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DISCUSSION PAPER

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The Real Effects of Bank Distress: Evidence from Bank Bailouts in Germany

The real effects of bank distress: evidence from bank bailouts in Germany*

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Abstract

How does bank distress impact their customers' probability of default and trade credit availability? We address this question by looking at a unique sample of German firms from 2000 to 2011. We follow their firm-bank relationships through times of distress and crisis, featuring the different transmission of bank distress shocks into already weakened firm balance sheets. We find that a distressed bank bailout, which is subject to restructuring and deleveraging conditions, leads to a bank-induced increase of firms' probabilities of default. Moreover, bailouts tend to reduce trade credit availability and ultimately firms' sales. We further find that the direction and magnitude of the effects depends on firm quality and the relationship orientation of banks.

Keywords: bank distress, bank risk channel, firm risk channel, relationship banking, firm defaults, financial crisis

JEL-Classification: G01, G21, G24, G33

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1 Introduction

Bank distress may lead to important real effects. Shocks to bank liquidity or impairments of bank balance sheets translate into the real economy if firms cannot easily turn to alternative sources of financing. An unanswered question is how bank distress impacts on firms' probability of default (PD), and firms' availability of alternative sources of finance such as trade credit. We identify bank distress with a capital injection from a bank rescue scheme. Here, restructuring and deleveraging requirements imposed by the bank rescue schemes curb bailed-out banks' risk taking and lending activities (see Berger et al., 2016). Using data from an independent credit rating agency, we investigate whether bank distress (i.e., bailout) impacts this agency's assessment of a firm's probability of default, and its advised maximum trade-credit amount to a firm.

The impact of bank distress may not transmit homogeneously across firms, bank business models, and periods. Relationship-oriented banks, for example, help in smoothing out credit constraints that firms face (e.g., Berger and Udell, 1995; Berger and Udell, 2002; Bolton et al. 2016; Beck et al. 2018). We therefore examine how bank distress transmits to firms with different default probabilities, and whether relationship banks mitigate the potential adverse effects for firms. In addition, we investigate whether the impacts in an idiosyncratic bank distress event are different from the ones in times of a systemic banking crisis featuring different transmission of bank distress shocks into already weakened firm balance sheets. Finally, we analyze whether bank distress has an impact on firm real outcomes as measured by its sales.

It is important to make clear upfront that bank distress in our sample stems from sources unrelated to small firms' credit risk. Our distressed bank sample contains regional private banks, savings banks, and cooperative banks. The triggers for bank distress are related to problems with these banks' mortgage portfolio, the unexpected default of a single but large exposure, or structural problems with regard to specific business models.

We apply recent methods used in the literature on the transmission of shocks to identify a *bank risk channel*.[1] Banks affect firm risk through several factors, such as whether credit is granted or not, the loan amount, other loan conditions, or the general quality and extent of services provided. We classify supply-related factors affecting firm risk as

[1] There is a big literature that focuses on credit supply shocks which is typically referred to as the *bank lending channel* (e.g., Gambacorta, 2005; Kishan and Opiela, 2000; Khwaja and Mian, 2008; Nilsen, 2002).

the *bank risk channel*. We aim to control for what we call the *firm risk channel*, which captures demand-related factors affecting firm risk such as a firm's industry, location, size, general economic conditions, and the institutional environment the firm faces. To separate the *bank risk channel* and the *firm risk channel*, we apply the methods employed to disentangle supply and demand for loans (e.g., Khwaja and Mian, 2008; Morais, Peydró, and Ruiz, 2016; and Degryse et al., 2019) to a setting of risk transmission in bank-firm relationships. Specifically, we apply a clustering method similar to Degryse et al. (2019). In the environment of firms' PDs, this will make it possible to cancel out time, industry, regional, age and firm size effects on PDs that arise in the economy. In this way, we aim to identify the "bank-induced" impact of bank distress on the PDs of firms.

We also study whether the *bank risk channel* following bank distress differs depending upon whether bank distress is idiosyncratic or systemic in nature. In particular, we investigate whether the 2008-2009 banking crisis had different effects that go beyond the usual adjustments when banks are distressed. In times of financial crisis, banks may find it necessary (or be mandated by the regulator) to change their lending policy and make their loan decisions less opaque. This change might go beyond adjustments in loan characteristics, such as interest rates and collateral requirements but constitute a structural change in both the bank's lending policy and the transmission of bank distress shocks into already weakened firm balance sheets.[2] As the impact of banks' strategies might differ in normal times from a time when a systemic crisis exists (Degryse et al., 2015; Ivashina and Scharfstein, 2010), we also differentiate between normal times and times of crisis in the analysis.

We combine several unique datasets to tackle these questions. First, we employ the *Mannheim Enterprise Panel (MUP)*[3] which covers, for almost any German non-financial entity, an individual credit rating, its bank-firm relationships and other firm-specific information between 1999 and 2013. Second, we use regulatory and bank balance sheet data from the Deutsche Bundesbank. We combine the Bundesbank data with the MUP information on bank names in order to identify banks in distress. Third, we obtain information from MUP, such as banks' regional or industry-specific market and portfolio shares, default rates in corporate banking, and relationship orientation measures.

[2] In contrast, banks in distress may relax their credit standards, provide soft loan terms, and in this way evergreen the more risky borrowers in a bid to reduce potential losses on them (Peek and Rosengren, 1997) or comply with local political guidelines (Gropp et al., 2010).

[3] The *Mannheim Enterprise Panel* ("*Mannheimer Unternehmenspanel*", *MUP*) of the ZEW Leibnitz Centre for European Economic Research is the most comprehensive micro database for companies in Germany outside the official business register (which is not accessible to the general public).

Our findings can be summarized as follows. First, distress-induced bank bailouts lead to important increases in firms' expected probability of default as evaluated by the credit rating agency. In particular, firms borrowing from a bailed out bank see their probability of default increase with about 10% relative to similar firms borrowing from other banks. This effect is mainly driven by bailouts of transaction banks. Second, bailouts generate multiplier effects towards potential other sources of credit: the credit rating agency reduces its advisory trade credit limit to firms borrowing from bailed out banks with about 11% relative to similar firms that are engaging unaffected banks. This effect mainly stems from crisis times. We also find that a firm's actual sales drop with about 8% after bank bailout.

Our work mostly builds on the stream of literature dealing with the transmission of shocks from the financial industry into the real economy (e.g., Peek and Rosengren, 1997; Kishan and Opiela, 2000; Nilsen, 2002; Gambacorta, 2005; Khwaja and Mian, 2008; Amiti and Weinstein, 2011; Loutskina and Strahan, 2009, Santos, 2010; Puri et al., 2011; Jiménez et al., 2012; De Haas and Van Horen, 2012a and 2012b, Chodorow-Reich, 2014; Allen et al., 2017; Fernández et al., 2018). The literature shows that banks facing liquidity or credit constraints grant less credit and transmit shocks to the real economy. A part of this literature deals with the question whether bank rescue measures in financial crises (in particular TARP bailouts) help to mitigate the real consequences of crises (e.g., Berger and Roman, 2017 and Berger et al, 2017). The evidence suggests that banks bailouts programs improved credit supply.

A second stream of literature relevant to our work is the literature on relationship banking and financial intermediation between firms and banks over the business cycle (e.g. Holmstrom and Tirole, 1997; Ivashina and Scharfstein, 2010; Bolton et al., 2016; Degryse et al., 2015; Beck et al., 2018). Our paper contributes to these two strands of the literature. We study how bank distress affects the firms' PDs as perceived by an external credit rating agency, trade credit availability and firm sales. Moreover, we identify the role of banks' business models in this transmission process.

The remainder of this paper is organized as follows: Section 2 describes the institutional background of bank bailout schemes in Germany. Section 3 introduces our data. Section 4 presents the method of nearest neighbor matching as well as the outcome of the matching process. Section 5 describes our methodology for the regression analysis. In Section 6, the results for our research question are shown and discussed. Section 7 concludes.

2 Bank Bailout Schemes in Germany

Bank distress is usually identified by various rescue measures taken by supervisors or protection schemes operated by bankers associations (see, for example, Kick and Prieto, 2013; Bian et al., 2016; Kick et al., 2016). Typical rescue measures are capital support (i.e., capital injections and guarantees) as well as distressed mergers (which are often the last resort after previous capital support measures have failed). In the last few decades most bank bailouts in Germany have been privately organized by bankers associations, often with internal auditors in place to monitor member banks. In the wake of the global financial crisis, however, an additional rescue scheme was established by the government as the private schemes were not sufficient any more.

2.1 Organization of Bank Recovery and Resolution in Germany

There are privately organized and government-funded bank rescue schemes in Germany, if necessary accompanied by interventions by supervisors.

i) Privately organized insurance funds of the German banking system

The German banking system contains three banking pillars (i.e., commercial banks, savings banks, and cooperative banks). Each banking pillar has a voluntary financed insurance fund operated by the respective bankers' association that may provide *capital support* if a bank within the pillar is in distress. While supervisors[4] may be consulted during the process, the final decision on granting capital support rests with the respective protection scheme. The protection scheme and the member bank sign a contract which includes the specific shortcomings of the troubled bank that need to be addressed and plans on how to resolve the distress. The protection scheme usually gains far-reaching control rights if the member bank becomes distressed, and is generally accompanied by restructuring and deleveraging orders.[5]

If capital support measures are still considered insufficient (maybe if the distressed bank has reached a stage where recovery is no longer possible) bankers' associations have the power to order restructuring mergers (also called *distressed mergers*) in the course of the resolution process. That is, bank managers have very few incentives for their institution to be regarded as distressed. Therefore, they will apply for capital support measures only if they deem this absolutely necessary to fulfill supervisory minimum

[4] The responsible supervisors in Germany are the European Central Bank, the German federal financial supervisory authority ("*Bundesanstalt für Finanzdienstleistungsaufsicht*", *BaFin*) and the Deutsche Bundesbank.

