Credit rating migration risk and interconnectedness in a corporate lending network☆

Masayasu Kanno[a,*]

[a] *College of Commerce, Nihon University, Tokyo 157-8570, Japan*

Abstract

This study assesses the credit rating migration risk and interconnectedness in Japan's corporate lending market during the fiscal years 2008–2015. First, the study conducts a portfolio credit risk analysis by using outstanding lending data with borrowers and lenders names. The results show an expected shortfall with tail dependence of t-copula captures the heavy-tailed risk of Japanese institutions. The study also measures credit risk exposures and credit risk amounts by industry sector, and evaluates sector concentration risk. Subsequently, the study analyzes the network structure of lending contracts using network centrality measures. From the perspective of network, institutions play a central role in terms of degree centrality. Further, the study undertakes a stress test using a historical economic scenario pertaining to a credit rating migration matrix shortly after the Lehman Brothers' bankruptcy. The test finds a much sparser network structure because of a large number of firm defaults. The study's analysis offers banks and insurers important implications regarding the credit risk management of corporate lending.

Keywords: credit rating migration risk; sector concentration; interconnectedness; centrality measure; credit value at risk and expected shortfall; stress test
JEL classification: G32; G10; D85; L14; G28; F37.

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*Corresponding author. E-mail address: kanno.masayasu@nihon-u.ac.jp

1. Introduction

After the collapse of the bubble economy in Japan, Japanese banks suffered because of efforts to dispose of non-performing loans. In this regard, the "lost decade" was a term initially coined to describe the Japanese economy in the last decade of the prior millennium. However, the bursting of the huge real estate bubble in Japan in the 1980s led to sluggish performance not just in the subsequent "lost decade" but also in the first decade of the new millennium. The term "lost decade" has also been used to describe the state of the US economy from 2000 to 2009 because an economic boom in the middle of this period was not enough to offset the effects of two huge recessions.

In the past, banks in Japan have traditionally focused on the disposal of non-performing loans and compliance. Hence, the supervisory authority, the Financial Services Agency of Japan, conducted rigorous asset assessments based on certain criteria and inspected banks for compliance violations. By contrast, from the perspective of insurers, lending was undertaken as part of portfolio investments as well as shareholdings. However, because insurers hold large numbers of shares, the proportion of lending in their portfolios is relatively small.

Currently, internationally active banks in Japan are regulated based on the Basel III framework (BCBS, 2005). Most major banks, including mega banks and other large banks, adopt an internal ratings-based (IRB) approach. This approach calculates risk-weighted assets in terms of firms' lending assets in accordance with the firms own obligor credit risks. By contrast, insurance regulation in Japan depends on the Japanese local supervisory framework, which is based on the "solvency margin ratio." This framework is simple; moreover, it is a so-called first-generation solvency regulation, which is similar to Basel I in international banking regulations. The "solvency margin standard" was introduced for both life and general insurance firms in fiscal year (FY)[1] 1996. The solvency margin standard is calculated as the solvency margin divided by half of the risk amount, expressed as a percentage.

Triggered by the bankruptcy of Lehman Brothers, many Western banks and insurers suffered significant capital losses, with some also recording impairment losses. By contrast, Japanese banks were hardly affected owing to their experience of non-performing loan disposal in the country's bubble

[1] Japan's fiscal year runs from April 1 to March 31.

economy. However, a network analysis of contractual relationships in the corporate lending network has yet to be conducted, even though large firms ordinarily have accounts with 10 or so banks. Further, the bankruptcy, or credit rating downgrade, of a firm causes an increase in credit risk; thus, it is important to analyze the credit rating migration risk in the lending network.

The current study contributes to the literature by providing quantitative insights into the corporate lending network, taking into account credit rating migration risk. The study assesses the interconnectedness in the network that comprises various types of banks, insurers, and firms by using credit risk exposure implied by the credit ratings during and after the global financial crisis.

First, this study conducts a credit risk analysis using the credit rating migration approach. In this approach, credit risk exposure by bank or insurer is examined, depending on credit migration. In addition, this study ranks the industry sectors in terms of sector concentration risk measured by credit risk exposure and credit risk amounts measured by VaR and ES.

Second, this study analyzes interconnectedness in the lending network using various network centrality measures (Jackson, 2010; Kanno, 2015a). This network analysis is based on the outstanding lending dataset for all listed Japanese firms by financial institution (i.e., bank or insurer) in the Nikkei NEEDS FinancialQUEST database provided by Nikkei Inc., a Japanese newspaper firm. The dataset covers almost all lending contracts among bank-to-listed firms and insurer-to-listed firms. Thus, it is to be noted that the dataset with borrowers and lenders names is quite rare and valuable in the world.

Third, this study conducts a stress test to verify the resilience of the Japanese corporate lending market and the change of network structure. In this test, copula dependence is incorporated to investigate the tail dependence of portfolio value distribution.

In the rest of this paper, section 2 reviews the literature on lending and interconnectedness in various financial networks. Section 3 contains a credit risk analysis using some risk measures, while section 4 presents a network structure analysis of lending market. Section 5 conducts a stress test by combining both analyses and section 6 concludes the study.

2. Literature review

The current study contributes to the corporate lending literature by using a combined credit risk and network analytical approach to investigate the network structure of corporate lending contracts. Network analysis is a highly effective approach to examine the interconnectedness of relationships in lending contracts. Such contracts represent complex contractual networks using sets of "nodes" connected by "edges." In a corporate lending network, a node represents a lender or a borrower, and an edge represents the lending relationship between two entities.

A large body of financial literature exists on corporate lending in countries worldwide. However, the literature barely mentions the interconnectedness of corporate lending contracts in a country. Nonetheless, there are some studies in this area such as Abbassi et al. (2017), De Masi and Gallegati (2012), Hałaj et al. (2015), Lux (2016), and Silva et al. (2018).

Abbassi et al. (2017) analyze the relationship between market-based credit risk interconnectedness among banks during the global financial crisis and the associated balance sheet linkages via funding and securities holdings. In this regard, the authors use a German data set that has the interbank funding positions for 2006–2013, together with the investments of banks at the security level and the credit register. De Masi and Gallegati (2012) use a database of Italian firms provided by Bureau van Dijk to undertake an empirical assessment of the credit relationships between banks and firms. However, because contractual amounts are not included in the database, credit risk exposure is not captured; thus, a credit risk analysis is not conducted.

Hałaj et al. (2015) use network formation techniques based on a theoretical framework to construct networks of lending relationships between a large sample of banks and nonbanks in the European Union (EU). Lux (2016) employs a stochastic network model to review basic stylized facts found in the comprehensive data sets of bank–firm loans for a number of countries in order to consider credit linkages between banks and non-financial firms. Silva et al. (2018) simulate shocks to the real sector and evaluate how the financial system reacts; they then amplify these events using loan-level data in the Brazilian bank-bank (interbank) network and the bank-firm lending network.

In addition, although the structure of syndicated lending differs from corporate lending in terms of contractual features and data availability for researchers, there is literature on the interconnectedness of the syndicated lending market, such as Goldlewski et al. (2012), Wang and Wang (2012), and Wu et al. (2013). Goldlewski et al. (2012) use a data set of the French syndicated lending market from the DealScan database that includes detailed information on loan agreement and bank syndicate characteristics. This database is commonly used in empirical studies on syndicated lending. Wu et al. (2013) conduct theoretical and empirical investigations of the interactions among potential lenders and how these may influence contractual terms via informational cascade in the syndicated loan market.

Further, in terms of the use of network measures in an interfirm network, although somewhat different from a lending network, Garmaise and Moskowitz (2003) find they impact the availability of credit, which is vital for firms engaged in innovative activities. They affirm that firms need to have an appropriate level of financial incentives to encourage investments in long-development risky R&D intensive projects that risk-averse managers might not be willing to undertake. Chuluun et al. (2017) examine how various dimensions of an interfirm network affect innovation and pricing of innovation by market participants. They construct a set of network measures that capture a firm's centrality in an interfirm network (degree, eigenvector, and betweenness), cohesion and diversity within firm networks (density, network non-redundancy, and industry diversity), and innovativeness and propinquity of firm networks (network innovativeness and industry, geographic, innovative industry, and innovative geographic propinquity). Using these network measures, they assess if firm network characteristics impact innovation input and output.

An analytically tractable example of financial networks is the interbank network characterized by bilateral exposure in the interbank market. In this context, studies of financial networks adopt two approaches. The first assesses the strength of contagion channels and network resilience by observing the responses of financial network structures to shocks. Introducing a shock assumes a specific transmission mechanism, such as defaults by counterparties. Alves et al. (2013) refer to this approach as "dynamic network analysis." Cocco et al. (2009), Elsinger et al. (2006), and Haldane and May (2011) analyze contagion effects in their network analyses.

The second approach describes network structures using topological indicators, often relating these to model graphs based on network theory. This approach does not assume a mechanism by which shocks propagate within the network; thus, it is referred to as "static network analysis" (Alves et al., 2013). The studies of Boss et al. (2004), Eisenberg and Noe (2001), and Kanno (2015a, 2015c, 2018a) are examples of this approach. The current study adopts static network analysis. While many different centrality measures exist, most of them apply to static networks. The details of centrality measures are described later in Section 4.2.

3. Credit risk analysis

This study analyzes credit risk based on the credit rating migration approach, using a large-scale Japanese lending database.

3.1. Credit risk exposure for lending contracts

3.1.1. Methodology for credit risk exposure analysis

Credit rating migration is an essential component in credit portfolio valuation. This study outlines a framework for gauging the effects of credit rating migration on portfolio risk measurements. The approach is based on discounted cash flow valuation, whereby a lending asset is valued by discounting the expected cash flow at a discount rate adjusted for credit risk. The risk adjustment here can take the form of a higher discount rate. Discount rates adjusted for credit risk are obtained from credit rating curves provided by credit rating agencies such as Moody's and Standard & Poors.

Throughout this study, the filtered probability space, $(\Omega, \mathcal{F}, \mathcal{F}_t, Q)$, is also incorporated, thereby supporting the credit rating migration process in terms of discrete time, $t = 0, 1, \ldots, T$, where Q is a physical probability measure and the horizon, T, is assumed to be a positive integer indicating the maturity. The filtration, $\mathcal{F}_t$, models the flow of all the observations available to lenders. Formally, given an initial rating, C_0, of a borrower, future changes in the rating are described by a stochastic migration process, C.

This study assumes that the set of rating classes is $\{1, \ldots, K\}$, where the state, K, is assumed to correspond to the default event. In addition, according to the convention of Jarrow et al. (1997), the order of the states is fixed so that the state, $j = 1$, represents the highest ranking, whereas the state, $j = K - 1$, represents the lowest non-default ranking.

