DBJ Discussion Paper Series, No.0903

# How Does the Stability of Loan Relations Depend on its Duration? Evidence from Firm- and Bank-Level Data

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July 2009

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**Abstract**

This paper empirically studies the stability of loan relations between Japanese listed firms and banks. By using a unique data set for Japanese bank loan market, first, we estimate the hazard function for the loan relations through non-parametric duration models. Then, with considering empirical findings that bank loan relations are systematically governed by the characteristics of firms, banks, and matches, the stability of relations is formally examined through semi-parametric and parametric duration analyses. The results support the existence of relation-specific capital discussed in the theoretical literature.

*Key words*: Bank loan relation; Stability; Duration analysis
*JEL Classification*: G21, G32, C41

*I thank Hugo Hopenhayn, Andy Atkeson, Lee Ohanian, Daniel Ackerberg, Isabelle Perrigne, Christian Hellwig, Pierre-Olivier Weill, Pierre-Yves Yanni, Shogo Hamasaki, Junichi Nakamura, Keiichiro Oda, Pramuan Bunkanwanicha and seminar participants at UCLA Monetary Economics Proseminar, Industrial Organization Proseminar, and DBJ Applied Economics Workshop for useful comments and suggestions.

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# 1 Introduction

Bank loans are one of the most important long-term financing sources in many countries (see Freixas and Rochet (2008) for a comprehensive survey). In fact, during the early 80s in Japan, long-term bank loans comprised over 90% of the corporate's total long-term debt[1]. While this ratio decreased during the 1980-1990s, it is still more than 70% as of 2000 (see *Figure-1*).[2][3]

The dominant presence of bank loans in the liability of firms has encouraged various empirical studies regarding the determinants of loan relations. The existing empirical studies, however, focus almost exclusively on the determinants of the "number of banks" in a firm's liability while implicitly assuming that banks in a loan relations with a firm are homogeneous. Yet, in the data, we observe many firms repeatedly borrowing from the same banks, and in many cases, there is a "dominant" bank that accounts for a large share of the firm's total liability. To illustrate, *Figure-2* plots the number of banks from which a firm borrows a long-term loan (horizontal axis) and the loan concentration of the firm's long-term bank loan structure (vertical axis).[4] For a given number of banks, we can clearly see a large dispersion of loan concentration. While there are some firms exhibiting very flat loan share structures (i.e., the firms locating close to the lower envelop of the scatter plot), a number of firms hold highly asymmetric loan relations. Furthermore, in order to see whether such asymmetric loan shares have any stability or not, *Table-1* also shows the implied Markov transition matrix for the loan share of each bank in each firm's loan portfolio (computed from our data set detailed below). The large numbers on the diagonal elements roughly imply that the loan shares for each bank has some persistence, and the loan relations are somewhat stable.[5] This could provide us some predictions that bank loan shares are both stable and asymmetric. The current literature, however, has not considered these features in analyzing the determinants of loan relations.

In this paper, we study the stability of loan relations between Japanese listed firms and banks, and its determinants by using a unique data set for the Japanese bank loan market. Our paper complements the existing literature by incorporating the heterogeneous and stable nature of loan relations into the analysis. In our view, the asymmetric and stable loan share structure reflects various characteristics specific to each firm and bank, along

[1] Total long-term debt is defined as the sum of long-term bank loans and corporate bonds, both of which have original maturities longer than one year.

[2] This is the average of all the Japanese listed firms (excluding the emerging markets like JASDAQ). Note that we condition the data with a criteria that each firm is operating over the sample period 1982-1999.

[3] All the figures and the tables are in the appendix.

[4] The loan concentration is computed as the Herfindahl index of each firm's long-term loan share vector in 1999. A firm's loan Herfindahl index is defined as a squared sum of long-term loan shares of each bank lending to the firm. In this scatter plot, we use firms belonging to all the industries.

[5] This has been predicted in a few empirical literature (e.g., Tachibanaki and Taki (1991)). Other existing papers (e.g., Horiuchi (1994)) also use various descriptive statistics to claim that this is a concrete feature.

with some relation-specific capital that makes loans not perfectly substitutable[6]. This "relation-specific" capital is a distinct feature of bank financing. For example, this type of capital typically does not exist in the transaction-based financing in capital markets (i.e., bond and/or equity issuance).[7] We conduct a duration analysis to examine the stability of bank loan relations. The results support the existence of relation-specific capital, which gives rise to the stability of loan relations, as discussed in theoretical literature. This is a relatively new perspective for the characterization of bank loan relations.[8]

We also discuss the implications of having a "mainbank" status for the loan structure.[9][10] Suppose a bank has a certain amount of shares of a firm. This might extend the firm's credit availability from the bank, which in turn may improve the firm's outcome. Alternatively, the existence of such a mainbank may send a good signal to other banks and this can also improve credit availability. Thus, each bank's position as a shareholder may affect the firm's loan structure and we are interested in investigating this issue.

This paper is structured as follows. Section 2 briefly surveys the related literature. As a starting point, section 3 demonstrates a non-parametric estimation for a duration model so as to study a potential shape of hazard function. Then, section 4 studies the heterogeneous nature of loan relations and studies its determinants, which gives us some ideas for the determinants of the stability. Section 5 uses semi-parametric and parametric duration models for the nature of the stability and its determinants. Section 6 compares our empirical results with existing studies and discusses some technical issues. Section 7 concludes and presents future research questions.

# 2 Related Literature

As discussed in Ogawa et al. (2007), the existing theoretical literature regarding a firm's optimal loan relations have focused exclusively on analyzing the optimal number of banks. They summarize that the key determinants of the bank number are (i) transaction costs with banks (Bris and Welch (2005); Diamond (1984); Bolton and Scharfstein (1996)), (ii) interbank competition (Broecker (1990)), (iii) the severity of the hold-up problem (Sharpe (1990), Rajan (1992)), (iv) aggregate shocks (Detrangiache et al. (2000)), (v) the severity of the soft-budget constraint problem (Bris and Welch (2005); Bolton and

[6]For example, Freixas and Rochet (2008) surveys various models explaining how the relationship between two parties becomes a valuable asset through dealing with each other. Lummer and McConnel (1989) also documents a progressive transmission of privileged information to lenders.

[7]We are not claiming that these relations associated with the capital market does not contain any relationship-capital. Yasuda (2005) is one recent study that extends this view to the corporate-bond underwriting. However, this type of capital is less important or not practical in capital markets.

[8]See Ongena and Smith (2001) as one reference.

[9]Mainbank is defined, for example, as a bank owning a major position as a share holder and loan holder (Aoki and Patrick (1994)).

[10]In Japan, banks are allowed to hold up to 5% of a firm's stock. Most European countries have similar rules but this is prohibited in the U.S.

Scharfstein (1996)), and (vi) the type of business activity (Von Rheinbaben and Ruckes (1998)).

As with these theoretical studies, existing empirical studies have also taken a somewhat narrow perspective by analyzing this issue by only considering the number of banks a firm borrows from. For example, Ogawa et al. (2007) finds that the firm's size, solvability, liquidity, and availability of alternative financing determine this number. The negative correlation between the firm's profitability and number of banks has been established in a number of papers (see Degryse and Ongena (2001); Harhoff and Korting (1998); Foglia et al. (1998); Gordon and Schmid (2000); and Machauer and Weber (1999)). However, Weinstein and Yafeh (1998) and a few other papers claim the opposite. Also, some studies establish a negative correlation between the number of banks and interest rates, a proxy for risk (see Peterson and Rajan (1994); Degryse and Van Cayseele (2000); Angelini et al. (1998); Machauer and Weber (1999)).

There are a few empirical papers referring to the multiple and heterogeneous bank loan relations. For example, Peterson and Rajan (1994) mentions that small U.S. firms have a very asymmetric bank loan structure. Similarly, Elsas (2005) documents that banks holding a very close relationship with medium-sized German firms contributes, on average, 44% of the firm's debt financing.[11] In particular, Elsas (2005) examines what characteristics of borrowers and lenders determine the incidence of haubank relationships by using the self assessments of German universal banks. Our motivation is to supplement these casual findings by using more objective variables. Specifically, we consider the share of the top lender and the duration of loan relations.[12]

Most of the existing theoretical studies for dynamic bank loan relations (e.g., Rajan (1992), Boot and Thakor (1994)) take the view that longer loan relations can mitigate the information asymmetry between firms and banks more effectively. This implies that longer loan relations are less likely to break up.[13][14] In the context of the duration model, these theoretical studies predict that the hazard ratio of the loan relation exhibits the negative duration dependency.

Contrary to this simple theoretic prediction, the results in the empirical literature are somewhat controversial. Onegena and Smith (2001), a paper most closely related to ours, examines such a theoretical prediction by applying the duration model to a panel data for Norwegian bank loan market from 1979 to 1995 and finds that such a theoretical prediction is not necessarily supported by their data.[15] They actually emphasize the

[11] Those banks are called as hausbanks in Germany and mainbanks in Japan. We will get back to the definitions of those banks later in this paper.

[12] Obviously, an asymmetric loan share structure at a specific moment could just be a due to luck. Hence, such objective items cannot be perfect either.

[13] The duration is also called a "spell" in the literature. Following the literature, we use this terminology from this section.

[14] This is a reason that the pricing pattern in Rajan (1992)'s model exhibits a similar dynamics to switching cost models.

[15] The data consists of matches between banks and Norwegian listed firms. In their data set, the number of observed matches is around 100 to 150. This small number of matches partially reflects the fact that the data set does not contain a complete list of bank loan relations for each firm (i.e., it only

presence of a "positive" duration dependency of the hazard ratio in bank relations, which is opposite to the theoretical prediction. They also examine firms' characteristics as explanatory variables for the hazard function and establish that smaller, higher-levered, and higher-growth firms, which are presumably exposed to a larger information asymmetry and can get a larger benefit from a longer relation, tend to have shorter relationships. They conjecture that these two results potentially reflect the firms' anxiety to be trapped in a relation with the incumbent banks, which are presumably seeking some monopolistic rent. We intends to revisit their study by using a larger data set in the Japanese bank loan market. The information in our data allows us to study the hazard ratio of the relationship as a function of the length of spell and some relation-specific factors along with other firms' and banks' characteristics studied in Ongena and Smith (2001). Farinha and Santos (2002) is another related paper that applies the duration model to the data in Portugal from 1980 to 1996. They are interested in how switching from a single relationship to multiple relationships happens. Their main finding is that the likelihood of having switching from a single to multiple relations becomes higher as the duration of a single relation becomes longer. Similar to Ongena and Smith (2001), they conjecture that these results suggest that firms are concerned about hold-up problems arising from an exclusive loan relation.

# 3 Stability of Loan Relation

In the introduction, we attempt to overview the stability of the loan relations through a Markov Transition Matrix. Unfortunately, one caveat of the implied transition matrix comes from the fact that we are using the data of outstanding "long-term" bank loans. In fact, the large number in the diagonal elements might simply reflect the nature of the long-term loan. One alternative way to examine the persistency of the loan share structure is a dynamic panel regression. Unfortunately, aside from the usual technical problems associated with the estimation of a dynamic panel, we have the exactly same problem as in the discussion of the implied transition matrix. Considering this point, we employ duration models in this section to study the stability of loan relations.

The duration model allows us to explicitly analyze how the length of loan relations between firms and banks affect the marginal stability of their loan relations. If the longer loan relation helps the parties to accumulate some relation-specific capital, which we expect to be the case, the hazard rate of the loan relation is decreasing as the duration becomes longer. The goal of this section is to see whether or not our data exhibits such a negative duration dependency of the hazard rate. The duration dependency gives us an indirect evidence for the stability of loan structure.

Several existing literature has provided a view that a relationship between two parties becomes more and more valuable for both sides over its duration, which might result in lower costs and/or improved qualities of services (Freixas and Rochet (2008)). Following

contains the names of top 4 banks in a very subjective definition).

this view, we conjecture the positive correlation between the duration of relations and the stability of the relation[16].

