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Who do borrowers borrow from?
Evidence from multi-bank relationships

Tobias Berg[1] Felix Brinkmann[2] Philipp Koziol[3]

Abstract

Most firms have multiple banking relationships. This raises an important question: If a borrower needs new funds, which bank will provide these funds to the borrower? Using data from the German credit registry on the bank-borrower-quarter level, we are able to answer this question using borrower x quarter and bank x quarter fixed effects. We find three main determinants for lending decisions: First, and most significantly, banks with the largest exposure to a borrower are less likely to provide new funds (diversification argument). Second, banks assigning a lower probability of default to a borrower are more likely to provide new funding, suggesting that adverse selection plays a role. Third, banks with a larger and longer relationship scope – measured by the length of the bank borrower relationship and as having a derivatives exposure with the borrower – are more likely to provide new funds.

Keywords: diversification, internal ratings, loan granting, winner's curse, derivatives, bank relationships

JEL-Classification: G21, G28

[1] Bonn University, Adenauerallee 24-42, 53113 Bonn, Germany. E-Mail: tobias.berg@uni-bonn.de.
[2] Deutsche Bundesbank, Wilhelm-Epstein-Str. 14, 60431 Frankfurt/Main, Germany. E-Mail: felix.brinkmann@bundesbank.de. This paper represents the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank or its staff.
[3] Deutsche Bundesbank, Wilhelm-Epstein-Str. 14, 60431 Frankfurt/Main, Germany. E-Mail: philipp.koziol@ecb.int. This paper represents the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank or its staff.

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1 Introduction

Most firms have multiple banking relationships. This raises an important question: If a borrower needs new funds, which bank will provide these funds to the borrower? One conjecture would be that banks evaluate borrowers independently, with the most optimistic bank providing fund to the borrower. However, from a bank perspective, solely providing loans based on the bank's screening result may not be optimal as it may subject them to the “winner’s curse”. If other banks do not provide loans to the borrower at the same terms, this provides a signal to the bank that it might be too optimistic. Refusing to fund a very large portion of a borrower’s liabilities can therefore be a prudent strategy, even if the own screening does not give any warning lights (diversification argument). Banks may also take into account the length and depth of their relationship with the client, as this likely reflects a comparative advantage in evaluating the borrower. Second, from the borrower’s perspective, fully relying on the most optimistic bank as a provider of its funds might subject the borrower to a hold-up problem. It might therefore also be in the interest of the borrower to diversify its funding sources across banks.

In this paper, we analyze the relative importance of three determinants of bank lending: First, the aggregate screening result of banks as measured by their bank-internal probability (PD) of default estimate. Second, the relationship angle, as measured by the scope and duration of bank-borrower relationships. Third, diversification argument as measured by the relative shares of each lender.

Our data comes from the German credit registry and provides us with a complete overview of all lending relationships above EUR 1.5mn loan volume. Importantly, we have access to the bank internal probability of default (PD) estimates on the borrower-bank-quarter level, i.e. for each borrower-quarter our dataset contains PD estimates for all banks that have exposure to a specific borrower. The data set thus allows us analyze the three determinants of bank lending discussed above using both borrower x quarter as well as bank x quarter fixed effects. We can therefore look at an individual borrower and evaluate changes to the lender composition from quarter to quarter. Furthermore, using bank x quarter fixed effects allows us to control for any changes in credit policies of a bank that is unrelated to a specific borrower.

We find three main determinants for lending decisions: First, and most significantly, banks with the largest exposure to a borrower are less likely to provide new funds (diversification argument). In particular, if a bank's exposure towards a borrower is above the average exposure of all banks in a respective quarter, then the amount the bank is willing to provide to borrower in the next quarter is about 12.38% lower than for banks with below average exposure towards the borrower. Second, banks assigning a lower probability of default to a borrower are willing to provide more funding. We document that bank's funding is about 2.43% higher in the next quarter than for banks who are more pessimistic about the borrower's creditworthiness. These results suggest that banks are subject to adverse selection, with banks having lower PD estimates being more likely to end up with high exposures. Third, banks with a larger relationship scope – measured by the length of the bank-borrower relationship and as having a derivatives exposure with the borrower – are more likely to provide new funds. These results suggest that the scope of the relationship plays a major role in the loan granting decision. These results are both consistent with an information-view of bank relationships (the bank having better access to information due to the scope of the relationship) as well as with a cross-selling view of bank relationships (the bank being willing to provide more funding if the borrower buys more products from the bank). We find that all three channels are important for both the intensive as well as the extensive margin.

There exists a large literature on the relative importance of multiple versus single banking relationships. Since exclusive bank-creditor relationships avoid free-riding problems and duplicated monitoring efforts as well as the more appropriate handling of financially distressed but fundamentally solvent firms (Koziol, 2006), single bank relationships seem to be reasonable, for instance in a situation where a firm borrows once as monitoring costs are then minimized (Bannier, 2010; Carletti et al., 2007). Nevertheless, the existence of single bank lending relationships is limited as several empirical studies show (e.g. Detragiache et al., 2000; Ongena et al., 2012). The majority of the literature approves that multiple banking is beneficial for lending. Reasons discussed in the literature are the costs of confidential information leakage (Bhattacharya and Chiesa, 1995; Yosha, 1995), the costs of renegotiations (Bolton and Scharfstein, 1996), higher bank competition (Petersen and Rajan, 1995) as well as the sharing of firm risks (Foglia et al., 1998). In general, the number of bank relationships depends on the firm's size, credit risk and demand for financial services (Neuberger and Räthke, 2009). Petersen and Rajan (1994) and Berger and Udell (1995) find that borrowers with longer bank relationships are charged less by their lenders. The length of the relationship and the number of bank relations determined how a borrower was impacted by the financial crisis in the loan market (Cotugno et al., 2013).

However, there is only limited research on loan granting decisions if a borrower has multiple relationships.

Beyond these gains of multiple banking, the problem of asymmetric information arises and leads to winner's curse as a bank may lend to an obligor whose rating is worse than the forecasted one of the creditor. The phenomenon of winner's curse has been extensively discussed in the literature with a strong focus on theoretical approaches. Studies like, Broecker (1990), Riordan (1993), and Shaffer (1998) apply game theory models which show that banks are concerned that their internal ratings might be too positive when granting additional or new loans. Especially in case of granting to new firm imperfect information play an important role in order to anticipate a profitable loan contract and winner's curse occur as well (Sharpe, 1990; Rajan, 1992; von Thadden, 2004). Until now the winner's curse phenomena is only briefly empirically tested. Ogura (2010) shows empirically that increased bank competition reduces the banks' efforts of screening the borrowers. Kick et al. (2013) find that excessive credit growth increases the risk-taking of banks significantly as these banks underestimate the risk level in the credit market.

