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Abstract

Relationship lending refers to lending a close relationship between a bank and a borrower, which is expected to help reduce borrowing costs. However, the extent to which they are used is unclear. This measurement difficulty makes it challenging to evaluate its benefits accurately. This paper proposes a novel empirical framework to identify relationship lending in transaction data between banks and borrowers in a more objective manner by determining the set of *significant ties* from an ensemble of undirected and unweighted bipartite networks. Using the detected relationship lending between banks and borrowers, we estimate the magnitude of additional lending volumes based on relationship lending. From the financial data in Japan from 1977 to 2021, the usage of relationship lending is estimated to be over 50% throughout the sample period but has varied considerably over time. We find that the volume of relationship lending is 34% larger than that of transactional lending. Although the relative volume of relationship lending against transaction lending has been declining, the importance of relationship lending remains substantial in obtaining a larger volume of lending.

JEL Classification: C81, G12, G21, L14;
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1 Introduction

Relationship lending is economically important, because it helps alleviate the impact of credit shortages (Bolton et al. (2016); Beck et al. (2018)). A strong bank-borrower relationship facilitates the bank's access to the borrower's soft information, potentially reducing information asymmetry. Borrowers who rely on non-relationship or transaction lending may face higher loan rates and be at a higher risk of default if the bank decides to change loan terms in response to changes in borrowers' circumstances. However, relationship lending is expected to act as insurance by easing credit constraints during economic downturns through loan rate smoothing (Berger and Udell (1992); Berlin and Mester (1999)). Therefore, the benefits of relationship lending are expected to include consistently lower loan rates and increased lending volumes, bringing advantages to borrowers.

Relationship lending, which relies on soft information, cannot be directly observed, thus necessitating the use of various proxies in previous literature. Kysucky and Norden (2016), in its extensive and detailed meta-analysis on the effects of relationship lending, categorizes the variables utilized as proxies for relationship lending into four distinct categories: time (e.g. duration of the lending relationship, age of borrowers, and so on), distance (e.g. physical, organizational, or personal distance), exclusivity (e.g. number of lending relationships, concentration of lending, or main bank status), and cross-product synergies (e.g. simultaneous provision of payment services, taking deposit, and so on). Most recent studies not included in their analysis also fit within their frameworks (Sette and Gobbi (2015); Bolton et al. (2016); Álvarez-Botas and González (2023)).[1]

The proxies for relationship lending employed in previous studies could incorporate non-negligible measurement errors, as Kobayashi and Takaguchi (2018) make a similar point in the context of the interbank market. Initially, the prolonged duration of the lending relationship could be attributed to a firm's strong credit demand. Companies with strong credit demand end up having longer lending relationships with certain banks by chance, even if they are conducting random transactions without intentionally favoring any particular bank. Such lending relationships are classified as transaction lending. Moreover, the age of borrowers and physical distance are not suitable proxies as building relationships requires a significant amount of time. This is because these proxies mistakenly suggest immediate establishment of a relationship when a bank initiates a new transaction with a well-established or nearby firm. Considering this, exclusivity and cross-product synergies are relatively good proxies. Typically, the process of expanding loan shares or encouraging companies to adopt other financial services requires time, which allows for the cultivation of strong relationships during this period. However, the use of these proxies can result in significant measurement errors. For instance, a large loan share for a company with a minimal credit demand does not necessarily indicate a relationship. In other words, a firm that can meet its credit demand through a few banks could coincidentally engage with one particular bank. Exclusivity can fully identify relationship lending only in cases in which all firms' credit demands are homogeneous. In addition, relationships can be

[1] For example, Sette and Gobbi (2015) identify relationship lending using physical distance, duration of the lending relationship, share of total lending, and their first principal component. Additionally, Bolton et al. (2016) conducted an empirical study that focused on physical distance while also considering the main bank status and duration of the lending relationship. Furthermore, Álvarez-Botas and González (2023) identify relationship lending through repeated borrowing from the same lender, a concept akin to the one employed by Bharath et al. (2011), and this approach closely aligns with the duration of the lending relationship. However, some studies fall outside the framework of Kysucky and Norden (2016), such as Beck et al. (2018), who identified relationship or transaction lenders by conducting face-to-face interviews with bank CEOs. Their identification method is groundbreaking; however, it does not fully elucidate the scenario in which the same bank employs relationship and transaction lending simultaneously.

developed without financial services. Therefore, significant measurement errors can occur, even when cross-product synergies are used as proxies.

The *significant tie* is the new network-based proxy for relationship lending proposed by Kobayashi and Takaguchi (2018), and serves as an effective solution to address the aforementioned issues. They identify significant ties (ST) as edges that are hardly judged to be created at random in the time-variant interbank network, in which the nodes are banks and the edges are the lending between banks, after controlling for banks' intrinsic lending capacity and credit demand. The method developed for detecting significant ties is called the *ST filter*, which is based on a fitness model, one of the gravity models, with a time-variant network known as a temporal network (Holme and Saramäki, 2019). The specification of the fitness model provides the theoretical null distribution of the number of two banks having a random lending relationship during a certain period as a binomial distribution. Although the method of detecting relationship lending by significant ties is similar to the duration of the lending relationship, the ST proxy can distinguish transactions maintained by a bank's irregularly good financial conditions. In this situation, the bank has a high lending or borrowing probability; that is, it naturally has many lending relationships, even if the transaction partners are chosen randomly.

