INTANGIBLE ASSETS AND THE DETERMINANTS OF A SINGLE BANK RELATION OF GERMAN SMES

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ABSTRACT

We focus on the determinants and potential benefits of relationship banking. Based on the existing literature and the unique role intangible assets play regarding firms' capital structure, we test two hypotheses using rich data on firm-bank relationships in Germany. We show that firstly, a high share of intangible assets does not worsen the access of firms to debt financing. And secondly, firms with a high share of intangible assets are statistically significantly more likely to choose an exclusive and persistent bank relation.

KEY WORDS

relationship banking, SME, bank lending, capital structure, intangible assets

JEL CODES

G21, G32, D82, C21

1 INTRODUCTION

Germany represents an example of a bank-based financial system (Allen and Gale, 1995) characterized by strong ties between banks and firms. The German economy is shaped by a strong role of small and medium enterprises (SMEs) which are mainly financed through bank loans, making firm-bank relationships very important in Germany. Furthermore, SMEs cannot easily substitute bank loans with corporate debt during a credit crunch (Giesecke et al., 2012). In addition, one very specific characteristic of the German banking system is the existence of long-term bank relationships that firms engage in with specific banks, referred to as "house banks". A house bank acts as the main lender of a firm and acquires more relevant and more timely information about it.

Recent work by Cecchetti and Kharroubi (2015) provides robust empirical evidence that financial sector growth is a drag on real growth. Regarding the mechanism behind this finding, Cecchetti and Kharroubi (2015) introduce the

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assumption that growth in finance reflects improving technology for recovering debt in cases of default. Their theoretical model implies that financial sector growth disproportionally benefits sectors with output or assets that are more tangible. Confronting their theoretical model with the data, Cecchetti and Kharroubi (2015) find that financial sector growth benefits industries with higher asset tangibility, but harms R&D-intensive industries. This distributional effect of financial sector growth harms what economists consider engines of growth – namely, industries with lower asset tangibility or high R&D-activities (Cecchetti and Kharroubi, 2015).

Compared with arm's-length lending, there are two distortions due to relationship banking (Rajan, 1992) emphasised in the literature. Firstly, relationship lending causes poor price signals which can distort the allocation of funds. Hoshi et al. (1990) find that investments 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). In addition, a more bank-based system has a comparative disadvantage in financing intangible assets (Rajan and Zingales, 2001; Hoshi et al., 1991).

However, Germany's economy, characterized by a bank-based financial system, strong ties between banks and firms and a high share of small and medium enterprises, delivered a stable performance during the years of crises and attracted international attention. German banks with strong ties to their clients actually finance intangible assets. Therefore, the specific characteristics of relationship banking in the German financial system warrant more detailed inspection.

Our paper contributes to a broad literature. Theoretical contributions emphasize the benefits of reduced asymmetric information but also the costs of an information monopoly by banks (Boot, 2000). Results of empirical studies regarding financing conditions associated with relationship banking are mixed (Kysucky and Norden, 2016). Studies devoted to financing conditions were followed by studies focusing on firms' choice of the number of bank relations (see e.g. Farinha and Santos, 2002; Ogawa et al., 2007). However, we should keep in mind that the question of how many bank relations a firm chooses is inherently different from the question of why a firm chooses a single instead of multiple bank relations. In the following, we will focus only on the second question.

In particular, we discuss the relationship between intangible assets, capital structure and a strong tie between the firm and the bank represented by a single bank relation for German SMEs. To the best of our knowledge, the relationship between intangible assets and the number of bank relations has not yet been analyzed in the previous literature. Yet, intangible assets represent an increasingly important phenomenon (Cecchetti and Kharroubi, 2015). Using a large dataset for German SMEs and their bank relations between 2005 and 2012, we test two hypotheses. Firstly, do intangible assets worsen firms' access to external finance, as capital structure literature predicts? Following the rejection of this hypothesis, we test, secondly, whether firms with a high fraction of intangible assets are more likely to have a single bank relation?

The centerpiece of our contribution is the question of why firms decide to have a single bank relation. Based on the results of testing the first hypothesis, we employ intangible assets as an explanatory variable in a binary regression in order to identify the determinants of a single bank relation. The share of intangible assets ought to increase the probability of a strong firm-bank relation due to the firm's need to use the associated soft information channel in order to reduce financing frictions. We find that the share of intangible assets significantly increases the probability of an exclusive and persistent bank relation.

Our paper is structured as follows: the second chapter provides a literature review which summarizes theoretical and empirical contributions; the third chapter outlines our hypotheses; the fourth chapter illustrates the data; the fifth chapter provides empirical results followed by robustness analyses in chapter six; chapter seven concludes.

2 LITERATURE REVIEW

2.1 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 so-called delegated monitoring model implies that firms operate with a single bank which pools the costs of asymmetric information (Diamond, 1984). By having only one lender the firm minimizes its transaction costs. The optimality of a single bank relation changes when repeated lending is considered (Sharpe, 1990). Other theoretical reasons for choosing more than one bank relation are e.g. diversification as insurance against the loss of 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 very similar firms prefer a strong firm-bank relation.

The theoretical literature 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.

The idea of an advantage in the firm-bank relationship arising from the 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 lower interest rates. This approach is compared to an approach where banks provide loans without “discriminating” between good and bad firms. The bank charges an average interest rate to firms. Boot and Thakor (1994) show that even if monitoring is costly, both, the firm and the bank profit from the close firm-bank relation. Therefore, banks acquire information about firms to be able to provide loans with terms and conditions specific to the individual firms’ situation.

Petersen and Rajan (1995) show that in a two-period model with *good* and *bad* entrepreneurs banks also have an incentive to charge high interest rates initially 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.

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 firm’s 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 is more pronounced if information asymmetry is high, i.e. if the difference between information of insiders vs. outsiders increases. One possible solution to 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 Empirical Evidence

To assess costs and benefits of a strong firm-bank relation empirically, one has to proxy for the strength of the relation. Kysucky and Norden (2016) 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. the number of banks the firm lends from), physical distance and the integration of the firm-bank relation (e.g. the number of financial services the firm obtains).

Empirical results are mixed. Petersen and Rajan (1994) were the first to empirically study the relationship between different dimensions of the strength of lending relationships with the availability and cost of funds. In a sample of US SMEs, collected from the National Survey of Small Business Finance (NSSBF), they find that firms borrowing from multiple lenders are charged significantly higher rates. The length and integration of the relationship do not affect price conditions. However, the availability of credit increases if firms spend more time in a relationship, if they increase the number of financial services they obtain in a relationship 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 the existence of a previous relationship, but not its length, is an important factor for credit availability.

Harhoff and Körting (1998) study a large sample of German SMEs. They proxy for the strength of the firm-bank relationship using 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 influence the costs of credit. However, collateral requirements improve with the strength of the relationship, as measured by both of these proxies.

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 about whether or not a bank has house bank status is used. They show that factors related to the information access of banks are important determinants. However, the duration of the bank-borrower relationship is not related to house bank status. They empirically show that house banks provide liquidity insurance in case of unexpected deteriorations of borrower ratings. Mayer et al. (1988) describe this insurance as banks 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.

Degryse and Ongena (2005) study the effect of geographical distance on bank loan rates. Using a unique data set of loans made to SMEs 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 relatively more credit is available to young firms. This finding is reflected in below-market rates for young firms and, conversely, above-market rates for more mature firms.

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 intensity after the IPO. The U-shaped pattern of interest rates is rationalized by information asymmetries between relationship banks and outside banks.

2.3 Number of Bank Relations

Early studies of relationship banking (see e.g. Petersen and Rajan, 1994; Harhoff and Körting, 1998; Cole, 1998) use the number of bank relationships as a proxy for competition among banks. The investigation of banks' choice of the number of relations then 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 relies on 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. Similarly to Houston and James (1996), Ongena and Smith (2000) find that firms with multiple bank relations 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, meaning that their results indicate that firms with considerable growth options are less likely to be financed by a single bank. Houston and James (2001) explain this finding by banks' lending being focused on so-called hard assets and their corresponding inability to fund firms with substantial amounts of intangible growth opportunities.