[5] Bian et al. (2016), for example, find for German savings banks that restructuring activities are significantly greater in a bailout by the bankers' association than when the bailout is undertaken by politicians.

capital requirements. On the other hand, for the respective bankers' associations it is an inherent part of having an impeccable reputation that their member institutions are "safe", and that the respective stakeholders are able to trust in the respective protection scheme even in times of crisis.

ii) Government-funded recovery and resolution schemes

At the end of 2008, as a response to the financial and economic crisis, the Financial Market Stabilization Fund ("*Sonderfonds Finanzmarktstabilisierung*", *SoFFin*) was established which supplements the described voluntary measures of the banking industry. Even though SoFFin support has been granted to only a small number of major German banks, such government bailout measures have been large in volume (see Kick and Koetter, 2016). SoFFin support also went along with far-reaching restrictions (e.g., compensation restrictions for executive board members) and control rights for the German government. In addition, some Landesbanks received capital injections from their owners (the respective state governments).

iii) Interventions by supervisors

In addition, if supervisors deem the described measures inadequate or insufficient, they can also intervene pursuant to the *German Banking Act* ("*Kreditwesengesetz*", *KWG*). This includes severe interventions such as moratoria or finally revoking the bank's charter. The bankers associations' and the supervisors' decisions are not independent of each other, with various decision-makers being involved (European Central Bank, BaFin, Bundesbank, bankers associations and the boards of the protection schemes). Even though the bailout process appears to be opaque, the interventions of the various stakeholders complement each other and constitute a kind of well-functioning "private-public partnership" (for a detailed description of the protection schemes in the German banking sector, see also Kick et al., 2016).

2.2 Cost-benefit Considerations

In Germany, only a few (mostly small) private banks have actually defaulted. Troubled savings banks, Landesbanks and cooperative banks have been resolved by means of capital support measures or restructuring mergers – in a few cases including the establishment of a "bad bank". In general, distressed banks were first provided with capital support measures, and hence the chance for recovery; the weakest banks, however, finally left the market mostly by means of distressed mergers (see Kick et al., 2016). The unresolved default of financial institutions would cause losses for stakeholders (investors, staff, depositors, etc.), but also serious reputational damage for the respective banking pillars (and their bankers associations) as well as for the German banking market as a whole (bank runs, credit crunch in the interbank markets, etc.). In addition, in some cases also the owners of troubled banks took measures (e.g. capital increases, restructuring measures and mergers) to resolve bank distress.

A prominent rescue scheme in the US was the *Troubled Asset Relief Program (TARP)* which was established in 2008. As in Germany, distressed banks were rescued by capital injections. The first nine banks were forced to participate in the program whereas the later ones were voluntary and had to apply for TARP funds (Berger, 2018). Approval to obtain TARP funds took then into account a bank's financial health with "healthy viable" ones being more likely to receive capital. TARP recipients were subject to compensation restrictions.

Compensation restrictions are also common in the different German rescue schemes. In addition, distressed banks obtaining capital support from private schemes in Germany are subject to substantial restructuring and deleveraging requirements. Moreover, the German system and TARP also differ with respect to the source providing capital. TARP was organized by the US Treasury whereas in most bailouts in Germany capital stems from the bankers associations.

2.3 Effects on the Real Economy

While the bank recovery and resolution schemes in Germany generate huge benefits through a stable and creditable financial system, our paper studies whether there is also some curbing effect on the real economy which goes along with restrictions from the bailout process. Distressed banks requiring capital support measures (and/or a restructuring merger as ultima ratio) are subject to restructuring and deleveraging conditions[6] which may cause a credit crunch in particular for their corporate clients. Following this line of argument, we investigate to which extent restrictions in the course of the bank bailout process are likely also to facilitate the actual default of firms in their credit portfolio, or contribute to a weakening of their creditworthiness (via increase of firms' probabilities of default, or a lowering of their maximum trade credit recommendation), and what the negative effects on these firms' sales are. Here, we confirm that a strong banking relationship can be beneficial to shield a firm from the credit crunch caused by bank distress. Moreover, the process helps to remove the weakest and most risky firms from the market (i.e., distressed banks were no longer able to pursue a strategy to keep inefficient contracts on the balance sheet).

[6] Note that the distressed bank agrees on restructuring and deleveraging conditions in order to receive capital support. Both privately organized and government-funded insurance schemes and also supervisors will strictly curb the activities of bailed out banks in case they do not adjust their business model, or misuse the capital support to maintain excessive risk taking.

3 Data

3.1 Firm Data

For firm data, we use the *Mannheim Enterprise Panel (MUP)*, a panel dataset generated by the ZEW – Leibniz Centre for European Economic Research. This contains the complete data pool of *Creditreform e.V.* (on a half-yearly basis), the largest credit rating agency in Germany. The MUP is the most comprehensive micro database of companies in Germany next to the official Business Register of the Federal Statistical Office (where the Register of the Federal Statistical Office is not accessible to the general public). Comparisons of MUP with the official Business Register reveal that the coverage of MUP represents nearly the universe of firms in Germany. It therefore provides a representative picture of the corporate landscape in Germany. For detailed information about data collection, processing and definitions, see Bersch et al. (2014).

The MUP contains a large number of firm characteristics. It includes firm size (annual sales, number of employed persons), industry (five-digit industry sector code according to NACE rev. 2), legal form, date of foundation and closure, the company's complete address, shareholder structure and personal details about the involved persons. More importantly for our analysis, the data also includes *Creditreform's* credit rating score and information on the firms' banking relationships. The credit rating score is an index ranging from 100 to 600, showing the firm's credit rating for each panel year. The credit rating is finally translated into PDs.

The most important drivers of the *Creditreform* rating are a firm's payment behavior, the *Creditreform* credit opinion as well as company development, industry and order situation. Furthermore, also information from financial reporting (i.e., balance sheet data), regional risk, managerial experience and performance indicators such as sales and capital enter the calculation of the score. Information about a firm's banking relationship most likely enters the component "credit opinion" making up to 25% of the index weight. While *Creditreform* leaves this component of their credit rating rather vague, it is reasonable to assume that qualitative information is used, such as whether banks tightened lending requirements, asked for more collateral, or did not extend credit lines. Furthermore, other components of the *Creditreform* rating such as payment behavior, company development and order situation will also directly or indirectly be influenced by bank behavior (e.g., if a bank tightens its lending requirements). The credit score has already been used in a number of recent papers (Brown et al., 2012; Cremers and Schliessler, 2014; Hoewer, 2016).

The dataset includes up to six banking relationships of a given company. The first relationship is denoted as the *main bank* ("*Hausbank*"), i.e., the bank used for day-to-day transactions, credit lines, and which is most likely to be the firm's main lender. Our analyses rely on the firm's main bank relationship, as it constitutes the prominent external financier for the firm.

3.2 Bank Data

We employ several data sources for information on banks. First, we use the *ZEW Bankpanel* combined with *Creditreform* data aggregated at the bank level. The *Creditreform* dataset contains the identity of the bank's branch employed by the company. The bank branches themselves are linked to the overall bank by the unique German bank identifier *BLZ*. Using this link, ZEW constructs a panel of all banks operating in Germany. By aggregating information on all firms connected to a particular bank, we obtain banks' market shares or portfolio shares by region and industry. Moreover, we are able to derive rates of firm failures by bank that go beyond information provided in banks' balance sheets.[7] A detailed description of the variables is given in Table 8 in the Appendix.

Second, we employ bank data from Bundesbank's prudential database *BAKIS* and the *Borrowers' Statistics* ("*Kreditnehmerstatistik*"). *BAKIS* contains information on banks' balance sheets and profit and loss accounts. Moreover, it includes the results of the quantitative audit reports which show confidential information on the quality of bank's loan portfolio. The data is used mainly for supervisory monitoring, but in several instances also for research (for a general description of *BAKIS*, see Memmel and Stein, 2008). In addition, we use the *Borrowers Statistics* to derive the industry structure of banks' loan portfolios.

Third, we employ information on extremely weak banks from Bundesbank's *Bank Distress Database*. For our research design we identify distressed banks as banks receiving an initial capital injection from privately or government funded rescue schemes (more details are provided in Section 2). This measure constitutes a unique event for the bank.

[7] The individual relationship entering a bank's portfolio may be weighted by its rank (main bank or not) as well as its PD or its number of employees.

4 Nearest-Neighbor Matching

4.1 Empirical Methodology

Our firm-level dataset contains information on the individual bank-firm relationship over the period 2000 to 2012. We focus on the main bank relationships. To investigate the treatment of bank distress on firms' outcomes (in particular, their PDs), only a selected sample of firms will be employed. The reason for this is that not all banks (and, in turn, their firms) are equally likely to receive such treatment.

We use nearest-neighbor matching of banks in order to find an appropriate control group of banks which would have had a similar likelihood of receiving an initial capital injection (treatment), but which did not receive one. Our method has to be distinguished from a standard matching approach, where the matching serves both to alleviate the bias of selection into treatment and to construct an adequate control group. In our setting, the problem of selection into treatment plays a subordinate role, as the treatment (i.e., capital injection to bank) may be assumed to be exogenous to an individual firm's performance in our sample.

First, most firms in our sample are small: 90% have fewer than 50 employees; the median firm has around six employees. We further exclude firms with more than 10,000 employees to reduce reverse causality as the unexpected default of such a single but large exposure could induce bank default. Second, there may be regional demand shocks which affect many firms in a single region at the same time, thereby triggering a bank default. We control for such regional shocks both by the matching of banks (the same macroeconomic environment is a precondition, see below) and in the firm-level regression by using "group" fixed effects in the estimation to compare firms within a group that are likely subject to the same demand shocks. Finally, neither banks nor the bankers' association's protection schemes announce capital injections. Given that we apply matching on bank performance covariates right before the treatment occurs, the treatment should not be foreseeable for customer-firms ex ante.

