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Estimating firms' bank-switching costs

Karolis Liaudinskas* and Kristina Grigaitė□

Abstract

We explore Lithuanian credit register data and two bank closures to provide a novel estimate of firms' bank-switching costs and a novel identification of the hold-up problem. We show that when a distressed bank's closure forced firms to switch, these firms started borrowing at lower interest rates immediately and permanently. This suggests that firms were held up and overcharged ex-ante, and reveals the lower bound of their ex-ante switching costs. Opaquer firms were overcharged more, which suggests that information asymmetries significantly contribute to switching costs. In line with banks' reputational concerns, a healthy bank's closure revealed no overcharging. To policy-makers, our results suggest potential benefits of distressed banks' closures.

Keywords: switching costs, lending relationships, hold-up, asymmetric information, bank closures, financial distress

JEL classification: D82, E51, G21, G33, L14

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1. Introduction

The 2007-9 financial crisis exposed the importance of firm-bank relationships. While they generally helped firms access credit (Bolton et al. 2016, Beck et al. 2018), relationships with severely hit banks were less helpful. Distressed banks cut lending (Ivashina and Scharfstein 2010) and raised interest rates (Santos 2011), and since bank-switching was costly, firms dependent on the distressed banks were forced to lay off staff (Chodorow-Reich 2014), cut investment (Carvalho et al. 2015), and even shut down (Jiménez et al. 2017). In this paper, we ask: how costly can switching be, especially from distressed to healthier banks? What causes these switching costs? Do banks exploit these switching costs to hold up and overcharge their customers? Although empirical evidence suggests that switching costs exist (Ioannidou and Ongena 2010) and stem primarily from information asymmetries (Bonfim et al. 2020), evidence on hold-up and rent extraction is mixed.[1] Moreover, since switching is normally endogenous, i.e., firms avoid costly switching, switching costs are difficult to observe in the data and, hence, little is known about their magnitude.[2] We use forced switches induced by bank closures and contribute to the literature with a novel lower-bound estimate of switching costs as well as a novel identification of the hold-up problem.

Lithuania offers an ideal setting for identification due to its exhaustive credit register that includes loan interest rates on even the smallest loans issued to the smallest, and, thus, opaquest firms.[3] Moreover, Lithuania experienced two largely unexpected simultaneous closures of banks, namely "Distressed bank" and "Healthy bank", which forced firms to switch to other lenders.[4] Normally, firms may face bank-

[1] See, e.g., Petersen and Rajan (1994), Berger and Udell (1995), Angelini et al. (1998), Berlin and Mester (1999), Dahiya et al. (2003), Schenone (2009), Ioannidou and Ongena (2010), Kysucky and Norden (2015), Sette and Gobbi (2015), Bolton et al. (2016), Lopez-Espinosa et al. (2017), Botsch and Vanasco (2019).
[2] To the best of our knowledge, only Kim et al. (2003) estimated switching costs in the loans' market and their estimates rely on elaborate modeling of demand and supply.
[3] Most credit registers include loans that are above certain loan size thresholds, and thus allow analyses of only relatively large firms.
[4] The names "Distressed bank" and "Healthy bank" are used instead of the banks' real names. The Bank of Lithuania uncovered that "Distressed bank" – the oldest bank in Lithuania – had misreported its asset values and therefore shut it down. The majority of the bank's misrepresented assets consisted of loans extended to firms closely related to the bank's major shareholder (OECD 2017). Although the bank was commonly known to be relatively risky, the closure was largely unexpected as even governmental institutions lost large uninsured deposits (Kuodis 2013). The bank's auditor "Deloitte" was penalized for the perfunctory audit of the bank (Vasiliauskaitė and Gudavičius 2014). Separately, in the same quarter, "Healthy bank" was closed by its international parent bank as part of its global cost-restructuring plan.

switching costs, which can include higher interest rates charged by the new (outside) bank due to information asymmetries (Sharpe 1990, Rajan 1992, von Thadden 2004), search costs, refinancing costs (e.g., early repayment fees), losses of benefits provided by the current (inside) bank (e.g., lower collateral requirements), and other shoe-leather switching costs (Klemperer 1987). An inside bank can hold up and overcharge its current customers as long as the overcharge does not exceed switching costs. Hence, the estimation of the overcharge would reveal the lower bound of firms' total switching costs. We show in a difference-in-differences framework that when "Distressed bank" closed, its customers switched and started borrowing on average at lower interest rates immediately and permanently. Moreover, roughly half of the switchers moved to better-reputation banks and borrowed at rates on average similar to those paid by old customers of the same banks. This suggests that "Distressed bank" had overcharged its borrowers, and since the borrowers had paid the overcharge instead of switching, their ex-ante switching costs had been even higher.

Even if healthy banks' borrowers face similar switching costs, distressed banks are more likely to overcharge their customers and thus to reveal those switching costs in the data. For example, distressed banks may care less about reputation (Boot et al. 1993) and therefore extract more rents from locked-in clients (Sharpe 1990). In addition, as distressed banks tend to face higher borrowing costs, they may try to pass these costs on to their borrowers. In line with these explanations, we find no evidence that "Healthy bank" overcharged its clients, at least no more than other banks.

We consider a few potential explanations why borrowing costs for "Distressed bank's" customers dropped. Firstly, inside banks have more information about their borrowers, thus, outside banks face a winner's curse and are discouraged from bidding for even seemingly good-quality firms (Sharpe 1990, Rajan 1992, von Thadden 2004). This interbank information asymmetry makes it difficult and costly for good-quality firms to switch and allows inside banks to overcharge them. A closure of an inside bank can alleviate the winner's curse for outside banks and encourage them to compete for seemingly good-quality borrowers. Secondly, "Distressed bank" was resolved by an auditor KPMG that split the bank into a "good bank" and a "bad bank". The separation of failing firms from the rest, reduced firm-bank information asymmetries, and transparency can reduce the hold-up problem (Padilla and Pagano 1997, Jappelli and Pagano 2002).[5] Thirdly, if switching costs were driven by shoe-leather costs, e.g., search costs, loan refinancing costs or loss of some benefits provided by "Distressed bank", then "Distressed bank's" customers might have always been able to borrow at lower interest rates but chose not to until they were forced to switch.

We exploit the exhaustive credit register provided by the Bank of Lithuania, which reports interest rates and other characteristics of all outstanding loans in Lithuania quarterly from 2011 q4 to 2018 q1. This paper is the first to use this credit register and, to the best of our knowledge, the first to study directly how firms' loan interest rates change when banks close.[6] We analyze jointly leasing contracts, term loans and credit lines, which make up 86% of all contracts in the database, yet our findings are similar when using term loans and leasing contracts separately. We disregard credit unions and consider the 12 banks that account for 95% of observations. Most Lithuanian firms are relatively small and bank-dependent. Our sample period is marked by an economic recovery after the 2007-9 crisis. In 2011, Lithuania's GDP grew by 6%, the financial system was stable and banks' total profits reached a close to record-high pre-crisis level (Bank of Lithuania 2011). A credit bureau "Creditinfo" provided lenders with firms' ten-year credit histories that included interest rates, collateral values, repayments but no lender names, thus, our results might extend to other firms that borrowed elsewhere.

We analyze two bank closures separately.[7] Firstly, on February 12, 2013, the Bank of Lithuania unexpectedly closed the oldest and one of the largest domestic-capital banks "Distressed bank" due to the uncovered misreporting of assets. The bank was resolved by first netting off firms' assets and liabilities with the bank and then KPMG assigned the remaining performing and non-performing loans to the "good" and "bad" banks, respectively. This setting gives us a unique opportunity to identify the poorest-quality

[5] Although the list of firms assigned to "bad bank" and "good bank" was not publicly known, firms could have used their privately held documentation to prove that their loans were assigned to "good bank".
[6] The closest study to ours is Bonfim et al. (2020). They compare post-shock (after bank-branch closures) loan interest rates of non-switchers vs. forced switchers. In contrast, we compare forced switchers' rates pre-shock vs. post-shock.
[7] One more bank closed in November 2011, but due to structural changes in the database, we do not observe interest rates before 2011 q4 and thus do not analyze this closure.

borrowers, based on ex-ante but not publicly available information, and to separate them from the rest of the firms. "Bad bank" was declared bankrupt while "good bank's" loans were assigned to another ("Acquiring") bank that was similar to "Distressed bank" in many aspects, including clientele (e.g., "Distressed bank" and "Acquiring bank" had the largest shares of firms with delayed repayments). A large portion of "Distressed bank's" customers that borrowed again after the shock, never switched for new loans to "Acquiring bank" and instead switched to other, hence better, banks. Secondly, on January 30, 2013, "Healthy bank" announced its closure and stopped issuing loans. It was a healthy but small branch of an international banking group, which implemented a cost restructuring plan and closed many branches around the globe. For instance, it also left Estonia but stayed in Latvia, where it had the largest and the oldest office in the Baltic countries. Old borrowers had to finish repaying their loans but could not take new loans and had to switch.[8]

We use a visual inspection of graphs and a (reverse) difference-in-differences (DID) method to compare firms' borrowing costs before and after the shocks.[9] Firm-quarter-level borrowing costs are calculated as an average interest rate on outstanding loans weighted by loan amounts. In the post-shock period, we consider only loans issued after the shock. A firm is called a bank's customer if it had debt outstanding with that bank within one year before the shock. The treatment group comprises customers of a closed bank, i.e., first "Distressed" then "Healthy", and the control group - customers of all other banks. In both groups, we consider firms that took at least one new loan in the post-shock period, and we address the endogenous firm selection using matching and the Heckman (1979) selection model.

We find that borrowing costs for "Distressed bank's" customers dropped immediately and permanently after the shock by 42 bp on average as compared to clients of all other banks. The drop was driven by good customers, i.e., those whose loans were not assigned to the "bad bank". These firms

[8] The Latvian branch of the same bank was not a feasible option for switching due to a different currency.
[9] We call it "reverse" difference-in-differences because the treatment – being locked-in by a distressed bank – happens in the pre-shock period. In the post-shock period, customers of "Distressed bank" are released from the treatment, switch to healthier banks and therefore more closely resemble the control group, i.e., all other firms borrowing from the same banks.

experienced an average drop of 60 bp, while bad customers, i.e., those assigned to the "bad bank", experienced no drop on average. A back of the envelope calculation suggests that each of the good customers could have paid nearly two extra average annual salaries had they not been overcharged on their loans. Opaquer firms, i.e., smaller, younger and borrowing from only one bank, were overcharged more, which suggests that information asymmetries are an important cause of switching costs.

We face two major challenges related to endogenous firm selection. The first is the difference between our treatment and control groups, e.g., firms in the treatment group might be on average of poorer quality and might therefore have self-selected into a relationship with "Distressed bank". We argue that while the difference-in-differences framework cancels out static differences between the two groups, intuitive dynamic shock-related differences point towards the underestimation of our results: e.g., (1) the continuously deteriorating quality of "Distressed bank's" clients might have caused the bank's closure; (2) the "Distressed bank's" closure might have hurt the image of its clients; (3) the decrease in banking competition might have particularly affected firms that were no longer locked-in by banks (Klemperer 1987). In these examples, the borrowing costs of our treatment group relative to the control group would be affected upwards, and we might therefore underestimate the drop. Nevertheless, to make our two groups as similar as possible, we match firms on their ex-ante characteristics, such as size, age, history of repayment delays, etc. The results remain very similar with matching. Both a graph and a regression analysis, whereby the treatment variable is interacted with individual time-period dummies, suggest that post-shock borrowing costs followed parallel trends, which is of primary importance given the "reverse" nature of our DID setting (Kim and Lee 2018). We find diverging pre-shock trends, which again suggests that we might underestimate the drop and that "Distressed bank" was not always overcharging its customers, at least, not to the same extent.

The second challenge is the sample attrition that occurs due to some firms not taking new loans after the shock. Our results are based on within-firm changes in borrowing costs (ensured by firm-fixed effects), which require that firms survived the shock and took at least one new loan both before and after the shock. The exclusion of firms that might have faced post-shock hikes in borrowing costs, and thus could not borrow again, could explain a drop in average borrowing costs. This would not be a problem if attrition occurred in both the treatment group and the control group, but the concern is that the shock affected the survival of the treatment group more. We show that the survival rate, i.e., the number of firms that borrowed both ex-post and ex-ante divided by the number of firms that borrowed ex-ante, is in fact larger for "Distressed bank's" customers than for other firms. Moreover, our results remain similar when applying the Heckman (1979) two-stage model that predicts firms' survival in the first stage and accounts for it when estimating the difference-in-differences in the second stage.

Non-survivors in both groups had the largest shares of firms with repayment delays, which suggests that we exclude on average the worst-quality firms. Yet, we do not intend to generalize our results to all firms and focus on better-quality firms for a number of reasons. First, we aim to measure switching costs that may primarily stem from interbank information asymmetries (Bonfim et al. 2020). According to informational hold-up theories (Sharpe 1990, Rajan 1992, von Thadden 2004), the worst-quality firms do not suffer from this type of switching costs because there are no worse-quality firms that they can be mistaken for by outside banks.[10] Second, "good" firms are of key importance to the economy for their productivity (Caballero et al. 2008) and employment (Falato and Liang 2016). Third, since "Distressed bank's" clients were on average of worse quality than other firms, e.g., as suggested by repayment delays, by focusing on the better quality clients, we make our treatment and control groups more similar. Fourth, "Distressed bank's" closure was primarily caused by bad quality firms that were assigned to the "bad bank", thus, for better firms the shock was less endogenous.

We re-run our analysis using "Distressed bank's" customers that switched for new loans not to "Acquiring bank" that was similar to "Distressed bank", but to other, hence, better-reputation banks that jointly held more than 80% of corporate loan amount in Lithuania. This setting arguably increases the average firm quality of our treatment group, makes it more comparable to the control group, and alleviates the concern that our results may be driven by post-shock loan pricing of a single "Acquiring bank". This

[10] In practice, if a firm cannot switch even when a closure of its inside bank eliminates information asymmetries between its inside and outside banks, then ex-ante switching costs caused by these asymmetries should be irrelevant.

setting may raise a concern that the difference-in-differences analysis is conditioned on a post-shock firm-quality indicator – the ability to switch to a good-reputation bank – which could be affected by the shock itself (e.g., Montgomery et al. 2018). If firms' quality improved between the shock and switching, this would explain our results, but given the immediacy of the drop in borrowing costs (it occurs in the first post-shock observation, i.e., within six weeks after the shock), we deem it unlikely that firms' quality could have changed, especially positively, so quickly. We find that the treatment group on average was overcharged by 1.1 pp, which, multiplied by loan amounts, results in almost four average annual salaries forgone by each firm. Graphs show that, after the shock, borrowing costs for the treatment group not only dropped but also converged to the rest of the market immediately and permanently. This suggests that the treatment and control groups were in expectation similar. As a robustness test, we implement a post-shock loan-matching exercise following Bonfim et al. (2020) to test if "Distressed bank's" customers and other firms that borrowed from the same banks at the same time after the shock received similar interest rates, while controlling for firm and loan characteristics. We find that the difference in rates was neither economically nor statistically significant.

Other robustness tests show that our main results remain similar when using (1) only term loans, (2) only leasing contracts, (3) only clients of the most similar ("Acquiring") bank as a control group, (4) only newly issued loans in every quarter, which suggests a limited contribution of loan refinancing fees to total switching costs, and (5) only firms that had their liabilities with "Distressed bank" completely netted off with assets, and, therefore, were not transferred to either the "good bank" or the "bad bank". These firms did not benefit from the assignation to the "good bank" and were unambiguously forced to switch. We find no evidence that other beneficial loan terms provided by "Distressed bank", i.e., lower collateral, longer maturities and larger loans, caused switching costs as the difference-in-differences analyses for these characteristics show no significant changes.

Our results suggest that in a highly concentrated banking market with relatively small firms, switching costs can be significant, they stem primarily from information asymmetries, and banks, especially distressed ones, may exploit that to hold up their good customers and overcharge them. This has policy implications. Firstly, although generally bank closures are costly (e.g., Kang et al. 2015), we provide one benefit for regulators to consider when resolving failed banks: a bank closure may help good-quality firms, which are particularly important for productivity and employment (Caballero et al. 2008), to borrow more cheaply. Secondly, regulators could monitor banks' loan rates for early signs of banks' distress. Thirdly, information asymmetries remain despite a credit bureau providing detailed ten-year credit histories and thus, regulators might be advised to aim to reduce these asymmetries further. For instance, a prevention of loan evergreening could improve the reliability of credit histories.