The method of detecting significant ties can be applied to bank-borrower relationships. Given the two sets of nodes, one is the set of banks and the other is the set of borrowers, we can construct a bank-borrower network with edges as lending relationships from banks to borrowers. This type of network, with two types of node sets, is called a bipartite network.[2] The ST filter must be adjusted for applicability to temporal bipartite networks.

In the first part of this paper, we develop the ST filter for a bipartite network, called the ST-B filter. The ST-B filter accepts any temporal bipartite network to detect significant ties, similar to the original method in Kobayashi et al. (2019). There are many possible applications of the ST-B filter because the detection method is given in a general form for a temporal bipartite network. Therefore, we apply the ST-B filter to identify the relationship lending in the bank-borrower network made up of the bank-borrower relationships in Japan after 1977.

In the second part of the paper, using the identified relationship lending, we evaluate the influence of relationship lending on the Japanese economy. This part presents two main empirical findings. First, relationship lending provides an additional loan volume to a borrower compared with transaction lending, which we call the relationship premium. In a simple econometric analysis using a fixed effects model, the relationship premium is over 30% in Japan. Second, although transaction lending has had an increasing trend since 2000 and has dominated relationship lending since 2013, the relationship premium has always been substantially positive during the sample period. This implies that, while the relative use of relationship lending has decreased over the last 40 years, its importance or influence has not diminished.

The remainder of this paper is organized as follows: In Part I, we present the ST-B filter (Sec. 2) and data (Sec. 3), and identify the relationship lending in Japan (Sec. 4). In Part II, beyond the ST-B filter, we examine the relationship premium and the dynamics of relationship lending (Sec. 5). Finally, the summary and conclusions are presented (Sec. 6).

[2]See the details of bipartite networks, also called bipartite graphs, in Newman (2018) and Barabási (2013).

Part I
Identification of significant ties in a temporal bipartite network

2 method

2.1 Temporal bipartite network

In this section, we construct the method to detect significant ties applicable to bipartite networks by modifying the proposed method (Kobayashi and Takaguchi, 2018; Kobayashi et al., 2019). Kobayashi et al. (2019) propose two methods: the edge-based test detecting significant ties and the node-based test giving a reasonable number of the connections of a node. Relationship lending can be identified using the edge-based test.

Let $B_t = (I_t, J_t, E_t)$ be an undirected and unweighted bipartite network in period $t \in \{1, \cdots \tau\}$, where I_t and J_t denote the sets of nodes and E_t denotes the set of edges. In a bank-borrower network, let I_t and J_t be the bank and borrower sets, respectively. Banks and borrowers are indexed as $i \in I_t$ and $j \in J_t$, respectively. If bank i lends a loan to borrower j in period t, then nodes i and j are connected by an edge, denoted by $(i, j) \in E_t$. Let $\mathcal{B}$ be an ensemble of B_t; that is, $\mathcal{B} = \{B_t\}_t$, and we call $\mathcal{B}$ a temporal bipartite network. B_t is called the snapshot at time t.

2.2 Significant ties

Based on the temporal network, the method for detecting significant ties (ST) is called the *ST filter* (Kobayashi et al., 2019), and the procedure is called the edge-based test. Following Kobayashi et al. (2019), we develop the ST filter that can be applied to a temporal bipartite network.

Let $u(a_i, b_j)$ denote the probability that bank i and borrower j have an edge in each period, where $a_i \geq 0$ and $b_j \geq 0$ are the activity levels of bank i and borrower j, respectively. An activity level, which is time-independent, is regarded as the intrinsic linkability in a network (i.e., the intrinsic lending ability of a bank and the credit demand of a borrower). Thus, $u(a_i, b_j)$ is assumed to be an increasing function of a_i and b_j. We assume that the connection probability is such that

$$u(a_i, b_j) = \frac{a_i b_j}{1 + a_i b_j}, \tag{1}$$

ensuring that $u(a_i, b_j) \in (0, 1)$.

Let M_t be the adjacency matrix for B_t. The aggregate adjacency matrix of $\mathcal{B}$ is defined as $M \equiv \sum_t M_t$. The i-j element of M, denoted by m_{ij}, is not larger than the number of snapshots τ. In the bank-borrower network, m_{ij} is the number of periods in which bank i lends a loan to borrower j during τ periods. We estimate the plausible parameter set $\mathbf{a} = \{a_i\}_i$ and $\mathbf{b} = \{b_j\}_j$ based on (1) and observe the aggregate adjacency matrix M.

If each bank-borrower pair acts independently for each period, the probability distribution of the sequence of $\{m_{ij}\}_{ij}$ conditional on $\mathbf{a}$ and $\mathbf{b}$ is given by

$$p(\{m_{ij}\} \mid \mathbf{a}, \mathbf{b}) = \prod_{i,j} \binom{\tau}{m_{ij}} u(a_i, b_j)^{m_{ij}} \left(1 - u(a_i, b_j)\right)^{\tau - m_{ij}}, \tag{2}$$

which is the likelihood function used to estimate **a** and **b**. By taking the logarithm of (2), we obtain the following log-likelihood function:

$$\log p(\{m_{ij}\} \mid \mathbf{a}, \mathbf{b}) = \sum_{ij} \left[m_{ij} \left(\log a_i + \log b_j\right) - \tau \log(1 + a_i b_j)\right] + const. \tag{3}$$

