Information Asymmetry, Relationship Banking and Financing Costs of SME's

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Abstract

We focus on the determinants and potentially associated benefits of relationship banking. Based on existing literature and the unique role intangible assets might play regarding asymmetric information, we derive three testable predictions. Using rich data on firm-bank relationships in Germany, we show that: firstly, intangible assets can be used to proxy asymmetric information but do not prevent firms to finance externally; secondly, firms' share of intangible assets statistically significantly determines firms' choice of an exclusive and persistent bank relation; thirdly, relationship banking is (potentially) associated with beneficial financing conditions.

Keywords: Relationship Banking, SME, Bank Lending, Information Asymmetry, Intangible Assets.

JEL Classifications: G21, G32, D82, C21.

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The usual disclaimer applies.

1 Introduction

Bank lending is crucially important for economic growth and development. Only strong and healthy banks can provide sufficient loans for expanding firms. In addition, small and medium enterprises (SMEs) cannot easily substitute bank loans with corporate debt during a credit crunch (Giesecke et al., 2012). Generally, Germany represents an example of a bank-based financial system (Allen and Gale, 1995). The German economy is characterized by a strong role of SMEs which are mainly financed through long-term bank loans which makes firm-bank relationships comparably important in Germany. The supply of bank loans to German SMEs is mainly organized by three main groups of financial intermediaries: (1) transaction banks such as Deutsche Bank, Commerzbank, Hypo-Vereinsbank (Uni Credit) plus smaller private banks and foreign banks; (2) saving banks which are organized as Sparkassen at the local level and Landesbanken at the regional level; (3) cooperative banks which are organized as Genossenschaftsbanken at the local level but also have two supra-regional institutions: WGZ Bank and DZ Bank. Landesbanken and WGZ Bank as well as DZ Bank are normally not heavily engaged in retail activities related to SMEs but rather take care of locally concentrated risks by pooling them across associated institutions. This composition of different banks is referred to as the German three-pillar system.

The different types of banks part of this three-pillar system differ in terms of many criteria such as ownership, mandate, market share, and branche density (Engel and Middendorf, 2009). Banks in the first pillar are (mainly) public, whereas saving banks are owned by municipalities. But the most important difference for our purpose is that banks according to these three pillars have explicitly different mandates. Banks in the first pillar are mandated by shareholders and stakeholders, respectively, as all publicly listed firms are. Since saving banks are owned by municipalities, they operate according to the responsibilities of the local government and their goal is, defined by law, to foster regional economic development and not to maximize profit. Cooperative banks, by law, are mandated to promote their memebers which are small local firms. Hence, institutions of pillar two and three have a mandate to support German SMEs and have strong regional ties but branche density of saving banks is higher since cooperative banks' regional appearance is voluntary. Given the different mandates accoring to the three pillars it is mainly assumed that saving banks and cooperative banks contribute more to the promotion of German SMEs and are naturally more engaged in relationship banking.

Relationship banking is well understood in the literature. Theoretical contributions emphasize the benefits of reduced asymmetric information but also the costs of an information monopoly by banks (Boot, 2000). The empirical literature regarding financing conditions associated with relationship banking is mixed (Kysucky and Norden, 2014). Studies devoted to financing conditions were followed by studies focusing on firms' choice of the number of bank relations. Noteworthy that the question of how many bank relations a firm chooses is not the same question like why a firms chooses one or many bank relations. We address the latter.

To be precise, we discuss the relationship between intangible assets, asymmetric information, relationship banking, and financing costs for German SME's. We contribute significantly by the combination of these topics and, in particular, by assigning a special role to connection of intangible assets, asymmetric information, and firms' choice of bank relation. We derive three testable predictions. Using a large dataset for German SME's including their bank relations between 2005 and 2012, we test the following three predictions: (1) if the fraction of intangible assets proxies for information asymmetry, a higher fraction should, *ceteris paribus*, lead to higher financing costs; (2) firms with a high fraction of intangible assets should, *ceteris paribus*, be more likely to engage in relationship banking, since a close-firm bank relation can help to reduce information asymmetry; (3) if asymmetric information is reduced by a strong firm-bank relation, *ceteris paribus*, relationship banking ought to improve financing conditions. For each prediction the null hypothesis can be rejected and results are in favor of our predictions.

The centerpiece of our contribution is to address the question why firms decide to have only one bank relation. We have information regarding the number of bank relations of each firm, which is best employed in a binary fashion. Based on the rejected null hypothesis of prediction 1, we employ intangible assets as proxy for asymmetric information. Hence, the share of intangible assets ought to increase the probability of strong firm-bank relation due to the firm's need to use the associated soft information channel in order to reduce asymmetric information or to reduce financing frictions, respectively. Indeed, we find that the share of intangible assets significantly increases the probability of an exclusive and persistent bank relation.

2 Literature Review

2.1 Literature - theoretical considerations

The seminal contribution of Diamond (1984) illustrates that a bank is the optimal channel for funds from investors to firms given costly information asymmetries between both parties. This delegated monitoring model of Diamond (1984) implies that firms operate with a single bank which pools the costs of asymmetric information. By having only one lender the firm minimizes its transaction costs. The optimality of a single bank relation changes by repeated lending (Sharpe, 1990). Other theoretical reasons for choosing more than one bank relation are e.g. diversification as insurance against the loss value-relevant information (Detragiache et al., 2000) or the lack of coordination among investors (see e.g. Bolton and Scharfstein, 1996; Hart, 1995; Dewatripont and Maskin, 1995). However, it is widely observed that many firms have multiple bank relations, whereas other even similar firms prefer a strong firm-bank relation.

The theoretical literature dealing with relationship lending comes to the conclusion that there are two sides to a strong firm-bank relation (Boot, 2000). On the one hand, a strong firm-bank relationship can be beneficial as information asymmetry is reduced and loan terms better reflect the actual quality of the borrower. On the other hand, the lender can use this information monopoly to extract additional rents. Therefore, a strong relationship can produce a hold-up problem.

Information asymmetry

The idea of an advantage due to resolved information asymmetry goes back to Boot and Thakor (1994) and Petersen and Rajan (1995).

Boot and Thakor (1994) consider a model with an infinitely repeated bank-borrower relationship. Thereby, they assume risk-neutrality and the absence of learning and find that nonetheless, the firm profits from a durable bank relation in the following sense: a bank charges higher interest rates and demands collateral for loans that go to firms which are not established yet. If the bank observes a positive outcome, e.g. a project success, the firm becomes established and is awarded with unsecured loans and a lower interest rate. Therefore, the bank acquires information about the firm due to costly monitoring. However, both, the firm and the bank profit from the close firm-bank relation.

Petersen and Rajan (1995) show that in a two-period model with *good* and *bad* entrepreneurs banks also have the incentive to charge high interest rates at the beginning and improve financing conditions for good entrepreneurs subsequently. The idea is similar to Boot and Thakor (1994) in the sense that information asymmetry about the quality of the entrepreneurs exists at the beginning and is resolved in later periods.

Taken together, both studies support the idea that a close firm-bank relationship is advantageous for firms and banks if asymmetric information exists.

Hold-up problem

The hold-up problem describes the concept that borrowing from a single bank can be costly for the firm. If a close bank-firm relationship reduces information asymmetry and if the firm cannot credibly transfer information to other parties, the bank can use this information advantage to extract additional rents (see e.g. Farinha and Santos, 2002; Sharpe, 1990; Greenbaum et al., 1989). The bank, with which the firm is in a close relationship has an information monopoly and becomes sort of an insider regarding information about the firms creditworthiness. In a world without information asymmetry a close firm-bank relation would not produce a the hold-up problem, since the firm could easily convey information to other lenders. Therefore, the problem should be more pronounced if information asymmetry is high, i.e. if the difference between information of insiders vs. outsiders increases. One possible solution of the hold-up problem is to establish multiple bank relations and therefore reduce the rents that arise due to the hold-up situation (Thadden, 1995).

2.2 Literature - empirical evidence

To assess costs and benefits of a strong firm-bank relation empirically, one has to proxy for the strength of the relationship. Kysucky and Norden (2014) conduct a meta analysis of the relationship banking literature and show that the most prominent proxies are the length of the firm-bank relation, the exclusivity of the relation (e.g. number of banks the firm lends from), physical distance and the integration of the firm-bank relation (e.g. number of financial services the firm obtains).

Empirical results are mixed. Petersen and Rajan (1994) were the first to empirically study the relation of different dimensions of the strength of lending relationships with the availability and cost of funds. In a sample of small and medium sized US enterprises (SME's), collected from the National Survey of Small Business Finance (NSSBF), they find that firms that borrow from multiple lenders are charged significantly higher rates. The length and integration of the relationship does not effect price conditions. However, the availability of credit increases if firms spend more time in a relationship, if they increase the number of financial services and if they concentrate their borrowing to a single or only a few lenders. In addition, Berger and Udell (1995) also use the NSSBF sample and focus their analysis on floating-rate lines of credit. They provide evidence that the length of the firm-bank relationship is negatively related to loan prices and to the probability that the lender will require collateral to secure the loan. In contrast, using a more recent NSSBF dataset, Cole (1998) finds that only a pre-existing relationship but not its length is an important factor for credit availability.

Schenone (2010) compares firms' interest rates before and after a large information shock (IPO) which exogenously levels the playing field among banks and, thus, erodes the relationship bank's information monopoly. Schenone (2010) finds that firms' interest rates prior to the IPO are a U-shaped function of relationship intensity but change to a decreasing function of relationship after the IPO. The U-shaped pattern of interest rates is rationalized by information asymmetries between relationship and outside banks. Degryse and Ongena (2005) study the effect of geographical distance on bank loan rates. Using a unique data set of loans made to SME's and single-person businesses by a Belgium bank, they show that loan rates improve with the distance between the firm and the bank and deteriorate with the distance between the firm and competing banks. In a similar vein, Petersen and Rajan (1995) find that in more concentrated markets relationship lending is more likely and that therefore relatively more credit is available to young firms. This finding is reflected in below-market rates for young firms but in turn above-market rates for more mature firms.

2.3 Literature - number of bank relations

Early studies studies of relationship banking (see e.g. Petersen and Rajan, 1994; Harhoff and Körting, 1998; Cole, 1998) used the number of bank relationships as a proxy for competition among banks. The assessment of the choice of the number of relations followed these initial contributions related to relationship banking.

