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Supply Chain Network and Credit Supply

Kensuke Fukunaga and Daisuke Miyakawa

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Kensuke Fukunaga* and Daisuke Miyakawa**

Abstract

How do supply chain networks affect credit supply? To answer this question, we empirically detect clusters of firms by using firm-to-firm transaction data, then measure banks' exposures to those clusters and borrowing firms by using bank-to-firm lending data. Through the panel estimations controlling for unobservable factors potentially affecting credit demand and supply, first, we find that the higher portfolio concentration of banks on the clusters of firms lowers credit supply to less creditworthy firms. Second, we also find that such a pattern is more apparent for banks lending to creditworthy firms. These results suggest that the change in real network propagates to credit supply through banks' risk management.

Keywords: Credit supply; supply chain network; cluster detection
JEL classification: D22, E44, G11, G21

* Economist, Institute for Monetary and Economic Studies, Bank of Japan (currently, Senior Analyst, UTokyo Economic Consulting Inc., E-mail: kensuke_fukunaga@utecon.net)
** Associate Professor, Hitotsubashi University Business School (E-mail: dmiyakawa@hub.hit-u.ac.jp)

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I. Introduction

Theoretical and empirical studies have modeled and identified the determinants of credit supply of banks to firms. The list of determinants consists of firm attributes, bank attributes, and aggregate-level shocks such as economic crisis, natural disasters, and economic policies. In the present paper, as a new determinant of banks' credit supply, we consider supply chain networks. We are specifically interested in how changes in supply chain networks affect the concentration of banks' exposure to the clusters of firms, inside of which firms are closely trading with each other, and eventually affect credit supply.

From a practical point of view, it is not necessarily novel to consider the "concentration" of credit supply as one of its determinants. Extant studies have theoretically modeled the concentration of credit supply and empirically examined its implication (e.g, Pyle 1971; Hart and Jaffee 1974; Adrian & Shin 2011). Consistent with these studies, financial authorities have been also encouraging banks to measure the concentration of credit supply to, for example, specific industries and take the degree of such concentration into account for their risk management.

The basic presumption of those extant studies and the practical responses is that borrowers in a same industry are likely to face a similar negative shock. An example of such a negative shock could be that hitting hospitality industry amid the pandemic of COVID-19. Those shocks result in a higher correlation among credit events (e.g., defaults) of the firms in the same industry. This is a reason that banks are supposed to diversify their loan provision over industries.

While banks are expected to care about such "industry" concentration of their exposure, they may also need to care about the concentration of credit supply in terms of "supply chain networks". Suppose a set of firms are linked by customer-supplier relationships and forming a cluster of firms. Each firm is located in either upstream or downstream of such a cluster and thus possibly belonging to various industries. Here, recent studies have pointed out that a negative shock hitting a firm could be propagated to upstream and/or downstream inside the cluster of firms (Barrot and Sauvagnat 2016; Carvalho et al. 2020; Herskovic et al. 2020; Kramarz et al. 2020; Arata and Miyakawa 2021, 2022). Thus, exactly same as in the episode of industry concentration, banks have a good reason to take into account their exposure to firm clusters when they decide on credit supply. The causal linkage running from the loan concentration in terms of firm clusters to banks' credit supply is what we test in the present paper.

Although the purpose of our empirical study is fairly straightforward, there are at least two difficulties. First, we need to be able to use comprehensive datasets accounting both for firms' supply chain network and firms' borrowings from banks. Such data on real and financial networks are necessary to examine how credit supply from a bank to a firm belonging to a cluster responds to changes in the bank's loan concentration in terms of supply chain network.

Recent empirical studies have started to extensively use firm-to-firm supply chain network data to examine, for example a transmission of a shock through supply chain network (e.g., Barrot and Sauvagnat 2016; Bohem et al. 2019; Carvalho et al. 2020; Arata and Miyakawa 2022) and aggregate fluctuations originating from micro-level shocks (e.g., Magerman et al. 2017; Arata and Miyakawa 2021). Regarding the data on firms' financial network, extant studies have been using granular data on bank-to-firm credit supply collected in various countries (e.g., Khawaja and Mian 2008; Jimenez et al. 2012; Hosono et al. 2016; Ono et al. 2016; Amiti and Weinstein 2018).

Although these empirical studies are intensively using either real network data or financial network data, as far as we concern, there are only a few studies simultaneously using both real and financial network data. Huremovic et al. (2020) and Alfaro et al. (2021) employ Spanish data and Dwenger et al. (2020) employ German data both on financial and real networks and empirically show the shocks originating from financial sector propagate through real network. Except for these very recent studies, the literature paying an attention to both the real and financial networks is still sparse.

Against this data concern, we employ the granular data accounting both for firm-to-firm supply chain network and bank-to-firm credit supply. Using these two datasets, first, the clusters of firms implied by supply chain networks are detected by employing standard methods used in the literature of network science. The detected clusters tell us the lists of firms closely trading in a specific year. Such time-variant lists of firms are used to measure the dynamics of banks' exposures to clusters of firms.

Second, identification could be a concern. For the clean identification of a specific mechanism governing credit supply, recent empirical studies have been intensively using bank-to-firm loan provision data. Such bank-firm pair-level panel data allow us to control for firm-time-level fixed effects, which effectively subsume time-variant firm-level loan demand, and estimate the relationship between credit supply and factors associated with banks. In this estimation, it is also standard in literature to take up a specific exogenous shock such as financial crisis (e.g., Huremovic et al. 2020) or natural disasters (Hosono et al. 2016; Barrot and Sauvagnat 2016; Bohem et al. 2019; Carvalho et al. 2020), and use the shock and the interaction between the shock and banks' attributes as determinants of loan provision[1].

Thus, an important remark here is that it is necessary for us to use exogenous shocks to identify a specific mechanism governing credit supply. In the present paper, we are specifically interested in how credit supply responds to the change in banks' exposure to clusters. As the change in the exposure to clusters could be endogenous, it is not ideal to simply regress pair-level loan variables on banks' exposure to clusters of firms. Thus, we need to measure the change in banks' loan exposure to clusters which could be considered exogenous to the banks.

In our analysis, to measure the concentration of each bank's exposure to the clusters they are exposed to, we use the Hirschman Herfindahl Index (*HHI*). HHI measures the concentration for each bank b to the clusters in each year t. Thus, the correlation between a bank's loan provision in year t and the *HHI* in year $t-1$ tells us how the bank reallocates credit to borrower firms in t given the concentration in $t-1$. Here, as already mentioned, banks' exposure to each cluster could be endogenous and thus we need to measure the exogenous variation of the portfolio concentration on clusters.

Given this specific concern, we measure the change in HHI "perceived" by banks but "not effectively controlled" by them so that we can regard it as an exogenous shock to banks. The intuition of the identification strategy is as follows: Suppose we measure HHI

[1] Amiti and Weinstein (2018) abstract the factors associated with supply side of credit by introducing bank-time-level fixed effects. This specification aims at quantifying the demand side factors and supply side factors through the estimation of fixed effects instead of explicitly estimating the contribution of specific bank attributes interacted with exogenous shocks, which we aim at doing in the present paper.

by taking into account the clusters implied by the transaction network among the firms directly borrowing from a bank (*HHI-F*). The exposure to the clusters measured in this way is mechanically affected by banks' choice of past credit supply and thus could be endogenous. Here, we further measure another HHI by taking into account the clusters implied not only by the transaction network among the firms directly borrowing from a bank but also by the transaction network among those direct borrowers and their transaction partners (i.e., customers and suppliers) not borrowing from the bank (*HHI-FT*). Under the identification assumptions that banks recognize the direct customers and suppliers of the borrowing firms but the formation of the links between the borrowers and their partners not borrowing from the bank is exogenous for the bank, we decompose *HHI-FT* to *HHI-F* and the residual (*HHI-T*) to measure the exogenous components of the variation in *HHI-FT* to the bank.

We estimate the correlation between the outstanding loan amounts from a bank to a firm at the end of *t* and both the *HHI-F* and *HHI-T* at the end of *t-1*. While the coefficient of *HHI-F* accounts for how past firm-to-firm real network and bank-to-firm financial network affect current bank-to-firm financial network, the coefficient of *HHI-T* presumably account for how past firm-to-firm real network affects current bank-to-firm financial network, which we would like to identify.

The results obtained from our estimation are summarized as follows: First, facing higher concentration of loan exposure to clusters, banks reallocate credit from firms with low to high creditworthiness. This suggests that portfolio concentration on firm clusters plays as an important determinant of credit supply. Quantitatively, when a bank's *HHI-T* increases by one standard deviation in *t-1*, a borrower firm with the credit score lower than average by one standard deviation in *t-1* receives 1.0% point smaller loan provision than the case of a bank not experiencing the change in *HHI-T* and a firm with average creditworthiness. The reduction in credit supply is apparently not negligible given the average growth rate of firm borrowing in our sample period is 1.5%. Unlike what we expected, facing higher concentration of loan exposure to specific firm clusters, banks do not reallocate significant amount of credit from the firms in high-exposed to low-exposed clusters.

Second, the responses of banks facing higher loan concentration on clusters are more (less) apparent for the banks that lend to more (less) creditworthy firms. On the one hand, when the average creditworthiness of borrower firms for a bank is in the top 20% of all the banks, the responsiveness of the bank's credit supply to the concentration of loan exposure to clusters is 40% higher than the average estimates. On the other hand, when the average creditworthiness of borrower firms for a bank is in the bottom 20% of all the banks, the bank's credit supply does not respond to the change in the concentration of loan exposure to clusters.

These two results jointly suggest that banks' risk management in terms of supply chain networks results in the reallocation of credit. As far as we know, the present paper is the first empirical study to report such a financial implication of real networks. This result is informative for enriching our understanding on the interaction between financial network and real network. The extant studies (Dwenger et al. 2020; Huremovic et al. 2020; Alfaro et al. 2021) have already reported that exogenous reduction of credit supply propagates through supply chain networks. As a complementary finding to them, the results obtained in the present paper suggests that changes in real networks propagates through financial network and eventually fed back to firms as a form of credit supply. The shock propagations both over the real and financial networks exemplify the complex and tight connections between real and financial sectors.

The organization of the following sections are as follows: In the section II, we go over our empirical methodologies consisting of cluster detection and panel estimation. Section III is for the exposition of the data we used for our empirical study. In Section IV and V, we present the empirical results and conclude, respectively.

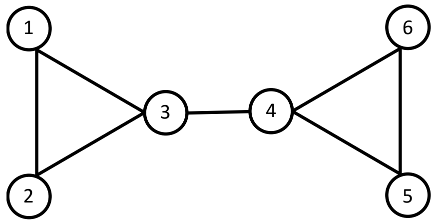
II. Empirical Methodology

A. Cluster Detection

First, we empirically detect clusters of firms, in which firms are trading with each other as customers and suppliers. Those clusters are detected by employing a standard method used in the field of network science.

