The Effect of Relationship Banking on Firm Efficiency

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Abstract

Do monitoring relationship banks produce private information about firms exceeding the minimum returns intended to forestall insolvency? I analyze the effect of relationship banking on the firm's technical efficiency, measured by both Data Envelopment Analysis and Stochastic Frontier Analysis. I find evidence that existence of a banking relationship improves the efficiency of firms that have high default probabilities. In contrast, efficiency of more creditworthy firms declines as monopoly rents on bank loans increase costs, consistent with hold-up problems. Results are robust to subsamples of high vs. low default risk firms grouped using Altman's z score, Whited-Wu financial constraint index and Jarrow-Merton probability of default model.

Keywords: Relationship banking, firm efficiency, data envelopment analysis, stochastic frontier analysis, default, bankruptcy, hold-up problem

JEL classification: G21, G30, G33

I. Introduction

Relationship banking involves screening and monitoring of borrowers in order to resolve information asymmetries that hamper firm access to arms-length market sources of financing (Boot and Thakor (2000), Elyasiani and Goldberg (2004), Ongena and Smith (1998)). Evidence of private information production by relationship banks is found in stock prices (James (1987), Li and Ongena (2015)), access to financing (Petersen and Rajan (1994)), and the cost of

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financing (Bharath et al. (2011)). However, despite an extensive academic literature, the content of private information gathered by relationship banks is still unclear. That is, do banks focus only on information about firm default probability or do they focus on firm profitability as well? Since insolvency risk and profitability are obviously linked, this question may appear redundant. However, bank lenders hold convex cash flow claims that expose them to losses upon firm default, but do not allow sharing in upside gain when the firm is profitable. Therefore, it is not apparent that banks would seek information about firm profitability exceeding the minimum returns intended to forestall insolvency.

Since the dual of the profit maximization objective function is cost minimization, in this paper, I examine the role of relationship banks in monitoring firm efficiency. In particular, I determine whether a firm with a banking relationship is more or less likely to operate efficiently in the years before, during and after a new lending relationship is established. I examine the impact of a banking relationship on firms that are close to the default boundary in contrast to solvent firms unlikely to default. This permits an examination of whether relationship bank's information production is narrowly focused on firm default risk or more broadly related to overall firm profitability even when the probability of default is low. I estimate a firm's technical efficiency by comparing the firm's production and operational costs with what is feasible given the technology set for the industry, i.e. boundary or frontier of the technology set. (Bogetoft and Otto 2011) To measure the firm's technical efficiency, I utilize the non-parametric and deterministic Data Envelopment Analysis (DEA) and parametric Stochastic Frontier Analysis (SFA). I use Altman's Z score to calculate the probability of default, (Altman 1968), and estimate the effect of likelihood of existence of relationship banking on the efficiency of firms in the first and fourth quartile of Altman's Z score. To check the robustness, I divide the sample according to Whited and Wu (2006) financial constraint analysis and Jarrow-Merton default probabilities.

Using the syndicated loans market data for public firms in the U.S., I find that the existence of relationship banking increases firm efficiency. However, the results show that the existence of relationship banks has a different impact on the efficiency of firms with high as opposed to low default risks. While firms with high probabilities of default experience an increase in their efficiency in the presence of a banking relationship, the efficiency of the firms with low probability of default is actually reduced. This suggests that relationship banks focus their monitoring activity on firms that are more likely to default, thereby imposing loan losses on the bank. Thus, in an attempt to reduce the firm's default probability and decrease the loan's loss given default, lending banks apparently intervene to improve efficiency at borrowing firms. In contrast, relationship banks do not appear to invest efficiency-improving resources in borrowing firms with low probabilities of default. Indeed, since bank loans are relatively costly due to monopoly rents and monitoring costs incorporated into loan rates, borrowing firms with low default risk experience a reduction in their efficiency. The effect is observed both in credit line relationships involving repeated lending activity (as the loan commitment is taken down) and one-time term loan relationships (in which the entire loan principal is paid out in one lump sum). Thus, relationship banks appear to invest screening and monitoring resources in producing information to improve the efficiency of only those firms with high risk of default, but hold up low default risk borrowers.

However, the decision to borrow from a relationship bank is itself endogenous, and may introduce bias to my analysis. Firms can obtain funds from publicly traded debt or equity markets in lieu of syndicated bank loans. Once borrowers obtain alternative sources of funds, such as access to the public debt markets, they typically face lower interest rates on bank debt as the lending bank's monopoly power is dissipated (Hale and Santos (2009)). Therefore, firms that are dependent on banks for financing may be the ones that are unable to access public debt markets because of severe adverse selection and potential moral hazard, thereby injecting bias into my analysis. I control for endogeneity of financing choice using several approaches. First, I perform a two-stage analysis in which I model the firm's choice to acquire a relationship bank. I focus on the decision to acquire a credit rating, as this is a key prerequisite for issuance of public debt. I then utilize the first-stage estimated probabilities in a control function regression analysis of the borrowing firm's technical efficiency measures for the sample of firms with and without credit rating as well as the whole sample firms. As an alternative endogeneity treatment method, I utilize propensity score matching to distinguish between firms that obtain credit ratings and therefore have access to public financing sources, as compared to bank-dependent firms without credit ratings. I find that unrated firms with relationship banking increase their efficiency more than the unrated firms without a relationship bank. Thus, informationally opaque firms benefit most from the existence of relationship banking.

Moreover, the salubrious role of relationship banks on firm efficiency for high risk borrowing firms is weakened over time by bank hold-up problems. That is, the bank's incentive to produce private information beneficial to the firm is reduced as the bank's monopoly control increases with lending. Since switching banks is costly to informationally opaque and high default-risk borrowers, bank lenders earn monopoly rents from loans that reduce firm profitability and operational efficiency. I estimate the effect of relationship banking within a 5-year window to examine how the impact of the relationship changes from 2 years before the relationship to 2 years after the relationship. I find that high default risk firms with bank relationships experience increases in their efficiency during and after the existence of relationship whereas low default risk firms do not experience any change. Furthermore the results show that the impact of relationship banking on firm efficiency diminishes in the years after the relationship takes place.

The remainder of the paper is organized as follows. A brief review of the literature and hypothesis construction is provided in Section II. Section III describes the data, and variable construction. Section IV introduces the model and presents the empirical findings measuring the impact of a bank relationship on borrowing firm's efficiency of operation. Section V concludes with a brief summary.

II. Literature Review and Hypothesis Construction

Arms-length debt is publicly traded on bond markets. Investors have access to public information about the debt issuer, but generally have no access to private information. Indeed, because of the free rider problem, investors in arms-length financial securities have little incentive to invest resources to become informed. Thus, credit ratings usually serve as a low cost mechanism to judge the credit quality of debt issues. In contrast, bank loans involve a long-term, multi-product relationship between the lending bank and borrowing firm. There is a presumption that borrowers will repeatedly borrow from their relationship bank. Bharath et al. (2007) find that the probability of subsequent borrowings is 42% from a relationship bank in contrast to 3% from a non-relationship bank. Moreover, the relationship bank will tend to sell many additional services to its borrowers (e.g., deposit-taking, factoring, merger and acquisition advice, underwriting). Thus, a banking relationship is information intensive (Boot and Thakor 2000). The relationship bank invests in obtaining customer-specific information, often proprietary in nature, and evaluates the profitability of these investments through multiple interactions with the same customer over time and/or across products. (Boot 2000) In addition, Leland and Pyle (1977), Diamond (1984), Fama (1985), and Boyd and Prescott (1986) argue that banks and other private lenders provide more efficient monitoring than arms-length investors do. Furthermore, Diamond (1991) argues that firms that are unable to borrow from the capital markets because of information asymmetries and potential moral hazard can benefit from informed bank borrowing. Relationship banks alleviate the moral hazard problem by closely monitoring the borrower's activities. In addition, Yosha (1995) and Bhattacharya and Chiesa (1995) argue that the firm chooses bank financing if there is proprietary information to be protected for competitive purposes.

While there are benefits of bank borrowing such as alleviating information asymmetries, providing reputation and discretion to disclose information, there is an extensive literature arguing that the reliance on bank borrowing creates a "hold-up" problem, in which a bank that lends to a firm learns more about the firm's characteristics than do other non-relationship banks. This asymmetric information results in ex post monopoly power of ex ante competitive bank so that the bank can charge ex post high interest rates (Sharpe, 1990). Therefore, once the borrower is informationally captured by the bank, it becomes reluctant to borrow from the bank as bank borrowing becomes costly. (Sharpe (1990), Rajan (1992), Boot (2000)) According to Ongena and Smith (2000) and Rajan (1992) engaging in multiple relationships can reduce the hold-up problem by limiting the power of the individual banks. On the other hand, there is a downside of multiple banking relationships; Thakor (1996) argues that the existence of multiple relationships reduces the value of information acquisition by any one bank. Petersen and Rajan (1994) find that the existence of multiple lenders increases the cost and reduces the availability of credit. One mechanism through which firms build reputation and lower information asymmetries is by acquiring a credit rating. A credit rating is a prerequisite for issuance of publicly traded debt at all levels of default risk (Denis and Mihov 2003). Thus, the monopoly power of the relationship bank is reduced, thereby alleviating the hold-up problems.

The syndicated loans market incorporates both the benefits and costs of relationship banking. A syndicated loan is formed by at least two lenders jointly offering funds to a borrowing firm. The "lead arranger" establishes a relationship with the firm (often as sole lender in non-syndicated bank loans), negotiates terms of the contract, and guarantees an amount for a price range. The lead arranger then turns to "participant" lenders that fund part of the loan. (Sufi 2007) As Dennis and Mullineaux (2000) argue the syndicated loans lie somewhere on the continuum between the relationship loans and arms-length debt. Accordingly, Sufi (2007) shows that the borrowers with little or no credit reputation obtain syndicated loans that are similar to sole-lender bank loans. In these loans, the lead arranger retains a larger share of the loan and there are fewer participant lenders on the syndicate. More transparent borrowers obtain syndicated loans that are similar to public debt; i.e., the syndicate is dispersed and the lead arranger retains a smaller share of the loan. Therefore, the syndicated loans market provides an opportunity to analyze firms with different levels of exposure to the hold-up problem and different expectations of bank certification through screening and monitoring.

Syndicated bank loans generally take the form of packaged deals consisting of more than one facility. Each facility can have different features and structures. A common syndicated loan package includes both a line of credit and a term loan. Lines of credit are also known as loan commitments or revolving loan facilities. A revolving credit line contains an option that allows borrowers to draw down, repay, and re-borrow any amount up until a maximum ceiling over a set commitment period of time. The facility acts much like a corporate credit card, except that borrowers are charged an annual commitment fee on unused amounts (the facility fee). A term loan is simply an installment loan. The borrower may draw on the loan shortly after the loan origination date and must repay the loan either using a scheduled series of repayments or a one-time lump-sum payment at maturity (bullet payment). There are two principal types of term loans: An amortizing term loan (A-term loans, or TLa) is a term loan with a progressive repayment schedule that typically runs six years or less. These loans are normally syndicated to banks along with revolving credits as part of a larger syndication. An institutional term loan (B-term, C-term, or D-term loans) is a term loan facility carved out for nonbank trading in the form of securitization, mutual fund holdings, hedge fund investments, etc. These loans came into broad usage during the mid-1990s as the institutional loan investor base grew (S&P 2012).