Farinha and Santos (2002) focus on firms' decisions 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 relationship 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 that have more growth opportunities or perform poorly, respectively. The first finding is explained by a lemon premium, increasing over time, which firms face when approaching an additional lender. The second finding is explained by banks limiting their exposure 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 of creditors for a firm given the existence of a main lender. It is 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 logistic regression to address the question of why firms choose a single or multiple loans. Hence, their question and approach is closely related to our analysis. 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 multinomial logistic regression they find that the determinants of the amount of bank relations conditional on having more than one bank relation are different the determinants of the choice of a single bank relation.

3 HYPOTHESES

Relationship banking received considerable attention throughout the literature. However, we intend to be less agnostic regarding the decision of engaging in only one bank relation.

Motivated by Hall and Lerner (2010), who argue that intangible assets[1] 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. It is worth noting that research and development, as well as a highly skilled workforce, are among the main determinants of the creation of intangible assets.

Even though they are in themselves conflicting theories, both the trade-off theory of capital structure (Modigliani and Miller, 1963) and the pecking order theory (Myers and Majluf, 1984) imply difficulties to debt-finance intangible assets. The trade-off theory of capital structure describes a firm's debt-equity decision as a trade-off between an interest tax shield and the costs of financial distress, where intangible assets ought to rely primarily on equity financing (Brealey et al., 2008). The pecking order theory implies that management prefers the issuance of debt over equity, but this does not apply to intangible assets for which equity is the preferable way of financing (Brealey et al., 2008).

Benmelech and Bergman (2009) construct a measure of asset redeployability as a proxy of the value of 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 as well as loan-to-value ratios in an economically significant manner. In addition, Fabbri and Menichini (2010) find that firms' financing decisions depend in multiple ways on the collateral value of their inputs, such that for example, trade credit for sufficiently liquid inputs purchased on account is not subject to credit rationing. Distinguishing between current assets and intangible assets, the former are understood to be relatively liquid and easier to redeploy than the latter.

Thus, taking into account the capital structure literature and the role of asset redeployability, we hypothesize that a higher share of intangible assets ought to be associated with more equity-financing. This leads to our first null-hypothesis, which we expect to reject:

Hypothesis 1. A higher fraction of intangible assets is not associated with a higher equity ratio.

In order to bring these considerations into connection with relationship banking and the number of bank relations, we look at the way that, as previously noted, relationship banking provides a channel for soft information. 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 (Göx and Wagenhofer, 2009) may theoretically give rise to the need of channeling soft information.

Thus, if achieving optimal financing conditions is a reason to engage in relationship banking with only one single bank and intangible assets represent by their nature a source of financing frictions, the causal chain we propose becomes clear. To the best of our knowledge, a causal relationship between intangible assets and the number of bank relations has not been studied in the literature yet.[2] Our second null-hypothesis states:

[1]Across the literature, definitions of intangible assets are manifold (see for example Ahonen, 2000; Petty and Guthrie, 2000; Sveiby, 1997) and even from the perspective of financial reporting according to the International Financial Reporting Standards (IFRS), valuing acquired as well as self-generated intangible assets is still seen as a black art due to the enormous difficulties and risks associated with measurement (Sharma, 2012).

[2]In addition, 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). As noted, research and development contributes to the creation of intangible assets.

Hypothesis 2. Firms with a high fraction of intangible assets should not be more likely to have only relations with one single bank.

Hence, our contribution focuses on firms' financing conditions and the corresponding borrowing relations; it thus emphasizes firms' decisions to engage in relationship banking. We understand *Hypothesis 2* to be our main contribution.

4 DATA AND DESCRIPTIVE STATISTICS

Our data come from the 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 firms is relatively good for data from the period of 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 on their balance sheets, with the debt part being composed of bank loans only.

4.1 Dependent Variable: Number of Bank Relations

In addition to information on balance sheets and profit and loss accounts, the Amadeus databank provides the amount of bank relations firms had between 2005 and 2012. The number of banks relations serves as the main dependent variable in the later analysis. However, the information about the number of bank accounts is aggregated in the following way: for each firm, the maximum number of different bank accounts within the time period from 2005 to 2012 is given. Assume for example a firm with bank accounts at Bank A and B for the period from 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. Thus, the information regarding the number of bank relations is not time-varying. Therefore, we limit our analysis to the cross section when the number of bank relations is used as dependent variable. After dropping observations subject to logical errors, missing data, and outliers at the firm level, the time-invariant nature of the variable for bank relations requires us to aggregate all variables over years by calculating their arithmetic means, which reduces our sample to a cross-section including roughly 22,000 observations. In the robustness section, we also look into selected years to ensure that our results are not driven by the aggregation of the data.

By collapsing our data into the cross-section, the variable *number of banks* satisfies two out of four prominent proxies for relationship banking (Kysucky and Norden, 2016). 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 the same bank over six years. This has the advantage that we can identify firms which operated with only one bank between 2005 and 2012. In addition, we are able to distinguish between the main players in the German banking market. For all firms that have only one bank relation, we can distinguish between relations with Deutsche Bank, Commerzbank, Cooperative Banks (Genossenschaftsbanken), and Saving Banks (Sparkassen).

Fig. 1 (Panel A) shows the distribution of 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 the 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

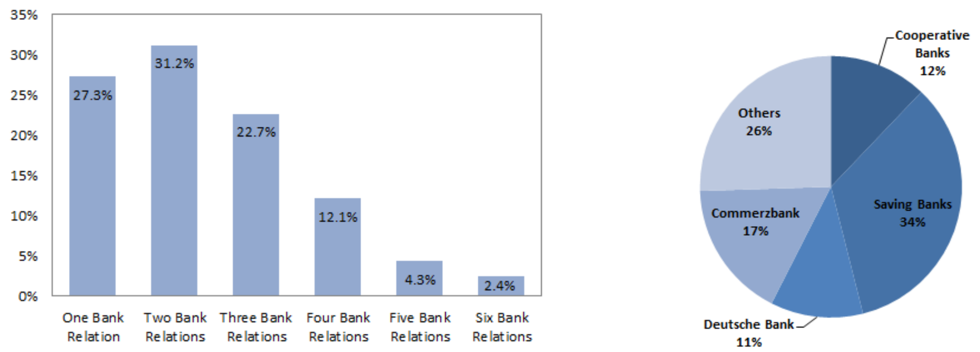

Fig. 1: Stylized Facts: This figure shows the distribution of the number of bank relations in our sample (Panel A) and the distribution of bank types among the firms with a single bank relation (Panel B).
Panel A (left): Bank Relations. This figure shows the distribution of bank relations for all 21,517 firms in our sample.
Panel B (right): Relationship Lending. This figure shows the distribution of bank types among all 5,874 firms with only one bank relation.

and more than one bank relations. Fig. 1 (Panel B) 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 the German banking market.

In Tab. 1, we present summary statistics of 21,517 firms. In columns (1), (2), and (3) we present the 25% quantile, the median, and the 75% quantile of firm characteristics, respectively. In columns (4), (5), and (6) the mean values of firm characteristics for 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 (as measured by total assets). We, therefore, conclude that size cannot be the main explanation for a difference in the number of banks. Most importantly, we find the most pronounced difference in the shares of intangible and current assets. Firms with only one bank relation have a higher share of intangible assets and a lower share of current assets on average, which is in line with our hypothesis.

4.2 Explanatory Variable: Share of Intangible Assets

Intangible assets are assets that are not physical in nature. Examples are corporate intellectual property, including items such as patents, trademarks, copyrights, software, and business methodologies, as well as goodwill, and brand recognition. Under IFRS intangible assets are defined as an identifiable non-monetary asset without physical substance. An asset is a resource that is controlled by the entity as a result of past events (for example, purchase or self-creation) and from which future economic benefits (inflows of cash or other assets) are expected. Thus, the three critical attributes of an intangible asset are identifiability, control (power to obtain a benefit from the intangible asset), and future economic benefits.