Figure-1 illustrates a hypothetical set of 6 firms linked by a supply chain network and transacting with each other[2]. In this example, the firm 1, 2, and 3 seem to be transacting with each other while the firm 4, 5, and 6 are forming another group. Firm 3 and 4 seem to play a role to connect those two cluster of firms. The purpose of cluster detection is to make these groups in a non-discretionary way. The basic procedure of clustering is to make groups of firms so that the resultant clusters highlight non-random features of the observed network.

Figure-1: An example of supply chain network



To demonstrate this basic idea of clustering explicitly, Figure-2 shows an adjacency matrix of the hypothetical supply chain network depicted in Figure-1. Each number in the row and column of the matrix corresponds to the six firms in Figure-1. The element of the matrix takes 1 if there is a link between the firms in the row and the column. By construction, the matrix is symmetric. As we do not have a "self-link" such as firm 1 is

[2] In the current analysis, we do not distinguish the direction of transaction. In other words, we do not explicitly take care of whether firm 1 is a customer or a supplier of firm 2. Because we do not have a comprehensive information on the size of transaction between two firms, we do not take into account the trade volume.

transacting with firm 1 in the current context, all the diagonal elements are zeros. This matrix in Fiture-2 contains exactly same information as Figure-1 has.

Figure-2: An adjacency matrix of the hypothetical supply chain network

$$
\begin{array}{c c}
 & \begin{array}{cccccc} 1 & 2 & 3 & 4 & 5 & 6 \end{array} \\
\begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{array} &
\begin{pmatrix}
0 & 1 & 1 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 0 & 0 \\
1 & 1 & 0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 & 1 & 1 \\
0 & 0 & 0 & 1 & 0 & 1 \\
0 & 0 & 0 & 1 & 1 & 0
\end{pmatrix}
\end{array}
$$

How can we make plausible groups of firms? As mentioned above, the basic idea is to highlight the non-randomness of the adjacent matrix. To see this point more explicitly, Figure-3 shows the adjacent matrix for the case that all the links among firms are randomly formulated. Given the number of off-diagonal elements are 30 (i.e., 6*6 - 6) and the number of observed links is 7, the probability for each pair is randomly linked is 14/30.

Figure-3: An adjacency matrix of randomly linked supply chain network

$$
\begin{pmatrix}
0 & 14/30 & 14/30 & 14/30 & 14/30 & 14/30 \\
14/30 & 0 & 14/30 & 14/30 & 14/30 & 14/30 \\
14/30 & 14/30 & 0 & 14/30 & 14/30 & 14/30 \\
14/30 & 14/30 & 14/30 & 0 & 14/30 & 14/30 \\
14/30 & 14/30 & 14/30 & 14/30 & 0 & 14/30 \\
14/30 & 14/30 & 14/30 & 14/30 & 14/30 & 0
\end{pmatrix}
$$

Using these two matrices in Figure-2 and Fiture-3, we can compute the following measure Q for a given number of clusters (i.c., C), which is called as modularity. Here, $A_{i,j}$ accounts for the element of (i,j) component of the actually observed adjacent matrix in Figure-2 while $R_{i,j}$ accounts for the element of (i,j) component of the random adjacent matrix in Figure-3. In this computation, we have C sets of (i,j) denoted by $G_1, \cdots, G_C$. N denotes the number of firms in the network.

$$
\mathrm{Q} = \frac{\left[\sum_{(i,j)\in G_1} A_{i,j} - \sum_{(i,j)\in G_1} R_{i,j}\right] + \cdots + \left[\sum_{(i,j)\in G_C} A_{i,j} - \sum_{(i,j)\in G_C} R_{i,j}\right]}{2 \times N}
$$

Intuitively, this measure Q becomes larger when the concentration of a set of (i, j) is larger than that of random link under a given set of clusters $G_1, \cdots, G_C$. In the example above, for a given C=2, this modularity measure Q is maximized under G_1 as the left-upper 3-by-3 matrix and G_2 as right-bottom 3-by-3 matrix as we conjectured. After finding the pattern of clustering for a given C, we repeat the same exercise for different C and track the change of Q so that we can identify the optimal number of clustering. Since it is computationally heavy, in general, to search for all the possible clustering for a given C, several conventional ways to implement this clustering has been proposed. In this present paper, we employ Louvain method (LV) as our main method and use fast greedy algorithm (FG) for the robustness check of our empirical results.

B. Identification Strategy

After detecting clusters, we measure the concentration of banks' exposures to those clusters. As already mentioned, we employ HHI to measure such concentration. Suppose a set of firms in year t are clustered into C groups, each of which is denoted by $S_{b,t}^1, \cdots, S_{b,t}^C$. Here, we put b to the subscript to explicitly denote that these firm clusters are specific for bank b. Bank b has an outstanding amount of credit supply $L_{b,f,t}$ to firm f at the end of year t. $B_{b,t}$ denotes a set of firms borrowing from bank b at the end of year t. The concentration of exposure of bank b in year t to clusters of borrower firms is thus computed as follows:

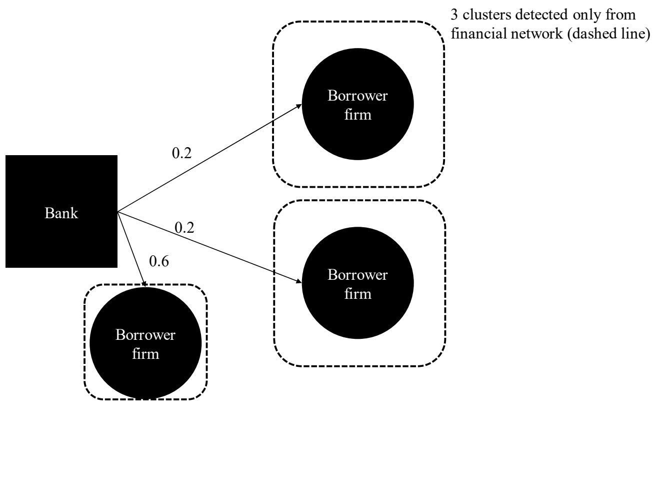
$$HHI_{b,t} = \left\{ \left(\frac{\sum_{f \in S_{b,t}^1} L_{b,f,t}}{\sum_{f \in B_{b,t}} L_{b,f,t}} \right)^2 + \cdots + \left(\frac{\sum_{f \in S_{b,t}^c} L_{b,f,t}}{\sum_{f \in B_{b,t}} L_{b,f,t}} \right)^2 + \cdots + \left(\frac{\sum_{f \in S_{b,t}^C} L_{b,f,t}}{\sum_{f \in B_{b,t}} L_{b,f,t}} \right)^2 \right\}$$

Each squared component in the right-hand side of the equation accounts for one cluster detected from the data. Sum of those squared components is the concentration measure of a bank to the clusters. This $HHI_{b,t}$ becomes larger if selected clusters' loan share out of total loan amounts of bank b's lending at the end of year t (i.e., $\sum_{f \in B_{b,t}} L_{b,f,t}$) increases. A higher number of $HHI_{b,t}$ means that banks loan exposure is tilted toward some specific clusters, and thus concentrated.

By construction, the size of this concentration measure depends both on the lending amount to each firm $L_{b,f,t}$ and the ways of clustering firms $S_{b,t}^{1}, \cdots, S_{b,t}^{C}$. Regarding $L_{b,f,t}$, we have a decent but not comprehensive coverage in terms of *f*. Given it is important to cluster as many firms as possible, we employ the following two alternative ways to proxy for $L_{b,f,t}$ so that we can include firms without outstanding loan information to our cluster detection. First, we use the sale size of firm *f* to proxy for $L_{b,f,t}$. Using this proxy, we assume that all the borrower firms are borrowing proportionally to the size of their sales. As a purpose of the robustness check associated with this assumption, second, we use the number of employees of firm *f* to proxy for $L_{b,f,t}$.

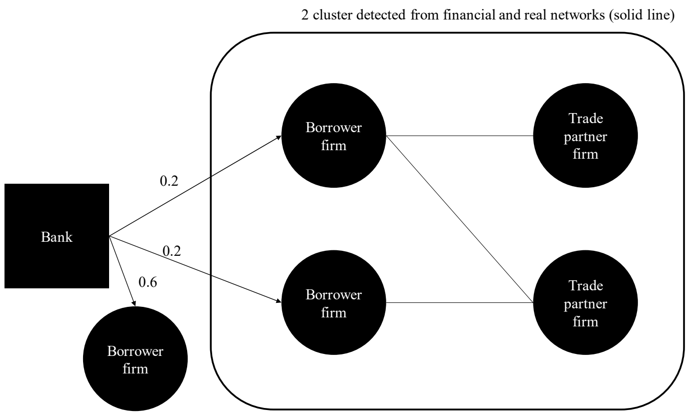
Regarding $S_{b,t}^{1}, \cdots, S_{b,t}^{C}$, we employ the two distinct ways to cluster firms. Our first measure considers all the borrower firms from bank *b* in year *t* for the cluster detection. Figure-4 illustrates the case where three borrower firms are borrowing from the bank. In this illustration, we expect that those three borrower firms are clustered into the three distinct groups as those firms are not transacting with each other at all. Given the share of the borrowing, *HHI-F* is computed as 0.44 (= 0.2^2 + 0.2^2 + 0.6^2).

Figure-4: Clustering based on borrower firms only (*HHI-F*)



Although this measure looks plausible as it covers at least all the borrower firms, banks are in practice likely to know not only those borrower firms but also their transaction partners such as customer and supplier of the borrower firms. The second HHI measure is taking care of this notion. Figure-5 extends the previous example to explicitly show those transaction partners. In this illustration, the two borrower firms are sharing a common partner firms. This additional information on the common transaction partner could affect the way to make clusters. In fact, the two borrower firms are detected to be in the same cluster. Given the share of the borrowing, *HHI-FT* computed in this example is 0.52 (= (0.2 + 0.2)^2 + 0.6^2). In other words, the portfolio concentration of bank *b* increases from 0.44 to 0.52 by taking into account the transaction partners for borrower firms.