Ongena and Smith (2000) investigate the determinants of multiple-bank relationships in a cross-country study including 1079 firms from 20 European countries. Their measure of the number of bank relationships relates to firms' reported number of banks they use for cash management purposes, which includes short-term lending, within their own country. They find that firms have more bank relationships in countries with a decentralized and healthy banking system, in countries with inefficient judicial systems, and in countries where the enforcement of creditors' rights is weak (La Porta et al., 1998). Similarly to Houston and James (1996), Ongena and Smith (2000) find that multiple-bank firms tend to be larger.

In order to identify the advantages of close banking relationships, Houston and

James (2001) focus on bank financing of publicly traded firms in the United States. They find that firms' size, leverage and market-to-book ratio decreases the likelihood of having a single bank relationship. Market-to-book ratio is employed to proxy firms' growth potential which indicates that firms with considerable growth options are less likely financed by a single bank. Houston and James (2001) explain this finding by banks' lending focus on so-called hard assets but inability to fund firms with substantial amounts of intangible growth opportunities.

Farinha and Santos (2002) focus on firms' decision to replace a single bank relation with several relationships and employ data of young small Portuguese firms between 1980 and 1996. They show that the likelihood of firms substituting a single bank relation in favor of several bank relation increases with the duration of its initial single bank relation. Furthermore, Farinha and Santos (2002) show that this substitution happens more frequently with firms which have more growth opportunities or perform poorly, respectively. The first finding is explained by a lemon premium, which increases over time, firms face when approaching an additional lender. The second finding is explained banks limiting their exopsure to poor credit which causes poor performing firms to approach an additional lender.

Ogawa et al. (2007) analyze the choice of the number of long-term banking relations of large listed Japanese firms between 1982 and 1999. In particular, they study why firms have additional bank relations besides their main bank and the optimal number creditors given the existences of a main lender. Noteworthy that their data include a period of deregulation in Japan and, most importantly, the period of stagnation in the aftermath of the collapse of Japan's economy in 1990 characterized by banks burdened with a huge amount of non-performing loans. However, they present a binomial logit regression to address the question why firms choose a single or multiple loans which is closely related to one of our analysis here. Ogawa et al. (2007) find that a higher indebtedness decreases the probability of a single loan relation and liquidity increases it. Firm size and profitability do not have a systematic impact. In a multinational logit regression they find that the determinants of the amount of bank relations conditional on having more than one bank relation are different to those which determine the choice of a single loan relation.

2.4 Relationship lending in Germany

Generally, Germany represents a bank-based financial system (Allen and Gale, 1995) characterized by strong ties between banks and firms. In addition, one very specific characteristic of the German banking system is the existence of house banks. A house bank acts as the main lender of a firm and acquires more relevant and more timely information about it. Hence, the notion of a housebank is closely related to the theoretical concept of relationship banking.

Harhoff and Körting (1998) study a large sample of German SME's. They proxy for the strength of the firm-bank relationship by the duration of the lending relationship, the number of financial institutions the firm is actually borrowing from, and a subjective indicator of trust. They find that neither the duration nor the number of financial institutions influences the costs of credit. However, collateral requirements improve for a stronger relationship in both of these dimensions.

Elsas and Krahnen (1998) follow a different approach. They study factors that determine whether a firm engages in relationship banking. To proxy for relationship banking a written statement of the firm of whether or not a bank has a house bank status is used. They show that factors related to information access of banks are important determinants. However, the duration of the bank-borrower relationship is not related to a house bank status. They empirically identify that house banks provide liquidity insurance in case of unexpected deteriorations of borrower ratings. Mayer et al. (1988) describe this insurance as using monopoly power in good times to charge above-market rates and in exchange therefore providing insurance by means of below-market rates in bad times. However, in a study investigating the determinants of the existence of house banks, Elsas (2005) finds that house bank relationships become more likely as competition increases. This contradicts the conjecture that relationship banking requires monopolistic market structures and encourages research addressing firms' choice of bank relations.

2.5 Literature - comparative analysis

Levine (2004) summarizes that there is no general rule that bank-based or market-based financial systems are more growth enhancing but also that the quality of financial intermediaries is negatively associated with inequality. However, compared with arm's-length lending two distortions due to relationship lending shall be emphasized briefly. Firstly, relationship lending causes poor price signals which can distort the allocation of funds. Hoshi et al. (1990) find that investment of firms with strong bank ties are less sensitive to their operating cash flow. Peek and Rosengren (1998) find that Japanese banks reallocated profitable funds into declining markets due to strong relations with borrowers. Secondly, relationship lending reduces the liquidity of financial assets (Diamond and Rajan, 2001). Finally, many scholars claim that a more bank-based system has comparative disadvantage in financing intangible assets (Rajan and Zingales, 2001; Hoshi et al., 1991).

3 Hypotheses

Relationship banking is well understood through the literature. However, we intend be less agnostic regarding the decision and benefits of running only one bank relation due to the reduction of asymmetric information. Our approach implicitly assumes homogenous firms in a sense that firms pledge collateral[1] in order to alleviate financial frictions.

Benmelech and Bergman (2009) construct a measure of asset redeployability to proxy for the value of the collateral to creditors in case of default. A higher asset redeployability increases the liquidation value of the collateral. They show that asset redeployability is negatively related to credit spreads, and positively related to credit ratings and loan-to-value ratios in an economically significant manner. In addition, Fabbri and Menichini (2010) find that firms' financing decisions depend in several ways on the collateral value of their inputs such that for example trade

[1] There is an extensive literature regarding the role of collateral in bank lending, see for example Holmstrom and Tirole (1997), Bester (1985), or Stiglitz and Weiss (1981).

credit for sufficiently liquid inputs purchased on account are not subject to credit rationing.

Motivated by Hall and Lerner (2010) who argue that intangible assets and knowledge created by innovation are difficult to quantify as collateral for debt financing, we emphasize the role of a firm's share of intangible assets when deciding on borrowing relations. Thus, with respect to asset redeployability, we mainly distinguish between current assets and intangible assets. The former are understood to be relatively liquid and easier to redeploy compared to the latter. Across the literature, definitions of intangible assets are manifold[2] and even from the perspective of financial reporting according to IFRS-3, valuing acquired as well as self-generated intangible assets is still seen as a black art due to enormous difficulties and risks associated with measurement (Sharma, 2012). Noteworthy that research and development as well as a highly skilled workforce are among the main determinants of the creation of intangible assets.

Relationship banking is often described by providing a channel for soft information. An objective assessment of the collateral value or redeployability, respectively, of intangible assets is impeded by the nature of intangible assets. Hence, intangible assets can be thought to proxy asymmetric information.[3] In order to achieve optimal financing conditions, channeling soft information is more beneficial to firms with a higher share of intangible assets. Moreover, conditionally conservative accounting systems (Gör and Wagenhofer, 2009) may theoretically give rise to the need of channeling soft information.

Thus, if resolving information asymmetry is a reason to engage in relationship banking and intangible assets represent by their nature a source asymmetric information, the causal chain we propose becomes obvious. To our best knowledge, a causal relationship between intangible assets and relationship banking has not been studied yet. We derive three testable predictions which emerge from the nature of

[2] See for example Ahonen (2000), Petty (2000), and Sveiby (1997).
[3] Farinha and Santos (2002) e.g. use intangible assets as proxy for asset opacity.

intangible assets, its relationship with the choice of bank relations and the associated benefits of channeling soft information to the lender.

Prediction 1. If the fraction of intangible assets proxies for information asymmetry, a higher fraction should, *ceteris paribus*, lead to higher financing costs.

Prediction 2. Firms with a high fraction of intangible assets should, *ceteris paribus*, be more likely to engage in relationship banking, since a close-firm bank relation can help to reduce information asymmetry.

Prediction 3. If asymmetric information is reduced by a strong firm-bank relation, relationship banking, *ceteris paribus*, ought to improve financing conditions.

Hence, we our contribution focuses on the decision of firms' borrowing relations, emphasizes potential benefits associated with reduced asymmetric information due to relationship lending and compares the general financing conditions of firms with an exclusive bank relation and others. We understand *Prediction 2.* to be our main contribution. In order to identify the firms' final benefits or hold-up costs potentially associated with relationship lending requires a level of detail our data lacks.

4 Data and Summary Statistics

Our data come from Amadeus databank provided by the Bureau van Dijk. The dataset includes information on balance sheets, profit and loss accounts, the legal form, and the industrial code (Nace, Rev. 2) for German firms. The coverage of high quality spans from 2005 to 2012. We limit our analysis to non-listed German firms of limited liability without floating debt between 2005 and 2012, for which we have at least 6 consecutive observations. Hence, firms in our sample have debt and equity. However, the debt part only consists of bank loans.

In addition to information on balance sheets and profit and loss accounts, Amadeus databank provides the amount of bank relations firms had between 2005 and 2012. However, the information about the number of bank accounts is aggregated in the following way: for each firm the number of different bank accounts within the time period from 2005 to 2012 is given[4]. Thus, it is not time-varying and, therefore, we limit our analysis to the cross section. After dropping observations subject to logical errors, missing data, and outliers at firm level, the time-invariant variable of bank relations requires us to aggregate all variables over years which reduces our sample to a cross-section which still includes roughly 22,000 observations.

By collapsing our data into the cross-section, the variable *number of banks* satisfies two out of four prominent proxies for relationship banking (e.g. Kysucky and Norden, 2014). First, the length of the firm-bank relation, which has to be at least six years. Second, the exclusivity of the relationship. If the amount of bank relations equals one, we know that the corresponding firm operated solely with same bank over six years. This has the advantage that we can identify firms which operated between 2005 and 2012 with only one bank. In addition, we are able to distinguish between the main players in the German banking market. If a firm has only one bank relation, we can distinguish between Deutsche Bank, Commerzbank, Cooperative Banks (Genossenschaftsbanken), and Saving Banks (Sparkassen).

