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RELATIONSHIP LENDING – EMPIRICAL EVIDENCE FOR GERMANY

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Abstract

Relationship lending is a common practice in credit financing all over the world, notably also in the European Union, which has been assumed to be particularly beneficial for Small and Medium-Sized Enterprises (SMEs). During recent years, there has been the impression that relationship lending loses ground due to a change of the banks' business models, which could ultimately yield to a worsening of the business environment for corporates and SMEs. In this study, we investigate the determinants of relationship lending for Germany, where relationship lending traditionally plays an important role. Compared to previous studies, we refer to much more comprehensive data with information on more than 16,000 firm-bank relationships. Our findings confirm the assumption that relationship lending seems to be an important pillar for economic growth and employment: We find that the firms that are most likely to contribute to (future) economic growth, namely small and R&D-intensive firms, tend to choose a relationship lender. The same is observed for firms of high credit quality, independent of their size or R&D intensity. Furthermore, we also observe that the importance of relationship lending did not decrease since the mid 1990s.

Contents

1 Introduction

It is common practice in credit financing for close ties[1] to exist between firms and banks, termed *relationship lending.*[2]

Relationship lending exists all over the world, including market-oriented banking systems such as the United States.[3] Within the European Union, one of the countries where relationship lending is supposed to be especially prevalent is Germany, often cited as the classical example of a bank-based system with strong customer-borrower-relationships (see, eg, Elsas and Krahnen (1998)). The so-called house banks are supposed to be particularly important for the financing of small and medium-sized companies, which play a crucial role in Germany, but also in many other EU economies such as France, and can therefore facilitate economic growth and employment (see, eg, Wagenvoort (2003); Dietsch (2003)).

However, over the last decade, a trend to less relationship lending is often mentioned both in market and in bank-based economies. Due to better information processing, more sophisticated rating tools and the growth of securitization market banks are supposed to become more and more to credit factories, whereby the credit decision is supposed to be more and more based on quantitative credit rating or credit scoring information, whereas qualitative information and personal relations become less important. Hence, a close bank-firm relationship gets seemingly less important.

Despite the importance of relationship lending in various EU countries and particularly in Germany it is remarkable that there are only a limited number of contributions on this subject, which, on top, mostly refer only to a very limited data base. This is where our study applies: Unlike most studies for Germany (see Elsas (2005), Machauer and Weber (2000) and Neuberger and Räthke (2006)) or other

[1] This studies focuses on one import aspect of relationship banking, lending relationships. A more comprehensive definition on relationship banking will be given in the next section.

[2] We thank Wolfgang Bessler, Ralf Elsas, Bronwyn Hall, Martin Hellwig, Wouter van Overfelt, Andreas Pfingsten, Birgit Schmitz, Isabell Schnabel, Mechthild Schrooten and the participants at the GBSA 2006 Workshop, the Kleistvilla Workshop 2006, the Verein fuer Socialpolitik 2006 Annual Congress, the DGF 2006 Annual Meeting, MPI Bonn seminar, the SGF 2007 Annual Meeting, the FMA 2007 European Conference, the 2007 Meeting of the Bundesbank Research Council and the Bankenworkshop 2007 at the University Muenster for fruitful comments.

[3] See, eg, Petersen and Rajan (1994) and Boot (2000).

countries (see, for example, Detragiache et al. (2000)), our analysis is based on a comprehensive database with a total of around 16,000 observations with an annual frequency for the period from 1993 to 2004. Moreover, in contrast to the previous literature our data set is not only a cross-section of observations, but contains also the time dimension based on time series of more than one decade. Thus, we are able to study how differences between firms and differences over time influence relationship lending. Finally, our definition of relationship lending differs from the literature which, except to Elsas (2005), for example, usually refers to the number of lending relationships as indicators for relationship lending.[4] While this variable is related to the concept of relationship lending, using solely this indicator appears too restrictive, as companies typically have several lending relationships, particularly larger ones.

Accordingly, we analyze the determinants of relationship lending. This is done as follows. First, it is typically assumed that relationship lending helps to reduce information asymmetries between borrower and lender by the close contact between the two parties. Therefore, companies that are especially exposed to high information problems, such as small companies and companies with a high R&D intensity, should choose a relationship lender. The evidence of our study is broadly consistent with these predictions. For young firms, the outcome is similar, but less significant.

Second, we analyze the influence of the firm's creditworthiness on relationship lending, which is being perceived contradictorily in the theoretical literature. Depending on the model a firm's credit quality influences the likelihood of relationship lending negatively (Bolton and Scharfstein (1996)), positively (von Thadden (2004)) or the relation is inversely u-shaped (Rajan (1992)). Our study shows that firms of a high credit quality tend to choose a relationship lender and is therefore in line with the predictions of von Thadden (2004). He explains this result by a positive selection process over time where bad firms are more likely to switch from a relationship lender to an arm's-length bank than high quality firms do.

[4] This statement applies to the literature regarding the determinants of relationship lending. Papers which take relationship lending as explanatory variable take a richer set of variables.

Finally, we also examine whether the importance of relationship lending decreased since the mid 90s. However, we cannot observe such a trend for Germany.

The paper is organized as follows. Section 3 outlines the hypotheses on the nature of relationship lending. In Section 4 we provide an overview of the underlying data set. Section 6 addresses descriptive statistics and shows first results. The results of the regressions are presented in Section 7. Finally, section 8 concludes.

2 Definition of Relationship Lending

A fundamental prerequisite to investigate relationship banking in general and relationship lending in particular is to begin with an appropriate definition, notably as many previous studies on relationship banking merely identified close bank relationships without becoming more specific. In a broader sense, there are two core elements relationship banking is based on, namely that relationship banks (1) engage in multiple interactions with the respective borrowers (2) through multiple products and over time and thereby invest in obtaining costly, proprietary information on borrowers that remains confidential (Boot (2000)). In this study, we investigate one major dimension of relationship banking, lending relationships between firms and banks. Relationship lending exists if a firm has close ties to a financial institution (Petersen and Rajan (1994)).