Figure-5: Clustering based on borrower firms and their transaction partners (*HHI-FT*)

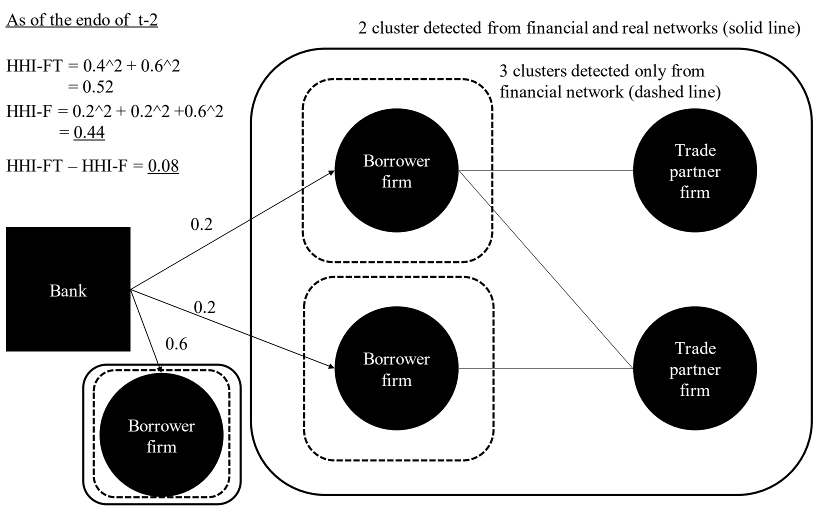


Although it is natural to guess that the *HHI-FT* measure matters for banks loan provision, it is controversial to simply use this measure to identify the causal impact running from banks' portfolio concentration to banks' loan provision as the endogeneity issue associated with the *HHI-FT*. As obvious from Figure-4 and Figure-5, *HHI-FT* is affected both by financial network between banks and borrower firms and real network among firms. Note that the latter is further categorized into the real network among borrower firms and that between borrower firms and their transacting partners not borrowing from bank *b*. Given that *HHI-FT* measure reflects the financial network which could be associated with bank-firm pair-level unobservable factors, credit supply from bank *b* and this *HHI-FT* could be confounded by a common factor and thus not ideal for the determinant of credit supply.

Our third measure *HHI-T* intends to take care of this endogeneity concern. Namely, we compute the *HHI-T* by subtracting *HHI-F* from *HHI-FT* so that *HHI-F* and *HHI-T* are sum up to *HHI-FT*. As the change in financial network, which contains the list of borrowing firms, could be taken into account when we measure *HHI-F*, the residual *HHI-T* could be considered as a component *HHI-FT* which is unrelated to the structure of bank-to-firm network. In addition to the simple subtraction of *HHI-F* from *HHI-FT*, we also estimate the orthogonal component of *HHI-FT* to *HHI-F* by regression the latter on the former to extract the residuals. We implement this analysis as our robustness check for the decomposition of *HHI-FT* into *HHI-F* and *HHI-T*.

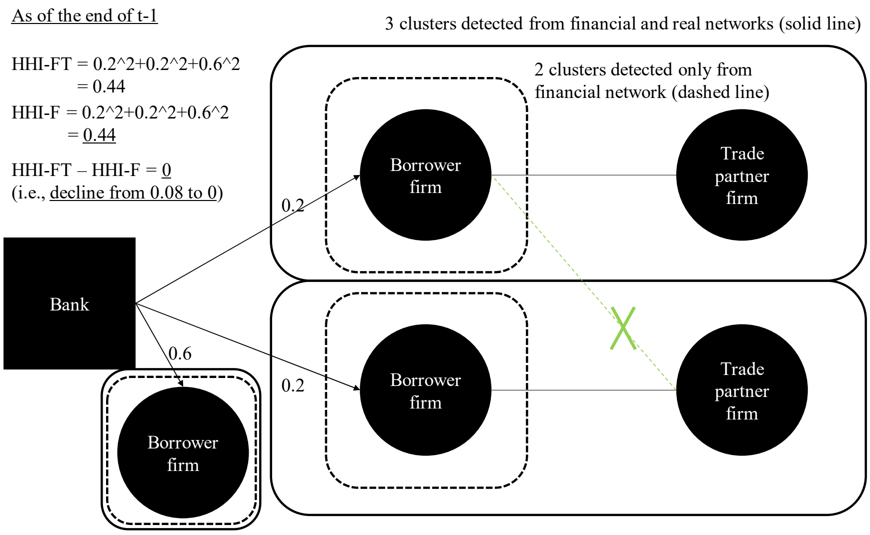
Below, we provide intuition about how this *HHI-T* measure works for our purpose. Suppose in the end of *t-2*, the financial and real networks take the form in Figure-6. This is exactly same as in Figure-4 and Figure-5 where the portfolio concentration becomes larger when taking into account the transaction partners of borrower firms.

Figure-6: Networks in the end of *t-2*



In *t-1*, the transaction relation between one of the borrower firms and the (previously common) transaction partners are dissolved as shown in Figure-7. As a result, while *HHI-F* is unchanged, *HHI-FT* decreases from 0.52 to 0.44.

Figure-7: Networks in the end of *t-1*



The most important point in Fugure-7 is that *HHI-T* measured as a difference between *HHI-FT* and *HHI-F* is decreasing from 0.08 to 0. This reduction of *HHI-T* (= *HHI-FT* - *HHI-F*) is solely attributed to the change in real network, which is exogenous under our identification assumption. We could predict possible reaction of credit supply in *t*. If bank *b* cares about loan concentration, after observing the reduction of *HHI-FT* due to the reduction of *HHI-T*, it can supply more credit to the firms, which we would like to empirically test.

Before formulating our estimation equation, we would like to mention another possible way to extract the exogenous component of *HHI-FT* to banks. One possible way is to employ instrument variables directly correlated with *HHI-T* but not directly correlated with banks' credit supply. However, given possible geographical concentration of banks, borrower firms, and their transaction partners, it is not straightforward to find such instrument variables. One candidate is natural disasters directly hitting the relationships between borrower firms and their transaction partners. We put these for our future research questions.

In our estimation, we use both the *HHI-F* and *HHI-T* as the potential determinants of banks' credit supply along with another concentration measure in regard of industry concentration as well as bank-level time-invariant fixed-effect and firm-year-level time-variant fixed-effect as in the extant studies.

$$LN(L_{b,f,t}) = F(\boldsymbol{X}_{b,\,t-1},\ \boldsymbol{Z}_{b,\,f,t-1}) + \mu_{b,f,t} + \varepsilon_{b,f,t} \;\; for\ t = 2010, \cdots, 2019$$

Here, $\boldsymbol{X}_{b,\,t-1}$ contains *HHI-F*, *HHI-T*, and industry-level HHI. We should note that the response of $L_{b,f,t}$ with respect to $\boldsymbol{X}_{b,\,t-1}$ is highly heterogeneous and crucially depending on how each firm is creditworthy and which cluster each firm is belonging to. Suppose a bank is facing the rise in *HHI-T*. It is natural to conjecture that the response of credit supply to the change in HHI depends on firms' creditworthiness. Also, if the bank cares about its portfolio concentration on clusters of firms as we illustrated above, it may attempt to reallocate credit so as to reduce the concentration. Along this process, firms in a cluster with higher share are expected to experience the reduction of credit while this might not be the case for firms in a cluster with lower share. To take care of this conjecture, we let $\boldsymbol{Z}_{b,\,f,t-1}$ include the credit score of the firm *f* ($credit\ score_{b,f,t-1}$) as well as the number of firms in a cluster to which firm *f* is belonging to ($density_{b,f,t-1}$). For the computation of density, we employ either equal-weighted, sales-weighted, and weighted by the number of employees so as to check the robustness of our results against the way to compute the density of clusters. The function $F(\cdot)$ generates the interaction terms between various HHI measures and those $\boldsymbol{Z}_{b,\,f,t-1}$. These terms accounts for the heterogeneous reaction of credit supply to those HHI measures conditional on $\boldsymbol{Z}_{b,\,f,t-1}$. The estimation equation always contains firm-year fixed effects, which accounts for firm-level time variant factors including credit demand. In addition to this fixed effects, we include the following four sets of fixed effects. As a first specification, we further include bank fixed-effect. Given the potential importance of the relations between firms and banks, as a second specification, we replace the bank fixed-effect with bank-firm pair-level fixed effects, which is suggested by, for example, Amiti and Weinstein (2018). Third, alternatively, we replace the bank fixed effect in the first specification with bank-year fixed effect given our estimation equation does not necessarily contain rich set of time-variant bank attributes. Finally, as our fourth and the most comprehensive specification, we include bank-year fixed effects and bank-firm pair-level fixed effects on top of the firm-year fixed effects. All the explanatory variables are demeaned so that we can directly interpret the coefficients. As we detail in the section of robustness check, we also estimate this equation for two ways of clustering methods (i.e., FG or LV) and industry classification (one-digit or two-digit).

III. Data

We use the three datasets, all of which are obtained from Tokyo Shoko Research Inc. (TSR) based on the joint research agreement between Hitotsubashi University and TSR. TSR is one of the largest credit reporting agencies and provide proprietary database accounting for a large part of Japanese firms.

First dataset is firm-level panel data. It contains basic firm characteristics such as location, industry classification, and financial statement information. Second dataset is firm-to-firm transaction (i.e., real) network data. It specifies in each year a list of customer firms, supplier firms, and shareholder firms for each firm.[3] Third dataset is bank-to-firm credit supply data. All the data are extracted from TSR master database as of the end of December in each year. Regarding the third data, as of 2019, it contains 10 large banks, 64 first-tier regional banks, and 38 second-tier regional banks. In cases where banks experienced mergers and acquisitions, we treat the banks with larger assets prior to the event as continuing banks. All the data are for the periods from 2010 to 2019.

First, Panel (a) of Table 1 shows the summary statistics of firm attributes. All the definitions are provided in the table. Among those attributes, $score_{f,t}$ accounts for the creditworthiness score provided by TSR. The variable takes the value from 0 to 100 and

[3] For cluster detection, we could either include or not include the shareholder firms as the inputs. The results reported in the present paper is not qualitatively affected by this treatment. In the present paper, we show the results of the cluster detection based on the data including the shareholding relation as a type of real network.

the larger number corresponds to higher creditworthiness. $rate_{f,t}$ is a firm-level variable accounting for the ratio of interest expense of firm *f* divided by the liability held by the firm, which we use for an additional exercise.

Table-1: Summary statistics

Panel (a): Summary statistics of firm characteristics

Variable	Definition	#samples	25%tile	median	mean	75%tile	sd
Firm Characteristics							
$\log(sales_{f,t})$	The logarithm of firm *f*'s gross sales.	1,159,390	5.3	5.7	5.8	6.2	0.7
$\#(employees)_{f,t}$	The number of firm *f*'s employees.	1,080,580	8.0	18.0	83.9	45.0	780
$score_{f,t}$	A score that summarizes an overall performance of firm *f* provided by TSR. It takes values from 0 to 100.	1,080,580	48.0	51.0	51.5	55.0	6
$rate_{f,t}$	Interest expense of firm *f* divided by liabilities of firm *f*.	1,080,580	1.0	1.8	3.8	2.6	229

Panel (b) of Table 1 shows the summary statistics of bank attributes. All the definitions are provided in the table. The panel lists the two cluster-HHI measures based on the two alternative detection algorithms and the two industry-HHI measures based on the large or intermediate industry classification. We report the two sets of those four HHIs for *HHI-FT* and *HHI-F*. In our dataset, banks hold on average 2,000 borrower firms that hold 10,000 real transactions. Reflecting the fact that the coverage of our data set is not necessarily complete, the number of borrowing firms looks rather limited in the comparison with the actual borrowing firms we can imagine. Nonetheless, the large standard deviation suggests that the banks included in our dataset consist of various banks ranging from small financial institutions to so-called mega banks. From the summary statistics of $\#(LV\ clusters)_{b,t}$, we can infer that banks lend to the firms belonging to 17 clusters on average. Again, relatively large standard deviation of $\#(LV\ clusters)_{b,t}$ (i.e., 5) suggests that banks included in our empirical study are highly heterogeneous.