Given the observed matrix M, the most plausible **a** and **b** are attained such that (3) is maximized. The first-order conditions are as follows:

$$\begin{aligned} \sum_{j=1}^{J} \frac{m_{ij}^{\mathrm{o}} - (\tau - m_{ij}^{\mathrm{o}}) a_i b_j}{1 + a_i b_j} &= 0, \quad \forall i = 1, 2, \cdots, I, \\ \sum_{i=1}^{I} \frac{m_{ij}^{\mathrm{o}} - (\tau - m_{ij}^{\mathrm{o}}) a_i b_j}{1 + a_i b_j} &= 0, \quad \forall j = 1, 2, \cdots, J. \end{aligned} \tag{4}$$

By solving (4) using a nonlinear root-finding method, we obtain the estimated values of the activity parameters denoted by $\hat{\mathbf{a}} = \{\hat{a}_i\}_i$ and $\hat{\mathbf{b}} = \{\hat{b}_j\}_j$.[3] Using the estimated activity parameters, we obtain the estimated probability that bank i and borrower j have an edge, $u(\hat{a}_i, \hat{b}_j)$.

We now obtain the null distribution of the number of edges connecting bank i and borrower j during τ periods, m_{ij}, as a binomial distribution:

$$q(m_{ij} \mid \hat{a}_i, \hat{b}_j) = \binom{\tau}{m_{ij}} u(\hat{a}_i, \hat{b}_j)^{m_{ij}} \left(1 - u(\hat{a}_i, \hat{b}_j)\right)^{\tau - m_{ij}}. \tag{5}$$

With a given significance level α, we can carry out the statistical test. Let m_{ij}^c denote the critical value calculated by using α. If the realized number of edges surpasses m_{ij}^c, the connection between borrower i and bank j is judged as a *significant tie* (ST). To distinguish the applicable networks of the ST filter clearly, we call the procedure for detecting significant ties in a bipartite network the *ST-B filter*.

Using the ST-B filter, the statistical test is performed $|\mathcal{I}| \times |J|$ times, where $\mathcal{I} \equiv \bigcup_t I_t$ and $\mathcal{J} \equiv \bigcup_t J_t$, and a multiple testing problem exists. To control for the false discovery rate, we adjust the significance level using the Bonferroni correction such that the threshold of the significance level α is divided by the number of tests ($|\mathcal{I}| \times |\mathcal{J}|$).

3 Data

The bank-borrower network is constructed by *The Nikkei Economic Electronic Databank System (NEEDS)*, which contains short-term and long-term loan relationships between over 2000 publicly listed companies and banks from which these companies borrow loans and their loan volume in Japan after 1977. The short-term and long-term loans are contracts for less than a year or over a year, respectively. We use short-term loan relationships from 1977 to 2021.[4] The nodes in the snapshot are companies and banks with lending

[3] In the estimation process, (4) may not include independent $I + J$ equations, because there could be linearly dependent equations. If banks i and i' have the exact same record in terms of partner banks and the number of debt (i.e., $m_{ij} = m_{i'j}\ \forall j$), we exclude either in estimation because $\hat{a}_i = \hat{a}_{i'}$.

[4] We use short-term loans in our estimation because our dataset includes only stock data for each year. If a short-term loan from a bank to a borrower is recorded, by definition, the bank and borrower have at least one loan contract in a year. This can be regarded as the cash flow from the bank to the borrower. To check the robustness of the method, we apply the ST-B filter to long-term loans and the sum of short-term and long-term loans in the Appendix.

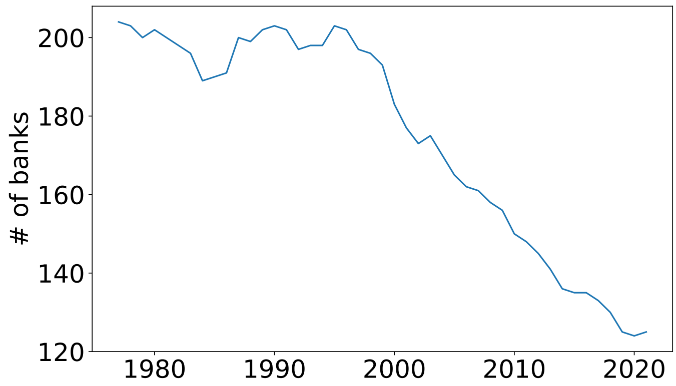

Fig. 1. Number of banks having at least one loan relationship during the sample period. It drastically decreases after 1995 owing to bank consolidations and bankruptcies.

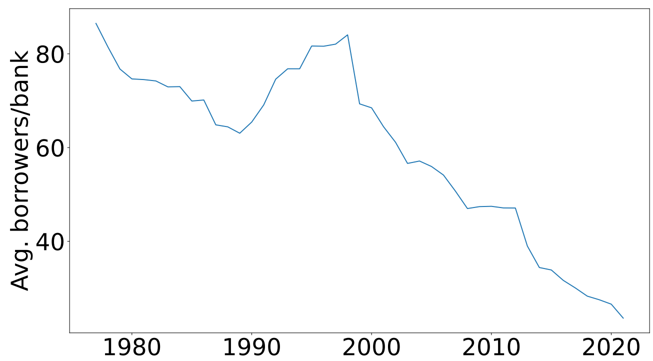

Fig. 2. Average number of borrowers per bank during the sample period. Banks reduce the number of transactions after 1998, creating significant challenges for borrowers to obtain loans.

relationships in a fiscal year, which is period, and the edges are these relationships. Henceforth, year and period are interpreted interchangeably.