In order to investigate relationship lending, it becomes essential to define appropriate indicators to measure it, such as the duration of a bank-borrower relationship, the number of lending relationships or a high share of debt financing by one bank.[5] We take the latter indicator, namely (i) a high portion of debt financing by one bank, as our main indicator.[6] In addition, we also consider (ii) the number of lending relationships as an alternative measure in order to enhance the robustness of the results.

[5] See, for example, Petersen and Rajan (1994) and Ongena and Smith (2001).

[6] It turns out that a bank that is the dominant lender in one year tends to be the dominant lender in the following year. Therefore, firms with a dominant lender tend to have long relationships with this lender, i.e. the first and third measure of relationship lending are correlated.

According to definition (ii), we call a bank a relationship lender if a firm has one single lending relationship with a bank in contrast to another firm which has multiple lending relationships ($RL_{100\%}$). The reasoning for choosing the number of lending relationships as a proxy is that exclusivity of a bank relationship fosters the ties between banks and firms. However, focussing on the number of lending relationships alone appears too restrictive, and can even lead to misleading results as firms will typically have several lending relationships.[7] Hence, in order to account for more general cases, we define relationship lending as the case in which there exists a bank with a dominant exposure (definition i) and set the threshold to 80% ($RL_{80\%}$) and 90% ($RL_{90\%}$), respectively, of the total bank loans of this firm. The latter indicator, a high share of financial debt at one bank, has empirically been shown to be a good proxy for relationship lending.[8]

3 Hypotheses

Subsequently, the importance of borrower characteristics for relationship lending will be shortly presented from a theoretical perspective. This represents the starting point for the empirical analysis. We will summarize the predictions in three hypotheses.

In their review of the financial intermediation literature, Bhattacharaya and Thakor (1993) conclude that informational frictions - asymmetric information and proprietary information - "provide the most fundamental explanation for the existence

[7] In our sample, the average number of lending relationships is 2.7, while Degryse et al. (2004) report a mean of around 1.3 lending relationships for Belgium and Sapienza (2002) 9 for Italy. A cross-country study on the number of lending relationships in 20 European countries based on data from 1,079 large firms has been carried out by **?**. Their finding are two-fold: first, they observe that there are substantial differences across countries, with the average number of lending relationships ranging from 2.3 in Norway to 15.2 in Italy; second, they find that the number of lending relationships tends to increase with firm size.

[8] Elsas (2005) empirically examined the quality of several potential indicators for relationship lending, for example the number of lending relationships and the duration of the relationship. He asked the banks for each customer in his sample if they classified themselves as relationship lender and compared these self assessments with the different possible indicators for relationship lending. It is shown that a high portion of debt financing by one bank has the highest explanatory power.

of (financial) intermediaries". This characterization of banks applies particularly for relationship lenders. Relationship lending implies close ties between borrower and lender; this facilitates information exchange between the two parties. As house banks can be assumed to be well informed on the well-being of firms credit rationing resulting from information asymmetry becomes relatively unlikely. Lenders invest in gathering information from their client firms, and borrowers are more inclined to reveal proprietary information.

As information asymmetries are especially large for small, young companies, we expect that relationship lending will be more likely if a company is relatively small and young. In our analysis, we take the logarithm of the company's assets and of the time since the company's birth as a proxy for size and age, respectively. Furthermore, we expect relationship lending to become more likely if the firm is R&D or knowledge-intensive, as proprietary information exists in such companies. As the firm's R&D intensity cannot be directly measured, we alternatively refer to information on the R&D and knowledge intensity of the firms' industry sector. The preceding discussion leads us to hypotheses 1 and 2:

Hypothesis 1: The probability of relationship lending decreases with the borrower's size and age.

Hypothesis 2: The probability of relationship lending increases with the R&D and knowledge intensity of the borrower's industry.

Relationship lending does not only come along with benefits, but also with costs. For example, companies with a relationship lender may face only a soft-budget constraint which makes it difficult for the relationship lender to enforce the credit contract (Bolton and Scharfstein (1996), see also Dewatripont and Maskin (1995)). In the event of a default, it is much easier for the company to renegotiate the debt contract if there is one main creditor than if there were multiple creditors. Thus, companies with a relationship lender have a greater incentive to default strategically, while firms with a large number of creditors tend to be disciplined by their lenders. However, the costs of inefficient renegotiation which exist with multiple creditors prevail also if the firm defaults for liquidity reasons. Thus, there exists a trade off between preventing strategic defaults (best achieved with multiple creditors) and low cost of renegotiation in case of liquidity defaults (best achieved with one creditor). As companies of a lower credit quality are likely to face a higher risk of a liquidity default, they could ensure that they receive high liquidation values, choose one creditor or concentrate their borrowing on one bank, their relationship lender.

Partly contradictory results are delivered by the models of Rajan (1992) and von Thadden (2004). The model of Rajan (1992) shows an additional reason why relationship lending may be costly, namely the hold-up problem. Unlike arm's-length lenders, relationship lenders obtain private information about borrowers which enables them to stop inefficient projects, but gives them also an "information monopoly". They could threat not to prolong a loan, thereby enforcing relatively high interest rates and reducing the incentives of the firm's owner. Thus, relationship lending is valuable for stopping inefficient projects whereas arm's length debt is good for providing high incentives. Rajan shows that firms of low credit quality prefer arm's-length debt, whereas firms with medium-quality projects tend to choose a relationship lender. High quality firms are indifferent.

The model of von Thadden (2004) analyzes also the hold-up-problem, but, unlike Rajan (1992), it is assumed that binding long-term contracts are not possible (see also Sharpe (1990)). At the refinancing stage, the terms of the credit contract are then determined by competition between the inside (relationship) lender and potential outside investors. He shows that there is a positive selection process where bad firms are more likely than high quality firms to switch from the insider lender to an arm's-length bank. Therefore, high-quality firms are more likely to be financed by relationship lenders.