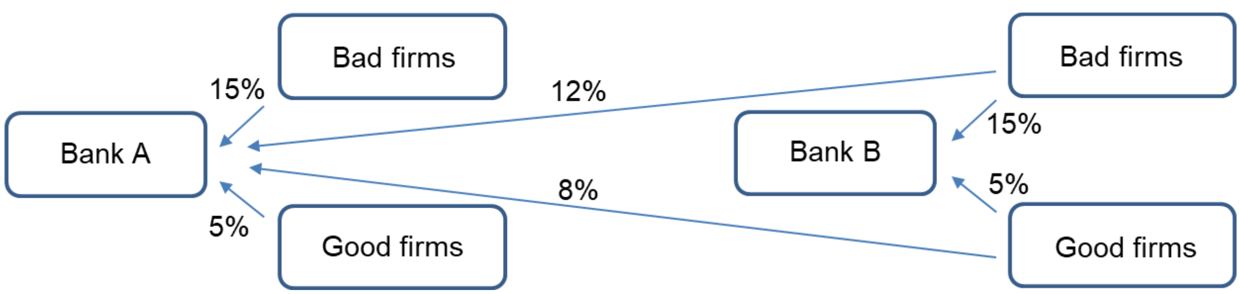
We contribute to a few strands of literature. First, we add to the literature on switching costs in the loan market (e.g., Kim et al. 2003, Ioannidou and Ongena 2010, Bonfim et al. 2020) and on the costs and benefits of lending relationships (e.g., Petersen and Rajan 1994, Berger and Udell 1995, Angelini et al. 1998, Berlin and Mester 1999, Dahiya et al. 2003, Dell'Ariccia and Marquez 2004, Schenone 2009, Ioannidou and Ongena 2010, Bharath et al. 2011, Kysucky and Norden 2015, Sette and Gobbi 2015, Bolton et al. 2016, Lopez-Espinosa et al. 2017, Botsch and Vanasco 2019, Li et al. 2019). Second, by differentiating between "Healthy bank" and "Distressed bank", we contribute to the literature studying how banks' health affects borrowers (e.g., Ivashina and Scharfstein 2010, Slovin et al. 1993, Ongena et al. 2003, Carvalho et al. 2015, Schnabl 2012, Chava and Purnanandam 2011, Khwaja and Mian 2008) and particularly, their loan rates (Hubbard et al. 2002, Santos 2011, Chodorow-Reich 2014). Third, we add to the literature on bank closures, which so far has focused on the effects on aggregate economic outcomes (Bernanke 1983, Ashcraft 2005) and firms' investments (Minamihashi 2011, Korte 2015).

The rest of the paper is structured as follows. Section 2 discusses the theoretical framework. Section 3 presents the data and the institutional setting. Section 4 describes the closures of the banks. Section 5 describes the methodology. Section 6 presents and discusses the results. Section 7 concludes.

2. Theoretical Framework

Lending relationships can make borrowing both cheaper and more expensive. On the one hand, repeated interactions reduce information asymmetries between firms and banks, which may alleviate firms' borrowing costs (e.g., Diamond 1984). On the other hand, firm-bank relationships create information asymmetries across banks. Inside banks know their borrowers better and can therefore offer lower interest rates than outside banks. This makes switching costly for good-quality firms and leads to an adverse selection of firms willing to switch banks (Sharpe 1990). In turn, this allows inside banks to hold up their good customers and extract rents from them and, as noted by Rajan (1992) and von Thadden (2004), creates a winner's curse for outside banks. If inside banks started to predictably extract all possible rents from their good customers, outside banks could start attracting those firms by offering them lower rates. But if outside banks predictably offered their best bids, inside banks would respond with their own best bids, and outside banks would always lose either by being outbid by better-informed inside banks or by bidding too generously, i.e., the winner's curse. The equilibrium solution is a mixed strategy, whereby outside banks actively randomize the bidding and inside banks randomize the rent extraction. In this case, inside banks would be able to extract some rents from their good customers and outside banks would be able to attract some of those customers (von Thadden 2004).

FIGURE 1
An example situation in the theoretical framework of Sharpe (1990), Rajan (1992) and von Thadden (2004)



For a numerical example, suppose there are two types of firms – good and bad – and two identical banks – A and B – with the same proportions of good and bad borrowers. A bank knows a firm's type with certainty only if it has a lending relationship with that firm, i.e., a bank is a firm's inside bank. An outside bank receives only a noisy signal about a firm's type. Sharpe (1990) shows that break-even loan rates in this situation can be ordered as follows: $r_G < r_{G'} < r_P < r_{B'} < r_B$, where r_G is a break-even rate offered by a bank to a firm if the bank knows with certainty that the firm is good, $r_{G'}$ – if the bank receives a noisy signal that the firm is good, r_P – if the bank has no information about the firm's type, $r_{B'}$ – if the bank receives a noisy signal that the firm is bad, and r_B – if the bank knows with certainty that the firm is bad. Figure 1 depicts this example and assumes that r_G = 5%; $r_{B'}$ = 8%; r_P = 10%; $r_{B'}$ = 12%; r_B = 15%. If a bad firm tried to switch from its inside Bank B to outside Bank A, it could expect to borrow more cheaply, i.e., at 12% instead of 15%, since Bank A receives only a noisy signal that the firm is bad. Similarly, if a good firm borrowing at 5% from its inside Bank B tried to switch, Bank A would offer 8% since it receives only a noisy signal that the firm is good. This results in an adverse selection of firms willing to switch banks and makes switching costly for good firms, which, in turn, allows Bank B to hold up its good customers and extract rents from them by charging them close to 8%. If Bank A knows that it can attract only "bad" firms, i.e., it is subject to the winner's curse, it may charge all approaching firms 15% or not bid at all. Now Bank B might be tempted to extract maximum rents from good firms by charging them close to 15% but it cannot do so predictably because Bank A would start bidding again. Bank A also cannot bid predictably, e.g., always offer its best bid of 8% to seemingly good firms, because it would always lose to better-informed Bank B either by being outbid or by bidding too generously, i.e., the winner's curse. The only way for Bank A to attract some good firms would be to randomize its bidding and thus allow Bank B to extract some rents by charging its good customers somewhere between 8% and 15%, e.g., 13% on average.

Bank B is more likely to extract these rents if it has weak concerns about its own reputation (Sharpe 1990), which may happen if the bank is in financial distress (Boot et al. 1993). If such a distressed Bank B was closed, Bank A would be no longer subject to the winner's curse and, thus, could charge all seemingly good firms 8% ($r_{G'}$) as initially intended.[11] Borrowing costs for good customers of Bank B would drop from the average of 13% to 8%, and the drop of 5 pp represents the lower bound of average ex-ante extracted rents of 8 pp (i.e., 13 minus 5), which in turn represents the lower bound of average ex-ante switching costs. Borrowing costs for bad customers would drop from 15% (r_B) to 12% ($r_{B'}$). In our empirical setting, KPMG separated good and bad firms and reduced firm-bank information asymmetries. In the theoretical example, this would bring $r_{G'}$ and $r_{B'}$ closer to r_G and r_B respectively, which means that borrowing costs for good firms could potentially drop to 5%, while borrowing costs for bad firms could remain almost unchanged at

[11] Intuitively, when firms try to switch, they may unintentionally signal that they are unable to borrow from their well-informed inside bank. However, if their bank closes, they have a good excuse to switch.

15%. A significant drop for good firms and a nearly zero drop for bad firms is possible even without the KMPG's intervention if $r_{G'}$ has always been very close to r_G and $r_{B'}$ to r_B, i.e., if Bank A could have always identified the type of Bank B's clients almost with certainty but did not bid for seemingly good firms due to the winner's curse.

According to this theoretical framework, only good firms are subject to switching costs caused by information asymmetries because they can be mistaken for bad firms. Therefore, in this paper we focus on good firms and primarily disregard non-survivors, i.e., arguably the worst-quality firms as suggested by the fact that they did not manage to borrow at all after their bank closed. Intuitively, if firms could not switch even after the reduction of information asymmetries, then their ex-ante switching costs caused by these asymmetries must have been irrelevant.

Other potential switching costs can be labeled as "shoe-leather costs" (Bonfim et al. 2020) and categorized as learning costs, transaction costs and artificial costs (Klemperer 1987). For example, they may include search costs (e.g., financial and time resources needed to look for a new bank or to negotiate loan terms), refinancing costs (e.g., fees for repaying loans ahead of schedule), and loss of benefits provided by inside banks (e.g., lower collateral requirements, longer maturities, larger loans).

3. Data and Institutional Setting

We use quarterly data on corporate loans outstanding between 2011 q4 and 2018 q1, provided by the Bank of Lithuania, and observe the following variables: year, quarter, loan id, loan type, firm id, bank id, loan issue date, loan maturity date, loan outstanding amount, loan interest rate, loan currency, loan collateral value, indicator if a firm had late repayments within a given quarter, firm's industry and firm's total loan amount. The database includes all debt contracts issued to all firms by all credit institutions registered in Lithuania. In addition, we observe firm id, bank id, loan initiation date and loan termination date of all loans between 1995 and 2011, which allows us to estimate lengths of all firm-bank relationships and to approximate firms' age.

We disregard credit unions and other small lenders and consider the 12 largest banks, which account for 95% of all observations. Five of the 12 banks were funded primarily by Lithuanian capital and had no or limited cross-border activities. The other seven banks were branches or subsidiaries of foreign – mostly Scandinavian – banks. The banking sector was concentrated as, at the beginning of our sample period (2011 Q4), the five Scandinavian-owned banks held 82% of the outstanding credit issued to firms. The three largest banks accounted for 65% of this credit. The Herfindahl-Hirschman Index (HHI) for outstanding loans throughout our sample period varied between 1,632 and 1,992.

In our sample period, the 12 banks had 190,728 outstanding debt contracts issued to 35,905 firms, which constitutes 1,635,779 quarterly observations. These include 117,557 new contracts that were issued to 25,436 firms within our sample period. All these contracts were issued in the local currency and only between one firm and one bank.[12] Table 1a provides loan summary statistics (aggregate and split by loan type). In our analyses, we use the three most popular loan types in terms of the number of contracts and the loan amount issued. They jointly constitute 86% of the total number of contracts: leasing – 69%, term loans – 13% and credit lines – 4%. The total amount issued was EUR 48 billion. Of this amount, 54% is term loans, 14% leasing contracts, 11% credit lines and the rest overdrafts, mortgages and other types of contracts. The average (median) loan size across all loans is EUR 0.25 million (EUR 0.026 million), the average (median) interest rate is 3.8% (3.2%), and the average (median) time to maturity of debt contracts at the time of issuance is 2.7 years (2.8 years). To avoid outliers' impact in all our regression analyses, we winsorize the top and bottom 0.5% of observations of each of these variables, but this has trivial effects on the results. Only 20% of contracts are collateralized, but for term loans and credit lines, this number is above 80%.

Firms in Lithuania are relatively small and reliant on banks' funding. As shown in Table 1b, at the beginning of the sample (2011 Q4), the average (median) outstanding debt across the 17,266 firms was almost EUR 1 million (EUR 0.06 million) and the aggregate firms' debt to banks was EUR 16.8 billion. This illustrates firms' relatively small size and their high reliance on banks, since, according to Nasdaq

[12] We have dropped 2,886 loans (<2%) issued in foreign currencies and 1,005 (<1%) collective loans taken jointly by more than one firm. Our database does not include syndicated loans, but their outstanding amount is relatively small, e.g., according to the ECB's Statistical Data Warehouse, at the end of 2011, syndicated loans to Lithuanian non-financial corporations amounted to EUR 0.7 bn, which is 4% of the loans outstanding in our dataset at the same time.

Baltic monthly statistics, at the same time the stock market capitalization was EUR 3.1 billion and the market value of all publicly traded corporate bonds was EUR 1.3 billion. At the end of 2011, 77% of firms had relationships with only one bank.[13] In our sample, the three largest sectors in terms of the number of firms were wholesale and retail (26%), transportation (12%), and manufacturing (10%). Throughout the whole sample period, 17% of all firms delayed at least one repayment.

Lithuania has been a member of the European Union since 2004 and the eurozone since 2015. The supervision of Lithuanian credit institutions follows the Basel III regulations (OECD 2017). Since 2003, a credit bureau "Creditinfo" has been collecting information on firms' liabilities in Lithuania, which makes the Lithuanian credit market more transparent than credit markets in many other countries. Banks can access a detailed ten-year history of their applicants' current and expired debt contracts. Information includes loan types, starting and maturity dates, repayment schedules, loan amounts, interest rates, number of payments delayed, number of days delayed, total amounts delayed, etc. Nevertheless, important interbank information asymmetries in the market remain. Firstly, the credit histories do not reveal bank names, thus outside banks could not know if a firm was borrowing from "Distressed bank" unless the firm voluntarily proved it with its personally held documentation. This suggests that other firms that were similar to "Distressed bank's" customers could have faced similar switching costs even if they were not overcharged. Secondly, due to the possibility of loan evergreening, banks may treat firms' credit histories with caution. Thirdly, firms are likely to keep borrowed funds in an account with the same bank, which, in turn, can observe firms' spending patterns.

The economic environment in our sample period was marked by a sharp recovery after the 2007-2009 financial crisis. In 2011, Lithuania's GDP grew by 6%, the financial system was stable and total profits in the banking sector almost reached a record-high pre-crisis level (Bank of Lithuania 2011).

[13] In line with Ioannidou and Ongena (2010) and Bonfim et al. (2020), a firm is said to have a relationship with a bank or be a bank's customer if it had an outstanding debt with that bank at any time within the previous 12 months. We thus assume that after 12 months of zero debt between a firm and a bank, their relationship ties are broken.

Throughout our sample period, average interest rates were gradually declining, following the expansionary monetary policies of the European Central Bank.

Our institutional setting is comparable to those of some other related papers. For instance, Bonfim et al. (2020) study another relatively small market in the eurozone – Portugal, where firms also largely rely on bank funding, and where a few of the largest banks dominate the market. For example, in the sample period of 2012-2015, six banks held 85% of the market (Bonfim et al. 2020). Some related papers examine even smaller markets; for example, Schäfer (2018) studies 6,649 firms in Armenia in 2009-2013, while Ioannidou and Ongena (2010) study 2,805 firms in Bolivia in 1999-2003. Our setting particularly differs from theirs in terms of credit market transparency, as in Portugal (Bonfim et al. 2020) and Bolivia (Ioannidou and Ongena 2010) banks could access only two months of their applicants' credit history, while in Armenia, a private credit bureau provided a history of five years. This strengthens the external validity of our results: if interbank information asymmetries matter in Lithuania, where banks can access ten years of firms' credit histories, they are likely to matter even more in less transparent markets. However, it is not clear if our results would be replicated in larger and less concentrated (more competitive) markets. On the one hand, more interbank competition makes relationship lending more important to banks (Boot and Thakor 2000). On the other hand, interbank competition generally makes it difficult for banks to internalize benefits from lending relationships (Petersen and Rajan 1995, Boot and Thakor 2000, Degryse and Ongena 2005). Also, results might be different for larger, and thus less opaque, firms. For example, adverse selection costs were shown to be minimal in the U.S. syndicated loan market (Darmouni 2020).

4. Closures of Banks

We use two almost simultaneous closures of banks. First, in 2013 q1 (January 30), "Healthy bank" [14] – a branch of a large international bank – announced its strategic decision to leave the Lithuanian and Estonian markets and to concentrate its business in Latvia, where it had the oldest and largest headquarters in the Baltic region. According to the bank's press release, this decision was part of the parent bank's

[14] Prior to the bank closure, borrowers of "Healthy bank" had on average the lowest borrowing costs and the lowest share of firms with at least one repayment delay, as compared to borrowers of all other banks in Lithuania.

strategic plan to save operational costs globally and to increase internal efficiency of activities in Central and Eastern Europe. After the announcement, the bank stopped issuing new loans and effectively abandoned its borrowers, who were forced to switch to other banks. Borrowing from the Latvian branch was not a feasible option since at that time Latvia and Lithuania had different currencies. Before the announcement, the bank lent to 153 firms (when considering term loans, leasing contracts and credit lines) and was eighth in terms of corporate loan portfolio size.

Second, "Distressed bank" [15] was a publicly traded Lithuanian bank (i.e., owned and controlled by a Lithuanian businessman) with EUR 0.3 billion lent to 1,158 firms (considering term loans, leasing contracts and credit lines) as of 2012 Q4 – the sixth largest corporate loan portfolio. The bank's activities were stopped in 2013 q1 (February 12), due to risk mismanagement and over-reporting of its asset values, as uncovered by the Bank of Lithuania. The majority of the bank's misrepresented assets consisted of loans extended to firms closely linked to the bank's major shareholder (OECD 2017). Although the bank was commonly known to be relatively risky via rumors and negative coverage in the media, the closure was largely unexpected not only by markets, but also by governmental institutions, which lost large uninsured deposits amounting to EUR 80 million (Kuodis 2013). Yet, the closure did not have systemic repercussions (OECD 2017). Financial markets reacted modestly and the total amount of deposits in the banking system even increased in the days following the shutdown (Kuodis 2013). The bank was resolved by first netting off firms' assets and liabilities with the bank and then, during a few days after the shutdown, KPMG Baltics manually reviewed all the remaining bank's assets and split them into a "good bank", which included remaining loans that were likely to perform normally and a "bad bank", which included remaining loans that had their values misrepresented and were likely to default. Based on a personal communication with an employee of KPMG Baltics, who was directly involved in the resolution process, the split was performed carefully but urgently and thus was based merely on pre-closure information: financial statements, loan agreements and other documents. The "bad bank" was liquidated and the "good bank" was acquired by

[15] Prior to the bank closure, borrowers of "Distressed bank" had on average the highest borrowing costs and the highest share of firms with at least one repayment delay, as compared to borrowers of all other banks in Lithuania.

another (“Acquiring”) bank. The total value of the “good bank” was EUR 0.52 billion, which included EUR 189 million in loans, EUR 126 million in fixed-income securities, EUR 106 million in cash and EUR 100 million in other assets. “Acquiring bank” took over all insured deposits of the failed bank, amounting to EUR 0.79 billion, and received a compensation of EUR 0.27 billion from the state in order to balance out the assumed assets and liabilities (Ciulada 2013).