During the sample period, the numbers of companies and banks are 2,494 and 238 after the data cleaning excluding ambiguous lenders such as “others,” and the number of edges is 355,604. The dynamics of the number of banks are shown in Fig. 1. The number of banks drastically decreases after 1995 owing to bank consolidation and bankruptcy. Furthermore, the average number of borrowers per bank decreases after 1998 (see Fig. 2).

The decline in the number of banks and reduced loan availability have heightened challenges for borrowers. It is essential to investigate how relationship lending has changed and what trends are emerging in the loan market.

4 Results

4.1 Estimated significant ties

We implement the edge-based test described in Sec. 2.2 and identify whether each bank loan to a borrower is a significant tie. If the loan from bank i to borrower j in year t is detected as a significant tie, the loan is judged as a relationship lending. To detect

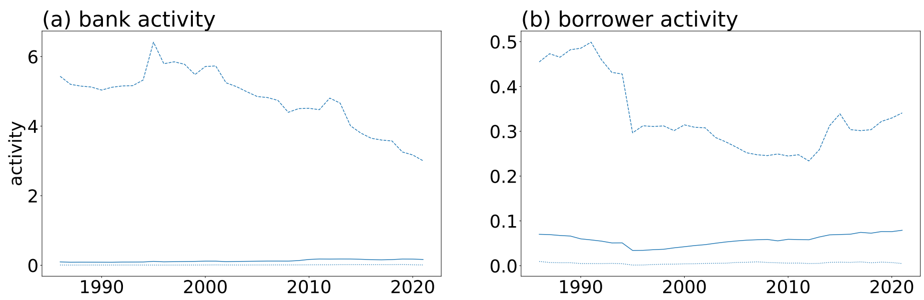

Fig. 3. Distribution of estimated activity parameters. The solid line represents the median and the top and bottom dotted lines indicate the 5th and 95th percentiles, respectively. (a) The distribution of bank activity parameters has a broad upper tail but remains relatively stable during the sample period. (b) The distribution of borrower activity parameters shows a structural change at 1995, although the median remains stable throughout the sample period.

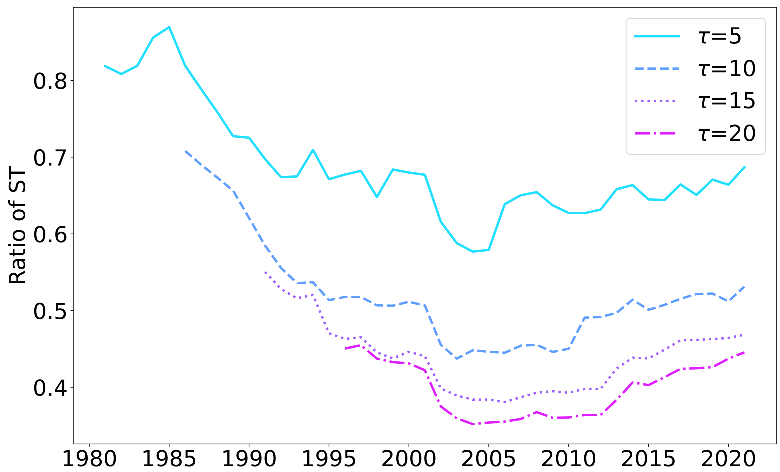

Fig. 4. Ratio of relationship lending by significant ties. The number of snapshots for estimation is set such that $\tau = \{5, 10, 15, 20\}$. The trend of each estimation is similar.

significant ties in period t, we use τ snapshots from periods $t - \tau + 1$ to t. The estimation is performed for all years using a moving window. For instance, if $\tau = 10$, significant ties in 2000 are computed using snapshots from 1991 to 2000.

For the estimated activity parameters $(\hat{a}_i)_i$, $(\hat{b}_j)_j$ based on (4), we draw the distribution of the activity parameters in Fig. 3. The medians of the bank and borrower activity parameters are stable during the sample period. Using the estimated activity parameters, we obtain the probability that bank i and borrower j have a lending relationship in a year, $u(\hat{a}_i, \hat{b}_j)$. With this probability, the null distribution of the number of transactions between i and j is computed and relationship lending is detected.

We summarize the estimated results for the ratio of relationship lending to all loan contracts for each year (Fig. 4), where the statistical level $\alpha = 0.01$ with the Bonferroni correction.[5] There are two notes on estimating significant ties at time t. First, banks

[5]The ST-B filter applies to long-term loans and to the sum of short-term and long-term loans in Appendix A. The results exhibit a similar tendency in all cases.

Tab. 1. Correlations matrix of various proxies for relationship lending by pooled samples over time.

Proxy by	ST-B	Distance	Exclusivity	Duration
ST-B	1.000			
Distance (same prefecture)	0.067	1.000		
Exclusivity (over 30% share)	0.004	0.059	1.000	
Duration (10y or more)	0.855	0.072	-0.023	1.000

The correlation between ST-B and duration proxy is over 0.8, meaning that the ST-B proxy is the most similar to the duration proxy. Other proxies have no substantial correlations.

consolidated during the time window $[t-\tau+1, t]$ are treated as one bank in the estimation. Second, bankrupt banks during the time window $[t-\tau+1, t]$ are included in the estimation, whereas even if there are significant ties to these banks, these edges are excluded from the result in time τ.