In our sample, the main channels for bank distress are related to problems with banks' mortgage portfolio, the unexpected default of a single but large exposure, or structural problems with regard to specific business models.

We carry out the matching to obtain an appropriate control group of banks that can be traced over the same time span and has a similar likelihood of receiving treatment. Therefore, we conduct the matching at the bank level and only later enrich the sample of nearest neighbors with firm data.

We match the treated banks (i.e., banks with a capital injection) with control banks at period *t-1*, i.e., one year before the initial capital support measure is conducted. We match with control banks that are not treated either in that year or in any of the three subsequent years following the treatment (including the treatment year). The matching yields at least one control bank for every treated bank. In order to obtain more observations for the firm-level analysis in the second step, we allow for up to three nearest neighbors. We trace the neighbors throughout the sample time span and link them to the firms having firm-bank relationships to these banks.

One challenging feature of the German banking market consists in the numerous bank mergers in almost any banking segment. The number of banks fell from approximately 4,300 banks in 1990 to 2,700 in 2000, and 2,000 banks in 2010. Mergers are often a means of restructuring a bank and preventing it from defaulting. Therefore, initial capital support occurs more frequently before a merger than it does in a situation where no merger takes places. From an econometric point of view, mergers are difficult to deal with for two major reasons. First, they are a second treatment which is not independent of the first treatment. Second, the merger makes it substantially more difficult to conduct a control group study, because the bank prior to the merger will be substantially different from the one afterwards (e.g., with respect to size, regional focus).

There are two ways to handle these problems in the analysis. One way is to introduce a differentiated analysis by type of treatment, i.e., whether only treatment 1 (capital support) takes place or treatment 1 is accompanied or followed by treatment 2 (the merger). The latter case will then be a different treatment effect that is estimated. Another way is to look only at treatment 1 and condition on a sufficient (e.g., three-year) time span before treatment 2 takes place. We would then be looking only at a maximum window of -3 to +3 years (including the treatment year) before and after treatment 1. Such a methodology yields a valid estimation framework for a control group setting, since the treated bank is still structurally the same. As a matter of fact, it has to be stated that this choice also limits the scope of our analysis because we cannot analyze cases where both treatment 1 and 2 occur.

We apply method 2 in our analysis. The sample of treated banks is therefore restricted to banks existing at least three years before and three years after the treatment as the same unit.[8] As we want to follow firms in a window -3 to +2, treatments before 2003 are not taken into account, nor are treatments taking place after 2010.

[8] We restrict our sample in the firm-level regression to firms that did not switch banks in these 6 years in order to avoid biases by entering or exiting customers. Main bank switching is very rare with annual switching rates of about 1.3% only.

In order to find the nearest neighbors, we use observables based on the CAMEL-rating components in the year just before the treatment. To use the components generating the CAMEL rating is a plausible way of identifying distressed banks as also deposit insurance and supervisory authorities like the *Federal Deposit Insurance Corporation (FDIC)* or the *National Credit Union Administration (NCUA)* use such ratings in order to conduct their bank examinations. Apart from a variety of observable characteristics of banks, we postulate the following fixed matching criteria:

1. Treatment and control observation are in the same year.

2. Treatment and control bank are localized in the same region.[9]

3. At the year of evaluation, both matched banks have at least three years of observations before and after the matched point in time.

4. Treatment and control bank are of the same type (commercial bank, savings bank, cooperative bank).

The first and second restrictions guarantee that treatment and control bank face the same (regional) macroeconomic conditions. The third restriction leaves us with those banks that can be traced over a sufficient time span. Condition four accounts for the fact that most of the capital injections stem from protection schemes, separately organized and operated by bankers' associations of the three banking pillars. Condition 2 also helps to comply with supervision based on the level of the respective region and also corresponds to the fact that the Eastern German banking sector has developed differently from the Western. In the matching equation, the dependent variable is "affected bank" which takes the value of 1 if a bank receives an initial capital injection in period $t+1$. The explanatory variables corresponding to the CAMEL-rating components are described in Table 8 in the Appendix.

4.2 Results

Table 1 shows the output of the matching regression. As expected, the *NPL Ratio* increases the probability of receiving a capital injection. Moreover, better capitalized banks (as measured by the *Reserves Ratio*) are less likely to receive a capital injection. Other variables are not statistically significant.

For each bank, the matching regression yields a propensity score for receiving an initial capital injection in period $t+1$, given the characteristics of period t. The propensity score is scaled by bank type, the region of the headquarters, as well as the year of observation. With the resulting scaled propensity score, we perform nearest neighbor matching.

[9] Measured by Eastern and Western Germany.

Table 1: Matching Regression

Method	**Logit**
Dependent Variable	Affected bank (Bank Receives Initial Capital Injection in Period t+1)
Bank Size	0.265
	(0.187)
Bank Customers	0.131
	(0.171)
Tier 1 Capital Ratio	-0.155
	(0.109)
Reserves Ratio	-1.088***
	(0.271)
NPL Ratio	0.064**
	(0.031)
Loan Portfolio HHI	0.006
	(0.015)
OBS Ratio	-0.004
	(0.026)
Share of Customer Loans	-0.003
	(0.012)
LLP Ratio	0.354
	(0.309)
CIR	0.001
	(0.006)
RoE	-0.008
	(0.008)
Cash Holdings Ratio	0.074
	(0.093)
Share of Distressed Customers	-7.775
	(9.701)
Constant	-10.280***
	(3.980)
Observations	5,815
Pseudo R-squared	0.207
Controls	Bank Type, Year and Region

The table shows the logit regression results used to calculate the propensity score for the matching. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Variables are explained in Table 8 in the Appendix.

Table 2 shows information on the propensity score matching by year of treatment. We obtain a sample of 93 banks, of which 25 banks receive a capital injection. The remaining 68 banks are control banks, i.e. they are in distress, but do not receive a capital injection. For each of the 25 treated banks, we have at least one and up to three control banks.[10] The number of distress events varies considerably across years. Most events occur in 2003, 2005 and in the period from 2007 to 2009. Hence, most of the distress events in our sample occurred before the onset of the global financial and economic crisis. As we do not have matches for 2010, we only use firm level data from 2000 to 2011.

Table 2: Number of Treated Banks and Control Banks

Treatment Year	Treated Banks (banks with a capital injection)	Control Banks (banks without a capital injection)	Total
2003	8	19	27
2004	2	6	8
2005	4	10	14
2006	1	3	4
2007	3	9	12
2008	4	12	16
2009	8	9	27
Total	25	68	93

For each treated bank up to three control banks are selected. Each bank is observed for a total of six years around the treatment year. The full sample period covers 2000 to 2011.

By comparing characteristics of treated and control banks we obtain a picture of the quality of our matching and how relevant the treatment is. Figure 1 shows mean bank covariates before and after the treatment for both treatment and control banks. Up to the matching *(t-1)*, most characteristics of treated and control banks evolved in a similar way and reached comparable levels at *t-1* (time of matching). While both types of banks are rather small (total assets of below 5 billion Euros), the average treated bank is somewhat larger.

After the treatment, the *NPL Ratio* increases for treated banks (in particular, two years after the capital injection), while it stays rather flat for control banks. This may reflect a tendency of distressed banks receiving a capital injection to clean up their balance sheet after a while. This interpretation is in line with the finding that the *Share of Distressed Customers* develops in a rather similar way for treated and control banks.

Moreover, treated banks decrease assets more than non-treated banks do, while they increase their off-balance sheet activities. Banks that receive a capital injection are put under pressure to restructure by the responsible deposit insurance fund and/or supervisors. They may have to shrink balance sheets in order to be able to pay back the capital injection. The *Tier 1 Capital Ratio* of treated banks improves after matching,

[10] A bank may serve as a control bank more than once within the sample. Treated banks are not used as control banks at another time.

mainly driven by the decrease in assets and the capital injections treated banks receive. For non-treated banks, the capital ratio stays almost constant.

Profitability and cost-efficiency of treated and control banks also develop very differently after the matching. The *RoE* of treated banks decreases sharply and improves again only two years after the capital injection. The profitability of control banks, however, increases immediately after the matching. Restructurings often lead (at least temporarily) to higher costs and lower profits. Two years after the capital injection, *RoE* of treated banks is still lower than that of control banks. This finding suggests that treated banks face very difficult conditions after the capital injection. In the same line of argument, cost-efficiency of treated banks, as measured by the *CIR*, reduces drastically after the treatment such that by year 2 after treatment, on average 80% of income is eaten up by costs. The likely cause of this is two-sided as both earnings drop and costs will rise through organizational restructuring.

To conclude, Figure 1 in the Appendix shows that bank characteristics of treated and control banks evolve similarly in terms of trends and levels before the treatment. After the treatment, treated banks seem to face very difficult conditions, which should have significant effects on their customer portfolio.

5 Regression Analysis

5.1 Data and Empirical Methodology

5.1.1 Data

To construct our firm-level dataset, we use the above sample of matched banks and connect the banks to all firms which use the respective bank as their main bank. We obtain a sample of about 70,000 individual firms, leading to about 285,000 observations over the total sample period.

Table 3 shows the size of the compound sample by year of observation and year of treatment. Some firms may occur multiple times within the sample because two different treated banks may have the same control bank. We introduce the variable *Neighbor* which captures the identifier of the current matched control bank (there may be up to three bank neighbors). The dataset is therefore uniquely defined at the firm-bank neighbor-year level.

Table 3: Firm-Observations by Year of Observation ("Left") and Year of Treatment ("Top")

Year of Observation	2003	2004	2005	2006	2007	2008	2009	Total
2000	7,013							7,013
2001	7,109	1,993						9,102
2002	7,102	2,005	3,555					12,662
2003	7,216	2,117	3,697	1,066				14,096
2004	7,208	2,110	3,825	1,113	6,132			20,488
2005	7,159	2,283	3,835	1,111	5,920	2,247		22,555
2006		2,281	4,069	1,429	5,817	2,474	24,619	40,689
2007			4,092	1,423	5,739	2,792	24,963	39,009
2008				1,402	5,710	3,134	24,805	35,051
2009					5,616	3,532	24,478	33,626
2010						3,862	24,008	27,870
2011							22,929	22,929
Total	42,807	12,889	23,073	7,544	34,934	18,041	145,802	285,090

Firms may occur multiple times because two treated banks may have the same control bank. The dataset is uniquely defined at the firm-bank-neighbor-year-level.