Panel (b): Summary statistics of bank characteristics

Variable	Definition	#samples	25%tile	median	mean	75%tile	sd
Bank Characteristics							
LV $HHI_{b,t}^{F+T}$	The value of HHI computed within clusters based on Louvain method applied to bank *b*.	1,088	0.07	0.08	0.09	0.10	0.04
FG $HHI_{b,t}^{F+T}$	The value of HHI computed within clusters based on Fast Greedy method applied to bank *b*.	1,088	0.11	0.14	0.15	0.17	0.05
Industry with large classification $HHI_{b,t}^{F+T}$	The value of HHI computed within clusters of the large classification industry applied to bank *b*.	1,088	0.22	0.26	0.26	0.29	0.05
Industry with intermediate classification $HHI_{b,t}^{F+T}$	The value of HHI computed within clusters of the intermediate classification industry applied to bank *b*.	1,088	0.05	0.06	0.07	0.07	0.04
LV $HHI_{b,t}^{F}$	The value of HHI computed within clusters based on Louvain method applied to bank *b*.	1,088	0.09	0.12	0.13	0.14	0.09
FG $HHI_{b,t}^{F}$	The value of HHI computed within clusters based on Fast Greedy method applied to bank *b*.	1,088	0.11	0.14	0.15	0.17	0.07
Industry with large classification $HHI_{b,t}^{F}$	The value of HHI computed within clusters of the large classification industry applied to bank *b*.	1,088	0.24	0.28	0.30	0.34	0.09
Industry with intermediate classification $HHI_{b,t}^{F}$	The value of HHI computed within clusters of the intermediate classification industry applied to bank *b*.	1,088	0.06	0.08	0.11	0.11	0.11
$\#(firms)_{b,t}$	The number of firms belonging to bank *b*'s supply chain network.	1,088	580	1,001	2,268	1,908	5,155
$\#(transactions)_{b,t}$	The number of transactions belonging to bank *b*'s supply chain network.	1,088	1,366	2,676	9,806	6,000	32,252
LV $modularity_{b,t}$	The value of modularity calculated from Louvain method applied to bank *b*.	1,088	0.57	0.61	0.62	0.87	0.09
FG $modularity_{b,t}$	The value of modularity calculated from Fast Greedy method applied to bank *b*.	1,088	0.55	0.59	0.59	0.66	0.14
#(LV $clusters)_{b,t}$	The number of clusters from Louvain method applied to bank *b*.	1,088	14.0	16.0	16.8	20.0	5.0

Panel (c) of Table 1 summarizes the variables measured for firm-bank pair. The log of the loan outstanding is measured for each firm-bank pair in the end of each year. The other two variables account for the loan term, which we use for an additional exercise. First, $Short\ term\ Loan\ Ratio_{b,f,t}$ accounts for the share of short-term loan provided by a bank b to a firm f out of the total loan outstanding from the bank b to firm f as of the end of each year. Second, $Collateral_{b,f,t}$ is a dummy variable taking the value of one if a bank b collects some types of collateral for its loan provision to a firm f and taking zero otherwise.

Panel (c): Summary statistics of bank-firm pair and bank-cluster characteristics

Variable	Definition	#samples	25%tile	median	mean	75%tile	sd
Bank-Firm Characteristics							
$\log(Exposure_{b,f,t})$	The logarithm of exposure from bank *b* to firm *f*.	545,859	4.4	4.8	4.8	5.3	0.7
$Short\text{-}term\ Loan\ Ratio_{b,f,t}$	The ratio of short-term loan to total exposure from bank *b* to firm *f*.	539,744	0.4	0.9	0.7	1.0	0.4
$Collateral_{b,f,t}$	The probability of collateral collection if bank *b* gives loan to firm *f*.	608,185	0.0	0.0	0.4	1.0	0.5

IV. Results

In this section, we present the results of our cluster detection, measured concentration of bank portfolio, and the response of banks' credit supply to their portfolio concentration.

A. Cluster Detection

As a first step of our empirical analysis, we implement cluster detection by using firm-to-firm supply chain data. Figure-8 depicts the computed maximum modularity for a given number of clusters in the case of measuring HHI-FT. Choosing the number of clusters corresponding to the maximum modularity, we determine the optimal number of clusters. As this cluster detection needs to be done for each bank, we repeat this procedure the number of banks times the number of years in our data periods.

Figure-8: Reaction of credit supply in *t*

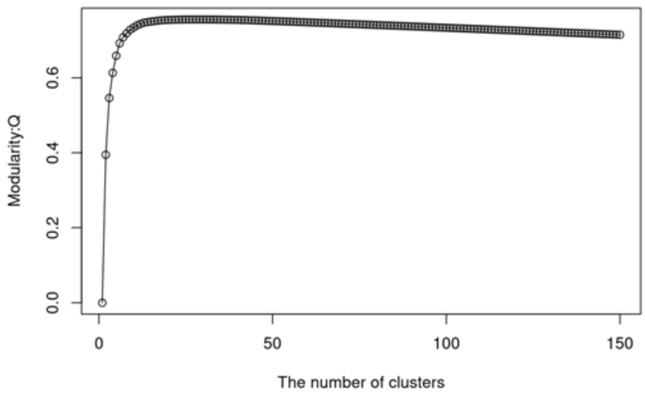
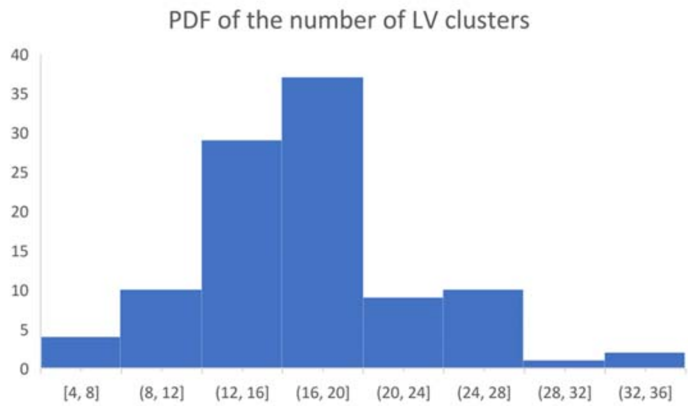


Figure-9 depicts the distribution of the number of clusters, which are obtained from the aforementioned optimization. As the number of borrowing firms for a bank largely varies, the optimized number of detected clusters ranges from 4 to 36. The mean and median of the number is around 16.

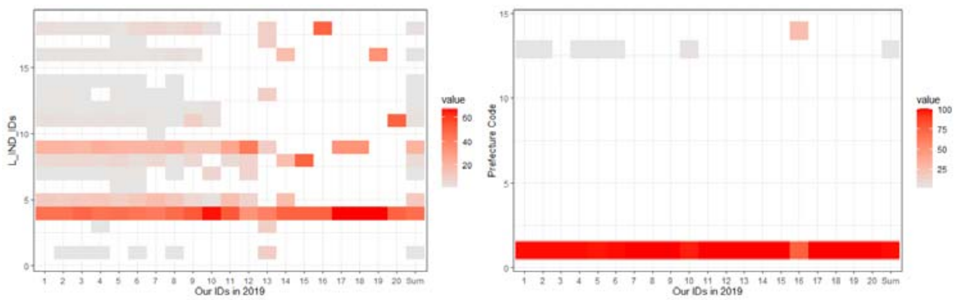
Figure-9: Distribution of the number of clusters held by a bank



As an example of detected clusters for a specific bank, Figure-10 and Figure-11 depicts the detected clusters for a regional bank and a large (i.e., mega) bank. The left and right figures of Panel (a) for those two banks show the industry (left panel) and prefectural (right panel) distributions of firms, which is measured in the vertical axis, belonging to each specific cluster indexed in the horizontal axis. First, the firms in a cluster belong to various industries in the cases of both banks. Second, while the firms belonging to a cluster in the case of the large bank tend to spread over various prefectures, that in the case of a regional bank is concentrated in a prefecture.

Figure-10: An example of detected clusters for a regional bank

Panel (a): Distributions of firms over industries (left) and prefectures (right)

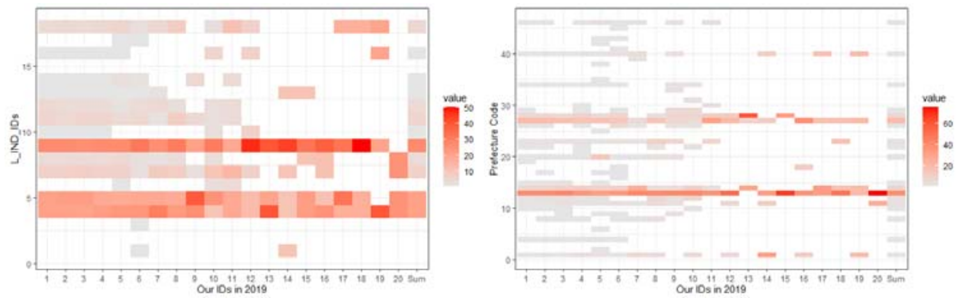


Panel (b): Selected clusters for a regional bank

The latter finding on the geographical concentration especially in the case of the regional bank raises a concern that the detected clusters are nothing but a replica of agglomeration patterns of borrowing firms. While we can negate this claim by taking a look at the right figure of Panel (a) in Figure-11, it is informative to explicitly see the geographical location of firms in a cluster more explicitly. The two figures of Panel (b) in Figure-10 and Figure-11 take up two clusters for each bank and depict the geographical location of firms in the cluster. First, the left figure in the case of the regional bank (i.e., Panel (b) in Figure-10) shows that firms in the cluster spread over various municipalities in the region. Although firms in the cluster depicted by the right figure locate more concentrated way, they still spread over distant cities.

Figure-11: An example of detected clusters for a large bank

Panel (a): Distributions of firms over industries (left) and prefectures (right)



Panel (b): Selected clusters for a large bank

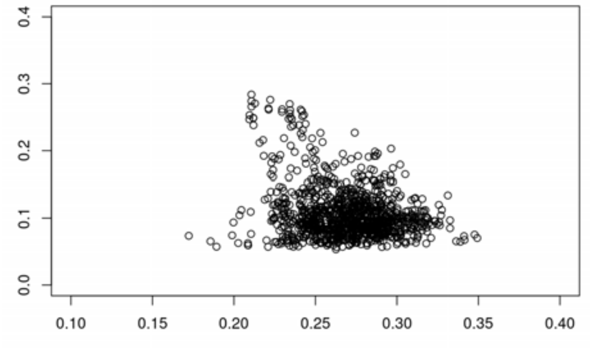
Second, it is same for the large bank. Namely, the left figure in the case of the large bank (i.e., Panel (b) in Figure-11) shows again that firms in the cluster spread over various prefectures in Japan, which is implied by the right figure of Panel (a) in Figure-11. Although firms in the cluster depicted by the right figure of Panel (b) in Figure-11 concentrate more, they still spread over the central to western regions of Japan.