In many ways, “Acquiring bank” was comparable to “Distressed bank”; for example, it was a publicly traded bank with the fifth largest corporate loan portfolio as of 2012 Q4. The largest shareholders were the European Bank for Reconstruction & Development (EBRD) and five Lithuanian companies and individuals. In 2012, there were rumors that “Acquiring bank” and "Distressed bank" might merge in order to exploit synergies stemming from similar clienteles. Both banks were known for lending to SMEs and having well-established networks of offices across the country (BNS and lrytas.lt 2012). Regarding the customers’ credit quality, “Distressed bank” had the largest share of borrowers with at least one repayment delay prior to the shock. Table 1c reports the share of 19% for all “Distressed bank’s” customers” (28% for those that were assigned to the “bad bank” and 17% for those that were not) and 16% for all other firms. “Acquiring bank” had the second-largest share while “Healthy bank” had the lowest share of borrowers with at least one repayment delay among all banks.

Table 1c shows that when considering term loans, credit lines and leasing contracts, at the moment of the closure, “Distressed bank” had 1,158 customers, and 260 of them were assigned to the “bad bank”. Out of the remaining 898 firms, 449 (50%) took at least one new loan in the period between the bank’s closure and the end of our data sample period and thus reappeared in the credit register, while the other 449 did not. This “survival rate” (50%=449/898) is higher than the “survival rate” of all other firms (46%=7,804/16,798). After the shock, out of the 449 firms that borrowed again, 227 firms took new loans from “Acquiring bank”, while 222 firms switched for new loans to other banks.

5. Empirical strategy

5.1. Difference-in-differences

We visually inspect graphs and use a ("reverse") difference-in-differences (DID) method to study how borrowing costs for "Distressed bank's" customers changed when the bank was closed and the firms were forced to switch to other banks. The graphs reveal the dynamics, i.e., the immediate and permanent drop in borrowing costs, and the DID regression formally tests if the drop is statistically significant. We then repeat the analysis with the customers of "Healthy bank".

Borrowing costs, i.e., our outcome variable, are calculated for each firm, at the end of every quarter, as an amount-weighted average interest rate across outstanding loans. We consider jointly the three most popular loan types: term-loans, leasing and credit lines, in terms of both the total amount issued (79% of the sample) and the number of contracts (86% of the sample). The data sample is split into two periods: "before" considers loans issued up to December 31, 2012, while "after" considers loans issued after February 12, 2013 – the day when "Distressed bank" was closed.[16]

The treatment group comprises customers of a closed bank, i.e., first "Distressed" then "Healthy", and the control group comprises customers of all other banks. In line with Ioannidou and Ongena (2010) and Bonfim et al. (2020), a firm is defined as a bank's customer if it had debt outstanding with that bank within the past year. A customer is called "exclusive" if it had no debts with other banks in the same year and it is called "surviving" if it reappeared in the credit register by taking at least one new loan after the shock. We identify banks' customers as of February 12, 2013, and measure the size, age, and average length of their ongoing relationships with banks (see subsection "Coarsened exact matching" below or Table 1c for a detailed description of these measures). Firm size is proxied by the total outstanding loan amount, while firm age is proxied by the first appearance in the credit register since 1995. Firms that are smaller, younger and with average relationships shorter than the median of "Distressed bank's" customers are called "small", "young" and "short-term", respectively.

[16] We ignore 15 loans (term loans, leasing or credit lines) issued between January 1, 2013 and February 11, 2013 by "Distressed bank" as information about these loans is observed after the shock - at the end of 2013 Q1. The reported values may be affected by the shock and thus might not accurately represent the situation in the pre-shock period. "Healthy bank" issued no loans (term loans, leasing or credit lines) within these dates. To split the time period for the "Healthy bank's" analysis, we use the day the bank announced its exit from the market – January 30, 2013.

We hypothesize that if "Distressed bank" overcharged its customers, we would see their borrowing costs decrease more than for other firms after the bank's failure. If switching costs stem from information asymmetries, these results should be driven by opaquer, i.e., exclusive, small, and young, firms. Also, we expect our results to be stronger for short-term customers either due to the correlation with age or due to banks' reputational concerns related to overcharging their most loyal clients. This would be in line with Lopez-Espinosa et al. (2017) who find a concave link between a loan interest rate and the length of a firm-bank relationship. In order to test these hypotheses, we run the following three regression specifications using surviving firms, i.e., those that took at least one new loan both before and after the shock.

$$borrowing\_costs_{f,q} = \beta_0 + \beta_1 * after_q + \beta_2 * closed_f + \boldsymbol{\beta_3 * after_q * closed_f} + FFE + TFE + \varepsilon_{f,q} \quad (1)$$

$$borrowing\_costs_{f,q} = \beta_0 + \beta_1 * after_q + \beta_2 * closed_f + \beta_3 * char_f + \boldsymbol{\beta_4 * after_q * closed_f * char_f} + [all\ other\ interactions] + FFE + TFE + \varepsilon_{f,q} \quad (2)$$

$$borrowing\_costs_{f,q} = \beta_0 + \beta_1 * after_q + \beta_2 * closed_f + \beta_3 * exclusive_f + \beta_4 * char_f + \boldsymbol{\beta_5 * after_q * closed_f * exclusive_f * char_f} + [all\ other\ interactions] + FFE + TFE + \varepsilon_{f,q} \quad (3)$$

Where

- $borrowing\_costs_{f,q}$ is an average interest rate weighted by loan outstanding amounts in quarter *q* for firm *f*.
- $after_q$ is a dummy variable equal to 1 if the quarter *q* is equal to or larger than 2013 q1, and zero otherwise.
- $closed_f$ is a dummy variable equal to 1 if firm *f* is in a treatment group, i.e., a customer of the closed bank, and zero if firm *f* is in a control group.
- $char_f$ is one of the following four firm characteristics:
    - $exclusive_f$ is a dummy variable equal to 1 if firm *f* is a customer of only one bank, and zero otherwise.

- $small_f$ is a dummy variable equal to 1 if firm's *f* maximum debt to banks in the pre-shock sample period was smaller than the median (EUR 43,445), and zero otherwise.
- $young_f$ is a dummy variable equal to 1 if at the moment of the shock, firm *f* was younger than median (6 years), and zero otherwise.
- $short\_term_f$ is a dummy variable equal to 1 if firm's *f* average length of existing lending relationships at the moment of the shock was shorter than median (4.75 years), and zero otherwise.

- FFE - firm-fixed effects.
- TFE - time-fixed effects.
- $[all\ other\ interactions]$ – all other possible double and triple interaction terms.

In specification (1), our coefficient of interest is β_3 on the interaction term, which, if negative and statistically significant, would suggest that after the bank's failure, borrowing costs for "Distressed bank's" customers decreased more than for others. In specification (2), the coefficient of interest is β_4 on the triple interaction, which if negative and statistically significant, would indicate that, depending on the firm characteristic $char_f$, borrowing costs for either "exclusive" or "small" or "young" or "short-term" customers of "Distressed bank" dropped the most. In specification (3), the coefficient of interest is β_5 on the quadruple interaction, which if negative and statistically significant, would suggest that, depending on the firm characteristic $char_f$, borrowing costs for either "exclusive" "small" or "exclusive" "young" or "exclusive" "short-term" customers of "Distressed bank" dropped the most.

By including fixed effects, we drop the non-interacted variables but we keep them in the description above because we re-run these regressions without fixed effects as a robustness check. Yet, controlling for fixed effects is important since our panel is unbalanced. For example, some firms may have constantly high borrowing costs and many observations pre-shock but few observations post-shock if they took new post-shock loans much later than others. Without fixed effects, the presence of such firms could inflate an average drop in borrowing costs. Firm-fixed effects ensure that our results are based on within-firm variation in borrowing costs, and not on firm-specific averages that could bias the results due to the uneven distribution of observations over time. To account for the possibility of standard errors being correlated within firms and quarters, we cluster errors multiway within both dimensions. Our results remain robust if we exclude either firm-fixed effects or time-fixed effects or both and if we leave errors unclustered or if we cluster only within either one of the two dimensions.

5.2. Coarsened exact matching

There are two major concerns regarding the endogenous firm selection and we address them as follows. The first concern is that our treatment and control groups might be fundamentally different, e.g., the treatment group may consist predominantly of bad-quality firms that might have self-selected into a relationship with a bad-quality bank – "Distressed bank". The difference-in-differences method by design cancels out the effects of all observable and unobservable static differences between the two groups, while the most intuitive potential transitory differences suggest that we might underestimate our results. For example, (1) the quality of "Distressed bank's" clients might have been deteriorating over time, which could have caused the bank's closure, (2) the "Distressed bank's" closure might have undermined the perceived quality of its clients, (3) the decline in banking competition associated with the bank closures might have affected all firms but particularly those that were no longer locked in by banks (Klemperer 1987). In these cases, borrowing costs for our treatment group relative to the control group would be affected upwards and we might therefore underestimate the drop.

Nevertheless, in order to make our treatment and control groups as similar as possible and hence minimize potential transitory differences, we combine difference-in-differences with coarsened exact matching.[17] We match firms from the treatment group with firms from the control group on the following seven ex-ante measured firm-level variables summarized in Table 1c: the four variables mentioned above in the difference-in-differences framework – (1) $exclusive_f$ (dummy 1 or 0), (2) $size_f$ (+-30%)[18], (3) age_f

[17] The combination of difference-in-differences and matching methods has been shown to be one of the most robust ways to minimize the selection bias in quasi-experimental studies (Heckman et al. 1998, Smith and Todd 2005).
[18] The window of +-30% is in line with the one used by Ioannidou and Ongena (2010) in their matching exercise.

(+- one year), and (4) rel_length_f (+- one year), as well as (5) rep_delays_f (dummy 1 or 0), (6) ttm_f (+- one year), and (7) $collateralization_f$ (+-30%), where

- $exclusive_f$ is defined below the specifications (1-3) above.
- $size_f$ is firm's *f* maximum debt (in m EUR) to banks in the pre-shock sample period.
- age_f is the time difference (in quarters) between the shock and the first appearance of firm *f* in the credit register since 1995.
- rel_length_f is firm's *f* average (across banks) length (in quarters) of existing lending relationships at the moment of the shock.
- rep_delays_f is a dummy variable equal to 1 if firm *f* had at least one repayment delay in the pre-shock sample period, and zero otherwise.
- ttm_f is the longest remaining time to maturity (in quarters) among firm's *f* loans outstanding at the moment of the shock.
- $collateralization_f$ is firm's *f* average (across loans and quarters) collateralization ratio, i.e., loan collateral value divided by loan outstanding amount, of loans outstanding in the pre-shock sample period.

We re-run the difference-in-differences analysis using only those firms in both the treatment group and the control group that were matched with at least one firm from another group.

5.3. Testing parallel trends

To further alleviate the concern about transitory differences, we test the parallel trends assumption using a framework often used in event studies to examine anticipation and phase-in effects. We regress our outcome variable $borrowing\_costs_{f,q}$ on interactions between the treatment variable $closed_f$ and time period dummies. We include firm-fixed effects and time period dummies (time-fixed effects) but omit one dummy, i.e., either 2011 q4 when our dataset starts, or 2013 q1 when the shock occurs, to use it as a base. The coefficients of interest β_t indicate the difference between the treatment group's change in borrowing costs from the base time period to period *t* and the corresponding control group's change.

$$borrowing\_costs_{f,q} = \beta_0 + \sum_{t=2012Q1}^{2018Q1} \beta_t * closed_f * dummy_t + FFE + TFE + \varepsilon_{f,q} \quad (4)$$

5.4. Heckman correction

The second major concern is that we are forced to condition our difference-in-differences analysis on a post-shock outcome – “survival”, i.e., we consider only those firms in both treatment and control groups that survived and hence took at least one new loan after the shock. Even if ex-ante all “Distressed bank’s” customers were identical, randomness or luck could lead to some firms obtaining cheaper loans and some more expensive loans ex-post. Excluding a portion of firms that could not borrow again due to excessively increased borrowing costs, could explain a drop in average borrowing costs and hence bias our results. Although this would not be a problem if both the treatment and control groups were affected equally by such an attrition, the concern is that the shock might have affected the treatment group’s chances of survival more (see e.g., Martin-Oliver et al. 2020). Table 1c shows that the rate of survival (the number of firms that borrowed both ex-post and ex-ante divided by the number of firms that borrowed ex-ante) of “Distressed bank’s” customers is very similar to and even higher than the rate of survival of the control group. This suggests that the shock had limited impact on the survival of “Distressed bank’s” customers.

Nevertheless, to account for the potential attrition bias, we adjust our difference-in-differences setting to fit the Heckman (1979) two-step selection model, in which the first-stage probit model predicts the likelihood of a firm taking a new loan after the shock and thus having a non-missing observation in the second-stage outcome equation estimated by OLS. To fit the model, we collapse our panel data into two time periods by averaging firm-level quarterly observations of borrowing costs across quarters before and after the shock, and calculate firm-level changes from the first period to the second. In the outcome equation (see specification (6) below), we regress these changes on a treatment dummy $closed_f$ defined below the specifications (1-3). This is equivalent to using the specification form (1) with two time periods.[19] In the selection equation (see specification (5) below), we regress a participation dummy on the same dummy

[19] Both coefficients β_3 in specification (1) and β_1 in specification (6) estimate the difference-in-differences.

$closed_f$ and a dummy instrumental variable $long\_maturity_f$ equal to 1 if a firm's average remaining time to maturity of loans outstanding before the shock was longer than three years.[20] Firms that had loans with very long remaining time to maturity are less likely to need new loans, at least within our sample period, which helps predict participation but not necessarily the magnitude of the change in borrowing costs (the dependent variable in the outcome equation). At least one such instrument is necessary for the model to return reliable results (Little and Rubin 1987, pp. 230). We also include the seven firm characteristics that were used for matching, since they can also help predict participation.[21] The model returns similar results with and without these seven characteristics. The selection and outcome equations are specified as follows:

Selection equation: $Participation_f = \beta_0 + \beta_1 * closed_f + \beta_2 * long\_maturity_f + \beta_3 * exclusive_f + \beta_4 * size_f + \beta_5 * age_f + \beta_6 * rel\_length_f + \beta_7 * rep\_delays_f + \beta_8 * ttm_f + \beta_9 * collateralization_f + \varepsilon_f$ (5)

Outcome equation: $\Delta borrowing\_costs_f = \beta_0 + \beta_1 * closed_f + \varepsilon_f$ (6)

Where

- $Participation_f$ is a dummy variable equal to 1 if firm *f* took at least one new loan after the shock and thus has a non-missing observation of $\Delta borrowing\_costs_f$, and zero otherwise.
- $long\_maturity_f$ is a dummy variable equal to 1 if firm's *f* average remaining time to maturity of loans outstanding before the shock was longer than three years, and zero otherwise.
- $\Delta borrowing\_costs_f$ is the difference between firm's *f* borrowing costs averaged across quarters after the shock and borrowing costs averaged before the shock. Firm-quarter level borrowing costs are defined below the specifications (1-3).

[20] Ideally, we would use a cut-off point of five years, i.e., the number of years in our post-shock sample period, but only 25 customers of "Distressed bank" would have the $long\_maturity_f$ variable equal to 1. The three-year cut-off provides more variation (see Table 1c). Yet, the results are very similar with either one of the two cut-off points.

[21] Generally, firm characteristics may predict both participation and the current level of borrowing costs but not necessarily the magnitude of a future change in borrowing costs (the dependent variable in the outcome equation). In our case, however, we hypothesize and find that the change in borrowing costs is larger for small, young, short-term and exclusive customers. In order to test if our instrument can also explain the magnitude of the drop in borrowing costs, we replace the $char_f$ variable in specification (2) with the $long\_maturity_f$ but we find no significant results.

- All other variables were defined either below the specifications (1-3) or in the description of the matching exercise above.

6. Results

6.1. Main results

Table 2 presents our main results. The treatment group in row (1) comprises both good and bad "Distressed bank's" customers, row (2) comprises only good, i.e., not assigned to the "bad bank", customers, row (3) contains only bad, i.e., assigned to the "bad bank", customers, and row (4) contains "Healthy bank's" customers. The control group in every row comprises customers of all remaining banks. The five columns represent different alterations of the difference-in-differences setting. Column (1) uses specification (1) and all surviving firms, column (2) uses specification (1) and those surviving firms in both the treatment group and the control group that were matched with at least one firm from the other group, column (3) uses specification (6) (but without the Heckman correction) and all surviving firms, column (4) uses specification (6) as part of the Heckman selection model and, hence, includes non-survivors, column (5) applies the Heckman selection model in the same way as column (4) but restricts the sample to only matched firms in both the treatment group and the control group.