Figure 1a to Figure 1f present the share of long- and short-term debt as well as financing costs depending on the number of bank relations. Both, the total share and the development over time seems to be independent of the number of bank relations. Firms shifted their financing from more long-term to more short-term between 2005 and 2012. However, it can be observed that firms with only one bank relation pay lower interest rates on average than firms with more bank relations. Figure 1g shows the distribution bank relations. The majority of observations lies between one and three bank relations and about one quarter of firms have a single bank relation. According to the Bureau van Dijk, information regarding number of banks is collected from the firms' annual report and capped at six. Therefore, firms in the last category can have six or more bank relations. In the empirical analysis we will mainly distinguish between one and more than one bank relations.

[4] Assume for example a firm with bank accounts at bank A and B for the period 2005 to 2008. If this firm terminates both accounts in 2009 and opens a new account at bank C from 2009 to 2012, the number of banks for this firm would equal three.

Figure 1h shows that one third of all firms having a single bank relation are served by Saving Banks, followed by Commerzbank (17%), Cooperative Banks (12%), and Deutsche Bank (11%). One quarter of firms with a single bank relation are financed by "non-main players" in German banking market.

[Figure 1 about here.]

In Table 1 firms with only one bank relation are compared to all other firms. Surprisingly, firms with only one bank relation are on average larger than other firms (measured by total assets). We therefore conclude, that size cannot be the main explanation for a difference in the number of banks. Most important, we find the most pronounced difference in the share of intangible and current assets. Firms with only one bank relation have on average a higher share of intangible assets and a lower share of current assets. In addition, Table 1 employes the possible distinction between Deutsche Bank, Commerzbank, Cooperative Banks, and Saving Banks. Note that we only include firms with only one bank relation in this analysis when distinguishing between banks. Regarding Cooperative Banks and Saving Banks we find that firms having their only bank relation with one of those banks are smaller, pay higher interest rates, and are less liquid on average. Moreover, firms exclusively working with those two banks have have a lower share of intangible assets on average. Finally, firms having an exclusive relationship with Saving Banks are more long-term financed. Comparing Deutsche Bank and Commerzbank with the remaining sample, firms having an exclusive relationship with those two lenders are more liquid, pay lower interest rates, and are more short-term financed. Furthermore, those firms have on average a higher share of intangible assets but a lower share of current assets. Finally, firms having an exclusive relationship with Deutsche Bank are on average larger.

[Table 1 about here.]

5 Estimation and Results

5.1 Prediction 1.

High quality firms, which are highly innovative and invest a lot in R & D activities, might prefer a single lender since they are not willing to share their knowledge with multiple lenders (Yosha, 1995). Research and development contributes to the creation of intangible assets. Thus, we have to check whether intangible assets really proxy asymmetric information. If the fraction of intangible assets proxies for information asymmetry, a higher fraction should *ceteris paribus* lead to higher financing costs.

To address this question, we apply propensity score matching according to Rosenbaum and Rubin (1983) and Rosenbaum and Rubin (1985) and implemented by Leuven and Sianesi (2003). We define two treatment groups which are firms whose share of intangible assets exceeds either the sample mean (≈1.44%) or median (≈0.03%), respectively. Firms whose share of intangible assets is above one of these thresholds ought to face, *ceteris paribus*, higher interest rates. Since the share of intangible assets is not assigned completely at random to firms, the probability of receiving treatment, $D = 0 \vee 1$, will be estimated conditional on the following confounders: sales; employees; tangible assets (standardized by total assets); current assets (standardized by total assets); long-term debt (standardized by total assets); short-term debt (standardized by total assets); cash flow; EBITDA; net income; industry dummies; main economic regions dummies. This is maximum amount of covariates we can include still avoiding (close to) perfect collinearity. The outcome variable, Y, is the interest rate firms are charged. The estimated “Average Treatment Effect on the Treated” (ATT) is

$$ATT = E[Y(1)|D = 1] - E[Y(0)|D = 0] + SB, \tag{1}$$

where $E[Y(1)|D = 1]$ is the expected outcome given treatment, $E[Y(0)|D = 0]$ is the expected outcome absent of treatment, and SB is the selection bias.

We estimate equation (1) in various permutations based on: treatment refers to the share of intangible assets exceeding sample mean or median; the matching algorithm is either the nearest neighbor, the two nearest neighbors, or a normally distributed kernel using a range of 0.06. All possible combinations make us run twelve propensity score matching estimations.

[Table 2 about here.]

Table 2 shows that in an unmatched comparison interest rates basically do not differ. In a few cases, interest rates for the treated group are even lower. However, once comparing conditional expected values, we find that firms with a high share of intangible assets face generally higher interest rates. This is robust across specifications and provides evidence that a firm's share of intangible assets is source a asymmetric information. Only in a very few cases the positive difference between the "Treated" and the "Controls" is not statistically significantly different from zero. The differences in interest rates are in an area of ten basis points. The low value of the pseudo R-squared reveals that average heterogeneity is low. For the main specifications Figure 2 visualizes that observations are quite equally distributed along the propensity score. The technically high quality of our estimations supports the approach.

[Figure 2 about here.]

The null hypothesis that the share of intangible assets does not affect financing conditions can be rejected and results are in favor of our prediction.

In addition, we calculate correlation coefficients of the growth rate of cash flow and growth rate of fixed assets for both groups. A higher correlation coefficients means that a firm's investment depends more on internal sources. Since asymmetric information complicates external financing, we expect firms with a higher share of intangible assets to reveal a larger correlation coefficient. Correlation coefficients are: share of intangible assets exceeds mean (0.1412; significant at 1%); share of intangible assets exceeds median (0.0357; significant at 1%). Since mean is located right of the median, this provides weak evidence that a higher share of intangible assets is associated with a greater need of internal financing.

Finally, the pecking order theory implies that asymmetric information causes management to prefer the issuance of debt over equity but this does not apply to intangible assets for which equity is the preferable way of finance (Myers and Majluf, 1984). Thus, Firms whose share of intangible assets is above one of the thresholds used here ought to have, *ceteris paribus*, higher equity ratios. In an unmatched comparison, the equity ratio of firms whose share of intangible assets is above one of the specified thresholds is statistically significantly higher. However, if we employ equity ratio as outcome variable, Y, according to equation (1), Table 3 shows that the differences in equity ratios disappear comparing matched firms. This suggests that there is another way than equity to finance intangible assets which we expect to be relationship banking.

[Table 3 about here.]

5.2 Prediction 2.

Based on previous studies we combine the following variables in order to explain the choice of the number of bank relations: size of the firm which is either proxied by sales or employees; asymmetric information proxied by intangible assets (standardized by total assets); redeployable collateral proxied by current assets (standardized by total assets); indebtedness which is either proxied by debt standardized by total assets or by short-term debt divided by long-term debt; liquidity/profitability proxied by EBITDA. In order to assess whether a higher share of intangible assets determines firms' number of bank relations we estimate the following baseline regression

$$Number\ Bank\ Relations_i = \beta \frac{Intangible\ Assets_i}{Total\ Assets_i} + X_i\gamma + I_i\delta + R_i\lambda + u_i, \quad (2)$$

where the dependent variable is the number of bank relations of firm i. β is the coefficient of main interest since it reflects the impact of the share of intangible assets of firm i on its number of bank relations. Covariates are represented by X_i. Covariates include: one proxy variable for firm size, which is either the number of employees or the amount of sales; current assets standardized by total assets; one variable of indebtedness, which is either debt divided by total assets or short-term debt divided by long-term debt; EBITDA is employed in order to proxy profitability and liquidity, respectively. I_i is a binary variable coded for industries at section level according to the industrial code (Nace, Rev. 2). R_i is binary variable which equals one in case the firm is located in one of three main economic regions in Germany (Bavaria, Baden-Wuerttemberg, Nordrhein-Westfalen) which are supposed to more competitive than other regions. Finally, u_i is the error term of the regression.

Regarding the expected signs of our control variables: proxies for firms size are expected to increase the number of bank relations; as we argue along the lines of collateral redeployability, current assets are expected to increase the number of bank relations because since the soft channel of a strong firm-bank relation is less needed.

Since our dependent variable in equation (2) is a count variable, which is discrete-valued and truncated, an ordinary least squares estimation produces biased results for both, slope coefficient and standard errors. However, our pre-estimation analysis includes the use of a Bayesian-moving-average based on OLS in order to test for the potential need of additional covariates available which is not the case.

Noteworthy that our variable of main interest, which is share of intangible assets, enters the regression standardized by total assets. The sample mean of the share of intangible assets equals approximately 1.44% and the 90%-quantile starts at approximately 2.88%. To classify the results appropriately it is important to keep in mind that a one unit change on average in the share of intangible assets represents a huge increase in intangible assets. Hence, β can be roughly interpreted as, *ceteris paribus*, entering the 90%-quantile of the share of intangible assets.

Tobit Regression

In order to take into account that there is left-censoring in the dependent variable, which is that firms cannot have less than one bank relation, we start with a tobit regression which is designed to estimate linear relationships between variables if there is either left- or right-censoring in the dependent variable. Hence, values below one bank relation are censored.

Table 4 provides the corresponding results where each specification is estimated with robust and bootstrapped standard errors. The use of sales instead of employees in order to proxy size is associated with less observations and a lower log pseudolikelihood ratio. The intercept is through all specifications significant. Tobit regression coefficients can be interpreted equivalently to OLS regression coefficients but the linear effect is on the uncensored latent variable and not the observed outcome.

[Table 4 about here.]

If firm size is proxied by employees it increases the number of bank relations but when proxied by sales it has no effect. However, according to the coefficient there are 20,000 more employees required to change the number of bank relations by one. Hence, the economic meaning of this statistically significant coefficient is questionable. The share of current assets is expected to enter the regression positively, given its high collateral redeployability, and it does. Yet the significance of the coefficient changes with the specification. Across all specifications more indebted and more short-term financed firms have less bank relations. EBITDA has a sometimes a significant but economically negligible effect on the number of bank relations.

Finally, the most robust finding is that the share of intangible assets is highly significant across specification and of considerable economic size. Firms with a higher share of intangible assets have significantly less bank relations.

Poisson Regression

Next we treat the dependent variable as a count variable. Our preliminary analysis of the dependent variables reveals the poisson regression to be appropriate since conditional variance does not exceed conditional mean. Poisson regression coefficients have to interpreted as follows: if e.g. the coefficient γ equals 1 this represents an expected increase in the log count for a one-unit increase in the corresponding independent variable which is 1.