The holding of derivatives with respect to a certain loan contract has only briefly discussed in the academic literature. Research by Cebenoyan and Strahan (2004), Franke and Krahnen (2007) and Goderis et al. (2007) has found that banks have used credit derivatives and loan sales to diversify credit risk exposures in order to increase the availability of loans. In contrast, Hirtle (2009) finds only limited evidence that greater use of credit derivatives is associated with greater supply of bank credit, so the benefits of the growth of the credit derivatives market concentrate mainly on the larger borrowers. With respect to interest rate derivatives Brewer et al. (2000) analyzed the relationship between bank participation in interest rate derivatives and bank lending and concluded that the use of these derivatives increases bank lending.

The high exposure hypothesis has so far only sparsely analyzed. To our knowledge the literature lacks theories or empirical studies that deal with the effect of the existing loan volume on loan growth. The "one-to-few" bank theory, as discussed by, for example, Sharpe (1990) and Rajan (1992) is connected to this topic and says that small firms tend to borrow from only one to few banks which underlines the different lending behavior of small and larger firms. Also related is the evidence that firms borrow for the first time from a single lender, but later they will borrow from multiple banks (e.g. Farinha and Santos, 2002).

The rest of the paper is organized as follows. Section 2 describes the dataset. Section 3 provides descriptive statistics. Section 4 explains our empirical strategy and presents the results. Section 5 concludes.

2 Data source and preparation

Our data source is the German credit register, the so called MiMiK.[4] It exhibits panel structure with respect to the individual borrower level as well as the borrower unit level. The dataset contains information on all loans on a quarterly basis which exceed the nominal level of € 1.5 million for each individual borrower at least once in the considered time period. The reported exposure amounts by banks rely on exposure from loans and the exposure from derivatives positions.

The level of individual borrowers (borrower level) is the most disaggregated form of the credit register. Additionally, the credit register aggregates the loans on the basis of borrower units which are mutually dependent legal entities, which are supposed to be likely to encounter financial problems given that one of the other dependent firms faces distress. This study makes use of the data on the borrower unit level. We also make use of the start of MiMiK in 1993 and track the length of a bank-borrower relationship. Finally we use information on credit derivatives which are written on a loan.

Since 2008 all banks that have internal rating models, independent of whether they are used for regulatory purpose or not, have to report their internal PD estimates alongside the exposure amount. This information is reported on the borrower-level using a common Bundesbank identifier for each borrower. Therefore, reports from different banks can easily be merged and compared. Although data on PDs is already available from the beginning of 2008, we drop the first two quarters as the data quality is rather low due to the launching period of the data base.[5]

Our sample ends in the fourth quarter of 2013. This gives us a final coverage of 22 quarters in our study (2008Q3-2013Q4). We apply the following filters to the original dataset: First, we focus on corporate borrowers and eliminate all borrowers from the financial institutions sector (14% of observations dropped). Second, we drop all borrowers that have only a single bank-relationship because these borrowers do not allow for an across-bank comparison. If a borrower has only one bank relationship in some quarters but several bank relationships in other quarters we only drop those quarters where only one bank relationship is reported (54% of observations dropped). Third, we drop all defaulted borrowers, i.e. all borrowers where at least one bank reported a PD of 100% in a given quarter (2% of observations dropped). These borrowers are also subsequently eliminated if they emerge from bankruptcy and banks start reporting PDs of less than 100% again. The reason for this is that the first quarter

[4] For detailed documentation of MiMiK see Schmieder (2006).
[5] Experts of the Deutsche Bundesbank strongly recommended leaving the first two quarters out of the data set.

where banks report a formerly defaulted borrower as non-defaulted varies from bank to bank. Fifth, we drop all borrower-quarter combinations where the borrower was assigned a PD of less than or equal to 0.03% (3% of observations dropped). A PD of 0.03% is the floor for calculating capital requirements based on internal models according to the Basel accord. Some banks reported PDs after application of this floor and some not, therefore the comparability of PD estimates for these borrowers is distorted.

The final dataset of our analyses includes 478,916 bank-borrower-quarter combinations from a total of 18,065 borrowers and 42 banks covering 22 quarter. Out of the total bank-borrower-quarter combinations, 140,817 refer to quarters where the borrower's aggregate loan volume increases across banks.

3 Descriptive statistics

Table 2 provides descriptive statistics for our dataset. The average borrower has € 38.5 million total loan volume outstanding, which is provided by 2.7 banks on average. The average bank-borrower relationship length is 27.5 quarters.

The dataset covers 830 bank-quarter observations from 42 different banks, where bank X provides in quarter t on average loans to 577 different borrowers. In each quarter banks report estimated internal PDs for 175,393 borrower-quarter combinations. The average PD is 1.66% with an interquartile range from 0.23% to 1.42%. The average across-bank PD dispersion which is the standard deviation of all PDs for each borrower per quarter is 1.33%. This undermines that estimated PD vary heavily overtime and also across banks, which has been shown by Berg and Koziol (2016).

Figure 1 shows the evolution of the respective figures over time. Panel A refers to the average loan volume and average PD. We find for both variables a decreasing trend since the third quarter of 2009. The average number of bank relationships is almost constant throughout the sample period in Panel B. The average relationship length increases as the time horizon of the dataset extents.

As highlighted in the introduction, the aim of the paper is to analyze determinants in the loan granting process, namely the assigned (internal) PD, the outstanding loan volume and the relationship scope between bank and borrower. To do so, we define the following four dummy variables on the bank-borrower-quarter level. First, the *Optimistic Bank* variable depicts banks which assign a lower PD than the average PD to the borrower. It is a signal for a more optimistic rating of the borrower's creditworthiness than the average assessment. Second, the *High Exposure Bank* variable identifies banks which have an over average exposure to a specific borrower. The variable captures therefore bank A's concentration risk with borrower X. The *Relationship* variable depicts banks which have an over average bank-borrower relationship length and last the *Relationship Derivative* variable shows if a bank has a derivative contract assigned to the granted loan, which indicates a long relationship between bank and borrower. The formal descriptions and definitions of our variables are summarized in Table 1.

Table 2 gives descriptive statistics for our four variables. It shows that 53% of all bank-borrower relationships are rated optimistically and 49% of all banks exhibit an exposure greater than the average exposure per borrower. Regarding the bank relationship, 59% of our bank-borrower relationships are of a length above the average and for 24% of all loans the banks hold a derivate position.

Figure 3 depicts the average loan volume and the average increase in loan volume with respect to our four determinants. Panel A shows that the average loan volume is higher with optimistic banks and higher with long bank-borrower relationship scopes.

Our main research interest lies in Panel B, which depicts the average positive change in loan volume. It gives a first identification of the direction of our determinants in the loan granting process. The figure shows that on average a bank (borrower) grants (lends) more loan volume if the bank is optimistic with the borrower, the bank has a below average loan volume and has an above relationship scope. In economic terms the difference in the loan volume is the most pronounced for the high exposure dummy. The relative change in loan volume is on average 81 percentage points higher with a bank that has a below average exposure with the borrower. This highlights that banks and borrowers try to diversify their lending and funding structure.