Table 4 compares characteristics of firms at treated and non-treated banks in the year before the treatment. Both groups of firms are, on average, young (about 20 years) and very small (about €3 million in sales). Most firms have a close relationship with their main bank, as indicated by the small number of bank relationships. Variables are defined in Table 9 in the Appendix.

Table 4: Comparison of Firms of Treated and Control Banks

	Number of Observations		**Mean (year before treatment)**		**Mean Difference**
Variables	Treated	Control	Treated	Control	
Firm PD	11,890	35,679	9.5%	11.2%	-0.0169***
Firm Age	11,890	35,679	21.9	21.3	0.6242
Employees	8,412	26,320	8.3	11.5	-3.1968
Firm Sales	8,372	25,212	2877.1	2957.2	-80.15
Bank Relationships	11,890	35,679	1.1	1.4	-0.0025
Actual Firm Default	10,758	31,475	8.9%	11.0%	-0.0206***
Single Relationship	11,890	35,679	74.0%	79.1%	-0.0509***
Firm MaxLoan	10,392	30,253	14.5	14.3	0.169

Significance levels *** p<0.01, ** p<0.05, * p<0.1. For a definition of firm variables see Table 9 in the Appendix.

5.1.2 Model

In order to capture the bank-induced effect on firm distress (i.e., supply effect), we control for firm-specific demand effects. Ideally, we would include firm-fixed effects, as in Khwaja and Mian, 2008, for example. In our setting this is not possible, as we focus on the firm's main bank relationship. We therefore follow recent literature and replace the firm-fixed effects by a grouping of firm observations where firms in one group face the same legal, macroeconomic, spatial, and industrial environment (e.g., Degryse et al., 2019; Morais et al., 2016). These papers show that controlling for firm demand in this way hardly affects the estimated supply effects.

We apply a grouping at the level of *industry-region-size class-age class-Creditreform division-matched banks-year*.[11] The highly granular grouping should capture firms' fundamental risk adequately. In particular, there should not be a correlation between fundamental firm-risk and the treatment within these groups which is the identifying assumption that we rely on. The grouping enables us to capture "demand-side" or macroeconomic effects that may influence firms' PDs but do not influence firms' fundamental risk. According to *Creditreform*, factors such as the individual market segment influence the PDs. Our group-fixed effect aims to net out such effects from the estimation.

We further control for potential differences related to the organization of the credit rating agency. *Creditreform* is organized in 130 divisions across Germany. Each division is identified as part of the firm ID. We control for a combination of division and year because risk assessment may slightly differ across divisions. Furthermore, the rating methodology undergoes some regular revisions, which might be implemented at different points in time by each division. Therefore, we include division-year fixed effects.

Due to our matching, we have an adequate control group at the bank-level in our regression. Therefore, we do not need to include any other bank-related characteristics for identification of the treatment effect. Robustness checks in Section 6.4 show that our results remain unaffected if we include various bank covariates. The same holds if we include more firm characteristics.

Our methodology combines a conditional difference-in-differences approach with a fixed effects approach. We want to estimate the impact of bank distress on firm distress

[11] For industry-classification see Table 11; for legal forms see Table 10. We divide firms into seven size classes (sole proprietor, 2-5, 6-14, 15-48, 50-99, 100-249, 250+), see Table 12, four age classes (younger than 8, 8-15, 16-25, 26+), see Table 13. Regions are the 16 German states ("Bundeslaender"), see Table 14.

and performance indicators. Like in any difference-in-differences setup, we need (in addition to an intercept on the right-hand side), *(i)* the treatment dummy *(affected bank)*, *(ii)* the indicator for after-treatment periods *(post)* and *(iii)* the interaction of both in order to represent our four states of the world. This interaction term shows the treatment effect, i.e. in our case how, for example, the PD of firms connected to banks in distress and bailed out evolves compared to the average PD of firms connected to banks not bailed out. Our final model therefore is specified as

$$firm\ outcome_{i,t} = \beta_0 + \beta_{post} * post_{ik,t} + \beta_{affected} * affected_{ik,t} \qquad (1)$$
$$+\beta_{ATET} * affected_{ik,t} * post_{ik,t} + \rho_{gk,t} + \varepsilon_{igk,t}$$

i: firm, k: bank, g: group, t: time

Firm outcome may be, in terms of distress, a firm's probability of default (*Firm PD*), the actual default of a firm (*Actual Firm Default*), the maximum trade credit recommendation for a firm in log (Log (*Firm MaxLoan*)) and, in terms of performance, the log value of sales a firm realizes in their P&L account (*Firm Sales*). Further, $post_{ik,t}$ takes the value of 1 if firm *i* has a relationship with bank *k* in period *t*, where period *t* is either the treatment year or the period after the treatment year. The indicator $affected_{ik,t}$ takes the value of 1 if firm *i* has a relationship with bank *k* in period *t*, where bank *k* is a treated bank. Much the same holds for the interaction of both.

$\rho_{gk,t}$ is a group fixed-effect consisting of: *industry-region-size class-age class-Creditreform division-matched banks-year*. The group effect $\rho_{gk,t}$ serves to absorb demand side and business cycle effects associated to each group of firms that may influence firms' outcomes. Our assumption to identify the "bank-induced" effects (β_{ATET}) is that we can control for demand shocks. Degryse et al. (2019) have shown that industry-size-location group fixed effects may serve as reasonable demand controls whenever firm-time fixed effects cannot be included. We further coarsen the groups to control for the *Creditreform* division to account for heterogeneous risk assessment methods across different *Creditreform* divisions and/or time. Finally, the group effects also contain an indicator for the set of matched banks, which allows identifying the treatment effect within the matched bank neighbor(s). We drop the i, k and t subscripts for the components of $\rho_{gk,t}$ as they always refer to a specific combination of i, k and t. While we interpret the estimated β_{ATET} as bank-induced, we acknowledge that this needs be interpreted with care as this is based upon our assumption that our firm-grouping absorbs demand shocks.

5.2 Model Estimation

In order to estimate our model we choose a population-average GLM-estimator, also referred to as a generalized estimating equation (GEE). The GEE framework is often used in settings where the covariance structure of residuals is unknown. As GEE estimators are population-average models, they focus on the average effect over an unspecified population of individuals. They are frequently used to estimate average responses in clustered samples. Our setting with 130 different clubs evaluating the PD of firms seems to be of exactly this kind. We do not know the covariance structure within the clusters, but are still able to obtain consistent estimates even if the covariance structure is misspecified. The estimator is similar to a random effects (RE) Tobit regression with a Gaussian random effect.[12]

Other than in a genuine fixed or random effects setting, we do not take our firm identifier as a panel variable and neither year as our time variable. Instead, a group identifier is our panel variable. Note that the timing of the observation *(year)* is part of the panel variable. The theoretical time variable is constituted by the individual firm-year observations that are part of group g in year t. We bundle the group identifier in a *fixed effect* $\widehat{\rho_{gk,t}}$ where we assume exchangeable correlation structure of residuals within each group. This structure is a reasonable assumption, since groups are narrowly defined and, in particular, are constituted within each division unit.

Our final dataset consists of about 285,000 observations representing about 70,000 individual firms, each over a period of up to six years. We follow firms in our matched sample three years before the treatment, in the treatment period, and two years after it. There are a couple of reasons to do so. First, we choose a short period of time after treatment in order to capture the direct impact of the treatment and to make sure that our measurement is less likely to be contaminated by other influences. Second, there are substantial dynamics in firms' outcomes, at least in their annual PDs. Hence, the longer the time window the more of these yearly movements will overlay each other and keep us from obtaining a valid estimate of the treatment effect.

6 Empirical Results

This section presents results for our conditional difference-in-differences estimations of bank risk and bailout on firm outcomes. Outcome variables are firm probability of default (*Firm PD*), actual default of a firm (*Actual Firm Default*), maximum trade credit

[12] Note that robustness checks in Section 6.4 show that our results are confirmed using OLS, RE or Tobit regressions.

recommendation (*Firm MaxLoan, in log*), and sales from the P&L account (*Firm Sales, in log*). Robustness checks are presented in Section 6.4 where we verify our results when we include other covariates, choose different regression techniques and different subsamples.

As a starting point, we apply the conditional difference-in-differences analysis to all firms and banks in our sample in order to identify a general bank-risk-induced effect on firms' *PDs* (and other firm outcome variables, see Section 6.1). In Section 6.2, we apply our model in (1) to different subsets of banks and firms that may yield insights into the heterogeneity of the treatment effect. We investigate whether the bank-risk-induced effect depends on firm risk classes and whether the bank's business model (*Relationship Bank* versus *Transaction Bank*) is relevant. Moreover, we also examine whether the bank-risk-induced effect on firms' *PDs* differs between crisis years and normal times.

6.1 Baseline Results

Table 5 shows the baseline GLM estimations on the full sample of firms and banks from 2000 to 2011. Specifications (A1) and (A2) show the results for our first research question, i.e., whether a bank-induced risk transmission effect exists from bank distress and bailout to customer firms. The coefficients are to be interpreted as a percentage change. We find that the PD of customers at rescued banks increased on average by 10.7% after the treatment occurred than that of similar customers at control banks that are not bailed out. Given an average *Firm PD* of 9.5% (of treated firms in *t-1*), this means that the average *Firm PD* of treated customers increased to 10.5% – which is quite substantial.

