Systemic Risk in the Consumer Credit Network across Financial Institutions

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Abstract

The main contribution of this paper is its construction of a network of financial institutions from the level of consumer credit. We assume that each consumer takes loans from multiple institutions, so that those institutions share risk from the same consumers regardless of the quality or type of loan. Then we construct a financial network comprised of those institutions and compute a contagion index based on their interconnections using a weight of probability of default for the individual borrowers. Using Korea Consumer Credit Panel (KCCP) we investigate a network of financial institutions in Korea. We found a strong connection between banking institutions and credit card firms due to the convenience of making small loans with credit cards. However, when we give a weighted probability of default to the linkages among institutions, the connections between banking institution and savings banks, non-credit card finance corporations and merchant bank are stronger than others, while banking institutions hold a central position and are exposed to the largest amount of loans individually. The contagion index hit a peak in 2013Q1 and then fell rapidly, before fluctuating at a relatively low level from 2016 to 2017Q2. Our results enable authorities to monitor systemic risk from the level of consumer credit, while accounting for specific types of consumers and their probability of default.

Keywords: systemic risk, network, consumer credit, financial stability

JEL Classification: C23, D14, G20, G21, G23.

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1 Introduction

Since the Great Recession, the understanding of systemic risk has risen due to serious spill-over effects between financial institutions. Starting with Bear Stearns in 2008, a number of commercial banks and other types of financial institutions faced serial bankruptcy, threatening the rest of the financial system (Hellwig, 2009). Thereafter, more attention has been paid to the measurement of systemic risk or spill-over effects in a financial network for the sake of financial stability and macro prudential regulation. For example, Cont and Moussa (2010) propose a quantitative approach, using a systemic risk index, which measures the systemic impact of the failure of a large financial institution. Amini et al. (2012) propose a simulation-free framework for stress testing the resilience of a financial network to external shocks that impact its balance sheets. Gai and Kapadia (2010) develop an analytical model of contagion in financial networks with an arbitrary structure, and Amini et al. (2016) propose a model for measuring the magnitude of contagion in a large counterparty network and give an analytical expression for the asymptotic fraction of defaults in terms of a network's characteristics.

Korea has recently experienced several financial crises, such as the Asian financial crisis in 1997, the credit crisis of 2003, and a savings bank run in 2011. The last two crises in particular were exacerbated by consumer credit, while corporate credit was managed well because of regulation like the Basel Accords and the government's macro-prudential policies. However, the recent increase in household debt is now regarded as a possible detonator of the next crisis in the financial system and therefore research has been conducted into the subject. In this ared of the literature, Suh (2011), Lee et al. (2013), Choi et al. (2015), and others have investigated systemic risk using the Copula or option pricing model. Kim et al. (2016) looked at systemic risk using network theory following th methodology of Das (2016). They used a theoretical network to model the Korean financial system and measure contagion risk, though their model lacked an empirical analysis.

Previous research on household debt focuses on the aggregate amount of consumer credit within the financial system. Those handle the household debt data as a measure of households' risk exposure no matter the characteristic of the credit extended, including the type of loan, spread, borrowers' credit rating, and so on. Authorities interested in financial stability focus on prudential measures at financial institutions to cope with economic fragility caused by household debt. For example, authorities like central banks conduct a number of stress tests, but no serious cracks are found at the aggregate level, since those financial intermediaries are well prepared due to Bank of International Settlements (BIS) and government regulations. Both researchers and regulators view consumer credit as a whole and do not take care to examine the field at a disaggregate level. Unlike corporate credit, consumer credit takes multifarious forms, but is usually lumped into a single category so that its idiosyncratic details are ignored. However, considering that the Great Recession was ignited by subprime mortgages, which were a small part of the entire mortgage market, it is worth to understanding the idiosyncratic characteristic of consumer credit. By doing so, we can identify the weak points in consumer credit and see how these points may affect the rest of the financial system, and therefore determine what policies are suited for the current credit market.

Thanks to the development of big data, the Bank of Korea has established a micro-level dataset for household debt, the "Korea Consumer Credit Panel" (KCCP) which includes the amount of debt, characteristics, borrower credit scores, the amount of credit card usage, and other related items. The panel reveals which institution debtors owe money to, what type of loans they have, and how long the borrowers have to repay those loans, so that we can compute how much each institution holds in loans from the same consumer. We can then assume that if one borrower cannot pay one of their loans back on time, the borrower possibly might not pay back others, which means that financial institutions share risks from the same consumers, which we can define as a financial linkage between institutions.

Though there is no extant literature on constructing a financial network from the level of consumer credit, we follow some established approaches in the network literature. Cont et al. (2010) measure the magnitude of the contagion effect by computing which institutions influence and are influenced by other institutions across the entire financial system. Acharya et al. (2017) and Huang et al. (2009) also estimate measures of risk for financial institutions in a similar manner. In an important contribution, Cont et al. (2010) simulated how risk can be affected by other variables and, which encouraged us to include macroeconomic variables as a factor in the vulnerability of the financial system. Therefore, we follow their steps to measure the how individual borrowers affect the financial network through financial institutions, along with other macro variables such as the policy rate. Consequently, our framework consists of three layers (consumers, financial institutions and the nationwide financial system) and control variables (interest rates and factors affecting consumers' behavior). Jung and Kim (2018) analyzed household debt's impact on financial stability using the panel data, with an emphasis on debt status considering borrowers' employment status. We more generally extend their point of view to examine overall financial stability and construct a numerical measure for this stability.

The next chapter introduces the data and the framework for measuring connectivity within a financial network using micro data. The third chapter establishes a contagion index as a measure of risk. In the fourth chapter, a scenario analysis is performed to test the robustness of our framework. The fifth chapter concludes the paper.

2 Financial Network

2.1 Data

The Bank of Korea introduced the KCCP[1] based on a database from the Korea Credit Bureau, beginning in the first quarter of 2012 and reporting with a quarterly frequency. The original database consists of 41 million observations[2], which seems sufficient to represent Korean population, considering that there are 47 million residents of Korea over the age of 18. 420,000 samples are extracted according to the statistical sampling strategy of the Bank of Korea, following those of the New

[1] This panel is limitedly open to the public so that you can access the data only with the terminal assigned by the Bank of Korea.

[2] The size of the database during our sample periods is more than 2GB.

York Fed's Consumer Credit Panel. With a randomly assigned personal identification number, each individual entry includes age, gender, postal code, credit rating, estimated income, total loans, and overdue loans, as well as credit and debit card usage. The postal code is based on the individual's registered address, which Jung and Kim (2018) used to add the average house price of the area where the individual resides. BSI is also added based on the individual's address at the metropolitan level. A line of credit in default is defined by missed payments that have been due for over 90 days. It is important to note that the panel is constructed at the level of the individual borrower, not at the household level.

Table 1 reports some interesting statistics that emerge from the KCCP. Male borrowers have been more prevalent than female borrowers historically and there are therefore more male borrowers in the sample. In the observed period, the distribution of credit grade has changed significantly. Overall, the proportion of highest grade (1-3) and lowest grade(8-10) borrowers has expanded, but the middle grade (4-7) proportion had declined. This indicates that there is a bifurcation even in consumers' credit levels. The ratio of secured loans to the total amount of loans changed little during the sample period. However, the proportion of self-employed people in the total population increased. Default rates, which measures the number of borrowers who have declared default, picked up during the sample period before stabilizing at the end of the sample. See the Bank of Korea's Financial Stability Report for more details about the panel. [3]

2.2 Framework of the Network

The existing literature has measured systemic risk in the financial network as a whole, which does not account for idiosyncratic factors within the network. Following Cont et al. (2010), we construct a financial network and measure the relative influence of different financial institutions due to systemic risk at the micro level. In this sense, our financial network is modeled at the micro level. More specifically, the counterparty relationship in a financial system is defined as a weighted directed graph or network,

[3] https://www.bok.or.kr/eng/bbs/E0000737/list.do?menuNo=400042

Table 1: Selected statistics from the KCCP from 2012Q1 to 2017Q2*

Variable	2012Q1	2014Q2	2016Q1	2017Q2
Gender (Male/Female)	0.610	0.610	0.610	0.610
Credit grade (1-3)	0.416	0.472	0.530	0.570
Credit grade (4-7)	0.487	0.415	0.354	0.326
Credit grade (8-10)	0.096	0.113	0.116	0.103
Secured loans/total loans	0.442	0.446	0.436	0.449
Use of loan corporations	0.084	0.094	0.094	0.078
Proportion of self-employed	0.113	0.124	0.126	0.134
Default rate	0.016	0.023	0.020	0.015

*Notes: Gender is the male to female ratio of borrowers in the sample. Credit grade is the ratio of borrowers of credit grades 1-3, 4-7 and 8-10 to the entire sample. Secured loans/total loans is the ratio of the amount of secured loans versus total loans. Use of loan corporations represent the proportion of borrowers who have used loans from loan corporations, a kind of private lender, in the entire sample. The number of self-employed is the ratio of self-employed borrowers out of the entire sample.
Source: KCCP, Bank of Korea

so that we define E as the matrix of bilateral exposure between two institutions. Then, E_i is the sum of loans issued by a single institution i represented as follows:

$$E_i = \sum_{n=1}^{N} l_{i,n} \tag{1}$$

where E_i is the average loss at an institution, i and $l_{i,n}$ is the total loans of individual n.