With regard to lending exposures that are not in default, the theoretical price of a lending asset with certain future cash flow at time t is expressed as an aggregate discounted present value, P, as follows:

$$P = E^Q \left[\sum_{t=1}^{T} \frac{CF_t}{(1 + r(C_t^i))^t} \middle| \mathcal{F}_t \right], \tag{1}$$

where E means taking an expectation under a physical probability measure, Q, and the lending type corresponds to a term loan of equal monthly payments with interest. Thus, maturity, T, corresponds to three years in the case of city banks and trust banks and five years in other cases. CF_t is cash flow scheduled at time t. $r(C_t^i)$ is a discount rate adjusted for credit risk with regard to the rating C_t^i at time t provided by a rating agency i.

3.1.2. Data for credit risk exposure analysis

For the purpose of credit risk analysis, this study calculates the credit risk exposure of a lending contract, discounting its cash flow at a discount rate adjusted for credit risk. To this end, the study uses firm-level outstanding lending contracts and financial data for FY2008–FY2015. The analysis requires outstanding data with borrowers and lenders names. These are obtained from the Nikkei NEEDS FinancialQUEST database (Table 1). The database contains lending information on bank-to-listed firms and insurer-to-listed firms. Large but non-listed firms are not included.[2] Thus, the coverage ratio of large firms in the database may not be that high overall. The banks include city banks, trust banks, Shinsei Bank and Aozora Bank, Norinchukin Bank, regional banks (i.e., regional banks I), second-tier regional banks (i.e., regional banks II), Shinkin banks and credit unions, other private financial institutions, government financial institutions, and foreign banks. The insurers include life insurers and non-life insurers. Finally, a certain amount of data for the lending contracts of unknown institutions is included in the database.

In addition, this study uses average interest rates for new lending contracts by bank type (i.e., city banks, regional banks I/II, and Shinkin banks) from the Bank of Japan. As shown in Figure 1, city banks set interest rates that are higher in the long term than the short term, whereas the other banks adopt a reverse approach. Further, after the global financial crisis, long- and

[2]Known examples of non-listed large firms are Suntory Holdings (a beverage products firm), the Takenaka Corporation (a general construction firm), and Yanmar (an agricultural machinery manufacturing firm).

short-term interest rate levels decreased year by year. Interest rate levels also fell after the Bank of Japan initiated a "negative interest rate policy" in February 16, 2016. As a result, in terms of the outstanding lending of domestic banks in Japan, the lending share with interest rates less than 1% reached 62% of the entire outstanding lending, according to the financial newspaper *Nihon Keizai Shimbun*, on February 16, 2018.

In terms of credit rating information, this study also uses credit rating historical data, including "date of change" and "old and new credit ratings" by entity from the Nikkei Astra Manager database provided by the QUICK Corporation. The data concern long-term issuer ratings related to the certainty of fulfillment of issuers' individual financial obligations, as promised. However, not all listed firms are endowed with a credit rating. Thus, for such firms, outstanding lending is substituted for credit risk exposure.

Further, this study employs yield curves by credit rating obtained as a "credit rating matrix" from the homepage of the Japan Securities Dealers Association (JSDA).[3] Yield by credit rating means the mathematical average of the compound interest yield for over-the-counter (OTC) bond transactions, calculated using the quotations reported to the JSDA. As shown in Figure 2, yield curves are provided for each business day by four credit rating agencies: Rating and Investment Information (R&I), Japan Credit Rating Agency (JCR), Moody's, and Standard & Poors (S&P).

However, Japanese financial institutions and scholars highlight two rate difference issues among the four credit rating agencies. One issue is the difference in the approaches of the Japanese credit rating agencies (R&I and JCR) and the American credit rating agencies (Moody's and S&P), which is the equivalent of "two notches." The other is the difference in the approaches of the R&I and JCR, which is the equivalent of "one notch." In order to correct these differences, this study adopts the lowest credit rating when two or more different credit ratings are assigned to a firm.

3.1.3. Results of credit risk exposure analysis

The estimation results of credit risk for lending contracts are now discussed. Table 2 reports the quartiles, and mean and standard deviations, in

[3]This body is an association that functions as a self-regulatory organization and interlocutor between market participants and various stakeholders, including government authorities. JSDA members consist of securities firms and other financial institutions operating securities businesses in Japan.

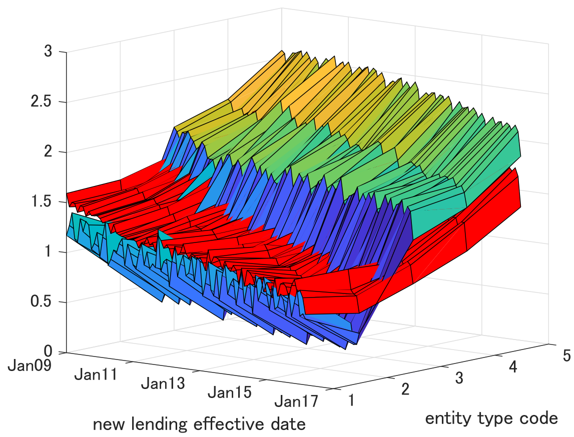

Figure 1: Average lending interest rate curves: Long-term lending (mixed color) and short-term lending (red) for the end of March 2009 to March 2017

Notes: The two graphs show short- and long-term interest rate yield curves by bank type for the end of January 2009 to August 2017. The indices are as follows. 1: domestic banks in Japan, including city banks, Shinsei Bank, Aozora Bank, trust banks, regional banks I/II, and Shinkin banks; 2: city banks; 3: regional banks I; 4: regional banks II and Shinkin banks.

the upper tier, and the outstanding sums by entity in the lower tier, that are related to credit risk exposure at the end of the period FY2008–FY2015. In addition, Figure 3 illustrates the percentile distribution of bilateral credit risk exposure by year.

As can be seen in the upper tier of Table 2 and in Figure 3, all of the exposure sizes are small at the median (i.e., the 50th percentile); however, the sizes increase sharply from the 99.5th percentile to the maximum, and range from 2 119 billion Japanese yen (JPY) in FY2008 to a maximum of JPY 3 881 billion in FY2010. This finding means that, for the purpose of reducing credit risk exposure, corporate lending decreased sharply just after the Lehman Brothers' bankruptcy. By contrast, since FY2011, outstanding lending has increased by 3% to 50% from FY2010.

Further, as can be seen in the lower tier of Table 2, the credit risk exposure size in the entire network remain almost unchanged from FY2008 to FY2009

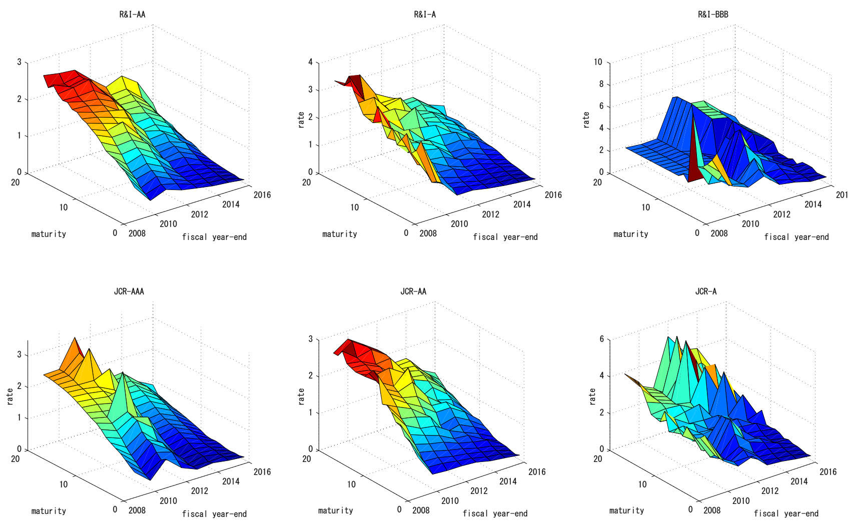

Figure 2: Credit yield curve

Notes: The six panels show credit rating curves for the end of March 2009 to March 2016. The AA to BBB ratings of R&I extend from the upper-left panel to the upper-right panel. The AAA to A ratings of JCR extend from the lower-left panel to the lower-right panel.

despite the global financial crisis. In addition, major banks and other large banks have a share of 50% to 59% of the total amount less the unknowns from FY2008–FY2015, an effect that is particularly large in the Japanese lending market. By contrast, regional banks (I and II) have an almost constant share of 9% to 12%, and insurers have a share of 8% to 14% during this period.

3.2. Portfolio credit risk

This study conducts an analysis of lending portfolio credit risk by institution based on value at risk (VaR) and expected shortfall (ES).

3.2.1. Methodology for portfolio credit risk analysis

This study considers a portfolio of lending exposures with a set of firms as counterparties. It then conducts a copula-based, multifactor simulation of

Table 1: Lending exposures and other related variables

Item	Description	Sources
Lendings outstanding	Data on bilateral lending relations, such as bank-to-listed firm and insurer-to-listed firm,	Nikkei NEEDS Financial QUEST
Lending interest rates	Average interest rates for lendings outstanding by bank type, drawn in the Figure 1	Bank of Japan
Credit ratings	Credit rating history data including both 'date of the change' and 'old and new credit ratings' by entity	Nikkei Astra Manager
Yield curves by credit rating	Yield curves added credit risk premium by rating assigned by four credit rating agencies, partly as shown in the Figure 2	JSDA

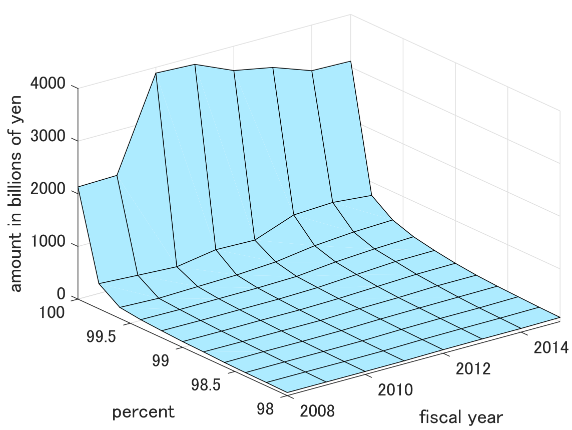

Figure 3: Credit risk exposure distribution for corporate lending

Notes: Exposure amounts are expressed in JPY billions. The distribution shows the range from the 98th percentile to the 100th percentile.