When using all good and bad surviving firms (row 1, column 1), the difference-in-differences estimate β_3 from regression specification (1) equals -0.424 pp and is statistically significant at 1% level. This indicates that borrowing costs for surviving "Distressed bank" customers after the shock dropped on average by 42.4 bp more than for other surviving firms. As shown in Figure 2.1, this drop was permanent and occurred primarily in the first quarter after "Distressed bank's" closure. This suggests that "Distressed bank" overcharged its customers and that since they agreed to pay the overcharge instead of switching, their ex-ante switching costs were even larger.

This result remains similar in magnitude and statistically significant at 1% level when using different alterations of our setting. First, when we restrict our treatment and control groups to matched firms (row 1, column 2), the difference-in-differences estimate β_3 from specification (1) equals -0.436 pp. Second, when we collapse borrowing costs for all surviving firms into two time periods and estimate specification (6) without the Heckman correction (row 1, column 3), the difference-in-differences estimate β_1 is equal to -0.457 pp. Third, when we estimate specification (6) with all firms as part of the Heckman selection model (row 1, column 4) the coefficient β_1 equals -0.480 pp. Finally, applying the Heckman selection model only to matched firms (row 1, column 5) returns the difference-in-differences estimate of -0.406 pp. In both estimations of the Heckman model, the results of the selection equation (5) (not reported in the table) suggest that our instrument $long\_maturity_f$ helps predict participation (β_2=-0.416 and p-value=0.000 with all firms, and β_2=-0.723 and p-value=0.000 with matched firms) in the expected direction, i.e., firms with long-maturity loans are less likely to take new loans in our post-shock sample period.[22] A statistically insignificant inverse Mills ratio (λ=0.028; p-value=0.720 with all firms, and λ=-0.104; p-value=0.571 with matched firms) suggests that firm survival does not cause a significant bias.

Rows (2) and (3) of Table 2 show that our results are exclusively driven by good "Distressed bank" customers, i.e., not assigned to the "bad bank". All surviving good customers (row 2, column 1) experienced an average drop of 59.6 bp (statistically significant at 1% level) in their borrowing costs as compared to customers of all other banks. The difference-in-differences increases and remains statistically significant at the 1% level in columns (2) to (5). When comparing only matched firms (row 2, column 2), the drop increases to 67.6 bp. When using the Heckman selection model and all firms (row 2, column 4), the drop becomes 72 bp. When applying the Heckman selection model only to matched firms (row 2, column 5), the drop equals 72.2 bp. In both estimations of the Heckman model, the inverse Mills ratio is not statistically significant, and the coefficient on the instrument $long\_maturity_f$ in the selection equation is negative and statistically significant at 1% level. Figure 2.2. shows that the drop in borrowing costs for good "Distressed bank" customers was permanent and occurred immediately after the shock.

Row (3) shows that bad firms, i.e., assigned to the "bad bank", on average experienced no significant drop (β_3=-0.270 and p-value=0.140 in row 3, column 1), and when estimated by the Heckman

[22] The selection equation (5) correctly predicts participation in 65% of cases (66% for cases of "Distressed bank" customers). A firm is said to participate if its probability of participation predicted by the probit model is equal to or larger than 0.5.

selection model, experienced a significant hike (β_1=0.493 and p-value=0.004 in row 3, column 4) in their borrowing costs. Figure 2.2. shows that the hike in borrowing costs for the bad "Distressed bank's" customers occurred immediately after the bank's closure. The figure also reveals that these firms borrowed on average more cheaply than the good customers before the shock. This can be explained by the personal connections between these firms and the bank's major shareholder as mentioned in Section 4. Hence, the hike in borrowing costs can be explained by both the end of the preferential treatment and the transparency introduced by KPMG regarding the firms' quality. In both estimations of the Heckman model, the coefficient on the instrument $long\_maturity_f$ in the selection equation remains negative and statistically significant at the 1% level. The inverse Mills ratio for the case represented by row (3), column (4) is statistically significant at 10% level (λ=0.138; p-value=0.081), which suggests that the attrition might bias our results for bad customers. This is in line with their lower survival rate of 43% (112/260) as compared to 50% (449/898) for good "Distressed bank" customers and 46% (7,804/16,798) for all other firms (see Table 1c). In the rest of the analysis, we focus on good "Distressed bank" customers and we do so for the following reasons.

First, we aim to measure switching costs that are likely to stem primarily from information asymmetries (Bonfim et al. 2020), and in theory (Sharpe 1990, Rajan 1992, von Thadden 2004), as explained in Section 2, only good firms suffer from such costs as they can be mistakenly assumed to be bad by outside banks. This explains why we are primarily interested in survivors, since not being able to borrow at all signals the worst-quality type.[23] Second, by dropping firms that caused the bank's closure, i.e., those assigned to the "bad bank" by KPMG, we retain those to which the closure was less endogenous and that are more comparable to the rest of the market, i.e., our control group. Third, good-quality firms are particularly important to the economy due to their productivity (Caballero et al. 2008) and employment (Falato and Liang 2016).

[23] Both "Distressed bank's" customers and other firms that did not take new loans after "Distressed bank's" closure on average were more likely to delay at least one loan repayment before the shock (see Table 1c).

Our results remain similar if we split "Distressed bank's" customers into good and bad differently – based on the ex-ante measured variable $collateralization_f$ defined in Section 5. Arguably, the best-quality firms would be trusted more and would thus require less collateral. We find that the least collateralized quarter of "Distressed bank's" surviving customers experienced a drop of 1.07 pp (p-value=0.001) in their borrowing costs, while the most collateralized quarter experienced no statistically significant drop. These results are even stronger when using different settings represented by columns (2) to (5) of Table 2. The main concern using this quality measure is that if ex-ante the least collateralized firms became more collateralized ex-post, this would explain the drop in their borrowing costs. However, in the robustness test section below, we show that the shock had no significant impact on the collateralization of good "Distressed bank" customers.

Overall, the results in Table 2 suggest that switching costs for good firms are statistically and economically significant especially considering their relatively small size. Back of the envelope calculation (i.e., multiplying firms' average debt to banks of EUR 1,892,636 from Table 1c by the average overcharge of 59.6 bp) suggests that each of the good "Distressed bank" customers on average overpaid EUR 11,280 on their yearly interest payments, which adds up to almost two average annual salaries in Lithuania in 2012. At least three factors related to the bank's closure can help explain why good firms' borrowing costs dropped: (1) the alleviation of the winner's curse (reduced interbank information asymmetries), (2) the transparency introduced by KPMG (reduced firm-bank information asymmetries), and (3) the possibility that these firms could have always switched and borrowed more cheaply, but chose not to, due to some shoe-leather switching costs, until they were forced to do so. Similarly, at least three factors can help explain why bad firms' borrowing costs did not drop: (1) the ex-ante low borrowing costs owing to connections with the bank's major shareholder, (2) the transparency introduced by KPMG, and (3) the possibility that before the shock, outside banks had at least some noisy information about these firms' quality.[24]

[24] As explained in Section 2 "Theoretical framework", when a bank is closed, good and bad customers of the closed bank will be pooled together and could experience similar drops in borrowing costs only if outside banks had virtually no information about these firms' quality. If outside banks have some noisy information, an alleviation of the winner's curse could lead to a large drop in borrowing costs for good firms and a virtually zero drop for bad firms.

Row (4) in Table 2 presents the results of the difference-in-differences analyses for “Healthy bank’s” customers used as a treatment group. In all five columns, the difference-in-differences is statistically insignificant. Figure 2.3 shows that average borrowing costs of “Healthy bank’s” customers followed the common trend without major shifts before and after the bank’s closure. This suggests that, on average, relationships with “Healthy bank” neither reduced nor inflated borrowing costs for firms. The contrasting results between the healthy and the distressed banks suggest that, in line with Sharpe (1990) and Boot et al. (1993), reputational concerns may be affected by a bank’s health and, in turn, may have an impact on a bank’s decision to exploit firms’ switching costs. In addition, distressed banks may overcharge their borrowers as an attempt to pass on their own increasing borrowing costs. Another explanation could be that “Healthy bank’s” customers were of the best-quality type, which is suggested by their lower-than-average borrowing costs in Figure 2.3 and the most infrequent repayment delays as compared to customers of other banks, and they managed to signal that to outside banks, which made it difficult for “Healthy bank” to hold up and overcharge these firms.

6.2. Parallel trends

We use the regression specification (4) to test the parallel trends assumption, which states that in the absence of the treatment, the difference between the treatment group and the control group would be constant over time. This should especially be the case when the two groups are as similar as possible. Thus, in this exercise we use matched firms in both groups and exclude bad, i.e., assigned to the “bad bank”, customers of “Distressed bank”. As shown above (see Table 2, row 2, column 2), the difference-in-differences in this setting equals -67.6 bp. Due to the “reverse” nature of our difference-in-differences setting, whereby in the post-shock period, customers of “Distressed bank” are released from the hold-up (treatment), switch to healthier banks and, thus, are more similar to the control group, i.e., all other firms borrowing from the same banks, post-shock trends are particularly important (Kim and Lee 2018).

Table 3 presents the results. In column (1), as we omit the first time period dummy representing 2011 q4, we use this time period as the base. We find that regression coefficients on interactions between the treatment variable and time dummies up to the shock are positive, statistically significant and gradually increasing in magnitude, which indicates that, as compared to 2011 q4, the average difference in borrowing costs between the treatment and control groups increased throughout the year preceding the shock. This suggests that pre-shock trends were not parallel but, in the absence of the bank closure, borrowing costs for "Distressed bank's" customers would have grown even larger. Thus, we might underestimate the lower bound of ex-ante switching costs. The diverging trends also suggest that the bank used to overcharge its customers less, if anything, but this gradually changed as the bank's health deteriorated, which may explain why firms borrowed from this bank in the first place. Negative and statistically significant coefficients on post-shock interaction terms indicate the sudden drop in borrowing costs immediately after the shock, in line with the difference-in-differences analysis.

In column (2), we test if post-shock trends were parallel by omitting the time period dummy representing the first quarter after the shock (2013 q1). All the post-shock coefficients on the interaction terms between the treatment variable and time dummies are statistically insignificant, which suggests that the difference in borrowing costs between the treatment and control groups has not changed significantly since the shock and, hence, that post-shock trends were parallel. The same conclusions, i.e., diverging pre-shock trends and parallel post-shock trends, are suggested by the visual inspection of Figure 3, which plots average borrowing costs of the treatment and control groups used in this setting. Columns (3) and (4) in Table 3 show that results remain similar when including bad, i.e., assigned to the "bad bank", firms in the treatment group.

6.3. Heterogeneous effects

In order to better understand sources of switching costs, we exploit the heterogeneity of firms. Opaquer firms, i.e., smaller, younger and those that borrow only from one bank, might be more vulnerable to switching costs stemming from information asymmetries. We use regression specifications (2) and (3) to test these hypotheses. The treatment group comprises only good "Distressed bank" customers that drive the results in our main difference-in-differences analysis above. In both groups, we include all, i.e., not only matched, firms as this setting provides the most conservative difference-in-differences estimate in the main analysis above (see column 1 in Table 2, row 2) and maximizes the number of firms in the sample, which helps exploit the heterogeneity.

Table 4 presents the results. Column (1) shows the difference-in-differences estimate of -0.596 pp (p-value=0.000) obtained using specification (1) (the same as in Table 2, row 2, column 1), columns (2) to (5) present coefficient estimates using regression specification (2) and columns (6) to (8) show the estimated coefficients for specification (3). The coefficient on the triple interaction with the variable $exclusive_f$ in column (2) equals -0.881 and is statistically significant at the 5% level, which suggests that the drop in borrowing costs was significantly larger for exclusive "Distressed bank" clients and on average amounted to 1.28 pp (the sum of coefficients reported in column 2). Similarly, negative and statistically significant coefficients on the other triple interactions in columns (3) to (5) suggest that the drop in borrowing costs was driven by small, young and short-term clients that experienced average drops of 0.95 pp, 1.26 pp, and 0.87 pp (sums of coefficients in each column), respectively. Negative and statistically significant coefficients (at least at the 10% level) on the quadruple interactions in columns (6) to (8) show that the drop was largest for exclusive small, exclusive young, and exclusive short-term customers. On average, they experienced drops of 1.72 pp, 2.38 pp, and 1.86 pp, respectively. The results suggest that asymmetric information is an important cause of switching costs.

Table 5 shows that these results are stronger if we exclude from both the treatment group and the control group firms that took new loans from "Acquiring bank" after the shock. As shown in Table 1c, 222 of the 449 surviving good "Distressed bank" customers switched to other banks and did not take any new post-shock loans from "Acquiring bank". Using these firms as the treatment group provides both advantages and disadvantages. On the one hand, this alleviates the concern that our results are driven by post-shock loan pricing of a single "Acquiring bank". Moreover, in this setting, the treatment group comprises better-quality firms, and is therefore more similar to the control group.[25] On the other hand, such firm selection

[25] As explained in Section 4, "Acquiring bank" was similar to "Distressed bank" in terms of many aspects including the clientele, and hence was likely to attract on average worse-quality firms than the rest of the market. Most of firms in the control group borrowed from well-reputed Scandinavian banks that jointly held more than 80% of the total corporate loan amount.

may raise endogeneity concerns since the difference-in-differences analysis becomes conditioned on a post-shock measure (see e.g., Montgomery et al. 2018) of firms' quality – the ability to switch to a well-reputed bank. In principle, it is possible that the quality of firms in the treatment group increased in the period between the shock and switching, which might have enabled them to both switch to well-reputed banks and borrow more cheaply, and this would explain our results. Yet, our estimated drop of borrowing costs occurs in 2013 q1, i.e., within 6 weeks after the shock, thus, we deem it unlikely that firms' quality could have fundamentally changed, especially positively, so quickly. In addition, these firms were among the best ex-ante, as indicated by their low collateralization and infrequent repayment delays (see Table 1c). As a robustness check, we re-estimate the difference-in-differences using matching and the Heckman selection model.

Table 5, column (1) shows that the difference-in-differences estimate from specification (1) equals -1.05 pp and is statistically significant at the 1% level. This suggests that "Distressed bank" overcharged its best-quality customers, i.e., firms that were not assigned to the "bad bank" by KPMG and switched for new loans to better-reputation banks than "Acquiring bank", by 1.05 pp on average. Back of the envelope calculation (i.e., multiplying firms' average debt to banks of EUR 2,455,343 from Table 1c by the average overcharge of 1.05 pp) suggests that each of these firms on average overpaid EUR 25,781 on their yearly interest payments, which adds up to almost four average annual salaries in Lithuania in 2012. We test the robustness of this estimate (not reported in Table 5), using matching and the Heckman selection model. The difference-in-differences remains always significant at the 1% level and is equal to -1.01 pp with matching, -1.15 pp without matching but with data collapsed into two periods, -1.20 pp without matching but with the Heckman correction, and -1.13 pp with both matching and the Heckman correction. Columns (2) to (8) of Table 5 report negative and statistically significant (at least at the 10% level) coefficients on the triple and quadruple interactions, which suggest that the overcharge was significantly larger for exclusive (3.10 pp), small (1.65 pp), young (1.79 pp), short-term (1.36 pp), and particularly for exclusive small (3.69 pp), exclusive young (4.32 pp) and exclusive short-term (4.08 pp) "Distressed bank" customers, respectively.[26]

The dynamics of average borrowing costs are presented in Figures (4.1) to (4.5). Figure 4.1 shows that, before the shock, firms in the treatment group were borrowing increasingly more expensively than other firms, but immediately after the shock, their borrowing costs dropped and permanently converged to the rest of the market.[27] This suggests that firms in the treatment group and the control group were in expectation similar and the treatment group was overcharged ex-ante. Figures (4.2) to (4.5) show that exclusive, and particularly exclusive small, exclusive young and exclusive short-term "Distressed bank" customers, respectively, were overcharged the most.

6.4. Robustness tests

We do a series of robustness checks and present the results in Table 6. We re-run regression specification (1) by altering the default setting used in the analysis of heterogeneous effects, whereby the treatment group comprises good, i.e., not assigned to the "bad bank", "Distressed bank" customers and both the treatment group and the control group include all, i.e., not only matched, surviving firms. This setting returns the difference-in-differences estimate of -0.596 pp (see Table 2, row 2, column 1).

Firstly, our results remain similar when using only term loans (column 1) and only leasing contracts (column 2).

Secondly, the results remain similar when using an alternative control group (column 3). Instead of customers of all banks other than "Distressed bank", we use customers of "Acquiring bank" – the bank that was most similar to "Distressed bank" in terms of size, customer quality (measured as a proportion of firms with delayed repayments) and customers' average loan rates.

