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Product Network Connectivity and Information for Loan Pricing

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Product Network Connectivity and Information for Loan Pricing[1]

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Abstract

A theory predicts that loan pricing is less sensitive to public information, such as a credit score provided by a credit information vendor, if the lender obtains more accurate private information about the credit quality of borrowers. We find that loan pricing is less sensitive to public information when a borrower is more connected with other borrowers of the lender through a supply network by using a unique database of inter-firm relationships and bank-firm relationships. This effect is significant statistically and economically after controlling for the bank-firm or inter-firm relationship characteristics and other firm characteristics. This finding provides evidence that banks make use of private information observed from their borrowers' network in their loan pricing.

Keywords: Inter-firm network, Loan pricing, Information production, Relationship banking

JEL classification: G21, L14

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1 Introduction

Innumerable studies have predicted and found the private information obtained through bank-firm relationship affects loan pricing. For example, Petersen and Rajan (1995) found evidence that relationship banking provides intertemporal interest-rate smoothing. Chemmanur and Fulghieri (1994) and Dinç (2000) found that banks have incentive to provide implicit insurance in order to acquire a reputation for making the "right" renegotiation rather than inefficient liquidation. More recently, Bolton et al. (2016) investigated the liquidity insurance role of bank relationships in the context of the global financial crisis. They found that relationship banks will charge a higher intermediation spread due to higher operating costs, but with the collected information, they are more likely to provide loans to profitable firms during the crisis. Meanwhile, the determinants of information production are also discussed in much of the existing literature, including the length of the relationship (Berger and Udell, 1995; Degryse and van Cayseele, 2000), bank organization and size (Stein, 2002; Berger et al., 2005; Liberti and Mian, 2009; Agarwal and Hauswald, 2010), competition (Petersen and Rajan, 1995; Boot and Thakor, 2000) and access to checking account information (Mester et al., 2007; Norden and Weber, 2010).

Most previous studies have focused on the information generated from a one-to-one bank-firm relationship, but they have not seriously studied the information generated from networks among borrowers through various types of relationships, such as supplier-customer relationships and ownership relationships. Recent studies have begun to directly investigate the impact of inter-firm connections on bank lending. Santikian (2014) investigated the referral relationships and found that the non-lending profitability from new referrals and cross-selling determine the risk-adjusted terms of lending. Gao (2015) argues that because of the positive spillover effect on the quality of the loan portfolio, firms that are closely connected to a bank are more likely to receive loans and to receive lower interest rate spreads. Campello and Gao (2017) found that a higher concentration of customers will increase loan spreads and the number of restrictive covenants. It can also shorten the loan maturity and bank-firm relationship. Ogura et al. (2015) show theoretically and empirically that a bank is more likely to provide rescue loans to a temporarily distressed firm with a larger influence on the total earnings of a supply network.

Our empirical study obtained clear evidence that a bank collects and makes use of information that is obtained through the supply network among its borrowers by using an identification strategy different from that in the existing studies.

First, we provide a theoretical explanation that loan pricing will be less sensitive to public information if the lender obtains more accurate private information about the credit quality of borrowers from the supply network with other borrowers.

Second, we statistically test this hypothesis by using a unique dataset on the supply network among firms including small and medium-sized enterprises (SMEs), which is collected from the Tokyo Shoko Research (TSR) database. The database provides a cross section of data on more than 5 million supplier-customer relationships, as well as more than 300,000 firms from all over Japan as of 2013. Moreover, the dataset enables us to identify the name and branch of the main bank of each firm. This dataset provides a great opportunity to rigorously investigate the impact of the supply chain network on bank lending.

We measure the connectivity of a firm with a bank through its supply network by the ratio of the number of direct suppliers and customers that shares the same main bank over the total number of direct suppliers and customers. The higher value of this ratio indicates that the bank can observe a larger part of the supply network of the firm, and so the bank can obtain more accurate information from the network. We test the above hypothesis by examining the sensitivity of the borrowing cost to the credit score provided by TSR, which is the public information available for any banks to purchase, declines as the connectivity increases.

Consistent with the prediction from our theory, we find that loan pricing for a firm is less sensitive to the public credit score if the supply chain network of the firm is more closely connected to its main bank. The results have both statistical and economic significance. These results do not change by controlling for the possible similar effect of bank-firm relationships. For a credit score increase by one standard deviation, the 90-percentile connectivity firm will have a smaller rate reduction relative to 10-percentile connectivity by 17% at the branch level and and 29% at the bank level.

We obtain further economically and statistically significant results from the instrumental variable estimation to address the possible endogeneity of the connectivity measures by using the proxy for the geographical proximity of a firm to other borrowers and its interaction term with the credit score as the excluded instruments.

From a subsample analysis with respect to the bank type, we find that the effect of connectivity is not significant for large banks operating nationwide but significant for smaller banks: regional banks and cooperative banks. This result is consistent with the existing evidence that larger banks are less willing or less competent in information production for SMEs (e.g., Berger et al., 2005).

We also find that this result for regional banks does not qualitatively change when we define the connectivity measure on the bank branch level instead of on the bank level, whereas the connectivity loses its significance for cooperative banks by this change of definition. This result is consistent with the fact that many regional banks introduce an online customer-relationship management system to share all available information among all branches and the head office, whereas cooperative banks, which are smaller than regional banks in general, do not (Nemoto et al., 2013).

Our research contributes to the existing literature by providing clear evidence that banks make use of private information from a borrower's network in their loan pricing. Moreover, the magnitude of the impact depends on the information collection abilities and sharing mechanisms of the banks. Our finding implies that a firm with lower credit score can minimize its borrowing cost by maximizing the connectivity of its local supply chain network to a bank. The resulting clustering of less creditworthy firms around a certain bank can exacerbate the financial stability in a local lending market by hampering the risk diversification at each bank.

The rest of the paper is organized as follows. Section 2 explains the theory and hypothesis for testing. Section 3 explains the data sources, processing procedures and descriptive statistics. Section 4 explains the results of empirical analysis. Section 5 shows the result of the robustness check. Section 6 presents several implications of our findings. Section 7 is the conclusion.

2 Theory and Hypotheses Development

2.1 Mean Interest Rate for Each Firm

We consider a symmetric Bertrand competition by two banks for a loan to a firm. The expected profit of bank j ($j = 1, 2, \cdots, m$) from a loan to firm i ($i = 1, 2, \cdots, n$) is

$$(1 - E[p_i|\Omega])(1 + R_i)l_i - (1 + r)l_i. \tag{1}$$

p_i is the true default probability of firm i. Banks do not know the exact value of it. Ω is the set of available information for banks , which will be specified later based on the borrower's network. R_i is the loan interest rate. r is the funding cost for each bank.