Table 2: Descriptive statistics of outstanding bilateral credit risk exposure by institution (in JPY billion)

	2008	2009	2010	2011	2012	2013	2014	2015
25%	261	254	233	210	232	205	207	203
Median	852	804	766	724	811	787	772	748
75%	2,855	2,677	2,543	2,446	3,002	3,016	2,922	2,954
Maximum	2,129,804	2,148,827	3,890,281	3,855,544	3,536,609	3,395,245	3,132,394	3,113,038
Mean	6,929	6,819	7,126	7,251	8,447	10,355	10,545	10,570
S.D.	45,793	47,901	56,770	59,471	65,772	85,854	83,514	78,388
City banks	22,155	19,770	19,302	19,784	20,858	15,293	16,649	18,877
Trust banks	6,713	6,340	6,201	5,771	7,235	5,929	5,851	6,309
Shinsei bank & Aozora bank	968	791	596	560	880	726	831	856
Norinchukin bank	2,204	2,193	2,008	2,093	2,072	1,345	1,353	1,535
Regional banks (I & II)	6,312	5,800	5,462	5,462	5,108	4,002	4,861	4,828
Shinkin banks & Credit unions	365	432	382	329	429	294	305	295
Other private FIs	4,311	4,044	3,984	4,343	4,995	3,660	3,624	3,793
Government FIs	5,090	5,842	7,455	6,086	6,268	5,238	4,812	4,395
Other foreign banks	138	113	92	66	35	28	34	35
Life insurers	7,912	6,656	7,051	7,006	6,588	4,195	3,340	3,319
Non-life insurers	82	83	90	66	85	72	80	98
Unknowns	37,752	39,841	41,810	46,306	43,019	65,172	93,804	92,994
Total	94,001	91,905	94,433	97,874	97,572	105,952	135,544	137,334

Notes: S.D. is standard deviation and FIs are financial institutions. Regional banks (I and II) include regional banks and second-tier regional banks. Three mega banks, the Mitsubishi UFJ Financial Group, the Mizuho Financial Group, and the Sumitomo Mitsui Financial Group, fall into the categories of city banks and trust banks. A category of "unknowns" includes financial institutions with names that are unknown on the Nikkei NEEDS FinancialQUEST database.

credit rating migrations. Typical portfolio credit risk models are explained in the literature, such as Crouhy et al. (2000), Gordy (2000), and Gupton et al. (1997).

Counterparty credit rating migrations and subsequent changes in portfolio values are calculated for each simulation scenario; moreover, some risk measurements are reported. Because a corporate lending contract has no market value, the portfolio value at the horizon is calculated by discounting future cash flow at a discount rate by credit rating, using equation (1). In turn, the value for each counterparty's lending exposure by scenario at the risk horizon is simulated based on the realized credit rating per counterparty. For example, in a given scenario, if a lending contract with a time to maturity of five years becomes a lending contract with a time to maturity of four years, the future cash flow of the contract is discounted by the discount rate of one-year forward four years maturity. Thus, the portfolio values of short-term exposures of less than one year are realized.

In order to incorporate the random variable by counterparty, this study uses a multifactor model, associating each counterparty's asset return with a latent random variable. This variable is mapped to a credit rating assigned from a credit quality at the horizon (Figure 4). Thresholds between credit ratings at the horizon are calculated directly from a rating transition matrix. The model's factors can depend on industry sectors such as construction and food; geographical regions such as Japan, the United States of America, and the eurozone; and any other credit risk driver. Each counterparty is assigned a series of weights that determine its sensitivity to each factor driving the underlying credit risk.

This study defines M as the number of borrowers in a portfolio and K as the number of systematic risk factors. Using a multifactor model, an asset return A_i $(i = 1, \ldots, M)$ as a latent variable is then expressed as follows:

$$A_i = \sum_{k=1}^{K} w_{i,k} Z_k + \sqrt{1 - \sum_{k=1}^{K} w_{i,k}^2}\,\epsilon_i, \tag{2}$$

where Z_k $(k = 1, \ldots, K)$ is a systematic risk factor associated with an underlying credit driver, which is typically assigned for a specific industry or a domestic geographical region, and ϵ_i is firm i's idiosyncratic risk factor, which represents the firm-specific credit risk. The factor loading $w_{i,k}$ $(i = 1, \ldots, M; k = 1, \ldots, K)$ expresses a weight of an underlying systematic risk factor, k, for firm i. The total of the weights for each firm (i.e., each row) is one. The weights are then calculated by regression analysis. In addition, this study assumes that a systematic risk factor, Z_k $(k = 1, \ldots, K)$, and an idiosyncratic risk factor, ϵ_i, are all mutually independent.

By contrast, because a pair of systematic risk factors are mutually correlated, a correlation coefficient, $\rho_{i,j}$, between A_i and A_j, is expressed as

$$\rho_{i,j} = corr(A_i, A_j) = \sum_{k=1}^{K} \sum_{k'=1}^{K} w_{i,k} w_{j,k'} \tilde{\rho}_{k,k'}, \tag{3}$$

where $\tilde{\rho}_{k,k'}$ is a correlation coefficient between Z_k and Z'_k. This study then assumes that a correlation coefficient between equity returns is a proxy variable of a correlation coefficient between asset returns. Further, a return for a TOPIX Sector Index to Z_k is allocated; thus, a correlation matrix between the systematic risk factors can be specified. If a correlation matrix between the systematic risk factors cannot be specified, the factor correlation matrix defaults to an identity matrix, meaning that the factors are not correlated.

With regard to each simulation scenario, the latent random variable, A_i, has a credit rating on the value distribution at the horizon (Figure 4). In turn, by using the credit rating curve, this study calculates the discounted value at the horizon of future cash flow at a later date than that of the horizon. When the latent variables A_i $(i = 1, \ldots, M)$ are normally distributed, there is a Gaussian copula. An alternative structure is to let the latent variables follow a t distribution, which leads to a t copula. The degree of freedom for a t copula controls the degree of tail dependence. The t copulas result in heavier tails than Gaussian copulas. Implied credit correlations are also larger with t copulas. Switching between these two copula approaches can provide important information on model risk (see, e.g., Cherubini et al., 2011).

Thus, we report risk measures such as VaR and ES for the value distribution at the horizon. First, in terms of VaR, given some confidence level $\alpha \in (0, 1)$, the VaR of a portfolio at confidence level α is given by the smallest number x such that the probability that the loss X exceeds x is no larger than $(1 - \alpha)$ as follows:

$$VaR_\alpha = \inf\{x \in \mathbb{R} | P(X > x) \leq 1 - \alpha\}.$$

Second, for an integrable loss X and any $\alpha \in (0, 1)$, ES is the expected loss,

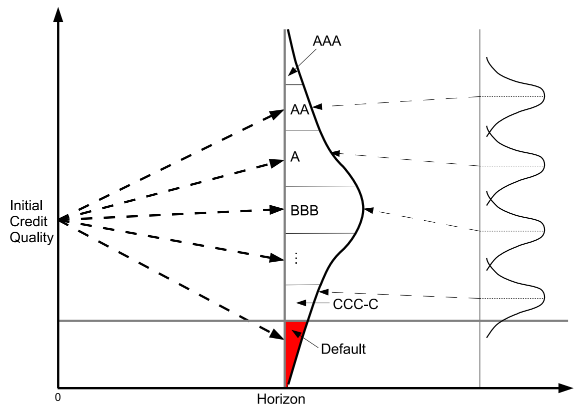

Figure 4: Portfolio value distribution at the horizon

given that the loss X is already beyond the pre-specified worst case level VaR_α as follows:

$$ES_\alpha = E(X|X \geq VaR_\alpha).$$

3.2.2. Data for portfolio credit risk analysis

In order to calculate portfolio credit risk, the parameters inputted to the model are shown in Table 3.

3.2.3. Results for portfolio credit risk analysis

Table 5 presents the results for credit risk amounts that are calculated based on VaR and ES for city banks, trust banks, Norinchukin Bank, major regional banks, and major life insurers. VaR and ES incorporate dependent structures among risk factors based on Gaussian copulas and t copulas with degree of freedom five, respectively.

Consequently, by applying the same 99.9% confidence level to selected institutions, Gaussian copula VaR, Gaussian copula ES, t copula VaR, and t copula ES are ranked in ascending order for the institutions, except for Meiji Yasuda Life and Dai-ichi Life. t copula ES is 3.48 times as large as Gaussian copula VaR for the Mizuho Bank and 3.37 times larger than the average of the 16 institutions. As a result, ES requires more capital than VaR for the

Table 3: Inputs to portfolio credit risk model

Item	Description	Sources
Portfolio values	Discounted present values for future cashflows of lending contracts calculated using equation (1), if there is no data for credit rating, lendings outstanding	JSDA
Ratings	Credit rating migration by firm: published by four credit rating agencies	Nikkei Astra Manager
Transition matrix	Matrix of credit rating transition probabilities with ratings as: 'AAA', 'AA', 'A', 'BBB', 'BB', 'B', 'CCC–C', and 'Default' as shown in the Table 4	R&I
LGD	Loss given default for corporate lending exposures: set to 45% evenly across all firms.	Fundamental internal rating-based approach in Basel III
Weights	Factor and idiosyncratic weights for model	
Confidence interval	Target for VaR and ES: set to 99.9%	Own calculations
Factor correlation matrix	33 × 33 correlations among returns of TOPIX Sector Indices	Nikkei Astra Manager and own calculations
Number of scenarios	Set to 500,000	—

institutions. Unless the availability of risk measures is validated, there may be inadequate credit risk management.

In addition, the three mega banks overwhelm other institutions in terms of credit risk amounts. This finding proves that the three mega banks have been selected as G-SIBs continuously since November 2011. For reference, core tier 1 capital by institution is shown in Table 5. In order to meet the capital requirement in Basel III, internationally active banks raise additional capital by various instruments. For example, the Mitsubishi UFJ Financial Group issued senior bonds worth USD 5 billion in March 2016 and USD 2 billion in April 2016 to meet total loss-absorbing capacity (TLAC) (BCBS, 2016; Kanno, 2018a).

Table 4: Transition matrix with averaged R&I's annual rating migration rates for FY1978–FY2015

	AAA	AA	A	BBB	BB	B	CCC-C	Default
AAA	91.00	9.00	0.00	0.00	0.00	0.00	0.00	0.00
AA	0.70	94.40	4.80	0.10	0.00	0.00	0.00	0.00
A	0.00	1.70	94.80	3.40	0.10	0.00	0.00	0.00
BBB	0.00	0.00	3.80	93.50	2.60	0.00	0.00	0.10
BB	0.00	0.00	0.20	8.10	86.50	2.60	0.10	2.50
B	0.00	0.00	0.00	0.80	9.80	76.60	0.80	12.00
CCC-C	0.00	0.00	0.00	0.00	0.00	6.50	87.00	6.50
Default	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00

Figure 5 gives us additional information about the distribution of portfolio values for selected institutions and the selection of risk measures. An orange vertical line corresponds to the current credit ranking. Thus, it should be noted that the difference between the market and current value corresponds to the loss amount and that the loss distribution has the same shape as the portfolio value distribution. The distributions of banks such as Norinchukin Bank and Yokohama Bank are asymmetrically unimodal distributions, whereas the distributions of institutions such as Chiba Bank and Meiji Yasuda Life are bimodal distributions and the distribution of Sumitomo Life is trimodal distribution. In a multimodal distribution with two or more modes, it is probable that any variation of VaR depends largely on the confidence interval. By contrast, ES does not cause such an issue because the measure calculates the average of loss in the range beyond a confidence interval.