Specification (A2) estimates the probability of actual default using a FE-Probit regression framework. Customers at a treated bank have a 10.4% higher probability of actually defaulting after the treatment, which is consistent with the results found in specification (A1).

Specification (A3) shows results when using *Firm MaxLoan*, an indicator for firm credibility, as dependent variable. *Creditreform* adds a maximum trade credit recommendation to most firms that are evaluated. Hence, *Firm MaxLoan* serves as a benchmark to trade creditors for how much credit could be granted to the firm. The regression coefficients in (A3) show that logarithmized maximum loan recommendations (*Log Firm MaxLoan*) go down on average by 11.5%. This constitutes a significant restriction and a potential negative multiplier effect, as most firms in the sample are small and also dependent on trade credit.

Finally, specification (A4) estimates the treatment effect on logarithmized firm sales (*Log Firm Sales*) in order to capture effects on the real economy via affected firms. We find a strongly significant negative effect of a -8.55% decrease in *Log Firm Sales* after the treatment. This result supports the finding that the increases in *Firm PD* and alongside reductions in trade credit recommendations substantially affect firm performance.

Table 5: Impact of Bank Distress on Firm Distress

Specification	A1	A2	A3	A4
Estimator	GLM logit link	FE Probit	OLS FE	OLS FE
Dependent Variable	*Firm PD*	*Actual Firm Default*	*Log Firm MaxLoan*	*Log Firm Sales*
Sample	all	all	all	all
Bank FE	Yes	Yes	Yes	Yes
Time	All Years	All Years	All Years	All Years
Treatment Effect	0.107***	0.104***	-0.115***	-0.0855***
Observations	285,090	210,852	223,212	195,806
Number of groups	67,972	52,091	48,405	44,763

Conditional difference-in-differences estimates on the firm-bank-neighbor-year-level. (Robust) standard errors in parentheses. Specification A1 shows GLM-estimates on firms' individual *PDs*. Specification A2 shows FE-Probit results on actual firm defaults. Specification A3 uses the variable *Log Firm MaxLoan* in a FE-OLS regression. Finally, specification A4 shows a FE-OLS regression on *Log Firm Sales*. Variables are explained in Table 9 in the Appendix. Specifications A1, A3 and A4 use robust standard errors, *** p<0.01, ** p<0.05, * p<0.1.

It is worthwhile to take a step back at this point and think about the channels which drive these findings. Firms not only suffer directly since their main banks may grant less credit, require more collateral or higher interest rates. They also suffer from a weaker position in business to business bargaining. *Creditreform* is the largest credit bureau in Germany and particularly specialized on the business to business market. Their key business is to provide firms with expertise that demand information on a client or supplier firm. Hence, a worsened credit rating and a reduction in trade credit recommendation may further affect a firm's performance on both market sides: On the input side, because supplier firms may become more reluctant to grant trade credit to the firm. Moreover on the output side because firms (and customers) may hesitate to place orders at a supplier firm if there are substantial insolvency risks.

Our results show that firms connected to bailed-out banks suffer. These findings are in contrast to the results for US TARP. Berger et al. (2017), Berger and Roman (2017) and Norden et al. (2013) document that TARP helped to increase credit supply and customers of banks that received capital through TARP benefitted. Moreover, Norden et al. (2018) show that corporate borrowers of TARP banks also increased their trade credit supply. Compared to US TARP, banks in Germany participating in bailouts schemes are required to substantially restructure and deleverage assets. This burden may force banks to cut loans and cause adverse effects on the real economy, in particular in a crisis.

We visualize our findings by plotting the outcome variables for treated and untreated banks around the treatment year. In order to do this, we first estimated the models and then removed the fixed-components $\widehat{\rho_{gk,t}}$ in (1) from the outcome variables. The resulting adjusted values for *Firm PD, Log Firm MaxLoan* and *Log Firm Sales* are shown in Figure 2 in the Appendix. We observe parallel trends for all three variables for the three years before the treatment and, afterwards, a visible increase in *Firm PD* and a substantial decrease in *Log Firm MaxLoan* and *Log Firm Sales*. Interestingly, we see differences in levels before the treatment for both variables, i.e., treated banks have, on average, slightly "better" (0.1 percentage points) customers before the treatment than control banks. After the treatment occurs, the average PD of customers at treated banks increases visibly above the level of control bank customers which is what the regression results in A1 suggest.

6.2 Risk Pass-Through in a Crisis

For a more detailed picture of the effects, we now turn to an analysis of different macroeconomic conditions. Specifically, we want to answer the question of whether distress-induced bank bailout events that happen during a systemic crisis affect firms differently than such events outside a systemic crisis featuring different transmission of bank distress shocks into already weakened firm balance sheets. We define crisis treatments as treatments occurring at the peak of the financial crisis 2008 and 2009 and all other treatment years as non-crisis years.

Table 6 shows the same specifications as in Table 5 but now we distinguish with respect to the timing of the treatment. The effects in crisis and non-crisis years are overall similar. While the impacts on *Firm PD* and *Actual Firm Default* differ only slightly, the treatment effect for *Log Firm MaxLoan* is only significant in crisis years with -10%. The differentiation for *Firm Sales* leaves us with insignificant coefficients for crisis and non-crisis years.

Taken together, our findings show that bank distress affects firm default risk both in crisis and in non-crisis times, although the impact is slightly stronger in crisis years when it comes to trade credit recommendations and sales.

Table 6: Impact of Bank Distress on Firm Distress: Crisis versus Normal Times

Panel a (Crisis)

Specification	**B1a**	**B3a**	**B2a**	**B4a**
Estimator	GLM logit link	FE Probit	GLM logit link	OLS FE
Dependent Variable	*Firm PD*	*Actual Firm Default*	*Log Firm MaxLoan*	*Log Firm Sales*
Sample	all	all	all	all
Bank FE	Yes	Yes	Yes	Yes
Time	Crisis	Crisis	Crisis	Crisis
Treatment Effect	0.102**	0.0979***	-0.100***	-0.0690
Observations	163,843	123,135	134,638	115,494
Number of groups	32,070	24,810	23,789	21,866

Panel b (Normal Times)

Specification	**B1b**	**B3b**	**B2b**	**B4b**
Estimator	GLM logit link	FE Probit	GLM logit link	OLS FE
Dependent Variable	*Firm PD*	*Actual Firm Default*	*Log Firm MaxLoan*	*Log Firm Sales*
Bank FE	Yes	Yes	Yes	Yes
Sample	all	all	all	all
Time	No Crisis	No Crisis	No Crisis	No Crisis
Treatment Effect	0.110**	0.0944***	-0.141	0.00308
Observations	12,1247	87,717	88,574	80,312
Number of groups	35,902	27,281	24,616	22,897

Conditional difference-in-differences estimates on the firm-bank-neighbour-year-level. (Robust) standard errors in parentheses Specifications B1a/b show GLM-estimates on firms' individual *PDs* for treatment years within the crisis (2008 and 2009) in panel a and for treatment years outside the crisis (2003 – 2007) in panel b. Accordingly, specifications B2a/b show FE-Probit results on actual firm defaults. Specifications B3a/b use the variable *Log Firm MaxLoan* in a FE-OLS regression. Finally, specifications B4a/b show a FE-OLS regression on *Log Firm Sales*. Variables are explained in Table 9 in the Appendix. Specifications B1a/b, B3a/b and B4a/b use robust standard errors,
*** p<0.01, ** p<0.05, * p<0.1.

6.3 Relationship Banks versus Transaction Banks

We now study whether a bank's business model influences the previously reported bank-induced risk effects. In particular, we investigate whether a relationship bank behaves differently than a transaction bank when it enters into distress and a bailout program. The question of whether close bank-firm relationship shield customers against crises has been investigated in various studies (e.g., Peek and Rosengren, 1997; Ivashina and Scharfstein, 2010). Relationship banks may provide liquidity insurance for customers (e.g., Berger and Udell, 1995; Bolton et al., 2016), i.e., they charge higher rates on average but keep on lending when firms are temporarily under pressure. If, however, relationship banks themselves are in distress, borrowers with high PDs could also be supported with further credit or eventually kept alive.

We develop three indicators to capture a bank's relationship orientation: *(i) Single Relationship Customers Share, (ii) Main Bank Customers Share* and *(iii) Regional Customers Share*.[13] The Single Relationship Customers Share is an indicator of how important bank k is on average for its customers. In a similar vein, the *Main Bank Customers Share* measures the average role bank *k* has with regard to its customers even when they have multiple relationships. The third indicator of relationship orientation, the *Regional Customers Share*, considers the geographical distribution of borrowers and is motivated by the results on the role of distance in relationship lending. Shorter distances may provide the bank with more information and allow relationship banking to be performed (e.g., Petersen and Rajan, 2002; Degryse and Ongena, 2005; Agarwal and Hauswald, 2010).

We call bank *k* a *Relationship Bank* in year *t* when it exceeds the 75th percentile among all banks in year *t* in at least two out of the three measures of relationship orientation.[14] By contrast, *Transaction Banks are defined* as banks which do not exceed the 75th percentile in any of the relationship orientation variables.

We now look in more detail at how the impact of bank distress interferes with the bank business model, but also with customer risk classes. We consider firm risk classes, since we expect the impact of bank distress on *Firm PD* not to be linear across the bank's risk portfolio. We use quantile regressions to empirically investigate the relationship, where we use the subset of firms which do not default.

To apply quantile regression techniques in the context of fixed effects, we rely on a method introduced in Canay (2011) that tackles the problem in a two-stage regression framework. In the first step, we estimate a fixed effects model with all non-time-constant regressors on the right-hand side (which equals the regression setup from (1) in a difference-in-differences framework) and then subtract the fixed part $\widehat{\rho_{gk,t}}$ from the outcome variable y (which is the variable of interest). In the second step, we estimate one equation for every quantile of this new variable $y*$ with bootstrapped standard errors from 50 replications. In our setup, the adjusted outcome variable $y*$ is exactly what we used to generate the graphs in Figure 2.