The bank bids down the interest rate R_i to the level where its profit is zero in the Bertrand Nash equilibrium.

$$(1 - E[p_i|\Omega])(1 + R_i) = 1 + r, \tag{2}$$

Taking a logarithm of both sides and the linear approximation of the both sides with respect to R_i, r, and $E[p_i|\Omega]$ round zero, we obtain

$$R_i \approx r + E[p_i|\Omega]. \tag{3}$$

2.2 Information Available for Bank

We consider the simplest situation where every bank can obtain additional information about the default probability of firm i from other borrowers who are direct suppliers and customers of firm i.

To formulate the information structure under this scenario, we apply the beta-binomial model, which has been introduced into the banking literature by Panetta et al. (2009). Each bank has a prior belief that the default probability of firm i, p_i, is randomly drawn from a beta distribution with parameters (a, b). The prior mean is $\bar{p} = \frac{a}{a+b}$. We interpret this mean as a default evaluation based on publicly readily available information, such as a credit score that any bank can buy from a credit information company. Each bank receives n_i binary signals about the default possibility of firm i from the neighborhood network of existing borrowers that have a direct transaction with firm i. Each binary signal indicates $s \in \{default,\ not\ default\}$ with $Pr(s = default) = p_i$. The number of signals n_i is a proxy for the accuracy of the information collected from the neighborhood network of firm i. According to the Bayes' rule, the posterior mean of the default probability after getting n_i signals and y among them indicates $default$ is

$$E[p_i|\Omega] = \frac{a + y}{a + b + n_i}, \tag{4}$$

where $\Omega_j = \{n_i, y\}$. Banks set their offer rates according to this posterior probability. Since $E[y] = n_i p_i$, the mean of this posterior probability is,

$$E[E[p_i|\Omega]] = \frac{a + n_i p_i}{a + b + n_i} = \alpha(n_i)\bar{p} + (1 - \alpha(n_i))p_i, \tag{5}$$

where $\alpha(n) \equiv \frac{a+b}{a+b+n}$. Obviously, $\alpha(n)$ is decreasing in n.

2.3 Estimation Model

Substituting (5) into the expected value of equation (3) gives

$$E[R_i] \approx \alpha(n_i)\bar{p} + (1 - \alpha(n_i))p_i + r. \tag{6}$$

Since $\alpha(n_i)$ is decreasing in n_i, the loan interest rate (3) is less responsive to the prior information $\bar{p}$ as n_i increases, i.e.,

$$\frac{\partial^2 E[R_i]}{\partial n_i \partial \bar{p}} < 0. \tag{7}$$

In the empirical study, we assume that the accuracy n_i is increasing in the ratio of the number of direct customers and suppliers who share the same main bank over the total number of direct customers and suppliers of firm i. We call the variable *connectivity* of firm i. It is plausible that a bank obtains more accurate information as this ratio increases since the higher ratio indicates that the bank can observe the larger part of the business-to-business transactions of the firm through the checking accounts of these connected firms in real time.

As a proxy for the prior information $\bar{p}$, we use the credit score that is available for all banks to purchase from a credit information company. The credit score is calculated based on the financial statement information and other firm characteristics, but it does not fully take into account the connectivity. Thus, the publicly available credit score is a strong candidate for the proxy variable for the prior information.

By using the model and these proxies we test the following hypothesis.

Hypothesis. *A loan interest rate is less responsive to a publicly available credit score if the borrower has a higher connectivity to the borrowers of the bank.*

The above equation suggests that we can test the hypothesis by regressing loan interest rates to the publicly and readily available credit score of each borrower and examine whether the coefficient of the credit score is negative but its absolute value is decreasing in the borrower's connectivity. From this consideration, we estimate the following linear model,

$$R_i = \beta_0 + \beta_1 score_i + \beta_2\, connectivity_i \times score_i + \gamma \mathbf{X_i} + \nu_j + \epsilon_i, \tag{8}$$

where $score_i$ is the publicly available credit score of firm i, $\mathbf{X_i}$ is the vector of control variables, β's and the vector γ are the coefficients to be estimated, ν_j is the bank (or bank branch) fixed effect, and ϵ_i is the error term. The funding cost of each bank in the model is controlled by the bank fixed effect.

Given that $score_i$ is negatively correlated with the default probability, the hypothesis predicts that β_2 is positive and significant.

3 Data Description

3.1 Data Sources

We construct our sample mainly based on three databases: the TSR Company Linkage Database, the TSR Company Information Database and the TSR Financial Database.[1] To measure a firm's connectivity with its main bank lender, we construct our sample using

[1]We gratefully acknowledge that these databases are provided by Research Institute of Economy, Trade and Industry (RIETI).

the TSR Company Linkage Database as of 2014. Each firm in the database reports up to 24 of its most important customers and suppliers. In addition, this database contains the cross-holding relationship. We obtain information about the firm's credit score and the names of bank lenders from the TSR Company Information database. Our second source of information comes from the TSR Financial Database. We calculate the firm's loan rates (*Rate*) and other financial variables from this database.

3.2 Key and Control Variables

We list the detailed definition for each variable in Table 1. The main dependent variable, the interest rate (*RATE*), is calculated as the interest expense over loans outstanding at the end of the accounting year in 2013. The credit score (*SCORE*) is obtained from the TSR Company Linkage database and scaled between 0 and 1. In order to measure a firm's connectivity with a bank, we construct connectivity measures at both branch and bank levels. To control for the difference in the total number of suppliers and customers, we scale the number of suppliers and customers by the total number of direct suppliers and customers. The branch-level connectivity is defined as:

$$\text{Branch connectivity} = \frac{\text{Number of suppliers and customers who share the same branch}}{\text{Number of direct suppliers and customers}}. \tag{9}$$

The bank level connectivity is defined as

$$\text{Bank connectivity} = \frac{\text{Number of suppliers and customers who share the same main bank}}{\text{Number of direct suppliers and customers}}. \tag{10}$$

We construct three sets of control variables following the existing empirical studies: firm characteristics, bank-firm relationship characteristics and firm network characteristics. For firm characteristics, we control for the size of the firm (*Number of employees*), leverage (*Leverage*), tangible assets (*Tangible assets*), firm age (*Ln(age)*), interest coverage (*Interest coverage*) and term structure of the loans (*Long-term loans ratio*). In addition, we control for alternative sources for firm funding including whether the firm is listed (*Listed*) and the ratio of bond finance over the total amount of loans and bond finance (*Bond ratio*).

For the bank-firm relationship, we control for its strength with two variables. The first variable is the number of bank lenders (*Number of banks*). The difference in bank lenders will affect the bargaining power between borrowers and lenders. The second variable *Switch bank* measures the stability of bank-firm relationship. It equals one if the firm changed its main bank during the last four years (2011, 2012 and 2014) and zero otherwise. The existing studies find that the soft information generated by relationship banking can provide the intertemporal smoothing of interest rates (Petersen and Rajan, 1995) and the insurance against a temporary financial distress (Bolton et al., 2016; Nemoto et al., 2016) by rendering the loan pricing less sensitive to public information. To control for this interest-smoothing effect, we include the interaction term between *Switch bank* and *Credit score*.