Note that there exist similar examples in the context of employment, business alliance, and various financial transactions. In this paper, we are especially interested in how valuable such an "intangible asset" is in the context of bank loan relations. Such a discussion is also motivated by the fact that governments are sometimes concerned about the survival of firms that hold a close and exclusive loan relationship with failed banks. The study of the relationship-capital allows us to see the implications of bank closures for firm survival or growth.

## 3.1 Structure of Duration Model

### 3.1.1 Model

In this section, we summarize the basic structure of the duration model.[17] The spell $T$ is defined as the duration of time passing before the occurrence of a certain random event. In our case, the random event is a break-up of a loan relation between a firm and a bank. The distribution of the spell can be summarized by a survivor function $S(t)$, which denotes a probability that the event has not happened yet as of $t$.

$$S(t) \equiv \Pr(T \geq t)$$

The survivor function can be used to further define the hazard function $\lambda(t)$. This represents a probability that the event happens in the next instantaneous moment conditional on that the event has not happened yet as of $t$.

$$\begin{cases} \lambda(t) \equiv \lim\limits_{\tau \to 0} \frac{\Pr(t+\tau > T \geq t | T \geq t)}{\tau} = -\frac{d \ln S(t)}{dt} = \frac{f(t)}{S(t)} \\ \text{where} \\ f(t): \text{ Density associated with the distribution of spells} \end{cases}$$

The goal of the duration model is to estimate the hazard function and the survivor function while considering the effects of some covariates.[18] Suppose $x$ and $\theta = \{\alpha, \beta\}$ denote the vector of the covariates and the model parameter, respectively. Then, the

[16] Several papers have attempted to establish the existence of relationship banking (see James (1987), Peterson and Rajan (1994), Berger and Udell (1995, 2006)). Most of these studies simply regress the credit availability of each firms on the existence of the relationship-lender by controlling for various covariates. The duration analysis employed in this paper aims at revisiting this question from a different perspective.

[17] For more detailed discussion about the duration model, see Kiefer (1988).

[18] By construction, a hazard function has the equivalent information to the corresponding survivor function.

survivor function takes the following structure.

$$S(t,x,\theta) \equiv \Pr(T \geq t, x, \theta)$$

The proportional hazard model, which is one of the most widely used model specification, assumes the hazard function $\lambda(t,x,\theta)$ takes a multiplicative form consisting of (i) a component depending only on the duration $\lambda_0(t,\alpha)$ and (ii) the other component exclusively capturing the effects of the covariates $\phi(x,\beta)$.

$$\lambda(t,x,\theta) \equiv \lim_{\tau \to 0} \tfrac{\Pr(t+\tau > T \geq t | T \geq t, x, \theta)}{\tau} = \lambda_0(t,\alpha)\,\phi(x,\beta)$$

If there is no censoring problem (discussed below) and we can somehow specify the functional forms for $\lambda_0(t,\alpha)$ and $\phi(x,\beta)$, it is possible to estimate $\theta = \{\alpha, \beta\}$ by using MLE with the data $\{(t_i, x_i)\}$.[19]

$$\begin{cases} \theta = \arg\max\{\ln L(\theta)\} \\ \text{where} \\ L(\theta) = \prod_{i=1}^{n} f(t_i, x_i, \theta), \quad f(t_i, x_i, \theta) = \lambda(t_i, x_i, \theta)\, S(t_i, x_i, \theta) \\ S(t_i, x_i, \theta) = \exp\left\{ -\int_0^t \lambda(s, x_i, \theta)\, ds \right\} \end{cases}$$

Note that all the objects in the likelihood function can be expressed as fairly simple objects under some simplification assumptions for $\lambda_0(t)$ and $\phi(x,\theta)$. For example, if we assume the Weibull distribution for the spell $\lambda_0(t,\alpha) = \lambda\alpha t^{\alpha-1}$ and use a standard specification $\phi(x,\beta) = \exp(\beta' x)$, we have $S(t,x,\theta) = \exp\{\lambda t^{\alpha} \exp(\beta' x)\}$.

## 3.2 Discussion

Before estimating the duration model, we discuss some technical issues.

### 3.2.1 Censoring Problem and the Adjustments

One typical problem associated with the duration data is censoring. *Figure-3* illustrates four major cases of censoring. The straight lines correspond to observed spells while the dashed lines represent unobserved spells. For example, we can observe the beginning of the spell for observation-2 but do not have information about the end of these spells. All we know is that the spell has survived at the end of the observation period.

If all of our observations are non-censored (i.e., observation-1), we can simply apply

[19] $t_i$ and $x_i$ denote the length of completed spell for $i$-th observation and the set of (potentially time-varying) explanatory variables for the $i$-th observation, respectively.

the MLE explained above to the data. However, the existence of censoring requires us to make adjustments.

**Right-Censoring** For right-censoring, the adjustment is well established and straightforward (Kiefer (1988)). The idea is to treat the right-censored observations as survivors at the end of the observation period. In order to use the information that the right-censored observations have survived at this timing, we can simply use a Tobit-type adjustment to the likelihood function.

$$\begin{cases} L^R(\theta) = \prod_{i=1}^{n} \{f(t_i, x_i, \theta)\}^{d_i^R} \{S(t_i, x_i, \theta)\}^{1-d_i^R} \\ \text{where} \\ d_i^R = \begin{cases} 1 & \text{if } i\text{-th observation is not right-censored} \\ 0 & \text{if } i\text{-th observation is right-censored} \end{cases} \end{cases}$$

We use this adjustment for our data.[20] Note that if we are only considering right-censoring, nonparametric estimation for the survivor function (e.g., Kaplan and Meier (1958)) can easily be done.

**Left-Censoring** The adjustment for left-censoring is less straightforward. One simple way to deal with this problem is to discard the left-censored observation, which has often been employed in empirical literature.[21] Ongena and Smith (2001) employs this strategy and discusses the possibility that their estimation for the duration is overestimated.[22] We follow the existing literature and simply discard the left-censored observations in this paper.

### 3.2.2 Determination of the spell

Ongena and Smith (2001) defines the duration of relationships to be the number of consecutive years for which a firm lists each bank as primary banks[23]. In our data set, determining the beginning and end of the relationship in itself is an issue. In particular, considering that we can only capture the match between banks and firms through the outstanding loan amount, we need to be careful about such determinations. Note that even if a bank-firm pair does not have a positive outstanding loan in a specific year, it does not necessarily mean that the relationship broke since it could be that the firm simply did not have financing needs that year. Considering this point, we employ the criteria that the end of match is defined as an observation of zero outstanding loans in

[20] Ongena and Smith (2001) is also using this adjustment.

[21] Heckman and Singer (1984) shows that this method leads to inefficient but consistent estimators.

[22] Amemiya (1999) proposes a likelihood function for the left-censored data.

[23] In Norway, listed firms are obliged to report its primary bank relationships (up to 4 banks) in its report to the Oslo Stock Exchange.

5 consecutive years. We assume that the absence of the loan provision for such a long period can be recognized as a termination of their relationship.[24]

#### 3.2.3 Heterogeneity in Loan Maturity

Our data set does not contain the detailed information about each loan contract but only the sum of long-term loan amounts from one bank to one firm. Considering that our definition of the duration is potentially affected by the maturity of each loan, it is better to control the heterogeneity in loan maturity. One way to control this effect is to include (i) firm's short-/long-term bank loan ratios for each incumbent bank and (ii) bank's type (e.g. long-term loan bank & trust bank dummy versus other banks dummy etc.) as explanatory variables. These terms can partly capture the heterogeneity on the loan maturity. Due to the limited availability of short-term bank loan amounts from a bank to a firm, we cannot use (i).[25] We employ (ii) in the later discussion.

### 3.3 Data

We construct a firm- and bank-level data set for the Japanese long-term bank loan market.[26] The first data source is DBJ Corporate Financial Databank, which stores the loan amounts from each bank to each firm and each firm's financial characteristics. The second data source is the financial statement of each bank provided by the Japanese Banker's Association, which stores each bank's financial characteristics. Following the literature, we exclude firms in utility, realty, construction, retail, and wholesale industries. Then, we merge these two large data sets and construct a balanced panel data from 1982 to 1999. As a result of this balancing, the data set consists of 1518 firms and 148 banks. We construct this balanced panel data in order to exclude the demographic effect associated with the entry and exit of firms. As far as we know, this combined data set has never been used to analyze bank loan relations. *Figure-4* illustrates the structure of the data.

The unique feature of this data set is that it contains the outstanding loan amount from each Japanese bank to each listed firm, as well as the financial characteristics of each firm. In comparison, Ongena and Smith (2001) uses a data set with a similar structure but contains only the name of at most three banks associated with each firm. The complete information about firms' loan structure and bank's information in our data set allows us to characterize each firm's bank financing structure in a much more precise

[24] Precisely speaking, this five-year rule affects the starting date of each spell since we need to observe at least five-year blank before each spell starts. Instead, we treat all the fresh spells over the sample period as starting from the date we observe the initiation of relationships. We think this does not make a serious problem with considering that the estimated results under different criteria for spell are similar to the current five-year rule.

[25] Short-term loan data is only available for 1998 and 1999 in our current data set.

[26] Throughout the paper, we use the standard definition for long-term loans; that is, loans with original maturities longer than 1 year.

way than existing studies.

We have some remarks about our data set. First, in order to capture the status of loan relations between a bank and a firm, it might be better to use short-term lending information. This is because a positive outstanding loan at a specific year does not necessarily imply that there was an active firm-bank loan relation in that year–it may just reflect a past transaction. Thus, using short-term loan data would decrease our exposure to this problem. However, our current data set only contains short-term loan data for 1998 and 1999, and thus, we need to rely on the long-term loan data (i.e., maturity greater than 1 year as of lending/borrowing)[27]. Nonetheless, we think that the provision of such long-term loan implies a close relationship between the firm and bank. In this paper, we exclusively focus on the long-term loan information based on this perspective. Second, we ignore all other transactions between firms and banks (e.g., payment transaction, bond/equity underwriting, provision of credit line, business consulting, debt guarantee, factoring, and bill discount) that might also represent the firm-bank relation. Because of the limitation of our data set, we cannot account for all of these transactions. Since loan provision is the most important activity for the relation between firms and banks, we believe that our approach is permissible.

From the data set detailed above, we can construct the duration data for each match between a given firm and a given bank. As already mentioned, each spell is assumed to end if we observe zero outstanding loans in 5 consecutive years. We discard the left-censored observations while the right-censoring is adjusted through the method explained in Kiefer (1988).[28] *Figure-5* illustrates the data structure and the number of observations. We use sample-1 and -2 for our duration analysis. *Figure-6* presents the distribution of the spells based on these two samples. We can see that the distribution is highly skewed but it contains a certain number of observations over the long duration.

## 3.4 Univariate Analysis

*Table-2* shows the summary statistics of our data set for 1999. The first group of variables (*L-Share*, *L-Amount*, *TOPL-Share*, and *TOPL-Amount*) are taken for each match. *L-Share* and *L-Amount* represents the bank's share in a firm's total long-term bank loan and its loan amount conditional of those two numbers are strictly greater than zero, respectively.[29] Similarly, *TOPL-Share* and *TOPL-Share* stands for the top lender's share in a firm's total long-term bank loan and its loan amount.

The second (*BankNum*, *F-TBLT*, *F-Size*, *F-ROA*, *F-LR*, *F-LEV*, *F-STLT*, *F-BTD*) and the third groups of variables (*B-Size*, *B-ROA*, *B-CTA*, *B-TETA*, *B-IHI*) are taken for each firm or bank. *BankNum* represents the number of banks a firm is borrowing from. *F-TBLT* is the amount of a firm's total long-term bank loan. *F-Size* is firm size,

[27] We are currently constructing a similar data set for short-term bank loans in Japan.