Our data allows to differentiating between four categories of intangible assets. First, patents which make the largest fraction with 37.21%. Second, Rights which include all forms of user rights, copyrights, and licenses (e.g., software). About 31.49% of intangible assets fall in this category. Third, goodwill which makes up 14.36%. This smaller fraction is not unusual since our dataset consists only of German SMEs, which are less likely to engage in M&A transactions. All other intangible assets are in the fourth group (other). The main fraction of intangible assets falls in the categories patents and rights. When firms apply for debt financing, intangible assets in both categories have high valuation risk and poor collateralizability. According to Lim et al. (2016) these characteristics of intangible assets can discourage debt financing. Yet, intangible assets can generate cash

Tab. 1: Descriptive Statistics: Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	25% Quantile	**Median**	**75% Quantile**	**> 1 Bank Relation** (mean)	**1 Bank Relation** (mean)	**Difference**
Size Variables						
Sales [TEUR]	9,540	20,891	53,808	83,214	94,162	10,948
Employees	43	90	191	286	281	−5
Total Assets [TEUR]	5,773	10,854	28,248	55,631	78,022	22,391***
Balance Sheet Items						
Equity / TA	0.1738	0.3044	0.4731	0.3350	0.3390	0.0040
ST_Debt / TA	0.1630	0.2979	0.4660	0.3300	0.3270	−0.0030
LT_DebT / TA	0.1975	0.3124	0.4463	0.3350	0.3340	−0.0010
Debt / TA	0.5269	0.6956	0.8262	0.6650	0.6610	−0.0040
Intangible Assets / TA	0.0861	0.2317	0.4664	0.0120	0.0190	0.0070***
Current Assets / TA	0.4551	0.6920	0.8587	0.6560	0.5960	−0.0600***
Profit & Loss						
Cashflow / TA	0.0494	0.0851	0.1350	0.1027	0.9811	0.8784
EBITDA / TA	0.0723	0.1224	0.1852	0.1446	0.0072	−0.1374
Interest Rate	0.0138	0.0242	0.0351	0.0260	0.0240	−0.0020***

Notes: This table presents firm characteristics for 21,517 firms. In column (6) the results of a difference in means test are reported. The null hypothesis is difference=0 where difference equals mean(1)-mean(0) with mean(1) representing firms with only one bank relation and mean(0) representing all other firms. Signs ***, **, and * denote significance on the 1%, 5%, and 10% level, respectively. Balance Sheet items, as well as Cashflow and EBITDA, are standardized by Total Assets (TA).

flows just as reliably as tangible assets and may, therefore, support debt like tangible assets do. The major challenge for banks is to assess the value of intangible assets when debt financing is required by the firm. Soft information, acquired by a strong firm-bank relation can help to reduce information asymmetry and make debt financing more attractive for both, banks and firms. We, therefore, argue that a strong bank firm relation helps to overcome the challenges and allows firms with a high share of intangible assets to finance with debt.

To test this hypothesis empirically, we use the fraction of intangible assets as explanatory. This creates a potential endogeneity problem. If firms with a higher share of intangible assets are on average more profitable compared to firms with a lower share of intangible assets, we might measure profitability by the fraction of intangible assets. To test whether an endogeneity problem exists, we employ three tests:[3] First, we check the correlation between the share of intangible assets and corporate performance measures (ROE, ROA, interest coverage ratio, and profit margin). Second, we regress corporate performance measures on the share of intangible assets including control variables in panel regression. Third, in Section 5, we compare the percentage of firms that have one bank relation between firms with a higher share of intangible assets and those with lower share, using propensity score matching.

Panel A of Tab. 2 shows the correlation coefficients between the share of intangible assets and Return on Equity, Return on Assets, Interest Coverage Ratio, and Profit Margin. All coefficients are close to zero and negative. In addition, only the correlations between the share of intangible assets and ROA and ROE are significant. These results provide support against an endogeneity problem.

[3]We thank an anonymous referee for this suggestion.

Tab. 2: The Relation between Profitability and the Share of Intangible Assets

	(1)	(2)	(3)	(4)
Panel A				
Profitability measure	**ROE**	**ROA**	**ICR**	**Profit Margin**
Correlation with Intangible Assets	−0.0052**	−0.0087**	−0.0007	−0.0001
Panel B				
Dependent variable	**ROE**	**ROA**	**ICR**	**Profit Margin**
Intangible Assets/Total Assets	−0.439	−0.032	−1,834.348	−14.214
Controls	yes	yes	yes	yes
State fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Number of Firms:	21,517	21,517	21,517	21,517
Number of Years:	6.71	6.71	6.71	6.71

Notes: This table presents results of a correlation analysis (Panel A) and of four panel regressions (Panel B). In Panel A the correlation between the share of intangible assets and four profitability measures are presented. The correlations are calculated in the cross section and average values per firm are used. In Panel B the results of four OLS panel regressions are presented. The profitability measures are Return on Equity (ROE, column 1), Return on Assets (ROA, Column 2), Interest Coverage Ratio (ICR, Column 3), and Profit Margin (Column 4). Signs ***, **, and * denote significance on the 1%, 5%, and 10% level, respectively.

We also analyze the relation of intangible assets and corporate performance in a multivariate panel framework. Panel B of Tab. 2 presents the results of four OLS panel regressions with ROA, ROE, Interest Coverage Ratio, and Profit Margin as the dependent variable, respectively. In all four regression firm and time fixed effects are included. The set of control variables contains the number of employees, fixed assets, current assets, and equity, all standardized by total assets. The coefficient of the share of intangible assets is insignificant in all four regressions, providing further support against an endogeneity problem. Results of the third test are presented in Section 5.

5 ESTIMATION AND RESULTS

5.1 Capital Structure

Both the trade-off theory of capital structure and the pecking order theory imply that intangible assets impair debt-financing. Thus, firms whose share of intangible assets is above one of the thresholds used here ought to have higher equity ratios.

To address this question, we apply propensity score matching as introduced by Rosenbaum and Rubin (1983 and 1985) and implemented by Leuven and Sianesi (2003). We use the Average Treatment Effect on the Treated (ATT) to identify the effects of a higher share of intangible assets on firms' capital structure. Thereby, our treatment group are firms with a high share of intangible assets. As stated by Stuart (2010), when estimating causal effects using observational data, it is desirable to replicate a randomized experiment as closely as possible by obtaining treated and control groups with similar covariate distributions. This goal can often be achieved by choosing well-matched samples of the original treated and control groups, thereby reducing bias due to the covariates. We apply this method to match firms with a high share of intangible assets with firms with a low share. However, since our matching variable (share of intangible assets) is continuous, defining the treatment group is not trivial. Therefore, we define three different treatment groups and match firms accordingly.

The first treatment group consists of firms with a share of intangible assets (IA) larger than zero. We match this group with firms without any intangible assets. However, since it might make a difference whether a firm has only a small fraction of intangible assets or almost entirely consists of intangible assets (e.g., Coca Cola) we use also the mean and median share of intangible assets as the threshold for the treatment group. The sample median is approximately 0.03%, whereas the mean is approximately 1.44%.

Firms whose share of intangible assets is above one of these three thresholds ought to face higher equity ratios, according to the capital structure literature and the role of asset redeployability. Since the share of intangible assets is not assigned completely at random to firms, the probability of receiving treatment $P(D=1)$ or receiving no treatment $P(D=0)$, will be estimated conditional on the following confounders: firm size (proxied by sales and number of employees); tangible assets (standardized by total assets); long-term debt (standardized by total assets); short-term debt (standardized by total assets); cash flow (standardized by total assets); EBITDA (standardized by total assets); net income (standardized by total assets); industry dummies; main economic regions dummies. We do not include current assets since current assets and tangible assets are highly correlated (correlation: -0.89***). The correlation between intangible assets and tangible assets is too small cause a multicollinearity problem (correlation: -0.0814). The outcome variable, Y, is firms' equity ratio, which equals equity divided by total assets. The estimated "Average Treatment Effect on the Treated" (ATT) is

$$\begin{aligned} \text{ATT} &= E\left[Y(1) \mid D=1\right] - \\ &\quad - E\left[Y(0) \mid D=0\right] + \text{SB}, \quad (1) \end{aligned}$$

where $E\left[Y(1) \mid D=1\right]$ is the expected outcome given treatment, $E\left[Y(0) \mid D=0\right]$ is the expected outcome in the absence of treatment, and SB is the selection bias.

