“Risky Banks and Risky Borrowers”

Relationship Banking in the Crisis

Johannes Bersch[Γ] Hans Degryse[‡] Thomas Kick[§] Ingrid Stein[¥]

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Abstract

How do banks deal with borrower risk in their corporate loan portfolio when banks enter into distress? Is there a pass-through of default risk into the real sector? If yes, is this pass-through more or less severe when there is a systemic banking crisis? We address these questions by looking at a unique sample of German firms from 2000 to 2012 and follow their firm-bank relationships through times of distress and crisis. We find that there is a risk pass-through and that the direction and magnitude of the effect depends on firms’ idiosyncratic risk as well as on the relationship orientation of banks.

Keywords: Distressed banks, bank risk channel, relationship banking, firm probability of default, Financial Crisis, Evergreening

JEL Classification: G01, G21, G24, G33

Γ Centre for European Economic Research (ZEW), Mannheim, email: bersch@zew.de
‡ KU Leuven and CEPR, email: hans.degryse@kuleuven.be
§ Deutsche Bundesbank, Frankfurt/Main, email: thomas.kick@bundesbank.de
¥ Deutsche Bundesbank, Frankfurt/Main, email: ingrid.stein@bundesbank.de

1 Introduction

The global financial crisis has shown that banks are important transmitters of shocks to the economy. This paper studies how firm default risk is affected when banks get into distress. We examine whether the generated effects are different in normal times or when a systemic crisis hits the banking sector and whether relationship oriented banks behave different in times of distress and crisis. We use detailed bank-firm level micro-data from Germany, a bank-based economy.

In most economies banks fulfill a pivotal role in providing credit and liquidity to the economy (Krahnen and Schmidt, 2004). In such bank-based systems, shocks to banks, stemming from liquidity dry outs or impairments of their balance sheet, will most likely translate into the real economy if banks find the need to adjust their risk portfolio structure, and firms cannot easily turn to alternative financing sources. The recent global financial crisis certainly constitutes such an event.

Specifically, we investigate how bank distress impacts a firm's probability of distress (PD). We examine how the risk pass-through impacts firms with different default probabilities, and whether the relationship orientation of banks mitigates the potential negative impacts on firms. Finally, we investigate whether banks' behaviour depends on the macroeconomic environment the distress event is occurring in, or rather, whether treatment effects differ in times of a systematic banking crisis. We apply recent methods used in the literature on the transmission of shocks to our framework. We aim to distinguish between a *bank risk channel* and a *firm risk channel*. Banks affect firm risk through a number of 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 the *bank risk channel*. On the contrary, the *firm risk channel* refers to demand related factors affecting firm risk such as a firm's industry, general economic conditions, the institutional environment the firm faces as well as a firm's idiosyncratic risk. Hence the setting applied in this article transforms the differentiation of supply and demand for loans to a setting of risk transmission in bank-firm relationships.

Apart from the general *bank risk channel* in times of bank distress, we also distinguish crisis times from normal times and investigate whether the 2008-2010 banking crisis had different effects that go beyond the usual adjustments when banks are distressed. In times of financial crises with high uncertainty, banks may find it necessary (or are mandated by the regulator) to change their lending policy and make their loan decisions less opaque. This change might go beyond interest rate adjustments and tighter collateral requirements but constitute a structural change in the bank's lending practice.

We investigate whether distressed banks adjust the riskiness of their loan portfolio and whether banks' distress has impacts on firms' PD. Specifically, we ask how distressed banks deal with their loan portfolio risk composition. Banks may change their lending practices and put even low to medium risk firms subject to tighter and more variable loan conditions. This may lead to an increase in perceived firm riskiness even for firms that have a viable financial condition. In contrast, banks in distress may also loosen their credit standards and evergreen the more risky borrowers in order to reduce potential losses on them (Peek and Rosengreen, 1997) or even to comply with local political guidelines (Gropp et al., 2010). If "Evergreening" is in place, we would expect PDs to decrease if banks are under distress. Because the impact of banks' strategies might differ from normal times compared to when a systemic crisis is in place (Degryse et al., 2013; Ivashina and Scharfstein, 2010), we differentiate between normal times and times of crisis in the analysis.

In order to analyze this, we combine several unique datasets. We can draw from a rich firm data set, the Mannheim Enterprise Panel[1] (MUP). It, covers for almost any German

[1] The Mannheim Enterprise Panel (*Mannheimer Unternehmenspanel* – MUP) of the Centre for European Economic Research (ZEW) is the most comprehensive micro database of companies in Germany outside

non-financial entity an individual credit rating, its bank relationships[2] and other firm-specific information between 1999 and 2013. We combine the information on the bank names with regulatory and bank balance sheet data from Deutsche Bundesbank in order to identify banks in distress, as well as other bank-specific characteristics from MUP such as regional or industry-specific market and portfolio shares, default rates in corporate banking or relationship orientation measures.

The literature on financial intermediation has put a lot of emphasis on the link between firms and banks when firms are in financial distress. A prominent question of interest is whether especially relationship oriented banks help in smoothing out credit constraints that firm face (e.g. Berger and Udell, 1995; Berger and Udell, 2002). Bolton et al. (2016) build a model where relationship banks compete against transaction oriented banks and conclude that whilst relationship banks charge higher rates in normal times, they are able to supply continued lending at more favorable terms in times of crisis. An assessment of Italian loan-level data confirms their basic predictions. A recent study by Degryse et al. (2013) studies the role of relationship banking in times of crises, finding that firms that go with more relationship oriented banks have a lower probability of experiencing credit constraints during economic downturns. In a cross-country study of relationship and transaction banks Beck et al. (2014) show that relationship lending alleviates credit constraints, especially for small and opaque firms.

In studies that analyze credit supply shocks, the above arguments usually are referred to as the so called *bank lending channel* (e.g. Gambacorta, 2005; Kishan and Opiela, 2000, Kwaja and Mian, 2008; Nilsen, 2002). Though we do not analyze the supply and demand for loans, we also want to make sure to differentiate between firm-related and bank-related changes in the PD. In Khwaja and Mian (2008), firm-related changes in

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the official business register (which is not accessible to the public). The MUP is based on the firm data pool of Creditreform e.V., which is the largest credit rating agency in Germany.

[2] We know up to six bank relationships for firms. The first bank is declared by Creditreform as the firm's main bank or "Hausbank".

demand are termed *firm borrowing channel*. In our environment, the term *firm risk channel* is the more appropriate, which we distinguish from a *bank risk channel.* Specifically, we apply a clustering method similar to Degryse et al. (2016) which is a way of introducing firm-year-fixed effects in the sense of Kwaja and Mian (2008) even when observing single bank relationship customers and the outcome variable is on the firm-year level. In the environment of PDs, this will enable to cancel out yearly industry, regional, age and firm size effects on PDs that arise in the economy.

Our work mostly builds up on the stream of literature dealing with the transmission of shocks in the financial industry into the real economy (among others e.g. Peek and Rosengren, 1997; Kishan and Opiela, 2000; Nilsen, 2002; Gambacorta, 2005; Khwaja and Mian, 2008; Amiti and Weinstein, 2009; 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).

A second stream of literature relevant for this work is the literature on relationship banking and financial intermediation between firms and banks in the business cycle (among others Holmstrom and Tirole, 1997; Ivashina and Scharfstein, 2010; Bolton et al., 2013; Degryse et al., 2013; Beck et al., 2014).

Our paper generally contributes to the wide literature on information asymmetries between firms and their financial intermediaries on the one hand and the market on the other hand (Stiglitz and Weiss, 1981; Sharpe, 1990; Rajan, 1992; Petersen and Rajan, 1994; Berger and Udell, 1995; Boot and Thakor, 2000; Agarwal and Hauswald. 2010).

The remainder of this article is organized as follows: Section 2 presents relevant strands of the literature, sketches the banking and corporate environment in Germany and introduces the applied data sources and the empirical methodology used to address the research questions. In Section 3 results are shown and discussed. Section 4 concludes.

2 Data and Empirical Methodology

2.1 Data

We draw from two extensive data sources for our analysis. First, for *firm data*, we use the *Mannheim Enterprise Panel (MUP)*, a panel dataset generated by Centre for European Economic Research (ZEW). It contains the complete data pool of Creditreform e.V. (on a half-yearly basis), which is the largest credit rating agency in Germany. Data of Creditreform is the most comprehensive micro database of companies in Germany outside the official business register (which is not accessible to the public). Comparisons with the Business Register of the Federal Statistical Office have shown that the MUP gives by and large a representative picture of the corporate landscape in Germany and nearly represents the universe of firms in Germany. For detailed information about data collection, processing and definitions see Bersch et al. (2015).

The MUP contains a large amount of firm information e.g. 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 of closure, the company's complete address, shareholder structure and personal details about the involved persons. The dataset also includes Creditreform's credit rating score, which is an index ranging from 100 to 600, showing the firm's credit rating for each panel year. The credit rating can be translated into probabilities of default using a definition provided by Creditreform. The credit score has already been used in a number of recent papers (Hoewer, 2009; Brown et al., 2012; Cremers and Schliessler, 2014).