Figure 2 provides a illustrative, but representative, example for the case that a more optimistic bank provides additional funds to a borrower. The borrower has relationships with two banks, bank A and bank B. In Q3 2008, the borrower has loans outstanding of approximately € 4.3mn with bank A and approximately € 2.4mn with bank B. In Q3 2009, the borrower takes out a loan of € 7mn from bank A, thereby increasing bank A's exposure to the borrower to more than € 11mn. Bank A's probability of default estimate for the borrower is 0.4%, while Bank B's estimate is 0.6%, and therefore Bank A is more optimistic about the borrower's future prospects.

Figure 1 and 2 also highlight that PD estimates can change heavily over time. A bank can therefore be optimistic for one borrower and pessimistic for another borrower and, for the same borrower, it may be optimistic in one quarter but pessimistic in another quarter. In the example in Figure 2, Bank B is the pessimistic bank for borrower X, while Bank A is the optimistic bank for borrower X throughout the entire sample period.

4 Empirical strategy and results

The example and descriptive statistics in the previous section provide a first picture about the determinants in the loan granting process: A new loan is higher in volume, if a bank is optimistic regarding the borrower's creditworthiness, has a long bank-borrower relationship length and has a derivative contract written on the loan. The volume is lower if a bank has an exposure over the average across all banks towards the borrower.

This section puts these first insights into formal econometric models. As we are interested in loan volume increases only, we focus on the subset of bank-borrower-quarter combinations where the borrower's aggregated loan volume increases.

4.1 Baseline regression

In the baseline analysis, we run the following regression on the change of log loan volume:

$$\begin{aligned}\Delta \log(loan\ volume)_{i,t\rightarrow t+1} = {} & \beta_1 \cdot OptBank_{i,t} + \beta_2 \cdot HighExp_{i,t} \\ & + \beta_3 \cdot Relationship_{i,t} + \beta_4 \cdot Derivate_{i,t} \\ & + FE_{i,t} + FE_{b,t} + \epsilon_{i,t} + constant\end{aligned} \tag{1}$$

where *OptBank*, *HighExp*, *Relationship* and *Derivate* are the bank-borrower specific dummy variables as of Table 1. $FE_{i,t}$ are borrower-quarter fixed effects and $FE_{b,t}$ bank-quarter fixed effect, respectively. We account for cross sectional and times series correlations of the error term $\varepsilon_{i,t}$ by estimating the regressions using three-way robust standard errors (Petersen (2009)) clustered by borrower, bank and quarter. Finally *constant* is the constant in the model.

To check for multicollinearity of our explanatory variables, we calculate pooled correlations across all dummy variables. Panel A of Table 3 provides the results for the full sample and Panel B for the subset of bank-borrower-quarter combinations with an increase in borrower's aggregated loan volume. Overall all correlations are quite low and do not show any high dependency among each other. The highest correlation lies between the High Exposure dummy and the Relationship derivate dummy of 11.5%. Interestingly, the Optimistic Bank and Relationship dummy show a negative correlation, indicating that the longer the relationship with a borrower, the bank is less likely to be optimistic with the borrower's creditworthiness.

Columns (1) to (4) of Table 4 provide results of univariate regressions of our four variables. The regressions show strong and significant relations between change in log loan volume and all dummy variables. The sign of the coefficient are in line with our first insights. A new loan is higher in volume, with optimistic banks, with long bank-borrower relationship length and if there exists a derivative written on the loan. The volume is lower, if the bank has an over average loan volume. When regressing all determinants simultaneously in column (5), the signs of the coefficients do not change and all variables keep significant at the 1 percent level. Finally in column (6), we add borrower-quarter and bank-quarter fixed effects to rule out any borrower or bank specific effects yielding regression (1). All signs and significant levels are stable.

Besides the statistical significance, the results in column (6) show also reasonable economic magnitudes. The granted loan volume is 2.43% (= $e^{0.024}$-1) higher for optimistic banks than for pessimistic banks of borrower's creditworthiness. A long bank-borrower relationship length yields a higher loan volume of 1.9%. The results are even stronger for the relationship derivative dummy. If a bank has a derivative contract written on the loan, and therefore hedges associated risks, the additional loan volume is 7.0% higher in comparison to a bank with no such derivative contracts. However, the highest economic impact on the new granted loan volume lies with the high exposure dummy. The loan volume is 12.28% lower, if a bank has a higher exposure towards the borrower than the average across banks.

In Table 5 we consider log loan volume changes greater than 5%, 10%, 20% and 30%, respectively. We find no differences in signs and significance levels of the coefficients. However, the economic magnitude of the coefficients rises. This indicates that the higher changes in the dependent variable are not fully subsumed in the constant coefficient, but that the loan volume increase is indeed driven by our four dummy variables. For example, in the case of an increase in log loan volume greater than 20% in column (3), the loan volume is 24.12% lower for high exposure banks than for a bank with a lower average exposure towards the borrower. This is almost double the size when considering all loan volume increases.

Summing up, the baseline regressions confirm our first insights from the previous section that a new loan is higher in volume, if a bank is optimistic regarding the borrower's creditworthiness, has a long bank-borrower relationship length and has a derivative contract written on the loan. The volume is lower if a bank has an exposure over the average across all banks towards the borrower.

4.2 Extensive versus intensive margin

In the loan granting process we can imagine a two-step approach. In the first one, banks decide whether to grant a loan or not and in the second step decide on the amount they are willing to provide, thus loan granting differentiates in an "extensive" margin (step one) and an "intensive" margin (step two). We ask the question: Which determinant drives step one and which determinant drives step two?

To analyze this, we first define a dummy variable that is equal to one whenever a bank provides a new loan to a borrower in a specific quarter reflecting the decision to grant a loan. We measure "new loans" by an increase of log loan volume of 10%, 20%.and 30%. The dummy variable is therefore defined on the bank-borrower-quarter level and not on the borrower-quarter level as before.

To distinguish "extensive" from "intensive" margin effects, we run two regressions. In the first one, we regress our determinants from (1) on the new variable *NewLoanIdent*

$$
\begin{aligned}
NewLoanIdent_{i,t\rightarrow t+1} = {} & \beta_1 \cdot OptBank_{i,t} + \beta_2 \cdot HighExp_{i,t} \\
& + \beta_3 \cdot Relationship_{i,t} + \beta_4 \cdot Derivate_{i,t} \\
& + FE_{i,t} + FE_{b,t} + \epsilon_{i,t} + constant
\end{aligned} \tag{2}
$$

which gives us the determinants for the "extensive" margin or the decision to grant the loan. In the second regression, we run (1) only on the subset of new loans yielding the "intensive" margin determinants.

Columns (3) and (4) of Table 6 show the results of the two-stage regressions for a new loan defined by an increase greater than 20% in log loan volume. Comparing the significance level of our dummy variables, we find that the optimistic bank dummy loses its significance from step one to step two. This suggests that the internal PD is more recognized in the decision phase of granting the loan rather than in the second stage which determines the amount provided by the bank. We find a similar pattern for the relationship dummy. However, the variable is not significant in the first step and turns significant in the second one. This suggests that in the decision phase of granting the loan the relationship length does not affect the decision, however, the length of the relationship, plays an important part when considering the amount the bank is willing to provide. The high exposure dummy and the relationship derivative dummy are significant in both regressions, suggesting that they are driving both, the extensive and intensive margin.