[28] Again, we treat all the fresh spells over the sample period as starting from the date we observe the initiation of relationships.

[29] In this sense, the average of those numbers are conditional means.

represented by the firm's total asset. Each firm's profitability is measured by *F-ROA* computed from the firm's EBITDA divided by its total asset where EBITDA denotes the earning before interest payment, tax payment, depreciation, and amotization. Each firm's liquidity asset-to-liquidity liability ratio *F-LR* is used to measure a firm's liquidity. *F-LEV* and *F-STLT* are used for measuring a firm's leverage and debt maturity.[30] The variables for banks (*B-Size*, *B-ROA*, *B-CTA*, *B-TETA*, *B-IHI*) are defined in a similar fashion. Note that *B-Size* is measured by the total loan assets (not simply by total assets), liquidity is measured by the cash-to-total asset ratio *B-CTA*, and *B-TETA* is used to denote the total equity-to-total asset ratio, a proxy for financial stability.

One unique feature of our analysis is that we compute the industry concentration of each bank's loan portfolio, denoted *B-IHI*. This represents the industry Herfindahl index for each bank's loan portfolio. Note that this index represents each bank's industry concentration only for listed firms and not for each bank's overall portfolio. Nonetheless, we think that this index is still useful to characterize the degree of specialization of each bank.

The last variable (*MKT-LOAN*) in the table represents the market size of the bank loan market, which is computed by the simple sum of all banks' loan assets.

From these summary statistics, we can obtain a rough impression that the top lender's share (0.47) is asymmetrically high on average, compared to other lenders if we consider the average number of banks (9.8 banks). Also, we can find a high dispersion in the distribution of loan shares. As we briefly observed in *Figure-2*, each banks' loan shares are asymmetric. In the later subsection, we use the top lender's loan share as one representation of the asymmetric loan share structure.

## 3.5 Non-Parametric Estimation Results

In this section, we show our estimation results based on a non-parametric estimation method. The benefit of this method is that we do not need to assume any specific functional form for the hazard function.

First, Kaplan-Meier's estimator defined below gives us an estimated survivor function. *Figure-7* depicts this non-parametrically estimated survivor function where two dashed lines represent 95% confidence intervals.

$$\begin{cases} \widehat{S}(t) = \prod_{j=0}^{t} \left( \frac{n_j - d_j}{n_j} \right) : \text{ Kaplan-Meier's estimator for survivor function} \\ \text{where} \\ n_j : \text{ Number of observations that have not failed or censored at the beginning of } j \\ d_j : \text{ Number of failures occurring to these observations during } j \end{cases}$$

[30] *F-STLT* represented the ratio of short-term debt to the long-term debt. For *F-STLT*, we use all the debts including bank loans and other debts (e.g., corporate bond).

Then, we can use the definition of the hazard function to compute the hazard function. *Figure-8* depicts this non-parametrically estimated hazard function with a polynomial approximation.

$$\widehat{\lambda}(t) = -\left\{\ln \widehat{S}(t) - \ln \widehat{S}(t-1)\right\}$$

Alternatively, we can use Nelson-Aalen's estimator for a cumulative hazard function (defined below). Then, we can approximate the hazard function by using a Gaussian kernel with a specific bandwidth. *Figure-9* depicts the estimated hazard function with the approximated hazard function smoothed by Gaussian kernel with bandwidth 2.

$$\widehat{H}(t) = \sum_{j|t_j \leq t} \left(\frac{d_j}{n_j}\right) : \text{ Nelson-Aalen's estimator for cumulative hazard function}$$

The downward sloping parts of these two estimated hazard functions imply the negative duration dependency of the hazard ratio. We also find a positive duration dependency over relatively shorter durations, which potentially reflects the nature of the sample. Since all the duration is measured solely by the outstanding long-term loan, it is possible for the duration to increase for the first few years. Presumably, the samples are simply paying back the debt over the first few years without borrowing again. An important finding is that we still have a negative duration dependency for the sample with a longer duration than 5 years.

# 4 A Detour: Asymmetry of Loan Share

The non-parametric method demonstrated in the previous section cannot control covariates. In order to proceed to semi-parametric and parametric duration models, we study the determinants of heterogenous bank loan relations in this section. As a proxy for the heterogeneity of loan relations, we use the top lender's loan share for each firm. If such a share is high, the firm is considered as having a highly heterogeneous and asymmetric loan relations.

## 4.1 Preliminary Discussion

In order to empirically establish the determinants of the top lender's share, we can use the established determinants for the number of banks in the existing literature. First, we can conjecture that a larger firm tends to have a top lender with a smaller share, which is a widely accepted empirical fact. Second, we examine the impact of a firm's risk as a potential determinant of the top lender's loan share. This reflects the view established in the existing literature (Peterson and Rajan (1994); Degryse and Van Cayseele (2000); Angelini et al. (1998); Machauer and Weber (1999)). Third, considering that a certain number of empirical studies have established that firms with high profitability tend to be financed with a more concentrated loan structure (e.g., Gordon and Schmid (1996); Foglia et al. (1998); Harhoff and Korting (1998); Machauer and Weber (1999); Degryse and Ongena (2001); Farinha and Santos (2002)), we use firms' profitability as one potential determinant of the top lender's loan share.

## 4.2 Firm Size

First, we check our conjecture that a larger firm has a less asymmetric loan share structure, which implies a smaller likelihood for a larger firm to have a top lender with a very high loan share. For example, the existence of a fixed transaction cost induces a small firm to use a limited number of banks (Diamond (1984)). The same argument holds when banks have some fixed cost for screening and/or monitoring. In order to cover these costs, the top lender's loan share may need to be high for small firms. Another possibility is that if the geographical distance is important for the implementation of screening and/or monitoring, larger firms (with many subsidies and projects) might need to deal with a wide range of banks located in various regions (Hauswald and Marquez (2005)). Alternatively, the existence of lending limits of each bank can also account for the negative correlation between firm size and top lender's loan share.

### 4.2.1 Firm's Assets

In order to examine this conjecture, *Figure-10* depicts the likelihood of having a top lender with at least a certain level of loan share (i.e., 50%, 70%, and 90%) over different levels of firm size.[31] Apparently, larger firms are more likely to have a top lender which holds a higher loan share. From these results, we can conjecture that there is a negative correlation between the top lender's share and the firm's total size. This will be examined more formally in a later section.

### 4.2.2 Firm's Debt

As another proxy for firm size, we can use the size of total debt.[32] This number can also be interpreted as the asset size financed by debt. *Figure-11* illustrates the likelihood of having a top lender with at least a certain level of loan share (i.e., 50%, 70%, and 90%) over the long-term bank loan size.[33] *Figure-12* repeats the same illustration for total long-term debt (i.e., bank loan and other long-term debt). Both graphs indicate the clear negative dependency of the top lender's loan share over firm size.

[31] We set the horizontal axis by thirty bins of the log of asset size.

[32] Firm's indebtedness might be recognized as a proxy for risk. However, since the size of debt itself does not represent the risk, we use leverage to represent the risk in the later discussion.

[33] For this figure, we set the horizontal axis by thirty bins of the log of long-term bank loan size.

## 4.3 Firm's Leverage

Second, as a proxy of a firm's risk, we use a firm's leverage. As Bolton and Scharfstein (1996) carefully models, banks may try to keep their loan share for risky firms at a certain (low) level. This reflects the banks anxiety about being locked-in to the loan relation. Their model demonstrates how such a dispersed loan share structure prevents a firms from strategically defaulting. Alternatively, the negative correlation between a firm's riskiness and its top lender's loan share can be interpreted as a reflection of each bank's optimal portfolio choice as modeled in Pyle (1971) or Hart and Jaffee (1974). In their models, each bank solves a standard optimal portfolio choice problem. As long as there is some correlation among the repayments of each firm, banks try to diversify the risk by choosing the appropriate sizes of loans for each firm.

*Figure-13* depicts the likelihood of having a top lender with a certain level of loan share over firm leverage.[34][35] Apparently, firms with a lower leverage, which is presumably associated with lower risk, are more likely to have a top lender with a high loan share. Although there is a spike over the very high leverage, the overall tendency implies that the top lender's share negatively depends on a firm's total size.

## 4.4 Firm's Profitability

Third, we examine the correlation between the firm's profitability and the top lender's loan share. Profitability is an well established determinant for the optimal number of banks in the existing literature (Degryse and Ongena (2001); Harhoff and Korting (1998); Foglia et al. (1998); Gordon and Schmid (2000); Machauer and Weber (1999)). Our conjecture is that there is a positive correlation between a firm's profitability and its top lender's loan share. Again, *Figure-14* depicts the likelihood of having a top lender with a certain level of loan share over firm profitability.[36]

Unlike the theoretical prediction, the profitability does not seem to affect the likelihood of having a top lender with a certain level of loan share. In order to see the marginal effect of the firm's profitability to the top lender's loan share more precisely, we might need to appropriately control covariates. This point is examined formally below.

[34] We set the horizontal axis by eighteen bins of the leverage.

[35] Note that interest rates associated with each loan from one bank to one firm or the averaged interest rate for the total outstanding loan of one firms can be interpreted a more direct measure of each firm's risk. Unfortunately, due to the limitation of our data, we cannot use the interest rate as a proxy for risk.

[36] We set the horizontal axis by thirty bins of the firm's ROA.

## 4.5 Panel Regression

### 4.5.1 Heterogeneous Loan Relations

For the graphical illustrations demonstrated so far, we have only used firm-specific characteristics as the potential determinants of the loan structure. In this section, we additionally incorporate bank-specific characteristics and an aggregate factor to the analysis. We run a panel regression using a top lender's loan share as a dependent variable while using the characteristics of each firm and its top lender, and an aggregate factor as explanatory variables. For this regression, we set each match between a firm and its top lender as a group. Since a firm might change its top lender for different years, our data inevitably takes the form of an unbalanced panel data.

For model selection, pooling estimate is rejected from Breusch-Pagan test and random-effect estimation survives. Then, Hausman-test rejects the null hypothesis that the random-effect estimation is not correlated with regressors. As a result of these standard test procedure for model selection, we choose the fixed-effect model. *Table-3* summarizes the estimation results.

First, our estimation result supports the three conjectures raised in the previous section. Both firm size and leverage have negative coefficients for the top lender's loan share. Moreover, firm profitability has a positive effect on the top lender's loan share in this panel regression, which is consistent with the results of the existing theoretical and empirical studies. Other than these three items, firm's liquidity has a positive effect on the top lender's loan share. This is somewhat consistent with the result established in Detrangiache et al. (2000), which argues that a liquidity shock to banks affect the optimal number of banks. Our result implies that firms with higher liquidity are more likely to choose the banks with higher loan shares. Firm's reliance on bank loan compared to other financing channels also has a negative effect on the top lender's loan share. This can be interpreted as one illustration of Bolton and Scharfstein (1996)'s argument explained above.

Second, bank size also has a positive effect on the top lender's loan share while the profitability, liquidity and financial stability have no significant effects. This contradicts the result in Detrangiache et al. (2000). This may reflect the fact that Japanese firms were not concerned about bank failures since the Japanese banking sector was highly protected until the 1980s. Another interesting result is that the bank's industry specialization index has a positive effect on the top lender's loan share, which implies that the industry specialization of each lender actually affects the loan structure.[37]

Third, from the aggregate view point, we can confirm that the size of loan market affects the top lender's loan share negatively. One interpretation would be that the larger availability of funds in the market, which can be accompanied with a higher interbank competition, reduces the relationship-lending as demonstrated in Rajan (1992). Lastly,

[37] This point is discussed theoretically in Boot and Thakor (2000) and empirically examined in, for example, Degryse and Ongena (2001).

firms are more likely to concentrate the loan relation during a boom (i.e., 1980s). This is consistent with the result of, for example, Detrangiache et al. (2000).

