity, which is developed in this paper leads a statistically significant impulse responses of CD rates and the spreads, implying its role in a co−cyclical indicator.

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Appendix A. List of firms by Sector

<Table 6> List of firms by Sector

Commercial banking			
1	Shinhan Financial Group Co., Ltd.	21	Chung Chong Bank, Ltd.
2	KB Financial Group Inc.	22	The Kwangju Bank, Ltd.
3	Hana Financial Group Inc.	23	Kyungki Bank, Ltd.
4	Woori Bank	24	The Jeonbuk Bank Ltd.
5	Industrial Bank Of Korea	25	Kangwon Bank
6	BNK Financial Group Inc.	26	Kyongnam Bank
7	Korea Investment Holdings Co., Ltd.	27	Chung Buk Bank, Ltd.
8	DGB Financial Group	28	Hana Bank
9	Meritz Financial Group Inc.	29	Boram Bank
10	JB Financial Group Co., Ltd.	30	Shinhan Bank
11	KwangjuBank Co., Ltd.	31	Koram Bank
12	Jeju Bank	32	Dong Hwa Bank
13	ChoHung Bank	33	Dae Dong Bank
14	Korea First Bank	34	Dong Nam Bank
15	Hanil Bank	35	Peace Bank of Korea
16	Hana Bank	36	Kookmin Bank, Ltd.
17	Korea Exchange Bank	37	Korea Housing & Commercial Bank
18	Korea Long Term Credit Bank	38	Woori Finance Holdings Co., Ltd.
19	Daegu Bank	39	Kookmin Bank
20	Busan Bank	40	Kyungnam Bank Co., Ltd.

Insurance			
1	Samsung Life Insurance Co., Ltd.	9	Tong Yang Life Insurance Co., Ltd.
2	Samsung Fire & Marine Insurance Co., Ltd.	10	Mirae Asset Life Insurance Co.,Ltd.

3	HanWha Life Insurance Co., Ltd.	11	Hanwha General Insurance Co., Ltd.
4	Dongbu Insurance Co., Ltd.	12	Lotte Non-Life Insurance Co., Ltd.
5	Hyundai Marine&Fire Insurance Co., Ltd.	13	Heungkuk Fire & Marine Insurance Co., Ltd.
6	Meritz Fire & Marine Insurance Co., Ltd.	14	Green Non-life Insurance Co., Ltd.
7	KB Insurance Co., Ltd.	15	First Fire & Marine Insurance Co., Ltd.
8	Korean Reinsurance Company	16	Regent Insurance Co., Ltd.

Securities			
1	Mirae Asset Daewoo CO.,LTD.	18	Dongbu Securities Co., Ltd.
2	NH Investment & Securities Co., Ltd.	19	Hanyang Securities Co., Ltd.
3	Samsung Securities Co., Ltd.	20	Golden Bridge Investment & Securities Co., Ltd.
4	Meritz Securities Co., Ltd.	21	Dongsuh Securities Co., Ltd.
5	Kiwoom Securities Co., Ltd.	22	KLB Securities Co., Ltd.
6	Yuanta Securities Korea Co., Ltd.	23	Woori Securities Co., Ltd.
7	Daishin Securities Co., Ltd.	24	Coryo Securities Corporation
8	Shinyoung Securities Co., Ltd.	25	Shinhan Securities Co., Ltd.
9	Ebest Investment & Securities Co., Ltd.	26	Hana Securities Co., Ltd.
10	Hanwha Investment &Securities Co., Ltd.	27	Hyundai Securities Co., Ltd.
11	SK Securities Co., Ltd.	28	Dongwon Securities Co., Ltd.
12	HMC Investment & Securities Co., Ltd.	29	Ileun Securities CO., LTD.
13	Kyobo Securities Co., Ltd.	30	Good Morning Shinhan Securities Co.,Ltd.
14	Eugene Investment & Securities CO., LTD.	31	NH Investment & Securities Co., Ltd.
15	Bookook Securities Co., Ltd.	32	Samsung Investment & Securities CO., LTD.
16	KTB Investment & Securities Co., Ltd.	33	I'M Investment & Securities CO.,LTD
17	Yuhwa Securities Co., Ltd.	34	Miraeasset Securitiles Co., Ltd.