A crucial piece of information provided in the MUP are the up to six banking relationships of a 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 the firm's main lender. Our analysis relies on the firm's main bank relationship as it constitutes the prominent external financier for the firm. Creditreform determines the bank relationships by assigning each company to bank branches. 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.. The dataset can be enriched with other firm level data from the MUP. Thereby, we make use of the fact that the MUP covers almost the whole population of German companies. By aggregating information on all firms connected to a certain bank, we are able to infer bank's market shares or portfolio shares by region or industry. Moreover, we are able to derive rates of firm failures by bank that go beyond balance sheet information usually provided for banks[3]. The ZEW Bankpanel therefore gives a clear picture of the structure of the corporate banking sector in Germany.

2.1.1 Bank data Bundesbank and measuring bank distress

The capital support measures we consider in our analyses are mainly provided by voluntarily financed insurance funds operated by bankers associations in each of the three German banking pillars (i.e. commercial banks, savings bank sector, and cooperative bank sector). Even when supervisors (i.e. BaFin and Bundesbank) may be consulted, the final decision on granting capital support measures rests on the respective insurance schemes. In the process both agreement on the specific shortcomings of the troubled bank and plans how to resolve the distress needs to be reached and stated in a contract between the insurance scheme and the member bank. If capital support measures are considered insufficient (maybe if the distressed bank has reached a stage in which 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. From end of 2008 on, as response to the financial and economic crisis, these voluntary measures by the banking industry are complemented by capital support measures from the Financial Market Stabilization Fund ("*Sonderfonds Finanzmarktstabilisierung*", SoFFin) which we also include into our data

[3] 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.

set. Even when SoFFin support is only granted to a small number of major German banks these government bailout measures are large in volume and therefore eligible to significantly impact the banking sector and to cause competitive distortions (see Kick and Koetter, 2016). In addition to the bankers associations' insurance schemes also supervisors can intervene, which means that, if BaFin and Bundesbank deem these measures inadequate or insufficient, they can also take various measures stated in the German Banking Act ("Kreditwesengesetz"), including severe measures like moratoria or finally revoking the bank's charter. Therefore, the bankers associations' and the supervisors' decisions are not independent of each other with various decision makers (BaFin, Bundesbank, bankers associations and the boards of the insurance schemes) involved. Even when the process of identifying distressed banks as well as deciding on capital support and/or restructuring mergers appears to be opaque, as shown in various instances the intervention scopes of the different stakeholders complement each other constituting a kind of "private-public partnership" in the recovery and resolution process in the German banking market. For a detailed description of the protection schemes in the German banking sector see also Kick et al. (2016).

We apply the definitions of bank risk of Kick and Prieto (2013) who investigate the competition-stability nexus in the German banking system. As measures of bank risk they use several definitions, among them distressed mergers (which are closest to outright bank defaults), capital injections and guarantees by the banks' respective head associations, as well as continuous measures such as Non-Performing Loans (NPL) ratios and Z-scores. Since outright default is a very rare event in Germany, we concentrate on capital injections, while we use the initial capital injection for the bank such that it really constitutes a unique event for the bank.

2.2 Empirical Methodology

The analysis is conducted on the level of the individual firm-bank relationship using a panel of firms between 2000 and 2012. We focus on main bank relationships. The sample of firms stems from the MUP, yet the selection of firms is a result of the banks chosen for the sample. We use *nearest neighbor matching of banks* in order to find an appropriate control group of banks that have not been in distress.

Our method has to be distinguished from a standard matching approach, where the matching both serves 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 state of distress in banks can be assumed to be exogenous to firm outcomes[4]. The matching rather serves as a device to obtain an appropriate control group of banks that can be traced over the same time span and has a similar likelihood of receiving the treatment. Therefore, we conduct the matching on the bank level and only later enrich the sample of nearest neighbors with firm data.

For the matching, banks with a capital injection (treated banks) are evaluated at period t-1, i.e. one year before the initial capital support measure is conducted. Afterwards, we look for control banks that are non-treated neither in that nor any subsequent year up to 3 consecutive years after the treatment (including the treatment year). The matching yields at least one control bank for every treated bank (initial capital support). 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.

A challenging feature of the data and the German Banking Market in general is the occurrence of numerous bank mergers happening every year and in almost any banking segment. The number of banks has decreased from 4,300 in 1990 to 2,700 in 2000, with only 2,000 being left in 2010. Mergers are often a means to restructure a bank and prevent it from defaulting. Therefore, the treatment of initial capital support occurs more frequently before a merger compared to the situation where the capital support injection had not been happening. The mergers put the econometrician in trouble for

[4] Though one may argue, that especially large customers may trigger default in banks. However, the median firm in our sample has 6 employees and we drop firms larger than 10,000 employees from the analysis.

two major reasons. On the one hand, they constitute a second treatment which is not independent upon the first treatment. On the other hand, the merger substantially impairs the conduction of a control group study because the bank before the merger will be different from the one afterwards.

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) happens 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 only look at treatment 1 and condition on a sufficient (e.g. 3 years) time span before treatment 2 happens. We would then only look at a maximum-3 to +3 years window (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 3 years before and 3 years after the treatment as a structural unit. As a consequence, treatments before 2003 are not taken into account, so are treatments taking place after 2010.

2.2.1 Nearest-Neighbor Matching

For the matching we employ the full sample of banks from 2000 to 2012, yet we only use treatments that happen between 2003 and 2010 to have enough before and after treatment observations. In order to find the nearest neighbors, we use observables in the year just before the treatment y_{t-1}.

When estimating the probability of receiving the treatment, we observed heavy heterogeneity between the treated banks. In order to reduce the heterogeneity within the treatment group, we split treated banks into two groups: one where banks encounter a heavy treatment (high Capital Injection to Equity ratio) and one where banks experience a weaker treatment (low, below median, CI to Equity ratio). The split of the treatment group ensures that we have more homogenous treatment groups and enables later distinguishing upon the size of the treatment. We therefore estimate two models to obtain the propensity score and afterwards unite the two sets of treated and control banks to a joint sample. 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. At the year of evaluation, both have at least 3 years of observations before and after the matched point in time.
3. Treatment and control bank are of the same type (savings bank sector, cooperative bank sector, private bank sector)
4. Treatment and Control Bank are localized in the same Bundesland

The first restriction guarantees that treatment and control bank are set into the same macroeconomic conditions; the second leaves us with those banks that can be traced over a sufficient time span. Condition three and four account for the fact that the bank deposit insurance schemes are organized by the respective head association for the individual banks and also comply with regulation based on the level of the respective Bundesland. Moreover, restriction 4 is also important to ensure the same regional macroeconomic conditions.

The matching equation itself includes a variety of variables that are summarized in Table 1. Bank balance sheet and bank income statement information comes from Deutsche Bundesbank Bank Supervisory Data. Aggregated Bank Customer information stems from the MUP. Table A2 in the Appendix shows the regression output of the matching regression where the dependent variable *affected bank* takes the value 1 if a bank receives an initial capital injection in period t +1. We see that size effects play a prominent role as well as the amount of loans the bank outs in place. Apart from these size effects, the expected effects are observed for the Share of non-performing loans (positive effect), the banks ratio of Reserves (negative) as well as the occurrence of hidden liabilities (positive) while effects are most pronounced for severe treatments.

Table 1:
Variables employed in the matching equation

Dependent	*Bank receives capital injection in treatment year t+1*
Bank Balance Sheet Information	*Total Assets (GDP deflated), Level* *Total Loans (GDP deflated), Level* *Non-Performing Loans over TA, Risk-Weighted Assets Growth, Reserves Ratio, Hidden Liabilities, Reserve Reduction, Share of Customer Loans*
Other Bank-specific Information	*14-Business Sector HHI, Return on Equity*
Aggregate Bank Customer Information	*Number of Bank Customers* *Share of Distressed Customers* *Share of Single Relationship Customers* *Share of Main Bank Customers* *Share of Customers within 50km Range*

The share of single relationship customers is negatively associated with receiving a capital injection, probably because the more intensely a bank is involved in customer relationships, the less involved it is in trading and investment banking activities and the more resilient it is to heavy write-offs or liquidity shocks. On the other hand, the share of corporate customers situated in a surrounding of 50km of the headquarters constitutes a regional concentration of customers and therefore less hedging against intra-regional shocks. In line with expectations, it is positively significant for severe treatments.

The matching regression yields us an estimated propensity score to receive an initial capital injection from banks' depository scheme in period t+1 given the characteristics of period t. The propensity score is scaled by bank type, the Headquarter Bundesland as well as the year of observation such that we compare banks with the same business model and within the same macroeconomic environment. With the resulting scaled propensity score, we perform nearest neighbor matching.