[26] The numbers in parentheses report the total average drops in borrowing costs for each sub-group in excess of the control group, and are calculated by summing up all coefficients reported in the respective columns of Table 5.
[27] The parallel trends' test, i.e., specification (4), with these treatment and control groups returns no significant coefficients on post-shock interaction terms, when omitting the dummy representing 2013 q1. This suggests parallel post-shock trends of borrowing costs. We show that borrowing costs were also of the same level using a robustness test below.

Thirdly, column (4) shows that our results remain very similar if we consider only newly issued loans in each quarter. This suggests that the refinancing costs of old loans were not the primary cause of the overall ex-ante switching costs. We use this setting as a robustness check and not as the main analysis since a reduced number of observations makes it challenging to exploit firms' heterogeneity.

Fourthly, column (5) shows that the results remain similar if we consider only "Distressed bank's" good customers whose loans were not assigned either to the "bad bank" or to the "good bank" by KPMG (175 firms). These firms had their loans removed from the credit register when the bank closed, which suggests that their assets and liabilities with "Distressed bank" had been netted off as part of the resolution process. Hence, these firms were unambiguously forced to switch and did not receive any potential benefits of being explicitly assigned to the "good bank".

Fifthly, the two almost simultaneous closures of "Healthy bank" and "Distressed bank" are likely to have affected loan market concentration, as indicated by the jump in the Herfindahl-Hirschman Index from 1,796 in 2012 Q4 to 1,959 in 2013 Q2. This would not affect the results of the difference-in-differences analysis if the change in concentration had equal effects on firms in both the treatment group and the control group. However, according to Klemperer (1987), in markets with switching costs, "the monopoly power that firms gain over their respective market segment leads to vigorous competition for market share before consumers have attached themselves to suppliers". Thus, firms that have lost and are lacking lending relationships (i.e., our treatment group) may be affected by the competition more than firms which are already locked-in by banks. Weakening competition should drive interest rates upwards, while our difference-in-differences analysis shows a steep drop. This suggests that, due to changes in competition, we may underestimate the drop. We run a robustness test in which we make our treatment and control groups as similar as possible with respect to the sensitivity to competition. We disregard forced switching loans of "Distressed bank" customers, i.e., the first loans taken from new banks after the bank's closure, and consider only subsequent loans taken after new relationships were started. As shown in column (6), the difference-in-differences remains similar to the default setting.

Sixthly, we could observe a drop of loan rates if customers of "Distressed bank" were either asked to provide more collateral or borrowed different amounts, or borrowed with different loan maturities, after switching to other banks. To test this, we replace interest rates with other loan characteristics in the calculation of the dependent variable in our default setting. Neither the percentage of loan collateralized (columns 7) nor maturity (column 8) nor loan size (column 9) show statistically significant changes. This suggests that our estimated ex-ante switching costs were not driven by a potential loss of other beneficial loan terms.

Finally, we run a robustness check to test whether borrowing costs of comparable firms from the treatment group and the control group converged as suggested by Figures (4.1) to (4.5). We implement a post-shock loan matching analysis that resembles the work of Bonfim et al. (2020). The authors find that firms received discounts on newly issued loans when switching banks endogenously, which is in line with Ioannidou and Ongena (2010), but no discounts when forced to switch by closures of bank branches. The authors interpret this as evidence that information asymmetries, and not shoe-leather costs, drive switching costs. The interpretation follows from an empirical prediction of von Thadden's (2004) model that explains regular-switching discounts as successful randomized attempts of uninformed outside banks to attract firms from better informed inside banks (see Section 2). Thus, if an inside bank closes, there is no reason to offer a discount. If, instead, shoe-leather switching costs and the competition for market share were causing discounts (Klemperer 1987), a firm should receive one regardless of whether it has an inside bank or not. In order to estimate the discounts, Bonfim et al. (2020) match newly issued forced-switching (or "transfer") loans with newly issued non-switching loans on a number of variables and compare interest rates between them. Similarly, we use matching variables defined in Table 7 to match newly issued post-shock loans of "Distressed bank's" good, i.e., not assigned to the "bad bank", customers with newly issued post-shock loans of other firms. Two loans were paired if they were of the same type (i.e., term loan, leasing or credit line), had similar size, collateral and time-to-maturity, and if they were issued in the same year-quarter, by the same bank, to two firms – one a good customer of "Distressed bank" and one other firm – that were similar in terms of age, size, collateralization, history of repayment delays, number of banking relationships and length of those relationships. For every matched pair we calculated an interest rate spread, i.e., an interest rate on a loan of a "Distressed bank" customer minus an interest rate on another firm's loan, and regress it on a constant. Every loan of "Distressed bank's" customers could be matched with more than one loan of other firms, thus, we cluster errors at the former loan level.

Table 8 presents the results. In column (1), we keep the number of matching variables to the minimum in order to maximize the number of observations. Two loans were matched if they were of the same type, issued in the same year-quarter, by the same bank to two similar firms in terms of age and size (we use a +-30% window in line with Ioannidou and Ongena (2010)). This setting provides 17,421 observations, i.e., matched loan pairs, comprising 2,119 loans issued to 393 "Distressed bank's" customers, and 7,244 loans issued to 2,661 other firms. The average interest rate spread equals -1.3 bp (p-value=0.709), which suggests that after the bank's closure, good "Distressed bank's" customers switched and borrowed on average at the same interest rates as other firms, when controlling for the matching variables. The spread remains statistically insignificant in columns (2) to (4) that include more control variables. Column (2) includes five other firm characteristics in line with the matching variables used in the difference-in-differences analysis above. Column (3) replaces firm-level size, collateralization and time-to-maturity with corresponding loan-level variables. Column (4) includes all matching variables. This result suggests that forced-switchers borrowed at roughly the same rates as old customers of the same banks and, thus, is broadly in line with the findings of Bonfim et al. (2020).

7. Conclusions

We explore loan-level data and two bank closures to understand how costly it can be for firms to switch banks, what causes these switching costs, and whether banks exploit these switching costs by overcharging their customers. In particular, we examine firms' loan interest rates in a difference-in-differences framework and address firm selection-related endogeneity concerns with the coarsened exact matching method and the Heckman (1979) selection model. We find that after the respective bank closures, the loan rates of "Healthy bank's" customers did not change, while loan rates for "Distressed bank's" customers dropped on average by 42 bp immediately and permanently. This suggests that "Distressed bank" overcharged its customers, and since they paid the overcharge instead of switching, their ex-ante switching costs must have been even higher. The contrasting evidence between the two banks suggest that distressed banks may try to extract more rents due to weaker reputational concerns (Sharpe 1990, Boot et al. 1993) and/or to pass on their own increasing borrowing costs to their borrowers. In addition, "Healthy bank" had few but arguably best-reputed borrowers, hence, they might have been difficult to hold up and overcharge.

In line with informational hold-up theories (Sharpe 1990, Rajan 1992, von Thadden 2004), the following evidence suggests that switching costs stem primarily from information asymmetries as opposed to shoe-leather costs. First, we find that better-quality and opaquer firms, i.e., those that were small, young and lacking other lending relationships, were overcharged the most. Second, we find no significant difference-in-differences in loan collateral, maturity and size, which suggests that switching costs were not driven by other ex-ante beneficial loan terms. Third, our results remain similar when using newly issued loans, which suggests a limited role of refinancing costs.

We demonstrate that lending relationships with distressed banks can be harmful, and, for the first time, show how hold-up costs disappear when a bank is shut down. In this way, we provide a novel identification of the hold-up problem and one of the first empirical estimates of firms' switching costs in the loan market. We would expect similar results in other loan markets, characterized by relatively small, opaque and bank-dependent firms and a high concentration of banks. A similar setting, whereby customers are forced to switch, could be applied to study switching costs in other markets.

Finally, our results have policy implications. First, we provide one benefit of bank closures for regulators to consider and weigh against the costs when resolving failed banks: a bank closure may help good-quality firms borrow more cheaply. Second, our results suggest that rising loan rates might be a sign of banks' distress; thus, monitoring these rates could help policy-makers protect financial stability. Third, as our evidence suggests that important information asymmetries remain despite a credit bureau providing detailed ten-year credit histories, regulators might be advised to aim to reduce these asymmetries further, e.g., with measures against loan evergreening.

FIGURE 2.1

Borrowing costs for "Distressed bank's" customers

Figure 2.1 complements the results of Table 2, column (1), row (1), which reports the difference-in-differences estimate of -42.2 pp. The figure shows how average borrowing costs for two groups of firms, namely surviving customers of "Distressed bank" and surviving customers of all other banks, evolve over time. "Surviving" is defined by taking at least one new loan both before and after "Distressed bank's" closure. A firm is considered a customer of a bank if it had any debt with that bank within one year prior to 2013 February 12 (failure of "Distressed bank"). This shock is marked by the vertical line. Borrowing costs for each firm equal an average interest rate weighted by loan outstanding amounts in each quarter. Leasing contracts, term loans and credit lines are considered. After the shock, only contracts issued after the shock are considered.

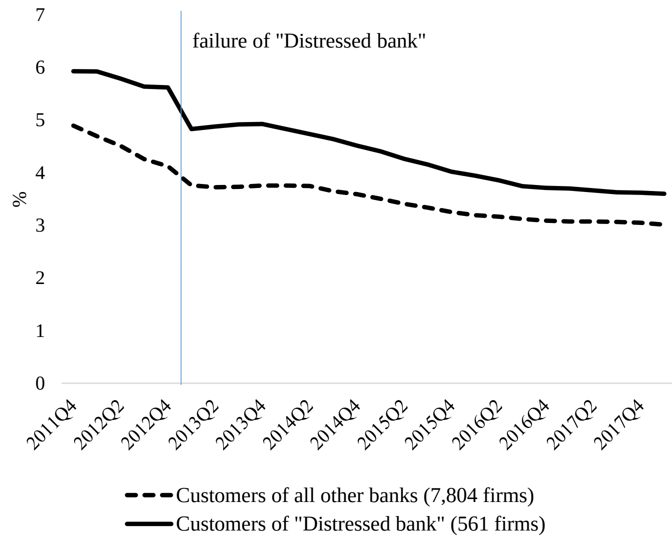


FIGURE 2.2

Borrowing costs for "Distressed bank's" good and bad customers

Figure 2.2 complements the results of Table 2, column (1), rows (2) and (3), which report the difference-in-differences estimates of -59.6 pp and 27pp, respectively. The figure shows how average borrowing costs for three groups of firms, namely good and bad surviving customers of "Distressed bank" and surviving customers of all other banks, evolve over time. "Surviving" is defined by taking at least one new loan both before and after "Distressed bank's" closure. A firm is considered a customer of a bank if it had any debt with that bank within one year prior to 2013 February 12 (failure of "Distressed bank"). This shock is marked by the vertical line. A firm is considered "bad" ("good") if it was (was not) assigned to the "bad bank" by KPMG. Borrowing costs for each firm equal an average interest rate weighted by loan outstanding amounts in each quarter. Leasing contracts, term loans and credit lines are considered. After the shock, only contracts issued after the shock are considered.

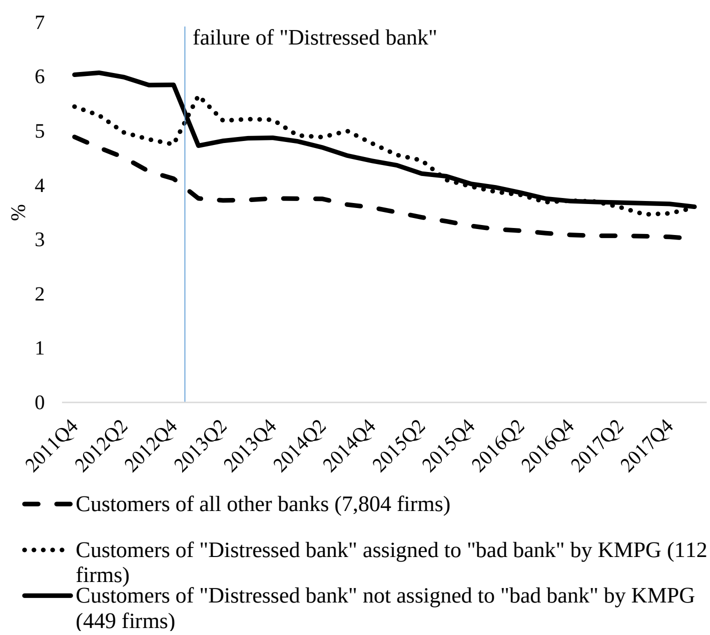


FIGURE 2.3

Borrowing costs for “Healthy bank’s” customers

Figure 2.3 complements the results of Table 2, column (1), row (4), which reports the difference-in-differences estimate of 18.4 pp. The figure shows how average borrowing costs of two groups of firms, namely surviving customers of “Healthy bank” and surviving customers of all other banks, evolve over time. “Surviving” is defined by taking at least one new loan both before and after “Healthy bank’s” closure. A firm is considered a customer of a bank if it had any debt with that bank within one year prior to January 30 (the day of “Healthy bank’s” announcement to stop business). This shock is marked by the vertical line. Borrowing costs for each firm equal an average interest rate weighted by loan outstanding amounts in each quarter. Leasing contracts, term loans and credit lines are considered. After the shock, only contracts issued after the shock are considered.

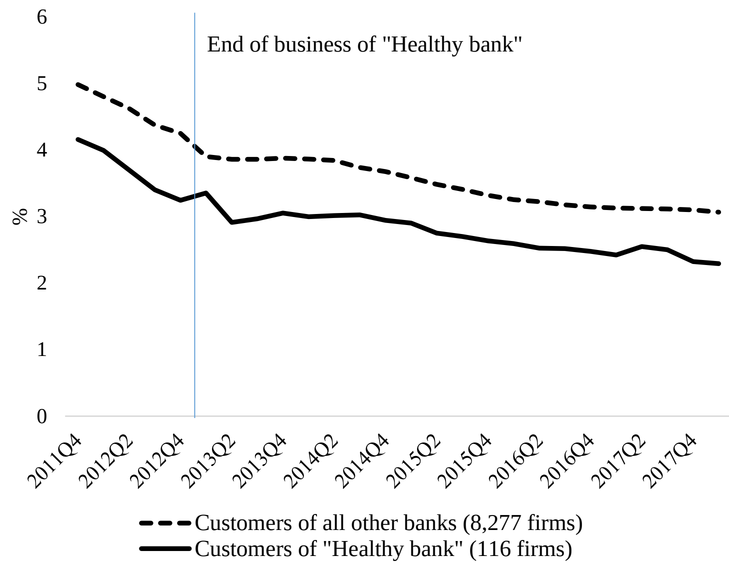


FIGURE 3

Borrowing costs for matched good “Distressed bank” customers

Figure 3 complements the results of Table 3, columns (1) and (2), and Table 2, column (2), row (2), which reports the difference-in-differences estimate of -67.6 pp. The figure shows how average borrowing costs of two groups of firms, namely good matched surviving customers of “Distressed bank” and matched surviving customers of all other banks, evolve over time. “Surviving” is defined by taking at least one new loan both before and after “Distressed bank’s” closure. A firm is considered a customer of a bank if it had any debt with that bank within one year prior to 2013 February 12 (failure of “Distressed bank”). This shock is marked by the vertical line. A firm is considered “good” if it was not assigned to the “bad bank” by KPMG. A firm is considered “matched” if the other group contained a similar firm in terms of the seven ex-ante characteristics defined in Section 5. Borrowing costs for each firm equal an average interest rate weighted by loan outstanding amounts in each quarter. Leasing contracts, term loans and credit lines are considered. After the shock, only contracts issued after the shock are considered.

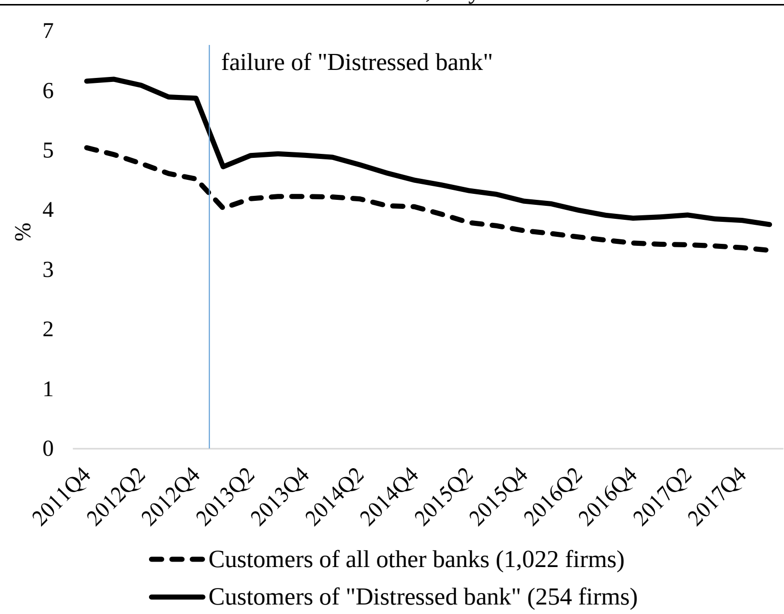


FIGURE 4.1

Borrowing costs for good customers that did not switch to "Acquiring bank"

Figure 4.1 complements the results of Table 5, column (1). The figure shows how average borrowing costs for two groups of firms, namely good surviving customers of "Distressed bank" and good surviving customers of all other banks, evolve over time. "Surviving" is defined by taking at least one new loan both before and after "Distressed bank's" closure. A firm is considered a customer of a bank if it had any debt with that bank within one year prior to 2013 February 12 (failure of "Distressed bank"). This shock is marked by the vertical line. A firm is considered "good" if it was not assigned to the "bad bank" by KPMG and took no new loans from "Acquiring bank" after the shock. Borrowing costs for each firm equal an average interest rate weighted by loan outstanding amounts in each quarter. Leasing contracts, term loans and credit lines are considered. After the shock, only contracts issued after the shock are considered.