Because the average coverage pertaining to the outstanding lending data in the database is 27.29% for all city banks (five banks), 36.39% for major trust banks (three banks), 5.35% for all regional banks I (64 banks), and 17.84% (Cov1) for major life insurers (four banks), the risk amounts do not necessarily represent each institution's total lending credit risk.[4] However, because the credit risk amounts for the three mega banks are JPY 159–223 billion based on Gaussian copula VaR and JPY 657–828 billion based on t

[4]With regard to trust banks, outstanding lending by money trusts is not fully captured, whereas with regard to regional banks I, the percentage shares for non-listed large firms are high.

copula ES, the figures need to be monitored carefully. The core tier 1 ratio for each bank is at a high enough level for capital adequacy requirements.

3.3. Credit risk by industry sector

This section analyzes the credit rating migration risk in industry sectors, which are categorized into 33 sectors indexed by TOPIX Sector Indices. First, each firm's credit risk exposure is aggregated in the industry sector to which the firm belongs. Table 6 indicates the ranking of the top 10 sectors in accordance with credit risk exposure for FY2008–FY2015. Sectors such as Wholesale Trade, Other Financing Business, Land & Transportation, Electric Power & Gas, and Real Estate especially have large credit risk exposures. The information & Communication sector has been ranked in the top 10 since FY2011, because during the period of FY2008–FY2015, the number of firms has monotonically increased from 97 in FY2008 to 172 in FY2015 and the total credit risk exposure for three major telecom carriers in Japan – Softbank Group, Nippon Telegraph & Telephone, and KDDI – has more than doubled from JPY 1.8 trillion in FY2008 to JPY 4.1 trillion in FY2015.[5]

In addition, two sectors, Other Financial Business (mainly, lease firms and credit card firms) and Real Estate, have higher credit risk owing to their large financial assets. Since the end of 2015, lending to the real estate sector has started to increase. The real estate sector has especially increased its outstanding ranking because of the effect of the negative interest rate policy announced by the Bank of Japan on January 29, 2016.

Further, since the Great East Japan Earthquake, which occurred on March 11, 2011 and the subsequent accident at the Tokyo Electric Power Company (TEPCO)'s Fukushima Daiichi Nuclear Power Plant, the TEPCO accounts for a large proportion of credit risk exposure in the Electric Power & Gas sector for FY2010 (i.e., at the end of March 2011), with a sudden large increase in proportion from 25% for FY2009 to 39% in FY2010.

[5]In particular, to conduct strategic M&A or form an alliance, Softbank Group borrowed a large amount of money, despite its S&P low credit rating of BB or BBB, incurring high interest costs for the period. For example, SoftBank Group and Sprint Nextel (a NYSE listed firm) completed their merger. SoftBank Group invested approximately USD 21.6 billion in Sprint, consisting of around USD 16.6 billion to be distributed to Sprint stockholders and an aggregate of USD 5 billion of new capital to strengthen Sprint's balance sheet. Sprint stockholders approved the transaction at a special meeting of stockholders held on June 25, 2013.

Table 5: Credit risk amounts at the end of March 2016 (in JPY million, %)

Institution name	IB/DB	GC-VaR	GC-ES	t_5-C-VaR	t_5-C-ES	SME lending & Housing loan ratio	Large firm lending ratio	Cov1	Cov2	CT1
Mizuho Bank	IB	223,169	335,775	534,140	828,288	59.49	40.51	12.50	30.86	11.20
BTMU	IB	159,295	263,986	422,863	662,339	55.17	44.83	9.35	20.85	12.04
SMBC	IB	182,301	266,236	438,885	657,177	67.90	32.10	10.88	33.90	13.15
Resona Bank	DB	32,088	48,418	86,631	124,705	82.32	17.68	5.72	32.36	10.58
Saitama Resona Bank	DB	6,083	9,441	9,663	13,322	87.83	12.17	0.87	7.17	11.58
Subtotal: City banks						63.57	36.43	9.94	27.29	–
MUTB	IB	67,084	88,784	161,365	247,364	51.27	48.73	22.45	46.08	15.87
SMTB	IB	98,154	145,625	250,653	374,527	57.68	42.32	13.48	31.86	10.76
Mizuho TB	IB	96,717	143,002	224,847	346,465	50.00	50.00	13.77	27.54	18.73
Subtotal: Trust banks						55.82	44.18	16.08	36.39	–
Norinchukin Bank	IB	41,131	55,364	107,991	164,692	–	–	10.72	–	18.44
Yokohama Bank	IB	22,617	28,912	42,698	61,472	80.61	19.39	3.76	19.39	11.63
Shizuoka Bank	IB	8,321	11,403	13,890	20,178	77.68	22.32	1.45	6.49	16.35
Chiba Bank	IB	8,289	9,680	13,120	18,226	81.70	18.30	1.38	7.55	12.09
Subtotal: Regional banks I (64banks)						70.25	29.75	1.59	5.35	–
Nippon Life	–	90,844	104,516	118,329	183,935	–	–	17.71	–	–
Meiji Yasuda Life	–	58,065	100,986	76,366	138,383	–	–	18.07	–	–
Dai-ichi Life	–	16,052	23,952	25,065	38,077	–	–	10.36	–	–
Sumitomo Life	–	16,719	20,252	23,131	33,718	–	–	11.38	–	–
Subtotal: Major life insurers						–	–	17.84	–	–

Notes 1: IB is an internationally active bank in accordance with Basel III; DB is a bank that focuses on domestic operations; GC denotes Gaussian copula; t_5-C denotes t copula with degree of freedom five; CT1 is core tier 1 capital; Cov1 is the ratio of outstanding lending in the database to one for each institution's financial statement; Cov2 is the ratio of outstanding lending in the database to one for each institution's outstanding lending to large firms.

Notes 2: SME & Housing loan ratio refer to the monthly *Kinyu Journal* and core tier 1 refers to the statistics of the Japanese Bankers Association. A hyphen indicates no relevant data. Large firms include listed and non-listed firms. The core tier 1 ratio is not published for life insurers. Resona Bank and Saitama Resona Bank have adopted the capital adequacy requirements for banks that focus on domestic operations; thus, their minimum capital requirement is 4%.

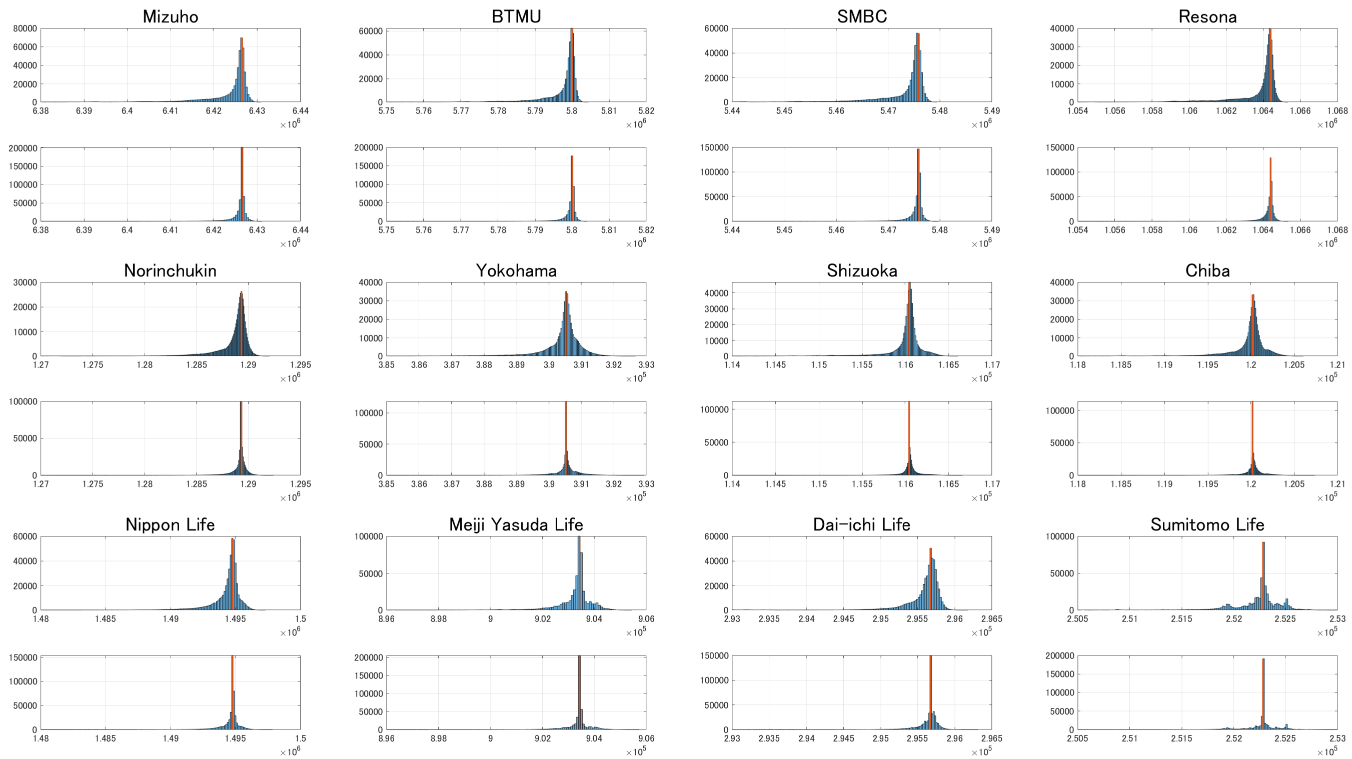

Figure 5: Distribution of portfolio values for selected institutions (in JPY million)

Notes: The panels show the distribution of portfolio values by institution at the end of March 2016. The upper panel by institution is for the Gaussian copula and the lower panel by institution is for the t copula. Each orange vertical line corresponds to the value for the current credit rating. The institutions are Mizuho Bank, the Bank of Tokyo-Mitsubishi UFJ (BTMU), Sumitomo Mitsui Banking Corporation (SMBC), and Resona Bank from the upper-left panel to the upper-right panel; Norinchukin Bank, Yokohama Bank, Shizuoka Bank, and Chiba Bank from the middle-left panel to the middle-right panel; Nippon Life, Meiji Yasuda Life, Dai-ichi Life, and Sumitomo Life from the lower-left panel to the lower-right panel.

In turn, we calculate risk measures such as VaR and ES by sector for FY2015 (i.e., at the end of March 2016). Because the one-year forward portfolio value distribution based on the credit rating migration is derived by industry sector, VaR and ES are calculated in relation to the distribution. Table 7 shows the ranking of the top 10 sectors in terms of credit risk as evaluated by four risk measures. In general, the top 10 sectors are all similar to the credit risk exposure for FY2015. However, the ranking for t_5-Copula-ES is a little bit different from the others, because some of them have multimodal distributions (Figure 6). Compared to the ranking for FY2015 in Table 6, sectors such as Electric Power & Gas, Chemicals, and Information & Communication are outside the ranking for all risk measures in Table 7. Although these sectors have large credit risk exposure, the volatilities of portfolio value distributions are all small, as shown in the three lower panels of the Figure 6. Hence, credit risk amounts measured by risk measures such as VaR and ES are also small.