In columns (1), (2), (5) and (6) we perform the same analysis for new loans defined by an increase greater than 10% or 30% in log loan volume. All results are comparable to the case of 20%. Only for new loans defined by an increase greater than 30%, the relationship and relationship derivate dummy are not significant for the intensive margin. This indicates that for large new loan volumes, banks mostly take the associated concentration risk into account and other factors, like the relationship scope, do not play an important part in the decision making process.

4.3 The effect of credit market conditions

In the final set of tests we ask the question, if bank's lending decisions depend on credit market conditions. We hypothesize that effects should be larger during periods of large credit growth, where many banks compete against each other, and it should be smaller during periods of credit contractions. We measure credit growth using aggregate data on credit growth by German banks to domestic customers as reported by Bundesbank. Figure 4 displays the evolution of the total credit volume in Germany. This variable is used to identify quarters in which the total loan volume contracts or increases by a year on year basis. Out of our 22 quarters, 9 quarters show credit growth, 12 quarters credit contractions and 1 quarter a stable credit exposure.

To test whether credit market conditions drive our determinants, we split our sample periods into two distinct groups. First, quarters with positive aggregate year-on-year credit growth. Second, quarters with aggregate year-on-year credit contraction. We run regression (1) on each group at a time and perform tests on coefficient equality to check for significant differences.

The results are shown in Table 7. Our main findings hold in both cases, suggesting that bank's lending decisions are driven by the same set of determinants in times of credit growth and credit contraction. However, the economic magnitude is higher in quarters of credit growth than in quarters of credit contraction. Therefore, the differences are not subsumed in the constant variable. We conclude that in times of high market competition the determinants of bank's lending decision are more pronounced than in economic terms, but not in statistical ones.

4.4 Median Splits

To check if our main findings are driven by specific borrower characteristics, we split our data sample in different groups of the same size, run regression (1) on both groups and perform tests on coefficient equality.

We start by splitting our sample by estimated PD yielding one group of Low PD borrowers and one group of High PD borrowers. Panel A of Table 8 shows the results. Our main findings from section 4.1 hold for both groups. Only for Low PD borrowers the coefficient of the optimistic bank dummy is not significant. The economic magnitude between Low and High PD borrowers, however, are significant for all variables except for the relationship dummy. In the case of a high exposure bank, we find that Low PD borrowers are granted less loan volume than High PD borrowers and that a bank will provide more loan volume to a Low PD borrower than to a High PD borrower, if there exists a derivative contract written on the loan.

In the second set of groups, we split our data sample by loan volume in small and large volume borrowers. The results are presented in Panel B of Table 8. Our main findings hold for both groups. Except for the high exposure dummy variable, which is lower for small loan volume borrowers, we do not detect any significant differences in parameter estimates.

Finally we split the data sample by the relationship length. Again, our main findings hold for both groups (Panel C of Table 8). Only the relationship dummy is not significant for borrowers with short relationships. Nevertheless, we find for all dummy variables significant economic differences. In all cases, the economic magnitudes are more pronounced for borrowers with long bank-borrower relationships.

Summing up, the median sample splits show that our main findings from section 4.1 are not driven by a specific borrower characteristic. However, the economic magnitudes vary across different groups of borrowers, in most of the cases the differences are statistically significant.

5 Conclusions

This paper analyzes borrowers with multiple bank relations on a borrower individual level. In the case that a debtor takes out a new loan, we address the question: Which bank will provide the new fund? And what are the driving factors in this decision process? To do so, we used data from the German credit registry on the bank-borrower-quarter level, which enabled us to control for bank-quarter and for borrower-quarter and fixed effects.

We found three main determinants for lending decisions: First, and most significantly, banks with the largest exposure to a borrower are less likely to provide new funds. This suggests that banks reduce concentration risk with a specific borrower and seek diversified loan portfolios. Or from a borrower's perspective, companies try to have a brought basis of funding. Second, banks assigning a lower probability of default to a borrower are more likely to provide new funding. This shows that adverse selection might play a role and that bank's screening results are a key determinant in the lending decision. Third, banks with a larger relationship scope and length are more likely to provide new funds. This follows the intuition that a long relationship indicates a trustworthy and reliant basis between borrower and lender.

We analyzed whether the decision to provide new funds towards a costumer is driven by an "extensive" or an "intensive" margin. Our results show that the estimated probability of default is a key driver in the decision phase of the loan granting process, whereas the borrower's exposure is crucial for the "intensive" margin, therefore determines the loan volume.

We checked whether our results are biased by credit market condition and found that our determinants are stable under credit growth and credit contraction regimes. However, during periods of credit growth the determinants are economically more pronounced. Finally, we checked whether our main findings are driven by specific borrower characteristics by splitting our sample in equal sizes. We found stable results of all main conclusions.

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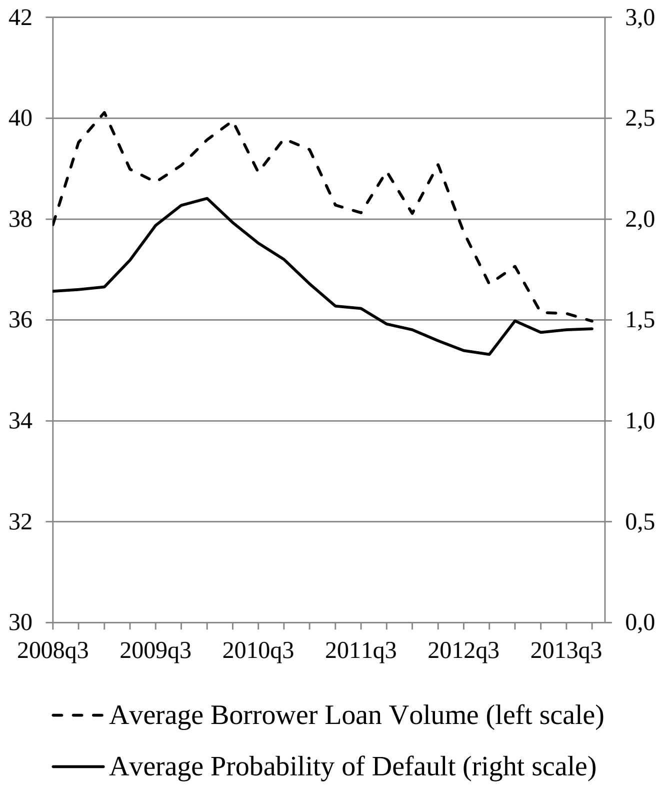
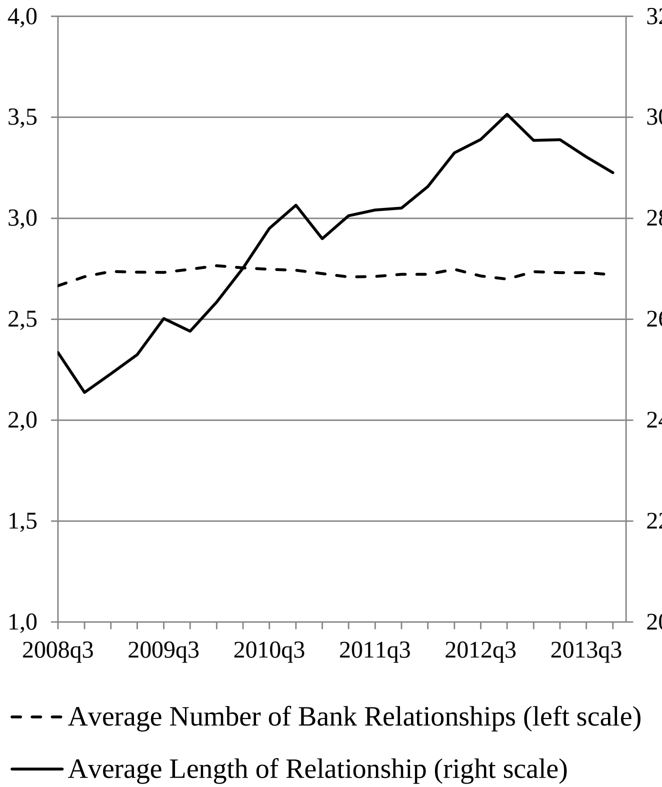
Appendix