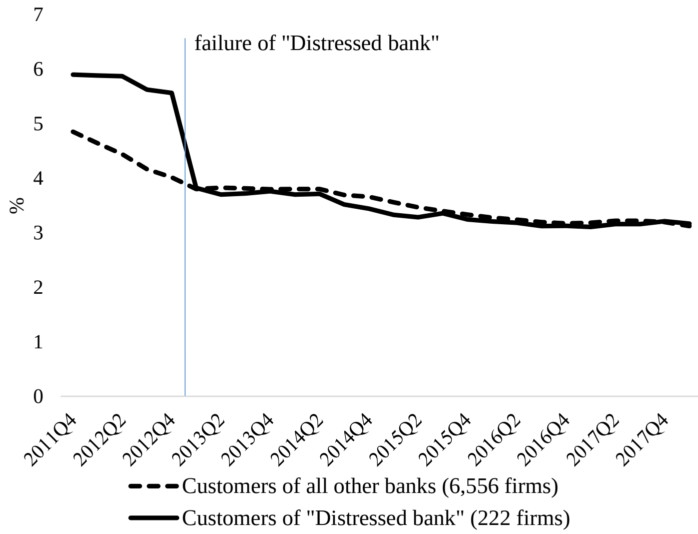


FIGURE 4.2

Borrowing costs for good exclusive customers that did not switch to "Acquiring bank"

Figure 4.2 complements the results of Table 5, column (2). The figure shows how average borrowing costs for four groups of firms, namely exclusive and non-exclusive customers of "Distressed bank" and exclusive and non-exclusive customers of all other banks, evolve over time. In all the groups we consider good surviving customers. "Surviving" is defined by taking at least one new loan both before and after "Distressed bank's" closure. A firm is considered a customer of a bank if it had any debt with that bank within one year prior to 2013 February 12 (failure of "Distressed bank"). This shock is marked by the vertical line. If a firm had debts only with that one bank, it is an "exclusive" customer. A firm is considered "good" if it was not assigned to the "bad bank" by KPMG and took no new loans from "Acquiring bank" after the shock. Borrowing costs for each firm equal an average interest rate weighted by loan outstanding amounts in each quarter. Leasing contracts, term loans and credit lines are considered. After the shock, only contracts issued after the shock are considered.

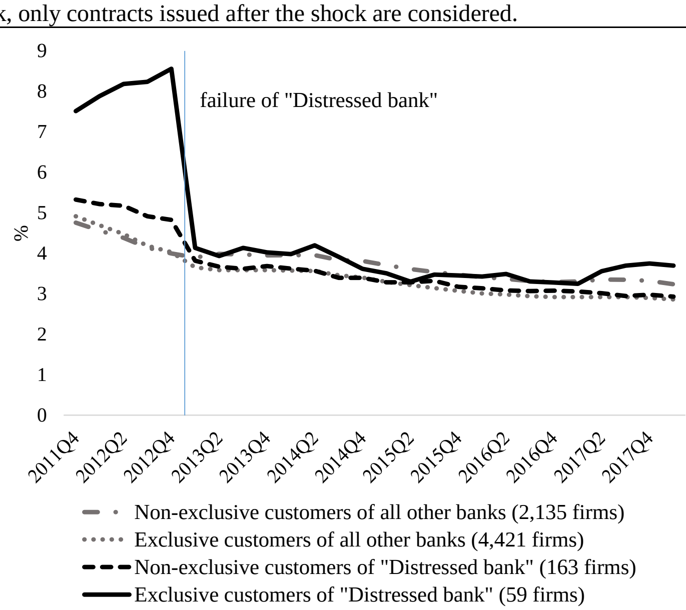


FIGURE 4.3

Borrowing costs for good exclusive small customers that did not switch to “Acquiring bank”

Figure 4.3 complements the results of Table 5, column (6). The figure shows how average borrowing costs for four groups of firms, namely exclusive and non-exclusive, large and small customers of “Distressed bank”, evolve over time. In all the groups we consider good surviving customers. “Surviving” is defined by taking at least one new loan both before and after “Distressed bank’s” closure. A firm is considered a customer of a bank if it had any debt with that bank within one year prior to 2013 February 12 (failure of “Distressed bank”). This shock is marked by the vertical line. If a firm had debts only with that one bank, it is an “exclusive” customer. If a firm’s total maximum debt to banks from 2011 q4 to 2013 q1 was smaller than the median of “Distressed bank’s” customers, it is a “small” customer. A firm is considered “good” if it was not assigned to the “bad bank” by KPMG and took no new loans from “Acquiring bank” after the shock. Borrowing costs for each firm equal an average interest rate weighted by loan outstanding amounts in each quarter. Leasing contracts, term loans and credit lines are considered. After the shock, only contracts issued after the shock are considered.

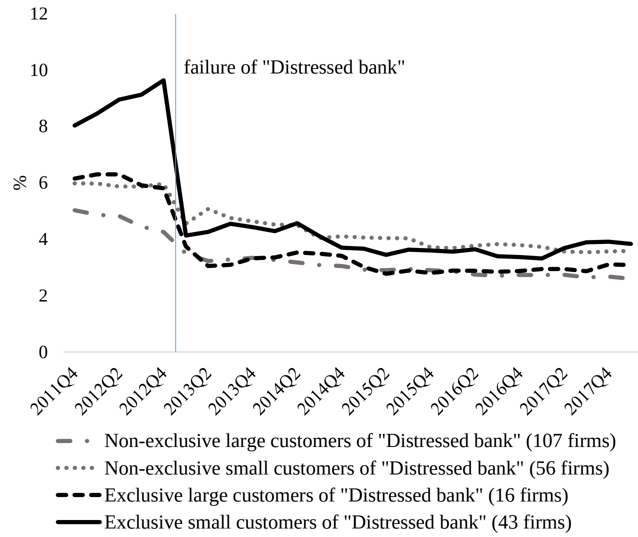


FIGURE 4.4

Borrowing costs for good exclusive young customers that did not switch to “Acquiring bank”

Figure 4.4 complements the results of Table 5, column (6). The figure shows how average borrowing costs of four groups of firms, namely exclusive and non-exclusive, old and young customers of “Distressed bank”, evolve over time. In all the groups we consider good surviving customers. “Surviving” is defined by taking at least one new loan both before and after “Distressed bank’s” closure. A firm is considered a customer of a bank if it had any debt with that bank within one year prior to 2013 February 12 (failure of “Distressed bank”). This shock is marked by the vertical line. If a firm had debts only with that one bank, it is an “exclusive” customer. If a firm’s first appearance on the credit register was later than the median of “Distressed bank’s” customers, it is a “young” customer. A firm is considered “good” if it was not assigned to the “bad bank” by KPMG and took no new loans from “Acquiring bank” after the shock. Borrowing costs for each firm equal an average interest rate weighted by loan outstanding amounts in each quarter. Leasing contracts, term loans and credit lines are considered. After the shock, only contracts issued after the shock are considered.

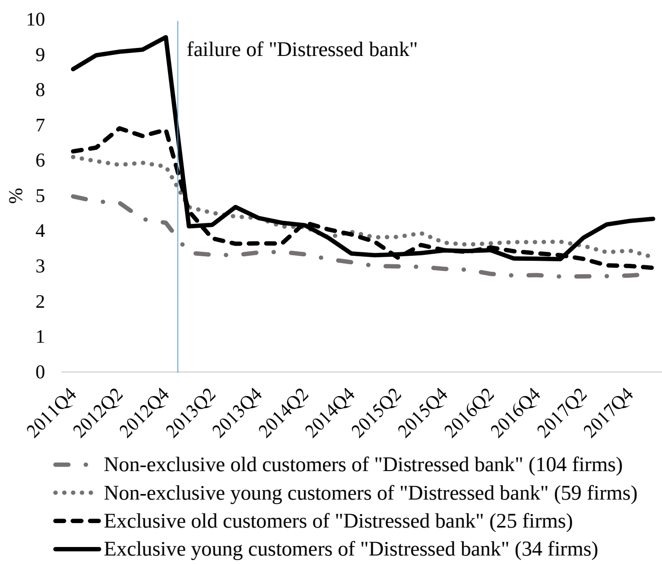


FIGURE 4.5

Borrowing costs for good exclusive short-term customers that did not switch to “Acquiring bank”

Figure 4.5 complements the results of Table 5, column (6). The figure shows how average borrowing costs of four groups of firms, namely exclusive and non-exclusive, long-term and short-term customers of “Distressed bank”, evolve over time. In all the groups we consider good surviving customers. “Surviving” is defined by taking at least one new loan both before and after “Distressed bank’s” closure. A firm is considered a customer of a bank if it had any debt with that bank within one year prior to 2013 February 12 (failure of “Distressed bank”). This shock is marked by the vertical line. If a firm had debts only with that one bank, it is an “exclusive” customer. If a firm’s average relationship length with its banks in 2013 q1 was shorter than the median of “Distressed bank’s” customers, it is a “short-term” customer. A firm is considered “good” if it was not assigned to the “bad bank” by KPMG and took no new loans from “Acquiring bank” after the shock. Borrowing costs for each firm equal an average interest rate weighted by loan outstanding amounts in each quarter. Leasing contracts, term loans and credit lines are considered. After the shock, only contracts issued after the shock are considered.

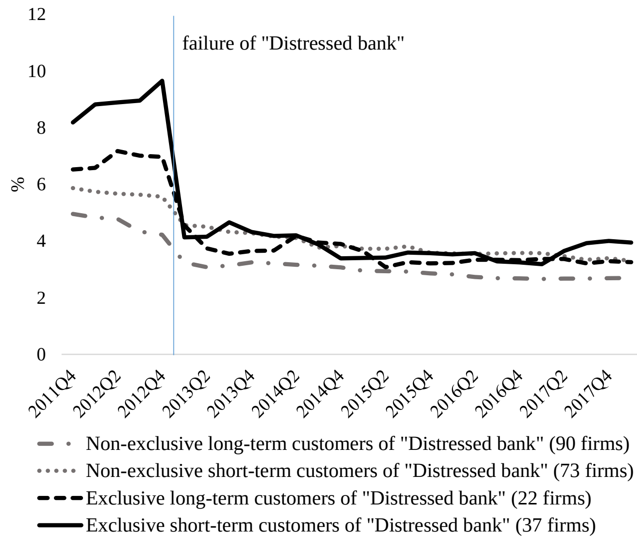


TABLE 1a

Summary statistics of loan characteristics

Loan type		Leasing	Term loans	Credit lines	Other	Total
Number of loans		131,238	24,507	7,847	27,136	190,728
Number of loans collateralized		2,170	20,045	6,700	9,850	38,765
Percentage of loans collateralized		2%	82%	85%	36%	20%
Loan size (EUR) average		49,443	1,039,184	696,573	374,643	249,509
	25th percentile	12,729	34,754	30,000	1,014	12,164
	median	23,364	113,143	94,127	10,000	25,809
	75th percentile	54,747	463,392	300,000	60,000	71,330
Loan maturity (years) average		2.9	3.4	1.0	1.3	2.7
	25th percentile	1.8	1.3	0.5	0.5	1.0
	median	2.8	2.8	0.8	0.8	2.8
	75th percentile	4.3	4.8	1.5	1.8	4.0
Loan interest rate (%) average		3.2	4.4	4.1	6.0	3.8
	25th percentile	1.9	2.9	2.8	1.4	2.0
	median	3.0	4.0	4.1	4.1	3.2
	75th percentile	4.2	5.5	5.4	8.8	4.8

Table 1a reports summary statistics of all the loans as of their first appearance in the dataset. Statistics are split by loan type.

TABLE 1b

Summary statistics of firm characteristics

Firms' industry	Manufacturing	Retail/Wholesale	Transportation	Other	Total
# of firms	3,721	9,218	4,203	18,763	35,905
# of firms without repayment delays	2,969	7,761	3,353	15,863	29,946
# of firms with repayment delays	752	1,457	850	2,900	5,959
% of firms with repayment delays	20%	16%	20%	15%	17%
Average firm size (proxied by debt to banks)	1,814,507	742,461	913,029	1,607,159	1,325,397
25th percentile	25,171	19,740	26,271	12,200	16,492
median	96,858	57,924	86,065	40,000	52,896
75th percentile	434,751	229,564	299,692	201,143	246,129
# of firms in 2011q4	2,079	4,682	2,163	8,342	17,266
Average firm size in 2011q4 (proxied by debt to banks)	1,143,001	609,154	640,372	1,216,805	970,929
25th percentile	27,343	20,273	33,596	14,731	19,028
median	101,367	57,729	101,367	44,685	59,923
75th percentile	438,606	225,415	322,799	257,413	275,412
# of firms with a single relationship in 2011Q4*	1,449	3,509	1,511	6,861	13,330
# of firms with multiple relationships in 2011Q4*	630	1,173	652	1,481	3,936

The top part of Table 1b reports summary statistics of all the firms in the dataset. Statistics are split by firms' industry. The bottom part report firms' statistics at a fixed point of time – the beginning of the sample period – 2011 Q4.

*A firm is said to have a relationship with a bank if it had some outstanding debt with that bank within the previous 12 months.

TABLE 1c

Summary statistics of pre-shock firm characteristics

	# of firms	# of firms with $exclusive_f$=1	% of firms with $exclusive_f$=1	# of firms with rep_delays_f=1	% of firms with rep_delays_f=1	Average firm $size_f$ (in euros)	Average firm age_f (in quarters)	Average firm rel_length_f (in quarters)	Average firm $collateralization_f$	Average ttm_f (in quarters)	# of firms with $long\_maturity_f$=1	% of firms with $long\_maturity_f$=1
1. "Distressed bank's" customers	**1,158**	**485**	**42%**	**224**	**19%**	**1,371,016**	**23**	**19**	**1.18**	**9**	**169**	**15%**
1.1. Assigned to "bad bank"	**260**	**141**	**54%**	**72**	**28%**	**1,427,151**	**26**	**21**	**1.19**	**10**	**33**	**13%**
1.1.1. Took new loans after shock	112	48	43%	3	3%	454,386	25	19	1.22	12	15	13%
1.1.2. No new loans after shock	148	93	63%	69	47%	2,163,298	28	23	1.17	8	18	12%
1.2. Not assigned to "bad bank"	**898**	**344**	**38%**	**152**	**17%**	**1,354,763**	**22**	**18**	**1.18**	**9**	**136**	**15%**
1.2.1. Took new loans after shock	449	132	29%	43	10%	1,892,636	26	19	1.03	11	66	15%
1.2.1.1. Not from "Acquiring bank"	222	59	27%	13	6%	2,455,343	25	19	0.77	11	31	14%
1.2.1.2. From "Acquiring bank"	227	73	32%	30	13%	1,342,322	26	19	1.28	12	35	15%
1.2.2. No new loans after shock	449	212	47%	109	24%	816,891	19	17	1.33	7	70	16%
2. All other firms	**16,798**	**12,285**	**73%**	**2,749**	**16%**	**663,703**	**24**	**21**	**0.78**	**10**	**3,784**	**23%**
2.1. Took new loans after shock	7,804	5,164	66%	492	6%	986,765	25	21	0.80	11	1,662	21%
2.2. No new loans after shock	8,994	7,121	79%	2,257	25%	383,385	23	21	0.75	8	2,122	24%
Total (1+2)	**17,956**	**12,770**	**71%**	**2,973**	**17%**	**709,318**	**24**	**21**	**0.80**	**10**	**3,953**	**22%**

Table 1c reports average pre-shock firm characteristics for different subgroups of firms. The sample is split into the treatment group (1. "Distressed bank's" customers) and the control group (2. All other firms). The treatment group is split into firms that were assigned to the "bad bank" (1.1.), and firms that were not (1.2.). All groups are the split into firms that took at least one new loan after the shock, and thus reappeared in the credit register after the bank closure, and firms that did not. "Distressed bank's" customers that were not assigned to the "bad bank" and borrowed again (1.2.1) are split further based on whether they took new loans from the "Acquiring bank" or not. The variables in the top row are defined as follows:

- $exclusive_f$ is defined below the specifications (1-3).
- $size_f$ is firm's *f* maximum debt (in m EUR) to banks in the pre-shock sample period.
- age_f is the time difference (in quarters) between the shock and the first appearance of firm *f* in the credit register since 1995.
- rel_length_f is firm's *f* average length (in quarters) of existing lending relationships at the moment of the shock.
- rep_delays_f is a dummy variable equal to 1 if firm *f* had at least one repayment delay in the pre-shock sample period, and zero otherwise.
- ttm_f is the longest remaining time to maturity (in quarters) of firm's *f* loans outstanding at the moment of the shock.
- $collateralization_f$ is firm's *f* average (across loans and quarters) collateralization ratio, i.e., loan collateral value divided by loan outstanding amount, of loans outstanding in the pre-shock sample period.
- $long\_maturity_f$ is a dummy variable equal to 1 if firm's *f* average remaining time to maturity of loans outstanding before the shock was longer than three years, and zero otherwise.