We estimate equation (1) in various permutations. The treatment is varied in that it refers to the share of intangible assets exceeding either the sample mean or the median or zero. The matching algorithm is varied between the nearest neighbor, the two nearest neighbors, the three nearest neighbors or a normally distributed kernel using a range of 0.06. Covering all possible combinations, we run twelve propensity score matching estimations.

The ATT is estimated in the cross section since our main dependent variable, the number of bank relations, is not time varying and we want to apply a consistent methodology throughout the analysis. The panel data is collapsed to the cross section by taking averages over time by firm. For example, if we observe the share of intangible assets for company A over a time period of six years, we use the average share of intangible assets over that time period. For robustness, we also apply panel estimations of the ATT. The results are similar and therefore not reported.

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. This can be seen for all three thresholds. For example, if we compare firms with a share of intangible assets greater than the median to those with intangible assets smaller or equal to the median, the mean difference in the equity ratio is 0.027. This difference is significant on the 1% level (t-value of 8.81). However, if we employ equity ratio as the outcome variable Y according to equation (1), Tab. 3 shows that the differences in equity ratios disappear comparing matched firms. This holds for all three thresholds and all four matching algorithms. We cannot reject the null-hypothesis 1. This suggests that intangible assets are determined without regard to capital structure. We expect the reason for this to be relationship banking.

The R-squared in logistic regressions can be interpreted as a measure of heterogeneity. In our specifications, the low value of the pseudo R-squared reveals that average heterogeneity is low. For the main specifications, Fig. 2, 3, and 4 visualize that observations are quite equally distributed along the propensity score, especially when the mean and median are used as thresholds. The technically high quality of our estimations supports the approach.

Tab. 3: Propensity Score Matching – Results – Inangible Assets and Equity Ratio

Treatment	Intangible Assets > Mean					Intangible Assets > Mean				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.344	0.335	0.009**	0.004	2.290	0.344	0.335	0.009**	0.004	2.290
ATT	0.344	0.343	0.001	0.006	0.090	0.344	0.344	0.000	0.005	0.020
pseudo R-squared	0.104					0.104				
Number of Obs	17004					17004				
Treatment	Intangible Assets > Mean					Intangible Assets > Mean				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.344	0.335	0.009**	0.004	2.290	0.344	0.335	0.009**	0.004	2.290
ATT	0.344	0.345	−0.001	0.005	−0.270	0.344	0.343	0.001	0.006	0.090
pseudo R-squared	0.104					0.104				
Number of Obs	17004					17004				
Treatment	Intangible Assets > Median					Intangible Assets > Median				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	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	0.356	−0.006	0.005	−1.220	0.350	0.354	−0.004	0.005	−0.970
pseudo R-squared	0.112					0.112				
Number of Obs	17004					17004				
Treatment	Intangible Assets > Median					Intangible Assets > Median				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	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	0.354	−0.004	0.004	−0.900	0.350	0.356	−0.006	0.005	−1.220
pseudo R-squared	0.112					0.112				
Number of Obs	17004					17004				
Treatment	Intangible Assets > 0					Intangible Assets > 0				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.341	0.289	0.052***	0.005	9.620	0.341	0.289	0.052***	0.005	9.620
ATT	0.341	0.351	−0.010	0.013	−0.730	0.341	0.341	0.001	0.012	0.050
pseudo R-squared	0.141					0.141				
Number of Obs	17004					17004				
Treatment	Intangible Assets > 0					Intangible Assets > 0				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.341	0.289	0.052***	0.005	9.620	0.341	0.289	0.052***	0.005	9.620
ATT	0.341	0.345	−0.003	0.011	−0.280	0.341	0.351	−0.010	0.013	−0.730
pseudo R-squared	0.141					0.141				
Number of Obs	17004					17004				

Notes: This table shows the results of twelve propensity score matching estimations. The term *Logit* expresses that the matching algorithm is based on a logistic regression framework. The twelve estimations are the combination of three different definitions for the treatment group (intangible assets larger than: zero, the sample median, or the sample mean) with four different matching algorithms (matching by: nearest neighbor, the two nearest neighbors, the three nearest neighbors, and a normally distributed kernel with a range of 0.06). For each estimation the average equity ratio for the treatment group (“treated”) and the control group (“Controls”), as well as the mean difference (“Difference is shown. Under S.E. we show the standard error of a mean comparison test and the corresponding t-statistic. The difference and the t-statistic of the “Average Treatment Effect on the Treated” (ATT) are the most important measures. The measures show whether the *equity ratio* (defined as equity / total assets) of treated firms significantly differs from that of untreated firms. Signs ***, **, and * indicate significance on the 1%, 5%, and 10% level, respectively.

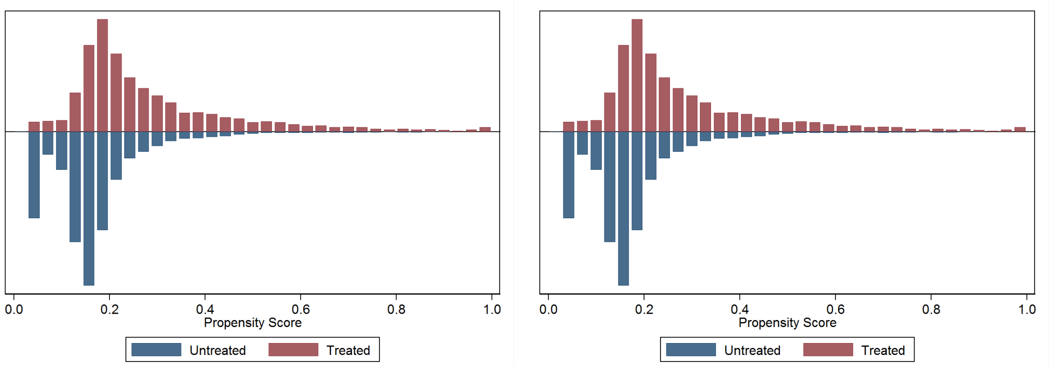

Fig. 2: Propensity Score Matching with threshold "mean share of intangible assets" – Quality. This figure shows the distribution of all 21,517 firms along the propensity score for the mean share of intangible assets as threshold and the nearest neighbor (panel A) and kernel (panel B) matching algorithm

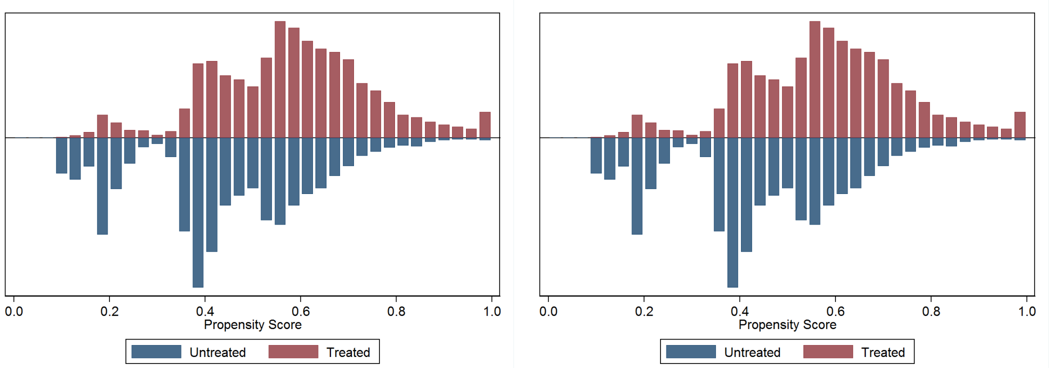

Fig. 3: Propensity Score Matching with threshold "median share of intangible assets" – Quality. This figure shows the distribution of all 21,517 firms along the propensity score for the median share of intangible assets as threshold and the nearest neighbor (panel A) and kernel (panel B) matching algorithm