Table 5 reveals many similarities compared with Table 4 in terms of the size, sign, and significance of all variables. Most importantly, the share of intangible assets is again highly significant across specification and of considerable economic size. Firms with a higher share of intangible assets have significantly less bank relations.

[Table 5 about here.]

Logistic Regression

Given the nature of our dependent variable, the logistic regression is the most appropriate estimation and, thus, the most important one. Since the number of bank relations between 2005 and 2012 is reported across years, we know that if it equals one the corresponding firm had exactly one bank relation in this time period. Hence, transforming the dependent variable such that it equals 1 for a firm with only one bank and 0 for everything else offers a sharp distinction.

Table 6 presents results of four logistic regressions with an indicator for firms which only have one bank relation (relationship banking = 1). Thereby, two different proxies for firm size and indebtedness are used. In specification I and II the number of employees proxy for size whereas in specification III and IV total sales are used. indebtedness is proxied by total debt divided by total assets (specification I and III) and by the fraction of short- to long-term debt (specification II and IV). Following prediction 2, the null hypothesis states that the share of intangible assets does not affect the probability of running an exclusive bank relation. We can reject the null hypothesis on a 1% significance level. The fraction of intangible assets significantly increases the probability of having only one bank relation. Thereby, the odds ratio can be interpreted as the factor by which the odds of having only one bank relation increase[5]. The odds ratio for an explanatory variable i with an coefficient β_i is calculated as e^{β_i}. In our case, this means, that an 1% point increase in the ratio of intangible assets ($\frac{1}{100}$unit increase) corresponds to an odds ratio of $e^{\frac{1}{100}\beta_i}$. For specification I this results in an odds ratio of $e^{0.02314} = 1.0234$. Therefore, the odds of having only one bank relation increase by 2.34% per 1% point increase in the fraction of intangible assets. Our results are robust to the use of different size and indebtedness proxies. In summary, we can confirm our second prediction.

[Table 6 about here.]

In addition, size proxies are neither statistically significant (sales) nor economically meaningful (employees). Both proxies for indebtedness are significant an positive. Firms with a higher fraction of debt are more likely to have a single bank relation. One interpretation of this finding is that greater indebtedness is a signal for low borrower quality (even if this is not true) to outside lenders. Therefore, firms are not able to establish a second bank relation, since they can not convincingly communicate their true quality. Not reported but worth mentioning is, that firms located in one of three main economic regions of Germany are less engaged in relationship banking which is in line with Petersen and Rajan (1995).

5.3 Prediction 3.

The previous results justify the use of intangible assets as a proxy for asymmetric information and illustrate the deterministic role of intangible assets regarding firms' choice of bank relations. Since we successfully identified one important determinant of firms' decision making regarding the choice between one or many lenders, we employ a one-firm one-bank relationship as treatment in a propensity score matching approach as presented in equation (1). Thereby, the firms' interest rate is defined

[5] For example, if a firm has a 10% probability of having only one bank relation, the odds for this firm are $\frac{10\%}{90\%} = .11$. An odds ratio now gives the change in the odds of having only one bank relation if intangible assets are increased by one unit. An odds ratio of 10.12 for example translates to odds of having only one bank relation of $0.11 * 10.12 = 1.12$, resulting in a new probability of having one bank relation of 53%. The odds ratio can range from 0 to ∞ with an odds ratio of 1 implying no effect of the explanatory variable.

as outcome variable. Thus, we employ different specifications according to Table 6. We estimate specifications (I) to (IV) according to Table 6 as either Logit or Probit, with one to the three nearest neighbors, and a normally distributed kernel using a range of 0.06 to match firms.

If firms decide to run an exclusive bank relation in order to reduce asymmetric information, *ceteris paribus*, relationship banking ought to improve financing conditions. However, a natural limitation of our data is that it provides one window of observations. We do not know whether we observe first or the last six years of a strong firm-bank relation. Thus, finding beneficial financing conditions related to relationship banking does not prove the non-existence of a hold-up problem.

[Table 7 about here.]

Table 7 shows that using the first row of Table 6 to estimate the probability of a firm having one bank relation does not reveal any differences between an unmatched and matched comparison of lending costs. Both comparisons show that firms engaged in relationship lending pay lower interest rates than other firms.

[Table 8 about here.]

A consistently decreasing T-Statistic from the unmatched to the matched difference in Table 8 indicates that the interest rate differential decreases by matching but is still significantly different from zero in all cases. Again both comparisons show that firms engaged in relationship lending are charged lower interest rates than other firms.

[Table 9 about here.]

Table 9 and Table 10 provide basically the same results.

[Table 10 about here.]

Finally, Table 11 shows that using a kernel instead of nearest neighbors to match observations does not alter the results. In all cases firms with a strong firm-bank relation face lower interest rates.

[Table 11 about here.]

In line with the low values obtained for the pseudo R-squared, Figure 3 shows that firms are quite equally distributed along the propensity score which indicates the high technical quality of the approach.

[Figure 3 about here.]

To sum it up, firms engaged in relationship banking face statistically significantly lower lending rates. However, difference are in an area below one percentage point. The null hypothesis that relationship lending does not affect financing conditions can be rejected and results are in favor of our prediction.

6 Conclusion

We discuss the relationship between intangible assets, asymmetric information, relationship banking, and financing costs for German SME's. These topics have separately already received much attention in the academic literature, thus we contribute significantly by the combination of all and, in particular, by assigning a special role to the connection of intangible assets, asymmetric information, and firms' choice of bank relation. We derive three testable predictions. For each the null hypothesis can be rejected and results are in favor of our predictions.

Using a large dataset for German SME's including their bank relations between 2005 and 2012, we test the following three predictions: (1) if the fraction of intangible assets proxies for information asymmetry, a higher fraction should, *ceteris paribus*, lead to higher financing costs; (2) firms with a high fraction of intangible assets should, *ceteris paribus*, be more likely to engage in relationship banking, since a close-firm bank relation can help to reduce information asymmetry; (3) if asymmetric information is reduced by a strong firm-bank relation, *ceteris paribus*, relationship banking ought to improve financing conditions.

We divide firms into two groups separated by their share of intangible assets. A descriptive comparison does not reveal any differences regarding financing costs.

Given the existence of potential confounders, we estimate a propensity score matching model. Once, we are able to compare "Treated" firms with the "Controls", we find a statistically significant difference in financing costs. Firms with a higher share of intangible assets are charged higher interest rates. However, the identified differences are small. In addition, firms with a higher share of intangible assets are not less equity financed as theory predicts. This suggests that there is way of debt financing for those firms which we propose to be relationship banking.

The centerpiece of our contribution is to address the question why firms decide to have only one bank relation. We have information regarding the number of bank relations of each firm, which is best employed in a binary fashion. If intangible assets proxy asymmetric information, the share of intangible assets ought to increase the probability of strong firm-bank relation due to the firm's need to use the associated soft information channel in order to reduce asymmetric information or to reduce financing frictions, respectively. Indeed, we find that the share of intangible assets significantly increases the probability of an exclusive and persistent bank relation.

Whether an exclusive and persistent bank relation reduces financing costs is addressed by a propensity score matching estimation using such a relationship as treatment. The interest rate differentials between the "Treated" and the "Controls" are both negative and statistically significant. This confirms that firms in a strong firm-bank relation face on average lower financing costs but does not provide any evince against the existence of the well-known hold-up problem attributable to such a firm-bank relation.

Given data availability, future research ought to address the hold-up problem more precisely which requires knowledge about the development of a strong firm-bank relationship over time. Intangible assets can be understood not only as a source of asymmetric information but also as a call option on growth (Myers, 1977). Thus, to address the question whether changing from one to many bank relations at some point in time is done by firms to protect from hold-up costs or to enhance further growth or caused by banks which want to share risks seems to be a very promising attempt.

The German three-pillar structure of the banking system is similar to banking systems in other European countries such as Austria, France, Italy, Spain and Sweden (Brunner et al., 2004). A cross-country analysis including those European countries is a natural extension which would allow to control for country-specific characteristics of relationship banking.

Finally, form our point of view, the different - and partly surprising - roles transaction banks compared to saving banks and cooparative banks play, also requires further research attention.

References

Ahonen, G. 2000. Generative and commercially exploitable assets. *In: J.E. Gröjer and H Stolowy (Eds) Classification of Intangibles. Groupe HEC, Jouy-en Josas.* 206–213.

Allen, F. and D. Gale. 1995. A welfare comparison of intermediaries and financial markets in germany and the us. *European Economic Review* 39: 179–209.

Benmelech, E. and N. Bergman. 2009. Collateral pricing. *Journal of Financial Economics* 91: 339–360.

Berger, A. N. and G. F. Udell. 1995. Relationship lending and lines of credit in small firm finance. *The Journal of Business* 68 (3): 351–381.

Bester, H. 1985. Screening vs. Rationing in Credit Markets with Imperfect Information. *American Economic Review* 75: 850–855.

Bolton, P. and D. Scharfstein. 1996. Optimal debt structure and the number of creditors. *Journal of Political Economy* 104: 1–25.

Boot, A. W. 2000. Relationship banking: What do we know? *Journal of Financial Intermediation* 9 (1): 7–25.

Boot, A. W. A. and A. V. Thakor. 1994. Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review* 35 (4): 899–920.

Brunner, A., J. Decressin, D. Hardy, and B. Kudela. 2004. Germany's three-pillar banking system: Cross-country perspectives in europe. *Internation Monetary Fund - Occasional Paper 233* .

Cole, R. A. 1998. The importance of relationships to the availability of credit. *Journal of Banking & Finance* 22: 959–977.

Degryse, H. and S. Ongena. 2005. Distance, lending relationships, and competition. *The Journal of Finance* 60 (1): 231–266.

Detragiache, E., P. Garella, and L. Guiso. 2000. Multiple versus Single Banking Relationships: Theory and Evidence. *Journal of Finance* LV (3): 1133–1161.

Dewatripont, M. and E. Maskin. 1995. Credit and efficiency in centralized and decentralized economies. *Review of Economic Studies* 62: 541–555.

Diamond, D. 1984. Financial intermediation and delegated monitoring. *Review of Economic Studies* 51: 314–393.

Diamond, D. and R. Rajan. 2001. Liquidity risk, liquidity creation and financial fragility: A theory of banking. *Journal of Political Economy* 109 (2): 287–237.