The ratio of relationship lending decreases until 2005, after which it increases slightly. For the time windows $\tau > 10$, the dynamics of the ratio of relationship lending appear robust. In the following discussion, we focus on estimating $\tau = 10$, which includes at least two business cycles without large structural changes in the economy.

4.2 Comparison with conventional proxies

To check the features of the significant ties, we compare the ST-B filter with conventional proxies for relationship lending. We select four representative conventional proxies: distance, concentration, lending share, and lending duration. Following Bolton et al. (2016), the distance proxy is constructed such that the loan from bank i to borrower j is relationship lending if bank i and borrower j are in the same region at time t. We set the unit of the region as a prefecture in Japan. The exclusivity proxy is built such that the loans by relationship lending are over 30% of the aggregate loans of borrower j (Elsas, 2005).[6] The proxy for lending duration is created such that the loans by relationship lending are those with 10 years or more consecutive lending relationships (Berger and Udell, 1995; Boot, 2000).[7]

We examine the similarity using correlations among these proxies. We select the number of snapshots $\tau = 10$ for the proxies using ST. Let RL^{ℓ}_{ijt} be a binary variable that takes the value of 1 if the loan from bank i to borrower j at time t is a relationship lending loan judged by proxy ℓ and 0 otherwise, where $\ell \in \{\text{ST}, \text{ Distance}, \text{ Exclusivity}, \text{ Duration}\}$.

Tab. 1 shows the correlation matrix of RL^{ℓ}_{ijt} computed from the pooled samples over time. While there are a few correlations of less than 0.1 between the ST-B proxy and the distance and exclusivity proxies, there is a strong correlation of over 0.8 between the ST-B and the duration proxy. This is a reasonable consequence because the ST-B proxy is irrelevant to physical distance and lending volume in the calculation, whereas it is calculated mainly based on the frequency of lending contracts.

This tendency is also verified by the dynamics of the ratio of relationship lending to all lending, as shown in Fig. 5. Overall, proxies other than those by ST-B could underestimate relationship lending in aggregates. The ST-B and duration proxies have almost the same

[6] Elsas (2005) indicates the average loan share from the main bank that borrowers recognize as 43.8% and the average loan share from the other banks as 26.0%. Around the mid-value of these shares, we use 30% of the threshold as the loan share proxy.

[7] Berger and Udell (1995) shows the average length of relationship with the current lender in years as 11.4.

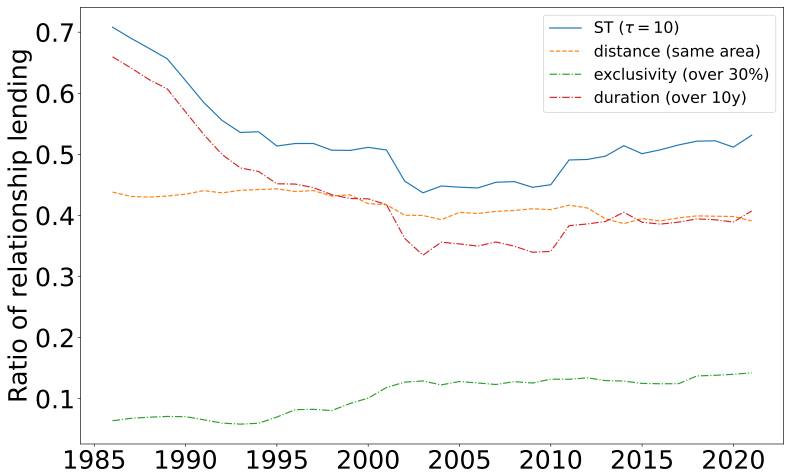

Fig. 5. Ratios of relationship lending, which are proxies by ST-B, distance, exclusivity, and duration, over time. The ratio could be underestimated by the proxies by distance, exclusivity, and duration. Although the proxies by distance and exclusivity are almost constant, the ones by ST-B are not.

dynamics during the periods, which shows a strong similarity between these proxies. In the next subsection, we discuss the difference between the ST-B and duration proxies with a more detailed description of the ST-B proxy.

The dynamics of the proxies based on distance and exclusivity are dissimilar to those of the ST-B proxy. The proxies by distance and exclusivity appear to be relatively stable over time compared to the others; however, it seems that each reason for the stability could be different. On the one hand, the distance proxy tends to be steady by definition, in which the headquarters of banks and companies rarely relocate. The exclusivity proxy could be stable, on the other hand, simply because of the low ratio of lending shares over 30%.

4.3 Fundamental features of ST-B proxy: comparing with duration proxy

By checking RL_{ijt}^{ST} and $RL_{ijt}^{Duration}$ for each transaction for bank-borrower pairs, we find interesting cases ascribed to the difference between the ST-B and duration proxies. There are two main examples that capture the features of the ST-B proxy: robustness for an incidental interruption of transactions and powerful identification ability for a small number of transactions.