We measure a firm's creditworthiness with its probability of default (PD), which is derived from a separate model.

Hypothesis 3 summarizes the above discussion:

Hypothesis 3: The probability of relationship lending depends on the borrower's creditworthiness.

Hypothesis 3a: The probability of relationship lending decreases with the borrower's creditworthiness. [Bolton and Scharfstein (1996)]

Hypothesis 3b: The probability of relationship lending is low for firms of low credit quality, high for medium-quality firms and mediocre for high-quality firms. [Rajan (1992)]

Hypothesis 3c: The probability of relationship lending increases with the borrower's creditworthiness. [von Thadden (2004)]

4 Data

The final database used in this study is composed of three different databases of Deutsche Bundesbank: i) the German credit register, containing single bank-firm credit relationships, ii) balance sheet data of German firms and iii) balance sheet data and audit reports of German banks. The data set used for this study thereby provides information as to whether a bank grants credit to a specific firm (through data set i) as well as the characteristics of the corresponding firms (ii) and banks (iii). Next, we will first provide information on the three databases in general and then elaborate more on the merged subset that has been used for this study.

The German credit register contains quarterly data on large exposures of banks to individual borrowers or single borrower units (eg groups). Banking institutions located in Germany are required to submit reports if their exposures to an individual borrower or the sum of exposures to borrowers belonging to one borrower unit exceeds the threshold of EUR 1.5m (formerly DEM 3m) once in the respective quarter.[9] As the banks have to report the quarter-end indebtedness, and particularly due to measuring indebtedness at the borrower unit level rather than for single credit entities, about 43% of all exposures in the database are below EUR 1.5m (see

[9] See section 14 of the German Banking Act.

Schmieder (2006)), which allows to use the data also to draw conclusions on (larger) SMEs. In the last quarter of 2004, for example, the credit register contained more than 750,000 reported bank-borrower-relationships, indicating the sheer size of the database.

The second data source used for this study, the corporate balance sheet database of Deutsche Bundesbank, is one of the most comprehensive databases for German non-financial firms. The database contains a total number of up to 60,000 firm balance sheets per year during the 1990s and approximately 20,000 firms since 2000. In order to ensure that the data are representative, we have accounted both for a potential quality bias resulting from the collection mechanism as well as for a bias towards larger firms as further discussed below.

Third, the balance sheet data of the German banks comprises the annual balance sheets and profit & loss accounts of all German banks and of some types of financial service providers (trade balances). In addition, it contains the yearly quantitative audit reports, which include information about the bank's loan quality and its regulatory capital.

For the purpose of this study, we used merged subset data from all three data sources.[10] Out of 3,288 firms that have been merged, roughly 60 firms have been excluded from the study for data quality reasons based on robustness tests. The final merged data set contains annual data from 3,231 firms as well as 11 groups (or borrower units) for the period from 1993 to 2004. In terms of the number of

[10] Whereas the German credit register and the balance sheet data of German banks are based on a common identifier for banks and can therefore be easily merged, the match between the credit register and the corporate balance has been done based on five firm criteria: i) name, ii) location, iii) legal form, iv) industry and v) an indicator comparing a firm's total indebtedness as stated by the credit register relative to bank loans shown by the balance sheet data. The last two criteria were primarily used as additional criteria in case of uncertainty about the validity of the match. Besides, additional information from the internet was used to check the correctness of the match.

observations, the final data set contains 16,349 observations based.[11] The resulting overall database has three dimensions: a time dimension, a dimension for the lenders and a dimension for the borrowers. In order to be able to use a panel framework, one of the three dimensions of the data set, the lender dimension, has been eliminated by referring to average bank characteristics per firm. The respective procedure is explained in the Appendix.

Regarding the representativeness of the final data set for the purpose of this study, we focussed on two potential issues, namely a bias resulting from the matching procedure (as companies may have not been selected randomly) and resulting from the original databases themselves, notably the truncation in the credit register. In both dimension, we found a certain increase in firm size, but the median firm in the final sample is still relatively small with a revenue of EUR 16m, so the outcome seems to be representative except for very small companies.

5 Variable definitions

Before entering the empirical analysis, we seek to define the most important dependent and explanatory variable used in this study.

5.1 Dependent Variable

The dependent variable is being specified based on the definition of relationship lending given in section 2. We refer to a dummy variable for definition i (denoting a high share of borrowing from one single bank) and the logarithmized number of lending relationships (definition ii). Both measures are only based on information

[11] In order to align the data sources with one another, the higher frequency of the quarterly credit register data was reduced by calculating four-quarter averages (aggregation method ii). In this way, one of the shortcomings of the credit register's reporting threshold can be mitigated, namely that only loans above EUR 1.5m are included. By referring to averages of quarterly values, smaller loans which exceed the threshold only in one quarter are more likely to be captured. As a robustness check, we have also included the values of the quarter to which the balance sheet accounts refer to, yielding to a total of 15,947 observations, referred to as aggregation method i.

from the credit register, as the definitions of debt are too different in the credit register and the corporate accounts statistics. As part of the bank loans which fall below the reporting threshold are not shown in the credit register this fact can potentially result to overstating a bank's debt financing. To account for this, we apply relatively strict measures of relationship lending (minimum share of a firm's bank loans of 80% or even more), so the identified relationship lenders are likely to be those found via more common definitions of relationship lending and "full" information on the credit side.

5.2 Explanatory Variables

We use a default risk measure (PD), which is calculated from the balance sheet data and can be interpreted as a one-year probability of default of the firms.[12]

We measure the R&D/knowledge intensity with a dummy variable which relies on long-term industry averages. The dummy becomes one if an industry was classified as R&D-intensive in Grupp and Legler (2000). Cyclicality is measured as the long-run sensitivity of each industry's gross value added to changes in the aggregated gross value added.