The third set of controls includes the mean of credit score of suppliers and customers. The creditworthiness of suppliers and customers may be an important factor in a bank's loan pricing. Moreover, we control for the connectivity of firm's subsidiaries and a parent firm because the loan decisions may be based on not only the supply chain network connectivity but also the ownership network connectivity. The definitions of these two variables are similar to the definitions of connectivity measures on the supply chain network (see Table 1).

3.3 Data-Processing Procedure and Descriptive Statistics

The data-processing procedure is as follows: We keep firms with an accounting date after the 2012 accounting year. We keep those with information on all key and control variables and drop outliers (above 99%) in interest rate, current ratio, leverage and tangible assets. We exclude firms in the finance and utility industries.

We present the summary statistics in Table 2. The mean and maximum of *Rate* are 2% and 11.2% respectively. The mean of *Branch connectivity* is 4.7%. The mean of *Bank connectivity* is 19.1%, which is much higher when we include the suppliers and customers with the same main bank in other branches.

Moreover, in our sample, most firms rely on bank financing as the main source of external financing and only 1.13% firms have access to the stock market. We also find multiple banks is common in our sample as the mean number of banks is 2.3 and the median is 3. However, the bank-firm relationship is relatively stable even firms borrows from multiple banks: 10% firms in our sample change their main bank during the last four years.

Our final sample after the data-processing procedure has 179,576 observations. The top three industries are construction (52.8%), manufacturing (12.7%), and wholesale (11.7%). We also check the distribution of firms by four different bank types in Table 4. 77.6% borrow mainly from regional banks (Region) or cooperative (Cooperative). Firms whose main bank is a large and nation-wide bank (City) represent 19.8%,[2] while firms whose main bank is a government-owned bank, online bank or foreign bank (Others) represent 12.5% in our sample.

4 Results and Discussion

4.1 Baseline Estimation

Our results for the baseline estimation at the branch level are listed in Table 6. We apply three different specifications to test our hypothesis. In all three specifications, we include branch, prefecture and industry fixed effects. The standard error is clustered at the bank branch level. In the first column, we only include the *Score*, *Branch connectivity* and the interaction term between them. We find that *Score* is negatively correlated with *Rate* while the interaction term is positively related to *Rate* at 1% level.

In column (2), we include firm characteristics and the bank-firm relationship as additional controls. In column (3), we include the firm's network characteristics. After including additional controls, in column (3), the score is still negatively correlated with interest rate at 1% significance level. The coefficient of the interaction term becomes smaller but is still positively correlated with the interest rate.

We repeat this analysis at the bank level and present the results on Table 7. *Score* and *Bank connectivity* are both negatively related to the interest rate, while the interaction

[2] City banks include Mizuho, Mitsubishi UFJ, Sumitomo Mitsui, Risona, Saitama Risona, Shinsei, Aozora, Mitsubishi UFJ Trust, Chuo-Mitsui Trust, Sumitomo Trust, and Mizuho Trust. Regional banks include those banks belonging to the Regional Banks Association of Japan, or the Second Association of Regional Banks. Cooperative banks include Shinkin banks.

between *Score* and *Bank Connectivity* is positively correlated with the interest rate.

The baseline estimations indicate that while higher credit is negatively correlated to interest rate, the sensitivity of rate to score decreases if firm's connectivity increases. This is consistent with our hypothesis at both branch level and bank level.

In addition, we find that a firm's connectivity is negatively correlated with the interest rate. A bank with a higher connectivity can detect whether a firm is potentially creditworthy by using more accurate private information, and provide a loan at a lower interest rate if that is the case. A firm will borrow from the bank with a higher connectivity if it knows that it is underestimated in terms of the public credit score. In other words, hidden good firms prefer to borrow from a highly connected bank. This firm choice may bring the negative coefficients of the connectivity measures. This suggests a potential endogeneity problem of the connectivity measures. We return to this point in the section for the robustness check.

For other control variables, we find that *Tangible assets*, *Current ratio*, *Interest coverage*, *Listed* and *Bond ratio* are all negatively correlated with the interest rate at the 1% significance level. This indicates that firms with a healthier financial condition and with access to alternative external funding can obtain a loan at a lower interest rate. Moreover, we find that *Switch bank* is positively correlated with the interest rate, while the interaction term between *Switch bank* and *Score* is negative. This indicates that the switching to a different main bank may increase the borrowing cost for less creditworthy firms.

We calculate the marginal effect of the credit score on the interest rate at various levels of connectivity. Figure 1 shows it with the a 95% confidence interval. The figure shows that the sensitivity of the interest rate to the credit score declines as the connectivity increases.

For example, assuming a credit score increase by one standard deviation (0.063), the 10-percentile branch connectivity firm (branch connectivity = 0) will have a rate reduction of 3.9 basis points, whereas the 90-percentile branch connectivity firm (branch connectivity = 0.167) will have a rate reduction of 1.5 basis points. The latter is smaller by 17%. The same size of increase in a credit score reduces the interest rate for the 10-percentile bank connectivity firm (bank connectivity = 0) by 15 basis points while it reduces the interest rate for the 90-percentile bank connectivity firm (bank connectivity = 0.5) by 10.6 basis points.

The latter is smaller by 29 %.

We also calculate the marginal effect of the connectivity on the interest rate at various levels of the credit score. Figure 2 shows it with the a 95% confidence interval. The figure indicates that the connectivity reduces the capital cost for firms evaluated as less creditworthy in terms of the public information. Furthermore, we find that the connectivity may even increase the capital costs for firms with a higher public credit score over 0.5. Assuming a connectivity increase by one standard deviation (0.116 at the branch level, 0.217 at the bank level), the 10-percentile credit score firms will have an additional rate reduction relative to 90-percentile firms by 4.0 basis points and 4.6 basis points respectively. The economic significance is non-negligible given that the sample median of the interest rate is 190 basis points.

4.2 Subsample Analysis by Bank Types

The existing literature shows that smaller banks with a shorter distance between branches and with loan decision authority are more efficient in producing soft information (e.g., Stein, 2002; Berger et al., 2005; Liberti and Mian, 2009; Agarwal and Hauswald, 2010). As for the information obtained through a supply network, Ogura et al. (2015) found that it is more significantly influential at regional banks than at large banks that operate nationwide and internationally, which we call city banks in this study. They argue that this is because of regional banks' relatively smaller organizational size and their dominance in each regional lending market.

We expect that the connectivity has a more significant influence on the borrowing costs for regional banks than larger banks based on the existing empirical results. To examine this prediction, we conduct a branch-level and bank-level analysis on three subsamples grouped by the firm's main bank type: city, regional and cooperative.