Savings Banking			
1	Pureun Mutual Savings Bank Co., Ltd.	9	Seoul Mutual Savings Bank
2	Tae-Jon Mutual Saving's&Finance CO.,LTD.	10	Jeil Savings Bank
3	Dae Dong Mutual Savings & Finance CO,LTD.	11	Hnamaum Mutual Savings Bank
4	Jinheung Savings Bank Co., Ltd.	12	Korea Savings Bank
5	Hae Dong Savings & Finance Co., Ltd.	13	Donga Mutual Savings & Finance Co., Ltd.
6	Solomon Savings Bank	14	Shinmin Mutual Savings Bank Co., Ltd.
7	Busan Mutual Savings bank CO., LTD.	15	Eutteum Mutual Savings Bank
8	Daeyang Mutual Savings & Finance Co., Ltd.	16	Union Savings Bank

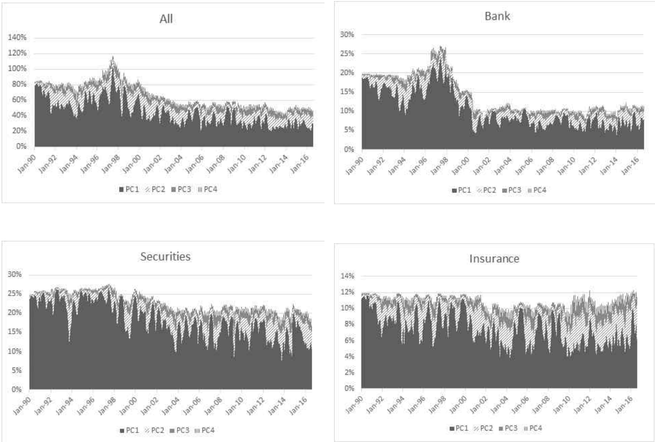
Merchant Banking			
1	Woori Investment Bank Co.,Ltd.	16	Hangil Merchant Banking Corporation
2	LGMerchant Banking	17	Samyang Merchant Bank

	Corporation		
3	Tongyang Investment Bank	18	Ssangyong Merchant Banking Corporation
4	Central Banking Corporation	19	Hang Do Merchant Bank
5	Daehan Investment Banking Corporation	20	Cheongsol Merchant Banking Corporation
6	Hansol Merchant Bank	21	Hyundai Ulsan Merchant Banking Corporation
7	Korea Merchant Banking Corporation	22	Regent Merchant Bank
8	Hyundai International Merchant Bank	23	Shinhan Investment Bank
9	Saehan Merchant Banking Corporation	24	Nara Banking Corporation
10	Meritz Investment Bank	25	Hanwha Merchant Bank
11	First Merchant Banking Corporation	26	Samsam Merchant Bank
12	H & S Investment Bank	27	Shinsegae Merchant Bank
13	Korea International Merchant Bank	28	Coryo Merchant Bank, Ltd.
14	Taegu Merchant Bank	29	Yeungnam Merchant Banking Corporation
15	Gyongnam Merchant Banking Corporation		

Credit financing			
1	Samsung Card Co.,Ltd.	12	kyongnam leasing co., ltd
2	KB Capital CO.,LTD.	13	Shinhan Capital CO., LTD.
3	Aju Capital Co., Ltd.	14	KEB Leasing CO.,LTD.
4	Han Kook Capital Co., Ltd.	15	Dongnam Leasing CO., LTD.
5	Q Capital Partners Co., Ltd.	16	Alpha Capital Corporation
6	Woori Technology Investment Co., Ltd.	17	Kookmin Credit Card Co., Ltd.
7	CNH Co., Ltd.	18	LG Card
8	Mason Capital Corporation	19	Korea Exchange Bank Credit Service CO., LTD.
9	KDB Capital Corporation	20	JoongAng Capital
10	Fine Asset Management Corporation	21	Jeil Capital Co.,LTD.
11	Star lease CO., LTD.		

Appendix B. Six-month rolling window

<Figure 11> Principal component analysis
of the weekly returns with six-month rolling window



Source: Author's calculation.
Notes: six-month window with one-week step size

한국 금융 산업의 상호연계성에 관한 연구

고현미* · 유재인**

본 연구에서는 1990년도부터 2016년까지의 기간 동안 한국 금융 시장에서의 충격전파 경로를 확인하기 위해 금융기관 간 상호연계도를 분석하였다. 한국 금융산업의 시스템 리스크 측정을 위하여 은행업, 보험업, 증권업, 신용금고업, 종합금융업, 여신금융업의 6개 업종의 금융 회사들의 주별 주가 수익률을 사용하였다. 본 연구에서는 그레인저 인과 검정과 주성분 분석을 통해 기관 간 평균 연결의 규모와 방향을 추정하고 그레인저 인과로 측정된 평균 연결 수의 변화 추세를 통해 상호 연계성의 정도와 연계 구조의 변화를 분석하였다. 실증분석 결과, 1997년과 2008년의 금융 위기 기간 동안, 금융 기관 간 강한 상호연계성을 보이는 것으로 나타났다. 본 상호연계도 지표는 두 위기 기간 동안 CD금리와 장단기 스프레드의 변화를 예측하는데 통계적으로 유의한 정보를 제공하고 있는 것으로 나타났다. 업종 간 분석에 따르면, 1997년 외환위기 동안 은행업과 종합금융업이 시스템 리스크를 심화되는 데에 큰 영향을 미치는 반면, 2008년 금융위기에는 증권업과 은행업이 주로 영향을 끼친 것을 알 수 있었다.

핵심주제어: 공적분; 그레인저 인과; 상호연계도; 주성분 분석; 시스템 리스크
JEL 분류번호: G20, G21, G28

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