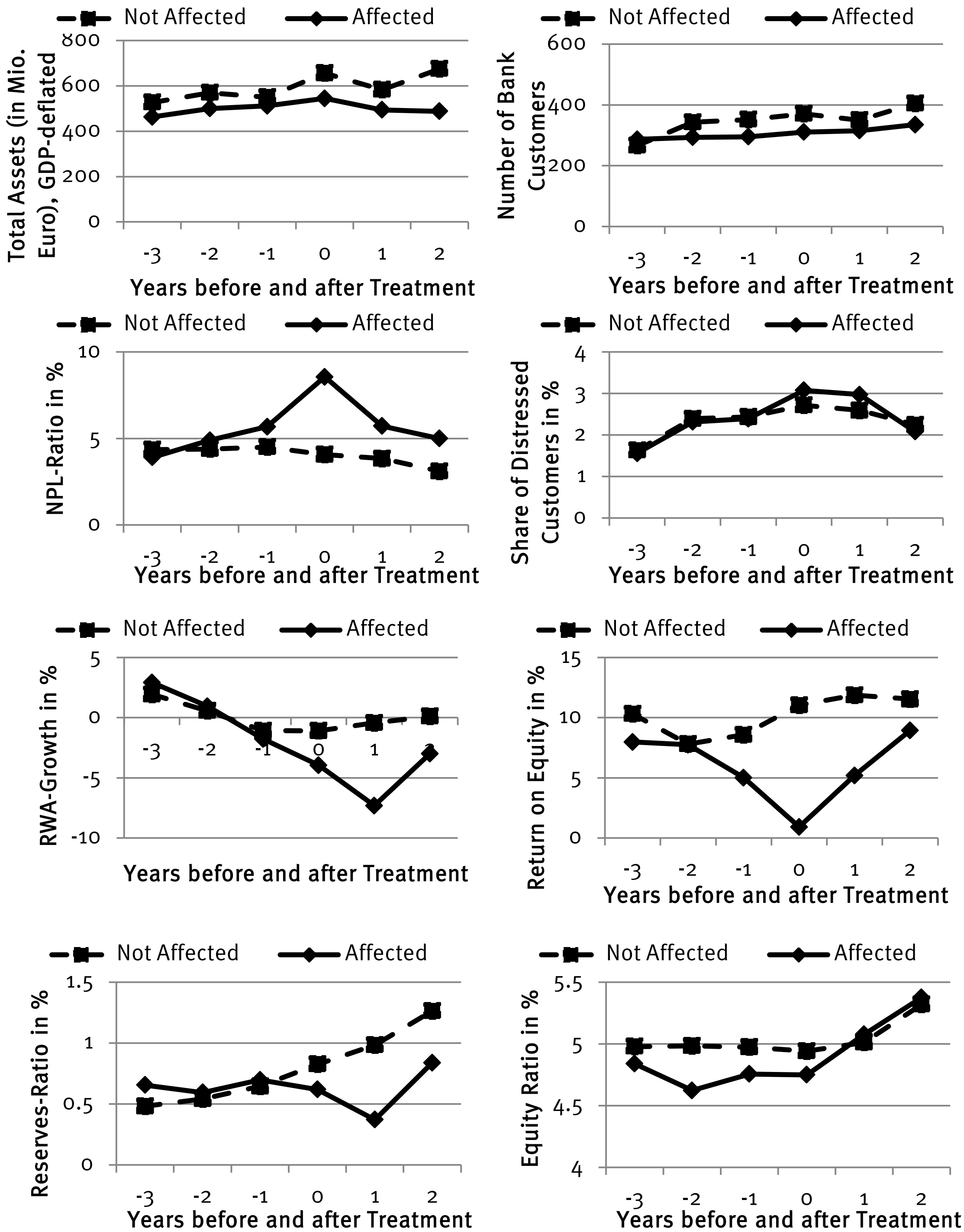
Table 2 shows an overview of the outcome of the propensity score matching by year of treatment. We obtain a sample of 74 banks, 23 treated and 51 untreated. For each of the 23 treated banks we have at least one and up to three control banks. The number of distress events varies heavily across years. Most events happen in the years 2003-2005. In the year just before the crisis, only 1 treatment occurs, while the number increases again for the crisis years.

Table 2:
Number of Treatment and Control Banks after Matching by year of Treatment. Note that for each treated bank up to 3 control banks are selected. Each bank is observed for a total of 6 years around the treatment year. The full sample period begins in 2000 and ends in 2012.

Treatment Year	Control Banks	Treated Banks	Total
2003	9	5	14
2004	7	3	10
2005	11	4	15
2006	2	1	3
2007	7	3	10
2008	8	4	12
2009	6	2	8
2010	1	1	2
Total	51	23	74

By comparing the treated and control banks we obtain from the matching in terms of different characteristics we receive a picture of how relevant the treatment is. Figure 2 shows median bank covariates by year before and after the treatment for treatment and control banks. Looking at GDP-deflated Total Assets (TA) one first observes that sample banks are on average small, with TA averaging only at 500 Mio. Euros at the median. Treated and Control banks show similar developments before the treatment while after the treatment, only for Control banks, an increase in TA is observable. The need to pay back the injection and shrink balance sheets in order to fulfil equity requirements might force treated banks to interrupt asset growth and thwart loan growth and instead build reserves. The number of customers yet does not decrease for treated banks after the treatment which already indicates that banks are on average not trying to get rid of customers.

Figure 1:
Median Bank-Characteristics after matching for treated banks (solid) and control banks (dashed) before and after treatment. 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.



The second row of Figure 2shows the developments in terms of non-performing loans (which is obtained from Bundesbank Supervisory Data) and the share of distressed customers (which stems from MUP-data). The two measures are highly related: every defaulted customer will represent a non-performing loan but not necessarily vice-versa. Correspondingly, NPL-Ratios are naturally higher than customer default rates.

Rates on defaulted customers appear to be rising over the observation period for both treatment and control banks which may reflect generally worsening macroeconomic conditions throughout the sample period. While both measures develop similarly before the treatment, higher rates at the time of and after the treatment for affected banks can be observed. However, rates seem to be less increasing for defaulting customers as NPL do and eventually return to the same level as for control banks. The absence of higher rates in payment default may already indicate a tendency to reduce balance sheet losses and evergreen customers.

A similar picture can be seen when looking at measure of riskiness and return of banks' asset and loan portfolio. The third column shows average growth in risk-weighted assets (RWA) on the left and Returns on Equity (ROE) on the right. We see a strong downward trend for treated banks on both measures (approaching -7% in RWA-Growth and 0% ROE), while control banks remain relatively stable at about minus 3% to plus 3% growth in RWA and about 10% ROE in maximum one year after the treatment, possibly to reduce risk on their balance sheets and increase equity ratios. The third row of graphs alone already indicates heavy circumstances at these banks. As a reaction, one expects banks to build up reserves and increase equity ratios. While the latter is observed for treatment banks when looking at the bottom row in Figure 2, Reserve Ratios remain substantially lower compared to control banks, possibly because banks first need to restore equity before being able to build up reserves.

In conclusion, the graphs show that bank characteristics evolve similarly in terms of trends and levels before and also, for non-performance related variables, after the treatment occurs. Sample banks are on average small banks with about 500 Mio. on TA. and about 400 corporate customers. Performance-related measures indicate heavy circumstances at distressed banks which should have evident effects on their customer portfolio.

2.2.2 Estimating Firm Outcomes using the Matched Bank Sample

After conducting the nearest-neighbor matching, we obtain 74 banks, among them 23 treated and 51 control banks while control may occur more than once within the sample. The bank sample is combined with firm data via the firms' main bank relationship. As outlined in section 3.1, the main bank constitutes the firms most prominent external financier and our analysis therefore relies on this relationship.

Table 3:
Firm-Observations by Year of Observation (left) and Year of Treatment (top). Note that firms may occur multiple times because two treated banks may have the same control bank. The dataset is uniquely defined on the firm-bank-neighbor-year-level.

Year of Observation	Treatment Year								
	2003	2004	2005	2006	2007	2008	2009	2010	Total
2000	10,144								10,144
2001	10,368	5,450							15,818
2002	10,514	5,330	5,166						21,010
2003	**10,972**	5,314	5,497	2,748					24,531
2004	11,631	**5,491**	5,604	2,808	1,652				27,186
2005	11,735	5,453	**5,258**	2,737	1,707	2,850			29,740
2006		5,348	5,344	**3,035**	1,833	3,066	12,114		30,740
2007			5,360	3,031	**1,941**	3,373	12,260	1,299	27,264
2008				3,045	2,145	**3,739**	12,487	1,604	23,020
2009					2,281	4,105	**12,536**	1,895	20,817
2010						4,426	12,534	**2,147**	19,107
2011							12,528	2,446	14,974
2012								2,844	2,844
Total	65,364	32,386	32,229	17,404	11,559	21,559	74,459	12,235	267,195

We obtain about 267,000 observations stemming from about 50,000 individual firms. Table 3 shows the size of the compound sample by year of observation and year of treatment. Note that some firms may occur multiple times within the sample because two different treated banks may have the same control bank. Therefore, the dataset is uniquely defined on the firm-bank-neighbor-year level with neighbor being an identifier for every matched set of bank neighbors.