We can expand our definition of exposure to include the sum of expected losses from an institution's own issued loans and the contagion effect from the insolvency. If insolvency occurs at a large scale, it may cause a "financial crisis". As a first step, we define the linked loans of institutions, i, as the following.

$$D_i = E_i + E_{ij} = E_i + \sum_{n \in N} l_{ij,n} \tag{2}$$

where $l_{ij,n} = \frac{1}{2}(l_{i,n} + l_{j,n})$ and l_{ij} is the average loans of an individual, and n is owed to two institutions, i and j. n_{ij} denotes the number of borrowers who have loans from these two institutions, i and j. For example, if borrower A borrows \$100 from institution 1 and \$50 from 2, $l_{12,A}$ is \$75. If this borrower does not pay back their loans from one institution, it is very likely that this borrower will not pay back their other loans. In this sense, institutions are more connected if the same borrowers owe money to larger numbers of institutions. As shown in Equation 2, the balance of loans that an institutions holds consists of its own total, E_i and the sum of its linked loans, E_ij. Table 2 introduces a list of financial institutions.

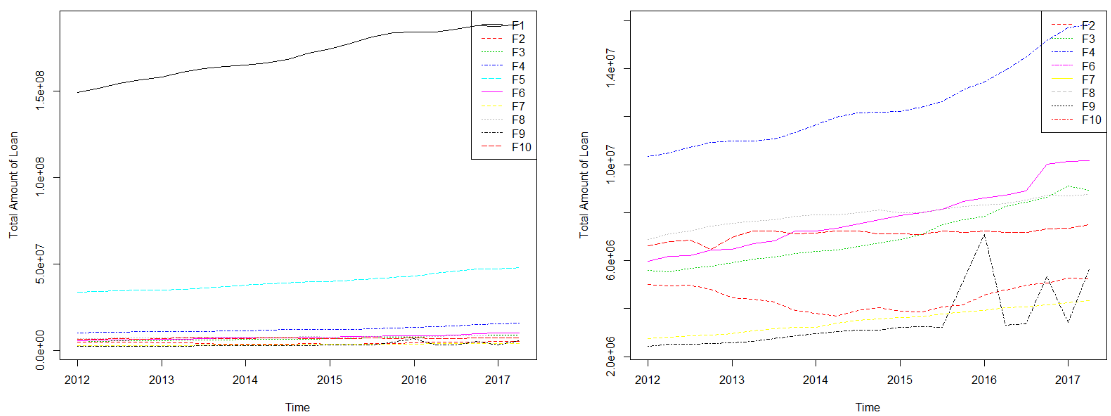
Table 2: List of financial institution types

Short	Description
F1	Banks (including Korea Housing Finance)
F2	Savings banks
F3	Credit unions
F4	Korean Federation of Community Credit Cooperatives
F5	Local unions for agriculture and fisheries*
F6	Insurance companies
F7	Credit card companies
F8	Non-card credit finance corporation
F9	Merchant banking, investment trust, venture capital, and securities company
F10	Guarantee organizations (credit guarantee fund, technology credit guarantee fund, and so on.), postal banks

* Note: The official name of the local unions for agriculture is the Agricultural Cooperative Federation and for fisheries is the Federation of Fisheries Cooperatives.

Figure 1 depicts the total balance of loans that each institution holds, D_i. As expected, most of the balance belongs to commercial banks (F1), including the Korea Housing Finance (KHF) corporation, which is a mortgage-specialized corporation managed by the government, akin to the Federal National Mortgage Association (Fannie Mae) or the Federal Home Loan Mortgage Corporation (Freddie Mac) in the U.S. The second largest creditors among financial institutions are the local unions for workers in the agricultural and fisheries industries (F5). Those institutions were established specifically to provide funds to rural households whose members work in those industries.

Figure 1: Balance of loans by institution*



(a) by all institutions (b) by institution excluding F1 and F5

Source: KCCP
* Note: See Table 2 for description of the legend.

We analyze the linkages between financial institutions in terms of consumer credit. As a first step, we count how many loan contracts are made by the same consumers between different institutions. We define

$$k_{ij,n} = \mathbf{1}\left\{l_{ij,n} > 0\right\} \tag{3}$$

and accordingly,

$$k_{ij} = \sum_{n=1}^{N} \mathbf{1}\left\{l_{ij,n} > 0\right\} \tag{4}$$

as the number of pairs of institutions that share a customer on their loan balances.

Most borrowers are able to borrow from commercial banks, since they have higher credit scores and their risks of default are relatively low. Thus, if we look at financial risk in the aggregate, the underside risk may not be revealed due to the huge share of loans from banking institutions. Therefore, we need to apply weighting to evaluate the balance of loans more appropriately. To do this, we follow Jung and Kim (2018) and estimate each individual's probability of default, p_n, using a dynamic probit model. This probability is estimated based on the individual's balance of loans, the spread due to their credit rating, the spread due to the purpose of the loan, and their employment status. Age, and gender, and BSI and HPI based on where the individual lives, are included as the control variables. More specifically, borrower i's default rate at time t is defined as follows:

$$\begin{aligned} P(y_{i,t} = 1 | y_{i,t-1}, y_{i,t-2}, ..., y_{i,0} \mathbf{w}_{i,t-1}, \mathbf{z}_{i,t-1}, \varsigma_i) \\ = \Phi(\mathbf{w}_{i,t-1} \beta_{\mathbf{w}} + \mathbf{z}_{i,t-1} \beta_{\mathbf{z}} + \beta_y y_{i,t-1} + \varsigma) \end{aligned} \tag{5}$$

where the dependent variable, $y_{i,t}$ is a binary response variable, which is 1 when the borrower's loans are more than 90 days overdue and 0 otherwise, and $\mathbf{z}$ is the key determinants of default rates,

$$\mathbf{z}_{i,t} \in \{spread_{p,i,t}, spread_{c,i,t}, \ln loan_{i,t}, iloan_{i,t}\} \tag{6}$$

where $spread_{p,i}$ is the spread depending on the purpose (secured/unsecured) of the loan for borrower i, $spread_{c,i}$ is the spread depending on borrower i's credit rating, *loan* is the loan balance of the borrower, *iloan* is a dummy variable which is 1 if the borrower has taken additional loans in the most recent two quarters, and 0 otherwise, and $\mathbf{w}$ is a set of control variables such as the borrower's age, gender, average house prices in the area, and BSI where the borrower resides. Note that both $\mathbf{z}$ and $\mathbf{w}$ are exogenous. See Jung and Kim (2018) for more computation details.

Most loans made by financial institution already pass institutional evaluation, so that the probability of default of existing loans is seriously skewed toward zero. As seen in Table 3, the proportion of borrowers whose probability of default is less than 0.1% is almost 24% of the population. That is, more than three quarters of borrowers in the sample have a probability of default less than 0.1%. The share of borrowers who have a relatively higher probability of default rose in 2014, but declined since then. This pattern is also seen in the average probability of default of entire sample, which has moved similarly moved on average along with the true default rate, as shown in Table 1.