[13] The variables are defined in Table 8 along with other bank covariates.

[14] By requiring at least two out of three conditions, we reduce the likelihood that our *Relationship Bank* indicator picks up other bank characteristics such as mainly servicing small clients, or offering a broader range of services.

Figure 3 in the Appendix shows quantile regression plots using the dependent variable *Firm PD* in all of the graphs. The plots show how large the average treatment effect is for differently risky customers. Separate regressions are carried out for *Transaction Banks* and *Relationship Banks*. As it is best practice with quantile regressions, we drop the lower and upper quantiles because effects are often unstable there. Note that the effects in Figure 3a are to be interpreted as percentage points as they now come from a FE-OLS-regression with *Firm PD* as the dependent variable. Figure 3b compares the quantile effects for *Relationship Banks* and *Transaction Banks*, but now showing percentage effects. They are calculated by dividing the percentage point effects from the regression by the respective mean *Firm PD* in that quantile.

The average treatment effect, i.e., the impact of bank distress on firm risk, is very different depending on whether the firm is the customer of a relationship or transaction bank. This holds particular for medium to high risk customers between the 40% and 70% quantile. At transaction banks, low-risk customers are little affected, whereas high-risk customers face a significant increase in their PDs. The relatively largest effect can be seen for customers at the 60% quantile where the effect adds up to a 20% increase in *Firm PD* (see Figure 3b). At relationship-banks, the path goes almost in the opposite direction. While for low-risk customers below the 40% quantile, almost no effect is obvious, high risk customers experience significantly negative effects, i.e., decreases in their PD up to the 70% quantile. Hence, low-risk customers are relatively less affected than high-risk customers. The strongest negative effect is found right at the median quantile with a -20% decrease in *Firm PD*.

This evidence suggests that transaction and relationship banks behave quite differently when they enter into distress: *Transaction Banks* punish bad, high-risk customers, probably by changing their lending policy towards them. However, good, low-risk customers seem to be untouched. By contrast, *Relationship Banks* follow a different strategy of shielding higher risk customers, potentially by providing even further liquidity or granting credit lines.

6.4 Robustness

We carry out various robustness checks. First, our results are robust to different estimators applied to the data. Table 7 shows the regression framework from specification A1 now using different estimators. Note that the coefficients shown in specifications C1 to C8 have to be interpreted as percentage point effects. We see that effects remain qualitatively similar no matter which estimator is used. However, genuine firm-fixed effects models (C3 and C4) show an underestimation of the effect. This finding is likely due to both the demand side (firms' order situation, idiosyncratic and market risk) and *Creditreform* division effects (differences in risk-assessment and application of new methodologies by rating agencies) that we aim to exclude by applying our grouping in equation (1). Moreover, columns C7 and C8 take into account the fact that the dependent variable is bounded between 0 and 1, which calls for a truncated regression.

Table 7: Robustness Checks for the Application of Different Estimators on *Firm PD*

Specification	Estimator	Number of Observations	Number of Groups	Treatment Effect
C1	*OLS*	285,090		0.00959***
C2	*OLS robust*	285,090		0.00959***
C3	*Genuine FE*	285,090	70,687	0.00401***
C4	*Genuine RE*	285,090	70,688	0.00434***
C5	*Group FE*	285,090	67,972	0.00653
C6	*Group RE*	285,090	67,973	0.00933***
C7	*Tobit robust*	285,090	67,974	0.00930***
C8	*GEE robust*	285,090	67,975	0.00883***

C1 and C2 show basic OLS estimations, C3 and C4 FE-estimates on the firm-level, C5 and C6 FE and RE estimates on the group-level, C7 is a random effects Tobit estimation with 0 lower and 1 upper bound. Finally, C8 is the GEE estimator applied in our main regressions, although this time with an identity-link, i.e. it gives the percentage point effect for reasons of comparison to the other models. All models are estimated using the full sample. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Second, Table 15 in the Appendix gives evidence on whether the inclusion of bank and firm covariates into the regression changes the coefficient estimates on *Firm PD*. Again, the baseline specification A1 forms the basis for this table. Moving more to the bottom of the table, we include more and more covariates into the regression. In a well-specified conditional difference-in-differences setup, coefficients ought to remain stable when including covariates from the matching equation. While firm characteristics are not part of the matching equation, they enter through the grouping applied in equation (1) and given little time variation in firm covariates, including these covariates should not change our coefficients on the treatment effect either. Table 15 shows this to be the case for the bank-covariates employed in the matching equation (compare Table 8 for an overview) and the firm characteristics entering into the group-fixed effect.

Third, in Table 16 in the Appendix, we examine whether the impact of bank distress on Firm PD is different for different subsamples. We find that our results are robust to firm location and restrictions on the macroeconomic environment. Results differ to some extent depending on the bank type. The treatment effect is, for example, stronger if cooperative or savings banks are excluded. Moreover, the treatment effect also depends on firm age. We find that the treatment effect increases with firm age up until firms of more than 50 years of age, i.e., medium to old firms are more strongly affected when their main bank gets into distress than younger ones.

7 Concluding Remarks

This paper analyses whether there is a curbing effect from distress-induced bank bailouts as reflected in a firm's probability of default. Bank bailouts not only affect banks actions towards firms, it may also generate multiplicator effects towards other firm financing sources such as trade credit.

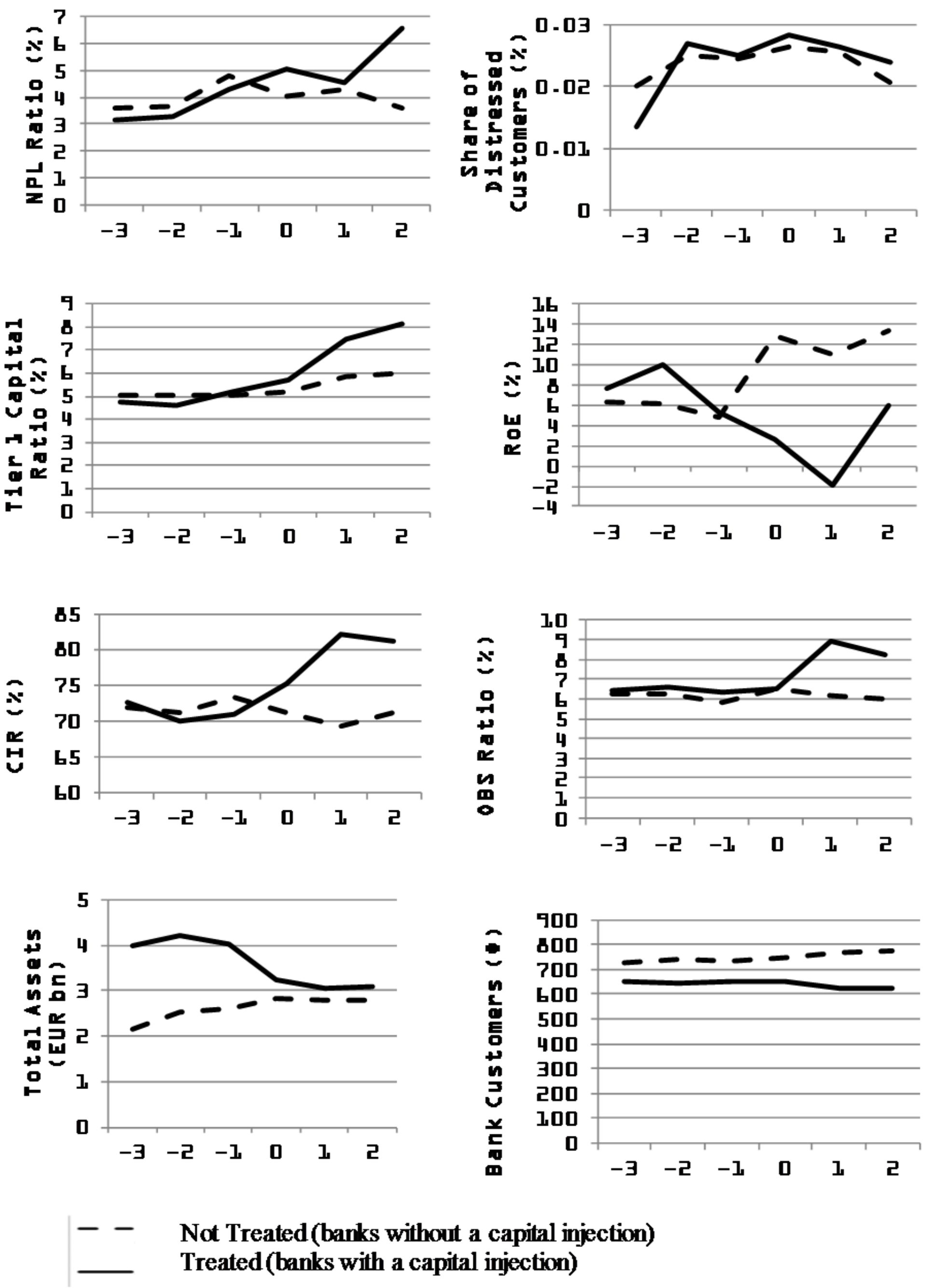
Our empirical analysis for Germany over the period 2000-2011 shows that a distressed bank bailout, which is subject to restructuring and deleveraging conditions, leads to a bank-induced increase in the probability of default of about 10%, and a lowering of the advised maximum trade credit loan of about 11%. Furthermore, distress-induced bank bailouts have real effects on firm outcomes as we find an 8.5% reduction in firm sales. We find that the effects are somewhat stronger when the bank entered into distress during the global financial crisis than outside, providing some indication for different transmission of bank distress shocks into already weakened firm balance sheets.

Relationship and transaction banks that are in distress and bailed out generate quite different bank-induced risk effects. Whereas bailouts of transaction banks lead to an increase in the probability of defaults for firms, relationship banks seem to shield high-risk firms from increases in the probability of default.