4. Network analysis

This section describes the study's analysis of the network structures of the Japanese lending market in terms of bank-to-listed firms' and insurer-to-listed firms' relationships. The analysis is based on credit risk exposure. Such an approach differs from the nominal exposure that is examined in most literature on credit risk management.

4.1. Data for network analysis

The following $(N \times N)$ matrix, X, represents Japanese corporate lending relationships:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1N} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{iN} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{NN} \end{bmatrix}, \tag{4}$$

where x_{ij} denotes the outstanding exposure pertaining to firm i in terms of the lending of institution j. The summation across row i provides firm i's total outstanding exposure of its borrowing liabilities. The summation of

Table 6: Top 10 sectors ranked by credit risk exposure

Ranking	2008	2009	2010	2011	2012	2013	2014	2015
1	Wholesale Trade	Wholesale Trade	Wholesale Trade	Wholesale Trade	Electric Power & Gas	Electric Power & Gas	Wholesale Trade	Electric Power & Gas
2	Other Financing Business	Other Financing Business	Other Financing Business	Electric Power & Gas	Wholesale Trade	Wholesale Trade	Electric Power & Gas	Wholesale Trade
3	Electric Power & Gas	Electric Power & Gas	Electric Power & Gas	Other Financing Business	Other Financing Business	Other Financing Business	Electric Appliances	Electric Appliances
4	Land Transportation	Land Transportation	Land Transportation	Land Transportation	Land Transportation	Land Transportation	Other Financing Business	Other Financing Business
5	Real Estate	Real Estate	Real Estate	Real Estate	Real Estate	Real Estate	Land Transportation	Real Estate
6	Electric Appliances	Transportation Equipment	Transportation Equipment	Electric Appliances	Chemicals	Information & Communication	Real Estate	Land Transportation
7	Transportation Equipment	Electric Appliances	Electric Appliances	Transportation Equipment	Iron & Steel	Chemicals	Transportation Equipment	Transportation Equipment
8	Chemicals	Chemicals	Chemicals	Chemicals	Information & Communication	Iron & Steel	Information & Communication	Chemicals
9	Machinery	Machinery	Machinery	Information & Communication	Securities & Commodities Futures	Securities & Commodities Futures	Chemicals	Information & Communication
10	Retail Trade	Retail Trade	Retail Trade	Machinery	Retail Trade	Retail Trade	Retail Trade	Retail Trade

Table 7: Top 10 sectors ranked by risk measures at the end of March 2016

Ranking	Gaussian Copula-VaR	Gaussian Copula-ES	t_5-Copula-VaR	t_5-Copula-ES
1	Electric Appliances	Electric Appliances	Electric Appliances	Electric Appliances
2	Transportation Equipment	Transportation Equipment	Real Estate	Transportation Equipment
3	Real Estate	Real Estate	Transportation Equipment	Real Estate
4	Other Financing Business	Other Financing Business	Other Financing Business	Land, Marine & Air Transportation
5	Land, Marine & Air Transportation	Land, Marine & Air Transportation	Land, Marine & Air Transportation	Other Financing Business
6	Wholesale Trade	Wholesale Trade	Wholesale Trade	Retail Trade
7	Oil, Coal, Rubber, Glass & Ceramics Products	Oil, Coal, Rubber, Glass & Ceramics Products	Retail Trade	Wholesale Trade
8	Retail Trade	Retail Trade	Oil, Coal, Rubber, Glass & Ceramics Products	Oil, Coal, Rubber, Glass & Ceramics Products
9	Mining	Securities & Commodities Futures	Foods	Foods
10	Foods	Pulp & Paper	Securities & Commodities Futures	Construction

Notes: Due to a limited number of firms in some sectors, those sectors are merged into aggregate sectors as follows: Oil, Coal, Rubber, Glass & Ceramics Products sector: Oil & Coal Products, Rubber Products, and Glass & Ceramics Products; and Land, Marine & Air Transportation sector: Land Transportation, Marine Transportation, and Air Transportation.

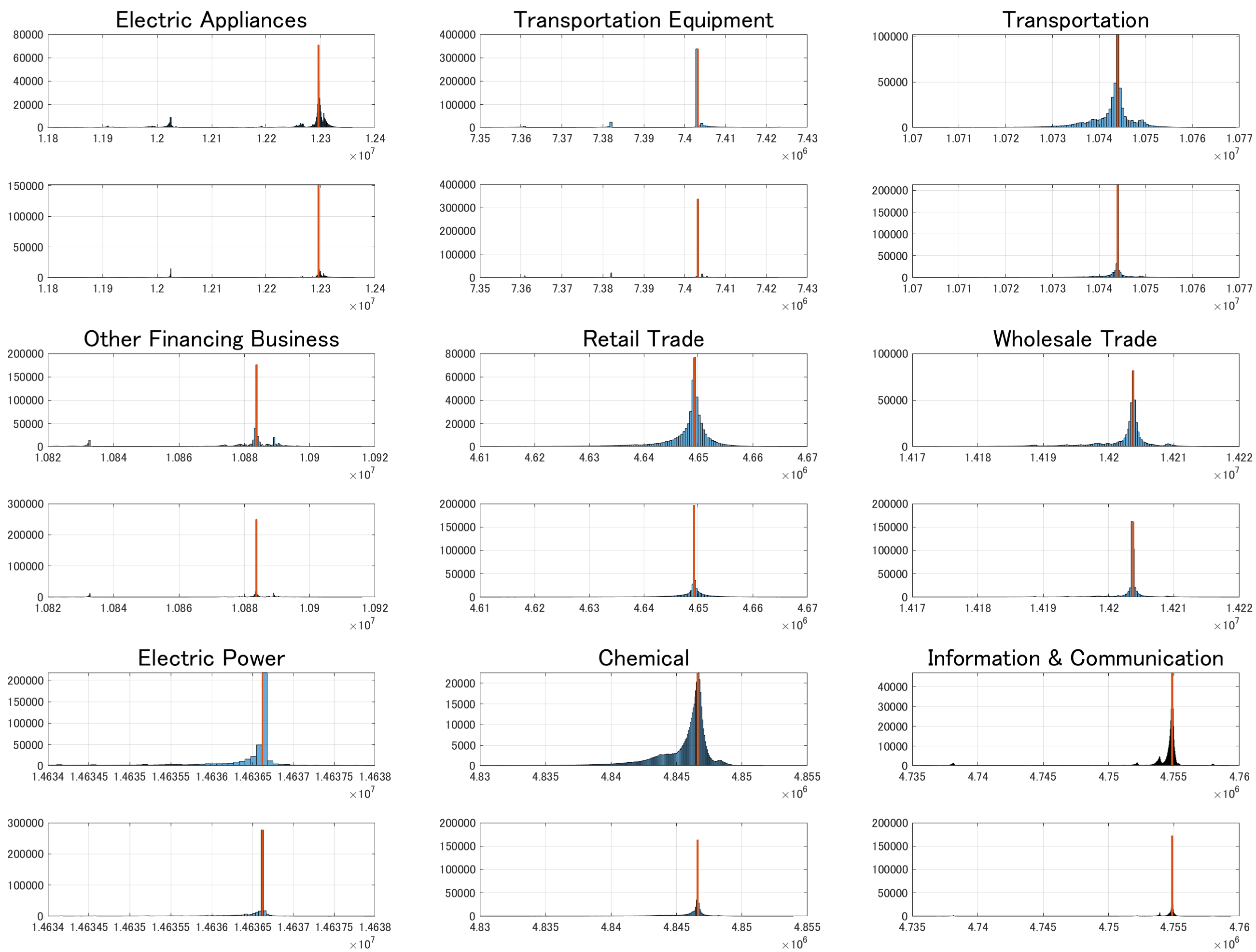

Figure 6: Distribution of portfolio values for selected sectors (in JPY million)

Notes: The panels show the distribution of portfolio values by sector at the end of March 2016. The upper panel by sector is for the Gaussian copula and the lower panel by sector is for the t copula. Each orange vertical line corresponds to the value for the current credit rating.

column j provides the total outstanding exposure of firm j's lending assets. Thus, matrix X is asymmetric.

Because the analysis requires outstanding data for the credit risk exposure matrix, X, on lending relationships, this study utilizes the details by entity, as shown in Table 2.

4.2. Methodology and analytical results

This study calculates the network statistics and centrality measures for FY2008–FY2015 (see Table 8). Network size indicates the total number of links in the lending network. Table 8 shows that after FY2008, network size remains unchanged overall. This study also calculates four centrality measures: degree centrality, eccentricity, hyperlink-induced topic search (HITS) hub centrality, and eigenvector centrality. Table 8 reports the averages for each of these.

"Direct" centrality measures capture the level of interconnectedness in a local region, based on adjacent connections, and are proxies for lending influence. These measures are degree centrality and eigenvector centrality. By contrast, "indirect" centrality measures enable the analysis of a counterparty's exposure in the entire network in accordance with its distance to all other entities. These measures are used here to evaluate networks oriented to information value. Eccentricity is an example of indirect centrality measures. It shows how close an entity node is to other nodes in the entire network in order to reflect the importance of one firm in the network (Renneboog and Zhao, 2014).

It is important to understand that managerial influence and information are two aspects of the same network. The two measures are not exclusive; the direct measures that express an entity's managerial influence on its counterparties also have the ability to capture information, which could benefit the entity. Nonetheless, the correlation between direct and indirect centrality measures is generally low (Kanno, 2018b), suggesting that such measures indeed capture different properties of the network. The two panels of Figure 7 indicate "network size and direct centralities" and "exposure size and indirect centrality."

4.2.1. Degree centrality

In terms of degree centrality, an entity's total degree is the sum of its in- and out-degrees. Because an institution is a lender, the institution has only one in-degree and no out-degree in terms of its relationship to a firm, whereas a firm has only one out-degree and no in-degree in terms of its relationship to an institution. An entity's *degree* is a proxy variable for its interconnectedness in the network. In a directed graph, all liabilities of a set of entities are directed from one borrowing firm to its lending institution. Degree centrality and network size are the same variables in a lending network owing to the one-way transaction from an obligor to a creditor.

4.2.2. Eccentricity

Eccentricity is a measure of the maximum distance between a single entity and any other entity in the network. The distance, $E(b_i, b_j)$, between the entities b_i and b_j is the sum of the edge weights expressed in the lending credit risk exposure on the shortest path from b_i to b_j in network G. Thus, the eccentricity of an entity b_i is

$$E(b_i) = \arg\max_{b_j \in G} d(b_i, b_j), \tag{5}$$

where $E(b_i) \geq 1$.

Table 8 shows that this centrality increases slowly for the period. In addition, the correlation between eccentricity and HITS hub centrality is 0.71 higher for the period, whereas the correlation between eccentricity and degree centrality is -0.94 for the period (see Figure 7).