B. Measures for Loan Concentration

Based on the detected clusters, we measure *HHI-FT*, *HHI-F*, and the difference of them *HHI-T* (i.e., *HHI-FT – HHI-F*), which we cluster-HHI, for each bank and year. In addition to these cluster-HHIs, we also compute the HHI in terms of industry concentration for each bank and year (industry-HHI).

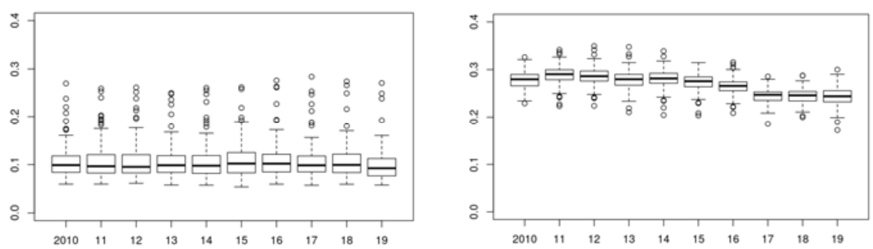
We have already confirmed that firm in various industries belong to a detected cluster. Nonetheless, it is important to see how those two HHI indexes comove and make sure that the cluster-HHI and the industry-HHI are not highly correlated. Figure-12 plots the cluster-HHI measure in the vertical axis and the industry-HHI in the horizontal axis, repsectively. Evidently, those two measures are negatively correlated (correlation coefficient = -0.249) and we reject the null hypothesis that those are uncorrelated in 1% significance level.

Figure-12: Cluster-HHI (vertical axis) and industry-HHI (horizontal axis)



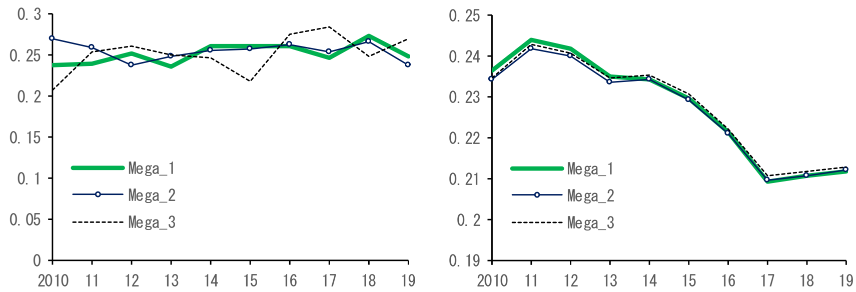
The two panels of Figure-13 depict the distribution of cluster-HHI and industry-HHI over years. While the median level of the industry concentration becomes lower over the years, the distribution of portfolio concentration on clusters of firms are stable.

Figure-13: Cluster-HHI (left panel) and industry-HHI (right panel)



To see the dynamics of those two concentration measures in representative cases, the two panels of Figure-14 depict the same two HHI indexes for the measure three large banks (i.e., Mega_1 to Mega_3). As we confirm from Figure-10, while the industry-HHI has been declining, the cluster-HHI exhibits stable dynamics.

Figure-14: Cluster-HHI (left panel) and industry-HHI (right panel) for 3 banks



C. Credit Supply

We are ready to estimate the responses of credit supply to the portfolio concentration measures. As we need to employ the outstanding amount of loan from each bank to each borrower firm, we focus on the bank-firm pair for which we have such bank-firm pair-level loan outstanding information.

It should be noted that we are using all the bank-firm pair-level information for our cluster detection and the computation of various HHI measures. The three panel in Figure-15 compare the firm sales, the number of employees, and credit score for the data used in cluster detection (noted as “all”) and the data for our panel estimation (noted as “processed”). It is clear that the firms considered in our panel estimation is larger in terms of sales and the number of employees as well as better in its creditworthiness. While the fact that we use narrower sets of firms for our credit supply estimation cast some concerns on the external validity of our estimation results, we can at least conjecture that the obtained estimation results are conservative in the sense that the firms considered in the panel estimation tends to be less likely to suffer from the shortage of credit supply. Thus, if we can confirm the statistical relationship between banks’ credit supply and the concentration measures in the current dataset, it is likely to have the qualitatively similar results for the entire economy.

Figure-15: Data for cluster detection (“all”) and panel estimation (“processed”)

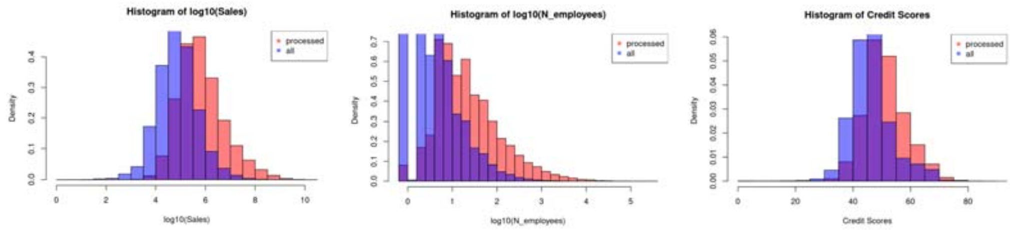


Table-2 summarize the results of our baseline credit supply estimation using the two HHI measures. $HHI^{F+T}_{b,t-1}$ denotes the HHI-FT measure from the cluster detection based on both the bank-to-firm and firm-to-firm (i.e., up to one link) information. We consider that this measure is what banks are actually monitoring. $HHI^{F}_{b,t-1}$ denotes the HHI-F measure from the cluster detection only on the bank-to-firm information. Using these two measures, we compute HHI-T measure as $HHI^{T}_{b,t-1} = (HHI^{F+T}_{b,t-1} - HHI^{F}_{b,t-1})$, which exhibits exogenous variations for lender banks. As a source of heterogeneous responses of credit supply to cluster-HHI, we use the credit score of the firm $credit\ score_{b,f,t-1}$. Each column corresponds to a different specification in terms of fixed effects.

Regardless of how we set up the fixed effects, we confirm that the coefficient of the interaction-term between *HHI-T* (i.e., $HHI^{F+T}_{b,t-1} - HHI^{F}_{b,t-1}$) and $credit\ score_{b,f,t-1}$ is positive and statistically away from zero at 1% statistically significance level. This means, facing higher *HHI-T* in *t-1*, banks tend to decrease (increase) their credit supply in *t* to the firms having lower (higher) creditworthiness as of *t-1*. The association between $\log(Exposure_{b,f,t})$ and *HHI-T* becomes weaker as we control for more fixed effects. Among those fixed effects, the inclusion of bank-year fixed effects, which subsume all the bank-year variation, results in the reduction of marginal impacts with respect to *HHI-T*. The estimated coefficient of the interaction-term between *HHI-T* and $credit\ score_{b,f,t-1}$ is 0.042. Given the standard deviations of *HHI-T* and $credit\ score_{b,f,t-1}$ are 0.078 (not reported in the tables for summary statistics) and 6, respectively, when a bank’s *HHI-T* increases by one standard deviation in *t-1*, a borrower firm with the credit score lower than average by one standard deviation in *t-1* receives 1.97% point (i.e., 100*0.042*0.078*6) smaller loan provision than the case of a bank not experiencing the change in *HHI-T* and a firm with average creditworthiness. This is not quantitatively negligible given the average growth rate of firm borrowing in our sample period is 1.5%.

Table-2: Baseline estimation using credit score

Dependent variable: $\log(Exposure_{b,f,t})$	Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.	
Transaction												
$HHI_{b,t-1}^{F}$	0.035	0.236		-0.427	0.132	***						
$credit\ score_{b,f,t-1} \times HHI_{b,t-1}^{F}$	0.127	0.018	***	0.053	0.018	***	0.120	0.019	***	0.068	0.019	***
$credit\ score_{b,f,t-1}$	0.259	0.057	***	0.005	0.032		0.269	0.058	***	0.016	0.033	
$HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F}$	0.036	0.185		-0.144	0.102							
$credit\ score_{b,f,t-1} \times (HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F})$	0.093	0.017	***	0.040	0.015	***	0.082	0.018	***	0.042	0.015	***
Industry												
$HHI_{b,t-1}$	0.109	0.120		0.153	0.069	**						
$credit\ score_{b,f,t-1} \times HHI_{b,t-1}$	-0.019	0.010	*	-0.017	0.010	*	-0.020	0.010	**	-0.023	0.010	**
$density_{b,f,t-1}$	0.497	0.050	***	0.194	0.151		0.495	0.050	***	0.165	0.157	
Constant	11.336	0.002	***	11.369	0.004	***	11.337	0.002	***	11.369	0.004	***
Firm-Year fixed-effect	yes			yes			yes			yes		
Bank fixed-effect	yes			no			no			no		
Bank-Firm fixed-effect	no			yes			no			yes		
Bank-Year fixed-effect	no			no			yes			yes		
HHI *weight*	sales			sales			sales			sales		
HHI *calculation*	residual			residual			residual			residual		
density weight	no			no			no			no		
clustering methodology	Louvain			Louvain			Louvain			Louvain		
industry classification	large			large			large			large		
#(obs)	268,990			243,599			268,984			243,593		
F	23.850			2.960			35.270			3.420		
Adj. R-squared	0.561			0.904			0.561			0.904		
Within R-squared	0.001			0.000			0.001			0.000		

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table-3 summarize the results of the similar estimation using the number of firm in each cluster ($density_{b,f,t-1}$) instead of $credit\ score_{b,f,t-1}$. In the first and the third columns where we are not controlling for bank-firm pair-level fixed effects, the coefficient of the interaction-term between *HHI-T* (i.e., $HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F}$) and $density_{b,f,t-1}$ is negative and statistically away from zero at 1% statistically significance level. This means that facing higher *HHI-T* in *t-1*, banks tend to decrease (increase) their credit supply in *t* to the firms belonging to clusters consisting of more (less) firms as of *t-1*. Although such reallocation of credit from more concentrated clusters to less looks natural as a response of banks to higher concentration of their exposure in terms of clusters, this result is not necessarily robust against the inclusion of bank-firm pair-level fixed effects (i.e., the second and the fourth columns).