The lead arranger in a syndicated loan produces information shared by all members of the syndicate. Indeed, covenants incorporated into syndicated bank loans require the regular release of private information about firm profitability, net worth and cash flows. Allen et al. (2008) finds that syndicated bank loan prices incorporate information about earnings approximately one month prior to public earnings announcements. The private information obtained by relationship banks, therefore, focuses on earnings as well as default risk. Thus, I hypothesize that monitoring by relationship banks is directed as improving firm operations, as measured by technical efficiency.

Hypothesis 1: *The existence of relationship banking increases the firm efficiency.*

Since bank lenders are exposed to downside losses, but have limited upside gain potential, I hypothesize that the focus of efficiency monitoring would be for high default risk firms. Accordingly I define the third hypothesis as;

Hypothesis 2: *The banks' monopoly control increases in the years after the relationship takes place, leading to hold-up problems that diminish the positive effect of relationship banking on firm efficiency.*

Hypothesis 3: *The existence of relationship banking increases the efficiency of high default-risk firms, whereas low default-risk firms experience no change in their efficiency.*

III. Data

The data for syndicated loans comes from Loan Pricing Corporation (LPC)'s Dealscan database. I match the firm financial statements with the syndicated loans market, focusing on the period 1990-2013. I collect data on the annual financial statements of U.S. firms from the Compustat database. For the Jarrow-Merton default probabilities, I use Kamakura Corporation's data (KRIS). The sample consists of all firms with non-missing values of sales and total assets. I exclude firms with sales and total assets less than $5 million. I also exclude finance (SIC codes 6000-6799) and utilities (SIC codes 4900-4942) industries since they are regulated and have different pricing mechanisms. All the firm level ratios are winsorized by 1% at both ends. Firms with gaps in the years are excluded from the sample. I also excluded those firms with less than three consecutive years of data. The analysis is at the firm-year level for the firms that appear on the Dealscan database. Therefore the analysis includes only those firms that have borrowed in the syndicated loans market at least once during the sample period. I define the facility as *credit line* if loan type on Dealscan is given as '364-day facility', 'Limited Line', 'Revolver/Line < 1 Yr.', 'Revolver/Line >= 1 Yr.' and 'Revolver/Term Loan'. Similarly, I define the facility as *term loan* if the loan type is given as 'Term Loan', 'Term Loan A' and 'Term Loan B' on Dealscan. The sample includes 12665 credit line facilities and 2761 term loan facilities of 4286 firms. In total the analysis includes 50925 firm-year observations.

In order to introduce the lead lender relationship, following Acharya, Almeida, Ippolito and Perez (2014), I first define the *Lead* dummy that is equal to one if the lender role is given as 'Agent', 'Arranger', 'Lead' or 'Manager'. I, then, define the relationship dummy (*Relationship_exists*)[2], which indicates whether the firm has a relationship with the same lead-lender within the previous 3 years. For the firms borrowing more than once in a given year, I choose the facility that is with a lead-lender, with which the firm has the longest relationship, as well as the facility that is longer in maturity and higher in amount. For the facilities with more than one lead bank, I include the one with the lead-lender that the firm has the longest duration of relationship with, the longest maturity and the highest facility amount among all the previous relationships of the firm with all lead-lenders of the same facility. As a result of this construction, the sample includes 7356 credit line relationships and 2173 term loan relationships. Furthermore, to check the strength of the bank relationship I define *duration* variable as the number of term loans (credit lines) the firm borrows from the same lead-lender during the whole sample period. To analyze if the higher number of lead lenders of a facility has an effect on the firm efficiency, I define *number of leads* variable as the number of lead lenders of a facility and *number of loans* variable that counts the number of loans each firm borrows from the same lead lender within the previous 3 years.

The intensity of the relationship is defined as the total amount of term loans and credit lines a firm receives from a lead bank within the last 3 years and scaled by total assets of each year. (*Relationship intensity)* If the firm does not have a 3-year relationship with a lead bank, but has borrowed in the syndicated loans market throughout the sample period, I use the facility amount of the loan scaled by total assets. The summary statistics for the loan characteristics are in Panel C of Table 1.

The focus on the bank relationship-firm efficiency link in the context of the syndicated loans market offers a new perspective for the analysis of firm efficiency as well as the relationship banking. Two common measures of firm efficiency are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The DEA method was introduced by Farrell (1957) and improved by Charnes, Cooper and Rhodes (1978) and Banker, Charnes and Cooper (1984). The aim of this non-parametric approach is to define a frontier envelopment surface for all sample observations. This surface is determined by those units that lie on it, that is the

[2] The definitions of the variables are provided in the Appendix I.

efficient decision-making units (DMUs). On the other hand, units that do not lie on that surface can be considered as inefficient and an individual inefficiency score will be calculated for each one of them. Unlike stochastic frontier techniques, DEA has no accommodation for noise, and therefore can be initially considered as a non-statistical technique where the efficiency scores and the envelopment surface are ‘calculated’ rather than estimated. (Murillo-Zamorano (2004)).

Aigner, Lovell and Schmidt (1977), Meeusen and van den Broeck (1977) and Battese and Corra (1977) simultaneously developed a Stochastic Frontier Analysis method (SFA) that, in addition to incorporating the efficiency term into the analysis (as do the deterministic approaches) it also captures the effects of exogenous shocks beyond the control of the analyzed units. Moreover, this type of model also covers errors in the observations and in the measurement of outputs. (Murillo-Zamorano 2004) In their analysis of cost efficiency in the banking sector, Ferrier and Lovell (1990) argue that the differences between the two approaches are due to the fact that a stochastic specification had been compared with a deterministic one.

More recent studies that utilize SFA and DEA models to estimate/calculate the firm efficiency have dealt with questions such as the effect of firm efficiency on stock returns (Frijns, Margaritis and Psillaki, 2012), on firm performance (Baik, Chae, Choi and Farber, 2012) and on mergers and acquisitions performance (Leverty and Qian, 2009). They all find positive effect of efficiency on the related performance measure. Furthermore as Leverty and Grace (2012) discuss, empirical research documents a strong relationship between property-liability insurer efficiency and traditional and market measures of performance. For example, Cummins et al. (2008) find that efficiency measures are directly related to the market value performance of publicly traded insurers. Leverty and Grace (2009) find that efficiency measures are closely related to traditional measures of firm performance, such as return on assets and return on equity. Demerjian, Lev and McVay (2012) introduce a new measure of managerial ability defining it as a component of firm efficiency and look at the performance of those firms with high vs. low ability managers. They show that high managerial ability increases firm performance.

I calculate firm efficiency scores using both non-parametric data envelopment analysis (DEA) and parametric stochastic frontier analysis (SFA) methods. DEA method measures the relative efficiency of a decision-making unit (DMU) in converting certain inputs into outputs.[3] I

[3] More details on DEA and the linear programming method of measuring technical efficiency by Murillo-Zamorano (2004) are provided in the Appendix II.

follow Demerjian et.al. (2012)'s measure of firm efficiency and solve the following optimization problem for all firms for each year and industry, using Fama-French 12 industry classification (Fama and French 1997);

$$\min_{\mu} \psi = (Sales) * (\mu_1 COGS + \mu_2 SG\&A + \mu_3 PPENT + \mu_4 OpsLease + \mu_5 R\&D + \mu_6 Goodwill + \mu_7 OtherIntan)^{-1} \quad (1)$$

where $\psi \in [0,1]$ is the efficiency measure. The output is the revenue of a firm (Sales) in a given year and the inputs are the cost of goods sold (COGS) that are the costs of production; selling, general and administrative expenses (SG&A), which are operational costs also known as the costs unrelated to the production process; net property, plant and equipment (PPENT) that accounts for fixed assets; net operating leases (OpsLease) that are included to capture the expenses of the firms that lease the fixed assets rather than purchase; research and development expenses (R&D); purchased goodwill (Goodwill), which is the excess of the purchase price for a business acquisition; and other intangibles (OtherIntan) that include items such as client lists, patent costs, and copyrights. The five stock variables (*PPENT, OpsLease, R&D, Goodwill* and *OtherIntan*) are measured at the beginning of year *t* and the two flow measures (*COGS* and *SG&A*) are measured over the year *t*. I follow Ge (2006) to calculate *Net Operating Leases* as the discounted present value of the next five years of required operating lease payments (MRC1-MRC5 on Compustat). I follow Lev and Sougiannis (2006), who use a five-year capitalization period of *R&D expense*. *Other Intangible Assets* item (*OtherIntan*) is calculated by subtracting *Goodwill* (*GDWL*) from the *Other Acquired and Capitalized Intangibles* (*INTAN*).

The second measure of technical efficiency is the stochastic frontier analysis (SFA) approach, which assumes that the error term of the regression of firm outputs on inputs includes both the randomness (statistical noise) and technical inefficiency. For the Cobb-Douglas production function, and in logarithmic terms, the single-output stochastic frontier can be shown as

$$lnY_i = \beta_0 + \sum_{n=1}^{N} \beta_n lnX_{ni} + v_i - u_i \quad (2)$$

where $v_i \sim N(0, \sigma_v^2),\ u_i \sim N_+(0, \sigma_u^2)$

The term $v_i - u_i$ is a composed error term where v_i represents randomness and u_i represents technical inefficiency. An important assumption in this model is that v_i and u_i are independent. If $u_i = 0$ the firm is 100% efficient, and if $u_i > 0$, then there is some inefficiency. The N_+ denotes a half-normal distribution, which is truncated at point 0 and the distribution is concentrated on the half-interval [0,∞). (Murillo-Zamorano, 2004) The firm-specific technical efficiency is given by

$$TE_i = \frac{f(lnX_{ni}, \hat{\beta}_n) - \hat{u}_i}{f(lnX_{ni}, \hat{\beta}_n)} = 1 - \frac{\hat{u}_i}{f(lnX_{ni}, \hat{\beta}_n)} \tag{3}$$

The output of the firm is the natural log of sales (*lnsale*) and the inputs are the natural log of cost of goods sold (*lncogs*) and selling, general and administrative expenses (*lnxsga*). The summary statistics for DEA and SFA efficiency scores are given in Panel A of Table 1. Mean (median) efficiency scores are 0.73 (0.76) for DEA efficiency score and 0.90 (0.91) for SFA efficiency.