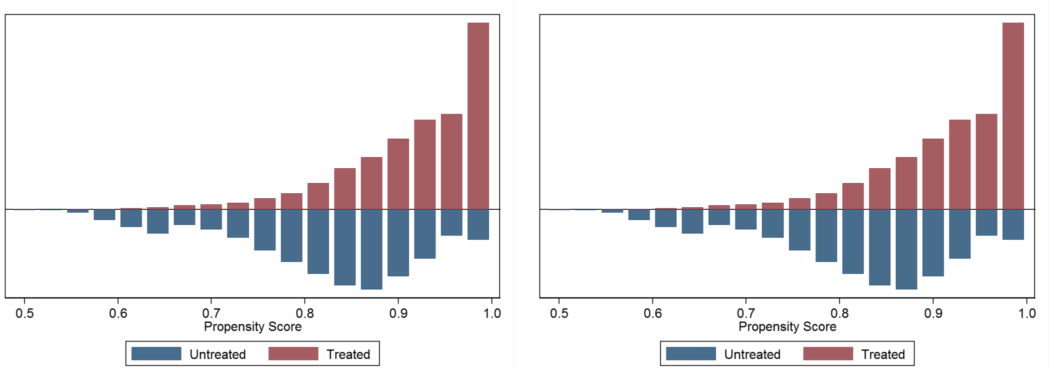

Fig. 4: Propensity Score Matching with threshold "share of intangible assets larger than zero" – Quality. This figure shows the distribution of all 21,517 firms along the propensity score for the share of intangible assets being larger than zero as threshold and the nearest neighbor (panel A) and kernel (panel B) matching algorithm

All in all, results show that intangible assets do not prevent German SMEs from debt financing. We expect that German SMEs can circumvent the financing frictions associated with intangible assets by a strong bank relation, referred to as relationship banking. This directly implies our second hypothesis, namely that a higher share of intangible assets increases the probability of having an exclusive and persistent bank relation.

5.2 Intangible Assets and Number of Bank Relations

Before we test the determinants of relationship banking (hypothesis 2), we want to compare the fraction of firms that have one bank relation in the treatment group and the untreated group. We apply the same matching algorithms and treatment thresholds as in Tab. 3. The difference is, that the outcome variable is now the fraction of firms with only one bank relation.

Tab. 4 shows the results of twelve propensity score matching estimations. The results are less clear compared to the previous estimation. In the unmatched comparison, the difference between treated and untreated firms is significant for all three thresholds. In all cases, the untreated group (less share of intangible assets) has a lower share of firms with only one bank relation. In general, this would support our hypothesis that intangible assets are one of the drivers to engage in relationship banking. However, the results of the matched comparison are mixed. We find a significant difference in the fraction of firms with only one bank relation in six out of twelve comparisons. For all thresholds, the 2 and 3 nearest neighbors algorithm lead to significant results. The results provide evidence in support of the idea, that firms with a high share of intangible assets engage more in relationship banking. Also, results show that the effect is not only driven by intangible assets since we find no significant effect for the nearest neighbor and kernel algorithm. To provide sharper evidence and to control for other potential drivers we estimate determinants of relationship banking in the following subsection.

5.3 Determinants of Relationship Banking

Based on previous studies we combine the following variables in order to explain the choice of the number of bank relations: firm size, proxied by either sales or employees; asymmetric information, proxied by intangible assets (standardized by total assets); redeployable collateral, proxied by current assets (standardized by total assets); indebtedness, proxied either by debt (standardized by total assets) or by the ratio of short term debt to long term debt; and 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:

$$\begin{aligned}
&\text{Probability (Relationship Banking} = 1) = \\
&\quad = f\,(\text{Size}, \text{Current Assets}, \\
&\qquad \text{Intangible Assets}, \text{Indebtedness}, \\
&\qquad \text{EBITDA}, \text{Control Variables}), \qquad (2)
\end{aligned}$$

where Relationship Banking equals 1 for firms with one bank relation and 0 otherwise. Control variables include binary variables for industries at the section level according to the industrial code (Nace, Rev. 2) and a binary variable which equals 1 in case the firm is located in one of three main economic regions of Germany (Bavaria, Baden-Wuerttemberg, Nordrhein-Westfalen), where bank concentration can be expected to be higher than in other regions.

Regarding the expected signs of our variables: proxies for firm 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 the soft channel of a strong firm-bank relation is less needed; indebtedness is expected to increase the probability of having only one bank relation since a strong bank relation may help to ease credit constraints; in the three main economic regions of Germany we expect relationship banking to be less likely, as suggested by to Petersen and Rajan (1995).

Tab. 4: Propensity Score Matching – Results – Intangible Assets and Probability of a Single Bank Relation

Treatment	Intangible Assets > Mean					Intangible Assets > Mean				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.312	0.266	−0.046***	0.009	−5.020	0.312	0.266	−0.046***	0.009	−5.020
ATT	0.312	0.290	−0.022	0.014	−1.530	0.312	0.287	−0.025**	0.012	−2.030
pseudo R-squared	0.104					0.104				
Number of Obs	15226					15226				
Treatment	Intangible Assets > Mean					Intangible Assets > Mean				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.312	0.266	−0.046***	0.009	−5.020	0.312	0.266	−0.046***	0.009	−5.020
ATT	0.312	0.284	−0.029**	0.012	−2.440	0.312	0.290	−0.022	0.014	−1.530
pseudo R-squared	0.104					0.104				
Number of Obs	15226					15266				
Treatment	Intangible Assets > Median					Intangible Assets > Median				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.267	0.284	−0.018**	0.007	−2.460	0.267	0.284	−0.018**	0.007	−2.460
ATT	0.267	0.285	−0.018	0.011	−1.600	0.267	0.291	−0.024**	0.010	−2.420
pseudo R-squared	0.112					0.112				
Number of Obs	15266					15226				
Treatment	Intangible Assets > Median					Intangible Assets > Median				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.267	0.284	−0.018**	0.007	−2.460	0.267	0.284	−0.018**	0.007	−2.460
ATT	0.267	0.289	−0.022**	0.010	−2.290	0.267	0.285	−0.018	0.011	−1.600
pseudo R-squared	0.112					0.112				
Number of Obs	15226					152664				
Treatment	Intangible Assets > 0					Intangible Assets > 0				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.267	0.361	−0.094***	0.013	−7.32	0.267	0.362	−0.094***	0.013	−7.320
ATT	0.267	0.300	−0.033	0.033	−1.01	0.267	0.296	−0.029**	0.014	−2.030
pseudo R-squared	0.140					0.140				
Number of Obs	15226					15226				
Treatment	Intangible Assets > 0					Intangible Assets > 0				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.267	0.361	−0.094***	0.013	−7.320	0.267	0.361	−0.094***	0.013	−7.320
ATT	0.267	0.295	−0.028**	0.014	−2.010	0.267	0.300	−0.033**	0.033	−1.010
pseudo R-squared	0.140					0.140				
Number of Obs	15226					15226				

Notes: This table shows the results of twelve propensity score matching estimations. The term *Logit* expresses that the matching algorithm is based on a logistic regression framework. The twelve estimations are the combination of three different definitions for the treatment group (intangible assets larger than: zero, the sample median, or the sample mean) with four different matching algorithms (matching by: nearest neighbor, the two nearest neighbors, the three nearest neighbors, and a normally distributed kernel with a range of 0.06). For each estimation the fraction of firms with only one bank relation for the treatment group ("treated") and the control group ("Controls"), as well as the mean difference ("Difference") are shown. Under S.E. we show the standard error of a mean comparison test and the corresponding t-statistic. The difference and the t-statistic of the "Average Treatment Effect on the Treated" (ATT) are the most important measures. The measures show whether the *fraction of firms with only one bank relation* of treated firms significantly differs from that of untreated firms. Signs ***, **, and * indicate significance on the 1%, 5%, and 10% level, respectively.

Since our dependent variable in equation (2) is a count variable, which is discrete-valued and truncated, an OLS 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, which is not given in our case.

Our variable of main interest, which is the 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, the corresponding coefficient can be roughly interpreted as entering the 90%-quantile of the share of intangible assets.