Table 3: Distribution of probability of default

	2012Q1	2014Q1	2016Q1	2017Q2
≥0.1%	0.248	0.240	0.233	0.240
≥1%	0.095	0.106	0.098	0.094
≥5%	0.034	0.039	0.028	0.030
≥10%	0.020	0.027	0.021	0.021
Average	0.014	0.018	0.014	0.013

In this circumstance, if we estimate Equation 5 using a fixed effects model, it may cause serious bias in our parameter. We therefore estimate the equation using the correlated random effects model following Wooldridge (2005) and Jung and Kim (2018). We use this probability as the weight for assessing institutional exposure at default. We can thus obtain a financial institution's expected losses from any given individual. We define the exposure at default E_i^* for one institution as the following:

$$E_i^* = \sum_{n_i \in N} l_{i,n} \times p_n \tag{7}$$

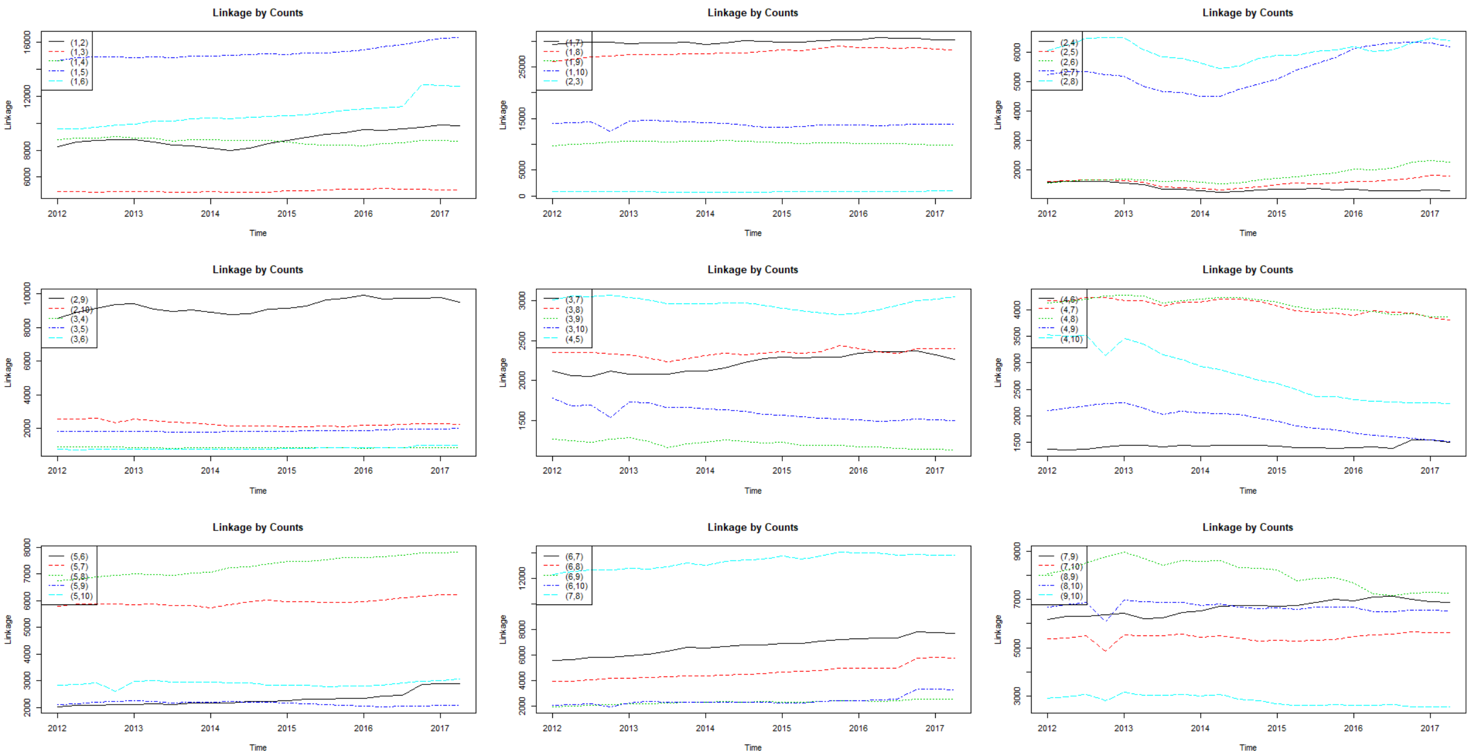
where p_n is the probability of default of borrower n and the exposure shared with other institution is

$$E_{ij}^* = \sum_{n_{ij} \in N} l_{ij,n} \times p_n \tag{8}$$

2.3 The Financial Network

Figure 2 depicts the linkages between financial institutions according to the number of loans shared between two institutions, k_{ij}. Since we measure 10 different kinds of financial institution, there are 45 ($_{10}C_2$) possible connections. There is not a good way to depict every connection in single plot. We therefore chart those 45 connections in nine smaller figures. Note that the scale of each subplot varies in Figure 2. Since a majority of customers owe money to banks (F1), the linkages among F1 institutions

Figure 2: Linkage of financial institutions by number of loans shared*



* Note: (i,j) denotes the number of loans that borrowers owe to both institutions, i and j. See notes to Table 2 for institution numbering and note that 'F' is dropped for brevity.

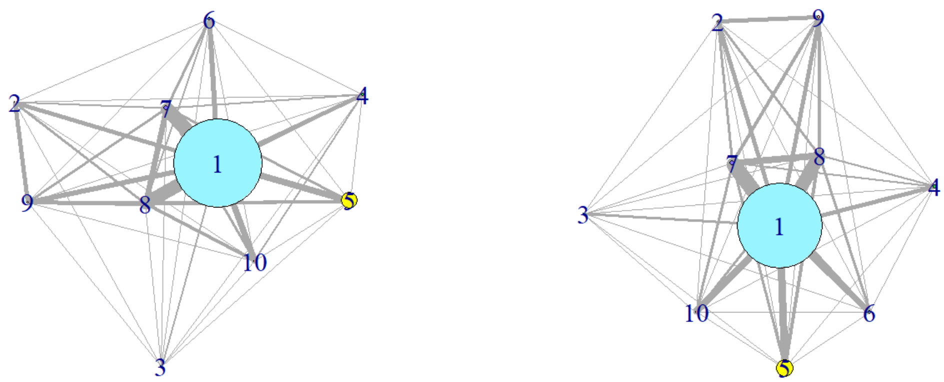
are greater than any other, and the composition of the linkages among F1 changes very marginally.

This linkage can be expressed as the network of ten types of financial institutions in terms of the number of loans, as seen in Figure 3. The thickness of the branch in each figure represents the number of loans shared between two institutions k_{ij}, which is also expressed in Figure 2. The size of each circle represents the number of loans owned by institution i individually, namely k_i. Since the network can be defined in any observation period, we show the network in two selective periods, 2013Q2 and 2017Q2. The former is when the contagion index, which will be introduced in the next chapter, was at its highest, and the latter is the last observation in the sample, when the contagion index stabilized at a lower level. No matter of the observation period, banking institution (F1) had the strongest connections with one another while they owned the largest number of loans among all institutions. Credit card companies (F7) and non-credit card finance corporations (F8) have the biggest connectivity with banks. It seems that many consumers use the short-term loans offered by these two institutions for convenience, as long as they have an eligible credit score. Local unions for agriculture and fisheries (F5) also have a significant number of loans, because many farmers and fishermen borrow easily from them in the name of taking policy loans for industry activity. It seems that there is no dramatic change in the number of loans shared among institutions between the two periods. Therefore, it is worth examining the amount of shared loans in the sample period.

Figure 4 depicts the amount of loans shared by two institutions, E_{ij}. Since we compute the average balance of loans for each institution, we overestimate the share of loans held by non-bank institutions. We are particularly interested in the change in loan balances with non-banking institutions. Considering the robustness of borrowers who have loans from banking institutions, we pay more attention to non-robust borrowers who usually pay higher interest rates at non-banking institutions. Different loans of different institutions share the identical risk because they deal with the same borrower, creating a point of connection between financial institutions.

Figure 5 shows the network of financial institutions in terms of the balance of loans shared. The size of the circle is E_i and the width of the branch is E_{ij}. While banking institutions hold the largest amounts of loans independently, they have more links with the local unions for agriculture and fisheries (F5), non-card credit finance corporations(F8), and guarantee organizations(F10) as well as the credit card companies (F7). The share held by banking institutions is so huge that we cannot measure its network connectivity meaningfully. The size of the node for each institution indicates the balance of the institution's own loans (which are not shared), and the width of the edge between nodes is the balance of loans shared between two institutions. Therefore, we need more a percipient measure to see financial linkages, which show expected exposure at default, E^*_{ij}.