While the bank recovery and resolution scheme in Germany has – during the period under review – contributed to stability in the banking system and its design limits the use of taxpayer money due to contributions from the collective protection schemes, we reveal a potential curbing effect on the real economy as it seems to generate negative effects for corporate borrowers linked to bailed out banks.

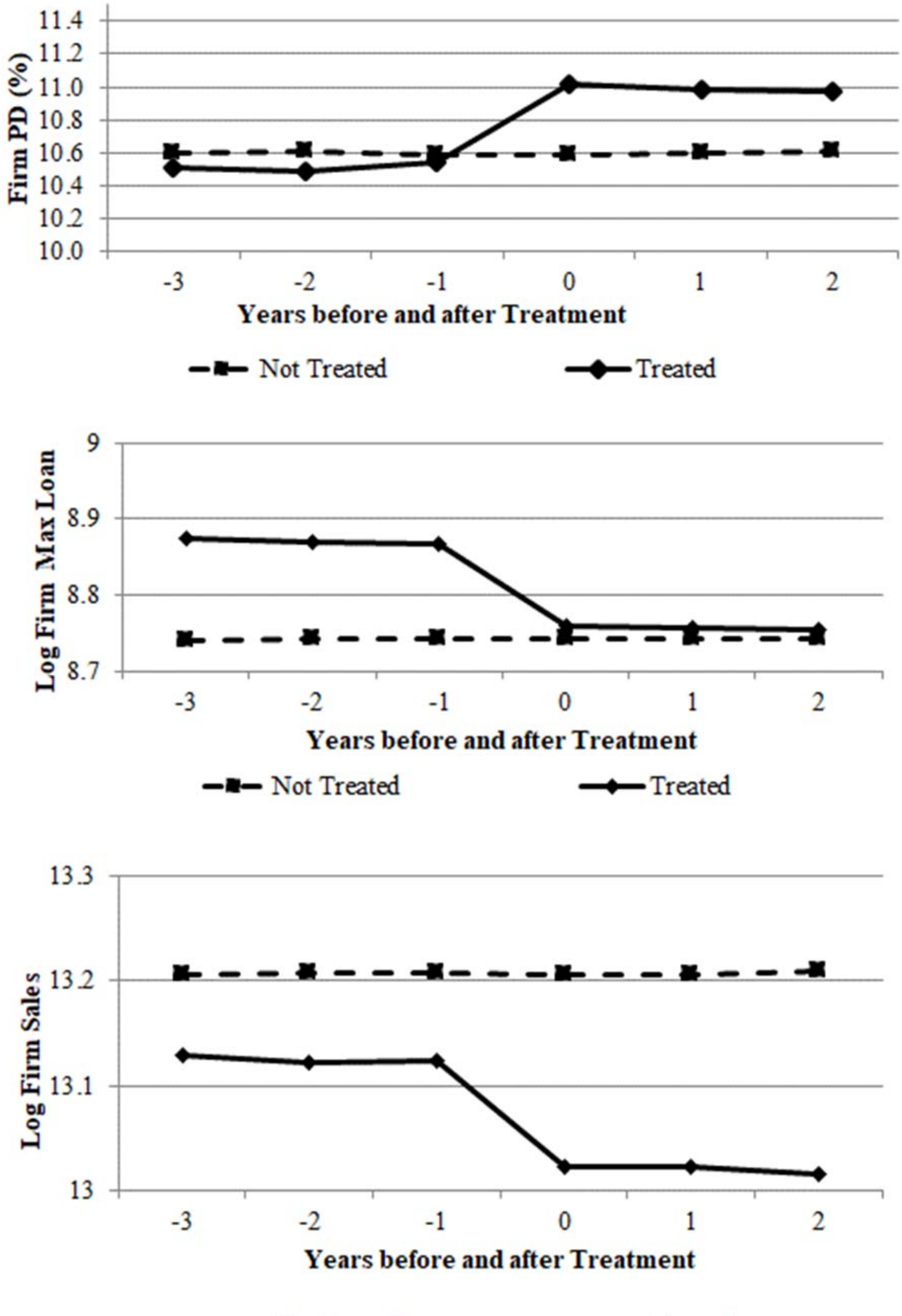
Appendix

Figure 1: Mean Characteristics of Banks with a Capital Injection ("Solid") and Banks without ("Dashed") Before and After Treatment



The timeline refers to years before and after matching. Matches are obtained using nearest-neighbor-matching on bank covariates in period *t-1*. The set of control banks may be constituted by the three nearest neighbors of bank *k*. Variables are explained in Table 8.

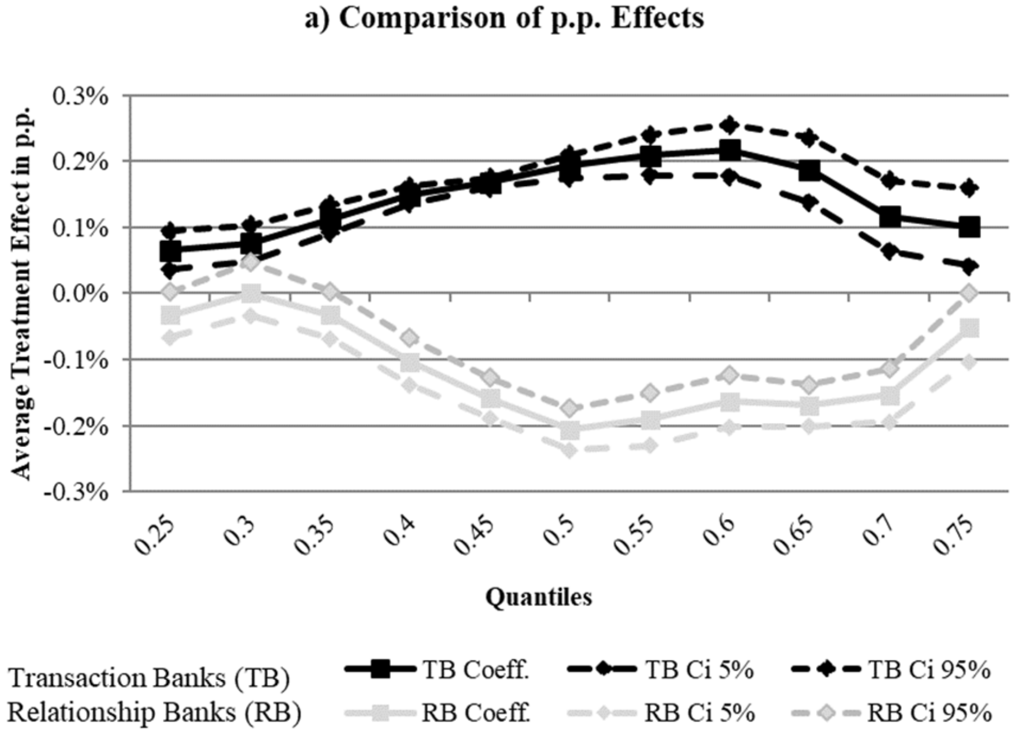
Figure 2: Average Adjusted Outcome Values from Regression Specifications A1 (“Top”), A3 (“Middle”) and A4 (“Bottom”)

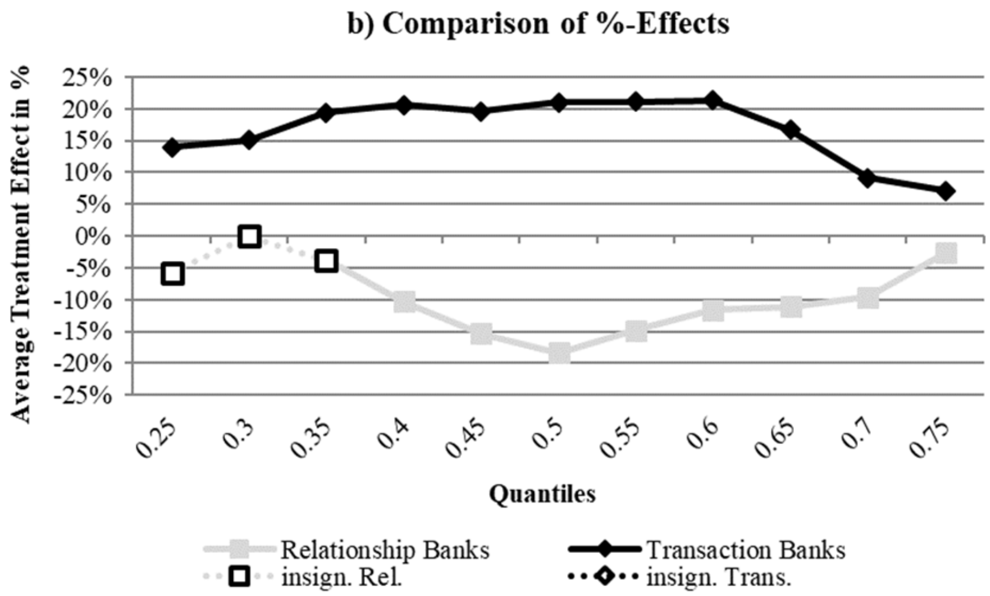


The figures show adjusted outcome values from the regression specifications A1, A3 and A4 differentiated by the time before and after treatment and the treatment status. Values are adjusted by the respective fixed-effect estimate from the regression. This methodology leaves us with the net treatment effect in the matched sample conditional on the group-fixed effect. For the definition of the variables see Table 9.

Figure 3: Results of Quantile Regressions

Firm PD as dependent variable and distinguishing upon relationship and transaction banks





We apply a method for fixed effects in quantile regressions introduced in Canay (2011). Standard errors are bootstrapped with 50 replications. Plot a) contains percentage point effects and 5% confidence intervals. Plot b) shows the percentage point effect in relation to the respective mean *Firm PD* in quantile q, i.e. the percentage effect. White boxes/prisms show insignificant areas at the 5% level.