5.4 Logistic Regression

Given the nature of our dependent variable, a logistic regression is the most appropriate estimation method. Since the number of bank relations between 2005 and 2012 is reported across years, we know that if it equals 1 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 relation and 0 for everything else offers a sharp distinction.

Tab. 5 presents the results of four logistic regression specifications. Two different proxies for firm size and indebtedness were 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 *Hypothesis 2*, the null hypothesis states that the share of intangible assets does not affect the probability of running an exclusive and persistent 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[4]. 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 a 1 percentage 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 percentage 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 reject our second null-hypothesis.

In addition, size proxies are neither statistically significant (sales) nor economically meaningful (employees). Both proxies for indebtedness are significant and positive. Firms with a higher fraction of debt are more likely to have a single bank relation which is in line with Ogawa et al. (2007). One interpretation of this finding is that greater indebtedness is a signal, albeit not necessarily a reliable one, for low borrower quality 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 the result 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).

Next, we estimate predicted probabilities and marginal effects of our logistic regression with an emphasis on variation in the share of intangible assets. Since more than 90% of firms have a share intangible assets between 0 and 9%, we vary the share of intangible assets

[4] 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 an explanatory variable is increased by one unit. An odds ratio of 10.12, for example, translates to odds of having only one bank relation of $0.11 \cdot 10.12 = 1.12$, 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.

Tab. 5: Logistic Regression – Determinants of Relationship Banking

	(I)		(II)		(III)		(IV)	
Dependent variable	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**
Employees	−0.011*** (0.003)	0.999	−0.009*** (0.003)	1.000				
Sales					0.001 (0.001)	1.000	0.001 (0.002)	1.000
Current Assets/ Total Assets	−0.257*** (0.073)	0.773	−0.261*** (0.078)	0.770	−0.170* (0.088)	0.843	−0.199** (0.082)	0.820
Intangible Assets/ Total Assets	2.594*** (0.324)	13.383	2.211*** (0.354)	9.125	2.782*** (0.313)	16.151	2.218*** (0.312)	9.189
Debt/ Total Assets	0.299*** (0.088)	1.349			0.197*** (0.074)	1.218		
EBITDA/ Total Assets	−0.084*** (0.096)	0.919	−0.075*** (0.101)	0.928	−0.063 (0.083)	0.939	−0.077 (0.068)	0.926
Constant	−0.539 (0.348)		−0.333 (0.293)		−0.521 (0.345)		−0.328 (0.299)	
Industry Dummies	yes		yes		yes		yes	
Main Region Dummies	yes		yes		yes		yes	
Number of Observations	21,517		21,517		17,166		17,166	
Correctly Classified	74.81%		72.21%		73.12%		71.27%	
Area under ROC Curve	0.699		0.665		0.679		0.618	

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

Tab. 6: Logistic Regression – Predicted Probabilities and Marginal Effects

	(I)	(II)	(III)	(IV)
Dependent variable	**Relationship Banking 0/1**	**Relationship Banking 0/1**	**Relationship Banking 0/1**	**Relationship Banking 0/1**
Pred. Prob. all Variables at means	0.260*** (0.003)	0.260*** (0.003)	0.276*** (0.004)	0.276*** (0.004)
Pred. Prob. if IA/TA = 0	0.254*** (0.003)	0.254*** (0.003)	0.268*** (0.004)	0.269*** (0.004)
Pred. Prob. if IA/TA = 1%	0.258*** (0.003)	0.258*** (0.003)	0.273*** (0.004)	0.273*** (0.004)
Pred. Prob. if IA/TA = 3%	0.267*** (0.003)	0.267*** (0.003)	0.283*** (0.004)	0.283*** (0.004)
Pred. Prob. if IA/TA = 5%	0.276*** (0.004)	0.277*** (0.004)	0.292*** (0.004)	0.293*** (0.004)
Pred. Prob. if IA/TA = 7%	0.286*** (0.005)	0.286*** (0.005)	0.302*** (0.006)	0.303*** (0.006)
Pred. Prob. if IA/TA = 9%	0.295*** (0.006)	0.296*** (0.006)	0.312*** (0.007)	0.313*** (0.007)

Notes: (1) Signs * (**) [***] denotes significance at the 10% (5%) [1%] level. (2) Robust standard errors are reported in parentheses. (3) Prod. Prob. stands for "Predicted Probability", IA and TA stands for Intangible Assets and Total Assets, respectively. (4) Roman numerals in the header refer to Tab. 5.

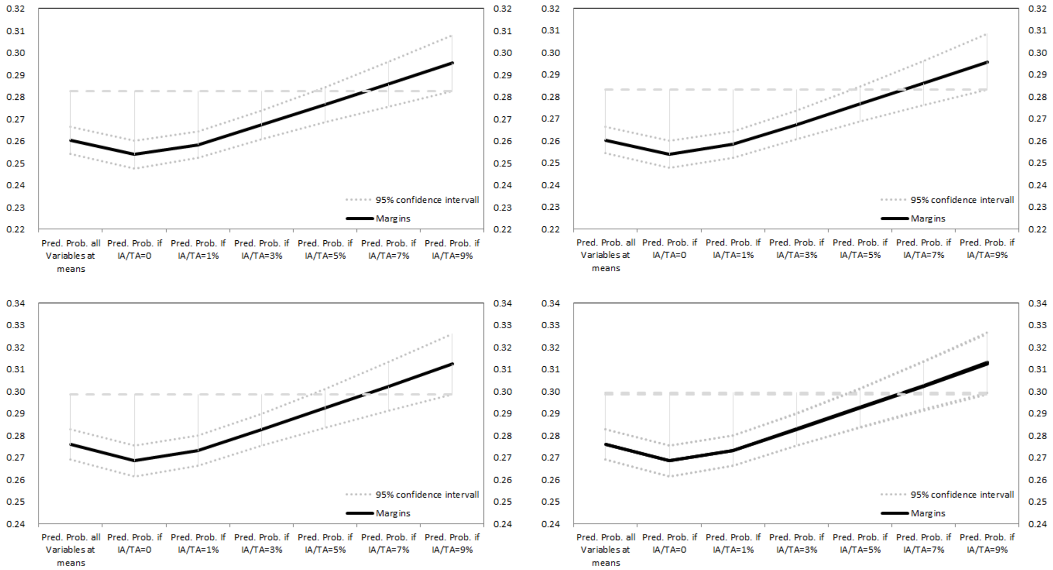

Fig. 5: Predicted Probabilities and Marginal Effects. Figures visualize the marginal effects and predicted probabilities from the estimation in Tab. 6 for all 21,517 observations. The horizontal axis shows groups of firms by the fraction of intangible assets. The fraction is defined as intangible assets (IA) divided by total assets (TA) and ranges from 0% to 9%. The vertical axis shows the estimated probability of having only a single bank relation. The 95% confidence interval of the estimated probability is displayed by the dashed gray line.

in that range and estimate the corresponding predicted probabilities. The first row of Tab. 6 shows the predicted probability of an exclusive and persistent bank relation, given that all independent variables are set to their mean. Below, the predicted probability of an exclusive and persistent bank relation, given that all independent variables are set to their mean but the share of intangible assets equals zero is shown. The next rows show the predicted probability of an exclusive and persistent bank relation, given that all independent variables are set to their mean but the share of intangible assets equals 1%, 3%, etc.

Tab. 6 shows that margins continuously increase in the share of intangible assets. However, standard errors and in turn confidence intervals also increase in the share of intangible assets.

Fig. 5 visualizes the margins and the corresponding confidence intervals. The lower end of the confidence interval of the predicted probability at a share of intangible assets of 9% remains in all cases untouched by the higher end of the confidence intervals of shares of intangible assets of 3% and below.

6 ROBUSTNESS

In order to provide robust results, we estimate equation (1) and equation (2) for selected subsamples. Since we calculate averages over time and perform a cross-sectional analysis, we run equation (1) and equation (2) for 2006 and 2012 with the aim of illustrating whether our obtained results are stable over time.