In order to determine concentration in the banking market, we referred to the HHI[13] based on 67 German regions[14].

6 Descriptive statistics and first results

6.1 Descriptive statistics

Table 3 contains descriptive statistics for the main indicator of relationship lending used in this study, a high concentration of borrowing on one single bank. Accord-

[12] We referred to a binary logistic regression model with a high discriminatory power. See Krueger et al. (2005) for further information.

[13] The Hirschmann-Herfindahl-Index (HHI), which is the sum of the squared portfolio portions

[14] Deutsche Bundesbank uses a proprietary to define regions in Germany, the so-called "ortsnummer". The "ortsnummer" of a German region or city is the code for the respective branch of the Bundesbank that is responsible for this region or city. The average size of these regions is approximately 5,000sqkm.

ingly, 54.2% (48.2%) of the firms in the sample raise at least 80% (90%) of their bank loans from one bank.[15]

Table 4 gives information on the distribution of the number of lending relationships in the sample: 41% of the companies in the sample have only one lending relationship and roughly 90% of the firms have 6 lending relationships or less. The maximum is 115 lending relationships.[16]

Table 5 shows the pairwise correlations of different house bank indicators. The correlation between the logarithmised number of lending relations ("ln NOB"), $RL_{80\%}$ and $RL_{90\%}$ is at least (-)75% . At the 0.1% level, all variables are significantly correlated. This points to the conclusion that the indicators contain relatively similar information.[17]

Table 6 summarizes descriptive statistics the explanatory variables used in this study.[18] The table shows that the firms exhibit a high creditworthiness[19], are relatively well established (average age 44.4 years) and that a substantial portion of the firms are SMEs (legal form "GmbH", asset below EUR 50m). Moreover, the table shows that one out of eight firms belongs to a R&D intense industry sector. For the banks, the average size in terms of total assets is about EUR 100bn. The level of the HHI indicates that the concentration in the banking market is relatively moderate.

6.2 First results

Next, we investigate our hypotheses using descriptive statistics and simple tests before moving forward to the regressions. We concentrate on one indicator, concen-

[15] The corresponding values for the aggregation method based on the quarterly averages are slightly higher.

[16] It has been ensured based on robustness checks that this number that appears to be very high, is appropriate. It occurred for a large German firm settled in various locations, whereby lending relationships with various different local banks have been established. For a relatively small sample of large European firms, **?** find a maximum of 70 lending relationships for Italy, which further confirms that the maximum used in this study seems to be adequate.

[17] As outlined before, the logarithmized number of lending relationships will be used for robustness purposes.

[18] As a means of quality check, all variables have been analyzed for outliers. To ensure robust results, we have censorized the equity ratio at one percent and 99%, respectively.

[19] The average equity ratio is 18.9%, the return on assets 4.7% and the average Probability of Default 0.52%.)

tration of debt of at least 80% at one bank. Table 7 shows that there is a strong negative correlation between a firm's size and its concentration of borrowing. The share of companies which borrow at least 80% of their credit from one bank steadily decreases with firm size. The same holds true for the share of the largest lender. This outcome is in line with our expectations (Hypothesis 1) that especially small informationally opaque firms choose a relationship lender.

Table 8 gives the means of firm variables subject to different size classes and conditioned by the relationship lending status. More specifically, firm age, R&D intensity and variables about a firm's quality (for example equity ratio) interfere with size and are therefore analyzed conditional on the firm size. Table 8 shows that R&D-intensive firms are more likely to choose a relationship lender. In each size class, companies with a relationship lender have a significantly higher R&D intensity than companies without a relationship lender. The only exception are very large companies where no significant difference exists. This evidence is consistent with Hypothesis 2 according to which R&D-intensive companies are exposed to higher information asymmetries and therefore tend to concentrate their borrowing on one bank. However, the relation between age and choosing a relationship lender is not in line with hypothesis 1. Whereas small companies with a relationship lender are, on average, significantly older than small companies without a relationship lender, the reverse is true for large companies.

Hypotheses 3a, 3b and 3c examine the influence of a firm's quality on relationship lending. Accordingly, the relationship between a firm's credit quality (measured by its PD or equity ratio) and the likelihood of relationship lending can be negative, inversely u-shaped or positively. As table 8 shows, medium-sized and large companies with a relationship lender exhibit significantly higher equity ratios and significant lower PD-values than medium-sized and large companies without a relationship lender, while small companies do not differ significantly with respect to both variables. This evidence indicates that high-quality firms above a certain size threshold tend to choose a relationship lender which is in line with hypothesis 3c and to some extent with hypothesis 3b.

7 Regressions

In the regressions, we focus again on the dependent variable "high share of debt financing by one bank (80% level)" ($RL_{80\%}$). Additionally, we run regressions with alternative indicators of relationship lending to ensure that the results are robust.

As our dependent variable is a dummy variable, we use limited dependent variable models. A shortcoming of these models for panel data sets is that a fixed effects regression is only possible for such observations where the dependent variable changed at least once during the sample period, while the other observations are excluded from the sample (see Baltagi (2005)). This procedure may lead to a bias as firms included in the regression (i.e. those that change their relationship lending status) can be systematically different from the excluded firms. We thus use a fixed and a random effects model and discuss the results of both models. [20].

Table 9 summarizes the regression results. We consider the lenders' average size as a control variable which is highly significant in statistical and economic terms. The negative sign is in line with evidence for Italy according to which especially small banks act as single or relationship lenders (see Detragiache et al. (2000)). Small banks probably have an advantage in processing soft information which is especially valuable for relationship lending (see Stein (2000)).