**Bank's Status as a Shareholder** In Japan and many European countries, banks are allowed to hold non-financial company's stocks as a large shareholder. This simultaneous position as a lender and a shareholder is sometimes called as a mainbank relation.[38] In this section, we study the impact of this mainbank status to the top lender's loan share.

We use the following three definitions of the mainbank relation: (i) the top lender is also the top shareholder, (ii) the top lender is among the top three shareholders, and (iii) the top lender is among the top ten shareholders. *Table-4* summarizes the panel regression based on definition (i). We are interested in the coefficient of the dummy variable taking one if the top lender satisfies definition (i). As the table shows, we cannot reject that the coefficient is zero for any of the definitions (see *Table-4* to *Table-6*).

Presumably, the mainbank status has several different effects on the top lender's loan share. First, the status as an important shareholder might induce the top lender to provide a larger credit availability which leads to a larger share. Second, contrarily, excess exposure to one firm induces its mainbank to reduce the loan share. Third, the existence of the mainbank might send a preferable signal about the firm to other lenders, which in turn extends the credit availability from other banks. The current panel regression roughly confirms that non of these forces are dominant.

### 4.6 Summary

In this section, we have illustrated how the observed heterogenous loan relations reflects firm-specific characteristics, bank-specific characteristics, aggregate variables, and relation-specific characteristics (i.e., the incumbent loan share). These casual observations are verified through a panel regression.

We have confirmed that (i) smaller, profitable, less risky firms with less reliance on bank loans are more likely to have a top lender with a larger loan share, (ii) larger banks with higher specialization are more likely to have a higher loan share as a top lender, and (iii) loan market size has a negative impact on top lender's share. These results are used to study semi-parametric and parametric duration models in the next section.

## 5 Stability of Loan Relation in Parametric Models

Using the findings we obtained in the previous section, we estimate parametric duration models in this section. First, we apply Cox's semi-parametric estimation method. Note

[38] For the intensive discussion about Japanese mainbank system, see Aoki and Patrick (1994) and Aoki and Saxonhouse (2000).

that we do not need to put any restrictions on the functional form for the baseline hazard function. By using the estimators, we can back out the hazard function graphically. This gives us some ideas for the model selection in parametric duration models, the results of which we discuss in the last section.

### 5.0.1 Semi-parametric Estimation

The negative duration dependency observed in the non-parametric estimation might reflect the characteristics of firms and banks. For example, firms with low profitability might find it difficult to finance their project through the capital market and may need to rely more on bank loan finance for a long period. The non-parametric estimation demonstrated above cannot distinguish such effects of covariates from the pure duration effect. Cox's partial likelihood model (Cox (1972)) is useful to extract this duration effect while controlling other characteristics.[39][40]

*Figure-15* depicts the estimated baseline hazard function $h_0(t)$ and *Table-7* summarizes the estimation results associated with the covariates. First, *Figure-15* shows the positive duration dependency for the shorter durations and the negative dependency of the duration for longer durations. These results have the same implication as in the non-parametric estimation. Second, several characteristics of firms and banks affect the duration. The estimated coefficients imply that firms with higher profitability, higher liquidity, and higher leverage tend to terminate loan relations in shorter periods. Furthermore, banks with smaller size, higher profitability, higher liquidity, and lower financial stability tend to terminate loan relations in shorter periods.

*Figure-16* and *Table-8* repeat the same estimation for the mode with the specialization matching index, which is the multiplication of each bank's industry specialization index (*B-SPI*) and the dummy variable taking one if a firm's industry is in the top three industries a bank is exposed to.[41] The important result is that such a specialization matching leads to a longer loan relations. Even after controlling for all these factors, we can still observe a negative duration dependency over the relatively longer duration (e.g., longer than 7 years). This supports our conjecture about the relationship-capital.

[39] This method is called a semi-parametric estimation since we still do not need to specify any functional form for the baseline hazard function.

[40] For this estimation, we use the characteristics of firms and banks, and one match-specific variable measured at the end of the previous year to the actual matching. In this sense, we estimate the duration model with time-invariant covariates.

[41] We define a variable B-SPI as a proxy for each bank's industry specialization: B-SPI for Bank$-b \equiv \sum_k \left(J_k^2/J^2\right) SPI_{bt-1}^k$ where $J$ is the total number of firms, $J_k$ is the total numbers of firms in Industry-$k$, and $SPI_{bt-1}^k$ is the ratio of (i) the probability that two firms from Industry-$k$ pool are borrowing from Bank-$b$ and the probability that two firms in ALL industries pool are borrowing from Bank-$b$. Intuitively, this variable represents how likely the firms in a specific industry are borrowing from a given bank$-b$.

### 5.0.2 Parametric Estimation

The result in the semi-parametric estimation gives us a conjecture about the appropriate distribution of the spell.

The Weibull distribution is widely used in the literature. This distribution allows us to check whether the baseline hazard exhibits a monotonically increasing or decreasing shape over spells. Since we have already observed the non-monotonic form for the baseline hazard from the Cox's method, it is not appropriate to assume the Weibull distribution. For the same reason, we cannot use the exponential distribution since it only covers the case that the hazard ration is independent from the duration. One possibility is the log-logistic distribution, which accounts for (i) the monotonically decreasing hazard and (ii) the hazard increasing initially and decreasing later over the duration.[42] *Tables-9* and *-10* summarize this estimation results.

First, the estimated gamma is smaller than 1, which means the hazard increases and then decreases over the spells. This confirms our observations in our parametric and semi-parametric estimations. Second, the estimated coefficients are consistent with the one in the parametric and semi-parametric estimations. Note that we are using the accelerated failure-time formulation for the current estimation while the proportional hazards formulation is employed for Cox's proportional hazard model. Due to this difference, the signs of each coefficient must be opposite in these two estimations.

# 6 Discussion

## 6.1 Comparison with Existing Studies

Ongena and Smith (2001) emphasizes the positive duration dependency of the hazard ratio and the estimated coefficients in their duration analysis as a reflection of firms' concern about the rent extraction of their incumbent banks. They conjecture that firms with a higher information asymmetry (e.g., higher leverage) try to terminate the loan relation in a shorter period since they anticipate that they will be locked in the loan relation with the incumbent banks.

In our estimation, we have a similar estimated coefficient for firm's leverage (i.e., higher leverages imply shorter durations) but a negative duration dependency. First, the negative duration dependency established in our semi-parametric estimation over the relatively longer duration range implies that the accumulation of relationship-capital has some value.[43] Actually, Ongena and Smith (2001) also finds the similar pattern of the duration dependency through a parametric estimation of log-logistic distribution.

[42] See, for example, Cleves et al. (2004) pp. 240-.

[43] For example, Miyakawa (2009) models the emergence of relationship-lending without relying on asymmetric information. It demonstrates how the sustained loan relation improves the quality of chosen projects, which originated from the perspective in Hauswald and Marquez (2003).

In this sense, our result is not necessarily inconsistent with theirs. We would rather emphasize the findings that (i) it takes a certain length of time to establish valuable bank relations and (ii) the duration data is contaminated by the nature of long-term loans. Through a further analysis based on, for example, the short-term bank loan data, we can actually verify this claim more precisely. Second, if we take the view explained above, the coefficient of firm's leverage can be interpreted in a different way from Ongena and Smith (2001). In particular, "banks" might try to keep the relation with these overindebted firms at a relatively low level since they consider the possibility of being trapped in the loan relation with them (Bolton and Scharfstein (1996)). Note that we have already confirmed in the previous section that firms with higher leverage tend to have a more dispersed loan structure. This gives us a conjecture that banks determine the optimal loan share by considering the firm's risk while sustaining loan relations still gives rise to some positive value. The estimated coefficients in our panel regression and duration analysis are consistent with this story.

## 6.2 Technical Issues

Note that there are still two potential problems: (i) heterogeneity in loan maturity and (ii) left-censoring problem. We have already discussed how we can potentially deal with the first problem. The second problem can be adjusted, for example, by the way explained in Amemiya (1999) which proposes a likelihood function for the left-censored data. The basic idea is to (i) separately express the likelihoods for the left-censored and non left-censored observations by using the following entry ratio function to the spell, and (ii) weight each likelihood by the probabilities of having these two types of observations.

$$e\left(-t \mid x, \theta\right) = \lim_{\tau \to 0} \frac{\Pr(\text{In the spell at } -t | \text{Not in the spell at} -t-\tau, x, \theta)}{\tau}$$

As Amemiya (1999) and D'Addio and Rosholm (2002) detail, however, we need to know the shape of $e\left(t \mid x, \theta\right)$ in order to implement MLE. If we employ the simplest specification for $e\left(t \mid x, \theta\right) = e\left(x, \theta\right)$ (i.e., stationary entry ratio), the likelihood function is known to become quite simple. We can combine this adjustment methods for left-censored data with the Tobit type adjustment for right-censored data. One remark is that the stationary entry ratio assumption is convenient but obviously restrictive. We need to implement a test for the stationarity assumption. We leave this adjustment for left-censoring as a future research question.

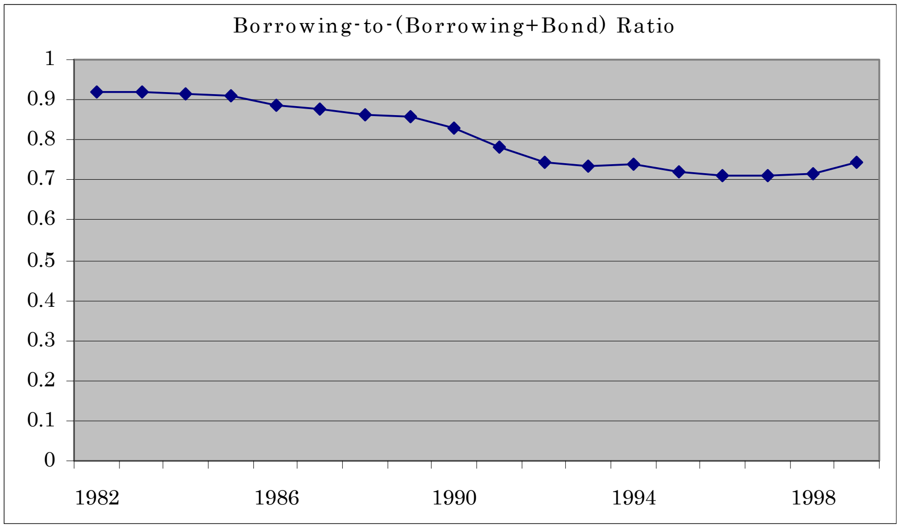
# 7 Concluding Remarks

This paper studies the determinants of a firm's bank financing structure. In addition to the number of banks, which has been exclusively discussed in the existing literature, the asymmetry of each bank's loan share is examined. By using a unique data set for the

Japanese bank loan market, we document the heterogenous and somewhat stable loan share structure, and establish the determinants of the loan relations. We have confirmed that (i) smaller, profitable, less risky firms with less reliance on bank loans are more likely to have a top lender with a larger loan share, (ii) larger banks with higher specialization are more likely to have a higher loan share as a top lender, and (iii) loan market size has a negative impact on top lender's share. The stability of bank loan relations are also examined through a duration analysis. The results support the existence of relation-specific capital, at least for a relatively longer duration range, which gives rise to the stability of loan relations as discussed in theoretical literature. We also confirm that firms with higher profitability, higher liquidity, higher leverage tend to terminate loan relations in shorter periods. Furthermore, banks with smaller size, higher profitability, higher liquidity, and lower financial stability also tend to terminate loan relations in shorter periods.