Table 8 shows the result of subsample analysis at the branch level. *Score* is negatively related to *Rate* at all three bank types. However, the interaction term between *Score* and *Branch connectivity* is positively correlated with *Rate* at the 5% significance level in regional banks and cooperative banks only.

This is consistent with the existing empirical finding that regional banks make use of network information more intensively.

Table 9 shows the result of subsample analysis at the bank level. For the regional bank group, the interaction term remains positive at the 1% level, while the interaction does not show significance at the 10% level for the cooperative bank group. This finding is consistent with the findings and arguments in the existing empirical studies. For example, Nemoto et al. (2013) finds from a survey of banks that regional banks have introduced a customer-relationship management system to share quantitative and qualitative information among branches and the headquarters, whereas cooperative banks fall behind in the introduction of such a system.

4.3 Nonlinear Impact of Credit Score on Sensitivity

We find that the connectivity significantly reduces the borrowing cost for low-score firms, whereas it increases the cost for high-score firms in the baseline regression. However, it is less plausible that a high-score firm keeps borrowing from a highly connected bank despite the fact that high-score firms find it easier to switch to other banks to avoid the high borrowing cost.

Based on this consideration, we further investigate the nonlinear impact of the credit score on the sensitivity of loan pricing to connectivity. For this purpose, we introduce a dummy variable, *Low score*, which equals one if a firm's credit score is below a certain cutoff, to see whether the coefficient of the interaction term between the score and connectivity is positive and significant for low-score firms only. Table 10 shows the results with cutoffs at 50%, 75%, and 90%, respectively. We expect that the interaction term of score and connectivity is significant and positive only for low-score firms.

We find that *Score* is negatively correlated with *Rate* at the 1% level in all three specifications. The interaction term is positively correlated with the interest rate at the 1% level in all columns as opposed to our expectation. The three-way interaction term (*Score* $\times$ *Bank connectivity* $\times$ *Low score*) has a positive and significant but small coefficient in the cases where we set the threshold at the 75 and 90 percentile. This indicates that the sensitivity reduction by the connectivity is significant in all range of the credit score, but it is somewhat smaller for high-score firms.

5 Robustness Check

Although we include as many controls as possible in our estimations, we still have a concern about the endogeneity problem on the connectivity measures. For example, a firm's choice of suppliers, customers, or banks may depend on uncontrolled firm characteristics and the structure of the supply chain network. If connectivity can help with the production of private information, firms that are perceived to be promising according to private information but are evaluated as less creditworthy according to public information will have incentives to connect to firms or banks with a higher connectivity to reduce borrowing costs. Thus, the error term, which include such positive private information that cannot be controlled by definition, can be negatively correlated with the connectivity.

To mitigate this concern, we run a two-stage least squares (2SLS) estimation with geographic distance (*Geographic proximity*) and its interaction with the credit score (*Geographic proximity* $\times$ *Score*) as instruments for connectivity and its interaction with the credit score. The geographic proximity is defined as:

$$\text{Geographic proximity} = \frac{\text{Number of suppliers and customers in the same prefecture}}{\text{Total number of suppliers and customers}}. \quad (11)$$

We argue that the geographical proximity to suppliers and customers is a reasonable instrumental variable because several empirical studies show that it is an important factor for the inter-firm network formation, while it is less plausible that the proximity to other firms directly affects the borrowing costs given our set of control variables.

Moreover, the first stage regression (Table 11) shows that the coefficients of both of these instrumental variables are significant at a 1% level. The F-test statistics for these excluded instruments are 215.66 and 210.08 at the branch level and 77.42 and 81.52 at the bank level, respectively. Thus, the instruments are not weak ones.

The results of the estimation with instrumental variables are listed in Table 12. The signs of the coefficients are consistent with the baseline results. We find that *Score* is negatively correlated and the interaction term between *Score* and the connectivity measures is positive. The endogeneity test by the C statistic in the lower part of the table indicates that the endogeneity is statistically significant at a 1% significance level.

The economic significance increases very much after we control for the possible endogeneity as we expected. Assuming that the credit score increases by one standard deviation, the 10-percentile connectivity firm will have an additional rate reduction relative to 90-percentile connectivity firms by 49 basis points at the branch level and 31 basis points at the bank level. The economic significance is reasonably high.

6 Discussion and Policy Implication

We have obtained reasonably robust evidence that a bank obtains more accurate information from the supply network among its borrowers. In addition, we find that a firm with a lower credit evaluation via public information can reduce its borrowing costs by choosing a bank from which its suppliers and customers are borrowing. This finding indicates several important policy implications and directions for the future research.

First, our results indicate that a firm with a low public score can reduce its borrowing costs by increasing its connectivity to a certain bank, i.e., borrowing from the same bank from which its suppliers and customers borrow, or starting transactions with firms who are borrowing from its main bank. In other words, those with low credit score are more likely to cluster at a certain bank. This tendency in the network formation potentially results in the emergence of a too-connected-to-fail status with a low credit score (Ogura et al., 2015). A bank anticipating this effect might try to diversify its loan portfolio. These dynamics in the network formation can be a potential determinant for the stability of the banking sector. On the flip side of this argument, firms increase the risk to face a failure of their main bank without insuring themselves by keeping multiple bank relationships.

Second, we do not explicitly analyze the interaction between a bank-firm relationship, which we measure by the possibility of switching main banks, and the connectivity. The correlation coefficient between these measures is negative in our dataset. The estimation results show that the connectivity rather increases the borrowing costs for a firm with a higher public credit score, and so that it has more incentive to switch main banks to avoid higher connectivity. In contrast, a firm with a lower public score should prefer to increase connectivity to reduce the borrowing cost. The negative correlation between connectivity and the relationship in our dataset indicates that the former force is stronger than the latter in our dataset. However, the latter might be stronger during a recession, where all firms suffer from a negative macroeconomic shock. Besides it, anecdotes suggest that a bank finds a new customer through referrals by existing customers. Santikian (2014) provides empirical evidence that the expectation for such referrals affects loan pricing. The cause and the consequence of such behavior have yet to be investigated thoroughly.

Third, Panetta et al. (2009) found that bank mergers improve the accuracy of the credit evaluation. Our finding suggests that this improvement may be due to the expansion of the observability of the supply network. In contrast, many studies find evidence that bank consolidation reduces lending to SMEs, which is considered to be more sensitive to soft information (e.g., Berger et al., 1998; Sapienza, 2002; Bonaccorsi di Patti and Gobbi, 2007). A possible consistent interpretation for these findings is that bank consolidations reveals hidden bad information of SMEs by improving the observability of transactions among borrowing SMEs and such SMEs are rejected in the screening for a loan renewal.