TABLE 2

Difference-in-differences of borrowing costs. Main results

	Model specification:	Specification 1 (**all** surviving firms)	Specification 1 (**matched** surviving firms)	Specification 6 (**all** surviving firms)	Specification 6 in the Heckman model (**all** firms)	Specification 6 in the Heckman model (**matched** firms)
		(1)	(2)	(3)	(4)	(5)
	1. Treatment group: all (good and bad) "Distressed bank's" customers					
Row 1	Difference-in-differences	-0.424***	-0.436***	-0.457***	-0.480***	-0.406***
		(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
	Observations	149,684	23,873	8,365	17,925	2,761
	# of firms in treatment group	561	344	561	1,158	677
	# of firms in control group	7,804	1,022	7,804	16,798	2,086
	2. Treatment group: Good "Distressed bank's" customers – not assigned to "bad bank" by KPMG					
Row 2	Difference-in-differences	-0.596***	-0.676***	-0.689***	-0.720***	-0.722***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Observations	147,636	22,210	8,253	17,725	2,621
	# of firms in treatment group	449	254	449	898	524
	# of firms in control group	7,804	1,022	7,804	16,798	2,086
	3. Treatment group: Bad "Distressed bank's" customers – assigned to "bad bank" by KPMG					
Row 3	Difference-in-differences	0.270	0.249	0.472**	0.493***	0.529**
		(0.140)	(0.224)	(0.037)	(0.004)	(0.014)
	Observations	141,275	19,215	7,916	17,002	2,225
	# of firms in treatment group	112	90	112	260	153
	# of firms in control group	7,804	1,022	7,804	16,798	2,086
	4. Treatment group: all "Healthy bank's" customers					
Row 4	Difference-in-differences	0.184	-0.341	0.201	0.241	-0.163
		(0.142)	(0.192)	(0.153)	(0.175)	(0.574)
	Observations	150,675	2,794	8,393	17,925	235
	# of firms in treatment group	116	36	116	153	54
	# of firms in control group	8,277	107	8,277	17,803	181

Table 2 reports difference-in-differences of borrowing costs between closed banks' customers and other firms around the banks' closures, estimated using five model specifications (listed in columns) and four treatment groups (listed in rows and underlined). In all four cases, the control group comprises firms that were not customers of the closed bank. Column (1) reports β_3 coefficient from specification (1) estimated using all "surviving" firms, i.e., those that took at least one loan both before and after the bank closure. Column (2) reports the same coefficient estimated using those "surviving" firms in both treatment and control groups that were matched on the seven ex-ante characteristics as described in Section "5. Empirical strategy". Column (3) reports β_1 coefficient from specification (6) using all "surviving" firms without the Heckman correction. Column (4) reports the same coefficient with the Heckman correction, i.e., including "non-surviving" firms for the estimation of the selection equation (specification 5). Column (5) reports the same coefficient with the Heckman correction but considers only matched firms. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, two-tailed, respectively. Robust standard errors are clustered multiway at the firm and quarter levels in columns (1) and (2), and unclustered in columns (3) to (5). Heckman's model in columns (4) and (5) is estimated using Heckman's two-step consistent estimator, but the results are robust to using maximum likelihood. The inverse mills ratio is never statistically significant, except when using unmatched bad, i.e., assigned to the "bad bank", customers of "Distressed bank" (i.e., column 4, row 3) as a treatment group (λ=0.138, p-value=0.081). The coefficient on the instrumental variable $long\_maturity_f$ is always negative and statistically significant at the 1% level.

TABLE 3

Test of the Parallel Trends Assumption

	Dependent variable: borrowing_costs			
Treatment group:	Matched surviving good "Distressed bank's" customers – not assigned to "bad bank" by KPMG		All matched surviving "Distressed bank's" customers	
	(1)	(2)	(3)	(4)
closed x dummy_2011q4	(omitted)	0.605***	(omitted)	0.296**
	-	(0.000)	-	(0.037)
closed x dummy_2012q1	0.106	0.711***	0.080	0.376**
	(0.196)	(0.000)	(0.293)	(0.016)
closed x dummy_2012q2	0.157**	0.762***	0.063	0.359**
	(0.033)	(0.000)	(0.307)	(0.019)
closed x dummy_2012q3	0.142**	0.747***	0.048	0.344**
	(0.039)	(0.000)	(0.397)	(0.023)
closed x dummy_2012q4	0.225***	0.830***	0.106***	0.402***
	(0.000)	(0.000)	(0.007)	(0.004)
closed x dummy_2013q1	-0.605***	(omitted)	-0.296**	(omitted)
	(0.000)	-	(0.028)	-
closed x dummy_2013q2	-0.563***	0.042	-0.275**	0.021
	(0.000)	(0.109)	(0.021)	(0.447)
closed x dummy_2013q3	-0.491***	0.114	-0.233**	0.063*
	(0.000)	(0.136)	(0.044)	(0.074)
closed x dummy_2013q4	-0.453***	0.152	-0.196*	0.100*
	(0.000)	(0.104)	(0.072)	(0.092)
closed x dummy_2014q1	-0.446***	0.160	-0.193*	0.103
	(0.000)	(0.101)	(0.071)	(0.143)
closed x dummy_2014q2	-0.541***	0.064	-0.266**	0.030
	(0.000)	(0.527)	(0.017)	(0.714)
closed x dummy_2014q3	-0.522***	0.083	-0.205*	0.091
	(0.000)	(0.408)	(0.067)	(0.309)
closed x dummy_2014q4	-0.601***	0.004	-0.322***	-0.026
	(0.000)	(0.968)	(0.006)	(0.790)
closed x dummy_2015q1	-0.569***	0.036	-0.322***	-0.026
	(0.000)	(0.756)	(0.007)	(0.799)
closed x dummy_2015q2	-0.544***	0.061	-0.297***	-0.001
	(0.000)	(0.603)	(0.010)	(0.989)
closed x dummy_2015q3	-0.623***	-0.018	-0.440***	-0.144
	(0.000)	(0.884)	(0.000)	(0.201)
closed x dummy_2015q4	-0.659***	-0.053	-0.497***	-0.201*
	(0.000)	(0.646)	(0.000)	(0.062)
closed x dummy_2016q1	-0.629***	-0.024	-0.476***	-0.180
	(0.000)	(0.848)	(0.000)	(0.113)
closed x dummy_2016q2	-0.599***	0.006	-0.460***	-0.164
	(0.000)	(0.958)	(0.000)	(0.146)
closed x dummy_2016q3	-0.592***	0.013	-0.458***	-0.162
	(0.000)	(0.916)	(0.000)	(0.151)
closed x dummy_2016q4	-0.565***	0.040	-0.433***	-0.137
	(0.000)	(0.741)	(0.000)	(0.219)
closed x dummy_2017q1	-0.524***	0.081	-0.420***	-0.124
	(0.000)	(0.505)	(0.000)	(0.270)
closed x dummy_2017q2	-0.462***	0.143	-0.395***	-0.099
	(0.000)	(0.291)	(0.000)	(0.408)
closed x dummy_2017q3	-0.487***	0.119	-0.432***	-0.136
	(0.000)	(0.397)	(0.000)	(0.268)
closed x dummy_2017q4	-0.505***	0.100	-0.436***	-0.140
	(0.000)	(0.454)	(0.000)	(0.241)
closed x dummy_2018q1	-0.524***	0.081	-0.404***	-0.108
	(0.000)	(0.522)	(0.000)	(0.346)
Observations	22,210	22,210	23,873	23,873
Adjusted R-squared	0.655	0.655	0.648	0.648

Table 3 reports coefficients from regression specification (4) on interaction terms between time period dummies and the treatment variable "closed" equal to 1 if a firm was a customer of "Distressed bank". We use two different treatment groups listed on top. In all cases, the control group comprises all surviving firms that were not customers of the closed bank. The base quarter (i.e., excluded dummy) is 2011 q4 in columns (1) and (3), and 2013 q1 in column (2) and (4). In parentheses we report P-values. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, two-tailed, respectively. Robust standard errors are clustered multiway at the firm and quarter levels. All regressions include a constant, time-fixed effects and firm-fixed effects.

TABLE 4								
Difference-in-differences of borrowing costs. Heterogeneous effects among good firms (by KPMG)								
	Dependent variable: borrowing_costs							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
after x closed	-0.596***	-0.399***	-0.392***	-0.244**	-0.339***	-0.384***	-0.301**	-0.353***
	(0.000)	(0.001)	(0.003)	(0.041)	(0.008)	(0.002)	(0.014)	(0.006)
after x closed x exclusive		-0.881**				-0.101	0.150	-0.042
		(0.018)				(0.785)	(0.602)	(0.898)
after x closed x small			-0.562**			-0.020		
			(0.041)			(0.935)		
after x closed x young				-1.011***			-0.279	
				(0.001)			(0.222)	
after x closed x short_term					-0.533**			-0.053
					(0.032)			(0.801)
after x closed x exclusive x small						-1.215*		
						(0.064)		
after x closed x exclusive x young							-1.948***	
							(0.006)	
after x closed x exclusive x short_term								-1.413**
								(0.036)
Firm-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	147,636	147,636	147,636	147,636	147,636	147,636	147,636	147,636
Adjusted R-squared	0.695	0.696	0.696	0.697	0.697	0.697	0.698	0.698

Table 4 reports coefficient estimates from difference-in-differences panel regression specification (1) (column 1), specification (2) (columns 2, 3, 4 and 5), and specification (3) (columns 6, 7 and 8) with different ex-ante firm characteristics replacing variable *char*. The data used in the analysis is at the quarter-firm level and includes all firms that took at least one new loan both before and after "Distressed bank's" closure except for firms that were assigned to the "bad bank" by KPMG. The dependent variable "borrowing_costs" is a firm's average interest rate weighted by loan outstanding amounts at each quarter. In quarters 2011q4 - 2012q4, we consider only leasing contracts, term loans and credit lines issued up to 2012 December 31. In quarters 2013q1 - 2018q1, we consider only leasing contracts, term loans and credit lines issued from 2013 February 12 (the day of "Distressed bank's" closure). The explanatory variables are dummies: "after" - equal to 1 if an observation is from quarters 2013q1 - 2018q1, and 0 otherwise; "closed" – equal to 1 if a firm belongs to the treatment group, i.e., had any debt outstanding with the closed "Distressed bank" within one year prior to 2013 February 12, and 0 otherwise; "exclusive" – equal to 1 if a firm had debts only with one bank within the same prior year, and 0 otherwise; "small" equal to 1 if a firm's maximum total debt to banks from 2011 q4 to 2013 q1 was smaller than the median of "Distressed bank's" customers, and zero otherwise; "young" equal to 1 if, as of 2013 q1, a firm's first appearance in the credit register was later than the median of "Distressed bank's" customers, and zero otherwise; "short_term" equal to 1 if, as of 2013 q1, a firm's average relationship length with its banks was shorter than the median of "Distressed bank's" customers, and 0 otherwise. Regressions include a constant and all double and triple interaction terms but, for brevity, only the interactions of interest are reported. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, two-tailed, respectively. Robust standard errors are clustered multiway at the firm and quarter levels.

TABLE 5
Difference-in-differences of borrowing costs. Heterogeneous effects among the best firms (those that were not assigned to the “bad bank” by KPMG and switched for new loans to other banks than “Acquiring bank”)

	Dependent variable: borrowing_costs							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
after x closed	-1.051***	-0.556***	-0.680***	-0.570***	-0.741***	-0.593***	-0.497***	-0.614***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
after x closed x exclusive		-2.544***				-1.005**	-0.816*	-0.989**
		(0.000)				(0.014)	(0.085)	(0.041)
after x closed x small			-0.969**			0.163		
			(0.022)			(0.573)		
after x closed x young				-1.220***			-0.109	
				(0.004)			(0.693)	
after x closed x short_term					-0.618*			0.222
					(0.096)			(0.396)
after x closed x exclusive x small						-2.255**		
						(0.018)		
after x closed x exclusive x young							-2.895***	
							(0.006)	
after x closed x exclusive x short_term								-2.696**
								(0.012)
Firm-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	120,756	120,756	120,756	120,756	120,756	120,756	120,756	120,756
Adjusted R-squared	0.700	0.703	0.702	0.702	0.703	0.705	0.706	0.707

Table 5 reports coefficient estimates from difference-in-differences panel regression specification (1) (column 1), specification (2) (columns 2, 3, 4 and 5), and specification (3) (columns 6, 7 and 8) with different ex-ante firm characteristics replacing variable *char*. The data used in the analysis is at the quarter-firm level and includes all firms that took at least one new loan both before and after “Distressed bank’s” closure except for firms that either were assigned to the “bad bank” by KPMG and/or took at least one post-shock loan from “Acquiring bank”. The dependent variable “borrowing_costs” is a firm’s average interest rate weighted by loan outstanding amounts at each quarter. In quarters 2011q4 - 2012q4, we consider only leasing contracts, term loans and credit lines issued up to 2012 December 31. In quarters 2013q1 - 2018q1, we consider only leasing contracts, term loans and credit lines issued from 2013 February 12 (the day of “Distressed bank’s” closure). The explanatory variables are dummies: “after” - equal to 1 if an observation is from quarters 2013q1 - 2018q1, and 0 otherwise; “closed” – equal to 1 if a firm belongs to the treatment group, i.e., had any debt outstanding with the closed “Distressed bank” within one year prior to 2013 February 12, and 0 otherwise; “exclusive” – equal to 1 if a firm had debts only with one bank within the same prior year, and 0 otherwise; “small” equal to 1 if a firm’s maximum total debt to banks from 2011 q4 to 2013 q1 was smaller than the median of “Distressed bank’s” customers, and zero otherwise; “young” equal to 1 if, as of 2013 q1, a firm’s first appearance in the credit register was later than the median of “Distressed bank’s” customers, and zero otherwise; “short_term” equal to 1 if, as of 2013 q1, a firm’s average relationship length with its banks was shorter than the median of “Distressed bank’s” customers, and 0 otherwise. Regressions include a constant and all double and triple interaction terms but, for brevity, only the interactions of interest are reported. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, two-tailed, respectively. Robust standard errors are clustered multiway at the firm and quarter levels.

TABLE 6									
Alternative explanations and robustness checks									
	Dependent variable: borrowing_costs						Different dependent variables		
Alterations of the default setting:	1. Only term loans	2. Only leasing contracts	3. Different control group	4. Only newly issued loans	5. Assigned neither to "bad" nor "good" bank	6. No first switching loans	9. Dep. var: collateral	10. Dep. var: maturity	11. Dep. var: loan size
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
after x closed	-0.566**	-0.525***	-1.026***	-0.523***	-0.506***	-0.496**	0.018	-0.506	28.995
	(0.013)	(0.000)	(0.000)	(0.009)	(0.003)	(0.027)	(0.857)	(0.168)	(0.792)
Firm-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	34,342	94,035	24,792	23,932	145,338	142,152	147,636	147,636	147,636
Adjusted R-squared	0.745	0.720	0.638	0.604	0.691	0.690	0.579	0.470	0.804

Table 6 reports coefficient estimates from difference-in-differences panel regression specification (1) for 9 alterations of the default setting (see Table 4), which is defined as follows. The dependent variable is firm-quarter level “borrowing_costs” (i.e., firm’s average interest rate weighted by loan outstanding amounts at each quarter). In quarters 2011q4 - 2012q4, we consider only leasing contracts, term loans and credit lines issued up to 2012 December 31. In quarters 2013q1 - 2018q1, we consider only leasing contracts, term loans and credit lines issued from 2013 February 12 (the day of “Distressed bank’s” closure). The explanatory variables are dummies: “after” - equal to 1 if an observation is from quarters 2013q1 - 2018q1, and 0 otherwise; “closed” – equal to 1 if a firm belongs to the treatment group, i.e., had any debt outstanding with the closed “Distressed bank” within one year prior to 2013 February 12, and 0 otherwise; and the interaction between the two. Only surviving good firms are considered, i.e., those that appeared in the credit register both before and after the shock and were not assigned to the “bad bank” by KPMG. The alterations of this setting are as follows (by column):

1) Only term loans: “borrowing_costs” are calculated using term loans only.
2) Only leasing contracts: “borrowing_costs” are calculated using leasing contracts only.
3) Different control group: the control group includes only those firms that were customers of “Acquiring bank” – the most similar one to “Distressed bank”.
4) Only newly issued loans: only newly loans issued in every quarter are considered.
5) Assigned neither to “bad” nor “good” bank: the treatment group comprises only those “Distressed bank’s” customers which had their assets and liabilities netted off during the bank closure and thus were not assigned either to “good bank” or to “bad bank”.
6) No first switching loans: the first loans taken by “Distressed bank’s” borrowers after they lost their sole lending relationships are excluded from the sample.
7) Dep. variable: collateral: the dependent variable is calculated using a percentage of loan collateralized (i.e., collateral value divided by the loan outstanding amount) instead of a loan’s interest rate.
8) Dep. variable: maturity: the dependent variable is calculated using a loan’s time to maturity (in years) instead of a loan’s interest rate.
9) Dep. variable: loan size: the dependent variable is calculated using a loan’s amount (in thousands of euros) instead of a loan’s interest rate.