Figure 1: Average Loan Characteristics

Panel A: Loan Volume (in EUR mn) and Probability of Default (in %)

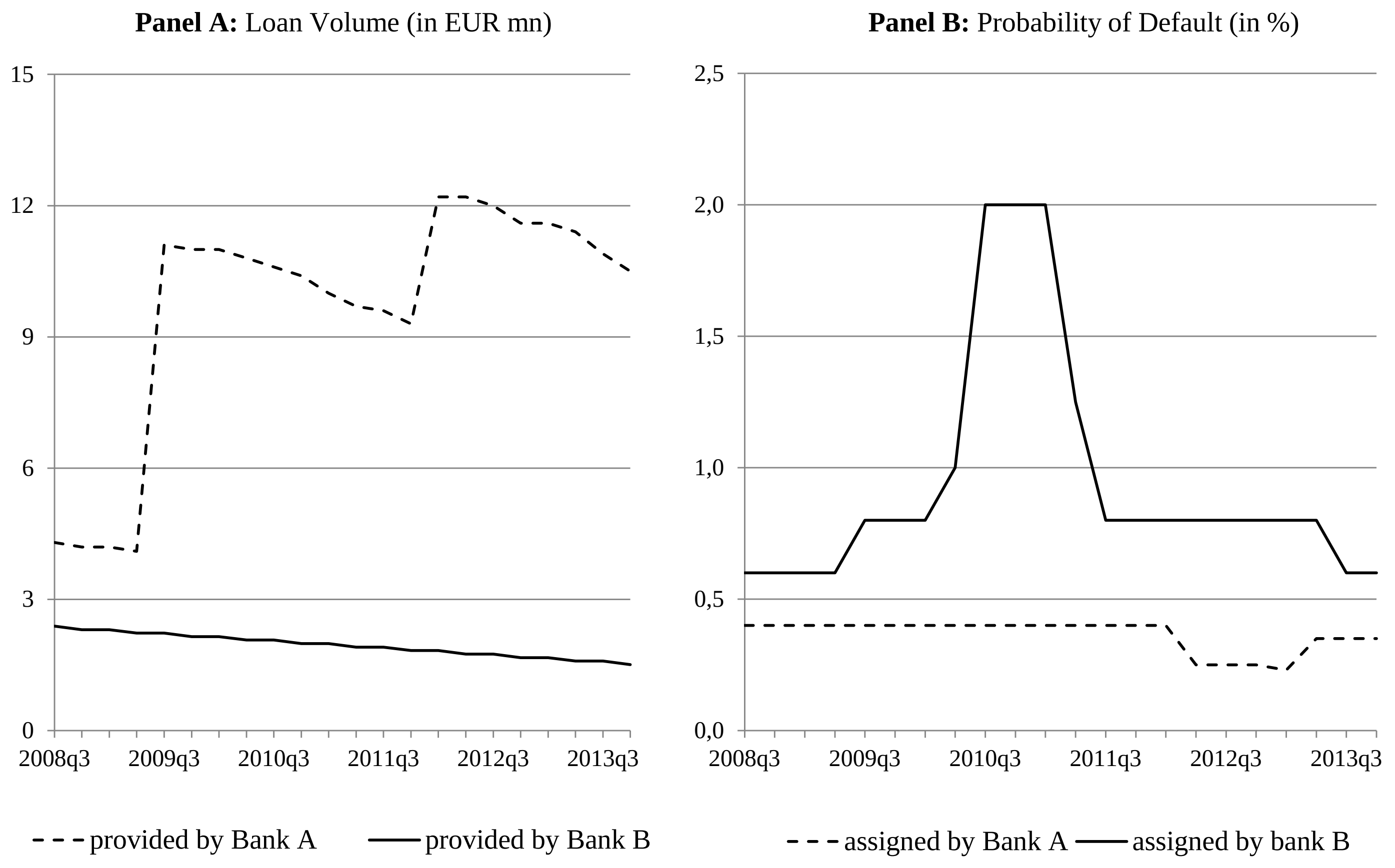


Panel B: Number of Bank Relationships and Length of Relationship (in quarters)



This Figure shows the evolution of the average borrower loan volume and the average probability of default in % (Panel A) and the average number of bank relationships and the average length of relationship in quarter (Panel B) on a quarterly basis.

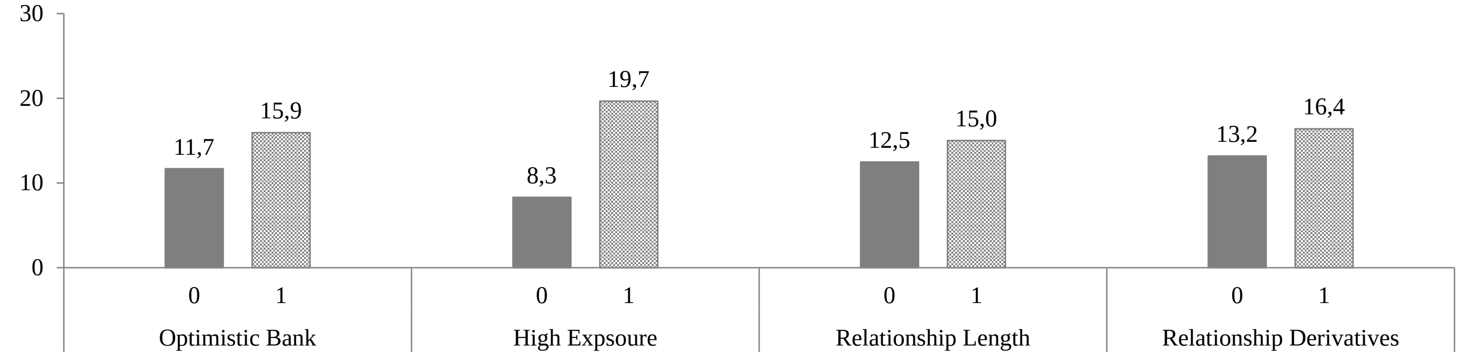
Figure 2: Loan Characteristics for Borrower X