Finally, our findings and the possible interpretations that we have mentioned so far imply an important policy implication that sharing information about inter-firm transactions and settlements could reduce the capital costs for firms that are informationally opaque but are potentially creditworthy on the private information basis. The online registration system for inter-firm trade credits (*Densai*), which began operation in 2013 in Japan, can be a potential platform for such information sharing among banks.

7 Conclusion

In this study, we have found that loan pricing is less sensitive to public information when a borrower is more connected to other borrowers of the lender through a business-to-business transaction network. This finding proves that banks extract useful information from a transaction network among their borrowers.

Higher connectivity enhances real-time observability of the flow of funds among borrowers. It may also facilitate prompt information propagation of private information on each borrower. The usefulness of the information from a neighborhood network has been anecdotally documented. Our study is the seminal empirical study proving the statistical and economic significance of it, to the best of our knowledge. Our findings shed light on a new direction for studies on information production in the banking sector and the relationship banking from the view point of the strategic network formation of firms and banks.

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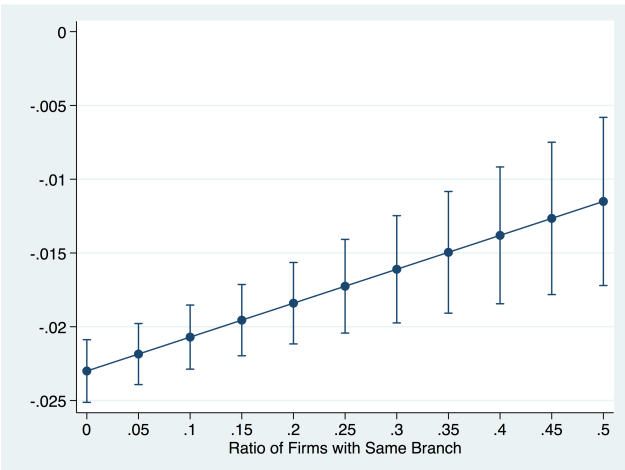
Figure 1: Marginal effect 1 ($d\ rate/d\ score$)

(Notes) Each dot indicates the marginal effect of score to rate at various level of the branch connectivity estimated by Column (3) in Table 6 (Panel (a)) and that estimated by Column (3) in Table 7 (Panel (b)). The values of the control variables are set at the sample mean. Vertical segments indicate 95% confidence intervals.

(a) by branch connectivity



(b) by bank connectivity

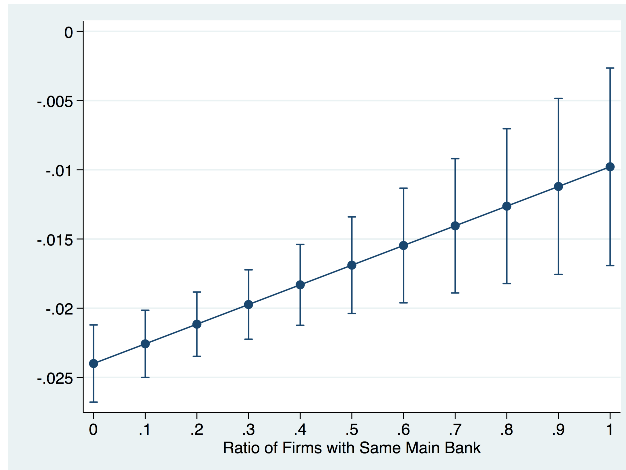
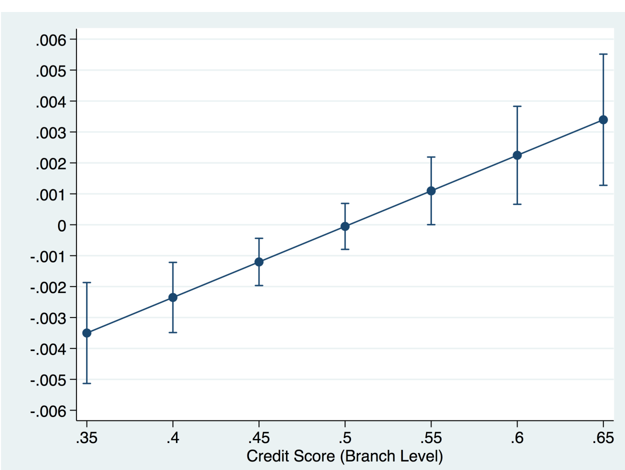


Figure 2: Marginal effect 2 ($d\ rate/d\ connectivity$)

(Notes) Each dot indicates the marginal effect of connectivity to rate at various level of credit score estimated by Column (3) in Table 6 (Panel (a)) and that estimated by Column (3) in Table 7 (Panel (b)). The values of the control variables are set at the sample mean. Vertical segments indicate 95% confidence intervals.

(a) $d\ rate/d\ branch\ connectivity$



(b) $d\ rate/d\ bank\ connectivity$

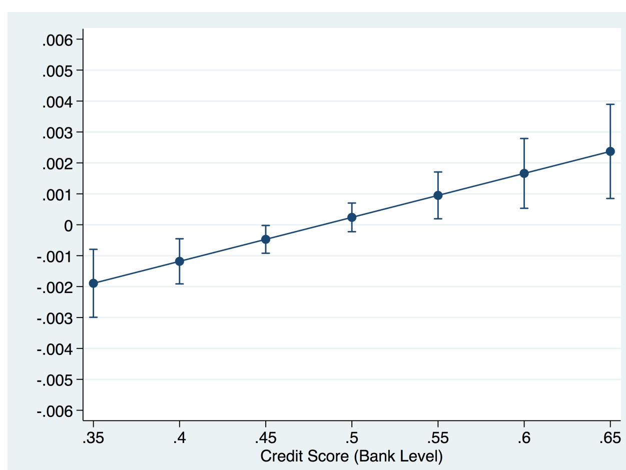


Table 1: Definition of Variables

Variables	**Definition**
Rate	Interest expense during FY ending in 2013 / loans outstanding at the end of FY 2013.
Score	0.01 $\times$ Credit score from Tokyo Shoko Research.
Branch connectivity	Number of suppliers and customers with the same main bank branch.
Bank connectivity	Number of suppliers and customers with the same main bank.
Mean score	Average credit score of customers and suppliers.
Number of employees	Number of employees / 100.
Leverage	Total liability / total assets.
Tangible assets	Tangible asset / total assets.
Current ratio	Current assets / current liability.
Interest coverage	Ln(1+EBITDA / (1 + interest expense)).
Listed	1 if firm is listed on a stock market, 0 otherwise.
Bond ratio	Bonds outstanding / (bonds outstanding + loans outstanding).
Ln(age)	Ln(firm age in years).
Long-term loan ratio	Amount of long-term loans / total amount of loans outstanding.
Subsidiary connectivity	Ratio of subsidiary firms with the same main bank.
Parent connectivity	Ratio of parent firms with the same main bank.
Bank switch	= 1 if firm changes its main bank from 2011 to 2014, 0 otherwise.
Number of banks	Number of lending banks. Maximum is 3.