Tab. 7 and 8 show that the equity ratio of firms whose share of intangible assets is above one of the specified thresholds is not statistically significantly higher, comparing matched firms. Thus, this relationship has not changed over time in our sample. Again, treatment refers to the share of intangible assets exceeding the

Tab. 7: Propensity Score Matching – Results – Intangible Assets and Equity Ratio – 2006

Treatment	Intangible Assets $>$ Mean					Intangible Assets $>$ Mean				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.350	0.339	0.011	0.004	2.730	0.350	0.339	0.011	0.004	2.730
ATT	0.350	0.352	−0.002	0.006	−0.250	0.350	0.349	0.001	0.005	0.240
pseudo R-squared	0.099					0.099				
Number of Obs	15209					15209				
Treatment	Intangible Assets $>$ Mean					Intangible Assets $>$ Mean				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.350	0.339	0.011	0.004	2.730	0.350	0.339	0.011	0.004	2.730
ATT	0.350	0.351	−0.001	0.005	−0.160	0.350	0.352	−0.002	0.006	−0.250
pseudo R-squared	0.099					0.099				
Number of Obs	15209					15209				
Treatment	Intangible Assets $>$ Median					Intangible Assets $>$ Median				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.354	0.328	0.026	0.003	7.870	0.354	0.328	0.026	0.003	7.870
ATT	0.354	0.362	−0.008	0.005	−1.450	0.354	0.359	−0.005	0.005	−1.140
pseudo R-squared	0.110					0.110				
Number of Obs	15209					15209				
Treatment	Intangible Assets $>$ Median					Intangible Assets $>$ Median				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.354	0.328	0.026	0.003	7.870	0.354	0.328	0.026	0.003	7.870
ATT	0.354	0.361	−0.007	0.005	−1.490	0.354	0.362	−0.008	0.005	−1.450
pseudo R-squared	0.110					0.110				
Number of Obs	15209					15209				
Treatment	Intangible Assets $>$ 0					Intangible Assets $>$ 0				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.345	0.298	0.047	0.006	7.830	0.345	0.298	0.047	0.006	7.830
ATT	0.345	0.344	0.001	0.014	0.080	0.345	0.340	0.005	0.013	0.380
pseudo R-squared	0.134					0.134				
Number of Obs	15209					15209				
Treatment	Intangible Assets $>$ 0					Intangible Assets $>$ 0				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.345	0.298	0.047	0.006	7.830	0.345	0.298	0.047	0.006	7.830
ATT	0.345	0.345	0.000	0.012	−0.030	0.345	0.344	0.001	0.014	0.080
pseudo R-squared	0.134					0.134				
Number of Obs	15209					15209				

Notes: This table shows the results of twelve propensity score matching estimations for a subsample of our dataset. The subsample consists of 21,517 firms in the year 2006. Observations from other years are not taken into account. The term *Logit* expresses that the matching algorithm is based on a logistic regression framework. The twelve estimations are the combination of three different definitions for the treatment group (intangible assets larger than: zero, the sample median, or the sample mean) with four different matching algorithms (matching by: nearest neighbor, the two nearest neighbors, the three nearest neighbors, and a normally distributed kernel with a range of 0.06). For each estimation the average equity ratio for the treatment group ("treated") and the control group ("Controls"), as well as the mean difference ("Difference") is shown. Under S.E. we show the standard error of a mean comparison test and the corresponding t-statistic. The difference and the t-statistic of the "Average Treatment Effect on the Treated" (ATT) are the most important measures. The measures show whether the *equity ratio* (defined as equity / total assets) of treated firms significantly differs from that of untreated firms. Signs ***, **, and * indicate significance on the 1%, 5%, and 10% level, respectively.

Tab. 8: Propensity Score Matching – Results – Intangible Assets and Equity Ratio – 2012

Treatment	Intangible Assets > Mean					Intangible Assets > Mean				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.346	0.336	0.010	0.004	2.350	0.346	0.336	0.010	0.004	2.350
ATT	0.346	0.346	0.000	0.006	0.070	0.346	0.348	−0.002	0.005	−0.290
pseudo R-squared			0.104					0.104		
Number of Obs			15226					15226		
Treatment	Intangible Assets > Mean					Intangible Assets > Mean				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.346	0.336	0.010	0.004	2.350	0.346	0.336	0.010	0.004	2.350
ATT	0.346	0.350	−0.004	0.005	−0.810	0.346	0.346	0.000	0.006	0.070
pseudo R-squared			0.104					0.104		
Number of Obs			15226					15226		
Treatment	Intangible Assets > Median					Intangible Assets > Median				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.353	0.323	0.029	0.003	8.970	0.353	0.323	0.029	0.003	8.970
ATT	0.353	0.354	−0.001	0.005	−0.250	0.353	0.356	−0.004	0.005	−0.790
pseudo R-squared			0.112					0.112		
Number of Obs			15226					15226		
Treatment	Intangible Assets > Median					Intangible Assets > Median				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.353	0.323	0.029	0.003	8.970	0.353	0.323	0.029	0.003	8.970
ATT	0.353	0.357	−0.005	0.004	−1.080	0.353	0.354	−0.001	0.005	−0.250
pseudo R-squared			0.112					0.112		
Number of Obs			15226					15226		
Treatment	Intangible Assets > 0					Intangible Assets > 0				
Matching	Nearest Neighbor					2 Nearest Neighbors				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.343	0.284	0.060	0.006	10.260	0.343	0.284	0.060	0.006	10.260
ATT	0.343	0.347	−0.003	0.014	−0.230	0.343	0.342	0.001	0.012	0.110
pseudo R-squared			0.140					0.140		
Number of Obs			15226					15226		
Treatment	Intangible Assets > 0					Intangible Assets > 0				
Matching	3 Nearest Neighbors					Kernel				
Model	Logit					Logit				
	Treated	Controls	Difference	S.E.	T-Statistic	Treated	Controls	Difference	S.E.	T-Statistic
Unmatched	0.343	0.284	0.060	0.006	10.260	0.343	0.284	0.060	0.006	10.260
ATT	0.343	0.344	−0.001	0.011	−0.050	0.343	0.347	−0.003	0.014	−0.230
pseudo R-squared			0.140					0.140		
Number of Obs			15226					15226		

Notes: This table shows the results of twelve propensity score matching estimations for a subsample of our dataset. The subsample consists of 21,517 firms in the year 2012. Observations from other years are not taken into account. The term *Logit* expresses that the matching algorithm is based on a logistic regression framework. The twelve estimations are the combination of three different definitions for the treatment group (intangible assets larger than: zero, the sample median, or the sample mean) with four different matching algorithms (matching by: nearest neighbor, the two nearest neighbors, the three nearest neighbors, and a normally distributed kernel with a range of 0.06). For each estimation the average equity ratio for the treatment group ("treated") and the control group ("Controls"), as well as the mean difference ("Difference") is shown. Under S.E. we show the standard error of a mean comparison test and the corresponding t-statistic. The difference and the t-statistic of the "Average Treatment Effect on the Treated" (ATT) are the most important measures. The measures show whether the *equity ratio* (defined as equity / total assets) of treated firms significantly differs from that of untreated firms. Signs ***, **, and * indicate significance on the 1%, 5%, and 10% level, respectively.

Tab. 9: Logistic Regression – Determinants of Relationship Banking – 2006

	(I)		(II)		(III)		(IV)	
Dependent variable	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**
Employees	−0.009** (0.004)	0.991	−0.009** (0.004)	0.993				
Sales					0.002 (0.002)	1.002	0.003 (0.002)	1.003
Current Assets/ Total Assets	−0.372*** (0.094)	0.689	−0.333*** (0.094)	0.717	−0.342*** (0.094)	0.711	−0.304*** (0.093)	0.738
Intangible Assets/ Total Assets	2.736*** (0.400)	14.425	2.598*** (0.404)	13.437	2.248*** (0.389)	9.473	2.231*** (0.387)	9.309
Debt/ Total Assets	0.285*** (0.106)	1.330			0.269** (0.110)	1.331		
EBITDA/ Total assets	−0.055* (0.031)	0.947	−0.031* (0.017)	0.967	−0.048 (0.056)	0.953	−0.029 (0.038)	0.972
Constant	−0.483 (0.332)		−0.326 (0.321)		−0.657** (0.334)		−0.542* (0.331)	
Industry Dummies	yes		yes		yes		yes	
Main Region Dummies	yes		yes		yes		yes	
Number of Observations	13,989		13,989		12,410		12,409	
Correctly Classified	75.12%		73.15%		73.72%		72.44%	
Area under ROC Curve	0.6576		0.6376		0.6444		0.6301	

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

sample mean or median or zero and the matching algorithm is either the nearest neighbor, the two nearest neighbors, the three nearest neighbors or a normally distributed kernel using a range of 0.06.