Table-3: Baseline estimation using density

Dependent variable: **log(*Exposure* $_{b,f,t}$)**	Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.	
Transaction												
$HHI_{b,t-1}{}^{F}$	0.255	0.235		-0.318	0.128	**						
$density_{b,f,t-1} \times HHI_{b,t-1}{}^{F}$	-9.031	2.051	***	0.345	1.225		-7.995	2.341	***	1.617	1.319	
$density_{b,f,t-1}$	0.290	0.058	***	0.006	0.033		0.291	0.058	***	0.009	0.033	
$HHI_{b,t-1}{}^{F+T}$ - $HHI_{b,t-1}{}^{F}$	0.166	0.183		-0.057	0.097							
$density_{b,f,t-1} \times (HHI_{b,t-1}{}^{F+T} - HHI_{b,t-1}{}^{F})$	-7.723	1.830	***	1.263	1.067		-8.344	1.994	***	0.649	1.126	
Industry												
$HHI_{b,t-1}$	0.041	0.120		0.110	0.068							
$density_{b,f,t-1} \times HHI_{b,t-1}$	-0.648	0.338	*	-0.748	0.360	**	-0.733	0.346	**	-0.831	0.374	**
$density_{b,f,t-1}$	0.517	0.050	***	0.222	0.152		0.512	0.050	***	0.192	0.157	
Constant	11.344	0.003	***	11.370	0.004	***	11.343	0.003	***	11.370	0.004	***
Firm-Year fixed-effect	yes			yes			yes			yes		
Bank fixed-effect	yes			no			no			no		
Bank-Firm fixed-effect	no			yes			no			yes		
Bank-Year fixed-effect	no			no			yes			yes		
HHI *weight*	sales			sales			sales			sales		
HHI *calculation*	residual			residual			residual			residual		
density weight	no			no			no			no		
clustering methodology	Louvain			Louvain			Louvain			Louvain		
industry classification	large			large			large			large		
#(obs)	268,990			243,599			268,984			243,593		
F	19.820			2.260			30.250			1.550		
Adj. R-squared	0.561			0.904			0.561			0.904		
Within R-squared	0.001			0.000			0.001			0.000		

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table-4 summarizes the results based on the specification including both the $credit\ score_{b,f,t-1}$ and $density_{b,f,t-1}$ as well as *HHI-T*. First, the aforementioned result on the positive association between $\log(Exposure_{b,f,t})$ and the interaction-term between *HHI-T* and $credit\ score_{b,f,t-1}$ is obtained regardless of the choice of fixed effects. The size of the estimated coefficient in the most comprehensive specification (i.e., fourth column) is virtually same as we report in Table-2 (i.e., 0.042). Thus, the heterogeneous impacts originating from the hike in *HHI-T* and the level of the credit score is confirmed to be sizable in this estimation. Second, the coefficient of the interaction-term between *HHI-F* and $credit\ score_{b,f,t-1}$ is also positive and statistically away from zero at 1% statistically significance level. We confirm this result when we control for the firm-year fixed effects, bank-firm pair-level fixed effects, bank-year fixed effects, and *HHI-T*. Thus the estimated coefficients account for the response of $\log(Exposure_{b,f,t})$ to the change in *HHI-F* due to the change in transaction relations among the borrower firms and/or the lending relations between the bank and the borrowing firms as of *t-1*.

Table-4: Baseline estimation using both credit score and density

Dependent variable: $\log(Exposure_{b,f,t})$	Coef.	S.E.		Coef.	S.E.		Coef.	S.E.		Coef.	S.E.	
Transaction												
$HHI_{b,t-1}^{F}$	0.056	0.237		-0.422	0.132	***						
$density_{b,f,t-1} \times HHI_{b,t-1}^{F}$	-7.127	2.169	***	-0.017	1.289		-6.064	2.414	**	1.334	1.379	
$credit\ score_{b,f,t-1} \times HHI_{b,t-1}^{F}$	0.124	0.018	***	0.051	0.018	***	0.116	0.019	***	0.066	0.019	***
$density_{b,f,t-1} \times credit\ score_{b,f,t-1} \times HHI_{b,t-1}^{F}$	-0.987	0.308	***	0.123	0.192		-1.035	0.321	***	0.107	0.193	
$density_{b,f,t-1}$	0.302	0.058	***	0.003	0.033		0.305	0.059	***	0.007	0.033	
$HHI_{b,t-1}^{F+T}$ - $HHI_{b,t-1}^{F}$	0.023	0.185		-0.140	0.102							
$density_{b,f,t-1} \times (HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F})$	-6.296	1.931	***	0.795	1.130		-6.537	2.075	***	0.286	1.188	
$credit\ score_{b,f,t-1} \times (HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F})$	0.091	0.017	***	0.039	0.015	***	0.079	0.018	***	0.042	0.015	***
$density_{b,f,t-1} \times credit\ score_{b,f,t-1} \times (HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F})$	-0.807	0.286	***	0.192	0.171		-0.843	0.296	***	0.163	0.172	
Industry												
$HHI_{b,t-1}$	0.075	0.121		0.148	0.070	**						
$density_{b,f,t-1} \times HHI_{b,t-1}$	-0.690	0.342	**	-0.825	0.366	**	-0.797	0.350	**	-0.916	0.379	**
$credit\ score_{b,f,t-1} \times HHI_{b,t-1}$	-0.024	0.010	**	-0.020	0.010	**	-0.026	0.010	**	-0.026	0.010	**
$density_{b,f,t-1} \times credit\ score_{b,f,t-1} \times HHI_{b,t-1}$	-0.072	0.055		0.045	0.053		-0.083	0.056		0.049	0.054	
$density_{b,f,t-1}$	0.503	0.050	***	0.229	0.152		0.499	0.050	***	0.193	0.157	
Constant	11.341	0.003	***	11.370	0.004	***	11.341	0.003	***	11.369	0.004	***
Firm-Year fixed-effect	yes			yes			yes			yes		
Bank fixed-effect	yes			no			no			no		
Bank-Firm fixed-effect	no			yes			no			yes		
Bank-Year fixed-effect	no			no			yes			yes		
HHI *weight*	sales			sales			sales			sales		
HHI *calculation*	residual			residual			residual			residual		
density weight	no			no			no			no		
clustering methodology	Louvain			Louvain			Louvain			Louvain		
industry classification	large			large			large			large		
#(obs)	268,990			243,599			268,984			243,593		
F	16.580			2.320			19.690			2.390		
Adj. R-squared	0.561			0.904			0.561			0.904		
Within R-squared	0.001			0.000			0.001			0.000		

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

D. Robustness

We have confirmed the association between banks' credit supply and their portfolio concentration, which is conditional on borrowing firms' creditworthiness. In this subsection, we summarize the robustness of those empirical results. All the results are in the appendix. First, we confirm the results when we use the number of employees as the weight for computing HHI (Table-A1). Second, the reported results are obtained when we compute *HHI-T* by regressing *HHI-FT* on *HHI-F* and taking out the residuals (Table-A2). Third, the results are not altered even we use the sales of the number of employees of firms to compute the density (Table-A3). Fourth, the reported results are confirmed when we use an alternative method for cluster detection (i.e., FG, the second column inTable-A4). Fifth, the results do not change when we use a finer industry classification (i.e., two-digit, the third column in Table-A4).

V. Discussion

Although we have successfully identified the pattern that banks do take care of their portfolio concentration on clusters of firms, there should be more features we can potentially extract from the current analytical setup.

First, we are interested in to what extent the identified association between supply chain network and credit supply depends on the bank attributes. While the responses of banks to the change in their exposure (i.e., concentration) to clusters are natural, it is not necessarily obvious all the banks are doing such a sophisticated risk management. Given this discussion, we compute the average credit score of each bank over the entire sample periods and split the sample based on the average score of borrowing firms. In the first and the second columns of Table 5, we show the estimation results based on the subsamples of banks exhibiting the top 20% and the bottom 20% of the average score of borrowing firms, respectively.[4] The former and latter presumably account for the pattern of credit supply of

[4] As the number of borrowing firms for a specific bank crucially depends on the size of the bank, which are correlated with the average credit score of each bank's borrowers in our dataset, the number of observation is different in each subsample. The estimation results based on the other specifications are showed in Table-A5 to Table-A7 in the appendix.

better and worse banks in terms of their borrowers' creditworthiness. Somewhat intuitively, only the former case (i.e., "better" banks) exhibit the patterns reported in the previous section. The size of the estimated coefficient of the interaction-term between *HHI-T* and $credit\ score_{b,f,t-1}$ (i.e., 0.060) suggests that the responsiveness of the bank's credit supply to the concentration of loan exposure to clusters is 40% higher than the average estimates. Contrary to this result, the bank's credit supply does not respond to the change in the concentration of loan exposure to clusters when the average creditworthiness of borrower firms for a bank is in the bottom 20% of all the banks.

Table-5: Subsample estimation using both credit score and density

Bank subgroup	Borrower firms' average credit score belongs to top 20%				Borrower firms' average credit score belongs to bottom 20%			
Dependent variable: $\log(Exposure_{b,f,t})$	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Transaction								
$HHI_{b,t-1}^{F}$								
$density_{b,f,t-1} \times HHI_{b,t-1}^{F}$	-3.380	4.602	2.480	2.903	-11.056	11.797	-5.296	6.081
$credit\ score_{b,f,t-1} \times HHI_{b,t-1}^{F}$	0.039	0.034	0.080	0.027 ***	-0.276	0.088 ***	0.058	0.061
$density_{b,f,t-1} \times credit\ score_{b,f,t-1} \times HHI_{b,t-1}^{F}$	-0.475	0.579	-0.338	0.378	3.587	0.927 ***	0.219	0.517
$density_{b,f,t-1}$	0.342	0.111 ***	0.010	0.069	0.810	0.541	0.394	0.286
$HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F}$								
$density_{b,f,t-1} \times (HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F})$	-7.568	4.081 *	0.873	2.598	-1.275	13.042	-7.140	6.855
$credit\ score_{b,f,t-1} \times (HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F})$	0.094	0.033 ***	0.060	0.029 **	-0.442	0.120 ***	-0.145	0.093
$density_{b,f,t-1} \times credit\ score_{b,f,t-1} \times (HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F})$	-0.791	0.469 *	0.091	0.302	-1.191	1.550	0.659	0.788
Industry								
$HHI_{b,t-1}$								
$density_{b,f,t-1} \times HHI_{b,t-1}$	-9.792	1.383 ***	2.039	1.795	0.182	3.278	-1.888	3.022
$credit\ score_{b,f,t-1} \times HHI_{b,t-1}$	0.044	0.022 **	-0.000	0.031	0.839	0.145 ***	-0.070	0.105
$density_{b,f,t-1} \times credit\ score_{b,f,t-1} \times HHI_{b,t-1}$	0.679	0.182 ***	0.265	0.221	-1.787	0.590 ***	-0.053	0.445
$density_{b,f,t-1}$	1.132	0.154 ***	0.229	0.571	-1.094	0.986	0.706	1.650
Constant	11.649	0.008 ***	11.642	0.024 ***	11.435	0.031 ***	11.371	0.038 ***
Firm-Year fixed-effect	yes		yes		yes		yes	
Bank fixed-effect	no		no		no		no	
Bank-Firm fixed-effect	no		yes		no		yes	
Bank-Year fixed-effect	yes		yes		yes		yes	
HHI *weight*	sales		sales		sales		sales	
HHI *calculation*	residual		residual		residual		residual	
density weight	no		no		no		no	
clustering methodology	Louvain		Louvain		Louvain		Louvain	
industry classification	large		large		large		large	
#(obs)	95,561		86,061		5,676		5,188	
F	11.310		1.630		6.420		0.930	
Adj. R-squared	0.635		0.902		0.652		0.935	
Within R-squared	0.002		0.000		0.024		0.005	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Second, we should take a look at how banks change (or do not change) their lending condition such as maturity, collateral, and interest rates. Based on our preliminary exercises (not reported in the present paper), facing higher portfolio concentration on clusters of firms, the firms with lower creditworthiness are also facing shorter loan maturity under some specifications. Somewhat consistent with this result, the probability of collateral collection for the aforementioned case becomes lower although we still need to check the robustness of the result in future researches. Regarding the interest rates, we cannot employ the exactly same empirical framework as we do not have pair-level interest rates. Following the extant studies (Khawaja and Mian 2008; Jimenez et al. 2012; Hosono et al. 2016), we estimate firm-level panel estimation by using the average portfolio concentration over the lender banks to each firm. The result implies that along the change in the volume of credit supply, maturity, and collateral collection, we do not observe the change in interest rate. The last result has some policy implication that hike in portfolio concentration leads to substantial reallocation of credit but not drastic change in the loan price. This means at least over our sample periods, it is not the case for banks facing higher concentration on clusters of firms to exhibit monopoly power. Those banks would rather reallocate the credit so that they can manage the credit risk entailed in their portfolio.