Elsas, R. 2005. Empirical determinants of relationship lending. *Journal of Financial Intermediation* 14: 32–57.

Elsas, R. and J. P. Krahnen. 1998. Is relationship lending special? evidence from credit-file data in germany. *Journal of Banking & Finance* 22: 1283–1316.

Engel, D. and T. Middendorf. 2009. Investment, internal funds and public banking in germany. *Journal of Banking & Finance* 33: 2132–2139.

Fabbri, D. and A. Menichini. 2010. Trade credit,collateral liquidation, and borrowing constraints. *Journal of Financial Economics* 96: 413–432.

Farinha, L. A. and J. A. Santos. 2002. Switching from single to multiple bank lending relationships: Determinants and implications. *Journal of Financial Intermediation* 11 (2): 124–151.

Giesecke, K., F. Longstaff, S. Schaefer, and I. Strebulaev. 2012. Macroeconomic Effects of Corporate Default Crises: A Long-Term Perspective. *NBER Working Paper Series - Working Paper 17854* .

Gör, R. and A. Wagenhofer. 2009. Optimal impairment rules. *Journal of Accounting and Economics* 48: 2–16.

Greenbaum, S. I., G. Kanatas, and I. Venezia. 1989. Equilibrium loan pricing under the bank-client relationship. *Journal of Banking & Finance* 13 (2): 221–235.

Hall, B. and J. Lerner, 2010. *Handbook of the Economics of Innovation*, North-Holland, chapter The Financing of R&D and Innovation.

Harhoff, D. and T. Körting. 1998. Lending relationships in germany – empirical evidence from survey data. *Journal of Banking & Finance* 22 (10–11): 1317–1353.

Hart, O. 1995. *Firms, Contracts, and Financial Structure.* Oxford University Press.

Holmstrom, B. and J. Tirole. 1997. Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics* 112: 663–691.

Hoshi, T., A. Kashyap, and D. Scharfstein, 1990. *Asymmetric Information, Corporate Finance, and Investment*, University of Chicago Press, chapter Bank Monitoring and Investment: Evidence from the Changing Structure of Japanese Corporate Banking Relationships, 105–126.

Hoshi, T., A. Kashyap, and D. Scharfstein. 1991. Corporate structure, liquidity, and investment: Evidence from japanese industrial groups. *The Quarterly Journal of Economics* 106 (1): 33–60.

Houston, J. and C. James. 1996. Bank information monopolies and the mix of private and public debt claimsauthor. *The Journal of Finance* 51: 1863–1889.

Houston, J. and C. James. 2001. Do Relationships Have Limits? Banking Relationships, Financial Constraints, and Investment. *Journal of Business* 73 (3): 347–374.

Kysucky, V. and L. Norden. 2014. The benefits of relationship lending in a cross-country context: A meta-analysis. *Management Science* forthcoming.

La Porta, R., F. Lopez-de Silanes, A. Schleifer, and R. Vishny. 1998. Law and Finance. *Journal of Political Economy* 106: 1113–1155.

Leuven, E. and B. Sianesi, 2003. Psmatch2: Stata module to perform full mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. http://ideas.repec.org/c/boc/bocode/s432001.html.

Levine, R. 2004. Finance and growth: Theory and evidence. *NBER Working Paper 10766* .

Mayer, C., G. Mankiw, and Y. Barroux. 1988. New issues in corporate finance. *European Economic Review* 32 (5): 1167–1189.

Myers, S. 1977. The determinants of corporate borrowing. *Journal of Financial Economics* 5: 147–75.

Myers, S. and N. Majluf. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13: 187–221.

Ogawa, K., E. Sterken, and I. Tokutsu. 2007. Why do Japanese firms prefer multiple bank relationship? Some evidence from firm-level data. *Economic Systems* 31: 49–70.

Ongena, S. and D. Smith. 2000. What determines the number of bank relationships? cross-country evidence. *Journal of Financial Intermediation* 9: 26–56.

Peek, J. and S. Rosengren. 1998. The international transmission of financial shocks: The case of japan. *American Economic Review* 87 (4): 495–505.

Petersen, M. A. and R. G. Rajan. 1994. The benefits of lending relationships: Evidence from small business data. *The Journal of Finance* 49 (1): 3–37.

Petersen, M. A. and R. G. Rajan. 1995. The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics* 110 (2): 407–443.

Petty, G. 2000. Voluntary disclosure of intellectual capital and the hidden value. *Journal of Economic Literature* .

Rajan, R. and L. Zingales. 2001. Financial systems, industrial structure, and growth. *Oxford Review of Economic Policy* 17 (4): 467–482.

Rosenbaum, P. and D. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70: 41–55.

Rosenbaum, P. and D. Rubin. 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician* 39 (1): 33–38.

Schenone, C. 2010. Lending relationships and information rents: Do banks exploit their information advantages? *Review of Financial Studies* 23 (3): 1149–1199.

Sharma, N. 2012. Intangible assets : A study of valuation methods. *BVIMR Management Edge* 5: 61–69.

Sharpe, S. A. 1990. Asymmetric information, bank lending and implicit contracts: A stylized model of customer relationships. *The Journal of Finance* 45 (4): 1069–1087.

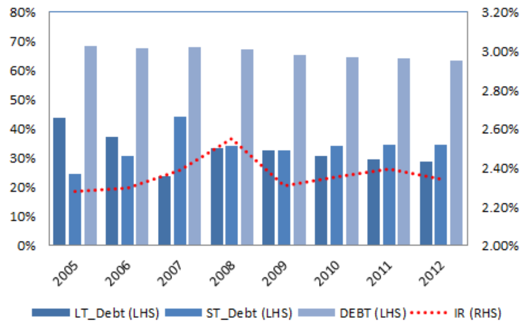
Stiglitz, J. and A. Weiss. 1981. Credit rationing in markets with imperfect information. *American Economic Review* 71: 393–410.

Sveiby, K. 1997. *The New Organizational Wealth: Managing and Measuring Knowledge based Assets*. Barrett-Kohler, Publishers, San Francisco.

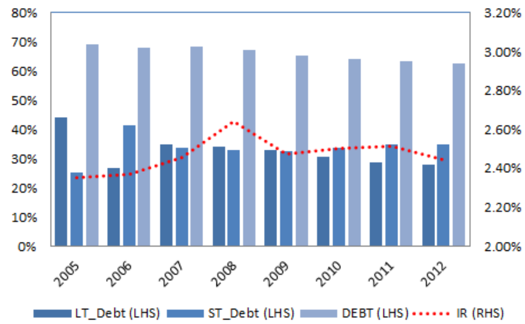
Thadden, E.-L. V. 1995. Long-term contracts, short-term investment and monitoring. *The Review of Economic Studies* 62 (4): 557–575.

Yosha, O. 1995. Information disclosure costs and the choice of financing source. *Journal of Financial Intermediation* 4: 3–20.