Figure 3: Networks of financial institutions by number of loans that borrower owes to both institutions*



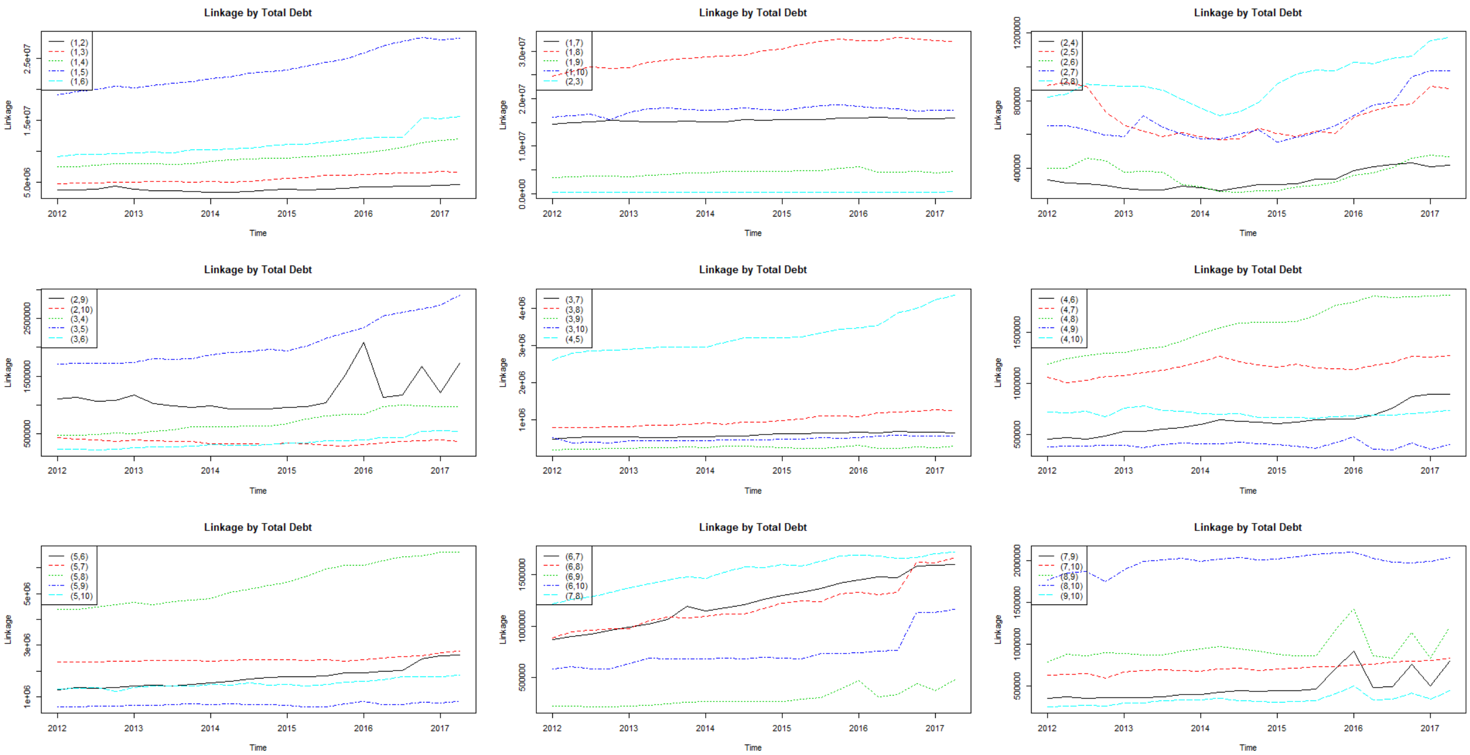
(a) 2013 Q2 (b) 2017 Q2

* Note: See notes to Figure 2. Width of branch stands for the number of loan that borrower owe to both institution.

Figure 6 shows the linkages among financial institutions by expected exposure at default, which is E^*_{ij}. As expected, the volume for exposure with banking institutions is relatively higher than any other type of institution, since the balance of loans in the banking sector is still high. However, the composition of shared risk is more dynamic than the simple number or balances of loans shared. Again, this figure is good for viewing time series structure of financial linkage, but not appropriate to fully understanding the financial network at a given time.

Figure 7 depicts the network of financial institutions in terms of expected exposure at default in each quarter. Similar to Figure 5, the size of each circle in the network is E^*_i and the width of each branch is E^*_{ij}. In 2013Q2, the individual expected exposure at default for local unions for agriculture and fisheries (F5) was as

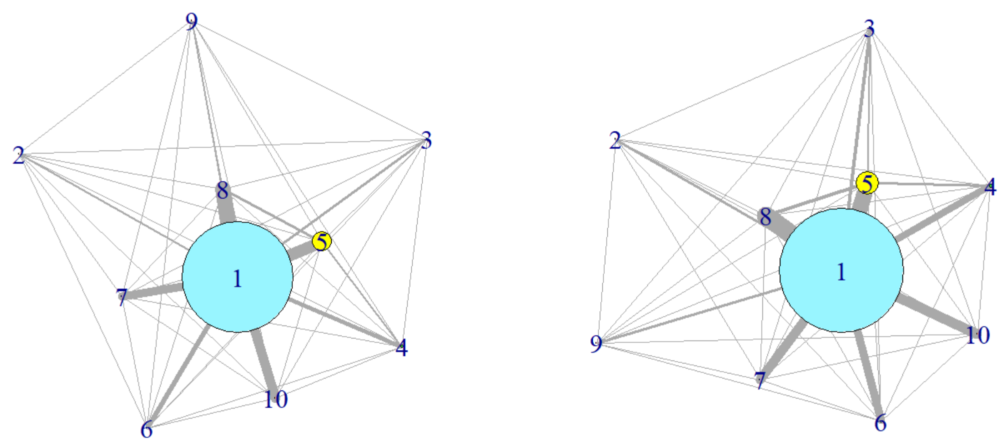
Figure 4: Linkage of financial institution by amount of loan shared*



* Notes: (i,j) denotes the aggregate amount of loan that borrowers owe in both institutions, i and j. See notes to Figure 2 and Table 2.

much as that for commercial banks due to the higher default rates of their loans, though the shared number of loans between them were not as high other institutions. Borrower at these two institutions were often distinctive. Closer linkages from commercial banks existed with savings banks (F2), non-credit card finance corporations (F8), merchant banking and others (F9), though their individual expected exposures were not meaningful. This shape had changed by 2017Q2. While the total expected exposure of commercial banks was still the largest, the expected exposures of saving banks had risen, but the linkage between the two types of banks became weaker. This also suggested that borrowers from the two institutions were heterogeneous. The size

Figure 5: Network of financial institution by amount of loans shared in each quarter*