We also control for the degree of competition as measured by the Hirschmann-Herfindahl-Index (HHI). We find that relationship lending tends to get more likely the lower the HHI and therefore the higher the competition in the lender's market is. The variable is significant only in the random effects specifications. This result is generally consistent with the predictions of the model of Boot and Thakor (2000). The authors show that increasing competition between banks leads to more relationship banking and less transaction banking, as relationship orientation helps

[20] A decision as to which model is more appropriate could also be done based on a Hausman test. However, a standard Hausman test compares the results of two models with different sets of observations. Furthermore, in the case of our regressions, the Hausman test statistics do not show clear results (the difference between the fixed and the random effects model is significant only at the 10% level)

to partially insulate the banks from pure price competition. The result contradicts Petersen and Rajan (1995).

Moreover, we included year dummies to examine the time trend in our data set. Generally, the dummies are neither significant in the random nor in the fixed effects model. The coefficients do not show a clear trend and heavily depend on the specification (for example model 3 versus model 5). Therefore, our results do not support the common view that banks have developed to credit factories and relationship lending has become less important.

According to Hypothesis 1 we expect informationally opaque small, young companies to prefer relationship lending. Concentrating their borrowing on one bank may help such firms to reduce information asymmetries and to avoid credit rationing. The results show that age and especially size are statistically and economically important variables for determining the probability of choosing a relationship lender. If size increases by 1%, the probability of relationship lending decreases by 4% in the random effects model. The coefficient in the fixed effects model is roughly the same.

Age decreases the probability of relationship lending as well. Older companies are significantly less likely to choose relationship lending. If age increases by 1%, the probability of relationship lending decreases by about 0.25% (random effects model). Surprisingly, the effect of age is about three and a half times larger in the fixed effects than in the random effects model.

Hypotheses 2 examines whether R&D- and knowledge-intensive firms are more likely to choose a relationship lender. If relationship lending is an efficient instrument for reducing information asymmetries, R&D- and knowledge-intensive companies should concentrate their borrowing on one relationship lender, as R&D activities are linked with proprietary information and information asymmetries are higher. We measure R&D/knowledge intensity with a dummy variable which relies on long-term industry averages. As this variable is time-constant, we can test Hypothesis 2 only in a panel regression with random effects. The results are in line with our prediction: R&D/knowledge-intensive companies are significantly more likely to choose a relationship lender. The probability increases by 13 percentage points.

Hypotheses 3a, 3b and 3c examine the influence of the firm's creditworthiness. The theoretical literature is ambiguous regarding the effect of a firm's credit quality on the probability of relationship lending. Depending on the theoretical model, a negative, an inversely u-shaped or a positive relation is possible. We measure a firm's credit quality with its PD (probability of default) and include a linear and a squared term to capture non-linear relations. At first glance, table 9 indicates a u-shaped influence of a firm's PD on the likelihood of relationship lending and thus does not support either of these predictions. The linear and the squared term are both significant. However, when calculating the combined effect over the range of relevant PD values it becomes clear that the influence of a firm's PD is negative for most observations. A firm's creditworthiness affects the probability of relationship lending positively only for very high PD values (values beyond the 98% quantile for fixed and random effects model). Overall, the results are consistent with Hypothesis 3c which is based on the model of von Thadden (2004). Accordingly, there exists a selection process over time where good firms stay at their relationship bank and bad firms choose an arm's-length bank. On average, relationship lenders thus finance firms of higher credit quality than arm's length banks do. The results are also to some extent consistent with hypothesis 3b (model of Rajan (1992)) as the hypothesis states that high-quality firms are indifferent between arm's-length finance and relationship lending. The model derives the decision for relationship lending from a trade-off between an efficient decision about which projects to finance versus providing high incentives to exert effort.

The results are not in line with the model of Bolton and Scharfstein, which predicts a negative influence of a firm's credit quality on the likelihood of relationship lending (Hypothesis 3a). The authors derive the optimal numbers of creditors from a trade-off between preventing strategic defaults and high renegotiation costs in the case of liquidity defaults.

One may be concerned that endogeneity problems may influence our results and may lead to reverse causality. For example, age may not only influence the likelihood of choosing a relationship lender, but the existence of a relationship lender may also increase a firm's survival probability and thereby the age distribution in our sample. Endogeneity problems may be relevant with regard to age and size, but are probably minor important or not relevant with regard to a firm's R&D-intensity or a firm's creditworthiness. However, as to age and size, endogeneity issues work into the opposite direction as our hypothesis states. Whereas our hypothesis states that young and small companies should choose a relationship lender, the endogeneity bias would lead to the effect that old and large companies are financed by relationship lenders. Therefore, if there is an endogeneity bias, it would reduce the effect of age and size. This may also explain the below results that age is not robustly significant.

Robustness checks

We ran several robustness checks. Firstly, we checked whether the influence of firm size results from information asymmetries or from the fact that banks avoid concentration risk.[21] For larger firms with - on average - larger credit exposures banks need more regulatory capital, implying that concentration risk in the bank's portfolio increases. We therefore ran a new regression excluding all companies from the sample where

$$\frac{\sum \textit{loans of company}_i}{\textit{liable capital of company i's smallest bank}} > 5\%.$$[22]

In the new regression, the coefficient of size goes sharply down, in the fixed effects model by over 30%, in the random effects model even by nearly 40%. However, the coefficient is still significant at the 1%-level in both models. We also ran a regression where we lowered the threshold further to 2%. Here, the effects are slightly more pronounced than in the model with a threshold of 5%, but the variables are, once again, significant at the 1%-level.[23]

[21] One potential additional explanation for the firm size effect are transaction costs. We implicitly controlled for this effect by including the asset size, so it is unlikely that transaction costs play a material role. However, the effect will be further investigated.

[22] The Large Exposures Regulation (German: "Grosskreditrichtlinie") sets a limit of 10% above which exposures have to be reported to Deutsche Bundesbank. This is also the threshold set by the Basel II framework.

[23] We acknowledge, however, that the robustness test may itself result again to bias, as smaller banks are more often excluded than larger one, so the robustness check may not provide ultimate clarification on this issue.