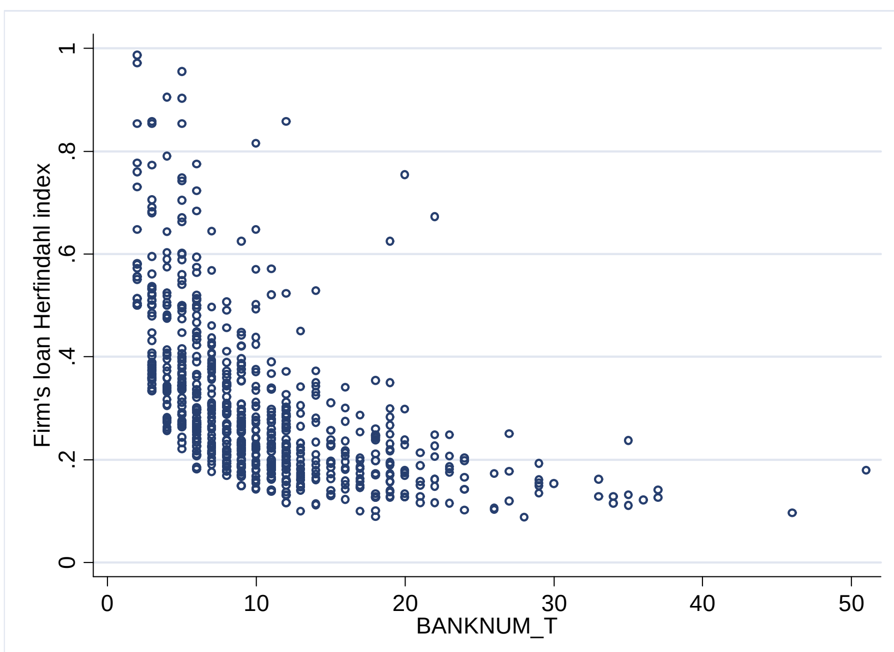
To conclude, we list several future research questions. First, we advance our analysis to the data on short-term bank loan relations. The contamination of the data set by the nature of long-term loan relations potentially biases the estimation of duration model. In order to extract the implication for the value of sustained loan relations and compare it with the existing literature, we need to finish such an additional analysis. Second, we need to refine the estimation with a proper treatment for the technical issues discussed in this paper. For example, the left-censoring problem needs to be adjusted by, for example, Amemiya (1999)'s method. The heterogeneity in loan maturity is also an important problem we need to address. Third, other transaction between financial institutions and firms can be analyzed. Yasuda (2005) empirically studies the relationship based on bond underwriting services and found somewhat similar result we obtained in this paper. Fourth, in order to directly establish the value of relationship-capital, it might be better to use some structural model instead of the reduced form analysis employed in this paper and other existing studies. In fact, the negative duration dependency itself cannot completely guarantee the existence of relationship-specific capital since it may just reflect an informational captivity. The structural model constructed in Miyakawa (2009) is one model that can be used to go in this direction.

# 8 Appendix: Table and Figure




Data source: DBJ Corporate Financial Databank

Figure-1: Long-Term Bank Loan / Total Long-Term Debt




Data source: DBJ Corporate Financial Databank

Figure-2: Asymmetric Bank Loan Structure in 1999

| | | SHARE=0 | (0, 0.01] | (0.01, 0.05] | (0.05, 0.1] | (0.1, 0.2] | (0.2, 0.3] | (0.3, 0.4] | (0.4, 0.5] | (0.5, 1.0) | SHARE=1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| SHARE=0 | 1 | 0% | 14% | 32% | 18% | 17% | 8% | 4% | 3% | 3% | 2% |
| (0, 0.01] | 2 | 20% | 70% | 8% | 1% | 0% | 0% | 0% | 0% | 0% | 0% |
| (0.01, 0.05] | 3 | 8% | 9% | 74% | 7% | 1% | 0% | 0% | 0% | 0% | 0% |
| (0.05, 0.1] | 4 | 5% | 0% | 14% | 68% | 10% | 1% | 0% | 0% | 0% | 0% |
| (0.1, 0.2] | 5 | 5% | 0% | 2% | 12% | 72% | 7% | 1% | 0% | 0% | 0% |
| (0.2, 0.3] | 6 | 5% | 0% | 1% | 2% | 17% | 65% | 9% | 1% | 1% | 0% |
| (0.3, 0.4] | 7 | 5% | 0% | 0% | 1% | 4% | 17% | 59% | 10% | 3% | 0% |
| (0.4, 0.5] | 8 | 6% | 0% | 0% | 0% | 2% | 6% | 17% | 55% | 13% | 1% |
| (0.5, 1.0) | 9 | 6% | 0% | 0% | 0% | 2% | 2% | 4% | 10% | 69% | 5% |
| SHARE=1 | 10 | 19% | 0% | 0% | 1% | 1% | 1% | 2% | 1% | 7% | 68% |