VI. Conclusion

In the present paper, we examine how banks' credit supply responds to the concentration of their loan portfolio on clusters of firms linked by supply chain. Using the granular data on banks' credit supply as well as borrower firms' transaction partners, we empirically detect clusters of firms, measure each bank's portfolio concentration both in terms of supply chain and industry, then estimate the impact of the portfolio concentration on banks' credit supply. Our findings suggest that facing higher portfolio concentration on clusters of firms, banks reduce credit supply to firms with lower creditworthiness.

Firm-to-firm transaction relationships (i.e., supply chain network) is formulated from various motivations including firms' real activities. While manufacturing firms are supplying intermediate products to other manufacturing firms, those procurement is done not only among manufacturing firms but also between non-manufacturing firms and manufacturing firms as a form of providing various professional services. Although the extant studies have started to report how the shock originating from financial side could propagates to these real side, little has been understood how the shocks in real side affect the financial side. The results provided in the present paper suggest that shocks from real network among firms do propagate to financial network between banks and firms.

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The research data for this article

The data used in this study are proprietary, and we gained access to the data through a joint research contract between Hitotsubashi University and TSR.

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Appendix

Table-A1: Robustness check (the weight for HHI computation)

	From Table 2					
Dependent variable: **log(*Exposure* $_{b,f,t}$)**	Coef.	S.E.		Coef.	S.E.	
Transaction						
$\mathrm{HHI}_{b,t\text{-}1}{}^{F}$	0.035	0.236		0.079	0.308	
credit score $_{b,f,t\text{-}1}$ × $\mathrm{HHI}_{b,t\text{-}1}{}^{F}$	0.127	0.018	***	0.205	0.022	***
credit scoreb,f,t-1	0.259	0.057	***	0.266	0.057	***
$\mathrm{HHI}_{b,t\text{-}1}{}^{F+T}$ - $\mathrm{HHI}_{b,t\text{-}1}{}^{F}$	0.036	0.185		0.288	0.227	
credit score $_{b,f,t\text{-}1}$ × ($\mathrm{HHI}_{b,t\text{-}1}{}^{F+T}$ - $\mathrm{HHI}_{b,t\text{-}1}{}^{F}$)	0.093	0.017	***	0.121	0.021	***
Industry						
$\mathrm{HHI}_{b,t\text{-}1}$	0.109	0.120		-0.146	0.189	
credit score $_{b,f,t\text{-}1}$ × $\mathrm{HHI}_{b,t\text{-}1}$	-0.019	0.010	*	0.022	0.011	**
density $_{b,f,t\text{-}1}$	0.497	0.050	***	0.488	0.050	***
Constant	11.336	0.002	***	11.336	0.003	***
Firm-Year fixed-effect	yes			yes		
Bank fixed-effect	yes			yes		
Bank-Firm fixed-effect	no			no		
Bank-Year fixed-effect	no			no		
HHI *weight*	sales			**employees**		
HHI *calculation*	residual			residual		
density weight	no			no		
clustering methodology	Louvain			Louvain		
industry classification	large			large		
#(obs)	268,990			268,990		
F	23.850			28.650		
Adj. R-squared	0.561			0.561		
Within R-squared	0.001			0.001		

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table-A2: Robustness check (the weight for HHI-T computation)

	From Table 2			
Dependent variable: **log(*Exposure* $_{b,f,t}$)**	Coef.	S.E.	Coef.	S.E.
Transaction				
$\mathrm{HHI}_{b,t\text{-}1}{}^{F}$	0.035	0.236	0.007	0.160
credit score $_{b,f,t\text{-}1} \times \mathrm{HHI}_{b,t\text{-}1}{}^{F}$	0.127	0.018 ***	0.054	0.016 ***
credit scoreb,f,t-1	0.259	0.057 ***	0.259	0.057 ***
$\mathrm{HHI}_{b,t\text{-}1}{}^{F+T}$ - $\mathrm{HHI}_{b,t\text{-}1}{}^{F}$	0.036	0.185	0.036	0.185
credit score $_{b,f,t\text{-}1} \times (\mathrm{HHI}_{b,t\text{-}1}{}^{F+T}$ - $\mathrm{HHI}_{b,t\text{-}1}{}^{F})$	0.093	0.017 ***	0.093	0.017 ***
Industry				
$\mathrm{HHI}_{b,t\text{-}1}$	0.109	0.120	0.109	0.120
credit score $_{b,f,t\text{-}1} \times \mathrm{HHI}_{b,t\text{-}1}$	-0.019	0.010 *	-0.019	0.010 *
density $_{b,f,t\text{-}1}$	0.497	0.050 ***	0.497	0.050 ***
Constant	11.336	0.002 ***	11.336	0.002 ***
Firm-Year fixed-effect	yes		yes	
Bank fixed-effect	yes		yes	
Bank-Firm fixed-effect	no		no	
Bank-Year fixed-effect	no		no	
HHI *weight*	sales		sales	
HHI *calculation*	residual		**regression**	
density weight	no		no	
clustering methodology	Louvain		Louvain	
industry classification	large		large	
#(obs)	268,990		268,990	
F	23.850		23.850	
Adj. R-squared	0.561		0.561	
Within R-squared	0.001		0.001	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table-A3: Robustness check (the weight for density computation)

	From Table 2					
Dependent variable: **log(*Exposure*$_{b,f,t}$)**	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Transaction						
$HHI_{b,t-1}{}^{F}$	0.035	0.236	0.136	0.237	0.105	0.237
credit score $_{b,f,t-1}$ × $HHI_{b,t-1}{}^{F}$	0.127	0.018 ***	0.131	0.018 ***	0.131	0.018 ***
credit scoreb,f,t-1	0.259	0.057 ***	-0.018	0.043	0.064	0.050
$HHI_{b,t-1}{}^{F+T}$ - $HHI_{b,t-1}{}^{F}$	0.036	0.185	0.018	0.185	0.020	0.185
credit score $_{b,f,t-1}$ × ($HHI_{b,t-1}{}^{F+T}$ - $HHI_{b,t-1}{}^{F}$)	0.093	0.017 ***	0.102	0.017 ***	0.101	0.017 ***
Industry						
$HHI_{b,t-1}$	0.109	0.120	0.035	0.121	0.061	0.121
credit score $_{b,f,t-1}$ × $HHI_{b,t-1}$	-0.019	0.010 *	-0.022	0.010 **	-0.021	0.010 **
density $_{b,f,t-1}$	0.497	0.050 ***	0.173	0.039 ***	0.296	0.048 ***
Constant	11.336	0.002 ***	11.318	0.002 ***	11.319	0.002 ***
Firm-Year fixed-effect	yes		yes		yes	
Bank fixed-effect	yes		yes		yes	
Bank-Firm fixed-effect	no		no		no	
Bank-Year fixed-effect	no		no		no	
HHI *weight*	sales		sales		sales	
HHI *calculation*	residual		residual		residual	
density weight	no		**sales**		**employees**	
clustering methodology	Louvain		Louvain		Louvain	
industry classification	large		large		large	
#(obs)	268,990		268,990		268,990	
F	23.850		11.190		13.550	
Adj. R-squared	0.561		0.561		0.561	
Within R-squared	0.001		0.001		0.001	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table-A4: Robustness check (cluster detection algorithm and industry classification)

Dependent variable: **log(*Exposure* $_{b,f,t}$)**	From Table 2 Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Transaction						
$\mathrm{HHI}_{b,t-1}{}^{F}$	0.035	0.236	0.132	0.161	0.016	0.248
credit score $_{b,f,t-1} \times \mathrm{HHI}_{b,t-1}{}^{F}$	0.127	0.018 ***	0.089	0.009 ***	0.134	0.018 ***
credit scoreb,f,t-1	0.259	0.057 ***	0.225	0.039 ***	0.256	0.057 ***
$\mathrm{HHI}_{b,t-1}{}^{F+T}$ - $\mathrm{HHI}_{b,t-1}{}^{F}$	0.036	0.185	0.119	0.125	0.093	0.187
credit score $_{b,f,t-1} \times (\mathrm{HHI}_{b,t-1}{}^{F+T} - \mathrm{HHI}_{b,t-1}{}^{F})$	0.093	0.017 ***	0.024	0.013 *	0.043	0.018 **
Industry						
$\mathrm{HHI}_{b,t-1}$	0.109	0.120	0.096	0.116	0.100	0.243
credit score $_{b,f,t-1} \times \mathrm{HHI}_{b,t-1}$	-0.019	0.010 *	-0.002	0.010	-0.158	0.018 ***
density $_{b,f,t-1}$	0.497	0.050 ***	0.472	0.050 ***	1.251	0.120 ***
Constant	11.336	0.002 ***	11.336	0.003 ***	11.343	0.003 ***
Firm-Year fixed-effect	yes		yes		yes	
Bank fixed-effect	yes		yes		yes	
Bank-Firm fixed-effect	no		no		no	
Bank-Year fixed-effect	no		no		no	
HHI *weight*	sales		sales		sales	
HHI *calculation*	residual		residual		residual	
density weight	no		no		no	
clustering methodology	Louvain		**Fast Greedy**		Louvain	
industry classification	large		large		**intermediate**	
#(obs)	268,990		268,990		268,990	
F	23.850		35.500		35.670	
Adj. R-squared	0.561		0.562		0.562	
Within R-squared	0.001		0.002		0.002	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table-A5: Subsample estimation based on bank characteristics using credit score