As a robustness test, I also estimate the impact of relationship banking on return on assets (ROA), net profit margin (NPM) and return on equity (ROE). I report the correlations of these financial ratios with DEA and SFA efficiency scores in Table 2. Consistent with the findings of Leverty and Grace (2009), DEA and SFA efficiency scores have a positive and statistically significant correlation with all three financial ratios. The correlation of both DEA and SFA efficiencies is much higher with ROA and NPM than with ROE. Therefore I argue that DEA and SFA efficiency measures are consistent with firm profitability ratios.

To control for firm-specific features, I use leverage, size, profitability, tangibility, firm age and rating dummy. *Leverage* measures the ratio of public debt to equity; the two forms of firm's outside financing. It is defined as the ratio of book value of debt to the total of market value of equity and book value of debt. Profitability is the return on assets (*ROA*) defined as the ratio of earnings before interest, taxes, depreciation and amortization to book value of assets. Firm *size* is the natural log of total assets. *Tangibility* is the ratio of net property, plant and equipment divided by total assets. *Firm age* is the number of years since the initial public offering. *Rating* is a dummy variable equal to one if the firm has S&P domestic long-term issuer credit rating and zero otherwise. I divide the sample into rated vs. not rated in order to capture the effect of bank relationship on firm efficiency for firms with different information asymmetries.

Summary statistics for the firm-level variables are provided in Panel B of Table 1. Mean (median) size of firms in the sample is about \$403 million (\$358 million). Average profitability is 12%. Tangibility, which measures the riskiness of the firm in terms of the fixed assets, has a mean (median) of 30% (24%). 30% of the sample has S&P domestic long-term issuer credit rating. The market-to-book ratio measures the growth opportunities of the firm, which has a mean of 1.43 in the sample. Mean leverage ratio is 0.25. Since the first and fourth quartiles of Altman's z score are within the range of distressed firms (1.35) and safety zone (2.92), respectively, in terms of predicted bankruptcies, the sample is a representative of both types of firms.

In order to analyze the impact of the existence of relationship banking on firms with low vs. high probability of default I use three measures of default probabilities. First, I use *Altman's z score* (Altman (1968), Denis and Mihov (2003)), which uses multiple discriminant analysis to predict banktrupcies. The calculation is:

$$Altman's\ z\ score_{it} = 1.2 * WC/TA_{it} + 1.4 * RE/TA_{it} + 3.3 * EBIT/TA_{it} + 0.6 * M/B_{it} + 0.999 * NS/TA_{it} \quad (4)$$

in which *WC/TA* (Working Capital/Total Assets) is the liquidity measure; *RE/TA* (Retained Earnings/Total Assets) is the cumulative profitability; *EBIT/TA* (Earnings Before Interest and Taxes/Total Assets) is the true productivity of a firm; *M/B* (Market Value of Equity/Book Value of Liabilities) measures insolvency; and *NS/TA* (Net Sales/Total Assets) is the capital turnover ratio, which measures the revenue generating ability of the assets. According to this construction, firms with higher z score are in safety zone (>2.99) and firms with low z score are in distress (<1.81). Univariate analysis of low vs. high default risk firms according to Altman's z score is in Panel A of Table 3. Low default risk firms have higher DEA and SFA efficiencies, ROA, ROE and NPM whereas, they are less financially constrained, have lower JM probability of default and are unrated.

Second measure is Whited and Wu (2006)'s financial constraint index constructed via generalized method of moments estimation of an investment Euler equation. The calculated parameters are as follows:

$$Financial\ Constraint_{it} = -0.091 * CF_{it} - 0.062 * DIVPOS_{it} + 0.021 * TLTD_{it} \quad (5)$$

$$-0.044 * LNTA_{it} + 0.102 * ISG_{it} - 0.035 * SG_{it}$$

in which *CF* is the ratio of cash flow to total assets; *DIVPOS* is an indicator that takes the value of one if the firm pays cash dividends; *TLTD* is the ratio of the long-term debt to total assets; *LNTA* is the natural log of total assets, *ISG* is the firm's industry sales growth; *SG* is firm sales growth. Firms with higher scores in this index are more financially constrained. Univariate analysis of low vs. high default risk firms according to Whited-Wu financial constraint index is in Panel B of Table 3. Low default risk firms have higher DEA and SFA efficiencies, ROA, ROE and NPM whereas, they are less financially constrained, have lower JM probability of default and are rated.

Third measure of probability of default is obtained from Jarrow Merton (JM) Hybrid Model, which is a statistical hazard model that relates the probability of firm default to the same explanatory variables as the Jarrow Chava Model (firm financial ratios, other firm attributes, industry classification, interest rates, macroeconomic factors, and information about firm and market equity price levels and behavior), and incorporates the default probability of the Merton Structural Model as an additional explanatory variable. The Merton Structural Model uses option pricing methods to relate the probability of firm default to its financial structure and information about the firm's market price of equity. The explanatory variables include a measure of the firm's outstanding debt, its market valuation, and information about firm and market equity price behavior. In this model firm default occurs when the market value of the firm's assets decline below a threshold related to the firm's outstanding debt. (Kamakura Corporation Public Firms Model 2011) Univariate analysis results of low vs. high default risk firms according to JM model are in Panel C of Table 3. Low default risk firms have higher DEA and SFA efficiencies, ROA, ROE and NPM whereas, they are less financially constrained, have lower JM probability of default and are unrated.

IV. Model and Results

I analyze the effect of relationship banking on the borrowing firm's efficiency using existence, duration and intensity of the relationship as proxies for the strength of the relationship banking. However, the decision to borrow from a relationship bank is endogenous, and may introduce bias to my analysis. The firms that can obtain funds from publicly traded debt or equity markets may choose to do so in lieu of syndicated bank loans since they typically face higher interest rates on bank debt. Therefore, firms that are dependent on banks for financing may be the ones that are unable to access public debt markets because of severe adverse selection and potential moral hazard, thereby injecting endogeneity into my analysis. In order to mitigate this concern, I endogenize the *Relationship_exists* variable and estimate the likelihood of the existence of relationship so that the results reflect the effect of relationship banking on firm efficiency conditional on the relationship exists (Bharath, Dahiya, Saunders and Srinivasan (2009), Dass and Massa (2011), Elsas (2005)). Table 3 Panel A provides the mean differences of each firm control variables between the firms with and without relationship banking. According to these results, firms with relationship banking have a higher DEA and SFA efficiency than those without relationship.

Given that the effect of existence of relationship banking on firm efficiency can be observed only for firms that have relationship banking, following Wooldridge (2010), I use a Heckman-type two-step correction model for endogeneity using probit in the first step and control function regression with 2SLS in the second step including inverse Mills ratio (*lambda*) calculated from the estimated probabilities from the first step probit. First step probit estimation is:

$$Prob(Relationship\_exists_{it} = 1 \mid X_{it}) = \Phi(X_{it} + Year\ FE + Industry\ FE) \qquad (6)$$

in which $\mathrm{X_{it}}$ includes number of previous bank relationships; dummy variable that indicates an outstanding bank relationship from previous period; tangibility; operational expenses (SG&A); research and development (R&D) expenses; dummy if the firm has R&D expenses; lagged market-to-book ratio; lagged leverage; lagged profitability; lagged size; firm age; fixed assets; cash; Fed's credit tightening score; and credit rating dummy.[4] I also estimate logit model for robustness test. The results of the first step analyses are in Table 5. According to these, firms that are large (*size)*; have higher number of previous bank relationships; outstanding bank relationship from previous period; less risky investments (*tangibility)*; high operating expenses (*SG&A expenses)*; high leverage (*leverage)*; high collateral (*property, plant and equipment); rating;* and use less cash (*cash)* have higher likelihood of forming a bank relationship. The credit

[4] The definitions of each variable are given in Appendix I.

tightening (*FED's credit tightening score)* is also positive and significant, suggesting that when there are tighter credit conditions firms are more likely to have a bank relationship.

Moreover, I endogenize the variables of the strength of relationship banking, namely *duration, number of leads, number of loans* and *relationship intensity*. I use Poisson regression to estimate *duration, number of leads* and *number of loans,* as these are count variables. For *relationship intensity*, I use OLS regression. The instruments are the industry average of each variable and a dummy variable indicating if the firm has an outstanding relationship from the previous period. The results are provided in Table 6. For all specifications the instruments are positive and significant at 1% level.

In the second step of the analysis, I estimate two-stage least squares using the estimated probabilities from the first step probit as instruments for the existence of relationship banking and estimate below specification:

$$\begin{aligned} DEA\ (SFA)\ Score_{it} &= \beta_0 + \beta_1 \widehat{relationship\_exists}_{it} + \beta_2 average\ efficiency \\ &+ \beta_3 average\ ROA + \beta_4 size_{it-1} + \beta_5 firm\ age_{it} + \beta_6 lambda_{it} \\ &+ Year\ FE + Industry\ FE + \varepsilon_{it} \end{aligned} \tag{7}$$

in which $\widehat{\text{relationship\_exists}}$ is the fitted values from the first stage regression of *relationship_exists* on estimated probabilities from Equation (7), *average_efficiency* is the 3-year average DEA (SFA) efficiency score (*t-1…t-3*), *average_ROA* is the 3-year average return on assets (*t-1…t-3*), *size* is the natural log of total assets of the previous period, *firm_age* is the number of years since the initial public offering and *lambda* is the inverse Mills ratio calculated from the probit regression from Equation (6). I also estimated Equation (7) using *duration, number of leads, number of loans* and *relationship intensity* as dependent variables to check the strength of relationship banking. I use bootstrapping at the firm level in all regressions to correct standard errors. The results are in Table (7) for DEA efficiency analysis and Table (8) for SFA efficiency analysis. One standard deviation increase in the probability of existence of relationship increases DEA efficiency by 0.1% (0.03*0.04), corresponding to 0.1% of mean DEA score and SFA efficiency by less than 0.1% (0.007*0.04) corresponding to 0.1% of mean SFA score. A similar increase in the duration of the relationship increases both DEA and SFA efficiencies by less than 0.1% (0.015*0.06 and 0.001*0.06 respectively). One standard deviation increase in *number of leads* and *number of loans* do not affect SFA efficiency but increase DEA efficiency by 0.2% (0.007*0.3) and by 0.1% (0.003*0.38) respectively. A similar increase in relationship intensity increases DEA efficiency by 0.4% (0.003*1.63) and SFA efficiency by 0.1% (0.001*1.63). All these results are statistically significant at 1% level and they suggest that the existence as well as strength of the relationship increases firm efficiency, measured by both DEA and SFA methods. Since the existence of relationship variable is defined such that it includes the longest duration, longest maturity and highest facility amount for each year a firm has a relationship with a lead-lender in the syndicated loans market, I use this variable as my main variable of interest that proxies the strength of relationship banking throughout the rest of the analysis. The results also show that among the firm control variables lagged efficiency scores and lagged firm size affect the firm efficiency positively at 1% significance level. Lambda is slightly significant in DEA efficiency results. However it is insignificant in the SFA efficiency results. Overall these results support *Hypothesis 1 that existence of relationship banking increases firm efficiency.*

The sample includes firms that have severe information asymmetries as well as those that are more informationally transparent. In order to see the effects of relationship banking on these two subsamples, I estimate Equation (7) for the rated and unrated firms. The results in Table 9 show that both rated and unrated firms benefit from the existence of relationship through an increase in their efficiencies. One standard deviation increase in the probability of existence of relationship increases DEA efficiency of rated firms by 0.1% (0.026*0.06), which corresponds to 0.1% of the mean DEA score, and that of unrated firms by less than 0.1%, corresponding to about 0.1% of the mean SFA score. The effect of a similar increase on SFA efficiency is also positive but smaller in economic significance for both rated and unrated firms.