In order to capture bank and firm side effects or rather, supply and demand side effects, we apply a grouping of observations which can be thought of as a fixed effects approach. Nevertheless, fixed effects are not “genuine” as they do not define a single firm but rather a group of firms which is seen as similarly affected by its legal, macroeconomic, spatial and industrial environment. When not having individual yearly variation in outcomes on the firm level, such as Khwaja & Mian (2008), grouping firms is superior to genuine fixed-effects since one can exploit right-hand-side variation in the treatment within the group on a yearly level. The grouping we apply is on the level of *industry, size class, legal form, single-relationship (yes, no), age class, region* and *year* (see the Appendix for a detailed overview of the respective underlying classifications).

Apart from the grouping, we further control for a second firm-related fixed effect. The credit rating agency Creditreform that provides us with their raw data is organized in about 130 clubs that are located all around Germany. The club can be identified as a part of the firm ID. We believe there are good reasons to control for a combination of club and year because risk assessment may differ across clubs. Furthermore, the rating methodology undergoes some regular revisions which might be differently applied by each club. Therefore the yearly component of the fixed effect is crucial. We conduct robustness checks in section 4 in order to verify our results for different choices of clubs.

2.2.3 Defining our Model

To sum up, we apply a nearest-neighbor matching approach for banks and we use group fixed effects for firms. We assume our treatment to be exogenous to firms. First, the firms in our sample are on average small (90% of the sample firms have less than 50 employees). It is unlikely that a single firm triggers default of the bank and regional demand shocks are controlled for both by the group fixed effects approach as well as the matching of banks which settles the estimation framework to the same macroeconomic environment. Second, we believe that banks will refrain from noticeably fancying capital injections up to the moment they are indispensable. 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. Hence we do not need to include any other firm or bank related characteristics for identification of the treatment effect; however, robustness checks in Section 3.3 show that our results remain unaffected by the inclusion of a variety of firm and bank covariate. The setting is a combination of a conditional difference in difference approach and a fixed effects approach.

For now, recall that the *PD* gives us the probability of default of firm i (over one year) evaluated by Creditreform. Like in any difference in difference setup, we need an intercept on the right-hand side, the treatment dummy *affected bank,* the indicator for after-treatment periods *post* and 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 the PD of firms connected to banks in distress behaves compared to the average PD of firms connected to banks not in distress. Our final model therefore is specified as:

$$\begin{aligned} PD_{i,t} = \beta_0 + \beta_{post} * i(post_{ik,t}) + \beta_{affected} * i(affected_{ik,t}) \\ + \beta_{ATET} * i(affected_{ik,t}) * i(post_{ik,t}) \\ + \rho_{gk,t}(f(.); a(.); p(.)) + \theta_{ik,t} + \varepsilon_{ik,t} \end{aligned} \tag{1}$$

Where $\rho_{gk,t}(f(.); a(.); p(.))$ is a year-group-fixed effect and $\theta_{ik,t}$ is a random effect.

Note that $\rho_{ik,t}(.)$ consists of:

$f(.)$: Firm group indicators:industry, size class, age class, region, year

$a(.)$: club group indicators:Creditreform agency area, year

$p(.)$: Bank pair, matched bank "neighbours"

$\varepsilon_{ik,t}$ is an i.i.d. error term

Note that we drop the i, k and t subscripts for the components of $\rho_{ik,t}$ as they always refer to a specific combination of i,k and t. Further recognize that $post_{ik,t}$ takes the value 1 if firm i has relationship with bank k in period t and period t is after the treatment year (or the treatment year). The indicator $affected_{ik,t}$, takes the value 1 if firm i has relationship with bank k in period t and bank k is a treated bank. Analogous holds for the interaction of both.

The contents of $\rho(.)$ serve to absorb different fragments of variation that would bias the estimation of the treatment effect. The firm grouping (Degryse et al., 2016) catches demand side and business cycle effects associated to each group of firms that may influence firms' yearly *PD*. The agency grouping a(.) serves as a control vector to account for heterogeneous risk assessment methodologies by different Creditreform agencies that may occur across agencies and/or time. Finally, the bank pair p(.) leaves us with an estimator of the treatment effect within the matched bank neighbors stemming from the bank-level propensity score matching.

2.2.4 Estimating our Model

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 exactly of such a kind. We do not know the covariance structure within the clusters but are still able to receive consistent estimates even if the covariance structure is misspecified. The estimator is similar to a random-effects Tobit regression with a Gaussian random-effect (Robustness Checks in Section 3.2 show that our results are confirmed using OLS, RE or Tobit regressions). Other than in a genuine fixed- or random-effects setting, we do not take our firm identifier as panel and neither year as our time variable. Instead, a group identifier defined by f(.), a() and p() yields us 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” $\rho(.)$. We assume exchangeable correlation structure of residuals within each group. This structure is a reasonable assumption since groups are narrowly defined and especially are constituted within each agency unit.

Our final dataset consists of about 267,000 observations which represent about 50,000 individual firms, each over a period of up to 6 years. We follow customer firms 3 periods before and 3 periods after the treatment (including the treatment year). 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 the treatment is not disturbed by other influences. Second, there is substantial dynamics in firms’ yearly *PD,* hence, the more periods of time we include, the more of these yearly movements will overlay each other and keep us from getting a valid estimate of the treatment effect. After all, taking three periods before and after treatment seemed to be a reasonable choice to us. The essence is that we aim to capture the exact period in time where the firm is exposed to its bank going into distress and identify the immediate effect of these turbulences.

3 Empirical Results

This section presents results for our conditional difference in difference estimations. We conduct robustness checks in Section 3.2 of this paper in order to verify our results for the inclusion of other covariates and the choice of different regression techniques. We carry out a variety of different regressions to investigate whether there is a pass-through of risk into the real sector. As a starting point, we conduct a simple conditional difference-in-difference analysis on all firms and banks in our sample in order to identify a potential global pass through of risk effect (see Section 3.1.1). From section 3.1.2 onwards, we apply our model in (1) to a variety of different subsets that yield us insights into the fragmentation of the treatment effect. Criteria of investigation are different risk classes of firms, the differentiation of relationship and transaction banks, firm industries, age and size classes as well as whether the treatment occurred during the peak years of the financial crisis 2008 and 2009. We are able to do this exactly because of the grouping of observations instead of using genuine fixed-effects which still leaves us with some firm-level variation on the right hand side within each year. In the subsequent section 3.2 various robustness checks are presented in order to verify the reliability of our analysis.

3.1 Baseline Results

Table 4 shows the baseline GLM estimations on the full sample of firms and banks from 2000 to 2012. Specifications (A1) and (A2) show the results that serve to answer our first research questions, i.e. whether there exists a risk transmission effect from bank distress events to customer firms. The coefficients are to be interpreted in percent, meaning, the PD of customers at distressed banks raised on average 12% after the treatment occurred than that of customers at control banks. With an average *PD* of about 10%, this means the average probability of default of treated customers increased to about 11%, a substantial increase. The strong results are by some fraction driven by customers entering the worst rating classes (80% PD+) which is obvious

Table 4:
Conditional Difference-in-Difference-Estimates on the firm-bank-neighbor-year-level. Specifications A1 and A2 show GLM-estimates on firms' individual *PD*, specification A3 and A4 introduce the new variable *MAXLOAN* in two FE-OLS estimations. Specification A5 shows FE-Probit results on actual default of firms. All specifications except specification A5 use robust standard errors

Specification	A1	A2	A3	A4	A5
Estimator	GLM logit link	GLM logit link	OLS FE	OLS FE	FE Probit
Dependent Variable	PD	PD	MAXLOAN	LOG MAXLOAN	DEFAULT
Sample	all	no defaulters	all	all	all
Time	All Years	All Years	All Years	All Years	All Years
Treatment Effect	0.120***	0.0694***	-905.0**	-0.0794***	0.0675**
Observations	267,195	228,708	214,833	214,833	197,692
Number of groups	54,407	53,332	51,443	51,443	-