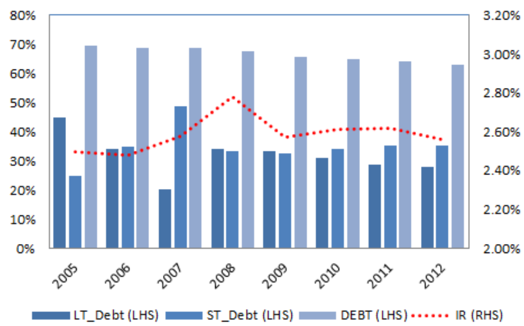
Figure 1: Stylized Facts



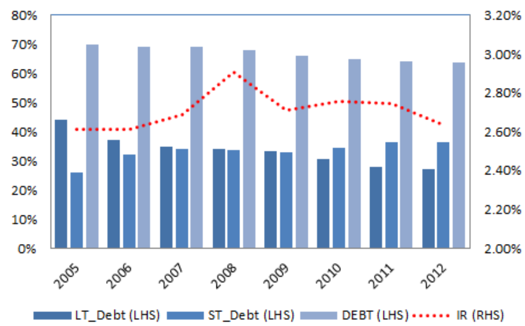
(a) One Bank Relation



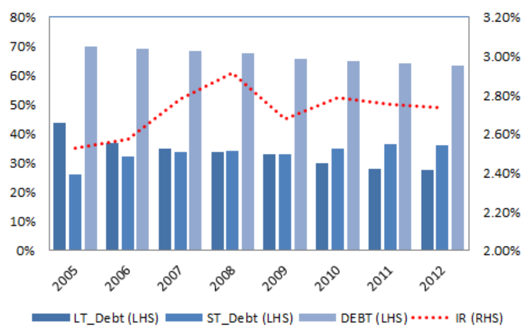
(b) Two Bank Relations



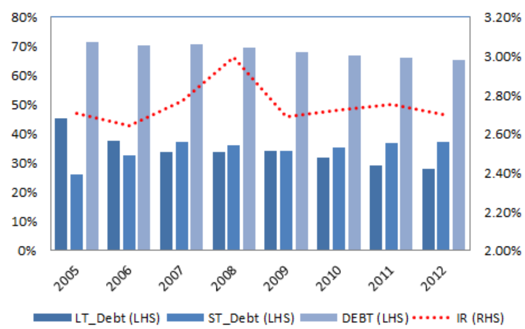
(c) Three Bank Relations



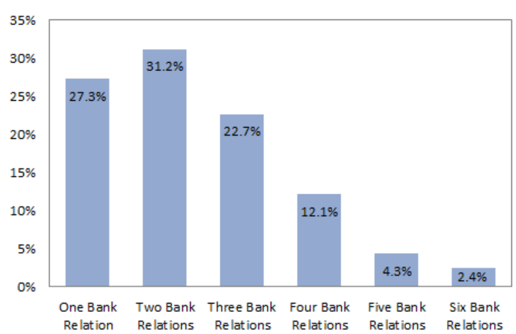
(d) Four Bank Relations



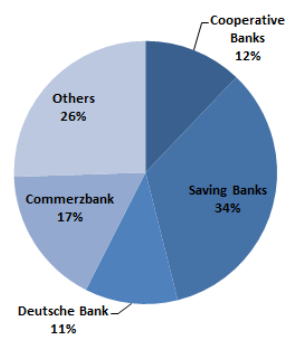
(e) Five Bank Relations



(f) Six or more Bank Relations

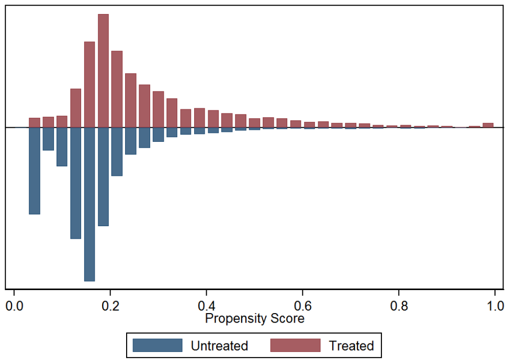


(g) Bank Relations

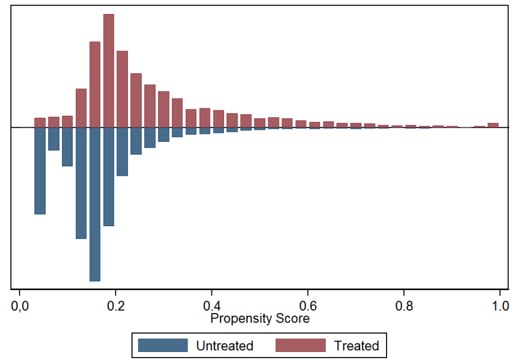


(h) Relationship Lending

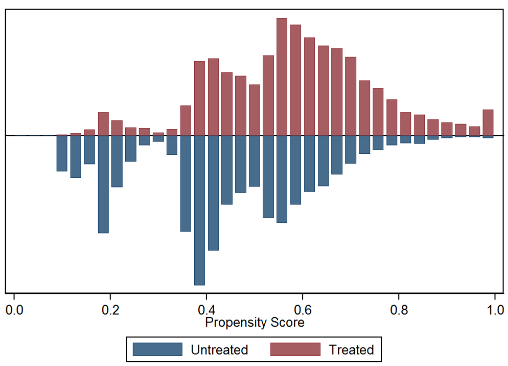
Figure 2: Propensity Score Matching - Quality Prediction 1.



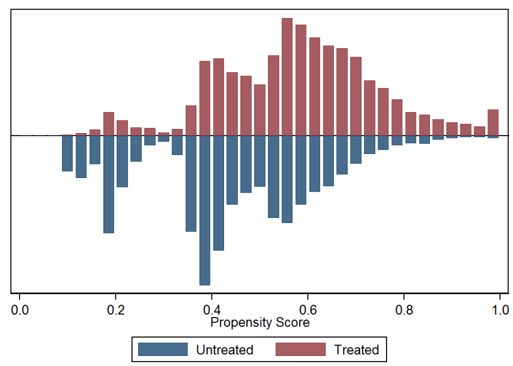
(a) Mean, nearest Neighbor, Logit.



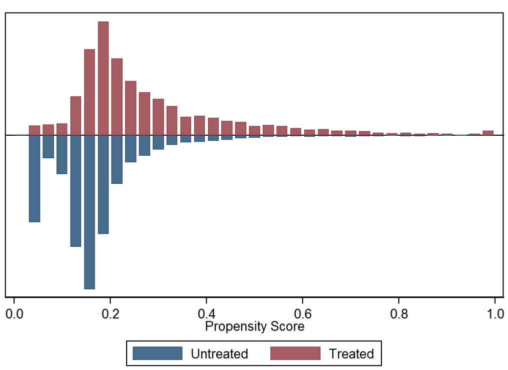
(b) Mean, 2 nearest Neighbors, Logit.



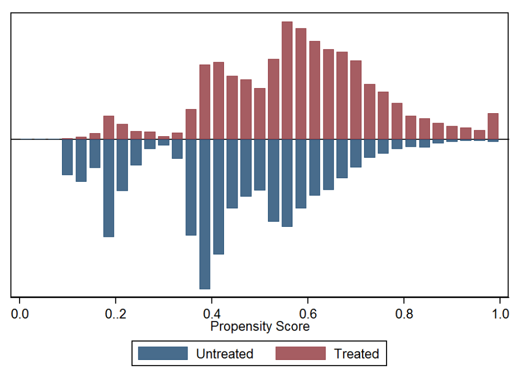
(c) Median, nearest Neighbor, Logit.



(d) Median, 2 nearest Neighbors, Logit.

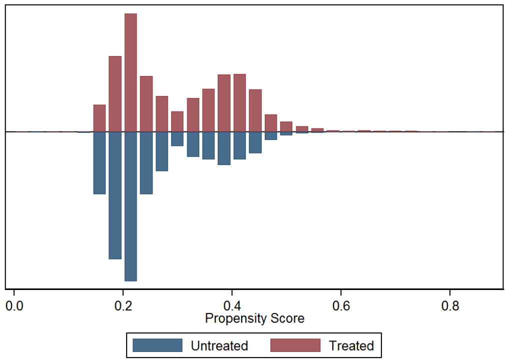


(e) Mean, Kernel, Logit.

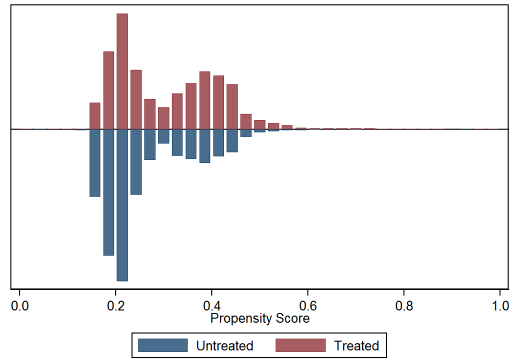


(f) Median, Kernel, Logit.

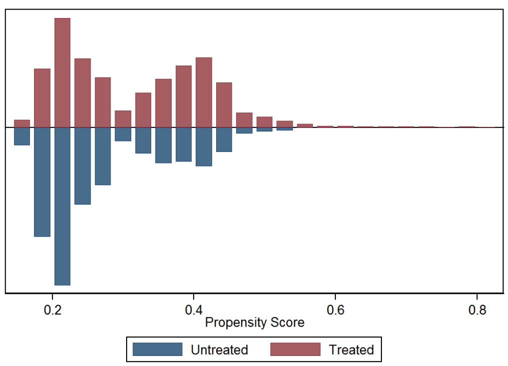
Figure 3: Propensity Score Matching - Quality Prediction 3.



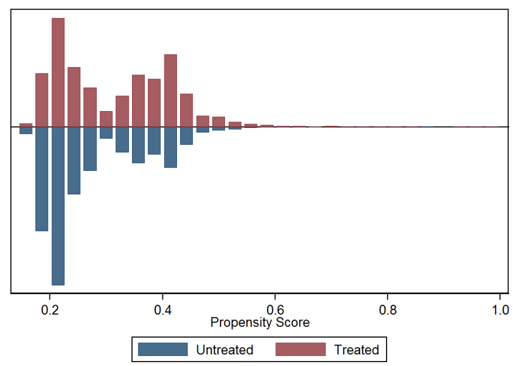
(a) (I), 3 nearest Neighbors, Logit.



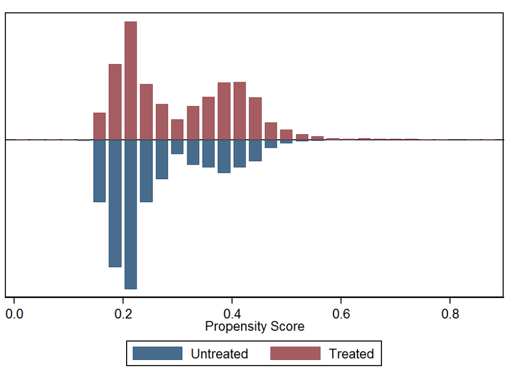
(b) (II), 3 nearest Neighbors, Logit.



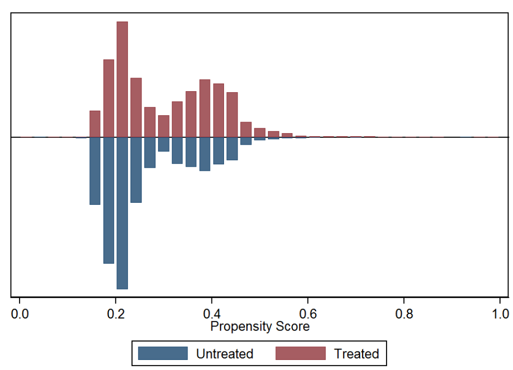
(c) (III), 3 nearest Neighbors, Logit.



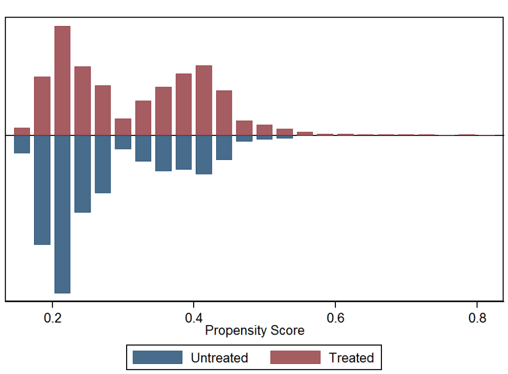
(d) (IV), 3 nearest Neighbors, Logit.



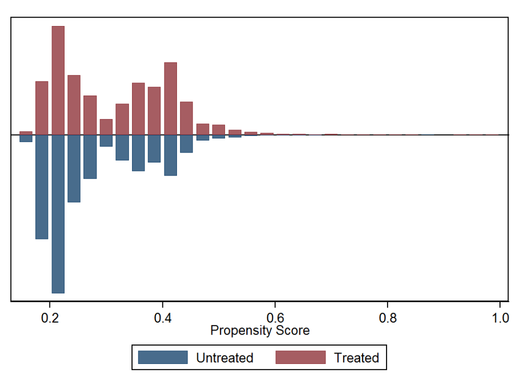
(e) (I), Kernel, Logit.



(f) (II), Kernel, Logit.



(g) (III), Kernel, Logit.



(h) (IV), Kernel, Logit.