However, having a credit rating is also endogenous as some firms might choose to be rated even though they don't issue public debt. Also, those firms that do not have access to public debt market due to severe information asymmetries have to borrow from the banks. Therefore having a credit rating does not solve the endogeneity in my analysis. In order to alleviate endogeneity concerns I use propensity score matching analysis with the nearest neighbor matching technique and match three firms that have the closest propensity score with a rated firm by estimating below equation with logistic regression:

$$Prob(rated_{it} = 1) = \Lambda(\alpha_0 + \alpha_1 log\ (sale)_{it} + \alpha_2 Growth_{it} + \alpha_3 tangibility_{it} + \alpha_4 ROA_{it} + \alpha_5 leverage_{it} + \alpha_6 Altman's\ z\ score_{it} + \alpha_7 log\ (indfrac)_{it} + Year\ FE + Industry\ FE) \tag{8}$$

in which $rated_{it}$ is a dummy that equals to one for the firms that have S&P domestic long-term issuer credit rating. $Growth_{it}$ is R&D scaled by sales, $log\ (indfrac)_{it}$ is the log of one plus the fraction of firms in the same three-digit industry that have credit ratings and $Altman's\ z\ score_{it}$ is calculated as in Equation (4). After I match unrated and rated firms, I track the efficiency of each rated and matched unrated firm within a five-year window. I also track the rated and matched unrated firms' banking relationship. According to these I calculate efficiency difference of the rated firm with each matched unrated firm under the below categories:

- *Relation_exists_both*: Both rated and matched unrated firm has bank relationship in the given year.
- *Relation_exists_rated*: Rated firm has bank relationship; matched unrated firm does not have relationship in the given year.
- *Relation_exists_unrated*: Rated firm does not have bank relationship; matched unrated firm has relationship in the given year.
- *Relation_nonexists*: Neither rated nor matched unrated firm has bank relationship in the given year.

Then I estimate OLS regressions of DEA and SFA efficiency differences of rated and matched unrated firms on each category. The results in Tables 10 and 11 show that both DEA and SFA efficiency differences are reduced by about 0.1% for the *Relation_exists_unrated* sample at the 1% significant level in the contemporaneous regressions. This result suggests that the unrated matched firms that have bank relationship gain efficiency and reduce the gap compared to unrated matched firms that do not have bank relationship. This effect becomes insignificant in the period after the year the relationship existed and turns to positive after two periods. These findings together lead to the conclusion that as the relationship ages, the firms become dependent on the bank. Furthermore in the SFA regression results firms in the *Relation_exists_rated* sample, which includes rated firms that have bank relationship and matched unrated firms do not have relationship in the given year, experience an increase in the efficiency gap. This shows that rated firms that have bank relationship increase their efficiency compared to unrated firms without banking relationship, increasing the efficiency gap between two samples. Therefore, the claim in *Hypothesis 2 that banks' monopoly control increases in the years after the relationship takes place, leading to hold-up problems that diminish the positive effect of relationship banking on firm efficiency* is also confirmed. The other categories do not experience statistically significant change.

To test *Hypothesis 3*, I analyze the effect of the existence of relationship banking on the firm efficiency for the subsample of firms that are in the lowest or highest quartile according to their default risk. Since banks don't share the upside gain from profitable firms but are exposed to loss given default, they have an incentive to monitor those firms that have higher probability of default. Using *Altman's z score, Whited and Wu (2006) financial constraint index and Jarrow-Merton probability of default model* as measures of default risk, I estimate Equation (7) for both subsamples to compare the impact of relationship banking on low vs. high default risk firms. The results are in Tables 12, 13 and 14, respectively. According to these, in Table 12 one standard deviation increase in the probability of existence of bank relationship increases the high-default risk firms' DEA efficiency by 0.7% (0.126*0.06), corresponding to 1% of the mean DEA score and SFA efficiency by 0.2% (0.038*0.06), corresponding to 0.2% of the mean SFA score at 1% significance level. The effect of a similar increase in the probability of existence of bank relationship on DEA and SFA efficiencies of low default risk firms are statistically insignificant. In the subsample analysis according to *Whited and Wu (2006) financial constraint index* in Table 13 one standard deviation increase in the probability of existence of relationship banking increases DEA efficiency of high default risk firms by 0.2% (0.093*0.03), which corresponds to 0.3% of the mean DEA score and SFA efficiency by 0.1% (0.054*0.03), corresponding to 0.1% of the mean SFA score at 1% significance level whereas, the same increase has no impact on the efficiencies of low default risk firms. The results are consistent for the subsamples grouped according to *Jarrow-Merton probability of default model* in Table 14. For the high default risk firms one standard deviation increase in the probability of existence of relationship banking increases DEA efficiency by 0.4% (0.08*0.05), corresponding to 0.6% of the mean DEA score and SFA efficiency by 0.1% (0.037*0.05), corresponding to 0.1% of the mean SFA score at 1% significance level. For the low default risk firms the impact is not statistically significant for DEA efficiency and lowers the efficiency by less than 0.1% (-0.006*0.04) at 5% significance level. Therefore the claim in *Hypothesis 3 that the existence of bank relationship increases the* *efficiency of high default risk firms but does not change the efficiency of low default risk firms* is confirmed.

As a robustness test for the hold-up problem claimed in *Hypothesis 2*, I also estimate the subsample analysis for low vs. high default risk firms, grouped according to Jarrow-Merton default probabilities, within a 5-year window. In Table 15 for the low default risk firms, the impact of two-year and one-year lagged probability of existence of relationship decreases DEA efficiency (coefficients are -0.035 and -0.028, respectively at 5% significance level). On the year of the relationship this decrease disappears and become statistically insignificant. However in the post-relationship period, the impact turns to negative again (with coefficients -0.030 and -0.046 one year after and two years after the relationship). For the high default risk firms, the negative effect of the two-year lagged probability of existence of relationship fades away and turns to positive and statistically significant on the year of the relationship (coefficients changing from -0.029 on two-year lagged to 0.080 on the year of the relationship). This positive effect also disappears in the post-relationship years. In Table 16 for the low default risk firms there is a decrease in the negative effect on SFA efficiency of one-year lagged probability from -0.012 to -0.006 on the relationship year. However it worsens in the post-relationship period and returns to previous magnitude. For the high default risk firms, the positive effect gradually diminishes in the post-relationship period from 0.037 to 0.015 two years after the relationship. Therefore efficiency improvement for both low default risk from negative to no impact in DEA efficiency (less negative in SFA efficiency) and for high default risk firms from negative to positive in DEA efficiency (no effect to positive in SFA efficiency) are not long lasting. Taken together these results suggest that although high default risk firms benefit from the existence of relationship banking on the year of the relationship, the monopoly power of the bank dominates the positive effect of monitoring for both low and high default risk firms.

To check whether the efficiency measures reflect the actual financial performance of the firms, I estimate the impact of existence of relationship banking on firm profitability using return on assets (ROA) and net profit margin (NPM) as dependent variables for both low and high default risk firms within a 5-year window. The results in Table 17 and 18 for ROA and NPM, respectively, show that not only cost efficiency but also profitability of assets and sales of high default risk firms increase due to the existence of relationship banking whereas, low default risk firms worse off during and after the years the relationship exists. Furthermore, the hold-up problem is still existent for both subsamples, and hence, additional support for *Hypothesis 2* and *Hypothesis 3*.

In addition to analyzing the subsamples divided according to the existence of credit rating and low vs. high default probabilities, I analyze subsamples divided according to the loan type. The credit lines and term loans exhibit different characteristics, especially in terms of cost of borrowing, purpose and timing. Therefore I estimate Equation (7) for both credit line and term loan relationship subsamples separately. The results in Table 19 and 20 for credit lines and term loans, respectively, are consistent and robust. The existence of credit line and term loan relationship, as well as the duration, number of leads, number of loans and relationship intensity of both facility types improve the DEA and SFA efficiencies of the firms. This suggests that banks have an incentive to monitor and increase the efficiency of the firms regardless of the relationship facility type.

In summary, the results of the analysis confirm the *Hypothesis 1 that after controlling for endogeneity, the likelihood of existence of relationship increases firm's DEA and SFA efficiencies*. In addition, I find evidence that supports *Hypothesis 2; banks' monopoly control increases in the years after the relationship takes place, leading to hold-up problems that diminish the positive effect of relationship banking on firm efficiency*. Lastly, I find strong evidence for the *Hypothesis 3 that existence of the relationship increases the efficiency of those firms that have high default risk.* I argue that this is because the relationship banks have more incentive to monitor not only the default risk but also the efficiency of the high default risk firms because they are exposed to downside risk when the firm defaults. However they don't have much incentive to monitor the efficiency of the low default risk firms, as banks are not subject to upside risk from the low default risk firms.

V. Conclusion

I analyze the effect of the relationship banking in the syndicated loans market on the firm efficiency, measured by Data Envelopment Analysis and Stochastic Frontier Analysis methods. To see this effect, I use control function regression approach of Wooldridge (2010). First I estimate the probability of existence of relationship banking with a probit regression to control for the endogeneity. Then I conduct two stage least square regression in the second step. Next, I divide the sample into two according to whether the firm had a credit rating or not and I estimate propensity score matching to correct for endogeneity in the rating decision. Then using the Altman's z score; Whited-Wu (2006) financial constraint index; and Jarrow-Merton default probabilities as proxies for default risk, I divide the sample into quartiles and use the first and forth quartile to analyze the effect of the existence of relationship banking on the firm efficiency for the firms that have low vs. high probability of default. Moreover, I estimate the baseline regression for low vs. high default risk firms within a 5-year window to analyze whether the impact of relationship banking endures. In order to check the robustness of my argument, I use profitability of assets (ROA) and profitability of sales (NPM) as additional dependent variables and estimate the impact of relationship banking on firm profitability. Furthermore, I divide the sample according to the major facility types of credit lines and term loans and estimate subsample regressions to identify whether bank monitoring incentive changes for different facility types.