(Robust) standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

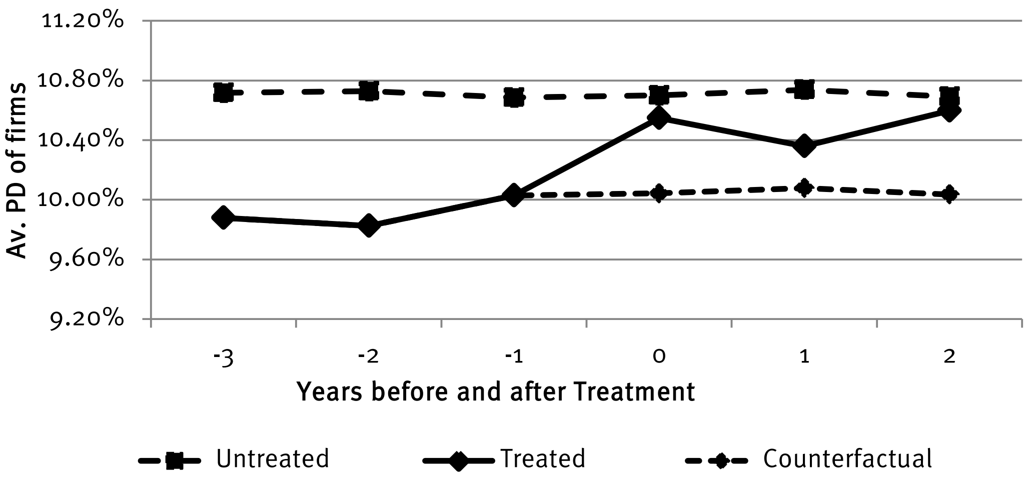
when looking at specification (A2) that excludes customers who default within the sample period. However, also for non-defaulting customers, we find a 7% increase in *PD* at treated banks. The fact that defaulting customers seem to drive results in part can also be observed when looking at specification (A5) that estimates the probability of actual default using a FE-Probit regression framework. Customers at treated bank have a 6.7% higher probability of actually defaulting after the treatment which coincides nicely with the results found in specification (A2).

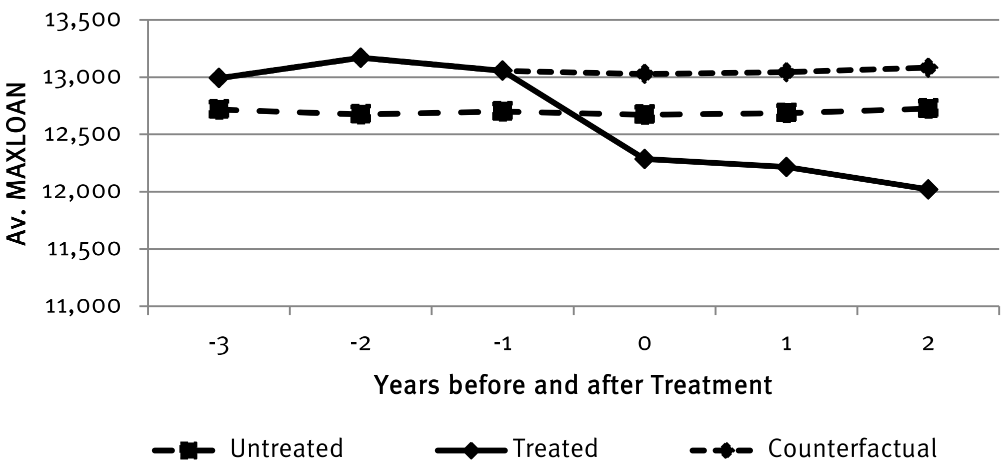
Yet, up to now, we do not know whether and if, to what extent, these results are economically relevant to firms. Specifications (A3) and (A4) show results when using another dependent variable as an indicator: the variable *MAXLOAN*. The agency Creditreform adds a maximum loan recommendation to almost every firm that is evaluated by them. So *MAXLOAN* serves as a benchmark to trade creditors on how much credit should be granted to the firm. As obvious from the regression coefficients in (A3) and (A4), loan recommendations go down on average by about 900 Euros in absolute terms and about 8% in relative terms, when looking at the log values. Given that most firms in the sample are small firms, this constitutes a severe slump in their scope of operation.

To get a visualization of these effects, one can plot the outcome variables for treated and untreated banks around the treatment year. In order to do that, we first estimated the models and then removed the fixed-components $\widehat{\rho_{gk,t}}\big(f(.); a(.); p(.)\big)$ in (1) from the outcome variables. The resulting adjusted values for *PD* and *MAXLOAN* are shown in Figure 2. We observe nice common trends of both *PD* and *MAXLOAN* for the three years before the treatment and afterwards a visible increase in *PD* and a decrease in *MAXLOAN* which naturally move contrariwise. Interestingly, we see differences in levels before the treatment for both variables, i.e. treated banks have on average better customers before the treatment than do control banks. After the treatment occurs, the average *PD* of customers at treated banks approaches the level of control bank customers.

This observation may first seem surprising, as we would expect banks that go into distress to be also lending to on average worse firms. On the other hand, there are good reasons to believe that a bank's turmoil does not originate in the corporate sector but rather in other areas of their business such as real estate, especially in the crisis years. The observation actually fits to our basic assumption that credit rating agencies take firms' funding situation at their main bank into account and adjust credit ratings if lending conditions, securitization requirements and services quality at firms' main

Figure 2:
Plot of average adjusted outcome values from regression specifications A1 (top) and A3 (bottom) by years before and after the treatment. Solid lines represent treated observations, long-dashed lines control observations. Short-dashed-lines sketch the counterfactual situation by applying the trends from control observations to treated observations after the time of the treatment





banks change. So if banks provide excess funding to firms of a certain efficiency level this will also not be hidden to the credit rating agency, assigning better credit ratings as long as banks carry on supplying firms with loans and in particular current accounts. Furthermore, if banks running into distress had the strategy to keep inefficient contracts on their balance sheets, fewer firms were actually defaulting before (compare specification A5) and this also will be expressed in better average credit ratings.

For a more detailed picture of the effects, we now turn to an analysis of different macroeconomic environments. Specifically, we want to answer the question whether distress events that happen within the crisis have different impact on customers. Furthermore, we want to focus our analysis on the behaviour of relationship and transaction banks in these two macroeconomic environments and investigate whether borrowers are differentially affected depending on their risk class.

3.2 Relationship Banking, the Crisis, and Evergreening

In this section, we apply our model (1) to subsets of firms, stratifying the sample on the level of risk classes, bank characteristics and treatment years. We define crisis treatments to be treatments occurring in the peak of the financial crisis 2008 and 2009 and all other treatment years as non-crisis years. The measures of relationship orientation that we use were partly already introduced in Bersch (2016) and are defined according to the composition of the customer portfolio of a particular bank along the arrays a) share of single relationship customers, b) share of main bank customers and c) customers within 50km distance around headquarters. These measures were already included in the matching equation from table Table 1. The share of single relationship customers is for example constructed as:

$$single\ share_{kt} = \frac{\sum_i I(bank_{it}=k)*I(\ singlerel_{it}==1)}{\sum_i I(bank_{it}=k)} \tag{2}$$

I.e. (2) calculates the sum of all customer firms of bank k who only have relationship with bank k over all customers of bank k, including multiple-relationship firms. This variable is an indicator of the average importance of bank *K* to its customers and thereby serves as a proxy of how much asymmetric information bank k on average holds on customer firms towards the market Analogously, the share of main customers of bank k takes the sum of all customers of bank k, who have their main bank with bank k over all customers of bank k including multiple-relationship customers:

$$main\ bank\ share_{kt} = \frac{\sum_i I(bank_{1,it}=k)}{\sum_{r=1}^{6}\sum_i I(bank_{r,it}=k)} \tag{3}$$

This measure defines the average role bank *k* has to its customers even if customers have multiple relationships. In other words, it gives us the average value bank k assigns to its customer portfolio The third measure of relationship orientation is justified by the results on the role of distance in relationship lending (compare e.g. the seminal works by Berger & Udell, 2002; Petersen & Rajan, 2002; Degryse & Ongena, 2005). It is simply defined as the share of customers located within 50km around the headquarters of bank k and indicates bank k's regional focus:

$$share\ 50km_{\mathrm{kt}} = \frac{\sum_{r=1}^{6}\sum_i I(\mathrm{bank}_{\mathrm{r},it}=k)*I(distance_{ik,t}\leq 50km)}{\sum_{\mathrm{r}=1}^{6}\sum_{\mathrm{i}} \mathrm{I}(\mathrm{bank}_{\mathrm{r,it}}=\mathrm{k})} \tag{4}$$

With these three measures at hand we construct a dummy variable *relationship bank* that indicates whether some bank k exceeds the 75 percentile among all banks in a year t in at least one of the measures.

We analyze the role of relationship banking in order to make a statement about the value of intense customer relationships when banks go into distress. The question of whether intense bank-firm relationship shield customers against crises has been subject to a variety of studies in the field of financial intermediation (e.g. Peek and Rosengren, 1997; Ivashina and Scharfstein, 2010).

In the following section we first start out with the question of whether treatments occurring within the crisis years have differential effects than those in non-crisis years and afterwards extent this analysis to the joint investigation of crisis and relationship bank effects.