Table 1: Bank Characteristics

		All Firms		1 Bank Relation			
	Mean	>1 Bank Relation	1 Bank Relation	Cooperative Banks	Saving Banks	Deutsche Bank	Commerzbank
Size	Sales	83,214	94,162	27,295	41,506	167,291	111,367
			(-1.138)	(2.705)	(4.371)	(-3.151)	(-0.949)
	Employees	286	281	145	222	399	335
			(0.141)	(3.533)	(2.952)	(-2.958)	(-1.693)
	Total Assets	55,631	78,022	14,959	37,557	210,930	90,623
			(-2.791)	(3.028)	(3.753)	(-6.188)	(-0.737)
Standardized Balance Items (in keur)	Equity/Total Assets	0.335	0.339	0.317	0.344	0.346	0.343
			(-1.159)	(2.783)	(-1.393)	(-0.935)	(-0.621)
	ST_Debt/Total Assets	0.330	0.327	0.338	0.299	0.355	0.355
			(0.952)	(-1.492)	(7.274)	(-3.497)	(-4.409)
	LT_Debt/Total Assets	0.335	0.334	0.344	0.357	0.299	0.303
			(0.243)	(-1.490)	(-6.562)	(4.989)	(5.658)
	ST_Debt/LT_Debt	1.892	2.569	2.505	1.706	3.065	4.181
			(-4.508)	(0.106)	(2.785)	(-0.801)	(-3.287)
	Debt/Total Assets	0.665	0.661	0.683	0.656	0.654	0.657
			(1.158)	(-2.783)	(1.393)	(0.934)	(0.622)
	Intangible Assets/Total Assets	0.012	0.019	0.011	0.013	0.029	0.024
			(-10.118)	(4.030)	(5.804)	(-4.597)	(-2.569)
	Current Assets/Total Assets	0.656	0.596	0.654	0.547	0.239	0.641
			(15.303)	(-5.791)	(9.401)	(9.023)	(-5.476)
P&L	Cashflow	3,798	4,221	1,369	2,647	6,375	6,856
			(-0.563)	(3.628)	(3.856)	(-2.587)	(-3.975)
	EBIDTA	5,664	7,038	1,824	3,424	15,029	9,652
			(-2.034)	(4.102)	(5.479)	(-6.028)	(-2.472)
	Interest Rate	0.026	0.024	0.025	0.025	0.021	0.021
			(9.567)	(-2.850)	(-6.491)	(4.988)	(5.559)

Notes: The t-statistic is reported in parentheses and if stating significance at the 5%-level highlighted. Null hypothesis is diff=0 where diff equals mean(0)-mean(1) and 1 represents the specific section.

Table 2: Propensity Score Matching - Results Prediction 1.

Treatment			Mean					Mean		
Matching			Nearest Neighbor					Nearest Neighbor		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.025	0.026	0.000	0.000	-1.420	0.025	0.026	0.000	0.000	-1.420
ATT	0.025	0.025	0.001	0.000	1.350	0.025	0.024	0.001	0.000	2.330
pseudo R-squared			0.104					0.106		
Number of Obs			17003					17003		
Treatment			Mean					Mean		
Matching			2 Nearest Neighbors					2 Nearest Neighbors		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.025	0.026	0.000	0.000	-1.420	0.025	0.026	0.000	0.000	-1.420
ATT	0.025	0.025	0.001	0.000	1.360	0.025	0.024	0.001	0.000	1.800
pseudo R-squared			0.104					0.106		
Number of Obs			17003					17003		
Treatment			Median					Median		
Matching			Nearest Neighbor					Nearest Neighbor		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.025	0.026	-0.001	0.000	-2.620	0.025	0.026	-0.001	0.000	-2.620
ATT	0.025	0.024	0.001	0.000	3.650	0.025	0.024	0.001	0.000	3.110
pseudo R-squared			0.112					0.109		
Number of Obs			17003					17003		
Treatment			Median					Median		
Matching			2 Nearest Neighbors					2 Nearest Neighbors		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.025	0.026	-0.001	0.000	-2.620	0.025	0.026	-0.001	0.000	-2.620
ATT	0.025	0.024	0.001	0.000	3.480	0.025	0.024	0.001	0.000	2.790
pseudo R-squared			0.112					0.109		
Number of Obs			17003					17003		
Treatment			Mean					Mean		
Matching			Kernel					Kernel		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.025	0.026	0.000	0.000	-1.420	0.025	0.026	0.000	0.000	-1.420
ATT	0.025	0.025	0.001	0.000	1.350	0.025	0.024	0.001	0.000	2.330
pseudo R-squared			0.1041					0.106		
Number of Obs			17003					17003		
Treatment			Median					Median		
Matching			Kernel					Kernel		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.025	0.026	-0.001	0.000	-2.620	0.025	0.026	-0.001	0.000	-2.620
ATT	0.025	0.024	0.001	0.000	3.650	0.025	0.024	0.001	0.000	3.110
pseudo R-squared			0.112					0.109		
Number of Obs			17003					17003		

The most important measure are Difference and the corresponding T-Statistic of the "Average Treatment Effect on the Treated" (ATT).

Table 3: Propensity Score Matching - Results Pecking Order Theory.

Treatment			Mean					Mean		
Matching			Nearest Neighbor					Nearest Neighbor		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.344	0.335	0.009	0.004	2.320	0.344	0.335	0.009	0.004	2.320
ATT	0.344	0.350	-0.006	0.006	-1.040	0.344	0.351	-0.007	0.006	-1.190
pseudo R-squared			0.104					0.106		
Number of Obs			17003					17003		
Treatment			Mean					Mean		
Matching			2 Nearest Neighbors					2 Nearest Neighbors		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.344	0.335	0.009	0.004	2.320	0.344	0.335	0.009	0.004	2.320
ATT	0.344	0.346	-0.002	0.005	-0.420	0.344	0.349	-0.006	0.005	-1.080
pseudo R-squared			0.104					0.106		
Number of Obs			17003					17003		
Treatment			Median					Median		
Matching			Nearest Neighbor					Nearest Neighbor		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.350	0.323	0.027	0.003	8.810	0.350	0.323	0.027	0.003	8.810
ATT	0.350	0.351	-0.001	0.005	-0.170	0.350	0.352	-0.002	0.005	-0.390
pseudo R-squared			0.112					0.109		
Number of Obs			17003					17003		
Treatment			Median					Median		
Matching			2 Nearest Neighbors					2 Nearest Neighbors		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.350	0.323	0.027	0.003	8.810	0.350	0.323	0.027	0.003	8.810
ATT	0.350	0.351	-0.001	0.005	-0.230	0.350	0.354	-0.004	0.005	-0.990
pseudo R-squared			0.112					0.109		
Number of Obs			17003					17003		
Treatment			Mean					Mean		
Matching			Kernel					Kernel		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.344	0.335	0.009	0.004	2.320	0.344	0.335	0.009	0.004	2.320
ATT	0.344	0.350	-0.006	0.006	-1.040	0.344	0.351	-0.007	0.006	-1.190
pseudo R-squared			0.104					0.106		
Number of Obs			17003					17003		
Treatment			Median					Median		
Matching			Kernel					Kernel		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.350	0.323	0.027	0.003	8.810	0.350	0.323	0.027	0.003	8.810
ATT	0.350	0.351	-0.001	0.005	-0.170	0.350	0.352	-0.002	0.005	-0.390
pseudo R-squared			0.112					0.109		
Number of Obs			17003					17003		

The most important measure are Difference and the corresponding T-Statistic of the “Average Treatment Effect on the Treated” (ATT).

Table 4: Tobit Regression, Number of Bank Relations

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Standard Errors	Robust	Bootsrap (50)	Robust	Bootsrap (50)	Robust	Bootsrap (50)	Robust	Bootsrap (50)
Dependent Variable	NBR	NBR	NBR	NBR	NBR	NBR	NBR	NBR
Employees	0.005***	0.005**	0.005***	0.005**				
	(0.001)	(0.002)	(0.001)	(0.003)				
Sales					0.000	0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)
Current Assets/Total Assets	0.132**	0.132***	0.168***	0.168***	0.105*	0.105	0.136**	0.136**
	(0.056)	(0.051)	(0.056)	(0.065)	(0.064)	(0.081)	(0.064)	(0.054)
Intangible Assets/Total Assets	-2.178***	-2.178***	-2.192***	-2.192***	-2.413***	-2.413***	-2.433***	-2.433***
	(0.299)	(0.293)	(0.299)	(0.338)	(0.326)	(0.351)	(0.326)	(0.317)
Debt/Total Assets	-0.126**	-0.126**			-0.150**	-0.150**		
	(0.058)	(0.049)			(0.068)	(0.075)		
ST_Debt/LT_Debt			-0.016***	-0.016***			-0.015***	-0.015***
			(0.003)	(0.003)			(0.003)	(0.003)
EBITDA	0.000**	0.000*	0.000**	0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.391***	1.391***	1.328***	1.328***	1.400***	1.400***	1.324***	1.324***
	(0.204)	(0.204)	(0.202)	(0.201)	(0.215)	(0.204)	(0.212)	(0.208)
Industry Dummies	yes		yes		yes		yes	
Main Region Dummies	yes		yes		yes		yes	
pseudo R-squared	0.017		0.018		0.017		0.018	
Log pseudolikelihood	-35063.48		-35042.50		-27959.69		-27944.91	
No of obs	21517		21517		17166		17166	

Note:
(1) * (**) [***] denotes significance at the 10% (5%) [1%] level.
(2) Robust standard errors are reported in parentheses.
(3) Employees is expressed in terms of 100.
(4) Left-censoring begins at 1.