Secondly, we ran several regressions to check how the problem of truncation in the credit register influences the results. As loans of less than EUR 1.5 million are only partly reported (see Section 4), the credit register shows a biased picture of the debt structure of companies. Firstly, we constructed variables combining information from the credit register (CR) with the balance sheet statistics (BS). Data from these two data sources may differ because i) loans of less than EUR 1.5m are only partly reported in the credit register and ii) the data sources apply different definitions of debt. As we are only interested in the effects of truncation, we constructed a new indicator for relationship lending in two steps. In the first step, we created an auxiliary variable which classifies a borrower as a customer with a relationship lender if

$$RL_{temp} = 1 \; if \frac{largest\ loan\ according\ to\ CR}{\sum bank\ loans\ according\ to\ BS} > 80\%.^{24}$$

$$RL_{temp} = 0 \; otherwise$$

We use a narrow definition of debt and include only bank loans in the denominator (see discussion in Section 4). When we compare the new variable with our old indicator $RL_{80\%}$, the two variables are identical in the ideal case. If the new one is 0 and the old one is 1, this is probably due to truncation in the register as for example smaller exposures of other banks are not shown. However, if the new one is 1 and the old one is 0, this combination is probably due to different definitions in the data sources. We thus combined the two indicators:

$$RL_{BSCR} = min[RL_{80\%}, RL_{temp}]$$

Table 10 shows the results using RL_{BSCR} as the dependent variable (model 3 and 4). The results differ quantitatively, but are qualitatively similar. The coefficients

[24] The credit register contains information about the structure of debt (off-balance sheet versus on-balance sheet) only since 1997. Therefore, we used data on total loans until 1996 and data on on-balance sheet loans since 1997.

of size and R&D intensity are smaller with the new indicator and the effect of age is not significant in the fixed effects model. We also ran regressions where we built our auxiliary variable referring to a broader definition of debt (bank loans, acceptances and bonds) and built the new combined indicator based on this broader definition. The results are similar to the specification with RL_{BSCR}. Except for age, these regressions confirm our above results.[25]

The credit register shows a more reliable picture for those companies where the sum of loans from the credit register is relatively high compared to the debt in the balance sheet. Therefore, we ran a second robustness check regarding truncation by restricting our observations to those companies where the sum of loans in the credit register is least 80% of the corresponding amount in the balance sheet statistics.[26] As Table 10 (model 5 and 6) shows, coefficients and significance levels change only minor. Size, age and credit quality are significant in the random and the fixed effects specification as well as R&D-intensity in the random effects model (which cannot be considered in the fixed effects model).

Furthermore, as especially small companies are exposed to the problem of truncation, we conducted a third robustness check with respect to truncation where we excluded small companies (assets below median) from our sample. The regression also leads to similar results (results not reported).

Finally, we conducted several robustness checks with respect to our dependent variable. We used the (log of) the number of relationships as the dependent variable. The results are similar to those above except that age is not significant anymore, while the significance of size increases. As the two variables are significantly correlated, the coefficient of size may also partly show the effect of age. Moreover, we changed the threshold of our relationship lending indicator. We increased (decreased) the threshold to 90% (70%), ie banks that finance at least 90% (70%) of a firm's loans are now classified as relationship lenders. The results are very similar

[25] We also controlled for the type of balance sheet (tax or trade balance) in order to exclude a potential effect resulting from this. As the variable is generally not significant, this can be excluded.

[26] As the credit register provides information about balance sheet loans only since 1997, we used a firm's total indebtedness before 1997.

to the above results. Finally, we calculated our relationship lending indicator based on aggregation method ii, which uses the yearly average values of the credit register instead of the values of the balance sheet quarter. The results are once again very similar.

8 Conclusion

In this study, we empirically analyze factors that determine relationship lending in a major EU economy, Germany. Unlike most previous empirical contributions, the data set used in this study is much more comprehensive.

Starting from the theoretical literature, we analyze the determinants for relationship lending in Germany. We find that relationship lending apparently reduces information asymmetries and thereby helps credit rationing to be avoided. In line with this argument, we find that small and R&D-intensive firms, which are supposed to particularly contribute to economic growth and employment, tend to choose a relationship lender. This does also apply to young firms, also if to a lesser degree. Whereas the effect of size and age is a common result in the literature, the effect of the R&D-intensity is partly in contrast to international evidence (see eg Detragiache et al. (2000)). Due to underdeveloped equity markets in Germany R&D-intensive firms rely more heavily on bank credits than in other countries, so relationship lending could therefore also serve the role as a means to substitute equity financing.

Second, we examine how a firm's credit quality influences the likelihood of relationship lending. We find that firms of high credit quality tend to choose a relationship lender. This is in line with a positive selection process over time where good borrowers stay at their relationship lender and bad borrowers switch to (outside) arm's length banks.

Finally, we also investigate whether relationship lending became less important since the mid 90s, which, however, cannot be observed for Germany.

This data set makes it possible to investigate further important questions concerning relationship lending. Possible research topics are: the duration of lending relationships, the impact of relationship lending on a firm's funding costs, and the behavior of a relationship bank when the borrower is in financial distress.

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Appendix

Processing of data (Example)

Below, a hypothetical example of how the raw data have been processed is shown. From the credit register we obtain the following information about the indebtedness of the four firms A1, A2, B and C with respect to the banks 1, 2, 3, 4 (See Table 1,

Table 1: Data from the Credit Register (extract)

Firm	Bank	Year	Indebtedness (th EUR)
A1	1	1999	700
A1	2	1999	1800
A2	1	1999	900
B	1	1999	50000
B	2	1999	1600
B	4	1999	1400
C	3	1999	2000

please note that the firms A1 and A2 belong to the borrower unit A). As mentioned above (See Section 4), not all exposures reported in the credit register are above the threshold of EUR 1.5m. The reason why bank 1 has to report the exposures to the firms A1 and A2 is that the combined exposure, ie the exposure to the borrower unit A, is above the threshold. The exposure of bank 4 to firm B has to be reported because presumably this exposure was above the EUR 1.5m threshold at least once in the preceding quarter (and the requirement to report depends on the maximum exposure during the preceding quarter whereas the exposure to be reported is that of the quarter end).