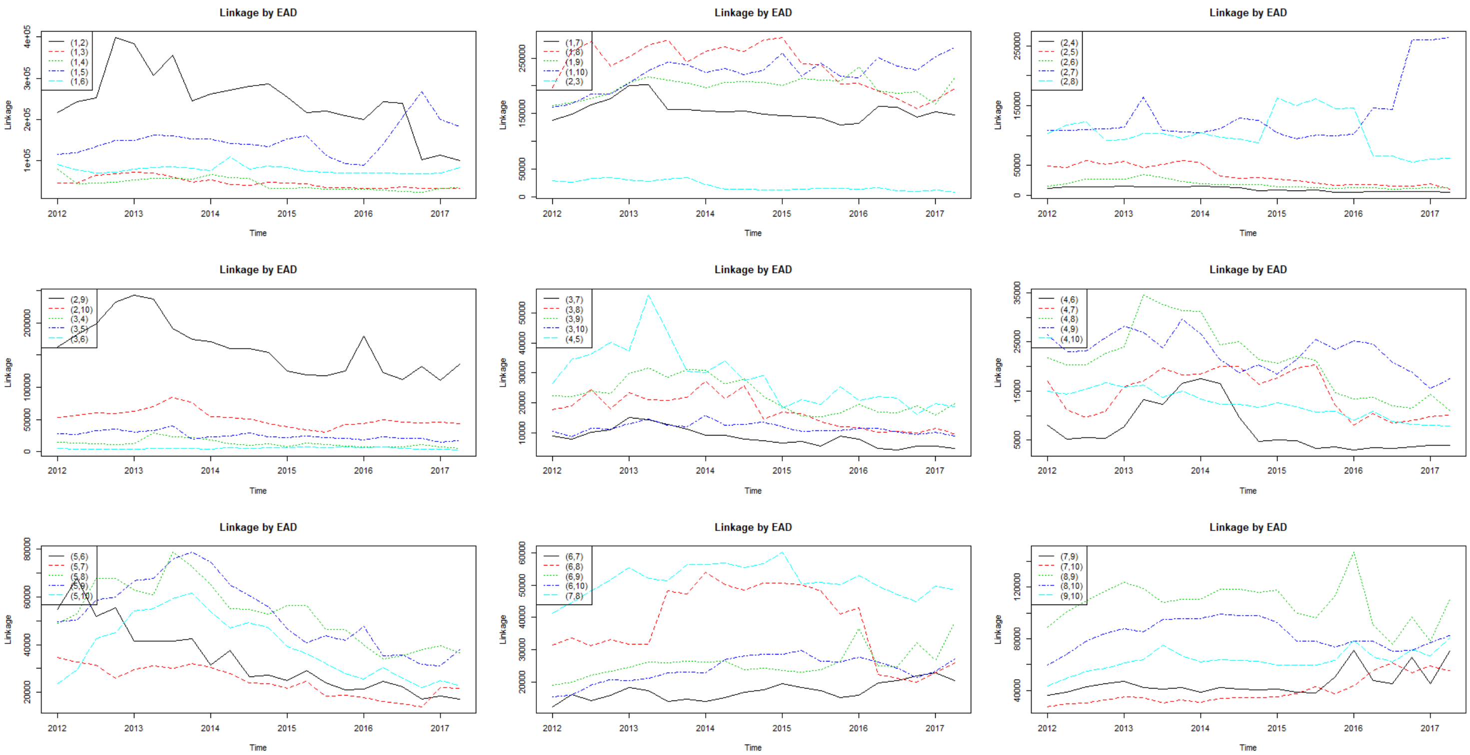


(a) 2013 Q2

(b) 2017 Q2

* Note: Numbers in circle represents the financial institution listed in Table 2. The size of the circle indicates the amount of loan owned only by institution i, and the width of branch stands for the amount fo loan shared by two institution, i and j. See notes to Figure 3.

Figure 6: Linkage of financial institution by expected exposure at default*

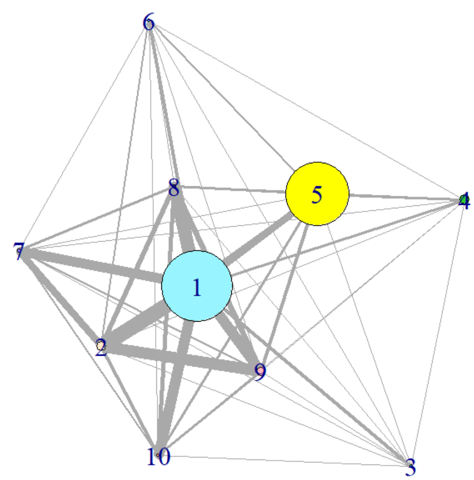


* Notes: (i,j) denotes the aggregate exposure to default shared by both institutions, i and j. See notes to Figure 2 and Table 2.

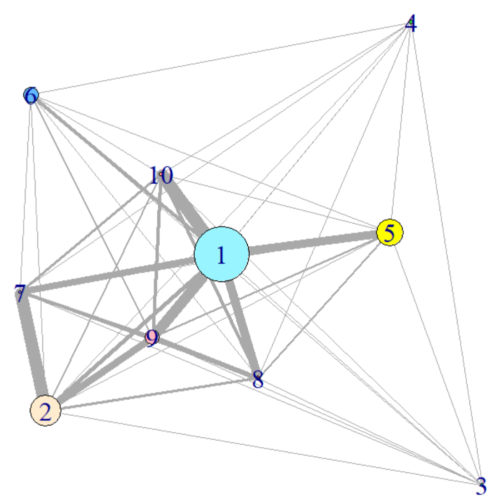
of F5 also shrunk, while it had a similar level of connection with banking institutions. The overall connection of non-commercial-bank financial institutions with commercial banks had weakened, since the probability of default of borrowers has declined as the economy has stabilized.

To measure the connectivity across the network, we can use semiparametric tail estimates of distribution. The maximum likelihood estimates for the tail exponent (Clause et al, 2009) are estimated. This determines the shape of the Pareto distribution and so that we can confirm that the network is more centralized, if we observe a higher value. Since we have the strong dominant player in the network, the banking

Figure 7: Network of financial institutions by the balance of expected exposure shared in each quarter*



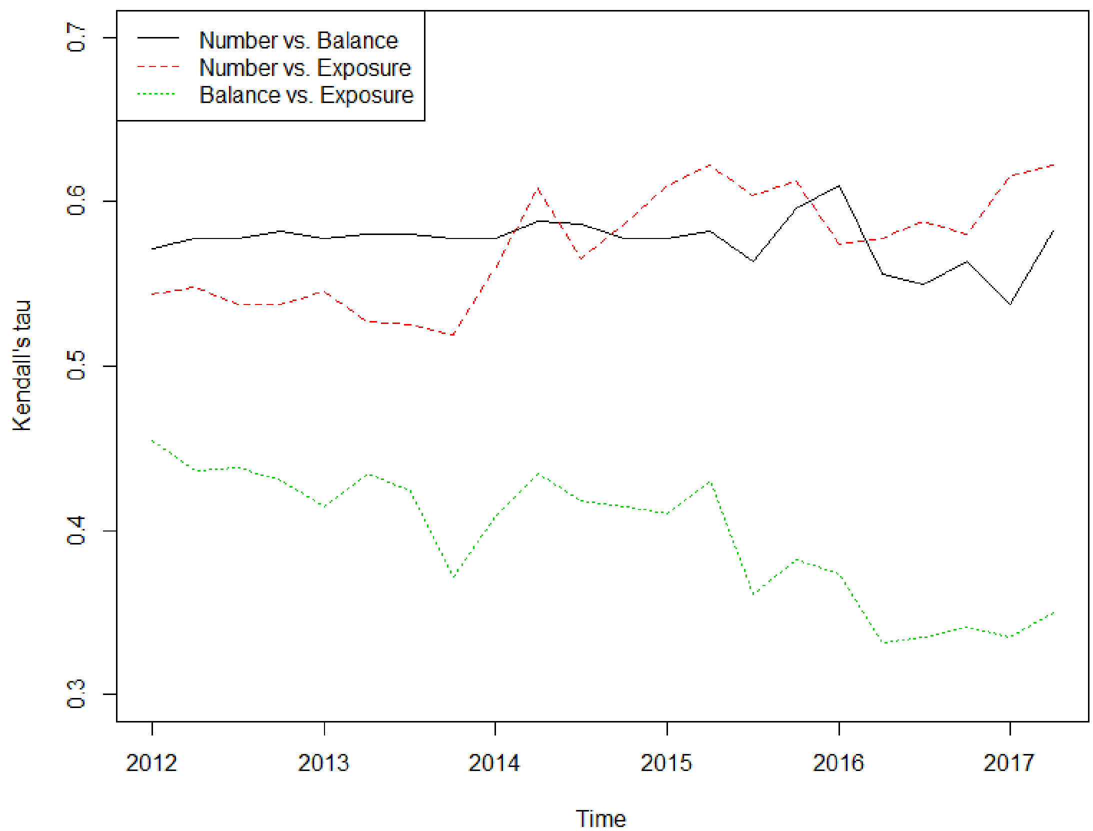
(a) 2013 Q2



(b) 2017 Q2

* Note: Numbers in circle represents the financial institution listed in Table 2. The size of the circle indicates exposures to default of institution i, and the width of branch stands for the exposure to default shared by two institution, i and j. See notes to Figure 3 and 5.

Figure 8: Kendall's Tau*



institutions, the value is over 100 in almost all cases and observations. Another interesting observation is that financial institutions that are highly connected tend to have larger exposure. We investigate the relationship between the number of shared loans and the balance of shared loans, and measure the shared exposure at default by computing Kendall's tau for each of these pairs. The results show that all pairs have a positive dependence, as shown in Figure 8.

We additionally construct a financial network following borrowers' characteristic such as gender, overdue loans, credit score, use of loan corporation loans, employment status and business type. The detailed results for this are summarized in the appendix.