I find evidence that existence of relationship has a positive and significant effect on both DEA and SFA efficiency scores. One standard deviation increase in the existence of relationship increases both efficiencies by about 0.1% on average.

For the rating decision, the results for both rated and unrated firms are similar to all sample results. But after endogenizing the rating decision and matching the firms according to their propensity scores, I find that unrated firms with relationship banking increase their efficiency compared to the unrated firms without relationship banking.

Furthermore, I find strong evidence that firms with high default risk experience increase in their DEA and SFA efficiencies due to the existence of relationship banking. However, I don't find a similar or consistent impact on the efficiency of the low default-risk firms. I also find that the effect of relationship banking diminishes in time and hold-up problem reduces the efficiency gain.

Lastly, the results of robustness tests using ROA and NPM as dependent variables are robust and consistent with my main findings. The existence of relationship banking not only improves efficiency of high default risk firms, but also increases profitability on assets and sales through monitoring. A similar impact does not exist for low default risk firms. These results hold regardless of the facility type of the syndicate deal.

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Appendix I:

Variable Definitions

Variable name	Definition
DEA efficiency score	Non-parametric, deterministic efficiency score calculated by Data Envelopment Analysis method for each year and industry.
SFA efficiency score	Parametric, stochastic efficiency score calculated by Stochastic Frontier Analysis method for each year and industry.
Relationship exists	Dummy variable equals to one if the firm has previous relationship with the same lead-lender within the previous 3 years and zero otherwise.
Duration	The number of loans (credit lines) the firm borrows from the same lead-lender during the whole sample period.
Number of leads	Number of lead lenders in a facility.
Number of loans	Number of loans each firm borrows from the same lead lender within the last 3 years.
Relationship intensity	Natural logarithm of the total amount of term loans and lines of credit a firm received from a lead bank within the last 3 years and scaled by total assets each year.
Net Operating Leases	Discounted present value of the next five years of required operating lease payments (MRC1-MRC5 on Compustat)
Other Intangible Assets	*Calculated* by subtracting *Goodwill* (GDWL) from the *Other Acquired and Capitalized Intangibles* (INTAN)
Leverage	Ratio of book value of debt to the sum of market value of equity and book value of debt.
ROA	Profitability measure defined as the ratio of earnings before interest, taxes, depreciation and amortization to book value of assets.
Size	Natural logarithm of total assets.
Net Profit Margin (NPM)	Net income scaled by sales
Rating	Dummy variable equal to one if firm has S&P domestic long-term issuer credit rating and zero otherwise.
Market-to-Book ratio (M/B)	Ratio of sum of market value of equity and book value of debt to book value of assets.
Growth	R&D scaled by sales.

Tangibility	Ratio of net property, plant and equipment divided by total assets
Credit Tightening	Credit tightening score from FED’s Senior Loan Officer Opinion Survey on Bank Lending Practices.
Firm age	Number of years since initial public offering.
Ln(SG&A)	Natural logarithm of selling, general and administrative expenses.
Ln(R&D)	Natural logarithm of research and development expenses.
R&D_dummy	Dummy variable equal to one if firm has R&D expenses.
Cash	Cash and short-term investments scaled by total assets.
Log(indfrac)	Log of one plus the fraction of firms in the same three-digit industry that have credit ratings.

Appendix II:

DEA method:

Farrell (1957) introduced a single-input/output efficiency measure for the measurement of productive efficiency, which is based on a production possibility set consisting of the convex hull of input-output vectors. This measure is generalized into a multiple-input/output case by Charnes, Cooper, and Rhodes (1978) and the authors named the method Data Envelopment Analysis (DEA).

A DEA model can be divided into an input-oriented model, which minimizes inputs while satisfying at least the given output levels, and an output-oriented model, which maximizes outputs without requiring more of any observed input values. DEA models can also be divided in terms of returns to scale by adding weight constraints. Charnes, Cooper, and Rhodes (1978) originally proposed the efficiency measurement of the DMUs for constant returns to scale (CRS), where all DMUs are operating at their optimal scale. Later Banker, Charnes, and Cooper (1984) introduced the variable returns to scale (VRS) efficiency measurement model, allowing the breakdown of efficiency into technical and scale efficiencies in DEA. (Ji and Lee, 2010)

The linear programming method of technical efficiency (TE) is stated by Murillo-Zamorano (2004) as:

$$\mathrm{TE}_{\mathrm{VRS}} = \min_{\mu} \psi^{0} \tag{A.1}$$

st.

$$\sum_{j=1}^{n} \mu_j X_{ij} \leq \psi X_i^0, \quad i = 1, \dots, m \tag{A.2}$$

$$\sum_{j=1}^{n} \mu_j Y_{rj} \geq Y_r^0, \quad r = 1, \dots, s \tag{A.3}$$

$$\sum_{j=1}^{n} \mu_j = 1 \tag{A.4}$$

where X_{ij} are the inputs, Y_{rj} are the outputs and ψ is the proportion of consumption of inputs. This method allows for flexibility in the weights (μ_j) assigned to each input and calculates the relative efficiency score of a DMU compared to the Pareto-efficient frontier technology as opposed to average efficiency comparisons done by OLS and stochastic frontier analysis. Therefore it is more flexible than OLS and stochastic frontier analysis (Demerjian et.al., 2012). I use the input minimization with variable returns to scale option of DEA. The equation (A.4) satisfies variable returns to scale condition.

Table 1: Summary Statistics						
Variable	Obs	Mean	Std. dev.	Q1	Median	Q3
Panel A: Firm Efficiency Measures						
DEA Efficiency Score	50925	0.73	0.21	0.60	0.76	0.90
SFA Efficiency Score	50925	0.90	0.05	0.87	0.91	0.94
Panel B: Firm Characteristics						
Market-to-Book	50925	1.43	1.09	0.77	1.11	1.70
Leverage	50925	0.25	0.23	0.05	0.20	0.40
ROA	50925	0.12	0.13	0.07	0.13	0.18
ROE	50925	0.20	5.38	0.15	0.27	0.41
Net profit margin (NPM)	50925	0.12	0.28	0.06	0.11	0.19
Tangibility	50925	0.30	0.23	0.12	0.24	0.42
Size	50925	6.00	1.97	4.54	5.88	7.33
Altman's z-score	50925	2.01	1.85	1.35	2.16	2.92
Whited-Wu financial constraint index	50925	-0.29	0.11	-0.36	-0.28	-0.21
Jarrow-Merton (JM) probability of default (bps)	50925	0.34	0.99	0.03	0.07	0.22
Rating Dummy	50925	0.30	0.46	0	0	1
Panel C: Syndicated Loan Facilities						
Relationship_exists	50925	0.19	0.39	0	0	0
Duration	50925	0.35	1.44	0	0	0
Number of leads	50925	0.75	2.51	0	0	0
Number of loans	50925	0.91	2.70	0	0	0
Relationship intensity	50925	3.65	5.56	0	0	11.22

Table 2: Correlations of Dependent Variables					
	DEA efficiency	SFA efficiency	ROA	NPM	ROE
DEA efficiency	1				
	0.0000				
SFA efficiency	0.5639	1			
	0.0000	0.0000			
ROA	0.3720	0.4235	1		
	0.0000	0.0000	0.0000		
NPM	0.2576	0.3680	0.5758	1	
	0.0000	0.0000	0.0000	0.0000	
ROE	0.0061	0.0195	0.0446	0.0179	1
	0.1686	0.0000	0.0000	0.0001	0.0000

p-values provided below the correlation coefficient.

Table 3: Univariate Analysis

Panel A: Existence of Relationship Banking

Variable	Number of obs (Relationship exists=Yes)	Number of obs (Relationship exists=No)	Mean (Relationship exists=Yes)	Mean (Relationship exists=No)	Difference (Yes-No)	T-stat
DEA Efficiency Score	9529	41396	0.719	0.773	0.054	22.62***
SFA Efficiency Score	9529	41396	0.903	0.899	0.003	6.61***
Market-to-Book	9529	41396	1.354	1.453	-0.099	-8.03***
Leverage	9529	41396	0.305	0.241	0.064	24.21***
ROA	9529	41396	0.131	0.113	0.017	11.82***
Tangibility	9529	41396	0.320	0.290	0.029	11.38***
Size	9529	41396	6.896	5.795	1.101	50.28***
Rating Dummy	9529	41396	0.500	0.256	0.244	47.94***

Panel B: Existence of Credit Rating

Variable	Number of obs (Rated=Yes)	Number of obs (Rated=No)	Mean (Rated=Yes)	Mean (Rated=No)	Difference (Yes-No)	T-stat
DEA Efficiency Score	15386	35539	0.824	0.688	0.135	68.89***
SFA Efficiency Score	15386	35539	0.902	0.898	0.004	8.04***
Market-to-Book	15386	35539	1.299	1.493	-0.194	-18.55***
Leverage	15386	35539	0.337	0.217	0.119	54.23***
ROA	15386	35539	0.140	0.116	0.034	26.78***
Tangibility	15386	35539	0.343	0.275	0.067	31.03***
Size	15386	35539	7.929	5.166	2.762	189.15***
Relationship exists	15386	35539	0.310	0.133	0.176	47.94***

Table 4: Univariate Analysis of Subsamples				
	Mean (Low PD)	Mean (High PD)	Difference (Low-High)	T-stat
Panel A: According to Altman's z score				
DEA Efficiency Score	0.79	0.63	0.16	59.75***
SFA Efficiency Score	0.92	0.87	0.05	69.87***
Market-to-Book	1.65	1.37	0.28	18.63***
Leverage	0.17	0.32	-0.15	-49.90***
ROA	0.18	0.02	0.16	86.43***
ROE	0.38	-0.11	0.49	5.63***
Net profit margin (NPM)	0.11	0.07	0.03	7.58***
Tangibility	0.24	0.34	-0.10	-33.33***
Size	5.56	5.95	-0.38	-15.75***
Altman's z-score	3.73	-0.00	3.73	167.84***
Whited-Wu financial constraint index	-0.28	-0.26	-0.02	-11.36***
Jarrow-Merton (JM) probability of default (bps)	0.15	0.73	-0.58	-38.67***
Rating Dummy	0.19	0.30	-0.11	-21.19***
Panel B: According to Whited-Wu financial constraint index				
DEA Efficiency Score	0.87	0.60	0.26	112.41***
SFA Efficiency Score	0.91	0.89	0.02	32.53***
Market-to-Book	1.39	1.44	-0.06	-4.08***
Leverage	0.26	0.25	0.01	4.21***
ROA	0.15	0.05	0.11	56.98***
ROE	0.20	0.04	0.16	1.93*
Net profit margin (NPM)	0.21	0.01	0.20	56.28***
Tangibility	0.34	0.25	0.09	32.06***
Size	8.49	3.68	4.81	375.58***
Altman's z-score	2.14	1.35	0.79	28.81***
Whited-Wu financial constraint index	-0.43	-0.15	-0.28	-454.92***
Jarrow-Merton (JM) probability of default (bps)	0.26	0.61	-0.35	-24.82***
Rating Dummy	0.73	0.02	0.71	172.90***
Panel C: According to JM probability of default model				
DEA Efficiency Score	0.77	0.69	0.08	30.75***
SFA Efficiency Score	0.91	0.88	0.03	40.38***
Market-to-Book	1.94	0.99	0.95	72.99***
Leverage	0.12	0.43	-0.31	-116.38***
ROA	0.18	0.04	0.14	77.33***
ROE	0.34	-0.03	0.37	4.65***
Net profit margin (NPM)	0.19	0.03	0.16	39.64***
Tangibility	0.29	0.30	-0.01	-4.05***
Size	6.38	5.88	0.49	18.93***
Altman's z-score	2.57	1.13	1.44	57.64***
Whited-Wu financial constraint index	-0.32	-0.26	-0.06	-43.07***
Jarrow-Merton (JM) probability of default (bps)	0.02	1.17	-1.15	-74.40***
Rating Dummy	0.30	0.36	-0.05	-8.86***