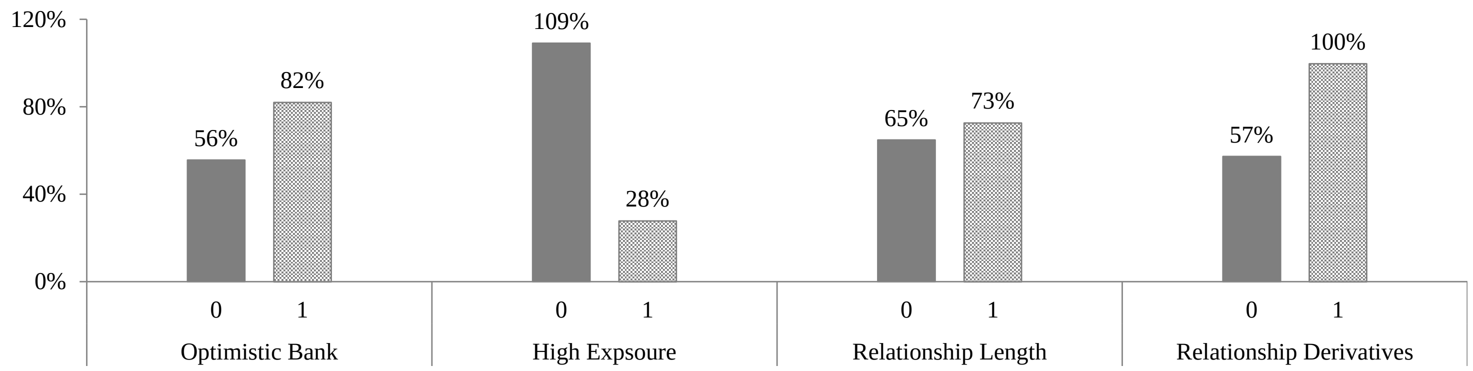
This Figure shows the evolution of loan volume (Panel A) and PD estimates (Panel B) of two different banks for the same borrower X on a quarterly basis.

Figure 3: Descriptive results

Panel A: Loan Volume (in EUR mn)

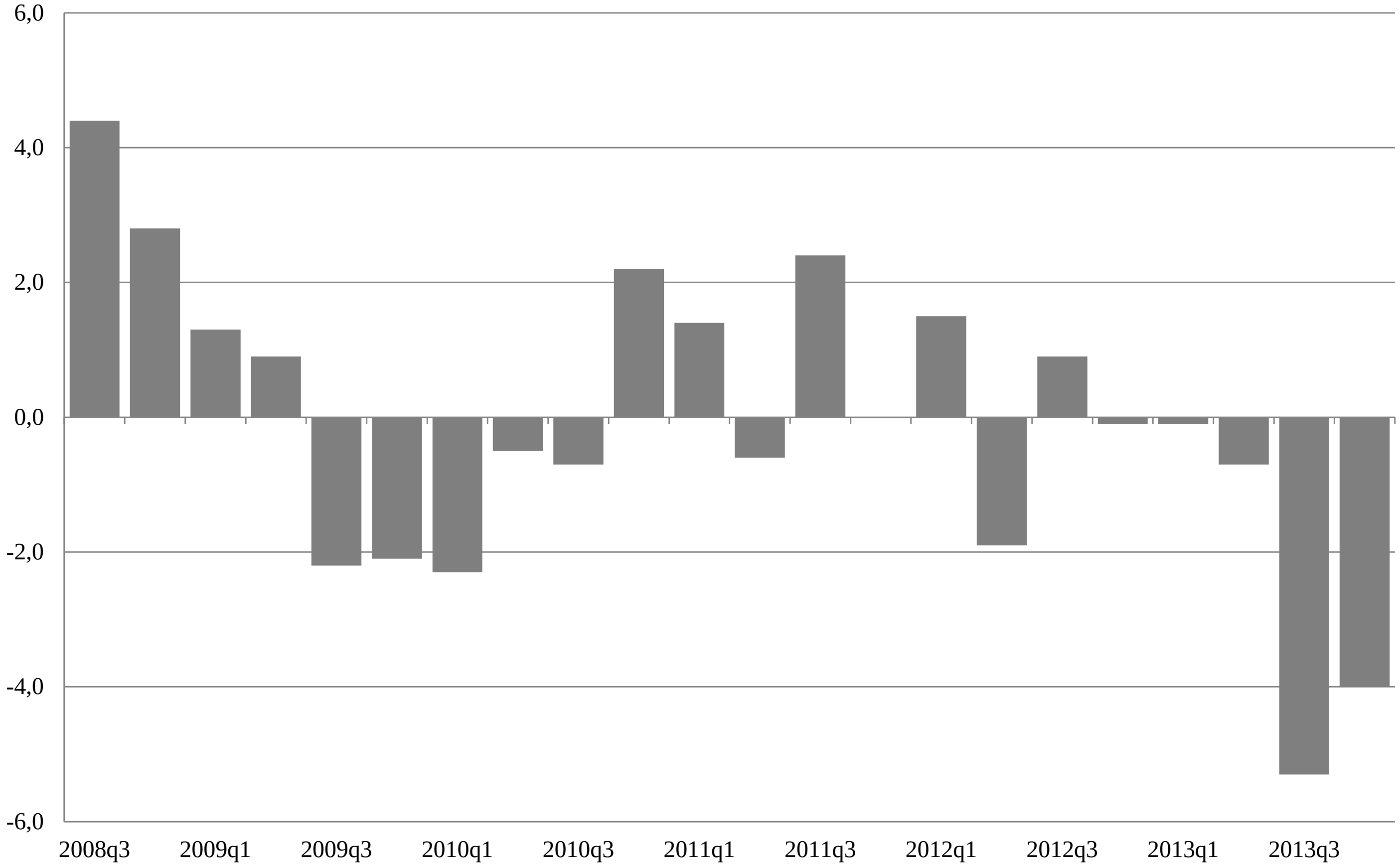


Panel B: Increase in Loan Volume (in %)



This Figure shows the mean of loan volume (Panel A), the mean of increases in loan volume in % (Panel B) for four dummy variables, namely optimistic bank dummy, high exposure dummy, relationship length dummy, and relationship derivatives dummy.

Figure 4: Change in Credit Volume (YoY in %)



This Figure shows increase or decrease of credit volume on a year on year basis for each quarter of our sample period. A quarter with an increase in credit volume is denoted as one with credit growth, a quarter with a decrease in credit volume is denoted as period of credit contraction.