We condense the data set by i) aggregating the firms to borrower units where adequate (firm in balance sheet statistics is a group) and ii) by replacing the lending information by summary statistics. The data processing in our example results in

Table 2: Final data set (extract)

Firm	Year	Total indebtedness (th EUR)	Largest bank loan (th EUR)	Number of lending rel.	Share of largest bank loan	Bank ID of relationship lender
A	1999	3400	1800	2	52.9%	N/A
B	1999	53000	50000	3	94.3%	1
C	1999	2000	2000	1	100.0%	3

the data set as displayed in Table 2. It has to be noted that the actual final data set additionally contains the firms' and the banks' balance sheets.

Table 3: Concentration of borrowing: descriptive statistics

Dependent Variable	$RL_{80\%}$	$RL_{90\%}$
Share of observations	54.1	48.2
N	16349	16349

$RL_{80\%}$ ($RL_{90\%}$) denotes that a firm concentrates at least 80% (90%) of its borrowing at one bank. The information shown in the table is based on aggregation method ii) (see section on data).

Table 4: Number of lending relationships per firm

Number of banks	in %	cumulative %
1	41.0	41.0
2	22.2	63.1
3	12.1	75.2
4	6.6	81.8
5	4.6	86.4
6	3.6	90.0
7	2.1	92.1
8	1.8	93.8
9	1.1	94.9
10+	5.1	100.0

The information shown in the table is based on aggregation method ii) (see section on data). For aggregation method i), the results are comparable.

Table 5: Correlation matrix of relationship lending indicators

Dependent Variable	ln NoB	$RL_{90\%}$	$RL_{80\%}$
ln NoB	1		
$RL_{90\%}$	-0.77	1	
$RL_{80\%}$	-0.75	0.89	1

ln NoB denotes the logarithmised number of lending relationships. $RL_{90\%}$ and $RL_{80\%}$ denote concentration of bank borrowing at 90% and 80% respectively. All variables are significantly correlated at the 0.1% level. The information shown in the table is based on aggregation method ii) (see section on data).

Table 6: Descriptive statistics of explanatory variables

Variable	Unit	Obs	Mean	Std. Dev.	Quantiles	
					25%	75%
Total assets (firm)	EUR 1000	16349	126907	1541739	4293	34528
Age (firm)	years	14477	44.4	41.8	16.0	63.0
Equity ratio (firm)	%	16348	18.9	17.9	5.0	27.7
Return on assets (firm), %	%	16347	4.7	14.1	0.1	8.6
Probability of Default (firm), %	%	14459	0.52	0.14	0.13	0.61
Corporation (AG or KGaA), %	%	16349	8.9			
Limited liability corporation (GmbH), %	%	16349	49.7			
Cyclicality (firm's industry), %	%	14974	69.1	116.5	-6.0	138.4
R&D intensive (firm's industry)	%	16349	12.7			
Total assets (banks)	EUR m	16230	99399	128615	4349	148462
Regional HHI (bank), %	%	16346	5.2	3.1	3.1	6.3

The Probability of Default (PD) denotes a one-year ratio determined based on a binary logit model. Cyclicality is measured as the long-run sensitivity of each industry's gross value added to changes in the aggregated gross value added. R&D intensity is a dummy variable which is equal to one if an industry was classified as R&D-intensive in Grupp and Legler (2000). The regional concentration in the banking market (Regional HHI) has been determined based on 67 German regions (see section on variable definitions.

Table 7: Relationship lending by firm size

	N	$RL_{80\%}$	Mean lending share of largest lender
<= EUR 2.5m	1778	94.5	97.6
EUR 2.5m - 5m	2806	88.6	95.1
EUR 5m - 10m	3152	71.4	87.6
EUR 10m - 25m	3263	46.6	75.0
EUR 25m - 100m	2884	32.0	63.9
> EUR 100m	2064	20.3	53.4

$RL_{80\%}$ denotes concentration of bank borrowing at one bank level at 80% or more.

Table 8: Firm characteristics by size

	Age		High R&D intensity		ROA		Equity ratio		PD	
Size classes	$RL_{80\%} = 0$	$RL_{80\%} = 1$	$RL_{80\%} = 0$	$RL_{80\%} = 1$	$RL_{80\%} = 0$	$RL_{80\%} = 1$	$RL_{80\%} = 0$	$RL_{80\%} = 1$	$RL_{80\%} = 0$	$RL_{80\%} = 1$
<= EUR 2.5m	17.9	26.5***	16.3%	23.6%*	1.6	4.5	12.9	13.6	0.7	0.7
EUR 2.5m - 5m	29.8	34.9**	16.3%	24.3%***	3.4	3.4	12.3	11.3	0.6	0.6
EUR 5m - 10m	44.2	41.7	18.2%	21.6%**	2.4	4.4***	12.7	15.5***	0.6	0.5**
EUR 10m - 25m	48.4	43.6***	27.0%	30.0%*	4.0	5.5***	17.1	20.0***	0.5	0.5***
EUR 25m - 100m	53.1	51.7	31.5%	43.2%***	4.7	9.0***	22.9	30.3***	0.5	0.3***
> EUR 100m	63.5	48.8***	59.5%	58.5%	4.4	6.5***	30.1	33.1***	0.4	0.3***
total	51.9	39.2	34.5%	27.9%	4.0	4.9	21.1	17.0	0.5	0.5
N	6178	7945	6671	9276	6670	9275	6671	9275	5752	8377

The table shows means for the different explanatory variables (see Table 6), conditioned by firm size and relationship lending status.
***/**/* indicate statistically significant differences in the means at the 1%, 5% and 10% levels, respectively.