4.2.3. HITS hub centrality

In terms of HITS hub centrality, HITS is known as "hubs" and "authorities." HITS was originally proposed to find the main structures in the World Wide Web (WWW). Web pages are divided into two categories: hubs and authorities. By the creation of a hyperlink from pages p to q, the author of page p increases the authority of page q. The authority of a WWW site would consider its in-degree (i.e., the hyperlinks required to return to the home page). Thus, HITS authority centrality is not suitable for measuring the credit risk of a firm as a borrower in the lending network. By contrast, a hub is defined as a WWW site that indicates many authorities. Thus, HITS hub centrality considers the credit risk of a borrower in terms of hub scores based on its out-degree. Institutions with the highest hub play a central role in the network. The weights are normalized to ensure that the sum of their squares is 1.

4.2.4. Eigenvector centrality

Eigenvector centrality is a natural extension of simple degree centrality. Degree centrality awards one centrality point for every network neighbor of an entity. However, not all neighbors are equivalent. In many cases, an entity's importance in a network increases owing to its connections to other important entities. This defines the concept of eigenvector centrality (Newman, 2010). The advantage of eigenvector centrality over other centrality measures is that it not only captures the number of entities linked to the target entity (degree centrality); it also captures the centrality of the adjacent entities. Thus, an entity has a higher eigenvector centrality score if it is connected to more entities with higher centrality scores.

Let $C^e(g)$ denote the eigenvector centrality associated with network g. An entity's centrality is proportional to the sum of the centrality of its neighboring entities, $\lambda C_i^e(g) = \sum_j g_{ij} C_j^e(g)$, for firm i. Using matrix notation,

$$\lambda C^e(g) = g C^e(g), \tag{6}$$

where λ is a proportionality factor. Thus, it can be seen that in Equation (6), $C^e(g)$ is an eigenvector of g and λ is its corresponding eigenvalue. Because eigenvector centrality is a measure with nonnegative values, this study uses the eigenvector associated with the largest eigenvalue (Jackson, 2010).

Table 8 shows that the average eigenvector centrality by year remains constant for FY2008–FY2012 and gradually decreases, together with the network size, after FY2012.

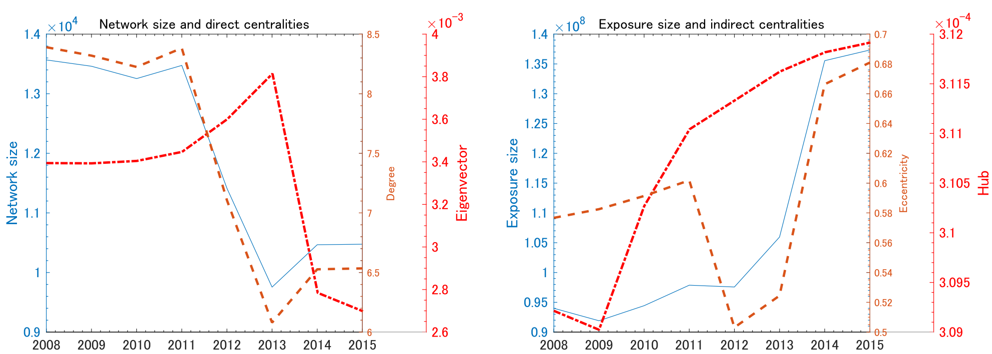

Figure 7: Time-transitions of centralities

Table 8: Lending network structure based on credit risk exposure with bank–firm and insurer–firm relationships.

FY	Network size	Degree	Eccentricity	Hub	Eigenvector
2008	13,567	8.39	0.577	0.000309	0.00339
2009	13,461	8.32	0.583	0.000309	0.00339
2010	13,254	8.22	0.591	0.000310	0.00340
2011	13,475	8.38	0.602	0.000311	0.00345
2012	11,414	7.11	0.503	0.000311	0.00360
2013	9,755	6.08	0.524	0.000312	0.00381
2014	10,466	6.53	0.666	0.000312	0.00278
2015	10,475	6.53	0.681	0.000312	0.00270

Note: Network size is the total number of lending relationships in the network.

4.2.5. Ranking by degree

Table 9 shows the ranking of the top 20 entities in accordance with interconnectedness, measured by the degree of their nodes. They include 15–17 banks and 2–4 insurers. Because no firm borrows money from hundreds of institutions, no firm ranks in the top 20. This table includes major banks such as the Mitsubishi UFJ Financial Group (BTMU and MUTB), the Mizuho Financial Group (Mizuho Bank, Mizuho Corporate Bank, Mizuho Trust & Banking), the Sumitomo Mitsui Financial Group (SMBC), Resona Holdings (Resona Bank), Sumitomo Mitsui Trust Holdings (SMTB) (Sumitomo Trust & Banking and Chuo Mitsui Trust & Banking prior to the merger); Norinchukin Bank; Government Financial Institutions (the Development Bank of Japan (DBJ) and Shoko Chukin Bank); major regional banks such as Yokohama Bank, Fukuoka Bank, Chiba Bank, Joyo Bank, and Iyo Bank; and major life insurers such as Nippon Life, Meiji Yasuda Life, and Dai-Ichi Life.

The degree centralities for financial institutions correspond to in-degrees in terms of the amount of borrowing by listed firms, whereas the degree centralities for listed firms correspond to out-degrees in terms of the number of lenders. However, in general, degree centralities, except for Mizuho Bank[6]

[6]The bank merged with Mizuho Corporate Bank on July 1, 2013.

and SMTB[7] decrease gradually, as can be seen in Figure 8.

Figures 9 and 10 offer a visual analysis by depicting directed graphs based on degrees over 40 as at the end of March 2009 and the end of March 2016 respectively. The direction of the arrow is from an obligor firm to a creditor institution. For example, BTMU has 1 236 in-degrees and 0 out-degrees in FY2008. As shown in Figures 9 and 10, because the edge is weighted by exposure, some thick ingoing edges flow into banks and life insurers from firms.

Figure 11 presents the six time-transition panels pertaining to a directed graph based on degrees over 40 for FY2009–FY2014. The graphs show that some mega banks were exposed to large credit risk exposure originating from the Orix Corporation[8] during FY2009–FY2012 and Kyushu Electric Power, an electric power firm, during FY2011–FY2014.

5. Stress test

This study conducts a stress test to verify the increase of credit risk in terms of the deterioration of lending assets in the lending network at a risk horizon in the future. Examples of the literature on stress tests of portfolio credit risk are Breuer et al. (2012), Tsaig et al. (2011), and Varotto (2012).[9] These studies' tests differ from typical macro stress tests that consider the shocks of macroeconomic variables on risk parameters for each entity (Henry and Kok, 2013; Kanno, 2015a, 2015b).

By contrast, according to R&I (2016), the empirical probabilities of default (PDs) pertaining to Japanese firms rated as speculative grades (i.e., BB category or lower) by R&I reached a peak of 15% during the Heisei great recession (1997–1998) and during the two years following Lehman Brothers' bankruptcy (2008–2009). Consequently, this study's test considers that the historical economic scenario pertaining to the credit rating migration matrix just after Lehman Brothers' bankruptcy is one of the worst scenario cases faced by the Japanese economy, as shown in Table 10. Comparing Table

[7]Sumitomo Trust & Banking merged Chuo Mitsui Trust & Banking and Chuo Mitsui Asset Trust and Banking (non-listed) on April 1, 2012.

[8]This firm conducts a leasing business and has expanded into related fields such as banking, insurance, and real estate.

[9]In addition, Schuermann (2014) lays out a framework for the stress testing of banks in terms of capital and liquidity.

Table 9: Top 20 entities ranked by interconnectedness: Degree centrality

Ranking	2008	2009	2010	2011	2012	2013	2014	2015
1	BTMU (1236)	BTMU (1226)	BTMU (1208)	BTMU (1216)	BTMU (987)	BTMU (797)	UNKNOWN (1172)	UNKNOWN (1211)
2	SMBC (1060)	SMBC (1042)	SMBC (1040)	SMBC (1063)	SMBC (876)	UNKNOWN (791)	BTMU (845)	BTMU (806)
3	UNKNOWN (698)	UNKNOWN (701)	UNKNOWN (769)	UNKNOWN (793)	UNKNOWN (664)	MIZUHO BANK (770)	MIZUHO BANK (797)	MIZUHO BANK (801)
4	MIZUHO BANK (659)	MIZUHO BANK (667)	MIZUHO BANK (661)	MIZUHO BANK (667)	SUMITOMO MITSUI TRUST BANK (565)	SMBC (713)	SMBC (762)	SMBC (764)
5	MIZUHO CORP BANK (535)	MIZUHO CORP BANK (505)	RESONA BANK (503)	RESONA BANK (526)	MIZUHO BANK (541)	SUMITOMO MITSUI TRUST BANK (443)	SUMITOMO MITSUI TRUST BANK (449)	SUMITOMO MITSUI TRUST BANK (444)
6	NIPPON LIFE (511)	RESONA BANK (499)	MUTB (491)	MUTB (490)	RESONA BANK (457)	RESONA BANK (401)	RESONA BANK (417)	RESONA BANK (409)
7	RESONA BANK (504)	NIPPON LIFE (497)	NIPPON LIFE (485)	MIZUHO CORP BANK (477)	MUTB (438)	MUTB (347)	MUTB (352)	NIPPON LIFE (368)
8	MUTB (499)	MUTB (493)	MIZUHO CORP BANK (483)	NIPPON LIFE (459)	MIZUHO CORP BANK (402)	NIPPON LIFE (328)	NIPPON LIFE (350)	MUTB (335)
9	SUMITOMO MITSUI TRUST BANK (404)	SUMITOMO MITSUI TRUST BANK (415)	SUMITOMO MITSUI TRUST BANK (415)	SUMITOMO MITSUI TRUST BANK (420)	NIPPON LIFE (394)	DBJ (255)	DBJ (252)	DBJ (248)
10	NORINCHUKIN BANK (375)	NORINCHUKIN BANK (350)	DBJ (345)	DBJ (357)	DBJ (320)	NORINCHUKIN BANK (236)	NORINCHUKIN BANK (224)	NORINCHUKIN BANK (228)
11	CHUO MITSUI TRUST & BANKING (341)	DBJ (333)	NORINCHUKIN BANK (336)	NORINCHUKIN BANK (335)	NORINCHUKIN BANK (302)	SHOKO CHUKIN BANK (229)	SHOKO CHUKIN BANK (224)	SHOKO CHUKIN BANK (206)
12	MEIJI YASUDA LIFE (296)	CHUO MITSUI TRUST & BANKING (325)	CHUO MITSUI TRUST & BANKING (334)	CHUO MITSUI TRUST & BANKING (331)	SHOKO CHUKIN BANK (274)	MEIJI YASUDA LIFE (156)	MEIJI YASUDA LIFE (168)	MEIJI YASUDA LIFE (180)
13	DBJ (293)	MEIJI YASUDA LIFE (275)	SHOKO CHUKIN BANK (302)	SHOKO CHUKIN BANK (331)	MEIJI YASUDA LIFE (195)	MIZUHO TRUST & BANKING (145)	YOKOHAMA BANK (157)	YOKOHAMA BANK (162)
14	YOKOHAMA BANK (258)	SHOKO CHUKIN BANK (274)	MEIJI YASUDA LIFE (269)	MEIJI YASUDA LIFE (249)	YOKOHAMA BANK (191)	YOKOHAMA BANK (137)	MIZUHO TRUST & BANKING (147)	MIZUHO TRUST & BANKING (151)
15	DAIICHI LIFE (219)	YOKOHAMA BANK (258)	YOKOHAMA BANK (247)	YOKOHAMA BANK (247)	MIZUHO TRUST & BANKING (174)	CHIBA BANK (99)	FUKUOKA BANK (106)	CHIBA BANK (108)
16	MIZUHO TRUST & BANKING (202)	MIZUHO TRUST & BANKING (199)	MIZUHO TRUST & BANKING (185)	MIZUHO TRUST & BANKING (187)	ORIX (122)	FUKUOKA BANK (99)	CHIBA BANK (104)	FUKUOKA BANK (106)
17	SHOKO CHUKIN BANK (202)	DAIICHI LIFE (173)	DAIICHI LIFE (143)	JOYO BANK (135)	JOYO BANK (122)	IYO BANK (97)	AOZORA BANK (96)	JOYO BANK (102)
18	AOZORA BANK (142)	ORIX (131)	ORIX (127)	CHIBA BANK (131)	CHIBA BANK (118)	AOZORA BANK (96)	IYO BANK (95)	SHINSEI BANK (94)
19	EXCEPT OTHER FI (137)	EXCEPT OTHER FI (129)	CHIBA BANK (125)	SHIGA BANK (130)	IYO BANK (110)	JOYO BANK (94)	JOYO BANK (93)	IYO BANK (93)
20	SUMITOMO LIFE (133)	CHIBA BANK (128)	SHIZUOKA BANK (123)	SHIZUOKA BANK (126)	UNKNOWN PRIVATE FI (110)	CREDIT FED OF AGRI COOP (86)	YAMAGUCHI BANK (88)	HIROSHIMA BANK (89)