3.2.1 Bank Distress in the Crisis

Table 5shows the same specifications as in Table 4 now differentiated by the timing of the treatment. We directly see that the effects are driven by those treatments occurring in the crisis years 2008 and 2009. The effects are stronger, with an average treatment effect of about 23% (B1a) increase in *PD*, 13% when only looking at non-defaulting firms (B2a) and a 10% decrease in the maximum loan recommendation *MAXLOAN* (B4a). However, the regression employing *MAXLOAN* loses significance (possibly due to non-linearities) but still shows a strong negative coefficient. Again, the treatment effect on

Table 5
Conditional Difference-in-Difference-Estimates on the firm-bank-neighbor-year-level depending on the year of treatment (within crisis or not). Specifications are the same as in Table 4).

Panel a

Specification	B1a	B2a	B3a	B4a	B5a
Estimator	GLM logit link	GLM logit link	OLS FE	OLS FE	FE Probit
Dep. Variable	PD	PD	MAXLOAN	Log MAXLOAN	DEFAULT
Sample	all	no defaulters	all	all	all
Time	Crisis	Crisis	Crisis	Crisis	Crisis
Treatment Effect	0.231***	0.132***	-1,323	-0.102***	0.141***
Observations	108,253	96,770	92,702	92,702	80,039
Number of groups	23,106	22,812	22,605	22,605	

Panel b

Specification	B1b	B2b	B3b	B4b	B5b
Estimator	GLM logit link	GLM logit link	OLS FE	OLS FE	FE Probit
Dep. Variable	PD	PD	MAXLOAN	Log MAXLOAN	DEFAULT
Sample	all	no defaulters	all	all	all
Time	No Crisis	No Crisis	No Crisis	No Crisis	No Crisis
Treatment Effect	0.0528	0.00916	-360.6	-0.0459	0.0199
Observations	158,942	131,938	122,131	122,131	117,653
Number of groups	31,301	30,520	28,838	28,838	

(Robust) standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

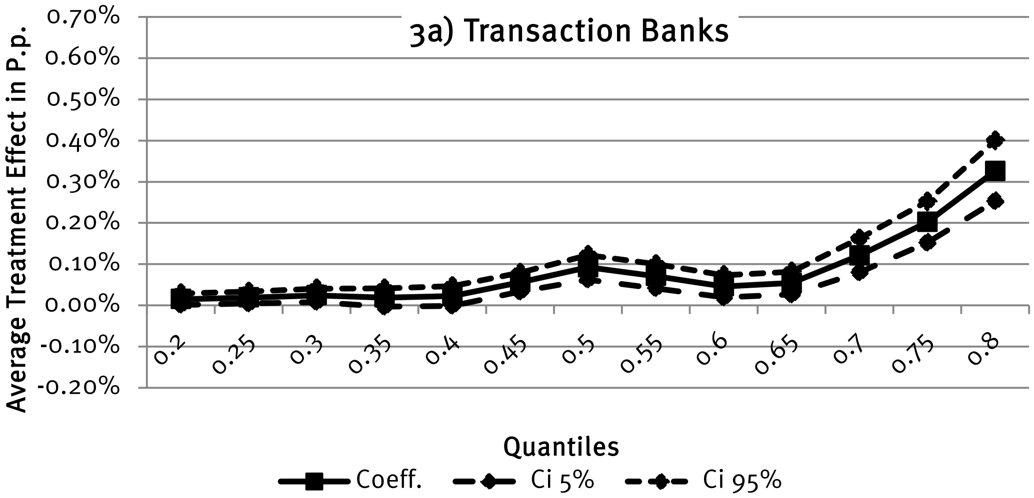
actual default (B5a) nicely coincides with the coefficient on *PD* without defaulters. This - rather as a side product - tells us that the assessment of *PD* by the credit rating agency is a reasonable estimate. For non-crisis years, none of the coefficients is significant, however, remaining qualitatively in line with the overall results. It seems therefore that distress events do not have a per se negative effect on borrowers but they do if the event happens in the course of a severe financial crisis. As a matter of fact though, we do only observe one period of macroeconomic turbulences. In order to obtain more robust evidence on that relationship, one would need to extent the timeframe of the analysis to other times of crisis (such as the 2000/2001 dotcom bubble) which is, however, not feasible with our data.

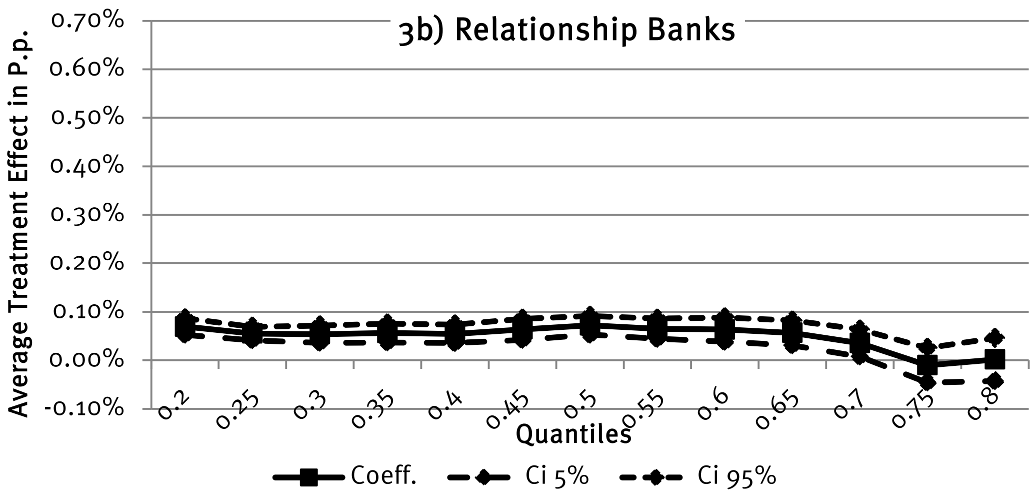
We have shown that macroeconomic environments influence the pass-through of risks into the real sector, identifying a *bank risk channel* from banks to their corporate customers. The question now to be studied is how the nature of the business orientation of a bank determines this pass-through-effect. We therefore turn to an analysis of relationship orientation and specifically address the differences in bank behaviour when dealing with different customer risk classes. The reason to do so is that the literature on relationship lending tells us that relationship banks act as liquidity insurance for customers (Petersen & Rajan, 1994), i.e. they charge on average higher rates but on the other hand keep providing liquidity even if firms are under pressure. The subsequent section introduces a set of quantile regressions using *PD* as the dependent variable. Note that we now use the subset of firms who do not default within the sample in order distinguish upon the assigned *PD* and actual default. The latter will be analyzed in a further step.

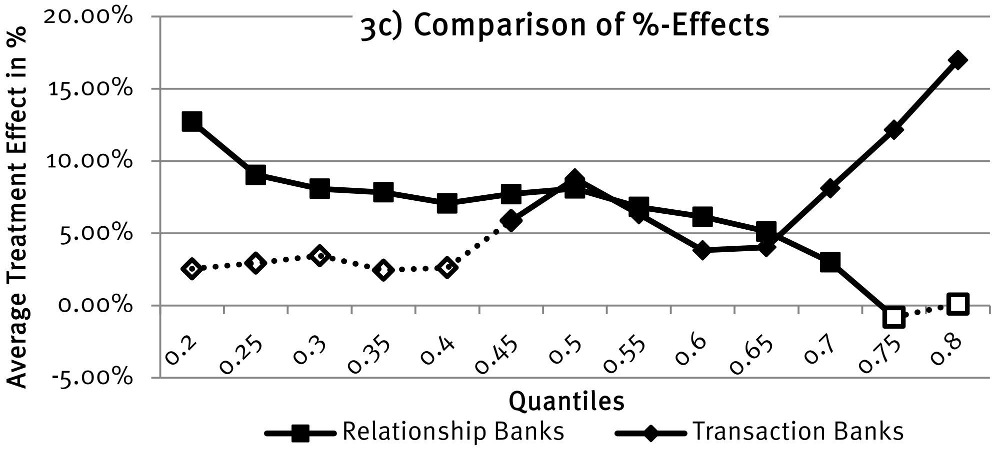
3.2.2 Relationship vs. Transaction Banks

In this section we introduce a more in-depth analysis of the environment around bank distress events by applying quantile regression (QR) techniques in order to disentangle the risk pass-through effect on different risk classes of customers. The application of QR techniques is not straight-forward in the context of fixed effects regressions

Figure 3:
QR-plots using *PD* as a dependent variable and distinguishing upon relationship and transaction banks. We apply a method for fixed-effects in QR introduced in Canay (2011). Standard errors are bootstrapped with 250 replications. Plots a) and b) are p.p. effects and show 5%-confidence intervals. Plot c) shows the p.p. effect in relation to the respective constant in quantile q, i.e. the percentage effect. White boxes/prisms show insignificant areas at the 5% level.







because standard software packages do not provide an a priori solution to such a regression set-upWe rely on a method introduced in Canay (2011) that tackles the problem in a two-stage regression framework by first estimating a fixed-effects model with all non-time-constant regressors on the right-hand-side (which equals the regression setup from (1) in a DiD-framework), subtracting the fixed part $\widehat{\rho_{gk,t}}(f(.);a(.);p(.))$ from the outcome variable y of interest and afterwards estimating one equation for every quantile on this new variable y* with bootstrapped standard errors from 250 replications. In our setup, the adjusted outcome variable y* is exactly what we used to generate the graphs in Figure 2.