Table 2: Summary Statistics

	Obs.	Mean	SD	Min	Median	Max
Rate	179576	0.020	0.014	0.000	0.019	0.119
Score	179576	0.493	0.063	0.140	0.490	0.850
Branch connectivity	179576	0.047	0.116	0.000	0.000	1.000
Bank connectivity	179576	0.191	0.217	0.000	0.130	1.000
Number of employees	179576	0.049	0.423	0.001	0.010	68.240
Leverage	179576	0.865	0.526	0.010	0.791	5.032
Tangible assets	179576	0.272	0.226	-0.016	0.223	0.997
Current ratio	179576	2.133	1.860	0.161	1.581	15.859
Interest coverage	179576	1.839	1.563	0.000	1.629	11.856
Listed	179576	0.013	0.114	0.000	0.000	1.000
Bond ratio	179576	0.006	0.038	0.000	0.000	0.953
Ln(age)	179576	3.317	0.636	0.000	3.401	4.905
Long-term loans ratio	179576	0.713	0.319	0.000	0.818	1.000
Switch bank	179576	0.100	0.300	0.000	0.000	1.000
Number of banks	179576	2.306	0.807	1.000	3.000	3.000
Mean score	172779	0.521	0.053	0.170	0.520	0.850
Subsidiary connectivity	179576	0.067	0.236	0.000	0.000	1.000
Parent connectivity	179576	0.069	0.239	0.000	0.000	1.000

Table 3: Number of Firms by Industry

	Frequency	Precent	Cum. Percent
Manufacturing	22760	12.67	12.67
Construction	94895	52.84	65.52
Communication	3666	2.04	67.56
Logistics	4871	2.71	70.27
Wholesale	20930	11.66	81.93
Retail	8098	4.51	86.44
Real Estate	5830	3.25	89.68
Service	17192	9.57	99.26
Other	1334	0.74	100.00
Total	179576	100.00	100.00

Table 4: Number of Firms by Bank Type

	Frequency	Precent	Cum. Percent
City	35623	19.84	19.84
Region	79961	44.53	64.36
Cooperative	41504	23.11	87.48
Others	22488	12.52	100.00
Total	179576	100.00	100.00

Table 5: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11
1	Rate	1.000										
2	Score	-0.105	1.000									
3	Branch connectivity	0.012	-0.010	1.000								
4	Bank connectivity	0.002	0.002	0.515	1.000							
5	Number of employess	-0.032	0.181	-0.017	-0.010	1.000						
6	Leverage	0.002	-0.539	-0.016	-0.016	-0.047	1.000					
7	Tangible assets	-0.054	0.047	0.034	0.009	0.012	-0.055	1.000				
8	Current ratio	-0.011	0.087	-0.004	-0.012	-0.024	-0.260	-0.129	1.000			
9	Interest coverage	-0.140	0.321	-0.017	0.013	0.050	-0.266	-0.130	0.067	1.000		
10	Listed	-0.050	0.218	-0.024	-0.016	0.304	-0.077	-0.012	-0.023	0.078	1.000	
11	Bond ratio	-0.042	0.158	-0.008	0.000	0.085	-0.060	0.022	0.025	0.012	0.096	1.000
12	Ln(age)	-0.040	0.320	0.018	0.030	0.083	-0.149	0.186	-0.027	-0.030	0.108	0.072
13	Long-term loans ratio	0.114	-0.155	-0.006	-0.005	-0.057	0.051	0.117	0.323	-0.080	-0.109	-0.039
14	Branch conn. × Score	0.008	0.041	0.991	0.512	-0.013	-0.045	0.037	0.002	-0.002	-0.019	-0.001
15	Bank conn. × Score	-0.009	0.120	0.510	0.986	0.008	-0.080	0.014	-0.002	0.050	0.005	0.019
16	Switch bank	-0.002	0.044	-0.046	-0.084	0.030	-0.011	-0.005	-0.009	0.001	0.031	0.019
17	Switch bank × Score	-0.008	0.083	-0.046	-0.083	0.044	-0.029	-0.004	-0.006	0.015	0.046	0.027
18	Number of banks	-0.006	0.325	-0.059	-0.071	0.067	-0.143	0.065	-0.043	-0.030	0.094	0.100
19	Mean socre	-0.067	0.624	-0.084	-0.067	0.122	-0.339	-0.005	0.102	0.235	0.135	0.108
20	Subsidiary connectivity	-0.034	0.266	0.065	0.074	0.092	-0.110	0.015	-0.040	0.044	0.183	0.098
21	Parent connectivity	-0.033	0.229	0.093	0.084	0.073	-0.085	-0.011	-0.040	0.063	0.091	0.062
22	Ratio same prefecture	0.049	-0.163	0.234	0.355	-0.063	0.047	-0.002	-0.030	-0.019	-0.088	-0.045

Table 5: (cont.)

		12	13	14	15	16	17	18	19	20	21	22
12	Ln(age)	1.000										
13	Long-term loans ratio	-0.107	1.000									
14	Branch conn. × Score	0.031	-0.012	1.000								
15	Bank conn. × Score	0.066	-0.024	0.521	1.000							
16	Switch bank	-0.015	0.006	-0.045	-0.082	1.000						
17	Switch bank × Score	-0.004	-0.001	-0.044	-0.077	0.992	1.000					
18	Number of banks	0.322	-0.049	-0.046	-0.036	0.115	0.124	1.000				
19	Mean socre	0.123	-0.070	-0.048	0.011	0.028	0.053	0.161	1.000			
20	Subsidiary connectivity	0.192	-0.106	0.084	0.113	-0.003	0.005	0.165	0.143	1.000		
21	Parent connectivity	0.097	-0.132	0.109	0.117	0.019	0.029	0.110	0.135	0.407	1.000	
22	Ratio same prefecture	0.020	0.040	0.228	0.336	-0.036	-0.043	-0.098	-0.320	-0.037	-0.064	1.000

Table 6: Interest Rate and Ratio of Firms with Same Bank Branch

(Notes) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The table presents the results from the fixed-effect models at the bank branch level. The dependent variable is *Rate*, which is the interest expense divided by loans outstanding in 2013. Columns (1) and (2) present the results without controlling firm characteristics. Column (3) presents the results after controlling the bank relationship variables. Each column reports the coefficient and standard errors. Standard errors in parentheses are clustered at the bank branch level.