Notes: Figures in parentheses indicate degree centrality. BTMU is Bank of Tokyo-Mitsubishi UFJ; SMBC is Sumitomo Mitsui Banking Corporation; MUTB is Mitsubishi UFJ Trust & Banking; and DBJ is Development Bank of Japan.

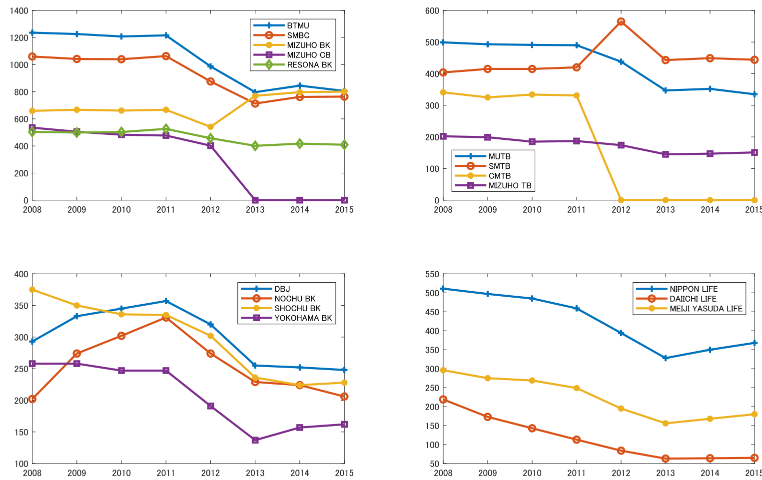

Figure 8: Degree time transition by institution

Notes: NOCHU is Norinchukin Bank and SHOCHU is Shoko Chukin Bank. The four panels show the degree time transition for 16 selected institutions.

10 with Table 4, the transition matrix for FY2008–FY2009 stands out with regard to large downgrading probabilities, such as 43.30% (marked in gray) for a downgrade of a BB rating to default and 50.00% (marked in gray) for a downgrade of a B rating to default.

In addition, loss given default (LGD) is assumed to be 100% because, in terms of network structure, the usual lending relationships between a defaulted firm and its lending institutions are interrupted after default; thus, recovery takes approximately three to five years. The evaluation time point and risk horizon are assumed to be the end of March 2019 and the end of March 2020 respectively. The other parameters (e.g., factor correlation matrix) in Table 3 are assumed to be the same as those at the end of March 2016.

Consequently, because many defaults occur, the lending network becomes much sparser. Table 11 indicates the number of defaulted firms, the number of defaulted contracts (i.e., a firm's default corresponds to a default for each one of its banks), and VaR and ES by dependence structure on the value

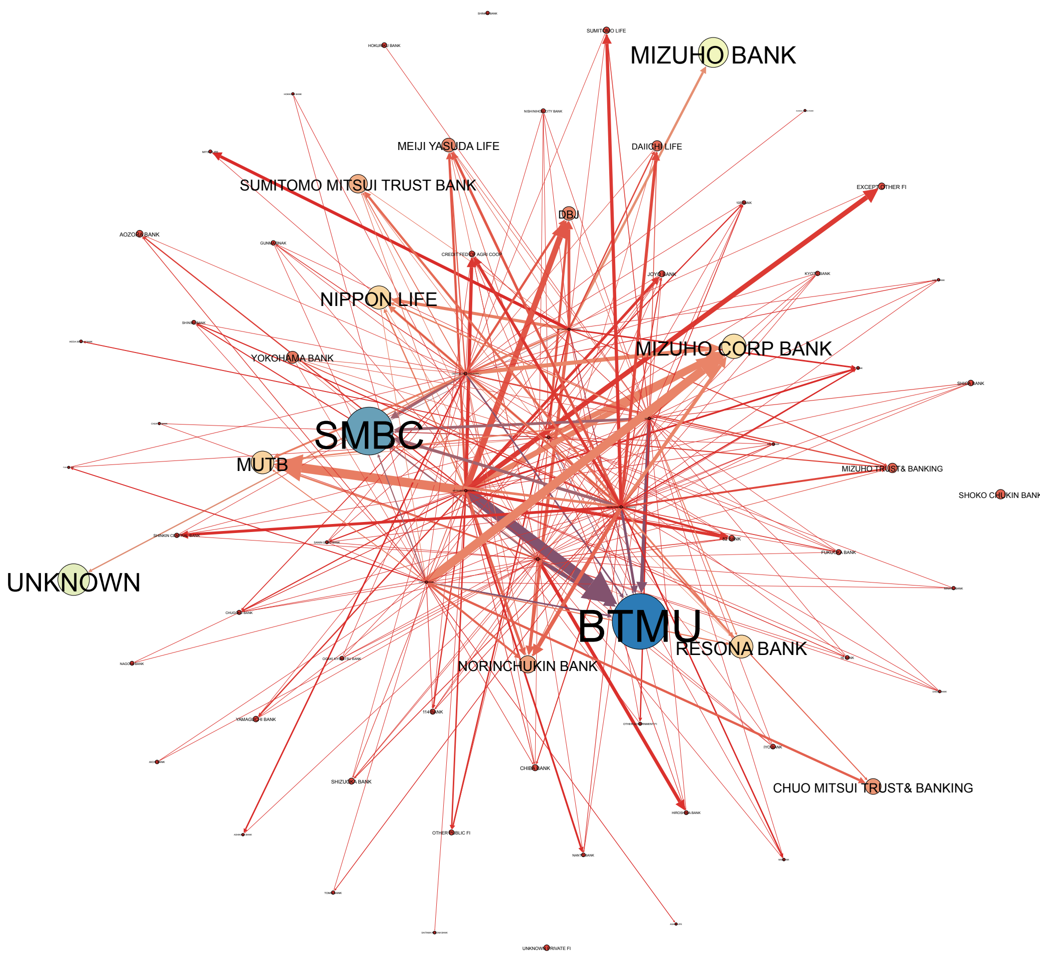

Figure 9: Directed graph of degrees over 40, end of March 2009 (just after the bankruptcy of Lehman Brothers)

Note: These graphs are drawn in accordance with the Fruchterman–Reingold algorithm.

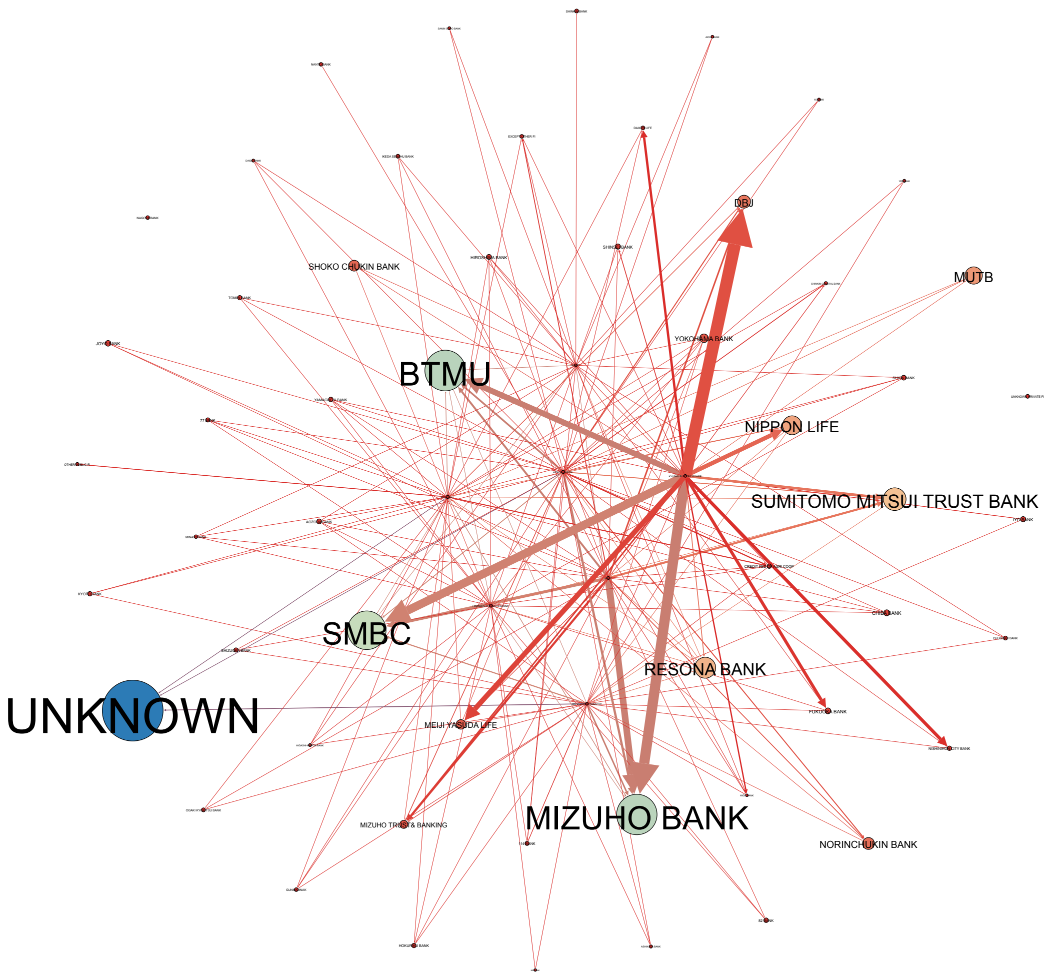

Figure 10: Directed graph of degrees over 40, end of March 2016

Note: These graphs are drawn in accordance with the Fruchterman–Reingold algorithm.