First, the continuity imposed by the duration proxy is relaxed using the ST-B proxy. If relationship lending is based on duration, the bank and the borrower must maintain successive loan relationships for a given number of years. With the ST-B proxy, however, we can observe that if a bank-borrower transaction, which is based on relationship lending, is broken up for a year, it will immediately become relationship lending when the next time the transaction is resumed. The appearance of such cases seems reasonable because these bank-borrower pairs are well-known to each other through past transactions. Thus, the ST-B proxy is robust to an incidental interruption of a bank-borrower relationship, because a bank and borrower do not have to hold a successive loan relationship during

Tab. 2. Summary statistics of the sample panel.

$N = 355,604$		Mean	SD	Max	Min
loan (in mil. yen)		$3,584.3$	16,881.4	1,224,359.0	1.00
$\log loan$		6.332	1.845	14.02	0.00
RL^{ℓ}	Proxy(ℓ)				
	ST-B	0.533	0.499	1.00	0.00
	Distance	0.423	0.494	1.00	0.00
	Exclusivity	0.095	0.293	1.00	0.00
	Duration	0.498	0.494	1.00	0.00

In the regression, relationship lending RL^{ℓ} is described by ST-B and conventional proxies. Relationship lending by exclusivity has a quite small mean, although relationship lending by other proxies including ST-B does not differ largely as seen in Fig. 5.

certain past periods.

Second, the ST-B proxy allows us to judge relationship lending even if the bank-borrower transaction has few transaction histories, although the duration proxy does not. We find that, for instance, a relationship lending between a bank and borrower is judged despite only three transactions in the past ten years. This can occur if the activity parameters of the bank and borrower are simultaneously small at the same time. Both small activity parameters lead to a low transaction probability per year in the null model, in which banks and borrowers randomly choose transaction partners. As a result, even if only a small number of transactions are realized in certain past years between a bank and a borrower, these transactions can become relationship lending depending on these activity parameters. This case can be regarded as an example of parametric modeling that works powerfully in the identification of relationship lending.

Both examples suggest that the ST-B proxy is more effective than the duration proxy in identifying relationship lending. There are transactions judged as relationship lending by the ST-B proxy, but not by the duration proxy. However, the opposite does not occur.

Part II

Application of the ST-B filter: influence of relationship lending

5 Relationship lending and lending volume

This part provides two simple exercises associated with relationship lending through lending volumes: relationship lending could lead to a larger lending volume than transaction lending, and an analysis of the dynamics of relationship and transaction lending.

5.1 Effects of relationship lending on lending volume

Relationship lending can provide additional volume to the lending volume. Through relationship lending, a bank lends loans to a borrower with soft information, which is not observed in the data, in addition to the hard information observed. Additional information reduces transaction costs. This can lead to larger lending volumes between banks and

Tab. 3. Comparison of relationship lending premium in lending volume.

		Conventional proxy		
Proxy (ℓ)	ST-B	Distance	Exclusivity	Duration
RL^{ℓ}	0.342	0.476	1.357	0.303
(SE)	(0.005)	(0.006)	(0.007)	(0.005)
Bank dummy		Yes		
Borrower dummy		Yes		
Time dummy		Yes		
Adj. R^2	0.531	0.533	0.561	0.530

The coefficients are estimated by the fixed effects model. Our main interest is the effect of ST-B proxy, in which relationship lending (significant tie) is identified by a 10-year time window ($\tau = 10$). With the interaction that the fixed effects of banks and borrowers are regarded as the lending volume explained by hard information, the pairwise effect of a bank-borrower relationship provides 34.2%pt additional loan volume to the borrower. As there could be sample selection bias led by unobserved $loan_{ijt} = 0$ samples, the estimated coefficient of RL^{ℓ} can be regarded as the lower bound of the effects of the relationship lending.

borrowers with relationship lending.

We check for the existence of additional loans with relationship lending using a simple fixed-effects model. We assume the following model:

$$\log loan_{ijt} = \beta RL^{\ell}_{ijt} + \mu_i + \phi_j + \psi_t + \varepsilon_{ijt}, \tag{6}$$

where $loan_{ijt}$ is the lending volume from bank i to borrower j at period t, RL^{ℓ}_{ijt} is the dummy variable taking 1 if the lending is made by relationship lending by proxy $\ell \in \{$ST-B, Distance, Exclusivity, Duration$\}$, and $\mu_i, \phi_j, \psi_t, \varepsilon_{ijt}$ are the bank dummy, borrower dummy, time dummy, and error term, respectively. The summary statistics for the sample panel are listed in Tab. 2.

Our main interest is determining whether $\beta = 0$ when the proxy is an ST. Tab. 3 summarizes the estimated results using Eq. (6) for various proxies, including conventional ones, to compare the results. Based on the ST-B proxy, relationship lending provides an average of 34.2 % additional loan volume to the loan between the bank and borrower. We call the additional lending volume led by relationship lending the *relationship premium*. Note that the coefficient of RL^{ℓ} is the lower bound of the effect of relationship lending, as it may be biased lower, as generated by sample selection.[8] The results show the existence of a pair-specific effect between a bank and borrower, excluding the bank- and borrower-specific effects, which are hard information of the bank and borrower abstracted by the bank and borrower dummies, respectively. In other words, loan volumes that cannot be explained by the hard information of a bank and borrower are generated from pair-specific relationships.

Among the conventional proxies, the duration proxy, which is the most correlated with ST, results in the coefficient similar to that of the ST-B proxies. The next nearest value is the result of the distance proxy. The ST-B, duration, and distance proxies have common properties, such that they do not include the lending volume in these computation procedures. However, the estimator using the exclusivity proxy, which includes the lending volume in the calculation procedure, has an upper bias and results in a larger value than the other proxies.