Table 5: Regressions for Relationship Banking Decision

The dependent variable in all columns is *Relationship exists* variable, which equals to one if the firm has previous relationship with the same lead lender within the previous 3 years and zero otherwise. All variable definitions are in Appendix I. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	Probit	Logit
Total number of previous relationships	0.006***	0.011***
	(9.26)	(9.02)
Dummy for outstanding relationship from previous period	0.452***	0.757***
	(21.74)	(21.51)
Tangibility	-0.181***	-0.310***
	(3.95)	(3.83)
Ln(SG&A)	0.238***	0.410***
	(6.16)	(6.02)
Ln(R&D)	-0.001	0.004
	(0.12)	(0.36)
R&D_dummy	0.013	0.031
	(0.55)	(0.73)
M/B_{t-1}	0.004	0.014
	(0.41)	(0.78)
$Leverage_{t-1}$	0.176***	0.294***
	(3.71)	(3.49)
ROA_{t-1}	0.181**	0.428**
	(2.00)	(2.46)
$Size_{t-1}$	0.099***	0.175***
	(12.64)	(13.05)
Firm age	-0.000	0.000
	(0.09)	(0.20)
Ln(PPE)	0.319***	0.611***
	(11.47)	(12.39)
Cash	-1.605***	-3.327***
	(10.70)	(12.33)
Credit tightening	0.002	0.002
	(0.65)	(0.28)
Rating dummy	0.247***	0.424***
	(10.05)	(10.04)
Constant	-2.199***	-3.855***
	(29.21)	(28.99)
N	46,205	46,205

Table 6: Regressions for the Strength of Relationship Banking

The period of analysis is between 1990-2013. All variable definitions are in Appendix I. All regressions include industry and year fixed effects. The standard errors are clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

Dependent variable:	Duration	Number of leads	Number of loans	Relationship intensity
	(Poisson)	(Poisson)	(Poisson)	(OLS)
Instruments				
Duration (industry average)	0.893***			
	(7.08)			
Number of leads (industry average)		0.568***		
		(11.36)		
Number of loans (industry average)			0.536***	
			(7.71)	
Relationship intensity (industry average)				0.892***
				(17.14)
Dummy for outstanding relationship from previous period	0.498***	0.525***	0.918***	0.749***
	(11.27)	(12.51)	(26.10)	(8.84)
Firm controls				
Tangibility	-0.125	-0.043	-0.163	-0.758***
	(1.01)	(0.42)	(1.36)	(4.60)
Ln(SG&A)	0.233***	0.368***	0.214***	0.977***
	(2.70)	(4.80)	(2.96)	(6.97)
Ln(R&D)	0.004	-0.015	0.005	0.005
	(0.27)	(1.25)	(0.30)	(0.20)
R&D_dummy	-0.036	-0.077	-0.004	0.122
	(0.56)	(1.50)	(0.07)	(1.53)
M/B_{t-1}	0.028	0.019	0.063***	0.032
	(0.99)	(0.75)	(2.67)	(1.09)
$Leverage_{t-1}$	-0.298*	0.100	0.649***	-0.147
	(1.86)	(1.00)	(5.23)	(0.95)
ROA_{t-1}	0.929***	0.545**	0.862***	-0.519**
	(3.78)	(2.55)	(3.41)	(2.28)
$Size_{t-1}$	0.264***	0.441***	0.295***	0.267***
	(14.54)	(26.31)	(15.45)	(10.49)
Firm age	0.003**	-0.001	0.003**	-0.003
	(2.02)	(0.89)	(2.49)	(1.17)
Ln(PPE)	0.492***	0.672***	0.597***	1.001***
	(7.64)	(17.16)	(11.38)	(10.82)
Cash	-3.256***	-2.470***	-3.218***	-5.289***
	(10.47)	(3.92)	(10.14)	(20.84)
Credit tightening	0.067***	-0.030***	0.013*	0.010
	(6.34)	(4.46)	(1.93)	(1.25)
Rating	0.386***	0.314***	0.405***	0.960***
	(5.65)	(5.70)	(6.68)	(11.20)
Constant	-4.986***	-4.820***	-4.155***	-1.606***
	(23.44)	(27.67)	(21.44)	(6.54)
N	46,205	46,205	46,205	46,205
R^2				0.09

Table 7: Second Stage DEA Regressions of Relationship Banking Variables

The dependent variable is the DEA Efficiency score. The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 and 4 as instruments in the first stage. All variable definitions are in Appendix I. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Relationship_exists	0.030***				
	(3.88)				
Duration		0.015***			
		(7.87)			
Number of leads			0.007***		
			(9.05)		
Number of loans				0.003***	
				(4.98)	
Relationship intensity					0.003***
					(3.63)
3-year average efficiency	0.697***	0.695***	0.694***	0.696***	0.697***
	(79.96)	(79.91)	(80.40)	(80.19)	(79.73)
3-year average ROA	0.015	0.015	0.018	0.017	0.014
	(1.37)	(1.34)	(1.64)	(1.50)	(1.28)
Size_{t-1}	0.012***	0.011***	0.011***	0.012***	0.012***
	(15.27)	(15.63)	(15.04)	(16.79)	(15.85)
Firm age	-0.000	-0.000***	-0.000**	-0.000**	-0.000
	(1.41)	(3.07)	(2.02)	(2.17)	(1.22)
Lambda	-0.011**	-0.006	-0.004	-0.008*	-0.012***
	(2.51)	(1.32)	(0.98)	(1.75)	(2.80)
Constant	0.186***	0.186***	0.192***	0.186***	0.183***
	(26.07)	(25.60)	(26.34)	(25.96)	(25.70)
R^2	0.68	0.68	0.68	0.68	0.68
N	36,765	36,765	36,765	36,765	36,765

Table 8: Second Stage SFA Regressions of Relationship Banking Variables

The dependent variable is the SFA Efficiency score. The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 and 4 as instruments in the first stage. All variable definitions are in Appendix I. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Relationship_exists	0.007***				
	(4.07)				
Duration		0.001***			
		(2.93)			
Number of leads			0.000		
			(0.59)		
Number of loans				0.000	
				(1.21)	
Relationship intensity					0.001***
					(4.32)
3-year average efficiency	0.781***	0.782***	0.782***	0.782***	0.779***
	(65.97)	(66.71)	(66.67)	(66.64)	(65.24)
3-year average ROA	-0.000	-0.001	-0.000	-0.000	-0.001
	(0.14)	(0.22)	(0.14)	(0.13)	(0.22)
Size_{t-1}	0.000**	0.000***	0.001***	0.001***	0.000
	(2.16)	(3.32)	(4.47)	(4.66)	(1.21)
Firm age	-0.000	-0.000*	-0.000	-0.000	-0.000
	(1.25)	(1.79)	(1.14)	(1.28)	(1.04)
Lambda	0.001	0.001	0.001	0.001	0.001
	(1.02)	(1.34)	(0.74)	(0.91)	(0.61)
Constant	0.190***	0.189***	0.189***	0.189***	0.190***
	(17.29)	(17.36)	(17.37)	(17.36)	(17.23)
R^2	0.76	0.76	0.76	0.76	0.76
N	36,765	36,765	36,765	36,765	36,765

Table 9: Subsample analysis according to credit rating

The dependent variable in the first three columns is DEA Efficiency score and in the last three columns is SFA efficiency score. The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 as instruments in the first stage. All variable definitions are in Appendix I. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	DEA		SFA	
	Rated	Unrated	Rated	Unrated
Relationship_exists	0.026**	0.028***	0.014***	0.006**
	(2.57)	(2.77)	(4.59)	(2.54)
3-year average efficiency	0.669***	0.704***	0.781***	0.771***
	(54.89)	(54.02)	(53.65)	(40.24)
3-year average ROA	0.020*	0.053***	-0.001	-0.000
	(1.87)	(3.43)	(0.32)	(0.01)
$Size_{t-1}$	0.012***	0.014***	0.000*	0.000
	(12.83)	(12.66)	(1.94)	(0.20)
Firm age	-0.000	-0.000**	0.000	-0.000*
	(0.53)	(2.21)	(1.47)	(1.82)
Lambda	-0.007	-0.012**	-0.000	0.000
	(0.90)	(2.39)	(0.25)	(0.03)
Constant	0.206***	0.158***	0.189***	0.205***
	(20.25)	(13.91)	(13.66)	(11.50)
R^2	0.66	0.64	0.76	0.77
N	24,348	12,417	24,348	12,417

Table 10: DEA efficiency score-difference regressions for all sample

The dependent variable in all columns is the difference in the DEA Efficiency scores of the rated and matched unrated firm.
Relation_exists_both: Both rated and matched unrated firm has bank relationship in the given year.
Relation_exists_rated: Rated firm has bank relationship; matched unrated firm does not have relationship in the given year.
Relation_exists_unrated: Rated firm does not have bank relationship; matched unrated firm has relationship in the given year.
Relation_nonexists: Both rated and matched unrated firm do not have bank relationship in the given year.
The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	t-2	*t-1*	*t*	*t+1*	*t+2*
Relation_exists_both	-0.005	0.006*	-0.000	-0.004	0.003
	(1.23)	(1.72)	(0.15)	(1.23)	(0.93)
Relation_exists_rated	-0.004	0.003	0.001	-0.001	-0.001
	(1.13)	(1.06)	(0.60)	(0.38)	(0.35)
Relation_exists_unrated	-0.008**	-0.003	-0.016***	-0.002	0.008**
	(2.33)	(1.16)	(8.57)	(0.76)	(2.37)
Constant	-0.015*	-0.016**	-0.016***	-0.038***	-0.038***
	(1.88)	(2.39)	(5.08)	(5.97)	(6.04)
R^2	0.01	0.01	0.01	0.01	0.01
N	23,770	38,641	79,856	34,955	29,079