P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, two-tailed, respectively. Robust standard errors are clustered multiway at the firm and quarter levels.

TABLE 7		
Post-shock loan matching variables		
Category	**Matching variable**	**Two loans were matched if:**
Macro	Year_quarter	Both loans were issued in the same year and quarter.
Bank	Bank	Both loans were issued by the same bank.
Firm	Age (+-1 year)	The first appearance of both firms in the credit register was in the same quarter (+- 1 year).
Firm	Size (+-30%)	In the quarter of the loan issuance, both firms had a similar (+-30%) total debt to banks.
Firm	Collateralization (+-30%)	In the quarter of the loan issuance, both firms had a similar (+-30%) average collateralization ratio, i.e., loan collateral value divided by loan outstanding amount, across their outstanding loans.
Firm	Rep_delays (1 or 0)	Either both firms had at least one or both firms had zero repayment delays up to the quarter of the loan issuance.
Firm	Exclusive (1 or 0)	Either both firms had loans outstanding with only one bank or both firms had loans outstanding with more than one bank within one year before the "Distressed bank's" closure.
Firm	Ttm (+-1 year)	In the quarter of the loan issuance, both firms' latest maturing loans had a similar (+-1 year) maturity date.
Firm	Rel_length (+-1 year)	In the quarter of the loan issuance, both firms had a similar (+-1 year) average (across their banks) length of existing lending relationships.
Loan	Loan_type	Both loans were of the same type, i.e., term loans, leasing contracts or credit lines.
Loan	Loan_ttm (+-1 year)	Both loans had a similar (+-1 year) time to maturity.
Loan	Loan_size (+-30%)	Both loans had a similar (+-30%) loan amount.
Loan	Loan_collateral (+-30%)	Both loans had a similar (+-30%) collateralization ratio, loan collateral value divided by loan amount.

Table 7 provides variables' descriptions for the post-shock loan matching analysis whereby loans of good, i.e., not assigned to the "bad bank" by KPMG, "Distressed bank's" ex-ante customers are matched with loans of other firms that were not ex-ante customers of "Distressed bank". Loans are matched by the variables Size, Collateralization, Loan_size and Loan_collateral if variable values of "Distressed bank's" customers fall within a (-30%; +30%) interval around the respective values of non-customers. Similarly, loans are matched on variables Age, Ttm, Rel_length and Loan_ttm if variable values of "Distressed bank's" customers fall within a (-1 year; +1 year) interval around the respective values of non-customers. We match loans on exact values of variables Year_quarter, Bank, Loan_type, Exclusive and Rep_delays.

TABLE 8				
Post-shock Loan Matching Results				
Matching variables:	(1)	(2)	(3)	(4)
Bank	Yes	Yes	Yes	Yes
Year_quarter	Yes	Yes	Yes	Yes
Loan_type	Yes	Yes	Yes	Yes
Age (+-1 year)	Yes	Yes	Yes	Yes
Size (+-30%)	Yes	Yes		Yes
Collateralization (+-30%)		Yes		Yes
Rep_delays (1 or 0)		Yes	Yes	Yes
Exclusive (1 or 0)		Yes	Yes	Yes
Ttm (+-1 year)		Yes		Yes
Rel_length (+-1 year)		Yes	Yes	Yes
Loan_ttm (+-1 year)			Yes	Yes
Loan_size (+-30%)			Yes	Yes
Loan_collateral (+-30%)			Yes	Yes
Number of “Distressed bank’s” clients	393	46	181	20
Number of other firms	2,661	68	513	23
Number of loans issued to “Distressed bank’s” clients	2,119	105	703	33
Number of loans issued to other firms	7,244	117	1,156	29
Number of observations (matched pairs)	17,421	234	2,142	45
Spread in basis points	**-1.3**	**-6.9**	**4.9**	**-24.9**
	(0.709)	**(0.365)**	**(0.323)**	**(0.244)**

Table 8 reports an average spread between an interest rate on a new loan issued after the “Distressed bank’s” closure to a good, i.e., not assigned to “bad bank” by KPMG, “Distressed bank’s” ex-ante customer and an interest rate on a similar new loan issued in the same quarter by the same bank to a similar firm which was not an ex-ante customer of “Distressed bank”. A firm is considered a bank’s ex-ante customer if it had any outstanding loans with that bank within one year before the “Distressed bank’s” closure. All loans in the analysis are considered only once, i.e., in a quarter of issuance. We use matching variables defined in Table 7 and listed in the first column of this table to pair every loan taken by “Distressed bank’s” customers with as many as possible loans taken by other firms. Estimated interest rate spreads are regressed on a constant. The estimated coefficients on the constant are reported in the bottom row. Every column represents a different set of matching variables used. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, two-tailed, respectively. Robust standard errors are clustered at the “Distressed bank” customers’ loan level.

References

Angelini P, Salvo RD, Ferri G (1998) Availability and cost of credit for small businesses: customer relationships and credit cooperatives. *Journal of Banking & Finance*. 22(6-8):925-954. doi:10.1016/s0378-4266(98)00008-9

Ashcraft AB (2005) Are banks really special? New evidence from the FDIC-induced failure of healthy banks. *American Economic Review*. 95(5):1712-1730.

Bank of Lithuania (2011) Informacija apie kredito ir mokėjimo įstaigų veiklą bei jų priežiūrą 2011 m. Retrieved May 17, 2021, https://www.lb.lt/uploads/documents/files/news/informacija_apie_kredito_ir_mokejimo_istaigu_veikla_bei_ju_prieziura_2011_m.pdf.

Beck T, Degryse H, Haas RD, van Horen N (2018) When arm's length is too far: relationship banking over the credit cycle. *Journal of Financial Economics*. 127(1):174-196. doi:10.1016/j.jfineco.2017.11.007

Berger AN, Udell GF (1995) Relationship lending and lines of credit in small firm finance. *The Journal of Business*, 68(3).

Berlin M, Mester LJ (1999) Deposits and relationship lending. *The Review of Financial Studies*. 12(3):579.

Bernanke BS (1983) Nonmonetary effects of the financial crisis in the propagation of the great depression. *American Economic Review*. 73:257-276.

Bharath ST, Dahiya S, Saunders A, Srinivasan A (2011) Lending relationships and loan contract terms. *The Review of Financial Studies*. 24(4):1141-1203. doi:10.1093/rfs/hhp064

BNS and lrytas.lt (2012). Ūkio ir Šiaulių bankai gali būti sujungti? Lrytas.lt. Retrieved May 17, 2021, https://www.lrytas.lt/verslas/rinkos-pulsas/2012/12/19/news/ukio-ir-siauliu-bankai-gali-buti-sujungti--5156246/.

Bolton P, Freixas X, Gambacorta L, Mistrulli PE (2016) Relationship and transaction lending in a crisis. *The Review of Financial Studies*. 29(10):2643-2676. doi:10.3386/w19467

Bonfim D, Nogueira G, Ongena SR (2020) Sorry, we’re closed: bank branch closures, loan pricing, and information asymmetries. *Review of Finance*. doi.org/10.1093/rof/rfaa036

Boot AW, Thakor AV (2000) Can relationship banking survive competition? *The Journal of Finance*. 55(2):679-713. doi:10.1111/0022-1082.00223

Boot AW, Greenbaum SI, Thakor AV (1993) Reputation and discretion in financial contracting. *American Economic Review*. 83(5):1165-1183.

Botsch M, Vanasco V (2019) Learning by lending. *Journal of Financial Intermediation*. 37:1-14. doi:https://doi.org/10.1016/j.jfi.2018.03.002

Caballero RJ, Hoshi T, Kashyap AK (2008) Zombie lending and depressed restructuring in Japan. *American Economic Review*. 98(5):1943–1977. doi: 10.1257/aer.98.5.1943

Carvalho DR, Ferreira MA, Matos PP (2015) Lending relationships and the effect of bank distress: evidence from the 2007-2008 financial crisis. *Journal of Financial and Quantitative Analysis*. 50(6):1165-1197.

Chava S, Purnanandam AK (2011) The effect of banking crisis on bank-dependent borrowers. *Journal of Financial Economics*. 99(1):116-135. doi:https://doi.org/10.1016/j.jfineco.2010.08.006

Chodorow-Reich G (2014) The employment effects of credit market disruptions: firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics*. 129(1):1-59. doi:10.1093/qje/qjt031

Ciulada P (2013). Gerosios Ūkio banko dalies gelbėjimo operacija valstybei kainuos 128 mln. Lt brangiau. Verslo Zinios. Retrieved May 17, 2021, https://www.vz.lt/archive/article/2013/10/11/gerosios-ukio-banko-dalies-gelbejimo-operacija-valstybei-kainuos-128-mln-lt-brangiau.

Dahiya S, Saunders A, Srinivasan A (2003) Financial distress and bank lending relationships. *The Journal of Finance*. 50(1):375-399.

Darmouni O (2020) Informational frictions and the credit crunch. *The Journal of Finance*. 75(4):2055-2094. https://doi.org/10.1111/jofi.12900

Degryse HA, Ongena SR (2005) Distance, lending relationships and competition. *The Journal of Finance*. 60(1):231-266. doi:https://doi.org/10.1111/j.1540-6261.2005.00729.x

Dell'Ariccia G, Marquez R (2004) Information and bank credit allocation. *Journal of Financial Economics*. 72(1):185-214. doi:10.1016/s0304-405x(03)00210-1

Diamond DW (1984) Financial intermediation and delegated monitoring. *The Review of Economic Studies*. 51(3):393. doi:10.2307/2297430

Falato A, Liang N (2016) Do creditor rights increase employment risk? Evidence from loan covenants. *The Journal of Finance*. 71(6):2545–2590. doi: 10.1111/jofi.12435

Heckman JJ (1979) Sample selection bias as specification error. *Econometrica*. 47:153—161.

Heckman JJ, Ichimura H, Smith JA, Todd PE (1998) Characterizing selection bias using experimental data. *Econometrica*. 66:1017–1099.

Hubbard RG, Kuttner KN, Palia D (2002) Are there bank effects in borrowers' costs of funds? Evidence from a matched sample of borrowers and banks. *The Journal of Business*. 75(4):559-581.

Ioannidou V, Ongena SR (2010) Time for a change: loan conditions and bank behavior when firms switch banks. *The Journal of Finance*. 65(5).

Ivashina V, Scharfstein DS (2010) Bank lending during the financial crisis of 2008. *Journal of Financial Economics*. 97(3):319-338.

Jappelli T, Pagano M (2002) Information sharing, lending and defaults: cross-country evidence. *Journal of Banking & Finance*. 26(10):2017–2045. doi: 10.1016/s0378-4266(01)00185-6

Jiménez G, Ongena S, Peydró JL, Saurina J (2017) Macroprudential policy, countercyclical bank capital buffers, and credit supply: evidence from the Spanish dynamic provisioning experiments. *Journal of Political Economy*. 125:2126–77.

Kang A, Lowery R, Wardlaw M (2015) The costs of closing failed banks: a structural estimation of regulatory incentives. *The Review of Financial Studies*. 28(4):1060–1102. doi: 10.1093/rfs/hhu076

Khwaja AI, Mian A (2008) Tracing the impact of bank liquidity shocks: evidence from an emerging market. *American Economic Review*. 98(4):1413-1442. doi:10.1257/aer.98.4.1413

Kim K, Lee MJ (2018) Difference in differences in reverse. *Empirical Economics*. 57(3):705–725. doi: 10.1007/s00181-018-1465-0

Kim M, Kliger D, Vale B (2003) Estimating switching costs: the case of banking. *Journal of Financial Intermediation*. 12(1):25–56. doi: 10.1016/s1042-9573(02)00005-0

Klemperer P (1987) Markets with consumer switching costs. *The Quarterly Journal of Economics*. 102(2):375-394.

Korte J (2015) Catharsis - tracing the real effects of bank insolvency and resolution. *Journal of Financial Stability*. 16:213-231.

Kuodis R (2013) R.Kuodis: Valstybės įstaigų vadovai turėjo suprasti, kad dėti pinigus į Ūkio banką yra rizikinga. Retrieved May 17, 2021, https://www.delfi.lt/verslas/archive/rkuodis-valstybes-istaigu-vadovai-turejo-suprasti-kad-deti-pinigus-i-ukio-banka-yra-rizikinga.d?id=60663867.

Kysucky V, Norden L (2015) The benefits of relationship lending in a cross-country context: a meta-analysis. *Management Science*. 62(1).

Li Y, Srinivasan A, Lu R (2019) Relationship bank behavior during borrower distress. *Journal of Financial and Quantitative Analysis*. 54(3):1231-1262. doi.org/10.1017/S0022109018001084

Little RJA, Rubin DB (1987) *Statistical analysis with missing data* (John Wiley & Sons, New York).

Lopez-Espinosa G, Mayordomo S, Moreno A (2017) When does relationship lending start to pay? *Journal of Financial Intermediation*. 31:16-29.

Martin-Oliver A, Toldrà-Simats A, Vicente S (2020) The real effects of bank branch closings and restructurings. Working paper, http://dx.doi.org/10.2139/ssrn.3644878

Minamihashi N (2011) Credit crunch caused by bank failures and self-selection behavior in lending markets. *Journal of Money, Credit and Banking*. 43(1):133-161. doi:10.1111/j.1538-4616.2010.00368.x

Montgomery JM, Nyhan B, Torres M (2018) How conditioning on posttreatment variables can ruin your experiment and what to do about it. *American Journal of Political Science*, 62(3):760–775. doi: 10.1111/ajps.12357

OECD (2017) Lithuania: review of the financial system (report). OECD. Retrieved May 17, 2021, https://www.oecd.org/finance/Lithuania-financial-markets-2017.pdf.

Ongena SR, Smith DC, Michalsen D (2003) Firms and their distressed banks: lessons from the Norwegian banking crisis. *Journal of Financial Economics*. 67(1):81-112. doi:10.1016/s0304-405x(02)00232-5

Padilla AJ, Pagano M (1997) Endogenous communication among lenders and entrepreneurial incentives. *Review of Financial Studies*. 10(1):205–236. doi: 10.1093/rfs/10.1.205

Petersen MA, Rajan RG (1994) The benefits of lending relationships: evidence from small business data. *The Journal of Finance*. 49(1):3. doi:10.2307/2329133

Petersen MA, Rajan RG (1995) The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics*. 110(2):407-443. doi:https://doi.org/10.2307/2118445

Rajan RG (1992) Insiders and outsiders: the choice between informed and arms-length debt. *The Journal of Finance*. 47(4):1367-1400. doi:10.1111/j.1540-6261.1992.tb04662.x

Santos JA (2011). Bank corporate loan pricing following the subprime crisis. *The Review of Financial Studies*. 24(6):1916-1943. doi:https://doi.org/10.1093/rfs/hhq115

Schäfer L (2018) Forgive but not forget: the behavior of relationship banks when firms are in distress. *Review of Finance*. doi:10.1093/rof/rfy031

Schenone C (2009) Lending relationships and information rents: do banks exploit their information advantages? *Review of Financial Studies*. 23(3):1149-1199. doi:10.1093/rfs/hhp080

Schnabl P (2012) The international transmission of bank liquidity shocks: evidence from an emerging market. *The Journal of Finance*. 67(3):897-932. doi:10.1111/j.1540-6261.2012.01737.x

Sette E, Gobbi G (2015) Relationship lending during a financial crisis. *Journal of the European Economic Association*. 13(3):453-481.

Sharpe SA (1990) Asymmetric information, bank lending and implicit contracts: a stylized model of customer relationships. *The Journal of Finance*. 45(4):1069. doi:10.2307/2328715

Slovin MB, Sushka ME, Polonchek JA (1993) The value of bank durability: borrowers as bank stakeholders. *The Journal of Finance*. 48(1):247-266. doi:10.1111/j.1540-6261.1993.tb04708.x

Smith JA, Todd PE (2005) Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics*. 125(1-2):305–353.

Vasiliauskaitė G, Gudavičius S (2014) Deloitte Lietuva nubausta už Ūkio banko auditą. Retrieved May 17, 2021, https://www.vz.lt/archive/article/2014/8/1/deloitte-lietuva-drausmines-nuobaudos-del-ukio-banko-audito.

von Thadden E (2004) Asymmetric information, bank lending and implicit contracts: The winners curse. *Finance Research Letters*. 1(1):11-23. doi:10.1016/s1544-6123(03)00006-0