3 The Contagion Index

Following Cont et al. (2010), we define the contagion index as the sum of the fundamental default risk and the risk of default by contagion. In this sense, we can use as the fundamental default risk and the shared exposure, E^*_{ij}, between institutions as the default risk by contagion. Therefore, we can construct our default impact as the following:

$$D^*_i = \sum_{i=1}^{10} \sum_{j=1}^{10} E^*_{ij} = \sum_{ij \in K} \sum_{n=1}^{N} l_{ij,n} \times p_n \tag{9}$$

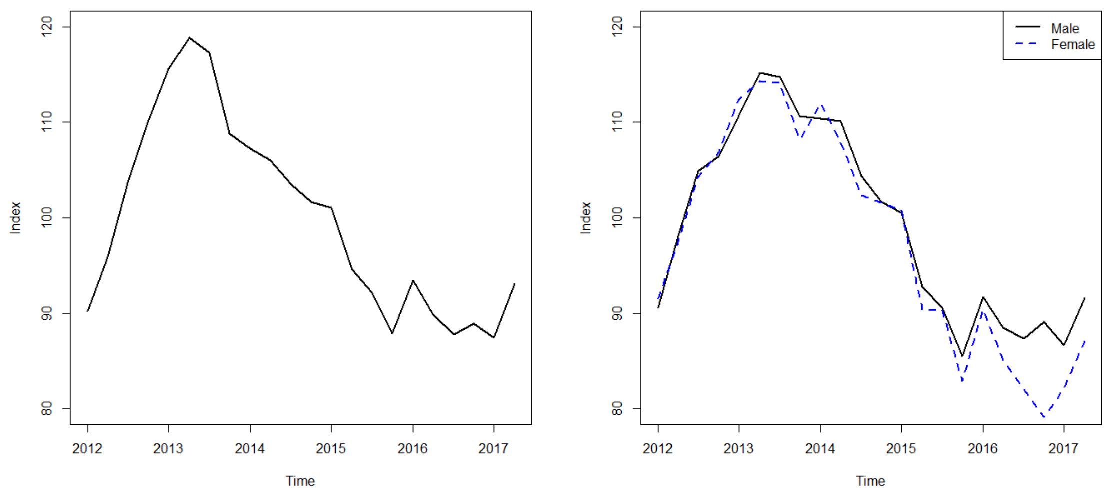
where K is the all combinations of financial institutions, ${}_{10}C_2$. Though we omit the time index for brevity, the index is defined at each observation period.

The contagion mechanism described above is similar to the one presented in Cont et al. (2010), Furfine (2003), Upper and Worms (2004) and Mistrulli (2007) in the sense that we divide the default risk into two terms. These are based on liabilities and assets between institutions, and all asset and liabilities have a unique risk. However, a borrower may have trouble paying back one of their loans on time. In that case, they are not likely to pay back their other loans either. The risk of these asset, the liabilities of consumers, can be varied and we take care to account for the heterogeneity of risk using micro data. The following left panel of Figure 9 is the overall contagion index from 2012Q2. The index is standardized by setting value of 2012 to be 100.

The index peaked in 2013Q1, and then fell rapidly despite small fluctuations during 2016 and 2017. The peak in 2012 and 2013 is considered to have occurred due to the crisis in Europe and relatively high interest rate at the time. The overall level in recent years is much lower than it was during 2012 and 2013.

Since the overall contagion index is still only incomplete explored due to the

Figure 9: Contagion Index of all borrowers and by gender



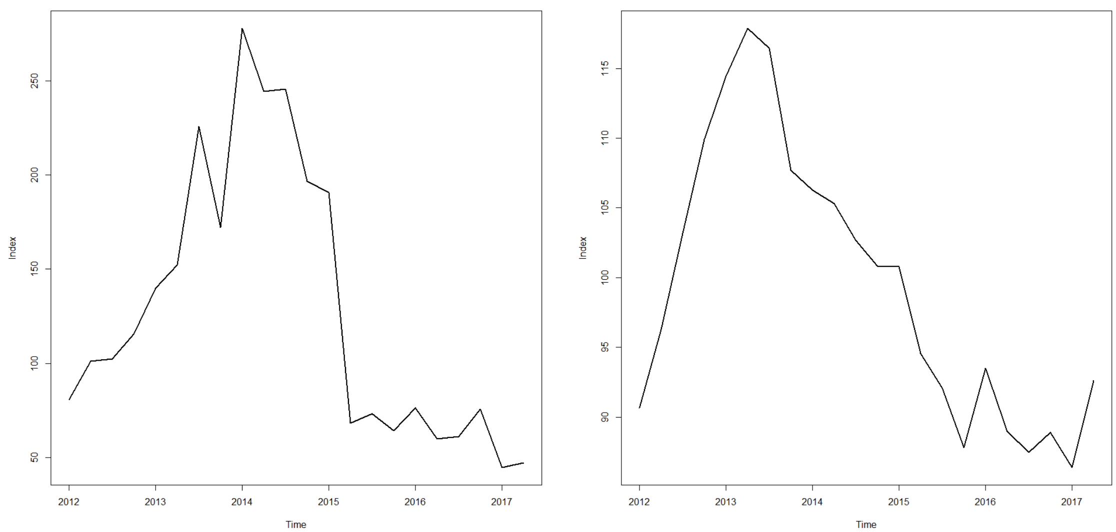
(a) all borrowers (b) by gender

* Notes: The contagion index as the sum of fundamental default risk and default by contagion. In this sense, we can use as the fundamental default risk and the shared exposure, E_{ij}^* between institutions as the default risk by contagion.

effect of averaging, we analyze the contagion index with sub-classification following the results of the network analysis. Note that all indices are standardized in the same manner, so that the levels of the indices are not comparable. The right panel of Figure 9 depicts the contagion index by gender of the borrower. While the two figures look similar, the female demonstrates a slightly bigger fluctuation during the sample periods.

Figure 10 depicts the contagion index for overdue borrowers, who are more than 90 days late paying back their interest, principal or both, and non-overdue ones. It is clear that most borrowers did not experience an ‘overdue’ notice, so that the non-overdue figure behaves similarly to the overall index. However, overdue borrowers’ contagion was still high even after the overall level of contagion fell after 2013Q1. It

Figure 10: Contagion Index by overdue borrowers*



(a) Overdue

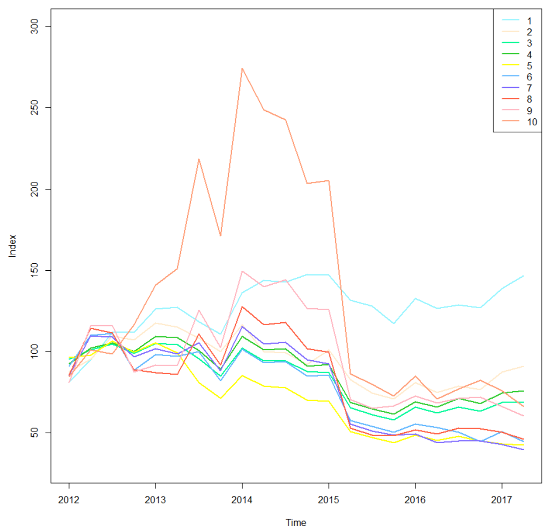
(b) Non-overdue

* Note: 'Overdue' is the borrower who are late to pay the interest more than 90 days in each period and 'Non-overdue' are ones who are not in 'Overdue'. See notes to Figure 9

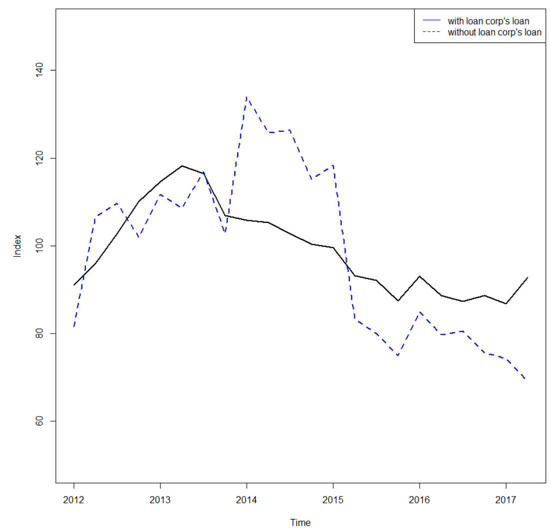
is still too early to generalize about the behavior of the overdue borrowers' contagion index.

Panel A in Figure 11 depicts the contagion index by credit score. We classify borrowers by credit score following Jung and Kim (2018). The lower the number, the better the individual's credit score is. As expected, a low credit score holder has a higher contagion index, while the others follow the overall index. However, middle credit score holders seem to have a more stable index those with higher credit scores. In particular, borrowers in Grade 1 display the highest contagion level since 2015, and it seems that borrowers in this group have more loans than other groups, because they are eligible to borrow. While we do not have enough information to draw strong conclusions, we doubt that most of the loans taken out by this group after 2015 were mortgage. Panel B of Figure 11 depicts the index used by loan corporations. 'with loan corporations' is the index of those who borrow from the loan corporations. Interestingly, the index of borrowers without loans from loan corporations rose in 2014 and then fell afterward. This rise seems to have been temporary, and we believe that the 'with loan corporation' index may produce a higher contagion level.