Table 9: Panel regression (1)

	Model 1	Model 2
Dependent Variable	$RL_{80\%}$	$RL_{80\%}$
log assets (firm)	-1.170	-1.306
	(25.15)***	(8.24)***
age (firm)	-0.187	-0.664
	(2.90)***	(2.43)**
PD (lagged, firm)	-0.657	-0.493
	(5.08)***	(2.78)***
squared PD (lagged, firm)	0.113	0.104
	(3.91)***	(2.49)**
R&D intensive (firm's industry)	0.583	
	(4.39)***	
log assets (bank(s))	-0.381	-0.312
	(13.59)***	(7.47)***
regional concentration (bank's market)	-0.038	-0.020
	(2.60)***	(1.18)
tax balance	0.113	0.174
	(1.14)	(1.47)
year = 1995	-0.053	-0.019
	(0.38)	(0.13)
year = 1996	0.029	0.057
	(0.20)	(0.37)
year = 1997	0.073	0.135
	(0.52)	(0.84)
year = 1998	0.001	0.056
	(0.00)	(0.33)
year = 1999	0.217	0.303
	(1.41)	(1.68)*
year = 2000	0.188	0.264
	(1.21)	(1.40)
year = 2001	0.180	0.319
	(1.12)	(1.61)
year = 2002	0.300	0.565
	(1.81)*	(2.68)***
year = 2003	0.152	0.340
	(0.88)	(1.54)
year = 2004	0.551	0.806
	(2.49)**	(3.00)***
Constant	16.508	
	(31.16)***	
Observations	10426	4302
Number of borrowers	1984	612
Panel method	random	fixed

The table shows the coefficients with the t-values in parentheses. The dependent variable is a dummy variable which is equal to one if a firm concentrates at least 80% of its borrowing at one bank ($RL_{80\%}$).
The Probability of Default (PD) denotes a one-year ratio determined based on a binary logit model. R&D intensity is a dummy variable which equals one if the borrower's industry is R&D- or knowledge-intensive. The HHI shows the regional concentration in the banking market. The tax balance is a dummy variable to ensure that the results are not driven by the balance sheet type referred to. The PD and the regional concentration are measures in percentage. The firms' and banks' assets are measured in real terms.
***/**/* indicate statistically significant results at the 1%, 5% and 10% levels, respectively.

Table 10: Panel regression (2)

	Model 3	Model 4	Model 5	Model 6
Dependent Variable	RL_{BSCR}	RL_{BSCR}	$RL_{80\%}$	$RL_{80\%}$
log assets (firm)	-0.782	-0.809	-1.136	-0.815
	(17.72)***	(5.35)***	(22.02)***	(4.26)***
age (firm)	-0.121	-0.161	-0.217	-0.654
	(1.90)*	(0.60)	(2.95)***	(1.85)*
PD (lagged, firm)	-0.668	-0.551	-0.852	-0.576
	(5.54)***	(3.31)***	(5.57)***	(2.71)***
squared PD (lagged, firm)	0.098	0.096	0.116	0.080
	(4.19)***	(2.89)***	(3.56)***	(1.84)*
R&D intensive (firm's industry)	0.257		0.519	
	(1.96)**		(3.42)***	
log assets (bank(s))	-0.122	-0.124	-0.369	-0.307
	(4.61)***	(2.99)***	(10.61)***	(5.14)***
regional concentration (bank's market)	-0.036	-0.012	-0.049	-0.016
	(2.45)**	(0.68)	(2.70)***	(0.71)
tax balance	0.050	0.082	0.124	0.291
	(0.50)	(0.68)	(1.04)	(1.92)*
year = 1995	0.176	0.198	0.032	0.017
	(1.31)	(1.36)	(0.19)	(0.09)
year = 1996	0.115	0.077	0.073	0.015
	(0.85)	(0.52)	(0.44)	(0.08)
year = 1997	-0.499	-0.615	0.046	0.021
	(3.64)***	(3.96)***	(0.27)	(0.10)
year = 1998	-0.348	-0.386	0.087	0.142
	(2.44)**	(2.34)**	(0.49)	(0.66)
year = 1999	-0.092	-0.080	0.311	0.411
	(0.61)	(0.45)	(1.67)*	(1.76)*
year = 2000	-0.072	-0.034	0.313	0.338
	(0.48)	(0.18)	(1.66)*	(1.40)
year = 2001	-0.119	-0.058	0.362	0.474
	(0.77)	(0.30)	(1.86)*	(1.87)*
year = 2002	0.022	0.165	0.435	0.730
	(0.13)	(0.80)	(2.17)**	(2.68)***
year = 2003	-0.118	-0.007	0.227	0.417
	(0.69)	(0.03)	(1.09)	(1.48)
year = 2004	0.220	0.402	0.815	1.029
	(1.00)	(1.50)	(3.13)***	(3.12)***
Constant	8.356		15.991	
	(17.25)***		(25.99)***	
Observations	10426	4427	7872	2557
Number of borrowers	1984	672	1750	410
Panel method	random	fixed	random	fixed

The table shows the coefficients with the t-values in parentheses.
Model 3 and model 4 are robustness checks with an alternative relationship lending indicator (RL_{BSCR}). Model 5 and 6 restrict the sample to those companies where the sum of loans in the credit register is at least 80% of the amount in the balance sheet statistics in order to ensure that the results are not driven by the potential mismatches of the databases used on the study. The dependent variable for model 5 and 6 is a dummy variable which is equal to one if a firm concentrates at least 80% of its borrowing at one bank ($RL_{80\%}$).
The Probability of Default (PD) denotes a one-year ratio determined based on a binary logit model. R&D intensity is a dummy variable which equals one if the borrower's industry is R&D- or knowledge-intensive. The HHI shows the regional concentration in the banking market. The tax balance is a dummy variable to ensure that the results are not driven by the balance sheet type referred to. The PD and the regional concentration are measures in percentage. The firms' and banks' assets are measured in real terms.
***/**/* indicate statistically significant results at the 1%, 5% and 10% levels, respectively.