Data source: DBJ Corporate Financial Databank

Table-1: Persistency in Asymmetric Bank Loan Structure

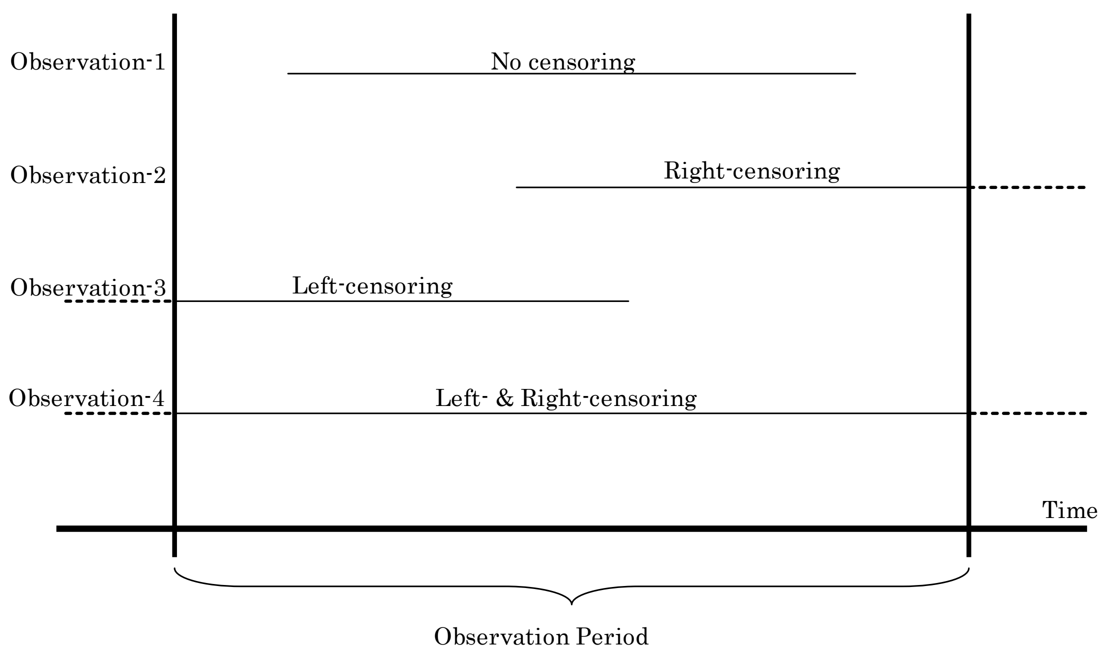



Figure-3: Four Types of Censoring

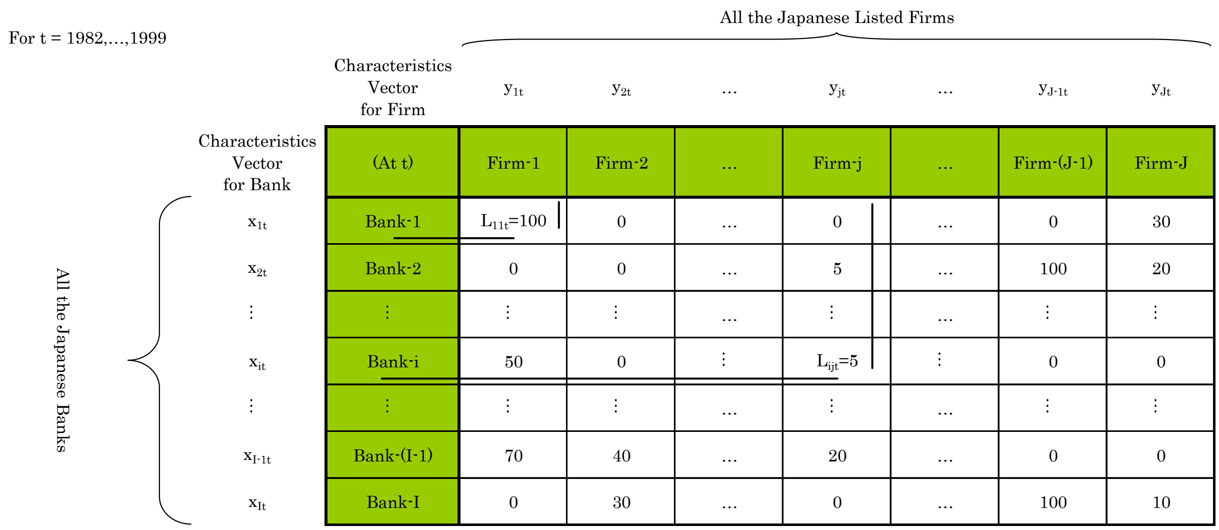



Figure-4: Illustration of Data Structure

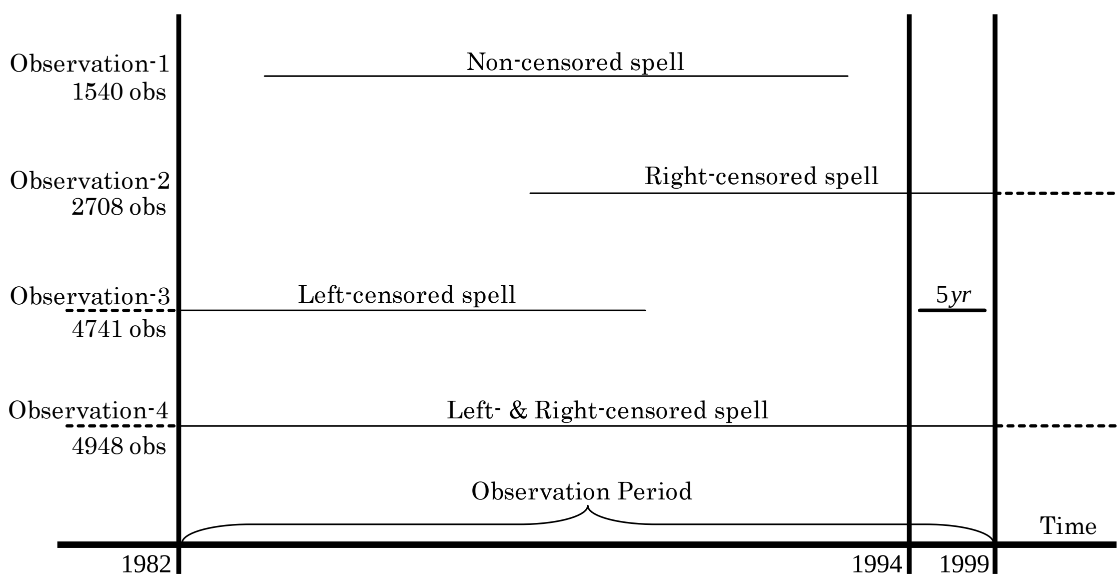



Figure-5: Data Structure

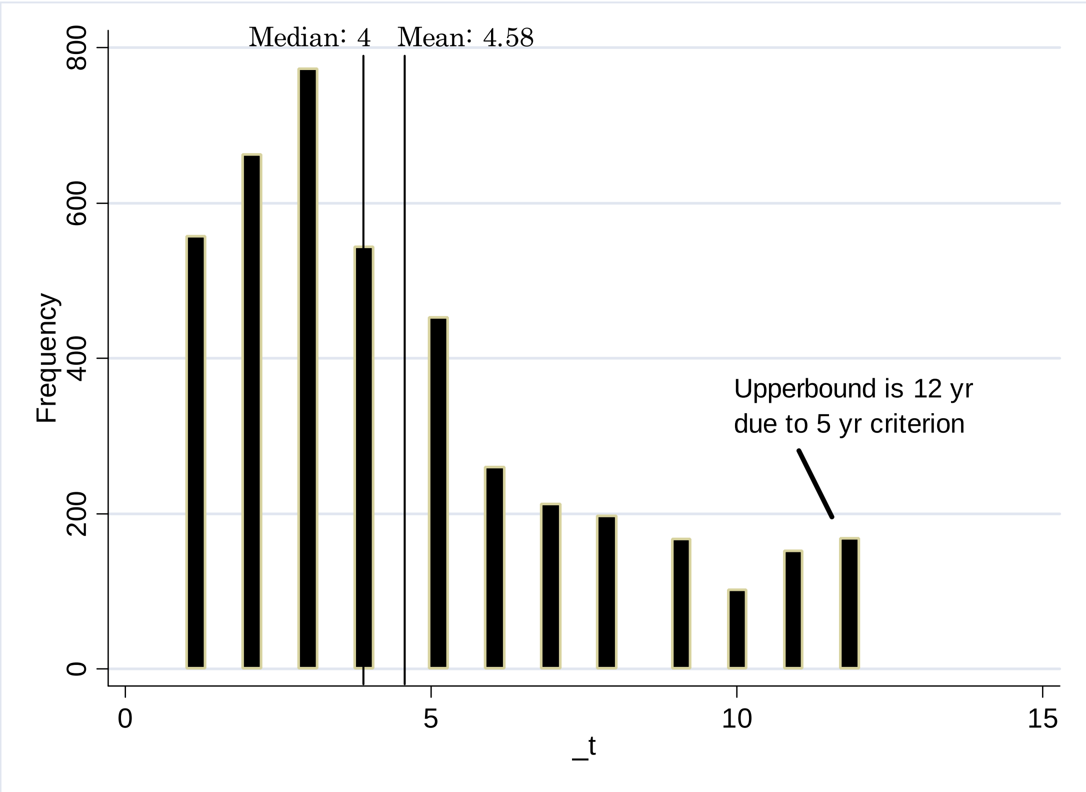



Figure-6: Distribution of Spells

| Variable | | Definition | Avr | Std. |
|---|---|---|---|---|
| *L-Share* | | A Bank's share in a Firm's total long-term bank loan | 0.15 | 0.18 |
| *L-Amount* | (M¥) | A Bank's loan amount for a Firm | 1,371 | 3,346 |
| *TOPL-Share* | | Top bank's share in a Firm's total long-term bank loan | 0.47 | 0.23 |
| *TOPL-Amount* | (M¥) | Top bank's loan amount for a Firm | 3,235 | 6,200 |
| *BankNum* | | Number of banks lending to a Firm | 9.8 | 6.7 |
| *F-TBLT* | (B¥) | Firm's total long-term bank loan | 17 | 43 |
| *F-Size* | (B¥) | Firm's total asset | 148 | 380 |
| *F-ROA* | (%) | Firm's EBITDA / total asset | 4.49 | 4.48 |
| *F-LR* | | Firm's liquidity asset / liquidity liability | 1.40 | 0.83 |
| *F-LEV* | | Firm's total debt / total asset | 0.64 | 0.21 |
| *F-STLT* | | Firm's short-term debt / long-term debt | 2.05 | 4.41 |
| *F-BTD* | | Firm's long-term bank loan / total long-term debt | 0.80 | 0.29 |
| *B-Size* | (T¥) | Bank's total loan asset | 22 | 11 |
| *B-ROA* | (%) | Bank's operational profit / total asset | 0.35 | 0.33 |
| *B-CTA* | | Bank's cash / total asset | 0.05 | 0.03 |
| *B-TETA* | | Bank's total equity / total asset | 0.05 | 0.01 |
| *B-IHI* | | Bank's industry specialization (Herfindahl Index) | 0.003 | 0.005 |
| *MKT-LOAN* | (T¥) | Sum of all banks' total loan asset | 493 | - |

Data source: DBJ Corporate Financial Databank

Note: 1999 data and exclude the firms in utility, realty, construction, retail, and wholesale industries

Table-2: Summary Statistics

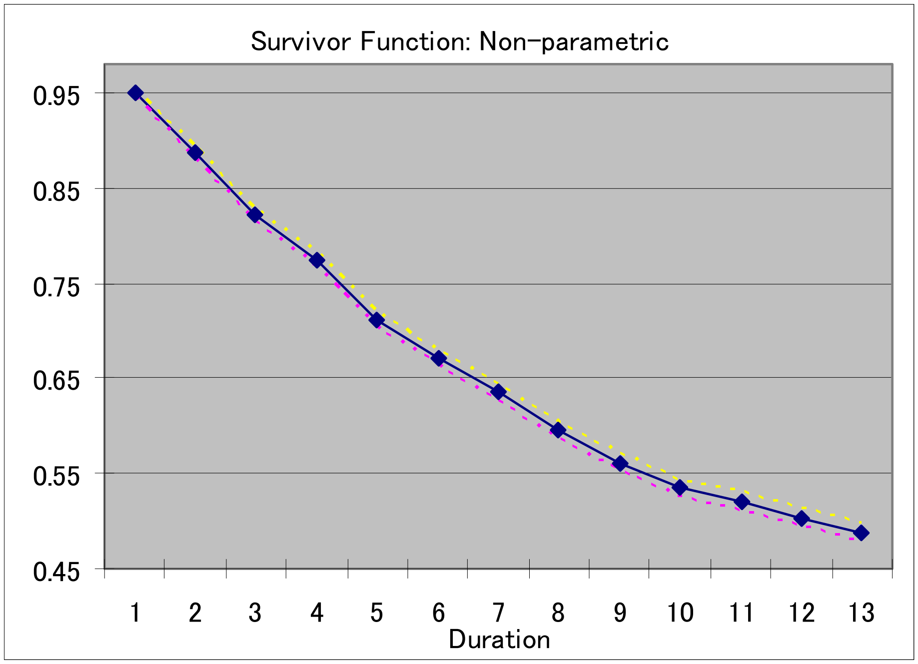



Figure-7: Non-parametrically Estimated Survivor Function

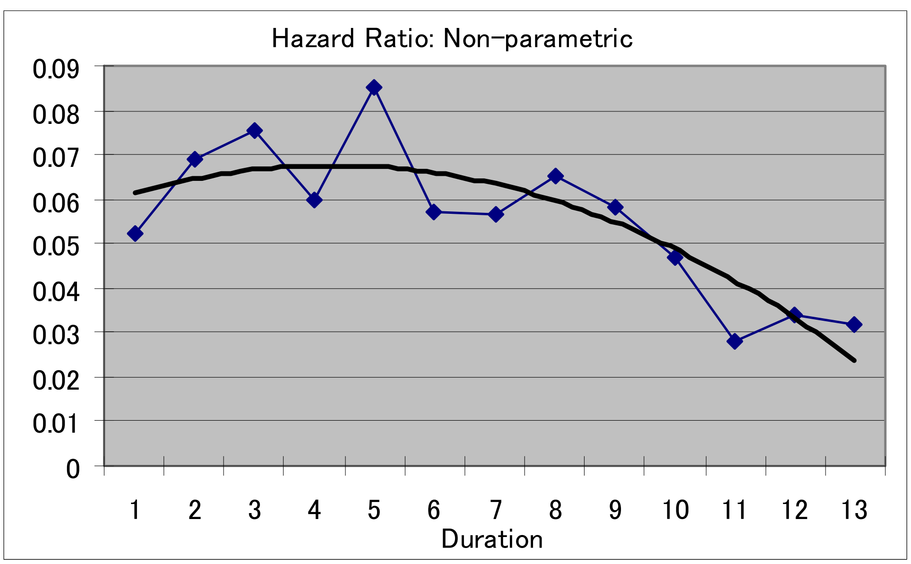



Figure-8: Non-parametrically Estimated Hazard Function

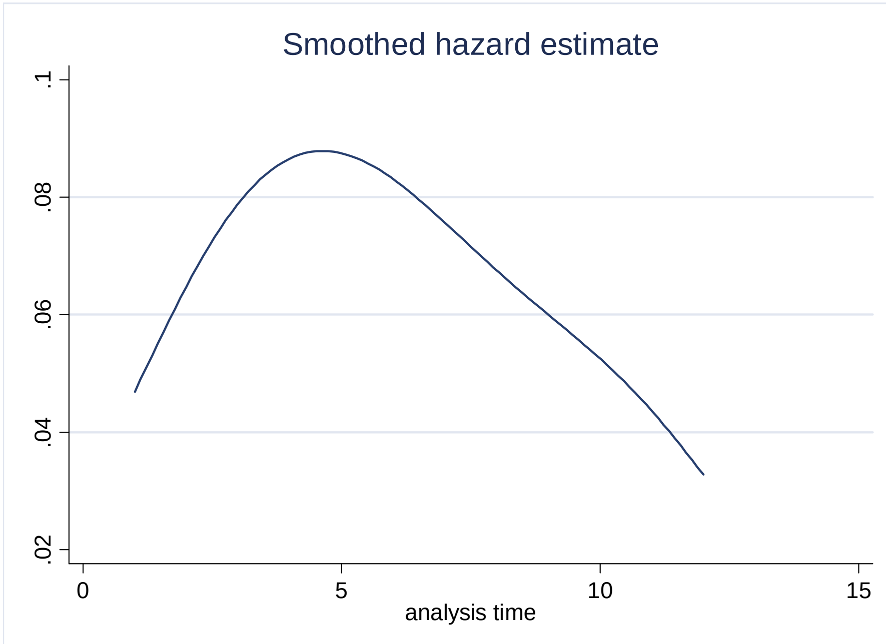
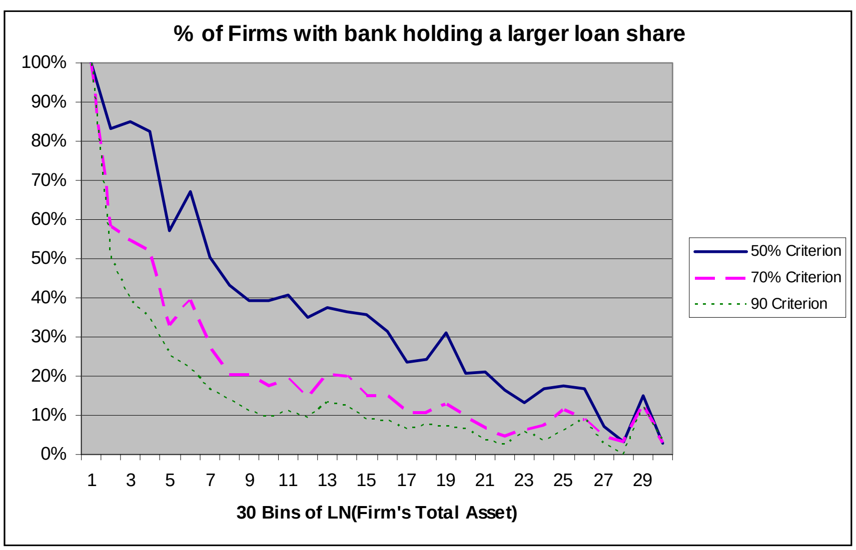
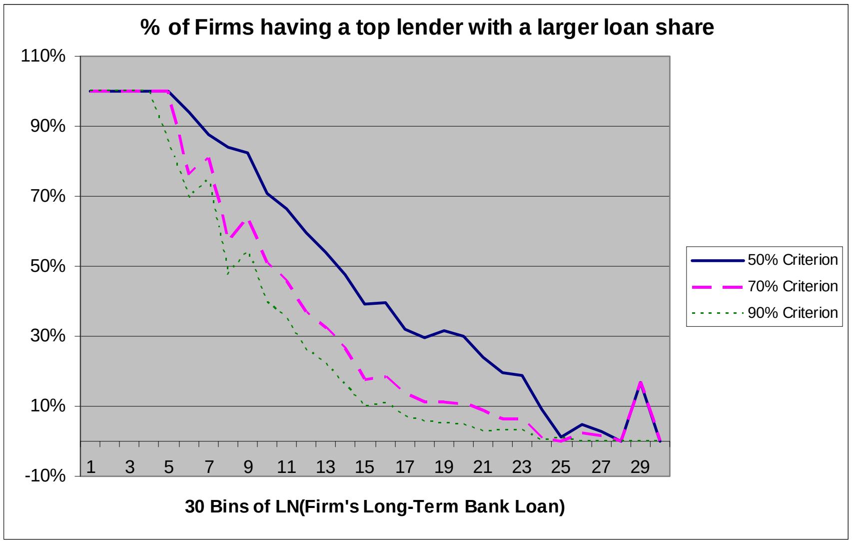