Figure 11: Contagion Index by credit score and use of loan corporations*



(a) By credit score

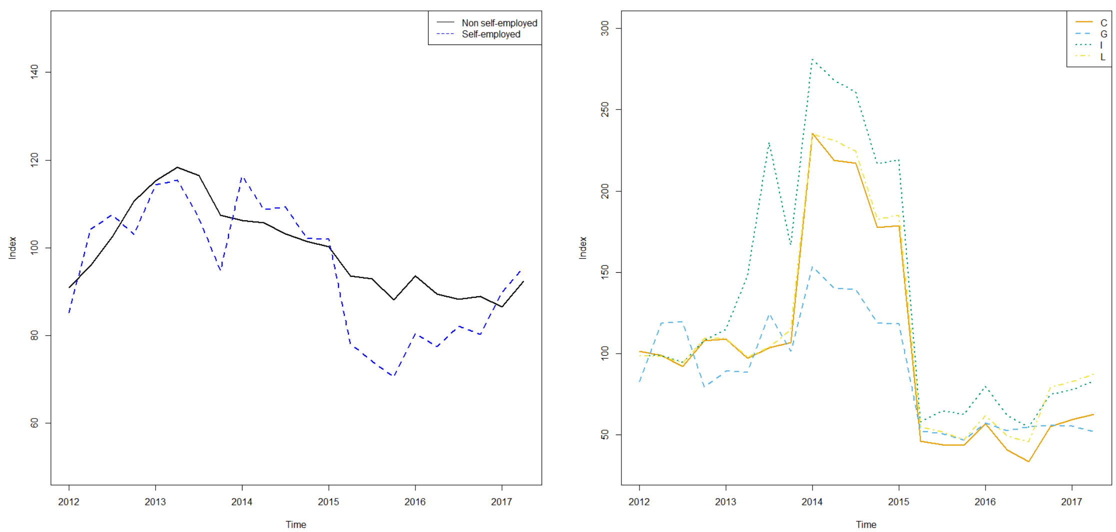


(b) Use of loan corporation

* Note: See notes to Figure 9

Panel A of Figure 12 depicts the index by employment status and type of business of self-employed borrowers. Employment status divides a borrower's employment into self-employed, and non-self-employed, which includes "not employed". The contagion effect from self-employed borrowers does not fluctuate over the sample period, except in 2015 when the index fell temporarily. Self-employed borrowers are classified by business type following the Korean Standard Industry Classification (KSIC) system, which was updated in 2017. For brevity, Panel B of Figure 12 shows the results

Figure 12: Contagion Index by employment status and business type*



(a) Self-employed vs. non-self-employed (b) Business type of self-employed borrowers

* Note: See notes to Figure 9

for selected industries where sufficient samples could be collected. The industries considered herein are manufacturing, wholesale and retail sales, hotels and restaurants, and real estate. The contagion effect for each of the four industries picked up in 2014, but fell quickly and stabilized afterward.

4 Scenario Analysis

We perform a scenario analysis to observe how systemic risk spreads due to an exogenous shock, such as a monetary policy or housing price change. We suppose a range of possible scenarios and examine the effects on systemic risk in our financial network. We assume that the exogenous shock occurs at the end, or one period before the end, of the sample period, and construct two scenarios depending on the direction of monetary policy: (1) an increase of 25 basis points and which is kept steady in the next period, and (2) an increase of 25 basis points in consecutive periods. For example, in Scenario (1), we suppose that the interest rate is raised by 25 basis points in one quarter before the end of sample, 2017Q2. On the other hand, since households hold most of their debt in mortgages, we suppose two scenarios: (3) housing prices in the Seoul metropolitan area increase by 1% in the last two periods, and (4) housing prices in the Seoul metropolitan area drop by 1% in the last two periods. We assess the effects of monetary policy and housing price shocks assuming all else is held equal.

In Scenario (1), the interest rate is raised by 25 basis points and is kept at that level during the next quarter. In these results, we can observe that financial institutions will have a larger burden from debtors when all other things are equal. This is expressed directly in the contagion effects as seen in Panel (a) of Figure 13. As compared with Figure 9, in this scenario, the contagion index increases in the last two quarters. This means that contractionary monetary policy negatively affects financial stability, as expected. A more interesting question regarding the effect of monetary policy is in the network of financial institutions and types of debtors. Panel (a) of Figure 14 depicts the network of financial institutions by expected shared exposure in Scenario 1 in 2017Q2.

The overall framework of the network is not significantly different from the situation without the monetary policy, but a thicker connection is found in the inner network. Therefore, a contractionary monetary policy may strengthen linkages inside the network. In Figure 15, we depicts the network of financial institutions when we observe self-employed borrowers, who are known to be more fragile, as in Jung and

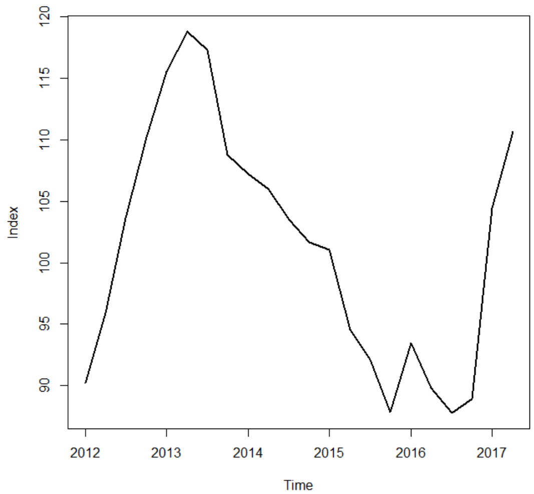
Kim (2018). As shown in Figure **??**, these burdens are condensed in savings banks. The size of the main players in this network increases the rate hikes were implemented, and the connectivity among those key components was also strengthened. In Scenario (2), even more contractionary monetary policy is implemented, so that the base rate is raised by 25 basis points twice, consecutively. As shown in Panel (b) of Figure 14, the overall network is not significantly different from Scenario 1. However, according to Panel (b) of Figure 13, the contagion index increases more than in Scenario 1. We therefore confirm that the network of financial institutions and the contagion effects among them are sensitive to monetary policy.

On the other hand, we observe the effects of housing price changes due to fact that the biggest portion of household debt derives from household mortgage. In Korea, housing prices are usually highest in the metropolitan area around Seoul, so we suppose that the price in those areas changes. In Scenario 3, where housing prices in the Seoul metro area increases by 1% during the most recent two periods, the contagion index also increases. The magnitude of the effect is not as severe as that of the monetary policy, as shown in Panel (c) of Figure 13. Network connection seems to be affected at a limited level. Connection among financial institutions are also strengthened marginally, but the size of the burden on individual institutions is slightly lower than in the original observation. The network of self-employed workers is not seriously affected by changes in housing prices, as expected and as is revealed in Panel (c) of Figure 15. In Scenario 4, we lower housing prices in the metro area by 1% in the last two quarters. We confirm that housing prices have a negative effect on the contagion index, as seen in Panel (d) of Figure 13. Just as in Scenario 3, the self-employed network is not significantly affected by the price of houses even in Scenario 4. The results of the two scenarios above may go against common sense, which suggests that financial risk will rise when the value of collateral drops, since the institution may not fully collect on its loans. However, financial risk in this analysis is measured from the consumer's prospective, and therefore as the price of housing rises, the amount of loans rises. As a result, greater amounts mean that borrowers have to borrow from more sources and therefore the contagion risk in the financial system rises. Since we conduct our analysis holding other variables equal, this relationship between housing price and network risk should only be interpreted in a limited way. It should also be noted that our systemic risk model is based on a static framework, so that the result of this analysis are limited due to the effects of second-round shocks. Nevertheless, it is worth reviewing the result of our hypothesis about the effects of shocks to the financial system, which are confirmed in our partial equilibrium model. More precise analysis can be conducted using a general equilibrium model, which we leave for future research.