[8] The panel does not include $loan_{ijt} = 0$ samples. This generates sample selection bias for RL^{ℓ} estimator.

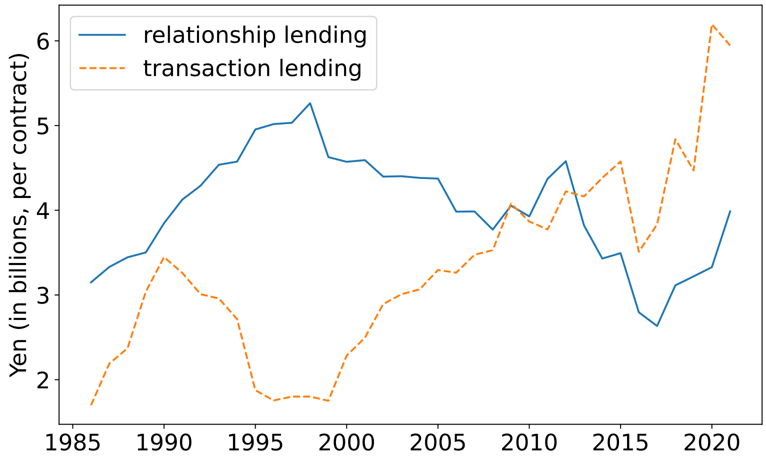

Fig. 6. Lending volumes per contract by transaction lending (blue) and relationship lending (orange-dashed). While relationship lending has been relatively stable, transaction lending has increased since 1999. After 2013, the average loan volume of transaction lending surpasses that of relationship lending.

5.2 Dynamics of relationship lending and its effects

We can see the dynamics of not only the number of bank-borrower contracts but also the loan volume by relationship lending detected by the ST-B filter. Fig. 6 shows the lending volume per bank-borrower contract by transaction(blue) and relationship (orange-dashed) lending, which raises three points. First, a structural change occurs in 1999. Since 1999, transactional and relationship lending have increased and decreased, respectively. Second, before 1999, the loan volume by transaction lending waves and by relationship lending steadily increases. This implies that transaction-lending loans are more sensitive to the business cycle than relationship-lending loans. Third, the volume of transaction lending becomes higher than that of relationship lending. Next, we discuss the third point.

The average loan volume by transactional lending surpassed the average loan volume by relationship lending after 2013. It is possible that the relationship premium decreased or became negative during these periods. To check this point, we adopt an alternative specification to attain the relationship premium for each year such that

$$\log loan_{ijt} = \gamma_t RL^{\ell}_{ijt} + \lambda_{it} + \xi_{jt} + \epsilon_{ijt}, \tag{7}$$

where λ_{it} and ξ_{jt} are the cross terms of the bank- and borrower-time dummies, respectively, and ϵ_{ijt} is the error term.[9] In this formulation, γ_t can be considered as the relationship premium for each year.

The estimated γ_t for each t, using the ST-B proxy, is shown in Fig. 7, where each error bar indicates a two standard error interval. The relationship premiums are significantly positive over the sample period and are almost stable after 2000, including after 2013. In other words, the relationship premium remains strong, even when transaction lending dominates relationship lending.

The trends in loan volumes for relationship lending versus transaction lending reflect an increase in loans for borrowers who rely solely on transaction lending. Fig. 8 shows the

[9] Actually, Eq. (7) can be estimated using the annual sample.

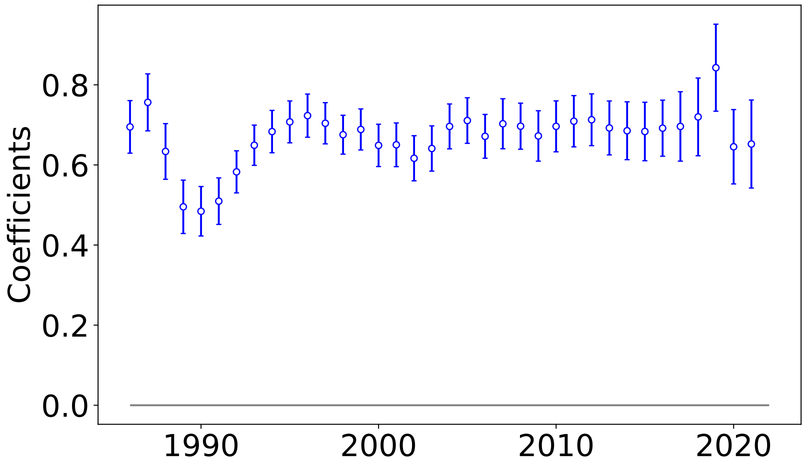

Fig. 7. Effects of relationship lending on lending volume (in logarithm) for each year. Error bar indicates two standard error interval. The estimated results are significantly positive throughout the sample periods and remain nearly stable after 2000, including the periods following 2013.

loan volume of transaction lending per bank-borrower contract conditional on borrowers using only transaction lending (blue line) and all borrowers using transaction lending (orange dashed). For the sample in which borrowers use transaction lending only, the average loan volume increased rapidly from 2000 compared to unconditional lending. As borrowers without relationship loans do not affect the estimation of γ_t, the relationship premium remains high even after 2013.