Figure-9: Non-parametrically Estimated Hazard Function
(Gaussian kernel with bandwidth 2)



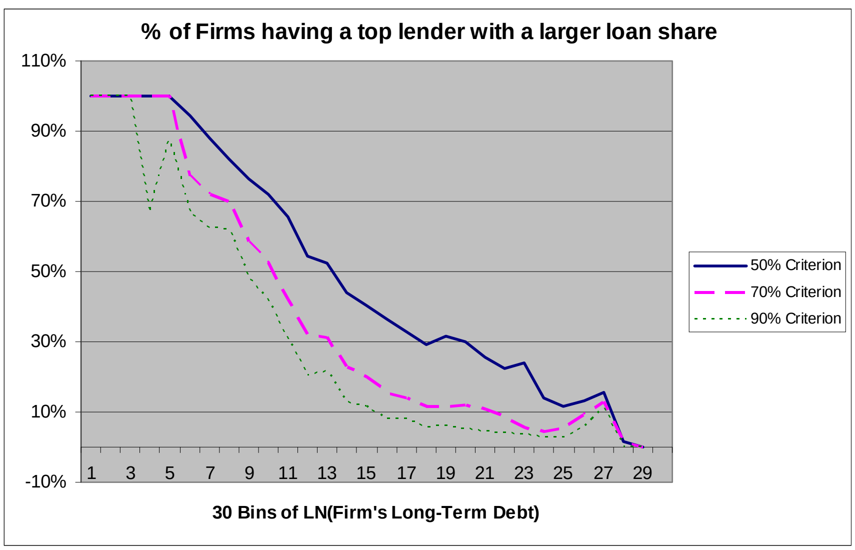

Data source: DBJ Corporate Financial Databank

Figure-10: Firm Distribution with a Top Lender with a High Share



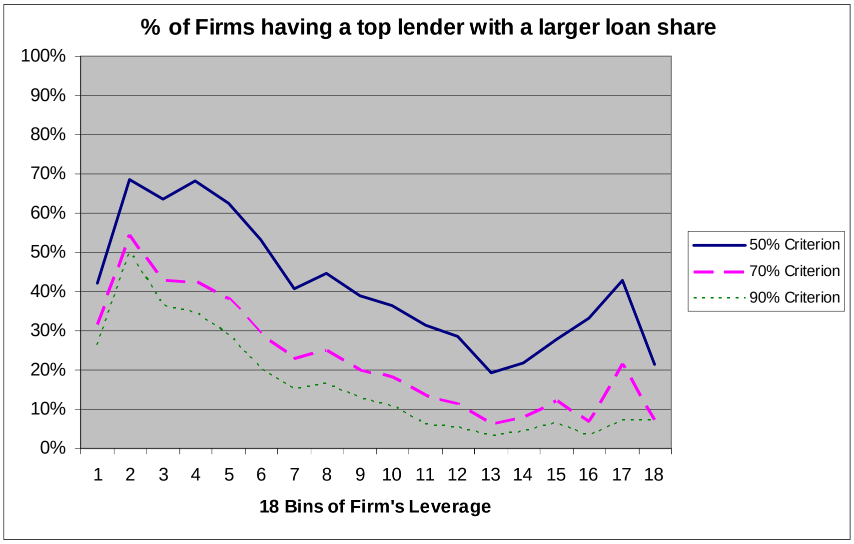

Data source: DBJ Corporate Financial Databank

Figure-11: Firm Distribution with a Top Lender with a High Share



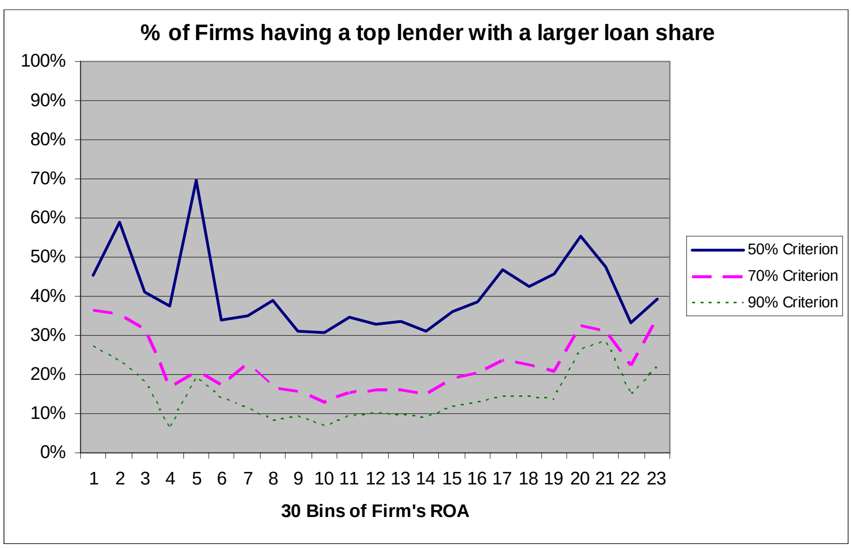

Data source: DBJ Corporate Financial Databank

Figure-12: Firm Distribution with a Top Lender with a High Share




Data source: DBJ Corporate Financial Databank

Figure-13: Firm Distribution with a Top Lender with a High Share




Data source: DBJ Corporate Financial Databank

Figure-14: Firm Distribution with a Top Lender with a High Share

| TOPL-Share (t) | Coeff | | t-stat | | |
|---|---|---|---|---|---|
| F-Size (t-1) | -0.0604276 | *** | -7.95 | Number of observations | 11811 |
| F-ROA (t-1) | 0.1456902 | *** | 3.33 | Number of groups | 1941 |
| F-LR (t-1) | 0.0219466 | *** | 4.93 | R2 (within) | 0.4013 |
| F-LEV (t-1) | -0.0970796 | *** | -4.41 | R2 (between) | 0.1526 |
| F-STLT (t-1) | 3.97E-06 | | 0.04 | R2 (overall) | 0.1923 |
| F-BTD (t-1) | -0.0292974 | *** | -3.49 | F-test all u_i=0 (Pr>F) | 0 |
| B-Size (t-1) | 0.0840175 | *** | 78.54 | Sigma_u | 0.20648467 |
| B-ROA (t-1) | 0.2309756 | | 1.42 | Sigma_e | 0.1390402 |
| B-CTA (t-1) | 0.0062733 | | 0.83 | rho | 0.68803016 |
| B-TETA (t-1) | 0.0263379 | | 0.12 | Observation per group | |
| B-IHI (t-1) | 0.0944128 | *** | 6.04 | Min | 1 |
| MKT-LOAN (t-1) | -0.0301059 | ** | -2.46 | Average | 6.1 |
| 1980s Dummy | 0.016211 | *** | 2.62 | Max | 17 |
| Year | 0.0008416 | | 0.9 | | |
| Constant | -1.260576 | | -0.75 | | |

Note-1: Breusch-Pagan test rejects pooling OLS

Note-2: Hausman test rejects random-effects model

Note-3: *** and ** denote significance at the1% and5% from a two-tailed t-test

Table-3: Panel Regression (1982-1999)

| TOPL-Share (t) | Coeff | | t-stat | | |
|---|---|---|---|---|---|
| F-Size (t-1) | -0.0601683 | *** | -7.92 | Number of observations | 11811 |
| F-ROA (t-1) | 0.1471617 | *** | 3..36 | Number of groups | 1941 |
| F-LR (t-1) | 0.0220271 | *** | 4.95 | R2 (within) | 0.4014 |
| F-LEV (t-1) | -0.0963166 | *** | -4.37 | R2 (between) | 0.1521 |
| F-STLT (t-1) | 2.95e-06 | | 0.03 | R2 (overall) | 0.1918 |
| F-BTD (t-1) | -0.0295199 | *** | -3.51 | F-test all u_i=0 (Pr>F) | 0 |
| B-Size (t-1) | 0.0839932 | *** | 78.51 | Sigma_u | 0.20652385 |
| B-ROA (t-1) | 0.2350157 | | 1.44 | Sigma_e | 0.13903422 |
| B-CTA (t-1) | 0.0064047 | | 0.85 | rho | 0.68813007 |
| B-TETA (t-1) | 0.0167272 | | 0.08 | Observation per group | |
| B-IHI (t-1) | 0.0927898 | *** | 5.92 | Min | 1 |
| MKT-LOAN (t-1) | -0.0301297 | ** | -2.46 | Average | 6.1 |
| 1980s Dummy | 0.0158594 | *** | 2.57 | Max | 17 |
| Year | 0.0007966 | | 0.85 | | |
| Mainbank Dummy | -0.0123936 | | -1.36 | | |
| Constant | -1.173964 | | -0.70 | | |

Note-1: Breusch-Pagan test rejects pooling OLS
Note-2: Hausman test rejects random-effects model
Note-3: *** and ** denote significance at the1% and5% from a two-tailed t-test
Note-4: Mainbank Dummy takes 1 if the top lender is also the top shareholder

Table-4: Panel Regression with Mainbank dummy (Def-(i) 1982-1999)

| TOPL-Share (t) | Coeff | | t-stat | | |
|---|---|---|---|---|---|
| F-Size (t-1) | -0.0604778 | *** | -7.96 | Number of observations | 11811 |
| F-ROA (t-1) | 0.1467597 | *** | 3.35 | Number of groups | 1941 |
| F-LR (t-1) | 0.0219588 | *** | 4.93 | R2 (within) | 0.4013 |
| F-LEV (t-1) | -0.0969715 | *** | -4.40 | R2 (between) | 0.1530 |
| F-STLT (t-1) | 3.43e-06 | | 0.04 | R2 (overall) | 0.1925 |
| F-BTD (t-1) | -0.0292964 | *** | -3.49 | F-test all u_i=0 (Pr>F) | 0 |
| B-Size (t-1) | 0.0840231 | *** | 78.53 | Sigma_u | 0.20644123 |
| B-ROA (t-1) | 0.2237683 | | 1.37 | Sigma_e | 0.1390457 |
| B-CTA (t-1) | 0.006207 | | 0.82 | rho | 0.68792286 |
| B-TETA (t-1) | 0.0402669 | | 0.18 | Observation per group | |
| B-IHI (t-1) | 0.0950287 | *** | 6.06 | Min | 1 |
| MKT-LOAN (t-1) | -0.0307906 | ** | -2.50 | Average | 6.1 |
| 1980s Dummy | 0.0165386 | *** | 2.66 | Max | 17 |
| Year | 0.0008964 | | 0.95 | | |
| Mainbank Dummy | 0.0023416 | | 0.47 | | |
| Constant | -1.352153 | | -0.80 | | |

Note-1: Breusch-Pagan test rejects pooling OLS
Note-2: Hausman test rejects random-effects model
Note-3: *** and ** denote significance at the1% and5% from a two-tailed t-test
Note-4: Mainbank Dummy takes 1 if the top lender is in the top 3 shareholders