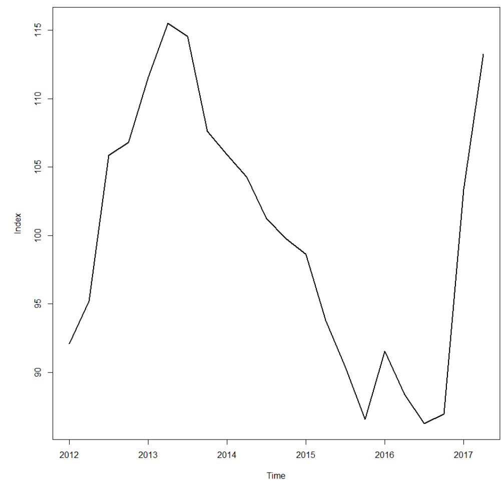
5 Concluding Remarks

We investigate the network of financial institutions in Korea using KCCP. The main contribution of this paper is its construction of a network of financial institutions from the level of consumer credit. We construct this network beginning in 2012, when the KCCP was established. Combined with the probability of default metric from Jung and Kim (2018), we construct an analysis of the risks posed by assets that each institution is exposed to, and which two institutions are exposed to simultaneously. As expected, more than a half of the total amount loans is held by commercial banks, so that the influence of commercial banks is quite large in the network and always central to the network overall. One interesting result is that the biggest linkage turns out to be the link between commercial banks and credit card companies. Due to the convenience of short-term loans from credit card companies, this link appears strong, but if we weight the amount of loans in the network, this link is not quite as strong as short-term loans from credit card companies are usually under 300,000 Korean won (about 270 US dollars). Using the consumer's probability of default, inspired by Jung and Kim (2018), we compute the expected exposure of institutions. In our results, the link between savings banks and credit card companies has increased over time. The linkages between commercial and savings banks, commercial banks and agricultural and fisheries unions are higher than any other linkage. Overall linkages among financial institutions turn out to be strong among commercial banks, agricultural and fisheries unions, non credit card finance corporations, merchant banking, investment trust, and guarantee organizations and postal

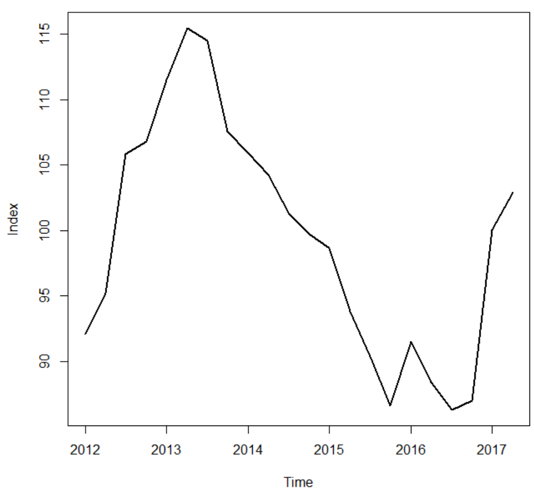
Figure 13: Contagion Index by Scenario*



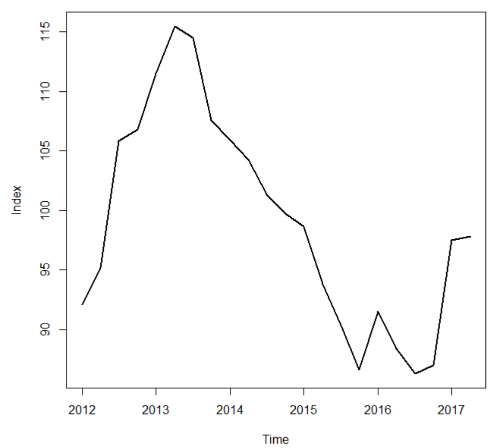
(a) Contagion Index of Scenario 1



(b) Contagion Index of Scenario 2



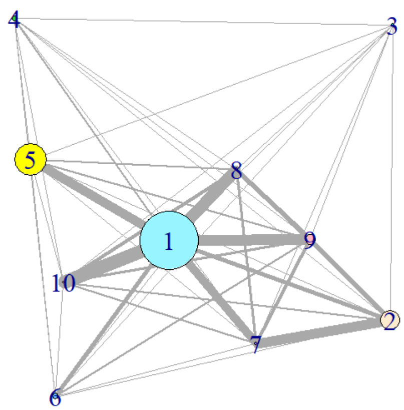
(c) Contagion Index of Scenario 3



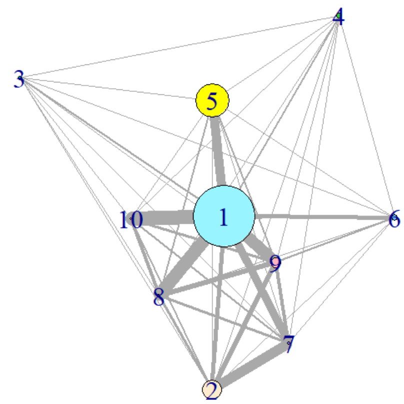
(d) Contagion Index of Scenario 4

* Note: See notes to Figure 9

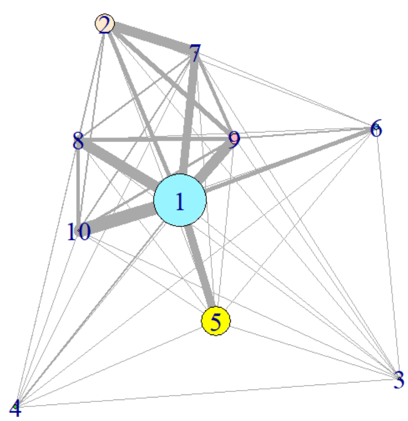
Figure 14: Network of financial institutions by expected exposure in selected scenarios*



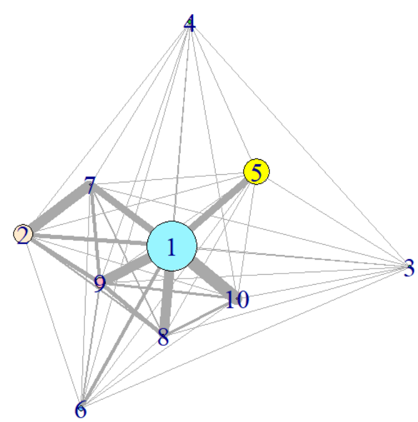
(a) Scenario 1 in 2017 Q2



(b) Scenario 2 in 2017 Q2



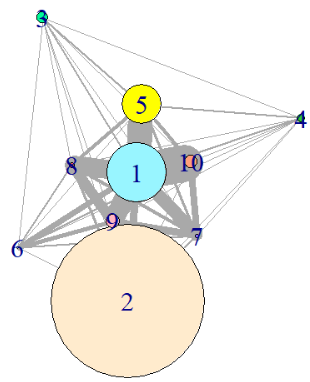
(c) Scenario 3 in 2017 Q2



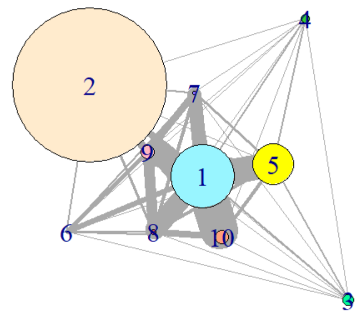
(d) Scenario 4 in 2017 Q2

* Note: See notes to Figure 7

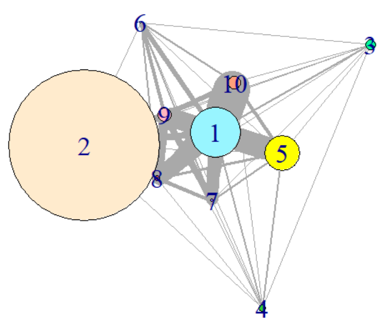
Figure 15: Network of financial institutions by expected exposure in selected scenarios [self-employed households]*



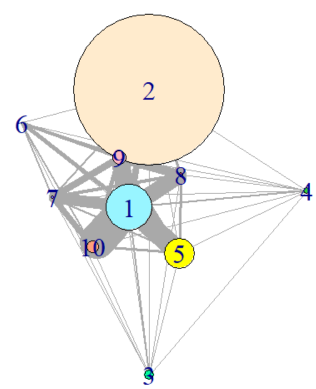
(a) Scenario 1 in 2017 Q2



(b) Scenario 2 in 2017 Q2



(c) Scenario 3 in 2017 Q2



(d) Scenario 4 in 2017 Q2

* Note: See notes to Figure 7

banks. The contagion index, constructed using the aggregate value of the risk shared by institutions, rose from 2012-2013Q2 before declining gradually until 2015Q3. After that point, there were small fluctuations in the level, which remained relatively low. We then performed scenario analysis for the robustness of our framework. We supposed exogenous shocks such as monetary policy and housing price changes. We found that contractionary monetary policy makes the inner section of the financial network denser and raises the contagion effect in the network. The contagion effect reacts positively to increases in housing price, but does not seem sensitive to housing price decreases.

For a more precise investigation of consumer credit, the assets held by households should be updated, for example, in the case of measuring the effect of housing prices on consumer credit. The current panel should also be recognized into household units. As both these consideration requires significant data work, we hope to develop our analysis to a more advanced level in future research.

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Data Reference

KCCP All data except following two series comes from KCCP (Korea Consumer Credit Panel), Bank of Korea
HPI Housing Price Index, Korea Appraisal Board
BSI Business Satisfaction Index, Bank of Korea