6 Conclusion

We propose a novel method for detecting lending relationships in bank-borrower networks by developing the ST filter (Kobayashi and Takaguchi, 2018; Kobayashi et al., 2019) and provide simple applications. The ST-B filter can detect the lending relationship for each loan between a bank and a borrower, which is a relative advantage over other competing proxies.

In the first part of this paper, we illustrate the ST-B filter method, developed from the ST filter (Kobayashi et al., 2019; Kobayashi and Takaguchi, 2018). Using the ST-B filter, we identify the relationship lending between banks and borrowers in Japan from the loan data. Based on the ST-B proxy, we found that the number of bank-borrower contracts for relationship lending had a decreasing trend until 2000 and then a stable or slightly increasing trend. Comparing relationship lending based on the ST-B filter with other conventional proxies, we find that the ST-B proxy has dynamics similar to those of the duration proxy. The ST-B proxy relaxes the strict condition of continuousness in the duration proxy to judge relationship lending, leading to more relationship lending than in the duration proxy. The model-based identification of the ST-B filter enables us to capture relationship lending as a transaction between a bank and borrower where such transactions are unlikely to be random.

In the second part, we provide two concrete examples of the application of the ST-B filter with detected relationship lending. First, we examine the effects of relationship lending

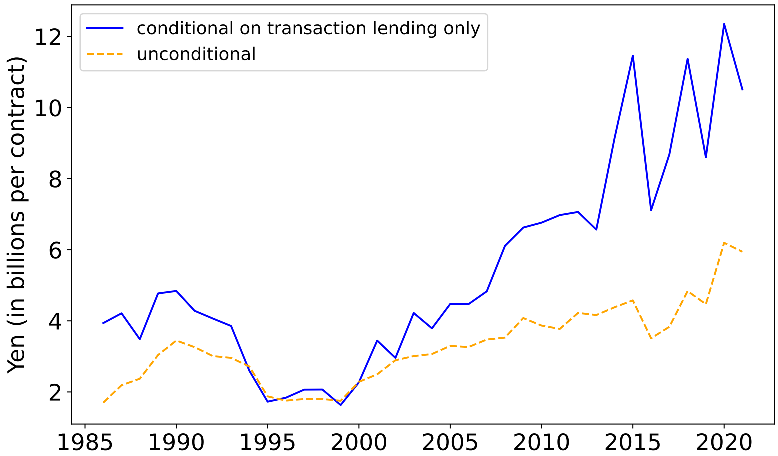

Fig. 8. Loan volume of transaction lending per bank-borrower contract conditional on the borrowers using only transaction lending (blue) and by all borrowers using transaction lending (orange braked). The blue line rapidly grows after 1999.

on the lending volume. Controlling for the hard information of banks and borrowers, we found a pair-specific effect of the combination of a bank and a borrower on lending volume: an additional loan volume by relationship lending. Second, we examine the dynamics of loan volume by relationship and transaction lending. The average transaction-lending loan has shown an increasing trend since 2000 and dominated relationship-lending loans after 2013. Despite this trend, the additional loan volume provided by relationship lending is substantial from 1986 to 2021.

Three possible future studies are left for the research. The first and second pertain to the ST-B filter and the third pertains to relationship lending. First, the method could be applied to a dataset other than a bank-borrower network. If the interest is non-randomness in the matching process in a bipartite network, the ST-B filter can be a powerful and general tool to detect it. Second, the node-based test method (Kobayashi and Takaguchi, 2018; Kobayashi et al., 2019) could be developed for temporal bipartite networks. Using the node-based test, we can determine the distribution of the number of connections if a node (bank or borrower) randomly chooses transaction partners. Based on the distribution, we could see the difference between major and minor banks using measures (e.g., the z-score). Third, a bank-borrower network could be constructed with small- and mid-sized firms. Relationship lending can affect these firms more than the large-sized firms studied here. This study provides a comprehensive understanding of the function of relationship lending in an economy.

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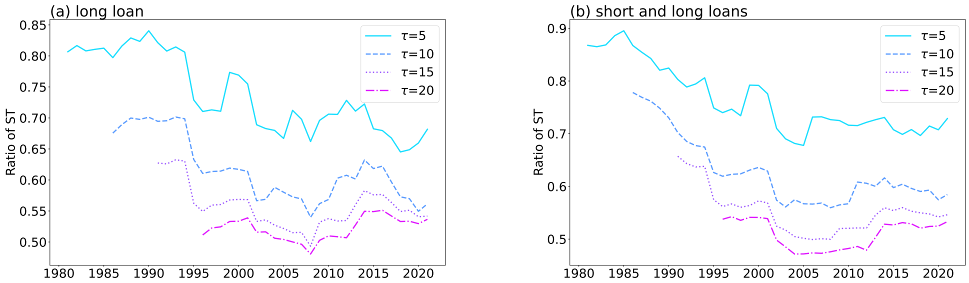

Fig. 9. Significant ties between banks and firms with (a) long-term loans, and (b) short- and long-term loans. The tendency of the detected ties is not different from the ST-B detected by short-term loans (Fig. 4)

Appendix A ST-B based on long-term and long-term & short-term loans

To check the robustness of the ST-B filter method and the estimation results, we estimate the significant ties in the bank-borrower network constructed by long loans and the sum of long-term and short-term loans. Fig. 9a and 9b show the estimated results for long-term loans and the sum of long-term and short-term loans, respectively. These trends are similar to the estimated results based only on short-term loans.