Table 8: Definition of Bank Variables

Type of Information (Source)	Corresponding CAMEL-category (where applicable)	Variable name	Variable Definition
***Treatment* (Bundesbank's *Bank Distress Database*)**		Affected Bank	Bank receives capital injection in treatment year *t+1*
Bank Balance Sheet Information (Bundesbank's prudential data base *BAKIS* and Bundesbank's *Borrowers Statistics*)		*Bank Size*	GDP deflated total assets (log)
	Capital Adequacy (C)	*Tier 1 Capital Ratio*	Tier 1 capital over total assets (%)
		Reserves Ratio	Bank reserves (pursuant to section 340 f/g of the German Commercial Code) over total assets (%)
	Asset Quality (A)	*NPL Ratio*	Non-performing loans over total assets (%)
		Loan Portfolio HHI	Hirschman Herfindahl Index (based on 23 business sectors in the loan portfolio)
		OBS Ratio	Off-balance sheet activities over total assets (%)
		Share of Customer Loans	Customer loans over total loans (%)
		LLP Ratio	Loan loss provisions over total assets (%)
	Management Skills (M)	*CIR*	Cost-to-income ratio (%)
	Earnings (E)	*RoE*	Return (raw result) on equity (%)
	Liquidity (L)	*Cash Holdings Ratio*	Cash holdings over total assets (%)
Aggregate Bank Customer Information (ZEW's *Mannheim Enterprise Panel*, *MUP*)	**Asset Quality (A)**	*Bank Customers*	Number of corporate customers of bank *k* (log)
		Share of Distressed Customers	Number of distressed corporate customers over total number of corporate customers (%)
		Share of Single Relationship Customers	Number of corporate customers of bank *k* (having a relationship with bank k only) over all corporate customers of bank *k*, including multiple-relationship firms (%)
		Share of Main Bank Customers	Number of corporate customers of bank *k* (using bank k as main bank) over total number of corporate customers of bank *k*, including multiple-relationship customers (%)
		Share of Regional Customers	Number of corporate customers within a range of 50km of bank k over total number of corporate customers of bank *k* (%)

Table 9: Definition of Firm Variables

Firm Age	Firm age in years
Employees	Number of full-time equivalent employees
(Log) Firm Sales	(Log of) Firm sales (1,000 Euros)
Firm PD	Firm probability of default (%, over one year) evaluated by *Creditreform*
Actual Firm Default	Actual firm default
Main Bank	Dummy indicating whether bank is firm's main bank relationship
Bank Relationships	Number of bank relationships
Single Relationship Firm	Dummy variable which takes the value of 1 if a firm has only one
Distance Firm-Bank	Distance between firm and its main bank (km)
(Log) Firm MaxLoan	(Log of) Recommendation for maximum trade credit exposure to firm; recommendation provided by *Creditreform* (1,000 Euros)

Table 10: Legal Forms

No.	Industry Sector Groups	Observations	Percent
1	Liberal Profession	12,008	4.2%
2	Commercial Operation ("Gewerbebetrieb")	144,657	50.7%
3	BGB-Company ("BGB Gesellschaft")	10,545	3.7%
4	Partnership ("Arbeitsgemeinschaft")	10	0.0%
5	One-Man Business ("Einzelfirma)	13,358	4.7%
6	General Partnership ("OHG")	791	0.3%
7	Limited Partnership ("KG")	1199	0.4%
8	Limited partnership with a limited liability company as general partner ("GmbH & Co. KG")	6,819	2.4%
9	Limited Liability Company ("GmbH")	91,831	32.2%
10	Corporation ("AG")	112	0.0%
11	Registered Co-Operative ("eG")	1,028	0.4%
12	Registered Association ("eV")	2,732	1.0%
	Total	285,090	100%

Table 11: Industry Definition and Distribution According to NACE Classification

No.	Industry Sector Groups	Observations	Percent	Industry sector classification (NACE rev. 2)
1	Cutting-edge technology manufacturing	956	0.34%	20.2, 21, 24.46, 25.4, 26.11, 26.2, 26.3, 26.4, 26.51, 26.6, 26.7, 30.3, 30.4
2	High-technology manufacturing	3,537	1.24%	20.13, 20.14, 20.16, 20.42, 20.51, 20.53, 20.59, 22.11, 23.19, 23.44, 26.12, 27.11, 27.12, 27.2, 27.31, 27.33, 27.4, 27.9, 28.11, 28.12, 28.13, 28.15, 28.23, 28.24, 28.29, 28.3, 28.41, 28.49, 28.92, 28.93, 28.94, 28.99, 29.1, 29.31, 29.32, 30.2, 33.2
3	Non-high-tech manufacturing	19,239	6.75%	10-33 (excl. sectors 1 and 2)
4	Technology-intensive services	12,037	4.22%	61.1-61.3, 62, 63.1, 71.1, 71.2, 72.1
5	Non-technical consulting services	11,319	3.97%	69, 70.2, 72.2, 73
6	Other business-oriented services	17,285	6.06%	61-63, 69-72, 77.1, 77.3, 77.4, 78, 80, 81 (ex 70.1, 74.2)
7	Consumer-oriented services	63,436	22.25%	55-56, 58-60, 68, 74.2, 75, 77.2, 79, 85.5-85.6, 86-88, 90-93, 95-96
8	Energy/Mining/Disposal	2,007	0.70%	5-9, 35-39
9	Construction	47,955	16.82%	41-43
10	Trade	80,490	28.23%	49-52
11/12	Traffic/Mailing	11,170	3.92%	49-53
13	Banks/ Insurances/ Financial Services	Excluded from Firm Sample		64 (excl. 64.2), 65, 66, 67
14	Holdings	7,784	2.73%	70.1, 64.2
0	Other (e.g. Forestry/ Agriculture)	6,983	2.45%	< 10
	Total	285,090	100%	

Source: The authors' classification, NIW/ISI/ZEW Listen 2012 (Gehrke et al., 2013).

Table 12: Size Classes

Size Class	Observations	Percent
Unknown	72,933	25.4%
Sole proprietor	66,029	23.5%
2 - 5	91,024	31.8%
6 - 14	35,593	12.3%
15 - 49	15,800	5.5%
50 - 99	2,140	0.8%
100 - 249	1,104	0.4%
250+	467	0.2%
Total	285,090	100%

Table 13: Age Classes

Age Class	Observations	Percent
Younger than 8	61,341	21.0%
8	91,710	32.4%
16	66,658	23.8%
26	65,381	22.7%
Total	285,090	100%

Table 14: Firm Locations

No.	Industry Sector Groups	Observations	Percent
1	Schleswig-Holstein	33,084	11.6%
2	Hamburg	2,159	0.8%
3	Niedersachsen	3,655	1.3%
4	Bremen	170	0.1%
5	Nordrhein-Westfalen	77,511	27.2%
6	Hessen	46,271	16.2%
7	Rheinland-Pfalz	26,570	9.3%
8	Baden-Württemberg	33,935	11.9%
9	Bayern	26,814	9.4%
10	Saarland	65	0.0%
11	Berlin	3,920	1.4%
12	Brandenburg	7,890	2.8%
13	Mecklenburg-Vorpommern	7,046	2.5%
14	Sachsen	8,994	3.2%
15	Sachsen-Anhalt	1,651	0.6%
16	Thüringen	5,355	1.9%
	Total	285,090	100%

Table 15: Robustness Checks for the Inclusion of Bank and Firm Covariates

		Control Variables										
Speci-fication	**Obser-vations**	***Firm Size Class, Firm Age Class***	***Industry Dummies, Firm Bundesland, Legal Form***	***Single Relationship Firm***	***Bank Size***	***Bank Customers***	***NPL Ratio***	***Capital Ratio, Share of Distressed Customers***	***Share of Customer Loans, Loan Portfolio HHI***	***Reserves Ratio, OBS Ratio, LLP Ratio, CIR, RoE***	***Cash Holdings Ratio***	**Treatment Effect (%)**
D1	277,614	X										0.0898***
D2	277,614	X	X									0.118***
D3	277,614	X	X	X								0.115***
D4	277,614	X	X	X	X							0.115***
D5	277,614	X	X	X		X						0.110***
D6	277,614	X	X	X	X	X						0.111***
D7	277,614	X	X	X	X	X	X					0.108***
D8	277,614	X	X	X	X	X	X	X				0.112***
D9	277,614	X	X	X	X	X	X	X	X			0.0904***
D10	277,614	X	X	X	X	X	X	X	X	X		0.0820**
D11	277,614	X	X	X	X	X	X	X	X	X	X	0.0892***

All models are estimated using the full regression sample. Baseline specification is specification A1 from Table 5 using all firms and a logit link function.
*** p<0.01, ** p<0.05, * p<0.1.

Table 16: Robustness Checks for Various Sample Restrictions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Firm PD	*Firm PD*	*Firm PD*	*Firm PD*	*Firm PD*	*Firm PD*	*Firm PD*	*Firm PD*	*Firm PD*	*Firm PD*	*Firm PD*
Sample restriction	**No counties from Eastern Germany**	**Two-year window**	**No counties with two subsequent years of neg. GDP growth**	**No private banks**	**No savings banks**	**No coop. banks**	**Savings banks only**	**Firms <= 5y**	**Firms <= 10y**	**Firms <= 20y**	**Firms > 50y**
Treatment effect	0.106***	0.141***	0.154***	0.0776**	0.170***	0.158***	0.0860*	-0.0426	0.109**	0.140***	0.0817
	(0.0347)	(0.0393)	(0.0372)	(0.0341)	(0.0448)	(0.0434)	(0.0468)	(0.0778)	(0.0492)	(0.0367)	(0.153)
Observations	250,234	191,124	186,127	237,889	127,779	204,512	157,311	39,213	96,526	187,355	17,199
Number of groups	57,323	45,457	56,044	50,261	40,270	45,413	27,702	12,829	28,665	47,447	9,388

Specifications estimated without Bank- Fixed-Effects. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

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