Table 5: Poisson Regression, Number of Bank Relations

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Standard Errors	Robust	Bootsrap (50)	Robust	Bootsrap (50)	Robust	Bootsrap (50)	Robust	Bootsrap (50)
Dependent Variable	NBR	NBR	NBR	NBR	NBR	NBR	NBR	NBR
Employees	0.001***	0.001**	0.001***	0.001*				
	(0.000)	(0.001)	(0.000)	(0.001)				
Sales					0.000	0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)
Current Assets/Total Assets	0.035**	0.035**	0.043***	0.043***	0.028	0.028	0.035*	0.035*
	(0.017)	(0.017)	(0.017)	(0.015)	(0.019)	(0.024)	(0.019)	(0.021)
Intangible Assets/Total Assets	-0.659***	-0.659***	-0.664***	-0.664***	-0.728***	-0.728***	-0.734***	-0.734***
	(0.088)	(0.086)	(0.088)	(0.100)	(0.095)	(0.094)	(0.095)	(0.090)
Debt/Total Assets	-0.029*	-0.029*			-0.036*	-0.036*		
	(0.017)	(0.017)			(0.020)	(0.019)		
ST_Debt/LT_Debt			-0.004***	-0.004***			-0.003**	-0.003**
			(0.001)	(0.001)			(0.001)	(0.001)
EBITDA	0.000**	0.000***	0.000**	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.609***	0.609***	0.594***	0.594***	0.617***	0.617***	0.599***	0.599***
	(0.061)	(0.065)	(0.061)	(0.065)	(0.063)	(0.072)	(0.063)	(0.075)
Industry Dummies	yes		yes		yes		yes	
Main Region Dummies	yes		yes		yes		yes	
pseudo R-squared	0.010		0.010		0.010		0.011	
Log pseudolikelihood	-35235.57		-35226.66		-28096.68		-28090.29	
No of obs	21517		21517		17166		17166	

Note:
(1) * (**) [***] denotes significance at the 10% (5%) [1%] level.
(2) Robust standard errors are reported in parentheses.
(3) Bootstrapped standard errors are calculated based on 50 replications.
(4) Employees is expressed in terms of 100.

Table 6: Logistic Regression, All Firms

	(I)		(II)		(III)		(IV)	
dependent variable	Relationship Banking 0/1		Relationship Banking 0/1		Relationship Banking 0/1		Relationship Banking 0/1	
	Coeff.	Odds Ratio	Coeff.	Odds Ratio	Coeff.	Odds Ratio	Coeff.	Odds Ratio
Employees	-0.009***	1.000	-0.008***	1.000				
	(0.003)		(0.003)					
Sales					0.000	1.000	0.000	1.000
					(0.000)		(0.000)	
Current Assets/Total Assets	-0.223***	0.800	-0.253***	0.776	-0.160*	0.852	-0.179**	0.836
	(0.076)		(0.077)		(0.084)		(0.085)	
Intangible Assets/Total Assets	2.314***	10.116	2.341***	10.389	2.371***	10.707	2.404***	11.069
	(0.354)		(0.354)		(0.369)		(0.369)	
Debt/Total Assets	0.269***	1.309			0.280***	1.323		
	(0.085)				(0.096)			
ST_Debt/LT_Debt			0.018***	1.018			0.015***	1.015
			(0.004)				(0.004)	
EBITDA	0.000***	1.000	0.000***	1.000	0.000	1.000	0.000	1.000
	(0.000)		(0.000)		(0.000)		(0.000)	
Constant	-0.469		-0.337		-0.508*		-0.368	
	(0.288)		(0.285)		(0.295)		(0.292)	
Industry Dummies	yes		yes		yes		yes	
Main Region Dummies	yes		yes		yes		yes	
No of obs	21517		21517		17166		17166	
Correctly Classified	73.10%		73.15%		71.60%		71.63%	
Area under ROC Curve	0.639		0.642		0.632		0.635	

Note:
(1) * (**) [***] denotes significance at the 10% (5%) [1%] level.
(2) Robust standard errors are reported in parentheses.
(3) Employees is expressed in terms of 100.

Table 7: Propensity Scor Matching - Results Prediction 3. - According to Table 6 (I).

Treatment			Relationship Banking					Relationship Banking		
Matching			Nearest Neighbor					Nearest Neighbor		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.700	0.024	0.026	-0.002	0.000	-9.700
ATT	0.024	0.026	-0.002	0.000	-7.670	0.024	0.026	-0.002	0.000	-7.140
pseudo R-squared			0.041					0.041		
Number of Obs			21517					21517		
Treatment			Relationship Banking					Relationship Banking		
Matching			2 Nearest Neighbors					2 Nearest Neighbors		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.700	0.024	0.026	-0.002	0.000	-9.700
ATT	0.024	0.026	-0.003	0.000	-9.840	0.024	0.026	-0.002	0.000	-7.930
pseudo R-squared			0.041					0.041		
Number of Obs			21517					21517		
Treatment			Relationship Banking					Relationship Banking		
Matching			3 Nearest Neighbors					3 Nearest Neighbors		
Model			Logit					Probit		
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.700	0.024	0.026	-0.002	0.000	-9.700
ATT	0.024	0.026	-0.003	0.000	-9.710	0.024	0.026	-0.002	0.000	-8.490
pseudo R-squared			0.041					0.041		
Number of Obs			21517					21517		

The most important measure are Difference and the corresponding T-Statistic of the "Average Treatment Effect on the Treated" (ATT).

Table 8: Propensity Scor Matching - Results Prediction 3. - According to Table 6 (II).

Treatment	Relationship Banking					Relationship Banking				
Matching	Nearest Neighbor					Nearest Neighbor				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.700	0.024	0.026	-0.002	0.000	-9.700
ATT	0.024	0.026	-0.002	0.000	-6.640	0.024	0.026	-0.002	0.000	-6.010
pseudo R-squared			0.042					0.042		
Number of Obs			21517					21517		
Treatment	Relationship Banking					Relationship Banking				
Matching	2 Nearest Neighbors					2 Nearest Neighbors				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.700	0.024	0.026	-0.002	0.000	-9.700
ATT	0.024	0.026	-0.002	0.000	-7.440	0.024	0.026	-0.002	0.000	-7.380
pseudo R-squared			0.042					0.042		
Number of Obs			21517					21517		
Treatment	Relationship Banking					Relationship Banking				
Matching	3 Nearest Neighbors					3 Nearest Neighbors				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.700	0.024	0.026	-0.002	0.000	-9.700
ATT	0.024	0.026	-0.002	0.000	-7.790	0.024	0.026	-0.002	0.000	-7.900
pseudo R-squared			0.042					0.042		
Number of Obs			21517					21517		

The most important measure are Difference and the corresponding T-Statistic of the "Average Treatment Effect on the Treated" (ATT).

Table 9: Propensity Scor Matching - Results Prediction 3. - According to Table 6 (III).

Treatment	Relationship Banking					Relationship Banking				
Matching	Nearest Neighbor					Nearest Neighbor				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.150	0.024	0.026	-0.002	0.000	-9.150
ATT	0.024	0.026	-0.002	0.000	-7.110	0.024	0.026	-0.002	0.000	-5.400
pseudo R-squared			0.037					0.037		
Number of Obs			17166					17166		
Treatment	Relationship Banking					Relationship Banking				
Matching	2 Nearest Neighbors					2 Nearest Neighbors				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.150	0.024	0.026	-0.002	0.000	-9.150
ATT	0.024	0.026	-0.003	0.000	-8.350	0.024	0.026	-0.002	0.000	-7.290
pseudo R-squared			0.037					0.037		
Number of Obs			17166					17166		
Treatment	Relationship Banking					Relationship Banking				
Matching	3 Nearest Neighbors					3 Nearest Neighbors				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.150	0.024	0.026	-0.002	0.000	-9.150
ATT	0.024	0.026	-0.003	0.000	-8.820	0.024	0.026	-0.002	0.000	-7.420
pseudo R-squared			0.037					0.037		
Number of Obs			17166					17166		

The most important measure are Difference and the corresponding T-Statistic of the "Average Treatment Effect on the Treated" (ATT).

Table 10: Propensity Scor Matching - Results Prediction 3. - According to Table 6 (IV).

Treatment	Relationship Banking					Relationship Banking				
Matching	Nearest Neighbor					Nearest Neighbor				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.150	0.024	0.026	-0.002	0.000	-9.150
ATT	0.024	0.026	-0.002	0.000	-5.810	0.024	0.026	-0.002	0.000	-6.520
pseudo R-squared			0.038					0.038		
Number of Obs			17166					17166		
Treatment	Relationship Banking					Relationship Banking				
Matching	2 Nearest Neighbors					2 Nearest Neighbors				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.150	0.024	0.026	-0.002	0.000	-9.150
ATT	0.024	0.026	-0.002	0.000	-6.960	0.024	0.026	-0.002	0.000	-7.310
pseudo R-squared			0.038					0.038		
Number of Obs			17166					17166		
Treatment	Relationship Banking					Relationship Banking				
Matching	3 Nearest Neighbors					3 Nearest Neighbors				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.150	0.024	0.026	-0.002	0.000	-9.150
ATT	0.024	0.026	-0.002	0.000	-7.340	0.024	0.026	-0.002	0.000	-8.000
pseudo R-squared			0.038					0.038		
Number of Obs			17166					17166		

The most important measure are Difference and the corresponding T-Statistic of the “Average Treatment Effect on the Treated” (ATT).

Table 11: Propensity Scor Matching - Results Prediction 3. - According to Table 6 - Kernel.

Treatment	Relationship Banking (I)					Relationship Banking (I)				
Matching	Kernel					Kernel				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.700	0.024	0.026	-0.002	0.000	-9.700
ATT	0.024	0.026	-0.002	0.000	-7.670	0.024	0.026	-0.002	0.000	-7.140
pseudo R-squared			0.041					0.041		
Number of Obs			21517					21517		
Treatment	Relationship Banking (II)					Relationship Banking (II)				
Matching	Kernel					Kernel				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.700	0.024	0.026	-0.002	0.000	-9.700
ATT	0.024	0.026	-0.002	0.000	-6.640	0.024	0.026	-0.002	0.000	-6.010
pseudo R-squared			0.042					0.042		
Number of Obs			21517					21517		
Treatment	Relationship Banking (III)					Relationship Banking (III)				
Matching	Kernel					Kernel				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.150	0.024	0.026	-0.002	0.000	-9.150
ATT	0.024	0.026	-0.002	0.000	-7.110	0.024	0.026	-0.002	0.000	-5.400
pseudo R-squared			0.037					0.037		
Number of Obs			17166					17166		
Treatment	Relationship Banking (IV)					Relationship Banking (IV)				
Matching	Kernel					Kernel				
Model	Logit					Probit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.024	0.026	-0.002	0.000	-9.150	0.024	0.026	-0.002	0.000	-9.150
ATT	0.024	0.026	-0.002	0.000	-5.810	0.024	0.026	-0.002	0.000	-6.520
pseudo R-squared			0.038					0.038		
Number of Obs			17166					17166		

The most important measure are Difference and the corresponding T-Statistic of the "Average Treatment Effect on the Treated" (ATT).