	(1) Rate coef./se	(2) Rate coef./se	(3) Rate coef./se
Score	-0.019***	-0.015***	-0.019***
	(0.001)	(0.001)	(0.001)
Branch connectivity	-0.012***	-0.008***	-0.009***
	(0.003)	(0.003)	(0.003)
Score × Branch connectivity	0.025***	0.017***	0.018***
	(0.006)	(0.006)	(0.006)
Switch bank		0.004***	0.004***
		(0.001)	(0.001)
Score × Switch bank		-0.008***	-0.008***
		(0.002)	(0.002)
Number of banks		0.000***	0.000***
		(0.000)	(0.000)
Number of employees		0.000	0.000
		(0.000)	(0.000)
Leverage		-0.003***	-0.003***
		(0.000)	(0.000)
Tangible assets		-0.006***	-0.006***
		(0.000)	(0.000)
Current ratio		-0.001***	-0.001***
		(0.000)	(0.000)
Interest coverage		-0.001***	-0.001***
		(0.000)	(0.000)
Listed		-0.001***	-0.001***
		(0.000)	(0.000)
Bond ratio		-0.008***	-0.008***
		(0.001)	(0.001)
Ln(age)		0.000	0.000
		(0.000)	(0.000)
Long-term loans ratio		0.005***	0.005***
		(0.000)	(0.000)
Mean score			0.005***
			(0.001)
Subsidiary connectivity			-0.000
			(0.000)
Parent connectivity			0.001***
			(0.000)
Observations	179576	179576	172779
Branch FE	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R-Sq.	0.014	0.053	0.054

Table 7: Interest Rate and Ratio of Firms with Same Main Bank

(Notes) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The table presents the results from the fixed-effect models at the bank level. The dependent variable is *Rate*, which is the interest expense divided by loans outstanding in 2013. Columns (1) and (2) present the results without controlling firm characteristics. Column (3) presents the results after controlling the bank relationship variables. Each column reports the coefficient and standard errors. Standard errors in parentheses are clustered at the bank level.

	(1)	(2)	(3)
	Rate	Rate	Rate
	coef./se	coef./se	coef./se
Score	-0.019***	-0.015***	-0.020***
	(0.002)	(0.001)	(0.001)
Bank connectivity	-0.006***	-0.004**	-0.006***
	(0.002)	(0.002)	(0.002)
Score × Bank connectivity	0.012***	0.009**	0.012***
	(0.004)	(0.004)	(0.004)
Switch bank		0.004***	0.003***
		(0.001)	(0.001)
Score × Switch bank		-0.007***	-0.007***
		(0.002)	(0.002)
Number of banks		0.000***	0.000***
		(0.000)	(0.000)
Number of employees		0.000	0.000
		(0.000)	(0.000)
Leverage		-0.003***	-0.003***
		(0.000)	(0.000)
Tangible assets		-0.006***	-0.006***
		(0.000)	(0.000)
Current ratio		-0.001***	-0.001***
		(0.000)	(0.000)
Interest coverage		-0.001***	-0.001***
		(0.000)	(0.000)
Listed		-0.001***	-0.001***
		(0.000)	(0.000)
Bond ratio		-0.008***	-0.008***
		(0.001)	(0.001)
Ln(age)		0.000	0.000
		(0.000)	(0.000)
Long-term loans ratio		0.005***	0.005***
		(0.000)	(0.000)
Mean score			0.005***
			(0.001)
Subsidiary connectivity			-0.000
			(0.000)
Parent connectivity			0.001***
			(0.000)
Observations	179576	179576	172779
Bank FE	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R-Sq.	0.015	0.055	0.056

Table 8: Interest Rate and Ratio of Firms with Same Bank Branch: Subsample by Bank types

(Notes) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The table presents the results from the fixed-effect models at the bank branch level on subsamples by bank type, including city banks, regional banks and cooperative banks. The dependent variable is *Rate*, which is the interest expense divided by loans outstanding in 2013. Each column reports the coefficient and standard errors. Standard errors in parentheses are clustered at the bank level.

	(1) City coef./se	(2) Region coef./se	(3) Cooperative coef./se
Score	-0.017***	-0.020***	-0.020***
	(0.002)	(0.002)	(0.002)
Branch connectivity	-0.007	-0.007**	-0.015**
	(0.008)	(0.003)	(0.007)
Score × Branch connectivity	0.011	0.015**	0.030**
	(0.016)	(0.007)	(0.014)
Switch bank	0.005***	0.004**	-0.001
	(0.002)	(0.002)	(0.002)
Score × Switch bank	-0.010***	-0.008**	0.002
	(0.004)	(0.003)	(0.005)
Number of banks	0.000	0.000***	0.001***
	(0.000)	(0.000)	(0.000)
Number of employees	0.000	-0.002***	-0.002
	(0.000)	(0.000)	(0.002)
Leverage	-0.002***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)
Tangible assets	-0.004***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)
Current ratio	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Interest coverage	-0.001***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)
Listed	-0.001**	-0.002***	0.006
	(0.000)	(0.000)	(0.005)
Bond ratio	-0.007***	-0.009***	-0.007**
	(0.001)	(0.001)	(0.003)
Ln(age)	-0.000**	0.000***	-0.000
	(0.000)	(0.000)	(0.000)
Long-term loans ratio	0.004***	0.005***	0.006***
	(0.000)	(0.000)	(0.000)
Mean score	0.002	0.003**	0.007***
	(0.002)	(0.001)	(0.002)
Subsidiary connectivity	-0.000	-0.000	0.001
	(0.000)	(0.000)	(0.000)
Parent connectivity	0.000	0.001***	0.001
	(0.000)	(0.000)	(0.001)
Observations	34192	77146	39712
Branch FE	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R-Sq.	0.050	0.052	0.053

Table 9: Interest Rate and Ratio of Firms with Same Main Bank: Subsample by Bank Type

(Notes) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The table presents the results from the fixed-effect models at the bank level on subsamples by bank type, including city banks, regional banks and cooperative banks. The dependent variable is *Rate*, which is the interest expense divided by loans outstanding in 2013. Each column reports the coefficient and standard errors. Standard errors in parentheses are clustered at the bank level.

	(1) City coef./se	(2) Region coef./se	(3) Cooperative coef./se
Score	-0.015***	-0.023***	-0.017***
	(0.001)	(0.003)	(0.003)
Bank connectivity	0.001	-0.009***	0.002
	(0.004)	(0.002)	(0.005)
Score × Bank connectivity	-0.003	0.018***	-0.005
	(0.009)	(0.005)	(0.010)
Switch bank	0.005***	0.004**	-0.000
	(0.001)	(0.002)	(0.002)
Score × Switch bank	-0.010***	-0.008**	0.001
	(0.003)	(0.003)	(0.004)
Number of banks	0.000*	0.000***	0.001***
	(0.000)	(0.000)	(0.000)
Number of employees	0.000	-0.002***	-0.003
	(0.000)	(0.000)	(0.002)
Leverage	-0.002***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)
Tangible assets	-0.004***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)
Current ratio	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Interest coverage	-0.001***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)
Listed	-0.001***	-0.002***	0.004
	(0.000)	(0.001)	(0.005)
Bond ratio	-0.007***	-0.008***	-0.003
	(0.000)	(0.002)	(0.003)
Ln(age)	-0.000***	0.000**	-0.000
	(0.000)	(0.000)	(0.000)
Long-term loans ratio	0.004***	0.005***	0.006***
	(0.000)	(0.000)	(0.000)
Mean score	0.003*	0.003*	0.006***
	(0.001)	(0.001)	(0.002)
Subsidiary connectivity	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)
Parent connectivity	0.000	0.001***	0.000
	(0.000)	(0.000)	(0.001)
Observations	34192	77146	39712
Bank FE	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R-Sq.	0.058	0.055	0.052

Table 10: Nonlinear Impact of Credit Score on the Sensitivity of Loan Pricing to Connectivity

(Notes) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The table presents the results from the fixed-effect models at the bank level. The dependent variable is *Rate*, which is interest expense divided by loans outstanding in 2013. *Low score* = 1 if the firm has credit score lower than a certain threshold (50%, 75%, 90%). Each column reports the coefficient and standard errors. Standard errors in parentheses are clustered at the bank level.