Table-5: Panel Regression with Mainbank dummy (Def-(ii) 1982-1999)

| TOPL-Share (t) | Coeff | | t-stat | | |
|---|---|---|---|---|---|
| F-Size (t-1) | -0.0603535 | *** | -7.94 | Number of observations | 11811 |
| F-ROA (t-1) | 0.1432642 | *** | 3.27 | Number of groups | 1941 |
| F-LR (t-1) | 0.0218654 | *** | 4.91 | R2 (within) | 0.4014 |
| F-LEV (t-1) | -0.0978993 | *** | -4.44 | R2 (between) | 0.1515 |
| F-STLT (t-1) | 1.77e-06 | | 0.02 | R2 (overall) | 0.1917 |
| F-BTD (t-1) | -0.0294299 | *** | -3.50 | F-test all u_i=0 (Pr>F) | 0 |
| B-Size (t-1) | 0.084026 | *** | 78.54 | Sigma_u | 0.20667581 |
| B-ROA (t-1) | 0.2715384 | | 1.62 | Sigma_e | 0.13903966 |
| B-CTA (t-1) | 0.0065036 | | 0.86 | rho | 0.6884289 |
| B-TETA (t-1) | -0.0357656 | | -0.16 | Observation per group | |
| B-IHI (t-1) | 0.0935383 | *** | 5.98 | Min | 1 |
| MKT-LOAN (t-1) | -0.0268402 | ** | -2.12 | Average | 6.1 |
| 1980s Dummy | 0.0152596 | *** | 2.44 | Max | 17 |
| Year | 0.0006125 | | 0.64 | | |
| Mainbank Dummy | -0.0055998 | | -1.04 | | |
| Constant | -0.8866308 | | -0.52 | | |

Note-1: Breusch-Pagan test rejects pooling OLS

Note-2: Hausman test rejects random-effects model

Note-3: *** and ** denote significance at the1% and5% from a two-tailed t-test

Note-4: Mainbank Dummy takes 1 if the top lender is in the top 10 shareholders

Table-6: Panel Regression with Mainbank dummy (Def-(iii) 1982-1999)

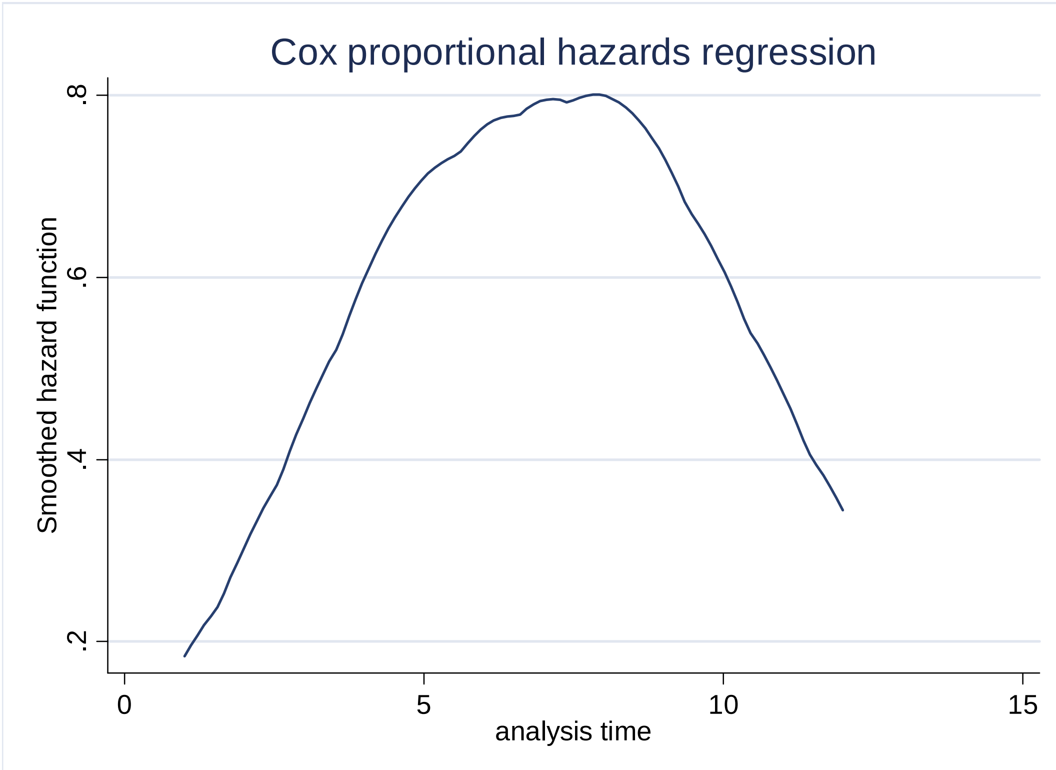



Figure-15: Semi-parametrically Estimated Hazard Function

| | | | Obs = | 4070 |
|---|---|---|---|---|
| Cox Proportional Hazard | Hazard Ratio | Std. | | $z$ |
| F-Size | 0.999793 | 0.0173687 | | -0.01 |
| FROA | 25.75275 | 16.71936 | *** | 5 |
| FLR | 1.229482 | 0.0577113 | *** | 4.4 |
| FLEV | 2.067779 | 0.4847136 | *** | 3.1 |
| B-Size | 0.8045732 | 0.020627 | *** | -8.48 |
| BROA | 1e+10 | 1.3e+101 | *** | 18.47 |
| BCTA | 2.749936 | 1.234649 | ** | 2.25 |
| BTETA | 5.55e-35 | 1.96e-34 | *** | -22.38 |

Note-1: Hazard ratio > (<) 1 means the covariate increases (decreases) the hazard ratio

Note-2: ***and **denote significance at the 1% and from a two-tailed z-test.

Table-7: Semi-parametric Estimation

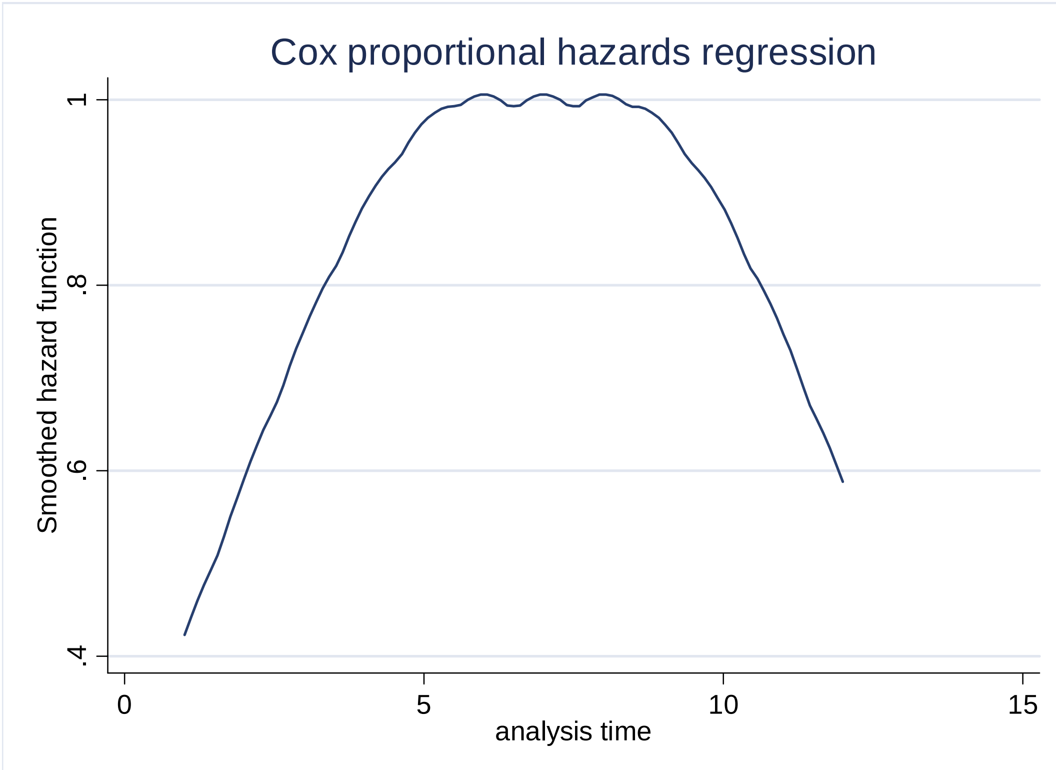



Figure-16: Semi-parametrically Estimated Hazard Function

| | | | | |
|---|---|---|---|---|
| | | | Obs = | 4070 |
| Cox Proportional Hazard | Hazard Ratio | Std. | | $z$ |
| F-Size | 1.00323 | 0.0174764 | | 0.19 |
| FROA | 29.59997 | 19.30651 | *** | 5.19 |
| FLR | 1.239904 | 0.0584251 | *** | 4.56 |
| FLEV | 2.202717 | 0.5192203 | *** | 3.35 |
| B-Size | 0.7893122 | 0.0209879 | *** | -8.9 |
| BROA | 1.56e+98 | 1.97e+99 | *** | 17.98 |
| BCTA | 2.675354 | 1.210344 | ** | 2.18 |
| BTETA | 4.9e-35 | 1.72e-34 | *** | -22.47 |
| Specialization Match | 0.7594184 | 0.0723587 | *** | -2.89 |

Note-1: Hazard ratio > (<) 1 means the covariate increases (decreases) the hazard ratio

Note-2: ***and **denote significance at the 1% and from a two-tailed z-test.

Table-8: Semi-parametric Estimation

| | | | Obs | = 4070 |
|---|---|---|---|---|
| Log-logistic | Coef. | Std. | | $z$ |
| F-Size | 0.008441 | 0.011006 | | 0.77 |
| FROA | -1.80794 | 0.415014 | *** | -4.36 |
| FLR | -0.15428 | 0.030288 | *** | -5.09 |
| FLEV | -0.43976 | 0.145138 | *** | -3.03 |
| B-Size | 0.137026 | 0.017651 | *** | 7.76 |
| BROA | -182.589 | 10.54746 | *** | -17.31 |
| BCTA | -0.47157 | 0.308917 | | -1.53 |
| BTETA | 49.36557 | 2.289116 | *** | 21.57 |
| Constant | -1.8122 | 0.485002 | *** | -3.74 |
| $\gamma$ | 0.446807 | 0.009242 | | |

Note-1: Coefficient > (<) 0 means the covariate increases (decreases) the failure time

Note-2: $\gamma <$ (>) 1 means the log-logistic hazard increases and decreases (monotonically decreases)

Note-3: ***denotes significance at the 1% from a two-tailed z-test.

Table-9: Parametric Estimation

| | | | Obs | = |
|---|---|---|---|---|
| Log-logistic | Coef. | Std. | | $z$ |
| F-Size | 0.008038 | 0.011025 | | 0.73 |
| FROA | -1.81946 | 0.415557 | *** | -4.38 |
| FLR | -0.15516 | 0.030296 | *** | -5.12 |
| FLEV | -0.44774 | 0.145635 | *** | -3.07 |
| B-Size | 0.135656 | 0.017764 | *** | 7.64 |
| BROA | -182.191 | 10.55966 | *** | -17.25 |
| BCTA | -0.46412 | 0.308933 | | -1.5 |
| BTETA | 49.38301 | 2.289598 | *** | 21.57 |
| Specialization Match | 0.000996 | 0.001506 | | 0.66 |
| Constant | -1.76991 | 0.489045 | *** | -3.62 |
| gamma | 0.446829 | 0.009242 | | |

Note-1: Coefficient > (<) 0 means the covariate increases (decreases) the failure time

Note-2: $\gamma <$ (>) 1 means the log-logistic hazard increases and decreases (monotonically decreases)

Note-3: ***denotes significance at the 1% from a two-tailed z-test.

Table-10: Parametric Estimation

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