Table 11: SFA efficiency difference regressions for all sample

The dependent variable in all columns is the difference in the DEA Efficiency scores of the rated and matched unrated firm.
Relation_exists_both: Both rated and matched unrated firm has bank relationship in the given year.
Relation_exists_rated: Rated firm has bank relationship; matched unrated firm does not have relationship in the given year.
Relation_exists_unrated: Rated firm does not have bank relationship; matched unrated firm has relationship in the given year.
Relation_nonexists: Both rated and matched unrated firm do not have bank relationship in the given year.
The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	t-2	*t-1*	*t*	*t+1*	*t+2*
Relation_exists_both	-0.001	0.000	-0.000	-0.001	0.000
	(1.43)	(0.59)	(0.75)	(1.18)	(0.47)
Relation_exists_rated	0.002***	0.003***	0.002***	0.002***	0.001**
	(3.10)	(4.24)	(6.04)	(3.13)	(2.01)
Relation_exists_unrated	-0.001*	-0.002**	-0.004***	-0.002**	0.000
	(1.65)	(2.48)	(9.34)	(2.50)	(0.41)
Constant	-0.005***	-0.005***	-0.002**	-0.004***	-0.004**
	(2.70)	(2.94)	(2.50)	(2.69)	(2.43)
R^2	0.02	0.02	0.01	0.02	0.02
N	23,770	38,641	79,856	34,955	29,079

Table 12: Subsample analysis according to Altman's z score

The dependent variable in the first three columns is DEA Efficiency score and in the last three columns is SFA efficiency score. The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 as instruments in the first stage. All variable definitions are in Appendix I. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	DEA		SFA	
	Low PD	High PD	Low PD	High PD
Relationship_exists	0.006	0.126***	-0.001	0.038***
	(0.43)	(6.51)	(0.69)	(7.01)
3-year average efficiency	0.700***	0.696***	0.857***	0.762***
	(46.07)	(38.87)	(52.00)	(38.56)
3-year average ROA	0.026*	-0.130***	-0.003	-0.032***
	(1.73)	(6.45)	(0.96)	(4.78)
Size_{t-1}	0.014***	0.010***	0.000	0.000
	(12.18)	(5.86)	(0.09)	(1.33)
Firm age	-0.000***	-0.000	0.000***	-0.000***
	(3.33)	(0.61)	(2.80)	(2.66)
Lambda	-0.015*	-0.027**	-0.002**	0.003
	(1.73)	(2.21)	(1.97)	(1.17)
Constant	0.200***	0.172***	0.126***	0.198***
	(16.69)	(8.75)	(8.47)	(10.36)
R^2	0.67	0.62	0.88	0.58
N	9,302	8,634	9,302	8,634

Table 13: Subsample analysis according to Whited-Wu (2006) financial constraint index

The dependent variable in the first three columns is DEA Efficiency score and in the last three columns is SFA efficiency score. The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 as instruments in the first stage. All variable definitions are in Appendix I. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	DEA		SFA	
	Low PD	High PD	Low PD	High PD
Relationship_exists	-0.005	0.093***	-0.001	0.054***
	(0.55)	(2.92)	(0.58)	(6.24)
3-year average efficiency	0.709***	0.531***	0.796***	0.711***
	(47.74)	(22.43)	(42.67)	(28.41)
3-year average ROA	0.066***	0.007	-0.009**	0.011*
	(4.76)	(0.42)	(2.05)	(1.83)
Size_{t-1}	0.010***	-0.029***	-0.001**	-0.009***
	(8.25)	(11.38)	(2.33)	(10.23)
Firm age	-0.000***	0.000	-0.000***	0.000**
	(2.75)	(1.01)	(3.23)	(2.40)
Lambda	-0.014***	0.015	-0.001	-0.008
	(3.14)	(0.61)	(0.73)	(1.48)
Constant	0.203***	0.418***	0.195***	0.281***
	(17.51)	(16.01)	(10.65)	(12.30)
R^2	0.58	0.65	0.83	0.70
N	10,448	7,803	10,448	7,803

Table 14: Subsample analysis according to JM Probability of Default Model

The dependent variable in the first three columns is DEA Efficiency score and in the last three columns is SFA efficiency score. The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 as instruments in the first stage. All variable definitions are in Appendix I. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	DEA		SFA	
	Low PD	High PD	Low PD	High PD
Relationship_exists	0.020	0.080***	-0.006**	0.037***
	(1.49)	(5.35)	(2.49)	(9.88)
3-year average efficiency	0.713***	0.697***	0.809***	0.704***
	(53.25)	(42.68)	(46.56)	(26.43)
3-year average ROA	0.060***	-0.090***	-0.011***	-0.000
	(3.84)	(4.77)	(3.33)	(0.00)
$Size_{t-1}$	0.013***	0.009***	0.000	0.000
	(10.84)	(7.19)	(1.17)	(0.82)
Firm age	-0.000***	0.000	-0.000***	-0.000
	(3.03)	(0.18)	(3.71)	(0.20)
Lambda	-0.016**	0.014*	-0.001	0.005***
	(2.30)	(1.73)	(0.60)	(2.63)
Constant	0.178***	0.126***	0.175***	0.242***
	(16.30)	(7.41)	(10.61)	(9.86)
R^2	0.69	0.69	0.85	0.69
N	9,676	9,049	9,676	9,049

Table 15: DEA Efficiency for Firms with Low vs. High Probability of Default

The dependent variable is the DEA Efficiency score. The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 as instruments in the first stage. All variable definitions are in Appendix I. In the period *(t-2) Relationship_exists* is lagged for two-period and in *(t-1)* analysis *Relationship_exists* is lagged for one-period. In *(t+1)* analysis one-period forward dependent variable is used and in *(t+2)* analysis two-period forward dependent variable is used. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	Low Probability of Default Firms					High Probability of Default Firms				
	t-2	*t-1*	*t*	*t+1*	*t+2*	*t-2*	*t-1*	*t*	*t+1*	*t+2*
Relationship_exists	-0.035**	-0.028**	0.020	-0.030**	-0.046**	-0.029*	-0.000	0.080***	0.028	-0.001
	(2.55)	(2.22)	(1.49)	(2.09)	(2.48)	(1.68)	(0.03)	(5.35)	(1.45)	(0.03)
3-year average efficiency	0.711***	0.711***	0.713***	0.665***	0.588***	0.698***	0.698***	0.697***	0.651***	0.616***
	(52.58)	(52.68)	(53.25)	(34.13)	(24.27)	(43.39)	(43.24)	(42.68)	(36.29)	(31.77)
3-year average ROA	0.060***	0.060***	0.060***	0.065**	0.076***	-0.080***	-0.082***	-0.090***	-0.107***	-0.135***
	(3.85)	(3.85)	(3.84)	(2.53)	(3.14)	(4.33)	(4.41)	(4.77)	(4.45)	(5.07)
$Size_{t-1}$	0.016***	0.016***	0.013***	0.019***	0.024***	0.014***	0.013***	0.009***	0.010***	0.012***
	(13.04)	(12.83)	(10.84)	(11.04)	(10.72)	(9.76)	(9.36)	(7.19)	(6.42)	(6.75)
Firm age	-0.000***	-0.000***	-0.000***	-0.000**	-0.000	0.000	0.000	0.000	-0.000	-0.000
	(3.01)	(3.06)	(3.03)	(1.99)	(1.16)	(0.31)	(0.34)	(0.18)	(0.06)	(1.02)
Lambda	-0.020***	-0.021***	-0.016**	-0.017**	-0.014	0.012	0.013	0.014*	0.009	-0.010
	(2.86)	(2.86)	(2.30)	(1.98)	(1.46)	(1.50)	(1.64)	(1.73)	(1.00)	(0.90)
Constant	0.172***	0.174***	0.178***	0.129***	0.143***	0.118***	0.120***	0.126***	0.130***	0.200***
	(16.08)	(16.01)	(16.30)	(9.25)	(7.95)	(7.00)	(7.14)	(7.41)	(7.68)	(9.05)
R^2	0.69	0.69	0.69	0.64	0.58	0.69	0.69	0.69	0.65	0.62
N	9,676	9,676	9,676	8,597	7,647	9,049	9,049	9,049	7,646	6,527

Table 16: SFA Efficiency for Firms with Low vs. High Probability of Default

The dependent variable is the SFA Efficiency score. The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 as instruments in the first stage. All variable definitions are in Appendix I. In the period *(t-2) Relationship_exists* is lagged for two-period and in *(t-1)* analysis *Relationship_exists* is lagged for one-period. In *(t+1)* analysis one-period forward dependent variable is used and in *(t+2)* analysis two-period forward dependent variable is used. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	Low Probability of Default Firms					High Probability of Default Firms				
	t-2	*t-1*	*t*	*t+1*	*t+2*	*t-2*	*t-1*	*t*	*t+1*	*t+2*
Relationship_exists	-0.012***	-0.012***	-0.006**	-0.012***	-0.012***	-0.005	0.001	0.037***	0.017***	0.015***
	(6.16)	(5.28)	(2.49)	(4.23)	(3.54)	(1.20)	(0.31)	(9.88)	(2.96)	(2.95)
3-year average efficiency	0.807***	0.808***	0.809***	0.745***	0.713***	0.714***	0.712***	0.704***	0.646***	0.610***
	(47.03)	(46.97)	(46.56)	(35.71)	(32.79)	(27.28)	(27.10)	(26.43)	(24.25)	(17.63)
3-year average ROA	-0.011***	-0.011***	-0.011***	-0.010**	-0.008	0.002	0.002	-0.000	-0.018**	-0.036***
	(3.31)	(3.33)	(3.33)	(2.13)	(1.42)	(0.37)	(0.33)	(0.00)	(2.22)	(3.87)
$Size_{t-1}$	0.001***	0.001***	0.000	0.000	0.000	0.002***	0.002***	0.000	0.001**	0.001**
	(3.06)	(2.98)	(1.17)	(1.48)	(0.91)	(6.83)	(6.21)	(0.82)	(2.37)	(2.35)
Firm age	-0.000***	-0.000***	-0.000***	-0.000	-0.000	0.000	0.000	-0.000	0.000	-0.000
	(3.60)	(3.68)	(3.71)	(1.64)	(0.02)	(0.13)	(0.13)	(0.20)	(0.17)	(0.47)
Lambda	-0.001	-0.001	-0.001	-0.002	-0.000	0.004**	0.004**	0.005***	0.004	-0.001
	(0.81)	(1.07)	(0.60)	(1.16)	(0.04)	(2.30)	(2.42)	(2.63)	(1.35)	(0.35)
Constant	0.175***	0.175***	0.175***	0.236***	0.264***	0.230***	0.232***	0.242***	0.304***	0.349***
	(10.73)	(10.72)	(10.61)	(12.10)	(13.06)	(9.57)	(9.60)	(9.86)	(12.43)	(10.94)
R^2	0.85	0.85	0.85	0.78	0.72	0.69	0.69	0.69	0.63	0.60
N	9,676	9,676	9,676	8,597	7,647	9,049	9,049	9,049	7,646	6,527