	(1) < 50% coef./se	(2) < 75% coef./se	(3) < 90% coef./se
Score	-0.020***	-0.019***	-0.019***
	(0.001)	(0.001)	(0.001)
Bank connectivity	-0.008***	-0.012***	-0.009***
	(0.002)	(0.002)	(0.002)
Score × Bank connectivity	0.015***	0.019***	0.014***
	(0.004)	(0.004)	(0.004)
Score × Bank connectivity × Low score	0.001	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
Number of employees	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Leverage	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
Tangible assets	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)
Current ratio	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Interest coverage	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Listed	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Bond ratio	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)
Ln(age)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Long-term loans ratio	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)
Switch bank	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Score × Switch bank	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)
Number of banks	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Mean score	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
Subsidiary connectivity	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Parent connectivity	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Observations	172779	172779	172779
Bank FE	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R-Sq.	0.056	0.056	0.056

Table 11: Interest Rate and Ratio of Firms with Same Main Bank: First Stage for 2SLS

(Notes) ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% level, respectively. The table presents the results for the first stage from the 2SLS models at the branch and bank level. For each estimation, we report the first-stage result for the endogenous variables (*Connectivity* and *Score* $\times$ *Connectivity*). Each column reports the coefficient and standard errors. Standard errors in parentheses are clustered at the bank level.

	Branch		Bank	
	Conn. coef./se	Score × Conn. coef./se	Conn. coef./se	Score × Conn. coef./se
Score	-0.039***	-0.024***	-0.151***	-0.018
	(0.015)	(0.007)	(0.034)	(0.018)
Geographic proximity	0.047***	-0.018***	0.166***	-0.040**
	(0.010)	(0.005)	(0.031)	(0.017)
Score × Geographic proximity	0.066***	0.118***	0.166**	0.331***
	(0.020)	(0.011)	(0.067)	(0.047)
Switch bank	-0.006	0.003	-0.013	0.017***
	(0.008)	(0.004)	(0.012)	(0.006)
Score × Switch bank	0.004	-0.011	-0.004	-0.049***
	(0.016)	(0.007)	(0.023)	(0.012)
Number of banks	-0.006***	-0.003***	-0.012***	-0.006***
	(0.001)	(0.000)	(0.001)	(0.001)
Number of employees	-0.001***	-0.001***	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Leverage	-0.002***	-0.001***	-0.000	0.001
	(0.001)	(0.000)	(0.001)	(0.001)
Tangible assets	0.002	0.001	-0.005**	-0.003**
	(0.002)	(0.001)	(0.002)	(0.001)
Current ratio	0.000**	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Interest coverage	-0.001***	-0.001***	-0.001*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Listed	-0.003***	-0.002***	0.002	0.002
	(0.001)	(0.001)	(0.003)	(0.002)
Bond ratio	0.005	0.002	0.005	0.004
	(0.009)	(0.005)	(0.009)	(0.005)
Ln(age)	-0.003***	-0.002***	-0.003***	-0.002***
	(0.001)	(0.000)	(0.001)	(0.001)
Long-term loans ratio	-0.002**	-0.001**	0.003*	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Mean score	-0.035***	-0.012**	0.075	0.037
	(0.010)	(0.005)	(0.058)	(0.029)
Subsidiary connectivity	0.011***	0.006***	0.027***	0.016***
	(0.002)	(0.001)	(0.002)	(0.001)
Parent connectivity	0.044***	0.022***	0.054***	0.028***
	(0.002)	(0.001)	(0.002)	(0.001)
Observations	170540	170540	172768	172768
F-test of excluded	237.42	233.91	77.82	81.98
R-sq.	0.0482	0.0536	0.1187	0.1368

Table 12: Interest Rate and Ratio of Firms with Same Main Bank: 2SLS

(Notes) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The table presents the results from the 2SLS models at the bank level. The dependent variable is *Rate*, which is interest expense divided by loans outstanding in 2013. Each column reports the coefficient and standard errors. Standard errors in parentheses are clustered at the bank level. The endogeneity test indicates the C-statistics for the null hypothesis that connectivity and connectivity × score are exogenous, whose asymptotic distribution is $\chi^2(2)$.

	(1) Rate coef./se	(2) Rate coef./se
Score	-0.028***	-0.032***
	(0.002)	(0.002)
Branch connectivity	-0.119***	
	(0.015)	
Score × Branch Connectivity	0.224***	
	(0.031)	
Bank connectivity		-0.039***
		(0.005)
Score × Bank Connectivity		0.074***
		(0.010)
Switch bank	0.002*	0.001
	(0.001)	(0.001)
Score × Switch bank	-0.004**	-0.003
	(0.002)	(0.002)
Number of banks	0.000***	0.000***
	(0.000)	(0.000)
Number of employees	0.000	0.000
	(0.000)	(0.000)
Leverage	-0.003***	-0.003***
	(0.000)	(0.000)
Tangible assets	-0.006***	-0.006***
	(0.000)	(0.000)
Current ratio	-0.001***	-0.001***
	(0.000)	(0.000)
Interest coverage	-0.001***	-0.001***
	(0.000)	(0.000)
Listed	-0.001***	-0.001***
	(0.000)	(0.000)
Bond ratio	-0.008***	-0.008***
	(0.001)	(0.001)
Ln(age)	0.000	0.000
	(0.000)	(0.000)
Long-term loans ratio	0.005***	0.005***
	(0.000)	(0.000)
Mean score	0.002**	0.004***
	(0.001)	(0.001)
Subsidiary connectivity	-0.000**	-0.000*
	(0.000)	(0.000)
Parent connectivity	0.001***	0.001***
	(0.000)	(0.000)
Observations	170540	172768
Endogeneity test	47.679***	49.123***
Bank FE	Yes	Yes
Prefecture FE	Yes	Yes
Industry FE	Yes	Yes
R-Sq.	0.025	0.039