Bank subgroup	Borrower firms' average credit score belongs to top 20%								Borrower firms' average credit score belongs to bottom 20%							
Dependent variable: **log(*Exposure* $_{b,f,t}$)**	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Transaction																
$HHI_{b,t-1}{}^{F}$	-0.299	0.299	-0.652	0.197 ***					-0.882	0.892	-0.637	0.435				
credit score $_{b,f,t-1} \times HHI_{b,t-1}{}^{F}$	0.033	0.032	0.069	0.026 ***	0.029	0.032	0.074	0.026 ***	-0.221	0.082 ***	0.038	0.057	-0.237	0.084 ***	0.055	0.059
credit scoreb,f,t-1	0.086	0.082	0.038	0.051	0.102	0.083	0.046	0.051	0.546	0.377	0.159	0.196	0.535	0.386	0.182	0.202
$HHI_{b,t-1}{}^{F+T} - HHI_{b,t-1}{}^{F}$	-0.346	0.324	-0.418	0.209 **					-1.675	1.268	-0.283	0.646				
credit score $_{b,f,t-1} \times (HHI_{b,t-1}{}^{F+T} - HHI_{b,t-1}{}^{F})$	0.100	0.032 ***	0.060	0.029 **	0.097	0.033 ***	0.062	0.029 **	-0.496	0.116 ***	-0.146	0.090	-0.533	0.118 ***	-0.140	0.092
Industry																
$HHI_{b,t-1}$	0.219	0.419	0.244	0.270					0.822	1.189	0.241	0.600				
credit score $_{b,f,t-1} \times HHI_{b,t-1}$	0.037	0.022 *	0.009	0.030	0.034	0.022	-0.007	0.031	0.739	0.137 ***	-0.013	0.096	0.784	0.143 ***	-0.066	0.102
density $_{b,f,t-1}$	1.041	1.041 ***	0.515	0.515	0.998	0.998 ***	0.309	0.309	-0.222	-0.222	-0.134	-0.134	-1.148	-1.148	0.563	0.563
Constant	11.644	0.010 ***	11.670	0.022 ***	11.632	0.008 ***	11.648	0.024 ***	11.416	0.052 ***	11.414	0.036 ***	11.388	0.026 ***	11.372	0.036 ***
Firm-Year fixed-effect	yes		yes		yes		yes		yes		yes		yes		yes	
Bank fixed-effect	yes		no		no		no		yes		no		no		no	
Bank-Firm fixed-effect	no		yes		no		yes		no		yes		no		yes	
Bank-Year fixed-effect	no		no		yes		yes		no		no		yes		yes	
HHI *weight*	sales		sales		sales		sales		sales		sales		sales		sales	
HHI *calculation*	residual		residual		residual		residual		residual		residual		residual		residual	
density weight	no		no		no		no		no		no		no		no	
clustering methodology	Louvain		Louvain		Louvain		Louvain		Louvain		Louvain		Louvain		Louvain	
industry classification	large		large		large		large		large		large		large		large	
#(obs)	95,561		86,063		95,561		86,061		5,708		5,218		5,676		5,188	
F	7.910		2.200		11.230		2.390		5.310		1.030		8.850		1.440	
Adj. R-squared	0.634		0.902		0.635		0.902		0.649		0.935		0.649		0.935	
Within R-squared	0.001		0.000		0.001		0.000		0.014		0.004		0.015		0.004	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table-A6: Subsample estimation based on bank characteristics using density

Bank subgroup	Borrower firms' average credit score belongs to top 20%								Borrower firms' average credit score belongs to bottom 20%							
Dependent variable: **log(*Exposure* $_{b,f,t}$)**	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Transaction																
$\text{HHI}_{b,t-1}{}^{F}$	-0.086	0.283	-0.371	0.172 **					-0.645	0.907	-0.609	0.443				
$density_{b,f,t-1} \times \text{HHI}_{b,t-1}{}^{F}$	-3.618	2.530	-2.128	2.260	-4.950	4.162	1.298	2.544	-6.541	10.121	-1.492	5.134	-13.631	11.865	-4.819	6.057
$density_{b,f,t-1}$	0.363	0.108 ***	0.001	0.067	0.341	0.111 ***	0.009	0.069	0.722	0.510	0.223	0.265	0.996	0.545 *	0.395	0.286
$\text{HHI}_{b,t-1}{}^{F+T} - \text{HHI}_{b,t-1}{}^{F}$	0.166	0.309	-0.242	0.184					-1.275	1.274	-0.329	0.647				
$density_{b,f,t-1} \times (\text{HHI}_{b,t-1}{}^{F+T} - \text{HHI}_{b,t-1}{}^{F})$	-12.207	3.293 ***	2.719	2.209	-10.065	3.751 ***	1.216	2.337	7.114	11.568	-1.822	5.959	-1.120	13.166	-6.735	6.836
Industry																
$\text{HHI}_{b,t-1}$	0.257	0.412	0.282	0.247					0.652	1.210	0.184	0.609				
$density_{b,f,t-1} \times \text{HHI}_{b,t-1}$	-5.524	1.132 ***	1.776	1.581	-7.332	1.207 ***	2.709	1.657	0.641	2.978	-0.426	2.680	0.152	3.249	-1.452	2.950
$density_{b,f,t-1}$	1.187	0.153 ***	0.457	0.523	1.135	0.154 ***	0.243	0.571	-0.145	0.910	-0.280	1.386	-0.846	0.974	0.418	1.633
Constant	11.653	0.010 ***	11.666	0.022 ***	11.653	0.008 ***	11.647	0.024 ***	11.370	0.053 ***	11.414	0.038 ***	11.349	0.027 ***	11.378	0.036 ***
Firm-Year fixed-effect	yes		yes		yes		yes		yes		yes		yes		yes	
Bank fixed-effect	yes		no		no		no		yes		no		no		no	
Bank-Firm fixed-effect	no		yes		no		yes		no		yes		no		yes	
Bank-Year fixed-effect	no		no		yes		yes		no		no		yes		yes	
HHI *weight*	sales		sales		sales		sales		sales		sales		sales		sales	
HHI *calculation*	residual		residual		residual		residual		residual		residual		residual		residual	
density weight	no		no		no		no		no		no		no		no	
clustering methodology	Louvain		Louvain		Louvain		Louvain		Louvain		Louvain		Louvain		Louvain	
industry classification	large		large		large		large		large		large		large		large	
#(obs)	95,561		86,063		95,561		86,061		5,708		5,218		5,676		5,188	
F	11.400		1.350		18.640		0.900		0.580		0.370		0.840		0.520	
Adj. R-squared	0.634		0.902		0.635		0.902		0.644		0.935		0.644		0.935	
Within R-squared	0.002		0.000		0.002		0.000		0.002		0.001		0.001		0.001	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table-A7: Subsample estimation based on bank characteristics using density

Bank subgroup	Borrower firms' average credit score belongs to top 20%								Borrower firms' average credit score belongs to bottom 20%							
Dependent variable: **log(*Exposure* $_{b,f,t}$)**	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Transaction																
$HHI_{b,t-1}^{F}$	-0.215	0.304	-0.644	0.199 ***					-0.907	0.902	-0.636	0.444				
$density_{b,f,t-1} \times HHI_{b,t-1}^{F}$	-4.134	3.647	-0.690	2.644	-3.380	4.602	2.480	2.903	-2.683	10.066	-1.696	5.149	-11.056	11.797	-5.296	6.081
$credit\ score_{b,f,t-1} \times HHI_{b,t-1}^{F}$	0.039	0.033	0.075	0.027 ***	0.039	0.034	0.080	0.027 ***	-0.256	0.086 ***	0.039	0.059	-0.276	0.088 ***	0.058	0.061
$density_{b,f,t-1} \times credit\ score_{b,f,t-1} \times HHI_{b,t-1}^{F}$	-0.046	0.551	-0.369	0.375	-0.475	0.579	-0.338	0.378	3.280	0.913 ***	0.186	0.509	3.587	0.927 ***	0.219	0.517
$density_{b,f,t-1}$	0.356	0.108 ***	-0.000	0.067	0.342	0.111 ***	0.010	0.069	0.549	0.506	0.214	0.265	0.810	0.541	0.394	0.286
$HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F}$	-0.187	0.328	-0.451	0.212 **					-1.724	1.268	-0.309	0.648				
$density_{b,f,t-1} \times (HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F})$	-8.515	3.774 **	2.192	2.482	-7.568	4.081 *	0.873	2.598	5.353	11.481	-2.271	5.981	-1.275	13.042	-7.140	6.855
$credit\ score_{b,f,t-1} \times (HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F})$	0.099	0.033 ***	0.057	0.029 **	0.094	0.033 ***	0.060	0.029 **	-0.417	0.118 ***	-0.153	0.091 *	-0.442	0.120 ***	-0.145	0.093
$density_{b,f,t-1} \times credit\ score_{b,f,t-1} \times (HHI_{b,t-1}^{F+T} - HHI_{b,t-1}^{F})$	-0.995	0.460 **	0.156	0.301	-0.791	0.469 *	0.091	0.302	-0.728	1.522	0.752	0.776	-1.191	1.550	0.659	0.788
Industry																
$HHI_{b,t-1}$	0.108	0.420	0.269	0.271					0.642	1.203	0.172	0.618				
$density_{b,f,t-1} \times HHI_{b,t-1}$	-8.176	1.325 ***	1.245	1.740	-9.792	1.383 ***	2.039	1.795	0.435	3.061	-0.692	2.752	0.182	3.278	-1.888	3.022
$credit\ score_{b,f,t-1} \times HHI_{b,t-1}$	0.048	0.022 **	0.013	0.030	0.044	0.022 **	-0.000	0.031	0.795	0.140 ***	-0.010	0.099	0.839	0.145 ***	-0.070	0.105
$density_{b,f,t-1} \times credit\ score_{b,f,t-1} \times HHI_{b,t-1}$	0.686	0.179 ***	0.188	0.210	0.679	0.182 ***	0.265	0.221	-1.649	0.560 ***	-0.126	0.416	-1.787	0.590 ***	-0.053	0.445
$density_{b,f,t-1}$	1.183	0.153 ***	0.458	0.523	1.132	0.154 ***	0.229	0.571	-0.451	0.917	-0.069	1.396	-1.094	0.986	0.706	1.650
Constant	11.655	0.011 ***	11.667	0.022 ***	11.649	0.008 ***	11.642	0.024 ***	11.458	0.054 ***	11.414	0.039 ***	11.435	0.031 ***	11.371	0.038 ***
Firm-Year fixed-effect	yes		yes		yes		yes		yes		yes		yes		yes	
Bank fixed-effect	yes		no		no		no		yes		no		no		no	
Bank-Firm fixed-effect	no		yes		no		yes		no		yes		no		yes	
Bank-Year fixed-effect	no		no		yes		yes		no		no		yes		yes	
HHI *weight*	sales		sales		sales		sales		sales		sales		sales		sales	
HHI *calculation*	residual		residual		residual		residual		residual		residual		residual		residual	
density weight	no		no		no		no		no		no		no		no	
clustering methodology	Louvain		Louvain		Louvain		Louvain		Louvain		Louvain		Louvain		Louvain	
industry classification	large		large		large		large		large		large		large		large	
#(obs)	95,561		86,063		95,561		86,061		5,708		5,218		5,676		5,188	
F	8.930		1.630		11.310		1.630		4.730		0.690		6.420		0.930	
Adj. R-squared	0.635		0.902		0.635		0.902		0.651		0.935		0.652		0.935	
Within R-squared	0.002		0.001		0.002		0.000		0.022		0.005		0.024		0.005	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.