Table 17: ROA for Firms with Low vs. High Probability of Default

The dependent variable is the return on assets (ROA). The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 as instruments in the first stage. All variable definitions are in Appendix I. In the period *(t-2) Relationship_exists* is lagged for two-period and in *(t-1)* analysis *Relationship_exists* is lagged for one-period. In *(t+1)* analysis one-period forward dependent variable is used and in *(t+2)* analysis two-period forward dependent variable is used. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	Low Probability of Default Firms					High Probability of Default Firms				
	t-2	*t-1*	*t*	*t+1*	*t+2*	*t-2*	*t-1*	*t*	*t+1*	*t+2*
Relationship_exists	-0.021**	-0.020**	-0.052***	-0.056***	-0.062***	0.059***	0.059***	0.137***	0.075***	0.062***
	(2.39)	(2.31)	(5.74)	(5.68)	(3.87)	(3.91)	(4.19)	(8.57)	(3.69)	(2.94)
3-year average ROA	0.824***	0.824***	0.823***	0.741***	0.673***	0.671***	0.669***	0.661***	0.542***	0.479***
	(37.78)	(37.81)	(38.62)	(26.19)	(17.31)	(20.96)	(20.67)	(20.25)	(11.22)	(11.31)
$Size_{t-1}$	0.000	0.000	0.002**	0.005***	0.007***	0.004***	0.004***	0.001	0.001	0.002
	(0.28)	(0.32)	(2.25)	(4.83)	(4.29)	(3.70)	(3.77)	(0.83)	(1.07)	(1.30)
Firm age	0.000	0.000	0.000	0.000**	0.000***	0.000	0.000	0.000	-0.000	-0.000
	(1.30)	(1.26)	(1.27)	(2.17)	(2.81)	(0.99)	(0.89)	(0.57)	(0.05)	(1.09)
Lambda	0.013***	0.012***	0.010***	0.007	0.009	0.033***	0.033***	0.030***	0.016**	0.004
	(3.45)	(3.27)	(2.70)	(1.57)	(1.54)	(5.16)	(5.17)	(4.57)	(2.02)	(0.53)
Constant	0.017*	0.017*	0.015	0.012	0.006	-0.065***	-0.066***	-0.058***	0.003	0.038**
	(1.66)	(1.75)	(1.52)	(1.04)	(0.35)	(6.05)	(6.09)	(5.48)	(0.22)	(2.49)
R^2	0.62	0.62	0.62	0.47	0.36	0.33	0.33	0.33	0.24	0.21
N	9,732	9,732	9,732	8,540	7,496	8,927	8,927	8,927	7,564	6,439

Table 18: NPM for Firms with Low vs. High Probability of Default

The dependent variable is the net profit margin (NPM). The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 as instruments in the first stage. All variable definitions are in Appendix I. In the period *(t-2) Relationship_exists* is lagged for two-period and in *(t-1)* analysis *Relationship_exists* is lagged for one-period. In *(t+1)* analysis one-period forward dependent variable is used and in *(t+2)* analysis two-period forward dependent variable is used. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	Low Probability of Default Firms					High Probability of Default Firms				
	t-2	*t-1*	*t*	*t+1*	*t+2*	*t-2*	*t-1*	*t*	*t+1*	*t+2*
Relationship_exists	-0.043***	-0.040***	-0.048***	-0.058***	-0.063***	0.084**	0.047	0.192***	0.066	0.072**
	(3.76)	(3.15)	(3.35)	(3.08)	(2.67)	(2.31)	(1.29)	(5.44)	(1.63)	(2.00)
3-year average NPM	0.843***	0.843***	0.843***	0.787***	0.818***	0.399***	0.401***	0.395***	0.312***	0.255**
	(13.55)	(13.56)	(13.57)	(11.13)	(16.39)	(4.08)	(4.08)	(4.07)	(3.45)	(2.54)
$Size_{t-1}$	0.006***	0.006***	0.006***	0.010***	0.011***	0.013***	0.015***	0.009**	0.014***	0.016***
	(3.86)	(3.88)	(4.48)	(5.51)	(4.86)	(3.47)	(3.95)	(2.52)	(4.67)	(4.82)
Firm age	-0.000	-0.000	-0.000	0.000	0.000**	0.000	0.000	-0.000	-0.000	-0.000**
	(0.14)	(0.19)	(0.20)	(0.89)	(2.15)	(0.12)	(0.01)	(0.23)	(1.51)	(2.04)
Lambda	-0.004	-0.005	-0.005	-0.004	0.005	0.038**	0.037**	0.034**	0.026*	0.013
	(0.54)	(0.70)	(0.79)	(0.43)	(0.41)	(2.52)	(2.46)	(2.29)	(1.67)	(1.15)
Constant	-0.004	-0.002	-0.002	-0.018	-0.036	-0.073***	-0.077***	-0.064***	-0.043**	-0.012
	(0.33)	(0.19)	(0.19)	(1.03)	(1.59)	(4.08)	(4.30)	(3.63)	(2.25)	(0.69)
R^2	0.79	0.79	0.79	0.66	0.59	0.27	0.27	0.28	0.28	0.30
N	9,732	9,732	9,732	8,540	7,496	8,927	8,927	8,927	7,564	6,439

Table 19: Credit lines sample second stage regressions of relationship variables

The dependent variable in the first five columns is DEA Efficiency score and in the last five columns is SFA efficiency score. The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 and 4 as instruments in the first stage. All variable definitions are in Appendix I. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	DEA					SFA				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Relationship_exists	0.042***					0.006***				
	(4.72)					(3.24)				
Duration		0.015***					0.001**			
		(8.39)					(2.09)			
Number of leads			0.006***					-0.000		
			(8.99)					(0.34)		
Number of loans				0.003***					0.000*	
				(7.30)					(1.81)	
Relationship intensity					0.003***					0.001***
					(3.48)					(4.15)
3-year average efficiency	0.696***	0.694***	0.694***	0.694***	0.697***	0.781***	0.782***	0.782***	0.782***	0.780***
	(80.23)	(79.88)	(80.35)	(80.30)	(79.77)	(66.21)	(66.74)	(66.70)	(66.68)	(65.34)
3-year average ROA	0.016	0.015	0.018*	0.018	0.014	-0.000	-0.000	-0.000	-0.000	-0.001
	(1.42)	(1.37)	(1.68)	(1.64)	(1.29)	(0.12)	(0.20)	(0.15)	(0.11)	(0.22)
$Size_{t-1}$	0.011***	0.011***	0.011***	0.012***	0.012***	0.000**	0.000***	0.001***	0.001***	0.000
	(13.99)	(15.61)	(15.82)	(16.73)	(15.94)	(2.39)	(3.79)	(5.09)	(4.26)	(1.36)
Firm age	-0.000**	-0.000***	-0.000**	-0.000**	-0.000	-0.000	-0.000*	-0.000	-0.000	-0.000
	(2.09)	(3.73)	(2.45)	(2.57)	(1.26)	(1.60)	(1.71)	(1.04)	(1.41)	(1.05)
Lambda	-0.010**	-0.003	-0.002	-0.004	-0.012***	0.001	0.001	0.000	0.001	0.000
	(2.16)	(0.78)	(0.51)	(0.85)	(2.71)	(0.83)	(0.99)	(0.38)	(0.98)	(0.30)
Constant	0.188***	0.185***	0.188***	0.186***	0.183***	0.190***	0.189***	0.189***	0.189***	0.190***
	(25.42)	(25.22)	(25.94)	(25.60)	(25.44)	(17.27)	(17.34)	(17.34)	(17.35)	(17.22)
R^2	0.68	0.68	0.68	0.68	0.68	0.76	0.76	0.76	0.76	0.76
N	36,765	36,765	36,765	36,765	36,765	36,765	36,765	36,765	36,765	36,765

Table 20: Term loans sample second stage regressions of relationship variables

The dependent variable in the first five columns is DEA Efficiency score and in the last five columns is SFA efficiency score. The estimation is done by control function regression with 2SLS using fitted values from the regressions in Table 3 and 4 as instruments in the first stage. All variable definitions are in Appendix I. The period of analysis is between 1990-2013. All regressions include industry and year fixed effects. The standard errors are corrected via bootstrap clustering at the firm level. T-stats are in parenthesis and *, **, *** denote 1%, 5% and 10% significance levels, respectively.

	DEA					SFA				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Relationship_exists	0.074***					0.027***				
	(4.21)					(6.18)				
Duration		0.051***					0.011***			
		(4.69)					(4.38)			
Number of leads			0.014**					0.002***		
			(2.04)					(3.24)		
Number of loans				0.008***					0.002***	
				(4.37)					(5.65)	
Relationship intensity					0.003***					0.001***
					(3.99)					(4.57)
3-year average efficiency	0.697***	0.697***	0.696***	0.696***	0.697***	0.779***	0.781***	0.781***	0.780***	0.779***
	(79.72)	(79.56)	(79.31)	(79.76)	(79.53)	(65.71)	(66.33)	(66.44)	(66.07)	(65.29)
3-year average ROA	0.015	0.015	0.016	0.016	0.014	-0.000	-0.000	-0.000	-0.000	-0.001
	(1.38)	(1.32)	(1.41)	(1.42)	(1.24)	(0.02)	(0.16)	(0.12)	(0.04)	(0.21)
Size_{t-1}	0.013***	0.013***	0.012***	0.013***	0.012***	0.000***	0.001***	0.000***	0.000***	0.000
	(19.99)	(20.27)	(18.35)	(19.75)	(15.67)	(4.68)	(5.13)	(4.47)	(4.68)	(0.83)
Firm age	0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000	-0.000
	(0.02)	(0.43)	(0.06)	(0.41)	(1.11)	(0.96)	(0.12)	(0.07)	(0.06)	(0.87)
Lambda	-0.020	0.002	0.007	0.000	-0.009	0.000	0.010***	0.012***	0.009**	0.005
	(0.96)	(0.09)	(0.32)	(0.01)	(0.45)	(0.04)	(2.66)	(2.97)	(2.32)	(1.25)
Constant	0.189***	0.172***	0.170***	0.174***	0.179***	0.191***	0.182***	0.181***	0.184***	0.187***
	(10.48)	(9.62)	(8.71)	(9.78)	(10.46)	(16.72)	(16.64)	(16.43)	(16.55)	(16.51)
R^2	0.68	0.68	0.68	0.68	0.68	0.76	0.76	0.76	0.76	0.76
N	36,765	36,765	36,765	36,765	36,765	36,765	36,765	36,765	36,765	36,765