Figure 3 shows QR-plots using the dependent variable *PD* in all of the graphs. Note that the effects here are to be interpreted as percentage points as they now come from a FE-OLS-regression. Figure 3a) shows the QR-plot only for transaction banks (i.e. banks who do not exceed the 75^{th} percentile in any of the relationship arrays introduced above), 3b) shows only relationship banks. As it is best practice with QR-regressions, we drop the lower and upper quantiles because effects are unstable there. 3c) compares the quantile effects for relationship and transaction banks, but now showing percentage effects that are generated by dividing the p.p. effects from the regression by the respective constant term in that quantile.

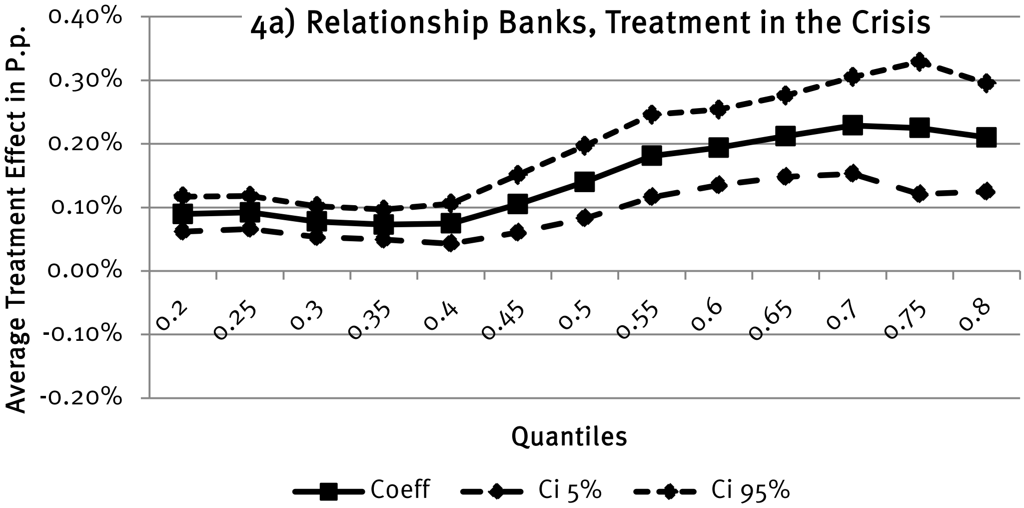
The differences in the effects are directly evident: while for both types of banks, the quantiles around the median between the 0.4 and 0.6 quantile are equally affected, at transaction banks, bad customers are affected strongly while remaining untouched at relationship banks. On the contrary, below median quantiles do not experience effects at transaction banks but are quite strongly affected at relationship banks where the p.p. effect remains quite stable for all quantiles below 0.7. This is possibly the most direct evidence that relationship banks may leave the worst customers untouched in order to reduce the risk of an actual default of those, a phenomenon often termed “Evergreening”. The resources that relationship banks keep at inefficient firms will be badly missed at more efficient firms, which may explain the strong effects for the good quantiles of the distribution at relationship banks. What is more, the relatively decent p.p. effects can be misleading when looking at the actual increase in default probability they represent in 3c), peaking at almost 15% increase in *PD* for the 0.2 quantile. Again be aware that for transaction banks, we find non-significant near-zero effects in this quantile.

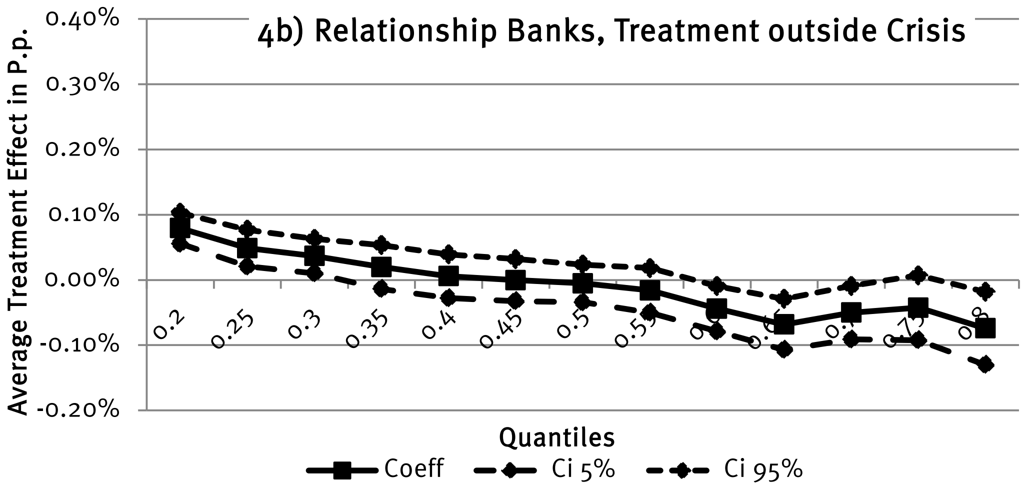
3.2.3 Relationship Banking in the Crisis

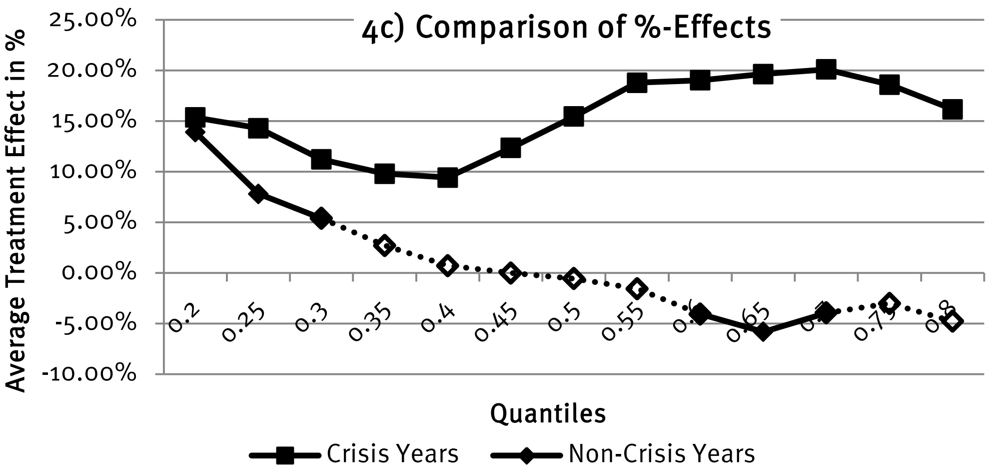
Having shown that relationship and transaction banks in fact behave contrariwise in times of distress, we can now turn our final research question, asking whether the benefits to customer firms of relationship banks, in the sense that inefficient firms are shielded from liquidity dry-outs, are still in place in times of a severe financial crisis. If the results found by Ivashina & Scharfstein (2010) hold also for this environment, we should expect relationship banks to behave differently in times of crisis. In order to do that, we apply the same methodology as before by employing QR techniques to address banks' behaviour towards different risk-classes but now only look at relationship banks and distinguish their behaviour in the crisis years and before them. It should be noted that the scope of this analysis is of course limited because the experimental setting that we are in is far from ideal. An ideal test would require observing the same bank in distress once in the crisis and once before.

Figure 4 shows the resulting QR-plots for the subset of relationship banks distinguished by treatment occurring within and those outside the crisis years. While the effects that we concluded for the below median quantiles still seem to be in place in crisis years, Evergreening of inefficient firms is only found for treatments in non-crisis years. Note in particular that we find even negative effects for non-crisis treatments in the upper quantiles of the risk-distribution. The evidence for crisis years is compelling: relationship banks in the crisis show nearly the same pattern of treatment effects than do transaction banks in Figure 3. We take this as evidence that the merits of relationship banking that are still in place for treatments in normal times

Figure 4
QR-plots using *PD* as a dependent variable and distinguishing relationship banks running into distress within and outside the crisis years. Plots 4a) and 4b) are p.p. effects and show 5%-confidence intervals. Plot 4c) shows the p.p. effect in relation to the respective constant in quantile q, i.e. the percentage effect. White boxes/prisms in 4c) show insignificant areas at the 5% level.







are out of force when a systematic crisis hits the economy. The logical explanation would be that distressed banks in the crisis are unable to shield inefficient firms from the shock and also cut down liquidity provision to them.