Table 1: Description of variables

Variable	Unit	Description
Borrower characteristics		
Borrower loan volume	Euro	Sum of the loan volume reported by all banks for a borrower in a particular quarter.
Bank relationships	Dummy(0/1)	Variable equal to one if a bank has a relationship with a borrower in a particular quarter.
Dispersion of PD	Percent (%)	Measure for the across-bank dispersion of PD estimates, defined by the standard deviation of all PDs for each borrower per quarter
Bank characteristics		
Borrower relationships	Number	Number of borrowers reported by the bank in a particular quarter. All borrowers whose loans of the bank exceed € 1.5 million at least once during the quarter have to be reported.
Bank-Borrower characteristics		
PD	Percent (%)	Probability of default over a 1-year horizon, measured from 0.00% to 100.00%.
Length of relationship	Number	Number of Quarters that a credit relationship lasts for a given bank-borrower pair, measured from the date of the first relationship to the actual date.
New Loan (1%-30%)	Dummy(0/1)	Variable is equal to one if the log of loan volume increases by 1%, 5%, 10%, 20% or 30%.
Optimistic Bank	Dummy(0/1)	Variable is equal to one if the demeaned log of PD is less than 0.
High Exposure Bank	Dummy(0/1)	Variable is equal to one if the log of Exposure of default for a bank if larger than the mean across all banks.
Relationship	Dummy(0/1)	Variable equal to one if the length of the relationship for a given bank-borrower pair is larger than the average of this borrower with all lender.
Relationship Der.	Dummy(0/1)	Variable equal to one if the lender has a derivative for the credit.

Table 2: Summary statistics

Variable	Level	Unit	N	Mean	Std.Dev.	p25	Median	p75
Panel A: Borrower characteristics								
Borrower loan volume	Borrower-Quarter	EUR mn	175,393	38.46	74.33	5.12	12.75	37.58
Bank relationships	Borrower-Quarter	Number	175,393	2.73	1.43	2	2	3
Dispersion PD	Borrower-Quarter	Percent	175,393	1.33%	2.57%	0.12%	0.38%	1.13%
Panel B: Bank characteristics								
Borrower relationships	Bank-Quarter	Number	830	577.01	669.82	163	311	849
Panel C: Bank-Borrower characteristics								
PD	Bank-Borrower-Quarter	Percent	478,916	1.66%	3.28%	0.23%	0.59%	1.42%
Optimistic Bank Dummy	Bank-Borrower-Quarter	Dummy	478,916	0.53	0.50	0	1	1
High Exposure Bank Dummy	Bank-Borrower-Quarter	Dummy	478,916	0.49	0.50	0	0	1
Relationship Dummy	Bank-Borrower-Quarter	Dummy	478,916	0.59	0.49	0	1	1
Derivative Dummy	Bank-Borrower-Quarter	Dummy	478,916	0.24	0.43	0	0	0
Length of Relationship	Bank-Borrower-Quarter	Number	478,916	27.53	22.90	9	21	43

This table provides summary statistics for borrower characteristics (Panel A), bank characteristics (Panel B) and for bank-borrower characteristics (Panel C). For variable definitions see Table 1.

Table 3: Correlations for Determinants of bank's lending decisions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Full Sample				Panel B: Increase in log loan volume			
Variables	Optimistic Bank Dummy	High Exposure Bank Dummy	Relationship Dummy	Relationship Derivate Dummy	Optimistic Bank Dummy	High Exposure Bank Dummy	Relationship Dummy	Relationship Derivate Dummy
Optimistic Bank Dummy	1.000				1.000			
High Exposure Bank Dummy	0.036	1.000			0.031	1.000		
Relationship Dummy	-0.014	0.073	1.000		-0.013	0.081	1.000	
Relationship Derivative Dummy	0.047	0.110	0.103	1.000	0.049	0.115	0.110	1.000

This table provides pooled correlations for four dummy variables, namely optimistic bank dummy, high exposure dummy, relationship dummy, and relationship derivatives dummy. Panel A refers to the full sample; Panel B to the subsample of log loan volume increases only.

Table 4: Baseline regression (univariate and multivariate regressions)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Δ log(Loan Volume)	Δ log(Loan Volume)	Δ log(Loan Volume)	Δ log(Loan Volume)	Δ log(Loan Volume)	Δ log(Loan Volume)
Optimistic Bank Dummy	0.019***				0.019***	0.024***
	(2.93)				(2.98)	(3.95)
High Exposure Bank Dummy		-0.104***			-0.115***	-0.131***
		(-6.18)			(-6.38)	(-6.08)
Relationship Dummy			0.015*		0.016**	0.019***
			(1.93)		(2.14)	(2.71)
Relationship Derivative Dummy				0.073***	0.085***	0.068***
				(10.22)	(12.35)	(9.41)
Borrower x Quarter Fes	no	no	no	no	no	yes
Bank x Quarter FEs	no	no	no	no	no	yes
Observations	129,374	129,374	129,374	129,374	129,374	129,374
Adj. R-squared	0.00	0.01	0.00	0.01	0.02	0.14

This table provides results of a regression of the increase in loan volume on four dummy variables, namely optimistic bank dummy, high exposure dummy, relationship dummy, and relationship derivatives dummy. We report t-values based on three-way robust standard errors clustered by company, bank and quarter in parentheses. Constant not reported. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

Table 5: Multivariate Regressions for different log loan volume changes

Variables	(1) Increase in log loan volume Δ log(Loan Volume)	(2) Increase in log loan volume > 10% Δ log(Loan Volume)	(3) Increase in log loan volume > 20% Δ log(Loan Volume)	(4) Increase in log loan volume > 30% Δ log(Loan Volume)
Optimistic Bank Dummy	0.024***	0.037***	0.048***	0.056***
	(3.95)	(4.28)	(3.07)	(2.77)
High Exposure Bank Dummy	-0.131***	-0.226***	-0.276***	-0.317***
	(-6.08)	(-8.38)	(-8.43)	(-8.65)
Relationship Dummy	0.019***	0.036***	0.048***	0.061***
	(2.71)	(3.42)	(3.39)	(3.35)
Relationship Derivative Dummy	0.068***	0.110***	0.138***	0.169***
	(9.41)	(11.78)	(10.94)	(11.10)
Borrower x Quarter FEs	yes	yes	yes	yes
Bank x Quarter FEs	yes	yes	yes	yes
Observations	129,374	57,688	36,510	24,375
Adj. R-squared	0.14	0.13	0.13	0.15

This table provides results of a regression of different increases in log loan volume on four dummy variables, namely optimistic bank dummy, high exposure dummy, relationship dummy, and relationship derivatives dummy. We report t-values based on three-way robust standard errors clustered by company, bank and quarter in parentheses. Constant not reported. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