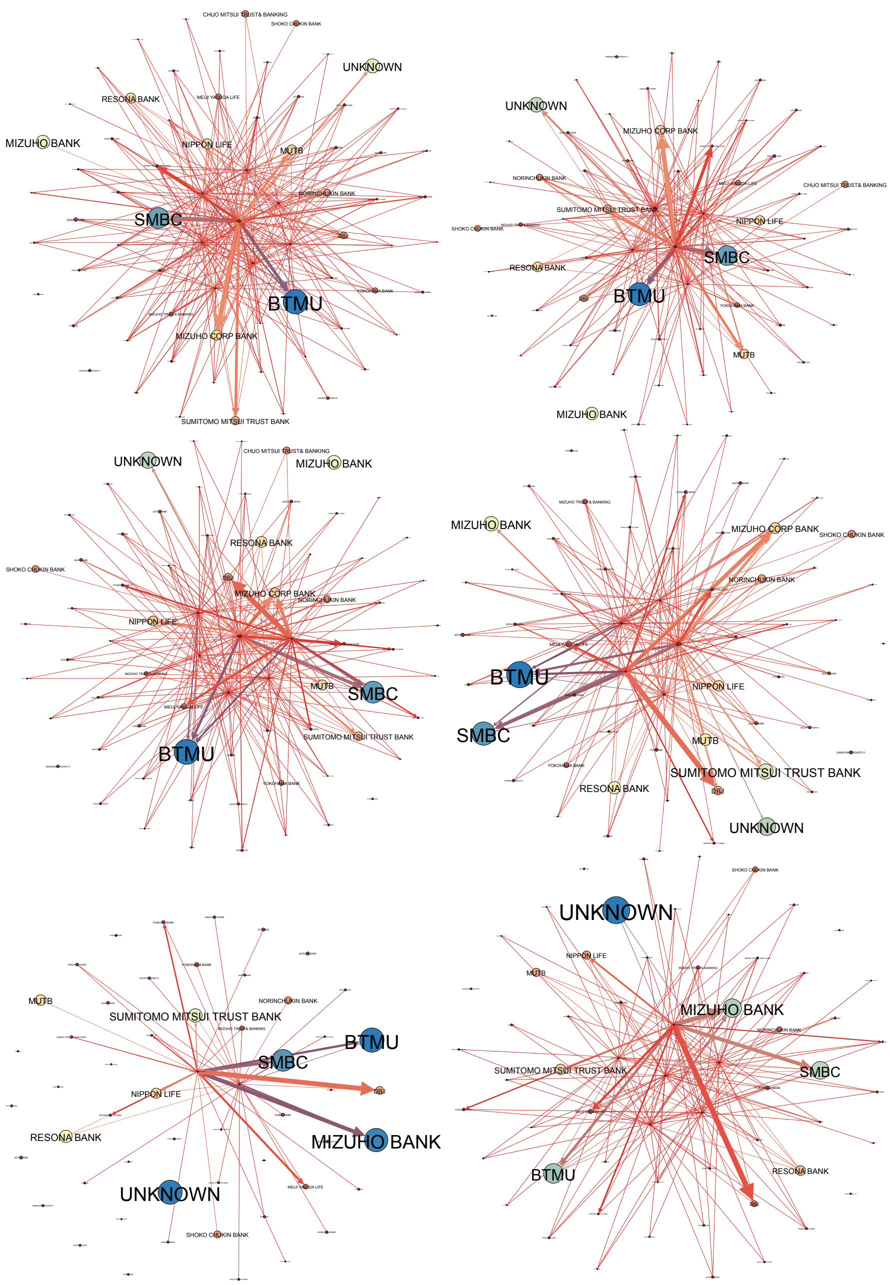

Figure 11: Directed graphs of degrees over 40

Notes: The six panels show directed graphs of firm nodes over 40 degrees at the end of March 2010 and March 2011 from the upper-left panel to the upper-right panel; at the end of March 2012 and March 2013 from the middle-left panel to the middle-right panel; and at the end of March 2014 and March 2015 from the lower-left panel to the lower-right panel.

Table 10: Transition matrix with averaged R&I's annual rating migration rates for FY2008–FY2009

	AAA	AA	A	BBB	BB	B	CCC-C	Default
AAA	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
AA	0.00	79.50	18.35	1.10	0.70	0.35	0.00	0.00
A	0.00	3.90	88.00	7.60	0.00	0.00	0.00	0.50
BBB	0.00	0.00	14.85	78.10	4.30	0.00	0.00	2.75
BB	0.00	0.00	20.00	13.35	23.35	0.00	0.00	43.30
B	0.00	0.00	0.00	0.00	50.00	0.00	0.00	50.00
CCC-C	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00
Default	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00

Notes: Stressed is loaded to the credit rating migration matrix for one year from a future time point to a risk horizon. The matrix is provided as a one-year average for the 2008 and 2009 cohorts provided by R&I.

distribution of lending assets: Gaussian copula or t_5 copula. As a result, defaulted firms account for 1.7% of all Japanese listed firms in terms of Gaussian copula dependence and 2.2% in terms of t_5 copula dependence. Stressed VaR and ES are over around 500 times greater than normal. In particular, the t_5 copula ES of JPY 38 trillion is an enormous sum in the Japanese financial system.

At the same time, Figure 12 indicates directed graphs of degrees over 40, pertaining to a scenario of a 99.9% confidence level of portfolio values at a risk horizon of all non-defaulted firms. The left panel of Figure 12 assumes Gaussian copula dependence and the right panel assumes t_5 copula dependence. Comparing both panels with Figure 11, each panel shows a sparser network structure. In particular, because t_5 copula brings tail dependency into the value distribution, t_5 VaR and t_5 ES are much larger than Gaussian copula VaR and Gaussian ES respectively.

6. Conclusions

This study contributes to the literature by analyzing credit rating migration risk in Japan's corporate lending market.

First, in corporate credit risk management, the study evaluated the credit risk exposure for all Japanese listed firms. Following the credit migration approach, a firm's credit risk exposure changes depending on its corporate

Table 11: Results calculated using the transition matrix for FY2008–FY2009 (in JPY billion)

	Defaulted firms		Defaulted contracts		VaR		ES	
	Number	%	Number	%	Amount	%	Amount	%
GC	38	1.7	201	1.5	17,181	530	20,748	547
t_5-C	48	2.2	374	2.9	31,254	579	37,650	501

Notes: GC is Gaussian copula and t_5-C is t copula with degree of freedom five. Because a firm generally borrows money from institutions, one firm's default results in losses for such institutions. Each percentage in the columns for "Defaulted firms" and "Defaulted contracts" denotes a multiple of the number of each total number. Each percentage in the columns for "VaR" and "ES" denotes a multiple of the risk amounts in normal times.

rating. The values of the outstanding lending of mega banks also substantially reduced just after the bankruptcy of Lehman Brothers. By contrast, the outstanding values for life insurers increased after FY2009. The analytical results show that banks are affected by the capital requirement of Basel II and III, whereas life insurers aimed to improve their investment performance during the studied period.

Second, this study measured the lending portfolio credit risk for major banks and other large banks, and major life insurers. The risk measures used are VaR and ES. In particular, ES is expected to ensure the prudent capture of tail risk and has actually been introduced in insurer solvency regulation, as illustrated by the Swiss Solvency Test. In addition, the choice of copula is critical for correctly measuring the dependence between systematic risk factors.

Third, this study ranked the industry sectors in accordance with credit risk exposure and lending portfolio credit risk. In terms of credit risk exposure, sectors such as Wholesale Trade, Other Financing Business, Land & Transportation, Electric Power & Gas, and Real Estate were ranked in the top ten. By contrast, sectors such as Electric Power & Gas, Chemicals, and Information & Communication, which are all ranked in the top ten in terms of credit risk exposure, are outside the ranking for all risk measures. Although these sectors have large credit risk exposure, credit risk amounts measured by VaR and ES are all small because of the small volatilities of portfolio value distributions.

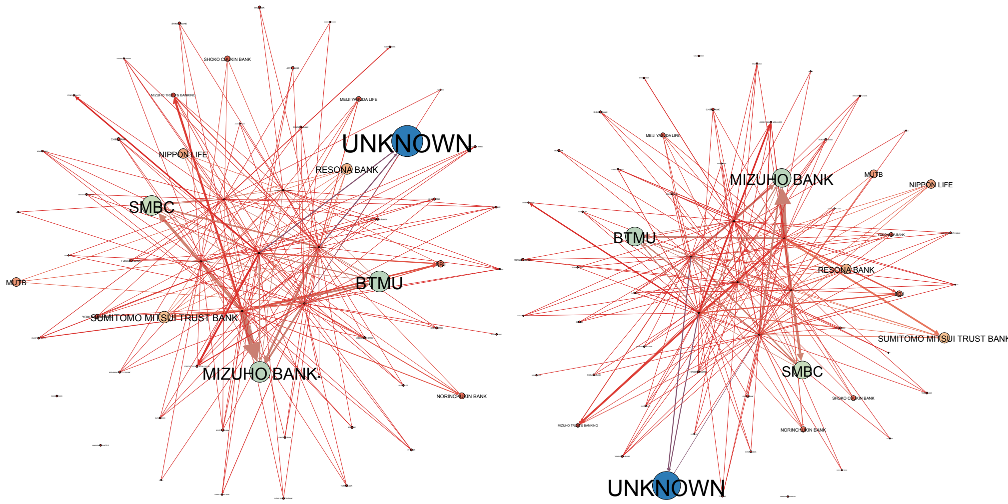

Figure 12: Directed graphs of degrees over 40, pertaining to a scenario of a 99.9% confidence level of portfolio values at a risk horizon (left panel: Gaussian copula; right panel: t_5 copula)

Note: The two panels show the stressed Gaussian and t_5 copula distributions of portfolio values for all institutions at the end of March 2019.

Fourth, this study analyzed the network structure of corporate lending among bank-to-listed firms and insurer-to-listed firms in Japan's lending market using major centrality measures. Banks and insurers play a central role in terms of degree centrality. However, degree centrality decreased gradually after the global financial crisis. This may mean a decrease in the number of counterparties.

Fifth, this study conducted a stress test in terms of network structure. Because 1.7% of all Japanese listed firms defaulted in terms of Gaussian copula dependence and 2.2% in terms of t_5 copula dependence, the network structure became much sparser.

Finally, this study's analyses on credit rating migration risk and interconnectedness in a lending network can serve as warnings to related entities such as financial institutions, supervisory authorities, and firms about risk perception.

To conclude, because our data are restricted to the Japanese market, it would be effective to apply our methodology to other financial markets for further studies.

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