3.3 Robustness of our Results

Our results are robust to different estimators applied to the data as well as to the inclusion of firm and bank covariates in the regression. Table 6 shows the regression framework from specification A2 now using different estimators. Note that the coefficients shown in specifications C1 to C8 have to be interpreted as p.p. effects. We see that effects remain qualitatively similar no matter which estimator is used. However, OLS and firm-fixed effects models (C1 to C4) show an underestimation of the effect which is likely due to both the demand side (firms' order situation, idiosyncratic and market risk) and agency area effects (differences in risk-assessment and application of new methodologies by rating agencies) that we aim to exclude by

Table 6:
Robustness Check for the application of different estimators on the variable *PD.* Columns 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, however, this time with an identity-link, i.e. it gives the p.p. effect for reasons of comparison to the other models. All models are estimated without firms who default within the sample duration.

Specification	C1	C2	C3	C4	C5	C6	C7	C8
Estimator	OLS	OLS robust	Genuine FE	Genuine RE	Group FE	Group RE	Group Tobit	Group GLM
LInk								Identity
Dep. Variable	PD							
Sample	no defaulters							
Time	All Years							
Treatment Effect	0.000548**	0.000548**	0.000695***	0.000690***	0.00198***	0.00101***	0.000914***	0.00110***
Observations	228,708							
Groups/ Firms	-	-	56,157	56,157	50,349	50,349	50,349	50,349

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

applying our grouping in equation (1). Moreover, column C7 and C8 take into account that the dependent variable is bounded between 0 and 1, which calls for a truncated regression.

Table 7 gives evidence on whether the inclusion of bank and firm covariates into the regression changes the coefficient estimates on *PD*. Again, the baseline specification A2 builds the basis for this table, i.e. specification A2 equals specification D1, again this time with a logit link. Moving more to the right of the table, we include more and more covariates into the regression. In a well-specified conditional DiD-setup, coefficients ought to remain stable when

Table 7:
Robustness Check for the inclusion of bank and firm covariates. All models are estimated without firms who default within the sample duration. Baseline specification is specification A2 from Table 4 using all non-defaulting firms and a logit link function.

Specification	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
Estimator	GLM robust										
Observations	228,708	168,728	145,734	145,629	143,130	143,130	143,130	143,130	143,130	143,130	143,130
Dep. Variable	PD										
Link	Logit										
Sample	no defaulters										
Time	All Years										
Firm Sales			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Employees		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banktype Dummies						Yes	Yes	Yes	Yes	Yes	Yes
NPL Ratio				Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RWA Growth, Reserves, Hidden Liabilities, EQ Ratio, HHI Sec14, ROE					Yes	Yes	Yes	Yes	Yes	Yes	Yes
Share of Distressed Customers, Share of Single Relationship Customers, Share of Customers within 50km, Share of Main Bank Customers					Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total Assets						Yes			Yes	Yes	
Number of Customers							Yes		Yes		Yes
Total Loans								Yes		Yes	Yes
Treatment Effect	0.0694***	0.0554***	0.0500**	0.0682***	0.0556**	0.0683**	0.0630**	0.0670**	0.0731**	0.0532**	0.0677**

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

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 also not change our coefficients on the treatment effect. Table 7 proves this to be the case for the bank-covariates employed in the matching equation (compare Table 1 for an overview) and the firm characteristics entering into the group-fixed effect.

4 Concluding Remarks

The literature provides plenty of evidence to show that bank distress adversely affects borrowers. Our study extents the focus on loan supply to a wider view on borrowers' financial position. We show that bank distress is followed by a pass-through of risk into the real sector, weakening borrowers' financial health, lowering their maximum loan recommendations and increasing their likelihood of actual default. We show that effects are driven by such shocks that occurred during a systemic crisis. Furthermore, relationship and transaction banks behave very differently when they run into distress. While transaction banks pass-through risks to above median and especially bad-quality firms, relationship banks shield inefficient firms from liquidity dry outs, seemingly by withdrawing resources from more efficient firms. Nonetheless, the effects do not remain stable when a systemic crisis such as the 2008/2009 financial crisis hits the economy. In that environment, also bad quality customers of relationship banks are affected, with good-quality customers suffering equally high increases in *PD* as in non-crisis times. In conclusion, this article shows evidence for an Evergreening-motive of inefficient firms to exist for distressed relationship banks in normal macroeconomic environments which ceases away in times of crisis.

From a policy perspective, the strategies identified for normal times will please policy makers who are concerned of job losses and regional economic downturns. On the other hand, while these effects may have heavy bad short-term consequences for the local economy, it might actually help such banks to clean their balance sheets and enable future resources to be allocated to more efficient usages, eventually with beneficial long run effects for the local economy. It is important to note that public administrations can directly influence bank strategies especially for the German Savings bank sector where the board is partly constituted of regional political authorities. What policy makers often do not take into account is that the resilience of a regional economy to economic downturns crucially depends on a flexible economic environment. If resources stay at less efficient uses - which is another way of putting the term “Evergreening” - new firms will find it harder to obtain loans and get their projects financed. New ideas and technologies will have a harder time to develop in such an environment.

Our study takes a close look on an environment where banks enter into an unhealthy state and eventually customers suffer from that, at least in the short run. And as it turns out, the suffering customers are not those that should be expected to do so, at least in normal times. Distress and crises can enable banks to clean their balance sheets and relocate their resources to provide funding and support for young and innovative firms. This will also help them to shield against further recessions and crises which might hit the German economy heavier than the last one did.

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6 Appendix

6.1 Matching Table

Table A8:
Probit Regression used to calculate Propensity Score

Method	Logit	
Controls	Bank Type Dummies, Year Dummies, Headquarters in E/W Germany	
Observations	9,926	9,778
Pseudo R-squared	0.143	0.308
Dependent Variable	Bank Receives Initial Capital Injection (CI) in Period t+1	
log (Total Assets)	3.062**	3.690***
	(1.479)	(1.365)
Log (Number of Bank Customers)	0.188	-0.0198
	(0.342)	(0.212)
log (Total Loans	-2.543*	-3.314**
	(1.342)	(1.297)
RWA Growth	-0.0164	0.0139
	(0.0289)	(0.0140)
Share of Customer Loans	0.0114	0.0146
	(0.0184)	(0.0157)
NPL-RATIO	0.0576*	0.0541***
	(0.0325)	(0.0194)
Reserves Ratio	-0.848**	-1.912***
	(0.334)	(0.489)
Dummy Hidden Liabilities	-0.462	1.249**
	(0.695)	(0.487)
Dummy Reserve Reduction	0.431	0.341
	(0.638)	(0.531)
Equitiy Ratio	-0.174	-0.0690
	(0.192)	(0.118)
14-Business Sector Her	-0.0319	0.0271*
	(0.0335)	(0.0155)
Return on Equity	-0.00712	-0.00518
	(0.00870)	(0.00448)
Share of Customers in Distress	-46.29**	1.754
	(20.97)	(3.997)
Share of Single Relationship Customers	-1.283	-3.391*
	(2.341)	(1.927)
Share of Customers within 50km distance	-0.0437	5.972**
	(2.313)	(2.418)
Share of Main Bank Customers	2.527	0.816
	(1.777)	(1.778)
Constant	-15.03**	-17.24***
	(7.620)	(6.641)

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

6.2 Full Results Tables

6.3 Summary Statistics

6.3.1 Industry Distribution and according NACE Classification

No.	Industry Sector Groups	Observations	Percent	Industry sector classification
1	Cutting-edge technology manufacturing			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			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			10-33 (excl. sectors 1 and 2)
4	Technology-intensive services			61.1-61.3, 62, 63.1, 71.1, 71.2, 72.1
5	Non-technical consulting services			69, 70.2, 72.2, 73
6	Other business-oriented services			61-63, 69-72, 77.1, 77.3, 77.4, 78, 80, 81 (ex 70.1, 74.2)
7	Consumer-oriented services			55-56, 58-60, 68, 74.2, 75, 77.2, 79, 85.5-85.6, 86-88, 90-
8	Energy/Mining/Disposal			5-9, 35-39
9	Construction			41-43
10	Trade			49-52
11	Traffic/Mailing			49-53
	Total			

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

6.3.3 Legal Forms

No.	Industry Sector Groups	Observations	Percent
1	Liberal Profession		
2	Commercial Operation ("Gewerbebetrieb")		
3	BGB-Company ("BGB Gesellschaft")		
4	Partnership ("Arbeitsgemeinschaft")		
5	One-Man Business ("Einzelfirma)		
6	General Partnership ("OHG")		
7	Limited Partnership ("KG")		
8	limited partnership with a limited liability company as general partner ("GmbH & Co. KG")		
9	Limited Liability Company ("GmbH")		
10	Cooperation ("AG")		
	Registered Co-Operative ("eG")		
11	Registered Association ("eV")		
	Total		

6.3.4 Size Classes

6.3.5 Age Classes

6.3.6 Regions ("Raumordnungsregionen")

6.3.7 Creditreform-Clubs