Results in Tab. 9 and 10 illustrate that the statistically significant relationship between the probability of having only one bank relation and the fraction of intangible assets does not change over time. In the beginning, as well as in the end of our sample period the fraction of intangible assets statistically significantly increases the probability of having only one bank relation. We, therefore, conclude that our results are robust over time and not driven by the aggregation of the data.

However, the significance of the coefficient of current assets divided by total assets and the size of the coefficient of intangible assets divided by total assets change from 2006 to 2012. Yet, some variation of the results over time is more than acceptable.

Since we already emphasized the distribution of the fraction of intangible assets divided by total assets, we first exclude firms whose intangible assets equal zero. Doing so, we focus on firms where the change in the share of intangible assets excludes a change from zero to a positive value. Tab. 11 shows that if the share of intangible assets exceeds zero, the fraction of intangible assets still statistically significantly increases the probability of having only one bank relation.

In addition to excluding firms without intangible assets, we exclude firms whose share of intangible assets is in the highest 1%-quantile. However, the fraction of intangible assets still statistically significantly increases the probability of having only one bank relation (see Tab. 12).

In summary, these analyses confirm the robustness of our results.

Tab. 10: Logistic Regression – Determinants of Relationship Banking – 2012

	(I)		(II)		(III)		(IV)	
Dependent variable	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**
Employees	−0.006** (0.002)	1.000	−0.005** (0.002)	1.000				
Sales					0.003 (0.002)	1.003	0.002 (0.002)	1.002
Current Assets/ Total Assets	−0.062 (0.061)	0.940	−0.057 (0.080)	0.944	0.011 (0.098)	1.011	0.035 (0.098)	1.036
Intangible Assets/ Total Assets	1.742*** (0.359)	5.707	1.733*** (0.366)	5.661	1.680*** (0.379)	5.367	1.503*** (0.361)	4.497
Debt/ Total Assets	0.307*** (0.078)	1.359			0.444*** (0.103)	1.559		
EBITDA/ Total Assets	−0.053** (0.089)	0.948	−0.030** (0.163)	0.961	−0.032 (0.117)	0.957	−0.051 (0.091)	0.950
Constant	−0.716** (0.337)		−0.884 (0.991)		−0.992** (0.428)		−0.651** (0.300)	
Industry Dummies	yes		yes		yes		yes	
Main Region Dummies	yes		yes		yes		yes	
Number of Observations	20,166		20,166		13,853		13,850	
Correctly Classified	74.11%		73.84%		71.92%		70.76%	
Area under ROC Curve	0.6633		0.6453		0.6234		0.6210	

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

Tab. 11: Logistic Regression – Determinants of Relationship Banking – IA/TA > 0

	(I)		(II)		(III)		(IV)	
Dependent variable	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**
Employees	−0.005*** (0.001)	1.000	−0.004*** (0.001)	1.000				
Sales					0.003 (0.004)	1.003	0.002 (0.003)	1.001
Current Assets/ Total Assets	−0.224* (0.120)	0.801	−0.201** (0.086)	0.818	−0.079 (0.098)	0.924	−0.073 (0.107)	0.930
Intangible Assets/ Total Assets	2.227*** (0.327)	9.270	2.197*** (0.314)	8.999	2.694*** (0.311)	14.792	2.672*** (0.312)	14.469
Debt/ Total Assets	0.216** (0.089)	1.241			0.331** (0.147)	1.392		
EBITDA/ Total assets	−0.054 (0.101)	0.947	−0.071 (0.084)	0.932	−0.085 (0.099)	0.919	−0.064 (0.103)	0.939
Constant	−0.777* (0.391)		−0.873 (0.494)		−0.811** (0.316)		−0.743* (0.399)	
Industry Dummies	yes		yes		yes		yes	
Main Region Dummies	yes		yes		yes		yes	
Number of Observations	19,633		19,633		15,616		15,616	
Correctly Classified	73.18%		72.81%		72.11%		71.32%	
Area under ROC Curve	0.6432		0.6211		0.6337		0.6328	

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

Tab. 12: Logistic Regression – Determinants of Relationship Banking – 0 < IA/TA < 99-quantile

	(I)		(II)		(III)		(IV)	
Dependent variable	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**	**Relationship Coeff.**	**Banking 0/1 Odds Ratio**
Employees	−0.006** (0.003)	1.000	−0.007** (0.003)	1.000				
Sales					0.001 (0.001)	1.000	0.003 (0.002)	1.002
Current Assets/ Total Assets	−0.139* (0.081)	0.865	−0.152** (0.081)	0.859	−0.071 (0.089)	0.931	−0.089 (0.088)	0.914
Intangible Assets/ Total Assets	3.117*** (0.621)	22.578	3.241*** (0.611)	25.559	3.318*** (0.430)	27.605	3.574*** (0.399)	35.681
Debt/ Total Assets	0.224** (0.085)	1.251			0.211** (0.101)	1.234		
EBITDA/ Total assets	−0.054 (0.101)	0.947	−0.138 (0.187)	0.871	−0.143 (0.148)	0.865	−0.167 (0.167)	0.846
Constant	−0.578** (0.299)		−0.493* (0.287)		−0.632** (0.301)		−0.536* (0.297)	
Industry Dummies	yes		yes		yes		yes	
Main Region Dummies	yes		yes		yes		yes	
Number of Observations	19,415		19,415		15,419		15,419	
Correctly Classified	72.98%		72.66%		71.93%		71.11%	
Area under ROC Curve	0.6256		0.6181		0.6111		0.6009	

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

7 CONCLUSION

We discuss the relationship between intangible assets, capital structure and the number of bank relations of German SMEs. Separately, these topics have already received much attention in the academic literature. We thus contribute significantly by combining them in a meaningful way and, in particular, by assigning a special role to the connection between intangible assets and firms' choice of bank relation. Based on the existing literature we derive two hypotheses. For each of them, the null hypothesis can be rejected and results are in favor of our hypotheses.

Using a large dataset for German SMEs including their bank relations between 2005 and 2012, we test two hypotheses. First, a higher fraction of intangible assets should lead to a higher equity ratio. We find that in a matched comparison there is no statistically significant difference in equity ratios among firms due to their share of intangible assets. We propose a strong firm-bank relation to helping firms circumvent the financing frictions related to intangible assets emphasized in the literature. This naturally yields our next hypothesis. Secondly, we hypothesize that firms with a high fraction of intangible assets should be more likely to engage in relationship banking, which we proxy for by the number of bank relations. We find that firms with a higher share of intangible assets are more likely to have a relationship with only one single bank. This close firm-bank relation can help to overcome debt-financing problems.

We divide firms into three groups separated by their share of intangible assets. A descriptive comparison reveals substantial differences in equity ratios. 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 no statistically significant difference in equity ratios anymore. If relationship banking helps firms with a higher share of intangible assets to receive bank loans, firms' borrower decision ought to be determined by their share of intangible assets.

Hence, the centerpiece of our contribution is to address the question of 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. Using this data, we indeed find that the share of intangible assets significantly increases the probability of an exclusive and persistent bank relation. This result turns out to be robust with regard to the analysis of several subsamples of our data.

Since our research is also motivated by Germany's stable performance during the global financial crisis and recent insights into the connection of financial sector growth and real growth (Cecchetti and Kharroubi, 2015), we show a possible, but marginal explanation for these observations.

Given data availability, future research should be extended to cross-country studies. The three-pillar structure of German 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 of our analysis, which would allow to controlling for country-specific characteristics of relationship banking.

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