Table 6: Intensive vs. Extensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Increase in log loan volume > 10% (bank-borrower level)		Panel B: Increase in log loan volume > 20% (bank-borrower level)		Panel C: Increase in log loan volume > 30% (bank-borrower level)	
	Extensive Margin	Intensive Margin	Extensive Margin	Intensive Margin	Extensive Margin	Intensive Margin
Variables	New Loan Dummy	Δ log(Loan Volume)	New Loan Dummy	Δ log(Loan Volume)	New Loan Dummy	Δ log(Loan Volume)
Optimistic Bank Dummy	0.005**	0.013	0.004**	0.019	0.004**	0.002
	(2.25)	(0.75)	(2.44)	(0.87)	(2.29)	(0.04)
High Exposure Bank Dummy	-0.042***	-0.322***	-0.048***	-0.362***	-0.048***	-0.384***
	(-4.94)	(-9.51)	(-5.31)	(-10.26)	(-5.60)	(-10.61)
Relationship Dummy	-0.000	0.051***	-0.000	0.050**	-0.000	0.050
	(-0.11)	(3.70)	(-0.03)	(2.43)	(-0.05)	(1.56)
Relationship Derivative Dummy	0.033***	0.051**	0.028***	0.046*	0.023***	0.041
	(8.76)	(2.33)	(8.96)	(1.94)	(7.89)	(1.09)
Borrower x Quarter FEs	yes	yes	yes	yes	yes	yes
Bank x Quarter FEs	yes	yes	yes	yes	yes	yes
Observations	388,933	45,754	388,933	33,170	388,933	25,218
Adj. R-squared	0.29	0.45	0.26	0.43	0.24	0.43

This table provides results of a regression of the dummy variables for different identification of new loans and increase/deacrease in loan volume on four dummy variables, namely optimistic bank dummy, high exposure dummy, relationship dummy, and relationship derivatives dummy. We report t-values based on three-way robust standard errors clustered by company, bank and quarter in parentheses. Constant not reported. ***, **, * denote significance at the 1, 5 and 10 % level, respectively. Panel A refers to log loan volume increases greater than 10% on the bank-borrower level, Panel B to changes greater than 20% and Panel C to changes greater than 30%.

Table 7: The effect of credit market conditions

	(1)		(2)	(3)		(4)	(5)		(6)
	Panel A: Increase in log loan volume			Panel B: Increase in log loan volume > 10%			Panel C: Increase in log loan volume > 30%		
	Quarters with Credit Growth		Quarters with Credit Contraction	Quarters with Credit Growth		Quarters with Credit Contraction	Quarters with Credit Growth		Quarters with Credit Contraction
Variables	Δ log(Loan Volume)	Mean Diff.	Δ log(Loan Volume)	Δ log(Loan Volume)	Mean Diff.	Δ log(Loan Volume)	Δ log(Loan Volume)	Mean. Diff	Δ log(Loan Volume)
Optimistic Bank Dummy	0.029***	0.008	0.020***	0.042***	0.009	0.033***	0.061***	0.024	0.037*
	(2.60)	(p=0.452)	(3.49)	(3.15)	(p=0.478)	(3.68)	(2.85)	(p=0.357)	(1.84)
High Exposure Bank Dummy	-0.135***	-0.008	-0.127***	-0.232***	-0.011	-0.222***	-0.281***	-0.011	-0.271***
	(-5.71)	(p=0.557)	(-5.75)	(-8.34)	(p=0.485)	(-7.74)	(-8.25)	(p=0.646)	(-7.58)
Relationship Dummy	0.022**	0.005	0.017***	0.039***	0.005	0.033***	0.053***	0.008	0.045***
	(2.14)	(p=0.491)	(2.88)	(2.74)	(p=0.627)	(3.34)	(2.83)	(p=0.511)	(3.48)
Relationship Derivative Dummy	0.070***	0.004	0.067***	0.111***	0.002	0.109***	0.143***	0.009	0.133***
	(6.20)	(p=0.896)	(7.34)	(7.13)	(p=0.950)	(6.63)	(9.87)	(p=0.764)	(5.50)
Borrower x Quarter FEs	yes		yes	yes		yes	yes		yes
Bank x Quarter FEs	yes		yes	yes		yes	yes		yes
Observations	54,850		74,524	25,570		32,118	16,423		20,087
Adj. R-squared	0.12		0.16	0.11		0.15	0.11		0.15

This table provides results of a regression of different increases in log loan volume on four dummy variables, namely optimistic bank dummy, high exposure dummy, relationship dummy, and relationship derivatives dummy. Periods of credit growth and credit contraction are identified according the total loan volume in Germany. See Figure 3 for details. We report t-values based on three-way robust standard errors clustered by company, bank and quarter in parentheses. Constant not reported. ***, **, * denote significance at the 1, 5 and 10 % level, respectively. The p-Value of the test on coefficient equality within each Panel is provided in the column Mean Diff. Panel A refers to increases in log loan volume, Panel B to log loan volume changes greater than 10% and Panel C to changes greater than 20%.

Table 8: Median sample splits for PD, loan volume, and relationship

	(1)		(2)	(3)		(4)	(5)		(6)
	Panel A: PD			Panel B: Loan volume			Panel C: Relationship		
	Low PD borrowers		High PD borrowers	Small loan volume borrowers		Large loan volume borrowers	Borrowers with short relationships		Borrowers with long relationships
Variables	Δ log(Loan Volume)	Mean Diff.	Δ log(Loan Volume)	Δ log(Loan Volume)	Mean Diff.	Δ log(Loan Volume)	Δ log(Loan Volume)	Mean. Diff	Δ log(Loan Volume)
Optimistic Bank Dummy	0.010	-0.024**	0.034***	0.021**	-0.005	0.025***	0.015**	-0.017**	0.032***
	(1.17)	(p=0.036)	(4.06)	(2.37)	(p=0.664)	(3.36)	(2.08)	(p=0.017)	(5.18)
High Exposure Bank Dummy	-0.146***	0.031***	-0.115***	-0.149***	-0.033***	-0.117***	-0.094***	0.071***	-0.166***
	(-5.70)	(p=0.004)	(-6.27)	(-7.68)	(p=0.009)	(-5.18)	(-5.19)	(p=0.000)	(-6.93)
Relationship Dummy	0.025***	0.011	0.013*	0.013*	-0.010	0.023**	0.005	-0.025***	0.030***
	(2.74)	(p=0.142)	(1.93)	(1.73)	(p=0.304)	(2.47)	(0.99)	(p=0.004)	(3.02)
Relationship Derivative Dummy	0.082***	0.027***	0.055***	0.053***	-0.024	0.077***	0.041***	-0.050***	0.091***
	(7.78)	(p=0.008)	(7.95)	(5.78)	(p=0.139)	(6.58)	(4.91)	(p=0.000)	(10.38)
Borrower x Quarter FEs	yes		yes	yes		yes	yes		yes
Bank x Quarter FEs	yes		yes	yes		yes	yes		yes
Observations	65,262		64,112	53,842		75,532	66,928		62,446
Adj. R-squared	0.15		0.13	0.07		0.19	0.21		0.12

This table provides results of a regression of the increase in loan volume on four dummy variables, namely optimistic bank dummy, high exposure dummy, relationship dummy, and relationship derivatives dummy. We report t-values based on three-way robust standard errors clustered by company, bank and quarter in parentheses. Constant not reported. ***, **, * denote significance at the 1, 5 and 10 % level, respectively. This table reports robustness tests for a median sample split based on the borrowers' average PD, average loan volume, and average relationship. The p-Value of the test on coefficient equality within each split is provided in the column Mean Diff.